# Short-term socio-ecological effects of a localised change in commercial fishing pressure in Queensland, Australia


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**Abstract**

Commercial netting closures near three regional cities of Queensland were implemented in 2015 to conserve commercially and recreationally important species by reducing commercial harvest pressure on fish stocks, increase recreational fishing opportunities, marine-based tourism, and resultant economic growth. Understanding the social, ecological, and economic effects of the closures can allow for future adjustments to improve recreational catch and effort factors. The current study compared the values of the three recently established net-free zones (NFZs) with three reference areas of Queensland where commercial net fishing activities continue.

For the social aspect, the study determined and compared the recreational fishers' satisfaction and expectations between a NFZ and a reference site. Recreational fishers were surveyed when returning from fishing tackle stores. Along with the graphical summary of Likert scale responses, non-parametric tests and regression analyses were carried out to analyse fishes' satisfaction. The underlying relationship among recreational fishers' satisfaction, overall satisfaction, and expectation was identified by developing a structural equation model for a NFZ and a reference site. The result suggested that fishing satisfaction and expectations are higher in the NFZ than in the reference site. The structural equation modelling (SEM) identified the most influential factors that represent latent variable satisfaction and expectation and demonstrated the relationship and the strength of their relationship for each of the study sites.

It is expected that the netting closure might improve the stock structure of the commercially and recreationally important fish barramundi (*Lates calcarifer*) through natural recruitment. For the ecological aspect, the study developed and tested autoregressive integrated moving average with exogenous input (ARIMAX) models and lagged multiple linear regression (MLR) models to predict and establish the relationship between barramundi catch per unit effort (CPUE) and some fishery and environmental factors that affect barramundi. The study used 30 years of time series data from the secondary sources for the three NFZs and three reference sites. The finding suggests that the ARIMAX model outperformed the MLR model. The study also demonstrated that both fishery and environmental parameters played a role in influencing the CPUE, but most scenarios showed that environmental parameters such as rainfall, streamflow, and stream water level and fishery parameters such as licences and price are the key determinants of CPUE. The study provided valuable insights into the effect of management changes in the commercial CPUE to ensure recreational opportunities and sustainable management of barramundi.

For the economic aspects, the study integrated boat ramp survey data and secondary data to develop postcode, zoned, and geographic travel cost method (TCM) models for the six study sites. The postcode and zoned models were designed to include fishers of maximum 100 km and 300 km distance thresholds, and the geographic model included all of the dataset comprising all of the fishers travelling from far distances. The results indicate that the consumer surplus of NFZs is higher than the reference sites when considered from the closest visitors (i.e., fishers of 100 km and 300 km distance exclusions) in the postcode and zoned models, and lower in the geographic model that included all distant fishers. The findings suggest that there is potential to increase the consumer surplus in NFZs as more fishers are attracted to fish in these recreational fishing areas.

The outcomes of this study have significant implications for commercial and recreational fishing sectors in Queensland. Moreover, the study demonstrated the short-term effect of management adjustments to ensure the balance between commercial and recreational fishing. The study output could be used to address similar fisheries management issues at the local, national, and international levels.

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## Candidate's statement

By submitting this thesis for formal examination at CQUniversity Australia, I declare that it meets all requirements as outlined in the Research Higher Degree Theses Policy and Procedure.

## Statement authorship and originality

By submitting this thesis for formal examination at CQUniversity Australia, I declare that all of the research and discussion presented in this thesis is original work performed by the author. No content of this thesis has been submitted or considered either in whole or in part, at any tertiary institute or university for a degree or any other category of award. I also declare that any material presented in this thesis performed by another person or institute has been referenced and listed in the reference section.




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## Publications included in this thesis

None of the chapters in this thesis prepared as journal articles have been published yet. However, of the three relevant chapters, Chapters 4 and 5 are ready to submit, and Chapter 6 is under review process in the *Marine Policy* journal.

**Declaration of co-authorship and co-contribution**

1. **Marine**, **S. S.,** Flint, N., & Rolfe, J. (2021). Recreational fishers' satisfaction and expectations in fishing sites with reduced commercial fishing: Queensland's net-free zone as a case study. Manuscript in preparation.

| Contributor | Statement of contribution |
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| Sabiha Sultana Marine | Data processing and analysis (100%)<br>Research direction and manuscript writing (75%) |
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| John Rolfe | Research direction and manuscript review (15%) |

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**Research involving human or animal subjects**

Human subjects were involved in this research while conducting a questionnaire survey with recreational. The research was carried out in accordance with conditions of approval from the CQUniversity Human Research Ethics Committee (ethics approval number 0000020847).

**Declaration of authorship**

This thesis is composed of my original work and contains no material previously published or written by another person except where due reference has been made in the text. I have clearly stated the contribution of others to jointly-authored works that I have included in my thesis.

I have clearly stated the contribution of others to my thesis as a whole, including statistical assistance, survey design, data analysis, significant technical procedures, professional editorial advice, financial support, and any other original research work used or reported in my thesis. The content of my thesis is the result of work I have carried out since the commencement of my higher degree by research candidature and does not include a substantial part of work that has been submitted to qualify for the award of any other degree or diploma in any university or other tertiary institution.

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Sabiha Sultana Marine

CQUniversity, Australia

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**Table of contents** **Page no.**

**List of figures**

**List of tables**

**List of acronyms**

| | |
|---|---|
| ABARES | Australian Bureau of Agricultural and Resource Economics and Sciences |
| ABS | Australian Bureau of Statistics |
| ACF | Autocorrelation Function |
| ADF | Augmented Dickey-Fuller |
| AIC | Akaike Information Criterion |
| ANN | Artificial Neural Network |
| AR | Autoregressive |
| ARIMA | Autoregressive Integrated Moving Average |
| ARIMAX | Autoregressive Integrated Moving Average with exogenous input |
| ATO | Australian Taxation Office |
| AUD | Australian Dollar |
| BIC | Bayesian Information Criterion |
| CFA | Confirmatory Factor Analysis |
| CFI | Comparative Fit Index |
| CPUE | Catch Per Unit Effort |
| CNN | Computational Neural Networks |
| CS | Consumer Surplus |
| CV | Contingent Valuation |
| DAF | Department of Agriculture and Fisheries |
| FGD | Focus Group Discussion |
| FMZ | Fisheries Management Zone |
| GAM | Generalized Additive Models |
| GARCH | Generalised Autoregressive Conditional Heteroscedasticity |
| GBR | Great Barrier Reef |
| GBRMPA | Great Barrier Reef Marine Park Authority |
| GLMs | Generalized Linear Models |
| GP | Geographic Model |
| GVP | Gross Value of Production |
| HREG | Harmonic Regression |
| IPA | Inshore Potting Agreement |
| ITCM | Individual Travel Cost Method |
| MA | Moving Average |
| MAE | Mean Absolute Error |
| MAPE | Mean Absolute Percentage Error |
| MARS | Multivariate Adaptive Regression Splines |
| MEY | Maximum Economic Yield |
| MPAs | Marine Protected Areas |
| MSY | Maximum Sustainable Yield |
| MEY | Maximum Economic Yield |
| MLR | Multiple Linear Regression |
| NAO | North Atlantic Oscillation |
| NFS | Numerical Fish SurrogateTM |
| NFZs | Net-free Zones |
| NLR | Non-Linear Regression |
| NMPs | National Marine Parks |
| NN | Neural Network |
| OLS | Ordinary Least Squares |

| | |
|---|---|
| PACF | Partial Autocorrelation Function |
| PC | Postcode Model |
| POAMA | Predictive Ocean Atmosphere Model for Australia |
| RMSE | Root Mean Square Error |
| RMSEA | Root Mean Square Error of Approximation |
| RUM | Random Utility Model |
| SARIMA | Seasonal Autoregressive Integrated Moving Average |
| SARIMAX | Seasonal Auto-Regressive Integrated Moving Average with exogenous input |
| SEM | Structural Equation Modelling |
| SETARMA | Self-Exciting Threshold Autoregressive Moving Average |
| SPSS | Statistical Package for the Social Sciences |
| SRMR | Standardised Root Mean Square Residual |
| SSM | Single Site Model |
| SSR | Sum of Squares of Residuals |
| TEV | Total Economic Value |
| TGF | Trip Generation Function |
| TCM | Travel Cost Method |
| TLI | Tucker-Lewis Index |
| UK | United Kingdom |
| VAR | Vector Auto Regression |
| VECM | Vector Error Correction Model |
| WLS | Weighted Least Square |
| WTP | Willingness-To-Pay |
| ZTCM | Zonal Travel Cost Method |

# Chapter 1 INTRODUCTION AND SIGNIFICANCE OF THE RESEARCH

*No scientific article is associated with this chapter.*

## 1.1 Overview of the research context

Commercial wild-caught marine fisheries in Australia are highly diverse and provide a considerable contribution to the country's social, economic, and cultural well-being (Evans et al., 2016). Australia's wild-caught fisheries generated $1.6 billion[1] in 2014-15, up from $1.5 billion in 2013-14, and produced around 151,439 tonnes of seafood to local, domestic, and international markets (Flood et al., 2014; Savage, 2015). Marine wild fisheries are also important for the state economy in Queensland since they contribute to the provision of local fish and seafood supply, revenue, and employment. However, over the past decades, Queensland's commercial fishing sector has observed an overall reduction in the tonnage and value of catches and a high latency rate (Savage, 2015). For example, the gross value of production (GVP) of wild-caught marine fisheries has been declining since early 2000s (Australian Bureau of Agricultural and Resource Economics and Sciences, 2019), declining by 7% to 19,815 tonnes in 2014-15, with a value of approximately $177 million (Savage, 2015). These declines indicate the need for increased certainty about the status of commercially important fishes and emphasise the existing risk to their sustainability (Smith et al., 2013).

Since 2000, the decline in Queensland's GVP and catch tonnage has been driven by a number of factors including increased rate of commercial fishing, decrease in fish stocks, reductions in catch quotas, increasing total expenditures, increasing fuel and maintenance costs, and a substantial increase in the value of the Australian dollar (Moore et al., 2007). The prospects of commercial fisheries sectors are likely to vary over time due to changes in various fishing gears and methods, which have varying impacts on by-catch species and fish habitats. If fisheries are not carefully managed, the trophic structure and productivity of ecosystems may be impacted by long-term declines in population of target or non-target species (Smith et al., 2011) or by degradation of habitats by commercial fishing (Jennings & Kaiser, 1998), resulting in a destructive influence on marine ecosystems and processes (Jackson et al., 2001; Myers et al., 2007; Halpern et al., 2008). When species or regions are overexploited, increased competition for the use of a scarce resource also has social and economic consequences (Sharma & Leung, 2001).

Commercial, charter, and recreational fisheries are the three primary sectors of Queensland's marine fishing industry. Queensland's commercial fisheries include a range of net and line

[1] All currency mentioned in this chapter are in Australian dollars. Currently, AUD$1 = US$0.73

fisheries targeting finfish, trawl fisheries targeting crustaceans and various by-product species, pot and trap fisheries, as well as smaller fisheries for shell, and ornamental species. The charter fisheries include game fishing, spear fishing, guided river or coastal fishing, reef fishing are categorised as fishing operations where service charges apply. Recreational (non-charter) fishing includes gears such as rod and lines, spear guns, some small nets (e.g., cast nets, dilly nets, scoop or dip nets, and drag nets), pots and traps with varying restrictions relating to the size of gear, fish size limits, daily bag limits, and seasonal and spatial closures (Queensland DAF, 2020). Recreational fishers may account for the majority of harvest in certain fisheries and are difficult to manage (Brown et al., 2020). Fisheries managers aim to balance the needs and values of all fishery sectors and fishery-associated stakeholders, such as seafood wholesalers and retailers, tourism operators, tackle shops and the wider community by accounting for the "triple-bottom-line" of social, economic, and ecological values. These values are stipulated in legislation, including the Queensland *Fisheries Act 1994*, which defines "Fisheries Queensland's responsibilities for the economically viable, socially acceptable, and ecologically sustainable development of Queensland's fisheries resources" (Queensland DAF, 2017a). Recent concerns about the effects of fishing on commercially and recreationally important fish species in certain Queensland waters has provided an impetus for the development of the Sustainable Fisheries Strategy 2017-2027 (Queensland Government, 2017a).

Management and policy actions in accordance with the ecologically sustainable development goals have led to the implementation of commercial net fishing closures in November 2015 and subsequent commercial fishing licence buybacks in three regional cities in Queensland, namely Cairns, Mackay, and Rockhampton (Queensland DAF, 2015a). Commercial netting closures (which includes fixed mesh nets, seine nets, and drift nets) in Queensland were designed to conserve species by reducing pressure on fish stocks from commercial harvest, increase recreational fishing opportunities, marine-based tourism, and resultant economic growth in regional areas (Brown, 2016; Queensland Government, 2016). The closure areas extend from Keppel Bay to the Fitzroy River for Rockhampton, St Helens Beach to Cape Hillsborough for Mackay, and Trinity Bay for Cairns (Queensland Government, 2017b). Beyond net fisheries, other commercial fishing activities such as commercial crabbing, trawling, and line fisheries are still permitted in the areas. Moreover, these net-free zones (NFZs) do not affect the commercial netting activities occurring outside of the zone. The implementation of NFZs would potentially lead to a decrease in total fishing pressure and an increase in recreational catch rates of species previously targeted by commercial netting.

There are a number of potential and predicted socio-ecological flow-on effects could result from a shift in fishing effort from commercial to recreational, including a decline in retail availability of locally caught seafood in the region (which could be offset by local catches from other fisheries or catches in nearby regions), decreased commercial fishing value, and increased economic and social benefits from recreational fishing and marine-based tourism (Kelleher et al., 1995). The recreational fishing effort in the three-NFZs is expected to increase with an increase in recreational catch rates of species previously targeted by commercial netting. Similar closures are also being introduced in other Australian states (Victorian Fisheries Authority, 2018) to benefit recreational fishers by providing more and larger fish (Spelitis, 2015) and boosting the local economy through increased recreational and charter fishing opportunities (Queensland Government, 2016).

Recreational fishing is a widespread and popular leisure activity in Australia that contributes social and economic benefits to the country, particularly in regional areas (Mclnnes et al., 2013; Brown et al., 2020). Reduced commercial fishing benefits recreational fishers in a variety of ways (Brown, 2016). Firstly, population productivity may be enhanced, which allows recreational fishers to catch more fish. Secondly, lower total fishing mortality enhances fish size and abundance, and larger fish are a more appealing target for recreational fishers than smaller fish. Finally, recreational fisheries may have access and aesthetic advantages if commercial fishing is closed.

However, the total benefits of recreational fishing cannot be quantified only in terms of the quantity of fish caught, the number of trips taken per year, or the amount spent on a fishing trip. It is also important to evaluate whether fishers are satisfied with their fishing experiences, what drives them to go fishing, and what expectations they have for the fishing (Mclnnes et al., 2013). In addition to the social benefits, economic value and benefits of recreational fishing are also important to understand. Management analysts often require the estimate of recreational values when assessing the importance of recreation over alternative uses of any site or changes to policy settings, such as shifting effort from commercial to recreational fishing (Rolfe & Prayaga, 2007; Raguragavan, Hailu, & Burton, 2013). Such recreational values are difficult to compare to the gross value of production measures used to evaluate the commercial sector. As a result of these constraints, economic valuations of recreational fishing are often unavailable (Brown et al., 2020).

Spatial fishery closures (a fisheries management technique that prohibits fishing in a certain area) are likely to influence the productivity of fish stocks and help to achieve biological sustainability (Ocean Studies Board, 1999). Marine Protected Areas (MPAs), no-take or marine reserves are important management tools (Hilborn et al., 2004) for fish stocks and have been shown to increase yields (Halpern & Warner, 2002) by modifying fishing effort (Chakravorty & Nemoto, 2000; Little et al., 2009; Powers & Abeare, 2009) and protecting broodstock and ecosystem function. For instance, in the Hvitá River of Iceland, recreational catch rates in the 'closure' area between 1991 and 2000 were compared to catch rates in the previous ten years prior to the introduction of netting closure. Results showed that the recreational catch increased by 28-35% following the ten-year closure of commercial netting in that area. Additionally, catch rates following closure were compared to catch rates in two other Icelandic rivers that were still open for commercial fishing. The findings suggested that post-closure rod catches increased significantly, while catches in the two open rivers decreased (Einarsson & Gudbergsson, 2003). Similarly, seven years after implementing a seasonal closure area, Beets and Friedlander (1999) observed a considerable increase in average size and better sex ratio at a grouper spawning aggregation location. Fishery closures are considered an important way of administering ecosystem-based management to protect coastal habitats, target and bycatch stocks, and ecological processes (Garcia-Charton et al., 2000; Goni et al., 2000; Roberts et al., 2005; Brown, 2016)

Fishery closures have been shown to have significant ecological benefits for the local fish population and can protect the abundance of a target species with their habitats (Abbott & Haynie, 2012). Closures are expected to aid in the management of commercial fishery stocks in such a way that a large number of fish remain available to recreational fishers, implying that sustainable management of fisheries resources will be achieved. In a fishery, CPUE (catch per unit effort) data serve as an indirect measure of the abundance of a species. The CPUE is calculated by dividing the total catch by the total fishing effort in a given period (Van Hoof et al., 2001). Provided other variables affecting catch and effort are accounted for, a declining CPUE may indicate overexploitation, whereas an unchanged CPUE indicates sustainable harvest of the stock (Yadav et al., 2016). Modelling and forecasting of commercial CPUE and the factors that influence CPUE are used as a useful tool for understanding fishery dynamics and providing short-term quantitative guidelines for fisheries management.

Several previous studies have identified control areas and compared the social, ecological, and economic effects between the sites to evaluate and compare the relative effect of fishery closures (Einarsson & Gudbergsson, 2003; Queensland DAF, 2017b; Martin et al., 2019). For instance, in order to quantify and compare the effects of the net fishery closure on angling catch in Iceland's Hvitá River, two groups of rivers were identified as control sites (Einarsson & Gudbergsson, 2003). In the case study of focus, three coastal areas in Queensland, namely Townsville, Hinchinbrook, and Hervey Bay, were identified as prospective control or reference sites to ascertain any differences in the socio-ecological effect of the NFZs. The three reference sites are evenly distributed close to the NFZs and provide opportunities for commercial and recreational fishing. Since 2015, Queensland's Department of Fisheries and Agriculture (DAF) has been conducting a series of studies to examine the effect of NFZs on recreational fishing as part of the monitoring programme of recent management changes (Queensland DAF, 2017b; Martin et al., 2019). In addition to three NFZs, DAF used the same sites as reference sites in their study. The current study used the same study sites as the DAF for consistency.

## 1.2 Knowledge gap and problem statement

The purpose of commercial netting closures in Queensland is to conserve species by reducing commercial fishing pressure on fish stocks, and to increase recreational fishing opportunities, marine-based tourism, and resulting economic development in regional areas (Brown, 2016; Queensland Government, 2016). If the commercial harvest is large in comparison to the recreational harvest, it is expected that the recent management changes would enhance recreational catch. Recreational fisheries provide fishers and society with a variety of psychological, social, educational, and economic benefits that are not associated with commercial fisheries (Food and Agriculture Organization, 2012). An assessment of recreational fishers' satisfaction and expectations are required to understand the social benefits of recreational fishing since it is necessary to understand if fishers are satisfied with their fishing experiences, what motivates them to go fishing, and what expectations they have for the fishing experience (Mclnnes et al., 2013). The measurement of recreational fishers' satisfaction is an important component of assessing views about fishing and has been established as an outcome indicator of a high-quality fishing experience (Graefe & Fedler, 1986; Holland & Ditton, 1992). A good understanding of fishers' satisfaction and expectations could assist fisheries managers to tailor management plans for different groups of recreational fishers (Brinson & Wallmo, 2017). Moreover, it could provide knowledge of the motives, interests, reactions, and expectations of recreational fishers to different policies (Mclnnes et al., 2013). The determination of fishers' satisfaction and expectations of the newly established

NFZs is important to evaluate the effectiveness of the closures. This study has aims to evaluate and compare recreational fishers' satisfaction and expectations between a NFZ and a reference site, to identify the change in recreational fishers' satisfaction and expectations between sites.

Commercial fishery closures may increase the potential for more desirable stock structures which in turn enhances successful reproduction and local recruitment (Bohnsack, 1998; Jennings, 2000). Queensland's iconic species, the barramundi (*Lates calcarifer*), is one of the popular target fish for commercial and recreational fishers and contributes a vital role in the regional economy of Queensland (Rose et al., 2009). To achieve the management objectives of the barramundi fishery, future catch predictions can be useful for identifying and modelling the important factors that influence catch, which may inform the sustainable management of that stock. Forecasting is a widely used technique in fishery dynamics that helps to provide guidance and support on long-term strategic planning, by formulating an educated estimate of future catch. A good forecast only records the original patterns and trends in the historical data but does not repeat past occurrences that will not appear again (Hyndman & Athanasopoulos, 2018). Functionally, forecasting provides policy analysts with information on sustainable management issues, especially before or after the implementation of management regulations. The current study will develop a forecasting model of the barramundi population of the NFZs and the reference sites and established a relationship between nominal barramundi CPUE (catch per unit effort) and both fishery and environmental predictors to understand the effect of reduced commercial fishing pressure and make inferences on future recreational barramundi catch.

The recreational fishing sector has the potential to influence economic development (Food and Agriculture Organization, 2017). The value of commercial catches can be estimated using market data, but the value of recreational fishing is more difficult to quantify and cannot be derived directly from market prices. Hence, non-market valuation approaches must be used to determine the value of recreational fishing (Gregg & Rolfe, 2013; Brown et al., 2020). The expected economic benefits of recreational fishing come from the recreational fishers' participation in fishing, which involves expenses for their travel, boat, fishing gear, services, facilities, and other accessories (Gregg & Rolfe, 2013). The determination of economic value of recreational fishing is important to justify recreation against other uses of the marine environment (Rolfe & Prayaga, 2007). To measure the welfare impact of a particular policy, it is necessary to understand the values of recreational fishing (Raguragavan et al., 2013). In Australia, a number of studies have been undertaken to estimate the economic values of recreational fishing, but the economic values for newly established fishery closures and other non-closure areas in Queensland are little explored. Hence, this study will also evaluate and compare the economic values of recreational fishing and assess their implications for the three NFZs and three reference sites.

## 1.3 Significance and contribution to knowledge

This project was designed to investigate the expected and actual short-term socio-ecological effects of removing commercial net fishing and provide an assessment of the extent to which netting closures may enhance the future availability of fish stocks, recreational facilities, and regional economic benefits. To determine the effectiveness of the policy change from commercial to recreational, this research will explore the recreational fishers' satisfaction and expectations, their inherent causal relationship, and the strength of that relationship. The output of the study may have significant implications for understanding the factors that best describe satisfaction and expectations for each of the study sites, to inform management bodies when planning measures to improve recreational fishing opportunities.

Commercial fishery closures may have significant ecological benefits for fish populations and can reduce the total fishing pressure on target species within the closure area and beyond. To understand the effect of reduced commercial fishing pressure on commercial barramundi CPUE the study will forecast future barramundi CPUE by identifying and modelling the important environmental and fishery parameters that affect barramundi and made inferences on future recreational barramundi catch. Modelling and forecasting the barramundi population within the study areas could help policy analysts to predict future fish production and sustainable management of fisheries resources.

Policymakers require independent data on the values of recreational activities to support the development of beneficial programs. This study will provide an economic evaluation of the non-market value of the ecosystem services associated with recreational fishing and assess the implications for the three NFZs and three reference sites. By providing data from an actual scenario of a closure, the research could help to inform fisheries management decisions on present and future closures in Australia or other parts of the world.

## 1.4 Aim of the study, research questions, and objectives

### 1.4.1 Aim

This study aims to assess the socio-ecological effects of a localised change in commercial fishing pressure.

### 1.4.2 Research questions

1. Do commercial netting closures increase recreational fisher satisfaction and expectations?
2. How do environmental and fishery drivers influence the future prediction of barramundi (*Lates calcarifer*) catch?
3. Does the value of recreational fishing increase after the establishment of netting closures?

### 1.4.3 Objectives

To achieve the aim and answer the research questions, this study sets the following specific objectives to fulfil:

1. evaluate recreational fishers' satisfaction and expectations towards NFZs,
2. develop a best-fitting forecasting model for the barramundi (*Lates calcarifer)* population of NFZs and reference sites, and
3. estimate the economic values of recreational fishing.

## 1.5 Thesis structure

The structure of the thesis is organised by publication format. Chapters 4, 5, and 6 follow a typical publication format that includes a separate introduction, methodology, result and discussion, and conclusion. A short description of the thesis chapters is presented below.

**Chapter 1 – Introduction**

This chapter of the dissertation contextualised the research themes by providing background information on the research topic. Some relevant acknowledgment of previous studies has been described to identify the research gap. The scope and significance of the research have been described along with the research aims, objectives, and research questions.

**Chapter 2 – Literature review**

Literature regarding research themes has been identified, summarised, and critically analysed in a systematic way. An explicit focus has been given to national and international literature on the social, ecological, and economic effects of special closures.

**Chapter 3 – Research approach**

This chapter provides the comprehensive methodological approach that has been taken to address the research problem and the justification of specific methods or techniques used for achieving each of the research objectives.

**Chapter 4 – Short-term social effects of the Queensland netting closures**

This chapter described and analysed survey data on various social aspects of recreational fishing. This study compared the satisfaction and expectations between a NFZ and a non-NFZ. In particular, the study justified the relationship between satisfaction, overall satisfaction, and expectation and the strength of their relationship.

**Chapter 5 – Short-term ecological effects of the Queensland netting closures**

So as to promote the sustainable management of commercial barramundi (*Lates calcarifer*) fishery, this chapter developed best fitting forecasting models to determine the future barramundi (*Lates calcarifer*) CPUE from six study sites and described its implications for sustainable management of the barramundi (*Lates calcarifer*) population.

**Chapter 6 – Short-term economic effects of the Queensland netting closures**

This chapter determined and compared the economic values and benefits of recreational fishing in three NFZs and reference sites. The study analysed boat ramp survey data using three models of the travel cost method (TCM) and assessed their implications for netting closure.

**Chapter 7 – Conclusions and recommendations**

The overall effects of Queensland's net fishing closures and how well they align with the expected effects were discussed. A refined conceptual model was developed based on the results of the study. This chapter also includes concluding remarks and provides recommendations and guidelines for further research.

# Chapter 2 LITERATURE REVIEW

*No scientific article is associated with this chapter*.

## 2.1 Overview

This section describes and summarises the available literature on study-related themes, topics, terminologies, procedures/methodological approaches, and results. The themes include summary texts around recreational fishing values and benefits. Relevant articles and theses were downloaded through Central Queensland University Library and digital databases, including ScienceDirect, Web of Science, Scopus, Cambridge Scientific Abstracts, Taylor & Francis, WorldWideScience, WorldCat, Ingenta connect search, SlideShare to Endnote. Books, book chapters, government and institutional reports, and relevant government websites, have been accessed. In addition, several locally and internationally published documents were collected through direct searching (by using different terms related to this study, e.g., 'socio-economic effect of MPAs', 'recreational fishers' satisfaction', 'expectations', 'economic value', etc.) in Google and Google Scholar. The extensive literature from different sources that are considered reliable (e.g., peer-reviewed articles, general websites, and books) were then read, synthesised, and presented in this document as a review.

### 2.1.1 Potential effects of a spatial closure

Spatial tools which include marine reserves and fishery closures are becoming more popular in fisheries management to address sustainability issues (Gell & Roberts, 2003; Hilborn et al., 2004; Sumaila et al., 2007). Closures may benefit people who value the natural environment of marine areas for leisure and recreation, visitors who want to see intact marine environments and wildlife, divers who want to see flourishing marine habitats including coral reefs, sponges, and seagrass beds, and fishers who want long-term yields and revenue from more sustainable fish stocks (National Research Council, 2001). Fully protected fishing areas show the likelihood of quick recovery of species, habitat, and trophic structures that promote spillover and provide a source of recruits to surrounding areas. This greater larval dispersion lead to wider fishery benefits for the regional economy (Gell & Roberts, 2002). A number of authors have recommended compensation for the most impacted fishers who have limited access to other fishing grounds or job opportunities (Roberts & Hawkins, 2000; Gell & Roberts, 2002). This financial assistance greatly improves fisher support for establishing protected areas and paves the way for successful fisheries management (Gell & Roberts, 2002). The potential effects of a spatial closure in social, ecological, and economic contexts are provided in Figure 2-1.

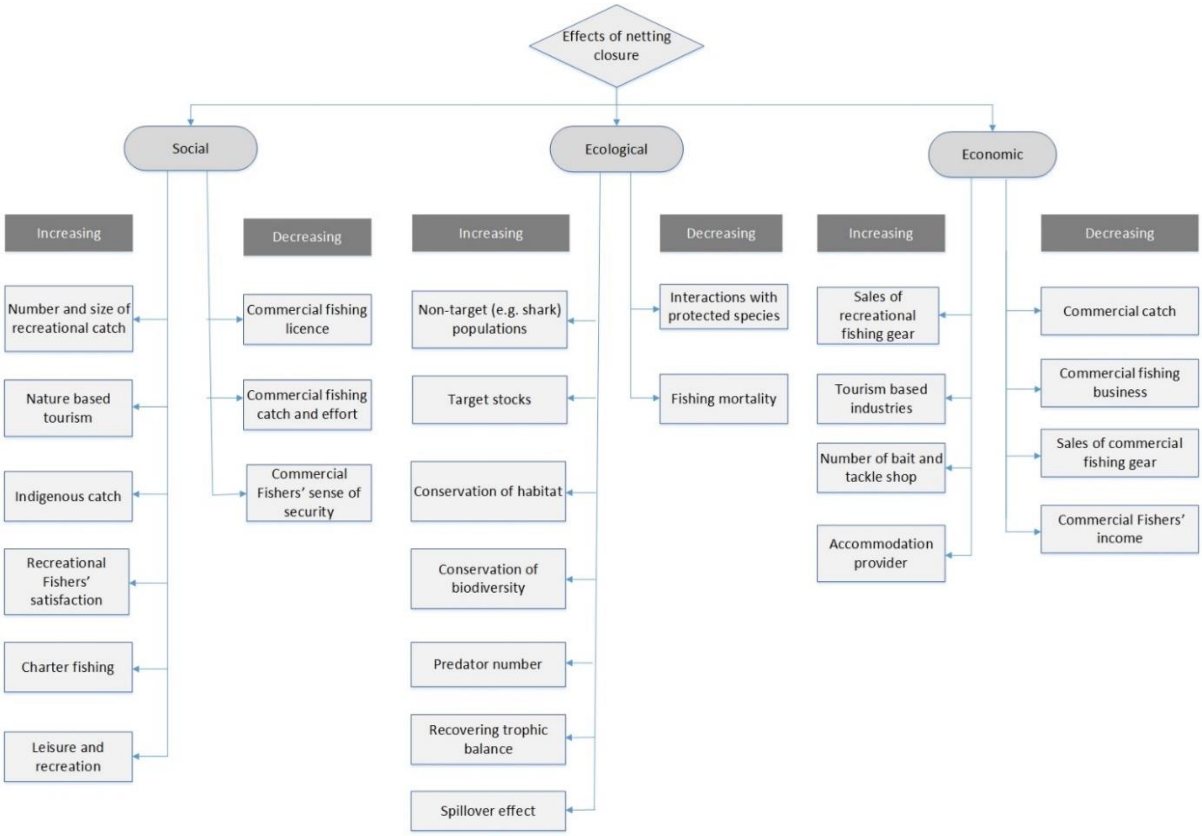



Figure 2-1: Flow diagram showing the potential effects of spatial closures on social, economic, and ecological values

## 2.2 Definitions of terminologies and concepts related to the title

Definition and clarification of the terminologies and concepts used in this dissertation may facilitate improved understanding of the topic. In the following paragraphs, frequently used terms and ideas have been described in detail.

### 2.2.1 Different 'terms' of effects

In environmental studies, a 'term' means 'duration', 'time' or 'incidence' related to an event. Short-term, medium-term, and long-term are used to distinguish an interval. The timeframes are often flexible according to the research question and/or the level of work conducted.

Short-term impacts are easier to define and conceptualise as the changes occur in a very short period, i.e., within months or years (usually less than 3 years) (Halpern & Warner, 2002). Short-term studies can provide for accurate detection of immediate effects and utilise simple measurement techniques. Methods including short-term surveys, interviews, specialised environmental monitoring techniques (such as before-after-control-impact studies), direct experimental manipulations, laboratory-based experiments, etc., are well suited for this type of study (Ward, 2012). Medium-term changes are denoted as the phenomena which are observed in time frames of 3 to 5 years (Heagney et al., 2015). Finally, longer-term impacts extend over a relatively long period (more than 5 years). Some phenomena may not be detected unless studied over a time frame of decades or much longer than that.

### 2.2.2 Closures and MPAs

Closures in any waterbody generally prevent people from fishing. This prevention is applicable to both recreational and commercial fishers (Primary Industries and Regions South Australia, 2017). There are various types of closures used to restrict fishing to a certain depth, gear type, location, and time of the year (Australian Fisheries Management Authority, 2017). Depending on the management scenarios, closure can be permanent, temporary, or seasonal (Primary Industries and Regions South Australia, 2017). Authorities introduce such closures to reduce fishing pressures and thus protect endangered and other non-target species. They may replenish fish stocks by providing a safer environment for growth and activity by protecting their habitats and spawning areas. Seasonal closures are mainly declared to protect fishes in their breeding season (Primary Industries and Regions South Australia, 2017).

Closures can take place in MPAs (marine protected areas), and MPAs can take place in any large waterbodies, such as seas, oceans, estuaries, or large lakes. Most of the MPAs do not restrict fishing but some MPAs (that encompass fewer than 10% of the global MPA area) restrict all types of fishing activity and contribute to the protection and conservation of marine biodiversity (Day, 2017). MPAs include no-take reserves, marine sanctuaries, marine reserves, and marine parks that protect fishes, reefs, lagoons, salt marshes, mangroves, seagrass beds, rock platforms, and other systems (Commonwealth Department of Environment and Heritage, 2013).

Literature about the social, ecological, and economic effects of closure is limited (Beets & Manual, 2007), hence the study has discussed the effects of MPAs alongside the effects of closures because the aims of both management measures are similar.

### 2.2.3 Social effects

The social effect can be defined as the significant, positive, or negative effect of an activity or action on the community as a whole and the well-being of individuals. The effect can be evaluated through the collection of relevant information on various variables, such as social values, attitude, participation, satisfaction, motivation, perception, and beliefs on particular issues (Sutton, 2006). MPAs have social implications for commercial fishers' livelihood and lifestyle to varying degrees (Mayo-Ramsay, 2014). A number of researchers have acknowledged that protected areas could negatively impact the livelihood of marginal fishers, especially those who do not have any other alternative job opportunities other than fishing (Christie et al., 2003; Christie, 2004; Stoffle & Minnis, 2008; Mascia & Claus, 2009). Other studies have also revealed that commercial fishers are directly impacted by the establishment of MPAs (Badalamenti et al., 2000; Jones, 2008). In addition, the success or failure of MPAs partially depends on the fishers' perception and attitude towards the establishment of MPAs (Himes, 2007; Jones, 2008; Charles & Wilson, 2009; Dimech et al., 2009). In some cases, conflicts are very common with different stakeholder groups for the same resource use which might be crucial for establishing such closure areas (Charles & Wilson, 2009; Jennings, 2009; Mascia & Claus, 2009). Recreational fishers can utilise the greater opportunities for fishing, while commercial fishers have to contemplate alternative activities or even careers.

The body of literature on the social implications of MPAs is relatively small but growing steadily (Hoagland et al., 1995; Farrow, 1996; Milon, 2000; Sanchirico, 2000). Mangi et al. (2011) noted that local communities have a higher awareness of the increasing numbers of no-take zones. It is widely acknowledged that stakeholder participation is very effective for the protection and conservation of marine resources (Pomeroy & Douvere, 2008; Hoelting et al., 2013) and they are considered an indispensable part of the management of any ecological system (Fleming & Jones, 2012; Cárcamo et al., 2014).

To mitigate the impact of the GBR (Great Barrier Reef) zoning plan on various resource users of the GBR region, GBRMPA (Great Barrier Reef Marine Park Authority, an Australian Government agency tasked with managing the GBR Marine Park) was meticulous to involve stakeholders in the management program (Fernandes et al., 2005). The Australian Government also accommodated fishers and fishery-related businesses by providing a structural adjustment package as part of managing uncontrolled commercial fishing in that area (Macintosh et al., 2010). Many recent studies have investigated commercial and charter fishers' response, adaptation, and resilience to the GBR zoning plan five years after its establishment (Lédée et al., 2012; Sutton & Tobin, 2012). They found that only a few fishers were not supportive of the plan, and some had already started adjusting themselves to the newly implemented plan (Lédée et al., 2012; Sutton & Tobin, 2012). Sutton and Tobin (2009) reported that high-resilience fishers were supportive and adaptive to the plan and could understand its positive impacts on the environment.

A South Australian spatial closure of the snapper (*Pagrus auratus*) fishery showed a negative impact on commercial fishers (Morison et al., 2013). The study found evidence that some fishers had to move to adjacent open areas for fishing, and others did not change their location but changed their target species of interest (Morison et al., 2013). Hamilton (2007) observed that closures had an impact on social capital and resulted in the loss or alteration of employment structure. Furthermore, closures could affect rural livelihoods as commercial fishers have to spend more for relatively longer travel to suitable fishing places (Taylor & Buckenham, 2003).

Social impact studies are dynamic as perceptions can change rapidly with time (Gell & Roberts, 2002). One of the best examples is the study of Mangi et al. (2011), where they depicted the real social impact of the Lyme Bay closure on commercial fishers and fish merchants. Soon after the closure, the livelihood of commercial fishers was found to be heavily impacted by the closure. However, the situation changed over time, as fishers adjusted to the current rules imposed by the government. Gell and Roberts (2002) found that fishers were not willing to support the closure as they were aware of other reasons for fisheries degradation, such as poor management of coastal waters, habitat degradation, pollution, and other external influences. They felt they were unfairly treated and therefore never supported closures. However, effective governance requires liaison with fishing communities, and knowledge transfer to fishers to address such issues and thus contribute to the effective and efficient management of waterbodies (Gell & Roberts, 2002; Jones et al., 2011; McCay & Jones, 2011).

Commercial fishers have been observed to have a wide range of attitudes and perceptions concerning the conservation value of MPAs (Pita et al., 2011). A substantial number of studies found that some commercial fishers could understand the benefit of MPAs for conserving biodiversity and ecological systems (Blyth et al., 2002; Gelcich et al., 2005; Gelcich et al., 2008; Jimenez-Badillo, 2008; Gelcich et al., 2009) and some could not (Oikonomou & Dikou, 2008; Dimech et al., 2009). Blyth et al. (2002) examined static gear (net and pot) and towed-gear (dredge and trawl) fishers' perceptions towards an Inshore Potting Agreement (IPA). The study found that towed gear fishers were less satisfied with the IPA establishment than the static gear fishers because the towed gear fishers were impacted by the IPA, while the static gear fishers were not impacted. Irrespective of this, the two groups of fishers believed that the IPA works as a reserve for finfish and scallop species that were previously targeted by towed gears. Jimenez-Badillo (2008) found that Mexican fishers were very supportive of conservation plans for fishery resources and that they could identify the potential cause of resource degradation in that area. In another study, Dimech et al. (2009) observed that most of the fishers in Malta believed that the Fisheries Management Zone (FMZ) had no beneficial effect to commercial fishermen but provide plenty of opportunities for recreational fishers.

Previous studies have yielded some important insights into the communication between management authorities and the fishers for the development of MPA strategies. Fishers' participation in management and decision-making processes was found by some studies to be poor (Suman et al., 1999; Himes, 2003; Stump & Kriwoken, 2006; Oikonomou & Dikou, 2008), but the fisher groups who were already involved in the different management activities were highly motivated to obtain empowerment on a greater scale (Gelcich et al., 2009). In most cases where consultation has been evaluated, fishers were found not to be satisfied with the consultation process (Stump & Kriwoken, 2006) or perceived that there was a strong communication gap with the management bodies (Himes, 2003; Oikonomou & Dikou, 2008).

A number of authors have compared the attitude of fishers and other resource users toward several aspects of MPAs. Suman et al. (1999) observed varying attitudes and perceptions towards the Florida Keys National Marine Sanctuary while working with the fishers and stakeholder groups (divers and environmental group members). Fishers were not supportive of the Sanctuary, whereas other stakeholders were highly supportive and cooperative. Mangi and Austen (2008) conducted a survey in various Mediterranean countries and evaluated the stakeholders' perceptions in a number of areas such as fisheries management, conservation, education, and research and tourism development. The responses of fishers and other stakeholder groups (governmental officials, researchers, conservationists, managers of MPAs, recreational users, and local inhabitants) vary. Fishers have given more emphasis to establishing MPAs for fisheries management and considered that conservation is the less important reason for MPA establishment. Other stakeholders' views were opposite to those of the fishers; they give higher priority to conservation than to fisheries management objectives. Oikonomou and Dikou (2008) noticed that the management of MPAs in Greece was ineffective due to the general conflict between fishers and other resource user groups. Another study conducted by McClanahan et al. (2005) and McClanahan et al. (2008) found that stakeholders (marine attendants, park services, and fisheries department officials) in both Kenya and Tanzania perceived that MPAs are not beneficial to them, rather they are beneficial only to the government.

The social impact of MPAs is poorly understood with limited studies on this topic (National Research Council, 2001; Christie et al., 2003; Mascia, 2004; West et al., 2008). Although there is limited evidence of data on the social perspectives of MPAs in Australia (Heagney et al., 2015), social perspectives are often discussed in conjunction with the economic perspective of MPAs. Evaluation of social impacts and evaluation of economic impacts are usually carried out individually and use specialised methodologies, but they are complimentary and occasionally overlap. For example, demographic changes could be examined by both forms of evaluation; however, economic evaluation may focus on employment data, while a social evaluation may also be concerned with population change or migration. An integrated approach may deliver a complete and cost-effective result by giving information on possible economic implications as well as key social values associated with the activity, which guide expected attitudes and reactions to the proposed change (Bureau of Rural Sciences, 2005). Some relevant studies on the socio-economic impacts of MPAs on marine stakeholders are given in

Table 2-1.

Table 2-1: Relevant studies dealing with the socio-economic impact of protected areas on marine stakeholders

| Authors | Indicator | Method | Result/ output | Study site |
|---|---|---|---|---|
| Mascia et al. (2010) | • Food security<br>• Resource rights<br>• Employment<br>• Community organization<br>• Income | Literature review (based on 21 articles) | In a few older and smaller MPAs, food security remained stable or improved to some extent.<br><br>Stakeholders' control over resources had been increased with MPA zoning and regulations.<br><br>Employment, community organisation and income are precluded from statistical analysis due to their small sample size. | Philippines, Kenya, Egypt, Italy, and St. Lucia |
| McClanahan (2010) | Income | Purposive sampling | Closure and gear restriction together result in higher individual income through the harvesting of bigger-sized fishes located in nearby areas. | Kenya |

| Authors | Indicator | Method | Result/ output | Study site |
|---|---|---|---|---|
| Lédée et al. (2012) | Fishers' response and adaptation to closure | Face-to-face interview | Fishers were not supportive of the new zoning plan for the GBR region. However, they have since relocated their fishing activities and businesses into other areas and started adapting themselves to the new regulation. | Queensland, Australia |
| Rees et al. (2013) | Social impacts in a case study | Telephone interview and a face-to-face interview | The respondents were observed to support MPAs in their locality. They have identified the issues involving MPAs and developed strategies to overcome and maintain a small-scale, profitable fishing industry. | North Devon Biosphere Reserve, UK |
| Bennett and Dearden (2014) | Social impacts (livelihoods, governance, and management) in multiple case studies | Literature review and face to face interview | The implementation of National Marine Parks (NMPs) was found to have negatively impacted on community livelihood, governance, and management systems. | Thailand |
| Hattam et al. (2014) | Social impacts in a case study | Face-to-face interview | Mobile gear fishers were not likely to support the closure because they thought that they were being deprived of their rights on resource use. On the other hand, static gear fishers had positive views about the establishment of the closure. Recreational users and recreational service providers benefited from improved recreational experiences. | Lyme Bay, UK |
| Heagney et al. (2015) | • Employment<br>• Income<br>• Housing<br>• Business development<br>• Local government revenue | Based on secondary data | The study proposed and tested three pathways via which protected areas could benefit local stakeholders. The result showed an increased number of socio-economic indicators. | New South Wales, Australia |

| Authors | Indicator | Method | Result/ output | Study site |
|---|---|---|---|---|
| Rees et al. (2015) | • Diving businesses<br>• charter boat operator<br>• marine fishing | Questionnaire survey using e-mails, online/ web surveys, postal surveys, telephone, and face to face interviews | The study examined the socio-economic effects of MPAs on the provision of beneficial ecological services such as leisure and recreation. The study found an increase in the frequency of activity in dive businesses both inside and outside the MPA, as well as an increase in charter boat operators and marine fishing inside MPAs compared to outside areas. This equates to a possible increase in the value of the MPA resource of £2.2 million (as measured by the proportionate spending and related turnover of these groups). | Lyme Bay, UK |

### 2.2.4 Ecological effects

An ecological impact describes the cumulative effect on living organisms and their non-living environment due to anthropogenic or natural changes. In the literature, the ecological effect of fishery closures includes increases in sizes of organisms, increase in fish stocks and production, higher species richness, increase in biomass and density of economically important species, as well as changes in total ecosystem productivity, high fecundity and longevity, a more vibrant benthic ecosystem, and recovery of trophic structure (Selig & Bruno, 2010; Giakoumi & Pey, 2017).

Research on the ecological effects of closed areas suggests that the ecological effects are diverse (Halpern & Warner, 2002) and fall into two distinct categories such as changes occurring inside of the closure and outside the closure (Lester et al., 2009). It is widely accepted that spatial closures have positive ecological effects that occur within the closure, particularly on target species, stock structure, food webs, biodiversity, and habitats (Francour et al., 2001; Roberts et al., 2001; Halpern, 2003). However, the use of no-take reserves as a fisheries management tool is still under debate, since demonstrations of their effectiveness are quite difficult to implement (Abesamis & Russ, 2005). A study conducted by Pascual et al. (2016) reported that the Mediterranean respondents showed a neutral impact of MPAs on industrial fishing activities, while Black Sea respondents were negatively impacted in terms of lower catch, landing, and biomass. For artisanal and recreational fishing, Mediterranean stakeholders gave positive feedback for the establishment of MPAs, especially increased catch rate and biomass. In contrast, Black Sea respondents were neither positively nor negatively impacted by the MPAs. Barrett et al. (2007) reported statistically significant increases in abundance of bastard trumpeter (*Latridopsis forsteri)* and other large fish (greater than 300 mm), as well as an about ten-fold increase in abundance of large fish and an almost two-fold increase in per-site species richness of large fish in the Tinderbox Marine Reserve relative to control sites after 10 years of protection in Tasmanian MPAs.

The changes outside the closure include both spillover and export of larvae and fishes from the reserve to the water outside the reserve (Botsford et al., 2001; Gell & Roberts, 2003; Sale et al., 2005). A study conducted in the GBR region showed that no-take reserves benefit the overall ecosystem health of a waterbody (McCook et al., 2010) with a spillover effect evident in the supply of target fishes in nearby fished areas (Roberts et al., 2001; Russ, 2002; Russ et al., 2003; Silva et al., 2015). On the other hand, Williamson et al. (2004) provided empirical evidence against the concept of spillover effects when they studied the biomass and density of coral trout (*Plectropomus leopardus*) for about 3-4 years before, and 12-13 years after, the establishment of no-take reserves at two islands in the GBR. The result showed that the density and biomass of coral trout increased in protected areas but not in the adjacent fished areas (Williamson, et al., 2004). More recent research by Buxton et al. (2014) ascertained that the spillover benefit is only evident in poorly managed fisheries whereas very little or no spillover effect is found in well-managed protected areas.

Closures help restore the population density and size composition of harvested species, which helps to sustain ecosystem biodiversity and the integrity of ecosystem functions (Barrett et al., 2007; Russ et al., 2008; Lester et al., 2009). In the short term, following 1.5-2 years of rezoning of Australia's GBR, the density of the main target of reef line fisheries, coral trout, increased significantly in Palm and Whitsunday Island (Russ et al., 2008). Edgar and Barrett (2012) conducted a study and discovered that four species increased in biomass while only 2 of the 11 exploited fish species and none of the 7 exploited invertebrate species showed significant indications of population recovery 3 years after the establishment of marine protected areas in temperate region of Australia. Several authors have argued that temperate reserves could lead to less changes in exploited species than tropical reserves due to two key reasons. First, populations in temperate climates are migratory and seem to be less likely to benefit from a reserve (Shipp, 2003; Kaiser, 2004). If the majority of fish are outside of reserve boundaries, their populations will not be safeguarded. Second, temperate species usually have longer larval stages, have stronger larval dispersion capability, and more gene flow than tropical populations (Laurel & Bradbury, 2006; O'Connor et al., 2007).

MPAs are likely to have a varying effect on individual species, depending on how they are exploited or affected by other activities outside the reserve, as well as physical attributes such as mobility, dispersal ability, reproductive ability, and life span; the nature of density dependence; and indirect effects due to interactions with other species that are directly impacted by reserve protection (Gaines et al., 2003; Micheli et al., 2004; Gerber et al., 2005). Notwithstanding empirical data showing that MPAs have a strong effect on fish biomass and size structure (Edgar & Stuart-Smith, 2009; Harrison et al., 2012; Edgar et al., 2014), its effect on benthic invertebrate communities is underrepresented (Micheli et al., 2004). Research conducted by Ferrari et al. (2018) found that as a short-term effect of MPA, several ecologically important invertebrates, such as massive sponges, brown macroalgae, and octocorals were widespread and numerous in no-take reserves. Similarly, Joshua et al. (2018) demonstrated that macro-benthic assemblage, richness, and diversity of species were significantly greater inside the MPA than outside and located shallower than deeper zones.

The degree of recovery of fish stocks varies greatly depending on various factors such as locations, the magnitude of change, the extent to which power to detect the change in species of interest is possible, the amount of time it takes for species to respond the following protection, and the amount of confounding that stems from pre-existing spatial and temporal patterns, and errors caused by changing the behaviour of individual species (Willis et al., 2003). Because of these numerous constraints, it is impossible to provide an accurate assessment of geographic patterns associated with the effects of fishing and the suitability of the various size and design configurations used in MPAs. Furthermore, the inadequacy of "before" data may obfuscate the extent of change predicted as well as the interpretation of observed differences between protected and fished areas (Edgar et al., 2004). Before-after-control-impact analysis conducted by Edgar and Barrett (1999) in the no-take MPAs of Tasmania demonstrated the density of large fish increased in abundance compared to neighbouring areas that were fished. Such effects were not detected in the smaller reserves. During the declaration of MPAs, anecdotal evidence showed that fishing significantly modified the abundance of many Tasmanian inshore fishes with a few remarkable exceptions (Harries & Croome, 1989).

### 2.2.5 Economic values and economic effects

The majority of the fisheries management suggestions are based on the conventional method to fisheries economics (Clark, 2006), which is based on Schaefer (1954) and Gordon (1954). The Gordon- Schaefer model is used to analyse fishery management and policy (Zhang & Smith, 2006), particularly in three primary areas: such as monopoly, open access, and maximum sustainable yield (MSY). MSY and maximum economic yield (MEY) are management targets for fisheries resources. MSY is the largest amount of sustainable catch (tonnes) that can be harvested from a fish stock over an indefinite period under constant environmental conditions. MEY refers to the sustainable level of catch or effort that creates the largest positive difference between total revenues and the total fishing-related costs. In economics, marginal cost and marginal revenue are used to identify the level of output and per-unit price of a product that will maximise profits. In a broader sense, marginal cost is the additional cost derived from the production of an additional unit of that good or product, whereas marginal revenue is the additional revenue generated from an increase in the sale of that product as an additional unit. Similarly, marginal utility is the additional benefit or satisfaction derived from consuming one or more units of goods or services. Economists often use this concept to measure consumers' satisfaction, happiness, and pleasure. Measuring the marginal utility of recreational fishing is more difficult than for commercial fishing (Frijlink & Lyle, 2010).

The term 'economic value' can be described as the welfare (utility) benefits obtained for a good or service and usually measured in monetary units (i.e., currency). There are some goods and services where the welfare (utility) benefit cannot be measured directly. Various methods have been developed for quantifying or estimating economic value (Bergstrom, 1990).

Total economic value (TEV) is an established structure can assemble a variety of values related to coastal ecosystems (International Union for Conservation of Nature, 1998). The TEV of MPAs includes components of their use and non-use values. The use-value of MPAs can be classified as direct and indirect use values that supply a range of economic values for the society, which, subsequently, have a substantial effect on the regional economy (Mayo-Ramsay, 2014). MPAs have a number of use benefits that can be categorised as direct and indirect values that include both market and non-market activities. Another category is the option value, which incorporates the value for future generations through the preservation and conservation of economically significant marine resources (Akhter & Yew, 2013). Non-use values are associated with the benefits that derive without any physical use and simply relate to the benefits of understanding that a natural resource is protected (Abdullah et al., 2011). The non-use value is further sub-divided into bequest and existence values. Bequest values are related to the benefits derived from the knowledge that future generations will achieve benefits from the conservation of marine resources. Existence values are not related to the actual or possible use of the resources but are often reflected as the knowledge about marine resources which exists independently, regardless of the potential present or future use by the individuals (Hageman, 1985; Abdullah et al., 2011). Some of the various components of TEV are illustrated in Figure 2-2.

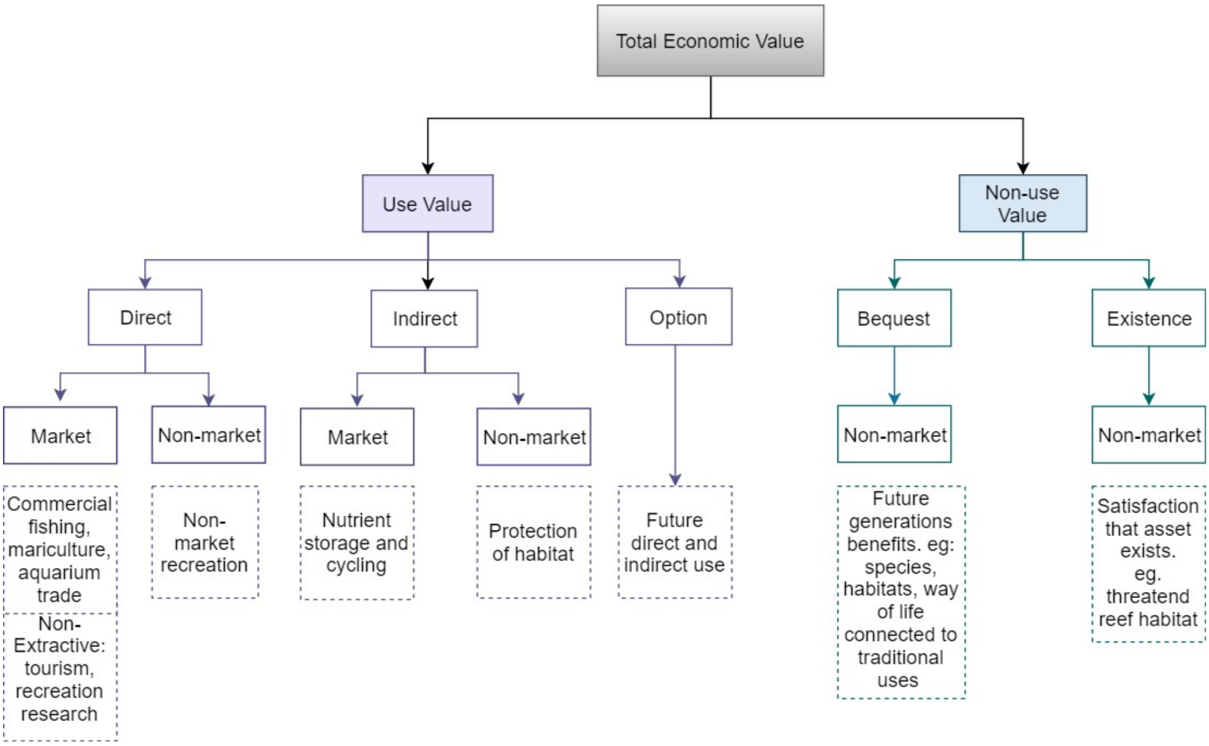



Figure 2-2: Total economic value (TEV) chart with some examples. Source: The Victorian Coastal Council (2007)

Unlike market goods, most environmental goods or services cannot be traded (Gregg & Rolfe, 2013). Non-market valuation approaches are the only way to assign their monetary values. Mayo-Ramsay (2014) identified that the main uses of MPAs are market activities (e.g., commercial fishing, charter operations, whale and dolphin watching, etc.), and non-market activities (e.g., recreational fishing, education and research, scuba diving, boating, and snorkelling, etc.). Increased interest in recreational assets and the requirement for more efficient management have prompted management personnel to pursue economic valuation of recreational benefits.

The economic impact examines the effect of an event, decision, or policy on the economy in a specified region. It generally evaluates changes in economic activity between two scenarios, such as before and after of any policy implementation. The establishment of new NFZs in three regions might have an overall economic impact on a different group of stakeholders, which is related to revenue, wages, employment, and business profiles. Generally, economic impacts imply the effects of expenditure on various fishery resource activities filtering down through the community (European Inland Fisheries Advisory Commission, 2004). It does not indicate the most effective way of utilising a resource. Economic impact analysis depends on the consumers' or producers' expenditure for the product. The higher the spending on the goods, the greater will be the economic impact (European Inland Fisheries Advisory Commission, 2004). The establishment of the NFZs could have a significant impact on local economies, such as the upgrading of recreation-based amenities and the deceleration of commercial seafood businesses.

Economists identify a distinct difference between economic value and economic effect. Economic value is the net benefit achieved by society, while economic effects determine the flow of various economic actions through their regional economy (Miller & Blair, 1985). To implement any decision regarding resources, decision-makers give priority to the economic viability of the services. An increased value supports the decision in a positive way, while decreased value conversely indicates a negative result of the decision (European Inland Fisheries Advisory Commission, 2004). In contrast, economic impacts are not used to implement any specific decision or action, but they are instead used to investigate what distinctive section of the economy is affected either positively or negatively by a certain policy at a certain level.

## 2.3 Effects of spatial closures

### 2.3.1 Social implications

Spatial closures that are specific to commercial fishing will provide increased opportunities for recreational fishers (Voyer et al., 2014). Globally, from a social point of view, commercial fishing closures will increase recreational fishers' satisfaction and the opportunity for tourism

(Davis & Tisdell, 1996; Agardy et al., 2003; Hargreaves-Allen et al., 2011), and result in an increase in recreation facilities (Lynch et al., 2004). The term ‘satisfaction’ is the measure of the performance of any product or service (Burns et al., 2003; Oliver, 2010) and is generally determined as the basic ‘product’ of the recreational fishing experience (Driver & Tocher, 1970; Driver & Knopf, 1976; Hendee & Bryan, 1978). The determination of satisfaction is a very complex cognitive process (Arlinghaus, 2006), and a number of factors are likely to contribute to satisfaction (Holland & Ditton, 1992; Schultz & Dodd, 2008). The factors are subjective (e.g., catch related desire, the perception of weather and fishermen, etc.) and situational (e.g., weather condition, harvest, and crowding, etc.) in nature where overall satisfaction is directly influenced by subjective determinants and indirectly by situational determinants (Graefe & Fedler, 1986). According to Ditton and Fedler (1988), satisfaction could be estimated by determining the difference between the outcomes one thinks or expects should be received (motivation) and the perceived fulfilment of those outcomes.

Fishers’ satisfaction is a very significant element of recreational fishing, and this is one of the preliminary objectives of management officials as it is likely related to subsequent fishing events (Graefe & Fedler, 1986; Holland & Ditton, 1992; Radomski et al., 2001; Game, Fish and Parks Commission, 2019). The main goal of determining recreational fishers’ satisfaction is to obtain a maximum human benefit through providing a quality fishing opportunity to its users (Pollock et al., 1994; Weithman, 1999). Feddler & Ditton (1994) concluded that the amount of entertainment obtained from a fishing trip is positively related to the size and/or number of fish harvested from waterbodies. Graefe and Fedler (1986) studied marine recreational fishers’ satisfaction, however, and noted that satisfaction is not solely dependent on the size or number of fish caught. It is rather dependent on how fishers’ have evaluated their catch considering their expectations and preferences. This view is supported by Holland et al. (1992), who assigned priorities to overall benefits that were gained from recreational experiences over the entire range of benefits achieved from catching fish. In the literature, another broader concept of satisfaction is ‘overall satisfaction’ that refers to fishers’ satisfaction with all aspects and experiences associated with fishing (Bitner & Hubbert, 1994). Previous observational studies have shown that users perceive these two satisfaction conceptualisations differently (Bitner & Hubbert, 1994). However, there is a link between the two concepts, as overall satisfaction is dependent on information from past encounters and experiences, it can be viewed as a function of all previous satisfaction (Teas, 1993; Parasuraman et al., 1994; Jones & Suh, 2000). Satisfaction could be argued to be a predictor of overall satisfaction (Teas, 1993).

Sometimes satisfaction is confused with anglers' motivations; however, the two concepts, while related, are mostly independent (Peyton & Gigliotti, 1989; Arlinghaus, 2006). Some authors have described the motivations which drive recreational fishers to participate in fishing activities (Fedler & Ditton, 1994; Arlinghaus, 2006). Fishing motivations may be divided into two categories: fishing-specific elements (e.g., catching fish) and more general psychological goals unrelated to the catching process (commonly referred to as activity general aspects) (e.g., a desire to be outdoors, enjoying nature, and relaxation). Although the relative relevance of catch and non-catch motives varies per fishing community, most studies agree that both catch and non-catch motives must be considered (Fedler & Ditton, 1994; Ditton, 2004; Beardmore et al., 2011).

The level of satisfaction depends on some catch and non-catch related outcomes (Holland & Ditton, 1992) and the extent to which recreational fishers could achieve a blend of experiences that he or she might expect from a fishing trip (Hendee, 1974; Graefe & Fedler, 1986; Arlinghaus, 2006). Fedler (1984) suggested that fishing trip satisfaction-related studies should include three dimensions of experience: enjoying nature, relaxation, and reflection (nostalgia). Similarly, the results of surveys by Holland and Ditton (1992) for American anglers identified two important aspects of recreational fishing trip satisfaction: feeling a sense of independence and passing quality time with nature. Ormsby (2004) found similar results for fishers in the GBR region, who also identified a preference for being outdoors and enjoying nature.

A large and growing body of literature has investigated angler satisfaction. A recent study conducted in New Mexico by Davis Innovations (2015) categorised anglers as very satisfied (36.2%), satisfied (72.1%), and not satisfied (10.0%) from a total of 410 respondents. Sutton (2006) carried out empirical studies on recreational fishers' satisfaction from a total of 1,385 respondents of GBR and non-GBR regions in Queensland and noticed a large number of fishers (73% non-GBR; 75% GBR) were moderately or very satisfied with their fishing. This body of research implies that the determination of anglers' satisfaction is very crucial as managers can modify policies with respect to different angler types (e.g., commercial and recreational) (Brinson & Wallmo, 2017).

Different fisher groups have different expectations (a strong belief that something will happen in the future). The main driving force of satisfaction is related to catch expectations (Hudgins & Davies, 1984; Graefe & Fedler, 1986; McMichael & Kaya, 1991; Spencer & Spangler, 1992; Arlinghaus, 2006). In terms of the relationship between satisfaction and expectation, expectation can be defined as advance estimations made by stakeholders while receiving service (Oliver, 1981; Aksu et al., 2010). Satisfaction with previous performance is likely to serve as the basis for expectations of future performance (Ofir & Simonson, 2007). According to Graefe and Fedler (1986) satisfaction relies not on the actual number of catches, but on how fishers evaluate catches in relation to their expectations and desires. Satisfaction may be derived from either catch-related or non-catch-related outcomes (Spencer, 1993) which may influence future expectations. It is critical for management bodies to determine fishers' expectations in advance, since failure to do so may result in negative disconfirmation (i.e., expectations are not met) of expectations (Brunke & Hunt, 2008). Some research suggests that fishers' expectations varies with net-free zones (NFZs), fishing frequency (Martin et al., 2019), fishing experience, and age of fishers (Aas, 1996; McCormick & Porter, 2014). According to Martin et al. (2019), fishing expectations may be regarded as independent of satisfaction, which indicates that an individual might be satisfied without expecting significant change in the future. Other studies indicate that satisfaction is frequently defined in terms of expectations (Spencer & Spangler, 1992; Manning, 1999), but the literature lacks a study examining an alternative theoretical prediction about the relationship between fisher satisfaction, overall satisfaction with past performance, and expectations for future performance.

The evaluation of recreational fishers' satisfaction and expectations are an important component of assessing fishers' feelings towards, and understanding of, existing policies that are implemented to benefit recreational fishers (McCormick & Porter, 2014). A comprehensive understanding of fishers' satisfaction and expectations can assist managers in tailoring management plans for various groups of recreational fishers (Brinson & Wallmo, 2017). Additionally, it could provide insight into the motivations, attitudes, interests, and expectations of recreational fishers in response to various policies (Mclnnes et al., 2013). Hence, a better understanding of the relationship between satisfaction, overall satisfaction, and expectation and the strength of their relationship is required to assess the effectiveness of the policy shift from commercial to recreational.

### 2.3.2 Ecological implications

In recent years, fish stock management issues have drawn considerable international attention. It is well recognised that the world's capture fisheries are under increasing threat from overexploitation, habitat destruction, and water pollution (Balston, 2009a). For the long-term sustainable harvest of fishery resources, quantitative science-based management initiatives have been introduced (Geromont & Butterworth, 2014). Among these initiatives, commercial fishery closures are considered a beneficial strategy for managing the effects of commercial fishing on certain fish or habitats (Australian Fisheries Management Authority, 2017). Fishery closures may help to conserve the abundance of a target species, as well as their habitats (Abbott & Haynie, 2012). In a fishery, CPUE (catch per unit effort) data is often used to represent an indirect measure of the abundance of a fished species. The CPUE is calculated by dividing the total catch by the total fishing effort during a certain time period (Van Hoof et al., 2001). Assuming other variables affecting catch and effort are accounted for, a declining CPUE implies overexploitation of stock, while an unchanged CPUE indicates sustainable harvesting of that stock (Yadav et al., 2016). Forecasting of the future CPUE is a widely used approach where statistical models describe a particular fishery and underlying fishery dynamics based on historical data to predict future catches. The annual CPUE estimate may assist management bodies to understand the features of stock assessment to set objectives and thus predict, warn, and regulate unforeseen alterations in stock size, yield, and market demand (Alder et al., 2008).

Modelling and forecasting of future CPUE is an essential tool in terms of understanding the fishery dynamic and for making quantitative recommendations for the short-term management of fisheries resources (Stergiou & Christou, 1996). In order to achieve accurate and reliable forecasts of fish catch, a range of time series models with various levels of complexity have been established and evaluated (Mini et al., 2015). Among them, autoregressive integrated moving average (ARIMA), vector auto regression (VAR), multiple linear regression (MLR), neural network (NN), state space model, exponential smoothing are widely used time series models. These models either alone or in a combination have been applied in a range of fishery dynamics situations (Stergiou et al., 1997; Tsitsika et al., 2007; Abdelaal & Aziz, 2012). However, in Australia, applications are much more limited. For instance, in the Princess Charlotte Bay of Queensland, the effect of climate variability on commercial barramundi catch has been examined, and a prediction model has been developed by Balston (2007). Eveson et al. (2015) developed a seasonal habitat preference model for forecasting the southern bluefin tuna of Great Australian Bight.

Time series is a sequence of data points measured over a period of time at regular time intervals (Adhikari & Agrawal, 2013). Time series analysis aims to understand patterns that evolve over time and use these patterns to predict future behaviours. The units of time used for time series varies with the situation to be modelled and could be years, quarters, month, days, hours, minutes, or even microseconds (Bako, 2014). For the time series, equally spaced observations are more important than the unit of time (Iffat, 2009), and time lags, delays or steps are more important than the actual time. The lag operator allows models to quantify the connection among past, present, and future values (Malik, 2018). Time series models often use the natural one-way time order to express values for a given period as they are derived in some way from past values rather than future values (Brid, 2018). One of the main objectives of time series analysis is modelling and forecasting. Time series forecasting involves three fundamental approaches: regression-based methods, heuristic smoothing methods, and general time series (Montgomery et al., 2002). Among the most notable are ARIMA models, MLR, harmonic regression (HREG), non-linear regression (NLR), dynamic models, smoothing models, generalised autoregressive conditional heteroscedasticity (GARCH), Gaussian autoregressive models, VAR, and the vector error correction model (VECM) (Raman et al., 2018). The regression-based forecasting model is widely used in fisheries management (Raman et al., 2017). Longer-term forecasting can be carried out by regression analysis using moving average models or series containing deterministic patterns (Yaffee & McGee, 1999).

Prediction of future fish catch is a key component of fish stock management because it plays a vital role in strategy development and policy formulation (Stergiou & Christou, 1996). Predictions are useful for in-season or post-season accountability, which provides a guideline for proposed management measures. The body of knowledge on forecasting applications in fisheries management is consistently increasing. Borges et al. (2003) applied time series analysis to explore the impact of wind conditions as well as the North Atlantic Oscillation (NAO) on sardine (*Sardina pilchardus* W.) catches. The analysis demonstrated evidence of a climate-controlled regime-shift, where recruitment was forced to a lower level when the wind exceeded a certain threshold in the winter season. In order to evaluate the interrelationships between the ranges of 15 freshwater species and their environment, Leathwick et al. (2006) have used two analytical techniques: generalized additive models (GAM) and multivariate adaptive regression splines (MARS). The result suggests that there is little difference between the performance of the two models. Hanson et al. (2006) assessed the annual landings of Atlantic menhaden (*Brevoortia tyrannus)* using three-time series models and found that artificial neural networks and multiple regression might be utilized for this commercial menhaden fishery. Sathianandan (2007) used VAR models to forecast the relationship between landings of eight commercially significant fishes in Kerala from the year 1960 to 2005. The analysis resulted in 16 individual time series models and the relationship and behaviour of each time series were extensively examined.

Along with other time series models, a number of authors have employed the ARIMA, SARIMA (seasonal ARIMA), and SETARMA (self-exciting threshold autoregressive moving average models). For example, Prista et al. (2011) used a SARIMA model using monthly catch data to identify the future landings of meagre fishery in Portugal. Ghosh et al. (2014) employed a very versatile SETARMA model, which describes cyclic fluctuations in the prediction of mackerel (*Rastrelliger kanagurta)* harvest in India. Farmer and Froeschke (2015) compared the forecast performance of generalized linear models (GLMs), GAMs, and SARIMA for recreational catch in the south-eastern United States. For all stocks of interest, none of the models yielded the best results. Mini et al. (2015) applied three univariate forecasting methods such as Holt-Winters, ARIMA, and neural network autoregression to model the CPUE (catch per unit effort) series along the northeast coast of India. Coro et al. (2016) forecasted skipjack tuna (*Katsuwonus pelamis*) catch from the Indian Ocean using historic catch and effort data. Lawer (2016) evaluated the performance of three time series models (ARIMA, artificial neural network, and exponential smoothing) for the prediction of annual fish catch in Ghana. The results show that none of the models are ideal for modelling all of the fish catch. The study also recommended comparing different methods before choosing a suitable one for use. Karunarathna and Karunarathna (2017) and Ogunbadejo et al. (2018) found the ARIMA (1,1,1) model was the best-fitting and parsimonious model for forecasting fish production in Sri Lanka and Nigeria. Raman et al. (2017) found ARIMA with log-transformed data had a better fit than the intervention model based on the Akaike information criterion (AIC) and Bayesian information criterion (BIC). A recent study by Sydeman et al. (2018) predicted herring biomass using population and environmental parameters. Their model offers management scenarios which can inform harvest control rules. In Australia, a barramundi catch prediction was made by Balston (2009a) for the Princess Charlotte Bay of Queensland, where the author used a forward stepwise ridge regression model to predict the catch. Some relevant studies that used forecasting in fisheries management are presented in Table 2-2.

Table 2-2: Summary of studies that used forecasting in fisheries management

| Authors | Method employed | Research interest | Study site | The output of the study |
|---|---|---|---|---|
| Monteiro (2002) | Growth model | To study fish population growth in coastal waters | Tagus estuary of Portugal | The growth model provides the basis for developing a model of fish movement in the coastal environment based on their environmental preference |
| Haque et al. (2005) | ARIMA model | Forecasting marine and inland fish production | Bangladesh | Result estimated that the annual fish production for the year 2000-01 to 2004-05 were respectively 1763, 1867, 1974, 2085, and 2199 thousand tons |
| Komontree et al. (2006) | One-way analysis of variance, multiple linear regression, and time series model | Forecasting the number of various varieties of fish landings, allowing for seasonality and trend | Thailand | Result found evidence of decreased catch rates for Mackerel, squid, shrimp, and crab but increased for scads catch only |
| Godwin et al. (2007) | Numerical fish surrogateTM (NFS) | Designed fish bypasses and instructive structures at hydroelectric facilities through combing three sorts of modelling approaches | Snake and Columbia rivers in the Pacific Northwest | Predicted fish behaviour and trajectories |
| Gutiérrez-Estrada et al. (2007) | Various models of computational neural networks (CNN) and ARIMA | One-month ahead forecast of anchovy catch | North area of Chile | Recurrent neural networks and seasonal hybrid CNN + ARIMA models recorded the general trend of the historical data |
| Chesoh and Choonpradub (2011) | Regression model | To cluster fish community structures using monthly fish catch data | Songkhla Lake of Thailand | The model was found efficient in clearly separating fish community clusters with no overlap in between freshwater and marine water clusters |
| Sankar (2011) | ARIMA model | Forecasting fish product export | Tamilnadu of India | ARIMA (0,1,2) model predicted that the fish export has increased |

| Authors | Method employed | Research interest | Study site | The output of the study |
|---|---|---|---|---|
| | | | | 114,695 tons in 2015 from 74,549 tons in 2008 |
| Hobday et al. (2016) | Predictive ocean atmosphere model for Australia (POAMA) | Seasonal forecasting of aquaculture and marine fisheries | Australia | Depending on the season and region of interest, forecast factors include rainfall, air, and water temperature are regarded as useful for up to about 4 months in the future |
| Raman et al. (2018) | Seasonal auto-regressive integrated moving average with exogenous input (SARIMAX) model | Forecasting of monthly total fish landings with the influence of three external physicochemical factors | Chilika lagoon of India | Result found a positive influence of temperature and salinity on fish catch, contributing more than 26% to the total annual catch |
| Mahalingaray et al. (2018) | ARIMA and artificial neural network (ANN) | Forecasting of total fish production | India | The ANN model produced the best forecast for future fish production |

The barramundi (*Lates calcarifer*), an emblematic species in Queensland, is an important fin-fish species for commercial, recreational, and indigenous fisheries in Australia (Balston, 2009a), and contributes a vital role in the regional economy of coastal Queensland (Rose et al., 2009). In terms of stock status, Queensland's barramundi is estimated to be composed of seven genetically different populations. According to the status of the Australian Fish Stocks report in 2016, stocks in the southern Gulf of Carpentaria account for more than half of Queensland's annual commercial barramundi catch and were recognised as the most decreasing stock in comparison to others (Saunders et al., 2016). Since 1981, several management programmes have been implemented to reduce fishing pressures on this population. More stringent access to the sea has been imposed on the Gulf of Carpentaria's Inshore Fin Fish Fishery, resulting in a reduction in the number of commercial licences from 109 in 1998 to 85 in 2015 (Queensland Government, 2017c).

In 2015, a new restriction on the use of nets in commercial net fishing for barramundi was implemented in three regional Queensland cities on the grounds that fish population (including barramundi) will be conserved, recreational fishing will be increased, and spending on local fishing tourism-related businesses will be increased (Queensland Government, 2016). The resulting shift in fishing pressure was considered likely to improve the barramundi stock structure. No prior research has used forecasting applications to assess the ecological effect of netting closures on CPUE, particularly in Queensland.

### 2.3.3 Economic implications

There is a growing body of literature that examines the economic implications of spatial closures (Farrow, 1996; Milon, 2000; Sanchirico et al., 2002). Closure areas have the potential to improve coastal economies through enhancing recreational and charter fisheries, although a decrease in profitability from the commercial fishery is also evident (Brown, 2016). Pascoe et al. (2014) suggest that the closure areas can boost regional economies through supporting recreation-related businesses, such as fishing tackle shops, tourism, recreational and charter fishing, whose economic value can outweigh the loss in the commercial fishery. The economic implications of spatial closures are broadly described in the following sub-sections.

#### 2.3.3.1 Economic effects

Spatial closures have some influential economic impacts on both commercial and recreational fishers. Recent studies in protected areas of the GBR have shown that ‘no-take’ reserves serve as an area of increased tourism that in turn broadens the local economy (Kenchington, 2003). Mclnnes et al. (2013) also argued in support of this viewpoint, stating that closures negatively impact commercial seafood business but alternatively strengthen the local economy by offering some businesses or job opportunities such as tackle shops, tourism-based industries, and accommodation providers, etc.

The economic effect can be determined by assessing the implicit linkage among different economic activities, and it is expected that the total effect will exceed the initial expenses and the activity-specific differences may occur which varies over time (Reid, 2008). The total effect is the sum of the direct, indirect, and induced economic effects that underpin the impacts (wages, income, and employment) perceived by the demand for goods or services (Kirkley, 2009). The direct effect is the effect that emerges directly from an initial expenditure (e.g., purchase) that results in an increase in local income (wages, income, and employment) and inputs. The impact that emerged from the purchase of locally produced inputs in following spending rounds is often termed as an indirect effect. Induced effects are the economic activity that is created as a result of personal consumption expenditures by workers in all of the directly and indirectly impacted industries, including accountants, wholesalers, and other workers in these sectors who spend their income.

In order to fully predict the effects of fisheries management on the economy, an economic impact study is often performed in connection with proposed legislation or regulatory changes. The novel economic impact assessment process consists of four steps (Stoeckl et al., 2010). The first involves determination of expenditure patterns of each visitor category and the sectors in which most of the money was spent. The second involves conducting multiple regression tests to examine the drivers of expenditure, especially to check whether nature-related trip motives and activities are statistically significant determinants for each visitor category, after controlling for other determinants. In the third, data collected from participants is used to determine the effect that different hypothetical scenarios including environmental deterioration and/or higher pricing might have had on their choice to visit the location and/or the duration of their stay. In the fourth step the test will identify responses to hypothetical bias, which must be controlled. Once this has been completed, the controlled responses will be integrated with the expenditure data to estimate the reduction in visitor expenditure that would result from each hypothetical scenario (Stoeckl et al., 2010).

Spatial commercial fishing closures have an immediate economic impact on the livelihood of commercial fishers, as they decrease the profitability of commercial fishing operations (Brian et al., 2005). At the same time, charter fishing and related tourism industries may generate new economic opportunities based on a commercial fishing closure (Brown, 2016). Moreover, closures can affect a number of other stakeholders, such as recreational fishers, bait and tackle retailers, seafood retailers, and seafood consumers. Young et al. (2016) suggested that recreational-only fishing areas could strengthen the coastal economy by providing a range of supporting amenities (e.g., bait and tackle shops, tourism-based industries, etc.) through which the economic value of the recreational sector could exceed the change in the value of the commercial sector. Morison et al. (2013) has summarised some economic consequences of spatial closures on a commercial snapper fishery (*Chrysophrys auratus*). A reduction in catch rate following the closures lowered the income of commercial fishers, and some had to relocate their fishing business to other areas due to the negative impact of the closure on their businesses.

### 2.3.3.2 Economic values

Economic valuation is considered one of many feasible ways to outline and measure values. The appropriate measures for assessing these values incorporate the determination of consumer and producer surplus (NSW Marine Parks Authority, 2004). Consumer surplus is the difference between the amount of money consumers pay for a good and the maximum amount that they would be willing to pay for the service. Consumer surplus (CS) is the area under the demand curve and situated above the price line. From Figure 2-3, line BA describes the demand curve for a good X that indicates how much an individual is willing to pay for each unit of X. When the price is P, the customer purchases the Q amount from good X. The customer’s willingness to pay for that good is at P1 for Q1 and P2 for Q2 which is greater than the actual price P*. Hence, the difference between the money that the customer has already paid and what they are willing-to-pay for that good is termed as consumer surplus. In the figure, C1, C2, and C are the equilibrium points where the supply and demand are equal. If the price changes from P1 to P2 then the consumer surplus (the triangular area in the figure) also changes from BP1C1 to BP2C2.

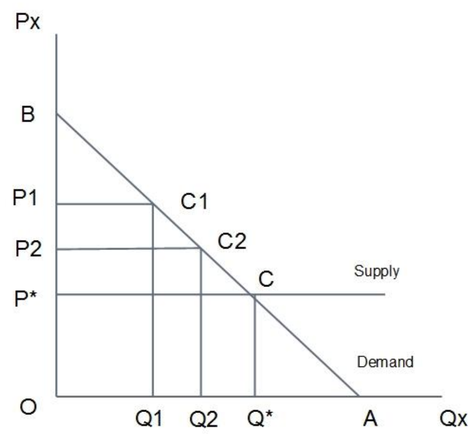



Figure 2-3: Consumer surplus. Modified from European Inland Fisheries Advisory Commission (2004)

Where market information is not available it becomes difficult to estimate consumer surplus amounts. There are two widely used approaches to estimate the economic values of a non-market outcome: revealed preference and stated preference techniques (see Figure 2-4). Revealed preference techniques use data on choices that have been made by people in the course of their normal life to evaluate statistical models of recreation demand. The model captures tradeoffs for recreational fishing trips in terms of expected catch, trip cost, environmental conditions, management rules, and other factors deemed significant in explaining recreational site choice (Hicks, 2002). Stated preference techniques are much more flexible (researchers may enquire about circumstances that are rare or do not yet exist), but they are potentially hindered by social desirability bias/hypothetical bias. In contrast, revealed preference techniques are less flexible (researchers can only consider behaviours that occur in the "real" world), but they generally do not suffer from social desirability bias and are seldom influenced by hypothetical bias.

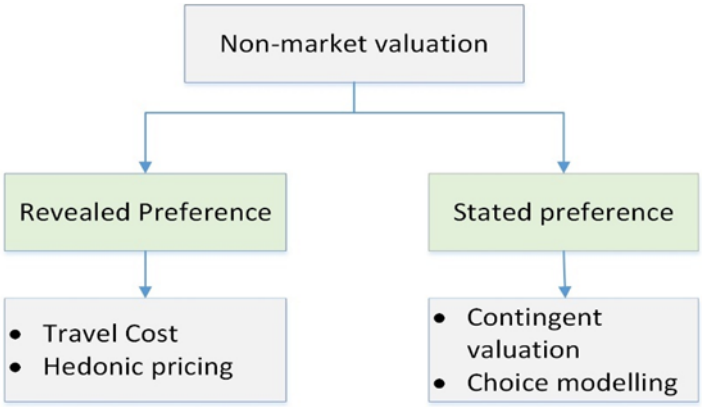



Figure 2-4: Summary of non-market valuation methods

The travel cost method (TCM) and hedonic pricing approach are two extensively used revealed preference techniques. TCM has been widely used over the past four decades for valuing site-specific recreational opportunities (Ward & Beal, 2000; Haab & McConnell, 2002). The fundamental concept is that visitors must travel to the recreational site and incur the cost to cover the distance from their original location to the site (Haab & McConnell, 2002). The model can represent consumer choice and preferences as it is based on consumer theory, and it uses data from the real market situation (Haab & McConnell, 2002). Depending on the definition of a dependent variable, TCM has two basic variants: the zonal travel cost method (ZTCM) and the individual travel cost method (ITCM) (Ward & Beal, 2000; Stoeckl & Mules, 2006). ZTCM is applied to the areas with very low individual visitation patterns where recreational visitors are divided into the different zones they came from. ITCM is useful for the areas that have high individual visitation rates (Bateman, 1993; Bennett, 1996; Prayaga et al., 2006). ITCM relates the number of visits made by an individual over a specific period of time to the related travel cost. Parsons (2017) categorised TCM into two distinctive models:

single site model (SSM) and random utility model (RUM). SSM can be used to value the recreational function of an entire recreational site and is suitable to measure the values of some closing areas due to pollution or contamination. RUM allows visitors to identify a suitable site from a number of alternatives (Rolfe & Prayaga, 2007).

The hedonic pricing approach is used to estimate the implicit price for a set of attributes that make up the good (Baker & Ruting, 2014). The calculation employed in this method is simple and mostly used for valuing environmental facilities that influence the price of market goods (Akhter & Yew, 2013). The approach is often used in the valuation of properties, such as houses, and accounts for economic expenses or advantages that may impact the total value of the asset. If non-environmental elements are adjusted for (kept constant) while running this sort of model, any residual price variances will indicate changes in the goods' external surroundings. The hedonic pricing model has some advantages such as it is generally simple to use when evaluating properties since it is based on real market values and comprehensive, readily accesible data sets. At the same time, the technique is adaptable enough to account for linkages between other market commodities and external factors. Hedonic pricing also has important limitations, such as its capacity to only capture customers' willingness to pay for what they perceive to be environmental differences and the repercussions of those changes. Furthermore, hedonic pricing does not always account for external factors or regulations (e.g., taxes and interest rates), which may have a substantial influence on prices (Marshall, 2021).

Stated preference techniques require information from people about how much they value a constructed non-market outcome. Data collection involves a survey that asks people about their willingness to pay for a non-market service (Baker & Ruting, 2014). Contingent valuation creates a hypothetical market scenario that might involve non-marketed goods. The contingent valuation method works by directly asking a sample of individuals from a population to make choices about the amount they are willing-to-pay (WTP) for some environmental goods (Boyle, 2003). WTP is the maximum sum of money an individual is willing to hand over for a product or service (Job, 2009). The direct survey approach offers an open-ended question that asks consumers' maximum willingness to pay for the products or services.

Regardless of some biases associated with this Contingent Valuation (CV) method, it has several advantages. Firstly, it can estimate both use and non-use values. Secondly, it is possible to get useful information even if the consumer's past behavioural data had not been collected. Thirdly, the method is capable of providing valid and reliable data for the study (Hoevenagel, 1994). Among various question formats, six broad types of formats viz. open-ended, closeended, referendum, payment card, payment ladder, and bidding or bargaining formats are used to determine the WTP for different hypothetical scenarios (Frew et al., 2003). The choice of question format is very important for CV studies as the WTP is sensitive to the different question formats (Uehleke, 2017). Many studies found that the response rate is higher in a closed-ended format than the open-ended format as it is easier for respondents to provide monetary assessment when they are driven by a price (Whynes et al., 2003). In the referendum format, a status quo alternative and a single improvement in the hypothetical scenario that incurs an extra cost are presented to the respondents (Rolfe & Dyack, 2010). The payment card format comprises a set of values where the respondents are asked to identify the highest amount they would like to pay for the goods or services. The payment ladder is the discrepancy between the amount that respondents are willing to pay (for sure) and the amount they would not pay (for sure) for a good or service. Lastly, the bidding format is like an auction, where the respondents are asked to nominate a certain amount for a hypothetical good or service. Depending on their responses, they are further asked for lower/higher bids and through this process, the maximum WTP is determined (Sakashita et al., 2012).

Choice modelling is one of the stated preference approaches which is widely used to measure consumer preferences. It is considered as the most scientifically sound tool for investigating and comprehending decision-making processes. In this method, a direct survey approach (e.g., conjoint analysis and discrete choice analysis) determines WTP by evaluating customers' choice from a number of alternatives including a 'none' choice option (Breidert et al., 2006). Choice modelling is a method that offers individuals a choice from multiple options that are made up of the number of characteristics that describe a particular policy outcome (Baker & Ruting, 2014). There are four basic variants of choice modelling viz. contingent ranking, contingent rating, paired comparisons, and choice experiments. The contingent ranking method allows respondents to identify and rank a number of alternative options, which are defined by a variety of scenarios provided at various levels across options (Slothuus et al., 2002). In the contingent rating format, respondents are introduced to some objects or scenarios to which they rate their preferences on a numerical scale (Ahmad, 2009). In the paired comparisons method, respondents select the most preferred answer from a set of two choice options on a numerical scale (Hanley et al., 2001). Lastly, from a set of alternative options provided in a choice experiment method, respondents are asked to select a single preferred combination of scenarios (Yacob et al., 2008).

#### 2.3.3.3 Recreational fishing values in Queensland

There is a growing body of research focused on the economic valuation of protected areas (Ambrey & Fleming, 2012). Akhter and Yew (2013) identified approximately 17 studies dealing with the economic valuation in MPAs in Southeast Asia from 1998 to 2009. However, in Australia little research has been done on the economic valuation of recreational fishing (Rolfe & Gregg, 2012; Yamazaki et al., 2013), especially in the field of spatial fishery closures. Some notable studies are reported as follows.

Swait et al. (2004) and Pascoe et al. (2014) evaluated recreational fishing values in Western Australia and Queensland by using revealed preference techniques, whilst Yamazaki et al. (2013) and Wheeler and Damania (2001) used stated preference techniques to estimate recreational values of fishing in Tasmania and New Zealand. Rolfe and Prayaga (2007) and Prayaga et al. (2010) used both techniques to calculate recreational fishing values in the GBR region and three Queensland freshwater impoundments.

Rolfe and Prayaga (2007) used TCM and CV to value recreational fishing in three freshwater impoundments of Queensland. The consumer surplus per fishing group per trip for the frequent anglers was estimated at $543.36, $958.30, and $1,776.30 respectively at the three dams, or $220.88, $358.92, and $440.77 per person per trip, respectively. The CV value for occasional anglers travelling on longer trips was found $191.49, $1,006.34, and $3,436.74 per group per trip, respectively, or $59.65, $348.22, and $904.40 per person per trip, respectively.

Prayaga et al. (2010) used TCM to estimate the values of recreational fishing trips off the Capricorn Coast of Central Queensland. Values were recorded as $385.34 per group/trip and $166.82 per individual/trip. The average length of the trip was for 1.54 days, this translates to $108.32 per individual fisher per day.

Pascoe et al. (2014) also used TCM to estimate recreational fishing value in Moreton Bay of Queensland. The value was found to increase between $1.3m to $2.5m per year with a current total annual value of around $20m. The average consumer surplus per person per trip ranged from $60 to $110.

Windle et al. (2017) used TCM to identify the economic value of beach, other land-based, and fishing (land and water) in the Gladstone Harbour area of Queensland. The study estimated the recreational value of fishing was $143 per trip per household.

A more recent study conducted by Farr and Stoeckl (2018) used TCM to identify the recreational fishing values under the condition of uncertainty in Townsville, Queensland.

### 2.3.4 Conclusions

Spatial closures are an example of a highly contested conservation tool that also have non-conservation benefits, such as increased opportunities for recreational fishing, nature-based tourism, a flourishing charter industry, and resulting economic growth. The introduction of the new closures may have a number of potential and predicted socio-ecological flow-on effects. The effects might come from social, ecological, and economic perspective. In terms of the social aspect, the implementation of closures could result in an increase in recreational catch rates of species previously targeted by commercial netting, as well as higher recreational fishers' satisfaction and expectations. In terms of the ecological aspect, the closures help to achieve sustainability by reducing fishing mortality, increasing the spillover effect, which allows more fish for commercial harvest outside of the closure, and maintaining an abundant fish population for recreational harvests. In terms of the economic aspect, spatial closures have significant economic effects on both commercial and recreational fishers. Closure may serve as an area of increased tourism which broadens the local economy and helps to increase the economic value of recreational fishing, which may surpass the loss in commercial fishing.

The newly established commercial netting closures near three regional areas in Queensland is expected to widen recreational fishing opportunities, improve stock structure of recreationally and commercially important fish species, and boost recreation-based economic growth. However, the existing literature has done little to investigate the actual social, ecological, and economic consequences of changes in commercial fishing pressure in these areas. Hence, the study has attempted to identify some research approaches to deal with the research gaps indicated by the literature review.

# Chapter 3 RESEARCH APPROACH

*No scientific article is associated with this chapter.*

## 3.1 Overview

The purpose of this study was to develop an understanding of the short-term effects of removing net fishing pressures (from the Cairns, Mackay, and Rockhampton) and assess the extent to which netting closures may enhance ecological diversity and social, and economic benefits. To determine and compare the social, ecological, and economic values and benefits of netting closures, the study considered three non-closure areas (reference sites) along with three closure areas where commercial net fishing is permitted to operate.

To assist management bodies in taking further steps to enhance recreational fishing opportunities and guiding overall fisheries management, it was necessary to examine the social, ecological, and economic effects of the recent management change. This could not be achieved in a single study, so each analysis required a different assessment and modelling approach. The study employed three different modelling approaches to quantify the social, ecological, and economic effects of commercial netting closures. Improved methodological approaches allow the incorporation of an increasing amount of socio-economic and ecological realism in modelling that helped to achieve desirable outcomes. The socio-ecological implications of commercial net fishing closures are important to identify when designing, implementing, and evaluating the effect of new closures. This case study offers a broader and more in-depth methodological approach in order to assess the social, ecological, and economic effects of Queensland's NFZs using both field survey and secondary data. It is expected that this empirical study will help to inform management decisions by providing critical insight into the ability of the NFZs to achieve fisheries management goals. The overall methodological approach employed in this research is demonstrated in Figure 3-1. After the demonstration of the overall methodological approach, the following sections provide an in-detail description of study areas, dataset, and data processing and analysis methods employed in this study to address the literature gap.

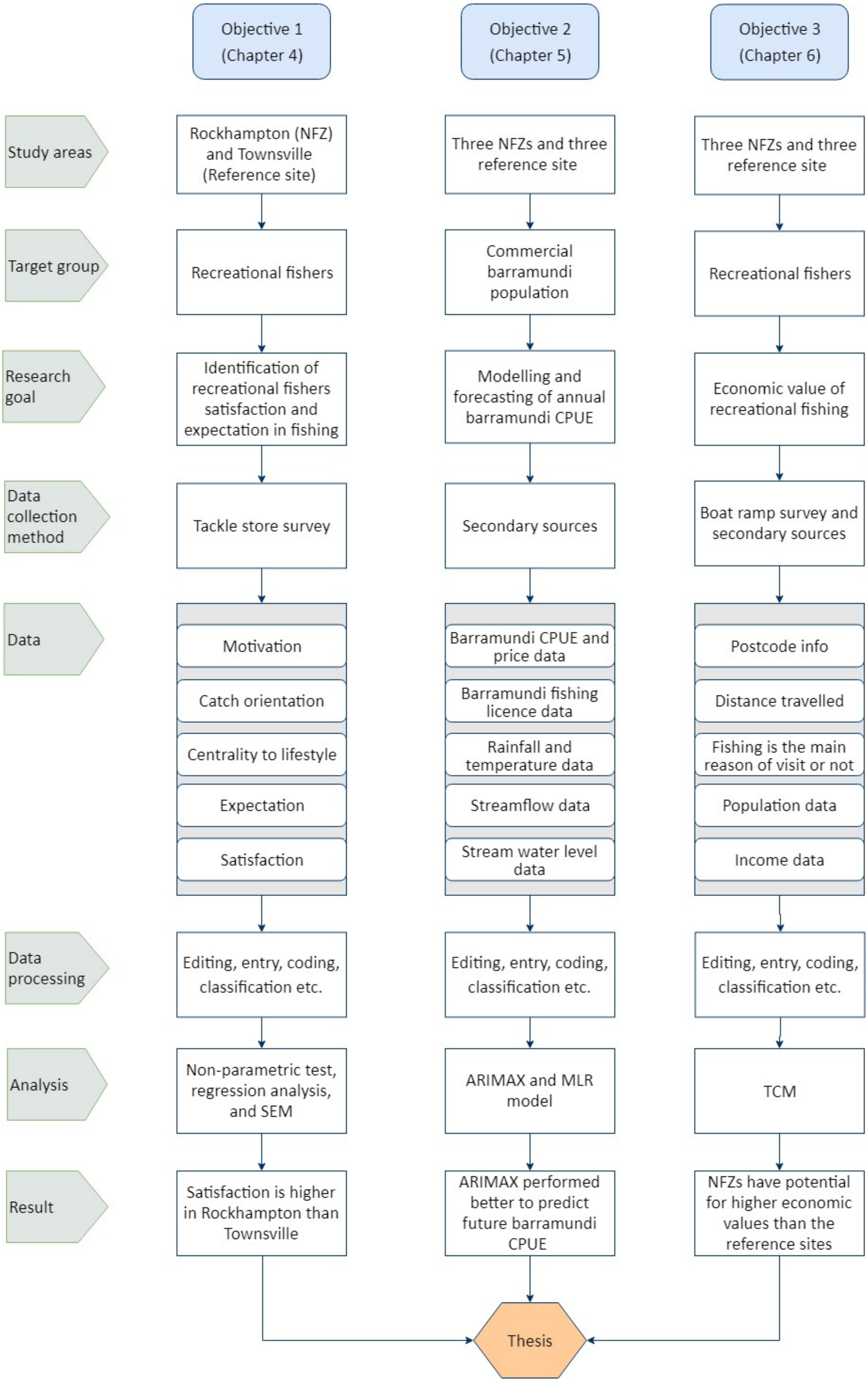



Figure 3-1: Overall methodological approach used in this study

## 3.2 Study sites

In November 2015, the Queensland Government implemented net fishing closures to conserve species by lowering commercial harvest pressure on fish stocks, increase recreational fishing opportunities, marine-based tourism, and the resulting economic growth in three regional areas of Queensland (Brown, 2016; Queensland Government, 2016). The closure areas extend from Keppel Bay to the Fitzroy River for Rockhampton, St Helens Beach to Cape Hillsborough for Mackay, and Trinity Bay for Cairns (Queensland Government, 2017b). To understand the social, ecological, and economic effect of newly established net-free zones (NFZs), this study employed these three NFZs as study sites, alongside three reference sites located in Townsville, Hinchinbrook, and Hervey Bay in Queensland (Figure 3-2).

Trinity Bay is a large bay in the Coral Sea, and presently about 85.58 square kilometres (16º46.517' -16º52.263' S; 145º41.686' -145º50.933' E) area is demarcated as a net-free-fishing zone (Queensland DAF, 2015a). It includes an inlet, which is the main estuary system of Cairns. It supports a long-colonised mangroves system and is used as a fish habitat reserve and a breeding and nursery ground for many juvenile fishes.

The second NFZ at Mackay is 147.47 square kilometres (20º46.746' - 20º56.205' S; 148º53.131'- 149º2.669' E) in size, extending from St Helens Beach to Cape Hillsborough (Queensland DAF, 2015a). This region is known as a unique location for fishing as it works as a junction of southern and northern fish species on the east coast of Australia.

The third NFZ in Rockhampton extends between Keppel Bay and the Fitzroy River, covering 2,013.05 square kilometres (22º56.676'- 23º34.414' S; 150º45 - 151º1.065' E). This area also includes a part of the Capricorn Coast and Yeppoon. The Fitzroy River is the estuary of the largest river basin that flows into the GBR (the Fitzroy Basin).

Recent closures may produce more varied survey results than longer-term closures to which people have become habituated. Reference sites are areas that are not affected by recent policy action changes and are often used to benchmark the efficacy of different programs (Einarsson & Gudbergsson, 2003). This study included three reference sites (Townsville, Hinchinbrook, and Hervey Bay) as they provide opportunities for commercial and recreational fishing. They are evenly distributed across the NFZs and located along the north-eastern coast of Queensland, and their distance from the state capital Brisbane is, respectively, 1114 km, 1240 km, and 290 km. The three reference sites are also being used as reference sites by the Queensland Department of Agriculture and Fisheries (DAF) for their boat ramp surveys.

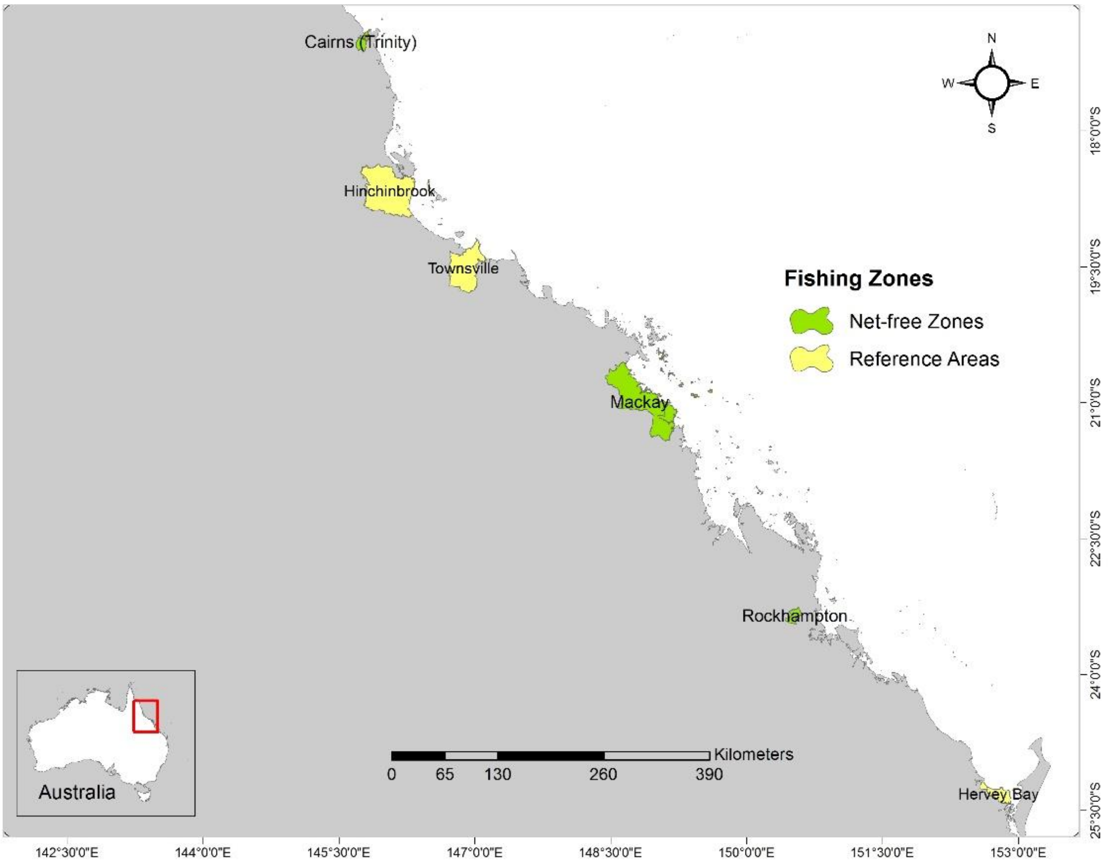



Figure 3-2: Locations of the areas providing access to the three NFZs and three reference sites in Queensland. Map shape file source: DIVA-GIS (http://diva-gis.org/)

## 3.3 Datasets

### 3.3.1 Recreational fishers' satisfaction and expectations data

In order to assess the recreational fishers' satisfaction and expectations, no secondary data could be identified that would be appropriate to conduct the analysis. Therefore, primary data needed to be collected.

A number of basic data collection methods can be used to collect fishers' information. Many authors have found that face-to-face interviews, telephone interviews, mail surveys, postal surveys, and focus group discussions (FGD) to be suitable for studying fisher satisfaction (Sutton, 2006; Brinson & Wallmo, 2013; Henderson & Gigliotti, 2015; Brinson & Wallmo, 2017). Pollock et al. (1994) described some methods of socio-economic data collection from recreational fishers with their potential limitations. Telephone interviews and mail surveys are easier, cheaper, and quicker than the other interview methods (Sutton, 2006), but both are highly subjected to recall bias (Pollock et al., 1994). Additionally, mail surveys are vulnerable to non-response bias (Griffiths et al., 2007). Likewise, postal returned surveys are cost-effective, require less time and labour, but the response rate is relatively lower. FGD is suitable to obtain group perceptions, values, attitudes, and feelings. However, it is not effective in revealing in-depth information about a particular topic. Sometimes the participants are unwilling to share their personal thoughts with other people. A face-to-face survey using a structured questionnaire is well suited for surveys that cover a small range of the population. It is more expensive and laborious, but the response rate is higher than for other methods. Moreover, the questionnaire survey gives more accurate information on demographics and keeps respondents engaged in each session. By considering the relative implications of different data collection methods, this research has chosen to use a survey approach with the members of the recreational fishing community to elicit perceived improvements in recreational fishing values.

The recreational fisher's satisfaction data analysed in this study were collected by the Queensland Department of Agriculture and Fisheries (DAF) from a NFZ (Rockhampton) and a reference site (Townsville) in October 2018. The DAF surveyed a total of 293 recreational fishers from both sites, 163 from Rockhampton and 130 from Townsville. The survey questionnaire was organised into five broad sections: (a) catch orientation, (b) motivation, (c) centrality to lifestyle, (d) expectations, and (e) satisfaction. Each of the sections contained a set of questions regarding theme areas. The survey questionnaire was tested in a NFZ (Rockhampton) and a reference site (Townsville). Most of the questions involve a 7-point Likert scale (e.g., strongly disagree, disagree, somewhat disagree, neutral, somewhat agree, agree, strongly agree) which is used to allow the respondents to express how much they agree or disagree with a particular statement. A few questions are organised into closed-ended and multiple-choice formats. For analysis, the Likert-scale responses from each statement were coded as 1 for strongly disagree, 7 for strongly agree, and 4 for neutral. The questionnaire contained some positively and some negatively worded questions. Negatively worded questions have been reverse-scored before analysis. For closed-ended questions, 'yes' and 'no' responses have been coded as 1 and 2. For multiple-choice questions, each of the categories was coded as 1, 2, 3, 4, and so forth. The responses from the survey were edited where necessary. After data entry, the raw data were analysed using SPSS 24 (https://www-01.ibm.com/support/docview.wss?uid=swg24041224) and STATA SE 12 (https://www.stata.com/ stata12/) for quantitative data analysis.

The recreational fishers were approached in fishing tackle shops located in Rockhampton, and Townsville (Table 3-1). The surveyors attended outside at the tackle store and approached its customers when they left the store. The recreational fishers were asked a set of questions related to their recalled avidity from the past 12 months (i.e., how many times they went fishing in the last 12 months), awareness of NFZs, fishing experience, motivation (i.e., which aspect drives them to go fishing), catch orientation (i.e., how important is catching a fish rather than other aspects), centrality to lifestyle (i.e., how deeply engrained fishing is in their lifestyle), expectations (i.e., over the next 12 months, what they expect from the site), satisfaction (i.e., are they really satisfied with their fishing from the past 12 months) and some demographic questions including their age, gender, and residential information (Appendix A, Table A 2 and Appendix A, Table A 3). The survey was conducted in accordance with conditions of approval from the CQUniversity Human Research Ethics Committee (ethics approval number 0000020847).

Table 3-1: Survey locations of a NFZs and a reference site conducted in 2018

| **Sites** | **Fishing tackle stores** |
|---|---|
| Rockhampton (NFZ) | BCF, Rockhampton |
| | Barra Jacks, Rockhampton |
| Townsville (Reference site) | Akwa Pro Tackle, Townsville |
| | The Fishing Warehouse, Townsville |

### 3.3.2 Barramundi CPUE data for forecasting

In Australia, there is a variety of fish that are both recreationally and economically important such as barramundi, bream, threadfin, whiting, tuna, cod, trout, anchovy, herring, and sardine, etc. Among them, barramundi (*Lates calcarifer*) is an iconic species of Queensland, loved by both recreational and commercial fishers due to its delicious flesh (Fisheries Research and Development Corporation, 2018).

For the forecasting of commercial barramundi CPUE, the relevant secondary data that could be used for analysis were identified. A total of 30 years (1990-2019) of time series data from relevant websites were collected to conduct this analysis. In particular, data on commercial barramundi fishery parameters (catch, effort, and licence) were collected from the QFish website (http://qfish.fisheries.qld.gov.au/) for the fishing grid areas associated with the six study areas. Another fishery parameter, the price of annual barramundi production in Queensland were extracted from the annual fisheries statistics publication of the Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES) (website: http://www.agriculture.gov.au/abares/).

Previous research indicates that environmental variables (such as rainfall, temperature, streamflow, and stream water level) have a significant effect on marine fish populations. (Benson & Trites, 2002; Morrongiello et al., 2014). Rainfall and temperature have a significant impact on the biological processes of fish such as growth, recruitment, and population productivity (Morrongiello et al., 2014). Balston (2007) revealed tangible evidence that climatic variability has an influence on the north-east Queensland barramundi fisheries. Heavy precipitation has a significant positive effect on barramundi spawning and early life stages, which improves fishing in the following year (Balston, 2009a). Similarly, optimum water temperature is important for the survival of new recruits as well as the growth rates of juvenile fish (Agcopra et al., 2005). Streamflow and stream water level was expected to have an impact on barramundi catch. Previous observation has revealed increased recruitment of barramundi after the strong river flows in the Fitzroy area from December to February (Sawynok, 1998). The same study identified a correlation between river flows and barramundi catch in the Gladstone and Central Queensland region.

Regardless of fishery parameters used in this study, four environmental parameters were also considered depending on their effect on the barramundi population. Annual rainfall and temperature data were accumulated from the Bureau of Meteorology database (http://www.bom.gov.au/climate/data/). Interpolated maximum and minimum annual temperatures were considered for the analysis. Streamflow and stream water level data were collected from the Queensland Government Water Monitoring Information Portal (https://water-monitoring.information.qld.gov.au/). Stream discharge volume in megalitres and mean stream water level in metres were extracted for the analysis.

### 3.3.3 Economic valuation data

To assess the economic value of recreational fishing, suitable primary field and secondary data were identified for the project. The field survey was conducted by DAF and the secondary data were collected from relevant websites.

The study surveyed recreational fishers at 14 boat ramps located in three NFZs and three reference sites in Queensland. The survey included a set of questions on fishers' residential area, ramp details, whether fishing is the main purpose of travel or not, postcode, and distance (km) travelled to reach the site. This study also involved the collection of data from secondary sources. Travel distance (kilometres) data were collected using Google maps (Google, n.d.) from the centroid of statistical division to the particular fishing sites. Census data (2016) on population and income was extracted from the Australian Bureau of Statistics (ABS) website (https://quickstats.censusdata.abs.gov.au/census_services/getproduct/census/2016/quickstat/3?opendocument) for each of the postcodes and zones.

The DAF's staff collected data from a total of 24,624 fishers (11,151 from the three NFZs and 13,473 from the three reference sites) from November 2015 to June 2017. Among them, 12,344 observations (6,142 from the three NFZs and 6,202 from the three reference sites) were used for analysis. The rest of the observations were not used in the study since recreational fishing was assumed to be the sole aim of the visit, and visitors with undefined purposes were excluded from this analysis.

Travel cost method (TCM) and contingent valuation (CV) approaches are widely used to estimate economic benefits from different sites (Rolfe & Dyack, 2010). Both methods are inexpensive to apply, and the results are easily interpretable. However, the application of the TCM is more problematic when multi-destination and multi-purpose trips are involved. CV methods are an alternative (Rolfe & Dyack, 2010), but sample selection and limitations of biases can be challenging. Raguragavan et al. (2013) and Schuhmann and Schwabe (2004) used a random utility model to determine the economic values of recreational fishing. The random utility model gives precise results but is expensive and complicated to calculate and explain (Vieira et al., 2009). This study used TCM because of data availability and the potential to provide an accurate estimate of consumer preferences.

The selection of the appropriate TCM model depends on factors such as the type of visitation data to be collected and the nature of the recreational area to be assessed for economic values. To fit an individual travel cost method (ITCM), the study requires data on individual visitation rates, demographics (age, sex, residential area, etc.), and fishing trip-related information (e.g., the number of trips made per individual fisher over a specific time period, total travel costs per individual, total time spent on-site, total travelling time, etc.) (Stoeckl & Mules, 2006; Farr & Stoeckl, 2018). The zonal travel cost method (ZTCM) is suitable for sites with very low visitation rates and ITCM is appropriate for higher visitation patterns (Bateman, 1993; Bennett, 1996; Prayaga et al., 2006). This study used DAF's boat ramp survey data, which was suitable to employ ZTCM but not ITCM.

## 3.4 Data processing and analysis

### 3.4.1 Assessment of recreational fishers' satisfaction and expectations

The purpose of the data collection was to allow testing of two broad hypotheses. The hypotheses were:

- the responses of Rockhampton (NFZ) and Townsville (reference site) fishers are different and the satisfaction and expectations from fishing will be higher in the Rockhampton than in Townsville,
- there is a relationship among satisfaction, overall satisfaction, and expectation, and more particularly,
    - hypothesis: Past satisfaction has a direct positive effect on past overall satisfaction;
    - hypothesis: Past satisfaction has a direct positive effect on future expectation; and
    - hypothesis: Past overall satisfaction has a direct positive effect on future expectation.

#### 3.4.1.1 Statistical analysis

Likert scale data are at the ordinal level and require non-parametric analysis (Shah & Madden, 2004; Mircioiu & Atkinson, 2017). To identify any difference between the two distributions of Rockhampton and Townsville respondent data, a Mann-Whitney U test was employed (McIntosh et al., 2010). Similarly, to examine the correlations between overall satisfaction and expectations, a non-parametric correlation test (Spearman rank correlation) was carried out for both study areas (McIntosh et al., 2010). In addition to this non-parametric analysis, a proportion test was presented graphically to observe the relative percentage of responses for the variables of interest.

To evaluate the relationship between overall satisfaction and other variables, ordered probit regression and backward stepwise regression were conducted. Since it is important to know the information about recreational fishing visits per year (avidity) and the factors that influence fishers to go fishing, a negative binomial regression test was undertaken where avidity (days of fishing in that area) was regressed against all other variables. Additionally, backward regression with the same set of dependent and independent variables was performed to observe and compare the results between the tests and sites. These analyses are more likely to generate more robust insight than the Mann-Whitney U test and Spearman rank correlation tests because regression analysis can determine which factors are most important, which factors may be ignored, and how these variables interact with one another. Furthermore, it is an effective mathematical tool for examining the relationship between two or more variables of interest (Bewick et al., 2003).

Structural equation modelling (SEM) is a multivariate statistical analysis technique that is used to examine structural relationships between measured variables and latent constructs (Tarka, 2018). A latent variable is one that cannot be measured directly but should be inferred from other variables that are observed (directly measured). Two structural equation models were developed for two study sites to identify the structural relationship and strength of the relationship between an observed variable (overall satisfaction) and two of the latent variables (satisfaction and expectations). The output of this model has useful implications for understanding the components that influence satisfaction and expectations, both of which contribute to successful fishing experiences.

### 3.4.2 Time series forecasting of barramundi CPUE

The use of time series models to analyse fish CPUE is undoubtedly the most efficient technique for fisheries management and decision making since it can identify hidden trends and seasonal patterns (Koutroumanidis et al., 2006). Forecasting is used to account for in-season or post-season predictions and provides a basis for predicting the effect of management actions (Farmer & Froeschke, 2015). Time series forecasting involves three fundamental approaches: regression-based methods, heuristic smoothing methods, and general time series (Montgomery et al., 2002). Among them, autoregressive integrated moving average (ARIMA), multiple linear regression (MLR), vector auto regression (VAR), neural network (NN), state-space model, exponential smoothing are widely used time series models. These models either alone or in a combination have been applied in a range of fishery dynamics situations (Stergiou et al., 1997; Tsitsika et al., 2007; Abdelaal & Aziz, 2012). The research employed by Stergiou (1989, 1991), Stergiou et al. (1997), and Romilly (2005) showed that the validation error of the ARIMA model is significantly lower than other models.

The ARIMAX model is an extension of the ARIMA model, which also includes other exogenous variables. The addition of exogenous variables in the model makes the process complex in relation to capturing the influence of external elements and management controllable (Andrews et al., 2013). This study focuses on the forecasting of barramundi stocks and catches using multiple linear regression (MLR) and ARIMAX modelling approaches. In the MLR model, the dependent variable (CPUE) was regressed against a set of independent variables including both fishery and environmental parameters. In the MLR models, environmental variables were lagged for three years. The use of lagged environmental variables was limited to 3 years since young barramundi spend up to 2-3 years in freshwater habitats before reaching legal size (580-999 mm) and migrating to the estuary to spawn. (Food and Agriculture Organization, 2019). Within that time span, recruits are quite likely to mature into adult barramundi, migrate to brackish water, and become vulnerable to commercial fishing. (Robinson et al., 2019).

On the other hand, ARIMAX modelling was more complicated because of the ability to identify inherent patterns in time series data and measure the potential effect of external influences (Andrews et al., 2013). The final fitting ARIMAX model incorporates the addition of highly correlated and highly significant predictor variables that better describe the dependent variable. The validation of the constructed model is necessary to provide insight into its accuracy/precision in forecasting. There are a number of cross-validation techniques widely used in time series analysis. Among them, the walk-forward or sliding window approach provides the most realistic assessment of time series data and produces accurate forecasts at each time step (Brownlee, 2016). The study used a series of walk-forward validation or sliding window approaches which generated out-of-sample results up to the year 2019 (more details are in chapter 5). Then the performance of each model was compared and evaluated in a systematic way. The ARIMAX model building algorithm is depicted in Figure 3-3.

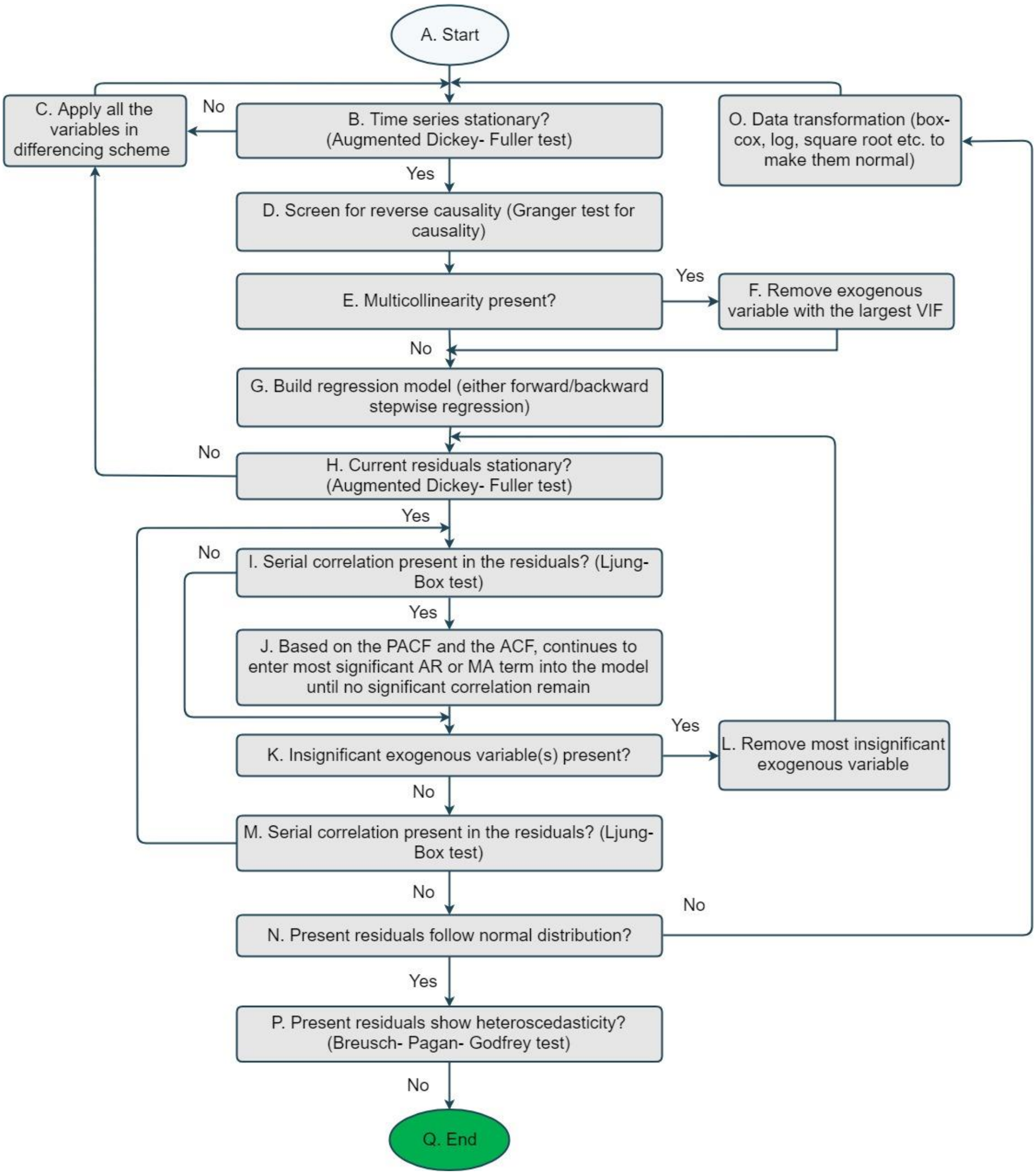



Figure 3-3: ARIMAX building protocol (modified from Andrews et al., 2013)

### 3.4.3 Assessment of economic value of recreational fishing

The study employed three ZTCM models: the postcode model, the zoned model, and the geographic model. The postcode model includes fishers up to two distinct distance thresholds of 100 and 300 kilometres, and the zones were identified by postcode. Using the same distance thresholds, the zoned model analysed pooled postcode data for three NFZs and three non-NFZs (reference sites). No distance threshold was applied for the geographic model because it includes people from remote areas, and geographical regions were employed as zones.

There are three basic approaches or options to consider when determining travel costs (Bateman 1993; Bennett 1996; Rolfe and Prayaga 2007): fuel costs only (option 1), total car costs including fuel, insurance, and maintenance cost (option 2), or the cost estimated by the respondents (option 3). Option 2 was used for this study since data on respondents' one-way travel distance (km) from home to fishing sites was available. The travel cost for each trip was calculated by multiplying the two-way travel cost by a standard vehicle cost per kilometre.

The algebraic form of a relationship between a dependent variable and explanatory variables is referred to as a functional form. The choice of functional form is essential for developing the best fitting model for determining consumer surplus (Crooker & Kling, 2000; Rolfe et al., 2005). The economic theory remains ambiguous on the optimal functional form for either of the two functions that must be calculated (Hanley & Spash, 1993). It is crucial to select the suitable functional form in order to obtain accurate and reliable estimations of consumer surplus, regardless of whether travel costs are precisely calculated or not (Stoeckl, 2003a, 2003b). The trip generated functions (TGF) and demand functions should be chosen in light of pre-existing economic theory, predictability, and statistical specification (Prayaga et al., 2006). Bateman (1993) and Hanley and Spash (1993) used four functional forms such as linear, quadratic, semi-log, and double log to specify TGF and the demand function. However, the method of ZTCM analysis employed in the study is demonstrated in Figure 3-4.

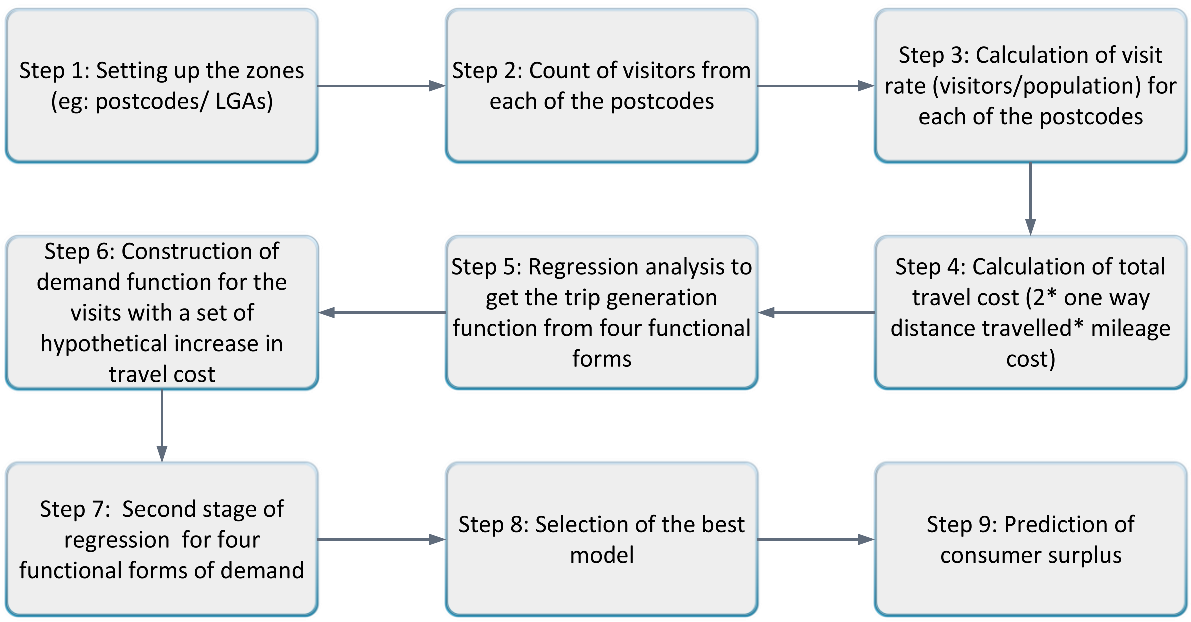



Figure 3-4: Method of ZTCM analysis

### 3.4.4 Conclusions

This chapter has provided a brief overview of the research sites, data, and data analysis. More details about the research methods and findings are presented in the following three chapters (chapter 4, 5, and 6). Each of the three chapters is aimed at evaluating a different type of effect (e.g., social, ecological, and economic). The chapters are designed as stand-alone, but some discussion of methodologies will be repeated in the chapters.

# Chapter 4 SHORT-TERM SOCIAL EFFECTS OF THE QUEENSLAND NETTING CLOSURES

Expected journal article

**Marine**, **S. S.,** Flint, N., & Rolfe, J. (2021). Recreational fishers' satisfaction and expectations in fishing sites with reduced commercial fishing: Queensland's net-free zone as a case study. Manuscript in preparation.

# Abstract

Queensland's newly designed net-free-zones (NFZs), which prohibit commercial net fishing in coastal areas near Cairns, Mackay, and Rockhampton, were implemented to support recreational fisheries by conserving recreationally important fishes and thereby improve fishing satisfaction, support tourism, and stimulate local recreation-based businesses. Although some investigations on the effectiveness of establishing NFZs have been carried out by the Queensland Department of Agriculture and Fisheries (DAF), the analysis of recreational fishers' fishing satisfaction and expectations from a NFZ relative to a non-NFZ (reference site) is yet to be explored. In this study, recreational fishers were surveyed at fishing tackle stores located in the regional cities of Rockhampton (NFZ) and Townsville (reference site). A total of 163 recreational fishers from Rockhampton and 130 fishers from Townsville were sampled in 2018 and completed a survey where fishers rated their responses on a 7-point Likert scale. The findings suggest that the satisfaction and expectations of fishers are higher in the NFZ compared to the reference site. Furthermore, the study demonstrated the inherent causal relationship between satisfaction and expectation components and also the strength of their relationship. These results have significant implications for understanding the factors that best describe satisfaction and expectation for each of the study sites. The output of this study will help management bodies to take further measures to improve recreational fishing opportunities and guide overall fisheries management.



*Keywords:* recreational fishing, satisfaction, expectations, structural equation modelling (SEM), net-free zones (NFZs), resource allocation, fisheries management

## 4.1 Introduction

Recreational fishing is a popular outdoor activity in Australia, leading to the development of a sector with significant economic and social value. In the 12 months prior to November 2013, approximately 642,000, or 15% of Queenslanders aged 5 years or older, went recreational fishing in the east coast Australian state of Queensland (Webley et al., 2015). Recreational fishing plays a significant role in providing non-monetary social benefits to society (McManus et al., 2011; Schmidt et al., 2016; Arlinghaus et al., 2019). These include the physical stimulus and mental serenity gained from practicing nature-based recreational activities (Kaplan & Kaplan, 2011; Young et al., 2016). If recreational fishing is managed in a sustainable manner, improved access to, and involvement in, recreational fishing would probably result in these non-monetary social benefits being transferred to more members of the society (Queensland DAF, 2017b).

The measurement of recreational fishers' satisfaction is an important component of assessing fishers' views about fishing and has been adopted widely as an outcome indicator of quality fishing experience. According to the literature, satisfaction with an activity is a complex process that varies across time between persons and circumstances (Peyton & Gigliotti, 1989) and is regarded as the main product of recreational fishing (Graefe & Fedler, 1986; Holland & Ditton, 1992). Satisfaction is based on the relationship between the results (motivations) one expects and the achievement of those results (Ditton et al., 1981; Holland & Ditton, 1992). The driver of satisfaction varies from person to person. For example, catching a smaller number of fish than expected might result in dissatisfaction and vice-versa. On the other hand, a number of people believe that even without catching fish, a fishing trip could be successful (Mclnnes et al., 2013). Therefore, satisfaction should not only be measured by the number, size, or variety of fish caught (Queensland DAF, 2017b) but also the satisfaction from trip and environment as most fishers consider these two dimensions differently (Hudgins & Davies, 1984; Fedler & Ditton, 1994; Arlinghaus, 2006). As an end product of recreational fishing, fisheries managers would like to learn whether fishers are satisfied with their fishing experiences and the relative contributions of each dimension (Holland & Ditton, 1992). In literature, another broader concept of satisfaction is 'overall satisfaction' that includes all aspects and experiences associated with fishing (Bitner & Hubbert, 1994). Previous observational studies indicate that users perceive these two satisfaction conceptualisations differently (Bitner & Hubbert, 1994). Though there is a link between the two concepts, overall satisfaction depends on information from past encounters and experiences and can be considered as a function of all previous satisfaction (Teas, 1993; Parasuraman et al., 1994; Jones & Suh, 2000). Satisfaction could be claimed as a predictor of overall satisfaction (Teas, 1993).

Understanding the reasons driving anglers to go fishing has been a frequent motivation for research into the human aspect of recreational fishing (Ditton, 2004; Arlinghaus, 2006). Recreational fishing can be viewed as a goal-oriented behavioural system in which fishers select activities to yield psychologically desired outcomes (Manfredo et al., 1996; Beardmore et al., 2011). Fishers can be asked either what inspired them or what satisfaction they received (Holland & Ditton, 1992). The motivations for fishing can be classified as either to fishing-specific aspects (e.g., to catch fish) or to more general psychological outcomes that are not specifically related to the catching process, usually referred to as activity general aspects (e.g., a desire to be outdoors, enjoying nature and relaxation). Although the relative importance of catch and non-catch motivations differs among fisher communities, most researchers have concluded that both catch and non-catch related motivations are important to consider (Fedler & Ditton, 1994; Ditton, 2004; Beardmore et al., 2011). Previous research suggests that motivation has a strong link with satisfaction (Spencer, 1993) notwithstanding the fact that some exceptions were evident (Fedler & Ditton, 1986; Aas & Kaltenborn, 1995).

In relation to the different aspects of the catch or non-catch-related outcomes, satisfaction and overall satisfaction may also vary with the degree of catch orientation (Arlinghaus, 2006; Mostegl, 2011). Catch orientation is a measure of how fishers prioritise catching fish during each trip (Martin et al., 2019). Fedler and Ditton (1986) and Arlinghaus (2006) categorised catch-oriented fishers into low, medium, and high catch orientation groups, where the analysis found that fishers with high catch orientation would be better suited to meeting their need for activity-specific motivations such as catching a fish, catching a trophy size fish, catching many or some types of fish, etc. For low catch-oriented fishers, activity-general components (e.g., to be outdoors, close to nature, for relaxation, being with friends and family, etc.) of motivation tended to be related to increased levels of satisfaction (Graefe & Fedler, 1986; Arlinghaus, 2006; Mcilgorm et al., 2016).

Avidity is one of the ways of measuring the degree of fishing commitment (Hawkins et al., 2009; Mcilgorm et al., 2016). Researchers have used commitment as one of the primary tools in creating and optimising a 'specialisation index', with preliminary findings showing that commitment could be used as a representative for specialisation levels (that means more avid fishers are more inclined to be highly specialised) (Hawkins et al., 2009; Mcilgorm et al., 2016). This finding was supported by studies that explored the importance of commitment in specialisation indexes. These studies revealed that fishing plays an important role in the life of a highly specialised fisher, and they were more inclined to spend a significant amount of money and time in fishing (Salz et al., 2001; Schroeder et al., 2006). Recreational fishers, however, can be broadly categorised as avid and non-avid fishers (Tink, 2015). Graefe (1980) suggested that fishing participation be classified according to participation level such as avid or non-avid fishers where avid fishers fish more frequently than non-avid fishers (Fisher, 1997; Salz et al., 2001). According to the literature, variables such as motivation and the centrality of fishing in one's lifestyle have been identified as significant determinants of avidity (Sutton, 2006; Tink, 2015)

Another indicator of ‘specialisation’ is the centrality of fishing to lifestyle, which measures how closely a particular recreational activity is linked to one's social network and overall lifestyle (Kim et al., 1997; Beardmore et al., 2015). Centrality has proven to be an important psychological element in outdoor recreation studies and is sometimes used as a surrogate for specialisation in recreational fishing (Sutton & Ditton, 2001; Dorow et al., 2010; Dorow & Arlinghaus, 2012). According to the literature, fishers who are more central to fishing in their lifestyle, have a high level of avidity (Mcilgorm et al., 2016) and expectations in fishing (Queensland DAF, 2015b). This would have an effect on a fisher's level of satisfaction in fishing (Queensland DAF, 2015b). In a variety of surveys, the centrality of the lifestyle scale has served to understand the difference between how the recreational fishing population reacts to management decisions (Mcilgorm et al., 2016). A study conducted by Li et al. (2010) found that more centralised fishers of Central Queensland are more likely to be accessible to scientific communication and are more involved in management actions. Most fishers believed that, although fishing is enjoyable, other forms of recreation are also pleasant, and that socialising with friends is not solely dependent on fishing (Teixeira et al., 2021).

The term "expectation" refers to a strong belief that something will happen in the future. Various types of fisher groups have different expectations. The main driving force of satisfaction is related to catch expectations (Hudgins & Davies, 1984; Graefe & Fedler, 1986; McMichael & Kaya, 1991; Spencer & Spangler, 1992; Arlinghaus, 2006). In regard to the relationship between satisfaction and expectation, expectation can be described as advance estimations made by stakeholders while receiving service (Oliver, 1981; Aksu et al., 2010). Satisfaction with past performance is likely to serve as the foundation for expectations of future performance (Ofir & Simonson, 2007). Graefe and Fedler (1986) reported that satisfaction relies not on the actual number of catches, but on how fishers assess catches in the context of their expectations and preferences. Satisfaction can be achieved through catch or non-catch-related outcomes (Spencer, 1993) which might have an effect on future expectations. It is important for management bodies to determine fishers' expectations in advance, as failing to reach satisfaction could result negative disconfirmation (i.e., expectations are not met) of expectations (Brunke & Hunt, 2008). Some research suggests that fishers' expectations vary with net-free zones (NFZs), fishing frequency (Martin et al., 2019), fishing experience, and age of fishers (Aas, 1996; McCormick & Porter, 2014). According to Martin et al. (2019), fishing expectations can be considered independent of satisfaction, which means a person can be satisfied without expecting much change in the future. Other studies indicate that satisfaction is often characterised in terms of expectations (Spencer & Spangler, 1992; Manning, 1999), but a study on an alternative theoretical prediction about the relationship among fishers' satisfaction, overall satisfaction with past performance, and expectations of future performance is inadequate in the literature.

## 4.2 Research approach

The establishment of three new NFZs in Queensland (near the regional cities of Cairns, Mackay, and Rockhampton) came into effect on 1st November 2015. The aim of Queensland's commercial net fishing closures in these zones was to improve recreational fishing opportunities, thereby promoting tourism and economic growth by reducing the pressure on fish stocks arising from commercial fishing (Queensland Government, 2016). Subsequent to the closures, the Queensland Department of Agriculture and Fisheries (DAF) collected recreational fishers' satisfaction and expectations data on an annual basis to identify any changes in satisfaction and expectations towards NFZs following their implementation. Monitoring conducted by Martin et al. (2019) suggests that satisfaction with fishing in the newly established NFZs is increasing. In the 2018 DAF survey, fishers in NFZs are reporting quality fishing opportunities with more exciting fights with fish and greater satisfaction with the number and size of fish caught, compared to the survey data collected in 2015 and 2016. However, comparisons of recreational fishers' satisfaction and expectations between a NFZ and a non-NFZ (reference sites) have not been explored. In particular, the relationship between satisfaction, overall satisfaction, and expectation and the strength of their relationship is yet to be identified.

The present study is set out to evaluate two broad categories of hypotheses. The first hypothesis is that the responses of Rockhampton (NFZ) and Townsville (reference site) fishers are different. It is anticipated that the satisfaction and expectations from fishing will be higher in the Rockhampton than in Townsville. The study also has investigated the conceptual relationship among satisfaction, overall satisfaction, and expectation by setting three hypotheses. The hypotheses that were tested are as follows: hypothesis 2a: Past satisfaction has a direct positive effect on past overall satisfaction; hypothesis 2b: Past satisfaction has a direct positive effect on future expectation; and hypothesis 2c: Past overall satisfaction has a direct positive effect on future expectation. Jones and Suh (2000) hypothesised the three models where it was tested that satisfaction might have an influence on overall satisfaction and Aksu et al. (2010) found there is a positive and strong relationship exists between satisfaction and expectation. In order to illustrate the relationships among expectation, satisfaction, and overall satisfaction, the theory, and the measurement model were formulated for the exogenous variable and the endogenous variables, as depicted in Figure 4-1. Exogenous variables are variables in a model that are not determined by other variables and variables that are determined by other variables are referred to as endogenous variables.

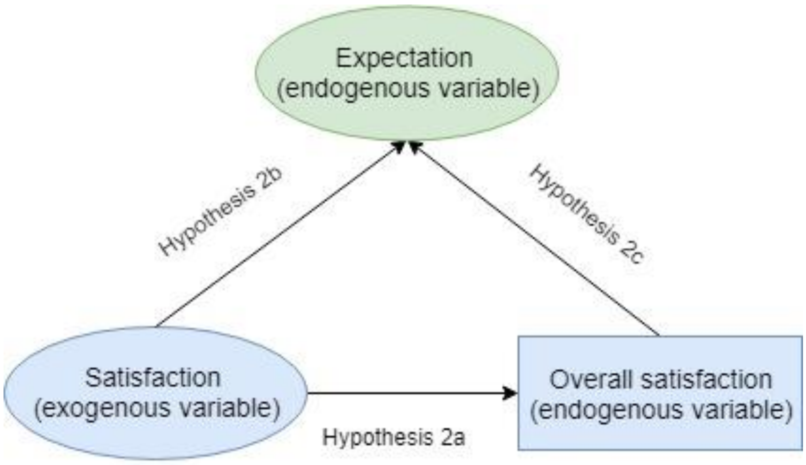



Figure 4-1: Mediators in satisfaction and expectation relationship

## 4.3 Study methods

### 4.3.1 Study sites and data

The study was conducted in a NFZ (Rockhampton) and a reference site (Townsville) in Queensland (Figure 4-2). The two study areas were chosen as both of the fishing areas are geographically similar to each other, being rivers and coasts located in close proximity to regional cities. The distance between two sites are 720 kilometres. The research was conducted in accordance with conditions of approval from the CQUniversity Human Research Ethics Committee (ethics approval number 0000020847). The DAF surveyed a total of 293 recreational fishers from the Rockhampton and Townsville zones in October 2018, where 163 surveys were from Rockhampton and 130 were from Townsville. The survey collection locations were near fishing tackle stores in the two zones, and a face-to-face questionnaire survey was undertaken by DAF's survey staff. Fishers were asked to participate in a structured questionnaire survey when they were returning from the fishing tackle stores. Recreational fishers who had fished at least once in the past 12 months at any of the fishing sites were identified as eligible to participate in this survey. The respondents were selected randomly when they were leaving the tackle stores. To avoid bias in the wording of social survey questions, a social scientist reviewed the questions prior to data collection and the interviewers received training on how to ask such questions in an unbiased way (DAF, 2017, 2019).

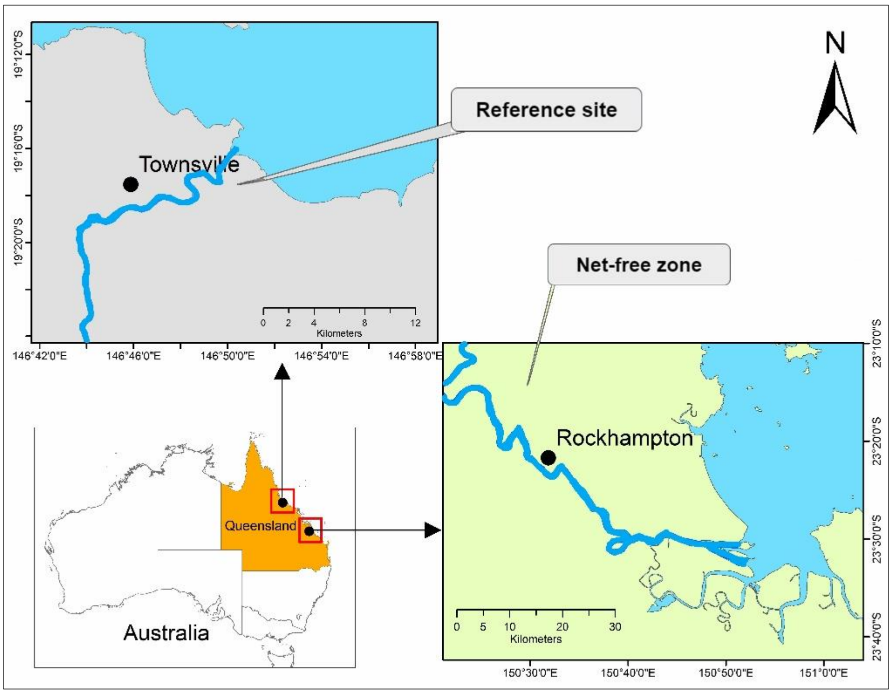



Figure 4-2: Map showing a NFZ (Rockhampton) and a reference site (Townsville) in Queensland, Australia. Map shape file source: DIVA-GIS (http://diva-gis.org/)

The survey questionnaire consisted of several sections, with a number of statements in each that were either positively or negatively worded, and some background and demographic questions. Depending on the type of statement, participants were asked to rate their level of agreement or disagreement, important or not important, satisfied or dissatisfied on a 1-7-point Likert scale, ranging from 1= strongly disagree/ not important/ very dissatisfied to 7= strongly agree/ very important/very satisfied. The different concepts tested in the survey were motivation, catch orientation, the centrality of fishing to fisher's lifestyle, expectations, and satisfaction (Appendix A, Table A 2 and Appendix A, Table A 3). For satisfaction-related questions, fishers were asked about their satisfaction with fishing in this area over the previous 12 months. There were 5 questions about satisfaction with catch-related aspects (e.g., satisfaction with the number, size, and variety of fish caught) and 2 about non-catch-related aspects (e.g., satisfaction in number of uncrowded fishing spots and satisfaction in access to parking sites and boat ramps). There was also a question about overall satisfaction with fishing in the previous 12 months. In addition to satisfaction, fishers were asked about their expectations with fishing over the next 12 months and beyond. There were 12-13 questions about various aspects of expectations.

### 4.3.2 Statistical analysis

The data analysis was conducted using SPSS 24 and STATA SE 12. At the beginning of the data analysis, missing data were replaced by the mean imputation method as the amount of missing data were less than 10% of the sample for each variable (Raymond, 1986). From the survey, the results for the eight negatively worded questions were reversed before analysis. For example, when a positively worded question is scored, the Likert response 1 indicates strongly disagree/ not important/ very dissatisfied, and the Likert response 7 indicates strongly agree/ very important/very satisfied; when a negatively worded question is scored, the Likert response 7 indicates strongly disagree/ not important/ very dissatisfied, and the Likert response 1 indicates strongly agree/ very important/very satisfied. (Suárez Álvarez et al., 2018). An example of a negatively worded question is “When you go fishing, you’re just as happy even if you don’t catch a fish”.

#### 4.3.2.1 Non-parametric test for categorical variables

The aim of Queensland’s NFZs is to conserve recreationally important species and improve recreational opportunities, allowing anglers to catch more and bigger fish and provide recreational fishers with a higher degree of fishing experience and satisfaction (Martin et al., 2019). The study collected ordinal data and tested if there were differences in the responses between Rockhampton and Townsville respondents. In order to deal with ordinal data, non-parametric statistical tests were required (Shah & Madden, 2004; Mircioiu & Atkinson, 2017). A Mann-Whitney U test was employed to identify any difference between the two distributions of Rockhampton and Townsville. The study also used Spearman rank correlation tests to identify the correlation between overall satisfaction and components of satisfaction and expectation.

#### 4.3.2.2 Regression analysis

The study conducted regression analysis to understand the most influencing factors that affect fishing frequency (avidity) and overall satisfaction in both study sites. Other alternative options determining motivation, expectations, catch orientation, and centrality of fishing to lifestyle were available to quantify the difference between responses of two sites. However, the study only evaluated the factors that affect avidity and overall satisfaction. The data here used are ordinary and this study used regression analysis, as regression is flexible and can handle ordinal data (DeYoreo & Kottas, 2020).

Factors that influence overall satisfaction were examined and compared between sites using ordered probit regression and backward stepwise regression. Negative binomial regression was used to identify the extent to which avidity (days of fishing in that area) could be predicted by other variables. In addition, backward stepwise regression was performed with the same dependent and independent variables to observe and compare the results between the tests and sites. These analyses are likely to provide more robust insight than the Mann-Whitney U test and Spearman rank correlation tests as the significance of regression analysis is that it can decide which variables matter most, which variables can be ignored, and how these variables interact with each other. Moreover, it is a useful mathematical tool for investigating the relationship between two or more variables of interest (Bewick et al., 2003). For the dependent variable avidity, the mid-value of the responses was considered instead of taking the whole range for each of the responses. For example, if a recreational fisher goes fishing 3-12 days in the last 12 months, then the value would be the mid-value of this range (i.e., 7.5) (Appendix A, Table A 2). The regression tests were evaluated at $p$ = .05.

#### 4.3.2.3 Structural equation modelling (SEM)

Structural equation modelling (SEM) is a multivariate statistical analysis technique that is used to analyse structural relationships between measured variables and latent constructs. A latent variable is one that cannot be measured directly but should be inferred from other variables that are observed (directly measured). In a factor analysis, the "factors" are latent variables. A structural equation model contains two elements: first, a measurement model, which describes the relationship between latent and observable variables based on the pre-existing measurement theory, which is then validated with confirmatory factor analysis (CFA) to concentrate on the “validity” of the latent constructs; and, second, the structural model describes the relationship of endogenous and exogenous latent variables and/or observed variables which helps the investigator to determine the nature and magnitude of the effects among these variables (Tarka, 2018). To test the hypothesis that rationale in past fishing satisfaction influences fishers’ expectations, the study developed SEM models for both study sites. Measurement parameters and full SEM models were evaluated using maximum likelihood estimation by using software STATA SE 12.

Based on the insights obtained from the reliability test, a confirmatory factor analysis (CFA) was employed to evaluate and confirm latent variables that best represent the group of indicator variables. The outcome of the CFA is related to the measurement component of the SEM model, which explains the loading of indicator variables on the corresponding latent variables. Then the study extracted the measurement component and structural component of the SEM model, which provides an overall assessment of the interrelation among the variables (Dragan & Topolšek, 2014).

##### 4.3.2.3.1 Fitting accuracy of SEM

Based on the early literature on SEM, the chi-square estimate of the entire model was the most important fit statistic for SEM. However, it is worth noting that the chi-square value reflects the 'low-fitness', as a high chi-square value represents a large difference between the models and the data, and a significant test statistic could cast doubt on the model specification (Aas & Vitters, 2000). Experts have cautioned against selecting models only based on the chi-square test (Bentler & Bonett, 1980; Jöreskog & Sörbom, 1993). The test consistently rejects the best-fitting models as it is highly sensitive to the sample size and the number of variables used in the model (MacCallum et al., 1996). Considering the limitation of the chi-square model fit test, it is recommended that an alternative 'goodness-of-fit' test should be reported along with chi-square test statistics (Aas & Vitters, 2000). The 'goodness-of-fit' index evaluates the fit between the proposed model and the observed covariance matrix. In case of model fit, the values for the chi-square test should be above 0.05, CFI (comparative fit index) and TLI (Tucker-Lewis index) should be above 0.90, RMSEA (root mean square error of approximation) and the SRMR (standardised root mean square residual) should be as low as possible. RMSEA and SMRM values of 0.05-0.08 indicate a fair fit, 0.08-0.10 indicates a moderate fit, and above 0.10 indicates a poor fit (MacCallum et al., 1996). If the model demonstrates a poor fit, some additional modifications of the model must be made (Dragan & Topolšek, 2014).

## 4.4 Results

### 4.4.1 Non-parametric test for the categorical variable

From the survey, most (> 90%) of the participants were local and recorded as male with ages ranging between 35-44 years for Rockhampton and 45-54 for Townsville. Female participants were 3.7% in Rockhampton and 2.3% in Townsville. Fishers interviewed in Townsville were slightly older than Rockhampton, with most Townsville participants in the 45-54 years bracket and Rockhampton participants in the 35-44 years bracket (Figure 4-3).

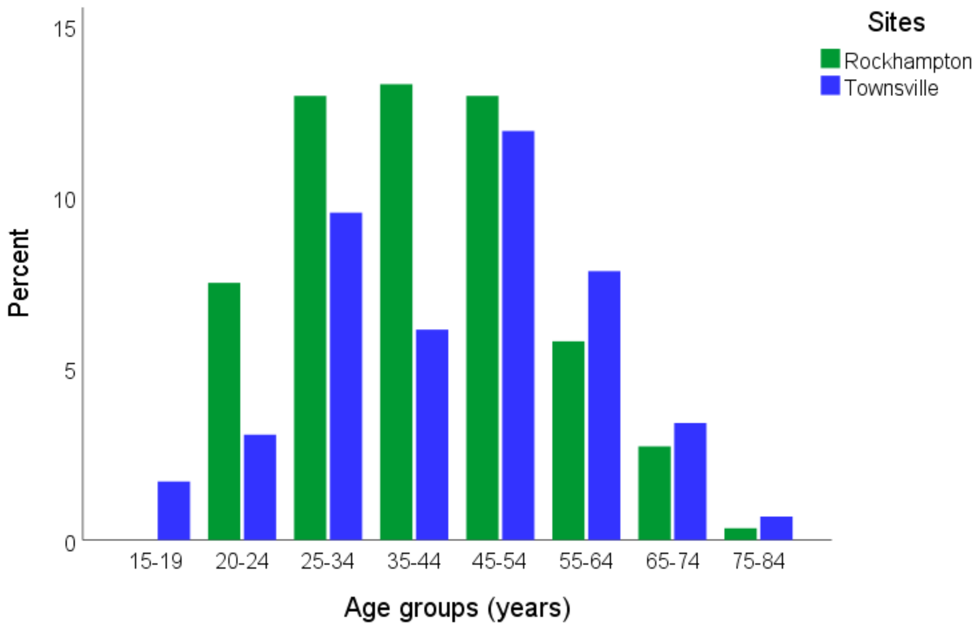
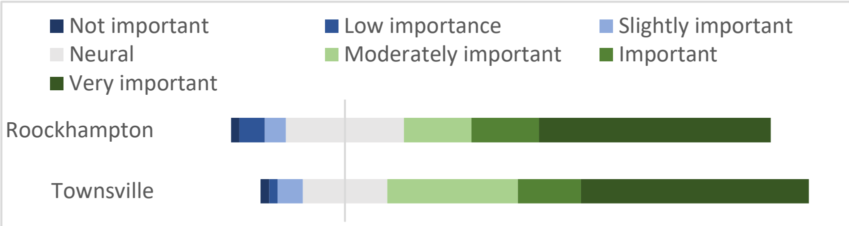
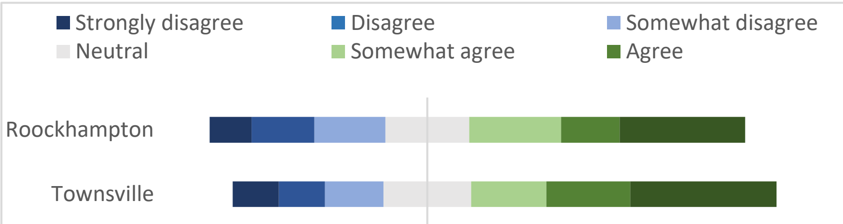
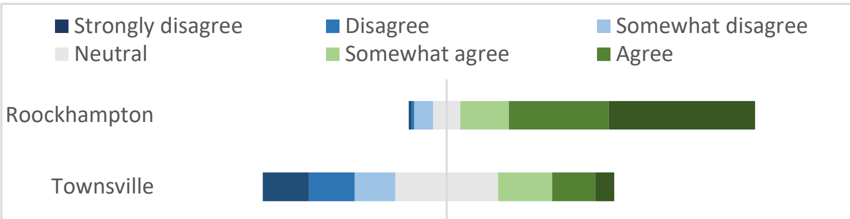
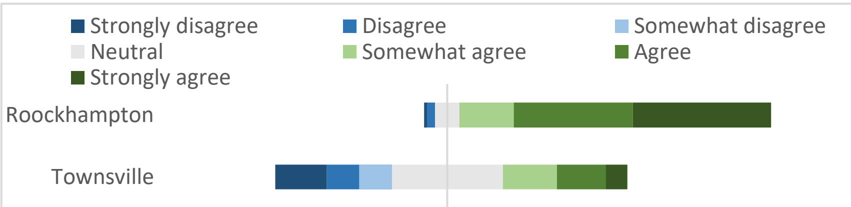
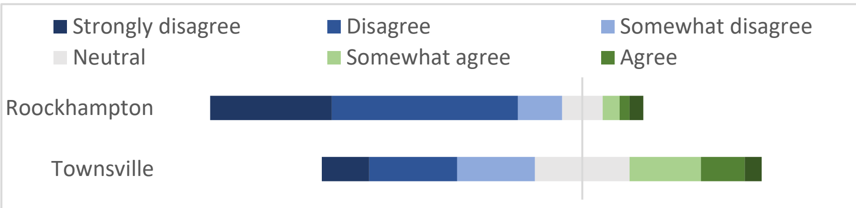
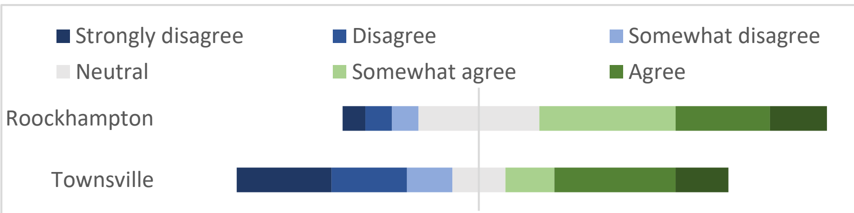
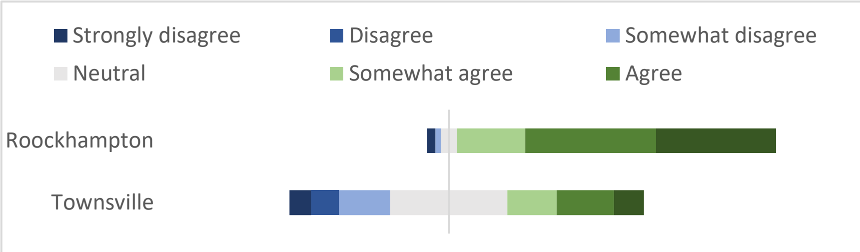
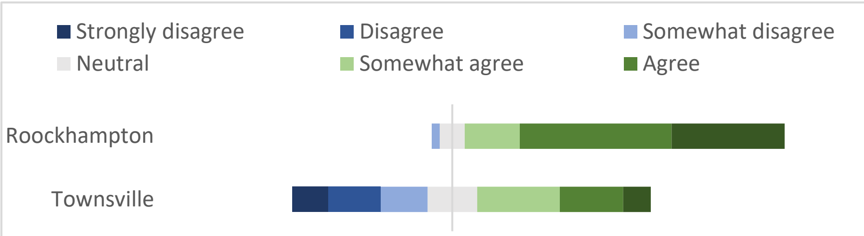
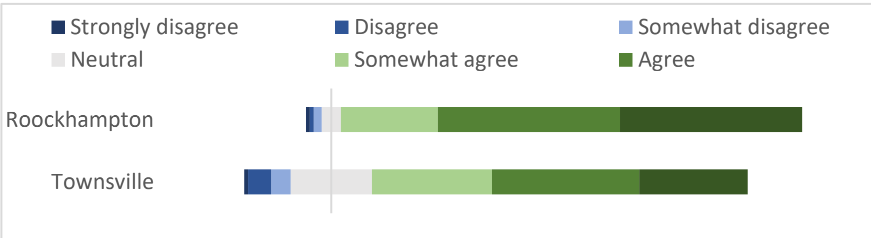
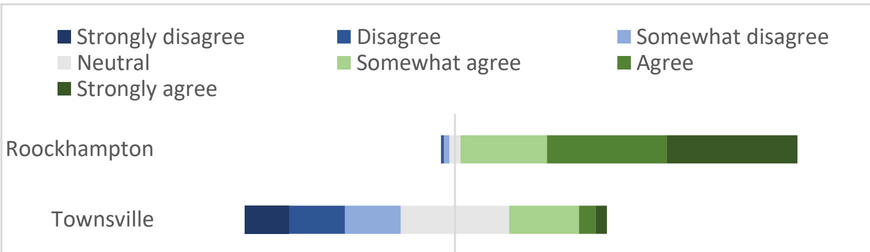
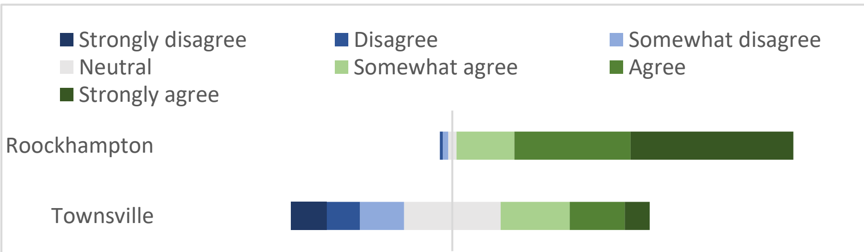
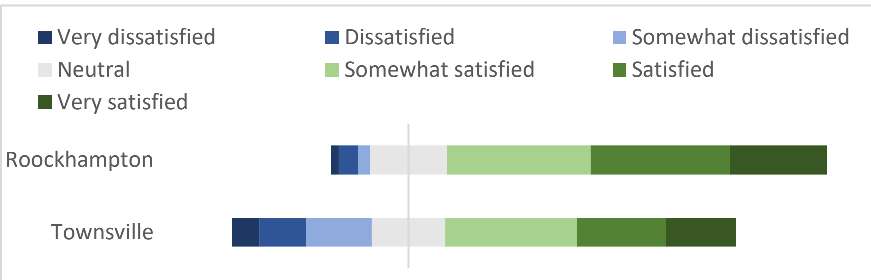


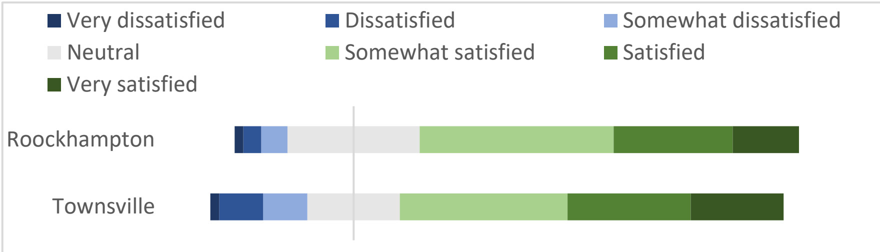
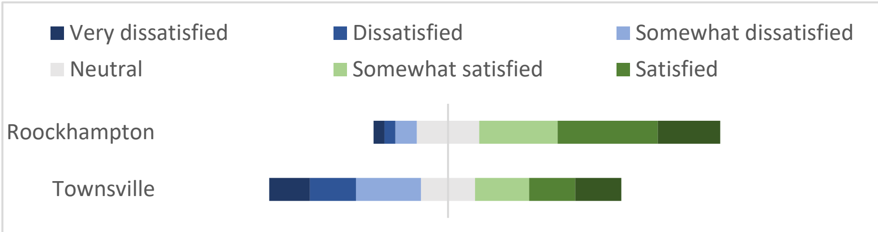
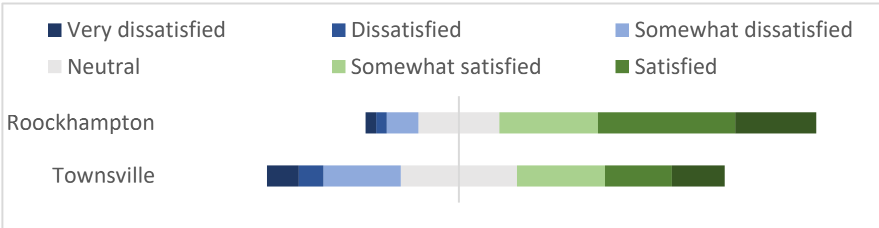
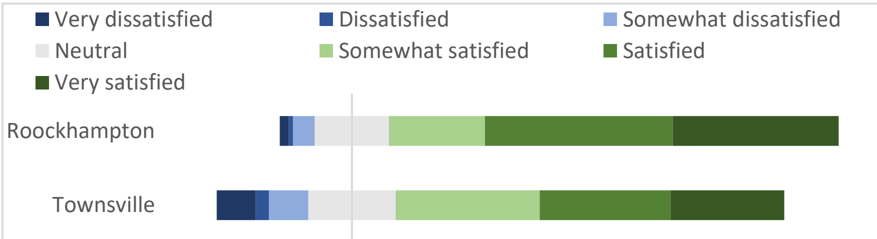
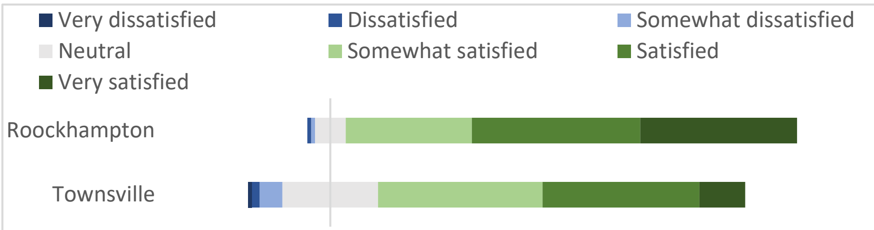

Figure 4-3: Age groups of recreational fishers interviewed from Rockhampton and Townsville in 2018

From the raw responses of the survey, it is evident that the satisfaction and expectations of Rockhampton fishers (one of the NFZs) are higher than the Townsville fishers (reference site) (Table 4-1). There was no statistical difference between the two sites for two questions related to catching a fish (Table 4-1). Rockhampton has greater expectations for an increase in fish number, size, variety, new species, increased satisfaction, quality fishing, the involvement of more people, catch, and abundance of more fish than Townsville. Similarly, Rockhampton outperforms Townsville in terms of satisfaction in fish number, size, variety, exciting fights, and overall satisfaction Table 4-1).

Table 4-1: 7- point Likert scale response for catch-related statements for Rockhampton and Townsville.

<table>
<tr><th>Concepts</th><th>Responses</th></tr>
<tr><td colspan="2">Motivation:</td></tr>
<tr><td>To catch fish*</td><td>
</td></tr>
<tr><td colspan="2">Catch orientation:</td></tr>
<tr><td>The main reason you go fishing is to catch a fish*</td><td>
</td></tr>
<tr><td colspan="2">Expectations:</td></tr>
<tr><td>Increase of variety of species</td><td>
</td></tr>
<tr><td>Increase in the number of species</td><td>
</td></tr>
<tr><td>Decrease of the size of fish</td><td>
</td></tr>
<tr><td>Target new species</td><td>
</td></tr>
</table>

| **Concepts** | **Responses** |
|---|---|
| Increase in fishing satisfaction |  |
| Quality fishing opportunities for the future generation |  |
| More people will go fishing |  |
| Catch more fish |  |
| Availability of more sea life |  |
| **Satisfaction:** | |
| Number of fish |  |

| Concepts | Responses |
|---|---|
| Variety of fish* |  |
| Number of big fish |  |
| Size of fish |  |
| Number of exciting fights |  |
| Overall satisfaction |  |

Note 1: the response of 1 indicates not important/strongly disagree/very dissatisfied and 7 indicates very important/ strongly agree/ very satisfied. Note 2: An asterix (*) in the statement indicates that the differences are not statistically significant between the two populations.

A Mann- Whitney U test indicates that the mean rank value of Rockhampton respondents was greater for satisfaction and expectations-related statements than those of Townsville respondents (*p*-value is < .05) (Appendix A, Table A 1). That means the distributions of Rockhampton and Townsville are different, and there is a significant difference between the mean ranks for both satisfaction and expectations-related statements. However, there is no significant difference between the mean ranks of the two sites while considering the three statements viz. (a) to catch fish (U=9839.0, *p*= .274), (b) the main reason you go fishing is to catch a fish (U=10008.50, *p* = .409), and (c) the variety of fish you have caught (U=10275.00, *p*=.648).

The Spearman's rank correlation test suggests that the overall satisfaction for Rockhampton has a positive and moderately strong correlation with expectation components compared to Townsville (Table 4-2). In addition, fishers of Rockhampton and Townsville have a similar positive and highly strong correlation with overall satisfaction and satisfaction, especially in terms of the number, size, variety, and number of exciting fights with fish (Table 4-2).

Table 4-2: Spearman's rank correlation test for the statements

| Spearman's rho | Overall satisfaction in the past 12 months (Rockhampton) | Overall satisfaction in the past 12 months (Townsville) |
|---|---|---|
| You expect the variety of species you catch to increase over the next 12 months | .441** | .241** |
| You expect the number of fish you catch to increase over the next 12 months | .433** | .198* |
| You expect the size of the fish you catch to decrease over the next 12 months | .214** | .208* |
| You expect to be able to target new species of fish you have not targeted before over the next 12 months | .193* | .076 |
| Your satisfaction with fishing in this area will increase over the next 12 months | .438** | .383** |
| You expect future generations will have quality fishing opportunities in this area | .527** | .444** |
| In the future, you expect that more people will go recreational fishing in this area | .494** | .194* |
| In the future, you expect recreational fishers to catch more fish in this area | .456** | .223* |
| In the future, you expect there to be more sea life of all kinds within this area | .405** | .299** |
| The number of fish you have caught | .509** | .689** |

| Spearman’s rho | Overall satisfaction in the past 12 months (Rockhampton) | Overall satisfaction in the past 12 months (Townsville) |
|---|---|---|
| The variety of fish you have caught | .538** | .561** |
| The number of big fish you have caught | .519** | .604** |
| The size of the fish you have caught | .520** | .657** |
| The number of exciting fights with fish you have had | .570** | .524** |

Note: Coefficients represent correlation statistics, ** and * = significant at the 1% and 5% level respectively

### 4.4.2 Regression analysis

To identify the relationship between overall satisfaction and other influencing factors, an ordered probit regression and backward stepwise regression was performed where ‘overall satisfaction’ was considered as the dependent variable against contributing variables. Though the presence of significant variables is different in both analyses, more motivation and satisfaction related variables have a positive and significant effect in Rockhampton than in Townsville (

Table 4-3). In order to keep the results concise, the study only reported positive or negative signs to indicate the significant positive or negative effect for each variable on each site.

Table 4-3: Ordered probit regression and backward stepwise regression to determine overall satisfaction

| Statements | Rockhampton | Townsville |
|---|---|---|
| **Ordered probit regression:** | | |
| To enjoy nature | + | + |
| To catch fish | + | |
| To be with family or friends | + | − |
| To be outdoors | | + |
| You usually have a good time fishing even if no fish are caught | + | |
| The main reason you go fishing is to catch a fish | + | |
| The number of fish you have caught | + | + |
| The variety of the fish you have caught | + | |
| The number of big fish you have caught | + | |
| The size of the fish you have caught | + | |
| The number of uncrowded fishing spots | + | + |
| The number of exciting fights with fish you have had | + | |
| Access to parking spaces and boat ramps | + | |
| Age of the participants | | + |
| **Backward stepwise regression:** | | |
| To enjoy nature | + | + |
| The number of fish you have caught | + | + |
| The size of fish you have caught | + | |
| The number of uncrowded fishing spots | + | + |

Note: here '+' indicates the variable was found to have a positive and statistically significant effect at a significance level of .05, '−' indicates a negative and statistically significant effect and a blank indicates not significant.

To evaluate the relationship between frequency of recreational fishing (avidity) and other influencing factors, negative binomial regression and backward stepwise regression analysis were performed where 'avidity' was considered as a dependent variable against all other independent variables (Table 4-4). Rockhampton's avidity is favourably influenced by more satisfaction and expectations-based elements than Townsville (Table 4-4). Negative binomial regression showed that 'fishing experience' and 'satisfaction with the size of fish caught' had a strongly negative relationship with avidity in Townsville, but positive in Rockhampton.

Table 4-4: Negative binomial regression and backward stepwise regression to determine the frequency of fishing (avidity)

| Statements | Rockhampton | Townsville |
|---|---|---|
| **Negative binomial regression:** | | |
| Fishing experience | + | − |
| To catch fish | + | |
| To be outdoor | + | |
| To be with family or friends | | − |
| To get away from other people | + | |
| You are getting more involved in fishing these days | | + |
| Other people would probably say you spend most of your free time fishing | | + |
| When you go fishing, you enjoy other parts of the experience more than catching fish | + | |
| Many of your friends go fishing | + | |
| Other leisure activities do not interest you as much as fishing | + | |
| Going fishing is one of the most enjoyable things you do | + | |
| You are getting more involved in fishing these days | + | |
| The number of fish you have caught | + | |
| The variety of the fish you have caught | + | |
| The number of big fish you have caught | + | |
| The size of the fish you have caught | + | − |
| The number of exciting fights with fish you have had | + | + |
| Overall satisfaction | + | |
| Age of participants | + | |
| **Backward stepwise regression:** | | |
| Fishing experience | + | |
| To catch fish | + | |
| To be outdoors | + | |
| When you go fishing, you are just as happy even if you don't catch a fish | − | |
| Other people would probably say you spend most of your free time fishing | + | + |
| How much would you miss fishing if you could not go anymore? | + | |
| The number of the fish you have caught | + | |
| The number of exciting fights with fish you have had | + | + |
| The number of uncrowded fishing spots | + | |

Note: here '+' indicates the variable was found to have a positive and statistically significant effect at a significance level of .05, '−' indicates a negative and statistically significant effect and a blank indicates not significant.

### 4.4.3 Structural equation modelling (SEM)

Statistical methods have been used to evaluate the accuracy and validity of the survey and to achieve insight into the influence of past satisfaction on recreational fishers' future expectations. To develop an SEM, the minimum sample size requirement is 100, where the model should contain five or fewer latent variables (variables that cannot be measured directly but should be inferred from other variables that are observed) with more than three indicator variables (items or observed variables) and the items should have higher communalities (0.6 or higher) (Hair et al., 2010). The conceptual framework of SEM for this study is presented in Figure 4-4.

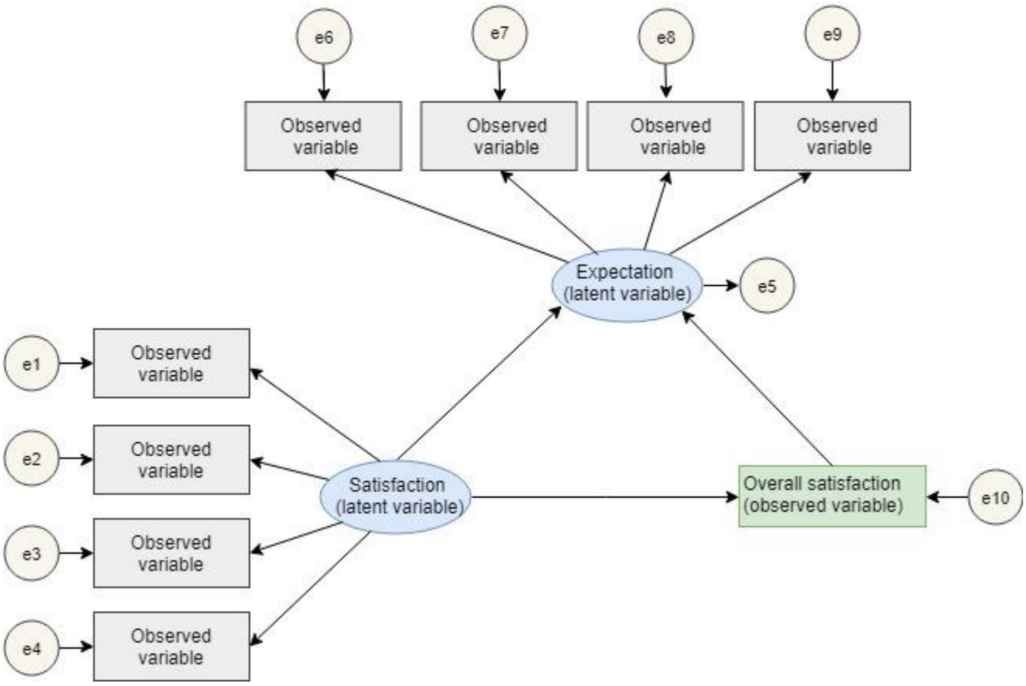



Figure 4-4: Conceptual framework of SEM

#### 4.4.3.1 Reliability test

To measure the consistency of variables in a construct, a reliability test was performed using Cronbach's alpha. Variables with the item-total correlation value less than 0.3 were removed from the test to improve the internal consistency (Nurosis, 2005; Cristobal et al., 2007). Table 4-5 represents the Cronbach's alpha value after deleting a few variables from the two constructs (e.g., expectation and satisfaction) for the two study sites. The deleted variables are reported in Appendix A, Table A 4.

Table 4-5: Cronbach's alpha value for the two constructs of Rockhampton and Townsville

| Constructs | Rockhampton | Townsville |
|---|---|---|
| | Cronbach's alpha | Cronbach's alpha |
| Expectation | 0.873 | 0.837 |
| Satisfaction | 0.921 | 0.927 |

#### 4.4.3.2 Confirmatory factor analysis (CFA)

Confirmatory Factor Analysis (CFA) was employed to confirm the validity of the constructs. Convergent validity is the proof of the existence of a construct determined by the correlations displayed by the associated independent measures of the construct (Wantara, 2013). To evaluate convergent validity, the reliability of each construct and factor loadings were investigated using the software STATA SE 12. The standardised factor loadings less than 0.6 were removed from the analysis (Guadagnoli & Velicer, 1988). The deleted variables are reported in Appendix A, Table A 5. Table 4-6 represents the factor loadings above 0.6 that were used to run the CFA. Confirmatory factor analysis showed that the three variables (one observed variable: overall satisfaction and two latent variables: satisfaction and expectation) are positively correlated with each other (Table 4-7). The correlation between satisfaction and overall satisfaction for both sites are highly correlated and the correlation between satisfaction and expectation; and overall satisfaction and expectation were found to be moderately correlated (Table 4-7). A multicollinearity test did not identify multicollinearity among the satisfaction and expectation components (Appendix A, Table A 6 and Appendix A, Table A 7).

Table 4-6: Latent variable loadings for expectation and satisfaction from confirmatory factor analysis

| Sites | Variables in CFA | | Question abbreviation | Standardised factor loadings |
|---|---|---|---|---|
| Rockhampton | **Latent variable 1: Expectation** | | | |
| | Q9a | You expect the variety of species you catch to increase over the next 12 months | Species variety | 0.66 |
| | Q9b | You expect the number of fish you catch to increase over the next 12 months | Fish number | 0.76 |
| | Q9e | Your satisfaction with fishing in this area will increase over the next 12 months | Satisfaction increase | 0.60 |
| | Q9i | You expect future generations will have quality fishing opportunities in this area | Quality fishing | 0.67 |
| | Q9j | In the future, you expect that more people will go recreational fishing in this NFZ | More people | 0.69 |
| | Q9k | In the future, you expect recreational fishers to catch more fish in this NFZ | Catch more fish | 0.82 |
| | Q9l | In the future, you expect there to be more sea life of all kinds within this NFZ | More sea life | 0.75 |
| | Q9m | In the future, you expect that the NFZs will benefit local businesses | Benefit businesses | 0.67 |
| | **Latent variable 2: Satisfaction** | | | |
| | Q10a | The number of fish you have caught | Number of fish caught | 0.82 |
| | Q10b | The variety of the fish you have caught | Variety of fish caught | 0.76 |
| | Q10c | The number of big fish you have caught | Number of big fish caught | 0.93 |

| Sites | Variables in CFA | | Question abbreviation | Standardised factor loadings |
|---|---|---|---|---|
| | Q10d | The size of the fish you have caught | Size of fish caught | 0.92 |
| | Q10e | The number of exciting fights with fish you have had | Exciting fights | 0.73 |
| Townsville | **Latent variable 1: Expectation** | | | |
| | Q8a | You expect the variety of species you catch to increase over the next 12 months | Species variety | 0.67 |
| | Q8b | You expect the number of fish you catch to increase over the next 12 months | Fish number | 0.72 |
| | Q8e | Your satisfaction with fishing in this area will increase over the next 12 months | Satisfaction increase | 0.75 |
| | Q8k | In the future, you expect recreational fishers to catch more fish in this area | Catch more fish | 0.65 |
| | Q8l | In the future, you expect there to be more sea life of all kinds within this area | More sea life | 0.63 |
| | **Latent variable 2: Satisfaction** | | | |
| | Q9a | The number of fish you have caught | Number of fish caught | 0.85 |
| | Q9b | The variety of the fish you have caught | Variety of fish caught | 0.78 |
| | Q9c | The number of big fish you have caught | Number of big fish caught | 0.90 |
| | Q9d | The size of the fish you have caught | Size of fish caught | 0.90 |
| | Q9e | The number of exciting fights with fish you have had | Exciting fights | 0.81 |

Table 4-7: Correlations between observed (overall satisfaction) and latent variables (satisfaction and expectation) for Rockhampton and Townsville

| **Covariances** | **Rockhampton** | | **Townsville** | |
|---|---|---|---|---|
| | **Coefficient** | ***p*-value** | **Coefficient** | ***p*-value** |
| Satisfaction Overall Satisfaction | .6937533 | .000 | 1.095016 | .000 |
| Satisfaction Expectation | .5640234 | .000 | .4982039 | .003 |
| Overall Satisfaction Expectation | .5633263 | .000 | .554337 | .000 |

The fit statistics for the primary model were not at an acceptable level. So, the model was modified by linking the errors of closely related indicator variables that have a theoretical background in order to provide an acceptable fit. The Goodness of fit statistics is provided in Table 4-8.

Table 4-8: Goodness of fit for confirmatory factor analysis for Rockhampton and Townsville

| **Goodness of fit** | **Rockhampton** | **Townsville** |
|---|---|---|
| | **Values** | **Values** |
| N | 163 | 130 |
| $Chi^2$ | 140.18 | 55.11 |
| *p*-value | .00 | .06 |
| RMSEA | 0.07 | 0.05 |
| CFI | 0.95 | 0.98 |
| TLI | 0.94 | 0.97 |
| SRMR | 0.04 | 0.04 |

#### 4.4.3.3 Structural equation model

A structural model fitted to the expectation, satisfaction, and overall satisfaction data according to the model structure is demonstrated in Figure 4-5 and Figure 4-6. According to the findings, satisfaction is the most powerful predictor of overall satisfaction, and overall satisfaction is also a strong determinant of expectation at both study sites. Furthermore, satisfaction was found to be an important predictor of expectation in Rockhampton but not in Townsville.

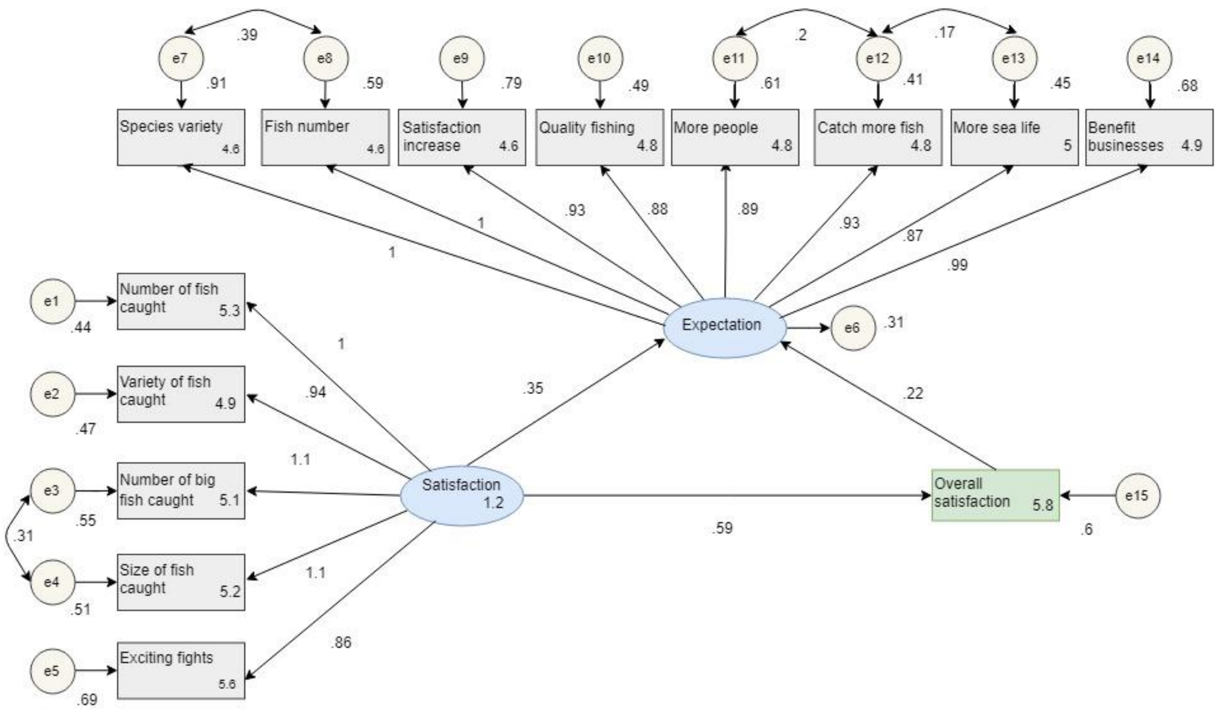



Figure 4-5: Revised structural equation model for Rockhampton

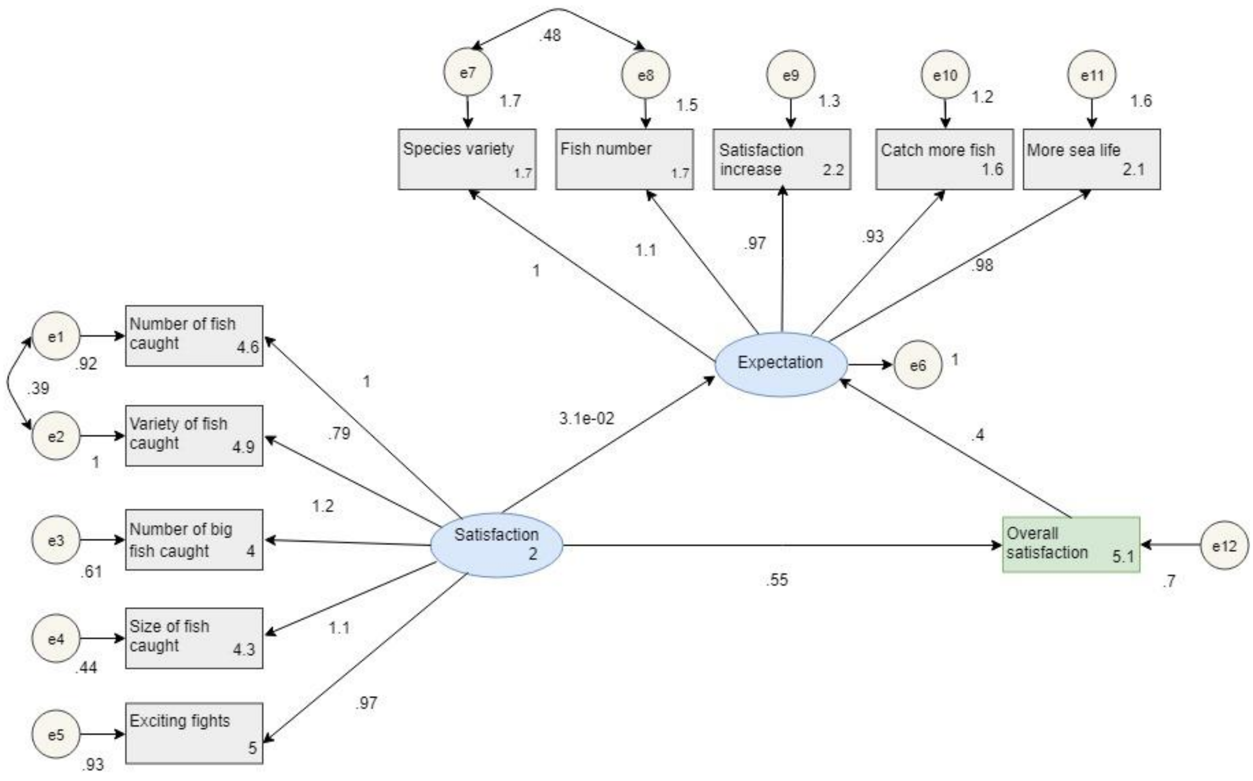



Figure 4-6: Revised structural equation model for Townsville

Three paths (satisfaction to overall satisfaction, satisfaction to expectation, and overall satisfaction to expectation) are demonstrated where all of the standardised coefficients are positive and significant at a .05 level. The goodness of fit values for the structural model is provided in Table 4-9. The goodness of fit statistics for CFA and SEM for Rockhampton, demonstrated by the *p*-value for $chi^2$ statistics, is below .05 (Table 4-8 and Table 4-9). As the $chi^2$ statistic is highly sensitive to the sample size and the number of variables used in the model (MacCallum et al., 1996), the decision has been made on the basis of ‘goodness-of-fit’ statistics. From both sites, the CFI and TLI values were more than 0.9, and RMSEA and SMRM values were less than 0.08 which was reported as a good model by Kline (2015) and Hooper et al. (2007).

Table 4-9: Goodness of fit for SEM for Rockhampton and Townsville

| **Goodness of fit** | **Rockhampton** | **Townsville** |
|---|---|---|
| | **Values** | **Values** |
| $Chi^2$ | 140.18 | 55.11 |
| *p*-value | .00 | .06 |
| RMSEA | 0.07 | 0.05 |
| CFI | 0.95 | 0.98 |
| TLI | 0.94 | 0.97 |
| SRMR | 0.04 | 0.04 |

The regression output of SEM presented in Table 4-10 shows that the regression weight of satisfaction to overall satisfaction, satisfaction to expectation, and overall satisfaction to expectation has a positive and direct effect. The results show that the recreational fishers’ satisfaction has a positive and significant effect on overall satisfaction for both study sites (coefficient = 0.59, *p*-value = .00 < .05 for Rockhampton and coefficient = 0.55, *p*-value = .00 < .05 for Townsville), as suggested in hypothesis 2a. Similarly, as proposed in hypothesis 2b, satisfaction is positively and significantly related to expectation in Rockhampton but not in Townsville (coefficient = 0.35, *p*-value = .00 < .05 for Rockhampton and coefficient = 0.03, *p*-value = .06 > .05 for Townsville). This analysis further shows that overall satisfaction is positively related to expectation at both sites (coefficient = 0.22, *p*-value = .00 < .05 for Rockhampton and coefficient = 0.40, *p*-value = .00 < .05 for Townsville), as indicated by hypothesis 2c (Table 4-10).

Table 4-10: An overview of hypothesis testing results for Rockhampton and Townsville

| Sites | Path | Standardised $\beta$ value | Standard error | *p*-value | Results |
|---|---|---|---|---|---|
| Rockhampton | Satisfaction → Overall satisfaction | 0.589 | 0.067 | .000 | Supported |
| | Satisfaction→ Expectation | 0.350 | 0.079 | .000 | Supported |
| | Overall satisfaction → Expectation | 0.219 | 0.073 | .003 | Supported |
| Townsville | Satisfaction → Overall satisfaction | 0.554 | 0.063 | .000 | Supported |
| | Satisfaction→ Expectation | 0.031 | 0.105 | .768 | Not Supported |
| | Overall satisfaction → Expectation | 0.399 | 0.132 | .003 | Supported |

## 4.5 Discussion

This study explored various viewpoints of satisfaction and expectations by comparing a NFZ and a reference site for the year 2018 (three years after the implementation of the NFZ). While the findings are specific to the research, they are instructive in a number of ways to consider recreational fishers' satisfaction and expectations and to compare to those reported by Martin et al. (2019). This study found that recreational fishers' satisfaction and expectations vary across sites, with a stronger positive relationship in Rockhampton than in Townsville. This finding corroborates that of Martin et al. (2019), who reported that satisfaction and expectations towards NFZs have increased over time, and the performance of Rockhampton and Cairns were higher in the 2018 survey compared to those of 2015 and 2016 surveys.

Some responses did not vary between the sites, such as catch motivation, the main reason for going fishing and the variety of fish caught in both areas did not show any significant difference. However, the majority of the satisfaction and expectations-related responses showed significant differences for these two sites. So, it is reasonable to assume that the main difference was found in satisfaction and expectations-related outcomes. Fishers of Rockhampton are more satisfied with their previous fishing experience and have positive expectations towards recreational fishing opportunities and long-term management of fisheries resources. A similar finding was reported by Martin et al. (2019), who confirmed that Rockhampton had the highest level of expectations in 2018, despite the fact that their study did not compare the level of expectations with either of the comparison sites.

The literature widely accepts that a number of factors including motivation, catch orientation, satisfaction, and age of the participants influence overall fishing satisfaction (Hunt & Grado, 2010; McCormick & Porter, 2014). This study also confirms the existence of similar types of influencing factors for overall satisfaction where fishers of Rockhampton are tended to be more highly motivated and highly satisfied than Townsville. Previous research suggests that older fishers were less satisfied in fishing than their younger counterparts (Mostegl, 2011; McCormick & Porter, 2014). This study, however, found a significant positive relationship between fishers' age and overall satisfaction in Townsville, where the majority of fishers were slightly older than Rockhampton and the ages range lies between 45-54 years. While the justification for such a relationship is unclear, it is rational to believe that fishing motivations and satisfactions change with age (Aas, 1996; McCormick & Porter, 2014). The study found that both catch-related and non-catch-related motivation and satisfaction components appeared to affect overall satisfaction in both locations, but Rockhampton had a greater effect on overall satisfaction than Townsville. One potential explanation for these findings is that owing to the improved opportunity of recreational fishing in Rockhampton, fishers appear to be more focused, highly motivated, and satisfied with fishing than those in Townsville. Similar findings were reported by Martin et al. (2019).

The study conducted by Brinson and Wallmo (2013) proposed avidity as a determinant of satisfaction. However, research on the reverse relationship between satisfaction and frequency of fishing (avidity) has not been well discussed. However, this study revealed that the variables affecting avidity in Rockhampton are different than those of Townsville, and the majority of the components of satisfaction, motivation, and centrality of fishing to lifestyle were found to be the most contributing factors of avidity in Rockhampton, although only a few of them were found to affect the avidity of Townsville fishers. Research conducted by Tink (2015) described that motivation other than competition was the important determinant of avidity, while Sutton (2006) found that fishers who have a higher centrality of fishing to their lifestyle have higher avidity. Fishing experience and satisfaction in the size of fish were found to have a positive effect on avidity in Rockhampton but a negative effect in Townsville. This could be interpreted as the increased level of satisfaction and experience in Rockhampton influencing fishers to engage more in fishing activities in Rockhampton than Townsville.

The structural model confirmed the hypothesis and demonstrated that past satisfaction and past overall satisfaction were positively and directly related to future expectation in Rockhampton, despite the fact that there is little empirical evidence in the recreational fishing literature to support those conceptualisations. However, while there was no evidence of a relationship between past satisfaction and future expectations for Townsville, there was a strong positive and direct relationship between past overall satisfaction and future expectations.

As anticipated, satisfaction, overall satisfaction, and expectations are highly/moderately correlated due to the various dimensions and attributes involved with the behavioural and cognitive aspects of fishers' expectations associated with satisfaction. Similar findings were also reported by Aksu et al. (2010) where they identified a strong correlation between tourist satisfaction and expectations in Turkey. As an alternative theoretical prediction of concepts, future expectations were found to be influenced by past satisfaction (significant in Rockhampton only) and past overall satisfaction (significant in both sites). However, previous studies confirmed that catch expectation is the primary predictor of satisfaction (Hampton & Lackey, 1976; Arlinghaus, 2006), and fishers with more realistic expectations would have higher levels of fishing satisfaction (Spencer & Spangler, 1992). The explanation for this conceptual difference can be described by the fact that this study hypothesised the relationship in a different way to address the temporal inconsistency between 12 months prior to satisfaction, and 12 months ahead of expectations. The study also found a significant positive and direct effect of satisfaction towards overall satisfaction. This concept is also supported by Teas (1993), Parasuraman et al. (1994), and Jones and Suh (2000).

The structural equation modelling approach enables several multiple regression equations to be calculated simultaneously in a single framework and estimates relationships through setting causal hypotheses. The number of indicator variables under the latent variable 'expectation' is different between sites though the satisfaction components are the same with varying significant positive beta (β) values. For the Rockhampton, the latent variable expectation represents eight observed variables including expectations on variety and the number of fishes caught will increase over the next 12 months, expectations on quality fishing opportunities, availability of more sea life in the future, more people will go fishing, and will catch more fish from this site. They also expect the satisfaction with fishing in this area will be increased and the increased level of recreational fishing will, in turn, benefit local businesses. On the other hand, the expectations of Townsville fishers are limited to only five expectation components.

Considering the expectation components of Rockhampton, fishers of Townsville expect a smaller number of fish with low-quality fishing opportunities, and few people are expected to go fishing over the next 12 months.

These findings support the idea that fishers of Rockhampton have higher expectations of future recreational fishing opportunities than those of Townsville. The insignificant relationship between satisfaction and expectation in Townsville may be clarified by the fact that the components of satisfaction have no causal relationship with the components of expectation owing to its limited scope than Rockhampton. But surprisingly, the relationship between overall satisfaction and expectation is stronger in Townsville than in Rockhampton. This can be described as the overall satisfaction involves all aspects and experiences associated with fishing. Regression analysis other than SEM revealed that along with the satisfaction components, certain non-catch-related motivations are significant determinants of overall satisfaction in Townsville, and these non-catch-related aspects of overall satisfaction were found to have a strong causal relationship with given expectation components in Townsville. Furthermore, on the other two hypotheses, the regression weight between variables indicates that Rockhampton has a stronger effect of satisfaction on overall satisfaction (0.59) and expectation (0.35) than Townsville. This finding may be attributed to a higher degree of satisfaction and expectations in Rockhampton than in Townsville.

The findings of the study are limited to the fishers who have visited the tackle shop during the data collection in October 2018. They might not be representative of the case at all times of the year, or of fishers who are not frequent to those fishing tackle shops. Furthermore, the survey participants were self-selected and usually from an undefined recreational fishing population with no sampling frame. There is no empirical data in the recreational fishing literature to endorse certain conceptualisations of past satisfaction and past overall satisfaction influencing future expectations. The findings indicate that fishers' satisfaction and overall satisfaction in Rockhampton have a positive and significant effect on their expectations.

It is speculated that the findings of the study could be biased by some other factors. First, there might have a fundamental flaw in the way the survey questionnaire was structured. Participants in Rockhampton were questioned about NFZs prior to questioning about their satisfaction and expectations of fishing. The ways in which the questions were presented to the Rockhampton participants may have conditioned them to the concept of NFZs and their purposes, thereby influencing their responses and introducing bias into the results. Second, there is no replication of experimental units in this study and the geographical scope is very limited. Third, the study did not include all of the variables in non-parametric test but evaluated only few variables related to catch. Fourth, over the study period, a growing number of fishers travelled further afield to fish in Rockhampton but not in the other regions, which included the remaining two NFZs and three reference sites. According to Martin et al. (2019), Rockhampton offered extensive publicity and advertising in relation to the other sites. Because of the level of community involvement and promotion by local organisations, the reputation and appeal of Rockhampton as a NFZ were strong enough to attract more remote fishes of further afield. Fifth, the study did not consider other contributing variables that may have a direct or indirect effect on satisfaction and expectation in the structural equation model.

## 4.6 Conclusion

Returning to the question posed at the beginning of this study, the study set out to examine and compare the relationship between recreational fishers' satisfaction and expectations in fishing between a NFZ implemented in 2015 (Rockhampton) and a reference site (Townsville). The results of this investigation showed that the satisfaction and expectations of fishers in Rockhampton are higher than those of Townsville. These findings have significant implications for the understanding of the factors that influence satisfaction and expectation, both of which contribute to achieve successful fishing experiences. The present study has demonstrated, for the first time, the underlying causal relationship, and the strength of that relationship, between satisfaction and expectation components of recreational fishing. The findings of the study are relevant to recreational fisher communities, policy analysts, and interested groups (e.g., national fish and wildlife agencies, aquatic resource management association, recreational fishing and boating organisation, recreational fisheries and environmental protection association, and tourism industry) to identify the relationship between satisfaction and expectation that received little attention in the literature. Understanding recreational fishers' attitudes, motivation, preferences, catch orientation, lifestyle centrality, expectations, and satisfaction with recreational fishing management improves overall satisfaction and expectations and can contribute to greater fishing participation and higher social benefits.

The outputs presented in this study can be helpful when considering management measures to improve recreational fishing opportunities. One of the strengths of this study is that it represents a comprehensive examination of the relationship between satisfaction and expectation components in the field of fisheries science. This study can be replicated with other NFZs and reference sites by including a greater variety of variables affecting fishers' satisfaction and expectations in fishing. Along with other analyses used in this study, future work could employ similar approach to investigate causal relationships proposed by the theories and could be conducted in other regions where recreational fishing is considered socially or economically important.

# Chapter 5 SHORT-TERM ECOLOGICAL EFFECTS OF THE QUEENSLAND NETTING CLOSURES

Associated journal article

**Marine**, **S. S.,** Flint, N., & Rolfe, J. (2021). Effect of reduced commercial fishing pressure on barramundi catch per unit effort: Implications for Queensland's net-free fishing zones. Manuscript in preparation.

# Abstract

The Queensland state government introduced commercial net fishing closures in Cairns, Mackay, and Rockhampton in November 2015 which may increase the recreational fishing opportunities, nature-based tourism, and economic benefits in these three regional areas. This management change is likely to improve the potential for more desirable stock structures through natural recruitment. Barramundi (*Lates calcarifer*) is one of the popular target fish for recreational and commercial fishers in Northern Australia. However, it is difficult to predict the relationship between reduced commercial fishing pressure and fish stocks. In this research, an autoregressive integrated moving average with exogenous input (ARIMAX) model and a lagged multiple linear regression (MLR) model were developed using 30 years of commercial catch per unit effort (CPUE) data to identify the influence of some of the exogenous variables that affect commercial barramundi CPUE. The walk-forward or sliding window approach was used to generate out-of-sample forecasts and the model accuracy was compared using mean absolute error, mean absolute percent error, and root mean square error. The results indicate that ARIMAX models provide the best forecast for all of the study sites except two samples of Cairns. Overall, the study suggests the ARIMAX model should be applied due to its accuracy and flexibility, especially considering the limited data availability. The study also suggested that both environmental and fishery parameters are equally important for prediction. Environmental parameters such as rainfall, streamflow, and stream water level and fishery parameters such as licences and prices are the most important determinant of CPUE for most of the study sites. This study provides valuable insights into the effect of management changes in the commercial CPUE to ensure sustainable management of fisheries resources. The study output as a whole will inform the management of fisheries resources in Queensland, where the potential for increased recreational allocation is high.



*Keywords:* barramundi, ARIMA model, ARIMAX model, MLR model, fishery management

## 5.1 Introduction

Overfishing is one of the most damaging anthropogenic disruptions to the sustainable management of wild fisheries in the world. The marine environment and the economically important fishing community are adversely affected by the depletion of stocks through overfishing (Myers & Worm, 2003). In recent years, the commercial catch and nominal CPUE (catch per unit effort) have substantially declined in Australia due to overfishing (Moore et al., 2007; Gaughan & Santoro, 2020). Measures show that 17.5% of the fish stocks in Australia are overfished or too heavily fished, and the status of 16.5% of fish is unknown (Australian Marine Conservation Society, 2020). The entire aquatic ecosystem can be impacted by significant declines in stock abundance. It may alter the genetic structure of the population (Conover & Munch, 2002; Mora et al., 2009), damage the recovery potential of stocks (Hutchings, 2000; Mora et al., 2009), create imbalances that can damage the food web and contribute to the destruction of other aquatic life (Pauly et al., 2002; World Wildlife Fund Inc., 2020), and decrease food and economic security (Pauly et al., 2005), and disrupt hunger mitigation efforts (Pauly et al., 2005; World Health Organization, 2005).

Given the significant ecological and socio-economic consequences of overfishing on global fisheries, a range of management procedures has been undertaken to combat overexploitation and improve sustainable exploitation of marine fisheries resources. Among the initiatives, commercial fishery closure is a useful and substantial means of managing the impacts of commercial fishing on certain fishery or habitat (Australian Fisheries Management Authority, 2017). Fishery closure can protect the abundance of a target species with their habitats (Abbott & Haynie, 2012). In a fishery, CPUE data represents an indirect measure of the abundance of a species. The CPUE is determined by dividing the total catch by the total fishing effort in a given period (Van Hoof et al., 2001). A declining CPUE indicates overexploitation of stock and an unchanged CPUE indicates sustainable harvest of that stock (Yadav et al., 2016). Modelling and forecasting of the CPUE are used as a useful tool for the understanding of the underpinning factors that affect fishery dynamics and provide short-term quantitative guidelines for fisheries management (Stergiou & Christou, 1996).

Queensland's iconic species, barramundi (*Lates calcarifer*), is a valuable fin-fish species for commercial, recreational, and indigenous fisheries in Australia (Balston, 2009a), and contributes a vital role in the regional economy of coastal Queensland (Rose et al., 2009). In 2013-14, the commercial wild harvest of barramundi from Queensland waters was recorded at

826 tonnes, which contributed more than $7.58 million in the wholesale product (Mobsby & Koduah, 2017). In relation to stock status, Queensland’s barramundi is thought to be made up of seven genetically distinct populations. According to the status of the Australian Fish Stocks report in 2016, stocks of southern Gulf of Carpentaria account for more than half of Queensland's annual commercial barramundi catch and was designated as the most depleting stock relative to others (Saunders et al., 2016). To reduce the fishing pressures in this stock, several management plans have been introduced since 1981. More restrictive access to the water has been applied to the Gulf of Carpentaria's Inshore Fin Fishery, which resulted in reductions from the number of commercial permits from 109 in 1998 to 85 in 2015 (Queensland Government, 2017c). In November 2015, a new restriction on the use of nets on commercial barramundi fishing was implemented in the three regional cities of Queensland, Cairns, Mackay, and Rockhampton, on the grounds that fish species will be conserved, recreational fishing and expenditure on local fishing tourism-related businesses will be increased (Queensland Government, 2016). The resultant change in fishing pressure is likely to improve the stock structure of barramundi. No previous study has evaluated the ecological effect of commercial netting closure on barramundi fishery, especially in those areas. This indicates a need to understand the original effect of reduced commercial fishing pressure on future barramundi catch.

The life cycle of barramundi involves fresh, brackish, and marine stages. Spawning occurs in brackish water environments at the start of the wet season with the strongest tidal activity (Government of Western Australia, 2011). The complex life cycle provides the opportunity to survive in a wide range of environmental conditions. Several studies suggest that the barramundi population is highly influenced by some environmental parameters (e.g., rainfall and/or streamflow) that particularly influence recruitment, productivity, and catchability (Dunstan, 1959; Davis, 1985; Russell & Garrett, 1985; Griffin, 1987; Russell & Rimmer, 2004). Sawynok (1998) found a significant positive relationship between the growth rate of the barramundi in the Fitzroy River, Rockhampton, and the amount of freshwater flow. Other studies have identified that catch rate and recruitment are significantly positively correlated with river discharge (Staunton-Smith et al., 2004; Robins et al., 2005; Balston, 2009b; Halliday et al., 2010). Balston (2009a) found a significant positive correlation with two years later barramundi catch and warm sea surface temperature, low evaporation, high rainfall, and high freshwater flow. Along with environmental parameters, some studies have reported that fishery-dependent parameters are also important to describe CPUE (Walters, 2003; Maunder et al., 2006; Petrere Jr. et al., 2010; Sweke et al., 2015) that could be useful to understand the potential barramundi harvest.

## 5.2 Review and approach

Analysis of fish CPUE using time series models is arguably the most efficient tool for fisheries management and decision making as it can identify hidden trends and seasonal patterns (Koutroumanidis et al., 2006). Forecasting is used to account for in-season or post-season predictions and provide a basis for the predictions of the effects of management measures (Farmer & Froeschke, 2015). Time series forecasting involves three fundamental approaches: regression-based methods, heuristic smoothing methods, and general time series (Montgomery et al., 2002). Among them, the regression-based forecasting autoregressive integrated moving average model (ARIMA) is widely used in fisheries management (Raman et al., 2017). The research employed by Stergiou (1989, 1991), Stergiou et al. (1997) and Romilly (2005) showed that the validation error of the ARIMA model is significantly lower than other models. To date, a limited number of studies have used forecasting applications in fisheries management (Farmer & Froeschke, 2015). A barramundi catch model was developed by Balston (2009a) for Princess Charlotte Bay in Far North Queensland, where the author used a forward stepwise ridge regression model to predict the commercial barramundi catch. Some notable examples of ARIMA models are available in the literature for other fish species. Tsitsika et al. (2007) used univariate and multivariate ARIMA models to forecast pelagic fish production, whilst Prista et al. (2011) used a SARIMA (seasonal ARIMA) model using monthly landing data to identify the future landings of meagre fishery in Portugal. A number of studies have compared several time series models and provided insights into the best fitting models. Saila et al. (1980) tested monthly averages, harmonic regression analysis, and ARIMA models to forecast monthly catches and found ARIMA to be the most suitable model for forecasting 12 months ahead of production. Likewise, Hanson et al. (2006) suggested that while multiple-regression and artificial neural network models performed equally well for both Atlantic and Gulf menhaden catches, the ARIMA only predicted well for Atlantic samples whilst the State Space model only predicted well for Gulf menhaden samples. Raman et al. (2017) found that an ARIMA model with log-transformed data had a better fit than an intervention model based on Akaike information criterion (AIC) and Bayesian information criterion (BIC).

The Fitzroy River system that passes through the regional city of Rockhampton and the Mary River near Hervey Bay are home to the largest breeding populations of barramundi on the east coast of Queensland (Radosevic, 2018). In this study, along with the three NFZs (Net-free-zones), three reference sites (Townsville, Hinchinbrook, and Hervey Bay) were also chosen considering their prominent commercial fishing and availability of the barramundi population. Very little work has been done in these areas for annual CPUE prediction of barramundi using either the ARIMA (autoregressive integrated moving average) or MLR (multiple linear regression) models. Moreover, the influence of environmental and fishery parameters to determine the effect of reduced commercial fishing pressure on future barramundi catch is little explored.

Time series forecasting of future catches involves the modelling of all the factors that influence the fish catch (Ward et al., 2014). To achieve the management objectives of a barramundi fishery, it is first necessary to obtain the future catch predictions through identifying the important factors that are responsible for the prediction and then identifying the factors that might be helpful for the sustainable management of fishery stocks. Hence, this study took a broad exploratory approach to understand the influence of environmental and fishery predictors of the annual barramundi catch. An exploratory analysis was required for this study as both environmental and fishery drivers are likely to affect fish and marine life (Sydeman et al., 2014; Sydeman et al., 2018). In this study, two different types of empirical statistical catch prediction models were investigated for the six study sites separately and two pooled sites; one for the three NFZs together and another for the three reference sites together using the pooled average data for each variable for each year. Here, the study included MLR and ARIMAX models for predicting the barramundi CPUE. For the MLR model, the study tested a general hypothesis based on the barramundi growth rate where lagged environmental parameters might have an influence on barramundi catch as well as in the prediction. This study assessed the accuracy of each technique for each of the study sites, including pooled sites, and established a relationship between nominal CPUE and both fishery and environmental predictors to understand the effect of reduced commercial fishing pressure and made inferences on future recreational barramundi catch.

## 5.3 Materials and method

### 5.3.1 Data

#### 5.3.1.1 Study sites and barramundi data

The study sites were Queensland's three net-free zones (NFZs), namely Cairns, Mackay, and Rockhampton, and three reference sites, namely Townsville, Hinchinbrook, and Hervey Bay. To understand the actual ecological effects of netting closure, a four-year post-closure period may be insufficient to compare and draw conclusions about the change. To address this issue, this study considered three similar sites as reference sites where commercial fishing activities are still in place and being used as reference sites by the Queensland Department of Agriculture and Fisheries (DAF). There may be some spatial-temporal heterogeneity associated with the sites and they may not adhere to the same standard as NFZs. The exact grid squares of study areas were identified from commercial fishing logbook maps of Queensland. Figure 5-1 indicates the fishing grids of the six study sites in Queensland. Commercial barramundi fishery parameters such as catch, effort, and licence data of the inshore net fishery were collected from the QFish website (http://qfish.fisheries.qld.gov.au/) for the grid squares of the six study areas, namely Cairns (G15, H16, H17), Mackay (N24, O24, O25), Rockhampton (R28, R29, R30, S29), Townsville (J21, k21), Hinchinbrook (I19, I20), and Hervey Bay (V33, V34, W33, W34) for the years 1990 to 2019. This study did not use recreational catch data due to the inadequate spatiotemporal record and the complexity of assuming post-release survival.

Commercial barramundi catch data were recorded in tonnes per year, whereas effort data were recorded as the number of net fishing days (i.e., the number of days when net is set to catch barramundi). Then nominal CPUE was estimated by diving catch and effort data (Ghosn et al., 2012). Commercial fisheries licence data were recorded as numbers of fishing permits in a year. Another fishery parameter, the price of yearly barramundi production (per tonne) in Queensland was collected from the annual fisheries statistics publication of the Australian Bureau of Agricultural and Resource Economics and Sciences (ABARES) (website: http://www.agriculture.gov.au/abares/), and the price was adjusted for yearly inflation to 2019 using an online consumer price index inflation calculator (website: https://www.abs.gov.au/Price-Indexes-and-Inflation)

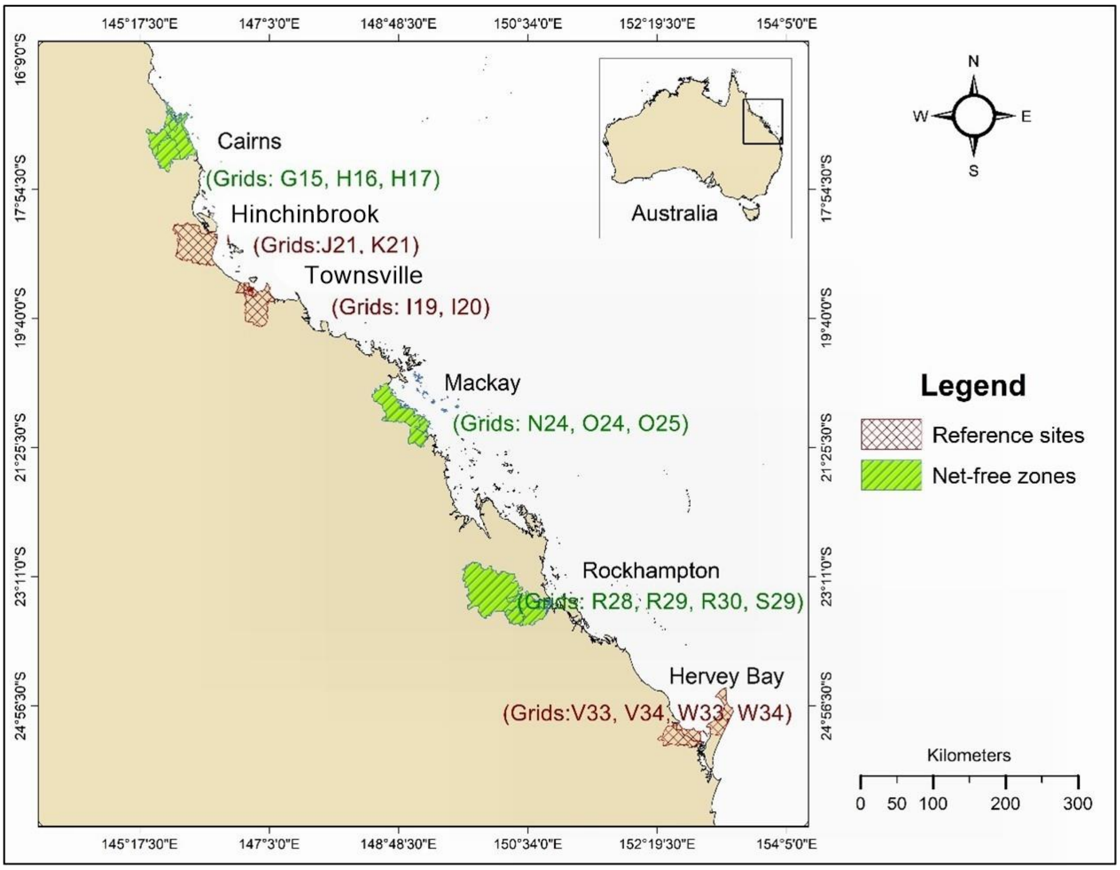



Figure 5-1: Map indicating the fishing grids of the six study sites. Map shape file source: DIVA-GIS (http://diva-gis.org/)

#### 5.3.1.2 Environmental parameters

Evidence from previous research suggests that environmental parameters (e.g., rainfall, temperature, streamflow, and stream water level) have a significant effect on marine fish populations (Benson & Trites, 2002; Morrongiello et al., 2014). Several studies found that there is a strong relationship between environmental parameters (Lun et al., 2011; Cong & Brady, 2012; Yang et al., 2012; Nkuna & Odiyo, 2016; Bui et al., 2019). For example, Lun et al. (2011) reported a positive relationship between rainfall and stream water level. On the other hand, rainfall and temperature demonstrated a negative relationship (Cong & Brady, 2012; Nkuna & Odiyo, 2016). Similarly, streamflow is negatively related to temperature but positively related to rainfall (Yang et al., 2012) and stream water level (Kumar et al., 2020). However, environmental parameters such as rainfall, terrestrial temperature, streamflow, and stream water level are always the external factors that affect and influence the dynamic process of fish (Jobling, 2002).

#### 5.3.1.3 Rainfall and terrestrial temperature

Rainfall and temperature play important role in the biological processes of fish such as growth, recruitment, and population productivity (Morrongiello et al., 2014). Balston (2007) found concrete evidence that climate variability impacts on barramundi fishery of north-east Queensland. Heavy rainfall has a significant positive correlation with spawning and early life stages of barramundi that ultimately improves the catch for the following year (Balston, 2009a). Similarly, water temperature is important for the survival of new recruits and the growth rates of young fish (Agcopra et al., 2005). For the study, the yearly rainfall and temperature data for each case study area were extracted from the Bureau of Meteorology database (http://www.bom.gov.au/climate/data/). Considerable spatial heterogeneities are associated with rainfall; particularly in the tropics and thus weather stations that capture rainfall in the areas of catchments that generate most streamflow for barramundi were averaged. For the temperature data, interpolated maximum and minimum yearly average of terrestrial temperature were extracted for the six study sites. Total annual rainfall for Cairns was averaged from the following stations, namely Cairns Severin St, Parramatta Park, Cairns Racecourse, Cairns Aero, Mt Sheridan. For Mackay, rainfall data were averaged from Mackay Alert, Mackay Aero, Ooralea Racecourse, Mackay M.O., and Farleigh Co-Op Sugar Mill stations. For Rockhampton, Townsville, and Hinchinbrook only one station in each area such as Rockhampton Aero, Townsville Aero, and Cardwell Marine Pde was selected as the nearby stations are located 10.3 km, 12.1 km, and 26.6 km away from the study site. For Hervey Bay, data from Hervey Bay Airport and Urangan Hibiscus St were averaged. Interpolated maximum and minimum yearly average temperature data were extracted from Cairns Racecourse and Cairns Aero for Cairns; Mackay Aero, Ooralea Racecourse, and Mackay M.O for Mackay; Rockhampton Aero for Rockhampton; Townsville Aero for Townsville, Cardwell Marine Pde for Hinchinbrook; and Hervey Bay Airport and Maryborough for Hervey Bay.

#### 5.3.1.4 Streamflow and stream water level

Streamflow and stream water level were expected to influence barramundi catch. Previous monitoring has identified higher recruitment of barramundi following good river flows in the months of December to February in the Fitzroy region (Sawynok, 1998). The same study found a correlation between river flows and barramundi catch in the Gladstone region, also in Central Queensland. For this analysis, streamflow and stream water level data for each study site were extracted from the Queensland Government Water Monitoring Information Portal (https://water-monitoring.information.qld.gov.au/). Most of the stations within the study sites do not have enough data from the year 1990 to 2019. To overcome this problem, this study has opted for the nearby stations that have available data. Stream discharge volume (megalitres) and mean stream water level (metres) for the six study locations were extracted for Barron River at Myola (Cairns), Sandy Creek at Homebush (Mackay), Fitzroy River at The Gap (Rockhampton), Burdekin River at Clare (Townsville), Gowrie Creek at Abergowrie (Hinchinbrook), and Gregory River at Isis Highway (Hervey Bay).

#### 5.3.1.5 Data preparation

Before further analysis, data were cleaned and pre-processed by replacing outliers (Kwak & Kim, 2017), and missing values were replaced by generating values using the linear interpolation technique (Fleig et al., 2011; Hamzah et al., 2020). The analysis was repeated three times for each site for successive three-year periods using two different models: autoregressive integrated moving average with exogenous input (ARIMAX) and a lagged multiple linear regression (MLR). This involved using a walk-forward validation or sliding window approach from 2011 through 2019 which generated out-of-sample results up to 2019. For example, the first model was built using yearly data from 1990 to 2010 (1$^{st}$ training dataset) and tested out-of-sample from the period of 2011 to 2013. The second model used data from the year 1992 to 2013 (2$^{nd}$ training dataset) and forecasted for the year 2014-2016 and the last model used data from 1994 to 2016 (3$^{rd}$ training dataset) to forecast out-of-sample data for the year 2017 to 2019. All the statistical analyses were performed using modelling and forecasting software EViews 10, STATA SE 12, IBM SPSS Statistics 25, and Microsoft excel. A summary of the dataset collated for the ARIMAX and MLR analyses is shown in Table 5-1.

Table 5-1: Summary of the collated data for analysis in each of the study sites

| Sites | Variables | N[1] | Minimum | Maximum | Mean | Std. Dev. |
|---|---|---|---|---|---|---|
| Cairns | CPUE (tonnes/net fishing days) | 30 | 0.02 | 0.05 | 0.03 | 0.01 |
| | Licences | 30 | 6.0 | 20.0 | 12.0 | 3.80 |
| | Price/tonne of Fish (AUD)[2] | 30 | 9182.54 | 22183.47 | 11410.7 | 2881.57 |
| | Rainfall (mm) | 30 | 721.0 | 3425.60 | 2106.09 | 581.88 |
| | Temperature (°C) | 30 | 24.35 | 26.05 | 25.14 | 0.35 |
| | Streamflow (gigalitres) | 30 | 106151.98 | 1827060.42 | 680912.99 | 493862.38 |
| | Stream Water Level (metres) | 30 | 0.35 | 1.18 | 0.69 | 0.23 |
| Mackay | CPUE (tonnes/net fishing days) | 30 | 0.02 | 0.07 | 0.05 | 0.01 |
| | Licences | 30 | 16 | 28 | 21.97 | 3.06 |
| | Price/tonne of Fish (AUD) | 30 | 9182.54 | 22183.47 | 11410.7 | 2881.57 |
| | Rainfall (mm) | 30 | 830.67 | 2953.67 | 1535.46 | 544.18 |
| | Temperature (°C) | 30 | 22.65 | 24.62 | 23.78 | 0.54 |
| | Streamflow (gigalitres) | 30 | 7771.75 | 627070.98 | 184386.02 | 180790.50 |
| | Stream Water Level (metres) | 30 | 0.43 | 1.23 | 0.69 | 0.20 |
| Rockhampton | CPUE (tonnes/net fishing days) | 30 | 0.02 | 0.10 | 0.04 | 0.02 |
| | Licences | 30 | 5 | 52 | 34.73 | 13.15 |
| | Price/tonne of Fish (AUD) | 30 | 9182.54 | 22183.47 | 11410.7 | 2881.57 |
| | Rainfall (mm) | 30 | 203.10 | 1424.00 | 735.02 | 289.70 |
| | Temperature (°C) | 30 | 22.20 | 23.95 | 23.12 | 0.49 |
| | Streamflow (gigalitres) | 30 | 357504.13 | 12355838.00 | 3099440.95 | 2890299.61 |
| | Stream Water Level (metres) | 30 | 1.14 | 6.89 | 4.82 | 1.68 |

| Sites | Variables | N[1] | Minimum | Maximum | Mean | Std. Dev. |
|---|---|---|---|---|---|---|
| Pooled NFZs data | CPUE (tonnes/net fishing days) | 30 | 0.02 | 0 .07 | 0.04 | 0.01 |
| | Licences | 30 | 10 | 31 | 22.90 | 5.47 |
| | Price/tonne of Fish (AUD) | 30 | 9182.54 | 22183.47 | 11410.7 | 2881.57 |
| | Rainfall (mm) | 30 | 650.93 | 2397.72 | 1458.86 | 354.05 |
| | Temperature (°C) | 30 | 23.37 | 24.81 | 24.01 | 0.38 |
| | Streamflow (gigalitres) | 30 | 171992.33 | 4768500.73 | 1321579.99 | 1066400.56 |
| | Stream Water Level (metres) | 30 | 0.69 | 3.00 | 2.07 | 0.61 |
| Townsville | CPUE (tonnes/net fishing days) | 30 | 0.02 | 0.08 | 0.05 | 0.02 |
| | Licences | 30 | 14 | 34 | 23.33 | 4.95 |
| | Price/tonne of Fish (AUD) | 30 | 9182.54 | 22183.47 | 11410.7 | 2881.57 |
| | Rainfall (mm) | 30 | 397.60 | 2399.80 | 1121.53 | 555.13 |
| | Temperature (°C) | 30 | 24.00 | 25.85 | 24.77 | 0.45 |
| | Streamflow (gigalitres) | 30 | 540507.06 | 38758859.92 | 9251417.96 | 9955919.56 |
| | Stream Water Level (metres) | 30 | 1.29 | 2.82 | 1.85 | 0.48 |
| Hinchinbrook | CPUE (tonnes/net fishing days) | 30 | 0.02 | 0.07 | 0.04 | 0.01 |
| | Licences | 30 | 10 | 32 | 20.93 | 5.49 |
| | Price/tonne of Fish (AUD) | 30 | 9182.54 | 22183.47 | 11410.7 | 2881.57 |
| | Rainfall (mm) | 30 | 1149.50 | 3322.70 | 2053.49 | 583.00 |
| | Temperature (°C) | 30 | 23.70 | 25.20 | 24.25 | 0.40 |
| | Streamflow (gigalitres) | 30 | 18240.02 | 367455.95 | 157082.86 | 94054.10 |
| | Stream Water Level (metres) | 30 | 0.90 | 1.32 | 1.10 | 0.13 |

| Sites | Variables | N[1] | Minimum | Maximum | Mean | Std. Dev. |
|---|---|---|---|---|---|---|
| Hervey Bay | CPUE (tonnes/net fishing days) | 30 | 0.02 | 0.06 | 0.04 | 0.01 |
| | Licences | 30 | 19 | 44 | 31.27 | 6.66 |
| | Price/tonne of Fish (AUD) | 30 | 9182.54 | 22183.47 | 11410.7 | 2881.57 |
| | Rainfall (mm) | 30 | 579.30 | 1635.85 | 1037.32 | 272.69 |
| | Temperature (°C) | 30 | 20.90 | 22.15 | 21.50 | 0.34 |
| | Streamflow (gigalitres) | 30 | 939.90 | 234500.69 | 69286.70 | 80270.67 |
| | Stream Water Level (metres) | 30 | 0.91 | 1.87 | 1.48 | 0.22 |
| Pooled reference sites data | CPUE (tonnes/net fishing days) | 30 | 0.02 | 0.07 | 0.04 | 0.01 |
| | Licences | 30 | 14 | 33 | 25.18 | 5.12 |
| | Price/tonne of Fish (AUD) | 30 | 9182.54 | 22183.47 | 11410.7 | 2881.57 |
| | Rainfall (mm) | 30 | 887.93 | 2260.72 | 1404.11 | 367.01 |
| | Temperature (°C) | 30 | 22.90 | 24.25 | 23.51 | 0.32 |
| | Streamflow (gigalitres) | 30 | 251387.37 | 13078352.69 | 3159262.51 | 3343467.31 |
| | Stream Water Level (metres) | 30 | 1.22 | 1.95 | 1.48 | 0.21 |

[1] The data are annual and represent the 30 years from 1990-2019

[2] All currency mentioned in this chapter are in Australian dollars. Currently, AUD$1 = US$0.73

### 5.3.2 ARIMAX methodology

The ARIMA model has been selected to predict future fish CPUE over time because this model provides relatively accurate and unbiased forecasts and has proven effective in making short-term predictions. The application is simple and straightforward, and in a short run application, the ARIMA model typically outperforms other complex structural models (Meyler et al., 1998). Box and Jenkins (1970) use the notation ARIMA (*p, d, q*), where *p* refers to the orders of autoregressive part, *d* is the number of differencing to remove non-stationary trends, and *q* is the moving average part (Saila et al., 1980), which can be defined as follows:

$$y_t = \mu + \sum_{j=1}^{p} \varphi_j \, y_{t-j} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \text{......................................Eq (5.1)}$$

where,

$y_t$= value at time t,

μ=intercept,

φ= coefficient of the autoregressive parameter,

θ= coefficient of moving average parameter, and

$\varepsilon_t$= random error at time t.

A basic assumption of time series analysis is that some features of the past values will continue to appear in the future (Raman et al., 2017) and that a set of exogenous variables could affect the forecasting of the dependent variable. The ARIMAX model is a logical extension of the pure ARIMA model, which includes other predictor variables (Andrews et al., 2013). The ARIMAX methodology has two basic phases: the first phase is to run a statistically sound regression model and the second stage is to use the errors from the regression to identify the potential AR (autoregressive) and MA (moving average) terms to remove any serial correlation that persists in the residual time series (Andrews et al., 2013). This study has followed the widely used Box and Jenkins (1970) method, with limited data of 30 annual observations, noting that Box-Jenkins methodology recommended using at least 50 observations. Recent research by Watson and Nicholls (1992) provided evidence that a small dataset (between 30 or 20 observations) does not affect the model, and it is still statistically feasible to build a good and effective ARIMAX model below the Box-Jenkins limit. ARIMAX includes four distinct steps of estimation: identification, estimation, diagnostic checking, and forecasting. The

ARIMAX equation modified from Box and Jenkins (1970) with a predictor variable is given in Equation 5.2.

$$y_t = \mu + \beta x_t + \sum_{j=1}^{p} \varphi_j \, y_{t-j} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{Eq (5.2)}$$

where,

$y_t$= value at time t,

μ=intercept,

β= coefficient of the predictor variable,

$x_t$= predictor variable at time t,

φ= coefficient of the autoregressive parameter,

θ= coefficient of moving average parameter, and

$\varepsilon_t$= random error at time t.

#### 5.3.2.1 ARIMAX Identification

The first stage of data preparation is to check for seasonality, trend, and stationarity. The stationary process is a stochastic process whose statistical properties, such as mean and variance, do not change over time (Karunarathna & Karunarathna, 2017). In this case study, time series data do not show seasonality, but a steady positive/negative secular trend of CPUE data were evident in all of the sites Figure 5-2. An augmented Dickey-Fuller (ADF) test was used to check whether the series was stationary or not. The ADF unit root test statistics value was greater than the 5% significance level and indicates that all of the series were non-stationary. Therefore, non-stationary variables were converted to first-order differencing to make them stationary (details are in Appendix).

The next step was to employ a Granger causality test of the variables and remove any independent variables that showed any significant evidence of reverse causality. Any variable with a *p*-value below .05 led to the rejection of the null hypothesis, thus eliminating this variable as a candidate for inclusion in the model. In the analysis, none of the variables displayed reverse causality. The presence of multicollinearity is problematic since it undermines the statistical significance of an independent variable (Allen, 2004).

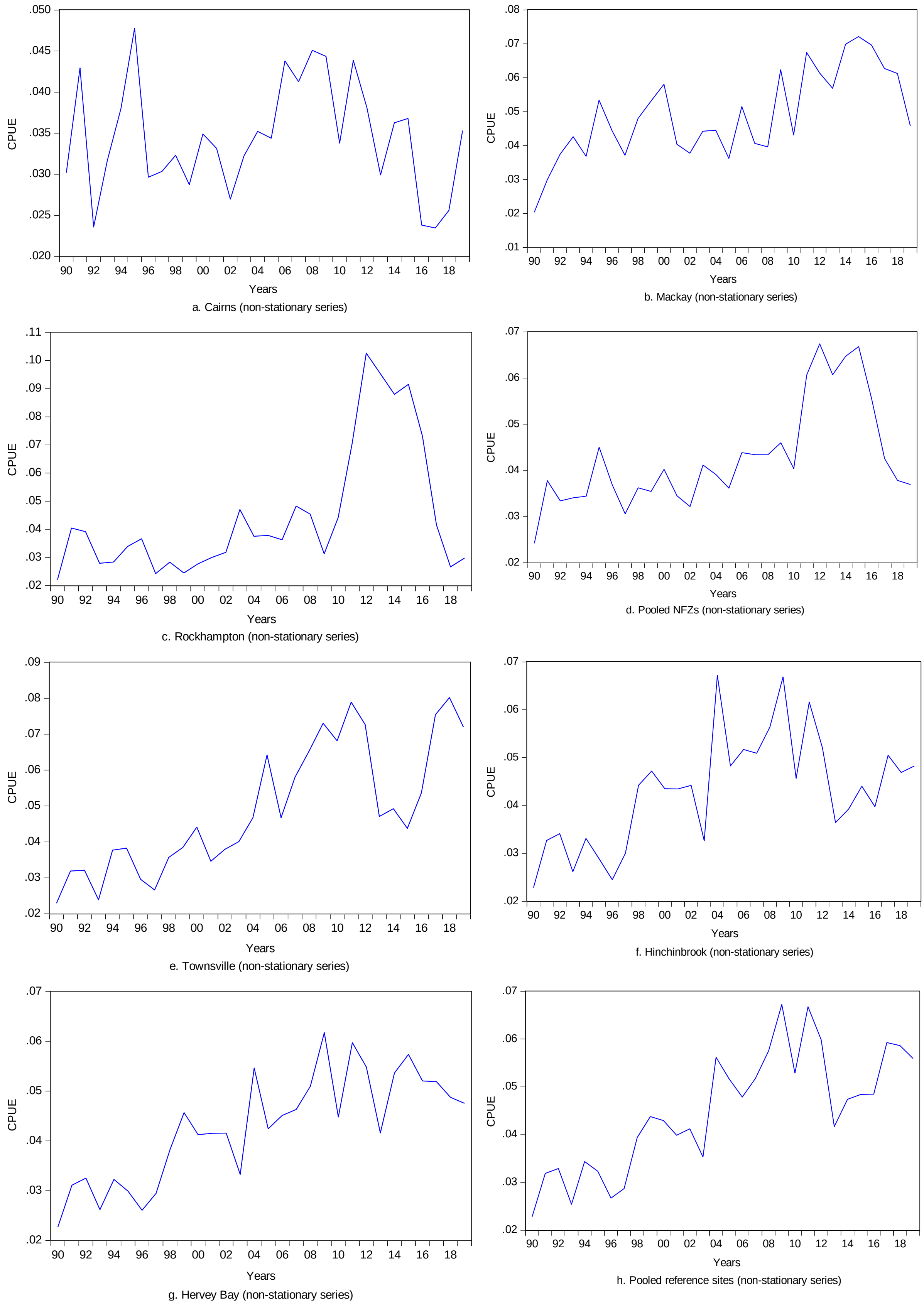



Figure 5-2: Non-stationary series for dependent variable CPUE for all of the study sites

A multicollinearity test was conducted to remove highly correlated independent variables from the pool. Some of the samples found the presence of multicollinearity between streamflow and stream water level. To remove highly correlated variables from the model, two separate regression models were built: one including all the predictor variables except stream water level and another model including all variables except streamflow. The model with improved $R^2$ value and significant *p*-value was chosen to proceed for further analysis.

Then, forward or backward regressions were employed to remove insignificant variables at the significant-level threshold of .05. A structural break was considered for all the NFZs and pooled NFZs samples for the known break in the year 2015 when the netting closure was implemented. A dummy variable was created and interacted with other independent variables to test the significance of structural break. A standard regression model was then built that included only highly significant independent variables and/or dummy interacted independent variables. It was assumed that the residuals of regression were white noise. White noise is a stochastic process where no correlation exists between its values at different times, and the values are identically distributed with a mean of zero (Shao, 2011). Afterward, the stationarity of regression residuals was tested by the ADF test, where it was found that the residuals were stationary.

The next step was to perform the Ljung-Box test to observe whether the model had a serial correlation or not. The correlogram (contains ACF and PACF plots) had displayed significant spikes at different lags that indicated whether to consider AR and/or MA terms to the model. The study found a maximum of four significant spikes in both ACF (autocorrelation function) and PACF (partial autocorrelation function) plots for Cairns 1994-2016 samples.

#### 5.3.2.2 Estimation

From a number of models fitted with various combinations of *p, d*, and *q*, the best ARIMAX model can be identified using some statistical criteria based on forecast accuracy and assumptive constancy. In this analysis, ACF and/or PACF spikes were evident in some samples of Cairns, Mackay, Hervey Bay, and pooled reference sites and resultant AR and MA terms were considered during model building. If any insignificant independent variable was present in the final ARIMAX model, then the variable was removed, and the model re-estimated using standard regression analysis.

#### 5.3.2.3 Diagnostic Reports

It is important in time series modelling to incorporate analysis of residuals to confirm the accuracy and validity of a model. The Ljung-Box test at different lags indicated the residuals were flat and the model did not contain any serial correlation (Table 5-3). The residuals were not heteroscedastic, and the residual plot indicated a normal distribution (Appendix B, Table B 2).

#### 5.3.2.4 Forecasting

Selected ARIMAX (*p, d, q*) models for six study sites were used to predict the future fish CPUE with a 95% prediction interval. The complete audit trail for this method is provided in Appendix B, Table B 3.

### 5.3.3 MLR methodology

Multiple linear regression (MLR) is a technique for modelling the relationship between a dependent variable and two or more independent variables. MLR aims at modelling the linear relationship between explanatory and response variables (Uyanık & Güler, 2013). In this study, MLR analysis was performed to provide an alternative test to ARIMAX that identifies the relationship between the barramundi CPUE and a group of fishery and environmental predictor variables that affect barramundi. A study conducted by Meynecke et al. (2006) found that 80% of the CPUE variation of barramundi is explained by the lagged effect of climate parameters such as rainfall and streamflow. Environmental variables were lagged for 3 years in the MLR models. The assessment of lagged environmental variables was carried out for 3 years only because the juvenile barramundi remains in freshwater habitats for up to 2-3 years before it reaches a legal size (580-999 mm) and migrates to the estuary for spawning (Food and Agriculture Organization, 2019). Within that time frame recruits are very likely to grow to adult barramundi, move into brackish water and become subject to harvest by commercial fishers (Robinson et al., 2019).

A multicollinearity test was conducted to remove highly correlated independent variables. Similar to the ARIMAX model, for all of the NFZs and Pooled NFZs samples, a structural break was considered for the year 2015, and then a dummy variable was created and interacted with significant independent variables. The statistical significant-level threshold of .05 was considered for this analysis. Insignificant dummy and/or interacted dummy variables were removed and re-estimated the model. The diagnostic checking of the MLR regression residuals was performed, where the residuals were shown to have no serial correlation at different lags (Table 5-3), were not heteroscedastic and followed a normal distribution (Appendix B, Table B 2).

The MLR equation with a set of predictor variables is given in Equation 5.3:

$$y = \mu + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \cdots + \beta_n X_n + \mathcal{E}_i \quad \text{Eq (5.3)}$$

Here, $i=1,2,3,4....n$

where,

$y$ = expected or predicted value of the dependent variable,

$\mu$ = intercept,

$X_1$ through $X_n$ are $n$ distinct independent variables,

$\beta_1$ through $\beta_n$ are the estimated regression coefficients for each of the independent variables, and

$\mathcal{E}$ = random error.

#### 5.3.3.1 Forecasting

Significant predictors were used to forecast future CPUE with a 95% prediction interval. The complete audit trails for MLR models are provided in Appendix B, Table B 3.

### 5.3.4 Forecast evaluation method

Three criteria have been used to compare the forecasting ability of ARIMAX time series models and MLR models. The first criterion is the mean absolute error (MAE). MAE is the average of all absolute errors, while absolute error is the discrepancy between the actual and expected values. The second criterion is the mean absolute percentage error (MAPE%) which is similar to MAE, but the error is calculated in percentage terms. The third criterion is the root mean square error (RMSE) which is used to determine the overall performance of a model. The formula is given in equations (5.4 - 5.6).

$$\text{MAE} = \frac{1}{\text{n}} \sum_{\text{i}=0}^{\text{n}} |A_i - P_i| \quad \text{Eq (5.4)}$$

$$\text{MAPE (\%)} = \left(\frac{1}{\text{n}} \sum_{\text{i}=0}^{\text{n}} \frac{|A_i - P_i|}{A_i}\right) \times 100 \quad \text{Eq (5.5)}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=0}^{n}(A_i - P_i)^2} \quad \text{………………………………………………..……..…Eq (5.6)}$$

Here $n$ is the number of predictions, $A_i$ is the actual CPUE, $P_i$ is the predicted CPUE.

In addition, the independent sample t-test was used to determine the significant difference between the mean of two models and also two different groups of study sites (Audit trails are presented in Appendix B, Table B 4).

## 5.4 Results

### 5.4.1 ARIMAX and MLR model

The steps in fitting time series data in the ARIMAX model were described previously. Selection and identification of appropriate ARIMAX model were done by computing and inspecting the auto-correlation functions. In the final model, insignificant intercept, AR and MA terms were not excluded from the model as the exclusion may harm the model and violates the assumption of non-zero intercept (Brooks, 2019). On the other hand, the ARIMAX model with two orders of differencing does not usually have a constant term (Nau, 2020). A list of the variables used to construct the ARIMAX and MLR models are provided in Table 5-2. The remaining variables that were not used in the MLR model construction are listed in Appendix B, Table B 1.

Table 5-2: List of the variables used to construct the ARIMAX and MLR models for all of the study sites

| **Sites** | **Models** | **Suitable models** | **Years** | **Adjusted $R^2$** | **Variables** | **Regression coefficients** | ***p*-level** |
|---|---|---|---|---|---|---|---|
| Cairns | ARIMAX | ARIMAX (0,1,0) | 1990-2010 | 0.14 | Intercept | 0.000234 | .89 |
| | | | | | Streamflow | 0.00000000601 | .05 |
| | | ARIMAX (0,2,0) | 1992-2013 | 0.43 | Licences | 0.001608 | .00 |
| | | | | | Rainfall | 0.00000537 | .01 |
| | | ARIMAX (4,1,4) | 1994-2016 | 0.72 | Licences | 0.001751 | .00 |
| | | | | | Rainfall | 0.00000448 | .00 |
| | | | | | AR (4) | -0.707865 | .02 |
| | | | | | MA (4) | -0.109640 | .81 |

| **Sites** | **Models** | **Suitable models** | **Years** | **Adjusted $R^2$** | **Variables** | **Regression coefficients** | ***p*-level** |
|---|---|---|---|---|---|---|---|
| | MLR | | 1990-2010 | 0.01 | Intercept | -0.048518 | .72 |
| | | | | | Licences | -0.001098 | .04 |
| | | | 1992-2013 | 0.14 | Intercept | 0.028749 | .77 |
| | | | | | Price | 0.0000000803 | .04 |
| | | | 1994-2016 | 0.56 | Intercept | 0.020117 | .77 |
| | | | | | Licences | -0.000814 | .04 |
| | | | | | Price | 0.000000124 | .00 |
| | | | | | Stream water level | 0.017270 | .02 |
| Mackay | ARIMAX | ARIMAX (2,1,0) | 1990-2010 | 0.15 | Intercept | 0.000712 | .72 |
| | | | | | Price | 0.0000000581 | .04 |
| | | | | | AR (2) | -0.308852 | .31 |
| | | ARIMAX (0,1,0) | 1992-2013 | 0.26 | Intercept | 0.000280 | .90 |
| | | | | | Price | 0.0000000681 | .01 |
| | | ARIMAX (0,1,0) | 1994-2016 | 0.31 | Intercept | 0.001387 | .52 |
| | | | | | Price | 0.0000000777 | .00 |
| | MLR | | 1990-2010 | 0.22 | Intercept | 0.076576 | .49 |
| | | | | | Price | 0.0000000765 | .02 |
| | | | 1992-2013 | 0.67 | Intercept | 0.165160 | .06 |
| | | | | | Price | 0.000000112 | .00 |
| | | | 1994-2016 | 0.77 | Intercept | 0.088337 | .35 |
| | | | | | Price | 0.000000114 | .00 |
| Rockhampton | ARIMAX | ARIMAX (0,1,0) | 1990-2010 | 0.52 | Intercept | -0.000315 | .83 |
| | | | | | Price | 0.0000000301 | .00 |
| | | | | | Stream water level | 0.003304 | .01 |
| | | ARIMAX (0,1,0) | 1992-2013 | 0.65 | Intercept | -0.000161 | .92 |
| | | | | | Licences | -0.000580 | .03 |
| | | | | | Price | 0.0000000607 | .00 |
| | | ARIMAX (0,1,0) | 1994-2016 | 0.66 | Intercept | 0.002668 | .09 |
| | | | | | Price | 0.0000000396 | .00 |
| | MLR | | 1990-2010 | 0.77 | Intercept | 0.130760 | .09 |

| Sites | Models | Suitable models | Years | Adjusted $R^2$ | Variables | Regression coefficients | *p*-level |
|---|---|---|---|---|---|---|---|
| | | | | | Price | 0.0000000561 | .00 |
| | | | 1992-2013 | 0.97 | Intercept | 0.113970 | .18 |
| | | | | | Licences | -0.000418 | .04 |
| | | | | | Price | 0.0000000745 | .00 |
| | | | 1994-2016 | 0.97 | Intercept | 0.185985 | .05 |
| | | | | | Licences | -0.000494 | .04 |
| | | | | | Price | 0.0000000787 | .00 |
| | | | | | Dummy Licences | 0.008238 | .00 |
| | | | | | Dummy Price | -0.0000000092 | .00 |
| Pooled NFZs | ARIMAX | ARIMAX (0,1,0) | 1990-2010 | 0.06 | Intercept | 0.000397 | .77 |
| | | | | | Stream water level | 0.004150 | .05 |
| | | ARIMAX (0,1,0) | 1992-2013 | 0.12 | Intercept | 0.000673 | .58 |
| | | | | | Price | 0.0000000383 | .05 |
| | | | | | AR (2) | -0.322216 | .39 |
| | | ARIMAX (0,1,0) | 1994-2016 | 0.24 | Intercept | 0.001188 | .39 |
| | | | | | Price | 0.0000000396 | .01 |
| | MLR | | 1990-2010 | 0.27 | Intercept | 0.002052 | .99 |
| | | | | | Streamflow | 0.00000000489 | .04 |
| | | | 1992-2013 | 0.82 | Intercept | 0.096471 | .43 |
| | | | | | Price | 0.0000000747 | .00 |
| | | | 1994-2016 | 0.91 | Intercept | 0.184945 | .04 |
| | | | | | Licences | -0.001358 | .00 |
| | | | | | Price | 0.0000000749 | .00 |
| Townsville | ARIMAX | ARIMAX (0,1,0) | 1990-2010 | 0.10 | Intercept | 0.002106 | .27 |
| | | | | | Licences | -0.000777 | .05 |
| | | ARIMAX (0,1,0) | 1992-2013 | 0.32 | Intercept | 0.000586 | .76 |
| | | | | | Streamflow | 0.00000000089 | .00 |
| | | ARIMAX (0,1,0) | 1994-2016 | 0.33 | Intercept | 0.000767 | .67 |
| | | | | | Streamflow | 0.00000000087 | .00 |

| Sites | Models | Suitable models | Years | Adjusted $R^2$ | Variables | Regression coefficients | *p*-level |
|---|---|---|---|---|---|---|---|
| MLR | | | 1990-2010 | 0.90 | Intercept | 0.178083 | .25 |
| | | | | | Licences | -0.001237 | .00 |
| | | | | | Price | 0.0000000658 | .00 |
| | | | 1992-2013 | 0.88 | Intercept | -0.089768 | .11 |
| | | | | | Licences | -0.001969 | .00 |
| | | | | | Price | 0.0000000924 | .00 |
| | | | | | Rainfall | -0.0000103 | .00 |
| | | | | | Streamflow | 0.00000000085 | .00 |
| | | | 1994-2016 | 0.90 | Intercept | -0.111578 | .13 |
| | | | | | Licences | 0.002070 | .00 |
| | | | | | Price | 0.0000001 | .00 |
| | | | | | Rainfall | -0.0000097 | .03 |
| | | | | | Temperature | 0.007105 | .02 |
| | | | | | Streamflow | 0.00000000084 | .00 |
| Hinchinbrook | ARIMAX | ARIMAX (0,1,0) | 1990-2010 | 0.27 | Intercept | 0.000626 | .79 |
| | | | | | Licences | -0.001446 | .05 |
| | | | | | Streamflow | 0.0000000651 | .02 |
| | | ARIMAX (0,1,0) | 1992-2013 | 0.28 | Intercept | -0.000302 | .90 |
| | | | | | Streamflow | 0.0000000769 | .00 |
| | | ARIMAX (0,1,0) | 1994-2016 | 0.23 | Intercept | 0.000234 | .92 |
| | | | | | Streamflow | 0.0000000671 | .01 |
| | MLR | | 1990-2010 | 0.67 | Intercept | 0.152382 | .26 |
| | | | | | Licences | -0.002269 | .00 |
| | | | | | Rainfall | -0.0000116 | .05 |
| | | | 1992-2013 | 0.71 | Intercept | 0.037856 | .70 |
| | | | | | Licences | -0.002499 | .00 |
| | | | | | Price | 0.0000000676 | .00 |
| | | | 1994-2016 | 0.61 | Intercept | 0.045559 | .62 |
| | | | | | Price | 0.0000000496 | .04 |
| | | | | | Stream water level | 0.079889 | .01 |

| **Sites** | **Models** | **Suitable models** | **Years** | **Adjusted $R^2$** | **Variables** | **Regression coefficients** | ***p*-level** |
|---|---|---|---|---|---|---|---|
| Hervey Bay | ARIMAX | ARIMAX (0,1,0) | 1990-2010 | 0.06 | Intercept | 0.001229 | .52 |
| | | ARIMAX (0,1,0) | 1992-2013 | 0.05 | Stream water level | -0.012688 | .04 |
| | | | | | Stream water level | -0.013646 | .16 |
| | | ARIMAX (1,1,0) | 1994-2016 | 0.36 | Intercept | 0.001016 | .44 |
| | | | | | Streamflow | -0.0000000547 | .05 |
| | | | | | AR (1) | -0.469464 | .03 |
| | MLR | | 1990-2010 | 0.33 | Intercept | 0.005335 | .97 |
| | | | | | Licences | -0.000958 | .04 |
| | | | 1992-2013 | 0.47 | Intercept | -0.017038 | .89 |
| | | | | | Price | 0.0000000625 | .00 |
| | | | 1994-2016 | 0.68 | Intercept | -0.130502 | .15 |
| | | | | | Licences | -0.000850 | .00 |
| | | | | | Price | 0.0000000648 | .00 |
| | | | | | Streamflow | -0.0000000697 | .03 |
| | | | | | Stream water level | 0.038942 | .01 |
| Pooled reference site | ARIMAX | ARIMAX (2,1,0) | 1990-2010 | 0.32 | Intercept | 0.001326 | .18 |
| | | | | | Rainfall | 0.0000163 | .00 |
| | | | | | Streamflow | 0.00000000132 | .03 |
| | | | | | Stream water level | -0.039680 | .01 |
| | | | | | AR (2) | -0.519450 | .14 |
| | | ARIMAX (0,1,0) | 1992-2013 | 0.21 | Intercept | 0.000321 | .86 |
| | | | | | Streamflow | 0.00000000194 | .02 |
| | | ARIMAX (0,1,0) | 1994-2016 | 0.20 | Intercept | 0.000673 | .69 |
| | | | | | Streamflow | 0.00000000185 | .02 |
| | MLR | | 1990-2010 | 0.72 | Intercept | -0.038104 | .80 |
| | | | | | Licences | -0.001849 | .00 |
| | | | | | Price | 0.0000000771 | .00 |
| | | | 1992-2013 | 0.77 | Intercept | -0.033425 | .78 |

| Sites | Models | Suitable models | Years | Adjusted $R^2$ | Variables | Regression coefficients | *p*-level |
|---|---|---|---|---|---|---|---|
| | | | | | Licences | -0.001719 | .00 |
| | | | | | Price | 0.000000077 | .00 |
| | | | 1994-2016 | 0.78 | Intercept | -0.059318 | .50 |
| | | | | | Licences | -0.001380 | .00 |
| | | | | | Price | 0.0000000818 | .00 |

5.4.1.1 Diagnostic reports

A maximum of second differenced series of original data were used to remove trend and non-stationary characteristics. Ljung-Box test statistics at different lags are reported in Table 5-3 shows that there is no serial correlation in the final model and the probability is greater than 5%. This means that the residuals of the estimated models are in 'white noise' meaning that the residuals are independently distributed from each other. The residual of the ARIMAX and MLR models were tested for normality and heteroscedasticity. Appendix B, Table B 2 shows that the probabilities are greater than the significance level of .05, which means the residuals are not heteroskedastic and follow a normal distribution.

Table 5-3: Ljung-Box test for the ARIMAX and MLR model at different lags

| Sites | Year | Lag | ARIMAX model | | MLR model | |
|---|---|---|---|---|---|---|
| | | | Obs*R-squared | Probability | Obs*R-squared | Probability |
| Cairns | 1990-2010 | 2 | 4.509 | 0.10 | 0.368 | 0.83 |
| | | 4 | 4.629 | 0.32 | 3.160 | 0.53 |
| | | 8 | 6.198 | 0.62 | 8.618 | 0.37 |
| | 1992-2013 | 2 | 4.488 | 0.10 | 0.451 | 0.79 |
| | | 4 | 8.476 | 0.07 | 3.777 | 0.43 |
| | | 8 | 10.759 | 0.21 | 5.978 | 0.64 |
| | 1994-2016 | 2 | 4.678 | 0.09 | 0.720 | 0.69 |
| | | 4 | 4.819 | 0.10 | 0.825 | 0.93 |
| | | 8 | 11.477 | 0.17 | 5.834 | 0.66 |
| Mackay | 1990-2010 | 2 | 4.818 | 0.06 | 7.266 | 0.08 |
| | | 4 | 8.888 | 0.06 | 9.268 | 0.06 |
| | | 8 | 10.672 | 0.22 | 6.536 | 0.06 |
| | 1992-2013 | 2 | 4.148 | 0.06 | 1.751 | 0.41 |
| | | 4 | 3.401 | 0.07 | 7.528 | 0.11 |

| Sites | Year | Lag | ARIMAX model | | MLR model | |
|---|---|---|---|---|---|---|
| | | | Obs*R-squared | Probability | Obs*R-squared | Probability |
| | | 8 | 11.874 | 0.15 | 9.440 | 0.30 |
| | 1994-2016 | 2 | 6.970 | 0.06 | 0.559 | 0.75 |
| | | 4 | 7.783 | 0.09 | 2.623 | 0.62 |
| | | 8 | 9.225 | 0.32 | 13.66 | 0.09 |
| Rockhampton | 1990-2010 | 2 | 1.303 | 0.52 | 3.826 | 0.15 |
| | | 4 | 1.766 | 0.77 | 5.250 | 0.26 |
| | | 8 | 5.519 | 0.70 | 7.272 | 0.07 |
| | 1992-2013 | 2 | 4.241 | 0.11 | 1.771 | 0.41 |
| | | 4 | 4.885 | 0.29 | 3.741 | 0.44 |
| | | 8 | 5.824 | 0.66 | 6.719 | 0.57 |
| | 1994-2016 | 2 | 0.235 | 0.88 | 1.731 | 0.42 |
| | | 4 | 2.315 | 0.67 | 2.267 | 0.69 |
| | | 8 | 5.765 | 0.67 | 7.526 | 0.06 |
| Pooled NFZs | 1990-2010 | 2 | 3.928 | 0.14 | 2.054 | 0.36 |
| | | 4 | 4.363 | 0.35 | 6.056 | 0.19 |
| | | 8 | 8.937 | 0.34 | 14.847 | 0.06 |
| | 1992-2013 | 2 | 7.973 | 0.06 | 3.304 | 0.19 |
| | | 4 | 10.478 | 0.06 | 8.480 | 0.07 |
| | | 8 | 12.408 | 0.13 | 15.899 | 0.06 |
| | 1994-2016 | 2 | 7.355 | 0.06 | 0.941 | 0.62 |
| | | 4 | 9.218 | 0.06 | 7.211 | 0.12 |
| | | 8 | 9.868 | 0.27 | 17.81 | 0.06 |
| Townsville | 1990-2010 | 2 | 5.177 | 0.07 | 2.932 | 0.23 |
| | | 4 | 10.580 | 0.06 | 8.076 | 0.09 |
| | | 8 | 10.095 | 0.06 | 10.099 | 0.26 |
| | 1992-2013 | 2 | 1.978 | 0.37 | 3.293 | 0.19 |
| | | 4 | 4.590 | 0.33 | 4.940 | 0.29 |
| | | 8 | 7.397 | 0.49 | 8.769 | 0.36 |
| | 1994-2016 | 2 | 1.063 | 0.58 | 9.610 | 0.08 |
| | | 4 | 4.418 | 0.35 | 13.374 | 0.09 |
| | | 8 | 9.449 | 0.30 | 13.824 | 0.08 |
| Hinchinbrook | 1990-2010 | 2 | 5.181 | 0.07 | 9.081 | 0.06 |
| | | 4 | 6.088 | 0.19 | 9.517 | 0.06 |
| | | 8 | 14.992 | 0.06 | 13.807 | 0.08 |
| | 1992-2013 | 2 | 5.457 | 0.06 | 3.125 | 0.20 |
| | | 4 | 6.125 | 0.19 | 4.882 | 0.29 |
| | | 8 | 7.128 | 0.52 | 10.96 | 0.20 |

| Sites | Year | Lag | ARIMAX model | | MLR model | |
|---|---|---|---|---|---|---|
| | | | Obs*R-squared | Probability | Obs*R-squared | Probability |
| | 1994-2016 | 2 | 6.953 | 0.06 | 3.111 | 0.21 |
| | | 4 | 7.552 | 0.10 | 3.204 | 0.52 |
| | | 8 | 8.297 | 0.40 | 4.495 | 0.80 |
| Hervey Bay | 1990-2010 | 2 | 5.624 | 0.06 | 0.198 | 0.90 |
| | | 4 | 8.578 | 0.07 | 2.516 | 0.64 |
| | | 8 | 14.604 | 0.06 | 11.528 | 0.17 |
| | 1992-2013 | 2 | 5.363 | 0.06 | 0.649 | 0.72 |
| | | 4 | 6.334 | 0.17 | 1.923 | 0.74 |
| | | 8 | 9.278 | 0.31 | 11.003 | 0.20 |
| | 1994-2016 | 2 | 5.885 | 0.06 | 8.055 | 0.06 |
| | | 4 | 7.879 | 0.09 | 11.509 | 0.06 |
| | | 8 | 8.615 | 0.37 | 14.228 | 0.07 |
| Pooled Reference Sites | 1990-2010 | 2 | 6.748 | 0.06 | 1.303 | 0.52 |
| | | 4 | 8.360 | 0.07 | 1.358 | 0.85 |
| | | 8 | 10.02 | 0.26 | 14.625 | 0.06 |
| | 1992-2013 | 2 | 5.269 | 0.07 | 1.419 | 0.49 |
| | | 4 | 7.2719 | 0.12 | 3.455 | 0.48 |
| | | 8 | 11.448 | 0.17 | 9.406 | 0.30 |
| | 1994-2016 | 2 | 5.718 | 0.06 | 1.741 | 0.41 |
| | | 4 | 9.289 | 0.06 | 1.956 | 0.74 |
| | | 8 | 11.915 | 0.15 | 13.330 | 0.10 |

#### 5.4.1.2 Forecasting Evaluation

Out-of-sample forecast for the ARIMAX and MLR models from the year 1990-2016 are presented in Table 5-4. Considering the estimate of MAE, MAPE%, the ARIMAX model outperformed the MLR model. The greater accuracy of the ARIMAX models is evident in all of the study sites except for 1992-2013 and 19994-2016 samples of Cairns. Table 5-4 also demonstrates the rejection of the null hypothesis that the mean prediction of CPUE levels of ARIMAX and MLR are equal. That indicates that the CPUE prediction between the two models is statistically different from each other, and the prediction performed by ARIMAX models are superior to the MLR models. Furthermore, both models show that the mean CPUE prediction of NFZs and reference sites are not statistically different from each other, implying that the null hypothesis is accepted.

Table 5-4: Result of out-of-sample prediction for the ARIMAX and MLR models from the year 1990-2016

| Site | Year | ARIMAX | | | MLR | | |
|---|---|---|---|---|---|---|---|
| | | MAE[1] | MAPE%[2] | RMSE[3] | MAE | MAPE% | RMSE |
| Cairns | 1990-2010 | 0.002 | 7.540 | 0.003 | 0.096 | 261.913 | 0.096 |
| | 1992-2013 | 0.012 | 39.631 | 0.012 | 0.003 | 13.704 | 0.008 |
| | 1994-2016 | 0.019 | 65.047 | 0.023 | 0.006 | 21.082 | 0.006 |
| Mackay | 1990-2010 | 0.008 | 12.834 | 0.009 | 0.042 | 68.881 | 0.042 |
| | 1992-2013 | 0.009 | 14.002 | 0.010 | 0.138 | 195.700 | 0.138 |
| | 1994-2016 | 0.007 | 14.598 | 0.009 | 0.055 | 99.490 | 0.055 |
| Rockhampton | 1990-2010 | 0.029 | 32.381 | 0.032 | 0.101 | 117.103 | 0.101 |
| | 1992-2013 | 0.020 | 25.877 | 0.022 | 0.063 | 74.455 | 0.065 |
| | 1994-2016 | 0.041 | 135.874 | 0.042 | 0.196 | 624.843 | 0.196 |
| Pooled NFZs | 1990-2010 | 0.022 | 35.980 | 0.023 | 0.075 | 119.471 | 0.075 |
| | 1992-2013 | 0.007 | 12.273 | 0.008 | 0.060 | 97.060 | 0.061 |
| | 1994-2016 | 0.016 | 42.651 | 0.017 | 0.138 | 355.134 | 0.138 |
| Townsville | 1990-2010 | 0.012 | 24.342 | 0.017 | 0.114 | 184.139 | 0.114 |
| | 1992-2013 | 0.003 | 7.801 | 0.004 | 0.160 | 329.263 | 0.160 |
| | 1994-2016 | 0.014 | 18.518 | 0.017 | 0.018 | 23.916 | 0.019 |
| Hinchinbrook | 1990-2010 | 0.005 | 11.936 | 0.006 | 0.027 | 61.589 | 0.029 |
| | 1992-2013 | 0.008 | 19.267 | 0.009 | 0.027 | 67.141 | 0.028 |

| Site | Year | ARIMAX | | | MLR | | |
|---|---|---|---|---|---|---|---|
| | | MAE[1] | MAPE%[2] | RMSE[3] | MAE | MAPE% | RMSE |
| | 1994-2016 | 0.005 | 10.211 | 0.007 | 0.095 | 196.111 | 0.095 |
| Hervey Bay | 1990-2010 | 0.008 | 17.598 | 0.009 | 0.078 | 150.529 | 0.078 |
| | 1992-2013 | 0.008 | 16.379 | 0.009 | 0.047 | 86.675 | 0.0471 |
| | 1994-2016 | 0.006 | 13.490 | 0.007 | 0.131 | 270.658 | 0.132 |
| Pooled reference sites | 1990-2010 | 0.012 | 22.436 | 0.014 | 0.109 | 201.051 | 0.109 |
| | 1992-2013 | 0.023 | 37.651 | 0.024 | 0.094 | 196.647 | 0.094 |
| | 1994-2016 | 0.006 | 11.001 | 0.007 | 0.119 | 205.997 | 0.119 |
| **T value** | For model comparison, MAE= -6.737**, MAPE= -4.985**, RMSE= -6.702** | | | | | | |
| **T value** | For comparison between NFZs and reference sites, ARIMAX model: MAE =1.921*, MAPE=1.810*, RMSE=1.802*; MLR model: MAE=-0.182*, MAPE= 0.111*, RMSE=-0.173* | | | | | | |

[1]Mean Absolute Error

[2]Mean Absolute Percent Error

[3]Root Mean Square Error

** Indicates the null hypothesis of the equal mean for the prediction of CPUE level for the ARIMAX and MLR model rejected at a 5% level of significance

*Indicates the null hypothesis of the equal mean for the prediction of CPUE level for the NFZs and reference sites of ARIMAX and MLR model accepted at a 5% level of significance

## 5.5 Discussion

This study aimed to access the effect of netting closure on commercial barramundi catch per unit effort (CPUE) through identifying the most important fishery and environmental parameters that influence future barramundi CPUE and provide insight for the recreational fishing opportunities in Queensland. Two modelling approaches were employed to determine the most suitable model for each of the study sites. The model was also tested for two pooled sites, where the pooled average data for the three NFZs and three reference sites were employed to get more consistent and homogenous predictions. For validation, a walk-forward or sliding window approach was undertaken to generate out-of-sample forecasts. This study found that the ARIMAX model is more suitable and statistically superior to the MLR model. The ARIMAX model presented a good fit with the lowest validation error values in MAE, MAPE%, RMSE for all of the years and all of the study sites excluding 1992-2013 and 1994-2016 samples of Cairns (Table 5-4). One of the possible explanations for the best performance of the ARIMAX model over the lagged MLR model is that MLR model only deals with the observed data whilst the ARIMAX incorporates unobserved variables, such as the lagged error terms in the moving average (MA) part. This result seems to be consistent with other research, which found ARIMA performs well in terms of forecast accuracy with a minimal error percentage (Saila et al., 1980; Stergiou, 1991; Romilly, 2005; Prista et al., 2011; Farmer & Froeschke, 2015). In both models, the mean value of the prediction error for the ARIMAX and MLR are statistically different from each other. Such widespread application can particularly render ARIMAX models helpful for the management of data-poor fisheries. It is therefore important to note that over a certain period of time, both the model fit and the prediction might fail, even though the model's parameters are updated and adjusted annually and other factors might have to be taken into consideration on a timely basis (Dement'Eva, 1987).

Here are some caveats to note for all models built here. Firstly, the CPUE and other fishery-related data used in this study are derived from nearby grid squires, while the environmental data are derived from the closest or available stations to that grid squares. Secondly, the sites being compared are not of the same standard, thirdly, the study was unable to account for recreational catch due to the absence of sufficient spatiotemporal record and the complexity of assuming post-release survival, fourthly, for lagged MLR model, the CPUE and other parameters were assumed to have a linear relationship. However, it is well established that environmental parameters affect a large number of biological processes that possibly operate across a range of time scales. Additionally, non-linear relationships allow a biological variable to respond 'optimally' to an environmental variable (Roy et al., 1992; Stergiou & Christou, 1996).

According to the findings of the study, both fishery and environmental parameters play an equal role in influencing the CPUE. In both models, most scenarios demonstrated that environmental parameters such as rainfall, temperature, streamflow, and stream water level have a positive relationship with CPUE. Rainfall, streamflow, and stream water level, in particular, were found to be the most important determinants of CPUE. These findings are consistent with previous observational studies, which showed that after adequate rainfall and freshwater flow in the summer season, the catchability of barramundi has been considerably improved (Balston, 2007, 2009a). The MLR model of Townsville and Hinchinbrook also showed two distinct cases in which rainfall has a negative interaction with CPUE. This could be due to the heavy rainfall that triggered many flood events during the summer months of study period (Bureau of Meteorology, 2019), resulting in death and decomposition of underwater vegetation, which causes low concentrations of dissolved oxygen and the death of fish and other aquatic organisms, resulting in lower CPUE for those two areas. Similar fish kill events in Eastern Australia during the flood recession phase were reported by Steffe et al. (2007), Kroon and Ludwig (2010), Wong et al. (2010), and Wong et al. (2018). The streamflow and stream water level at the Hervey Bay sample has a surprisingly negative relationship with the CPUE, although all other sites have positive relationships. There might be other factors associated with this change. A study revealed that the population of Hervey Bay increased rapidly since 2006 due to inflow of retirees and high tourist pressure from Southeast Queensland (Queensland Government, 2011). Fish population decline as a consequence of overfishing by a large number of visitors and insufficient recruitment to replace those fish populations as a consequence of area avoidance and the subsequent modification of spawning and feeding areas, as well as harvesting of broodfish during spawning season (Dines, 2010). This could explain the negative relationship between streamflow/ stream water level and CPUE in this region.

In population dynamics, fishing mortality is considered the biggest issue for the declining fish population in an ecosystem (Beddington et al., 2007). The raw CPUE data from the reference sites showed a steady fluctuation in the early years with a sudden increase in the CPUE during the years of 2008 to 2012 for Townsville, Hinchinbrook, Hervey Bay, and pooled reference sites (Figure 5-2). The raw data for those periods suggests that there might be a possibility of overexploitation for those years that leads to a significant reduction in the CPUE for the following years and after that, the trend is gradually increasing with some small fluctuations. This observation suggests that the upward trend will continue unless management measures to combat overexploitation are implemented.

As shown in this study and others, not all closures have the same effect (Edgar et al., 2014; Cresswell et al., 2019). It varies according to the type of harvesting regulations employed, level of enforcement undertaken, neighbouring habitats, age, and area covered by the closure, etc. (Edgar et al., 2014). The CPUE trend in NFZs shows that commercial fishing pressure was comparatively high during pre-closure periods and has been slowly declining since 2016 (after closure) (Figure 5-2), which is expected to increase recreational fishing opportunities. In the ARIMAX model, insignificant dummy variable (which was used to identify a known structural break in 2015 when the closure was established) in three NFZs and pooled NFZs sample indicate that the implementation of closure in those areas did not affect commercial CPUE very much. But the MLR model applied for Rockhampton found dummy variable of structural break is significant as the CPUE was usually high for a few successive years starting from 2011 to 2015 and then had a sudden drop after 2016. This abrupt change of CPUE was noticed after a series of floods in 2010, 2011, and 2013. A five-fold increase in commercial catch was observed in Fitzroy catchments due to the movement of stocks from the nearby impoundments. This contributed to the increased CPUE from the year 2011 to 2015 (Saunders et al., 2018).

The research found no statistical difference between NFZs and reference sites in both models because CPUE in three NFZs did not change abruptly after closure, but rather has been steadily declining since 2016. Both fisheries and environmental parameters are major determinants CPUE in reference sites and NFZs, but fishery parameter price is more relevant in Mackay NFZ. Considering the best model for each of the sites, the high positive relationship between the price of fish and CPUE most clearly demonstrates that CPUE will increase if prices rise. The study found an inverse relationship between the commercial fishing licences and CPUE for most of the sites except Cairns and Townsville. The presence of a negative licence coefficient in the model could be explained by the fact that some commercial fishing licence boat holders operate their boats for a longer period of time. The study suggests that by considering the effects of fisheries and environmental variables in each study site, it is possible to improve both forecast and sustainable management of future barramundi CPUE.

## 5.6 Conclusion

To conclude, this study has discussed the application of two forecasting approaches such as the ARIMAX and the MLR to identify the effect of reduced commercial fishing pressure on commercial barramundi CPUE through identifying the most important fishery and environmental factors that influence CPUE. The predictive ability of each model was also compared using MAE, MAPE%, and RMSE. The study suggests that the ARIMAX model outperformed the MLR model in terms of dealing with the unobserved error terms and preventing overfitting of input data, providing higher accuracy, and the best prediction of future CPUE. In relation to forecasting models, this study demonstrated that both fishery and environmental parameters played an equal role in influencing the CPUE, but most scenarios showed that environmental parameters such as rainfall, streamflow, and stream water level and fishery parameters such as licences and price are the key determinants of CPUE. The study also emphasised the changes that occurred after the introduction of closures in NFZs in comparison to the reference site and drew conclusions regarding the recreational opportunities in those regions.

The reliability of a prediction depends on the accuracy and consistency of the historical data. Along with other limitations discussed earlier, the most important limitation lies in the fact that the ARIMAX models were developed using yearly time series data, with only 30 observations. However, the fitting accuracy of the ARIMAX model did not restrict the construction of a comparatively strong and accurate model using smaller data sets below the Box-Jenkins limit. The study suggests more sophisticated time series analysis may be used on a regular basis by reviewing yearly data and carefully analysing the effect of reduced commercial fishing pressure on barramundi CPUE.

# Chapter 6 SHORT-TERM ECONOMIC EFFECTS OF THE QUEENSLAND NETTING CLOSURES

Associated journal article

**Marine, S. S.,** Flint, N., & Rolfe, J. (2021). Economic valuation of recreational fishing: Examining the effects of Queensland's net-free zones. Manuscript submitted for publication.

## Abstract

The Queensland state government introduced net fishing closures in November 2015 near the regional areas of Cairns, Mackay, and Rockhampton to provide increased opportunities for recreational fishing and regional economic development. This management change presented a unique opportunity to study the effects of commercial fishing closures on regional communities. This study compared the recreational fishing values and benefits of the three net-free zones with three reference sites that still involve commercial fishing. Data were collected from 14 boat ramps across six study sites from November 2015 to June 2017 and analysed using different models of the travel cost method to assess the economic value of recreational fishing across sites and models. Results demonstrated strong evidence of variation in economic values across sites and models and that the net-free zones have higher economic values than the reference sites for closer fishers, but lower values when more distant fishers are included. Outputs of this study have implications for government, non-governmental organisations, decision-makers and management authorities, as well as resource economists who are working with them to develop economic monitoring and evaluation programmes.



*Keywords:* travel cost method, consumer surplus, net-free zones, recreational fishing, Queensland

## 6.1 Introduction

Recreational fishing is a widespread and popular activity in Australia (Kearney, 2002), and the economic contribution of recreational fishing is important for regional economies (Voyer et al., 2016). It was estimated that approximately 642,000 Queenslanders aged over 5 years fish at least once a year (Webley et al., 2015), and the resultant value of catch and fishing expenditure was estimated at around $73 million[2] in 2013-14 (AgTrends, 2014). Many aquatic systems that sustain recreational fisheries, however, are under threat from a variety of processes, including overfishing, habitat loss, shifts in species abundance and distribution, and changes in ecosystem functions (Cooke & Cowx, 2004; Worm et al., 2006; Yamazaki et al., 2013).

Commercial fishing mortality could have a significant effect on coastal fish stocks, causing commercial fishers to compete with recreational fisheries (Townhill et al., 2019). In Queensland, wild-caught commercial finfish production was 8,224 tonnes in 2014-15, with a value of about $60 million (Australian Bureau of Agricultural and Resource Economics and Sciences, 2018). To minimise commercial fishing pressure, increase recreational fishing opportunities, and long-term management of fisheries resources to enable economic growth, the Queensland Government implemented commercial netting closures in three areas near Cairns, Mackay, and Rockhampton in 2015 (Queensland Government, 2016). It is expected that restricting access to a limited number of users to a scarce resource will result in benefits for those who are allowed access due to lower competition (Brown, 2016). As a result of the shift in fishing pressure from commercial to recreational, benefits would be generated for recreational fishers both the short and long term (Rolfe & Prayaga, 2007). The commercial benefits of recreational fishing are much more evident and quantifiable. Short-term commercial benefits include employment and revenue in a business, while long-term commercial benefits include introducing new business to regions as well as the profitability of established businesses (Rolfe & Prayaga, 2007). Recreational fishing has a direct effect on fishing and tourism industries and boosts coastal economies by supporting charter vessels, travel guide services, accommodation, fishing tackle and bait shops, and storage industries that may surpass the importance of commercial fishing (Brown, 2016).

[2] All currency mentioned in this chapter are in Australian dollars. Currently, AUD$1 = US$0.73

It is expected that the three new net-free zones (NFZs) in Queensland will attract distant recreational fishers to a location where they can expect to have an improved recreational fishing experience (Queensland DAF, 2017b). This requires people to be aware of the areas and choose that site over others. However, it is more challenging to evaluate the importance of recreation over alternative uses of any site or changes to policy settings such as shifting from commercial to recreational (Rolfe & Prayaga, 2007; Raguragavan, Hailu, & Burton, 2013). The value of commercial catches can be determined from market statistics, but the value of recreational fishing is more difficult to determine and cannot be calculated directly from market prices. Non-market valuation techniques must be used to determine the value of recreational sites/activities and environmental services (Gregg & Rolfe, 2013).

There are two widely used approaches to estimate the economic values of a non-market outcome: stated preference and revealed preference techniques. The stated preference techniques are based on the fisher's responses to hypothetical scenarios. For instance, the researcher might explain a hypothetical fishing trip to a fisher and enquire whether or not the fisher will participate in the trip (Hicks, 2002). Revealed preference techniques use data on choices that have been made in the course of normal life for people to evaluate statistical models of recreation demand. The model captures tradeoffs for recreational fishing trips in terms of expected catch, trip cost, environmental conditions, management rules, and other considerations deemed important in describing recreational site choice (Hicks, 2002). Stated preference techniques are flexible (researchers may enquire about circumstances that are rare or do not yet exist) but this means they are potentially hindered by social desirability bias/hypothetical bias. On the other hand, revealed preference techniques are less flexible (researchers can only consider behaviours that occur in the "real" world), but they generally do not suffer from social desirability bias and are seldom influenced by hypothetical bias. Revealed preference methods have also been widely used in fisheries valuation due to the discrete nature of fishing events and the ability to utilise the travel cost method (TCM) that is well-established as a robust approach to generating data on revealed preferences (Czajkowski et al., 2019).

The TCM has been widely used over the past four decades for valuing site-specific recreational opportunities (Ward & Beal, 2000; Haab & McConnell, 2002). The model can estimate consumer choice and preference as it is based on consumer theory and use data from the real market situation (Haab & McConnell, 2002). Depending on whether the visit rate as a dependent variable is described as a population group or as an individual, TCM has two basic variants: the zonal travel cost method (ZTCM) and the individual travel cost method (ITCM) (Ward & Beal, 2000; Stoeckl & Mules, 2006). The ZTCM is more often used in areas with very low individual visitation patterns, where a set of zones are identified, and data is collected from the number of visitors in each zone. The ITCM is useful for areas that have high individual visitation rates and is similar to the zonal approach, but instead of using data from each zone, it analyses survey data from individual visitors. (Bateman, 1993; Bennett, 1996; Prayaga et al., 2006). From an economic point of view, the amount of money people are willing to spend on a particular activity, including all direct and indirect costs, will serve as a reliable basis for estimating its value.

The TCM is designed to determine the consumer surplus (values in currency units) for site users based on their travel expenditures to the sites. Conceptually the TCM is simple and easy to apply in practical situations (Jiang, 2015) and can provide realistic and consistent outcomes (Bennett, 1996). Internationally, it has been widely used to value recreational fishing (e.g., Johnston et al. 2006), but there has been a more limited application in Australia, especially in the field of spatial fishery closures. Some notable examples include the research of Rolfe and Prayaga (2007), where TCM was used to estimate consumer surplus (consumer surplus is the discrepancy between the maximum amount a consumer is willing to pay for a service and the price they already paid) from two groups of recreational fishers in three freshwater impoundments in Queensland. In other studies, Prayaga et al. (2010) used TCM to estimate the consumer surplus of recreational fishing trips off the Capricorn Coast in Central Queensland at $385.34 per group/trip and $166.82 per individual/trip, while Windle et al. (2017) assessed the consumer surplus per household for recreational fishing trips in the Gladstone Harbour at $143 per trip. Pascoe et al. (2014) also used TCM to estimate the economic values of recreational fishing in Moreton Bay in south-east Queensland. In these more urbanised areas, the average consumer surplus per person per trip ranged from $60 to $110. Farr and Stoeckl (2018) used TCM to identify the recreational fishing values under condition of uncertainty in Townsville, Queensland.

The ZTCM models require limited secondary or primary data, which are very simple and easy to collect and require less time and effort than data for the ITCM (Kowuor, 2005). In Australia, only a few studies have applied the ZTCM for valuing recreational fishing and sites (Herath, 1999; Prayaga et al., 2006; Rolfe & Prayaga, 2007; Fleming & Cook, 2008; Ezzy & Scarborough, 2011), with more researchers applying the ITCM (Lockwood & Tracy, 1995; Bennett, 1996; Whitten & Bennett, 2002; Rolfe & Prayaga, 2007; Rolfe & Dyack, 2011; Pascoe et al., 2014; Zhang et al., 2015). In cases where data on the visit, fishing success, various socioeconomic and site quality variables (e.g., age, gender, education, income, employment status, and group size, etc.) are available, the ITCM analysis gives more precise results than ZTCM (Ezebilo, 2016; Farr et al., 2011; Farr & Stoeckl, 2018). Prayaga et al. (2006) used ZTCM to estimate the consumer surplus of Gemfest (a special and annual event in Central Queensland) by comparing the values for the yearly data from 1998 and 2002. Stoeckl and Mules (2006) used ZTCM to determine economic values of Australian Alps. Rolfe and Prayaga (2007) determined the recreational fishing values of three freshwater dams in Australia, using ZTCM to calculate the consumer surplus for frequent and occasional anglers. A more recent study by Ezzy and Scarborough (2011) also used ZTCM to estimate the recreational fishing value associated with southern bluefin tuna (*Thunnus maccoyii*) in Portland, Australia.

As stated earlier, a small number of studies have been conducted in Australia to quantify the economic value of recreational fishing (Galeano et al., 2004; Rolfe & Prayaga, 2007; Ezzy & Scarborough, 2011; Raguragavan et al., 2013; Yamazaki et al., 2013; Pascoe et al., 2014); however, in the light of changing management settings from commercial to recreational, the values of newly established commercial fishery closures and other non-closure areas in Queensland are rarely explored. To address this gap, this study has applied three models of zonal TCM, namely the postcode model, zoned model, and geographic model. The postcode model included fishers from up to two individual distance thresholds of 100 km and 300 km and the zones were identified by postcode. The zoned model analysed combined postcode data for three NFZs and three non-NFZs (reference sites) separately, using the same distance thresholds. For the geographic model, no distance threshold was used as it includes all of the participants from distant areas and geographical regions were used as zones. The study evaluated and compared the economic values between models and sites and assessed their implications for the three NFZs and three reference sites. The objectives of the study were to:

a. estimate the recreational fishing values of three NFZs and three reference sites using the travel cost method,
b. estimate recreational fishing values by using a postcode, zoned, and geographic TCM model,
c. compare the results of the different TCM models,
d. assess the implications of the results for commercial netting closures, and
e. provide recommendations for future studies.

## 6.2 ZTCM methodology

The ZTCM involves two fundamental steps (Read et al., 1999). The first is to determine a 'trip generation function' (TGF) based on the travel cost and other socioeconomic and site quality variables associated with visits, such as income, education, gender, age, occupation, the attractiveness of substitute sites, and recreational fishing success, etc. available data about visitation (Blackwell, 2007; Carpio et al., 2008; du Preez & Hosking, 2011; Farr & Stoeckl, 2018).

The study has used travel cost, income, and population data for analysis, allowing the TGF to be written as:

$$V_{ij} / K_i = f\,(TC_i\,, MWPI_i) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{Eq 6.1)}$$

here $V_{ij} / K_i$ is visit rate, and $V_{ij}$ = visits from zone $i$ to site $j$, $K_i$= population of zone $i$, $TC_i$ = travel cost from zone $i$, and $MWPI_i$ = median weekly personal income of zone $i$. The visit rate $V_{ij} / K_i$ is frequently expressed as visits per 1,000 people in each zone.

The second step is to generate the demand function for additional price increases from the trip generation function using a hypothetical set of increased trip costs. This function is written as follows:

$$Q = \alpha + \beta P \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{Eq (6.2)}$$

where Q = number of visits, and P = additional travel cost

Once the demand curve is defined, it is just a short step to estimating the consumer surplus, which is the area under the demand curve and above the current price line (Layard & Walters, 1978). However, before conducting travel cost analysis of the recreational fishing sites, there are a few methodological issues that need to be addressed. The most significant ones are discussed in the following sub-sections.

### 6.2.1 Identification of zones

The commonly used method of identifying zones involves creating hypothetical concentric circles (e.g., 50 km, 100 km, or 150 km width) around the study sites (Herath, 1999), or demarcating sites by geographical/statistical divisions (Beal, 1995). An alternative approach is to use postcode clusters as a zone, as was applied by Lockwood and Tracy (1995) and Lansdell and Gangadharan (2003). Bateman (1993) concluded that there is no single rule to identify the zones and the process varies depending on the availability of population data.

The present study used two distinct methods to identify a zone. In the first method, the postcode model, fishers' residential postcodes have been used as zones where 100 km and 300 km distance thresholds were applied to limit fishers from further away (model 1). In this research, recreational fishing was assumed to be the main objective of the visit to the study sites. Because of the existence of more distant visitor in the study, there is a possibility of multi-purpose or multi-destination trips. To address this issue, more distant travellers were omitted from the postcode and the zoned model by only considering fishers travelling up to 100 km or 300 km. In this method, fishers from each postcode area were grouped together, then the travel cost from their postcode to the fishing site was estimated. The dependent variable, visit rate, was calculated as the visits per 1000 people to the sites predicted by fishers from that postcode.

In the second method, referred as a geographic model, statistical divisions have been used as zones where no distance thresholds were applied (model 3). In this method, fishers from any statistical division were grouped together, and the travel cost and visit rate were measures for analysis. The geographic model has been calculated for all the study sites for comparative purposes. These allocate fishers to regional zones rather than postcodes, and hence all data has been sampled (no distance thresholds were applied). A total of sixteen zones were identified for the geographic model (Appendix C, Table C 1). Google map (Google, n.d.) was used to calculate the distance of zones to the study sites and ABS 2016 census data (https://quickstats.censusdata.abs.gov.au/census_services/getproduct/census/2016/quickstat/036) were used to generate population and income data for each zone. In addition, a zoned analysis using postcode data were performed (model 2), in which all data were pooled together based on the two predetermined distance thresholds (e.g., 100 km and 300 km), and dummy variables for each of the sites were used to identify the source case studies.

### 6.2.2 Calculation of travel cost

The next topic to address is the concept and management of travel and time expenses. Several issues underpin these concepts, including the subjectivity of options, the varying nature of expenditure in durable products used for travel, and the controversy about the inclusion and treatment of opportunity costs (Randall, 1994). For calculating travel costs, there are three different methods or options to consider (Bateman 1993; Bennett 1996; Rolfe and Prayaga

2007): fuel costs only (option 1), total car costs including fuel, insurance, and maintenance cost (option 2), or the cost estimated by the respondents (option 3). Option 2 was chosen for this study because data were available on respondents' one-way travel distance (km) from home to fishing sites. The travel cost for each trip was calculated by multiplying the two-way travel distance by a standard vehicle cost per kilometre. According to the Australian Taxation Office (ATO), in 2016, the full car cost for standard vehicles per kilometre was \$0.66 (Australian Taxation Office, 2017).

The measurement of opportunity cost for time can be problematic due to the different opportunity costs of individuals and the participation of unemployed fishers on the site, which can lead the estimation to be inaccurate (Wheatley, 2020). Although the majority of the researchers agree that opportunity costs should be included with travel costs, the calculation of the opportunity cost is contentious (Prayaga et al., 2006). In the current study, the opportunity cost of time was not considered when calculating total travel cost because, generally, people choose to travel to recreational areas when they are on holiday, so there is no loss of work time and income (Ward & Beal, 2000). The travel cost has been estimated by using the following formula:

TC = One-way distance travelled * 2 * \$0.66 ……………………………………….……Eq (6.3)

### 6.2.3 Addition of other variables

Several studies have found that the inclusion of other relevant variables (e.g., respondents' perception, onsite purchases, income, socio-demographic characters, etc.) could improve the specification of recreational demand models (McKean et al., 1996; Siderelis et al., 2000). Due to the unavailability of other data, the current study has used ABS 2016 census data to include the median weekly personal income of the relevant zone in the model as an additional independent variable.

### 6.2.4 Multi-purpose and multi-destination travels

The TCM requires some assumptions to calculate costs for multi-purpose and multi-destination trips. One of the principal assumptions is that people only visit one single site per trip. If people visit multiple sites in one trip, then the assumption will no longer be valid for that analysis (Haspel & Johnson, 1982). Other research showed that in most cases, visiting a site is not the only reason for the trip (Bennett, 1996). This concern is similar to the multiple-destination issue. When visitors have travelled for multiple purposes, their expenses should be allocated to the various events they participated in along the way (Whitten & Bennett, 2002). Casey et al. (1995) argued that multi-purpose and multi-destination trip data are rarely used in demand models as the data are difficult to collect and cost shares cannot be properly allocated to all relevant recreational activities.

In this research, recreational fishing was assumed to be the sole aim of the visit to the study sites. To guard against the possibility that multi-purpose or multi-destination trips may be involved, more distant travellers were excluded from the postcode model and the zoned model by only including fishers travelling a maximum distance of 100 km or 300 km.

### 6.2.5 Choice of functional forms

The choice of functional form is important to develop the best fitting model for consumer surplus determination (Crooker & Kling, 2000; Rolfe et al., 2005). The economic theory remains ambiguous on the optimal functional form for any of the two functions that must be calculated (Hanley & Spash, 1993). It is critical to choose the appropriate functional form in order to achieve precise and reliable calculations of consumer surplus, regardless of whether travel costs are accurately calculated or not (Stoeckl, 2003a, 2003b). The TGF and demand functions should be chosen in light of pre-existing economic theory, predictability, and statistical specification (Prayaga et al., 2006).

Four functional forms, linear, quadratic, semi-log, and double log can be used to specify TGF and the demand function (Bateman, 1993; Hanley & Spash, 1993). The functional forms used in this study are provided in the following table, Table 6-1.

Table 6-1: Functional forms of models used to determine the TGF and demand function

| Models | Functional forms |
|---|---|
| Linear | Visit rate= a+ b (Travel cost) + c (Income) |
| Semi-log Independent | Visit rate = a+ b (LN Travel cost) + c (Income) |
| Semi-log Dependent | LN Visit rate = a+ b (Travel cost) + c (Income) |
| Double log | LN Visit rate = a+ b (LN Travel cost) + c (Income) |

Note: Here, LN indicates ‘natural log’

## 6.3 Survey sites and data

To evaluate the economic values of recreational fishing in Queensland, this study used data collected by DAF from 14 boat ramps (2 in Cairns, 2 in Mackay, 4 in Rockhampton, 2 in Townsville, 2 in Hinchinbrook, and 2 in Hervey Bay). The boat ramps were selected based on their proximity to the city and the availability of a larger number of respondents. DAF collected data from a total of 24,624 fishers (11,151 from the three NFZs and 13,473 from the three reference sites). Among them, 12,344 data (6,142 from the three NFZs and 6,202 from the three reference sites) were used for TCM analysis, and the rest of them were removed as their reason for fishing was unknown. The data collection sites were the three NFZs (Cairns, Mackay, and Rockhampton) and three reference sites (Townsville, Hinchinbrook, and Hervey Bay) (Figure 6-1).

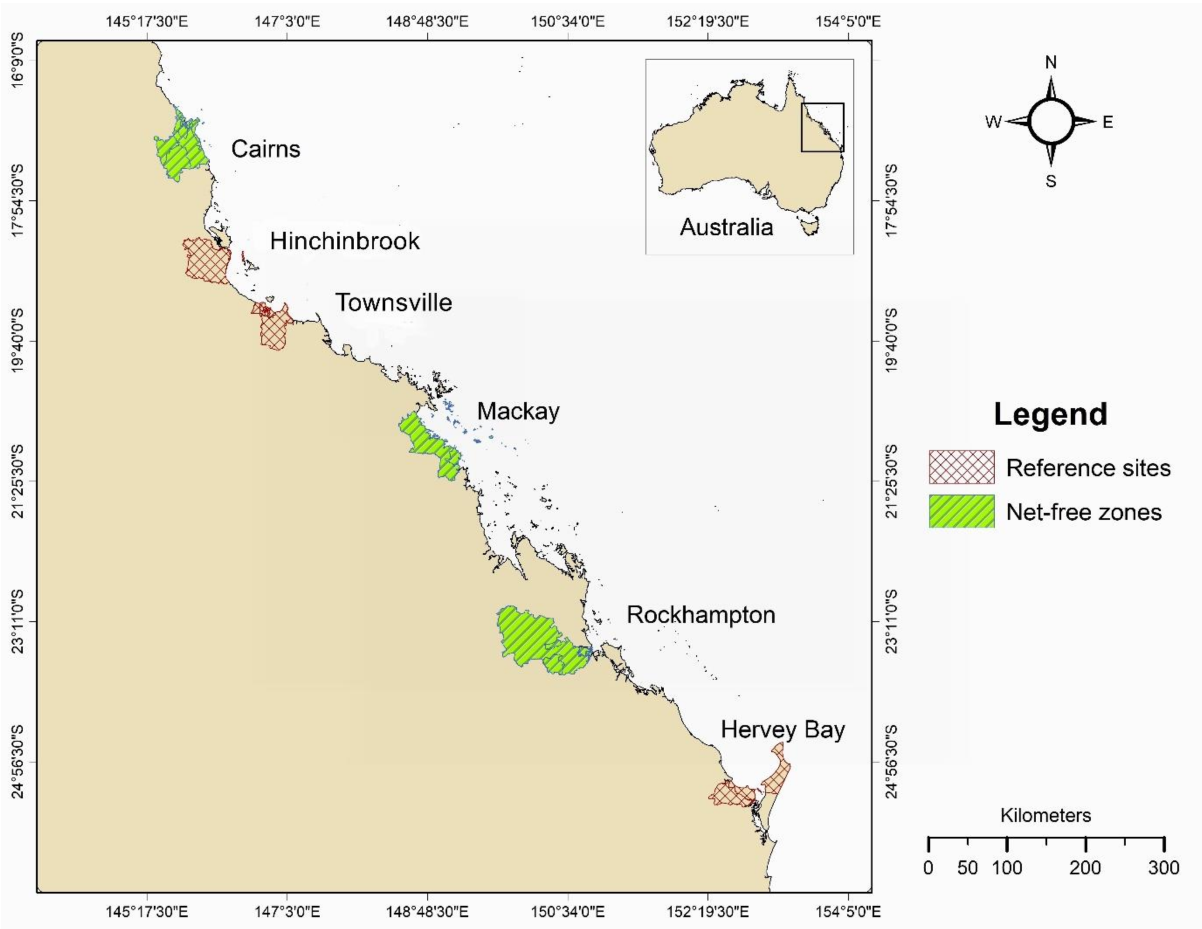



Figure 6-1: Locations of the areas providing access to the three NFZs and three reference sites in Queensland. Map shape file source: DIVA-GIS (http://diva-gis.org/)

The survey data were collected from November 2015 to June 2017 and include information regarding fishers' residential area (postcodes and town ID), boat ramp details, whether fishing is the main purpose of the trip or not, and distance travelled by the participants to reach the fishing sites. For the geographic model, respondents' travel distance was calculated from the centroid of the zone provided using the shortest road route to the particular fishing site (km) using Google map (Google, n.d.).

Census data on population and income was sourced from the Australian Bureau of Statistics (ABS) 2016 website (https://quickstats.censusdata.abs.gov.au/census_services/getproduct\census/2016/quickstat/3?opendocument) for each of the postcodes and zones. Data analysis was conducted using MS Excel, Software STATA SE 12, and SPSS 24. A summary of the main data and variables used in the postcode model (model 1) and geographic model (model 3) are provided in Table 6-2 and Table 6-3.

Table 6-2: Summary statistics for NFZs

| | Cairns | | | Mackay | | | Rockhampton | | |
|---|---|---|---|---|---|---|---|---|---|
| | PC 100 km | PC 300 km | GP | PC 100 km | PC 300 km | GP | PC 100 km | PC 300 km | GP |
| Total number of respondents | 1,045 | 1,045 | 1,050 | 1,984 | 2,038 | 2,094 | 2,799 | 2,888 | 2,998 |
| Average of one-way travel distance to reach in the fishing sites (km) | 11.3 | 11.3 | 17.46 | 36.36 | 41.18 | 71.60 | 23.63 | 28.70 | 51.26 |
| Average of visit rate (Dependent variable) | 0.0028 | 0.0028 | 0.0013 | 0.02 | 0.015 | 0.00085 | 0.026 | 0.016 | 0.0027 |
| Average of total travel cost ($) (Independent variable) | 57.42 | 57.42 | 931.08 | 72.49 | 125.02 | 1550.18 | 45.76 | 153.53 | 1272.67 |
| Average of weekly income ($) (Independent variable) | 612.71 | 612.71 | 631.33 | 645.38 | 716.58 | 638.64 | 606.64 | 667.88 | 722.16 |

Note that the geographic models include all data, whereas the postcode models exclude anglers more than 100 or 300 km from home. Here, PC = postcode model and, GP =geographic model (statistical regions model)

Table 6-3: Summary statistics for reference sites

| | Townsville | | | Hinchinbrook | | | Hervey Bay | | |
|---|---|---|---|---|---|---|---|---|---|
| | PC 100 km | PC 300 km | GP | PC 100 km | PC 300 km | GP | PC 100 km | PC 300 km | GP |
| Total number of respondents | 2,002 | 2,018 | 2,034 | 1,484 | 1,669 | 1,909 | 2,013 | 2,127 | 2,259 |
| Average of one-way travel distance to reach the fishing sites (km) | 11.31 | 12.0 | 19.71 | 16.86 | 37.75 | 289.37 | 17 | 27 | 62.12 |
| Average of visit rate (Dependent variable) | 0.0082 | 0.0064 | 0.0024 | 0.0053 | 0.0045 | 0.00097 | 0.0079 | 0.001 | 0.00062 |
| Average of total travel cost ($) (Independent variable) | 24.89 | 80.58 | 939.6 | 18.64 | 70.05 | 2092.92 | 52.17 | 286.3 | 989.7 |
| Average of weekly income ($) (Independent variable) | 658.5 | 634.6 | 676.5 | 648 | 640.25 | 647.01 | 462 | 627.55 | 616.84 |

Note that the geographic models include all data, whereas the postcode models exclude anglers more than 100 or 300 km from home. Here, PC = postcode model and, GP =geographic model (statistical regions model)

## 6.4 Application of the zonal travel cost method

The ZTCM has been developed in three phases. The TGF is measured in the first phase, then it is used in the second phase to quantify the demand for visits at a hypothetical set of increases in travel cost. In the third phase, the estimated demand curve is used to calculate the consumer surplus. For brevity, the analysis for the cairns (Postcode model 100 km) is shown in detail (the result of other sites and models are reported in Appendix C, Table C 2), and then the consumer surplus of the other models and sites is presented for comparison.

***Phase 1***

The first phase of the analysis was to calculate the TGF, where four functional forms were tested. Ordinary least squares (OLS) regression was used, where the dependent variable visit rate (V/N) was regressed against the travel cost and income (independent variables). Coefficients and statistics for all the functional forms tested are demonstrated in Table 6-4. The presence of all negative travel cost coefficients in the analysis indicates that fishers with lower travel costs are more inclined to visit fishing sites than those with higher travel costs.

The best model for the TGF was chosen based on three criteria. The first criterion is that the functional forms should be theoretically consistent, and the coefficients should be statistically significant at the levels of interest (Ward & Beal, 2000). This study has used the 5% significance level. The second criterion is to choose the two functional forms that predict closest to the actual number of visits (Crooker & Kling, 2000). In the third criterion, the best model from the final two models should be chosen based on higher $R^2$ values. $R^2$ values should only be considered when the dependent variables are exactly the same and the number of independent variables is also the same in both models (Hanley & Spash, 1993). If the models do not satisfy the two conditions together, then Rao and Miller (1971) suggested to do an equivalence test[3]. If the test shows that the two models are equivalent, then the $R^2$ value could be used to choose the best model. On the other hand, if the two models were not equivalent, then the functional form that has the lowest sum of squares of residuals (SSR) should be selected as the best model in TGF.

[3] It is a non-parametric test, $d = \frac{T}{2}|\log\frac{\sum e1t^{*2}}{\sum e2t^{*2}}|$ where d follows the chi-squared distribution with one degree of freedom, T= sample size, $\sum e_{1t}^{*2}$ and $\sum e_{2t}^{*2}$ = residual sum of squares of two estimated equations

Heteroscedasticity is a major problem in regression analysis and is relevant in a TCM when observations are grouped under different zones or postcodes that do not have an equal number of observations. To remove heteroscedasticity from this stage of analysis, Kacapyr (2015) suggested to apply weighted least square (WLS) analysis and then re-calculate the model. Tests revealed no substantial evidence of heteroscedasticity in this study, so the best model from the TGF was used to calculate the demand function.

Considering the first criterion, the F statistics of each of the models are highly significant at the .05 level and all the coefficients except the income coefficient of the semi-log independent model are significant at the .05 level (Table 6-4). Therefore, the semi-log independent model was rejected and not considered for further analysis.

Table 6-4: Regression statistics for four functional forms of the TGF for Cairns (Postcode model 100 km)

| Model | Coefficients | | | Test statistics | |
|---|---|---|---|---|---|
| | Constant (t statistic) | Travel cost (t statistic) | Personal income (t statistic) | $R^2$ | F (*p*-value) |
| Linear | 0.0019281* (-1.34) | -.0000443*** (-2.75) | 0.0000119* (1.47) | 0.7491 | 16.42 (.0005) |
| Semi-log independent | .0102822* (1.90) | -.002741*** (-5.08) | 0.00000431 (0.71) | 0.8736 | 38.03 (.0000) |
| Semi-log dependent | 11.1223*** (-5.20) | -.017889** (-2.94) | .0088817** (2.92) | 0.8500 | 31.16 (.0000) |
| Double log | 7.58737** (-2.97) | -0.950748*** (-3.74) | .0071597** (2.49) | 0.8823 | 41.21 (.0000) |

Note: *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Except for the semi-log independent model, which predicts significantly higher values than the others, all models come close to predicting the actual number of trips (Table 6-6). This is because the data did not fit well with the semi-log independent model and the model exhibited a flat tail problem in TGF. However, according to the second criterion, the linear and double log models predict the closest number of fishers to the actual (Table 6-6). As the two models do not have exactly the same dependent variables (e.g., ‘visit rate’ is the dependent variable in the linear model, and ‘LN visit rate’ is the dependent variable in the double log model) then an equivalence test is required. In the analysis, the sample size was 14 and the residual sums of squares for the linear and the double log model were 0.000031 and 3.467902 respectively, generating a *d* value of - 81.375. The value is smaller than the critical chi-square value at a 5% level of significance (22.68), indicating that the two equations are equivalent. Using the third step in the evaluation process, the double log model is selected as it has a higher $R^2$ value than the linear model. A Breusch-Pagan test was conducted to detect heteroscedasticity from the regression residual of the double log model. The result indicates no sign of heteroscedasticity (Table 6-5).

Table 6-5: Breusch-Pagan test for heteroscedasticity

| Heteroscedasticity test result for double log model |
|---|
| Null hypothesis ($H_o$): Constant variance (no heteroscedasticity in residual) |
| Variables: fitted values of ln_visit rate |
| $chi^2(1)$ = 2.24 |
| Prob > $chi^2$ = 0.1345 |

Table 6-6: Predicted number of fishers for four functional forms of TGF

| Model | Predicted no. of fishers |
|---|---|
| Linear | 909 |
| Semi-log (I) | 211110 |
| Semi-log (D) | 878 |
| Double log | 1054 |
| Actual | 1045 |

***Phase 2***

The second phase of the analysis was to estimate the demand function. The travel cost was increased by a set of hypothetical values, and, consecutively, the number of visits was calculated for each of the increased levels of cost from the chosen trip generation function. Hypothetical values should be increased up to the level when the number of visits falls to zero.

The total expected visits for each degree of increase in travel cost are outlined in Table 6-7 that provides data for the calculation of the demand function.

Table 6-7: Demand schedules for Cairns (Postcode model 100 km)

| Increase in travel cost in ($) (P) | Number of visits |
|---|---|
| 0 | 1054 |
| 50 | 231 |
| 100 | 136 |
| 300 | 53 |
| 500 | 33 |
| 1000 | 17 |
| 3000 | 6 |
| 5000 | 3 |
| 10000 | 2 |
| 30000 | 0 |

To determine the demand functions, OLS regressions were used, where again four functional forms were tested. In the regression analysis, the number of estimated visits (Q) was regressed against the hypothetical increase in travel cost (P) values. The best model from the demand function was identified by applying similar criteria used to select the best model in TGF. The regression statistics for the demand function are demonstrated in Table 6-8.

Considering the first the F statistics, and coefficients of all the models except the linear model are highly significant at the at the .05 level (Table 6-8). Therefore, the linear model was rejected and not considered for further analysis.

Table 6-8: Regression statistics for four functional forms of demand for Cairns (Postcode model 100 km)

| Model | Coefficients | | Test statistics | |
|---|---|---|---|---|
| | Constant (t statistic) | Increase in travel cost (t statistic) | $R^2$ | F (*P*- value) |
| Linear | 246.9864*** (3.75) | -.0167472 (-1.45) | 0.1155 | 2.09 (0.1676) |
| Semi-log independent | 662.484*** (8.34) | -87.71773 *** (-6.33) | 0.7147 | 40.08 (0.0000) |
| Semi-log dependent | 4.828109 *** (13.45) | -.0002911 *** (-4.61) | 0.5710 | 21.30 (0.0003) |
| Double-log | 8.279693 *** (35.59) | -.7947134 *** (-19.58) | 0.9599 | 383.35 (0.0000) |

Note: *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

According to the second criterion, the semi-log dependent and double log models predict the closest number of fishers to the actual (Table 6-9). As the two models have exactly the same dependent variables, then the final model can be identified on the basis of higher R2 values. Based on economic theory, predictive ability, and statistical specification, the double-log model was chosen for the estimation of consumer surplus. The double-log demand function can be written as:

Log (Q) = 8.279693 - 0.7947134 Log P……………………………….……………Eq (6.4)

The demand curve for the Cairns (postcode model 100 km) is demonstrated in Figure 6-2. After the inversion of the equation, it becomes:

Log P = 10.35 - 1.25 Log Q ….……………...………………………………………Eq (6.5)

Table 6-9: Predicted number of fishers for four functional forms of the demand function

| Model | Predicted no. of fishers |
|---|---|
| Linear | 246 |
| Semi-log (I) | 0 |
| Semi-log (D) | 124 |
| Double log | 3942 |
| Actual | 1045 |

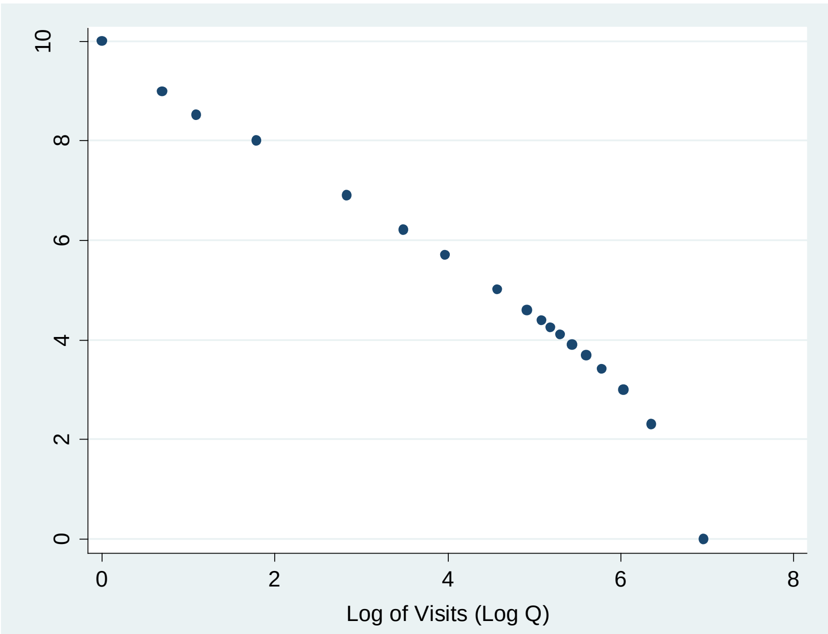



Figure 6-2: Demand curve of Cairns (postcode model 100 km)

In the case of the zoned model (model 2), the first step of analysis (the determination of TGF) is different from the other two models; (e.g., postcode model and geographic model), however, the second and third steps are almost alike. Here all data from the six sites were pooled, according to the distance threshold of 100 km or 300 km. To determine the TGF, a set of dummy variables for all of the study sites was created and treated as independent variables along with the travel cost and income variable. OLS regressions have been run and tested for four functional forms. For example, to test the effect of dummy site Cairns, all dummy sites except Cairns were used as independent variables along with the travel cost and income variable. The best models from the functional forms have been selected on the basis of the higher number of significant (5% level) coefficients, and dummy sites with the higher $R^2$ values.

### ***Phase* 3**

The third phase of the analysis was to calculate consumer surplus, which is demarcated as the area under the demand curve and above the price line. The demand functions for Cairns (Postcode model 100 km) were calculated based on the additional travel costs that fishers would be able to pay in addition to the travel cost they had already paid, so the whole area under the demand curve is customer surplus.

The total consumer surplus was calculated for different models of six study areas, with a bootstrapping method used to estimate 95% confidence intervals. The individual consumer surplus has been calculated by dividing the total consumer surplus by the total number of fishers in each case study.

The results of all three modelling approaches are provided in Table 6-10 and Figure 6-3.

Table 6-10: Consumer surplus of the six study areas

| Sites (NFZs) | Models | Data | Total consumer surplus ($) (values in bracket shows 95% confidence interval) | Individual consumer surplus ($) (values in bracket shows 95% confidence interval) |
|---|---|---|---|---|
| Cairns | Postcode model | 100 km | 159,111.17 | 152.26 |
| | | | (58,270 - 436,552) | (55.76 - 417.75) |
| | | 300 km | 159,111.17 | 152.26 |
| | | | (58,270 - 436,552) | (55.76 - 417.75) |
| | Zoned model | 100 km | 67,287 | 64.39 |
| | | | (59,898-75,093) | (57.32 - 71.86) |
| | | 300 km | 110,765 | 105.99 |
| | | | (6,899 - 273,385) | (6.60 - 261.61) |
| | Geographic model | Whole dataset | 14,878 | 74.02 |
| | | | (46,556- 85,754) | (44.34 – 81.67) |
| Mackay | Postcode model | 100 km | 37,765 | 19.03 |
| | | | (26,845 -49,200) | (13.53 - 24.80) |
| | | 300 km | 205,571 | 100.87 |
| | | | (29,867– 389,274) | (14.65 – 191.01) |
| | Zoned model | 100 km | 114,298 | 57.61 |
| | | | (28,193 -339,043) | (14.21 - 170.89) |
| | | 300 km | 239,100 | 117.32 |
| | | | (125,914 - 358,039) | (61.78 - 175.68) |
| | Geographic model | Whole dataset | 118,156 | 56.43 |
| | | | (28,282- 442,674) | (13.51 – 211.40) |
| Rockhampton | Postcode model | 100 km | 149,890 | 53.55 |
| | | | (19,540 -204,118) | (6.98 -72.92) |
| | | 300 km | 204,132 | 70.68 |
| | | | (165,716 -241,671) | (57.38 - 83.68) |
| | Zoned model | 100 km | 153,026 | 54.67 |
| | | | (143,768 – 162,434) | (51.36 -58.03) |
| | | 300 km | 253,920 | 87.92 |
| | | | (245,308 -262,094) | (84.94 -90.75) |
| | Geographic model | Whole dataset | 263,685 | 87.95 |
| | | | (79,826 – 521,434) | (26.63 - 173.93) |

| Sites (reference sites) | Models | Data | Total consumer surplus ($) (values in bracket shows 95% confidence interval) | Individual consumer surplus ($) (values in bracket shows 95% confidence interval) |
|---|---|---|---|---|
| Townsville | Postcode model | 100 km | 52,053 | 14.48 |
| | | | (4,899 -55,913) | (2.45 - 27.93) |
| | | 300 km | 72,053 | 20.05 |
| | | | (15,231-149,276) | (7.54 – 73.97) |
| | Zoned model | 100 km | 40,091 | 20.02 |
| | | | (12,234- 158,454) | (6.11 - 79.14) |
| | | 300 km | 296,226 | 146.79 |
| | | | (103,100 – 357,206) | (51.09 -177.01) |
| | Geographic model | Whole dataset | 211,831 | 104.14 |
| | | | (54,476– 467,694) | (26.78-229.94) |
| Hinchinbrook | Postcode model | 100 km | 58,047 | 39.11 |
| | | | (36,424 – 77,573) | (24.54 - 52.27) |
| | | 300 km | 242,938 | 145.56 |
| | | | (192,120 -293,538) | (115.11 -175.88) |
| | Zoned model | 100 km | 85,600 | 57.68 |
| | | | (72,522 – 97,078) | (48.87 - 65.42) |
| | | 300 km | 199,518 | 119.54 |
| | | | (176,660 -224,973) | (105.85 -134.79) |
| | Geographic model | Whole dataset | 1,229,705 | 644.50 |
| | | | (1,130,458 -1,274,972) | (592.48 - 668.22) |
| Hervey Bay | Postcode model | 100 km | 21,533 | 10.70 |
| | | | (9,240 - 77,154) | (4.59 - 38.33) |
| | | 300 km | 105,913 | 49.79 |
| | | | (34,639 – 324,870) | (16.28 - 152.74) |
| | Zoned model | 100 km | 75,329 | 37.42 |
| | | | (35,922 – 125,601) | (17.84 - 62.39) |
| | | 300 km | 94,000 | 44.19 |
| | | | (84,513-136,347) | (39.73 - 64.10) |
| | Geographic model | Whole dataset | 540,771 | 239.38 |
| | | | (89,787-1,241,395) | (39.75 - 549.53) |

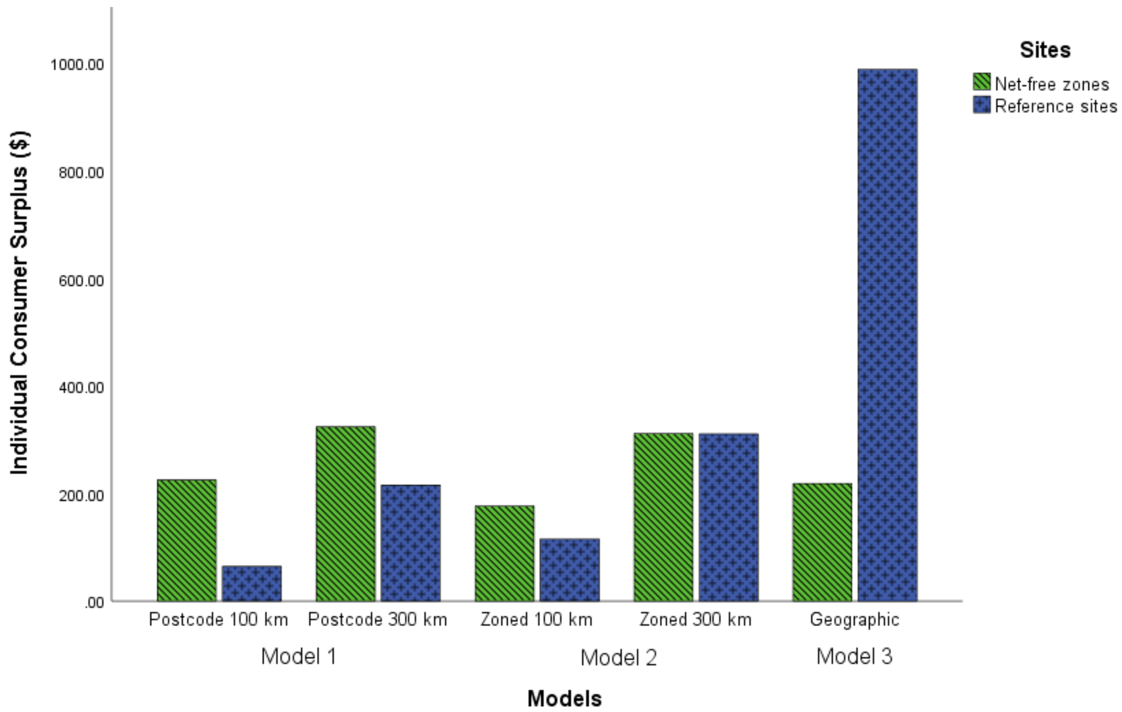



Figure 6-3: Total individual consumer surplus for pooled NFZs and reference sites

## 6.5 Discussion

This study's aim was to assess the economic values of recreational fishing in three net-free and three reference sites in Queensland. Three approaches to modelling the data were employed, using postcode, zoned, and geographic zone models, with two distance thresholds of 100 km and 300 km applied in the postcode model and zoned model. The study compared the consumer surplus between sites and models.

The results of the travel cost analysis demonstrated strong evidence of variation in economic values across sites and models. The lower value of $10.70 in the postcode model of Hervey Bay with the 100 km set, $20.02 in a zoned model of Townsville with the 100 km set, and $56.43 in the geographic model of Mackay indicate a higher number of local visitors who travelled short distances that generated lower consumer surplus. The postcode models generated more conservative values, with maximums of $152.26 /trip for the 100 km and 300 km set in Cairns, compared with the geographic models, which had a maximum of $644.50 for Hinchinbrook. The highest values for Cairns and Hinchinbrook using postcode and geographic model indicate the presence of more distant fishers and tourists in those regions. This is potentially because these the sites serve as a gateway to the Great Barrier Reef, and thousands of national and international tourists visit on a daily basis to participate in charter and recreational fishing activities. The average individual consumer surplus ranged from roughly

$144.57 to $603.22 depending on travel distances and trip expenditures. Similar findings were also reported in recent recreational fishing valuation studies in Australia (Prayaga et al., 2010; Ezzy & Scarborough, 2011; Pascoe et al., 2014). Further studies are required to determine the reasons for other variations in economic values.

The most striking result to emerge from the analysis is that with the exception of the geographic model, the economic value of recreational fishing in the three NFZs with 100 km and 300 km exclusions are currently higher than in three reference sites where commercial net fishing still occurs. In terms of the geographic model, more than four times higher consumer surplus was observed in reference sites than the NFZs. These differences were most pronounced in Hinchinbrook and Hervey Bay samples, where their individual consumer surplus was $644.50 and $239.38, respectively. This is because the three reference sites had a substantially higher number of distant fishers who travelled from more than 300 km away. It is possible that this model may contain more multi-purpose or multi-destination travellers as there were no data to identify the multi-purpose and multi-destination trips. Future research may identify the value for multi-purpose or multi-destination fishers, as well as values for potential improvements in the recreational fishing experience.

There are certain drawbacks associated with the data that was used to underpin the application of the model. The surveys only collected data on respondents' residential postcodes, boat ramp details, whether fishing was the main purpose of the trip or not, and distance travelled by the participants to reach the fishing sites. Ideally, future surveys should gather more information in order to refine the analysis. For example, the location of visitors' home (from where they have travelled to the site), the length of the trip, frequency of visits in a year or season, the amount of time spent in each site, overall travel expenses that includes all perceived cost by the travellers, personal income, socio-economic data (to allow an estimation of the value of their time), other locations visited during the same trip and the amount of time spent in each site, other reason for travel such as visiting a friend or relative, fishing success or experience at each site, perception of environmental quality or facilities at the fishing site, and alternative sites that the travellers may visit instead of this site.

There was also an issue with determining travel costs. The majority of studies that employ the travel cost method estimate demand functions using cross-sectional data from one season or year (Peterson et al., 1985; Cooper & Loomis, 1990). This is sufficient for making decisions with short timescales, but it is insufficient for making long-term decisions. Intertemporal data may be used to identify trends and assess behavioural stability (Hellerstein, 1993).

Furthermore, the results were sensitive to a number of factors. The exclusion of multi-purpose and multi-destination travellers from the models might have the potential to make a significant difference in consumer surplus estimates. The calculation of travel cost was only limited to the use of full car cost (option 2) but could be different if calculated more precisely using the perceived cost estimated by the respondents (option 3) (Bennett, 1996). The overall consumer surplus estimates might produce more specific values if the opportunity cost of time, onsite or offsite purchases, accommodation cost, other spendings could be added to the calculation.

The application of postcode models (model 1) can be more relevant and interpretable than geographic models (model 3) because the geographic model (model 3) is more applicable to large areas, such as regional Australia, where the population is not evenly distributed. Furthermore, the aggregation of the larger set of data in a geographic model results in the formation of fewer zones, that result in a loss of information. Postcode data, on the other hand, divides larger zones into smaller zones, allowing the study to use smaller observations to provide more accurate estimates, and the findings are more straightforward for application by government decision-makers. Chotikapanich and Griffiths (1998) corroborated similar conclusions. The study, however, acknowledges the possible bias emerging from the postcode model that did not address the zero visit problem as many postcodes near the sites have no fishers to the site. This suggested that a fisher from a postcode with a small population with a far distance from the site was giving much greater weight than a fisher from a postcode with a larger population. This results in a bias with increased travel cost which may lead to an increase in the consumer surplus estimate.

The zoned models (model 2) generate more accurate predictions for individual outcomes by pooling the whole dataset. The consumer surplus of zoned (model 2) and postcode models (model 1) are somewhat similar, but in most cases, the zoned models (model 2) show more precise results than the postcode models (model 1). A possible interpretation for this might be the tradeoffs between more data in the zoned model and heterogeneity from combining data from different sites. The inclusion of all highly significant coefficients with higher $R^2$ values in the models leads to improved outputs from zoned models, indicating that there are not substantial disparities across the sites. The study suggests that it is worth running a zoned model (using postcode data) instead of geographic models (model 3), especially for the similar studies where the number of respondents is high and the ensuing large dataset is influenced by multi-visit travellers who are on long, interstate driving holidays.

The application of geographic models (model 3) for the whole dataset has been affected by the large proportion of fishers visiting from distant areas, reflected in higher consumer surplus for the reference sites. Bateman (1993) claimed that respondents who reside closest to the site incur the lowest travel costs and obtain the least recreational value from accessing the site. The study, however, acknowledges that there is a possibility of misspecification bias as a result of participants providing their home postcode rather than the postcode from where they stayed and travelled throughout their trip, (e.g., they might have been staying with their friends or relatives while travelling). Tests of overlapping confidence intervals between the postcode, and the geographic models indicate no difference for the NFZs case study, but a large difference for the reference site case study.

One of the expectations of Queensland's NFZs is that they will support and strengthen the regional economy by increasing the economic value of recreational fishing (Queensland Government, 2016). This study suggests that currently the economic value of recreational fishing in NFZs is relatively higher when only the closest visitors (100 km and 300 km distance thresholds) were considered in the postcode and zoned models, and lower when distant visitors were included in the geographic model. However, as fishers from other areas become more aware of the improved fishing experience in the NFZs, there is a possibility that NFZs will attract distant visitors from far distances. There are some similarities between the attitudes expressed by Martin et al. (2019) in their study evaluating the performance of Queensland's NFZs. They found that the fishers of NFZs were more likely to travel long distances, and when compared to the reference sites in 2018, fishers of Cairns and Rockhampton exhibited an increase in travel distances over the last 3 years. The findings of the current study are in line with those from previous research by Pascoe et al. (2014). Their study showed an increase in the economic value and benefit of recreational fishing after rezoning in Moreton Bay, Southeast Queensland. The present study was, however, conducted in the very early stages after the net-free status was introduced, hence the effect of the visitation may not have been fully recorded, because any change in a management scheme requires adequate time for adjustment before its effects are identified (Queensland Government, 2014). Beets and Manual (2007) suggested that the evaluation of a fisheries management change requires several years to take effect and identified a significant improvement in fish growth and recruitment 7 years after the establishment of seasonal closures. This study used data collected during the 2 years immediately following the establishment of new net-free fishing zones in 2015. It is possible that the lag time between the management change and visitor response is longer than 2 years.

It is expected that in the longer term, the NFZs will be able to attract more distant travellers whose sole purpose of the visit would be recreational fishing.

## 6.6 Conclusions

The present study was designed to determine the economic value of recreational fishing following the introduction of NFZs at three sites in Queensland. The study has compared recreational fishing values between three new NFZs and three reference sites. The consumer surplus for net-free and reference sites varies between the three different models tested: postcode (model 1), zoned (model 2), and geographic (model 3). Considering the closest visitors (100 km and 300 km distance exclusions), the study indicates that, currently, the NFZs have higher economic values than the reference sites although the geographic model is showing a contrasting result as it also includes all of the distant visitors. There is potential for consumer surplus in NFZs to increase as more anglers are attracted from more distant areas. Among the three models, the zoned models (model 2) using postcode data are the most appropriate to apply for this type of dataset.

The generalisability of these results is subject to certain limitations. For instance, no sampling frames were chosen to obtain data from boat ramps; rather, boat ramps were chosen based on the availability of a larger number of respondents and proximity to the city. Information on multi-purpose and multi-destination trips, perceived travel cost by the fishers, fishing success, availability of recreationally-valued fish species, site facilities, the opportunity cost of time, substitute sites, and other variables were undetermined and therefore, could not be included in the model. The study was also influenced by the timing of data collection, shortly after the establishment of the NFZs. Mis-specification bias might exist as a consequence of individuals providing their home postcode rather than the postcode from where they stayed and travelled throughout their trip. Furthermore, while the cross-sectional data used in the study is adequate for making short-term decisions, the use of intertemporal data is more useful for identifying trends and making long-term decisions.

Until recently, there has been little focus on the value of recreational fishing in Australia, and this research presents a novel study comparing recreational fishing values between sites and through different TCM models, which serves as a foundation for future research in similar situations. To better assess the effectiveness of NFZs as mechanisms for improving recreational fishing values in Queensland, it is recommended that data on recreational fishing continues to be collected at the three NFZs and three reference sites for several more years with updated survey questionnaires, when recreational fishing is more likely to have improved and awareness of the NFZs has increased.

The results presented in this study would be useful when considering management actions aimed at improving recreational fishing opportunities. The main contribution of this study is the inclusion of three models of ZTCM that compare the economic values among the models and the sites. In terms of future studies, it is suggested that the study be replicated with more advanced data that overcome present limitations in order to produce result to support long-term decisions on fisheries management.

# Chapter 7 CONCLUSIONS AND RECOMMENDATIONS

*No journal article is associated with this chapter.*

## 7.1 Overview

Commercial netting closures were implemented in Queensland in 2015 to conserve species by reducing commercial harvest pressure on fish stocks, and to increase recreational fishing opportunities, marine-based tourism, and resultant economic growth in regional areas (Brown, 2016; Queensland Government, 2016). In this study, the social, ecological, and economic effects of commercial net fishing closures in three areas of Queensland were assessed using three different statistical procedures. Along with the three net-free zones (NFZs), three reference sites were selected to provide a complementary analysis.

To assess and compare the social effects, the study analysed data of recreational fishers' satisfaction and expectations collected from a NFZ (Rockhampton) and a reference site (Townsville) in October 2018. The output of this study revealed that the recreational fishers' satisfaction and expectations vary across sites, with a stronger positive relationship in Rockhampton than in Townsville. This result supports the findings of Martin et al. (2019), who reported that satisfaction and expectations for NFZs have increased over time, and the performance of Rockhampton and Cairns in the 2018 survey was higher than in the 2015 and 2016 surveys.

To evaluate and compare the ecological effects of the closure, the study used 30 years (1990-2019) of time series data from secondary sources for six study sites. The study developed two forecasting models, namely ARIMAX (autoregressive integrated moving average with exogenous input) and MLR (multiple linear regression) using fishery and environmental parameters that influence commercial barramundi CPUE (catch per unit effort). Except for two samples from Cairns, the results show that ARIMAX models provide the best forecast for all of the study sites. The study also revealed that both environmental and fishery parameters are important for prediction. For the majority of the study sites, the most significant predictors of CPUE were environmental parameters such as rainfall, streamflow, and stream water level, as well as fishery parameters such as licences and prices. These findings are consistent with previous observational studies, which found that after adequate rainfall and freshwater flow during the summer season, the catchability of barramundi improved significantly (Balston, 2007, 2009a). The study also highlighted the changes that occurred after the implementation of closures in NFZs in contrast to the reference site and made inferences about the recreational opportunities in those regions.

To determine and compare the economic value of recreational fishing, the study integrated secondary data and boat ramp survey data collected from 6 study sites from November 2015 to June 2017. The study developed three models (postcode, zoned, and geographic) of the TCM (travel cost method). The results showed that the consumer surplus for net-free and reference sites varies across the three models tested. According to the study, NFZs currently have higher economic values than reference sites when considering the postcode and zoned model that includes all of the closest visitors, though the geographic model shows a contrasting result because it includes all of the distant visitors. Consumer surplus in NFZs has the potential to increase as more fishers are attracted from further away. Among the three models, the zoned models based on pooled postcode data are the most appropriate to apply for this type of dataset. There are some similarities between the attitudes expressed by Martin et al. (2019) in their study evaluating the performance of Queensland's NFZs. They revealed that the fishers are likely to travel from long distances, and particularly fishers in Cairns and Rockhampton have increased their travel distances over the last three years when compared to the reference sites in 2018. The findings of the current study are consistent with previous research by Pascoe et al. (2014). Their research revealed an increase in the economic value and benefit of recreational fishing following rezoning in Moreton Bay, Southeast Queensland.

The evidence in this study supports the concept that the removal of commercial net fishing had substantial positive effects on recreational fishers and the commercial barramundi population from a socio-economic and ecological standpoint. This chapter of the thesis, however, draws conclusions from the findings of the analysis through providing summary statements, main findings and outcomes, study limitations and future research directions, contribution to knowledge, and concluding statements.

## 7.2 Summary

The net-free zones (NFZs) near Cairns, Mackay, and Rockhampton were introduced by the Queensland Government in November 2015 to conserve species by reducing commercial fishing pressure on fish stocks, enhance recreational fishers' participation and deliver economic benefit through recreational and charter fishing and tourism. The newly designed closure areas of Queensland have not been thoroughly assessed for their social, ecological, and economic effects though some early social surveys were conducted by the Queensland Department of Agriculture and Fisheries (DAF). To assess and compare the effects of three netting closures in Queensland, three reference sites (non-NFZs) were identified which were not under the management scheme. The study collected data from both primary and secondary sources to quantify the original effect of netting closure. To identify the social effect, the study analysed and compared recreational fishers' satisfaction and expectation in fishing between a NFZ and a reference site. The study also developed two structural equation models (SEMs) to identify the causal relationship among satisfaction, overall satisfaction, and expectations and the strength of their relationship. To assess and compare the ecological effects of the closure on the barramundi population, the study developed two forecasting models (ARIMAX and MLR) for three NFZs and reference sites using fishery and environmental parameters that influence commercial barramundi CPUE. The study also demonstrated the changes that occurred after the implementation of closures in NFZs in comparison to the reference site and provided inferences about the recreational opportunities in those regions. To determine and compare the economic values of recreational fishing in three NFZs and reference sites, the study determined the consumer surplus using the TCM. Overall, the models and methods used in this study to identify the change after the implementation of netting closure were found to be highly accurate and acceptable.

Policy analysts often require data to evaluate the effectiveness of any beneficiary program. The study presented in this thesis is one of the first investigations to explore the effect of newly implemented NFZs in Queensland from social, ecological, and economic perspectives. The main purpose of this study was achieved by addressing the three research objectives which are described in the following section.

## 7.3 Main findings and outcomes

*Objective 1: To evaluate recreational fishers' satisfaction and expectations towards NFZs* (see Chapter 4)

This objective evaluated recreational fishers' satisfaction and expectations with fishing at a NFZ and a reference site. Along with the graphical presentation of the Likert scale responses, non-parametric tests and regression analyses were carried out to assess satisfaction. The results showed that the fishers in the NFZ were more satisfied and had higher expectations than fishers in the reference site. The study also developed two structural equation models (SEMs) to identify the underlying structural relationship and the strength of the relationship among satisfaction, overall satisfaction, and expectation. The SEM identified the most influential factors for latent variable satisfaction and expectation and demonstrate the relationship and the strength of their relationship for each of the study sites. The positive social effects of the netting closures in Queensland identified in this study are relevant to recreational fisher communities, policy analysts, and interested groups in identifying the relationship between satisfaction and expectation that has received little attention in the literature.

*Objective 2: To develop a best-fitting forecasting model for barramundi (Lates calcarifer) in net-free zones and reference sites* (see Chapter 5)

Reduced commercial fishing can improve natural fish recruitment and stock structure, potentially leading to higher catches in subsequent years. There are some fishery and environmental parameters that contribute to the prediction of future CPUE. The CPUE forecast has recently been used as an effective tool for providing accurate information on potential catch and effort, as well as advice on fisheries management. In this study, 30 years (1990-2019) of historical commercial barramundi CPUE data were analysed for the six study sites using ARIMAX and MLR models to identify the exogenous variables that affect barramundi CPUE. The results showed that the ARIMAX model outperformed the MLR model at most sites. In relation to forecasting models, this study demonstrated that both fishery and environmental parameters played an equal role in influencing the CPUE; however, the majority of scenarios revealed that environmental parameters such as rainfall, streamflow, and stream water level, as well as fishery parameters such as licences and price, are the primary determinants of CPUE. The research provided useful insights into the effect of management changes in the commercial CPUE on the provision of recreational opportunities and the long-term management of barramundi in the region.

*Objective 3: To estimate the economic values of recreational fishing* (see Chapter 6)

The objective of the study was to determine the economic value of recreational fishing in the three NFZs and three reference sites. Three models (postcode, zoned, and geographic) of the TCM were tested to investigate the economic values of the six study sites. The postcode and zoned models assessed economic values for the fishers up to 100 km and 300 km distance thresholds, but the geographic model included all of the fishers travelling from distant locations. The results indicate that the performance of the zoned models is similar to the postcode models and offers more accurate results as the model includes highly significant travel cost coefficients and dummy sites with higher $R^2$ values. The consumer surplus of NFZs was relatively higher when only the closest visitors (100 km and 300 km distance thresholds) were considered in the postcode and zoned models, and lower when distant visitors were included in the geographic model. However, as fishers from other areas become more aware of the improved fishing experience in the NFZs, there is a possibility that NFZs will attract distant visitors from far distances.

## 7.4 Study limitations and future research

Although individual chapters have outlined some limitations and future research directions, some key limitations of this study and future research options are noted, as follows.

The principal limitation of this study is the extrapolation of the results established here to other areas with different environmental conditions. The results of this research are specific to these case study sites and if used elsewhere may vary in terms of the influencing factors, data availability, and timing of data collection. That means that in order to obtain a complete socio-ecological assessment of any management measures, this approach needs to be modified or applied independently for every distinct scenario. Unlike other objectives, in objective 1, the study was unable to evaluate recreational fishers' satisfaction for all of the study sites, as sufficient survey data were only able to be collected at priority sites (Rockhampton and Townsville). Further studies assessing all of the study sites, or other sites with different management situations, would improve and justify the global applicability of the models developed here.

The second most important limitation of the study is the small sample size, which is a common constraint. Acquiring a sufficient dataset for objective 1 was challenging and for objective 2, only 30 years of barramundi commercial CPUE data were available to include in the time series analysis. Due to a lack of sufficient spatiotemporal data and the complexities of assuming post-release survival, the study was unable to account for the recreational catch in objective 2. In time series analysis, however, more data is always preferable because a larger dataset captures all of the information and provides more accurate forecasts with negligible bias.

In addition, acquiring a dataset with various parameters related to TCM for objective 3 was difficult as the data collected by DAF included limited parameters. Future investigations using TCM with updated and additional data are important to determine the economic values of recreational fishing in those areas.

One of the caveats of this study is that it is primarily concerned with the changes to policy settings, such as shifting fishing efforts from commercial to recreational rather than with identifying the management issues. However, it might be reasonable to consider the overall fishing pressure, rather than closing commercial netting and provide open access for recreation. This is another area in which future study may be conducted.

The survey results were only based on fishers who recreationally fished or went to the fishing tackle stores during the data collection period. The findings might be different if an appropriate sample frame was used or if the data were obtained at a different period of the year. It is expected that the above-mentioned limitations should be considered in future research.

## 7.5 Contribution to knowledge

The statistical approaches and models presented in this research provide a fundamental framework for evaluating the localised change in fishing pressure in Queensland. The study has successfully integrated field survey data and secondary data to generate the more accurate and reliable information required for the effective and efficient management of fisheries resources. The study has evaluated recreational fishers' satisfaction and expectations towards a NFZ and a reference site and revealed explicit relationships between satisfaction and expectations. In addition, the study developed models to forecast future barramundi CPUE and established the relationship with catch and some fishery and environmental parameters that affect barramundi. The study has also tested different models of TCM to identify the economic value of recreational fishing through sites. The approaches and models applied in this thesis support existing approaches practiced in the field of fisheries research to inform management decisions more accurately and efficiently.

The key contributions of this thesis to the body of scientific knowledge are summarised as it:

- being the first identified effort to develop a structural equation model that evaluated the underlying causal relationship and the strength of the relationship between recreational fishers' satisfaction, overall satisfaction, and expectation that received little attention to the literature,
- identifying an explicit relationship between barramundi CPUE and environmental and fishery parameters,
- developing fish CPUE forecasting models in a data-poor fishery for the sustainable management of barramundi,
- being the first identified effort to develop and compare several different models of the travel cost method (TCM) to determine the economic values of recreational fishing, and

- providing the fundamental basis to employ zoned TCM using pooled postcode data for similar studies.

## 7.6 Concluding remarks

The evaluation of the socio-ecological effect of netting closures in Queensland has become an emerging issue to be addressed. The existing literature has done little to explore the social, ecological, and economic effects of a change in commercial fishing pressure in these areas. In response, this thesis has provided comprehensive approaches to determine the socio-economic and ecological effects of the closures using both field survey and secondary data. The study compared the change to three reference sites. Several models were developed as part of the study to assess the change. To understand the social change, the study found that the satisfaction and expectations in recreational fishing have increased in a NFZ than a reference site. The study also developed SEMs to determine the relationship among three concepts discussed in the study: satisfaction, overall satisfaction, and expectation. The study developed and compared CPUE prediction models (ARIMAX and MLR) to examine the effects of netting closure in commercial barramundi CPUE and found that in most sites, the ARIMAX model outperformed the MLR model. For most of the study sites, environmental parameters such as rainfall, streamflow, and stream water level, as well as fishery parameters such as licences and prices, are the most important determinants of CPUE. The study provided valuable insights for increased recreational opportunities and sustainable management of barramundi in the study areas. For the economic aspect, the study developed three models (postcode, zoned, and geographic) of TCM and found that the economic value of recreational fishing is higher in NFZs when considered from the closest visitors (100 km and 300 km distances thresholds) in the postcode and zoned models and lower when considered from the distant visitors (travelled more than 300 km or beyond) in the geographic model.

This study has explicitly identified and addressed fishery management issues related to the implementation of netting closures in Queensland. The approaches and models established in this study have previously been tested in other applications and are methodologically sound and scientifically acceptable. As regards one possible application of the approaches and models developed, newly implemented management measures often require effective monitoring, review, and evaluation of whether they achieved the expected outcomes. Periodic follow-up could help managers to tailor policy decisions for these and other net-free areas where necessary. A successful management policy applied in these areas could be used as an influential paradigm for managing other areas where resource allocation is an issue.

To conclude, this study can be used as a baseline for researchers, academics, interested groups, policymakers, and fisheries management authorities. Finally, the approaches employed in this thesis can be used (with relevant modification) to address similar fisheries management concerns at the local, national, and international levels.

## References


Aas, Ø. (1996). Use of two approaches to measure children's motivations to fish in Norway. *Human Dimensions of Wildlife, 1*(3), 15-28. doi:10.1080/10871209609359067

Aas, Ø., & Kaltenborn, B. P. (1995). Consumptive orientation of anglers in Engerdal, Norway. *Environmental Management, 19*(5), 751-761.

Aas, Ø., & Vitters, J. (2000). Re-examining the consumptiveness concept: Some suggestions from a confirmatory factor analysis. *Human Dimensions of Wildlife, 5*(4), 1-18. doi:10.1080/10871200009359191

Abbott, J. K., & Haynie, A. C. (2012). What are we protecting? Fisher behavior and the unintended consequences of spatial closures as a fishery management tool. *Ecological Applications, 22*(3), 762-777.

Abdelaal, M. M. A., & Aziz, E. F. (2012). Modeling and forecasting fish production using univariate and multivariate ARIMA models. *Far East Journal of Theoretical Statistics, 41*(1), 1-26.

Abdullah, S., Markandya, A., & Nunes, P. A. (2011). Introduction to economic valuation methods. In A. Batabyal & P. Nijkamp (Eds.), *Research tools in natural resource and environmental economics* (pp. 143-187). United States: World Scientific

Abesamis, R. A., & Russ, G. R. (2005). Density-dependent spillover from a marine reserve: Long-term evidence. *Ecological Applications, 15*(5), 1798-1812. doi:doi.org/10.1890/05-0174

Adhikari, R., & Agrawal, R. K. (2013). *An introductory study on time series modeling and forecasting*. Germany, Saarland: LAP Lambert Academic Publishing.

Agardy, T., Bridgewater, P., Crosby, M. P., Day, J., Dayton, P. K., Kenchington, R., . . . Peau, L. (2003). Dangerous targets? Unresolved issues and ideological clashes around marine protected areas. *Aquatic Conservation: Marine and freshwater ecosystems, 13*(4), 353-367. doi:10.1002/aqc.583

Agcopra, C., Balston, J. M., Bowater, R., Rodgers, L. J., & Williams, A. A. J. (2005). Predictive system for aquaculture ponds. *Queensland Aquaculture News* 27, 23.

AgTrends. (2014). *Queensland AgTrends 2014–15: Forecasts and trends in Queensland agricultural, fisheries and forestry production*. Retrieved from https://www.daf.qld.gov.au/business-priorities/agriculture/trends/agtrends

Ahmad, S. A. (2009). *Visitors' Willingness to Pay for an entrance fee: A case study of marine parks in Malaysia.* (Unpublished doctoral dissertation), University of Glasgow, United Kingdom,

Akhter, S., & Yew, T. S. (2013). Economic valuation of marine protected areas: A review of studies in Southeast Asia. *The International Journal of Social Sciences, 14*(1), 1-16.

Aksu, A., İçigen, T. E., & Ehtiyar, R. (2010). A comparison of tourist expectations and satisfaction: A case study from Antalya region of Turkey. *Turizam, 14*(2), 66-77.

Alder, J., Campbell, B., Karpouzi, V., Kaschner, K., & Pauly, D. (2008). Forage fish: From ecosystems to markets. *Annual Review of Environment and Resources, 33*, 153-166. doi:https://doi.org/10.1146/annurev.environ.33.020807.143204

Allen, M. P. (2004). The problem of multicollinearity. In *Understanding Regression Analysis* (pp. 176-180): Springer, Boston, MA.

Ambrey, C. L., & Fleming, C. M. (2012). Valuing Australia's protected areas: A life satisfaction approach. *New Zealand Economic Papers, 46*(3), 191-209. doi:10.1080/00779954.2012.697354

Andrews, B. H., Dean, M. D., Swain, R., & Cole, C. (2013). *Building ARIMA and ARIMAX models for predicting long-term disability benefit application rates in the public/private sectors.* Retrieved from https://www.soa.org/globalassets/assets/files/research/projects/research-2013-arima-arimax-ben-appl-rates.pdf

Arlinghaus, R. (2006). On the apparently striking disconnect between motivation and satisfaction in recreational fishing: The case of catch orientation of German anglers. *North American Journal of Fisheries Management, 26*(3), 592-605. doi:10.1577/M04-220.1

Arlinghaus, R., Abbott, J. K., Fenichel, E. P., Carpenter, S. R., Hunt, L. M., Alós, J., . . . Jensen, O. P. (2019). Opinion: Governing the recreational dimension of global fisheries. *Proceedings of the National Academy of Sciences, 116*(12), 5209-5213.

Australian Bureau of Agricultural and Resource Economics and Sciences. (2018). *Australian Fisheries and Aquaculture Statistics 2017*. Retrieved from https://www.agriculture.gov.au/sites/default/files/sitecollectiondocuments/abares/publications/AustFishAquacStats_2017_v1.2.0.pdf

Australian Bureau of Agricultural and Resource Economics and Sciences. (2019). *Australian Fisheries and Aquaculture Statistics 2018*. Retrieved from: https://www.agriculture.gov.au/abares/research-topics/fisheries/fisheries-and-aquaculture-statistics/production-2018

Australian Fisheries Management Authority. (2017). Fishing closures. Retrieved from Australian Fisheries Management Authority website: http://www.afma.gov.au/sustainability-environment/fishing-closures/

Australian Marine Conservation Society. (2020). Retrieved from https://www.marineconservation.org.au/fisheries/

Australian Taxation Office. (2017). *Cents per kilometre method*. Retrieved from Australian Taxation Office website: https://www.ato.gov.au/Business/Income-and-deductions-for-business/Deductions/Motor-vehicle-expenses/Claiming-motor-vehicle-expenses-as-a-sole-trader/Cents-per-kilometre-method/

Badalamenti, F., Ramos, A., Voultsiadou, E., Lizaso, J. S., D'anna, G., Pipitone, C., . . . Riggio, S. (2000). Cultural and socio-economic impacts of Mediterranean marine protected areas. *Environmental Conservation, 27*(2), 110-125. doi:10.1017/S0376892900000163

Baker, R., & Ruting, B. (2014). *Environmental policy analysis: A guide to non-market valuation*. Retrieved from https://www.pc.gov.au/research/supporting/non-marketvaluation/non-market-valuation.pdf

Bako, H. Y. (2014). *Forecasting pelagic fish in Malaysia using ETS state space approach.* (Unpublished master's dissertation), University Tun Hussein Onn Malaysia,

Balston, J. (2007). *Climate impacts on barramundi and banana prawn fisheries of Queensland tropical east coast*. Queensland, Australia. Retrieved from https://www.daf.qld.gov.au/__data/assets/pdf_file/0017/63008/FRDC-Final-Report-3.pdf

Balston, J. (2009a). Short-term climate variability and the commercial barramundi (*Lates calcarifer*) fishery of north-east Queensland, Australia. *Marine and Freshwater Research, 60*(9), 912-923. doi:10.1071/MF08283

Balston, J. (2009b). An analysis of the impacts of long-term climate variability on the commercial barramundi (*Lates calcarifer*) fishery of north-east Queensland, Australia. *Fisheries Research, 99*(2), 83-89. doi:10.1016/j.fishres.2009.05.001

Barrett, N. S., Edgar, G. J., Buxton, C. D., & Haddon, M. (2007). Changes in fish assemblages following 10 years of protection in Tasmanian marine protected areas. *Journal of Experimental Marine Biology and Ecology, 345*(2), 141-157.

Bateman, I. J. (1993). Valuation of the environment methods and techniques: Revealed preference methods. In T. R.K. (Ed.), *Sustainable Environmental Economics and Management* (pp. 192–233). London: Belhaven Press.

Beal, D. J. (1995). A travel cost analysis of the value of Carnarvon Gorge National Park for recreational use. *Review of Marketing and Agricultural Economics, 63*(2), 292-303. doi:10.22004/ag.econ.12337

Beardmore, B., Haider, W., Hunt, L. M., & Arlinghaus, R. (2011). The importance of trip context for determining primary angler motivations: Are more specialized anglers more catch-oriented than previously believed? *North American Journal of Fisheries Management, 31*(5), 861-879. doi:https://doi.org/10.1080/02755947.2011.629855

Beardmore, B., Hunt, L. M., Haider, W., Dorow, M., & Arlinghaus, R. (2015). Effectively managing angler satisfaction in recreational fisheries requires understanding the fish species and the anglers. *Canadian Journal of Fisheries and Aquatic Sciences, 72*(4), 500-513. doi:doi:10.1139/cjfas-2014-0177

Beddington, J. R., Agnew, D. J., & Clark, C. W. (2007). Current problems in the management of marine fisheries. *Science, 316*(5832), 1713-1716. doi:10.1126/science.1137362

Beets, J., & Friedlander, A. (1999). Evaluation of a conservation strategy: A spawning aggregation closure for red hind, Epinephelus guttatus, in the US Virgin Islands. *Environmental Biology of Fishes, 55*(1-2), 91-98. doi:https://doi.org/10.1023/A:1007404421518

Beets, J., & Manual, M. (2007). *Temporal and seasonal closures used in fisheries management: A review with application to Hawai`i.* . (Unpublished manuscript). Department of Marine Science, University of Hawai`i-Hilo. Retrieved from https://dlnr.hawaii.gov/coralreefs/files/2015/02/BeetsTempClosuresRpt08.pdf

Bennett, J. (1996). Estimating the recreation use values of national parks. *Tourism Economics, 2*(4), 303-320. doi:https://doi.org/10.1177/135481669600200402

Bennett, N. J., & Dearden, P. (2014). Why local people do not support conservation: Community perceptions of marine protected area livelihood impacts, governance and management in Thailand. *Marine Policy, 44*, 107-116. doi:https://doi.org/10.1016/j.marpol.2013.08.017

Benson, A. J., & Trites, A. W. (2002). Ecological effects of regime shifts in the Bering Sea and eastern North Pacific Ocean. *Fish and Fisheries, 3*(2), 95-113. doi:https://doi.org/10.1046/j.1467-2979.2002.00078.x

Bentler, P. M., & Bonett, D. G. (1980). Significance tests and goodness of fit in the analysis of covariance structures. *Psychological Bulletin, 88*(3), 588. doi:10.1037/0033-2909.88.3.588

Bergstrom, J. C. (1990). Concepts and measures of the economic value of environmental quality: A review. *Journal of Environmental Management, 31*(3), 215-228. doi:https://doi.org/10.1016/S0301-4797(05)80035-0

Bewick, V., Cheek, L., & Ball, J. (2003). Statistics review 7: Correlation and regression. *Critical Care, 7*(6), 1-9.

Bitner, M. J., & Hubbert, A. R. (1994). Encounter satisfaction versus overall satisfaction versus quality. *Service Quality: New Directions in Theory and Practice, 34*(2), 72-94. doi:10.4135/9781452229102.N3

Blackwell, B. (2007). The value of a recreational beach visit: An application to Mooloolaba beach and comparisons with other outdoor recreation sites. *Economic Analysis and Policy, 37*(1), 77-98. doi:10.1016/S0313-5926(07)50005-6

Blyth, R. E., Kaiser, M. J., Edwards-Jones, G., & Hart, P. J. (2002). Voluntary management in an inshore fishery has conservation benefits. *Environmental Conservation, 29*(4), 493-508. doi:https://doi.org/10.1017/S0376892902000358

Bohnsack, J. A. (1998). Application of marine reserves to reef fisheries management. *Austral Ecology, 23*(3), 298-304. doi:https://doi.org/10.1111/j.1442-9993.1998.tb00734.x

Borges, M., Santos, A., Crato, N., Mendes, H., & Mota, B. (2003). Sardine regime shifts off Portugal: A time series analysis of catches and wind conditions. *Scientia Marina, 67*(S1), 235-244. doi:10.3989/scimar.2003.67s1235

Botsford, L. W., Hastings, A., & Gaines, S. D. (2001). Dependence of sustainability on the configuration of marine reserves and larval dispersal distance. *Ecology Letters, 4*(2), 144-150. doi:https://doi.org/10.1046/j.1461-0248.2001.00208.x

Box, G. E., & Jenkins, G. M. (1970). *Time series analysis: Forecasting and control*. San Francisco, USA: Holden-Day.

Boyle, K. (2003). Contingent valuation in practice. In P. Champ, K. J. Boyle, & T. C. Brown (Eds.), *A primer on nonmarket valuation*. Dordrecht, The Netharlands: Kluwer Academic Publishers.

Breidert, C., Hahsler, M., & Reutterer, T. (2006). A review of methods for measuring willingness-to-pay. *Innovative Marketing, 2*(4), 8-32.

Brid, R. S. (2018). Introduction to time series. Retrieved from https://medium.com/greyatom/time-series-b6ef79c27d31

Brinson, A. A., & Wallmo, K. (2013). Attitudes and preferences of saltwater recreational anglers: Report from the 2013 national saltwater angler survey [NOAA technical memorandum NMFS-F/SPO-13]. United States: Department of Commerce. Retrieved from http://spo.nmfs.noaa.gov/tm/.

Brinson, A. A., & Wallmo, K. (2017). Determinants of saltwater anglers' satisfaction with fisheries management: Regional perspectives in the United States. *North American Journal of Fisheries Management, 37*(1), 225-234. doi:https://doi.org/10.1080/02755947.2016.1235629

Brooks, C. (2019). *Introductory econometrics for finance*. Cambridge University Press.

Brown, A., De Costa, C., & Guo, F. (2020). *Our food future: Trends and opportunities*. ABARES, Research Report 20.1, Canberra, DOI: 10.25814/5d9165cf4241d. CC BY 4.0.

Brown, C. J. (2016). Social, economic and environmental effects of closing commercial fisheries to enhance recreational fishing. *Marine Policy, 73*, 204-209. doi:https://doi.org/10.1016/j.marpol.2016.08.010

Brownlee, J. (2016). How to backtest machine learning models for time series forecasting. Retrieved from https://machinelearningmastery.com/backtest-machine-learning-models-time-series-forecasting/

Brunke, K. D., & Hunt, K. M. (2008). Mississippi waterfowl hunter expectations, satisfaction, and intentions to hunt in the future. *Human Dimensions of Wildlife, 13*(5), 317-328. doi:https://doi.org/10.1080/10871200802227422

Bui, A., Johnson, F., & Wasko, C. (2019). The relationship of atmospheric air temperature and dew point temperature to extreme rainfall. *Environmental Research Letters, 14*(7), 1-9. doi:https://doi.org/10.1088/1748-9326/ab2a26

Bureau of Meteorology. (2019). Detailed reports on notable Queensland floods http://www.bom.gov.au/qld/flood/fld_reports/reports.shtml

Bureau of Rural Sciences. (2005). *Socio-economic impact assessment toolkit: A guide to assessing the socio-economic impacts of marine protected areas in Australia*. Retrieved from http://www.environment.gov.au/

Burns, R. C., Graefe, A. R., & Absher, J. D. (2003). Alternate measurement approaches to recreational customer satisfaction: Satisfaction-only versus gap scores. *Leisure Sciences, 25*(4), 363-380. doi:10.1080/01490400390240473

Buxton, C., Hartmann, K., Kearney, R., & Gardner, C. (2014). When is spillover from marine reserves likely to benefit fisheries? *PloS One, 9*(9), 1-7. doi:10.1371/journal.pone.0107032

Cárcamo, P. F., Garay-Flühmann, R., Squeo, F. A., & Gaymer, C. F. (2014). Using stakeholders' perspective of ecosystem services and biodiversity features to plan a marine protected area. *Environmental Science and Policy, 40*, 116-131. doi:10.1016/j.envsci.2014.03.003

Carpio, C. E., Wohlgenant, M. K., & Boonsaeng, T. (2008). The demand for agritourism in the United States. *Journal of Agricultural and Resource Economics*, 33(2), 254-269. doi: https://www.jstor.org/stable/41220626

Casey, J. F., Vukina, T., & Danielson, L. E. (1995). The economic value of hiking: Further considerations of opportunity cost of time in recreational demand models. *Journal of Agricultural and Applied Economics, 27*(2), 658-668. doi:10.22004/ag.econ.15282

Chakravorty, U., & Nemoto, K. (2000). Modeling the effects of area closure and tax policies: A spatial-temporal model of the Hawaii longline fishery. *Marine Resource Economics, 15*(3), 179-204. doi:10.1086/mre.15.3.42629301

Charles, A., & Wilson, L. (2009). Human dimensions of marine protected areas. *ICES Journal of Marine Science, 66*(1), 6-15. doi:https://doi.org/10.1093/icesjms/fsn182

Chesoh, S., & Choonpradub, C. (2011). A model for clustering fish community structure with application to Songkhla Lake bi-monthly catches 2003-2006. *Turkish Journal of Fisheries and Aquatic Sciences, 11*(2), 177-184. doi: 10.4194/trjfas.2011.0201

Chotikapanich, D., & Griffiths, W. E. (1998). Carnarvon Gorge: A comment on the sensitivity of consumer surplus estimation. *Australian Journal of Agricultural and Resource Economics, 42*(3), 249-261. https://doi.org/10.1111/1467-8489.00049

Christie, P. (2004). Marine protected areas as biological successes and social failures in Southeast Asia. *American Fisheries Society Symposium, 42*, 155-164.

Christie, P., McCay, B. J., Miller, M. L., Lowe, C., White, A. T., Stoffle, R., . . . Pomeroy, C. (2003). Toward developing a complete understanding: A social science research agenda for marine protected areas. *Fisheries, 28*(12), 22-26.

Clark, C. W. (2006). *The worldwide crisis in fisheries: Economic models and human behavior*. Cambridge: Cambridge University Press.

Commonwealth Department of Environment and Heritage. (2013). The Benefits of Marine Protected Areas. Retrieved from https://parksaustralia.gov.au/marine/management/resources/scientific-publications/benefits-marine-protected-areas-discussion-paper/

Cong, R.-G., & Brady, M. (2012). The interdependence between rainfall and temperature: Copula analyses. *The Scientific World Journal, 2012*, 1-11. doi:https://doi.org/10.1100/2012/405675

Conover, D. O., & Munch, S. B. (2002). Sustaining fisheries yields over evolutionary time scales. *Science*, *297*(5578), 94-96. doi:10.1126/science.1074085

Cooke, S. J., & Cowx, I. G. (2004). The role of recreational fishing in global fish crises. *BioScience, 54*(9), 857-859. doi:10.1641/0006-3568(2004)054[0857:TRORFI]2.0.CO;2

Cooper, J., & Loomis, J. (1990). Pooled time-series cross-section travel cost models: Testing whether recreation behavior is stable over time. *Leisure Sciences, 12*(2), 161-171. doi:https://doi.org/10.1080/01490409009513097

Coro, G., Large, S., Magliozzi, C., & Pagano, P. (2016). Analysing and forecasting fisheries time series: Purse seine in Indian Ocean as a case study. *ICES Journal of Marine Science*, *73*(10), 2552-2571.

Cresswell, A., Langlois, T., Wilson, S., Claudet, J., Thomson, D. P., Renton, M., . . . Babcock, R. (2019). Disentangling the response of fishes to recreational fishing over 30 years within a fringing coral reef reserve network. *Biological Conservation, 237*, 514-524. doi:https://doi.org/10.1016/j.biocon.2019.06.023

Cristobal, E., Flavian, C., & Guinaliu, M. (2007). Perceived e-service quality (PeSQ) measurement validation and effects on consumer satisfaction and web site loyalty. *Managing Service Quality: An International Journal, 17*(3), 317-340. doi:https://doi.org/10.1108/09604520710744326

Crooker, J., & Kling, C. L. (2000). Nonparametric bounds on welfare measures: A new tool for nonmarket valuation. *Journal of Environmental Economics and Management, 39*(2), 145-161. doi:https://doi.org/10.1006/jeem.1999.1099

Czajkowski, M., Giergiczny, M., Kronenberg, J., & Englin, J. (2019). The individual travel cost method with consumer-specific values of travel time Savings. *Environmental and Resource Economics, 74*(3), 961-984.

Davis Innovations. (2015). *New Mexico department of game and fish angler satisfaction survey.* Retrieved from http://www.wildlife.state.nm.us/

Davis, D., & Tisdell, C. (1996). Economic management of recreational scuba diving and the environment. *Journal of Environmental Management, 48*(3), 229-248. doi:10.1006/jema.1996.0075

Davis, T. (1985). Seasonal changes in gonad maturity, and abundance of larvae and early juveniles of barramundi, *Lates calcarifer* (Bloch), in Van Diemen Gulf and the Gulf of Carpentaria. *Marine and Freshwater Research, 36*(2), 177-190.

Day, J. (2017). Perspective: When is fishing allowed in an MPA? *MPA News*. Retrieved from https://mpanews.openchannels.org/news/mpa-news/perspective-when-fishing-allowed-mpa

Dement'Eva, T. (1987). A method for correlation of environmental factors and year-class strength of fishes. *Journal of Icthyology, 27*, 55-59.

DeYoreo, M., & Kottas, A. (2020). Bayesian nonparametric density regression for ordinal responses. In Y. Fan, D. Nott, M. S. Smith, & J.-L. Dortet-Bernadet (Eds.), *Flexible Bayesian Regression Modelling* (pp. 65-89): Elsevier.

Dimech, M., Darmanin, M., Smith, I. P., Kaiser, M. J., & Schembri, P. J. (2009). Fishers' perception of a 35-year old exclusive fisheries management zone. *Biological Conservation, 142*(11), 2691-2702. doi:https://doi.org/10.1016/j.biocon.2009.06.019

Dines, L. (2010). Proposal for the creation of recreational fishing havens: Cooloola and Fraser Island. http://www.frasercoastfishingalliance.com.au/media/DinesRFH2011LR.pdf

Ditton, R. B. (2004). *Human dimensions of fisheries.* In M.J. Manfredo, J.J. Vaske, B.L. Bruyere, D.R. Field & P.J. Brown (Eds.), *Society and natural resources: A summary of knowledge prepared for the 10th International Symposium on Society and Resource Management* (pp. 199-208). Jefferson, USA: Modern Litho.

Ditton, R. B., & Fedler, A. J. (1988). Importance of fish consumption to sport fishermen: A reply to Matlock et al., 1988. *Fisheries, 14*(4), 4-6.

Ditton, R., Graefe, A., & Fedler, A. (1981). *Recreational satisfaction at Buffalo National River: Some measurement concerns*. St. Paul, MN, USDA Forest Service, North Central forest experiment station. Retrieved from https://digital.lib.uidaho.edu/digital/collection/rrrd/id/265

Dorow, M., & Arlinghaus, R. (2012). The relationship between personal commitment to angling and the opinions and attitudes of German anglers towards the conservation and management of the European eel *Anguilla anguilla*. *North American Journal of Fisheries Management, 32*(3), 466-479. doi:10.1080/02755947.2012.680006

Dorow, M., Beardmore, B., Haider, W., & Arlinghaus, R. (2010). Winners and losers of conservation policies for European eel, *Anguilla anguilla*: An economic welfare analysis for differently specialised eel anglers. *Fisheries Management and Ecology, 17*(2), 106-125. doi:https://doi.org/10.1111/j.1365-2400.2009.00674.x

Dragan, D., & Topolšek, D. (2014). *Introduction to structural equation modeling: Review, methodology and practical applications.* Paper presented at the 11th International Conference on Logistics and Sustainable Transport, Celje, Slovenia.

Driver, B. L., & Knopf, R. C. (1976). Temporary escape: One product of sport fisheries management. *Fisheries*, *1*(2), 21-29. doi:10.1577/1548-8446-1-2

Driver, B. L., & Tocher, R. S. (1970). Toward a behavioral interpretation of recreational engagements, with implications for planning. In B. L. Driver (Ed.), *Elements of outdoor recreation planning* (pp. 1-31). Ann Arbor, MI: University Microfilms International.

du Preez, M., & Hosking, S. G. (2011). The value of the trout fishery at Rhodes, North Eastern Cape, South Africa: A travel cost analysis using count data models. *Journal of Environmental Planning and Management, 54*(2), 267-282.

Dunstan, D. (1959). Dunstan, D. (1959). *The barramundi Lates calcarifer (Bloch) in Queensland waters* [Technical paper no. 5]. Melbourne, Australia: CSIRO publication. Retrieved from https://publications.csiro.au/rpr/download?pid=procite:aee2b212-f9f8-4f0f-b436-c6d56e0f49b8&dsid=DS1

Edgar, G. J., & Barrett, N. S. (1999). Effects of the declaration of marine reserves on Tasmanian reef fishes, invertebrates and plants. *Journal of Experimental Marine Biology and Ecology, 242*(1), 107-144. doi:https://doi.org/10.1016/S0022-0981(99)00098-2

Edgar, G. J., & Barrett, N. S. (2012). An assessment of population responses of common inshore fishes and invertebrates following declaration of five Australian marine protected areas. *Environmental Conservation, 39*(3), 271-281. doi:10.1017/S0376892912000185

Edgar, G. J., & Stuart-Smith, R. D. (2009). Ecological effects of marine protected areas on rocky reef communities-a continental-scale analysis. *Marine Ecology Progress Series, 388*, 51-62. doi:https://doi.org/10.3354/meps08149

Edgar, G. J., Stuart-Smith, R. D., Willis, T. J., Kininmonth, S., Baker, S. C., Banks, S., . . . Berkhout, J. (2014). Global conservation outcomes depend on marine protected areas with five key features. *Nature, 506*, 216-220. doi:https://doi.org/10.1038/nature13022

Edgar, G., Bustamante, R., Farina, J.-M., Calvopina, M., Martinez, C., & Toral-Granda, M. (2004). Bias in evaluating the effects of marine protected areas: The importance of baseline data for the Galapagos Marine Reserve. *Environmental Conservation*, 31(3), 212-218. doi:10.1017/S0376892904001584

Einarsson, S., & Gudbergsson, G. (2003). The effects of the net fishery closure on angling catch in the River Hvita, Iceland. *Fisheries Management and Ecology, 10*(2), 73-78. doi:10.1046/j.1365-2400.2003.00317.x

European Inland Fisheries Advisory Commission. (2004). *Methodologies for assessing socio-economic benefits of European inland recreational fisheries* [EIFAC occasional paper no. 46]. Retrieved from http://www.fao.org/docrep/013/i1723e/i1723e00.htm

Evans, K., Bax, N. J., & Smith, D. C. (2016). *Australia state of the environment 2016: Marine environment*. Canberra, Australia. Retrieved from: https://soe.environment.gov.au/theme/marine-environment/topic/2016/commercial-and-recreational-fishing

Eveson, J. P., Hobday, A. J., Hartog, J. R., Spillman, C. M., & Rough, K. M. (2015). Seasonal forecasting of tuna habitat in the Great Australian Bight. *Fisheries Research, 170*, 39-49. doi:https://doi.org/10.1016/j.fishres.2015.05.008

Ezebilo, E. E. (2016). Economic value of a non-market ecosystem service: An application of the travel cost method to nature recreation in Sweden. *International Journal of Biodiversity Science, Ecosystem Services & Management, 12*(4), 314-327. doi:https://doi.org/10.1080/21513732.2016.1202322

Ezzy, E., & Scarborough, H. (2011). *Estimation of the recreational use value gained from recreational fishing of Southern Bluefin Tuna at Portland, Australia*. Paper presented at the Australasian Agricultural & Resource Economics Society (AARES), Melbourne, Australia. http://hdl.handle.net/10536/DRO/DU:30041505

Farmer, N. A., & Froeschke, J. T. (2015). Forecasting for recreational fisheries management: What's the catch? *North American Journal of Fisheries Management, 35*(4), 720-735. doi:https://doi.org/10.1080/02755947.2015.1044628

Farr, M., & Stoeckl, N. (2018). Overoptimism and the undervaluation of ecosystem services: A case-study of recreational fishing in Townsville, adjacent to the Great Barrier Reef. *Ecosystem Services, 31*, 433-444. doi:10.1016/j.ecoser.2018.02.010

Farr, M., Stoeckl, N., & Beg, R. A. (2011). The efficiency of the environmental management charge in the Cairns management area of the Great Barrier Reef Marine Park. *Australian Journal of Agricultural and Resource Economics, 55*(3), 322-341. doi:10.22004/ag.econ.186960

Farrow, S. (1996). Marine protected areas: Emerging economics. *Marine Policy, 20*(6), 439-446. doi:10.1016/S0308-597X(96)00034-6

Fedler, A. J. (1984). Elements of motivation and satisfaction in the marine recreational fishing experience. *Marine Recreational Fisheries, 9*, 75-83.

Fedler, A. J., & Ditton, R. B. (1986). A framework for understanding the consumptive orientation of recreational fishermen. *Environmental Management, 10*(2), 221-227. doi:https://doi.org/10.1007/BF01867360

Fedler, A. J., & Ditton, R. B. (1994). Understanding angler motivations in fisheries management. *Fisheries, 19*(4), 6-13. doi:https://doi.org/10.1577/1548-8446(1994)019<0006:UAMIFM>2.0.CO;2

Fernandes, L., Day, J., Lewis, A., Slegers, S., Kerrigan, B., Breen, D., . . . Lowe, D. (2005). Establishing representative no-take areas in the Great Barrier Reef: Large-scale implementation of theory on marine protected areas. *Conservation Biology, 19*(6), 1733-1744. doi:https://doi.org/10.1111/j.1523-1739.2005.00302.x

Ferrari, R., Marzinelli, E. M., Ayroza, C. R., Jordan, A., Figueira, W. F., Byrne, M., . . . Steinberg, P. D. (2018). Large-scale assessment of benthic communities across multiple marine protected areas using an autonomous underwater vehicle. *PloS One, 13*(3), 1-20. doi:https://doi.org/10.1371/journal.pone.0193711

Fisher, M. R. (1997). Segmentation of the angler population by catch preference, participation, and experience: A management-oriented application of recreation specialization. *North American Journal of Fisheries Management, 17*(1), 1-10. doi:https://doi.org/10.1577/1548-8675(1997)017<0001:SOTAPB>2.3.CO;2

Fisheries Research and Development Corporation. (2018). Queensland fish fact sheet: Barramundi (*Lates calcarifer*). https://ozfish.org.au/wp-content/uploads/2020/05/Habitat-factsheet_Qld_Barramundi-FINAL.pdf

Fleig, A. K., Tallaksen, L. M., Hisdal, H., & Hannah, D. M. (2011). Regional hydrological drought in north-western Europe: Linking a new regional drought area index with weather types. *Hydrological Processes, 25*(7), 1163-1179. doi:10.1002/hyp.7644

Fleming, C. M., & Cook, A. (2008). The recreational value of Lake McKenzie, Fraser Island: An application of the travel cost method. *Tourism Management, 29*(6), 1197-1205. doi:https://doi.org/10.1016/j.tourman.2008.02.022

Fleming, D. M., & Jones, P. J. S. (2012). Challenges to achieving greater and fairer stakeholder involvement in marine spatial planning as illustrated by the Lyme Bay scallop dredging closure. *Marine Policy, 36*(2), 370. doi:10.1016/j.marpol.2011.07.006

Flood, M., Stobutzki, I., Andrews, J., Ashby, C., Begg, G., Fletcher, R., . . . Wise, B. e. (2014). *Status of key Australian fish stocks reports 2014*. Canberra, Australia. Retrieved from http://ecite.utas.edu.au/99933

Food and Agriculture Organization. (2012). Technical guidelines for responsible fisheries: Recreational fisheries. Retrieved from http://www.fao.org/3/i2708e/i2708e00.htm

Food and Agriculture Organization. (2017). *The role of recreational fisheries in the sustainable management of marine resources*. Retrieved from Rome, Italy: http://www.fao.org/in-action/globefish/fishery-information/resource-detail/en/c/1013313/

Food and Agriculture Organization. (2019). *The effects of fishing and environmental variation on the regeneration of fish stocks*. Retrieved from http://www.fao.org/3/Y4593E/y4593e06.htm

Francour, P., Harmelin, J. G., Pollard, D., & Sartoretto, S. (2001). A review of marine protected areas in the northwestern Mediterranean region: Siting, usage, zonation and management. *Aquatic Conservation: Marine and Freshwater Ecosystems, 11*(3), 155-188. doi:https://doi.org/10.1002/aqc.442

Frew, E. J., Whynes, D. K., & Wolstenholme, J. L. (2003). Eliciting willingness to pay: Comparing closed-ended with open-ended and payment scale formats. *Medical Decision Making, 23*(2), 150-159. doi:10.1177/0272989X03251245

Frijlink, S., & Lyle, J. (2010). *A socio-economic assessment of the Tasmanian recreational rock lobster fishery*. Retrieved from www.tasfish.com/161-salt-water-fishing/rock-lobster/862-a-socio-economic-assessment-of-the-tasmanian-recreational-rock-lobster-fishery

Gaines, S. D., Gaylord, B., & Largier, J. L. (2003). Avoiding current oversights in marine reserve design. *Ecological Applications, 13*(1), 32-46. doi:https://www.jstor.org/stable/3099996

Galal, N., Ormond, R., & Hassan, O. (2002). Effect of a network of no-take reserves in increasing exploited reef fish stocks and catch per unit effort at Nabq. South Sinai, Egypt. *Marine Freshwater Research, 53*, 199-205. doi:10.1071/MF01158

Galeano, D., Langenkamp, D., Levantis, C., Shafron, W., & Redmond, I. (2004). *Economic value of charter and recreational fishing in Australia's eastern tuna and billfish fishery*. Canberra, Australia. Retrieved from https://www.cabdirect.org/cabdirect/abstract/20053196474

Game, Fish and Parks Commission. (2019). *Fisheries and aquatic resources adaptive management system.*Retrieved from https://gfp.sd.gov/userdocs/docs/SEFMA_Strategic_Plan_2019_2023_Commission_Adopted.pdf

Garcia-Charton, J. A., Williams, I. D., Ruzafa, A. P., Milazzo, M., Chemello, R., Marcos, C., . . . Riggio, S. (2000). Evaluating the ecological effects of Mediterranean marine protected areas: Habitat, scale and the natural variability of ecosystems. *Environment Conservation, 27*(2), 159-178. doi:https://doi.org/10.1017/S0376892900000199

Gaughan, D. J., & Santoro, K. (2020). *Status reports of the fisheries and aquatic resources of Western Australia 2018/19: The state of the fisheries*. Western Australia. Retrieved fromhttp://www.fish.wa.gov.au/Documents/sofar/status_reports_of_the_fisheries_and_aquatic_resources_2018-19.pdf

Gelcich, S., Edwards-Jones, G., & Kaiser, M. J. (2005). Importance of attitudinal differences among artisanal fishers toward co-management and conservation of marine resources. *Conservation Biology, 19*(3), 865-875. doi:https://www.jstor.org/stable/3591076

Gelcich, S., Godoy, N., & Castilla, J. C. (2009). Artisanal fishers' perceptions regarding coastal co-management policies in Chile and their potentials to scale-up marine biodiversity conservation. *Ocean & Coastal Management, 52*(8), 424-432. doi:https://doi.org/10.1016/j.ocecoaman.2009.07.005

Gelcich, S., Kaiser, M. J., Castilla, J. C., & Edwards-Jones, G. (2008). Engagement in co-management of marine benthic resources influences environmental perceptions of artisanal fishers. *Environmental Conservation, 35*(1), 36-45. doi:https://doi.org/10.1016/j.ocecoaman.2009.07.005

Gell, F. R., & Roberts, C. M. (2002). *The fishery effects of marine reserves and fishery closures*. Washington, DC 20037, USA. Retrieved from: https://www.researchgate.net/publication/265149966_The_Fishery_Effects_of_Marine_Reserves_and_Fishery_Closures

Gell, F. R., & Roberts, C. M. (2003). Benefits beyond boundaries: The fishery effects of marine reserves. *Trends in Ecology & Evolution, 18*(9), 448-455. doi:https://doi.org/10.1016/S0169-5347(03)00189-7

Gerber, L. R., Heppell, S. S., Ballantyne, F., & Sala, E. (2005). The role of dispersal and demography in determining the efficacy of marine reserves. *Canadian Journal of Fisheries and Aquatic Sciences, 62*(4), 863-871. doi:10.1139/f05-046

Geromont, H. F., & Butterworth, D. S. (2014). Generic management procedures for data-poor fisheries: Forecasting with few data. *ICES Journal of Marine Science, 72*(1), 251-261. doi:https://doi.org/10.1093/icesjms/fst232

Ghosh, H., Prajneshu, & Samanta, S. (2014). Fitting of self-exciting threshold autoregressive moving average nonlinear time-series model through genetic algorithm and development of out-of-sample forecasts. *Statistics, 48*(5), 1166-1184. doi:https://doi.org/10.1080/02331888.2013.822502

Ghosn, D., Collins, D., Baiada, C., & Steffe, A. (2012). *Catch per unit effort and size composition of striped marlin caught by recreational fisheries in southeast Australian waters.* Retrieved from https://www.dpi.nsw.gov.au/__data/assets/pdf_file/0004/438097/2189_Australian-Striped-Marlin-Rec-Fisheries-Report_Ghosn-et-al.pdf

Giakoumi, S., & Pey, A. (2017). Assessing the effects of marine protected areas on biological invasions: A global review. *Frontiers in Marine Science, 4*, 49.

Godwin, R., Nestler, J., Anderson, J., & Webber, L. (2007). A new tool to forecast fish movement and passage. *Hydro Review, 26*.

Goni, R., Polunin, N. V., & Planes, S. (2000). The Mediterranean: Marine protected areas and the recovery of a large marine ecosystem. *Environmental Conservation, 27*(2), 95-97. doi:10.1017/S0376892900000126

Google. (n.d.). [Google Maps directions to drive from Byfield to Rockhampton]. Retrieved December 7, 2017, from shorturl.at/apqyD

Gordon, H. S. (1954). The economic theory of a common property resource: The fishery. *Journal of Political Economy, 62*, 124-142.

Government of Western Australia. (2011). Barramundi Fact Sheet. Retrieved from https://www.fish.wa.gov.au/Documents/recreational_fishing/fact_sheets/fact_sheet_barramundi.pdf

Graefe, A. R. (1980). *The relationship between level of participation and selected aspects of specialization in recreational fishing.* (Unpublished doctoral dissertation), Texas A&M University, USA. Retrieved from https://hdl.handle.net/1969.1/DISSERTATIONS-647453

Graefe, A. R., & Fedler, A. J. (1986). Situational and subjective determinants of satisfaction in marine recreational fishing. *Leisure Sciences, 8*(3), 275-295. doi:10.1080/01490408609513076

Gregg, D., & Rolfe, J. (2013). An economic assessment of the value of recreational angling at Queensland dams involved in the Stocked Impoundment Permit Scheme. from Environmental economics programme centre for environmental management, Central Queensland University, Rockhampton, Australia. Retrived from https://www.ffsaq.com.au/value%20of%20fisheries.pdf

Griffin, R. (1987). Life history, distribution, and seasonal migration of barramundi in the Daly River, Northern Territory, Australia. *American Fisheries Society Symposium, 1*, 358–363. https://doi.org/10.1071/MF03198

Griffiths, S., Pepperell, J., Tonks, M., Fay, G., Venables, W., Lyle, J., . . . Edgar, S. (2007). *Developing innovative and cost-effective tools for monitoring recreational fishing in Commonwealth fisheries*. FRDC final report 2007/014. Retrived from https://www.researchgate.net/publication/274375714_Developing_innovative_and_cost-effective_tools_for_monitoring_recreational_fishing_in_Commonwealth_fisheries

Guadagnoli, E., & Velicer, W. F. (1988). Relation of sample size to the stability of component patterns. *Psychological bulletin, 103*(2), 265. doi:10.1037//0033-2909.103.2.265

Gutiérrez-Estrada, J. C., Silva, C., Yáñez, E., Rodríguez, N., & Pulido-Calvo, I. (2007). Monthly catch forecasting of anchovy *Engraulis ringens* in the north area of Chile: Non-linear univariate approach. *Fisheries Research, 86*(2-3), 188-200. doi:https://doi.org/10.1016/j.fishres.2007.06.004

Haab, T. C., & McConnell, K. E. (2002). *Valuing environmental and natural resources: The econometrics of non-market valuation*. Gloucestershire, England: Edward Elgar Publishing. https://doi.org/10.1111/j.0002-9092.2005.740_2.x

Hageman, R. K. (1985). *Valuing marine mammal populations: Benefit valuations in a multi-species ecosystem*. La Jolla, California: National Marine Fisheries Service, Southwest Fisheries Center.

Hair, J. F. J., Black, W. C., Babin, B. J., & Anderson, R. E. (2010). *Multivariate data analysis*. Edinburgh Gate, UK: Pearson Education Limited.

Halliday, I., Robins, J., Mayer, D., Staunton-Smith, J., & Sellin, M. (2010). *Freshwater flows affect the year-class strength of barramundi lates calcarifer in the Fitzroy River estuary, Central Queensland.* Paper presented at the Proceedings of the Royal Society of Queensland, Australia. Retrieved from https://www.researchgate.net/publication/286136149_Freshwater_flows_affect_the_yearclass_strength_of_barramundi_lates_calcarifer_in_the_fitzroy_river_estuary_Central_Queensland

Halpern, B. S. (2003). The impact of marine reserves: Do reserves work and does reserve size matter? *Ecological Applications*, S117-S137. doi:https://doi.org/10.1890/1051-0761(2003)013[0117:TIOMRD]2.0.CO;2

Halpern, B. S., & Warner, R. R. (2002). Marine reserves have rapid and lasting effects. *Ecology Letters, 5*(3), 361-366. doi:https://doi.org/10.1046/j.1461-0248.2002.00326.x

Halpern, B. S., Walbridge, S., Selkoe, K. A., Kappel, C. V., Micheli, F., D'Agrosa, C., . . . Fox, H. E. (2008). A global map of human impact on marine ecosystems. *Science, 319*(5865), 948-952. doi:10.1126/science.1149345

Hamilton, L. C. (2007). Climate, fishery and society interactions: Observations from the North Atlantic. *Deep Sea Research Part II: Topical Studies in Oceanography, 54*(23), 2958-2969. doi:https://doi.org/10.1016/j.dsr2.2007.08.020

Hampton, E. L., & Lackey, R. T. (1976). *Analysis of angler preferences and fisheries management objectives with implications for management*. Proceedings of the 29th Annual Conference of the Southeastern Association Game and Fish Commissioners. 29, 310-316.

Hamzah, F. B., MohdHamzah, F., Razali, S. F. M., Jaafar, O., & AbdulJamil, N. (2020). Imputation methods for recovering streamflow observation: A methodological review. *Cogent Environmental Science, 6*(1), 1745133. doi:https://doi.org/10.1080/23311843.2020.1745133

Hanley, N., & Spash, C. L. (1993). *Cost-benefit analysis and the environment*. Cheltenham, United Kingdom: Edward Elgar Publishing.

Hanley, N., Mourato, S., & Wright, R. E. (2001). Choice modelling approaches: A superior alternative for environmental valuatioin? *Journal of Economic Surveys, 15*(3), 435-462. doi:https://doi.org/10.1111/1467-6419.00145

Hanson, P. J., Vaughan, D. S., & Narayan, S. (2006). Forecasting annual harvests of Atlantic and Gulf Menhaden. *North American Journal of Fisheries Management, 26*, 753-764. doi:10.1577/M04-096.1

Haque, M., Hossain, M., & Rahman, K. (2005). Forecasting fish production in Bangladesh using ARIMA model. *Journal of the Bangladesh Agricultural University, 3*(2), 381-392. doi: 10.22004/ag.econ.276514

Hargreaves-Allen, V., Mourato, S., & Milner-Gulland, E. J. (2011). A global evaluation of coral reef management performance: Are MPAs producing conservation and socio-economic improvements? *Environmental Management, 47*(4), 684-700. doi:10.1007/s00267-011-9616-5

Harries, D., & Croome, R. (1989). *A review of past and present inshore gill netting in Tasmania with particular reference to the Bastard trumpeter Latridopsis forsteri Castelnau.* Paper presented at the Papers and Proceedings of the Royal society of Tasmania.

Harrison, H. B., Williamson, D. H., Evans, R. D., Almany, G. R., Thorrold, S. R., Russ, G. R., . . . Srinivasan, M. (2012). Larval export from marine reserves and the recruitment benefit for fish and fisheries. *Current Biology, 22*(11), 1023-1028. doi:https://doi.org/10.1016/j.cub.2012.04.008

Haspel, A. E., & Johnson, F. R. (1982). Multiple destination trip bias in recreation benefit estimation. *Land Economics, 58*(3), 364-372. doi:https://doi.org/10.2307/3145943

Hattam, C. E., Mangi, S. C., Gall, S. C., & Rodwell, L. D. (2014). Social impacts of a temperate fisheries closure: Understanding stakeholders' views. *Marine Policy, 45*, 269-278. doi:10.1016/j.marpol.2013.09.005

Hawkins, C., Loomis, D. K., & Salz, R. J. (2009). A replication of the internal validity and reliability of a multivariable index to measure recreation specialization. *Human Dimensions of Wildlife, 14*(4), 293-300. doi:https://doi.org/10.1080/10871200902894568

Heagney, E. C., Kovac, M., Fountain, J., & Conner, N. (2015). Socio-economic benefits from protected areas in southeastern Australia. *Conservation Biology, 29*(6), 1647-1657. doi:10.1111/cobi.12554

Hellerstein, D. (1993). Intertemporal data and travel cost analysis. *Environmental and Resource Economics, 3*(2), 193-207. doi:https://doi.org/10.1007/BF00338785

Hendee, J. C. (1974). A multiple-satisfaction approach to game management. *Wildlife Society Bulletin*, 104-113. doi:https://www.jstor.org/stable/3781623

Hendee, J. C., & Bryan, H. (1978). *Social benefits of fish and wildlife conservation.* Paper presented at the Proceedings of the Western Association of Fish and Wildlife Agencies and the Western Division American Fisheries Society, San Diego, CA.

Henderson, K. R., & Gigliotti, L. M. (2015). *Angler satisfaction in South Dakota.* Paper presented at the Proceedings of the South Dakota Academy of Science, USA.

Herath, G. (1999). Estimation of community values of lakes: A study of Lake Mokoan in Victoria, Australia. *Economic Analysis and Policy*, *29*(1), 31-44.

Hicks, R. L. (2002). A comparison of stated and revealed preference methods for fisheries management. *2002 Annual meeting*. Long Beach, CA 19853: American Agricultural Economics Association.

Hilborn, R., Stokes, K., Maguire, J.-J., Smith, T., Botsford, L. W., Mangel, M., . . . Walters, C. (2004). When can marine reserves improve fisheries management? *Ocean & Coastal Management, 47*, 197-205. doi:http://dx.doi.org/10.1016/j.ocecoaman.2004.04.001

Himes, A. H. (2003). Small-scale Sicilian fisheries: Opinions of artisanal fishers and sociocultural effects in two MPA case studies. *Coastal Management*, *31*(4), 389-408. doi:https://doi.org/10.1080/08920750390232965

Himes, A. H. (2007). Performance indicators in MPA management: Using questionnaires to analyze stakeholder preferences. *Ocean & Coastal Management, 50*(5), 329-351. doi:https://doi.org/10.1016/j.ocecoaman.2006.09.005

Hoagland, P., Kaoru, Y., Broadus, J. M., Economics, W. B. E., Division, P., & Development, W. B. E. S. (1995). *A methodological review of net benefit evaluation for marine reserves*. [Environmental Department Paper no. 27]. Washington, D.C., USA: The World Bank.

Hobday, A. J., Spillman, C. M., Paige Eveson, J., & Hartog, J. R. (2016). Seasonal forecasting for decision support in marine fisheries and aquaculture. *Fisheries Oceanography, 25*, 45-56. doi:https://doi.org/10.1111/fog.12083

Hoelting, K. R., Hard, C. H., Christie, P., & Pollnac, R. B. (2013). Factors affecting support for Puget Sound marine protected areas. *Fisheries Research, 144*, 48-59. doi:10.1016/j.fishres.2012.10.006

Hoevenagel, R. (1994). *The contingent valuation method: Scope and validity*. (Unpublished doctoral dissertation), Vrije Universiteit, Amsterdam, The Netharlands,

Holland, D. S., & Ditton, R. B. (1992). Fishing trip satisfaction: A typology of anglers. *North American Journal of Fisheries Management, 12*(1), 28-33. doi:https://doi.org/10.1577/1548-8675(1992)012<0028:FTSATO>2.3.CO;2

Holland, Lal, P., & Power, P. (1992). Valuing fishing in recreational fishing. *Australian Fisheries, 51*(8), 24-27.

Hooper, D., Coughlan, J., & Mullen, M. (2007). Structural equation modelling: Guidelines for determining model fit. *Electronic Journal of Business Research Methods 6*(1), 53-60.

Hudgins, M. D., & Davies, W. D. (1984). Probability angling: A recreational fishery management strategy. *North American Journal of Fisheries Management, 4*(4A), 431-439. doi:10.1577/1548-8659(1984)4<431:PA>2.0.CO;2

Hunt, K. M., & Grado, S. C. (2010). Use of social and economic information in fisheries assessments. In W. A. Hubert & M. C. Quist (Eds.), *Inland fisheries management in North America* (3rd ed.). Bethesda, Maryland: American Fisheries Society.

Hutchings, J. A. (2000). Collapse and recovery of marine fishes. *Nature, 406*(6798), 882-885. doi:https://doi.org/10.1038/35022565

Hyndman, R. J., & Athanasopoulos, G. (2018). *Forecasting: Principles and practice* (2nd ed.). Melbourne, Australia: OTexts.

Iffat, A. G. (2009). *Novel computationally intelligent machine learning algorithms for data mining and knowledge discovery*. (Unpublished doctoral dissertation), University of Stirling, Scotland, UK.

International Union for Conservation of Nature. (1998). *Economic values of protected areas: Guidelines for protected area managers,* Task Force on Economic Benefits of Protected Areas of the World Commission on Protected Areas (WCPA) of IUCN, in collaboration with the Economics Service Unit of IUCN. Gland, Switzerland and Cambridge, UK. Retrieved from https://www.iucn.org/downloads/pag_002.pdf

Jackson, J. B., Kirby, M. X., Berger, W. H., Bjorndal, K. A., Botsford, L. W., Bourque, B. J., . . . Estes, J. A. (2001). Historical overfishing and the recent collapse of coastal ecosystems. *Science, 293*(5530), 629-637. doi:10.1126/science.1059199

Jennings, S. (2000). Patterns and prediction of population recovery in marine reserves. *Reviews in Fish Biology and Fisheries, 10*(2), 209-231.

Jennings, S. (2009). The role of marine protected areas in environmental management. *ICES Journal of Marine Science, 66*(1), 16-21. doi:10.1093/icesjms/fsn163

Jennings, S., & Kaiser, M. J. (1998). The effects of fishing on marine ecosystems. *Advances in marine biology, 34*, 213-352. doi:https://doi.org/10.1016/S0065-2881(08)60212-6

Jiang, L. (2015). *Economic value of freshwater recreational angling in Otago: A travel cost method approach.* (Unpublished master's dissertation ), University of Otago, New Zealand, Retrieved from http://hdl.handle.net/10523/5614

Jimenez-Badillo, L. (2008). Management challenges of small-scale fishing communities in a protected reef system of Veracruz, Gulf of Mexico. *Fisheries Management and Ecology, 15*(1), 19-26. doi:10.1111/j.1365-2400.2007.00565.x

Job, C. A. (2009). *Groundwater economics*. Boca Raton, USA: CRC Press.

Jobling, M. (2002). Environmental factors and rates of development and growth. In Paul J.B. Hart & J. D. Reynolds (Eds.), *Handbook of Fish Biology and Fisheries* (Vol. 1, pp. 97-122): Wiley-Blackwell.

Jones, M. A., & Suh, J. (2000). Transaction-specific satisfaction and overall satisfaction: An empirical analysis. *Journal of Services Marketing, 14*(2), 147-159. doi:https://doi.org/10.1108/08876040010371555

Jones, P. J. S. (2008). Fishing industry and related perspectives on the issues raised by no-take marine protected area proposals. *Marine Policy, 32*(4), 749-758. doi:https://doi.org/10.1016/j.marpol.2007.12.009

Jones, P. J., Qiu, W., & De Santo, E. (2011). *Governing marine protected areas- Getting the balance right*. Retrieved from www.mpag.info

Jöreskog, K. G., & Sörbom, D. (1993). *LISREL 8: Structural equation modeling with the SIMPLIS command language*. USA: Scientific Software International, Lawrence Erlbaum Associates, Inc.

Joshua, T., Toefy, R., Sparks, C., Kirkman, S., & Samaai, T. (2018). Macro-benthic invertebrate assemblages in the Betty's Bay marine protected area (Kogelberg region South Africa). *Regional Studies in Marine Science, 22*, 1-8. doi:https://doi.org/10.1016/j.rsma.2018.04.001

Kacapyr, E. (2015). *A guide to basic econometric techniques*. New York: M.E. Sharpe, Inc.

Kaiser, M. J. (2004). Marine protected areas: The importance of being earnest. *Aquatic Conservation Marine and Freshwater Ecosystems, 14*(6), 635-638. doi:10.1002/aqc.665

Kaplan, R., & Kaplan, S. (2011). Well-being, reasonableness, and the natural environment. *Applied Psychology: Health and Well-Being, 3*(3), 304-321. doi:https://doi.org/10.1111/j.1758-0854.2011.01055.x

Karunarathna, B., & Karunarathna, K. A. N. K. (2017). Forecasting fish production in Sri Lanka by using ARIMA model. *Scholars Journal of Agriculture and Veterinary Sciences, 4*(9), 344-349. doi:10.21276/sjavs.2017.4.9.4

Kearney, R. E. (2002). Recreational fishing: Value is in the eye of the beholder. In T. J. Pitcher & H. C. E. (Eds.), *Recreational fisheries: Ecological, economic and social evaluation* (pp. 17-33): Blackwell Science Ltd

Kenchington, R. A. (2003). *The benefits of marine protected areas*. Retrieved from Canberra: https://www.environment.gov.au/system/files/resources/5eaad4f9-e8e0-45d1-b889-83648c7b2ceb/files/benefits-mpas.pdf

Kim, S.-S., Scott, D., & Crompton, J. L. (1997). An exploration of the relationships among social psychological involvement, behavioral involvement, commitment, and future intentions in the context of birdwatching. *Journal of Leisure Research, 29*(3), 320-341. doi:https://doi.org/10.1080/00222216.1997.11949799

Kirkley, J. (2009). *The NMFS commercial fishing & seafood industry input/output model*. Retrieved from https://www.st.nmfs.noaa.gov

Kline, R. B. (2015). *Principles and practice of structural equation modeling, Fourth Edition*. New York, USA: Guilford publications.

Komontree, P., Tongkumchum, P., & Karntanut, W. (2006). Trends in marine fish catches at Pattani fishery port (1999-2003). *Songklanakarin Journal of Science and Technology, 28*(4), 887-895.

Koutroumanidis, T., Iliadis, L., & Sylaios, G. K. (2006). Time-series modeling of fishery landings using ARIMA models and fuzzy expected intervals software. *Environmental Modelling & Software, 21*(12), 1711-1721. doi:https://doi.org/10. 1016/j.envsoft.2005 .09.001

Kowuor, C. O. N. (2005). *An application of travel cost method in the valuation of recreational properties.* (Unpublished master's dissertation), University of Nairobi, Nairobi, Kenya.

Kroon, F., & Ludwig, J. (2010). Response and recovery of fish and invertebrate assemblages following flooding in five tributaries of a sub-tropical river. *Marine and Freshwater Research, 61*(1), 86-96. doi:https://doi.org/10.1071/MF08357

Kumar, M., Kumari, A., Kushwaha, D. P., Kumar, P., Malik, A., Ali, R., & Kuriqi, A. (2020). Estimation of daily stage-discharge relationship by using data-driven techniques of a Perennial River, India. *Sustainability, 12*(19), 1-21. doi:https://doi.org/10.3390/su12197877

Kwak, S. K., & Kim, J. H. (2017). Statistical data preparation: Management of missing values and outliers. *Korean Journal of Anesthesiology, 70*(4), 407-411. doi:10.4097/kjae.2017.70.4.407

Lansdell, N., & Gangadharan, L. (2003). Comparing travel cost models and the precision of their consumer surplus estimates: Albert Park and Maroondah Reservoir. *Australian Economic Papers, 42*(4), 399-417. doi:https://doi.org/10.1111/1467-8454.00207

Laurel, B. J., & Bradbury, I. R. (2006). "Big" concerns with high latitude marine protected areas (MPAs): Trends in connectivity and MPA size. *Canadian Journal of Fisheries and Aquatic Sciences, 63*(12), 2603-2607. doi:10.1139/f06-151

Lawer, E. A. (2016). Empirical modeling of annual fishery landings. *Natural Resources, 7*(04), 193-204. doi:10.4236/nr.2016.74018

Layard, P. R. G., & Walters, A. A. (1978). *Microeconomic theory* (McGraw-Hill Ed.). New York McGraw-Hill.

Leathwick, J., Elith, J., & Hastie, T. (2006). Comparative performance of generalized additive models and multivariate adaptive regression splines for statistical modelling of species distributions. *Ecological Modelling, 199*(2), 188-196. doi:https://doi.org/10.1016/j. ecolmodel.2006.05.022

Lédée, E. J. I., Sutton, S. G., Tobin, R. C., & De Freitas, D. M. (2012). Responses and adaptation strategies of commercial and charter fishers to zoning changes in the Great Barrier Reef Marine Park. *Marine Policy, 36*(1), 226-234. doi:https://doi.org/10.1016/j.marpol.2011.05.009

Lester, S. E., Halpern, B. S., Grorud-Colvert, K., Lubchenco, J., Ruttenberg, B. I., Gaines, S. D., . . . Warner, R. R. (2009). Biological effects within no-take marine reserves: A global synthesis. *Marine Ecology Progress Series, 384*, 33-46. doi:https://doi.org/10.3354/meps08029

Li, O., Sutton, S. G., & Tynan, L. (2010). Communicating scientific information to recreational fishers. *Human Dimensions of Wildlife, 15*(2), 106-118. doi:https://doi.org/10.1080/10871200903366939

Little, L. R., Punt, A. E., Mapstone, B. D., Begg, G. A., Goldman, B., & Williams, A. J. (2009). An agent-based model for simulating trading of multi-species fisheries quota. *Ecological Modelling, 220*(23), 3404-3412. doi:https://doi.org/10.1016/j.ecolmodel.2009.08.004

Lockwood, M., & Tracy, K. (1995). Nonmarket economic valuation of an urban recreation park. *Journal of Leisure Research, 27*(2), 155-167. doi:https://doi.org/10.1080/00222216.1995.11949740

Lun, P. I., Gasim, M. B., Toriman, M. E., Rahim, S. A., & Kamaruddin, K. A. (2011). Hydrological pattern of Pahang River Basin and their relation to flood historical event *Jurnal e-Bangi, 6*(1), 29-37.

Lynch, T. P., Wilkinson, E., Melling, L., Hamilton, R., Macready, A., & Feary, S. (2004). Conflict and impacts of divers and anglers in a marine park. *Environmental Management, 33*(2), 196-211. doi:10.1007/s00267-003-3014-6

MacCallum, R. C., Browne, M. W., & Sugawara, H. M. (1996). Power analysis and determination of sample size for covariance structure modeling. *Psychological Methods, 1*(2), 130-149. doi:https://doi.org/10.1037/1082-989X.1.2.130

Macintosh, A., Bonyhady, T., & Wilkinson, D. (2010). Dealing with interests displaced by marine protected areas: A case study on the Great Barrier Reef marine park structural adjustment package. *Ocean & Coastal Management, 53*(9), 581-588. doi:10.1016/j.ocecoaman.2010.06.012

Mahalingaray, Rathod, S., Sinha, K., R.S., S., & Chavan, S. (2018). Statistical modeling and forecasting of total fish production of India: A time series perspective. *International Journal of Current Microbiology and Applied Sciences, 7*(3), 1698-1707. doi:10.20546/ijcmas.2018.703.201

Malik, F. (2018). How do I predict time series? Retrieved from https://medium.com/fintechexplained/forecasting-time-series-explained-5cc773b232b6

Manfredo, M. J., Driver, B. L., & Tarrant, M. A. (1996). Measuring leisure motivation: A meta-analysis of the recreation experience preference scales. *Journal of Leisure Research, 28*(3), 188-213. doi:10.1080/00222216.1996.11949770

Mangi, S. C., & Austen, M. C. (2008). Perceptions of stakeholders towards objectives and zoning of marine-protected areas in southern Europe. *Journal for Nature Conservation, 16*(4), 271-280. doi:https://doi.org/10.1016/j.jnc.2008.09.002

Mangi, S. C., Rodwell, L. D., & Hattam, C. (2011). Assessing the impacts of establishing MPAs on fishermen and fish merchants: The case of Lyme Bay, UK. *Ambio, 40*(5), 457-468. doi:10.1007/s13280-011-0154-

Manning, R. E. (1999). *Studies in outdoor recreation: Search and research* (Second ed.). Corvallis: Oregon State University Press.

Marshall, H. (2021). Hedonic pricing. Retrieved from https://www.investopedia.com/terms/h/hedonicpricing.asp

Martin, T., Wild, S., Webley, J., & Staunton-Smith, J. (2019). *Performance of Queensland's net-free zones*. Retrieved from http://era.daf.qld.gov.au/id/eprint/6438/1/NFZ_Report_FINAL_03012019.pdf.

Mascia, M. (2004). Social dimensions of marine reserves. In C. Dahlgren & J. Sobel (Eds.), *Marine reserves: A guide to science, design and use* (pp. 164-186). Washington D. C., USA: Island Press.

Mascia, M. B., & Claus, C. (2009). A property rights approach to understanding human displacement from protected areas: The case of marine protected areas. *Conservation Biology, 23*(1), 16-23. doi:10.1111/j.1523-1739.2008.01050.x

Mascia, M. B., Claus, C. A., & Naidoo, R. (2010). Impacts of marine protected areas on fishing communities. *Conservation Biology, 24*(5), 1424-1429. doi:10.1111/j.1523-1739.2010.01523.x

Maunder, M. N., Sibert, J. R., Fonteneau, A., Hampton, J., Kleiber, P., & Harley, S. J. (2006). Interpreting catch per unit effort data to assess the status of individual stocks and communities. *ICES Journal of Marine Science, 63*(8), 1373-1385.

Mayo-Ramsay, J. (2014). *Measuring the economic, social, cultural and environmental value of marine protected areas in New South Wale*. Paper presented at the 23rd Annual NSW Coastal Conference, New South Wales, Australia. https://www.coastalconference.com/2014/papers2014/Julia%20MayoRamsay%20Full%20Paper.pdf

McCay, B. J., & Jones, P. J. S. (2011). Marine protected areas and the governance of marine ecosystems and fisheries. *Conservation Biology, 25*(6), 1130-1133. doi:10.1111/j.1523-1739.2011.01771.x

McClanahan, T. R. (2010). Effects of Fisheries Closures and Gear Restrictions on Fishing Income in a Kenyan Coral Reef. *Conservation Biology, 24*(6), 1519-1528. doi:10.1111/j.1523-1739.2010.01530.x

McClanahan, T. R., Cinner, J., Kamukuru, A. T., Abunge, C., & Ndagala, J. (2008). Management preferences, perceived benefits and conflicts among resource users and managers in the Mafia Island Marine Park, Tanzania. *Environmental Conservation, 35*(4), 340-350. doi:https://doi.org/10.1017/S0376892908005250

McClanahan, T., Davies, J., & Maina, J. (2005). Factors influencing resource users and managers' perceptions towards marine protected area management in Kenya. *Environmental Conservation, 32*(1), 42-49. doi:10.1017/S0376892904001791

McCook, L. J., Ayling, T., Cappo, M., Choat, J. H., Evans, R. D., De Freitas, D. M., . . . Williamson, D. H. (2010). Adaptive management of the Great Barrier Reef: A globally significant demonstration of the benefits of networks of marine reserves. *Proceedings of the National Academy of Sciences of the United States of America, 107*(43), 18278-18285. doi:10.1073/pnas.0909335107

McCormick, J. L., & Porter, T. K. (2014). Effect of fishing success on angler satisfaction on a central Oregon rainbow trout fishery: Implications for establishing management objectives. *North American Journal of Fisheries Management, 34*(5), 938-944. doi:10.1080/02755947.2014.932869

Mcilgorm, A., Voyer, M., Magee, C., Pepperell, J., O'toole, E., & Li, O. (2016). *Improving our understanding of the motivations and attitudes towards fisheries management of recreational fishers in NSW*. Retrieved from https://documents.uow.edu.au/content/ groups /public/@web/@law/@ancors/documents/doc/uow224967.pdf

McIntosh, A. M., Sharpe, M., & Lawrie, S. M. (2010). Research methods, statistics and evidence-based practice. In E. C. Johnstone, D. C. Owens, S. M. Lawrie, A. M. McIntosh, & M. Sharpe (Eds.), *Companion to Psychiatric Studies* (pp. 157-252): Churchill Livingstone Elsevier.

McKean, J. R., Walsh, R. G., & Johnson, D. M. (1996). Closely related good prices in the travel cost model. *American Journal of Agricultural Economics, 78*(3), 640-646. doi:https://doi.org/10.2307/1243281

Mclnnes, K., Taylor, S., & Webley, J. (2013). *Social, attitudinal and motivational recreational fishing survey, part of the 2010 Statewide Recreational Fishing Survey*. Retrieved from https://www.daf.qld.gov.au/__data/assets/pdf_file/0016/.../RFISH-social-report.pdf

McManus, A., Newton, W., Storey, J., & White, J. (2011). *Identifying the health and well-being benefits of recreational fishing*. Retrieved from http://hdl.handle.net/20.500.11937/27359

McMichael, G. A., & Kaya, C. M. (1991). Relations among stream temperature, angling success for rainbow trout and brown trout, and fisherman satisfaction. *North American Journal of Fisheries Management, 11*(2), 190-199. doi:https://doi.org/10.1577/1548-8675(1991)011<0190:RASTAS>2.3.CO;2

Meyler, A., Kenny, G., & Quinn, T. (1998). *Forecasting Irish inflation using ARIMA models* Retrieved from https://mpra.ub.uni-muenchen.de/11359/

Meynecke, J.-O., Lee, S. Y., Duke, N. C., & Warnken, J. (2006). Effect of rainfall as a component of climate change on estuarine fish production in Queensland, Australia. *Estuarine, Coastal and Shelf Science, 69*(3-4), 491-504. doi:https://doi.org/10.1016/j.ecss.2006.05.011

Micheli, F., Halpern, B. S., Botsford, L. W., & Warner, R. R. (2004). Trajectories and correlates of community change in no-take marine reserves. *Ecological Applications, 14*(6), 1709-1723. doi:https://doi.org/10.1890/03-5260

Miller, R. E., & Blair, P. D. (1985). *Input-Output Analysis: Foundations and extensions*. Englewood Cliffs, New Jersey: Prentice-Hall.

Milon, J. W. (2000). Pastures, fences, tragedies and marine reserves. *Bulletin of Marine Science, 66*(3), 901-916.

Mini, K., Kuriakose, S., & Sathianandan, T. (2015). Modeling CPUE series for the fishery along northeast coast of India: A comparison between the Holt-Winters, ARIMA and NNAR models. *Journal of the Marine Biological Association of India, 57*(2), 75-82. doi:http://mbai.org.in/php/journal.php

Mircioiu, C., & Atkinson, J. (2017). A comparison of parametric and non-parametric methods applied to a Likert scale. *Pharmacy, 5*(2), 1-26. doi:10.3390/pharmacy5020026

Mobsby, D., & Koduah, A. (2017). *Australian fisheries and aquaculture statistics 2016*. Retrieved from http://www.agriculture.gov.au/abares/publications/display?url= http://143.188.17.20/anrdl/DAFFService/display.php?fid=pb_afastats15d9abmd20171220_11a.xml

Monteiro, R. S. O. (2002). *Fish growth modelling: Growth of the European anchovy (Engraulis encrasicolus) in the Tagus Estuary, Portugal*. DEA Modelling of the Marine Environment. Retrieved from https://pdfs.semanticscholar.org/5208/232d8061ad746a25ab5443d00e9941dee756.pdf?_ga=2.143159921.557238991.1578752635491385329.1578752635

Montgomery, D. C., Jennings, C. L., & Kulahci, M. (2002). *Introduction to time series and forecasting*. Hoboken, New Jersey: John Wiley & Sons, Inc.

Moore, A., Summerson, R., Sahlqvist, P., Kellett, S., McNee, A., Maller, C., . . . Pickworth, J. (2007). *East Marine Region - Description of commercial, recreational and charter fishing activities*. Canberra, Australia. Retrieved from https://parksaustralia.gov.au/marine/management/resources/scientific-publications/description-commercial-recreational-and-charter-fishing-activities-east-marine-region/

Mora, C., Myers, R. A., Coll, M., Libralato, S., Pitcher, T. J., Sumaila, R. U., . . . Worm, B. (2009). Management effectiveness of the world's marine fisheries. *PLoS Biology, 7*(6), 1-11. doi:https://doi.org/10.1371/journal.pbio.1000131

Morison, J., Schirmer, J., & Rippin, L. (2013). *Regional economic and social impact of Snapper spawning spatial closure options 2012-2013* Retrieved from http://www.econsearch.com.au/

Morrongiello, J. R., Walsh, C. T., Gray, C. A., Stocks, J. R., & Crook, D. A. (2014). Environmental change drives long-term recruitment and growth variation in an estuarine fish. *Global Change Biology, 20*(6), 1844-1860. doi:10.1111/gcb.12545

Mostegl, N. (2011). *Where is the catch? A closer look into the fishing surveys of British Columbia to reveal angler motivation and satisfaction.* (Unpublished doctoral dissertation), Simon Fraser University, Canada, Retrieved from https://summit.sfu.ca/item/11981

Myers, R. A., & Worm, B. (2003). Rapid worldwide depletion of predatory fish communities. *Nature, 423*(6937), 280-283.

Myers, R. A., Baum, J. K., Shepherd, T. D., Powers, S. P., & Peterson, C. H. (2007). Cascading effects of the loss of apex predatory sharks from a coastal ocean. *Science, 315*(5820), 1846-1850. doi:10.1126/science.1138657

National Research Council. (2001). Societal values of marine reserves and protected areas. In *marine protected areas: Tools for sustaining ocean ecosystems.* Washington, D.C., USA: National Academy Press. https://www.nap.edu/read/9994/chapter/7

Nau, R. (2020). Statistical forecasting: Notes on regression and time series analysis. Retrieved from https://people.duke.edu/~rnau/411arim2.htm

Nkuna, T. R., & Odiyo, J. O. (2016). The relationship between temperature and rainfall variability in the Levubu sub-catchment, South Africa. *International Journal of Education and Learning Systems, 1*, 66-75.

NSW Marine Parks Authority. (2004). *Economic values of NSW marine parks*. Retrieved from www.environment.nsw.gov.au/

Nurosis, M. J. (2005). *SPSS 13.0: Guide to data analysis.* Englewood Cliffs: Prentice Hall.

Ocean Studies Board. (1999). Options for achieving sustainability. In E. A. R. Commision on Geoscience, National Research Council (Ed.), *Sustaining Marine Fisheries*. USA: National Academies Press.

O'Connor, M. I., Bruno, J. F., Gaines, S. D., Halpern, B. S., Lester, S. E., Kinlan, B. P., & Weiss, J. M. (2007). Temperature control of larval dispersal and the implications for marine ecology, evolution, and conservation. *Proceedings of the National Academy of Sciences, 104*(4), 1266-1271. doi:https://doi.org/10.1073/pnas.0603422104

Ofir, C., & Simonson, I. (2007). The effect of stating expectations on customer satisfaction and shopping experience. *Journal of Marketing Research, 44*(1), 164-174. doi:10.1509/jmkr.44.1.164

Ogunbadejo, Alliu, H. K. a., & Adewale, K. (2018). Forecasting fish production in Nigeria using univariate arima models. *IOSR Journal of Agriculture and Veterinary Science, 11*, 22-28.

Oikonomou, Z.-S., & Dikou, A. (2008). Integrating conservation and development at the National Marine Park of Alonissos, Northern Sporades, Greece: Perception and practice. *Environmental Management, 42*(5), 847-866. doi:10.1007/s00267-008-9163-x

Oliver, R. L. (1981). Measurement and evaluation of satisfaction process in retail setting. *Journal of Retailing, 57*(3), 25-48.

Oliver, R. L. (2010). *Satisfaction: A behavioral perspective on the consumer* (2nd ed.). New York: Routledge. https://doi.org/10.4324/9781315700892

Ormsby, J. (2004). *A review of the social, motivational and experiential characteristics of recreational anglers from Queensland and the Great Barrier Reef Region*: [Research publication no. 78]. Great Barrier Reef Marine Park Authority. Retrieved from http://elibrary.gbrmpa.gov.au/jspui/bitstream/11017/384/1/A-review-of-the-social-motivational-and-experiential-characteristics-of-recreational-anglers-from-Queensland-and-the-Great-Barrier-Reef-Region.pdf

Parasuraman, A., Zeithaml, V. A., & Berry, L. L. (1994). Reassessment of expectations as a comparison standard in measuring service quality: Implications for further research. *Journal of marketing, 58*(1), 111-124. doi:https://doi.org/10.1177/002224299405800109

Parsons, G. R. (2017). Travel cost models. In P. A. Champ, K. Boyle, & T. C. Brown (Eds.), *A primer on non-market valuation.* USA: Springer.

Pascoe, S., Doshi, A., Dell, Q., Tonks, M., & Kenyon, R. (2014). Economic value of recreational fishing in Moreton Bay and the potential impact of the marine park rezoning. *Tourism Management, 41*, 53-63. doi:https://doi.org/10.1016/j.tourman.2013.08.015

Pascual, M., Rossetto, M., Ojea, E., Milchakova, N., Giakoumi, S., Kark, S., . . . Melià, P. (2016). Socioeconomic impacts of marine protected areas in the Mediterranean and Black Seas. *Ocean & Coastal Management, 133*, 1-10. doi:10.1016/j.ocecoaman.2016.09.001

Pauly, D., Christensen, V., Guénette, S., Pitcher, T. J., Sumaila, U. R., Walters, C. J., . . . Zeller, D. (2002). Towards sustainability in world fisheries. *Nature, 418*(6898), 689-695. doi:http://dx.doi.org.ezproxy.cqu.edu.au/10.1038/nature01017

Pauly, D., Watson, R., & Alder, J. (2005). Global trends in world fisheries: Impacts on marine ecosystems and food security. *Philosophical Transactions of the Royal Society B: Biological Sciences, 360*(1453), 5-12. doi:10.1098/rstb.2004.1574

Peterson, G. L., Stynes, D. J., & Arnold, J. R. (1985). The stability of a recreation demand model over time. *Journal of Leisure Research, 17*(2), 121-132.

Petrere Jr., M., Giacomini, H. C., & De Marco Jr., P. (2010). Catch-per-unit-effort: Which estimator is best? *Brazilian Journal of Biology, 70*(3), 483-491. doi:10.1590/S1519-69842010005000010

Peyton, R. B., & Gigliotti, L. M. (1989). The utility of sociological research: A reexamination of the East Matagorda Bay experience. *Fisheries, 14*(4), 5-8. doi:10.1577/1548-8446-14-4

Pita, C., Pierce, G., Theodossiou, I., & Macpherson, K. (2011). An overview of commercial fishers' attitudes towards marine protected areas. *Hydrobiologia, 670*(1), 289-306. doi:10.1007/s10750-011-0665-9

Pollock, K. H., Jones, C. M., & Brown, T. L. (1994). *Angler survey methods and their application in fisheries management*. Bethesda, Maryland: American Fisheries Society.

Pomeroy, R., & Douvere, F. (2008). The engagement of stakeholders in the marine spatial planning process. *Marine Policy, 32*(5), 816-822. doi:10.1016/j.marpol.2008.03.017

Powers, J. E., & Abeare, S. M. (2009). Fishing effort redistribution in response to area closures. *Fisheries Research, 99*(3), 216-225. doi:https://doi.org/10.1016/j.fishres.2009.06.011

Prayaga, P., Rolfe, J., & Sinden, J. (2006). A travel cost analysis of the value of special events: Gemfest in Central Queensland. *Tourism Economics, 12*(3), 403–420. doi:https://doi.org/10.5367/000000006778493592

Prayaga, P., Rolfe, J., & Stoeckl, N. (2010). The value of recreational fishing in the Great Barrier Reef, Australia: A pooled revealed preference and contingent behaviour model. *Marine Policy, 34*(2), 244-251. doi:https://doi.org/10.1016/j.marpol.2009.07.002

Primary Industries and Regions South Australia. (2017). Closures and aquatic reserves. Retrieved from http://www.pir.sa.gov.au/fishing/closures_and_aquatic_reserves

Prista, N., Diawara, N., Costa, M. J., & Jones, C. M. (2011). Use of SARIMA models to assess data-poor fisheries: A case study with a sciaenid fishery off Portugal. *Fishery Bulletin-National Oceanic and Atmospheric Administration, 109*(2), 170-185.

Queensland DAF (2015b). Recreational fisher satisfaction survey: Methods and questionnaires relating to net free zones.

Queensland DAF. (2015a). *Proposed net-free fishing zone,*. Brisbane, Australia: Queensland Department of Agriculture and Fisheries. Retrieved from https://www.daf.qld.gov.au/__data/assets/pdf_file/0011/263459/proposed-net-free-fishing-zone-trinity-bay.pdf.

Queensland DAF. (2017a). *Fisheries legislation*. Retrieved from https://www.daf.qld.gov.au/fisheries/consultations-and-legislation/legislation

Queensland DAF. (2017b). *Recreational fishers' satisfaction and expectations of Queensland's net-free zones*. Brisbane, Australia. Retrieved from https://publications.qld.gov.au/dataset/recreational-fishers-satisfaction-and-expectations-of-qld-net-free-zones.

Queensland DAF. (2020). *Commercial, charter, and recreational fishing*. Retrieved from https://www.daf.qld.gov.au/business-priorities/fisheries/commercial

Queensland Government. (2011). *Wide Bay Burnett regional plan: Cultivating a strong, healthy and sustainable future for the Wide Bay Burnett*. Brisbane, Australia. Retrieved from https://cabinet.qld.gov.au/documents/2011/sep/wide%20bay%20burnett%20reg%20plan/Attachments/Att%201%20-%20regional-plan.PDF.

Queensland Government. (2014). *Change management best practices guide : Five (5 ) key factors common to success in managing organisational change*. Retrieved from http://www.psc.qld.gov.au/publications/subject-specific-publications/assets/change-management-best-practice-guide.pdf

Queensland Government. (2016). *Net-free fishing zones*. Retrieved from https://www.business.qld.gov.au/industries/farms-fishing-forestry/fisheries/net-free-zones.

Queensland Government. (2017a). *Queensland sustainable fisheries strategy*. Retrieved from https://www.publications.qld.gov.au/dataset/queensland-sustainable-fisheries-strategy/resource/319c7e02-f07b-4b2e-8fd5-a435d2c2f3c9

Queensland Government. (2017b). *Location of net-free fishing zones*. Retrieved from https://www.business.qld.gov.au/industries/farms-fishing-forestry/fisheries/net-free-zones/location

Queensland Government. (2017c). Assessment of the barramundi (*Lates calcarifer*) fishery in the Southern Gulf of Carpentaria, Queensland, Australia.

Radomski, P. J., Grant, G. C., Jacobson, P. C., & Cook, M. F. (2001). Visions for recreational fishing regulations. *Fisheries, 26*(5), 7-18. doi:https://doi.org/10.1577/1548-8446(2001)026<0007:VFRFR>2.0.CO;2

Radosevic, D. (2018). Catching barra in South East Queensland. *Fishing Monthly Magazines*. Retrieved from http://wp.fishingmonthly.com.au/2018/04/19/catching-barra-in-southeast-queensland/

Raguragavan, J., Hailu, A., & Burton, M. (2013). Economic valuation of recreational fishing in Western Australia: Statewide random utility modelling of fishing site choice behaviour. *Australian Journal of Agricultural and Resource Economics, 57*, 539-558. doi:https://doi.org/10.1111/1467-8489.12009

Raman, R. K., Sathianandan, T. V., Sharma, A. P., & Mohanty, B. P. (2017). Modelling and forecasting marine fish production in Odisha using seasonal ARIMA model. *The National Academy of Science Letters, 40*(6), 393-397. doi:10.1007/s40009-017-0581-2

Raman, R., Mohanty, S., Bhatta, K., Karna, S., Sahoo, A., Mohanty, B., & Das, B. (2018). Time series forecasting model for fisheries in Chilika lagoon (a Ramsar site, 1981), Odisha, India: A case study. *Wetlands Ecology and Management, 26*(4), 677-687. doi:10.1007/s11273-018-9600-4

Randall, A. (1994). A difficulty with the travel cost method. *Land Economics, 70*(1), 88-96. doi:https://doi.org/10.2307/3146443

Rao, P., & Miller, R. L. R. (1971). *Applied econometrics*. USA: Wadsworth Publishing Company.

Raymond, M. R. (1986). Missing data in evaluation research. *Evaluation & the Health Professions, 9*(4), 395-420. doi:https://doi.org/10.1177/016327878600900401

Read, M., Sinden, J. A., Branson, J., & Sturgess, N. H. (1999). *Recreational use values for Victoria's parks.* Paper presented at the 1999 Conference (43$^{th}$) Australian Agricultural and Resource Economics Society, Christchurch, New Zealand

Rees, S. E., Mangi, S. C., Hattam, C., Gall, S. C., Rodwell, L. D., Peckett, F. J., & Attrill, M. J. (2015). The socio-economic effects of a marine protected area on the ecosystem service of leisure and recreation. *Marine Policy, 62,* 144-152. doi:10.1016/j.marpol.2015.09.011

Rees, S. E., Rodwell, L. D., Searle, S., & Bell, A. (2013). Identifying the issues and options for managing the social impacts of marine protected areas on a small fishing community. *Fisheries Research, 146,* 51-58. doi:10.1016/j.fishres.2013.04.003

Reid, D. (2008). Overview of recreational fishing in Australia. In D. Reid, O. Aas, R. Arlinghaus, R. Ditton, D. Policansky, & H. L. Schramm Jr (Eds.), *Global challenges in recreational fisheries* (pp. 13-18). Oxford, United Kingdom: Blackwell Science.

Roberts, C. M., & Hawkins, J. P. (2000). *Fully-protected marine reserves: A guide*. 24th Street, NW, Washington, DC 20037, USA and Environment Department, University of York, York, YO10 5DD, UK. Retrieved from https://wwfeu.awsassets.panda.org/downloads/marinereservescolor.pdf

Roberts, C. M., Bohnsack, J. A., Gell, F., Hawkins, J. P., & Goodridge, R. (2001). Effects of marine reserves on adjacent fisheries. *Science, 294*(5548), 1920-1923. doi:10.1126/science.294.5548.1920

Roberts, C. M., Hawkins, J. P., & Gell, F. R. (2005). The role of marine reserves in achieving sustainable fisheries. *Philosophical Transactions of the Royal Society B, 360,* 123-132. doi:10.1098/rstb.2004.1578

Robins, J. B., Halliday, I. A., Staunton-Smith, J., Mayer, D. G., & Sellin, M. J. (2005). Freshwater-flow requirements of estuarine fisheries in tropical Australia: A review of the state of knowledge and application of a suggested approach. *Marine and Freshwater Research, 56*(3), 343-360. doi:https://doi.org/10.1071/MF04087

Robinson, J., Cully, T., & CRC, C. (2019). Economic value of estuarine commercial fisheries. Retrieved from https://ozcoasts.org.au/indicators/coastal-issues/econ_value_commercial_fisheries/

Rolfe, J., & Dyack, B. (2010). Testing for convergent validity between travel cost and contingent valuation estimates of recreation values in the Coorong, Australia. *Australian Journal of Agricultural and Resource Economics, 54*(4), 583-599. doi:10.1111/j.1467-8489.2010.00513.x

Rolfe, J., & Dyack, B. (2011). Valuing recreation in the Coorong, Australia, with travel cost and contingent behaviour models. *Economic Record, 87*(277), 282-293. doi: https://doi.org/10.1111/j.1475-4932.2010.00683.x

Rolfe, J., & Gregg, D. (2012). Valuing beach recreation across a regional area: The Great Barrier Reef in Australia. *Ocean & Coastal Management, 69,* 282-290. doi:https://doi.org/10.1016/j.ocecoaman.2012.08.019

Rolfe, J., & Prayaga, P. (2007). Estimating values for recreational fishing at freshwater dams in Queensland. *Australian Journal of Agricultural and Resource Economics, 51*(2), 157-174. doi: https://doi.org/10.1111/j.1467-8489.2007.00369.x

Rolfe, J., Prayaga, P., Long, P., & Cheetham, R. (2005). *The economic value of freshwater impoundment fisheries in Queensland: The Bjelke-Petersen, Boondooma and Fairbairn dams: Summary report*. Retrieved from https://catalogue.nla.gov.au/Record/3712234

Romilly, P. (2005). Time series modelling of global mean temperature for managerial decision-making. *Journal of Environmental Management, 76*(1), 61-70. doi:https://doi.org/10.1016/j.jenvman.2005.01.008

Rose, D., Garrett, R., Gribble, N., & Whybird, O. (2009). Fisheries long term monitoring program summary of barramundi (*Lates calcarifer*) survey results: 2000-06. Brisbane, Australia: Department of Employment, Economic Development and Innovation.Retrieved from http://era.daf.qld.gov.au/id/eprint/6419/1/Barramundi-Report-2009.pdf

Roy, C., Cury, P., & Kifani, S. (1992). Pelagic fish recruitment success and reproductive strategy in upwelling areas: Environmental compromises. *South African Journal of Marine Science, 12*(1), 135-146. doi:10.2989/02577619209504697

Russ, G. R. (2002). Yet another review of marine reserves as reef fishery management tools. In P. S. Sale (Ed.), *Coral reef fishes: dynamics and diversity in a complex ecosystem* (pp. 421-443). San Diego, CA, USA: Elsevier.

Russ, G. R., Alcala, A. C., & Maypa, A. P. (2003). Spillover from marine reserves: The case of Naso vlamingii at Apo Island, the Philippines. *Marine Ecology Progress Series, 264*, 15-20. doi:10.3354/meps264015

Russ, G. R., Cheal, A. J., Dolman, A. M., Emslie, M. J., Evans, R. D., Miller, I., . . . Williamson, D. H. (2008). Rapid increase in fish numbers follows creation of world's largest marine reserve network. *Current Biology, 18*(12), R514-R515. doi:https://doi.org/10.1016/j.cub.2008.04.016

Russell, D., & Garrett, R. (1985). Early life history of barramundi, *Lates calcarifer* (Bloch), in north-eastern Queensland. *Marine and Freshwater Research, 36*(2), 191-201. doi:10.1071/mf9850191

Russell, D., & Rimmer, M. (2004). Stock enhancement of barramundi in Australia. In B. D. M. & L. K. M. (Eds.), *FAO Fisheries Technical Paper 429. Marine Ranching* (pp. 73-108). Rome, Italy: FAO.

Saila, S. B., Wigbout, M., & Lermit, R. J. (1980). Comparison of some time series models for the analysis of fisheries data. *ICES Journal of Marine Science, 39*(1), 44-52. doi:https://doi.org/10.1093/icesjms/39.1.44

Sakashita, C., Jan, S., & Ivers, R. (2012). *The application of contingent valuation surveys to obtain willingness to pay data in road safety research: Methodological review and recommendations.* Paper presented at the Australian Road Safety Research Policing and Education Conference, Wellington, New Zealand.

Sale, P. F., Cowen, R. K., Danilowicz, B. S., Jones, G. P., Kritzer, J. P., Lindeman, K. C., . . . Sadovy, Y. J. (2005). Critical science gaps impede use of no-take fishery reserves. *Trends in Ecology & Evolution, 20*(2), 74-80. doi:https://doi.org/10.1016/j.tree.2004.11.007

Salz, R. J., Loomis, D. K., & Finn, K. L. (2001). Development and validation of a specialization index and testing of specialization theory. *Human Dimensions of Wildlife, 6*(4), 239-258. doi:https://doi.org/10.1080/108712001753473939

Sanchirico, J. N. (2000). *Marine protected areas as fishery policy: A discussion of potential costs and benefits*. [Discussion paper, 00-23]. Washington, DC USA: Resources for the Future.

Sanchirico, J. N., Cochran, K. A., & Emerson, P. M. (2002). *Marine protected areas: Economic and social implications*. [Discussion paper, 02-26]. Washington, DC, USA: Resources for the Future.

Sankar, T. J. (2011). Forecasting fish product export in Tamilnadu – A stochastic model approach. *Recent Research in Science and Technology, 3*(7). doi:http://updatepublishing.com/journal/index.php/rrst/article/view/749

Sathianandan, T. (2007). Vector time series modeling of marine fish landings in Kerala. *Journal of the Marine Biological Association of India, 49*(2), 197-205.

Saunders, T., Whybird, O., & Newman, S. (2016). Barramundi *Lates calcarifer*. Retrieved from http://www.fish.gov.au/

Saunders, T., Whybird, O., Trinnie, F., & Newman, S. (2018). Barramundi *Lates calcarifer*. In C. Stewardson, Andrews, J., , C. Ashby, M. Haddon, Hartmann, K., , P. Hone, P. Horvat, S. Mayfield, Roelofs, A., Sainsbury, K., Saunders, T., Stewart, J., , S. Nicol, & B. Wise (Eds.), *Status of Australian Fish Stocks Reports 2018*. Canberra, ACT, Australia: Fisheries Research and Development Corporation.

Savage, J. (2015). *Australian fisheries and aquaculture statistics*. Canberra, Australia. Retrieved from https://frdc.com.au/project/2016-246

Sawynok, B. (1998). *Fitzroy river-effects of freshwater flows on fish: Impact on barramundi recruitment, movement and growth*. Rockhampton, Australia. Retrieved from http://publisher.onepixel.com.au/document_detail.asp?serviceid=26&documentsetid=34&documentid=331

Schaefer, M. B. (1954). Some aspects of the dynamics of populations important to the management of the commercial marine fisheries. *Inter-American Tropical Tuna Commission Bulletin, 1*(2), 23-56.

Schmidt, K., Sachse, R., & Walz, A. (2016). Current role of social benefits in ecosystem service assessments. *Landscape and Urban Planning, 149*, 49-64. doi:https://doi.org/10.1016/j.landurbplan.2016.01.005

Schroeder, S. A., Fulton, D. C., Currie, L., & Goeman, T. (2006). He said, she said: Gender and angling specialization, motivations, ethics, and behaviors. *Human Dimensions of Wildlife, 11*(5), 301-315. doi:10.1080/10871200600894928

Schuhmann, P., & Schwabe, K. (2004). An analysis of congestion measures and heterogeneous angler preferences in a random utility model of recreational fishing. *The Official Journal of the European Association of Environmental and Resource Economists, 27*(4), 429-450. doi:10.1023/B:EARE.0000018517.33432.0b

Schultz, R. D., & Dodd, B. J. (2008). *Characteristics of an lowa put-and-take rainbow trout fishery and associated economic benefits*. Paper presented at the Urban and community fisheries programs: Development, management, and evaluation. American Fisheries Society, Symposium

Selig, E. R., & Bruno, J. F. (2010). A global analysis of the effectiveness of marine protected areas in preventing coral loss. *PloS One, 5*(2), 1-7. doi:https://doi.org/10.1371/journal.pone.0009278

Shah, D., & Madden, L. (2004). Nonparametric analysis of ordinal data in designed factorial experiments. *Phytopathology, 94*(1), 33-43. doi:10.1094/PHYTO.2004.94.1.33

Shao, X. (2011). Testing for white noise under unknown dependence and its applications to diagnostic checking for time series models. *Econometric Theory, 27*(2), 312-343. doi:https://doi.org/10.1017/S0266466610000253

Sharma, K., & Leung, P. S. (2001). Economic impacts of catch reallocation from the commercial fishery to the recreational fishery in Hawaii. *North American Journal of Fisheries Management, 21*(1), 125-134. doi:https://doi.org/10.1577/1548-8675(2001)021<0125:EIOCRF>2.0.CO;2

Shipp, R. L. (2003). A perspective on marine reserves as a fishery management tool. *Fisheries, 28*(12), 10-21. doi:10.1577/1548-8446(2003)28[10:APOMRA]2.0.CO;2

Siderelis, C., Moore, R., & Lee, J. (2000). Incorporating users' perceptions of site quality in a recreation travel cost model. *Journal of Leisure Research, 32*(4), 406-414. doi:https://doi.org/10.1080/00222216.2000.11949924

Silva, I., Hill, N., Shimadzu, H., Soares, M., & Dornelas, M. (2015). Spillover effects of a community-managed marine reserve. *PloS One, 10*(4), 1-18. doi:10.1371/journal.pone.0111774

Slothuus, U., Larsen, M. L., & Junker, P. (2002). The contingent ranking method—A feasible and valid method when eliciting preferences for health care? *Social Science & Medicine, 54*(10), 1601-1609. doi:10.1016/S0277-9536(01)00139-3

Smith, A. D., Brown, C. J., Bulman, C. M., Fulton, E. A., Johnson, P., Kaplan, I. C., . . . Shannon, L. J. (2011). Impacts of fishing low–trophic level species on marine ecosystems. *Science, 333*(6046), 1147-1150. doi:10.1126/science.1209395

Smith, K., Lewis, P., Brown, J., Dowling, C., Howard, A., Lenanton, R., & Molony, B. (2013). *Status of nearshore finfish stocks in south-western Western Australia Part 2: Tailor*. Retrieved from http://www.fish.wa.gov.au/Documents/research_reports/frr247.pdf

Spelitis, H. (2015). Net-free zones mean 'more fish, bigger fish' for recreation. *Gladstone Observer*. Retrieved from https://www.gladstoneobserver.com.au/news/zones-mean-more-fish-bigger-fish-for-recreation/2715640/

Spencer, P. D. (1993). Factors influencing satisfaction of anglers on Lake Miltona, Minnesota. *North American Journal of Fisheries Management, 13*(2), 201-209. doi:10.1577/1548-8675(1993)013<0201:FISOAO>2.3.CO;2

Spencer, P. D., & Spangler, G. R. (1992). Effect that providing fishing information has on angler expectations and satisfaction. *North American Journal of Fisheries Management, 12*(2), 379-385. doi:https://doi.org/10.1577/1548-8675(1992)012<0379:ETPFIH>2.3.CO;2

Staunton-Smith, J., Robins, J., Mayer, D., Sellin, M., & Halliday, I. (2004). Does the quantity and timing of fresh water flowing into a dry tropical estuary affect year-class strength of barramundi (*Lates calcarifer*)? *Marine and Freshwater Research, 55*(8), 787-797. doi:10.1071/MF03198

Steffe, A. S., Macbeth, W. G., & Murphy, J. J. (2007). Status of the recreational fisheries in two Australian coastal estuaries following large fish-kill events. *Fisheries Research, 85*(3), 258-269. doi:http://dx.doi.org/10.1016/j.fishres.2007.02.003

Stergiou, K. (1989). Modelling and forecasting the fishery for pilchard (*Sardina pilchardus*) in Greek waters using ARIMA time-series models. *ICES Journal of Marine Science, 46*(1), 16-23. doi:https://doi.org/10.1093/icesjms/46.1.16

Stergiou, K. (1991). Short-term fisheries forecasting: Comparison of smoothing, ARIMA and regression techniques. *Journal of Applied Ichthyology, 7*(4), 193-204. doi:https://doi.org/10.1111/j.1439-0426.1991.tb00597.x

Stergiou, K. I., Christou, E. D., & Petrakis, G. (1997). Modelling and forecasting monthly fisheries catches: Comparison of regression, univariate and multivariate time series methods. *Fisheries Research, 29*, 55-95. doi:https://doi.org/10.1016/S0165-7836(96)00482-1

Stergiou, K., & Christou, E. (1996). Modelling and forecasting annual fisheries catches: Comparison of regression, univariate and multivariate time series methods. *Fisheries Research, 25*(2), 105-138. doi:https://doi.org/10.1016/0165-7836(95)00389-4

Stoeckl, N. (2003a). Measurement error and functional form: Implications for welfare estimates. *Applied Economics Letters, 10*(5), 259-270. doi:10.1080/1350485031000112673

Stoeckl, N. (2003b). A 'Quick and Dirty' travel cost model. *Tourism Economics : The Business and Finance of Tourism and Recreation, 9*(3), 325-335. doi:10.1177/135481660300900306

Stoeckl, N., & Mules, T. (2006). A travel cost analysis of the Australian Alps. *Tourism Economics : The Business and Finance of Tourism and Recreation, 12*(4), 495-518. doi:10.5367/000000006779320006

Stoeckl, N., Birtles, A., Farr, M., Mangott, A., Curnock, M., & Valentine, P. (2010). Live-aboard dive boats in the Great Barrier Reef: Regional economic impact and the relative values of their target marine species. *Tourism Economics, 16*(4), 995-1018. doi:https://doi.org/10.5367/te.2010.0005

Stoffle, R., & Minnis, J. (2008). Resilience at risk: Epistemological and social construction barriers to risk communication. *Journal of Risk Research, 11*(1-2), 55-68. doi:10.1080/13669870701521479

Stump, N. E., & Kriwoken, L. K. (2006). Tasmanian marine protected areas: Attitudes and perceptions of wild capture fishers. *Ocean & Coastal Management, 49*(5), 298-307. doi:https://doi.org/10.1016/j.ocecoaman.2006.03.007

Suárez Álvarez, J., Pedrosa, I., Lozano, L. M., García Cueto, E., Cuesta Izquierdo, M., & Muñiz Fernández, J. (2018). Using reversed items in Likert scales: A questionable practice. *Psicothema, 30*(2), 149-158. doi:10.7334/psicothema2018.33

Sumaila, U. R., Zeller, D., Watson, R., Alder, J., & Pauly, D. (2007). Potential costs and benefits of marine reserves in the high seas. *Marine Ecology Progress Series, 345*, 305-310. doi:10.3354/meps07065

Suman, D., Shivlani, M., & Milon, J. W. (1999). Perceptions and attitudes regarding marine reserves: A comparison of stakeholder groups in the Florida Keys National Marine Sanctuary. *Ocean & Coastal Management, 42*(12), 1019-1040. doi:https://doi.org/10.1016/S0964-5691(99)00062-9

Sutton, S. G. (2006). *An assessment of the social characteristics of Queensland's recreational fishers*. Retrieved from https://www.researchgate.net/publication/242671642_ An_ Assessment_of_the_Social_Characteristics_of_Queensland's_Recreational_Fishers

Sutton, S. G., & Ditton, R. B. (2001). Understanding catch-and-release behavior among US Atlantic bluefin tuna anglers. *Human Dimensions of Wildlife, 6*(1), 49-66. doi:https://doi.org/10.1080/10871200152668698

Sutton, S. G., & Tobin, R. C. (2009). Recreational fishers' attitudes towards the 2004 rezoning of the Great Barrier Reef Marine Park. *Environmental Conservation, 36*(3), 245-252. doi:10.1017/S0376892909990270

Sutton, S. G., & Tobin, R. C. (2012). Social resilience and commercial fishers' responses to management changes in the Great Barrier Reef Marine Park. *Ecology and Society, 17*(3), 1-6. doi:http://dx.doi.org/10.5751/ES-04966-170306

Swait, J., Adamowicz, W., & van Bueren, M. (2004). Choice and temporal welfare impacts: Incorporating history into discrete choice models. *Journal of Environmental Economics and Management, 47*(1), 94-116. doi:https://doi.org/10.1016/S0095-0696(03)00077-9

Sweke, E. A., Su, Y., Baba, S., Denboh, T., Ueda, H., Sakurai, Y., & Matsuishi, T. (2015). Catch per unit effort estimation and factors influencing it from recreational angling of sockeye salmon (*Oncorhynchus nerka*) and management implications for Lake Toya, Japan. *Lakes & Reservoirs: Research & Management, 20*(4), 264-274. doi:10.1111/lre.12115

Sydeman, W. J., García-Reyes, M., Szoboszlai, A. I., Thompson, S. A., & Thayer, J. A. (2018). Forecasting herring biomass using environmental and population parameters. *Fisheries Research, 205*, 141-148. doi:https://doi.org/10.1016/j.fishres.2018.04.020

Sydeman, W. J., Thompson, S. A., García-Reyes, M., Kahru, M., Peterson, W. T., & Largier, J. L. (2014). Multivariate ocean-climate indicators (MOCI) for the central California Current: Environmental change, 1990–2010. *Progress in Oceanography, 120*, 352-369. doi:https://doi.org/10.1016/j.pocean.2013.10.017

Tarka, P. (2018). An overview of structural equation modeling: its beginnings, historical development, usefulness and controversies in the social sciences. *Quality & quantity, 52*(1), 313-354.

Taylor, C. N., & Buckenham, B. (2003). *Social impacts of marine reserves in New Zealand*. Retrieved from http://www.doc.govt.nz

Teas, R. K. (1993). Expectations, performance evaluation, and consumers' perceptions of quality. *Journal of marketing, 57*(4), 18-34. doi:https://www.jstor.org/stable/1252216

Teixeira, D., Janes, R., & Webley, J. (2021). *2019/20 Statewide recreational fishing survey: Social and attitudinal results*. Retrieved from https://era.daf.qld.gov.au/id/eprint/7879/

The Victorian Coastal Council. (2007). *Assessing the value of coast to Victoria*. Victoria. Australia. Retrieved from www.vcc.vic.gov.au/assets/media/files/AssessingtheValueoftheCoasttoVictoria.pdf

Tink, C. (2015). *Use of surveys and agent based modelling to assess the management implications of the behaviours of specialised recreational boat fishers.* (Unpublished PhD dessertation), Murdoch University, Retrieved from https://researchrepository.murdoch.edu.au/id/eprint/26029/1/whole.pdf

Townhill, B. L., Radford, Z., Pecl, G., van Putten, I., Pinnegar, J. K., & Hyder, K. (2019). Marine recreational fishing and the implications of climate change. *Fish and Fisheries, 20*(5), 977-992. doi:https://doi.org/10.1111/faf.12392

Tsitsika, E. V., Maravelias, C. D., & Haralabous, J. (2007). Modeling and forecasting pelagic fish production using univariate and multivariate ARIMA models. *Fisheries Science, 73*, 979-988. doi:https://doi.org/10.1111/j.1444-2906.2007.01426.x

Uehleke, R. (2017). Convergent validity in contingent valuation: An application to the willingness to pay for national climate change mitigation targets in Germany. *Australian Journal of Agricultural and Resource Economics, 61*(1), 76-94. doi:https://doi.org/10.1111/1467-8489.12148

Uyanık, G. K., & Güler, N. (2013). A study on multiple linear regression analysis. *Procedia-Social and Behavioral Sciences, 106*, 234-240. doi:https://doi.org/10.1016/j.sbspro.2013.12.027

Van Hoof, L., Salz, P., & Patijnlaan, B. (2001). *Applying CPUE as management tool*. Paper presented at the XIII EAFE Conference Salerno, Italy.

Victorian Fisheries Authority. (2018). Removal of net fishing from Port Phillip Bay. Retrieved from https://vfa.vic.gov.au/commercial-fishing/removal-of-net-fishing-from-port-phillip-bay

Vieira, S., Schirmer, J., & Loxton, E. (2009). *Social and economic evaluation methods for fisheries: A review of the literature*. Retrieved from https://trove.nla.gov.au/work/31961125

Voyer, M., Barclay, K., McIlgorm, A., & Mazur, N. (2016). *Does professional fishing still play a role in regional communities?* Paper presented at the 25th NSW Coastal Conference Sydney, New South Wales. https://www.coastalconference.com/2016/papers2016/Michelle%20Voyer.pdf

Voyer, M., Gladstone, W., & Goodall, H. (2014). Understanding marine park opposition: The relationship between social impacts, environmental knowledge and motivation to fish. *Aquatic Conservation: Marine and Freshwater Ecosystems, 24*(4), 441-462. doi:https://doi.org/10.1002/aqc.2363

Walters, C. (2003). Folly and fantasy in the analysis of spatial catch rate data. *Canadian Journal of Fisheries and Aquatic Sciences, 60*(12), 1433-1436. doi:10.1139/f03-152

Wantara, P. (2013). Using structural equation modelling to evaluate the service quality, satisfaction and customers loyalty in hypermart department store, Bangkalan, Indonesia. *Global Journal of Management And Business Research, 13*(8), 29-36.

Ward, D. (2012). *Biological environmental impact studies: Theory and Methods*. New York-London: Academic press inc.

Ward, E. J., Holmes, E. E., Thorson, J. T., & Collen, B. (2014). Complexity is costly: A meta-analysis of parametric and non-parametric methods for short-term population forecasting. *Oikos, 123*(6), 652-661. doi:https://doi.org/10.1111/j.1600-0706.2014.00916.x

Ward, F. A., & Beal, D. (2000). V*aluing nature with travel cost models: A manual*. Cheltenham, United kingdom: Edward Elgar Publishing.

Watson, P., & Nicholls, S. M. (1992). ARIMA modelling in short data sets: Some Monte Carlo results. *Social and Economic Studies, 41*(4), 53-75.

Webley, J., McInnes, K., Teixeira, D., Lawson, A., & Quinn, R. (2015). *Statewide recreational fishing surveys 2013–14*. Queensland Government's Department of Agriculture and Fisheries, Australia. Retrieved from http://era.daf.qld.gov.au/id/eprint/6513/1/2013-14SRFS%20Report.pdf

Weithman, A. S. (1999). Socioeconomic benefits of fisheries. In C. C. Kohler & W. A. Hubert (Eds.), *Inland fisheries management in North America* (pp. 193-213). Bethesda, USA: American Fisheries Society.

West, P., Igoe, J., & Brockington, D. (2008). Parks and peoples: The social impact of protected areas. *Annual Review of Anthropology, 35*(1), 251-277. doi:10.1146/annurev.anthro.35.081705.123308

Wheatley, D. (2020). Travel cost method (TCM). Retrieved from http://www.cbabuilder.co.uk/Quant4.html

Wheeler, S., & Damania, R. (2001). Valuing New Zealand recreational fishing and an assessment of the validity of the contingent valuation estimates. *Australian Journal of Agricultural and Resource Economics, 45*(4), 599-621. doi:https://doi.org/10.1111/1467-8489.00159

Whitten, S. M., & Bennett, J. W. (2002). A travel cost study of duck hunting in the upper south east of South Australia. *Australian Geographer, 33*(2), 207-221. doi:https://doi.org/10.1080/00049180220151016

Whynes, D. K., Frew, E., & Wolstenholme, J. L. (2003). A comparison of two methods for eliciting contingent valuations of colorectal cancer screening. *Journal of Health Economics, 22*(4), 555-574. doi:10.1016/S0167-6296(03)00006-7

Williamson, D. H., Russ, G. R., & Ayling, A. M. (2004). No-take marine reserves increase abundance and biomass of reef fish on inshore fringing reefs of the Great Barrier Reef. *Environmental Conservation, 31*(2), 149-159. doi:10.1017/S0376892904001262

Willis, T. J., Millar, R., Babcock, R., & Tolimieri, N. (2003). Burdens of evidence and the benefits of marine reserves: Putting descartes before des horse? *Environmental Conservation, 30*(2), 97-103. doi:10.1017/s03768929030000092

Windle, J., Rolfe, J., & Pascoe, S. (2017). *Assessing recreational benefits as an economic indicator for the Gladstone Harbour Report Card*. Paper presented at the 61st Australian Agricultural and Resource Economics Society Conference, Brisbane, Australia 10.22004/ag.econ.258681

Wong, V. N., Johnston, S. G., Bush, R. T., Sullivan, L. A., Clay, C., Burton, E. D., & Slavich, P. G. (2010). Spatial and temporal changes in estuarine water quality during a post-flood hypoxic event. *Estuarine, Coastal and Shelf Science, 87*(1), 73-82. doi:https://doi.org/10.1016/j.ecss.2009.12.015

Wong, V. N., Walsh, S., & Morris, S. (2018). Climate affects fish-kill events in subtropical estuaries of eastern Australia. *Marine and Freshwater Research, 69*(11), 1641-1648. doi:10.1071/MF17307

World Health Organization. (2005). *Ecosystems and human well-being: Health synthesis: A report of the millennium ecosystem* assessment, Geneva,Switzerland: WHO Press. Retrived from https://apps.who.int/iris/bitstream/handle/10665/43354/9241563095.pdf

World Wildlife Fund Inc. (2020). Overfishing. Retrieved from https://www.worldwildlife.org/threats/overfishing

Worm, B., Barbier, E. B., Beaumont, N., Duffy, J. E., Folke, C., Halpern, B. S., . . . Palumbi, S. R. (2006). Impacts of biodiversity loss on ocean ecosystem services. *Science, 314*(5800), 787-790.

Yacob, M. R., Radam, A., & Awang, K. W. (2008). *Economic valuation of marine parks ecotourism Malaysia: The case of Redang Island marine park.* Universiti Putra Malaysia Press, Malaysia

Yadav, V. K., Jahageerdar, S., Ramasubramanian, V., Bharti, V. S., & Adinarayana, J. (2016). Use of different approaches to model catch per unit effort (CPUE) abundance of fish. *Indian Journal of Geo Marine Sciences 45*(12), 1677-1687. doi:http://nopr.niscair.res.in/handle/123456789/40547

Yaffee, R. A., & McGee, M. (1999). *An Introduction to time series analysis and forecasting: With applications of SAS and SPSS*: Academic Press, Inc.

Yamazaki, S., Rust, S., Jennings, S., Lyle, J., & Frijlink, S. (2013). Valuing recreational fishing in Tasmania and assessment of response bias in contingent valuation. *Australian Journal of Agricultural and Resource Economics, 57*(2), 193-213. doi:10.1111/j.1467-8489.2012.00614.x

Yang, Z., Yan, Y., & Liu, Q. (2012). The relationship of streamflow-precipitation-temperature in the Yellow River Basin of China during 1961-2000. *Procedia Environmental Sciences, 13*, 2336-2345. doi:https://doi.org/10.1016/j.proenv.2012.01.222

Young, M. A., Foale, S., & Bellwood, D. R. (2016). Why do fishers fish? A cross-cultural examination of the motivations for fishing. *Marine Policy, 66*, 114-123. doi:https://doi.org/10.1016/j.marpol.2016.01.018

Zhang, F., Wang, X. H., Nunes, P. A. L. D., & Ma, C. (2015). The recreational value of gold coast beaches, Australia: An application of the travel cost method. *Ecosystem Services, 11*, 106-114. doi:https://doi.org/10.1016/j.ecoser.2014.09.001

Zhang, J., & Smith, M. D. (2006). *Estimating a generalized Gordon-Schaefer model with heterogeneous fishing data.* Paper presented at the International Institute of Fisheries Economics and Trade, portsmouth, UK.

# Appendices

## Appendix A

Table A 1: Mann- Whitney test for the survey responses of Rockhampton and Townsville

| Statements | Name of the sites | N | Mean Rank | Mann-Whitney U | Wilcoxon W | Z | Asymp. Sig. (2-tailed) |
|---|---|---|---|---|---|---|---|
| To catch fish* | Rockhampton<br>Townsville | 163<br>130 | 142.36<br>152.82 | 9839.0 | 23205.0 | -1.093<br>.274 | .274 |
| The main reason you go fishing is to catch a fish* | Rockhampton<br>Townsville | 163<br>130 | 143.40<br>151.51 | 10008.5 | 23374.5 | -.826 | .409 |
| You expect the variety of species you catch to increase over the next 12 months | Rockhampton<br>Townsville | 163<br>130 | 190.48<br>92.48 | 3507.0 | 12022.0 | -10.021 | .000 |
| You expect the number of fish you catch to increase over the next 12 months | Rockhampton<br>Townsville | 163<br>130 | 191.13<br>91.67 | 3401.50 | 11916.5 | -10.203 | .000 |
| You expect the size of the fish you catch to decrease over the next 12 months | Rockhampton<br>Townsville | 163<br>130 | 174.89<br>112.03 | 6049.5 | 14564.5 | -6.473 | .000 |
| You expect to be able to target new species of fish you have not targeted before over the next 12 months | Rockhampton<br>Townsville | 163<br>130 | 159.32<br>131.56 | 8587.50 | 17102.5 | -2.829 | .005 |
| Your satisfaction with fishing in this area will increase over the next 12 months | Rockhampton<br>Townsville | 163<br>130 | 184.78<br>99.63 | 4437.0 | 12952.0 | -8.740 | .000 |
| You expect future generations will have quality fishing opportunities in this area | Rockhampton<br>Townsville | 163<br>130 | 185.64<br>98.55 | 4296.0 | 12811.0 | -8.981 | .000 |

| Statements | Name of the sites | N | Mean Rank | Mann-Whitney U | Wilcoxon W | Z | Asymp. Sig. (2-tailed) |
|---|---|---|---|---|---|---|---|
| In the future, you expect that more people will go recreational fishing in this Net Free Zone | Rockhampton<br>Townsville | 163<br>130 | 164.09<br>125.58 | 7810.0 | 16325.0 | -4.020 | .000 |
| In the future, you expect recreational fishers to catch more fish in this Net Free Zone | Rockhampton<br>Townsville | 163<br>130 | 199.34<br>81.37 | 2063.000 | 10578.0 | -12.053 | .000 |
| In the future, you expect there to be more sea life of all kinds within this Net Free Zone | Rockhampton<br>Townsville | 163<br>130 | 191.91<br>90.68 | 3274.000 | 11789.0 | -10.404 | .000 |
| The number of fish you have caught | Rockhampton<br>Townsville | 163<br>130 | 162.04<br>128.14 | 8143.50 | 16658.5 | -3.485 | .000 |
| The variety of fish you have caught* | Rockhampton<br>Townsville | 163<br>130 | 145.04<br>149.46 | 10275.0 | 23641.0 | -.457 | .648 |
| The number of big fish you have caught | Rockhampton<br>Townsville | 163<br>130 | 167.95<br>120.73 | 7180.50 | 15695.5 | -4.810 | .000 |
| The size of the fish you have caught | Rockhampton<br>Townsville | 163<br>130 | 166.37<br>122.71 | 7437.000 | 15952.0 | -4.470 | .000 |
| The number of exciting fights with fish you have had | Rockhampton<br>Townsville | 163<br>130 | 158.59<br>132.47 | 8706.0 | 17221.0 | -2.692 | .007 |
| Overall, how would you rate your overall satisfaction with recreational fishing in the Net Free Zone in the last 12 months? | Rockhampton<br>Townsville | 163<br>130 | 167.29<br>121.56 | 7288.0 | 15803.0 | -4.770 | .000 |

Note: An asterix (*) in each statement indicates that there are no significant differences between the mean ranks of two sites

Table A 2: Satisfaction survey questionnaire for NFZ (Rockhampton)

SurveyID: ___________ Verify ___________
SessionID: ___________ Check ___________

**NFZ (NET FREE ZONES TACKLE STORE SURVEY)**
**INTERVIEW SHEET 2018**
DAF FISHERY MONITORING

| Session: ___ ___ ___: ___ ___ ___ ___ ___ ___ ___ | Store: |
|---|---|

| | | |
|---|---|---|
| **Q1** Hi, My name is [*your name here*] and I am doing some research on recreational fishing for Fisheries Queensland. Have you done any recreational fishing or crabbing in this area in the last 12 months?<br>**** Show map if necessary. If No, record as ineligible on the cover sheet **** | **YES**.<br>If **NO**, do not interview. | Interview # |

| | | |
|---|---|---|
| **Q2** How many days have you been recreational fishing **in this area** in the last 12 months? | □ 1-2 days / *1 or 2 times year*<br>□ 3-12 days / *Once a year to once a month*<br>□ 13-24 days / *1 or 2 times month* | □ 25-36 days / *2 or 3 times a month*<br>□ 37-51 days ****Only tick if specified****<br>□ 52+ days / *Once a week or more* |
| **Q3** How many days have you been recreational fishing **in Queensland** in the last 12 months? | □ 1-2 days / *1 or 2 times year*<br>□ 3-12 days / *Once a year to once a month*<br>□ 13-24 days / *1 or 2 times month* | □ 25-36 days / *2 or 3 times a month*<br>□ 37-51 days ****Only tick if specified****<br>□ 52+ days / *Once a week or more* |

| | |
|---|---|
| **Q4** Are you familiar, or have you previously heard of, the Net Free Zone implemented in November 2015 in [*insert applicable area*]? | □ **YES**<br>□ **NO** [If unsure, note as no] |
| **Q5** For the following question, I'd like you to rate your answer on a scale of 1 to 7 where 1 is novice and 7 is expert. So using this scale, how would you rate your level of fishing experience? ****Show respondent the scale sheet**** | **1 : 2 : 3 : 4 : 5 : 6 : 7** |

| **Q6** People go recreational fishing for a range of reasons. Using a scale of 1 to 7 where 1 is not important and 7 is very important, how important are the following to you when you go recreational fishing? ****Show respondent the scale sheet*** | |
|---|---|
| a. "To enjoy nature" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| b. "To be with family or friends" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| c. "To be outdoors" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| d. "To catch fish" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| e. "To get away from other people" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |

| **Q7** These next few statements are about catching fish and what it means to you. Some questions may sound a bit similar so please listen carefully as they are all slightly different. So using the 1 to 7 scale again, where 1 is strongly disagree and 7 is strongly agree, could you please rate your level of agreement with the following statements: ****Show respondent the scale sheet**** | |
|---|---|
| a. "When you go fishing, you're not happy unless you catch something" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| b. "When you go fishing, you're just as happy even if you don't catch a fish" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| c. "You usually have a good time fishing even if no fish are caught" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| d. "When you go fishing, you enjoy other parts of the experience more than catching fish" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| e. "The main reason you go fishing is to catch a fish" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| f. "You usually enjoy the journey to the fishing spot as much as you enjoy catching fish" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |

| **Q8** The following set of questions are about your general **fishing activities over the last 12 months**. Looking at this scale, rate how strongly you agree or disagree with the following statements: ****Show respondent the scale sheet**** | |
|---|---|
| a. "Many of your friends go fishing" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| b. "Other leisure activities do not interest you as much as fishing" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| c. "You would see some your friends less if you stopped fishing" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| d. "Going fishing is one of the most enjoyable things you do" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| e. "You are getting more involved in fishing these days" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| f. "Other people would probably say you spend most of your free time fishing" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| g. "How much would you miss fishing if you couldn't go anymore?" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |

| | | |
|---|---|---|
| **Q9** These following statements are about your expectations of recreational fishing in the [*insert as applicable area*] Net Free Zone over the **next 12 months and beyond**: So using the same scale, rate how strongly you agree or disagree with the following statements: **** Show respondent the scale sheet**** | | |
| Catch | a. "You expect the variety of species you catch to increase over the next 12 months" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| | b. "You expect the number of fish you catch to increase over the next 12 months" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| | c. "You expect the size of the fish you catch to decrease over the next 12 months" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| | d. "You expect to be able to target new species of fish you haven't targeted before over the next 12 months" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| Expectation | e. "Your satisfaction with fishing in this area will increase over the next 12 months" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| | f. "Your enjoyment of fishing in this area will not improve over the next 12 months" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| | g. "You expect the boat ramps in this area will become overcrowded over the next 12 months" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| | h. "You expect the fishing spots in this area won't become overcrowded over the next 12 months" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| | i. "You expect future generations will have quality fishing opportunities in this area" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| Management | j. "In the future, you expect that more people will go recreational fishing in this Net Free Zone" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| | k. "In the future, you expect recreational fishers to catch more fish in this Net Free Zone" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| | l. "In the future, you expect there to be more sea life of all kinds within this Net Free Zone" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| | m. "In the future, you expect that the Net Free Zones will benefit local businesses " ***this question may provoke complicated responses such as unsure – refer to manual for assistance*** | **1 : 2 : 3 : 4 : 5 : 6 : 7** |

| | |
|---|---|
| **Q10** These questions are about your **satisfaction of recreational fishing in this net free zone over the last 12 months**. So thinking back over the **previous 12 months** in the [*insert as applicable*] Net Free Zone, on a scale of 1 to 7, where 1 is very dissatisfied and 7 is very satisfied how satisfied have you been with the following? ****Show respondent the scale sheet**** | |
| a. "The number of fish you've caught" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| b. "The variety of fish you've caught" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| c. "The number of big fish you've caught" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| d. "The size of the fish you've caught" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| e. "The number of exciting fights with fish you have had" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| f. "The number of uncrowded fishing spots" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| g. "Access to parking spaces and boat ramps" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |

| | |
|---|---|
| **Q11** Overall, how would you rate your overall satisfaction with recreational fishing in the [*insert as applicable*] Net Free Zone in the last 12 months? | **1 : 2 : 3 : 4 : 5 : 6 : 7** |

Almost done, just a couple of quick demographic questions and then we are done…

| | | | | |
|---|---|---|---|---|
| **Q12** What age range (years) do you fall into? / Age? | **15-19 : 20-24 : 25-34 : 35-44 : 45-54 : 55-64 : 65-74 : 75-84 : 85 +** | | | |
| **Q13** Gender ****do not ask, just record**** | | | | **Male : Female** |
| **Q14** What town or suburb do you live in? **** OR**** Postcode? | **Suburb or Town:** | | **Postcode:** | |

*Thank the participant for their time. If they are interested in more information they can contact Fisheries Queensland Customer Service Centre on 13 25 23 or at www.daf.qld.gov.au/fisheries.*

| | | |
|---|---|---|
| Session: __ __ __: __ __ __ __ __ __ __ __ | Store: | Interview #: |

Table A 3: Satisfaction survey questionnaire for reference site (Townsville)

SurveyID: ____________ Verify ____________
SessionID: ____________ Check ____________

**TACKLE STORE SURVEY**
**INTERVIEW SHEET 2018**
DAF FISHERY MONITORING

| Session: _ _ _: _ _ _ _ _ _ _ | Store: |
|---|---|

| | | |
|---|---|---|
| **Q1** Hi, My name is [*your name here*] and I am doing some research on recreational fishing for Fisheries Queensland. Have you done any recreational fishing or crabbing in this area in the last 12 months? **** Show map if necessary. If No, record as ineligible on the cover sheet **** | **YES**. If **NO**, do not interview. | Interview # |

| | | |
|---|---|---|
| **Q2** How many days have you been recreational fishing **in this area** in the last 12 months? **** Show map if necessary***** | □ 1-2 days / *1 or 2 times year*<br>□ 3-12 days / *Once a year to once a month*<br>□ 13-24 days / *1 or 2 times month* | □ 25-36 days / *2 or 3 times a month*<br>□ 37-51 days ****Only tick if specified****<br>□ 52+ days / *Once a week or more* |

| | | |
|---|---|---|
| **Q3** How many days have you been recreational fishing **in Queensland** in the last 12 months? | □ 1-2 days / *1 or 2 times year*<br>□ 3-12 days / *Once a year to once a month*<br>□ 13-24 days / *1 or 2 times month* | □ 25-36 days / *2 or 3 times a month*<br>□ 37-51 days ****Only tick if specified****<br>□ 52+ days / *Once a week or more* |

| | |
|---|---|
| **Q4** For the following question, I'd like you to rate your answer on a scale of 1 to 7 where 1 is novice and 7 is expert. So using this scale, how would you rate your level of fishing experience? ****Show respondent the scale sheet**** | **1 : 2 : 3 : 4 : 5 : 6 : 7** |

| | |
|---|---|
| **Q5** People go recreational fishing for a range of reasons. Using a scale of 1 to 7 where 1 is not important and 7 is very important, how important are the following to you when you go recreational fishing? ****Show respondent the scale sheet*** | |
| a. "To enjoy nature" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| b. "To be with family or friends" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| c. "To be outdoors" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| d. "To catch fish" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| e. "To get away from other people" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |

| | |
|---|---|
| **Q6** These next few statements are about catching fish and what it means to you. Some questions may sound a bit similar so please listen carefully as they are all slightly different. So using the 1 to 7 scale again, where 1 is strongly disagree and 7 is strongly agree, could you please rate your level of agreement with the following statements: ****Show respondent the scale sheet**** | |
| a. "When you go fishing, you're not happy unless you catch something" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| b. "When you go fishing, you're just as happy even if you don't catch a fish" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| c. "You usually have a good time fishing even if no fish are caught" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| d. "When you go fishing, you enjoy other parts of the experience more than catching fish" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| e. "The main reason you go fishing is to catch a fish" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| f. "You usually enjoy the journey to the fishing spot as much as you enjoy catching fish" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |

| | |
|---|---|
| **Q7** The following set of questions are about your general **fishing activities over the last 12 months**. Looking at this scale, rate how strongly you agree or disagree with the following statements: ****Show respondent the scale sheet**** | |
| a. "Many of your friends go fishing" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| b. "Other leisure activities do not interest you as much as fishing" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| c. "You would see some your friends less if you stopped fishing" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| d. "Going fishing is one of the most enjoyable things you do" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| e. "You are getting more involved in fishing these days" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| f. "Other people would probably say you spend most of your free time fishing" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| g. "How much would you miss fishing if you couldn't go anymore?" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |

**Q8** These following statements are about your expectations of recreational fishing in the [*insert as applicable area*] over the **next 12 months and beyond**: So using the same scale, rate how strongly you agree or disagree with the following statements: **** Show respondent the scale sheet****

| | | |
|---|---|---|
| Catch | a. "You expect the variety of species you catch to increase over the next 12 months" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| | b. "You expect the number of fish you catch to increase over the next 12 months" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| | c. "You expect the size of the fish you catch to decrease over the next 12 months" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| | d. "You expect to be able to target new species of fish you haven't targeted before over the next 12 months" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| Expectation | e. "Your satisfaction with fishing in this area will increase over the next 12 months" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| | f. "Your enjoyment of fishing in this area will not improve over the next 12 months" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| | g. "You expect the boat ramps in this area will become overcrowded over the next 12 months" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| | h. "You expect the fishing spots in this area won't become overcrowded over the next 12 months" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| | i. "You expect future generations will have quality fishing opportunities in this area" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| MGMT | j. "In the future, you expect that more people will go recreational fishing in this area" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| | k. "In the future, you expect recreational fishers to catch more fish in this area" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| | l. "In the future, you expect there to be more sea life of all kinds within this area" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |

**Q9** These questions are about your **satisfaction of recreational fishing in this area over the last 12 months**. So thinking back over the **previous 12 months** in the [*insert as applicable*] area, on a scale of 1 to 7, where 1 is very dissatisfied and 7 is very satisfied how satisfied have you been with the following?
****Show respondent the scale sheet****

| | |
|---|---|
| a. "The number of fish you've caught" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| b. "The variety of fish you've caught" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| c. "The number of big fish you've caught" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| d. "The size of the fish you've caught" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| e. "The number of exciting fights with fish you have had" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| f. "The number of uncrowded fishing spots" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |
| g. "Access to parking spaces and boat ramps" | **1 : 2 : 3 : 4 : 5 : 6 : 7** |

| | |
|---|---|
| **Q10** Overall, how would you rate your overall satisfaction with recreational fishing in the [*insert as applicable*] area in the last 12 months? | **1 : 2 : 3 : 4 : 5 : 6 : 7** |

Almost done, just a couple of quick demographic questions and then we are done...

| | | | |
|---|---|---|---|
| **Q11** What age range (years) do you fall into? / Age? | **15-19 : 20-24 : 25-34 : 35-44 : 45-54 : 55-64 : 65-74 : 75-84 : 85 +** | | |
| **Q12** Gender ****do not ask, just record**** | | | **Male : Female** |
| **Q13** What town or suburb do you live in? **** OR**** Postcode? | **Suburb or Town:** | **Postcode:** | |

*Thank the participant for their time. If they are interested in more information they can contact Fisheries Queensland Customer Service Centre on 13 25 23 or at www.daf.qld.gov.au/fisheries.*

| | | |
|---|---|---|
| Session: __ __ __: __ __ __ __ __ __ __ | Store: | Interview #: |

Table A 4: Deleted variables in the reliability test that had low corrected item-total correlation values

| Deleted variables | Corrected item-total correlation for Rockhampton | Corrected item-total correlation for Townsville |
|---|---|---|
| **Construct: Expectation** | | |
| You expect to be able to target new species of fish you have not targeted before over the next 12 months | .322 | - |
| Your enjoyment of fishing in this area will not improve over the next 12 months | .267 | - |
| You expect the boat ramp in the area will become overcrowded over the next 12 months | -.003 | -.039 |
| You expect fishing spots in this area will not become overcrowded over the next 12 months | .059 | -.173 |
| In the future, you expect that more people will go recreational fishing in this area | - | .257 |
| **Construct: Satisfaction** | | |
| The number of crowded fishing spots | .224 | .300 |
| Access to parking spaces and boat ramps | .161 | .219 |

Note: Corrected item-total correlation values smaller than .4 for each question were removed from the test.

Table A 5: Deleted variables in the confirmatory factor analysis test that had low factor loadings

| Deleted variables | Low factor loadings for Rockhampton | Low factor loadings for Townsville |
|---|---|---|
| **Construct: Expectation** | | |
| You expect the size of the fish you catch to decrease over the next 12 months | .46 | |
| You expect the size of the fish you catch to decrease over the next 12 months | | .48 |
| You expect to be able to target new species of fish you have not targeted before over the next 12 months | | .50 |
| Your enjoyment of fishing in this area will not improve over the next 12 months | | .55 |

| | |
|---|---|
| You expect future generations will have quality fishing opportunities in this area | .54 |

Note: Low factor loading values smaller than .6 for each question were removed from the test.

Table A 6: Multicollinearity test result for satisfaction and expectation components of Rockhampton

| Statements | Coefficients | Sig. | Tolerance | VIF |
|---|---|---|---|---|
| **Latent variable: Satisfaction** | | | | |
| The number of fish you have caught | .020 | .81 | .321 | 3.113 |
| The variety of fish you have caught | .170 | .03 | .387 | 2.584 |
| The number of big fish you have caught | -.006 | .95 | .190 | 5.272 |
| The size of the fish you have caught | .104 | .31 | .198 | 5.058 |
| The number of exciting fights with fish you have had | .288 | .00 | .488 | 2.050 |
| **Latent variable: Expectation** | | | | |
| You expect the variety of species you catch to increase over the next 12 months | .135 | .09 | .430 | 2.323 |
| You expect the number of fish you catch to increase over the next 12 months | -.019 | .84 | .357 | 2.802 |
| Your satisfaction with fishing in this area will increase over the next 12 months | .056 | .44 | .616 | 1.623 |
| You expect future generations will have quality fishing opportunities in this area | .303 | .00 | .556 | 1.797 |
| In the future, you expect that more people will go recreational fishing in this Net Free Zone | .205 | .02 | .452 | 2.214 |
| In the future, you expect recreational fishers to catch more fish in this area | .040 | .74 | .302 | 3.315 |
| In the future, you expect there to be more sea life of all kinds within this area | .005 | .96 | .369 | 2.713 |
| In the future, you expect that the Net Free Zones will benefit local | -.005 | .95 | .531 | 1.883 |

Table A 7: Multicollinearity test result for satisfaction and expectation components of Townsville

| Statements | Coefficients | Sig. | Tolerance | VIF |
|---|---|---|---|---|
| **Latent variable: Satisfaction** | | | | |
| The number of fish you have caught | .285 | .00 | .294 | 3.403 |
| The variety of fish you have caught | .103 | .19 | .376 | 2.657 |
| The number of big fish you have caught | -.005 | .95 | .230 | 4.340 |
| The size of the fish you have caught | .134 | .14 | .236 | 4.241 |
| The number of exciting fights with fish you have had | .019 | .79 | .378 | 2.647 |
| **Latent variable: Expectation** | | | | |
| You expect the variety of species you catch to increase over the next 12 months | .039 | .59 | .546 | 1.831 |
| You expect the number of fish you catch to increase over the next 12 months | -.055 | .46 | .494 | 2.022 |
| Your satisfaction with fishing in this area will increase over the next 12 months | .260 | .00 | .642 | 1.557 |
| In the future, you expect recreational fishers to catch more fish in this area | .042 | .59 | .596 | 1.676 |
| In the future, you expect there to be more sea life of all kinds within this area | .089 | .18 | .665 | 1.504 |

**Appendix B**

Table B 1: Variables of MLR model with their regression coefficients, standard error, and *p*-level

| Sites | Models | Years | Adjusted $R^2$ | Variables | Regression coefficients | *p*-level |
|---|---|---|---|---|---|---|
| Cairns | MLR | 1990-2010 | 0.01 | Price | 5.89E-08 | 0.16 |
| | | | | Rainfall | -2.04E-06 | 0.58 |
| | | | | Temperature | 0.003621 | 0.51 |
| | | | | Stream water level | 0.005764 | 0.57 |
| | | 1992-2013 | 0.14 | Licences | -0.000845 | 0.15 |
| | | | | Rainfall | -5.45E-06 | 0.14 |
| | | | | Temperature | 0.000368 | 0.92 |
| | | | | Stream water level | 0.014348 | 0.17 |
| | | 1994-2016 | 0.56 | Rainfall | -4.17E-06 | 0.09 |
| | | | | Temperature | 0.000227 | 0.93 |
| Mackay | MLR | 1990-2010 | 0.22 | Licences | -0.000326 | 0.64 |
| | | | | Rainfall | -9.65E-07 | 0.89 |
| | | | | Temperature | -0.001498 | 0.72 |
| | | | | Streamflow | -2.32E-08 | 0.25 |
| | | 1992-2013 | 0.67 | Licences | -0.000832 | 0.14 |
| | | | | Rainfall | -5.30E-06 | 0.39 |
| | | | | Temperature | -0.004982 | 0.15 |
| | | | | Streamflow | 1.94E-08 | 0.32 |
| | | 1994-2016 | 0.77 | Licences | -0.000684 | 0.24 |
| | | | | Rainfall | -2.20E-06 | 0.73 |
| | | | | Temperature | -0.002068 | 0.57 |
| | | | | Streamflow | 1.30E-08 | 0.50 |
| Rockhampton | MLR | 1990-2010 | 0.77 | Licences | -0.000332 | 0.11 |
| | | | | Rainfall | -5.73E-06 | 0.33 |
| | | | | Temperature | -0.004320 | 0.17 |
| | | | | Streamflow | -1.74E-10 | 0.83 |
| | | 1992-2013 | 0.97 | Rainfall | -7.11E-06 | 0.28 |
| | | | | Temperature | -0.003561 | 0.30 |
| | | | | Streamflow | 1.92E-10 | 0.69 |
| | | | | Stream water level | -0.000611 | 0.46 |

| **Sites** | **Models** | **Years** | **Adjusted $R^2$** | **Variables** | **Regression coefficients** | ***p*-level** |
|---|---|---|---|---|---|---|
| | | 1994-2016 | 0.97 | Rainfall | -1.47E-05 | 0.07 |
| | | | | Temperature | -0.006863 | 0.08 |
| | | | | Streamflow | 1.58E-10 | 0.77 |
| | | | | Stream water level | 0.001482 | 0.27 |
| Pooled NFZs | MLR | 1990-2010 | 0.27 | Licences | -0.000299 | 0.50 |
| | | | | Price | 1.67E-08 | 0.52 |
| | | | | Rainfall | 5.48E-06 | 0.43 |
| | | | | Temperature | 0.001516 | 0.78 |
| | | | | Stream water level | 0.000463 | 0.83 |
| | | 1992-2013 | 0.82 | Licences | -0.000808 | 0.07 |
| | | | | Rainfall | -1.93E-07 | 0.96 |
| | | | | Temperature | -0.002095 | 0.67 |
| | | | | Streamflow | 1.06E-09 | 0.43 |
| | | | | Stream water level | -0.002604 | 0.39 |
| | | 1994-2016 | 0.91 | Rainfall | -1.57E-06 | 0.66 |
| | | | | Temperature | -0.005469 | 0.11 |
| | | | | Streamflow | 1.53E-09 | 0.15 |
| | | | | Stream water level | 0.000950 | 0.73 |
| Townsville | MLR | 1990-2010 | 0.90 | Rainfall | -4.33E-07 | 0.96 |
| | | | | Temperature | -0.005114 | 0.41 |
| | | | | Streamflow | 8.00E-10 | 0.39 |
| | | 1992-2013 | 0.88 | Temperature | 0.006293 | 0.37 |
| | | 1994-2016 | 0.90 | - | - | - |
| Hinchinbrook | MLR | 1990-2010 | 0.67 | Price | 2.65E-08 | 0.24 |
| | | | | Temperature | -0.003364 | 0.52 |
| | | | | Stream water level | 0.034699 | 0.24 |
| | | 1992-2013 | 0.71 | Rainfall | -8.60E-06 | 0.24 |
| | | | | Temperature | 0.002230 | 0.59 |
| | | | | Streamflow | 4.80E-08 | 0.34 |
| | | 1994-2016 | 0.61 | Licences | -0.001103 | 0.07 |
| | | | | Rainfall | -9.80E-06 | 0.08 |
| | | | | Temperature | -0.002017 | 0.62 |
| | | | | Streamflow | -6.45E-08 | 0.13 |

| **Sites** | **Models** | **Years** | **Adjusted $R^2$** | **Variables** | **Regression coefficients** | ***p*-level** |
|---|---|---|---|---|---|---|
| Hervey Bay | MLR | 1990-2010 | 0.33 | Price | 2.84E-08 | 0.28 |
| | | | | Rainfall | 5.88E-06 | 0.60 |
| | | | | Temperature | 0.002942 | 0.67 |
| | | | | Streamflow | 1.65E-09 | 0.98 |
| | | | | Stream water level | -0.008797 | 0.65 |
| | | 1992-2013 | 0.47 | Licences | -0.000853 | 0.08 |
| | | | | Rainfall | 3.70E-06 | 0.72 |
| | | | | Temperature | 0.001810 | 0.75 |
| | | | | Streamflow | -6.04E-08 | 0.32 |
| | | | | Stream water level | 0.018203 | 0.40 |
| | | 1994-2016 | 0.68 | Rainfall | -6.99E-06 | 0.29 |
| | | | | Temperature | 0.006312 | 0.10 |
| Pooled reference site | MLR | 1990-2010 | 0.72 | Rainfall | 3.00E-07 | 0.95 |
| | | | | Temperature | 0.004562 | 0.46 |
| | | | | Streamflow | -1.10E-09 | 0.11 |
| | | 1992-2013 | 0.77 | Rainfall | -5.40E-06 | 0.25 |
| | | | | Temperature | 0.004413 | 0.36 |
| | | | | Streamflow | 8.39E-10 | 0.30 |
| | | 1994-2016 | 0.78 | Rainfall | -5.26E-06 | 0.24 |
| | | | | Temperature | 0.005381 | 0.14 |
| | | | | Streamflow | 1.00E-09 | 0.30 |
| | | | | Stream water level | -0.005337 | 0.70 |

Table B 2: Normality and heteroscedasticity test result for the residual of the ARIMAX and MLR model

| Sites | Year | ARIMAX | | | | MLR | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Normality test: Jarque-Bera | | Heteroscedasticity test: Breusch-Pagan-Godfrey | | Normality test: Jarque-Bera | | Heteroscedasticity test: Breusch-Pagan-Godfrey | |
| | | Jarque-Bera | Probability | Obs*R-squared | Probability | Jarque-Bera | Probability | Obs*R-squared | Probability |
| Cairns | 1990-2010 | 2.403 | 0.301 | 0.010 | 0.92 | 3.208 | 0.201 | 4.021 | 0.55 |
| | 1992-2013 | 0.943 | 0.624 | 0.129 | 0.94 | 3.040 | 0.219 | 0.392 | 0.99 |
| | 1994-2016 | 0.743 | 0.689 | 1.256 | 0.53 | 1.426 | 0.490 | 0.204 | 0.99 |
| Mackay | 1990-2010 | 0.886 | 0.642 | 4.267 | 0.07 | 0.822 | 0.663 | 5.279 | 0.38 |
| | 1992-2013 | 1.980 | 0.371 | 2.320 | 0.13 | 0.466 | 0.792 | 6.359 | 0.27 |
| | 1994-2016 | 1.344 | 0.510 | 1.112 | 0.29 | 1.669 | 0.434 | 0.337 | 0.99 |
| Rockhampton | 1990-2010 | 1.226 | 0.542 | 0.703 | 0.70 | 0.571 | 0.751 | 7.290 | 0.29 |
| | 1992-2013 | 4.475 | 0.107 | 1.029 | 0.59 | 1.872 | 0.392 | 6.937 | 0.33 |
| | 1994-2016 | 1.021 | 0.599 | 0.102 | 0.75 | 2.939 | 0.230 | 8.444 | 0.39 |
| Pooled NFZs | 1990-2010 | 0.283 | 0.868 | 3.617 | 0.06 | 1.612 | 0.446 | 9.385 | 0.15 |
| | 1992-2013 | 2.127 | 0.345 | 0.448 | 0.50 | 5.402 | 0.067 | 9.414 | 0.15 |
| | 1994-2016 | 0.638 | 0.727 | 0.551 | 0.46 | 1.542 | 0.462 | 6.069 | 0.41 |

| Sites | Year | ARIMAX | | | | MLR | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Normality test: Jarque-Bera | | Heteroscedasticity test: Breusch-Pagan-Godfrey | | Normality test: Jarque-Bera | | Heteroscedasticity test: Breusch-Pagan-Godfrey | |
| | | Jarque-Bera | Probability | Obs*R-squared | Probability | Jarque-Bera | Probability | Obs*R-squared | Probability |
| Townsville | 1990-2010 | 1.440 | 0.487 | 0.303 | 0.58 | 0.455 | 0.796 | 1.123 | 0.06 |
| | 1992-2013 | 1.242 | 0.537 | 0.052 | 0.82 | 0.106 | 0.948 | 9.402 | 0.09 |
| | 1994-2016 | 1.440 | 0.487 | 0.087 | 0.77 | 0.422 | 0.809 | 6.121 | 0.29 |
| Hinchinbrook | 1990-2010 | 2.240 | 0.326 | 0.049 | 0.97 | 0.685 | 0.709 | 1.567 | 0.90 |
| | 1992-2013 | 1.439 | 0.487 | 0.013 | 0.91 | 0.862 | 0.649 | 4.218 | 0.52 |
| | 1994-2016 | 1.215 | 0.545 | 0.000 | 0.98 | 0.464 | 0.793 | 6.647 | 0.35 |
| Hervey Bay | 1990-2010 | 0.565 | 0.754 | 0.187 | 0.66 | 1.762 | 0.414 | 2.550 | 0.86 |
| | 1992-2013 | 0.689 | 0.708 | 0.077 | 0.78 | 0.731 | 0.694 | 3.822 | 0.15 |
| | 1994-2016 | 4.695 | 0.096 | 0.551 | 0.46 | 0.805 | 0.669 | 3.728 | 0.71 |
| Pooled reference sites | 1990-2010 | 0.588 | 0.745 | 0.702 | 0.87 | 1.019 | 0.601 | 7.054 | 0.22 |
| | 1992-2013 | 2.510 | 0.285 | 0.029 | 0.86 | 0.243 | 0.885 | 7.773 | 0.07 |
| | 1994-2016 | 2.732 | 0.255 | 0.068 | 0.79 | 1.745 | 0.418 | 8.294 | 0.06 |

Table B 3: Audit trail for ARIMAX and MLR model for all of the study sites

# 1. Cairns:

### Data cleaning and processing:

**For outlier detection**: Analyze> Descriptive statictics> Explore> provide variables> statistics tab, select outliers and percentiles, unselect Descriptives > Plots tab, select Histogram and Normality plots with test, unselect stem-and-leaf > continue> ok

**Percentiles**

| | | Percentiles | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | 5 | 10 | 25 | 50 | 75 | 90 | 95 |
| Weighted Average(Definition 1) | cpue | .02352581 | .02399902 | .02984943 | .03409168 | .03889317 | .04431021 | .04630746 |
| | licence | 6.00 | 7.00 | 9.50 | 11.50 | 16.00 | 17.00 | 18.90 |
| | price | 47376.70878 | 56621.41750 | 84478.94000 | 115450.83000 | 158401.36250 | 191548.83624 | 202566.89300 |
| | rainfall | 1080.13625 | 1421.28000 | 1701.45000 | 2051.15000 | 2472.70833 | 2948.86500 | 3178.95250 |
| | temperature | 24.57000 | 24.85000 | 24.85000 | 25.10000 | 25.27500 | 25.81000 | 25.95375 |
| | streamflow | 109305.27850 | 118523.26600 | 309825.83750 | 553090.58500 | 936464.24000 | 1603204.12200 | 1740377.18600 |
| | streamwaterlevel | .3523 | .4110 | .4658 | .6750 | .8585 | 1.0103 | 1.0965 |
| Tukey's Hinges | cpue | | | .02991936 | .03409168 | .03810170 | | |
| | licence | | | 10.00 | 11.50 | 16.00 | | |
| | price | | | 87194.15000 | 115450.83000 | 157420.27000 | | |
| | rainfall | | | 1710.35000 | 2051.15000 | 2408.90000 | | |
| | temperature | | | 24.85000 | 25.10000 | 25.25000 | | |
| | streamflow | | | 315049.79000 | 553090.58500 | 920250.69000 | | |
| | streamwaterlevel | | | .4680 | .6750 | .8520 | | |

**Extreme Values**

| | | | Case Number | Value |
|---|---|---|---|---|
| cpue | Highest | 1 | 6 | .047783 |

| | | | | |
|---|---|---|---|---|
| | | 2 | 19 | .045100 |
| | | 3 | 20 | .044357 |
| | | 4 | 22 | .043890 |
| | | 5 | 17 | .043810 |
| | Lowest | 1 | 28 | .023460 |
| | | 2 | 3 | .023580 |
| | | 3 | 27 | .023821 |
| | | 4 | 29 | .025600 |
| | | 5 | 13 | .026969 |
| licence | Highest | 1 | 2 | 20 |
| | | 2 | 1 | 18 |
| | | 3 | 3 | 17 |
| | | 4 | 4 | 17 |
| | | 5 | 9 | 16[a] |
| | Lowest | 1 | 30 | 6 |
| | | 2 | 29 | 6 |
| | | 3 | 28 | 7 |
| | | 4 | 21 | 7 |
| | | 5 | 27 | 8[b] |
| price | Highest | 1 | 19 | 206831.670 |
| | | 2 | 17 | 199077.530 |
| | | 3 | 9 | 191824.820 |
| | | 4 | 1 | 189064.982 |
| | | 5 | 4 | 177223.510 |
| | Lowest | 1 | 28 | 46817.348 |
| | | 2 | 29 | 47834.368 |
| | | 3 | 27 | 56566.053 |
| | | 4 | 30 | 57119.702 |
| | | 5 | 13 | 71565.650 |
| rainfall | Highest | 1 | 11 | 3425.600 |
| | | 2 | 29 | 2977.150 |
| | | 3 | 22 | 2949.850 |
| | | 4 | 15 | 2940.000 |
| | | 5 | 21 | 2815.500 |
| | Lowest | 1 | 13 | 721.000 |
| | | 2 | 27 | 1373.975 |
| | | 3 | 14 | 1407.333 |
| | | 4 | 3 | 1546.800 |
| | | 5 | 24 | 1579.933 |
| temperature | Highest | 1 | 21 | 26.050 |

| | | | | |
|---|---|---|---|---|
| | | 2 | 27 | 25.875 |
| | | 3 | 9 | 25.850 |
| | | 4 | 28 | 25.450 |
| | | 5 | 16 | 25.400 |
| | Lowest | 1 | 8 | 24.350 |
| | | 2 | 11 | 24.750 |
| | | 3 | 25 | 24.850 |
| | | 4 | 22 | 24.850 |
| | | 5 | 10 | 24.850[c] |
| streamflow | Highest | 1 | 22 | 1.827E+6 |
| | | 2 | 11 | 1.669E+6 |
| | | 3 | 19 | 1.607E+6 |
| | | 4 | 10 | 1.569E+6 |
| | | 5 | 30 | 1.158E+6 |
| | Lowest | 1 | 13 | 106151.980 |
| | | 2 | 14 | 111885.250 |
| | | 3 | 27 | 114981.230 |
| | | 4 | 3 | 150401.590 |
| | | 5 | 4 | 190384.180 |
| streamwaterlevel | Highest | 1 | 22 | 1.18 |
| | | 2 | 11 | 1.03 |
| | | 3 | 19 | 1.01 |
| | | 4 | 10 | 1.00 |
| | | 5 | 30 | .97 |
| | Lowest | 1 | 14 | .35 |
| | | 2 | 13 | .36 |
| | | 3 | 27 | .41 |
| | | 4 | 3 | .45 |
| | | 5 | 5 | .45 |

a. Only a partial list of cases with the value 16 are shown in the table of upper extremes.

b. Only a partial list of cases with the value 8 are shown in the table of lower extremes.

c. Only a partial list of cases with the value 24.850 are shown in the table of lower extremes.

Easy method to determine outliers using box plot is: Any asteric marks (*) below or above the box is outlier.

In Cairns sample, no outlier and missing values was found.

**Year: 1990-2010**

**Check for seasonality and trend**: Line diagram showing no seasonality pattern but a steady positive secular trend for the dependent variable "cpue".

Select variables>Quick>graph>provide variables>ok>check options>ok

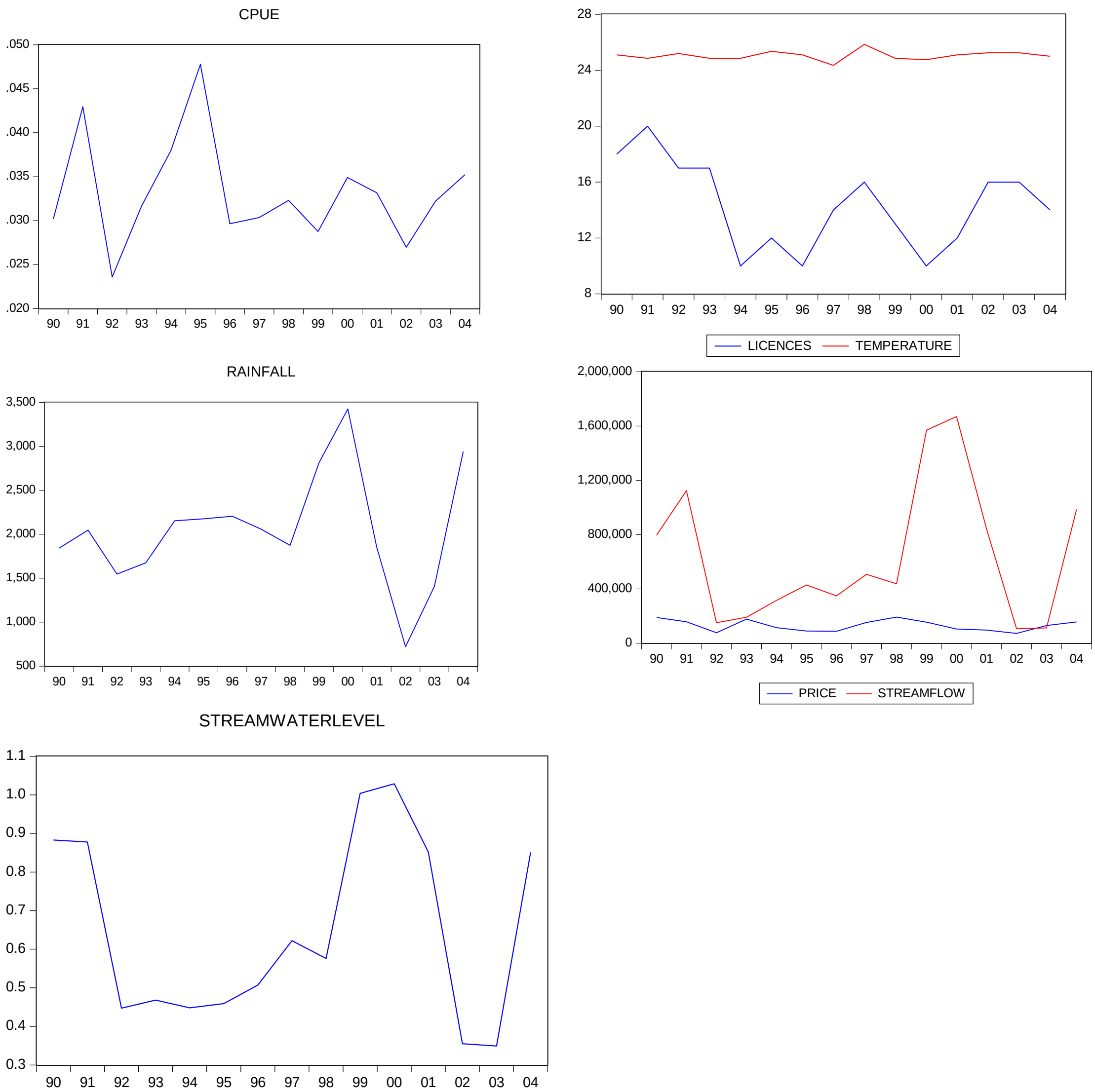



Figure: Line graph of all the variables

**Unit root test:**

Quick> series statistics> unit root test> Provide variable> ok> if the prob is greater than .05 then, there is unit root in the series (null: there is a unit root, if *p* value is less than .05 then reject the null hypothesis).

CPUE doesn't have unit root
Licences has unit root
Price+Rainfall+Temp+ streamflow+ streamwaterlevel have no unit root

As licence has unit root, natural log does not work to remove unit root, so 1st difference of the series was used. Now the series is stationary.

**Lag selection**:
Stata command: varsoc dcpue dlicences dprice drainfall dtemperature dstreamflow dstreamwaterlevel

```
. varsoc dcpue dlicences dprice drainfall dtemperature dstreamflow dstreamwaterlevel

  Selection-order criteria
  Sample:  1995 - 2010                         Number of obs      =        16
```

| lag | LL | LR | df | p | FPE | AIC | HQIC | SBIC |
|---|---|---|---|---|---|---|---|---|
| 0 | -518.227 | | | | 7.7e+19 | 65.6534 | 65.6707 | 65.9914 |
| 1 | -470.401 | 95.653 | 49 | 0.000 | 1.8e+20 | 65.8001 | 65.9386 | 68.5041 |
| 2 | . | . | 49 | . | -1.8e-78* | . | . | . |
| 3 | 3120.07 | . | 49 | . | . | -376.008 | -375.731 | -370.6 |
| 4 | 3225.77 | 211.4* | 49 | 0.000 | . | -389.221* | -388.944* | -383.813* |

```
  Endogenous:  dcpue dlicences dprice drainfall dtemperature dstreamflow
               dstreamwaterlevel
   Exogenous:  _cons
```

Selected lag 4 for the granger causality test.

**Granger Causality test**: Screen for reverse causality in EViews.

Granger causality is sensitive to lag selection. Granger causality considers whether the lags of other variables have predictive power once the lags of the dependent variable itself are accounted for.

Select and open all the variables of interest (differenced series)>Quick>Group statistics>Granger causality test>all the variables come in a window and press ok> lags to include (4)> ok

Pairwise Granger Causality Tests
Date: 03/04/21 Time: 22:48
Sample: 1990 2010
Lags: 4

| Null Hypothesis: | Obs | F-Statistic | Prob. |
|---|---|---|---|
| DLICENCES does not Granger Cause DCPUE | 16 | 0.64288 | 0.6491 |
| DCPUE does not Granger Cause DLICENCES | | 1.90491 | 0.2145 |
| DPRICE does not Granger Cause DCPUE | 16 | 0.74173 | 0.5928 |
| DCPUE does not Granger Cause DPRICE | | 0.87283 | 0.5252 |
| DRAINFALL does not Granger Cause DCPUE | 16 | 0.01746 | 0.9992 |
| DCPUE does not Granger Cause DRAINFALL | | 0.12945 | 0.9668 |
| DTEMPERATURE does not Granger Cause DCPUE | 16 | 0.46735 | 0.7589 |
| DCPUE does not Granger Cause DTEMPERATURE | | 0.39340 | 0.8077 |
| DSTREAMFLOW does not Granger Cause DCPUE | 16 | 0.36473 | 0.8267 |
| DCPUE does not Granger Cause DSTREAMFLOW | | 0.19887 | 0.9312 |
| DSTREAMWATERLEVEL does not Granger Cause DCPUE | 16 | 0.08751 | 0.9835 |
| DCPUE does not Granger Cause DSTREAMWATERLEVEL | | 0.11177 | 0.9744 |

**Causality with Dependent Variable to Independent Variable and Independent Variable to Dependent Variable:** Here, screening for reverse causality was done. Reverse causality is if independent variable X effects on dependent variable Y and Y has also effect on X, this condition is called reverse causality. Any variable with a *p*-value below .05 led to the rejection of the null hypothesis, thus eliminating it as a candidate for inclusion in the model. Here, all the variables passed the test as they did not show any sort of reverse causality.

No reverse causality was found.

**Test for multicollinearity**: SPSS

Criteria for no multi collinearity: Tolerance should be higher than 0.1, VIF should be less than 10 and condition index should be less than 15.

Analyse> regression> linear> DV (dcpue), IV (all independent variables)> Method (Enter)>statistics (select collinearity diagnosis, unselect others)>continue>ok

**Coefficients**[a]

| Model | | Collinearity Statistics Tolerance | VIF |
|---|---|---|---|
| 1 | dlicence | .436 | 2.296 |
| | lnprice | .591 | 1.691 |
| | drainfall | .201 | 4.974 |
| | lntemperature | .785 | 1.274 |
| | dstreamflow | .113 | 8.812 |

| | | |
|---|---|---|
| dstreamwaterlevel | .107 | 9.350 |

a. Dependent Variable: dcpue

**Collinearity Diagnostics[a]**

| Model | Dimension | Eigenvalue | Condition Index | Variance Proportions (Constant) | dlicence | lnprice | drainfall | lntemperature | dstreamflow | dstreamwaterlevel |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 3.175 | 1.000 | .00 | .00 | .01 | .02 | .03 | .01 | .01 |
| | 2 | 1.521 | 1.445 | .09 | .14 | .12 | .01 | .00 | .00 | .00 |
| | 3 | .967 | 1.812 | .67 | .01 | .07 | .00 | .13 | .00 | .00 |
| | 4 | .710 | 2.114 | .22 | .02 | .00 | .02 | .79 | .00 | .00 |
| | 5 | .432 | 2.709 | .01 | .25 | .68 | .00 | .02 | .04 | .01 |
| | 6 | .134 | 4.874 | .00 | .49 | .04 | .93 | .02 | .04 | .13 |
| | 7 | .061 | 7.211 | .00 | .09 | .09 | .02 | .01 | .90 | .85 |

a. Dependent Variable: dcpue

Here, multicollinearity is absent among independent variables. Tolerance is higher than 0.1, VIF should be less than 10 and condition index is less than 15.

**Multiple Regression Test**: SPSS

**Backward Regression:**

Analyse> regression>Linear>Provide variables> Method (backward)> Statistics (select Confidence interval, R square change and descriptives)>continue>ok

**Coefficients[a]**

| Model | | Unstandardized Coefficients B | Std. Error | Standardized Coefficients Beta | t | Sig. |
|---|---|---|---|---|---|---|
| 1 | (Constant) | .001 | .002 | | .280 | .784 |
| | dlicence | .001 | .001 | .321 | .901 | .384 |
| | dprice | 1.748E-8 | .000 | .106 | .346 | .735 |
| | drainfall | 3.919E-6 | .000 | .364 | .693 | .500 |
| | dtemperature | .000 | .004 | .009 | .035 | .973 |
| | dstreamflow | 3.981E-9 | .000 | .286 | .409 | .689 |
| | dstreamwaterlevel | -.005 | .024 | -.155 | -.215 | .833 |
| 2 | (Constant) | .001 | .002 | | .295 | .772 |
| | dlicence | .001 | .001 | .322 | .940 | .363 |
| | dprice | 1.753E-8 | .000 | .106 | .360 | .724 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | drainfall | 3.927E-6 | .000 | .365 | .721 | .483 |
| | dstreamflow | 3.985E-9 | .000 | .286 | .425 | .677 |
| | dstreamwaterlevel | -.005 | .023 | -.160 | -.235 | .817 |
| 3 | (Constant) | .001 | .002 | | .326 | .749 |
| | dlicence | .001 | .001 | .331 | 1.002 | .332 |
| | dprice | 1.441E-8 | .000 | .087 | .317 | .755 |
| | drainfall | 3.685E-6 | .000 | .342 | .712 | .487 |
| | dstreamflow | 2.271E-9 | .000 | .163 | .397 | .697 |
| 4 | (Constant) | .001 | .002 | | .335 | .742 |
| | dlicence | .001 | .001 | .382 | 1.362 | .192 |
| | drainfall | 4.114E-6 | .000 | .382 | .848 | .409 |
| | dstreamflow | 2.387E-9 | .000 | .172 | .431 | .672 |
| 5 | (Constant) | .001 | .002 | | .338 | .740 |
| | dlicence | .001 | .001 | .442 | 1.865 | .080 |
| | drainfall | 5.875E-6 | .000 | .546 | 2.303 | .034 |
| 6 | (Constant) | .001 | .002 | | .129 | .898 |
| | dstreamflow | 6.01E-09 | 2.96E-09 | .442 | 2.033 | .055 |

a. Dependent Variable: dcpue

### Excluded Variables[a]

| Model | | Beta In | t | Sig. | Partial Correlation | Collinearity Statistics Tolerance |
|---|---|---|---|---|---|---|
| 2 | dtemperature | .009[b] | .035 | .973 | .010 | .785 |
| 3 | dtemperature | .021[c] | .082 | .936 | .022 | .818 |
| | dstreamwaterlevel | -.160[c] | -.235 | .817 | -.063 | .111 |
| 4 | dtemperature | .018[d] | .075 | .941 | .019 | .818 |
| | dstreamwaterlevel | -.094[d] | -.147 | .885 | -.038 | .120 |
| | dprice | .087[d] | .317 | .755 | .082 | .639 |
| 5 | dtemperature | -.005[e] | -.022 | .983 | -.005 | .862 |
| | dstreamwaterlevel | .092[e] | .234 | .818 | .058 | .295 |
| | dprice | .094[e] | .353 | .729 | .088 | .641 |
| | dstreamflow | .172[e] | .431 | .672 | .107 | .287 |
| 6 | dtemperature | -.006[f] | -.012 | .883 | -.008 | .662 |
| | dstreamwaterlevel | .090[f] | .134 | .718 | .358 | .745 |
| | dprice | .094[f] | .453 | .629 | .288 | .541 |
| | dlicences | .162[f] | .461 | .872 | .407 | .567 |
| | drainfall | .006 | .345 | .678 | .106 | .287 |

a. Dependent Variable: dcpue

b. Predictors in the Model: (Constant), dstreamwaterlevel, dlicence, dprice, drainfall, dstreamflow

c. Predictors in the Model: (Constant), dlicence, dprice, drainfall, dstreamflow

d. Predictors in the Model: (Constant), dlicence, drainfall, dstreamflow

e. Predictors in the Model: (Constant), dlicence, drainfall

f. Predictors in the Model: (Constant), dstreamflow

**Regression in Eviews**: dcpue c dstreamflow

Dependent Variable: DCPUE
Method: Least Squares
Date: 03/11/21 Time: 21:16
Sample: 1991 2010
Included observations: 20

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.000232 | 0.001794 | 0.129195 | 0.8986 |
| DSTREAMFLOW | 6.01E-09 | 2.96E-09 | 2.033034 | 0.0551 |

| | | | |
|---|---|---|---|
| R-squared | 0.186743 | Mean dependent var | 0.000180 |
| Adjusted R-squared | 0.141562 | S.D. dependent var | 0.008657 |
| S.E. of regression | 0.008021 | Akaike info criterion | -6.718901 |
| Sum squared resid | 0.001158 | Schwarz criterion | -6.619328 |
| Log likelihood | 69.18901 | Hannan-Quinn criter. | -6.699463 |
| F-statistic | 4.133227 | Durbin-Watson stat | 2.596456 |
| Prob(F-statistic) | 0.057067 | | |

**Unit root test for the residuals of regression model** (including dcpue c dstreamflow):

Getting residuals in EViws:

Quick> estimate equation>Provide variables (dcpue dstreamflow)> ok> view tab> Actual, fitted, residual> Actual, fitted, residual table>save residual as variable 'R'> unit root test for variable 'R'

Null Hypothesis: R has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=4)

| | | t-Statistic | Prob.* |
|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | -6.524201 | 0.0000 |
| Test critical values: | 1% level | -3.831511 | |
| | 5% level | -3.029970 | |
| | 10% level | -2.655194 | |

*MacKinnon (1996) one-sided p-values.
Warning: Probabilities and critical values calculated for 20 observations and may not be accurate for a sample size of 19

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(R)

Method: Least Squares
Date: 03/15/21 Time: 23:42
Sample (adjusted): 1992 2010
Included observations: 19 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| R(-1) | -1.423292 | 0.218156 | -6.524201 | 0.0000 |
| C | -0.000334 | 0.001628 | -0.204904 | 0.8401 |

| | | | |
|---|---|---|---|
| R-squared | 0.714598 | Mean dependent var | -0.001083 |
| Adjusted R-squared | 0.697810 | S.D. dependent var | 0.012876 |
| S.E. of regression | 0.007078 | Akaike info criterion | -6.964225 |
| Sum squared resid | 0.000852 | Schwarz criterion | -6.864810 |
| Log likelihood | 68.16014 | Hannan-Quinn criter. | -6.947400 |
| F-statistic | 42.56520 | Durbin-Watson stat | 1.836766 |
| Prob(F-statistic) | 0.000005 | | |

The residuals have no unit root.

**Serial correlation test:**

Quick>estimate equation> dcpue c dstreamflow>ok>view tab> residual diagnostics>correlogram and Q-statistics (Ljung-Box test) >lag selection (12)> ok.

The probability of Q stat (Ljung-Box test) is more than .05. So, I should accept the null hypothesis. (Null: there is no serial correlation).

Dependent Variable: DCPUE
Method: Least Squares
Date: 03/11/21 Time: 21:20
Sample: 1991 2010
Included observations: 20

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.000232 | 0.001794 | 0.129195 | 0.8986 |
| DSTREAMFLOW | 6.01E-09 | 2.96E-09 | 2.033034 | 0.0551 |

| | | | |
|---|---|---|---|
| R-squared | 0.186743 | Mean dependent var | 0.000180 |
| Adjusted R-squared | 0.141562 | S.D. dependent var | 0.008657 |
| S.E. of regression | 0.008021 | Akaike info criterion | -6.718901 |
| Sum squared resid | 0.001158 | Schwarz criterion | -6.619328 |
| Log likelihood | 69.18901 | Hannan-Quinn criter. | -6.699463 |
| F-statistic | 4.133227 | Durbin-Watson stat | 2.596456 |
| Prob(F-statistic) | 0.057067 | | |

**Correlogram plot:**

Date: 03/11/21 Time: 21:20
Sample: 1991 2010
Included observations: 20

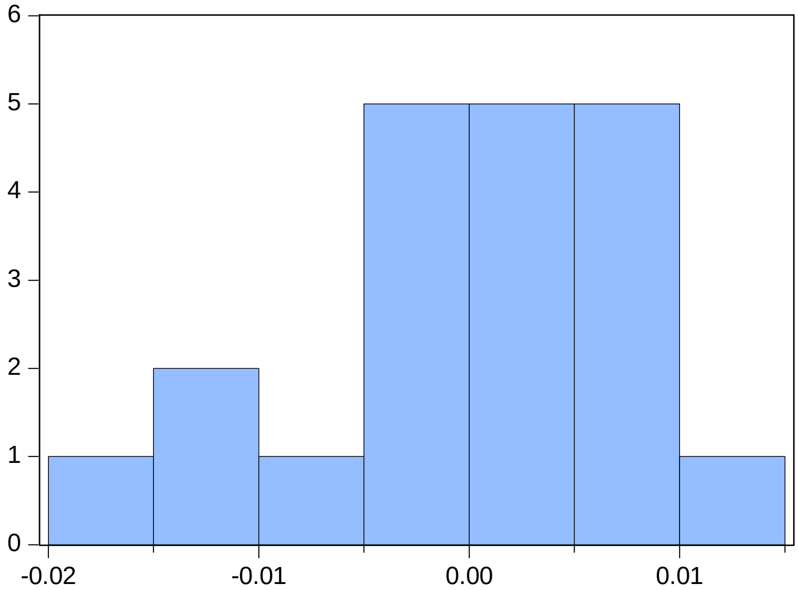
| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|---|---|
| | | 1 | -0.390 | -0.390 | 3.5157 | 0.061 |
| | | 2 | -0.055 | -0.243 | 3.5886 | 0.166 |
| | | 3 | 0.085 | -0.045 | 3.7763 | 0.287 |
| | | 4 | 0.029 | 0.050 | 3.8001 | 0.434 |
| | | 5 | -0.184 | -0.163 | 4.7881 | 0.442 |
| | | 6 | 0.022 | -0.154 | 4.8040 | 0.569 |
| | | 7 | -0.014 | -0.153 | 4.8111 | 0.683 |
| | | 8 | -0.047 | -0.148 | 4.8916 | 0.769 |
| | | 9 | -0.015 | -0.136 | 4.9003 | 0.843 |
| | | 10 | -0.099 | -0.300 | 5.3326 | 0.868 |
| | | 11 | 0.076 | -0.239 | 5.6166 | 0.898 |
| | | 12 | 0.158 | 0.006 | 6.9855 | 0.859 |

Ther ACF and PACF plot is flat.

**Diagnostic reports:**

**Normality test of residuals:**

Quick>estimate equation> dcpue c dstreamflow >ok>view tab> residual diagnostics> Histogram- Normality test




Series: Residuals
Sample 1991 2010
Observations 20

| | |
|---|---|
| Mean | 5.20e-19 |
| Median | 0.002436 |
| Maximum | 0.010570 |
| Minimum | -0.017893 |
| Std. Dev. | 0.007807 |
| Skewness | -0.843312 |
| Kurtosis | 2.800562 |
| Jarque-Bera | 2.403730 |
| Probability | 0.300633 |

The probability of Jarque-Bera test in more than 5%, so the residual series follows normal distribution.

## Breusch-Godfrey Serial Correlation LM Test:

Lag (2)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 2.328696 | Prob. F(2,16) | 0.1295 |
| Obs*R-squared | 4.509177 | Prob. Chi-Square(2) | 0.1049 |

Lag (4)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 1.054235 | Prob. F(4,14) | 0.4149 |
| Obs*R-squared | 4.629691 | Prob. Chi-Square(4) | 0.3274 |

Lag (8)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.561426 | Prob. F(8,10) | 0.7875 |
| Obs*R-squared | 6.198715 | Prob. Chi-Square(8) | 0.6250 |

## Heteroscedasticity test:

Quick>estimate equation> dcpue c dstreamflow >ok>view tab> residual diagnostics>Breusch-Pagan-Godfrey test>ok

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 0.009411 | Prob. F(1,18) | 0.9238 |
| Obs*R-squared | 0.010451 | Prob. Chi-Square(1) | 0.9186 |
| Scaled explained SS | 0.008013 | Prob. Chi-Square(1) | 0.9287 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/04/21 Time: 23:14
Sample: 1991 2010
Included observations: 20

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 5.79E-05 | 1.78E-05 | 3.253977 | 0.0044 |
| DSTREAMFLOW | -2.85E-12 | 2.94E-11 | -0.097010 | 0.9238 |

| | | | |
|---|---|---|---|
| R-squared | 0.000523 | Mean dependent var | 5.80E-05 |
| Adjusted R-squared | -0.055004 | S.D. dependent var | 7.75E-05 |
| S.E. of regression | 7.96E-05 | Akaike info criterion | -15.94425 |
| Sum squared resid | 1.14E-07 | Schwarz criterion | -15.84467 |
| Log likelihood | 161.4425 | Hannan-Quinn criter. | -15.92481 |
| F-statistic | 0.009411 | Durbin-Watson stat | 1.754946 |
| Prob(F-statistic) | 0.923791 | | |

Probability is greater than 5%, so the model is not heteroscedastic.

**ARIMAX (0,1,0) Forecasting**:

Extend workfile size (from 1990-2013) by double clicking the range> provide actual value in dstreamflow from 2010-2013>Quick >estimate equation> dcpue c dstreamflow > Forecast> Forecast sample (1990-2013)>ok>

Associated excel file to determine MAPE, RAMSE, MAE etc. of the year 2011-2013.

**Year 1992-2013:**

**Unit root test:** 1st differenced series has unit root; hence 2nd difference of the series has taken and the final series has no unit root

**Lag selection:** Varsoc ddcpue ddlicences ddprice ddrainfall ddtemperature ddstreamflow ddstreamwaterlevel

Lag 4 was selected.

**Granger Causality test**

Pairwise Granger Causality Tests
Date: 03/05/21 Time: 11:39
Sample: 1992 2013
Lags: 4

| Null Hypothesis: | Obs | F-Statistic | Prob. |
|---|---|---|---|
| DDLICENCES does not Granger Cause DDCPUE | 16 | 1.66198 | 0.2614 |
| DDCPUE does not Granger Cause DDLICENCES | | 1.36118 | 0.3379 |
| DDPRICE does not Granger Cause DDCPUE | 16 | 0.37499 | 0.8199 |
| DDCPUE does not Granger Cause DDPRICE | | 1.00729 | 0.4641 |
| DDRAINFALL does not Granger Cause DDCPUE | 16 | 0.11014 | 0.9750 |
| DDCPUE does not Granger Cause DDRAINFALL | | 0.27962 | 0.8822 |
| DDTEMPERATURE does not Granger Cause DDCPUE | 16 | 2.37399 | 0.1501 |
| DDCPUE does not Granger Cause DDTEMPERATURE | | 1.00730 | 0.4641 |
| DDSTREAMFLOW does not Granger Cause DDCPUE | 16 | 0.12451 | 0.9690 |
| DDCPUE does not Granger Cause DDSTREAMFLOW | | 0.51497 | 0.7281 |
| DDSTREAMWATERLEVEL does not Granger Cause DDCPUE | 16 | 0.22396 | 0.9166 |
| DDCPUE does not Granger Cause DDSTREAMWATERLEVEL | | 0.14643 | 0.9588 |

No reverse causality detected.

**Test for multicollinearity:**

**Coefficients[a]**

| | | Collinearity Statistics | |
|---|---|---|---|
| Model | | Tolerance | VIF |
| 1 | ddlicence | .317 | 3.152 |
| | ddprice | .396 | 2.524 |
| | ddrainfall | .180 | 5.562 |
| | ddtemperature | .607 | 1.649 |

| | | | |
|---|---|---|---|
| | ddstreamflow | .097 | 10.353 |
| | ddseamwaterlevel | .083 | 12.116 |

a. Dependent Variable: ddcpue

**Collinearity Diagnostics[a]**

| Model | Dimension | Eigenvalue | Condition Index | Variance Proportions (Constant) | ddlicence | ddprice | ddrainfall | ddtemperature | ddstreamflow | ddseamwaterlevel |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 3.358 | 1.000 | .00 | .00 | .02 | .01 | .02 | .01 | .01 |
| | 2 | 1.450 | 1.522 | .01 | .14 | .06 | .02 | .00 | .00 | .00 |
| | 3 | .996 | 1.836 | .97 | .00 | .00 | .00 | .00 | .00 | .00 |
| | 4 | .746 | 2.121 | .01 | .01 | .08 | .02 | .60 | .00 | .00 |
| | 5 | .293 | 3.384 | .02 | .12 | .62 | .00 | .25 | .08 | .02 |
| | 6 | .108 | 5.577 | .00 | .62 | .11 | .93 | .06 | .04 | .11 |
| | 7 | .049 | 8.280 | .00 | .11 | .12 | .02 | .07 | .87 | .87 |

a. Dependent Variable: ddcpue

Here, multicollinearity is present between streamflow and stream water level. Tolerance is less than 0.1, VIF is more than 10.

So, run the analysis two-times: first time, with all the variables excluding stream water level and for the second time, with all the variable excluding streamflow. Then compared results of the two models, specifically R squares and P values. Model including all other variables excluding streamflow showed improved result than the other. So, I deleted streamflow from the model.

Result of including streamflow and excluding stream water level in the model:

**Model Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate | Change Statistics R Square Change | F Change | df1 | df2 | Sig. F Change |
|---|---|---|---|---|---|---|---|---|---|
| 1 | .691[a] | .477 | .290 | .009832567 | .477 | 2.554 | 5 | 14 | .076 |

a. Predictors: (Constant), ddstreamflow, ddlicence, ddtemperature, ddprice, ddrainfall

Result of including stream water level and excluding streamflow in the model:

**Model Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate | Change Statistics R Square Change | F Change | df1 | df2 | Sig. F Change |
|---|---|---|---|---|---|---|---|---|---|

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 1 | .681[a] | .463 | .271 | .009962003 | .463 | 2.416 | 5 | 14 | .089 |

a. Predictors: (Constant), ddseamwaterlevel, ddlicence, ddtemperature, ddprice, ddrainfall

Model with streamflow gives better $R^2$ than streamwaterlevel. So, I have deleted streamwaterlevel from the analysis.

**Regression Test:**

**Forward Stepwise:**

**Coefficients[a,b]**

| Model | | Unstandardized Coefficients B | Std. Error | Standardized Coefficients Beta | t | Sig. |
|---|---|---|---|---|---|---|
| 1 | ddlicence | .002 | 0.000 | .474 | 3.441 | .003 |
| | ddrainfall | 5.37E-6 | 1.73E-6 | .448 | 3.109 | .006 |

a. Dependent Variable: ddcpue

b. Linear Regression through the Origin

**Excluded Variables[a,b]**

| Model | | Beta In | t | Sig. | Partial Correlation | Collinearity Statistics Tolerance |
|---|---|---|---|---|---|---|
| 1 | ddprice | 7.224E-8[c] | .000 | .476 | 2.357 | .829 |
| | ddtemperature | -.120[c] | -.570 | .576 | -.133 | .952 |
| | ddstreamflow | .243[c] | .990 | .335 | .227 | .678 |

a. Dependent Variable: ddcpue

b. Linear Regression through the Origin

c. Predictors in the Model: ddlicence, ddrainfall

**Eviews**: ddcpue ddlicences ddrainfall

Dependent Variable: DDCPUE
Method: Least Squares
Date: 03/09/21 Time: 12:29
Sample: 1994 2013
Included observations: 20

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| DDLICENCES | 0.001608 | 0.000467 | 3.441423 | 0.0029 |
| DDRAINFALL | 5.37E-06 | 1.73E-06 | 3.109179 | 0.0061 |

| | | | |
|---|---|---|---|
| R-squared | 0.457497 | Mean dependent var | -0.000813 |
| Adjusted R-squared | 0.427358 | S.D. dependent var | 0.011671 |
| S.E. of regression | 0.008832 | Akaike info criterion | -6.526259 |

| | | | |
|---|---|---|---|
| Sum squared resid | 0.001404 | Schwarz criterion | -6.426686 |
| Log likelihood | 67.26259 | Hannan-Quinn criter. | -6.506821 |
| Durbin-Watson stat | 2.512024 | | |

## Unit root test of residual:

Null Hypothesis: R has a unit root
Exogenous: Constant
Lag Length: 4 (Automatic - based on SIC, maxlag=4)

| | | t-Statistic | Prob.* |
|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | -5.679735 | 0.0004 |
| Test critical values: | 1% level | -3.959148 | |
| | 5% level | -3.081002 | |
| | 10% level | -2.681330 | |

*MacKinnon (1996) one-sided p-values.
Warning: Probabilities and critical values calculated for 20 observations and may not be accurate for a sample size of 15

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(R)
Method: Least Squares
Date: 03/09/21 Time: 12:31
Sample (adjusted): 1999 2013
Included observations: 15 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| R(-1) | -4.000816 | 0.704402 | -5.679735 | 0.0003 |
| D(R(-1)) | 2.035804 | 0.536595 | 3.793933 | 0.0043 |
| D(R(-2)) | 1.454829 | 0.384332 | 3.785347 | 0.0043 |
| D(R(-3)) | 1.072281 | 0.238207 | 4.501469 | 0.0015 |
| D(R(-4)) | 0.522137 | 0.161299 | 3.237084 | 0.0102 |
| C | -0.000219 | 0.001027 | -0.213061 | 0.8360 |

| | | | |
|---|---|---|---|
| R-squared | 0.935038 | Mean dependent var | -0.000507 |
| Adjusted R-squared | 0.898948 | S.D. dependent var | 0.012119 |
| S.E. of regression | 0.003852 | Akaike info criterion | -7.991084 |
| Sum squared resid | 0.000134 | Schwarz criterion | -7.707864 |
| Log likelihood | 65.93313 | Hannan-Quinn criter. | -7.994100 |
| F-statistic | 25.90853 | Durbin-Watson stat | 1.165891 |
| Prob(F-statistic) | 0.000043 | | |

The residual has no unit root.

**Serial correlation test**: EViews

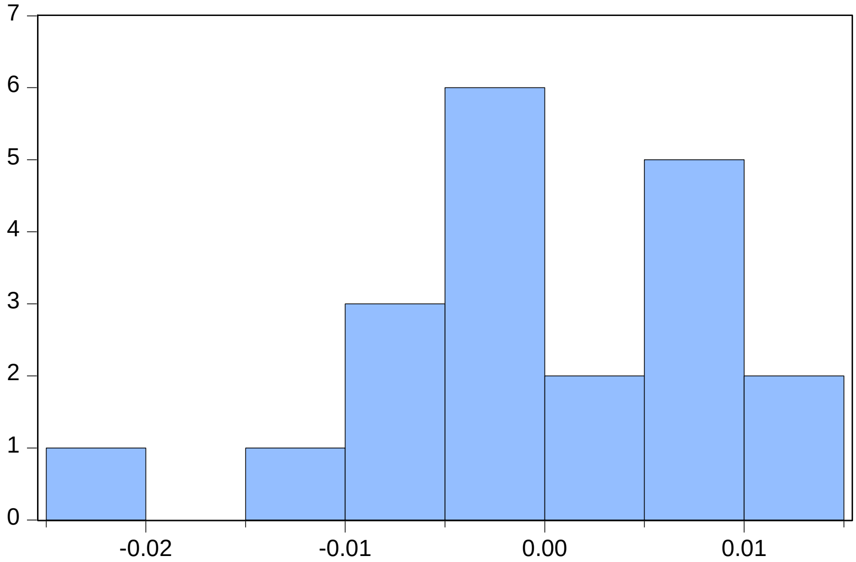
Date: 03/09/21 Time: 12:34
Sample: 1994 2013
Included observations: 20

| | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|
| 1 | -0.286 | -0.286 | 1.8953 | 0.169 |
| 2 | -0.277 | -0.390 | 3.7652 | 0.152 |
| 3 | 0.240 | 0.023 | 5.2515 | 0.154 |
| 4 | -0.341 | -0.446 | 8.4568 | 0.076 |
| 5 | -0.043 | -0.336 | 8.5108 | 0.130 |
| 6 | 0.478 | 0.138 | 15.706 | 0.015 |
| 7 | -0.252 | -0.108 | 17.859 | 0.013 |
| 8 | 0.049 | 0.133 | 17.945 | 0.022 |
| 9 | 0.039 | -0.120 | 18.006 | 0.035 |
| 10 | -0.310 | -0.120 | 22.246 | 0.014 |
| 11 | 0.129 | -0.097 | 23.060 | 0.017 |
| 12 | 0.148 | -0.147 | 24.258 | 0.019 |

The residuals are flat and no serial correlation.

**Diagnostic Checking:**

**Normality test of residuals**:




| Series: Residuals | |
|---|---|
| Sample 1994 2013 | |
| Observations 20 | |
| Mean | -0.000489 |
| Median | -0.002663 |
| Maximum | 0.011436 |
| Minimum | -0.021539 |
| Std. Dev. | 0.008582 |
| Skewness | -0.522540 |
| Kurtosis | 2.801306 |
| Jarque-Bera | 0.943059 |
| Probability | 0.624047 |

**Breusch-Godfrey Serial Correlation LM Test:**

Lag (2)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 2.314721 | Prob. F(2,16) | 0.1309 |
| Obs*R-squared | 4.488189 | Prob. Chi-Square(2) | 0.1060 |

Lag (4)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 2.574380 | Prob. F(4,14) | 0.0836 |
| Obs*R-squared | 8.476191 | Prob. Chi-Square(4) | 0.0756 |

Lag (8)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 1.455362 | Prob. F(8,10) | 0.2839 |
| Obs*R-squared | 10.75909 | Prob. Chi-Square(8) | 0.2157 |

**Heteroscedasticity test:**

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 0.055590 | Prob. F(2,17) | 0.9461 |
| Obs*R-squared | 0.129949 | Prob. Chi-Square(2) | 0.9371 |
| Scaled explained SS | 0.101255 | Prob. Chi-Square(2) | 0.9506 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/09/21 Time: 13:56
Sample: 1994 2013
Included observations: 20

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 7.04E-05 | 2.36E-05 | 2.986256 | 0.0083 |
| DDLICENCES | -2.27E-07 | 5.57E-06 | -0.040817 | 0.9679 |
| DDRAINFALL | 5.89E-09 | 2.06E-08 | 0.285652 | 0.7786 |

| | | | |
|---|---|---|---|
| R-squared | 0.006497 | Mean dependent var | 7.02E-05 |
| Adjusted R-squared | -0.110385 | S.D. dependent var | 9.99E-05 |
| S.E. of regression | 0.000105 | Akaike info criterion | -15.34255 |
| Sum squared resid | 1.88E-07 | Schwarz criterion | -15.19319 |
| Log likelihood | 156.4255 | Hannan-Quinn criter. | -15.31339 |
| F-statistic | 0.055590 | Durbin-Watson stat | 1.755817 |
| Prob(F-statistic) | 0.946098 | | |

Probability is greater than 5%, so the model is not heteroscedastic.

**ARIMAX (0,2,0) Forecasting**: Extend workfile size (from 1994-2016) by double clicking the range> provide original values in ddlicences and ddrainfall from 2013-2016>Quick >estimate equation> ddcpue ddlicences ddrainfall > Forecast> Forecast sample (1994-2016)>ok>

Associated excel file to determine MAPE, RAMSE, MAE etc. of the year 2014-2016.

**Sample 1994-2016:**

**Unit root test**: All variables have unit root; 1st difference did not remove unit root. So 2nd difference of all variables was taken.

**Lag selection**: Lag 4 was selected for granger causality test

**Granger causality test**

Pairwise Granger Causality Tests
Date: 03/10/21 Time: 22:09
Sample: 1996 2016
Lags: 4

| Null Hypothesis: | Obs | F-Statistic | Prob. |
|---|---|---|---|
| DDLICENCES does not Granger Cause DDCPUE | 17 | 1.40950 | 0.3142 |
| DDCPUE does not Granger Cause DDLICENCES | | 2.13250 | 0.1681 |
| DDPRICE does not Granger Cause DDCPUE | 17 | 0.09332 | 0.9818 |
| DDCPUE does not Granger Cause DDPRICE | | 1.41820 | 0.3117 |
| DDRAINFALL does not Granger Cause DDCPUE | 17 | 0.41164 | 0.7960 |
| DDCPUE does not Granger Cause DDRAINFALL | | 0.71170 | 0.6066 |
| DDTEMPERATURE does not Granger Cause DDCPUE | 17 | 0.39016 | 0.8103 |
| DDCPUE does not Granger Cause DDTEMPERATURE | | 1.66329 | 0.2502 |
| DDSTREAMFLOW does not Granger Cause DDCPUE | 17 | 0.57434 | 0.6894 |
| DDCPUE does not Granger Cause DDSTREAMFLOW | | 0.71239 | 0.6062 |
| DDSTREAMWATERLEVEL does not Granger Cause DDCPUE | 17 | 0.39222 | 0.8090 |
| DDCPUE does not Granger Cause DDSTREAMWATERLEVEL | | 0.71005 | 0.6075 |

No reverse causality was found.

**Test for multicollinearity**:

**Coefficients**[a]

| | | Collinearity Statistics | |
|---|---|---|---|
| Model | | Tolerance | VIF |
| 1 | ddlicence | .402 | 2.485 |
| | ddprice | .347 | 2.882 |
| | ddrainfall | .234 | 4.277 |
| | ddtemperature | .544 | 1.837 |
| | ddstreamflow | .097 | 10.266 |
| | ddstreamwaterlevel | .082 | 12.256 |

a. Dependent Variable: ddcpue

Here multicollinearity is present between streamflow and Stream water level. Tolerance is less than 0.1, VIF is more than 10.

Result of including streamflow and excluding stream water level in the model:

**Model Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate | Change Statistics R Square Change | F Change | df1 | df2 | Sig. F Change |
|---|---|---|---|---|---|---|---|---|---|
| 1 | .774[a] | .600 | .474 | .008843318 | .600 | 4.791 | 5 | 16 | .007 |

a. Predictors: (Constant), ddstreamflow, ddlicence, ddtemperature, ddprice, ddrainfall

Result of including stream water level and excluding streamflow in the model:

**Model Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate | Change Statistics R Square Change | F Change | df1 | df2 | Sig. F Change |
|---|---|---|---|---|---|---|---|---|---|
| 1 | .754[a] | .569 | .434 | .009173304 | .569 | 4.226 | 5 | 16 | .012 |

a. Predictors: (Constant), ddstreamwaterlevel, ddlicence, ddtemperature, ddprice, ddrainfall

So I will take streamflow and delete streamwaterlevel from the analysis

**Regression Test :**

**Forward regression**:

**Coefficients[a,b]**

| Model | | Unstandardized Coefficients B | Std. Error | Standardized Coefficients Beta | t | Sig. |
|---|---|---|---|---|---|---|
| 1 | ddlicence | .002 | .000 | .415 | 4.185 | .000 |
| | ddrainfall | 5.92E-6 | 1.56E-6 | .457 | 3.781 | .001 |

a. Dependent Variable: ddcpue

b. Linear Regression through the Origin

**Excluded Variables[a,b]**

| Model | | Beta In | t | Sig. | Partial Correlation | Collinearity Statistics Tolerance |
|---|---|---|---|---|---|---|
| 1 | ddprice | 4.71E-7[c] | .107 | .915 | .137 | .807 |

| | | | | | |
|---|---|---|---|---|---|
| | ddtemperature | -.154[c] | -.795 | .436 | -.179 | .929 |
| | ddstreamflow | .142[c] | .562 | .581 | .128 | .558 |

a. Dependent Variable: ddcpue

b. Linear Regression through the Origin

c. Predictors in the Model: ddlicence, ddrainfall

**Regression Eviews**: ddcpue ddlicences ddrainfall

Dependent Variable: DDCPUE
Method: Least Squares
Date: 03/11/21 Time: 13:04
Sample: 1996 2016
Included observations: 21

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| DDLICENCES | 0.002083 | 0.000498 | 4.185305 | 0.0005 |
| DDRAINFALL | 5.92E-06 | 1.56E-06 | 3.780882 | 0.0013 |

| | | | |
|---|---|---|---|
| R-squared | 0.552148 | Mean dependent var | -0.001084 |
| Adjusted R-squared | 0.528577 | S.D. dependent var | 0.012226 |
| S.E. of regression | 0.008394 | Akaike info criterion | -6.632131 |
| Sum squared resid | 0.001339 | Schwarz criterion | -6.532653 |
| Log likelihood | 71.63738 | Hannan-Quinn criter. | -6.610542 |
| Durbin-Watson stat | 2.459192 | | |

Created a dummy variable and interacted with DDlicences and DDrainfall from 2015:

ddcpue ddlicences ddrainfall dummyddlicences dummyddrainfall

Dependent Variable: DDCPUE
Method: Least Squares
Date: 03/28/21 Time: 00:23
Sample: 1996 2016
Included observations: 21

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| DDLICENCES | 0.002173 | 0.000536 | 4.053180 | 0.0008 |
| DDRAINFALL | 6.04E-06 | 1.66E-06 | 3.640201 | 0.0020 |
| DUMMYDDLICENCES | -0.004544 | 0.003944 | -1.152115 | 0.2652 |
| DUMMYDDRAINFALL | 1.68E-05 | 1.74E-05 | 0.964796 | 0.3482 |

| | | | |
|---|---|---|---|
| R-squared | 0.584619 | Mean dependent var | -0.001084 |
| Adjusted R-squared | 0.511317 | S.D. dependent var | 0.012226 |
| S.E. of regression | 0.008547 | Akaike info criterion | -6.516921 |
| Sum squared resid | 0.001242 | Schwarz criterion | -6.317964 |
| Log likelihood | 72.42767 | Hannan-Quinn criter. | -6.473742 |
| Durbin-Watson stat | 2.384817 | | |

Here ‘dummy’ variable was omitted as the variables is collinear, In the regression, the interacted dummy term for ddlicences and ddrainfall are not significant, hence dummy terms will be removed from the regression and rerun the model.

Dependent Variable: DDCPUE
Method: Least Squares
Date: 03/28/21 Time: 00:24
Sample: 1996 2016
Included observations: 21

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| DDLICENCES | 0.002083 | 0.000498 | 4.185305 | 0.0005 |
| DDRAINFALL | 5.92E-06 | 1.56E-06 | 3.780882 | 0.0013 |

| | | | |
|---|---|---|---|
| R-squared | 0.552148 | Mean dependent var | -0.001084 |
| Adjusted R-squared | 0.528577 | S.D. dependent var | 0.012226 |
| S.E. of regression | 0.008394 | Akaike info criterion | -6.632131 |
| Sum squared resid | 0.001339 | Schwarz criterion | -6.532653 |
| Log likelihood | 71.63738 | Hannan-Quinn criter. | -6.610542 |
| Durbin-Watson stat | 2.459192 | | |

## Unit root test of residual

Null Hypothesis: R has a unit root
Exogenous: Constant
Lag Length: 4 (Automatic - based on SIC, maxlag=4)

| | | t-Statistic | Prob.* |
|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | -5.275888 | 0.0008 |
| Test critical values: | 1% level | -3.920350 | |
| | 5% level | -3.065585 | |
| | 10% level | -2.673459 | |

*MacKinnon (1996) one-sided p-values.
Warning: Probabilities and critical values calculated for 20 observations and may not be accurate for a sample size of 16

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(R)
Method: Least Squares
Date: 03/15/21 Time: 22:44
Sample (adjusted): 2001 2016
Included observations: 16 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| R(-1) | -4.288994 | 0.812943 | -5.275888 | 0.0004 |
| D(R(-1)) | 2.376983 | 0.650827 | 3.652249 | 0.0044 |
| D(R(-2)) | 1.749649 | 0.521327 | 3.356146 | 0.0073 |
| D(R(-3)) | 1.268770 | 0.350618 | 3.618664 | 0.0047 |
| D(R(-4)) | 0.535634 | 0.200796 | 2.667562 | 0.0236 |
| C | 1.13E-05 | 0.001131 | 0.010023 | 0.9922 |

| | | | |
|---|---|---|---|
| R-squared | 0.916359 | Mean dependent var | -0.000677 |
| Adjusted R-squared | 0.874539 | S.D. dependent var | 0.012433 |
| S.E. of regression | 0.004404 | Akaike info criterion | -7.732691 |
| Sum squared resid | 0.000194 | Schwarz criterion | -7.442970 |
| Log likelihood | 67.86153 | Hannan-Quinn criter. | -7.717855 |
| F-statistic | 21.91174 | Durbin-Watson stat | 1.896630 |
| Prob(F-statistic) | 0.000043 | | |

Residual does not have unit root.

**Serial correlation test**: EViews

Quick>estimate equation> ddcpue ddlicences ddrainfall >ok>view tab> residual diagnostics>correlogram and Q-statistics (Ljung-Box test) >lag selection (12)> ok.

Date: 03/11/21 Time: 13:11
Sample: 1996 2016
Included observations: 21

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|---|---|
| | | 1 | -0.372 | -0.372 | 3.3454 | 0.067 |
| | | 2 | -0.103 | -0.280 | 3.6134 | 0.164 |
| | | 3 | 0.207 | 0.067 | 4.7601 | 0.190 |
| | | 4 | -0.489 | -0.500 | 11.557 | 0.021 |
| | | 5 | 0.121 | -0.357 | 12.001 | 0.035 |
| | | 6 | 0.349 | 0.141 | 15.926 | 0.014 |
| | | 7 | -0.198 | 0.116 | 17.282 | 0.016 |
| | | 8 | 0.125 | -0.041 | 17.863 | 0.022 |
| | | 9 | 0.001 | -0.024 | 17.863 | 0.037 |
| | | 10 | -0.335 | -0.077 | 22.800 | 0.012 |
| | | 11 | 0.158 | -0.058 | 24.013 | 0.013 |
| | | 12 | 0.049 | -0.102 | 24.142 | 0.019 |

**Selection of MA and AR term:**

ddcpue ddlicences ddrainfall ar(4) ma(4)

Dependent Variable: DDCPUE
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 03/11/21 Time: 13:09
Sample: 1996 2016
Included observations: 21
Convergence achieved after 25 iterations
Coefficient covariance computed using outer product of gradients

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| DDLICENCES | 0.001751 | 0.000423 | 4.138181 | 0.0008 |
| DDRAINFALL | 4.48E-06 | 1.01E-06 | 4.444770 | 0.0004 |
| AR(4) | -0.707865 | 0.283873 | -2.493597 | 0.0240 |
| MA(4) | -0.109640 | 0.465917 | -0.235321 | 0.8169 |
| SIGMASQ | 3.14E-05 | 1.44E-05 | 2.182308 | 0.0443 |

| | | | |
|---|---|---|---|
| R-squared | 0.779751 | Mean dependent var | -0.001084 |
| Adjusted R-squared | 0.724689 | S.D. dependent var | 0.012226 |
| S.E. of regression | 0.006415 | Akaike info criterion | -6.892905 |
| Sum squared resid | 0.000658 | Schwarz criterion | -6.644209 |
| Log likelihood | 77.37550 | Hannan-Quinn criter. | -6.838932 |
| Durbin-Watson stat | 2.368970 | | |

| | | | | |
|---|---|---|---|---|
| Inverted AR Roots | .65-.65i | .65-.65i | -.65+.65i | -.65+.65i |
| Inverted MA Roots | .58 | .00-.58i | -.00+.58i | -.58 |

**Serial correlation test:**

The residuals are flat and no serial correlation.

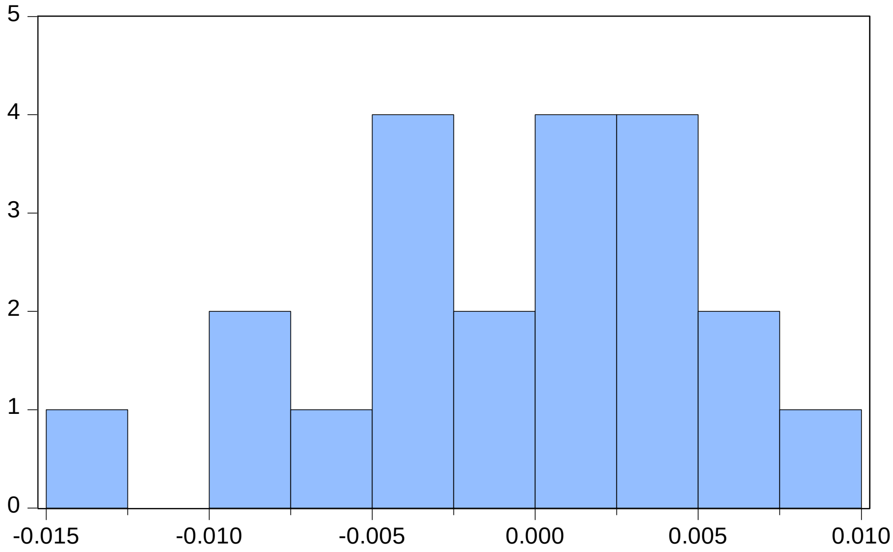
Date: 03/11/21 Time: 13:16
Sample: 1996 2016
Included observations: 21
Q-statistic probabilities adjusted for 2 ARMA terms

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob* |
|---|---|---|---|---|---|---|
| | | 1 | -0.346 | -0.346 | 2.8937 | |
| | | 2 | -0.070 | -0.215 | 3.0169 | |
| | | 3 | -0.078 | -0.217 | 3.1822 | 0.074 |
| | | 4 | 0.129 | -0.005 | 3.6560 | 0.161 |
| | | 5 | -0.148 | -0.161 | 4.3156 | 0.229 |
| | | 6 | 0.326 | 0.280 | 7.7333 | 0.102 |
| | | 7 | -0.184 | 0.040 | 8.8959 | 0.113 |
| | | 8 | -0.020 | 0.008 | 8.9102 | 0.179 |
| | | 9 | -0.124 | -0.131 | 9.5340 | 0.217 |
| | | 10 | 0.084 | -0.138 | 9.8459 | 0.276 |
| | | 11 | -0.144 | -0.230 | 10.851 | 0.286 |
| | | 12 | 0.177 | -0.099 | 12.527 | 0.251 |

*Probabilities may not be valid for this equation specification.

**Diagnostic Checking:**

**Normality test of residuals**:




Series: Residuals
Sample 1996 2016
Observations 21

| | |
|---|---|
| Mean | -0.000695 |
| Median | 4.17e-05 |
| Maximum | 0.008957 |
| Minimum | -0.013703 |
| Std. Dev. | 0.005693 |
| Skewness | -0.417700 |
| Kurtosis | 2.610674 |
| Jarque-Bera | 0.743283 |
| Probability | 0.689601 |

**Breusch-Godfrey Serial Correlation LM Test:**

Lag (2)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 2.436706 | Prob. F(2,17) | 0.1174 |
| Obs*R-squared | 4.678815 | Prob. Chi-Square(2) | 0.0964 |

Lag (4)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 2.293814 | Prob. F(4,15) | 0.1399 |
| Obs*R-squared | 4.819977 | Prob. Chi-Square(4) | 0.1036 |

Lag (8)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 1.657339 | Prob. F(8,11) | 0.2148 |
| Obs*R-squared | 11.47765 | Prob. Chi-Square(8) | 0.1761 |

**Heteroscedasticity test:**

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 0.572965 | Prob. F(2,18) | 0.5738 |
| Obs*R-squared | 1.256900 | Prob. Chi-Square(2) | 0.5334 |
| Scaled explained SS | 0.665655 | Prob. Chi-Square(2) | 0.7169 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/11/21 Time: 13:17
Sample: 1996 2016
Included observations: 21

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 3.09E-05 | 9.70E-06 | 3.189922 | 0.0051 |
| DDLICENCES | -2.43E-06 | 2.64E-06 | -0.922140 | 0.3687 |
| DDRAINFALL | 1.60E-09 | 8.28E-09 | 0.193713 | 0.8486 |

| | | | |
|---|---|---|---|
| R-squared | 0.059852 | Mean dependent var | 3.14E-05 |
| Adjusted R-squared | -0.044608 | S.D. dependent var | 4.34E-05 |
| S.E. of regression | 4.44E-05 | Akaike info criterion | -17.07712 |
| Sum squared resid | 3.54E-08 | Schwarz criterion | -16.92790 |
| Log likelihood | 182.3098 | Hannan-Quinn criter. | -17.04474 |
| F-statistic | 0.572965 | Durbin-Watson stat | 1.117942 |
| Prob(F-statistic) | 0.573805 | | |

**ARIMAX (4,1,4) Forecasting**: Extend workfile size (from 1996-2019) by double clicking the range> provide original values in ddlicences and ddrainfall from 2017-2019>Quick >estimate equation> ddcpue ddlicences ddrainfall ar(4) ma(4) > Forecast> Forecast sample (1996-2019)>ok>

Associated excel file to determine MAPE, RAMSE, MAE etc. of the year 2017-2019.

**Regression model:** 3 years lag of Env. variables

**Sample 1990-2010:**

**Multicollinearity test:**

**Coefficients[a]**

| Model | | Collinearity Statistics | |
|---|---|---|---|
| | | Tolerance | VIF |
| 1 | licence | .518 | 1.930 |
| | price | .676 | 1.479 |
| | rainfall | .289 | 3.460 |
| | temperature | .742 | 1.348 |
| | streamflow | .054 | 18.417 |
| | streamwaterlevel | .089 | 11.267 |

a. Dependent Variable: cpue

**Collinearity Diagnostics[a]**

| Model | Dimension | Eigenvalue | Condition Index | Variance Proportions | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | (Constant) | licence | price | rainfall | temperature | streamflow | streamwaterlevel |
| 1 | 1 | 6.525 | 1.000 | .00 | .00 | .00 | .00 | .00 | .00 | .00 |
| | 2 | .361 | 4.254 | .00 | .00 | .03 | .00 | .00 | .03 | .00 |
| | 3 | .052 | 11.208 | .00 | .01 | .60 | .02 | .00 | .03 | .00 |
| | 4 | .036 | 13.403 | .00 | .31 | .16 | .22 | .00 | .01 | .00 |
| | 5 | .021 | 17.423 | .00 | .16 | .06 | .43 | .00 | .00 | .15 |
| | 6 | .004 | 39.371 | .00 | .49 | .14 | .32 | .00 | .92 | .84 |
| | 7 | 5.651E-5 | 339.823 | 1.00 | .03 | .02 | .02 | 1.00 | .01 | .00 |

a. Dependent Variable: cpue

Here, multicollinearity is present between streamflow and Stream water level. Tolerance is less than 0.1, VIF is more than 10.

So, run the analysis two-times: first time, with all the variables excluding stream water level and for the second time, with all the variable excluding streamflow. Then compared results of the two models, specifically R squares and P values. Model including all other variables excluding streamflow showed improved result than the other. So, I deleted streamflow from the model.

Result of including streamflow and excluding stream water level in the model:

**Model Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | .541[a] | .292 | -.003 | .006208518 |

a. Predictors: (Constant), streamflow, price, temperature, licence, rainfall

Result of including stream water level and excluding streamflow in the model:

**Model Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | .547[a] | .300 | .008 | .006175941 |

a. Predictors: (Constant), streamwaterlevel, licence, price, temperature, rainfall

MLR:

regress cpue licences price rainfall temperature streamwaterlevel

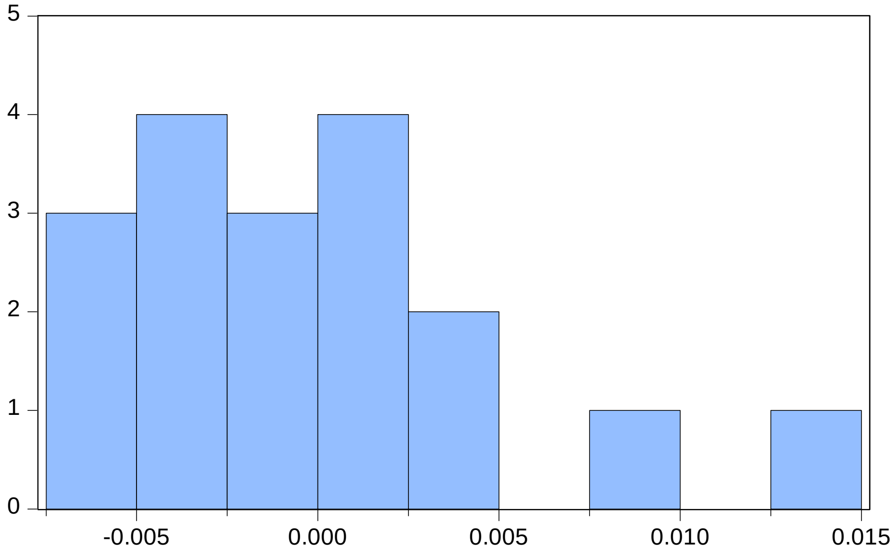
Dependent Variable: CPUE
Method: Least Squares
Date: 03/22/21 Time: 22:04
Sample: 1993 2010
Included observations: 18

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| LICENCES | -0.001098 | 0.000607 | -1.808567 | 0.0456 |
| PRICE | 5.89E-08 | 4.00E-08 | 1.471868 | 0.1668 |
| RAINFALL | -2.04E-06 | 3.63E-06 | -0.561568 | 0.5847 |
| TEMPERATURE | 0.003621 | 0.005431 | 0.666676 | 0.5176 |
| STREAMWATERLEVEL | 0.005764 | 0.010081 | 0.571714 | 0.5781 |
| C | -0.048518 | 0.136467 | -0.355532 | 0.7284 |

| | | | |
|---|---|---|---|
| R-squared | 0.299734 | Mean dependent var | 0.035762 |
| Adjusted R-squared | 0.007957 | S.D. dependent var | 0.006201 |
| S.E. of regression | 0.006176 | Akaike info criterion | -7.075109 |
| Sum squared resid | 0.000458 | Schwarz criterion | -6.778319 |
| Log likelihood | 69.67598 | Hannan-Quinn criter. | -7.034186 |
| F-statistic | 1.027270 | Durbin-Watson stat | 2.058828 |
| Prob(F-statistic) | 0.444462 | | |

**Diagnostic checking:**

**Normality test**:




| | |
|---|---|
| Series: Residuals | |
| Sample 1993 2010 | |
| Observations 18 | |
| Mean | -2.12e-18 |
| Median | -0.000639 |
| Maximum | 0.013561 |
| Minimum | -0.006842 |
| Std. Dev. | 0.005189 |
| Skewness | 0.964754 |
| Kurtosis | 3.745228 |
| Jarque-Bera | 3.208777 |
| Probability | 0.201012 |

## Breusch-Godfrey Serial Correlation LM Test:

Lag (2)
Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.094178 | Prob. F(2,9) | 0.9110 |
| Obs*R-squared | 0.368990 | Prob. Chi-Square(2) | 0.8315 |

Lag(4)
Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.372747 | Prob. F(4,7) | 0.8214 |
| Obs*R-squared | 3.160735 | Prob. Chi-Square(4) | 0.5313 |

Lag(8)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.344533 | Prob. F(8,3) | 0.8986 |
| Obs*R-squared | 8.618921 | Prob. Chi-Square(8) | 0.3755 |

## Heteroscedasticity test:

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 0.690328 | Prob. F(5,12) | 0.6403 |
| Obs*R-squared | 4.020900 | Prob. Chi-Square(5) | 0.5464 |
| Scaled explained SS | 2.452953 | Prob. Chi-Square(5) | 0.7836 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/22/21 Time: 22:52
Sample: 1993 2010
Included observations: 18

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | -0.000590 | 0.001005 | -0.586706 | 0.5683 |
| LICENCES | -1.89E-06 | 4.47E-06 | -0.422642 | 0.6800 |
| PRICE | -3.55E-10 | 2.94E-10 | -1.207143 | 0.2506 |
| RAINFALL | 9.61E-09 | 2.67E-08 | 0.359982 | 0.7251 |
| TEMPERATURE | 2.83E-05 | 4.00E-05 | 0.708604 | 0.4921 |
| STREAMWATERLEVEL | -6.46E-05 | 7.42E-05 | -0.870597 | 0.4011 |

| | | | |
|---|---|---|---|
| R-squared | 0.223383 | Mean dependent var | 2.54E-05 |
| Adjusted R-squared | -0.100207 | S.D. dependent var | 4.34E-05 |
| S.E. of regression | 4.55E-05 | Akaike info criterion | -16.89771 |
| Sum squared resid | 2.48E-08 | Schwarz criterion | -16.60092 |
| Log likelihood | 158.0794 | Hannan-Quinn criter. | -16.85678 |
| F-statistic | 0.690328 | Durbin-Watson stat | 2.257637 |
| Prob(F-statistic) | 0.640323 | | |

**Sample 1992-2013:**

**Multicollinearity test**:

### Coefficients[a]

| Model | | Collinearity Statistics Tolerance | VIF |
|---|---|---|---|
| 1 | licence | .505 | 1.982 |
| | price | .852 | 1.174 |
| | rainfall | .363 | 2.756 |
| | temperature | .937 | 1.067 |
| | streamflow | .058 | 17.202 |
| | streamwaterlevel | .065 | 15.463 |

a. Dependent Variable: cpue

### Collinearity Diagnostics[a]

| Dimension | Eigenvalue | Condition Index | Variance Proportions (Constant) | licence | price | rainfall | temperature | streamflow | streamwaterlevel |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 6.508 | 1.000 | .00 | .00 | .00 | .00 | .00 | .00 | .00 |
| 2 | .363 | 4.237 | .00 | .00 | .03 | .00 | .00 | .03 | .00 |
| 3 | .067 | 9.875 | .00 | .01 | .57 | .05 | .00 | .04 | .00 |
| 4 | .039 | 12.856 | .00 | .33 | .39 | .10 | .00 | .01 | .00 |
| 5 | .019 | 18.428 | .00 | .10 | .00 | .82 | .00 | .00 | .07 |
| 6 | .004 | 42.968 | .01 | .54 | .00 | .02 | .01 | .91 | .92 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 7 | | 9.955E-5 | 255.695 | .99 | .02 | .00 | .00 | .99 | .00 | .00 |

a. Dependent Variable: cpue

Here, multicollinearity is present between streamflow and Stream water level. Tolerance is less than 0.1, VIF is more than 10.

So, run the analysis two-times: first time, with all the variables excluding stream water level and for the second time, with all the variable excluding streamflow. Then compared results of the two models, specifically R squares and *P* values. Model including all other variables excluding streamflow showed improved result than the other. So, I deleted streamflow from the model.

Result of including streamflow and excluding stream water level in the model:

**Model Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate | Change Statistics: R Square Change | F Change | df1 | df2 | Sig. F Change |
|---|---|---|---|---|---|---|---|---|---|
| 1 | .591[a] | .349 | .099 | .006067745 | .349 | 1.394 | 5 | 13 | .289 |

a. Predictors: (Constant), streamflow, price, temperature, licence, rainfall

Result of including stream water level and excluding streamflow in the model:

**Model Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate | Change Statistics: R Square Change | F Change | df1 | df2 | Sig. F Change |
|---|---|---|---|---|---|---|---|---|---|
| 1 | .618[a] | .383 | .145 | .005909553 | .383 | 1.611 | 5 | 13 | .226 |

a. Predictors: (Constant), streamwaterlevel, licence, temperature, price, rainfall

**MLR:**

regress cpue licences price rainfall temperature streamwaterlevel

Dependent Variable: CPUE
Method: Least Squares
Date: 03/22/21 Time: 22:11
Sample: 1995 2013
Included observations: 19

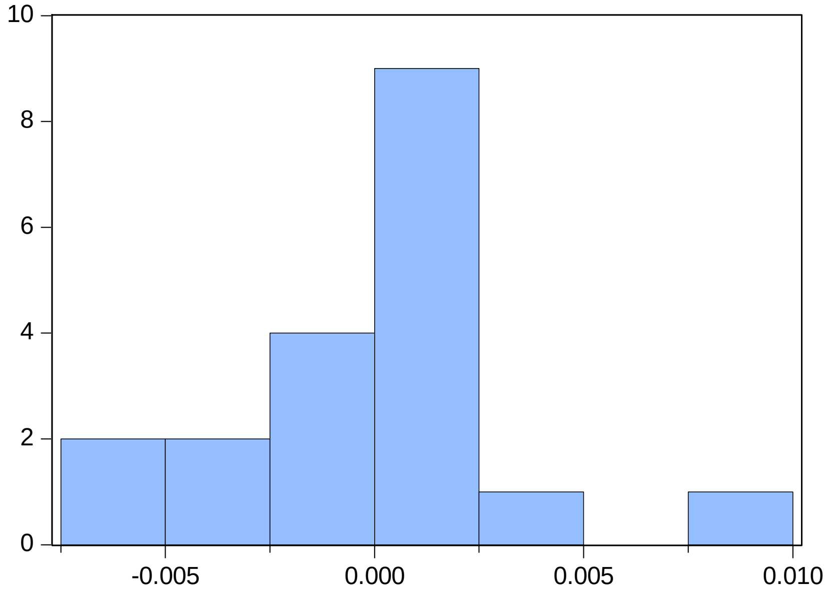
| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| LICENCES | -0.000845 | 0.000563 | -1.501174 | 0.1572 |
| PRICE | 8.03E-08 | 3.57E-08 | 2.249503 | 0.0424 |
| RAINFALL | -5.45E-06 | 3.52E-06 | -1.549445 | 0.1453 |

| | | | | |
|---|---|---|---|---|
| TEMPERATURE | 0.000368 | 0.003783 | 0.097162 | 0.9241 |
| STREAMWATERLEVEL | 0.014348 | 0.009983 | 1.437291 | 0.1743 |
| C | 0.028749 | 0.097132 | 0.295978 | 0.7719 |

| | | | |
|---|---|---|---|
| R-squared | 0.382539 | Mean dependent var | 0.036103 |
| Adjusted R-squared | 0.145054 | S.D. dependent var | 0.006391 |
| S.E. of regression | 0.005910 | Akaike info criterion | -7.172404 |
| Sum squared resid | 0.000454 | Schwarz criterion | -6.874160 |
| Log likelihood | 74.13784 | Hannan-Quinn criter. | -7.121929 |
| F-statistic | 1.610791 | Durbin-Watson stat | 1.761983 |
| Prob(F-statistic) | 0.225677 | | |

## Diagnostic Checking:

## Normality test:




| | |
|---|---|
| Series: Residuals | |
| Sample 1995 2013 | |
| Observations 19 | |
| Mean | 2.87e-18 |
| Median | 0.000432 |
| Maximum | 0.008935 |
| Minimum | -0.005316 |
| Std. Dev. | 0.003246 |
| Skewness | 0.686420 |
| Kurtosis | 4.398612 |
| Jarque-Bera | 3.040639 |
| Probability | 0.218642 |

## Breusch-Godfrey Serial Correlation LM Test:

Lag (2)
Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.133767 | Prob. F(2,11) | 0.8762 |
| Obs*R-squared | 0.451131 | Prob. Chi-Square(2) | 0.7981 |

Lag (4)
Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.558431 | Prob. F(4,9) | 0.6987 |
| Obs*R-squared | 3.777977 | Prob. Chi-Square(4) | 0.4369 |

Lag (8)
Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.286961 | Prob. F(8,5) | 0.9426 |
| Obs*R-squared | 5.978611 | Prob. Chi-Square(8) | 0.6496 |

## Heteroscedasticity Test:

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 0.054886 | Prob. F(5,13) | 0.9976 |
| Obs*R-squared | 0.392795 | Prob. Chi-Square(5) | 0.9955 |
| Scaled explained SS | 0.312477 | Prob. Chi-Square(5) | 0.9974 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/22/21 Time: 22:58
Sample: 1995 2013
Included observations: 19

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.000142 | 0.000375 | 0.379695 | 0.7103 |
| LICENCES | -5.86E-07 | 2.03E-06 | -0.288313 | 0.7777 |
| PRICE | 4.13E-11 | 1.45E-10 | 0.285171 | 0.7800 |
| RAINFALL | 2.54E-09 | 1.27E-08 | 0.200468 | 0.8442 |
| TEMPERATURE | -5.25E-06 | 1.45E-05 | -0.363377 | 0.7222 |
| STREAMWATERLEVEL | -6.10E-06 | 3.54E-05 | -0.172346 | 0.8658 |

| | | | |
|---|---|---|---|
| R-squared | 0.020673 | Mean dependent var | 9.98E-06 |
| Adjusted R-squared | -0.355991 | S.D. dependent var | 1.89E-05 |
| S.E. of regression | 2.20E-05 | Akaike info criterion | -18.35756 |
| Sum squared resid | 6.30E-09 | Schwarz criterion | -18.05932 |
| Log likelihood | 180.3968 | Hannan-Quinn criter. | -18.30709 |
| F-statistic | 0.054886 | Durbin-Watson stat | 2.188735 |
| Prob(F-statistic) | 0.997613 | | |

## Sample 1994-2016:

## Multicollinearity test:

### Coefficients[a]

| Model | | Collinearity Statistics Tolerance | VIF |
|---|---|---|---|
| 1 | licence | .529 | 1.889 |
| | price | .724 | 1.381 |
| | rainfall | .386 | 2.591 |
| | temperature | .872 | 1.146 |
| | streamflow | .063 | 15.772 |
| | streamwaterlevel | .064 | 15.648 |

a. Dependent Variable: cpue

### Collinearity Diagnostics[a]

| | | Variance Proportions |
|---|---|---|

| Model | Dimension | Eigenvalue | Condition Index | (Constant) | licence | price | rainfall | temperature | streamflow | streamwaterlevel |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 6.501 | 1.000 | .00 | .00 | .00 | .00 | .00 | .00 | .00 |
| | 2 | .371 | 4.186 | .00 | .01 | .04 | .00 | .00 | .03 | .00 |
| | 3 | .066 | 9.961 | .00 | .02 | .44 | .03 | .00 | .05 | .00 |
| | 4 | .038 | 13.163 | .00 | .48 | .50 | .06 | .00 | .01 | .00 |
| | 5 | .021 | 17.567 | .00 | .06 | .01 | .91 | .00 | .01 | .04 |
| | 6 | .004 | 41.253 | .00 | .41 | .00 | .00 | .00 | .89 | .95 |
| | 7 | 8.885E-5 | 270.490 | .99 | .02 | .00 | .00 | .99 | .00 | .00 |

a. Dependent Variable: cpue

Here, multicollinearity is present between streamflow and Stream water level. Tolerance is less than 0.1, VIF is more than 10.

So, run the analysis two-times: first time, with all the variables excluding stream water level and for the second time, with all the variable excluding streamflow. Then compared results of the two models, specifically R squares and P values. Model including all other variables excluding streamflow showed improved result than the other. So, I deleted streamflow from the model.

Result of including streamflow and excluding stream water level in the model:

**Model Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate | Change Statistics | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | R Square Change | F Change | df1 | df2 | Sig. F Change |
| 1 | .778[a] | .605 | .463 | .004429200 | .605 | 4.281 | 5 | 14 | .014 |

a. Predictors: (Constant), streamflow, licence, temperature, price, rainfall

Result of including stream water level and excluding streamflow in the model:

**Model Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate | Change Statistics | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | R Square Change | F Change | df1 | df2 | Sig. F Change |
| 1 | .821[a] | .674 | .557 | .004023732 | .674 | 5.780 | 5 | 14 | .004 |

a. Predictors: (Constant), streamwaterlevel, licence, temperature, price, rainfall

**MLR:**

regress cpue licences price rainfall temperature streamwaterlevel

Dependent Variable: CPUE
Method: Least Squares
Date: 03/22/21 Time: 22:38
Sample: 1997 2016
Included observations: 20

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| LICENCES | -0.000814 | 0.000365 | -2.228720 | 0.0427 |
| PRICE | 1.24E-07 | 2.46E-08 | 5.040874 | 0.0002 |
| RAINFALL | -4.17E-06 | 2.30E-06 | -1.810349 | 0.0918 |
| TEMPERATURE | 0.000227 | 0.002643 | 0.085956 | 0.9327 |
| STREAMWATERLEVEL | 0.017270 | 0.006397 | 2.699745 | 0.0173 |
| C | 0.020117 | 0.068441 | 0.293931 | 0.7731 |

| | | | |
|---|---|---|---|
| R-squared | 0.673672 | Mean dependent var | 0.035272 |
| Adjusted R-squared | 0.557126 | S.D. dependent var | 0.006046 |
| S.E. of regression | 0.004024 | Akaike info criterion | -7.949889 |
| Sum squared resid | 0.000227 | Schwarz criterion | -7.651169 |
| Log likelihood | 85.49889 | Hannan-Quinn criter. | -7.891576 |
| F-statistic | 5.780316 | Durbin-Watson stat | 1.948757 |
| Prob(F-statistic) | 0.004241 | | |

Created a dummy variable and interact with licences, price and streamwaterlevel from 2015:

Dependent Variable: CPUE
Method: Least Squares
Date: 03/28/21 Time: 00:46
Sample: 1997 2016
Included observations: 20

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| LICENCES | -0.000763 | 0.000456 | -1.673530 | 0.1224 |
| PRICE | 1.09E-07 | 2.71E-08 | 4.018093 | 0.0020 |
| RAINFALL | -4.24E-06 | 2.45E-06 | -1.728628 | 0.1118 |
| TEMPERATURE | 4.83E-05 | 0.002716 | 0.017796 | 0.9861 |
| STREAMFLOW | -4.22E-09 | 7.30E-09 | -0.578299 | 0.5747 |
| STREAMWATERLEVEL | 0.024408 | 0.016536 | 1.476102 | 0.1680 |
| DUMMYLICENCES | -0.002957 | 0.002384 | -1.240452 | 0.2406 |
| DUMMYPRICE | 2.98E-07 | 2.62E-07 | 1.139306 | 0.2788 |
| C | 0.024452 | 0.069884 | 0.349899 | 0.7330 |

| | | | |
|---|---|---|---|
| R-squared | 0.735318 | Mean dependent var | 0.035272 |
| Adjusted R-squared | 0.542822 | S.D. dependent var | 0.006046 |
| S.E. of regression | 0.004088 | Akaike info criterion | -7.859264 |
| Sum squared resid | 0.000184 | Schwarz criterion | -7.411185 |
| Log likelihood | 87.59264 | Hannan-Quinn criter. | -7.771795 |
| F-statistic | 3.819916 | Durbin-Watson stat | 2.199096 |
| Prob(F-statistic) | 0.021704 | | |

Here 'dummy' variable itself and its interaction dummy term 'dummystreamwaterlevel' were omitted as the variables are exactly collinear. In the regression, dummylicences and dummyprice are not significant, hence the interacted dummy terms will be removed from the regression and rerun the model.

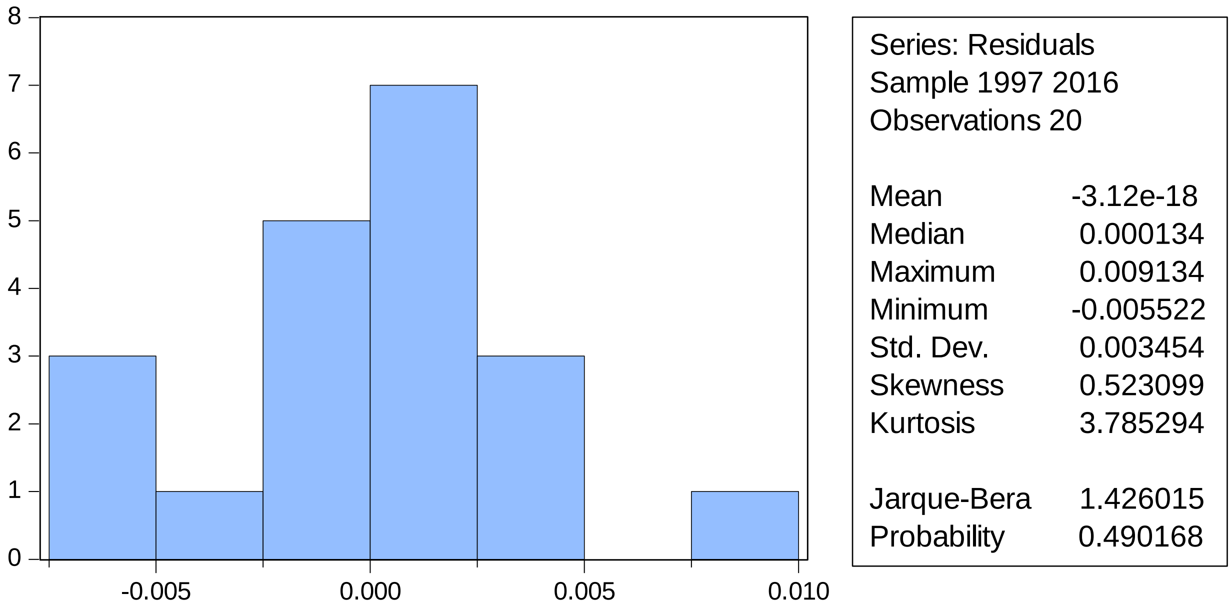
Dependent Variable: CPUE
Method: Least Squares
Date: 03/22/21 Time: 22:38
Sample: 1997 2016
Included observations: 20

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| LICENCES | -0.000814 | 0.000365 | -2.228720 | 0.0427 |
| PRICE | 1.24E-07 | 2.46E-08 | 5.040874 | 0.0002 |
| RAINFALL | -4.17E-06 | 2.30E-06 | -1.810349 | 0.0918 |
| TEMPERATURE | 0.000227 | 0.002643 | 0.085956 | 0.9327 |
| STREAMWATERLEVEL | 0.017270 | 0.006397 | 2.699745 | 0.0173 |
| C | 0.020117 | 0.068441 | 0.293931 | 0.7731 |

| | | | |
|---|---|---|---|
| R-squared | 0.673672 | Mean dependent var | 0.035272 |
| Adjusted R-squared | 0.557126 | S.D. dependent var | 0.006046 |
| S.E. of regression | 0.004024 | Akaike info criterion | -7.949889 |
| Sum squared resid | 0.000227 | Schwarz criterion | -7.651169 |
| Log likelihood | 85.49889 | Hannan-Quinn criter. | -7.891576 |
| F-statistic | 5.780316 | Durbin-Watson stat | 1.948757 |
| Prob(F-statistic) | 0.004241 | | |

## Diagnostic Checking:

### Normality Test:




### Breusch-Godfrey Serial Correlation LM Test:

Lag (2)
Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.224324 | Prob. F(2,12) | 0.8023 |

| | | | |
|---|---|---|---|
| Obs*R-squared | 0.720798 | Prob. Chi-Square(2) | 0.6974 |

Lag (4)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.107686 | Prob. F(4,10) | 0.9771 |
| Obs*R-squared | 0.825912 | Prob. Chi-Square(4) | 0.9349 |

Lag (8)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.308938 | Prob. F(8,6) | 0.9359 |
| Obs*R-squared | 5.834870 | Prob. Chi-Square(8) | 0.6657 |

**Heteroscedasticity test:**

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 0.028957 | Prob. F(5,14) | 0.9995 |
| Obs*R-squared | 0.204718 | Prob. Chi-Square(5) | 0.9991 |
| Scaled explained SS | 0.139699 | Prob. Chi-Square(5) | 0.9996 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/22/21 Time: 22:40
Sample: 1997 2016
Included observations: 20

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.000124 | 0.000383 | 0.323519 | 0.7511 |
| LICENCES | -2.73E-07 | 2.04E-06 | -0.133847 | 0.8954 |
| PRICE | -8.21E-12 | 1.37E-10 | -0.059764 | 0.9532 |
| RAINFALL | -2.54E-10 | 1.29E-08 | -0.019693 | 0.9846 |
| TEMPERATURE | -4.08E-06 | 1.48E-05 | -0.276051 | 0.7865 |
| STREAMWATERLEVEL | -7.09E-06 | 3.58E-05 | -0.198175 | 0.8458 |

| | | | |
|---|---|---|---|
| R-squared | 0.010236 | Mean dependent var | 1.13E-05 |
| Adjusted R-squared | -0.343251 | S.D. dependent var | 1.94E-05 |
| S.E. of regression | 2.25E-05 | Akaike info criterion | -18.32359 |
| Sum squared resid | 7.08E-09 | Schwarz criterion | -18.02487 |
| Log likelihood | 189.2359 | Hannan-Quinn criter. | -18.26528 |
| F-statistic | 0.028957 | Durbin-Watson stat | 2.379836 |
| Prob(F-statistic) | 0.999494 | | |

## 2. Mackay:

**Data cleaning and processing:** Box plot shows no outlier is detected.

**Year: 1990-2010**

**Check for seasonality and trend**: Line diagram showing no seasonality pattern but a steady positive secular trend for the dependent variable "cpue".

**Unit root test:** CPUE and licences do not have unit root. All other variable has unit root, 1st difference of all the series has made them stationary.

**Lag selection**: Lag 4 selected for the granger causality test for granger causality test.

**Granger Causality test:**

Pairwise Granger Causality Tests
Date: 03/11/21 Time: 16:17
Sample: 1991 2010
Lags: 4

| Null Hypothesis: | Obs | F-Statistic | Prob. |
|---|---|---|---|
| DLICENCES does not Granger Cause DCPUE | 16 | 0.46952 | 0.7575 |
| DCPUE does not Granger Cause DLICENCES | | 0.66924 | 0.6336 |
| DPRICE does not Granger Cause DCPUE | 16 | 0.71826 | 0.6057 |
| DCPUE does not Granger Cause DPRICE | | 0.18576 | 0.9385 |
| DRAINFALL does not Granger Cause DCPUE | 16 | 0.48611 | 0.7467 |
| DCPUE does not Granger Cause DRAINFALL | | 0.89309 | 0.5155 |
| DTEMPERATURE does not Granger Cause DCPUE | 16 | 0.41318 | 0.7946 |
| DCPUE does not Granger Cause DTEMPERATURE | | 0.61924 | 0.6632 |
| DSTREAMFLOW does not Granger Cause DCPUE | 16 | 0.41468 | 0.7936 |
| DCPUE does not Granger Cause DSTREAMFLOW | | 1.93181 | 0.2100 |
| DSTREAMWATERLEVEL does not Granger Cause DCPUE | 16 | 0.69364 | 0.6196 |
| DCPUE does not Granger Cause DSTREAMWATERLEVEL | | 1.07055 | 0.4381 |

No reverse causality was found.

**Test for multicollinearity**: SPSS

**Coefficients[a]**

| Model | | Collinearity Statistics Tolerance | VIF |
|---|---|---|---|
| 1 | dlicence | .496 | 2.017 |
| | dprice | .468 | 2.138 |
| | drainfall | .198 | 5.055 |
| | dtemperature | .630 | 1.588 |
| | dstreamflow | .063 | 15.968 |
| | dstreamwaterlevel | .051 | 19.540 |

a. Dependent Variable: dcpue

**Collinearity Diagnostics[a]**

| Model | Dimension | Eigenvalue | Condition Index | Variance Proportions (Constant) | dlicence | dprice | drainfall | dtemperature | dstreamflow | dstreamwaterlevel |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 2.973 | 1.000 | .00 | .00 | .00 | .02 | .02 | .01 | .01 |
| | 2 | 1.805 | 1.283 | .01 | .09 | .11 | .00 | .06 | .00 | .00 |
| | 3 | 1.053 | 1.680 | .71 | .01 | .02 | .00 | .03 | .00 | .00 |
| | 4 | .643 | 2.151 | .06 | .36 | .04 | .00 | .34 | .01 | .00 |
| | 5 | .373 | 2.823 | .13 | .08 | .49 | .09 | .51 | .00 | .00 |
| | 6 | .123 | 4.919 | .04 | .41 | .34 | .80 | .04 | .10 | .04 |
| | 7 | .030 | 9.977 | .05 | .04 | .00 | .08 | .01 | .88 | .95 |

a. Dependent Variable: dcpue

Here, multicollinearity is present in streamflow and streamwaterlevel. Tolerance is less than 0.1 and VIF is more than 10.

So, run the analysis two-times: first time, with all the variables excluding stream water level and for the second time, with all the variable excluding streamflow. Then compared results of the two models, specifically R squares and P values. Model including all other variables excluding streamflow showed improved result than the other. So, I deleted streamflow from the model.

Result of including streamflow and excluding stream water level in the model:

**Model Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate | Change Statistics R Square Change | F Change | df1 | df2 | Sig. F Change |
|---|---|---|---|---|---|---|---|---|---|
| 1 | .567[a] | .321 | .079 | .010840723 | .321 | 1.326 | 5 | 14 | .309 |

a. Predictors: (Constant), dstreamflow, dprice, dlicence, dtemperature, drainfall

Result of including stream water level and excluding streamflow in the model:

**Model Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate | Change Statistics | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | R Square Change | F Change | df1 | df2 | Sig. F Change |
| 1 | .534[a] | .286 | .030 | .011123140 | .286 | 1.119 | 5 | 14 | .394 |

a. Predictors: (Constant), dstreamwaterlevel, dlicence, dtemperature, dprice, drainfall

Model with streamflow gives better $R^2$ than streamwaterlevel. So, I have deleted streamwaterlevel from the analysis.

**Multiple Regression Test:** SPSS

**Forward stepwise:**

**Coefficients[a]**

| Model | | Unstandardized Coefficients | | Standardized Coefficients | t | Sig. | 95.0% Confidence Interval for B | |
|---|---|---|---|---|---|---|---|---|
| | | B | Std. Error | Beta | | | Lower Bound | Upper Bound |
| 1 | (Constant) | .001 | .002 | | .392 | .700 | -.004 | .006 |
| | dprice | 5.599E-8 | .000 | .458 | 2.185 | .042 | .000 | .000 |

a. Dependent Variable: dcpue

**Excluded Variables[a]**

| Model | | Beta In | t | Sig. | Partial Correlation | Collinearity Statistics Tolerance |
|---|---|---|---|---|---|---|
| 1 | dlicence | -.157[b] | -.613 | .548 | -.147 | .693 |
| | drainfall | -.140[b] | -.656 | .520 | -.157 | .999 |
| | dtemperature | -.037[b] | -.155 | .879 | -.037 | .800 |
| | dstreamwaterlevel | -.208[b] | -.988 | .337 | -.233 | .991 |

a. Dependent Variable: dcpue

b. Predictors in the Model: (Constant), dprice

**Regression in Eviws**: dcpue c dprice

Dependent Variable: DCPUE
Method: Least Squares
Date: 03/11/21 Time: 18:11
Sample: 1991 2010
Included observations: 20

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| DPRICE | 5.60E-08 | 2.56E-08 | 2.184867 | 0.0424 |
| C | 0.000905 | 0.002310 | 0.391766 | 0.6998 |

| | | | |
|---|---|---|---|
| R-squared | 0.209613 | Mean dependent var | 0.001139 |
| Adjusted R-squared | 0.165702 | S.D. dependent var | 0.011297 |
| S.E. of regression | 0.010318 | Akaike info criterion | -6.215167 |
| Sum squared resid | 0.001916 | Schwarz criterion | -6.115594 |
| Log likelihood | 64.15167 | Hannan-Quinn criter. | -6.195730 |
| F-statistic | 4.773644 | Durbin-Watson stat | 2.730524 |
| Prob(F-statistic) | 0.042366 | | |

**Unit root test for the residuals of regression model** (including dcpue c dprice):

Null Hypothesis: R has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=4)

| | | t-Statistic | Prob.* |
|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | -6.866076 | 0.0000 |
| Test critical values: | 1% level | -3.857386 | |
| | 5% level | -3.040391 | |
| | 10% level | -2.660551 | |

*MacKinnon (1996) one-sided p-values.
Warning: Probabilities and critical values calculated for 20 observations and may not be accurate for a sample size of 18

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(R)
Method: Least Squares
Date: 03/15/21 Time: 20:53
Sample (adjusted): 1993 2010
Included observations: 18 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| R(-1) | -2.335413 | 0.340138 | -6.866076 | 0.0000 |
| D(R(-1)) | 0.614240 | 0.208154 | 2.950888 | 0.0099 |
| C | -0.000593 | 0.001806 | -0.328523 | 0.7471 |

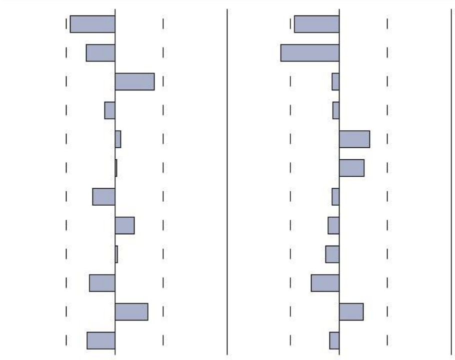
| | | | |
|---|---|---|---|
| R-squared | 0.831258 | Mean dependent var | -0.001082 |
| Adjusted R-squared | 0.808759 | S.D. dependent var | 0.017509 |
| S.E. of regression | 0.007657 | Akaike info criterion | -6.755405 |
| Sum squared resid | 0.000879 | Schwarz criterion | -6.607010 |
| Log likelihood | 63.79865 | Hannan-Quinn criter. | -6.734944 |
| F-statistic | 36.94655 | Durbin-Watson stat | 2.156211 |
| Prob(F-statistic) | 0.000002 | | |

The residual has no unit root.

**Serial correlation test**:

**Correlogram plot:**

Date: 03/11/21 Time: 18:14
Sample: 1991 2010
Included observations: 20




| | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|
| 1 | -0.418 | -0.418 | 4.0367 | 0.045 |
| 2 | -0.270 | -0.538 | 5.8122 | 0.055 |
| 3 | 0.363 | -0.059 | 9.2187 | 0.027 |
| 4 | -0.097 | -0.055 | 9.4754 | 0.050 |
| 5 | 0.057 | 0.280 | 9.5712 | 0.088 |
| 6 | 0.019 | 0.236 | 9.5825 | 0.143 |
| 7 | -0.204 | -0.064 | 10.994 | 0.139 |
| 8 | 0.182 | -0.099 | 12.203 | 0.142 |
| 9 | 0.029 | -0.123 | 12.238 | 0.200 |
| 10 | -0.236 | -0.259 | 14.683 | 0.144 |
| 11 | 0.310 | 0.227 | 19.383 | 0.055 |
| 12 | -0.257 | -0.089 | 23.003 | 0.028 |

**Selection of MA and AR term:**

There is a spike in lag 2 of PACF plot. So I have to take AR(2)

Dcpue c dprice AR(2)

Dependent Variable: DCPUE
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 03/11/21 Time: 18:15
Sample: 1991 2010
Included observations: 20
Convergence achieved after 20 iterations
Coefficient covariance computed using outer product of gradients

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.000712 | 0.001975 | 0.360481 | 0.7232 |
| DPRICE | 5.81E-08 | 2.56E-08 | 2.272685 | 0.0372 |
| AR(2) | -0.308852 | 0.297883 | -1.036825 | 0.3152 |
| SIGMASQ | 8.69E-05 | 3.74E-05 | 2.325114 | 0.0335 |

| | | | |
|---|---|---|---|
| R-squared | 0.283271 | Mean dependent var | 0.001139 |
| Adjusted R-squared | 0.148884 | S.D. dependent var | 0.011297 |
| S.E. of regression | 0.010422 | Akaike info criterion | -6.102967 |
| Sum squared resid | 0.001738 | Schwarz criterion | -5.903821 |
| Log likelihood | 65.02967 | Hannan-Quinn criter. | -6.064092 |
| F-statistic | 2.107878 | Durbin-Watson stat | 2.852502 |
| Prob(F-statistic) | 0.139440 | | |
| Inverted AR Roots | -.00+.56i | -.00-.56i | |

Here, constant and AR(2) is not significant but we will include these parameters while forecasting as deleting this parameter will harm the analysis.

**Significance Test of the ARIMAX model:**

Here all of the variables are significant.

**Serial correlation test**:

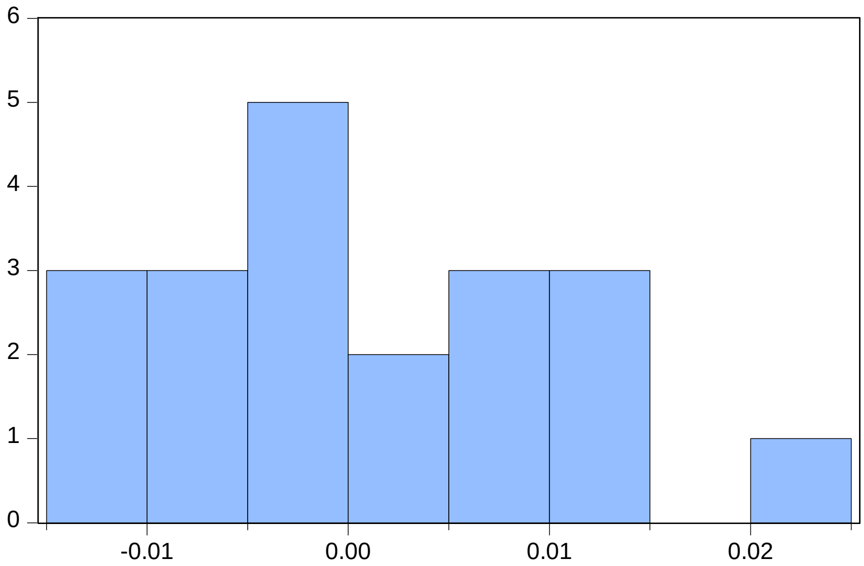
Date: 03/11/21 Time: 20:43
Sample: 1991 2010
Included observations: 20

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|---|---|
| | | 1 | -0.055 | -0.055 | 0.0696 | 0.792 |
| | | 2 | -0.262 | -0.266 | 1.7489 | 0.417 |
| | | 3 | -0.019 | -0.056 | 1.7587 | 0.624 |
| | | 4 | -0.207 | -0.306 | 2.9387 | 0.568 |
| | | 5 | 0.140 | 0.088 | 3.5162 | 0.621 |
| | | 6 | 0.249 | 0.137 | 5.4652 | 0.486 |
| | | 7 | -0.280 | -0.241 | 8.1133 | 0.323 |
| | | 8 | -0.203 | -0.221 | 9.6209 | 0.293 |
| | | 9 | -0.053 | -0.211 | 9.7346 | 0.372 |
| | | 10 | -0.054 | -0.194 | 9.8627 | 0.453 |
| | | 11 | 0.162 | -0.160 | 11.146 | 0.431 |
| | | 12 | 0.151 | -0.029 | 12.397 | 0.414 |

The residuals are not flat and no serial correlation i.e. in white noise.

**Diagnostic Checking:**

**Normality test of residuals:**




Series: Residuals
Sample 1991 2010
Observations 20

| | |
|---|---|
| Mean | 0.000187 |
| Median | -0.001377 |
| Maximum | 0.020135 |
| Minimum | -0.014422 |
| Std. Dev. | 0.009562 |
| Skewness | 0.329724 |
| Kurtosis | 2.207126 |
| Jarque-Bera | 0.886268 |
| Probability | 0.642021 |

The probability of Jarque-Bera test in more than 5%, so the residual series follows normal distribution

**Breusch-Godfrey Serial Correlation LM Test:**

Lag (2)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 3.309486 | Prob. F(2,16) | 0.0955 |
| Obs*R-squared | 4.818606 | Prob. Chi-Square(2) | 0.0622 |

Lag (4)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 2.799590 | Prob. F(4,14) | 0.0672 |
| Obs*R-squared | 8.888166 | Prob. Chi-Square(4) | 0.0640 |

Lag (8)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 1.430381 | Prob. F(8,10) | 0.2925 |
| Obs*R-squared | 10.67297 | Prob. Chi-Square(8) | 0.2209 |

**Heteroscedasticity test:**

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 4.882169 | Prob. F(1,18) | 0.0603 |
| Obs*R-squared | 4.267226 | Prob. Chi-Square(1) | 0.0689 |
| Scaled explained SS | 1.685340 | Prob. Chi-Square(1) | 0.1942 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/11/21 Time: 18:23
Sample: 1991 2010
Included observations: 20

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 8.90E-05 | 2.02E-05 | 4.403612 | 0.0003 |
| DPRICE | -4.95E-10 | 2.24E-10 | -2.209563 | 0.0403 |

| | | | |
|---|---|---|---|
| R-squared | 0.213361 | Mean dependent var | 8.69E-05 |
| Adjusted R-squared | 0.169659 | S.D. dependent var | 9.90E-05 |
| S.E. of regression | 9.02E-05 | Akaike info criterion | -15.69341 |
| Sum squared resid | 1.47E-07 | Schwarz criterion | -15.59384 |
| Log likelihood | 158.9341 | Hannan-Quinn criter. | -15.67397 |
| F-statistic | 4.882169 | Durbin-Watson stat | 2.496829 |
| Prob(F-statistic) | 0.040332 | | |

Probability is greater than 5%, so the model is not heteroscedastic.

**ARIMAX (2,1,0) Forecasting:**

Extend workfile size (from 1990-2013) by double clicking the range> provide actual value in dstreamflow from 2010-2013>Quick >estimate equation> dcpue c dprice ar(2) > Forecast> Forecast sample (1990-2013)>ok>

Associated excel file to determine MAPE, RAMSE, MAE etc. of the year 2011-2013.

**Year 1992-2013:**

**Unit root test**: The series has unit root, hence 1st difference of the series has taken and the final series has no unit root

**Lag selection:** Lag 4 was selected.

**Granger Causality test**

Pairwise Granger Causality Tests
Date: 03/12/21 Time: 21:54
Sample: 1993 2013
Lags: 4

| Null Hypothesis: | Obs | F-Statistic | Prob. |
|---|---|---|---|
| DLICENCES does not Granger Cause DCPUE | 17 | 0.42408 | 0.7876 |
| DCPUE does not Granger Cause DLICENCES | | 1.95944 | 0.1940 |
| DPRICE does not Granger Cause DCPUE | 17 | 0.57869 | 0.6867 |
| DCPUE does not Granger Cause DPRICE | | 0.16124 | 0.9522 |
| DRAINFALL does not Granger Cause DCPUE | 17 | 2.74199 | 0.1048 |
| DCPUE does not Granger Cause DRAINFALL | | 1.68256 | 0.2460 |
| DTEMPERATURE does not Granger Cause DCPUE | 17 | 0.10722 | 0.9766 |
| DCPUE does not Granger Cause DTEMPERATURE | | 0.10576 | 0.9772 |
| DSTREAMFLOW does not Granger Cause DCPUE | 17 | 1.89616 | 0.2046 |
| DCPUE does not Granger Cause DSTREAMFLOW | | 1.11422 | 0.4136 |
| DSTREAMWATERLEVEL does not Granger Cause DCPUE | 17 | 1.42392 | 0.3101 |
| DCPUE does not Granger Cause DSTREAMWATERLEVEL | | 1.43622 | 0.3066 |

No reverse causality detected.

**Test for multicollinearity:**

**Coefficients[a]**

| Model | | Collinearity Statistics Tolerance | VIF |
|---|---|---|---|
| 1 | dlicence | .590 | 1.696 |
| | dprice | .443 | 2.257 |
| | drainfall | .239 | 4.177 |
| | dtemperature | .601 | 1.665 |

| | | | |
|---|---|---|---|
| | dstreamflow | .089 | 11.190 |
| | dstreamwaterlevel | .077 | 13.053 |

a. Dependent Variable: dcpue

**Collinearity Diagnostics[a]**

| Model | Dimension | Eigenvalue | Condition Index | Variance Proportions (Constant) | dlicence | dprice | drainfall | dtemperature | dstreamflow | dstreamwaterlevel |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 2.851 | 1.000 | .00 | .00 | .01 | .02 | .00 | .01 | .01 |
| | 2 | 1.840 | 1.245 | .00 | .09 | .09 | .00 | .10 | .00 | .00 |
| | 3 | 1.036 | 1.659 | .80 | .01 | .00 | .00 | .05 | .00 | .00 |
| | 4 | .713 | 2.000 | .08 | .49 | .02 | .00 | .24 | .00 | .00 |
| | 5 | .368 | 2.783 | .10 | .07 | .53 | .13 | .39 | .01 | .00 |
| | 6 | .146 | 4.419 | .01 | .20 | .32 | .79 | .20 | .11 | .06 |
| | 7 | .044 | 8.011 | .00 | .14 | .03 | .05 | .00 | .87 | .93 |

a. Dependent Variable: dcpue

Here, multicollinearity is present between streamflow and Stream water level. Tolerance is less than 0.1, VIF is more than 10.

So, run the analysis two-times: first time, with all the variables excluding stream water level and for the second time, with all the variable excluding streamflow. Then compared results of the two models, specifically R squares and P values. Model including all other variables excluding streamflow showed improved result than the other. So, I deleted streamflow from the model.

Result of including streamflow and excluding stream water level in the model:

**Model Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate | Change Statistics: R Square Change | F Change | df1 | df2 | Sig. F Change |
|---|---|---|---|---|---|---|---|---|---|
| 1 | .670[a] | .449 | .265 | .010380129 | .449 | 2.443 | 5 | 15 | .083 |

a. Predictors: (Constant), dstreamflow, dlicence, dtemperature, dprice, drainfall

Result of including stream water level and excluding streamflow in the model:

**Model Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate | Change Statistics | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | R Square Change | F Change | df1 | df2 | Sig. F Change |
| 1 | .625[a] | .391 | .187 | .010914344 | .391 | 1.923 | 5 | 15 | .150 |

a. Predictors: (Constant), dstreamwaterlevel, dlicence, dtemperature, dprice, drainfall

Model with streamflow gives better $R^2$ than streamwaterlevel. So, I have deleted streamwaterlevel from the analysis.

**Regression Test :**

**Forward Stepwise:**

**Coefficients[a]**

| Model | | Unstandardized Coefficients B | Unstandardized Coefficients Std. Error | Standardized Coefficients Beta | t | Sig. |
|---|---|---|---|---|---|---|
| 1 | (Constant) | .000 | .002 | | .122 | .904 |
| | dprice | 6.811E-8 | .000 | .544 | 2.823 | .011 |

a. Dependent Variable: dcpue

**Excluded Variables[a]**

| Model | | Beta In | t | Sig. | Partial Correlation | Collinearity Statistics Tolerance |
|---|---|---|---|---|---|---|
| 1 | dlicence | -.200[b] | -.898 | .381 | -.207 | .753 |
| | drainfall | -.132[b] | -.661 | .517 | -.154 | .963 |
| | dtemperature | -.127[b] | -.553 | .587 | -.129 | .728 |
| | dstreamflow | -.278[b] | -1.438 | .168 | -.321 | .940 |

a. Dependent Variable: dcpue

b. Predictors in the Model: (Constant), dprice

Regression Eviews: dcpue c dprice

Dependent Variable: DCPUE
Method: Least Squares
Date: 03/12/21 Time: 22:11
Sample: 1993 2013
Included observations: 21

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.000280 | 0.002287 | 0.122266 | 0.9040 |

| | | | | |
|---|---|---|---|---|
| DPRICE | 6.81E-08 | 2.41E-08 | 2.822754 | 0.0109 |

| | | | |
|---|---|---|---|
| R-squared | 0.295460 | Mean dependent var | 0.000924 |
| Adjusted R-squared | 0.258379 | S.D. dependent var | 0.012108 |
| S.E. of regression | 0.010427 | Akaike info criterion | -6.198414 |
| Sum squared resid | 0.002066 | Schwarz criterion | -6.098936 |
| Log likelihood | 67.08335 | Hannan-Quinn criter. | -6.176825 |
| F-statistic | 7.967941 | Durbin-Watson stat | 2.932335 |
| Prob(F-statistic) | 0.010871 | | |

**Unit root test of residual:**

Null Hypothesis: R has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=4)

| | | t-Statistic | Prob.* |
|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | -6.536478 | 0.0000 |
| Test critical values: | 1% level | -3.831511 | |
| | 5% level | -3.029970 | |
| | 10% level | -2.655194 | |

*MacKinnon (1996) one-sided p-values.
Warning: Probabilities and critical values calculated for 20 observations and may not be accurate for a sample size of 19

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(R)
Method: Least Squares
Date: 03/12/21 Time: 22:12
Sample (adjusted): 1995 2013
Included observations: 19 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| R(-1) | -2.354515 | 0.360212 | -6.536478 | 0.0000 |
| D(R(-1)) | 0.549979 | 0.206306 | 2.665848 | 0.0169 |
| C | 0.001310 | 0.001825 | 0.717695 | 0.4833 |

| | | | |
|---|---|---|---|
| R-squared | 0.833523 | Mean dependent var | -1.03E-05 |
| Adjusted R-squared | 0.812713 | S.D. dependent var | 0.018278 |
| S.E. of regression | 0.007910 | Akaike info criterion | -6.697418 |
| Sum squared resid | 0.001001 | Schwarz criterion | -6.548296 |
| Log likelihood | 66.62547 | Hannan-Quinn criter. | -6.672180 |
| F-statistic | 40.05464 | Durbin-Watson stat | 1.692710 |
| Prob(F-statistic) | 0.000001 | | |

The residual has no unit root.

**Serial correlation test:** EViews

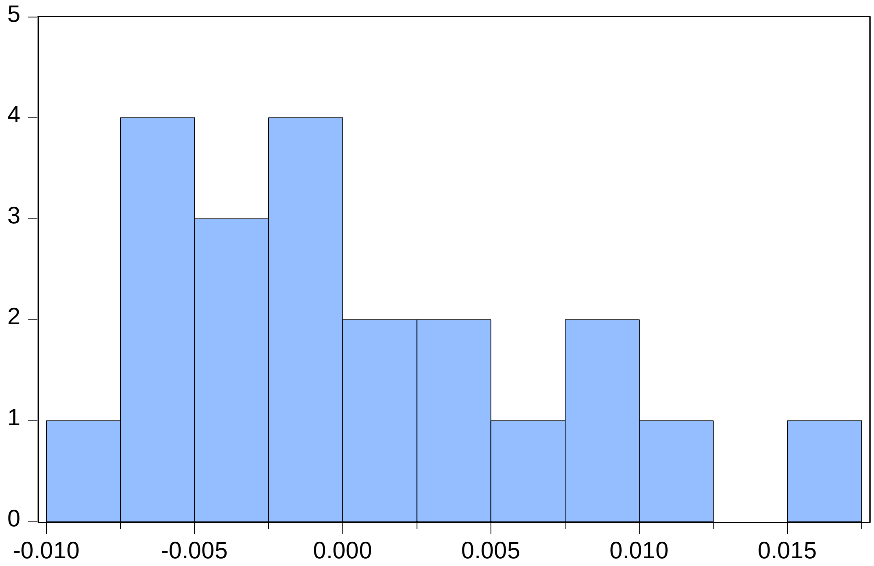
Date: 03/12/21 Time: 22:13
Sample: 1993 2013
Included observations: 21

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|---|---|
| | | 1 | -0.486 | -0.486 | 5.6984 | 0.017 |
| | | 2 | -0.131 | -0.480 | 6.1337 | 0.047 |
| | | 3 | 0.208 | -0.202 | 7.2996 | 0.063 |
| | | 4 | -0.200 | -0.372 | 8.4320 | 0.077 |
| | | 5 | 0.223 | -0.048 | 9.9282 | 0.077 |
| | | 6 | -0.034 | 0.060 | 9.9650 | 0.126 |
| | | 7 | -0.240 | -0.160 | 11.958 | 0.102 |
| | | 8 | 0.203 | -0.137 | 13.491 | 0.096 |
| | | 9 | -0.016 | -0.105 | 13.501 | 0.141 |
| | | 10 | -0.214 | -0.458 | 15.509 | 0.115 |
| | | 11 | 0.396 | -0.041 | 23.086 | 0.017 |
| | | 12 | -0.295 | -0.162 | 27.769 | 0.006 |

The residuals are flat and no serial correlation.

**Diagnostic Checking:**

**Normality test of residuals**:




Series: Residuals
Sample 1993 2013
Observations 21

| | |
|---|---|
| Mean | 0.000562 |
| Median | -0.001598 |
| Maximum | 0.016030 |
| Minimum | -0.007697 |
| Std. Dev. | 0.006598 |
| Skewness | 0.716984 |
| Kurtosis | 2.545415 |
| Jarque-Bera | 1.980049 |
| Probability | 0.371568 |

**Breusch-Godfrey Serial Correlation LM Test:**

Lag (2)
Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 6.561478 | Prob. F(2,17) | 0.0707 |
| Obs*R-squared | 4.148573 | Prob. Chi-Square(2) | 0.0603 |

Lag (4)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 4.453987 | Prob. F(4,15) | 0.0643 |
| Obs*R-squared | 3.40101 | Prob. Chi-Square(4) | 0.0724 |

Lag (8)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 1.789306 | Prob. F(8,11) | 0.1829 |
| Obs*R-squared | 11.87478 | Prob. Chi-Square(8) | 0.1569 |

**Heteroscedasticity test:**

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 2.360275 | Prob. F(1,19) | 0.1409 |
| Obs*R-squared | 2.320465 | Prob. Chi-Square(1) | 0.1277 |
| Scaled explained SS | 1.211505 | Prob. Chi-Square(1) | 0.2710 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/12/21 Time: 22:34
Sample: 1993 2013
Included observations: 21

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 4.36E-05 | 1.22E-05 | 3.582113 | 0.0020 |
| DPRICE | -1.98E-10 | 1.29E-10 | -1.536319 | 0.1409 |

| | | | |
|---|---|---|---|
| R-squared | 0.110498 | Mean dependent var | 4.18E-05 |
| Adjusted R-squared | 0.063682 | S.D. dependent var | 5.74E-05 |
| S.E. of regression | 5.56E-05 | Akaike info criterion | -16.66803 |
| Sum squared resid | 5.86E-08 | Schwarz criterion | -16.56856 |
| Log likelihood | 177.0144 | Hannan-Quinn criter. | -16.64644 |
| F-statistic | 2.360275 | Durbin-Watson stat | 2.135903 |
| Prob(F-statistic) | 0.140946 | | |

Probability is greater than 5%, so the model is not heteroscedastic.

**ARIMAX (0,1,0) Forecasting**: Extend workfile size (from 1994-2016) by double clicking the range> provide original values in dprice from 2013-2016>Quick >estimate equation> dcpue c dprice> Forecast> Forecast sample (1994-2016)>ok>

Associated excel file to determine MAPE, RAMSE, MAE etc. of the year 2014-2016.

**Sample 1994-2016:**

**Unit root test**: All variables have unit root, 1st difference of the series made them stationary.

**Lag selection**: Lag 4 was selected for granger causality test

**Granger causality test:**

Pairwise Granger Causality Tests
Date: 03/13/21 Time: 11:15
Sample: 1995 2016
Lags: 4

| Null Hypothesis: | Obs | F-Statistic | Prob. |
|---|---|---|---|
| DLICENCES does not Granger Cause DCPUE | 18 | 0.67163 | 0.6280 |
| DCPUE does not Granger Cause DLICENCES | | 3.14087 | 0.0710 |
| DPRICE does not Granger Cause DCPUE | 18 | 1.20935 | 0.3714 |
| DCPUE does not Granger Cause DPRICE | | 2.43133 | 0.1235 |
| DRAINFALL does not Granger Cause DCPUE | 18 | 0.47905 | 0.7509 |
| DCPUE does not Granger Cause DRAINFALL | | 3.66689 | 0.0489 |
| DTEMPERATURE does not Granger Cause DCPUE | 18 | 0.17975 | 0.9432 |
| DCPUE does not Granger Cause DTEMPERATURE | | 0.36632 | 0.8268 |
| DSTREAMFLOW does not Granger Cause DCPUE | 18 | 0.36694 | 0.8264 |
| DCPUE does not Granger Cause DSTREAMFLOW | | 2.36478 | 0.1304 |
| DSTREAMWATERLEVEL does not Granger Cause DCPUE | 18 | 0.46876 | 0.7578 |
| DCPUE does not Granger Cause DSTREAMWATERLEVEL | | 1.85016 | 0.2036 |

No reverse causality was found.

**Test for multicollinearity:**

**Coefficients**[a]

| Model | | Collinearity Statistics | |
|---|---|---|---|
| | | Tolerance | VIF |
| 1 | dlicence | .590 | 1.694 |
| | dprice | .331 | 3.025 |
| | drainfall | .226 | 4.426 |
| | dtemperature | .483 | 2.069 |
| | dstreamflow | .076 | 13.119 |
| | dstreamwaterlevel | .065 | 15.281 |

a. Dependent Variable: dcpue

Here multicollinearity is present between streamflow and Stream water level. Tolerance is less than 0.1, VIF is more than 10.

Result of including streamflow and excluding stream water level in the model:

**Model Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate | Change Statistics | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | R Square Change | F Change | df1 | df2 | Sig. F Change |
| 1 | .703[a] | .495 | .337 | .009767444 | .495 | 3.133 | 5 | 16 | .037 |

a. Predictors: (Constant), dstreamflow, dlicence, dtemperature, dprice, drainfall

Result of including stream water level and excluding streamflow in the model:

**Model Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate | Change Statistics | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | R Square Change | F Change | df1 | df2 | Sig. F Change |
| 1 | .671[a] | .451 | .279 | .010183709 | .451 | 2.625 | 5 | 16 | .064 |

a. Predictors: (Constant), dstreamwaterlevel, dlicence, dtemperature, dprice, drainfall

So I will take streamflow and delete streamwaterlevel from the analysis

**Regression Test :**

**Forward Stepwise:**

**Coefficients[a]**

| Model | | Unstandardized Coefficients | | Standardized Coefficients | t | Sig. |
|---|---|---|---|---|---|---|
| | | B | Std. Error | Beta | | |
| 1 | (Constant) | .001 | .002 | | .649 | .524 |
| | dprice | 7.773E-8 | .000 | .579 | 3.174 | .005 |

a. Dependent Variable: dcpue

**Excluded Variables[a]**

| Model | | Beta In | t | Sig. | Partial Correlation | Collinearity Statistics Tolerance |
|---|---|---|---|---|---|---|
| 1 | dlicence | -.234[b] | -1.184 | .251 | -.262 | .837 |
| | drainfall | -.091[b] | -.448 | .659 | -.102 | .831 |
| | dtemperature | -.098[b] | -.433 | .670 | -.099 | .683 |

| dstreamflow | -.271[b] | -1.421 | .171 | -.310 | .871 |
|---|---|---|---|---|---|

a. Dependent Variable: dcpue

b. Predictors in the Model: (Constant), dprice

**Regression Eviws**: dcpue c dprice

Dependent Variable: DCPUE
Method: Least Squares
Date: 03/13/21 Time: 11:24
Sample: 1995 2016
Included observations: 22

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.001387 | 0.002137 | 0.648849 | 0.5238 |
| DPRICE | 7.77E-08 | 2.45E-08 | 3.174201 | 0.0048 |

| | | | |
|---|---|---|---|
| R-squared | 0.335008 | Mean dependent var | 0.001490 |
| Adjusted R-squared | 0.301758 | S.D. dependent var | 0.011994 |
| S.E. of regression | 0.010022 | Akaike info criterion | -6.281581 |
| Sum squared resid | 0.002009 | Schwarz criterion | -6.182395 |
| Log likelihood | 71.09739 | Hannan-Quinn criter. | -6.258216 |
| F-statistic | 10.07555 | Durbin-Watson stat | 2.611284 |
| Prob(F-statistic) | 0.004769 | | |

Create a dummy variable and interact with price from 2015:

Dependent Variable: DCPUE
Method: Least Squares
Date: 03/28/21 Time: 16:59
Sample: 1995 2016
Included observations: 22

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| DPRICE | 8.13E-08 | 2.65E-08 | 3.063723 | 0.0067 |
| DUMMY | 0.005994 | 0.023285 | 0.257411 | 0.7998 |
| DUMMYPRICE | 2.24E-08 | 3.22E-07 | 0.069548 | 0.9453 |
| C | 0.000976 | 0.002352 | 0.415025 | 0.6830 |

| | | | |
|---|---|---|---|
| R-squared | 0.346462 | Mean dependent var | 0.001490 |
| Adjusted R-squared | 0.237540 | S.D. dependent var | 0.011994 |
| S.E. of regression | 0.010473 | Akaike info criterion | -6.117138 |
| Sum squared resid | 0.001974 | Schwarz criterion | -5.918767 |
| Log likelihood | 71.28852 | Hannan-Quinn criter. | -6.070408 |
| F-statistic | 3.180804 | Durbin-Watson stat | 2.641838 |
| Prob(F-statistic) | 0.049066 | | |

In the regression, variable dummy and dummyprice are not significant, hence the dummy variable and interacted dummy terms will be removed from the regression and rerun the model.

Dependent Variable: DCPUE
Method: Least Squares

Date: 03/28/21   Time: 17:01
Sample: 1995 2016
Included observations: 22

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| DPRICE | 7.77E-08 | 2.45E-08 | 3.174201 | 0.0048 |
| C | 0.001387 | 0.002137 | 0.648849 | 0.5238 |

| | | | |
|---|---|---|---|
| R-squared | 0.335008 | Mean dependent var | 0.001490 |
| Adjusted R-squared | 0.301758 | S.D. dependent var | 0.011994 |
| S.E. of regression | 0.010022 | Akaike info criterion | -6.281581 |
| Sum squared resid | 0.002009 | Schwarz criterion | -6.182395 |
| Log likelihood | 71.09739 | Hannan-Quinn criter. | -6.258216 |
| F-statistic | 10.07555 | Durbin-Watson stat | 2.611284 |
| Prob(F-statistic) | 0.004769 | | |

## Unit root test of residual

Residual does not have unit root.

Null Hypothesis: R has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=4)

| | | t-Statistic | Prob.* |
|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | -8.959945 | 0.0000 |
| Test critical values: | 1% level | -3.788030 | |
| | 5% level | -3.012363 | |
| | 10% level | -2.646119 | |

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(R)
Method: Least Squares
Date: 03/15/21   Time: 21:55
Sample (adjusted): 1996 2016
Included observations: 21 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| R(-1) | -1.454208 | 0.162301 | -8.959945 | 0.0000 |
| C | -0.001206 | 0.001583 | -0.761564 | 0.4557 |

| | | | |
|---|---|---|---|
| R-squared | 0.808623 | Mean dependent var | -0.000984 |
| Adjusted R-squared | 0.798551 | S.D. dependent var | 0.016163 |
| S.E. of regression | 0.007255 | Akaike info criterion | -6.923953 |
| Sum squared resid | 0.001000 | Schwarz criterion | -6.824475 |
| Log likelihood | 74.70151 | Hannan-Quinn criter. | -6.902364 |
| F-statistic | 80.28062 | Durbin-Watson stat | 2.662321 |
| Prob(F-statistic) | 0.000000 | | |

**Serial correlation test**: EViews

Date: 03/13/21 Time: 11:27
Sample: 1995 2016
Included observations: 22

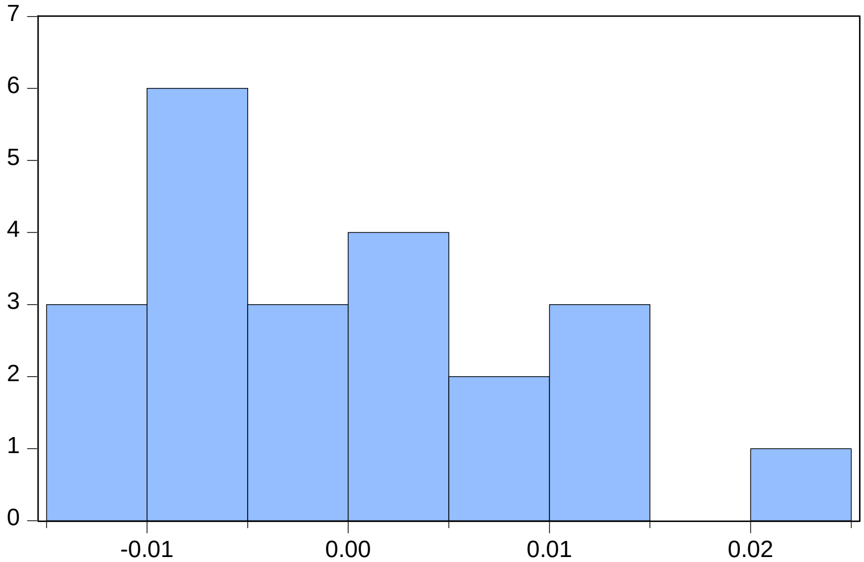
| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|---|---|
| | | 1 | -0.450 | -0.450 | 5.0904 | 0.024 |
| | | 2 | -0.048 | -0.314 | 5.1518 | 0.076 |
| | | 3 | 0.166 | -0.005 | 5.9204 | 0.116 |
| | | 4 | -0.250 | -0.236 | 7.7586 | 0.101 |
| | | 5 | 0.304 | 0.159 | 10.636 | 0.059 |
| | | 6 | -0.037 | 0.179 | 10.682 | 0.099 |
| | | 7 | -0.227 | -0.086 | 12.487 | 0.086 |
| | | 8 | 0.144 | -0.102 | 13.275 | 0.103 |
| | | 9 | -0.049 | -0.037 | 13.371 | 0.147 |
| | | 10 | -0.176 | -0.338 | 14.738 | 0.142 |
| | | 11 | 0.382 | 0.153 | 21.731 | 0.027 |
| | | 12 | -0.317 | -0.034 | 27.039 | 0.008 |

**Selection of MA and AR term**:

The residuals are flat and no serial correlation i.e. in white noise.

**Diagnostic checking:**

**Normality test of residuals**:




Series: Residuals
Sample 1995 2016
Observations 22

| | |
|---|---|
| Mean | -7.89e-20 |
| Median | -0.002046 |
| Maximum | 0.023864 |
| Minimum | -0.014314 |
| Std. Dev. | 0.009780 |
| Skewness | 0.582658 |
| Kurtosis | 2.670033 |
| Jarque-Bera | 1.344603 |
| Probability | 0.510532 |

**Breusch-Godfrey Serial Correlation LM Test:**

Lag(2)
Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 4.173681 | Prob. F(2,18) | 0.0624 |
| Obs*R-squared | 6.970032 | Prob. Chi-Square(2) | 0.0607 |

Lag(4)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 2.190143 | Prob. F(4,16) | 0.1164 |
| Obs*R-squared | 7.783851 | Prob. Chi-Square(4) | 0.0998 |

Lag(8)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 1.083223 | Prob. F(8,12) | 0.4346 |
| Obs*R-squared | 9.225262 | Prob. Chi-Square(8) | 0.3237 |

**Heteroscedasticity test:**

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 1.065098 | Prob. F(1,20) | 0.3144 |
| Obs*R-squared | 1.112369 | Prob. Chi-Square(1) | 0.2916 |
| Scaled explained SS | 0.767642 | Prob. Chi-Square(1) | 0.3809 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/13/21 Time: 11:30
Sample: 1995 2016
Included observations: 22

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 9.17E-05 | 2.57E-05 | 3.566827 | 0.0019 |
| DPRICE | -3.04E-10 | 2.95E-10 | -1.032036 | 0.3144 |

| | | | |
|---|---|---|---|
| R-squared | 0.050562 | Mean dependent var | 9.13E-05 |
| Adjusted R-squared | 0.003090 | S.D. dependent var | 0.000121 |
| S.E. of regression | 0.000121 | Akaike info criterion | -15.12190 |
| Sum squared resid | 2.91E-07 | Schwarz criterion | -15.02271 |
| Log likelihood | 168.3409 | Hannan-Quinn criter. | -15.09853 |
| F-statistic | 1.065098 | Durbin-Watson stat | 1.240630 |
| Prob(F-statistic) | 0.314375 | | |

**ARIMAX (0,1,0) Forecasting**: Extend workfile size (from 1996-2019) by double clicking the range> provide original values in dprice from 2017-2019>Quick >estimate equation> dcpue c dprice > Forecast> Forecast sample (1996-2019)>ok>

Associated excel file to determine MAPE, RAMSE, MAE etc. of the year 2017-2019.

**MLR model:** 3 years lag of Env. variables

**Sample 1990-2010**:

**Multicollinearity test:**

**Coefficients[a]**

| Model | | Collinearity Statistics Tolerance | VIF |
|---|---|---|---|
| 1 | licence | .322 | 3.110 |
| | price | .423 | 2.366 |
| | rainfall | .135 | 7.402 |
| | temperature | .284 | 3.520 |
| | streamflow | .067 | 14.890 |
| | streamwaterlevel | .058 | 17.324 |

a. Dependent Variable: cpue

**Collinearity Diagnostics[a]**

| Model | Dimension | Eigenvalue | Condition Index | Variance Proportions (Constant) | licence | price | rainfall | temperature | streamflow | streamwaterlevel |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 6.375 | 1.000 | .00 | .00 | .00 | .00 | .00 | .00 | .00 |
| | 2 | .517 | 3.511 | .00 | .00 | .00 | .00 | .00 | .06 | .00 |
| | 3 | .069 | 9.634 | .00 | .00 | .47 | .00 | .00 | .00 | .01 |
| | 4 | .021 | 17.605 | .00 | .02 | .03 | .44 | .00 | .18 | .00 |
| | 5 | .013 | 21.742 | .00 | .35 | .00 | .22 | .00 | .05 | .00 |
| | 6 | .005 | 37.158 | .00 | .07 | .28 | .18 | .00 | .39 | .67 |
| | 7 | 8.046E-5 | 281.498 | 1.00 | .56 | .22 | .16 | 1.00 | .33 | .32 |

a. Dependent Variable: cpue

Here, multicollinearity is present between streamflow and Stream water level. Tolerance is less than 0.1, VIF is more than 10.

So, run the analysis two-times: first time, with all the variables excluding stream water level and for the second time, with all the variable excluding streamflow. Then compared results of the two models, specifically R squares and P values. Model including all other variables excluding streamwaterlevel showed improved result than the other. So, I deleted streamwater from the model.

Result of including streamflow and excluding stream water level in the model:

**Model Summary**

| R | | | | Change Statistics |
|---|---|---|---|---|

| Model | | R Square | Adjusted R Square | Std. Error of the Estimate | R Square Change | F Change | df1 | df2 | Sig. F Change |
|---|---|---|---|---|---|---|---|---|---|
| 1 | .669[a] | .448 | .217 | .006767792 | .448 | 1.945 | 5 | 12 | .160 |

a. Predictors: (Constant), streamflow, licence, price, temperature, rainfall

Result of including stream water level and excluding streamflow in the model:

**Model Summary**

| | | | | | Change Statistics | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate | R Square Change | F Change | df1 | df2 | Sig. F Change |
| 1 | .626[a] | .391 | .138 | .007104400 | .391 | 1.543 | 5 | 12 | .249 |

a. Predictors: (Constant), streamwaterlevel, price, licence, temperature, rainfall

**MLR:**

cpue licences price rainfall temperature streamflow c

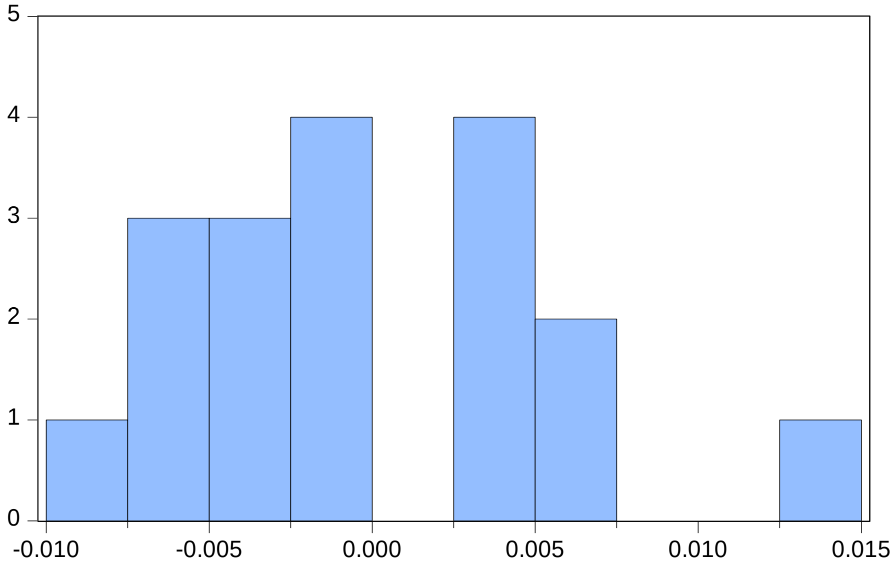
Dependent Variable: CPUE
Method: Least Squares
Date: 03/23/21 Time: 11:03
Sample: 1993 2010
Included observations: 18

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| LICENCES | -0.000326 | 0.000681 | -0.478984 | 0.6406 |
| PRICE | 7.65E-08 | 2.80E-08 | 2.726408 | 0.0184 |
| RAINFALL | -9.65E-07 | 7.06E-06 | -0.136714 | 0.8935 |
| TEMPERATURE | -0.001498 | 0.004185 | -0.357939 | 0.7266 |
| STREAMFLOW | -2.32E-08 | 1.93E-08 | -1.205619 | 0.2512 |
| C | 0.076576 | 0.108511 | 0.705700 | 0.4938 |

| | | | |
|---|---|---|---|
| R-squared | 0.447619 | Mean dependent var | 0.045230 |
| Adjusted R-squared | 0.217460 | S.D. dependent var | 0.007651 |
| S.E. of regression | 0.006768 | Akaike info criterion | -6.892082 |
| Sum squared resid | 0.000550 | Schwarz criterion | -6.595292 |
| Log likelihood | 68.02874 | Hannan-Quinn criter. | -6.851159 |
| F-statistic | 1.944823 | Durbin-Watson stat | 2.438029 |
| Prob(F-statistic) | 0.160127 | | |

**Diagnostic checking:**

**Normality test:**




| | |
|---|---|
| Series: Residuals | |
| Sample 1993 2010 | |
| Observations 18 | |
| Mean | 8.67e-19 |
| Median | -0.000795 |
| Maximum | 0.013398 |
| Minimum | -0.009640 |
| Std. Dev. | 0.005686 |
| Skewness | 0.523133 |
| Kurtosis | 2.964257 |
| Jarque-Bera | 0.821963 |
| Probability | 0.662999 |

## Breusch-Godfrey Serial Correlation LM Test:

Lag (2)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 3.384857 | Prob. F(2,10) | 0.0754 |
| Obs*R-squared | 7.266364 | Prob. Chi-Square(2) | 0.0764 |

Lag(4)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 2.122978 | Prob. F(4,8) | 0.1694 |
| Obs*R-squared | 9.268447 | Prob. Chi-Square(4) | 0.0647 |

Lag(8)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 5.648517 | Prob. F(8,4) | 0.0660 |
| Obs*R-squared | 6.53623 | Prob. Chi-Square(8) | 0.0653 |

## Heteroscedasticity test:

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 0.996035 | Prob. F(5,12) | 0.4602 |
| Obs*R-squared | 5.279282 | Prob. Chi-Square(5) | 0.3828 |
| Scaled explained SS | 2.304415 | Prob. Chi-Square(5) | 0.8056 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/23/21 Time: 11:05
Sample: 1993 2010

Included observations: 18

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | -0.000192 | 0.000706 | -0.271799 | 0.7904 |
| LICENCES | 6.54E-06 | 4.43E-06 | 1.476218 | 0.1656 |
| PRICE | 2.82E-11 | 1.83E-10 | 0.154313 | 0.8799 |
| RAINFALL | -8.75E-08 | 4.60E-08 | -1.903151 | 0.0813 |
| TEMPERATURE | 7.24E-06 | 2.72E-05 | 0.265825 | 0.7949 |
| STREAMFLOW | 2.08E-10 | 1.25E-10 | 1.658947 | 0.1230 |

| | | | |
|---|---|---|---|
| R-squared | 0.293293 | Mean dependent var | 3.05E-05 |
| Adjusted R-squared | -0.001168 | S.D. dependent var | 4.40E-05 |
| S.E. of regression | 4.41E-05 | Akaike info criterion | -16.96073 |
| Sum squared resid | 2.33E-08 | Schwarz criterion | -16.66394 |
| Log likelihood | 158.6466 | Hannan-Quinn criter. | -16.91981 |
| F-statistic | 0.996035 | Durbin-Watson stat | 2.365197 |
| Prob(F-statistic) | 0.460225 | | |

## Sample 1992-2013:

## Multicollinearity test:

### Coefficients[a]

| Model | | Collinearity Statistics | |
|---|---|---|---|
| | | Tolerance | VIF |
| 1 | licence | .391 | 2.555 |
| | price | .605 | 1.653 |
| | rainfall | .133 | 7.522 |
| | temperature | .565 | 1.771 |
| | streamflow | .060 | 16.761 |
| | streamwaterlevel | .043 | 23.340 |

a. Dependent Variable: cpue

### Collinearity Diagnostics[a]

| Model | Dimension | Eigenvalue | Condition Index | Variance Proportions (Constant) | licence | price | rainfall | temperature | streamflow | streamwaterlevel |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 6.416 | 1.000 | .00 | .00 | .00 | .00 | .00 | .00 | .00 |
| | 2 | .471 | 3.690 | .00 | .00 | .00 | .00 | .00 | .05 | .00 |
| | 3 | .080 | 8.956 | .00 | .00 | .77 | .00 | .00 | .00 | .00 |
| | 4 | .017 | 19.563 | .00 | .06 | .00 | .48 | .00 | .19 | .00 |
| | 5 | .013 | 22.454 | .00 | .47 | .00 | .31 | .00 | .04 | .00 |
| | 6 | .003 | 44.310 | .00 | .09 | .04 | .15 | .00 | .71 | .94 |
| | 7 | .000 | 237.013 | .99 | .38 | .17 | .05 | .99 | .00 | .06 |

a. Dependent Variable: cpue

Here, multicollinearity is present between streamflow and Stream water level. Tolerance is less than 0.1, VIF is more than 10.

So, run the analysis two-times: first time, with all the variables excluding stream water level and for the second time, with all the variable excluding streamflow. Then compared results of the two models, specifically R squares and P values. Model including all other variables excluding streamwaerlevel showed improved result than the other. So, I deleted streamwaterlevel from the model.

Result of including streamflow and excluding stream water level in the model:

**Model Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | .872[a] | .760 | .667 | .005460661 |

a. Predictors: (Constant), streamflow, temperature, price, licence, rainfall

Result of including stream water level and excluding streamflow in the model:

**Model Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | .864[a] | .746 | .649 | .005613274 |

a. Predictors: (Constant), streamwaterlevel, temperature, price, licence, rainfall

**MLR:**

cpue licences price rainfall temperature streamflow c

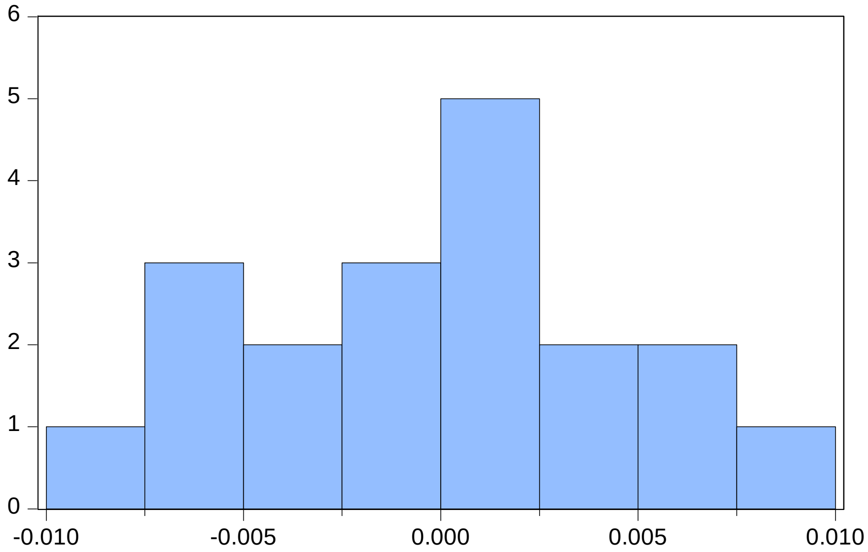
Dependent Variable: CPUE
Method: Least Squares
Date: 03/23/21 Time: 11:44
Sample: 1995 2013
Included observations: 19

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| LICENCES | -0.000832 | 0.000533 | -1.559291 | 0.1429 |
| PRICE | 1.12E-07 | 1.90E-08 | 5.856767 | 0.0001 |
| RAINFALL | -5.30E-06 | 6.02E-06 | -0.880325 | 0.3947 |
| TEMPERATURE | -0.004982 | 0.003262 | -1.527277 | 0.1507 |
| STREAMFLOW | 1.94E-08 | 1.88E-08 | 1.033984 | 0.3200 |
| C | 0.165160 | 0.083186 | 1.985441 | 0.0686 |
| R-squared | 0.759781 | Mean dependent var | | 0.048444 |

| | | | |
|---|---|---|---|
| Adjusted R-squared | 0.667389 | S.D. dependent var | 0.009468 |
| S.E. of regression | 0.005461 | Akaike info criterion | -7.330404 |
| Sum squared resid | 0.000388 | Schwarz criterion | -7.032161 |
| Log likelihood | 75.63884 | Hannan-Quinn criter. | -7.279930 |
| F-statistic | 8.223464 | Durbin-Watson stat | 2.283158 |
| Prob(F-statistic) | 0.001076 | | |

## Diagnostic Checking:

## Normality test:




Series: Residuals
Sample 1995 2013
Observations 19

| | |
|---|---|
| Mean | 7.60e-18 |
| Median | 0.000926 |
| Maximum | 0.008155 |
| Minimum | -0.008568 |
| Std. Dev. | 0.004641 |
| Skewness | -0.071055 |
| Kurtosis | 2.246191 |
| Jarque-Bera | 0.465835 |
| Probability | 0.792219 |

## Breusch-Godfrey Serial Correlation LM Test:

Lag(2)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.558343 | Prob. F(2,11) | 0.5876 |
| Obs*R-squared | 1.751058 | Prob. Chi-Square(2) | 0.4166 |

Lag (4)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 1.476710 | Prob. F(4,9) | 0.2873 |
| Obs*R-squared | 7.528756 | Prob. Chi-Square(4) | 0.1104 |

Lag (8)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.617241 | Prob. F(8,5) | 0.7411 |
| Obs*R-squared | 9.440665 | Prob. Chi-Square(8) | 0.3065 |

## Heteroscedasticity Test:

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 1.308079 | Prob. F(5,13) | 0.3197 |
| Obs*R-squared | 6.359519 | Prob. Chi-Square(5) | 0.2728 |
| Scaled explained SS | 1.855062 | Prob. Chi-Square(5) | 0.8688 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/23/21 Time: 11:48
Sample: 1995 2013
Included observations: 19

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.000376 | 0.000342 | 1.098498 | 0.2919 |
| LICENCES | 7.96E-07 | 2.19E-06 | 0.362834 | 0.7226 |
| PRICE | -4.30E-11 | 7.83E-11 | -0.549252 | 0.5921 |
| RAINFALL | -4.33E-08 | 2.48E-08 | -1.748848 | 0.1039 |
| TEMPERATURE | -1.33E-05 | 1.34E-05 | -0.989057 | 0.3407 |
| STREAMFLOW | 9.76E-11 | 7.73E-11 | 1.262244 | 0.2290 |

| | | | |
|---|---|---|---|
| R-squared | 0.334712 | Mean dependent var | 2.04E-05 |
| Adjusted R-squared | 0.078831 | S.D. dependent var | 2.34E-05 |
| S.E. of regression | 2.25E-05 | Akaike info criterion | -18.31771 |
| Sum squared resid | 6.56E-09 | Schwarz criterion | -18.01946 |
| Log likelihood | 180.0182 | Hannan-Quinn criter. | -18.26723 |
| F-statistic | 1.308079 | Durbin-Watson stat | 2.429493 |
| Prob(F-statistic) | 0.319687 | | |

## Sample 1994-2016:

## Multicollinearity test:

### Coefficients[a]

| Model | | Collinearity Statistics Tolerance | VIF |
|---|---|---|---|
| 1 | licence | .425 | 2.353 |
| | price | .645 | 1.551 |
| | rainfall | .142 | 7.022 |
| | temperature | .671 | 1.490 |
| | streamflow | .056 | 17.940 |
| | streamwaterlevel | .044 | 22.688 |

a. Dependent Variable: cpue

### Collinearity Diagnostics[a]

| Model | Dimension | Eigenvalue | Condition Index | Variance Proportions (Constant) | licence | price | rainfall | temperature | streamflow | streamwaterlevel |
|---|---|---|---|---|---|---|---|---|---|---|

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 6.523 | 1.000 | .00 | .00 | .00 | .00 | .00 | .00 | .00 |
| | 2 | .371 | 4.191 | .00 | .00 | .00 | .00 | .00 | .05 | .00 |
| | 3 | .076 | 9.260 | .00 | .00 | .94 | .00 | .00 | .00 | .00 |
| | 4 | .015 | 21.120 | .00 | .16 | .00 | .37 | .00 | .15 | .00 |
| | 5 | .012 | 23.312 | .00 | .45 | .00 | .48 | .00 | .08 | .00 |
| | 6 | .003 | 46.879 | .00 | .08 | .02 | .14 | .00 | .71 | 1.00 |
| | 7 | .000 | 244.362 | 1.00 | .31 | .04 | .00 | .99 | .01 | .00 |

a. Dependent Variable: cpue

Here, multicollinearity is present between streamflow and Stream water level. Tolerance is less than 0.1, VIF is more than 10.

So, run the analysis two-times: first time, with all the variables excluding stream water level and for the second time, with all the variable excluding streamflow. Then compared results of the two models, specifically R squares and P values. Model including all other variables excluding stream water level showed improved result than the other. So, I deleted stream water level from the model.

Result of including streamflow and excluding stream water level in the model:

**Model Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | .911[a] | .830 | .769 | .005859217 |

a. Predictors: (Constant), streamflow, temperature, price, licence, rainfall

Result of including stream water level and excluding streamflow in the model:

**Model Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | .908[a] | .825 | .762 | .005947268 |

a. Predictors: (Constant), streamwaterlevel, temperature, price, licence, rainfall

Create a dummy variable and interact with price from 2015:

Dependent Variable: CPUE
Method: Least Squares
Date: 03/28/21 Time: 17:09
Sample: 1997 2016
Included observations: 20

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| LICENCES | -0.000665 | 0.000491 | -1.353933 | 0.2007 |
| PRICE | 1.07E-07 | 1.51E-08 | 7.035766 | 0.0000 |
| RAINFALL | -3.33E-06 | 5.70E-06 | -0.584179 | 0.5699 |
| TEMPERATURE | -0.002264 | 0.003115 | -0.726698 | 0.4813 |
| STREAMFLOW | 1.46E-08 | 1.71E-08 | 0.851450 | 0.4112 |
| DUMMY | 0.037200 | 0.030070 | 1.237101 | 0.2397 |
| DUMMYPRICE | -7.75E-08 | 8.44E-08 | -0.917280 | 0.3771 |
| C | 0.094944 | 0.079623 | 1.192428 | 0.2561 |

| | | | |
|---|---|---|---|
| R-squared | 0.891016 | Mean dependent var | 0.051710 |
| Adjusted R-squared | 0.827443 | S.D. dependent var | 0.012196 |
| S.E. of regression | 0.005066 | Akaike info criterion | -7.443222 |
| Sum squared resid | 0.000308 | Schwarz criterion | -7.044929 |
| Log likelihood | 82.43222 | Hannan-Quinn criter. | -7.365471 |
| F-statistic | 14.01548 | Durbin-Watson stat | 2.543590 |
| Prob(F-statistic) | 0.000065 | | |

In the regression, variable dummy and dummyprice are not significant, hence the dummy variable and interacted dummy terms will be removed from the regression and rerun the model.

Dependent Variable: CPUE
Method: Least Squares
Date: 03/28/21 Time: 17:10
Sample: 1997 2016
Included observations: 20

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| LICENCES | -0.000684 | 0.000562 | -1.216448 | 0.2439 |
| PRICE | 1.14E-07 | 1.67E-08 | 6.821269 | 0.0000 |
| RAINFALL | -2.20E-06 | 6.29E-06 | -0.349627 | 0.7318 |
| TEMPERATURE | -0.002068 | 0.003584 | -0.577118 | 0.5730 |
| STREAMFLOW | 1.30E-08 | 1.91E-08 | 0.677027 | 0.5094 |
| C | 0.088337 | 0.091683 | 0.963505 | 0.3516 |

| | | | |
|---|---|---|---|
| R-squared | 0.829941 | Mean dependent var | 0.051710 |
| Adjusted R-squared | 0.769206 | S.D. dependent var | 0.012196 |
| S.E. of regression | 0.005859 | Akaike info criterion | -7.198276 |
| Sum squared resid | 0.000481 | Schwarz criterion | -6.899557 |
| Log likelihood | 77.98276 | Hannan-Quinn criter. | -7.139963 |
| F-statistic | 13.66492 | Durbin-Watson stat | 1.888361 |
| Prob(F-statistic) | 0.000058 | | |

**MLR:**

cpue licences price rainfall temperature streamflow c

Dependent Variable: CPUE
Method: Least Squares
Date: 03/23/21 Time: 11:55

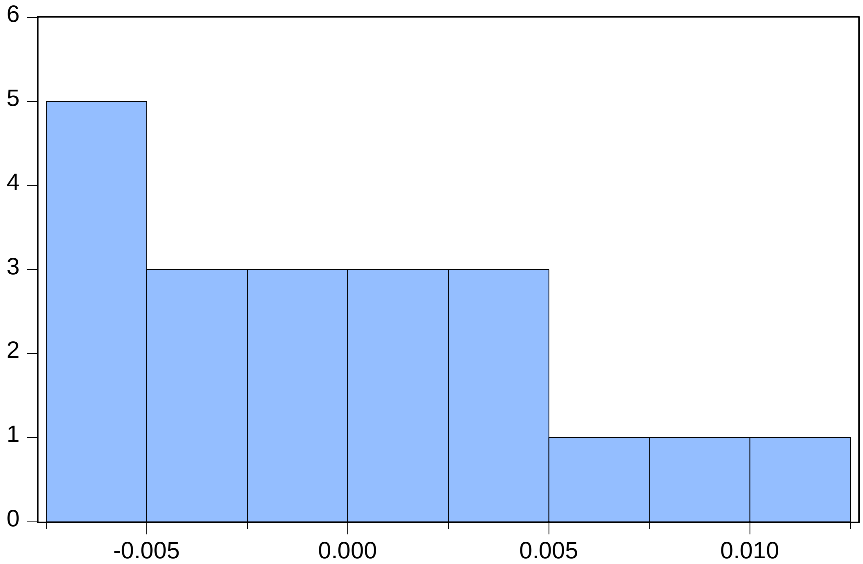
Sample: 1997 2016
Included observations: 20

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| LICENCES | -0.000684 | 0.000562 | -1.216448 | 0.2439 |
| PRICE | 1.14E-07 | 1.67E-08 | 6.821269 | 0.0000 |
| RAINFALL | -2.20E-06 | 6.29E-06 | -0.349627 | 0.7318 |
| TEMPERATURE | -0.002068 | 0.003584 | -0.577118 | 0.5730 |
| STREAMFLOW | 1.30E-08 | 1.91E-08 | 0.677027 | 0.5094 |
| C | 0.088337 | 0.091683 | 0.963505 | 0.3516 |

| | | | |
|---|---|---|---|
| R-squared | 0.829941 | Mean dependent var | 0.051710 |
| Adjusted R-squared | 0.769206 | S.D. dependent var | 0.012196 |
| S.E. of regression | 0.005859 | Akaike info criterion | -7.198276 |
| Sum squared resid | 0.000481 | Schwarz criterion | -6.899557 |
| Log likelihood | 77.98276 | Hannan-Quinn criter. | -7.139963 |
| F-statistic | 13.66492 | Durbin-Watson stat | 1.888361 |
| Prob(F-statistic) | 0.000058 | | |

## Diagnostic Checking:

## Normality Test:




Series: Residuals
Sample 1997 2016
Observations 20

| | |
|---|---|
| Mean | -2.43e-18 |
| Median | -0.001095 |
| Maximum | 0.011369 |
| Minimum | -0.006043 |
| Std. Dev. | 0.005030 |
| Skewness | 0.676021 |
| Kurtosis | 2.581224 |
| | |
| Jarque-Bera | 1.669492 |
| Probability | 0.433985 |

## Breusch-Godfrey Serial Correlation LM Test:

Lag(2)
Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.172721 | Prob. F(2,12) | 0.8434 |
| Obs*R-squared | 0.559627 | Prob. Chi-Square(2) | 0.7559 |

Lag(4)
Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.377424 | Prob. F(4,10) | 0.8198 |
| Obs*R-squared | 2.623344 | Prob. Chi-Square(4) | 0.6227 |

Laag(8)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 1.617085 | Prob. F(8,6) | 0.2875 |
| Obs*R-squared | 13.66309 | Prob. Chi-Square(8) | 0.0910 |

## Heteroscedasticity test:

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 0.048063 | Prob. F(5,14) | 0.9983 |
| Obs*R-squared | 0.337516 | Prob. Chi-Square(5) | 0.9969 |
| Scaled explained SS | 0.130754 | Prob. Chi-Square(5) | 0.9997 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/23/21 Time: 11:56
Sample: 1997 2016
Included observations: 20

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.000142 | 0.000560 | 0.252953 | 0.8040 |
| LICENCES | -1.37E-06 | 3.44E-06 | -0.398526 | 0.6963 |
| PRICE | 2.07E-11 | 1.02E-10 | 0.202278 | 0.8426 |
| RAINFALL | -5.47E-09 | 3.84E-08 | -0.142246 | 0.8889 |
| TEMPERATURE | -3.75E-06 | 2.19E-05 | -0.171221 | 0.8665 |
| STREAMFLOW | 2.66E-11 | 1.17E-10 | 0.227457 | 0.8234 |

| | | | |
|---|---|---|---|
| R-squared | 0.016876 | Mean dependent var | 2.40E-05 |
| Adjusted R-squared | -0.334240 | S.D. dependent var | 3.10E-05 |
| S.E. of regression | 3.58E-05 | Akaike info criterion | -17.39325 |
| Sum squared resid | 1.80E-08 | Schwarz criterion | -17.09453 |
| Log likelihood | 179.9325 | Hannan-Quinn criter. | -17.33494 |
| F-statistic | 0.048063 | Durbin-Watson stat | 1.473038 |
| Prob(F-statistic) | 0.998285 | | |

## 3. Rockhampton

## Data cleaning and processing:

**For outlier detection**: No outlier detected

**Treatment for missing values:**

Tsset time

ipolate cpue time, gen (newcpue) epolate ipolate streamflow time, gen (newstreamflow) epolate

ipolate streamwaterlevel time, gen (newstreamwaterlevel) epolate

**Year: 1990-2010**

**Check for seasonality and trend:** Line diagram showing no seasonality pattern but a steady positive secular trend for the dependent variable "cpue".

**Unit root test:** The series has unit root, so I will take 1st difference of all the series. Now the series is stationary.

**Lag selection**: Lag 4 was selected for the granger causality test.

**Granger Causality test:**

Pairwise Granger Causality Tests

Date: 03/13/21 Time: 23:03

Sample: 1991 2010

Lags: 4

| Null Hypothesis: | Obs | F-Statistic | Prob. |
|---|---|---|---|
| DLICENCES does not Granger Cause DCPUE | 16 | 0.33632 | 0.8455 |
| DCPUE does not Granger Cause DLICENCES | | 0.07284 | 0.9882 |
| DPRICE does not Granger Cause DCPUE | 16 | 1.27129 | 0.3657 |
| DCPUE does not Granger Cause DPRICE | | 1.26683 | 0.3672 |
| DRAINFALL does not Granger Cause DCPUE | 16 | 2.40463 | 0.1468 |
| DCPUE does not Granger Cause DRAINFALL | | 0.22240 | 0.9175 |
| DTEMPERATURE does not Granger Cause DCPUE | 16 | 0.86823 | 0.5275 |
| DCPUE does not Granger Cause DTEMPERATURE | | 0.74310 | 0.5921 |
| DSTREAMFLOW does not Granger Cause DCPUE | 16 | 2.30305 | 0.1581 |
| DCPUE does not Granger Cause DSTREAMFLOW | | 0.62081 | 0.6622 |
| DSTREAMWATERLEVEL does not Granger Cause DCPUE | 16 | 5.00191 | 0.0618 |
| DCPUE does not Granger Cause DSTREAMWATERLEVEL | | 2.13127 | 0.1798 |

No reverse causality was found.

**Test for multicollinearity**: SPSS

**Coefficients[a]**

| Model | | Collinearity Statistics Tolerance | VIF |
|---|---|---|---|
| 1 | dlicence | .637 | 1.569 |
| | dprice | .503 | 1.986 |
| | drainfall | .459 | 2.179 |
| | dtemperature | .739 | 1.354 |
| | dstreamflow | .501 | 1.995 |
| | dstreamwaterlevel | .613 | 1.632 |

a. Dependent Variable: dcpue

Here, there is no multicollinearity. Tolerance is more than 0.1 and VIF is less than 10.

**Multiple Regression Test**: SPSS
**Forward Stepwise regression:**

**Coefficients[a]**

| Model | | Unstandardized Coefficients B | Std. Error | Standardized Coefficients Beta | t | Sig. | 95.0% Confidence Interval for B Lower Bound | Upper Bound |
|---|---|---|---|---|---|---|---|---|
| 1 | (Constant) | .001 | .002 | | .328 | .747 | -.003 | .004 |
| | dprice | 3.626E-8 | .000 | .607 | 3.241 | .005 | .000 | .000 |
| 2 | (Constant) | .000 | .001 | | -.222 | .827 | -.003 | .003 |
| | dprice | 3.010E-8 | .000 | .504 | 3.108 | .006 | .000 | .000 |
| | dstreamwaterlevel | .003 | .001 | .466 | 2.873 | .011 | .001 | .006 |

a. Dependent Variable: dcpue

**Excluded Variables[a]**

| Model | Beta In | t | Sig. | Partial Correlation | Collinearity Statistics |
|---|---|---|---|---|---|

| | | | | | | Tolerance |
|---|---|---|---|---|---|---|
| 1 | dlicence | -.220[b] | -1.003 | .330 | -.236 | .728 |
| | drainfall | .082[b] | .384 | .706 | .093 | .812 |
| | dtemperature | .098[b] | .477 | .639 | .115 | .871 |
| | dstreamflow | -.082[b] | -.390 | .701 | -.094 | .834 |
| | dstreamwaterlevel | .466[b] | 2.873 | .011 | .572 | .951 |
| 2 | dlicence | -.176[c] | -.945 | .359 | -.230 | .722 |
| | drainfall | -.298[c] | -1.445 | .168 | -.340 | .553 |
| | dtemperature | .111[c] | .646 | .528 | .159 | .870 |
| | dstreamflow | -.334[c] | -1.898 | .076 | -.429 | .701 |

a. Dependent Variable: dcpue

b. Predictors in the Model: (Constant), dprice

c. Predictors in the Model: (Constant), dprice, dstreamwaterlevel

**Regression Test** : Eviws: dcpue c dprice dstreamwaterlevel

Dependent Variable: DCPUE
Method: Least Squares
Date: 03/13/21 Time: 23:13
Sample: 1991 2010
Included observations: 20

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| DPRICE | 3.01E-08 | 9.68E-09 | 3.107781 | 0.0064 |
| DSTREAMWATERLEVEL | 0.003304 | 0.001150 | 2.872619 | 0.0106 |
| C | -0.000315 | 0.001421 | -0.221558 | 0.8273 |

| | | | |
|---|---|---|---|
| R-squared | 0.574886 | Mean dependent var | 0.001106 |
| Adjusted R-squared | 0.524872 | S.D. dependent var | 0.008965 |
| S.E. of regression | 0.006180 | Akaike info criterion | -7.197584 |
| Sum squared resid | 0.000649 | Schwarz criterion | -7.048224 |
| Log likelihood | 74.97584 | Hannan-Quinn criter. | -7.168427 |
| F-statistic | 11.49462 | Durbin-Watson stat | 1.647383 |
| Prob(F-statistic) | 0.000696 | | |

**Unit root test for the residuals of regression model** (including dcpue c dprice dstreamwaterlevel)**:**

Null Hypothesis: R has a unit root

Exogenous: Constant

Lag Length: 1 (Automatic - based on SIC, maxlag=4)

| | | t-Statistic | Prob.* |
|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | -4.037712 | 0.0069 |
| Test critical values: | 1% level | -3.857386 | |
| | 5% level | -3.040391 | |
| | 10% level | -2.660551 | |

*MacKinnon (1996) one-sided p-values.

Warning: Probabilities and critical values calculated for 20 observations and may not be accurate for a sample size of 18

The residual has no unit root.

**Serial correlation test**: EViews

The probability of Q stat (Ljung-Box test) is more than .05. So, I should accept the null hypothesis. (Null: there is no serial correlation).

**Correlogram plot:**

Date: 03/13/21 Time: 23:19

Sample: 1991 2010

Included observations: 20

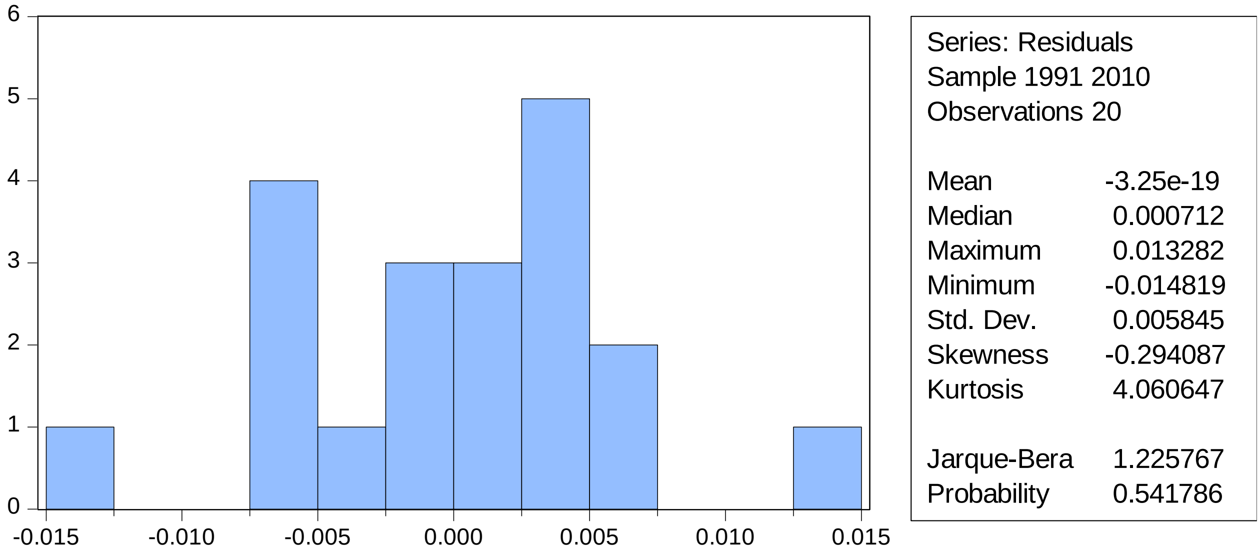
| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|---|---|
| | | 1 | 0.039 | 0.039 | 0.0353 | 0.851 |
| | | 2 | -0.188 | -0.190 | 0.9000 | 0.638 |
| | | 3 | -0.039 | -0.024 | 0.9392 | 0.816 |
| | | 4 | 0.133 | 0.104 | 1.4242 | 0.840 |
| | | 5 | -0.263 | -0.299 | 3.4467 | 0.631 |
| | | 6 | -0.175 | -0.116 | 4.4086 | 0.622 |
| | | 7 | -0.121 | -0.224 | 4.9066 | 0.671 |
| | | 8 | -0.091 | -0.222 | 5.2078 | 0.735 |
| | | 9 | -0.038 | -0.084 | 5.2642 | 0.811 |
| | | 10 | 0.016 | -0.172 | 5.2751 | 0.872 |
| | | 11 | 0.206 | 0.116 | 7.3495 | 0.770 |
| | | 12 | 0.043 | -0.114 | 7.4511 | 0.826 |

The residuals are flat and no serial correlation i.e. residuals are in white noise

**Diagnostic checking:**

**Normality test of residuals:**

Quick>estimate equation> dcpue c dprice dstreamwaterlevel >ok>view tab> residual diagnostics> Histogram- Normality test




The probability of Jarque-Bera test in more than 5%, so the residual series follows normal distribution.

**Breusch-Godfrey Serial Correlation LM Test:**

Lag(2)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.522965 | Prob. F(2,15) | 0.6032 |
| Obs*R-squared | 1.303670 | Prob. Chi-Square(2) | 0.5211 |

Lag(4)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.314870 | Prob. F(4,13) | 0.8630 |
| Obs*R-squared | 1.766516 | Prob. Chi-Square(4) | 0.7786 |

Lag(8)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.428799 | Prob. F(8,9) | 0.8764 |
| Obs*R-squared | 5.519367 | Prob. Chi-Square(8) | 0.7009 |

**Heteroscedasticity test:**

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 0.309763 | Prob. F(2,17) | 0.7377 |
| Obs*R-squared | 0.703227 | Prob. Chi-Square(2) | 0.7036 |
| Scaled explained SS | 0.777529 | Prob. Chi-Square(2) | 0.6779 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/13/21 Time: 23:23
Sample: 1991 2010
Included observations: 20

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 3.12E-05 | 1.39E-05 | 2.241051 | 0.0387 |
| DPRICE | 7.16E-11 | 9.48E-11 | 0.755148 | 0.4605 |
| DSTREAMWATERLEVEL | 5.55E-07 | 1.13E-05 | 0.049314 | 0.9612 |

| | | | |
|---|---|---|---|
| R-squared | 0.035161 | Mean dependent var | 3.25E-05 |
| Adjusted R-squared | -0.078349 | S.D. dependent var | 5.83E-05 |
| S.E. of regression | 6.05E-05 | Akaike info criterion | -16.45021 |
| Sum squared resid | 6.22E-08 | Schwarz criterion | -16.30085 |
| Log likelihood | 167.5021 | Hannan-Quinn criter. | -16.42106 |
| F-statistic | 0.309763 | Durbin-Watson stat | 1.818508 |
| Prob(F-statistic) | 0.737675 | | |

Probability is greater than 5%, so the model is not heteroscedastic.

**ARIMAX (0,1,0) Forecasting:**

Extend workfile size (from 1990-2013) by double clicking the range> provide actual value in dprice and dstreamwaterlevel from 2010-2013>Quick >estimate equation> dcpue c dprice dstreamwaterlevel > Forecast> Forecast sample (1990-2013)>ok>

Associated excel file to determine MAPE, RAMSE, MAE etc. of the year 2011-2013.

**Year 1992-2013:**

**Unit root test:** The series has unit root, hence 1st difference of the series has taken and the final series has no unit root

**Lag selection**: Lag 4 selected for the granger causality test.

**Granger Causality test**

Pairwise Granger Causality Tests
Date: 03/14/21 Time: 20:47
Sample: 1993 2013
Lags: 4

| Null Hypothesis: | Obs | F-Statistic | Prob. |
|---|---|---|---|
| DLICENCES does not Granger Cause DCPUE | 17 | 0.10908 | 0.9759 |
| DCPUE does not Granger Cause DLICENCES | | 0.51731 | 0.7260 |
| DPRICE does not Granger Cause DCPUE | 17 | 3.02982 | 0.0852 |
| DCPUE does not Granger Cause DPRICE | | 3.68846 | 0.0549 |
| DRAINFALL does not Granger Cause DCPUE | 17 | 2.19976 | 0.1592 |
| DCPUE does not Granger Cause DRAINFALL | | 0.47511 | 0.7537 |
| DTEMPERATURE does not Granger Cause DCPUE | 17 | 0.74472 | 0.5879 |
| DCPUE does not Granger Cause DTEMPERATURE | | 1.36111 | 0.3284 |
| DSTREAMFLOW does not Granger Cause DCPUE | 17 | 1.63036 | 0.2576 |
| DCPUE does not Granger Cause DSTREAMFLOW | | 0.45470 | 0.7672 |
| DSTREAMWATERLEVEL does not Granger Cause DCPUE | 17 | 0.83535 | 0.5393 |
| DCPUE does not Granger Cause DSTREAMWATERLEVEL | | 1.32861 | 0.3384 |

No reverse causality detected.

**Test for multicollinearity**

**Coefficients**[a]

| | | Collinearity Statistics | |
|---|---|---|---|
| Model | | Tolerance | VIF |
| 1 | dlicence | .705 | 1.418 |
| | dprice | .605 | 1.652 |

| | | | |
|---|---|---|---|
| | drainfall | .450 | 2.221 |
| | dtemperature | .772 | 1.296 |
| | dstreamflow | .509 | 1.963 |
| | dstreamwaterlevel | .500 | 2.000 |

a. Dependent Variable: dcpue

**Collinearity Diagnostics[a]**

| | | | | Variance Proportions | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Model | Dimension | Eigenvalue | Condition Index | (Constant) | dlicence | dprice | drainfall | dtemperature | dstreamflow | dstreamwaterlevel |
| 1 | 1 | 2.497 | 1.000 | .01 | .01 | .03 | .04 | .03 | .05 | .04 |
| | 2 | 1.266 | 1.404 | .06 | .26 | .12 | .01 | .01 | .02 | .03 |
| | 3 | 1.148 | 1.475 | .11 | .01 | .04 | .05 | .30 | .03 | .05 |
| | 4 | .978 | 1.598 | .49 | .20 | .01 | .05 | .00 | .01 | .00 |
| | 5 | .540 | 2.151 | .14 | .04 | .12 | .00 | .60 | .26 | .06 |
| | 6 | .315 | 2.814 | .19 | .15 | .50 | .09 | .03 | .31 | .46 |
| | 7 | .256 | 3.123 | .00 | .33 | .17 | .75 | .03 | .33 | .35 |

a. Dependent Variable: dcpue

Here, There is no multicollinearity among the independent variables. Tolerance is more than 0.1, VIF is less than 10.

**Regression Test :**

**Forward stepwise regression**:

**Coefficients[a]**

| | Unstandardized Coefficients | | Standardized Coefficients | | |
|---|---|---|---|---|---|
| Model | B | Std. Error | Beta | t | Sig. |

| | | | | | | |
|---|---|---|---|---|---|---|
| 1 | (Constant) | 8.374E-5 | .002 | | .047 | .963 |
| | dprice | 5.243E-8 | .000 | .772 | 5.293 | .000 |
| 2 | (Constant) | .000 | .002 | | -.101 | .921 |
| | dprice | 6.073E-8 | .000 | .894 | 6.306 | .000 |
| | dlicence | -.001 | .000 | -.328 | -2.312 | .033 |

a. Dependent Variable: dcpue

**Excluded Variables[a]**

| Model | | Beta In | t | Sig. | Partial Correlation | Collinearity Statistics Tolerance |
|---|---|---|---|---|---|---|
| 1 | dlicence | -.328[b] | -2.312 | .033 | -.479 | .861 |
| | drainfall | -.045[b] | -.295 | .771 | -.069 | .971 |
| | dtemperature | -.021[b] | -.130 | .898 | -.031 | .881 |
| | dstreamflow | -.049[b] | -.295 | .772 | -.069 | .822 |
| | dstreamwaterlevel | .169[b] | 1.163 | .260 | .264 | .991 |
| 2 | drainfall | .000[c] | .002 | .998 | .001 | .951 |
| | dtemperature | .031[c] | .214 | .833 | .052 | .859 |
| | dstreamflow | -.156[c] | -1.035 | .315 | -.244 | .756 |
| | dstreamwaterlevel | .160[c] | 1.228 | .236 | .285 | .990 |

a. Dependent Variable: dcpue

b. Predictors in the Model: (Constant), dprice

c. Predictors in the Model: (Constant), dprice, dlicence

**Regression in Eviws:** dcpue c dlicences dprice

Dependent Variable: DCPUE
Method: Least Squares
Date: 03/14/21 Time: 21:43
Sample: 1993 2013
Included observations: 21

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|

| | | | | |
|---|---|---|---|---|
| C | -0.000161 | 0.001596 | -0.101062 | 0.9206 |
| DLICENCES | -0.000580 | 0.000251 | -2.312073 | 0.0328 |
| DPRICE | 6.07E-08 | 9.63E-09 | 6.306149 | 0.0000 |

| | | | |
|---|---|---|---|
| R-squared | 0.688416 | Mean dependent var | 0.002677 |
| Adjusted R-squared | 0.653796 | S.D. dependent var | 0.011919 |
| S.E. of regression | 0.007013 | Akaike info criterion | -6.950466 |
| Sum squared resid | 0.000885 | Schwarz criterion | -6.801248 |
| Log likelihood | 75.97989 | Hannan-Quinn criter. | -6.918082 |
| F-statistic | 19.88468 | Durbin-Watson stat | 2.495451 |
| Prob(F-statistic) | 0.000028 | | |

**Unit root test of residual**:

Null Hypothesis: R has a unit root

Exogenous: Constant

Lag Length: 0 (Automatic - based on SIC, maxlag=4)

| | | t-Statistic | Prob.* |
|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | -6.510783 | 0.0000 |
| Test critical values: | 1% level | -3.808546 | |
| | 5% level | -3.020686 | |
| | 10% level | -2.650413 | |

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(R)

Method: Least Squares

Date: 03/14/21 Time: 21:45

Sample (adjusted): 1994 2013

Included observations: 20 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| R(-1) | -1.370857 | 0.210552 | -6.510783 | 0.0000 |
| C | 0.000660 | 0.001355 | 0.487371 | 0.6319 |

| | | | |
|---|---|---|---|
| R-squared | 0.701939 | Mean dependent var | 0.000141 |
| Adjusted R-squared | 0.685380 | S.D. dependent var | 0.010782 |
| S.E. of regression | 0.006048 | Akaike info criterion | -7.283557 |
| Sum squared resid | 0.000658 | Schwarz criterion | -7.183984 |

| | | | |
|---|---|---|---|
| Log likelihood | 74.83557 | Hannan-Quinn criter. | -7.264119 |
| F-statistic | 42.39030 | Durbin-Watson stat | 2.359043 |
| Prob(F-statistic) | 0.000004 | | |

The residual has no unit root.

**Serial correlation test:** EViews

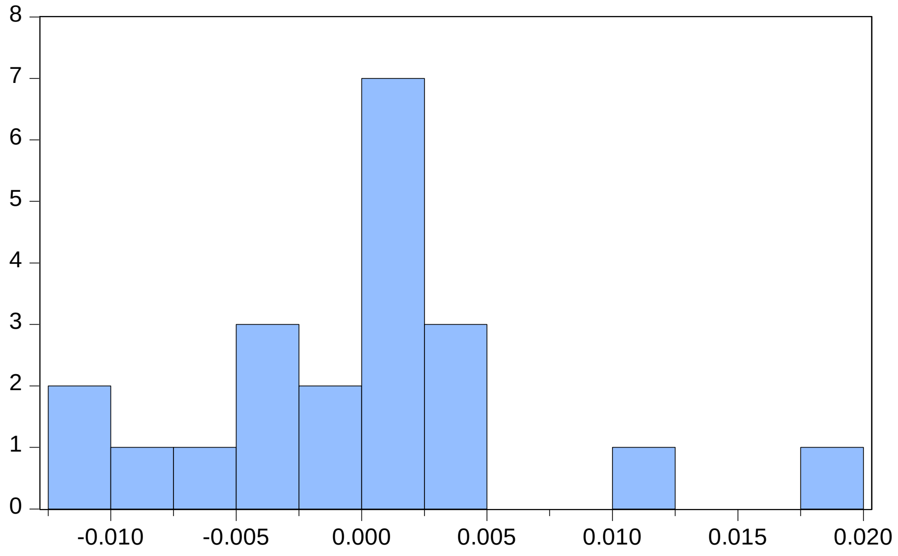
Date: 03/14/21 Time: 21:46
Sample: 1993 2013
Included observations: 21

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|---|---|
| | | 1 | -0.341 | -0.341 | 2.8109 | 0.094 |
| | | 2 | -0.114 | -0.260 | 3.1395 | 0.208 |
| | | 3 | 0.031 | -0.130 | 3.1651 | 0.367 |
| | | 4 | -0.033 | -0.122 | 3.1963 | 0.526 |
| | | 5 | 0.047 | -0.026 | 3.2638 | 0.659 |
| | | 6 | -0.096 | -0.129 | 3.5578 | 0.736 |
| | | 7 | -0.003 | -0.112 | 3.5582 | 0.829 |
| | | 8 | 0.104 | 0.019 | 3.9605 | 0.861 |
| | | 9 | -0.043 | -0.012 | 4.0345 | 0.909 |
| | | 10 | 0.018 | 0.022 | 4.0490 | 0.945 |
| | | 11 | -0.076 | -0.077 | 4.3291 | 0.959 |
| | | 12 | 0.140 | 0.105 | 5.3736 | 0.944 |

The residuals are flat and no serial correlation.

**Diagnostic checking:**

**Normality test of residuals:**




Series: Residuals
Sample 1993 2013
Observations 21

| | |
|---|---|
| Mean | 8.26e-20 |
| Median | 2.84e-05 |
| Maximum | 0.018686 |
| Minimum | -0.010395 |
| Std. Dev. | 0.006653 |
| Skewness | 0.879331 |
| Kurtosis | 4.421765 |
| Jarque-Bera | 4.475017 |
| Probability | 0.106724 |

**Breusch-Godfrey Serial Correlation LM Test:**

Lag(2)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 2.024904 | Prob. F(2,16) | 0.1645 |
| Obs*R-squared | 4.241734 | Prob. Chi-Square(2) | 0.1199 |

Lag(4)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 1.061185 | Prob. F(4,14) | 0.4118 |
| Obs*R-squared | 4.885767 | Prob. Chi-Square(4) | 0.2992 |

Lag(8)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.479799 | Prob. F(8,10) | 0.8449 |
| Obs*R-squared | 5.824826 | Prob. Chi-Square(8) | 0.6668 |

## Heteroscedasticity test:

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 0.463793 | Prob. F(2,18) | 0.6362 |
| Obs*R-squared | 1.029150 | Prob. Chi-Square(2) | 0.5978 |
| Scaled explained SS | 1.293615 | Prob. Chi-Square(2) | 0.5237 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/14/21 Time: 21:48
Sample: 1993 2013
Included observations: 21

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 4.50E-05 | 1.87E-05 | 2.405456 | 0.0271 |
| DLICENCES | 2.66E-06 | 2.94E-06 | 0.905640 | 0.3771 |
| DPRICE | -7.24E-11 | 1.13E-10 | -0.641856 | 0.5291 |

| | | | |
|---|---|---|---|
| R-squared | 0.049007 | Mean dependent var | 4.22E-05 |
| Adjusted R-squared | -0.056659 | S.D. dependent var | 7.99E-05 |
| S.E. of regression | 8.21E-05 | Akaike info criterion | -15.84462 |
| Sum squared resid | 1.21E-07 | Schwarz criterion | -15.69540 |

| | | | |
|---|---|---|---|
| Log likelihood | 169.3685 | Hannan-Quinn criter. | -15.81223 |
| F-statistic | 0.463793 | Durbin-Watson stat | 1.534936 |
| Prob(F-statistic) | 0.636202 | | |

Probability is greater than 5%, so the model is not heteroscedastic.

**ARIMAX (0,1,0) Forecasting**: Extend workfile size (from 1994-2016) by double clicking the range> provide original values in dprice from 2013-2016>Quick >estimate equation> dcpue c dlicences dprice> Forecast> Forecast sample (1994-2016)>ok>

Associated excel file to determine MAPE, RAMSE, MAE etc. of the year 2014-2016.

**Sample 1994-2016:**

**Unit root test:** All variables have unit root, 1st difference of the series made them stationary.

**Lag selection**: Lag 4 was selected for the granger causality test.

**Granger causality test:**

Pairwise Granger Causality Tests
Date: 03/14/21 Time: 23:16
Sample: 1995 2016
Lags: 4

| Null Hypothesis: | Obs | F-Statistic | Prob. |
|---|---|---|---|
| DLICENCES does not Granger Cause DCPUE | 18 | 0.30459 | 0.8678 |
| DCPUE does not Granger Cause DLICENCES | | 1.59035 | 0.2583 |
| DPRICE does not Granger Cause DCPUE | 18 | 1.66479 | 0.2410 |
| DCPUE does not Granger Cause DPRICE | | 2.89372 | 0.0855 |
| DRAINFALL does not Granger Cause DCPUE | 18 | 0.66986 | 0.6291 |
| DCPUE does not Granger Cause DRAINFALL | | 0.84362 | 0.5315 |
| DTEMPERATURE does not Granger Cause DCPUE | 18 | 0.88705 | 0.5093 |
| DCPUE does not Granger Cause DTEMPERATURE | | 0.53803 | 0.7120 |
| DSTREAMFLOW does not Granger Cause DCPUE | 18 | 1.81282 | 0.2106 |
| DCPUE does not Granger Cause DSTREAMFLOW | | 1.43006 | 0.3003 |
| DSTREAMWATERLEVEL does not Granger Cause DCPUE | 18 | 0.14044 | 0.9628 |
| DCPUE does not Granger Cause DSTREAMWATERLEVEL | | 0.50382 | 0.7345 |

No reverse causality was found.

**Test for multicollinearity:**

**Coefficients[a]**

| Model | | Collinearity Statistics | |
|---|---|---|---|
| | | Tolerance | VIF |
| 1 | dlicence | .590 | 1.694 |
| | dprice | .331 | 3.025 |
| | drainfall | .226 | 4.426 |
| | dtemperature | .483 | 2.069 |
| | dstreamflow | .076 | 13.119 |
| | dstreamwaterlevel | .065 | 15.281 |

a. Dependent Variable: dcpue

Here multicollinearity is present between streamflow and Stream water level. Tolerance is more than 0.1, VIF is less than 10.

**Regression Test :**

**Forward Stepwise:**

**Coefficients[a]**

| Model | | Unstandardized Coefficients | | Standardized Coefficients | t | Sig. | 95.0% Confidence Interval for B | |
|---|---|---|---|---|---|---|---|---|
| | | B | Std. Error | Beta | | | Lower Bound | Upper Bound |
| 1 | (Constant) | .003 | .002 | | 1.742 | .097 | -.001 | .006 |
| | dprice | 3.961E-8 | .000 | .823 | 6.469 | .000 | .000 | .000 |

a. Dependent Variable: dcpue

**Excluded Variables[a]**

| Model | | Beta In | t | Sig. | Partial Correlation | Collinearity Statistics Tolerance |
|---|---|---|---|---|---|---|
| 1 | dlicence | -.252[b] | -1.576 | .131 | -.340 | .591 |
| | drainfall | .008[b] | .065 | .949 | .015 | .998 |
| | dtemperature | -.053[b] | -.393 | .699 | -.090 | .924 |
| | dstreamflow | .022[b] | .157 | .877 | .036 | .894 |
| | dstreamwaterlevel | .149[b] | 1.176 | .254 | .260 | .993 |

a. Dependent Variable: dcpue

b. Predictors in the Model: (Constant), dprice

**Regression in Eviws:** dcpue c dprice

Dependent Variable: DCPUE
Method: Least Squares
Date: 03/14/21 Time: 23:19
Sample: 1995 2016
Included observations: 22

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| DPRICE | 3.96E-08 | 6.12E-09 | 6.468703 | 0.0000 |
| C | 0.002668 | 0.001532 | 1.741553 | 0.0969 |

| | | | |
|---|---|---|---|
| R-squared | 0.676606 | Mean dependent var | 0.002036 |
| Adjusted R-squared | 0.660437 | S.D. dependent var | 0.012307 |
| S.E. of regression | 0.007171 | Akaike info criterion | -6.950960 |
| Sum squared resid | 0.001029 | Schwarz criterion | -6.851774 |
| Log likelihood | 78.46056 | Hannan-Quinn criter. | -6.927595 |
| F-statistic | 41.84412 | Durbin-Watson stat | 1.982525 |
| Prob(F-statistic) | 0.000003 | | |

Create a dummy variable and interact with DPrice from 2015:

dcpue dprice dummy dummyprice  c

Dependent Variable: DCPUE
Method: Least Squares
Date: 03/28/21   Time: 18:57
Sample: 1995 2016
Included observations: 22

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| DPRICE | 4.94E-08 | 7.87E-09 | 6.277880 | 0.0000 |
| DUMMY | 0.000964 | 0.006912 | 0.139428 | 0.8907 |
| DUMMYPRICE | -2.17E-08 | 1.46E-08 | -1.486120 | 0.1546 |
| C | 0.001994 | 0.001553 | 1.283591 | 0.2156 |

| | | | |
|---|---|---|---|
| R-squared | 0.729744 | Mean dependent var | 0.002036 |
| Adjusted R-squared | 0.684701 | S.D. dependent var | 0.012307 |
| S.E. of regression | 0.006910 | Akaike info criterion | -6.948642 |
| Sum squared resid | 0.000860 | Schwarz criterion | -6.750271 |
| Log likelihood | 80.43506 | Hannan-Quinn criter. | -6.901912 |
| F-statistic | 16.20116 | Durbin-Watson stat | 2.327583 |
| Prob(F-statistic) | 0.000024 | | |

In the regression, the dummy variable and interacted dummy term for dprice are not significant, hence dummy terms will be removed from the regression and rerun the model.

Dependent Variable: DCPUE
Method: Least Squares
Date: 03/28/21   Time: 18:59
Sample: 1995 2016
Included observations: 22

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| DPRICE | 3.96E-08 | 6.12E-09 | 6.468703 | 0.0000 |
| C | 0.002668 | 0.001532 | 1.741553 | 0.0969 |

| | | | |
|---|---|---|---|
| R-squared | 0.676606 | Mean dependent var | 0.002036 |
| Adjusted R-squared | 0.660437 | S.D. dependent var | 0.012307 |
| S.E. of regression | 0.007171 | Akaike info criterion | -6.950960 |
| Sum squared resid | 0.001029 | Schwarz criterion | -6.851774 |
| Log likelihood | 78.46056 | Hannan-Quinn criter. | -6.927595 |
| F-statistic | 41.84412 | Durbin-Watson stat | 1.982525 |

| | |
|---|---|
| Prob(F-statistic) | 0.000003 |

**Unit root test of residual:**

Null Hypothesis: R has a unit root

Exogenous: Constant

Lag Length: 0 (Automatic - based on SIC, maxlag=4)

| | | t-Statistic | Prob.* |
|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | -4.899327 | 0.0009 |
| Test critical values: | 1% level | -3.788030 | |
| | 5% level | -3.012363 | |
| | 10% level | -2.646119 | |

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(R)

Method: Least Squares

Date: 03/14/21 Time: 23:33

Sample (adjusted): 1996 2016

Included observations: 21 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| R(-1) | -1.104106 | 0.225359 | -4.899327 | 0.0001 |
| C | -0.000552 | 0.001506 | -0.366197 | 0.7183 |

| | | | |
|---|---|---|---|
| R-squared | 0.558175 | Mean dependent var | -5.11E-05 |
| Adjusted R-squared | 0.534921 | S.D. dependent var | 0.010097 |
| S.E. of regression | 0.006886 | Akaike info criterion | -7.028278 |
| Sum squared resid | 0.000901 | Schwarz criterion | -6.928799 |
| Log likelihood | 75.79692 | Hannan-Quinn criter. | -7.006688 |
| F-statistic | 24.00341 | Durbin-Watson stat | 1.748331 |
| Prob(F-statistic) | 0.000100 | | |

Residual does not have unit root.

**Serial correlation test**: EViews

Quick>estimate equation> dcpue c dprice >ok>view tab> residual diagnostics>correlogram and Q-statistics (Ljung-Box test) >lag selection (12)> ok.

Date: 03/14/21 Time: 23:34
Sample: 1995 2016
Included observations: 22

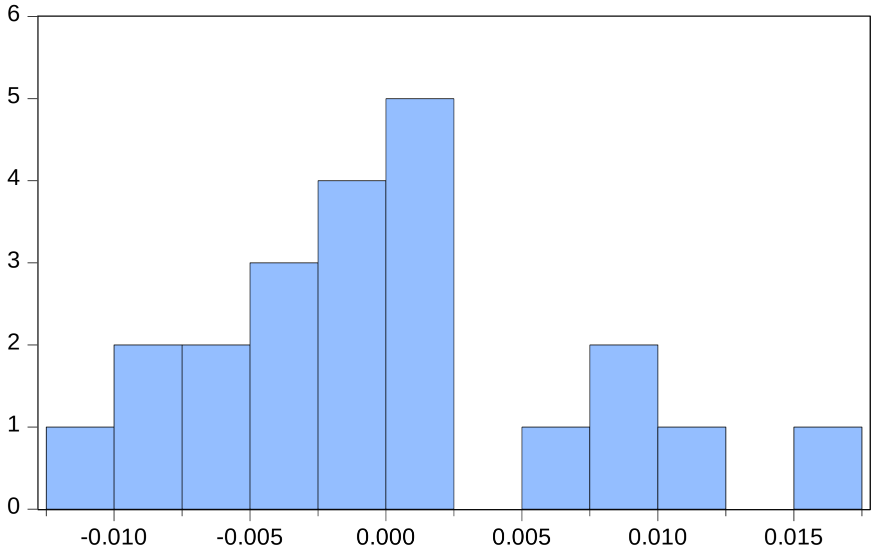
| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|---|---|
| | | 1 | -0.090 | -0.090 | 0.2029 | 0.652 |
| | | 2 | -0.027 | -0.035 | 0.2218 | 0.895 |
| | | 3 | -0.177 | -0.184 | 1.0898 | 0.780 |
| | | 4 | 0.144 | 0.113 | 1.6953 | 0.792 |
| | | 5 | 0.196 | 0.217 | 2.8897 | 0.717 |
| | | 6 | -0.100 | -0.094 | 3.2200 | 0.781 |
| | | 7 | 0.051 | 0.098 | 3.3115 | 0.855 |
| | | 8 | -0.183 | -0.137 | 4.5726 | 0.802 |
| | | 9 | 0.053 | -0.066 | 4.6848 | 0.861 |
| | | 10 | -0.034 | -0.031 | 4.7371 | 0.908 |
| | | 11 | -0.018 | -0.071 | 4.7528 | 0.943 |
| | | 12 | 0.015 | 0.025 | 4.7650 | 0.965 |

**Selection of MA and AR term:**

The residuals are flat and no serial correlation i.e. in white noise.

**Diagnostic checking:**

**Normality test of residuals:**




Series: Residuals
Sample 1995 2016
Observations 22

| | |
|---|---|
| Mean | -1.58e-19 |
| Median | -0.000265 |
| Maximum | 0.016292 |
| Minimum | -0.012152 |
| Std. Dev. | 0.006998 |
| Skewness | 0.525029 |
| Kurtosis | 2.889546 |
| Jarque-Bera | 1.021919 |
| Probability | 0.599920 |

Breusch-Godfrey Serial Correlation LM Test:

Lag(2)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.097531 | Prob. F(2,18) | 0.9075 |
| Obs*R-squared | 0.235854 | Prob. Chi-Square(2) | 0.8888 |

Lag(4)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.470549 | Prob. F(4,16) | 0.7566 |
| Obs*R-squared | 2.315618 | Prob. Chi-Square(4) | 0.6779 |

Lag(8)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.532706 | Prob. F(8,12) | 0.8110 |
| Obs*R-squared | 5.765486 | Prob. Chi-Square(8) | 0.6735 |

## Heteroscedasticity test:

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 0.093920 | Prob. F(1,20) | 0.7624 |
| Obs*R-squared | 0.102829 | Prob. Chi-Square(1) | 0.7485 |
| Scaled explained SS | 0.080289 | Prob. Chi-Square(1) | 0.7769 |

Test Equation:

Dependent Variable: RESID^2

Method: Least Squares

Date: 03/14/21 Time: 23:35

Sample: 1995 2016

Included observations: 22

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 4.70E-05 | 1.44E-05 | 3.273933 | 0.0038 |
| DPRICE | 1.76E-11 | 5.74E-11 | 0.306463 | 0.7624 |

| | | | |
|---|---|---|---|
| R-squared | 0.004674 | Mean dependent var | 4.68E-05 |
| Adjusted R-squared | -0.045092 | S.D. dependent var | 6.58E-05 |
| S.E. of regression | 6.72E-05 | Akaike info criterion | -16.28996 |
| Sum squared resid | 9.04E-08 | Schwarz criterion | -16.19078 |
| Log likelihood | 181.1896 | Hannan-Quinn criter. | -16.26660 |
| F-statistic | 0.093920 | Durbin-Watson stat | 1.134888 |
| Prob(F-statistic) | 0.762419 | | |

**ARIMAX (0,1,0) Forecasting**: Extend workfile size (from 1996-2019) by double clicking the range> provide original values in dprice from 2017-2019>Quick >estimate equation> dcpue c dprice > Forecast> Forecast sample (1996-2019)>ok>

Associated excel file to determine MAPE, RAMSE, MAE etc. of the year 2017-2019.

**Regression model:** 3 years lag of Env. variables

**Sample 1990-2010:**

**Multicollinearity test:**

**Coefficients**[a]

| Model | | Collinearity Statistics Tolerance | VIF |
|---|---|---|---|
| 1 | licence | .496 | 2.018 |
| | price | .669 | 1.495 |
| | rainfall | .451 | 2.217 |
| | temperature | .627 | 1.595 |
| | streamflow | .394 | 2.540 |
| | streamwaterlevel | .587 | 1.704 |

a. Dependent Variable: cpue

Here, multicollinearity is absent among variables.

**MLR:**

cpue licences price rainfall temperature streamflow streamwaterlevel c

Dependent Variable: CPUE
Method: Least Squares
Date: 03/23/21 Time: 12:09
Sample: 1993 2010
Included observations: 18

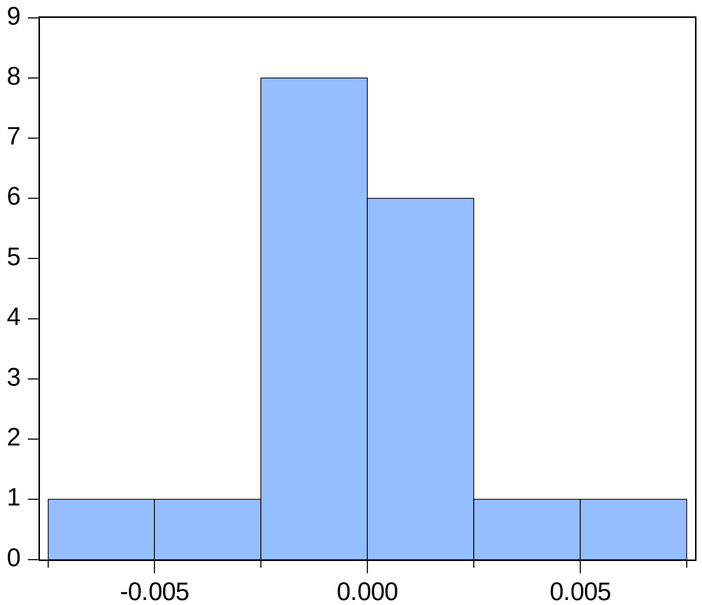
| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|

| | | | | |
|---|---|---|---|---|
| LICENCES | -0.000332 | 0.000193 | -1.721416 | 0.1131 |
| PRICE | 5.61E-08 | 8.59E-09 | 6.530599 | 0.0000 |
| RAINFALL | -5.73E-06 | 5.66E-06 | -1.012394 | 0.3331 |
| TEMPERATURE | -0.004320 | 0.002969 | -1.454984 | 0.1736 |
| STREAMFLOW | -1.74E-10 | 8.19E-10 | -0.212776 | 0.8354 |
| STREAMWATERLEVEL | 0.000115 | 0.000659 | 0.173891 | 0.8651 |
| C | 0.130760 | 0.072581 | 1.801571 | 0.0991 |

| | | | |
|---|---|---|---|
| R-squared | 0.853831 | Mean dependent var | 0.034495 |
| Adjusted R-squared | 0.774102 | S.D. dependent var | 0.007662 |
| S.E. of regression | 0.003642 | Akaike info criterion | -8.107490 |
| Sum squared resid | 0.000146 | Schwarz criterion | -7.761235 |
| Log likelihood | 79.96741 | Hannan-Quinn criter. | -8.059746 |
| F-statistic | 10.70922 | Durbin-Watson stat | 2.641540 |
| Prob(F-statistic) | 0.000478 | | |

**Diagnostic checking:**

**Normality test:**




Series: Residuals
Sample 1993 2010
Observations 18

| | |
|---|---|
| Mean | 3.08e-17 |
| Median | -0.000102 |
| Maximum | 0.006898 |
| Minimum | -0.006444 |
| Std. Dev. | 0.002929 |
| Skewness | 0.097356 |
| Kurtosis | 3.850664 |
| Jarque-Bera | 0.571156 |
| Probability | 0.751580 |

**Breusch-Godfrey Serial Correlation LM Test:**

Lag(2)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 1.214730 | Prob. F(2,9) | 0.3412 |
| Obs*R-squared | 3.826101 | Prob. Chi-Square(2) | 0.1476 |

Lag(4)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.720671 | Prob. F(4,7) | 0.6044 |
| Obs*R-squared | 5.250427 | Prob. Chi-Square(4) | 0.2626 |

Lag(8)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 8.904364 | Prob. F(8,3) | 0.0795 |
| Obs*R-squared | 7.272581 | Prob. Chi-Square(8) | 0.0674 |

## Heteroscedasticity test:

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 1.248141 | Prob. F(6,11) | 0.3542 |
| Obs*R-squared | 7.290840 | Prob. Chi-Square(6) | 0.2948 |
| Scaled explained SS | 3.880913 | Prob. Chi-Square(6) | 0.6928 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/23/21 Time: 12:10
Sample: 1993 2010
Included observations: 18

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | -0.000122 | 0.000269 | -0.454631 | 0.6582 |
| LICENCES | 9.44E-07 | 7.15E-07 | 1.319883 | 0.2137 |
| PRICE | -2.16E-11 | 3.18E-11 | -0.678075 | 0.5117 |
| RAINFALL | -1.57E-08 | 2.10E-08 | -0.750411 | 0.4688 |
| TEMPERATURE | 5.07E-06 | 1.10E-05 | 0.460521 | 0.6541 |
| STREAMFLOW | 1.48E-12 | 3.04E-12 | 0.488170 | 0.6350 |
| STREAMWATERLEVEL | -2.48E-06 | 2.44E-06 | -1.015840 | 0.3315 |

| | | | |
|---|---|---|---|
| R-squared | 0.405047 | Mean dependent var | 8.10E-06 |

| | | | |
|---|---|---|---|
| Adjusted R-squared | 0.080527 | S.D. dependent var | 1.41E-05 |
| S.E. of regression | 1.35E-05 | Akaike info criterion | -19.30236 |
| Sum squared resid | 2.00E-09 | Schwarz criterion | -18.95610 |
| Log likelihood | 180.7212 | Hannan-Quinn criter. | -19.25461 |
| F-statistic | 1.248141 | Durbin-Watson stat | 1.707868 |
| Prob(F-statistic) | 0.354212 | | |

**Sample 1992-2013:**

**Multicollinearity test:**

**Coefficients[a]**

| Model | | Collinearity Statistics Tolerance | VIF |
|---|---|---|---|
| 1 | licence | .522 | 1.916 |
| | price | .525 | 1.905 |
| | rainfall | .352 | 2.841 |
| | temperature | .488 | 2.049 |
| | streamflow | .501 | 1.997 |
| | streamwaterlevel | .487 | 2.055 |

a. Dependent Variable: cpue

Here, multicollinearity is absent among variables.

**MLR:**

cpue licences price rainfall temperature streamflow streamwaterlevel c

Dependent Variable: CPUE
Method: Least Squares
Date: 03/23/21 Time: 12:14
Sample: 1995 2013
Included observations: 19

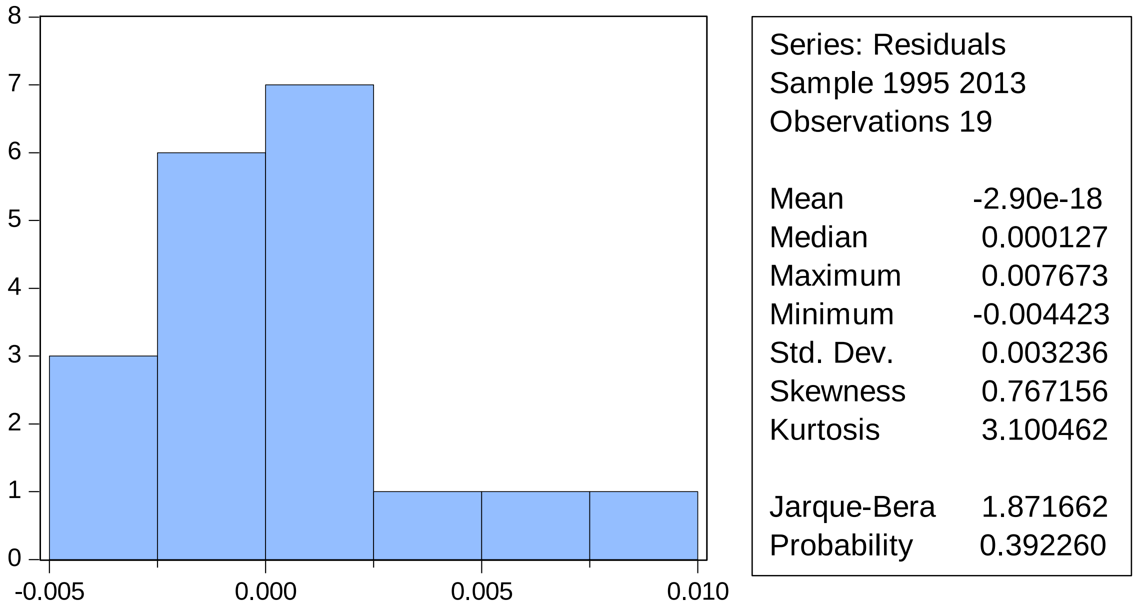
| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| LICENCES | -0.000418 | 0.000190 | -2.198872 | 0.0482 |
| PRICE | 7.45E-08 | 4.31E-09 | 17.27261 | 0.0000 |

| | | | | |
|---|---|---|---|---|
| RAINFALL | -7.11E-06 | 6.31E-06 | -1.126243 | 0.2821 |
| TEMPERATURE | -0.003561 | 0.003337 | -1.067019 | 0.3070 |
| STREAMFLOW | 1.92E-10 | 4.69E-10 | 0.408634 | 0.6900 |
| STREAMWATERLEVEL | -0.000611 | 0.000809 | -0.755860 | 0.4643 |
| C | 0.113970 | 0.081136 | 1.404669 | 0.1855 |

| | | | |
|---|---|---|---|
| R-squared | 0.978839 | Mean dependent var | 0.043858 |
| Adjusted R-squared | 0.968259 | S.D. dependent var | 0.022246 |
| S.E. of regression | 0.003963 | Akaike info criterion | -7.946159 |
| Sum squared resid | 0.000188 | Schwarz criterion | -7.598208 |
| Log likelihood | 82.48851 | Hannan-Quinn criter. | -7.887272 |
| F-statistic | 92.51370 | Durbin-Watson stat | 1.451333 |
| Prob(F-statistic) | 0.000000 | | |

**Diagnostic Checking:**

**Normality test:**




**Breusch-Godfrey Serial Correlation LM Test:**

Lag(2)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.514089 | Prob. F(2,10) | 0.6130 |
| Obs*R-squared | 1.771407 | Prob. Chi-Square(2) | 0.4124 |

Lag(4)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.490386 | Prob. F(4,8) | 0.7436 |
| Obs*R-squared | 3.741320 | Prob. Chi-Square(4) | 0.4421 |

Lag(8)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.273606 | Prob. F(8,4) | 0.9439 |
| Obs*R-squared | 6.719849 | Prob. Chi-Square(8) | 0.5671 |

## Heteroscedasticity Test:

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 1.150319 | Prob. F(6,12) | 0.3922 |
| Obs*R-squared | 6.937728 | Prob. Chi-Square(6) | 0.3266 |
| Scaled explained SS | 2.906413 | Prob. Chi-Square(6) | 0.8205 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/23/21 Time: 12:15
Sample: 1995 2013
Included observations: 19

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | -0.000170 | 0.000295 | -0.577469 | 0.5743 |
| LICENCES | 1.63E-07 | 6.91E-07 | 0.235537 | 0.8178 |
| PRICE | 8.22E-12 | 1.57E-11 | 0.523993 | 0.6098 |
| RAINFALL | -5.85E-09 | 2.29E-08 | -0.254835 | 0.8032 |
| TEMPERATURE | 8.53E-06 | 1.21E-05 | 0.702887 | 0.4955 |
| STREAMFLOW | 1.63E-12 | 1.71E-12 | 0.955967 | 0.3580 |
| STREAMWATERLEVEL | -5.72E-06 | 2.94E-06 | -1.944934 | 0.0756 |

| | | | |
|---|---|---|---|
| R-squared | 0.365144 | Mean dependent var | 9.92E-06 |
| Adjusted R-squared | 0.047715 | S.D. dependent var | 1.48E-05 |
| S.E. of regression | 1.44E-05 | Akaike info criterion | -19.17924 |
| Sum squared resid | 2.49E-09 | Schwarz criterion | -18.83128 |
| Log likelihood | 189.2027 | Hannan-Quinn criter. | -19.12035 |
| F-statistic | 1.150319 | Durbin-Watson stat | 1.932598 |
| Prob(F-statistic) | 0.392227 | | |

**Sample 1994-2016:**

**Multicollinearity test:**

**Coefficients[a]**

| Model | | Collinearity Statistics | |
|---|---|---|---|
| | | Tolerance | VIF |
| 1 | licence | .438 | 2.282 |
| | price | .806 | 1.241 |
| | rainfall | .441 | 2.269 |
| | temperature | .489 | 2.046 |
| | streamflow | .394 | 2.541 |
| | streamwaterlevel | .522 | 1.917 |

a. Dependent Variable: cpue

Here, multicollinearity is absent among variables.

Create a dummy variable and interact with Dlicences and DPrice from 2015:

cpue licences price rainfall temperature streamflow streamwaterlevel dummylicences dummyprice c

Dependent Variable: CPUE
Method: Least Squares
Date: 03/28/21 Time: 19:07
Sample: 1997 2016
Included observations: 20

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| LICENCES | -0.000494 | 0.000220 | -2.250865 | 0.0458 |
| PRICE | 7.87E-08 | 4.79E-09 | 16.42592 | 0.0000 |
| RAINFALL | -1.47E-05 | 7.49E-06 | -1.963497 | 0.0754 |
| TEMPERATURE | -0.006863 | 0.003570 | -1.922215 | 0.0808 |
| STREAMFLOW | 1.58E-10 | 5.43E-10 | 0.290234 | 0.7770 |
| STREAMWATERLEVEL | 0.001482 | 0.001287 | 1.151357 | 0.2740 |
| DUMMYLICENCES | 0.008238 | 0.001599 | 5.152320 | 0.0003 |
| DUMMYPRICE | -9.25E-09 | 1.89E-09 | -4.901979 | 0.0005 |
| C | 0.185985 | 0.087400 | 2.127969 | 0.0568 |

| | | | |
|---|---|---|---|
| R-squared | 0.982021 | Mean dependent var | 0.050774 |
| Adjusted R-squared | 0.968946 | S.D. dependent var | 0.026036 |
| S.E. of regression | 0.004588 | Akaike info criterion | -7.628565 |
| Sum squared resid | 0.000232 | Schwarz criterion | -7.180485 |
| Log likelihood | 85.28565 | Hannan-Quinn criter. | -7.541095 |
| F-statistic | 75.10402 | Durbin-Watson stat | 1.981277 |
| Prob(F-statistic) | 0.000000 | | |

Here ‘dummy’ variable was omitted as the variables is collinear. In the regression, the dummy variable and interacted dummy term for dlicences and dprice is significant. Hence all significant variables will be used to determine the future cpue.

**MLR:**

cpue licences price rainfall temperature streamflow streamwaterlevel dummylicences dummyprice c

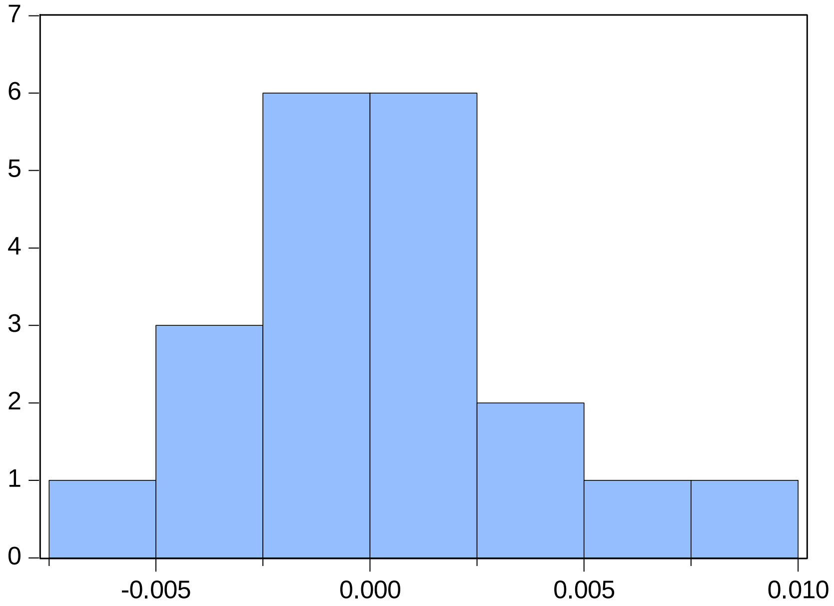
Dependent Variable: CPUE
Method: Least Squares
Date: 03/28/21 Time: 19:16
Sample: 1997 2016
Included observations: 20

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| LICENCES | -0.000494 | 0.000220 | -2.250865 | 0.0458 |
| PRICE | 7.87E-08 | 4.79E-09 | 16.42592 | 0.0000 |
| RAINFALL | -1.47E-05 | 7.49E-06 | -1.963497 | 0.0754 |
| TEMPERATURE | -0.006863 | 0.003570 | -1.922215 | 0.0808 |
| STREAMFLOW | 1.58E-10 | 5.43E-10 | 0.290234 | 0.7770 |
| STREAMWATERLEVEL | 0.001482 | 0.001287 | 1.151357 | 0.2740 |
| DUMMYLICENCES | 0.008238 | 0.001599 | 5.152320 | 0.0003 |
| DUMMYPRICE | -9.25E-09 | 1.89E-09 | -4.901979 | 0.0005 |
| C | 0.185985 | 0.087400 | 2.127969 | 0.0568 |

| | | | |
|---|---|---|---|
| R-squared | 0.982021 | Mean dependent var | 0.050774 |
| Adjusted R-squared | 0.968946 | S.D. dependent var | 0.026036 |
| S.E. of regression | 0.004588 | Akaike info criterion | -7.628565 |
| Sum squared resid | 0.000232 | Schwarz criterion | -7.180485 |
| Log likelihood | 85.28565 | Hannan-Quinn criter. | -7.541095 |
| F-statistic | 75.10402 | Durbin-Watson stat | 1.981277 |
| Prob(F-statistic) | 0.000000 | | |

**Diagnostic Checking:**

**Normality Test:**




| | |
|---|---|
| Series: Residuals | |
| Sample 1997 2016 | |
| Observations 20 | |
| Mean | 1.16e-18 |
| Median | -0.000289 |
| Maximum | 0.009291 |
| Minimum | -0.005696 |
| Std. Dev. | 0.003491 |
| Skewness | 0.830630 |
| Kurtosis | 3.875791 |
| Jarque-Bera | 2.938997 |
| Probability | 0.230041 |

**Breusch-Godfrey Serial Correlation LM Test:**

Lag(2)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.426542 | Prob. F(2,9) | 0.6653 |
| Obs*R-squared | 1.731608 | Prob. Chi-Square(2) | 0.4207 |

Lag(4)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.223828 | Prob. F(4,7) | 0.9167 |
| Obs*R-squared | 2.267955 | Prob. Chi-Square(4) | 0.6866 |

Lag(8)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 2.657740 | Prob. F(8,3) | 0.2273 |

| | | | |
|---|---|---|---|
| Obs*R-squared | 7.526996 | Prob. Chi-Square(8) | 0.0651 |

**Heteroscedasticity test:**

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 1.004808 | Prob. F(8,11) | 0.4832 |
| Obs*R-squared | 8.444448 | Prob. Chi-Square(8) | 0.3913 |
| Scaled explained SS | 3.673026 | Prob. Chi-Square(8) | 0.8854 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/28/21 Time: 19:17
Sample: 1997 2016
Included observations: 20

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.000227 | 0.000383 | 0.593273 | 0.5650 |
| LICENCES | -2.94E-07 | 9.63E-07 | -0.304886 | 0.7661 |
| PRICE | 2.21E-11 | 2.10E-11 | 1.053897 | 0.3145 |
| RAINFALL | -3.46E-08 | 3.28E-08 | -1.052034 | 0.3153 |
| TEMPERATURE | -9.71E-06 | 1.57E-05 | -0.619896 | 0.5480 |
| STREAMFLOW | 2.86E-12 | 2.38E-12 | 1.203234 | 0.2541 |
| STREAMWATERLEVEL | 4.86E-06 | 5.64E-06 | 0.861690 | 0.4073 |
| DUMMYLICENCES | -1.82E-06 | 7.01E-06 | -0.260140 | 0.7996 |
| DUMMYPRICE | 6.00E-13 | 8.28E-12 | 0.072453 | 0.9435 |

| | | | |
|---|---|---|---|
| R-squared | 0.422222 | Mean dependent var | 1.16E-05 |
| Adjusted R-squared | 0.002021 | S.D. dependent var | 2.01E-05 |
| S.E. of regression | 2.01E-05 | Akaike info criterion | -18.48725 |
| Sum squared resid | 4.45E-09 | Schwarz criterion | -18.03917 |
| Log likelihood | 193.8725 | Hannan-Quinn criter. | -18.39978 |
| F-statistic | 1.004808 | Durbin-Watson stat | 2.226766 |
| Prob(F-statistic) | 0.483181 | | |

## 4. Pooled NFZs site:

**Data Preparation**: Average value of all the variables were extracted from the three NFZs.

**Year: 1990-2010**

**Check for seasonality and trend:** Line diagram showing no seasonality pattern but a steady positive secular trend for the dependent variable "cpue".

**Unit root test:** All variable has unit root, so I took1$^{st}$ difference of all the series. Now the series is stationary.

**Lag selection**: Lag 4 was selected for the granger causality test.

**Granger Causality test:**

Pairwise Granger Causality Tests
Date: 03/17/21 Time: 15:45
Sample: 1990 2010
Lags: 4

| Null Hypothesis: | Obs | F-Statistic | Prob. |
|---|---|---|---|
| DLICENCES does not Granger Cause DCPUE | 16 | 0.06724 | 0.9899 |
| DCPUE does not Granger Cause DLICENCES | | 0.41425 | 0.7939 |
| DPRICE does not Granger Cause DCPUE | 16 | 1.87555 | 0.2196 |
| DCPUE does not Granger Cause DPRICE | | 0.37496 | 0.8199 |
| DRAINFALL does not Granger Cause DCPUE | 16 | 0.29277 | 0.8738 |
| DCPUE does not Granger Cause DRAINFALL | | 0.14669 | 0.9587 |
| DTEMPERATURE does not Granger Cause DCPUE | 16 | 0.80943 | 0.5569 |
| DCPUE does not Granger Cause DTEMPERATURE | | 0.34465 | 0.8400 |
| DSTREAMFLOW does not Granger Cause DCPUE | 16 | 1.05063 | 0.4461 |
| DCPUE does not Granger Cause DSTREAMFLOW | | 0.19200 | 0.9350 |
| DSTREAMWATERLEVEL does not Granger Cause DCPUE | 16 | 2.94451 | 0.1011 |
| DCPUE does not Granger Cause DSTREAMWATERLEVEL | | 1.02101 | 0.4583 |

No reverse causality was found.

**Test for multicollinearity**: SPSS

**Coefficients**[a]

| | | Collinearity Statistics | |
|---|---|---|---|
| Model | | Tolerance | VIF |
| 1 | dlicence | .571 | 1.753 |
| | dprice | .451 | 2.218 |

**Collinearity Diagnostics[a]**

| Model | Dimension | Eigenvalue | Condition Index | Variance Proportions (Constant) | dlicence | dprice | drainfall | dtemperature | dstreamflow | dstreamwaterlevel |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 2.396 | 1.000 | .00 | .00 | .03 | .04 | .03 | .05 | .02 |
| | 2 | 1.598 | 1.224 | .03 | .13 | .06 | .00 | .05 | .01 | .04 |
| | 3 | 1.078 | 1.491 | .52 | .05 | .03 | .00 | .06 | .02 | .01 |
| | 4 | .784 | 1.748 | .24 | .15 | .00 | .01 | .31 | .02 | .05 |
| | 5 | .619 | 1.968 | .00 | .11 | .17 | .05 | .05 | .27 | .08 |
| | 6 | .398 | 2.455 | .08 | .17 | .21 | .22 | .19 | .30 | .01 |
| | 7 | .128 | 4.330 | .13 | .39 | .50 | .67 | .31 | .33 | .80 |

a. Dependent Variable: dcpue

| | | | |
|---|---|---|---|
| | drainfall | .318 | 3.141 |
| | dtemperature | .606 | 1.650 |
| | dstreamflow | .501 | 1.996 |
| | dstreamwaterlevel | .326 | 3.071 |

a. Dependent Variable: dcpue

Here, multicollinearity is absent among variables. Tolerance is more than 0.1 and VIF is less than 10.

**Multiple Regression Test:** SPSS

**Stepwise (backward) regression:** SPSS

**Coefficients[a]**

| Model | | Unstandardized Coefficients B | Std. Error | Standardized Coefficients Beta | t | Sig. |
|---|---|---|---|---|---|---|
| 1 | (Constant) | -3.903E-5 | .002 | | -.025 | .980 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | dlicence | -2.825E-6 | .001 | -.001 | -.005 | .996 |
| | dprice | 1.533E-8 | .000 | .159 | .444 | .664 |
| | drainfall | 4.320E-7 | .000 | .032 | .075 | .941 |
| | dtemperature | .000 | .005 | -.024 | -.078 | .939 |
| | dstreamflow | -2.021E-9 | .000 | -.481 | -1.418 | .180 |
| | dstreamwaterlevel | .007 | .005 | .575 | 1.368 | .194 |
| 2 | (Constant) | -3.734E-5 | .001 | | -.026 | .980 |
| | dprice | 1.524E-8 | .000 | .158 | .581 | .570 |
| | drainfall | 4.410E-7 | .000 | .033 | .085 | .934 |
| | dtemperature | .000 | .004 | -.024 | -.083 | .935 |
| | dstreamflow | -2.018E-9 | .000 | -.480 | -1.605 | .131 |
| | dstreamwaterlevel | .007 | .005 | .575 | 1.534 | .147 |
| 3 | (Constant) | -4.305E-5 | .001 | | -.031 | .976 |
| | dprice | 1.537E-8 | .000 | .159 | .608 | .552 |
| | drainfall | 6.551E-7 | .000 | .048 | .150 | .883 |
| | dstreamflow | -2.004E-9 | .000 | -.477 | -1.666 | .116 |
| | dstreamwaterlevel | .007 | .004 | .562 | 1.688 | .112 |
| 4 | (Constant) | -7.178E-5 | .001 | | -.054 | .958 |
| | dprice | 1.692E-8 | .000 | .175 | .757 | .460 |
| | dstreamflow | -1.990E-9 | .000 | -.473 | -1.712 | .106 |
| | dstreamwaterlevel | .007 | .003 | .591 | 2.241 | .040 |
| 5 | (Constant) | 7.424E-5 | .001 | | .057 | .955 |
| | dstreamflow | -1.678E-9 | .000 | -.399 | -1.564 | .136 |
| | dstreamwaterlevel | .007 | .003 | .551 | 2.159 | .045 |
| 6 | (Constant) | .000 | .001 | | .297 | .770 |
| | dstreamwaterlevel | .004 | .003 | .333 | 1.499 | .051 |

a. Dependent Variable: dcpue

### Excluded Variables[a]

| Model | | Beta In | t | Sig. | Partial Correlation | Collinearity Statistics Tolerance |
|---|---|---|---|---|---|---|
| 2 | dlicence | -.001[b] | -.005 | .996 | -.001 | .571 |
| 3 | dlicence | .005[c] | .018 | .986 | .005 | .615 |
| | dtemperature | -.024[c] | -.083 | .935 | -.022 | .654 |
| 4 | dlicence | -.005[d] | -.019 | .985 | -.005 | .654 |
| | dtemperature | -.036[d] | -.149 | .884 | -.038 | .864 |
| | drainfall | .048[d] | .150 | .883 | .039 | .477 |
| 5 | dlicence | .092[e] | .417 | .682 | .104 | .984 |
| | dtemperature | -.079[e] | -.347 | .733 | -.087 | .932 |
| | drainfall | .129[e] | .444 | .663 | .110 | .572 |
| | dprice | .175[e] | .757 | .460 | .186 | .874 |
| 6 | dlicence | .133[f] | .587 | .565 | .141 | 1.000 |
| | dtemperature | .013[f] | .058 | .954 | .014 | 1.000 |
| | drainfall | .026[f] | .088 | .931 | .021 | .602 |
| | dprice | .035[f] | .152 | .881 | .037 | 1.000 |
| | dstreamflow | -.399[f] | -1.564 | .136 | -.355 | .702 |

a. Dependent Variable: dcpue

b. Predictors in the Model: (Constant), dstreamwaterlevel, dprice, dtemperature, dstreamflow, drainfall

c. Predictors in the Model: (Constant), dstreamwaterlevel, dprice, dstreamflow, drainfall

d. Predictors in the Model: (Constant), dstreamwaterlevel, dprice, dstreamflow

e. Predictors in the Model: (Constant), dstreamwaterlevel, dstreamflow

f. Predictors in the Model: (Constant), dstreamwaterlevel

**Regression Test** : Eviws: dcpue c dstreamwatrelevel

Dependent Variable: DCPUE

Method: Least Squares

Date: 03/17/21 Time: 15:58

Sample (adjusted): 1991 2010

Included observations: 20 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.000397 | 0.001338 | 0.296946 | 0.7699 |
| DSTREAMWATERLEVEL | 0.004150 | 0.002769 | 1.498872 | 0.0512 |

| | | | |
|---|---|---|---|
| R-squared | 0.110963 | Mean dependent var | 0.000808 |
| Adjusted R-squared | 0.061572 | S.D. dependent var | 0.006047 |
| S.E. of regression | 0.005858 | Akaike info criterion | -7.347542 |
| Sum squared resid | 0.000618 | Schwarz criterion | -7.247969 |
| Log likelihood | 75.47542 | Hannan-Quinn criter. | -7.328105 |
| F-statistic | 2.246618 | Durbin-Watson stat | 2.214506 |
| Prob(F-statistic) | 0.151241 | | |

**Unit root test for the residuals of regression model** (including dcpue c dstreamwaterlevel)**:**

Null Hypothesis: R has a unit root

Exogenous: Constant

Lag Length: 1 (Automatic - based on SIC, maxlag=4)

| | | t-Statistic | Prob.* |
|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | -4.878685 | 0.0013 |
| Test critical values: | 1% level | -3.857386 | |
| | 5% level | -3.040391 | |
| | 10% level | -2.660551 | |

*MacKinnon (1996) one-sided p-values.

Warning: Probabilities and critical values calculated for 20 observations and may not be accurate for a sample size of 18

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(R)

Method: Least Squares

Date: 03/17/21 Time: 16:00

Sample (adjusted): 1993 2010

Included observations: 18 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| R(-1) | -1.898580 | 0.389158 | -4.878685 | 0.0002 |
| D(R(-1)) | 0.379930 | 0.230889 | 1.645506 | 0.1207 |
| C | -0.000458 | 0.001159 | -0.395326 | 0.6982 |

| | | | |
|---|---|---|---|
| R-squared | 0.701701 | Mean dependent var | -0.000477 |
| Adjusted R-squared | 0.661928 | S.D. dependent var | 0.008449 |
| S.E. of regression | 0.004912 | Akaike info criterion | -7.643127 |
| Sum squared resid | 0.000362 | Schwarz criterion | -7.494732 |
| Log likelihood | 71.78815 | Hannan-Quinn criter. | -7.622666 |
| F-statistic | 17.64256 | Durbin-Watson stat | 1.796315 |
| Prob(F-statistic) | 0.000115 | | |

The residual has no unit root.

**Serial correlation test:** EViews

The probability of Q stat (Ljung-Box test) is more than .05. So, I should accept the null hypothesis. (Null: there is no serial correlation).

**Correlogram plot:**

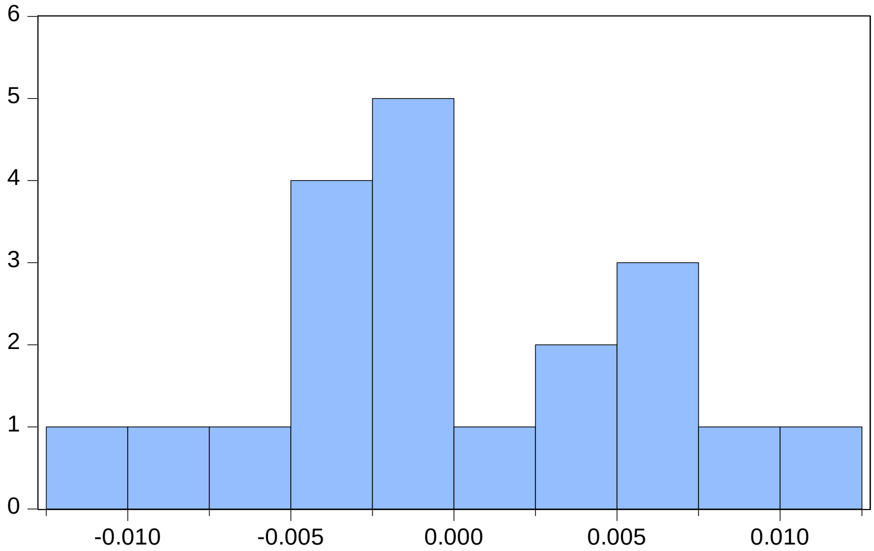
Date: 03/17/21 Time: 16:01
Sample: 1990 2010
Included observations: 20

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|---|---|
| | | 1 | -0.283 | -0.283 | 1.8594 | 0.173 |
| | | 2 | -0.203 | -0.307 | 2.8619 | 0.239 |
| | | 3 | 0.265 | 0.124 | 4.6851 | 0.196 |
| | | 4 | -0.104 | -0.041 | 4.9848 | 0.289 |
| | | 5 | -0.061 | -0.015 | 5.0940 | 0.405 |
| | | 6 | -0.040 | -0.158 | 5.1431 | 0.526 |
| | | 7 | -0.240 | -0.366 | 7.0971 | 0.419 |
| | | 8 | 0.166 | -0.078 | 8.1040 | 0.423 |
| | | 9 | 0.101 | 0.078 | 8.5140 | 0.483 |
| | | 10 | -0.263 | -0.118 | 11.564 | 0.315 |
| | | 11 | 0.112 | -0.089 | 12.180 | 0.350 |
| | | 12 | 0.071 | -0.147 | 12.455 | 0.410 |

The residuals are not flat and no serial correlation i.e. in white noise.

**Diagnostic checking:**

**Normality test of residuals:**




| | |
|---|---|
| Series: Residuals | |
| Sample 1991 2010 | |
| Observations 20 | |
| Mean | 2.60e-19 |
| Median | -0.001126 |
| Maximum | 0.010899 |
| Minimum | -0.010154 |
| Std. Dev. | 0.005701 |
| Skewness | 0.094068 |
| Kurtosis | 2.448085 |
| Jarque-Bera | 0.283338 |
| Probability | 0.867909 |

The probability of Jarque-Bera test in more than 5%, so the residual series follows normal distribution.

**Breusch-Godfrey Serial Correlation LM Test:**

Lag(2)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 1.955501 | Prob. F(2,16) | 0.1739 |
| Obs*R-squared | 3.928484 | Prob. Chi-Square(2) | 0.1403 |

Lag(4)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.976714 | Prob. F(4,14) | 0.4512 |
| Obs*R-squared | 4.363533 | Prob. Chi-Square(4) | 0.3590 |

Lag(8)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 1.009905 | Prob. F(8,10) | 0.4842 |
| Obs*R-squared | 8.937586 | Prob. Chi-Square(8) | 0.3476 |

**Heteroscedasticity test:**

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 3.975240 | Prob. F(1,18) | 0.0616 |
| Obs*R-squared | 3.617927 | Prob. Chi-Square(1) | 0.0572 |
| Scaled explained SS | 2.121822 | Prob. Chi-Square(1) | 0.1452 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/17/21 Time: 16:02
Sample: 1991 2010
Included observations: 20

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 2.76E-05 | 8.10E-06 | 3.404258 | 0.0032 |
| DSTREAMWATERLEVEL | 3.34E-05 | 1.68E-05 | 1.993800 | 0.0616 |

| | | | |
|---|---|---|---|
| R-squared | 0.180896 | Mean dependent var | 3.09E-05 |
| Adjusted R-squared | 0.135391 | S.D. dependent var | 3.81E-05 |
| S.E. of regression | 3.54E-05 | Akaike info criterion | -17.56226 |
| Sum squared resid | 2.26E-08 | Schwarz criterion | -17.46269 |
| Log likelihood | 177.6226 | Hannan-Quinn criter. | -17.54283 |
| F-statistic | 3.975240 | Durbin-Watson stat | 1.705341 |
| Prob(F-statistic) | 0.061550 | | |

Probability is greater than 5%, so the model is not heteroscedastic.

**ARIMAX (0,1,0) Forecasting**:

Extend workfile size (from 1990-2013) by double clicking the range> provide actual value in dstreamwaterlevel from 2010-2013>Quick >estimate equation> dcpue c dstreamwaterlevel > Forecast> Forecast sample (1990-2013)>ok>

Associated excel file to determine MAPE, RAMSE, MAE etc. of the year 2011-2013.

**Year 1992-2013:**

**Unit root test:** The series has unit root, 1$^{st}$ difference removed unit root from the series and the final series has no unit root

**Lag selection:** Lag 4 selected for the granger causality test for granger causality test.

**Granger Causality test:**

Pairwise Granger Causality Tests
Date: 03/17/21 Time: 16:58
Sample: 1992 2013
Lags: 4

| Null Hypothesis: | Obs | F-Statistic | Prob. |
|---|---|---|---|
| DLICENCES does not Granger Cause DCPUE | 17 | 0.09413 | 0.9816 |
| DCPUE does not Granger Cause DLICENCES | | 0.61196 | 0.6659 |
| DPRICE does not Granger Cause DCPUE | 17 | 0.66573 | 0.6334 |
| DCPUE does not Granger Cause DPRICE | | 0.11357 | 0.9741 |
| DRAINFALL does not Granger Cause DCPUE | 17 | 0.47333 | 0.7548 |
| DCPUE does not Granger Cause DRAINFALL | | 0.18774 | 0.9382 |
| DTEMPERATURE does not Granger Cause DCPUE | 17 | 0.39335 | 0.8082 |
| DCPUE does not Granger Cause DTEMPERATURE | | 0.35607 | 0.8331 |
| DSTREAMFLOW does not Granger Cause DCPUE | 17 | 1.40336 | 0.3160 |
| DCPUE does not Granger Cause DSTREAMFLOW | | 0.29912 | 0.8706 |
| DSTREAMWATERLEVEL does not Granger Cause DCPUE | 17 | 1.04475 | 0.4417 |
| DCPUE does not Granger Cause DSTREAMWATERLEVEL | | 0.80282 | 0.5563 |

No reverse causality detected.

**Test for multicollinearity:**

**Coefficients[a]**

| | | Collinearity Statistics | |
|---|---|---|---|
| Model | | Tolerance | VIF |
| 1 | ddlicence | .743 | 1.346 |
| | ddprice | .540 | 1.851 |
| | ddrainfall | .533 | 1.875 |
| | ddtemperature | .697 | 1.435 |
| | ddstreamflow | .537 | 1.861 |
| | ddstreamwaterlevel | .424 | 2.357 |

a. Dependent Variable: ddcpue

**Collinearity Diagnostics[a]**

| Model | Dimension | Eigenvalue | Condition Index | Variance Proportions (Constant) | ddlicence | ddprice | ddrainfall | ddtemperature | ddstreamflow | ddstreamwaterlevel |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 2.206 | 1.000 | .02 | .00 | .02 | .06 | .03 | .07 | .05 |
| | 2 | 1.692 | 1.142 | .00 | .13 | .11 | .01 | .07 | .00 | .03 |
| | 3 | 1.083 | 1.427 | .53 | .00 | .01 | .02 | .14 | .00 | .00 |
| | 4 | .786 | 1.675 | .01 | .48 | .02 | .10 | .06 | .08 | .05 |
| | 5 | .670 | 1.815 | .20 | .06 | .02 | .11 | .24 | .28 | .01 |
| | 6 | .343 | 2.535 | .09 | .17 | .47 | .37 | .43 | .05 | .09 |
| | 7 | .219 | 3.171 | .14 | .15 | .35 | .32 | .03 | .52 | .76 |

a. Dependent Variable: ddcpue

Here, multicollinearity is absent among variables. Tolerance is more than 0.1, VIF is less than 10.

**Regression Test**: SPSS

**Backward stepwise regression**:

**Coefficients[a]**

| Model | | Unstandardized Coefficients B | Std. Error | Standardized Coefficients Beta | t | Sig. |
|---|---|---|---|---|---|---|
| 1 | (Constant) | -2.882E-5 | .002 | | -.018 | .986 |
| | dlicence | -.001 | .001 | -.241 | -.970 | .349 |
| | dprice | 5.625E-8 | .000 | .605 | 2.073 | .057 |
| | drainfall | -5.303E-6 | .000 | -.319 | -1.087 | .296 |
| | dtemperature | -.004 | .004 | -.244 | -.949 | .359 |
| | dstreamflow | -2.170E-9 | .000 | -.426 | -1.455 | .168 |
| | dstreamwaterlevel | .009 | .005 | .561 | 1.702 | .111 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 2 | (Constant) | .000 | .002 | | -.166 | .871 |
| | dlicence | -.001 | .001 | -.239 | -.963 | .351 |
| | dprice | 6.445E-8 | .000 | .694 | 2.514 | .024 |
| | drainfall | -3.766E-6 | .000 | -.227 | -.821 | .425 |
| | dstreamflow | -2.012E-9 | .000 | -.395 | -1.362 | .193 |
| | dstreamwaterlevel | .008 | .005 | .497 | 1.545 | .143 |
| 3 | (Constant) | .000 | .002 | | -.068 | .947 |
| | dlicence | -.001 | .001 | -.228 | -.929 | .366 |
| | dprice | 6.113E-8 | .000 | .658 | 2.440 | .027 |
| | dstreamflow | -1.968E-9 | .000 | -.386 | -1.346 | .197 |
| | dstreamwaterlevel | .006 | .004 | .349 | 1.324 | .204 |
| 4 | (Constant) | 7.550E-5 | .002 | | .049 | .961 |
| | dprice | 4.994E-8 | .000 | .537 | 2.282 | .036 |
| | dstreamflow | -1.577E-9 | .000 | -.309 | -1.131 | .274 |
| | dstreamwaterlevel | .005 | .004 | .333 | 1.269 | .221 |
| 5 | (Constant) | .000 | .002 | | .202 | .842 |
| | dprice | 3.923E-8 | .000 | .422 | 1.973 | .064 |
| | dstreamwaterlevel | .003 | .003 | .159 | .742 | .468 |
| 6 | (Constant) | .001 | .001 | | .382 | .707 |
| | dprice | 3.749E-8 | .000 | .403 | 1.922 | .050 |

a. Dependent Variable: dcpue

**Excluded Variables[a]**

| Model | | Beta In | t | Sig. | Partial Correlation | Collinearity Statistics Tolerance |
|---|---|---|---|---|---|---|
| 2 | dtemperature | -.244[b] | -.949 | .359 | -.246 | .697 |
| 3 | dtemperature | -.151[c] | -.620 | .545 | -.158 | .783 |
| | drainfall | -.227[c] | -.821 | .425 | -.207 | .599 |
| 4 | dtemperature | -.153[d] | -.630 | .537 | -.156 | .783 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | drainfall | -.212[d] | -.772 | .451 | -.190 | .601 |
| | dlicence | -.228[d] | -.929 | .366 | -.226 | .745 |
| 5 | dtemperature | -.125[e] | -.511 | .616 | -.123 | .791 |
| | drainfall | -.206[e] | -.741 | .469 | -.177 | .601 |
| | dlicence | -.133[e] | -.553 | .588 | -.133 | .813 |
| | dstreamflow | -.309[e] | -1.131 | .274 | -.265 | .594 |
| 6 | dtemperature | -.134[f] | -.557 | .584 | -.130 | .794 |
| | drainfall | -.024[f] | -.113 | .911 | -.027 | .998 |
| | dlicence | -.153[f] | -.652 | .523 | -.152 | .826 |
| | dstreamflow | -.106[f] | -.469 | .645 | -.110 | .906 |
| | dstreamwaterlevel | .159[f] | .742 | .468 | .172 | .986 |

a. Dependent Variable: dcpue

b. Predictors in the Model: (Constant), dstreamwaterlevel, dlicence, dprice, dstreamflow, drainfall

c. Predictors in the Model: (Constant), dstreamwaterlevel, dlicence, dprice, dstreamflow

d. Predictors in the Model: (Constant), dstreamwaterlevel, dprice, dstreamflow

e. Predictors in the Model: (Constant), dstreamwaterlevel, dprice

f. Predictors in the Model: (Constant), dprice

**Regression Eviws**: dcpue c dprice

Dependent Variable: DCPUE
Method: Least Squares
Date: 03/17/21 Time: 17:03
Sample (adjusted): 1993 2013
Included observations: 21 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.000565 | 0.001478 | 0.382271 | 0.7065 |
| DPRICE | 3.75E-08 | 1.95E-08 | 1.922128 | 0.0507 |

| | | | |
|---|---|---|---|
| R-squared | 0.162796 | Mean dependent var | 0.001301 |
| Adjusted R-squared | 0.118732 | S.D. dependent var | 0.006968 |
| S.E. of regression | 0.006542 | Akaike info criterion | -7.130864 |
| Sum squared resid | 0.000813 | Schwarz criterion | -7.031386 |

| | | | |
|---|---|---|---|
| Log likelihood | 76.87407 | Hannan-Quinn criter. | -7.109275 |
| F-statistic | 3.694577 | Durbin-Watson stat | 2.617714 |
| Prob(F-statistic) | 0.069715 | | |

## Unit root test of residual:

Null Hypothesis: R has a unit root

Exogenous: Constant

Lag Length: 0 (Automatic - based on SIC, maxlag=4)

| | | t-Statistic | Prob.* |
|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | -6.242512 | 0.0001 |
| Test critical values: | 1% level | -3.808546 | |
| | 5% level | -3.020686 | |
| | 10% level | -2.650413 | |

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(R)

Method: Least Squares

Date: 03/17/21 Time: 17:05

Sample (adjusted): 1994 2013

Included observations: 20 after adjustments

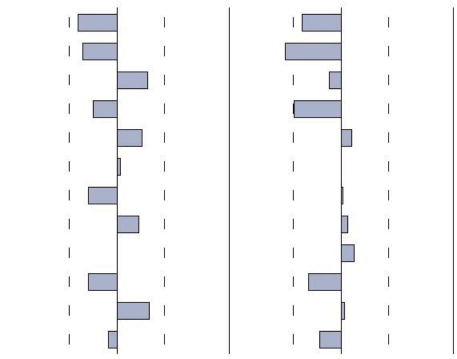
| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| R(-1) | -1.381734 | 0.221343 | -6.242512 | 0.0000 |
| C | 0.000397 | 0.001369 | 0.290379 | 0.7748 |

| | | | |
|---|---|---|---|
| R-squared | 0.684038 | Mean dependent var | -8.18E-05 |
| Adjusted R-squared | 0.666485 | S.D. dependent var | 0.010584 |
| S.E. of regression | 0.006112 | Akaike info criterion | -7.262446 |
| Sum squared resid | 0.000672 | Schwarz criterion | -7.162873 |
| Log likelihood | 74.62446 | Hannan-Quinn criter. | -7.243009 |
| F-statistic | 38.96895 | Durbin-Watson stat | 2.387014 |
| Prob(F-statistic) | 0.000007 | | |

The residual has no unit root.

**Serial correlation test**: EViews

Date: 03/17/21 Time: 17:05
Sample: 1992 2013
Included observations: 21



| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|---|---|
| | | 1 | -0.356 | -0.356 | 3.0562 | 0.080 |
| | | 2 | -0.318 | -0.509 | 5.6212 | 0.060 |
| | | 3 | 0.280 | -0.110 | 7.7280 | 0.052 |
| | | 4 | -0.221 | -0.429 | 9.1139 | 0.058 |
| | | 5 | 0.234 | 0.099 | 10.762 | 0.056 |
| | | 6 | 0.037 | 0.007 | 10.806 | 0.095 |
| | | 7 | -0.265 | 0.022 | 13.227 | 0.067 |
| | | 8 | 0.197 | 0.065 | 14.669 | 0.066 |
| | | 9 | 0.006 | 0.116 | 14.670 | 0.100 |
| | | 10 | -0.268 | -0.296 | 17.821 | 0.058 |
| | | 11 | 0.295 | 0.040 | 22.033 | 0.024 |
| | | 12 | -0.081 | -0.194 | 22.390 | 0.033 |

**Selection of AR and MA term:**

dcpue c dprice ar(2)

Dependent Variable: DCPUE
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 03/17/21 Time: 17:06
Sample: 1993 2013
Included observations: 21
Convergence achieved after 5 iterations
Coefficient covariance computed using outer product of gradients

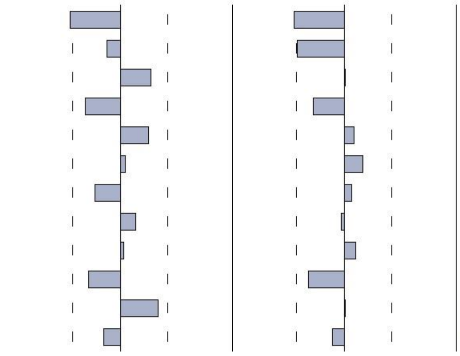
| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.000673 | 0.001218 | 0.552620 | 0.5877 |
| DPRICE | 3.83E-08 | 1.86E-08 | 2.061029 | 0.0549 |
| AR(2) | -0.322216 | 0.372483 | -0.865049 | 0.3991 |
| SIGMASQ | 3.44E-05 | 1.16E-05 | 2.959830 | 0.0088 |

| | | | |
|---|---|---|---|
| R-squared | 0.256638 | Mean dependent var | 0.001301 |
| Adjusted R-squared | 0.125456 | S.D. dependent var | 0.006968 |
| S.E. of regression | 0.006517 | Akaike info criterion | -7.048833 |
| Sum squared resid | 0.000722 | Schwarz criterion | -6.849876 |
| Log likelihood | 78.01274 | Hannan-Quinn criter. | -7.005654 |
| F-statistic | 1.956353 | Durbin-Watson stat | 2.884433 |

| | | |
|---|---|---|
| Prob(F-statistic) | 0.158889 | |
| Inverted AR Roots | -.00+.57i | -.00-.57i |

**Serial correlation test:**

Date: 03/17/21 Time: 17:07
Sample: 1992 2013
Included observations: 21
Q-statistic probabilities adjusted for 1 ARMA term



| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob* |
|---|---|---|---|---|---|---|
| | | 1 | -0.467 | -0.467 | 5.2697 | |
| | | 2 | -0.118 | -0.430 | 5.6221 | 0.018 |
| | | 3 | 0.286 | 0.011 | 7.8238 | 0.020 |
| | | 4 | -0.327 | -0.284 | 10.853 | 0.013 |
| | | 5 | 0.270 | 0.096 | 13.055 | 0.011 |
| | | 6 | 0.047 | 0.175 | 13.127 | 0.022 |
| | | 7 | -0.232 | 0.071 | 14.979 | 0.020 |
| | | 8 | 0.139 | -0.026 | 15.701 | 0.028 |
| | | 9 | 0.036 | 0.113 | 15.752 | 0.046 |
| | | 10 | -0.287 | -0.331 | 19.376 | 0.022 |
| | | 11 | 0.346 | 0.014 | 25.173 | 0.005 |
| | | 12 | -0.153 | -0.114 | 26.422 | 0.006 |

*Probabilities may not be valid for this equation specification.

The residuals are flat and no serial correlation.

**Unit root test of the residual:**

Null Hypothesis: R has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=4)

| | | t-Statistic | Prob.* |
|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | -7.228139 | 0.0000 |
| Test critical values: | 1% level | -3.808546 | |
| | 5% level | -3.020686 | |
| | 10% level | -2.650413 | |

*MacKinnon (1996) one-sided p-values.

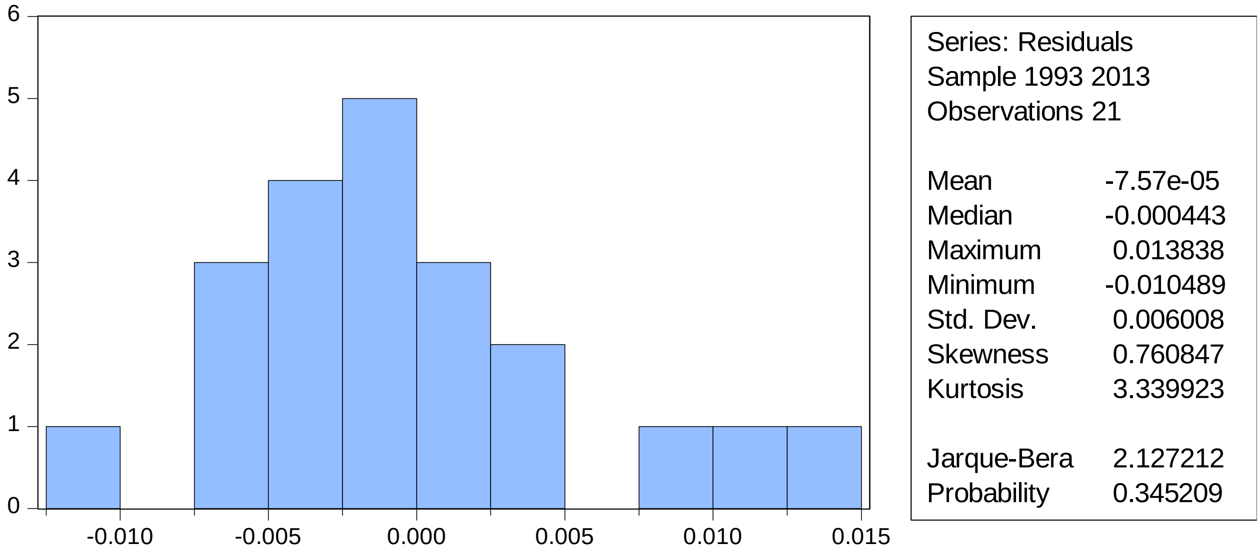
Augmented Dickey-Fuller Test Equation
Dependent Variable: D(R)
Method: Least Squares
Date: 03/17/21 Time: 17:08
Sample (adjusted): 1994 2013

| Included observations: 20 after adjustments | | | | |
|---|---|---|---|---|
| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
| R(-1) | -1.474394 | 0.203980 | -7.228139 | 0.0000 |
| C | 0.000218 | 0.001217 | 0.178684 | 0.8602 |

| | | | |
|---|---|---|---|
| R-squared | 0.743758 | Mean dependent var | 0.000108 |
| Adjusted R-squared | 0.729522 | S.D. dependent var | 0.010468 |
| S.E. of regression | 0.005444 | Akaike info criterion | -7.493850 |
| Sum squared resid | 0.000534 | Schwarz criterion | -7.394277 |
| Log likelihood | 76.93850 | Hannan-Quinn criter. | -7.474412 |
| F-statistic | 52.24599 | Durbin-Watson stat | 2.462178 |
| Prob(F-statistic) | 0.000001 | | |

**Diagnostic checking:**

**Normality test of residuals:**




**Breusch-Godfrey Serial Correlation LM Test:**

Lag(2)

| Breusch-Godfrey Serial Correlation LM Test: | | | |
|---|---|---|---|
| F-statistic | 5.203288 | Prob. F(2,17) | 0.0573 |
| Obs*R-squared | 7.973929 | Prob. Chi-Square(2) | 0.0586 |

Lag(4)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 3.734357 | Prob. F(4,15) | 0.0766 |
| Obs*R-squared | 10.47805 | Prob. Chi-Square(4) | 0.0631 |

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 1.985890 | Prob. F(8,11) | 0.1445 |
| Obs*R-squared | 12.40853 | Prob. Chi-Square(8) | 0.1339 |

## Heteroscedasticity test:

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 0.414788 | Prob. F(1,19) | 0.5272 |
| Obs*R-squared | 0.448655 | Prob. Chi-Square(1) | 0.5030 |
| Scaled explained SS | 0.338199 | Prob. Chi-Square(1) | 0.5609 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/17/21 Time: 17:09
Sample: 1993 2013
Included observations: 21

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 3.23E-05 | 1.23E-05 | 2.639049 | 0.0162 |
| DPRICE | 1.04E-10 | 1.62E-10 | 0.644040 | 0.5272 |

| | | | |
|---|---|---|---|
| R-squared | 0.021365 | Mean dependent var | 3.44E-05 |
| Adjusted R-squared | -0.030143 | S.D. dependent var | 5.34E-05 |
| S.E. of regression | 5.42E-05 | Akaike info criterion | -16.71630 |
| Sum squared resid | 5.59E-08 | Schwarz criterion | -16.61682 |
| Log likelihood | 177.5212 | Hannan-Quinn criter. | -16.69471 |
| F-statistic | 0.414788 | Durbin-Watson stat | 1.715698 |
| Prob(F-statistic) | 0.527248 | | |

Probability is greater than 5%, so the model is not heteroscedastic.

**ARIMAX (2,1,0) Forecasting**: Extend workfile size (from 1992-2016) by double clicking the range> provide original values in dprice from 2013-2016>Quick >estimate equation> dcpue c dprice ar(2)> Forecast> Forecast sample (1994-2016)>ok>

Associated excel file to determine MAPE, RAMSE, MAE etc. of the year 2014-2016.

**Sample 1994-2016:**

**Unit root test:** All variables have unit root, 1st difference of the series made them stationary.

**Lag selection**: Lag 4 was selected for the granger causality test

**Granger causality test:**

Pairwise Granger Causality Tests

Date: 03/17/21 Time: 21:36

Sample: 1994 2016

Lags: 4

| Null Hypothesis: | Obs | F-Statistic | Prob. |
|---|---|---|---|
| DLICENCES does not Granger Cause DCPUE | 18 | 0.01216 | 0.9996 |
| DCPUE does not Granger Cause DLICENCES | | 0.22835 | 0.9156 |
| DPRICE does not Granger Cause DCPUE | 18 | 1.41628 | 0.3043 |
| DCPUE does not Granger Cause DPRICE | | 0.61491 | 0.6628 |
| DRAINFALL does not Granger Cause DCPUE | 18 | 0.34439 | 0.8415 |
| DCPUE does not Granger Cause DRAINFALL | | 0.62599 | 0.6559 |
| DTEMPERATURE does not Granger Cause DCPUE | 18 | 0.84762 | 0.5294 |
| DCPUE does not Granger Cause DTEMPERATURE | | 0.25641 | 0.8986 |
| DSTREAMFLOW does not Granger Cause DCPUE | 18 | 0.92173 | 0.4922 |
| DCPUE does not Granger Cause DSTREAMFLOW | | 1.12828 | 0.4019 |
| DSTREAMWATERLEVEL does not Granger Cause DCPUE | 18 | 0.87129 | 0.5172 |
| DCPUE does not Granger Cause DSTREAMWATERLEVEL | | 0.67141 | 0.6281 |

No reverse causality was found.

**Test for multicollinearity:**

**Coefficients[a]**

| Model | | Collinearity Statistics Tolerance | VIF |
|---|---|---|---|
| 1 | dlicence | .526 | 1.900 |
| | dprice | .427 | 2.343 |
| | drainfall | .518 | 1.932 |
| | dtemperature | .713 | 1.402 |
| | dstreamflow | .584 | 1.711 |
| | dstreamwaterlevel | .464 | 2.154 |

a. Dependent Variable: dcpue

**Collinearity Diagnostics[a]**

| | | | | Variance Proportions | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Model | Dimension | Eigenvalue | Condition Index | (Constant) | dlicence | dprice | drainfall | dtemperature | dstreamflow | dstreamwaterlevel |
| 1 | 1 | 2.117 | 1.000 | .01 | .02 | .00 | .07 | .00 | .06 | .08 |
| | 2 | 1.981 | 1.034 | .02 | .06 | .08 | .01 | .09 | .02 | .00 |
| | 3 | .985 | 1.466 | .73 | .01 | .04 | .02 | .02 | .00 | .00 |
| | 4 | .761 | 1.668 | .14 | .03 | .01 | .06 | .42 | .18 | .02 |
| | 5 | .635 | 1.826 | .00 | .25 | .01 | .12 | .11 | .28 | .10 |
| | 6 | .296 | 2.677 | .00 | .07 | .23 | .62 | .35 | .00 | .45 |
| | 7 | .225 | 3.069 | .10 | .55 | .63 | .09 | .01 | .46 | .36 |

a. Dependent Variable: dcpue

Here multicollinearity is absent among variables. Tolerance is more than 0.1, VIF is less than 10.

**Regression Test:**

**Forward Stepwise:**

**Coefficients[a]**

| Model | | Unstandardized Coefficients | | Standardized Coefficients | t | Sig. |
|---|---|---|---|---|---|---|
| | | B | Std. Error | Beta | | |
| 1 | (Constant) | .001 | .001 | | .867 | .396 |
| | dprice | 3.961E-8 | .000 | .523 | 2.745 | .012 |

a. Dependent Variable: dcpue

**Excluded Variables[a]**

| Model | | Beta In | t | Sig. | Partial Correlation | Collinearity Statistics |
|---|---|---|---|---|---|---|
| | | | | | | Tolerance |
| 1 | dlicence | -.095[b] | -.382 | .707 | -.087 | .607 |
| | drainfall | -.024[b] | -.124 | .902 | -.028 | .999 |
| | dtemperature | -.147[b] | -.686 | .501 | -.156 | .809 |
| | dstreamflow | -.165[b] | -.834 | .415 | -.188 | .940 |
| | dstreamwaterlevel | .117[b] | .601 | .555 | .137 | .995 |

a. Dependent Variable: dcpue

b. Predictors in the Model: (Constant), dprice

**Regression Test** : Eviws: dcpue c dprice

Dependent Variable: DCPUE

Method: Least Squares

Date: 03/17/21 Time: 22:02

Sample (adjusted): 1995 2016

Included observations: 22 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.001188 | 0.001371 | 0.866636 | 0.3964 |
| DPRICE | 3.96E-08 | 1.44E-08 | 2.745460 | 0.0125 |

| | | | |
|---|---|---|---|
| R-squared | 0.273719 | Mean dependent var | 0.000960 |
| Adjusted R-squared | 0.237405 | S.D. dependent var | 0.007349 |

| | | | |
|---|---|---|---|
| S.E. of regression | 0.006417 | Akaike info criterion | -7.173098 |
| Sum squared resid | 0.000824 | Schwarz criterion | -7.073913 |
| Log likelihood | 80.90408 | Hannan-Quinn criter. | -7.149733 |
| F-statistic | 7.537550 | Durbin-Watson stat | 2.557683 |
| Prob(F-statistic) | 0.012470 | | |

Create a dummy variable and interact with DPrice from 2015:

dcpue dprice dummy dummyprice c

Dependent Variable: DCPUE
Method: Least Squares
Date: 03/28/21 Time: 19:22
Sample: 1995 2016
Included observations: 22

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| DPRICE | 3.82E-08 | 2.08E-08 | 1.837903 | 0.0826 |
| DUMMY | 0.001160 | 0.007038 | 0.164822 | 0.8709 |
| DUMMYPRICE | 6.91E-09 | 3.83E-08 | 0.180427 | 0.8588 |
| C | 0.001171 | 0.001523 | 0.768992 | 0.4519 |

| | | | |
|---|---|---|---|
| R-squared | 0.275254 | Mean dependent var | 0.000960 |
| Adjusted R-squared | 0.154463 | S.D. dependent var | 0.007349 |
| S.E. of regression | 0.006757 | Akaike info criterion | -6.993397 |
| Sum squared resid | 0.000822 | Schwarz criterion | -6.795025 |
| Log likelihood | 80.92736 | Hannan-Quinn criter. | -6.946666 |
| F-statistic | 2.278767 | Durbin-Watson stat | 2.574422 |
| Prob(F-statistic) | 0.114175 | | |

In the regression, the dummy variable and interacted dummy term for dprice are not significant. significant, hence dummy terms will be removed from the regression and rerun the model.

Dependent Variable: DCPUE
Method: Least Squares
Date: 03/28/21 Time: 19:25
Sample: 1995 2016
Included observations: 22

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| DPRICE | 3.96E-08 | 1.44E-08 | 2.745460 | 0.0125 |
| C | 0.001188 | 0.001371 | 0.866636 | 0.3964 |

| | | | |
|---|---|---|---|
| R-squared | 0.273719 | Mean dependent var | 0.000960 |
| Adjusted R-squared | 0.237405 | S.D. dependent var | 0.007349 |
| S.E. of regression | 0.006417 | Akaike info criterion | -7.173098 |
| Sum squared resid | 0.000824 | Schwarz criterion | -7.073913 |
| Log likelihood | 80.90408 | Hannan-Quinn criter. | -7.149733 |
| F-statistic | 7.537550 | Durbin-Watson stat | 2.557683 |
| Prob(F-statistic) | 0.012470 | | |

## Unit root test of residual

Null Hypothesis: R has a unit root

Exogenous: Constant

Lag Length: 1 (Automatic - based on SIC, maxlag=4)

| | | t-Statistic | Prob.* |
|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | -5.926914 | 0.0001 |
| Test critical values: | 1% level | -3.808546 | |
| | 5% level | -3.020686 | |
| | 10% level | -2.650413 | |

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(R)

Method: Least Squares

Date: 03/17/21 Time: 22:03

Sample (adjusted): 1997 2016

Included observations: 20 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| R(-1) | -1.922655 | 0.324394 | -5.926914 | 0.0000 |
| D(R(-1)) | 0.420923 | 0.176958 | 2.378662 | 0.0294 |
| C | -0.000490 | 0.001020 | -0.480288 | 0.6371 |

| | | | |
|---|---|---|---|
| R-squared | 0.766602 | Mean dependent var | 0.000521 |
| Adjusted R-squared | 0.739143 | S.D. dependent var | 0.008852 |
| S.E. of regression | 0.004521 | Akaike info criterion | -7.822691 |

| | | | |
|---|---|---|---|
| Sum squared resid | 0.000347 | Schwarz criterion | -7.673331 |
| Log likelihood | 81.22691 | Hannan-Quinn criter. | -7.793534 |
| F-statistic | 27.91844 | Durbin-Watson stat | 1.937354 |
| Prob(F-statistic) | 0.000004 | | |

Residuals do not have unit root.

**Serial correlation test:** EViews

Date: 03/17/21 Time: 22:04
Sample: 1994 2016
Included observations: 22

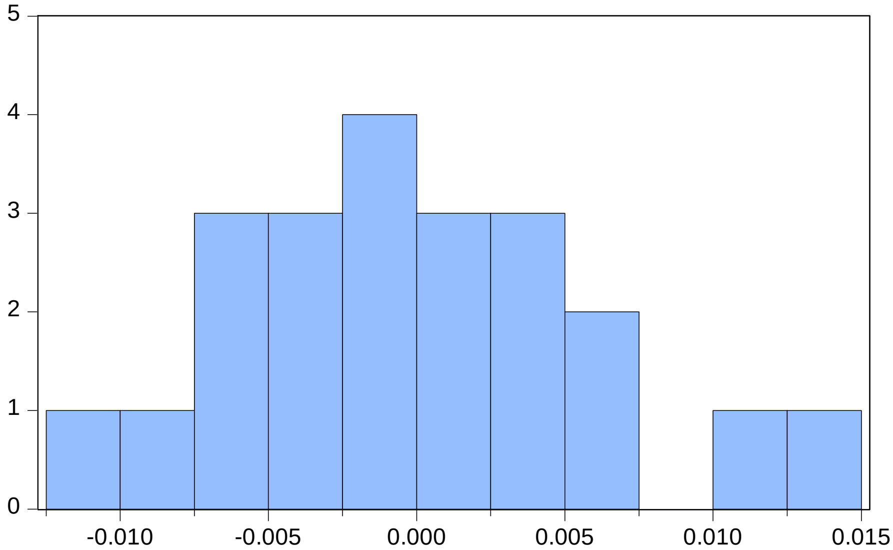
| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|---|---|
| | | 1 | -0.395 | -0.395 | 3.9203 | 0.048 |
| | | 2 | -0.222 | -0.448 | 5.2218 | 0.073 |
| | | 3 | 0.303 | -0.000 | 7.7815 | 0.051 |
| | | 4 | -0.304 | -0.341 | 10.489 | 0.033 |
| | | 5 | 0.278 | 0.182 | 12.888 | 0.024 |
| | | 6 | 0.034 | 0.086 | 12.926 | 0.044 |
| | | 7 | -0.249 | 0.065 | 15.116 | 0.035 |
| | | 8 | 0.178 | 0.000 | 16.310 | 0.038 |
| | | 9 | -0.013 | 0.092 | 16.317 | 0.061 |
| | | 10 | -0.259 | -0.362 | 19.264 | 0.037 |
| | | 11 | 0.298 | 0.020 | 23.534 | 0.015 |
| | | 12 | -0.112 | -0.207 | 24.201 | 0.019 |

**Selection of MA and AR term:**

Residual is flat and in white noise.

**Diagnostic checking:**

**Normality test of residuals:**




| | |
|---|---|
| Series: Residuals | |
| Sample 1995 2016 | |
| Observations 22 | |
| Mean | 9.86e-20 |
| Median | -0.001026 |
| Maximum | 0.013815 |
| Minimum | -0.010934 |
| Std. Dev. | 0.006263 |
| Skewness | 0.388700 |
| Kurtosis | 2.696962 |
| Jarque-Bera | 0.638168 |
| Probability | 0.726815 |

## Breusch-Godfrey Serial Correlation LM Test

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 4.520867 | Prob. F(2,18) | 0.0757 |
| Obs*R-squared | 7.355969 | Prob. Chi-Square(2) | 0.0653 |

Lag(4)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 2.885052 | Prob. F(4,16) | 0.0665 |
| Obs*R-squared | 9.218687 | Prob. Chi-Square(4) | 0.0659 |

Lag(8)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 1.220193 | Prob. F(8,12) | 0.3647 |
| Obs*R-squared | 9.868507 | Prob. Chi-Square(8) | 0.2744 |

## Heteroscedasticity test:

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 0.514169 | Prob. F(1,20) | 0.4816 |
| Obs*R-squared | 0.551410 | Prob. Chi-Square(1) | 0.4577 |
| Scaled explained SS | 0.511298 | Prob. Chi-Square(1) | 0.4746 |

Test Equation:

Dependent Variable: RESID^2

Method: Least Squares

Date: 03/17/21 Time: 13:56

Sample: 1995 2016

Included observations: 22

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 4.71E-05 | 1.73E-05 | 2.719229 | 0.0132 |
| DSTREAMFLOW | 1.46E-10 | 2.04E-10 | 0.717056 | 0.4816 |

| | | | |
|---|---|---|---|
| R-squared | 0.025064 | Mean dependent var | 4.72E-05 |
| Adjusted R-squared | -0.023683 | S.D. dependent var | 8.04E-05 |

| | | | |
|---|---|---|---|
| S.E. of regression | 8.13E-05 | Akaike info criterion | -15.91036 |
| Sum squared resid | 1.32E-07 | Schwarz criterion | -15.81117 |
| Log likelihood | 177.0139 | Hannan-Quinn criter. | -15.88699 |
| F-statistic | 0.514169 | Durbin-Watson stat | 1.791815 |
| Prob(F-statistic) | 0.481631 | | |

**ARIMAX (0,1,0) Forecasting**: Extend workfile size (from 1995-2019) by double clicking the range> provide original values in dprice from 2017-2019>Quick >estimate equation> dcpue c dprice > Forecast> Forecast sample (1996-2019)>ok>

Associated excel file to determine MAPE, RAMSE, MAE etc. of the year 2017-2019.

**Regression model:** 3 years lag of Env. variables

**Sample 1990-2010:**

**Multicollinearity test**:

**Coefficients[a]**

| Model | | Collinearity Statistics Tolerance | VIF |
|---|---|---|---|
| 1 | licence | .466 | 2.144 |
| | price | .543 | 1.843 |
| | rainfall | .160 | 6.267 |
| | temperature | .246 | 4.059 |
| | streamflow | .278 | 3.596 |
| | streamwaterlevel | .539 | 1.856 |

a. Dependent Variable: cpue

Here, multicollinearity is absent among variables.

**MLR:**

cpue licences price rainfall temperature streamflow streamwaterlevel c

Dependent Variable: CPUE

Method: Least Squares

Date: 03/24/21 Time: 12:47

Sample: 1993 2010

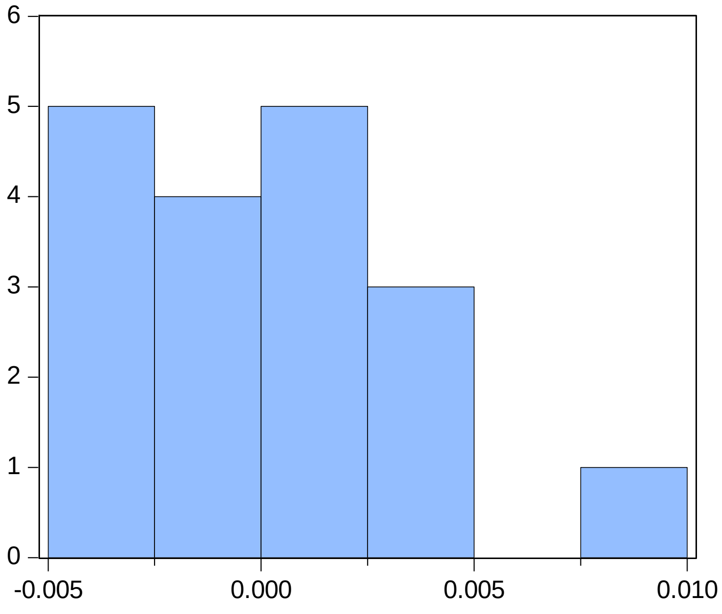
Included observations: 18

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| LICENCES | -0.000299 | 0.000434 | -0.688945 | 0.5051 |
| PRICE | 1.67E-08 | 2.55E-08 | 0.653361 | 0.5269 |
| RAINFALL | 5.48E-06 | 6.81E-06 | 0.804964 | 0.4379 |
| TEMPERATURE | 0.001516 | 0.005363 | 0.282789 | 0.7826 |
| STREAMFLOW | -4.89E-09 | 2.66E-09 | -1.841787 | 0.0426 |
| STREAMWATERLEVEL | 0.000463 | 0.002147 | 0.215450 | 0.8334 |
| C | 0.002052 | 0.134500 | 0.015258 | 0.9881 |

| | | | |
|---|---|---|---|
| R-squared | 0.525728 | Mean dependent var | 0.038495 |
| Adjusted R-squared | 0.267035 | S.D. dependent var | 0.004646 |
| S.E. of regression | 0.003978 | Akaike info criterion | -7.930837 |
| Sum squared resid | 0.000174 | Schwarz criterion | -7.584582 |
| Log likelihood | 78.37754 | Hannan-Quinn criter. | -7.883093 |
| F-statistic | 2.032243 | Durbin-Watson stat | 2.381818 |
| Prob(F-statistic) | 0.145951 | | |

**Diagnostic checking:**

**Normality test:**




| Series: Residuals | |
|---|---|
| Sample 1993 2010 | |
| Observations 18 | |
| Mean | -1.93e-19 |
| Median | 6.77e-05 |
| Maximum | 0.007690 |
| Minimum | -0.004134 |
| Std. Dev. | 0.003200 |
| Skewness | 0.731385 |
| Kurtosis | 2.897185 |
| Jarque-Bera | 1.612701 |
| Probability | 0.446485 |

## Breusch-Godfrey Serial Correlation LM Test:

Lag(2)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.579917 | Prob. F(2,9) | 0.5796 |
| Obs*R-squared | 2.054856 | Prob. Chi-Square(2) | 0.3579 |

Lag(4)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.887397 | Prob. F(4,7) | 0.5182 |
| Obs*R-squared | 6.056406 | Prob. Chi-Square(4) | 0.1950 |

Lag(8)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 1.766262 | Prob. F(8,3) | 0.3475 |
| Obs*R-squared | 14.84765 | Prob. Chi-Square(8) | 0.0622 |

## Heteroscedasticity test:

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 1.997386 | Prob. F(6,11) | 0.1516 |
| Obs*R-squared | 9.385431 | Prob. Chi-Square(6) | 0.1530 |
| Scaled explained SS | 3.324867 | Prob. Chi-Square(6) | 0.7671 |

Test Equation:

Dependent Variable: RESID^2

Method: Least Squares

Date: 03/24/21 Time: 12:49

Sample: 1993 2010

Included observations: 18

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.000110 | 0.000399 | 0.275634 | 0.7879 |
| LICENCES | 1.60E-06 | 1.29E-06 | 1.240888 | 0.2405 |
| PRICE | -1.34E-10 | 7.57E-11 | -1.774673 | 0.1036 |
| RAINFALL | 1.25E-08 | 2.02E-08 | 0.621139 | 0.5472 |
| TEMPERATURE | -4.65E-06 | 1.59E-05 | -0.292441 | 0.7754 |

| | | | | |
|---|---|---|---|---|
| STREAMFLOW | -1.34E-11 | 7.87E-12 | -1.703415 | 0.1165 |
| STREAMWATERLEVEL | -1.46E-06 | 6.36E-06 | -0.230049 | 0.8223 |

| | | | |
|---|---|---|---|
| R-squared | 0.521413 | Mean dependent var | 9.67E-06 |
| Adjusted R-squared | 0.260365 | S.D. dependent var | 1.37E-05 |
| S.E. of regression | 1.18E-05 | Akaike info criterion | -19.57387 |
| Sum squared resid | 1.53E-09 | Schwarz criterion | -19.22762 |
| Log likelihood | 183.1649 | Hannan-Quinn criter. | -19.52613 |
| F-statistic | 1.997386 | Durbin-Watson stat | 2.346309 |
| Prob(F-statistic) | 0.151591 | | |

**Sample 1992-2013:**

**Multicollinearity test:**

**Coefficients[a]**

| Model | | Collinearity Statistics | |
|---|---|---|---|
| | | Tolerance | VIF |
| 1 | licence | .588 | 1.702 |
| | price | .383 | 2.609 |
| | rainfall | .258 | 3.879 |
| | temperature | .343 | 2.915 |
| | streamflow | .500 | 2.002 |
| | streamwaterlevel | .282 | 3.552 |

a. Dependent Variable: cpue

Here, multicollinearity is absent among variables.

**MLR:**

cpue licences price rainfall temperature streamflow streamwaterlevel c

Dependent Variable: CPUE

Method: Least Squares

Date: 03/24/21 Time: 12:52

Sample: 1995 2013

Included observations: 19

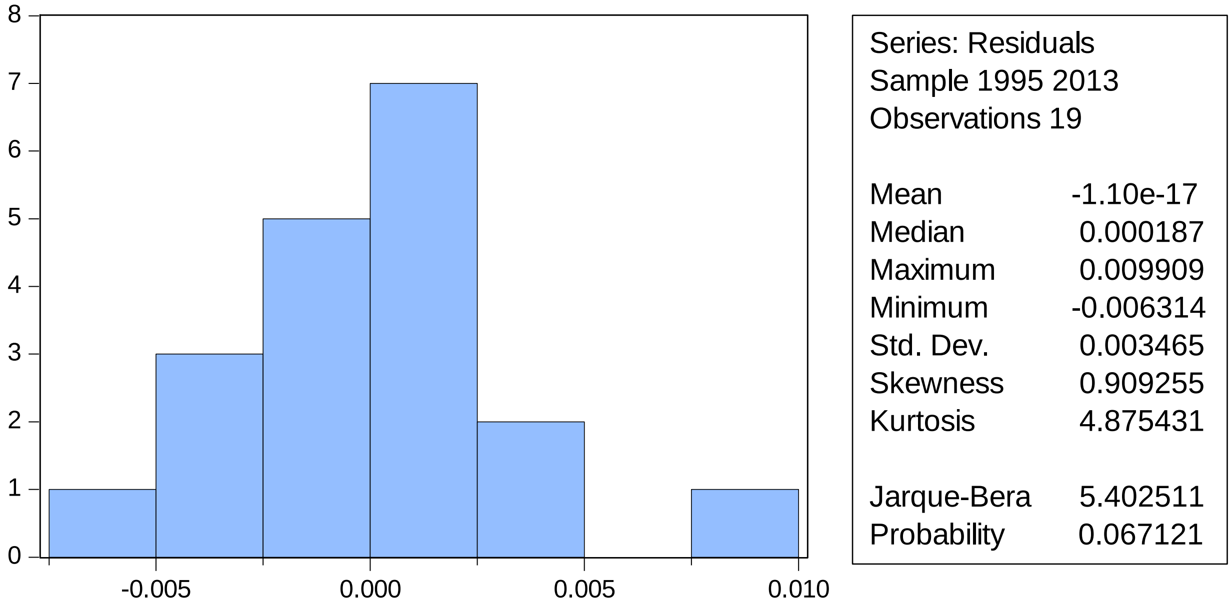
| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|

| | | | | |
|---|---|---|---|---|
| LICENCES | -0.000808 | 0.000406 | -1.988070 | 0.0701 |
| PRICE | 7.47E-08 | 1.36E-08 | 5.486018 | 0.0001 |
| RAINFALL | -1.93E-07 | 4.93E-06 | -0.039219 | 0.9694 |
| TEMPERATURE | -0.002095 | 0.004801 | -0.436298 | 0.6704 |
| STREAMFLOW | 1.06E-09 | 1.32E-09 | 0.803213 | 0.4375 |
| STREAMWATERLEVEL | -0.002604 | 0.002962 | -0.879068 | 0.3966 |
| C | 0.096471 | 0.117120 | 0.823689 | 0.4262 |

| | | | |
|---|---|---|---|
| R-squared | 0.879845 | Mean dependent var | 0.042802 |
| Adjusted R-squared | 0.819767 | S.D. dependent var | 0.009997 |
| S.E. of regression | 0.004244 | Akaike info criterion | -7.809331 |
| Sum squared resid | 0.000216 | Schwarz criterion | -7.461379 |
| Log likelihood | 81.18864 | Hannan-Quinn criter. | -7.750444 |
| F-statistic | 14.64512 | Durbin-Watson stat | 1.875979 |
| Prob(F-statistic) | 0.000068 | | |

**Diagnostic Checking:**

**Normality test:**




**Breusch-Godfrey Serial Correlation LM Test:**

Lag(2)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 1.052807 | Prob. F(2,10) | 0.3847 |
| Obs*R-squared | 3.304803 | Prob. Chi-Square(2) | 0.1916 |

Lag(4)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 1.612343 | Prob. F(4,8) | 0.2617 |
| Obs*R-squared | 8.480510 | Prob. Chi-Square(4) | 0.0755 |

Lag(8)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 2.564322 | Prob. F(8,4) | 0.1895 |
| Obs*R-squared | 15.89980 | Prob. Chi-Square(8) | 0.0638 |

## Heteroscedasticity Test:

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 1.964215 | Prob. F(6,12) | 0.1505 |
| Obs*R-squared | 9.414244 | Prob. Chi-Square(6) | 0.1516 |
| Scaled explained SS | 7.276638 | Prob. Chi-Square(6) | 0.2960 |

Test Equation:

Dependent Variable: RESID^2

Method: Least Squares

Date: 03/24/21 Time: 12:55

Sample: 1995 2013

Included observations: 19

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 2.60E-05 | 0.000552 | 0.047067 | 0.9632 |
| LICENCES | 3.13E-07 | 1.92E-06 | 0.163637 | 0.8727 |
| PRICE | -7.78E-12 | 6.42E-11 | -0.121034 | 0.9057 |
| RAINFALL | 8.67E-09 | 2.32E-08 | 0.373305 | 0.7154 |
| TEMPERATURE | 9.63E-07 | 2.26E-05 | 0.042523 | 0.9668 |
| STREAMFLOW | 2.67E-12 | 6.24E-12 | 0.427416 | 0.6766 |
| STREAMWATERLEVEL | -2.96E-05 | 1.40E-05 | -2.121342 | 0.0554 |

| | | | |
|---|---|---|---|
| R-squared | 0.495487 | Mean dependent var | 1.14E-05 |
| Adjusted R-squared | 0.243230 | S.D. dependent var | 2.30E-05 |
| S.E. of regression | 2.00E-05 | Akaike info criterion | -18.52288 |
| Sum squared resid | 4.81E-09 | Schwarz criterion | -18.17493 |
| Log likelihood | 182.9674 | Hannan-Quinn criter. | -18.46400 |
| F-statistic | 1.964215 | Durbin-Watson stat | 1.935008 |
| Prob(F-statistic) | 0.150536 | | |

**Sample 1994-2016:**

**Multicollinearity test:**

**Coefficients[a]**

| Model | | Collinearity Statistics Tolerance | VIF |
|---|---|---|---|
| 1 | licence | .581 | 1.722 |
| | price | .635 | 1.574 |
| | rainfall | .357 | 2.799 |
| | temperature | .491 | 2.036 |
| | streamflow | .454 | 2.203 |
| | streamwaterlevel | .342 | 2.925 |

a. Dependent Variable: cpue

Create a dummy variable and interact with Dlicences and DPrice from 2015:

cpue licences price rainfall temperature streamflow streamwaterlevel dummylicences dummyprice c

Dependent Variable: CPUE
Method: Least Squares
Date: 03/28/21 Time: 19:29
Sample: 1997 2016
Included observations: 20

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|

| | | | | |
|---|---|---|---|---|
| LICENCES | -0.000916 | 0.000271 | -3.382284 | 0.0061 |
| PRICE | 8.18E-08 | 8.32E-09 | 9.835388 | 0.0000 |
| RAINFALL | -2.82E-06 | 3.29E-06 | -0.857646 | 0.4094 |
| TEMPERATURE | -0.005532 | 0.002740 | -2.018781 | 0.0686 |
| STREAMFLOW | 3.94E-10 | 8.70E-10 | 0.453178 | 0.6592 |
| STREAMWATERLEVEL | 0.002359 | 0.002408 | 0.979385 | 0.3484 |
| DUMMYLICENCES | 0.002338 | 0.001166 | 2.006092 | 0.0701 |
| DUMMYPRICE | -1.07E-07 | 6.28E-08 | -1.708772 | 0.1155 |
| C | 0.173384 | 0.066913 | 2.591196 | 0.0251 |

| | | | |
|---|---|---|---|
| R-squared | 0.970097 | Mean dependent var | 0.045918 |
| Adjusted R-squared | 0.948349 | S.D. dependent var | 0.012103 |
| S.E. of regression | 0.002751 | Akaike info criterion | -8.651774 |
| Sum squared resid | 8.32E-05 | Schwarz criterion | -8.203694 |
| Log likelihood | 95.51774 | Hannan-Quinn criter. | -8.564304 |
| F-statistic | 44.60670 | Durbin-Watson stat | 2.864614 |
| Prob(F-statistic) | 0.000000 | | |

Here ‘dummy’ variable was omitted as the variables is collinear. In the regression, the dummy variable and interacted dummy term for dlicences and dprice are not significant, hence dummy terms will be removed from the regression and rerun the model.

Dependent Variable: CPUE
Method: Least Squares
Date: 03/28/21 Time: 19:31
Sample: 1997 2016
Included observations: 20

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| LICENCES | -0.001358 | 0.000262 | -5.182234 | 0.0002 |
| PRICE | 7.49E-08 | 7.99E-09 | 9.364375 | 0.0000 |
| RAINFALL | -1.57E-06 | 3.50E-06 | -0.448351 | 0.6613 |
| TEMPERATURE | -0.005469 | 0.003266 | -1.674871 | 0.1178 |
| STREAMFLOW | 1.53E-09 | 1.01E-09 | 1.511834 | 0.1545 |
| STREAMWATERLEVEL | 0.000950 | 0.002774 | 0.342425 | 0.7375 |
| C | 0.184945 | 0.081505 | 2.269113 | 0.0409 |

| | | | |
|---|---|---|---|
| R-squared | 0.941527 | Mean dependent var | 0.045918 |
| Adjusted R-squared | 0.914539 | S.D. dependent var | 0.012103 |

| | | | |
|---|---|---|---|
| S.E. of regression | 0.003538 | Akaike info criterion | -8.181173 |
| Sum squared resid | 0.000163 | Schwarz criterion | -7.832666 |
| Log likelihood | 88.81173 | Hannan-Quinn criter. | -8.113141 |
| F-statistic | 34.88741 | Durbin-Watson stat | 1.635004 |
| Prob(F-statistic) | 0.000000 | | |

**MLR:**

cpue licences price rainfall temperature streamflow streamwaterlevel c

Dependent Variable: CPUE

Method: Least Squares

Date: 03/24/21 Time: 12:58

Sample: 1997 2016

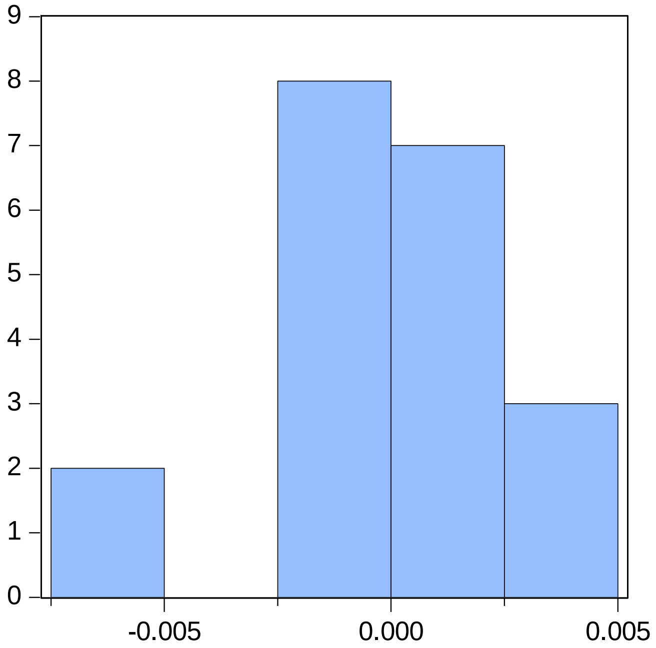
Included observations: 20

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| LICENCES | -0.001358 | 0.000262 | -5.182234 | 0.0002 |
| PRICE | 7.49E-08 | 7.99E-09 | 9.364375 | 0.0000 |
| RAINFALL | -1.57E-06 | 3.50E-06 | -0.448351 | 0.6613 |
| TEMPERATURE | -0.005469 | 0.003266 | -1.674871 | 0.1178 |
| STREAMFLOW | 1.53E-09 | 1.01E-09 | 1.511834 | 0.1545 |
| STREAMWATERLEVEL | 0.000950 | 0.002774 | 0.342425 | 0.7375 |
| C | 0.184945 | 0.081505 | 2.269113 | 0.0409 |

| | | | |
|---|---|---|---|
| R-squared | 0.941527 | Mean dependent var | 0.045918 |
| Adjusted R-squared | 0.914539 | S.D. dependent var | 0.012103 |
| S.E. of regression | 0.003538 | Akaike info criterion | -8.181173 |
| Sum squared resid | 0.000163 | Schwarz criterion | -7.832666 |
| Log likelihood | 88.81173 | Hannan-Quinn criter. | -8.113141 |
| F-statistic | 34.88741 | Durbin-Watson stat | 1.635004 |
| Prob(F-statistic) | 0.000000 | | |

**Diagnostic Checking:**

**Normality Test:**




Series: Residuals
Sample 1997 2016
Observations 20

| | |
|---|---|
| Mean | 3.04e-17 |
| Median | 0.000292 |
| Maximum | 0.004674 |
| Minimum | -0.007114 |
| Std. Dev. | 0.002927 |
| Skewness | -0.657480 |
| Kurtosis | 3.348654 |
| Jarque-Bera | 1.542232 |
| Probability | 0.462497 |

## Breusch-Godfrey Serial Correlation LM Test:

Lag(2)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.271734 | Prob. F(2,11) | 0.7670 |
| Obs*R-squared | 0.941602 | Prob. Chi-Square(2) | 0.6245 |

Lag(4)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 1.268919 | Prob. F(4,9) | 0.3505 |
| Obs*R-squared | 7.211980 | Prob. Chi-Square(4) | 0.1251 |

Lag(8)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 5.105348 | Prob. F(8,5) | 0.0646 |
| Obs*R-squared | 17.81863 | Prob. Chi-Square(8) | 0.0626 |

## Heteroscedasticity test:

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 0.944065 | Prob. F(6,13) | 0.4972 |

| | | | |
|---|---|---|---|
| Obs*R-squared | 6.069730 | Prob. Chi-Square(6) | 0.4154 |
| Scaled explained SS | 3.011516 | Prob. Chi-Square(6) | 0.8074 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/24/21 Time: 13:00
Sample: 1997 2016
Included observations: 20

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.000452 | 0.000297 | 1.518472 | 0.1528 |
| LICENCES | -1.53E-06 | 9.56E-07 | -1.595136 | 0.1347 |
| PRICE | 1.92E-11 | 2.92E-11 | 0.658447 | 0.5217 |
| RAINFALL | -1.15E-08 | 1.28E-08 | -0.902767 | 0.3831 |
| TEMPERATURE | -1.70E-05 | 1.19E-05 | -1.429141 | 0.1766 |
| STREAMFLOW | 8.17E-13 | 3.69E-12 | 0.221479 | 0.8282 |
| STREAMWATERLEVEL | 5.07E-06 | 1.01E-05 | 0.501249 | 0.6246 |

| | | | |
|---|---|---|---|
| R-squared | 0.303487 | Mean dependent var | 8.14E-06 |
| Adjusted R-squared | -0.017981 | S.D. dependent var | 1.28E-05 |
| S.E. of regression | 1.29E-05 | Akaike info criterion | -19.40805 |
| Sum squared resid | 2.17E-09 | Schwarz criterion | -19.05954 |
| Log likelihood | 201.0805 | Hannan-Quinn criter. | -19.34002 |
| F-statistic | 0.944065 | Durbin-Watson stat | 1.915901 |
| Prob(F-statistic) | 0.497188 | | |

## 5. Townsville

**Data cleaning and processing:** Box plot shows no outlier is detected.

**Year: 1990-2010**

**Check for seasonality and trend**: Line diagram showing no seasonality pattern but a steady positive secular trend for the dependent variable “cpue”.

**Unit root test**: All variable has unit root, so I took1$^{st}$ difference of all the series. Now the series is stationary.

**Lag selection**: Lag 4 was selected for the granger causality test.

**Granger Causality test**:

Pairwise Granger Causality Tests
Date: 03/15/21 Time: 15:10
Sample: 1990 2010
Lags: 4

| Null Hypothesis: | Obs | F-Statistic | Prob. |
|---|---|---|---|
| DLICENCES does not Granger Cause DCPUE | 16 | 1.12710 | 0.4161 |
| DCPUE does not Granger Cause DLICENCES | | 0.41098 | 0.7960 |
| DPRICE does not Granger Cause DCPUE | 16 | 1.10042 | 0.4263 |
| DCPUE does not Granger Cause DPRICE | | 1.51239 | 0.2965 |
| DRAINFALL does not Granger Cause DCPUE | 16 | 0.45234 | 0.7687 |
| DCPUE does not Granger Cause DRAINFALL | | 0.07793 | 0.9867 |
| DTEMPERATURE does not Granger Cause DCPUE | 16 | 1.54185 | 0.2891 |
| DCPUE does not Granger Cause DTEMPERATURE | | 0.09048 | 0.9825 |
| DSTREAMFLOW does not Granger Cause DCPUE | 16 | 0.07809 | 0.9866 |
| DCPUE does not Granger Cause DSTREAMFLOW | | 0.25664 | 0.8967 |
| DSTREAMWATERLEVEL does not Granger Cause DCPUE | 16 | 0.09766 | 0.9799 |
| DCPUE does not Granger Cause DSTREAMWATERLEVEL | | 0.17250 | 0.9456 |

No reverse causality was found.

**Test for multicollinearity**: SPSS

**Coefficients**[a]

| Model | | Collinearity Statistics | |
|---|---|---|---|
| | | Tolerance | VIF |
| 1 | dlicence | .806 | 1.241 |
| | dprice | .643 | 1.556 |
| | drainfall | .296 | 3.376 |
| | dtemperature | .809 | 1.236 |
| | dstreamflow | .086 | 11.651 |
| | dstreamwaterlevel | .062 | 16.099 |

a. Dependent Variable: dcpue

**Collinearity Diagnostics[a]**

| Model | Dimension | Eigenvalue | Condition Index | Variance Proportions (Constant) | dlicence | dprice | drainfall | dtemperature | dstreamflow | dstreamwaterlevel |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 2.896 | 1.000 | .00 | .00 | .03 | .02 | .03 | .01 | .01 |
| | 2 | 1.226 | 1.537 | .01 | .42 | .11 | .00 | .01 | .00 | .00 |
| | 3 | 1.106 | 1.618 | .60 | .02 | .04 | .00 | .13 | .00 | .00 |
| | 4 | .760 | 1.952 | .22 | .05 | .03 | .00 | .68 | .01 | .00 |
| | 5 | .521 | 2.357 | .03 | .06 | .05 | .33 | .08 | .04 | .00 |
| | 6 | .456 | 2.521 | .13 | .42 | .69 | .07 | .05 | .00 | .01 |
| | 7 | .035 | 9.149 | .02 | .02 | .06 | .56 | .03 | .94 | .98 |

a. Dependent Variable: dcpue

Here, multicollinearity is present in streamflow and streamwaterlevel. Tolerance is less than 0.1 and VIF is more than 10.

So, run the analysis two-times: first time, with all the variables excluding stream water level and for the second time, with all the variable excluding streamflow. Then compared results of the two models, specifically R squares and P values. Model including all other variables excluding streamflow showed improved result than the other. So, I deleted streamflow from the model.

Result of including streamflow and excluding stream water level in the model:

**Model Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate | Change Statistics R Square Change | F Change | df1 | df2 | Sig. F Change |
|---|---|---|---|---|---|---|---|---|---|
| 1 | .627[a] | .393 | .176 | .007981424 | .393 | 1.814 | 5 | 14 | .175 |

a. Predictors: (Constant), dstreamflow, dlicence, dtemperature, drainfall, dprice

Result of including stream water level and excluding streamflow in the model:

**Model Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate | Change Statistics | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | R Square Change | F Change | df1 | df2 | Sig. F Change |
| 1 | .636[a] | .405 | .192 | .007905263 | .405 | 1.903 | 5 | 14 | .158 |

a. Predictors: (Constant), dstreamwaterlevel, dlicence, dtemperature, dprice, drainfall

Model with streamwaterlevel gives better $R^2$ than streamflow. So, I have deleted streamflow from the analysis.

**Multiple Regression Test**: SPSS

Stepwise (backward) regression in SPSS

**Coefficients[a]**

| Model | | Unstandardized Coefficients | | Standardized Coefficients | t | Sig. |
|---|---|---|---|---|---|---|
| | | B | Std. Error | Beta | | |
| 1 | (Constant) | .001 | .002 | | .630 | .539 |
| | dlicence | -.001 | .000 | -.471 | -2.083 | .056 |
| | dprice | 3.078E-8 | .000 | .343 | 1.386 | .187 |
| | drainfall | -9.942E-7 | .000 | -.079 | -.266 | .794 |
| | dtemperature | .004 | .004 | .248 | 1.101 | .290 |
| | dstreamwaterlevel | .006 | .005 | .344 | 1.169 | .262 |
| 2 | (Constant) | .001 | .002 | | .661 | .519 |
| | dlicence | -.001 | .000 | -.469 | -2.144 | .049 |
| | dprice | 2.981E-8 | .000 | .333 | 1.405 | .180 |
| | dtemperature | .004 | .003 | .260 | 1.220 | .241 |
| | dstreamwaterlevel | .005 | .004 | .297 | 1.298 | .214 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 3 | (Constant) | .001 | .002 | | .774 | .450 |
| | dlicence | -.001 | .000 | -.502 | -2.274 | .037 |
| | dprice | 2.839E-8 | .000 | .317 | 1.320 | .205 |
| | dstreamwaterlevel | .004 | .004 | .221 | .988 | .338 |
| 4 | (Constant) | .001 | .002 | | .728 | .477 |
| | dlicence | -.001 | .000 | -.539 | -2.480 | .024 |
| | dprice | 3.739E-8 | .000 | .417 | 1.920 | .072 |

a. Dependent Variable: dcpue

**Excluded Variables[a]**

| Model | | Beta In | t | Sig. | Partial Correlation | Collinearity Statistics Tolerance |
|---|---|---|---|---|---|---|
| 2 | drainfall | -.079[b] | -.266 | .794 | -.071 | .483 |
| 3 | drainfall | -.147[c] | -.503 | .622 | -.129 | .505 |
| | dtemperature | .260[c] | 1.220 | .241 | .301 | .876 |
| 4 | drainfall | .049[d] | .214 | .833 | .053 | .834 |
| | dtemperature | .185[d] | .883 | .390 | .216 | .946 |
| | dstreamwaterlevel | .221[d] | .988 | .338 | .240 | .821 |

a. Dependent Variable: dcpue

b. Predictors in the Model: (Constant), dstreamwaterlevel, dlicence, dtemperature, dprice

c. Predictors in the Model: (Constant), dstreamwaterlevel, dlicence, dprice

d. Predictors in the Model: (Constant), dlicence, dprice

**Regression Test** : Eviws: dcpue c dlicences

Dependent Variable: DCPUE
Method: Least Squares
Date: 03/15/21 Time: 15:39
Sample (adjusted): 1991 2010
Included observations: 20 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|

| | | | | |
|---|---|---|---|---|
| C | 0.002106 | 0.001864 | 1.129904 | 0.2733 |
| DLICENCES | -0.000777 | 0.000435 | -1.786939 | 0.0508 |

| | | | |
|---|---|---|---|
| R-squared | 0.150669 | Mean dependent var | 0.002262 |
| Adjusted R-squared | 0.103484 | S.D. dependent var | 0.008795 |
| S.E. of regression | 0.008327 | Akaike info criterion | -6.643916 |
| Sum squared resid | 0.001248 | Schwarz criterion | -6.544343 |
| Log likelihood | 68.43916 | Hannan-Quinn criter. | -6.624478 |
| F-statistic | 3.193150 | Durbin-Watson stat | 2.427028 |
| Prob(F-statistic) | 0.090800 | | |

Unit root test for the residuals of regression model (including dcpue c dlicences):

Getting residuals in EViws:

Quick> estimate equation>Provide variables (dcpue c dlicences)> ok> view tab> Actual, fitted, residual> Actual, fitted, residual table

Null Hypothesis: R has a unit root

Exogenous: Constant

Lag Length: 2 (Automatic - based on SIC, maxlag=4)

| | | t-Statistic | Prob.* |
|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | -5.128781 | 0.0009 |
| Test critical values: | 1% level | -3.886751 | |
| | 5% level | -3.052169 | |
| | 10% level | -2.666593 | |

*MacKinnon (1996) one-sided p-values.

Warning: Probabilities and critical values calculated for 20 observations and may not be accurate for a sample size of 17

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(R)

Method: Least Squares

Date: 03/15/21 Time: 15:41

Sample (adjusted): 1994 2010

Included observations: 17 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|

| | | | | |
|---|---|---|---|---|
| R(-1) | -2.694762 | 0.525420 | -5.128781 | 0.0002 |
| D(R(-1)) | 1.122522 | 0.380153 | 2.952816 | 0.0112 |
| D(R(-2)) | 0.508743 | 0.236203 | 2.153835 | 0.0506 |
| C | 0.000260 | 0.001652 | 0.157061 | 0.8776 |

| | | | |
|---|---|---|---|
| R-squared | 0.794609 | Mean dependent var | 0.000241 |
| Adjusted R-squared | 0.747211 | S.D. dependent var | 0.013502 |
| S.E. of regression | 0.006789 | Akaike info criterion | -6.944778 |
| Sum squared resid | 0.000599 | Schwarz criterion | -6.748728 |
| Log likelihood | 63.03062 | Hannan-Quinn criter. | -6.925291 |
| F-statistic | 16.76464 | Durbin-Watson stat | 1.948780 |
| Prob(F-statistic) | 0.000094 | | |

The residual has no unit root.

**Serial correlation test**: The probability of Q stat (Ljung-Box test) is more than .05. So, I should accept the null hypothesis. (Null: there is no serial correlation).

**Correlogram plot:**

Date: 03/15/21 Time: 15:38
Sample: 1990 2010
Included observations: 20

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|---|---|
| | | 1 | -0.237 | -0.237 | 1.3048 | 0.253 |
| | | 2 | -0.367 | -0.448 | 4.5921 | 0.101 |
| | | 3 | -0.117 | -0.464 | 4.9470 | 0.176 |
| | | 4 | 0.297 | -0.170 | 7.3666 | 0.118 |
| | | 5 | 0.160 | 0.033 | 8.1189 | 0.150 |
| | | 6 | -0.107 | 0.155 | 8.4805 | 0.205 |
| | | 7 | -0.128 | 0.223 | 9.0337 | 0.250 |
| | | 8 | -0.144 | -0.106 | 9.7939 | 0.280 |
| | | 9 | 0.186 | -0.112 | 11.172 | 0.264 |
| | | 10 | 0.174 | -0.021 | 12.507 | 0.253 |
| | | 11 | -0.093 | 0.005 | 12.929 | 0.298 |
| | | 12 | -0.339 | -0.242 | 19.251 | 0.083 |

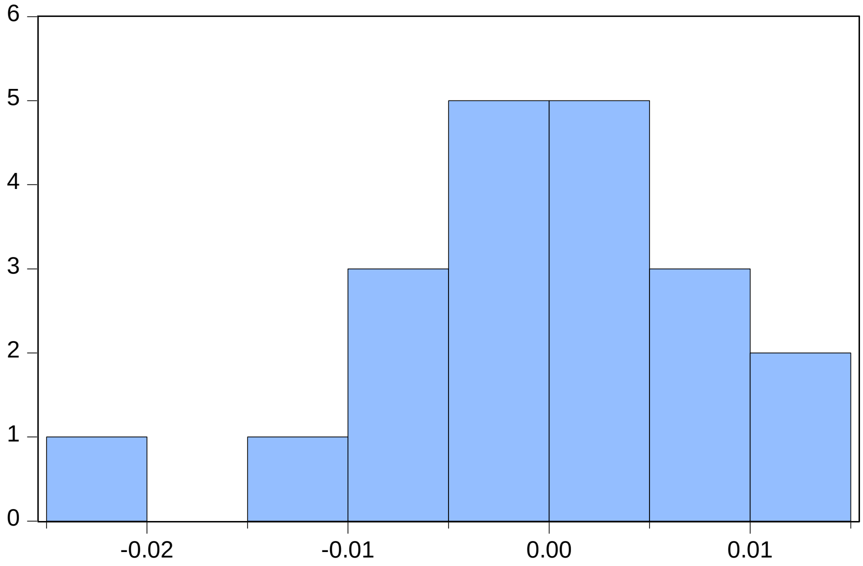
The residuals are not flat and no serial correlation i.e. in white noise.

**Significance Test of the ARIMAX model**

Here all of the variables are significant.

**Diagnostic checking:**

**Normality test of residuals**:




| | |
|---|---|
| Series: Residuals | |
| Sample 1991 2010 | |
| Observations 20 | |
| Mean | 5.20e-19 |
| Median | 0.000736 |
| Maximum | 0.011708 |
| Minimum | -0.020380 |
| Std. Dev. | 0.008105 |
| Skewness | -0.654806 |
| Kurtosis | 3.114857 |
| Jarque-Bera | 1.440229 |
| Probability | 0.486697 |

The probability of Jarque-Bera test in more than 5%, so the residual series follows normal distribution.

**Breusch-Godfrey Serial Correlation LM Test:**

Lag(2)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 2.794675 | Prob. F(2,16) | 0.0910 |
| Obs*R-squared | 5.177877 | Prob. Chi-Square(2) | 0.0751 |

Lag(4)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 3.931730 | Prob. F(4,14) | 0.0642 |
| Obs*R-squared | 10.58093 | Prob. Chi-Square(4) | 0.0617 |

Lag(8)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 3.847404 | Prob. F(8,10) | 0.0652 |
| Obs*R-squared | 10.09554 | Prob. Chi-Square(8) | 0.0673 |

**Heteroscedasticity test:**

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 0.277630 | Prob. F(1,18) | 0.6047 |
| Obs*R-squared | 0.303792 | Prob. Chi-Square(1) | 0.5815 |
| Scaled explained SS | 0.260203 | Prob. Chi-Square(1) | 0.6100 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/15/21 Time: 15:45
Sample: 1991 2010
Included observations: 20

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 6.29E-05 | 2.13E-05 | 2.961181 | 0.0084 |
| DLICENCES | 2.61E-06 | 4.95E-06 | 0.526906 | 0.6047 |

| | | | |
|---|---|---|---|
| R-squared | 0.015190 | Mean dependent var | 6.24E-05 |
| Adjusted R-squared | -0.039522 | S.D. dependent var | 9.31E-05 |
| S.E. of regression | 9.49E-05 | Akaike info criterion | -15.59203 |
| Sum squared resid | 1.62E-07 | Schwarz criterion | -15.49245 |
| Log likelihood | 157.9203 | Hannan-Quinn criter. | -15.57259 |
| F-statistic | 0.277630 | Durbin-Watson stat | 1.747298 |
| Prob(F-statistic) | 0.604692 | | |

Probability is greater than 5%, so the model is not heteroscedastic.

**ARIMAX (0,1,0) Forecasting:**

Extend workfile size (from 1990-2013) by double clicking the range> provide actual value in dlicences from 2010-2013>Quick >estimate equation> dcpue c dlicences > Forecast> Forecast sample (1990-2013)>ok>

Associated excel file to determine MAPE, RAMSE, MAE etc. of the year 2011-2013.

**Year 1992-2013:**

**Unit root test**: The series has unit root, hence 1st difference of the series has taken and the final series has no unit root

**Lag selection**: Varsoc dcpue dlicences dprice drainfall dtemperature dstreamflow dstreamwaterlevel

**Granger Causality test:**

Pairwise Granger Causality Tests
Date: 03/15/21 Time: 16:10
Sample: 1992 2013
Lags: 4

| Null Hypothesis: | Obs | F-Statistic | Prob. |
|---|---|---|---|
| DLICENCES does not Granger Cause DCPUE | 17 | 0.41963 | 0.7906 |
| DCPUE does not Granger Cause DLICENCES | | 0.74696 | 0.5866 |
| DPRICE does not Granger Cause DCPUE | 17 | 1.37424 | 0.3245 |
| DCPUE does not Granger Cause DPRICE | | 1.59970 | 0.2647 |
| DRAINFALL does not Granger Cause DCPUE | 17 | 1.75517 | 0.2309 |
| DCPUE does not Granger Cause DRAINFALL | | 0.05749 | 0.9926 |
| DTEMPERATURE does not Granger Cause DCPUE | 17 | 1.00790 | 0.4575 |
| DCPUE does not Granger Cause DTEMPERATURE | | 0.33422 | 0.8476 |
| DSTREAMFLOW does not Granger Cause DCPUE | 17 | 0.54296 | 0.7094 |
| DCPUE does not Granger Cause DSTREAMFLOW | | 0.27404 | 0.8867 |
| DSTREAMWATERLEVEL does not Granger Cause DCPUE | 17 | 0.17823 | 0.9433 |
| DCPUE does not Granger Cause DSTREAMWATERLEVEL | | 0.19829 | 0.9323 |

No reverse causality detected.

**Test for multicollinearity:**

**Coefficients[a]**

| Model | | Collinearity Statistics | |
|---|---|---|---|
| | | Tolerance | VIF |
| 1 | dlicence | .739 | 1.354 |
| | dprice | .458 | 2.184 |
| | drainfall | .421 | 2.373 |
| | dtemperature | .832 | 1.202 |
| | dstreamflow | .158 | 6.313 |
| | dstreamwaterlevel | .127 | 7.852 |

a. Dependent Variable: dcpue

**Collinearity Diagnostics[a]**

| Model | Dimension | Eigenvalue | Condition Index | Variance Proportions (Constant) | dlicence | dprice | drainfall | dtemperature | dstreamflow | dstreamwaterlevel |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 3.174 | 1.000 | .00 | .00 | .03 | .03 | .02 | .01 | .01 |
| | 2 | 1.175 | 1.644 | .00 | .47 | .05 | .01 | .01 | .00 | .00 |
| | 3 | 1.005 | 1.777 | .96 | .00 | .00 | .00 | .01 | .00 | .00 |
| | 4 | .784 | 2.012 | .02 | .02 | .02 | .03 | .91 | .00 | .00 |
| | 5 | .498 | 2.525 | .01 | .11 | .22 | .47 | .02 | .04 | .00 |
| | 6 | .290 | 3.306 | .00 | .38 | .63 | .17 | .02 | .10 | .06 |
| | 7 | .074 | 6.529 | .01 | .02 | .05 | .30 | .00 | .84 | .92 |

a. Dependent Variable: dcpue

Here, multicollinearity is absent among variables. Tolerance is more than 0.1, VIF is less than 10.

**Regression Test :**

Forward stepwise regression:

**Coefficients[a]**

| Model | | Unstandardized Coefficients B | Std. Error | Standardized Coefficients Beta | t | Sig. |
|---|---|---|---|---|---|---|
| 1 | (Constant) | .001 | .002 | | .305 | .764 |
| | dstreamflow | 8.859E-10 | .000 | .597 | 3.243 | .004 |

a. Dependent Variable: dcpue

**Excluded Variables[a]**

| Model | | Beta In | t | Sig. | Partial Correlation | Collinearity Statistics Tolerance |
|---|---|---|---|---|---|---|
| 1 | dlicence | -.219[b] | -1.205 | .244 | -.273 | 1.000 |
| | dprice | .128[b] | .535 | .599 | .125 | .619 |
| | drainfall | -.164[b] | -.713 | .485 | -.166 | .655 |
| | dtemperature | .108[b] | .534 | .600 | .125 | .855 |
| | dstreamwaterlevel | .248[b] | .587 | .565 | .137 | .197 |

a. Dependent Variable: dcpue

b. Predictors in the Model: (Constant), dstreamflow

Eviws: dcpue c dstreamflow

Dependent Variable: DCPUE
Method: Least Squares
Date: 03/15/21 Time: 16:20
Sample (adjusted): 1993 2013
Included observations: 21 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.000586 | 0.001923 | 0.304597 | 0.7640 |
| DSTREAMFLOW | 8.86E-10 | 2.73E-10 | 3.243113 | 0.0043 |

| | | | |
|---|---|---|---|
| R-squared | 0.356320 | Mean dependent var | 0.000712 |
| Adjusted R-squared | 0.322442 | S.D. dependent var | 0.010705 |
| S.E. of regression | 0.008811 | Akaike info criterion | -6.535129 |
| Sum squared resid | 0.001475 | Schwarz criterion | -6.435651 |
| Log likelihood | 70.61885 | Hannan-Quinn criter. | -6.513540 |
| F-statistic | 10.51778 | Durbin-Watson stat | 2.120167 |
| Prob(F-statistic) | 0.004279 | | |

## Unit root test of residual:

Null Hypothesis: R has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=4)

| | t-Statistic | Prob.* |
|---|---|---|

| | | t-Statistic | Prob.* |
|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | -6.536478 | 0.0000 |
| Test critical values: | 1% level | -3.831511 | |
| | 5% level | -3.029970 | |
| | 10% level | -2.655194 | |

*MacKinnon (1996) one-sided p-values.

Warning: Probabilities and critical values calculated for 20 observations and may not be accurate for a sample size of 19

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(R)

Method: Least Squares

Date: 03/12/21 Time: 22:12

Sample (adjusted): 1995 2013

Included observations: 19 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| R(-1) | -2.354515 | 0.360212 | -6.536478 | 0.0000 |
| D(R(-1)) | 0.549979 | 0.206306 | 2.665848 | 0.0169 |
| C | 0.001310 | 0.001825 | 0.717695 | 0.4833 |

| | | | |
|---|---|---|---|
| R-squared | 0.833523 | Mean dependent var | -1.03E-05 |
| Adjusted R-squared | 0.812713 | S.D. dependent var | 0.018278 |
| S.E. of regression | 0.007910 | Akaike info criterion | -6.697418 |
| Sum squared resid | 0.001001 | Schwarz criterion | -6.548296 |
| Log likelihood | 66.62547 | Hannan-Quinn criter. | -6.672180 |
| F-statistic | 40.05464 | Durbin-Watson stat | 1.692710 |
| Prob(F-statistic) | 0.000001 | | |

The residual has no unit root.

**Serial correlation test:** EViews

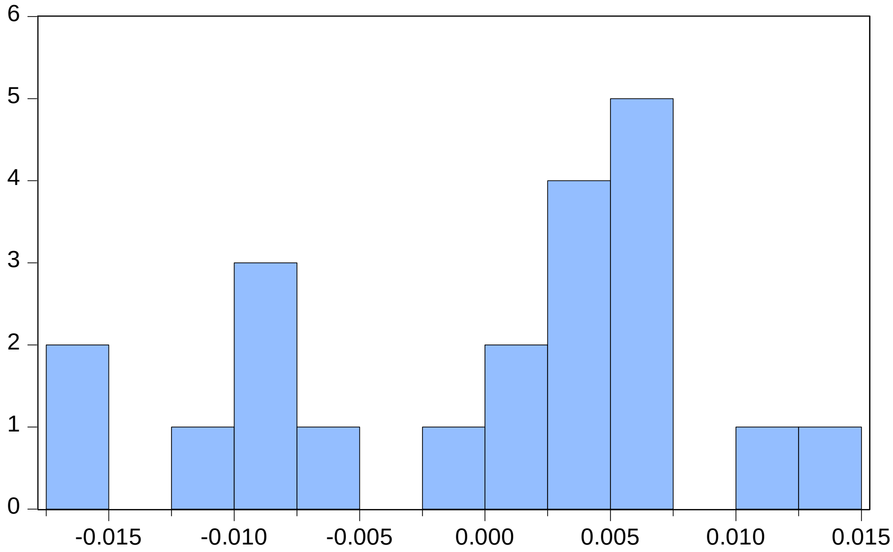
Date: 03/15/21 Time: 16:23
Sample: 1992 2013
Included observations: 21

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|---|---|
| | | 1 | -0.167 | -0.167 | 0.6697 | 0.413 |
| | | 2 | -0.178 | -0.212 | 1.4792 | 0.477 |
| | | 3 | -0.211 | -0.304 | 2.6752 | 0.444 |
| | | 4 | 0.066 | -0.106 | 2.8001 | 0.592 |
| | | 5 | 0.061 | -0.072 | 2.9134 | 0.713 |
| | | 6 | 0.048 | -0.025 | 2.9888 | 0.810 |
| | | 7 | 0.165 | 0.214 | 3.9335 | 0.787 |
| | | 8 | -0.257 | -0.160 | 6.3858 | 0.604 |
| | | 9 | -0.080 | -0.095 | 6.6439 | 0.674 |
| | | 10 | 0.065 | 0.018 | 6.8274 | 0.742 |
| | | 11 | 0.058 | -0.100 | 6.9911 | 0.800 |
| | | 12 | -0.123 | -0.204 | 7.7994 | 0.801 |

The residuals are flat and no serial correlation.

**Diagnostic reports:**

**Normality test of residuals:**



| Series: Residuals | |
|---|---|
| Sample 1993 2013 | |
| Observations 21 | |
| Mean | -4.96e-19 |
| Median | 0.003502 |
| Maximum | 0.014390 |
| Minimum | -0.016138 |
| Std. Dev. | 0.008588 |
| Skewness | -0.422911 |
| Kurtosis | 2.160641 |
| Jarque-Bera | 1.242444 |
| Probability | 0.537287 |

**Breusch-Godfrey Serial Correlation LM Test:**

Lag(2)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.883893 | Prob. F(2,17) | 0.4313 |
| Obs*R-squared | 1.978045 | Prob. Chi-Square(2) | 0.3719 |

Lag(4)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 1.049193 | Prob. F(4,15) | 0.4150 |
| Obs*R-squared | 4.590993 | Prob. Chi-Square(4) | 0.3319 |

Lag(8)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.747787 | Prob. F(8,11) | 0.6524 |
| Obs*R-squared | 7.397598 | Prob. Chi-Square(8) | 0.4944 |

## Heteroscedasticity test:

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 0.047471 | Prob. F(1,19) | 0.8298 |
| Obs*R-squared | 0.052337 | Prob. Chi-Square(1) | 0.8190 |
| Scaled explained SS | 0.024862 | Prob. Chi-Square(1) | 0.8747 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/15/21 Time: 16:24
Sample: 1993 2013
Included observations: 21

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 7.03E-05 | 1.73E-05 | 4.054646 | 0.0007 |
| DSTREAMFLOW | -5.37E-13 | 2.46E-12 | -0.217878 | 0.8298 |

| | | | |
|---|---|---|---|
| R-squared | 0.002492 | Mean dependent var | 7.02E-05 |
| Adjusted R-squared | -0.050008 | S.D. dependent var | 7.75E-05 |
| S.E. of regression | 7.95E-05 | Akaike info criterion | -15.95213 |
| Sum squared resid | 1.20E-07 | Schwarz criterion | -15.85266 |
| Log likelihood | 169.4974 | Hannan-Quinn criter. | -15.93054 |
| F-statistic | 0.047471 | Durbin-Watson stat | 1.563044 |
| Prob(F-statistic) | 0.829847 | | |

Probability is greater than 5%, so the model is not heteroscedastic.

**ARIMAX (0,1,0) Forecasting**: Extend workfile size (from 1994-2016) by double clicking the range> provide original values in dstreamflow from 2013-2016>Quick >estimate equation> dcpue c dstreamflow> Forecast> Forecast sample (1994-2016)>ok>

Associated excel file to determine MAPE, RAMSE, MAE etc. of the year 2014-2016.

**Sample 1994-2016:**

**Unit root test**: All variables have unit root, $1^{st}$ difference of the series made them stationary.

**Lag selection**: Lag 4 was selected for the granger causality test

**Granger causality test:**

Pairwise Granger Causality Tests

Date: 03/15/21 Time: 16:37

Sample: 1994 2016

Lags: 4

| Null Hypothesis: | Obs | F-Statistic | Prob. |
|---|---|---|---|
| DLICENCES does not Granger Cause DCPUE | 18 | 0.54912 | 0.7047 |
| DCPUE does not Granger Cause DLICENCES | | 0.59399 | 0.6760 |
| DPRICE does not Granger Cause DCPUE | 18 | 0.81429 | 0.5469 |
| DCPUE does not Granger Cause DPRICE | | 1.36714 | 0.3189 |
| DRAINFALL does not Granger Cause DCPUE | 18 | 1.95207 | 0.1859 |
| DCPUE does not Granger Cause DRAINFALL | | 0.21587 | 0.9230 |
| DTEMPERATURE does not Granger Cause DCPUE | 18 | 0.96242 | 0.4729 |
| DCPUE does not Granger Cause DTEMPERATURE | | 1.05917 | 0.4301 |
| DSTREAMFLOW does not Granger Cause DCPUE | 18 | 0.55448 | 0.7013 |
| DCPUE does not Granger Cause DSTREAMFLOW | | 0.19636 | 0.9341 |
| DSTREAMWATERLEVEL does not Granger Cause DCPUE | 18 | 0.32490 | 0.8545 |
| DCPUE does not Granger Cause DSTREAMWATERLEVEL | | 0.02039 | 0.9990 |

No reverse causality was found.

**Test for multicollinearity:**

**Coefficients[a]**

| Model | | Collinearity Statistics Tolerance | VIF |
|---|---|---|---|
| 1 | dlicence | .717 | 1.395 |
| | dprice | .447 | 2.235 |
| | drainfall | .424 | 2.357 |
| | dtemperature | .838 | 1.193 |
| | dstreamflow | .159 | 6.283 |
| | dstreamwaterlevel | .130 | 7.707 |

a. Dependent Variable: dcpue

**Collinearity Diagnostics[a]**

| | | | | Variance Proportions | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Model | Dimension | Eigenvalue | Condition Index | (Constant) | dlicence | dprice | drainfall | dtemperature | dstreamflow | dstreamwaterlevel |
| 1 | 1 | 3.142 | 1.000 | .00 | .00 | .03 | .03 | .02 | .01 | .01 |
| | 2 | 1.284 | 1.564 | .15 | .30 | .03 | .01 | .04 | .00 | .00 |
| | 3 | .950 | 1.819 | .73 | .14 | .03 | .00 | .03 | .00 | .00 |
| | 4 | .754 | 2.041 | .11 | .01 | .03 | .00 | .90 | .00 | .00 |
| | 5 | .489 | 2.534 | .00 | .08 | .11 | .56 | .00 | .06 | .00 |
| | 6 | .307 | 3.198 | .00 | .43 | .72 | .07 | .01 | .07 | .06 |
| | 7 | .074 | 6.502 | .00 | .03 | .07 | .32 | .00 | .86 | .92 |

a. Dependent Variable: dcpue

Here multicollinearity is absent among variables. Tolerance is more than 0.1, VIF is less than 10.

**Regression Test:**

Forward Stepwise:

**Coefficients[a]**

| Model | | Unstandardized Coefficients B | Unstandardized Coefficients Std. Error | Standardized Coefficients Beta | t | Sig. |
|---|---|---|---|---|---|---|
| 1 | (Constant) | .001 | .002 | | .433 | .670 |
| | dstreamflow | 8.673E-10 | .000 | .601 | 3.367 | .003 |

a. Dependent Variable: dcpue

**Excluded Variables[a]**

| Model | | Beta In | t | Sig. | Partial Correlation | Collinearity Statistics Tolerance |
|---|---|---|---|---|---|---|
| 1 | dlicence | -.257[b] | -1.479 | .155 | -.321 | 1.000 |
| | dprice | .124[b] | .542 | .594 | .123 | .628 |
| | drainfall | -.059[b] | -.267 | .793 | -.061 | .678 |
| | dtemperature | .083[b] | .424 | .676 | .097 | .875 |
| | dstreamwaterlevel | .253[b] | .626 | .539 | .142 | .202 |

a. Dependent Variable: dcpue

b. Predictors in the Model: (Constant), dstreamflow

**Regression Test** : Eviws: dcpue c dstreamflow

Dependent Variable: DCPUE
Method: Least Squares
Date: 03/15/21 Time: 16:42
Sample (adjusted): 1995 2016
Included observations: 22 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.000767 | 0.001772 | 0.432848 | 0.6698 |
| DSTREAMFLOW | 8.67E-10 | 2.58E-10 | 3.367062 | 0.0031 |
| R-squared | 0.361779 | Mean dependent var | | 0.000725 |

| | | | |
|---|---|---|---|
| Adjusted R-squared | 0.329868 | S.D. dependent var | 0.010152 |
| S.E. of regression | 0.008311 | Akaike info criterion | -6.656002 |
| Sum squared resid | 0.001381 | Schwarz criterion | -6.556816 |
| Log likelihood | 75.21602 | Hannan-Quinn criter. | -6.632636 |
| F-statistic | 11.33710 | Durbin-Watson stat | 2.357380 |
| Prob(F-statistic) | 0.003065 | | |

**Unit root test of residual**:

Null Hypothesis: R has a unit root

Exogenous: Constant

Lag Length: 0 (Automatic - based on SIC, maxlag=4)

| | | t-Statistic | Prob.* |
|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | -5.284354 | 0.0004 |
| Test critical values: | 1% level | -3.788030 | |
| | 5% level | -3.012363 | |
| | 10% level | -2.646119 | |

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(R)

Method: Least Squares

Date: 03/15/21 Time: 16:43

Sample (adjusted): 1996 2016

Included observations: 21 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| R(-1) | -1.216229 | 0.230157 | -5.284354 | 0.0000 |
| C | -0.000159 | 0.001820 | -0.087362 | 0.9313 |

| | | | |
|---|---|---|---|
| R-squared | 0.595093 | Mean dependent var | 0.000322 |
| Adjusted R-squared | 0.573783 | S.D. dependent var | 0.012756 |
| S.E. of regression | 0.008328 | Akaike info criterion | -6.648039 |
| Sum squared resid | 0.001318 | Schwarz criterion | -6.548561 |
| Log likelihood | 71.80441 | Hannan-Quinn criter. | -6.626450 |
| F-statistic | 27.92440 | Durbin-Watson stat | 1.881762 |
| Prob(F-statistic) | 0.000042 | | |

Residuals do not have unit root.

**Serial correlation test:** EViews

Date: 03/15/21 Time: 16:45
Sample: 1994 2016
Included observations: 22

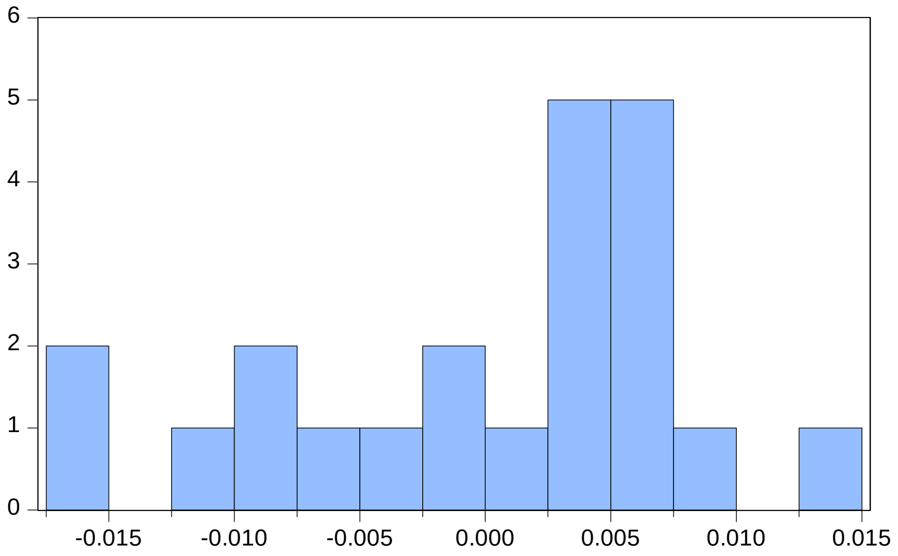
| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|---|---|
| | | 1 | -0.204 | -0.204 | 1.0514 | 0.305 |
| | | 2 | -0.015 | -0.059 | 1.0572 | 0.589 |
| | | 3 | -0.294 | -0.324 | 3.4661 | 0.325 |
| | | 4 | -0.066 | -0.239 | 3.5948 | 0.464 |
| | | 5 | 0.093 | -0.036 | 3.8657 | 0.569 |
| | | 6 | 0.112 | 0.007 | 4.2812 | 0.639 |
| | | 7 | 0.229 | 0.228 | 6.1311 | 0.525 |
| | | 8 | -0.425 | -0.344 | 12.929 | 0.114 |
| | | 9 | 0.031 | -0.079 | 12.969 | 0.164 |
| | | 10 | -0.102 | -0.040 | 13.424 | 0.201 |
| | | 11 | 0.055 | -0.223 | 13.568 | 0.258 |
| | | 12 | 0.128 | -0.046 | 14.427 | 0.274 |

**Selection of MA and AR term:**

The residuals are flat and no serial correlation i.e. in white noise.

**Diagnostic reports:**

**Normality test of residuals**:




Series: Residuals
Sample 1995 2016
Observations 22

| | |
|---|---|
| Mean | -1.58e-19 |
| Median | 0.003119 |
| Maximum | 0.014261 |
| Minimum | -0.016360 |
| Std. Dev. | 0.008111 |
| Skewness | -0.571267 |
| Kurtosis | 2.484618 |
| Jarque-Bera | 1.440085 |
| Probability | 0.486732 |

**Breusch-Godfrey Serial Correlation LM Test:**

Lag(2)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.456952 | Prob. F(2,18) | 0.6404 |
| Obs*R-squared | 1.063022 | Prob. Chi-Square(2) | 0.5877 |

Lag(4)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 1.005181 | Prob. F(4,16) | 0.4337 |
| Obs*R-squared | 4.418218 | Prob. Chi-Square(4) | 0.3524 |

Lag(8)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 1.129448 | Prob. F(8,12) | 0.4098 |
| Obs*R-squared | 9.449836 | Prob. Chi-Square(8) | 0.3058 |

## Heteroscedasticity test:

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 0.080097 | Prob. F(1,20) | 0.7801 |
| Obs*R-squared | 0.087756 | Prob. Chi-Square(1) | 0.7670 |
| Scaled explained SS | 0.053836 | Prob. Chi-Square(1) | 0.8165 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/15/21 Time: 16:46
Sample: 1995 2016
Included observations: 22

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 6.28E-05 | 1.71E-05 | 3.675611 | 0.0015 |
| DSTREAMFLOW | -7.02E-13 | 2.48E-12 | -0.283015 | 0.7801 |

| | | | |
|---|---|---|---|
| R-squared | 0.003989 | Mean dependent var | 6.28E-05 |
| Adjusted R-squared | -0.045812 | S.D. dependent var | 7.83E-05 |
| S.E. of regression | 8.01E-05 | Akaike info criterion | -15.94054 |
| Sum squared resid | 1.28E-07 | Schwarz criterion | -15.84135 |
| Log likelihood | 177.3459 | Hannan-Quinn criter. | -15.91717 |
| F-statistic | 0.080097 | Durbin-Watson stat | 1.842477 |
| Prob(F-statistic) | 0.780074 | | |

**ARIMAX (0,1,0) Forecasting:** Extend workfile size (from 1996-2019) by double clicking the range> provide original values in dstreamflow from 2017-2019>Quick >estimate equation> dcpue c dstreamflow> Forecast> Forecast sample (1996-2019)>ok>

Associated excel file to determine MAPE, RAMSE, MAE etc. of the year 2017-2019.

**Regression model:** 3 years lag of Env. variables

**Sample 1990-2010:**

**Multicollinearity test:**

**Coefficients[a]**

| Model | | Collinearity Statistics | |
|---|---|---|---|
| | | Tolerance | VIF |
| 1 | licence | .628 | 1.593 |
| | price | .751 | 1.331 |
| | rainfall | .143 | 7.017 |
| | temperature | .664 | 1.506 |
| | streamflow | .055 | 18.335 |
| | streamwaterlevel | .027 | 36.383 |

a. Dependent Variable: cpue

Here, multicollinearity is present between streamflow and Stream water level. Tolerance is less than 0.1, VIF is more than 10.

So, run the analysis two-times: first time, with all the variables excluding stream water level and for the second time, with all the variable excluding streamflow. Then compared results of the two models, specifically R squares and P values. Model including all other variables excluding streamwaterlevel showed improved result than the other. So, I deleted streamwater from the model.

Result of including streamflow and excluding stream water level in the model:

**Model Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | .942[a] | .886 | .839 | .005926913 |

a. Predictors: (Constant), streamflow, price, licence, temperature, rainfall

Result of including stream water level and excluding streamflow in the model:

**Model Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | .941[a] | .886 | .839 | .005930431 |

a. Predictors: (Constant), streamwaterlevel, price, licence, temperature, rainfall

**MLR**:

cpue licences price rainfall temperature streamflow c

Dependent Variable: CPUE
Method: Least Squares
Date: 03/23/21 Time: 12:51
Sample: 1997 2016
Included observations: 20

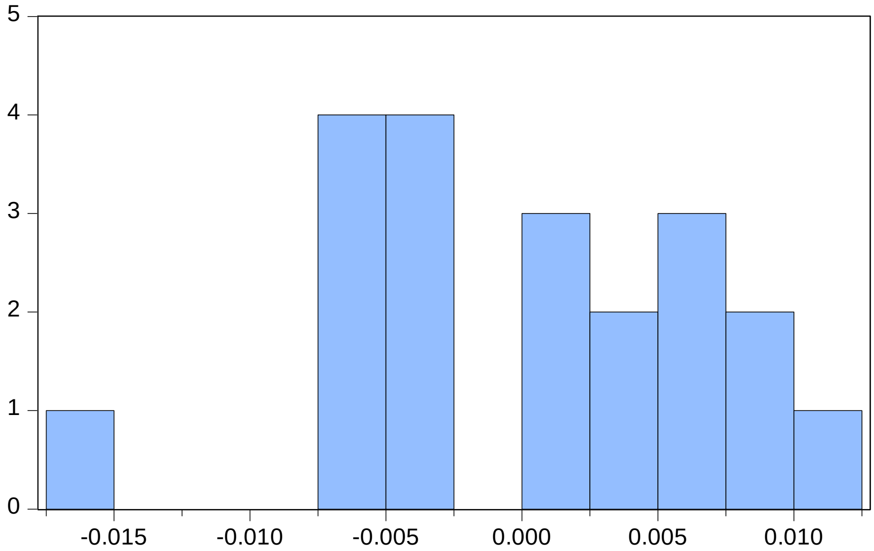
| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| LICENCES | -0.001237 | 0.000290 | -4.265821 | 0.0008 |
| PRICE | 6.58E-08 | 6.28E-09 | 10.48023 | 0.0000 |
| RAINFALL | -4.33E-07 | 9.62E-06 | -0.045042 | 0.9647 |
| TEMPERATURE | -0.005114 | 0.006028 | -0.848410 | 0.4105 |
| STREAMFLOW | 8.00E-10 | 9.04E-10 | 0.884199 | 0.3915 |
| C | 0.178083 | 0.148224 | 1.201448 | 0.2495 |

| | | | |
|---|---|---|---|
| R-squared | 0.929980 | Mean dependent var | 0.050774 |
| Adjusted R-squared | 0.904973 | S.D. dependent var | 0.026036 |
| S.E. of regression | 0.008026 | Akaike info criterion | -6.568981 |
| Sum squared resid | 0.000902 | Schwarz criterion | -6.270262 |

| | | | |
|---|---|---|---|
| Log likelihood | 71.68981 | Hannan-Quinn criter. | -6.510668 |
| F-statistic | 37.18877 | Durbin-Watson stat | 1.241932 |
| Prob(F-statistic) | 0.000000 | | |

## Diagnostic checking:

## Normality test:




| | |
|---|---|
| Series: Residuals | |
| Sample 1997 2016 | |
| Observations 20 | |
| Mean | -8.15e-18 |
| Median | 0.000341 |
| Maximum | 0.011592 |
| Minimum | -0.015908 |
| Std. Dev. | 0.006889 |
| Skewness | -0.301776 |
| Kurtosis | 2.572939 |
| Jarque-Bera | 0.455547 |
| Probability | 0.796304 |

## Breusch-Godfrey Serial Correlation LM Test:

Lag(2)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.973276 | Prob. F(2,10) | 0.4109 |
| Obs*R-squared | 2.932890 | Prob. Chi-Square(2) | 0.2307 |

Lag(4)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 1.627905 | Prob. F(4,8) | 0.2581 |
| Obs*R-squared | 8.076918 | Prob. Chi-Square(4) | 0.0888 |

Lag (8)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.639228 | Prob. F(8,4) | 0.7269 |
| Obs*R-squared | 10.09991 | Prob. Chi-Square(8) | 0.2581 |

## Heteroscedasticity test:

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 2.343904 | Prob. F(5,14) | 0.0595 |
| Obs*R-squared | 1.12369 | Prob. Chi-Square(5) | 0.0622 |
| Scaled explained SS | 4.057477 | Prob. Chi-Square(5) | 0.4089 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/23/21 Time: 12:54
Sample: 1997 2016
Included observations: 20

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.000191 | 0.000732 | 0.261232 | 0.7977 |
| LICENCES | -1.11E-06 | 1.43E-06 | -0.778564 | 0.4492 |
| PRICE | 7.08E-12 | 3.10E-11 | 0.228259 | 0.8227 |
| RAINFALL | -1.71E-08 | 4.75E-08 | -0.359412 | 0.7247 |
| TEMPERATURE | -6.14E-06 | 2.98E-05 | -0.206136 | 0.8397 |
| STREAMFLOW | 1.34E-11 | 4.47E-12 | 3.004434 | 0.0095 |

| | | | |
|---|---|---|---|
| R-squared | 0.656185 | Mean dependent var | 4.51E-05 |
| Adjusted R-squared | 0.533393 | S.D. dependent var | 5.80E-05 |
| S.E. of regression | 3.96E-05 | Akaike info criterion | -17.19054 |
| Sum squared resid | 2.20E-08 | Schwarz criterion | -16.89182 |
| Log likelihood | 177.9054 | Hannan-Quinn criter. | -17.13223 |
| F-statistic | 5.343904 | Durbin-Watson stat | 1.340929 |
| Prob(F-statistic) | 0.005918 | | |

## Sample 1992-2013:

## Multicollinearity test:

### Coefficients[a]

| Model | Collinearity Statistics |
|---|---|

| | | Tolerance | VIF |
|---|---|---|---|
| 1 | licence | .763 | 1.311 |
| | price | .614 | 1.628 |
| | rainfall | .157 | 6.375 |
| | temperature | .705 | 1.418 |
| | streamflow | .071 | 14.183 |
| | streamwaterlevel | .037 | 27.154 |

a. Dependent Variable: cpue

Here, multicollinearity is present between streamflow and Stream water level. Tolerance is less than 0.1, VIF is more than 10.

So, run the analysis two-times: first time, with all the variables excluding stream water level and for the second time, with all the variable excluding streamflow. Then compared results of the two models, specifically R squares and P values. Model including all other variables excluding streamwaerlevel showed improved result than the other. So, I deleted streamwaterlevel from the model.

Result of including streamflow and excluding stream water level in the model:

**Model Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | .959[a] | .919 | .888 | .005400661 |

a. Predictors: (Constant), streamflow, licence, temperature, price, rainfall

Result of including stream water level and excluding streamflow in the model:

**Model Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | .944[a] | .892 | .850 | .006247008 |

a. Predictors: (Constant), streamwaterlevel, licence, temperature, price, rainfall

## MLR:

cpue licences price rainfall temperature streamflow c

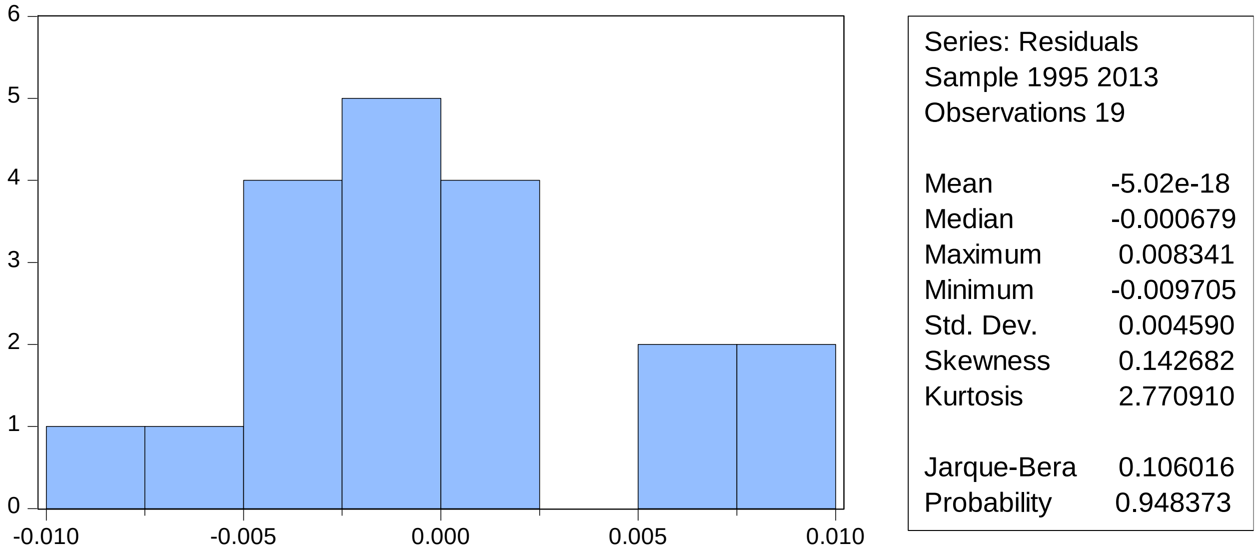
Dependent Variable: CPUE
Method: Least Squares
Date: 03/23/21 Time: 13:01
Sample: 1995 2013
Included observations: 19

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| LICENCES | -0.001969 | 0.000339 | -5.814719 | 0.0001 |
| PRICE | 9.24E-08 | 1.15E-08 | 8.009551 | 0.0000 |
| RAINFALL | -1.03E-05 | 3.30E-06 | -3.110474 | 0.0083 |
| TEMPERATURE | 0.006293 | 0.003766 | 1.671103 | 0.1186 |
| STREAMFLOW | 8.51E-10 | 2.39E-10 | 3.558546 | 0.0035 |
| C | -0.089768 | 0.097513 | -0.920576 | 0.3740 |

| | | | |
|---|---|---|---|
| R-squared | 0.919241 | Mean dependent var | 0.049808 |
| Adjusted R-squared | 0.888180 | S.D. dependent var | 0.016151 |
| S.E. of regression | 0.005401 | Akaike info criterion | -7.352502 |
| Sum squared resid | 0.000379 | Schwarz criterion | -7.054258 |
| Log likelihood | 75.84876 | Hannan-Quinn criter. | -7.302027 |
| F-statistic | 29.59470 | Durbin-Watson stat | 2.432065 |
| Prob(F-statistic) | 0.000001 | | |

## Diagnostic Checking:

## Normality test:




## Breusch-Godfrey Serial Correlation LM Test:

Lag(2)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 1.153335 | Prob. F(2,11) | 0.3510 |
| Obs*R-squared | 3.293591 | Prob. Chi-Square(2) | 0.1927 |

Lag(4)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.790549 | Prob. F(4,9) | 0.5598 |
| Obs*R-squared | 4.940037 | Prob. Chi-Square(4) | 0.2935 |

Lag(8)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.535788 | Prob. F(8,5) | 0.7938 |
| Obs*R-squared | 8.769878 | Prob. Chi-Square(8) | 0.3621 |

## Heteroscedasticity Test:

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 2.547034 | Prob. F(5,13) | 0.0810 |
| Obs*R-squared | 9.402240 | Prob. Chi-Square(5) | 0.0941 |
| Scaled explained SS | 3.897421 | Prob. Chi-Square(5) | 0.5643 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/23/21 Time: 13:03
Sample: 1995 2013
Included observations: 19

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 5.13E-05 | 0.000412 | 0.124564 | 0.9028 |
| LICENCES | -3.66E-06 | 1.43E-06 | -2.555170 | 0.0240 |
| PRICE | -4.58E-11 | 4.88E-11 | -0.938590 | 0.3651 |
| RAINFALL | -8.73E-10 | 1.40E-08 | -0.062566 | 0.9511 |
| TEMPERATURE | 3.36E-06 | 1.59E-05 | 0.210865 | 0.8363 |
| STREAMFLOW | -4.37E-13 | 1.01E-12 | -0.432955 | 0.6721 |

| | | | |
|---|---|---|---|
| R-squared | 0.494855 | Mean dependent var | 2.00E-05 |
| Adjusted R-squared | 0.300568 | S.D. dependent var | 2.73E-05 |
| S.E. of regression | 2.28E-05 | Akaike info criterion | -18.28587 |
| Sum squared resid | 6.77E-09 | Schwarz criterion | -17.98763 |
| Log likelihood | 179.7158 | Hannan-Quinn criter. | -18.23540 |
| F-statistic | 2.547034 | Durbin-Watson stat | 1.543318 |
| Prob(F-statistic) | 0.081012 | | |

## Sample 1994-2016:

## Multicollinearity test:

### Coefficients[a]

| Model | | Collinearity Statistics Tolerance | VIF |
|---|---|---|---|
| 1 | licence | .763 | 1.310 |
| | price | .513 | 1.950 |
| | rainfall | .258 | 3.873 |
| | temperature | .678 | 1.474 |
| | streamflow | .076 | 13.175 |
| | streamwaterlevel | .052 | 19.334 |

a. Dependent Variable: cpue

**Collinearity Diagnostics**[a]

| Model | Dimension | Eigenvalue | Condition Index | Variance Proportions (Constant) | licence | price | rainfall | temperature | streamflow | streamwaterlevel |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 6.417 | 1.000 | .00 | .00 | .00 | .00 | .00 | .00 | .00 |
| | 2 | .418 | 3.918 | .00 | .01 | .00 | .01 | .00 | .05 | .00 |
| | 3 | .077 | 9.117 | .00 | .00 | .51 | .00 | .00 | .00 | .00 |
| | 4 | .063 | 10.064 | .00 | .00 | .00 | .60 | .00 | .10 | .00 |
| | 5 | .021 | 17.299 | .00 | .99 | .15 | .01 | .00 | .02 | .00 |
| | 6 | .003 | 47.945 | .00 | .01 | .21 | .34 | .01 | .72 | .80 |
| | 7 | 9.157E-5 | 264.729 | 1.00 | .00 | .13 | .03 | .99 | .11 | .19 |

a. Dependent Variable: cpue

Here, multicollinearity is present between streamflow and Stream water level. Tolerance is less than 0.1, VIF is more than 10.

So, run the analysis two-times: first time, with all the variables excluding stream water level and for the second time, with all the variable excluding streamflow. Then compared results of the two models, specifically R squares and P values. Model including all other variables excluding stream water level showed improved result than the other. So, I deleted stream water level from the model.

Result of including streamflow and excluding stream water level in the model:

**Model Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | .964[a] | .929 | .903 | .004601674 |

a. Predictors: (Constant), streamflow, licence, temperature, price, rainfall

Result of including stream water level and excluding streamflow in the model:

**Model Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | .954[a] | .910 | .877 | .005181878 |

a. Predictors: (Constant), streamwaterlevel, licence, price, temperature, rainfall

**MLR:**

cpue licences price rainfall temperature streamflow c

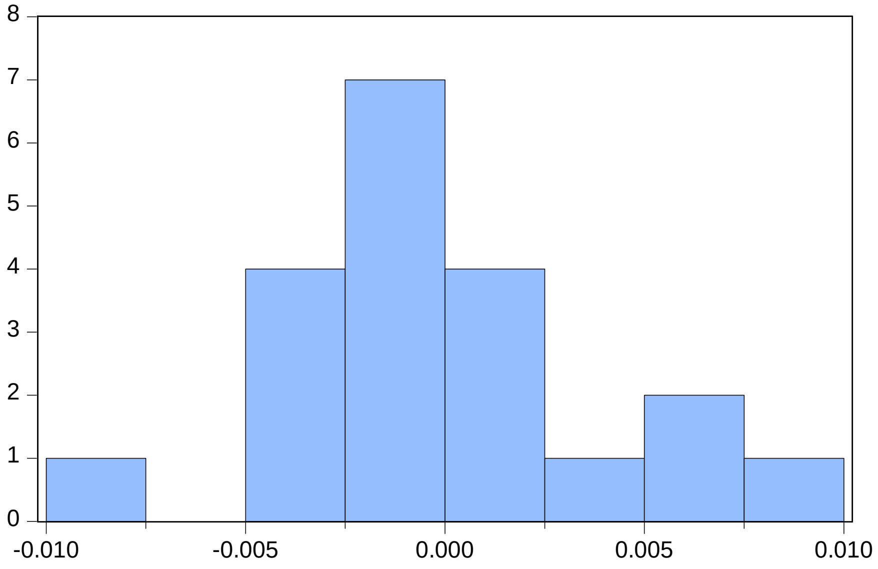
Dependent Variable: CPUE
Method: Least Squares
Date: 03/24/21 Time: 11:11
Sample: 1997 2016
Included observations: 20

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| LICENCES | -0.002070 | 0.000253 | -8.182282 | 0.0000 |
| PRICE | 1.00E-07 | 8.96E-09 | 11.17291 | 0.0000 |
| RAINFALL | -9.70E-06 | 2.78E-06 | -3.487834 | 0.0036 |
| TEMPERATURE | 0.007105 | 0.002745 | 2.588287 | 0.0215 |
| STREAMFLOW | 8.38E-10 | 1.82E-10 | 4.617143 | 0.0004 |
| C | -0.111578 | 0.069570 | -1.603833 | 0.1311 |

| | | | |
|---|---|---|---|
| R-squared | 0.928792 | Mean dependent var | 0.051258 |
| Adjusted R-squared | 0.903360 | S.D. dependent var | 0.014803 |
| S.E. of regression | 0.004602 | Akaike info criterion | -7.681468 |
| Sum squared resid | 0.000296 | Schwarz criterion | -7.382749 |
| Log likelihood | 82.81468 | Hannan-Quinn criter. | -7.623155 |
| F-statistic | 36.52115 | Durbin-Watson stat | 2.913617 |
| Prob(F-statistic) | 0.000000 | | |

**Diagnostic Checking:**

**Normality Test:**




Series: Residuals
Sample 1997 2016
Observations 20

| | |
|---|---|
| Mean | 1.46e-17 |
| Median | -0.000659 |
| Maximum | 0.008913 |
| Minimum | -0.009161 |
| Std. Dev. | 0.003950 |
| Skewness | 0.162159 |
| Kurtosis | 3.633560 |
| Jarque-Bera | 0.422150 |
| Probability | 0.809713 |

## Breusch-Godfrey Serial Correlation LM Test:

Lag(2)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 5.550027 | Prob. F(2,12) | 0.0971 |
| Obs*R-squared | 9.610414 | Prob. Chi-Square(2) | 0.0820 |

Lag(4)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 5.046294 | Prob. F(4,10) | 0.1730 |
| Obs*R-squared | 13.37423 | Prob. Chi-Square(4) | 0.0960 |

Lag(8)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 1.679137 | Prob. F(8,6) | 0.2721 |
| Obs*R-squared | 13.82497 | Prob. Chi-Square(8) | 0.0864 |

## Heteroscedasticity test:

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 1.234954 | Prob. F(5,14) | 0.3443 |
| Obs*R-squared | 6.121280 | Prob. Chi-Square(5) | 0.2946 |
| Scaled explained SS | 3.949585 | Prob. Chi-Square(5) | 0.5567 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/24/21 Time: 11:14
Sample: 1997 2016
Included observations: 20

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | -0.000258 | 0.000362 | -0.712683 | 0.4878 |
| LICENCES | -2.02E-06 | 1.32E-06 | -1.536037 | 0.1468 |
| PRICE | 2.67E-11 | 4.67E-11 | 0.572001 | 0.5764 |
| RAINFALL | -2.79E-10 | 1.45E-08 | -0.019251 | 0.9849 |
| TEMPERATURE | 1.29E-05 | 1.43E-05 | 0.901376 | 0.3826 |
| STREAMFLOW | -7.31E-13 | 9.45E-13 | -0.773424 | 0.4521 |

| | | | |
|---|---|---|---|
| R-squared | 0.306064 | Mean dependent var | 1.48E-05 |
| Adjusted R-squared | 0.058230 | S.D. dependent var | 2.47E-05 |
| S.E. of regression | 2.40E-05 | Akaike info criterion | -18.19785 |
| Sum squared resid | 8.03E-09 | Schwarz criterion | -17.89913 |
| Log likelihood | 187.9785 | Hannan-Quinn criter. | -18.13954 |
| F-statistic | 1.234954 | Durbin-Watson stat | 0.941947 |
| Prob(F-statistic) | 0.344326 | | |

## 1. Hinchinbrook:

**Data cleaning and processing:** Box plot shows no outlier is detected.

**Year: 1990-2010**

**Check for seasonality and trend**: Line diagram showing no seasonality pattern but a steady positive secular trend for the dependent variable “cpue”.

**Unit root test:** All variable has unit root, so I took1$^{st}$ difference of all the series. Now the series is stationary.

**Lag selection:** Lag 4 was selected for the granger causality test.

**Granger Causality test:**.

Pairwise Granger Causality Tests

Date: 03/16/21 Time: 00:09

Sample: 1990 2010

Lags: 4

| Null Hypothesis: | Obs | F-Statistic | Prob. |
|---|---|---|---|
| DLICENCES does not Granger Cause DCPUE | 16 | 0.48274 | 0.7489 |
| DCPUE does not Granger Cause DLICENCES | | 0.32590 | 0.8523 |
| DPRICE does not Granger Cause DCPUE | 16 | 1.23702 | 0.3770 |
| DCPUE does not Granger Cause DPRICE | | 0.99321 | 0.4701 |
| DRAINFALL does not Granger Cause DCPUE | 16 | 1.52545 | 0.2932 |
| DCPUE does not Granger Cause DRAINFALL | | 3.78284 | 0.0604 |
| DTEMPERATURE does not Granger Cause DCPUE | 16 | 0.41764 | 0.7916 |
| DCPUE does not Granger Cause DTEMPERATURE | | 0.30176 | 0.8680 |
| DSTREAMFLOW does not Granger Cause DCPUE | 16 | 0.86687 | 0.5281 |
| DCPUE does not Granger Cause DSTREAMFLOW | | 6.59669 | 0.0659 |
| DSTREAMWATERLEVEL does not Granger Cause DCPUE | 16 | 1.02097 | 0.4583 |
| DCPUE does not Granger Cause DSTREAMWATERLEVEL | | 3.50675 | 0.0710 |

No reverse causality was found.

**Test for multicollinearity**: SPSS

**Coefficients[a]**

| Model | | Collinearity Statistics | |
|---|---|---|---|
| | | Tolerance | VIF |
| 1 | dlicence | .916 | 1.092 |
| | dprice | .490 | 2.041 |
| | drainfall | .299 | 3.347 |
| | dtemperature | .444 | 2.251 |
| | dstreamflow | .136 | 7.366 |
| | dstreamwaterlevel | .185 | 5.409 |

a. Dependent Variable: dcpue

**Collinearity Diagnostics[a]**

| Model | Dimension | Eigenvalue | Condition Index | Variance Proportions (Constant) | dlicence | dprice | drainfall | dtemperature | dstreamflow | dstreamwaterlevel |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 3.010 | 1.000 | .00 | .01 | .02 | .03 | .00 | .01 | .01 |
| | 2 | 1.424 | 1.454 | .01 | .02 | .10 | .00 | .17 | .00 | .01 |
| | 3 | 1.061 | 1.684 | .62 | .25 | .01 | .00 | .00 | .00 | .00 |
| | 4 | .843 | 1.890 | .33 | .69 | .00 | .00 | .01 | .00 | .01 |
| | 5 | .340 | 2.977 | .03 | .03 | .79 | .03 | .41 | .03 | .01 |
| | 6 | .243 | 3.520 | .01 | .00 | .00 | .77 | .06 | .03 | .21 |
| | 7 | .081 | 6.113 | .00 | .01 | .08 | .17 | .35 | .92 | .75 |

a. Dependent Variable: dcpue

Here, multicollinearity is absent among variables. Tolerance is more than 0.1 and VIF is less than 10.

**Multiple Regression Test:** SPSS

Stepwise (backward) regression in SPSS

**Coefficients[a]**

| Model | | Unstandardized Coefficients B | Std. Error | Standardized Coefficients Beta | t | Sig. |
|---|---|---|---|---|---|---|
| 1 | (Constant) | .000 | .003 | | .126 | .902 |
| | dlicence | -.001 | .001 | -.414 | -1.857 | .086 |
| | dprice | 2.934E-8 | .000 | .324 | 1.062 | .307 |
| | drainfall | -3.862E-7 | .000 | -.022 | -.056 | .956 |
| | dtemperature | .007 | .007 | .320 | 1.001 | .335 |
| | dstreamflow | 8.476E-8 | .000 | .705 | 1.218 | .245 |
| | dstreamwaterlevel | -.024 | .048 | -.252 | -.508 | .620 |
| 2 | (Constant) | .000 | .002 | | .126 | .901 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | dlicence | -.001 | .001 | -.414 | -1.930 | .074 |
| | dprice | 2.902E-8 | .000 | .320 | 1.114 | .284 |
| | dtemperature | .007 | .007 | .318 | 1.039 | .317 |
| | dstreamflow | 8.279E-8 | .000 | .689 | 1.431 | .174 |
| | dstreamwaterlevel | -.024 | .046 | -.253 | -.529 | .605 |
| 3 | (Constant) | .000 | .002 | | .104 | .918 |
| | dlicence | -.001 | .001 | -.412 | -1.967 | .068 |
| | dprice | 2.600E-8 | .000 | .287 | 1.048 | .311 |
| | dtemperature | .005 | .005 | .233 | .917 | .374 |
| | dstreamflow | 5.613E-8 | .000 | .467 | 2.028 | .061 |
| 4 | (Constant) | .001 | .002 | | .234 | .818 |
| | dlicence | -.001 | .001 | -.418 | -2.007 | .062 |
| | dprice | 1.259E-8 | .000 | .139 | .632 | .536 |
| | dstreamflow | 5.786E-8 | .000 | .481 | 2.106 | .051 |
| 5 | (Constant) | .001 | .002 | | .271 | .790 |
| | dlicence | -.001 | .001 | -.427 | -2.093 | .052 |
| | dstreamflow | 6.508E-8 | .000 | .541 | 2.652 | .017 |

a. Dependent Variable: dcpue

**Excluded Variables[a]**

| Model | | Beta In | t | Sig. | Partial Correlation | Collinearity Statistics Tolerance |
|---|---|---|---|---|---|---|
| 2 | drainfall | -.022[b] | -.056 | .956 | -.016 | .299 |
| 3 | drainfall | -.026[c] | -.070 | .945 | -.019 | .299 |
| | dstreamwaterlevel | -.253[c] | -.529 | .605 | -.140 | .185 |
| 4 | drainfall | .024[d] | .065 | .949 | .017 | .306 |
| | dstreamwaterlevel | .009[d] | .021 | .983 | .006 | .256 |
| | dtemperature | .233[d] | .917 | .374 | .230 | .623 |
| 5 | drainfall | .059[e] | .164 | .872 | .041 | .314 |
| | dstreamwaterlevel | -.028[e] | -.070 | .945 | -.017 | .261 |

| | | | | | |
|---|---|---|---|---|---|
| dtemperature | .076[e] | .368 | .718 | .092 | .956 |
| dprice | .139[e] | .632 | .536 | .156 | .825 |

a. Dependent Variable: dcpue

b. Predictors in the Model: (Constant), dstreamwaterlevel, dtemperature, dlicence, dprice, dstreamflow

c. Predictors in the Model: (Constant), dtemperature, dlicence, dprice, dstreamflow

d. Predictors in the Model: (Constant), dlicence, dprice, dstreamflow

e. Predictors in the Model: (Constant), dlicence, dstreamflow

**Regression Test**: Eviws: dcpue c dlicences dstreamflow

Dependent Variable: DCPUE
Method: Least Squares
Date: 03/16/21 Time: 00:15
Sample (adjusted): 1991 2010
Included observations: 20 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| DLICENCES | -0.001446 | 0.000691 | -2.093428 | 0.0516 |
| DSTREAMFLOW | 6.51E-08 | 2.45E-08 | 2.652481 | 0.0168 |
| C | 0.000626 | 0.002312 | 0.270777 | 0.7898 |

| | | | |
|---|---|---|---|
| R-squared | 0.346871 | Mean dependent var | 0.001141 |
| Adjusted R-squared | 0.270032 | S.D. dependent var | 0.012065 |
| S.E. of regression | 0.010308 | Akaike info criterion | -6.174323 |
| Sum squared resid | 0.001806 | Schwarz criterion | -6.024963 |
| Log likelihood | 64.74323 | Hannan-Quinn criter. | -6.145166 |
| F-statistic | 4.514266 | Durbin-Watson stat | 2.777714 |
| Prob(F-statistic) | 0.026760 | | |

**Unit root test for the residuals of regression model (including dcpue c dlicences dstreamflow)**:

Null Hypothesis: R has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=4)

| | t-Statistic | Prob.* |
|---|---|---|

| | | | |
|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | -6.850524 | 0.0000 |
| Test critical values: | 1% level | -3.831511 | |
| | 5% level | -3.029970 | |
| | 10% level | -2.655194 | |

*MacKinnon (1996) one-sided p-values.

Warning: Probabilities and critical values calculated for 20 observations and may not be accurate for a sample size of 19

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(R)
Method: Least Squares
Date: 03/16/21 Time: 00:20
Sample (adjusted): 1992 2010
Included observations: 19 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| R(-1) | -1.494054 | 0.218093 | -6.850524 | 0.0000 |
| C | -0.000127 | 0.002033 | -0.062399 | 0.9510 |

| | | | |
|---|---|---|---|
| R-squared | 0.734083 | Mean dependent var | -0.001108 |
| Adjusted R-squared | 0.718441 | S.D. dependent var | 0.016657 |
| S.E. of regression | 0.008838 | Akaike info criterion | -6.520107 |
| Sum squared resid | 0.001328 | Schwarz criterion | -6.420692 |
| Log likelihood | 63.94101 | Hannan-Quinn criter. | -6.503282 |
| F-statistic | 46.92967 | Durbin-Watson stat | 2.002824 |
| Prob(F-statistic) | 0.000003 | | |

The residual has no unit root.

**Serial correlation test**: EViews
Quick>estimate equation> dcpue c dlicences dstreamflow >ok>view tab> residual diagnostics>correlogram and Q-statistics (Ljung-Box test) >lag selection (12)> ok.

The probability of Q stat (Ljung-Box test) is more than .05. So, I should accept the null hypothesis. (Null: there is no serial correlation).

**Correlogram plot:**

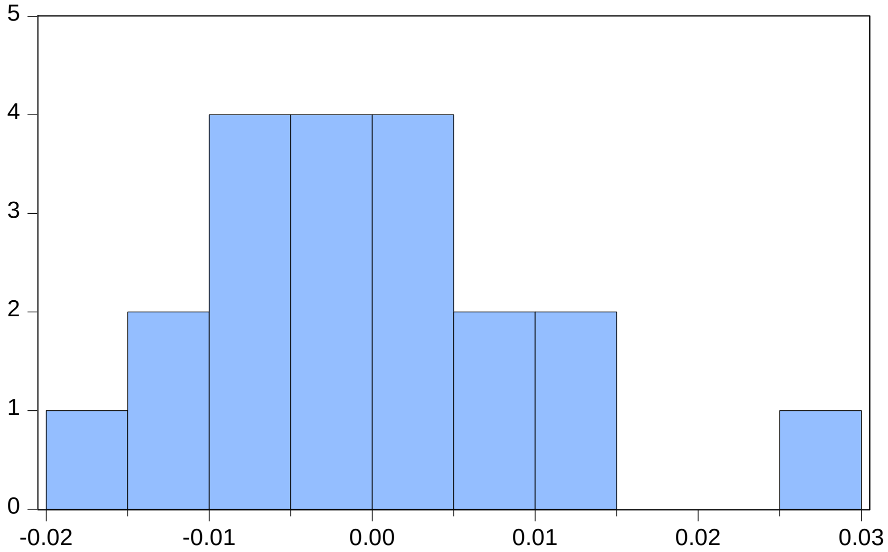
Date: 03/16/21 Time: 00:19
Sample: 1990 2010
Included observations: 20

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|---|---|
| | | 1 | -0.452 | -0.452 | 4.7381 | 0.030 |
| | | 2 | 0.169 | -0.045 | 5.4327 | 0.066 |
| | | 3 | -0.179 | -0.151 | 6.2644 | 0.099 |
| | | 4 | 0.056 | -0.101 | 6.3516 | 0.174 |
| | | 5 | 0.033 | 0.034 | 6.3841 | 0.271 |
| | | 6 | -0.196 | -0.232 | 7.5910 | 0.270 |
| | | 7 | 0.187 | -0.001 | 8.7784 | 0.269 |
| | | 8 | -0.275 | -0.239 | 11.543 | 0.173 |
| | | 9 | 0.081 | -0.277 | 11.807 | 0.224 |
| | | 10 | -0.008 | -0.106 | 11.810 | 0.298 |
| | | 11 | 0.015 | -0.163 | 11.822 | 0.377 |
| | | 12 | 0.125 | -0.009 | 12.679 | 0.393 |

The residuals are not flat and no serial correlation i.e. in white noise.

**Diagnostic checking:**

**Normality test of residuals**:




| | |
|---|---|
| Series: Residuals | |
| Sample 1991 2010 | |
| Observations 20 | |
| Mean | 7.81e-19 |
| Median | -0.000472 |
| Maximum | 0.026133 |
| Minimum | -0.015138 |
| Std. Dev. | 0.009750 |
| Skewness | 0.741253 |
| Kurtosis | 3.700197 |
| Jarque-Bera | 2.240083 |
| Probability | 0.326266 |

The probability of Jarque-Bera test in more than 5%, so the residual series follows normal distribution.

**Breusch-Godfrey Serial Correlation LM Test:**

Lag(2)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 2.622278 | Prob. F(2,15) | 0.1055 |
| Obs*R-squared | 5.181201 | Prob. Chi-Square(2) | 0.0750 |

Lag(4)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 1.422298 | Prob. F(4,13) | 0.2814 |
| Obs*R-squared | 6.088216 | Prob. Chi-Square(4) | 0.1927 |

Lag(8)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 3.368597 | Prob. F(8,9) | 0.0645 |
| Obs*R-squared | 14.99288 | Prob. Chi-Square(8) | 0.0693 |

## Heteroscedasticity test:

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 0.021064 | Prob. F(2,17) | 0.9792 |
| Obs*R-squared | 0.049439 | Prob. Chi-Square(2) | 0.9756 |
| Scaled explained SS | 0.048225 | Prob. Chi-Square(2) | 0.9762 |

Test Equation:

Dependent Variable: RESID^2

Method: Least Squares

Date: 03/16/21 Time: 00:22

Sample: 1991 2010

Included observations: 20

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 8.98E-05 | 3.61E-05 | 2.489173 | 0.0235 |
| DLICENCES | -1.59E-06 | 1.08E-05 | -0.147159 | 0.8847 |
| DSTREAMFLOW | 6.83E-11 | 3.83E-10 | 0.178349 | 0.8606 |

| | | | |
|---|---|---|---|
| R-squared | 0.002472 | Mean dependent var | 9.03E-05 |
| Adjusted R-squared | -0.114884 | S.D. dependent var | 0.000152 |
| S.E. of regression | 0.000161 | Akaike info criterion | -14.49567 |
| Sum squared resid | 4.39E-07 | Schwarz criterion | -14.34631 |
| Log likelihood | 147.9567 | Hannan-Quinn criter. | -14.46652 |
| F-statistic | 0.021064 | Durbin-Watson stat | 1.478742 |
| Prob(F-statistic) | 0.979182 | | |

Probability is greater than 5%, so the model is not heteroscedastic.

**ARIMAX (0,1,0) Forecasting:**

Extend workfile size (from 1990-2013) by double clicking the range> provide actual value in dlicences and dstreamflow from 2010-2013>Quick >estimate equation> dcpue c dlicences dstreamflow > Forecast> Forecast sample (1990-2013)>ok>

Associated excel file to determine MAPE, RAMSE, MAE etc. of the year 2011-2013.

**Year 1992-2013:**

**Unit root test**: The series has unit root, hence 1st difference of the series has taken and the final series has no unit root

**Lag selection:** Lag 4 was selected.

**Granger Causality test:**

Pairwise Granger Causality Tests
Date: 03/16/21 Time: 00:34
Sample: 1992 2013
Lags: 4

| Null Hypothesis: | Obs | F-Statistic | Prob. |
|---|---|---|---|
| DLICENCES does not Granger Cause DCPUE | 17 | 0.89701 | 0.5085 |
| DCPUE does not Granger Cause DLICENCES | | 0.22920 | 0.9144 |
| DPRICE does not Granger Cause DCPUE | 17 | 0.84885 | 0.5324 |
| DCPUE does not Granger Cause DPRICE | | 0.87611 | 0.5187 |
| DRAINFALL does not Granger Cause DCPUE | 17 | 4.45237 | 0.0647 |
| DCPUE does not Granger Cause DRAINFALL | | 0.71732 | 0.6033 |
| DTEMPERATURE does not Granger Cause DCPUE | 17 | 0.16533 | 0.9501 |
| DCPUE does not Granger Cause DTEMPERATURE | | 0.26991 | 0.8893 |
| DSTREAMFLOW does not Granger Cause DCPUE | 17 | 0.70236 | 0.6119 |
| DCPUE does not Granger Cause DSTREAMFLOW | | 6.24127 | 0.0640 |
| DSTREAMWATERLEVEL does not Granger Cause DCPUE | 17 | 1.41601 | 0.3123 |
| DCPUE does not Granger Cause DSTREAMWATERLEVEL | | 3.15876 | 0.0779 |

No reverse causality detected.

**Test for multicollinearity**

**Coefficients[a]**

| Model | | Collinearity Statistics Tolerance | VIF |
|---|---|---|---|
| 1 | dlicence | .958 | 1.044 |
| | dprice | .440 | 2.272 |
| | drainfall | .535 | 1.871 |
| | dtemperature | .385 | 2.596 |
| | dstreamflow | .231 | 4.329 |
| | dstreamwaterlevel | .195 | 5.129 |

a. Dependent Variable: dcpue

**Collinearity Diagnostics[a]**

| | | | | Variance Proportions | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Model | Dimension | Eigenvalue | Condition Index | (Constant) | dlicence | dprice | drainfall | dtemperature | dstreamflow | dstreamwaterlevel |
| 1 | 1 | 2.657 | 1.000 | .00 | .00 | .03 | .05 | .00 | .03 | .02 |
| | 2 | 1.499 | 1.331 | .00 | .00 | .08 | .01 | .14 | .00 | .02 |
| | 3 | 1.077 | 1.570 | .35 | .50 | .00 | .02 | .00 | .00 | .00 |
| | 4 | .945 | 1.676 | .64 | .39 | .00 | .00 | .00 | .00 | .00 |
| | 5 | .408 | 2.551 | .01 | .10 | .00 | .87 | .00 | .11 | .05 |
| | 6 | .308 | 2.936 | .00 | .00 | .77 | .05 | .34 | .11 | .01 |
| | 7 | .105 | 5.039 | .00 | .00 | .12 | .00 | .51 | .76 | .90 |

a. Dependent Variable: dcpue

Here, multicollinearity is absent among variables. Tolerance is more than 0.1, VIF is less than 10.

**Regression Test:** SPSS

Forward stepwise regression:

**Coefficients**[a]

| Model | | Unstandardized Coefficients B | Std. Error | Standardized Coefficients Beta | t | Sig. |
|---|---|---|---|---|---|---|
| 1 | (Constant) | .000 | .002 | | -.127 | .900 |
| | dstreamflow | 7.685E-8 | .000 | .564 | 2.974 | .008 |

a. Dependent Variable: dcpue

**Excluded Variables**[a]

| Model | | Beta In | t | Sig. | Partial Correlation | Collinearity Statistics Tolerance |
|---|---|---|---|---|---|---|
| 1 | dlicence | -.354[b] | -2.005 | .060 | -.427 | .993 |
| | dprice | .201[b] | .944 | .357 | .217 | .795 |
| | drainfall | -.057[b] | -.233 | .819 | -.055 | .629 |
| | dtemperature | -.068[b] | -.347 | .732 | -.082 | .980 |
| | dstreamwaterlevel | -.007[b] | -.020 | .984 | -.005 | .340 |

a. Dependent Variable: dcpue

b. Predictors in the Model: (Constant), dstreamflow

**Eviws**: dcpue c dstreamflow

Dependent Variable: DCPUE
Method: Least Squares
Date: 03/16/21 Time: 00:39
Sample (adjusted): 1993 2013
Included observations: 21 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| DSTREAMFLOW | 7.69E-08 | 2.58E-08 | 2.974056 | 0.0078 |
| C | -0.000302 | 0.002373 | -0.127180 | 0.9001 |

| | | | |
|---|---|---|---|
| R-squared | 0.317651 | Mean dependent var | 0.000110 |
| Adjusted R-squared | 0.281738 | S.D. dependent var | 0.012812 |

| | | | |
|---|---|---|---|
| S.E. of regression | 0.010858 | Akaike info criterion | -6.117454 |
| Sum squared resid | 0.002240 | Schwarz criterion | -6.017975 |
| Log likelihood | 66.23326 | Hannan-Quinn criter. | -6.095864 |
| F-statistic | 8.845008 | Durbin-Watson stat | 2.596273 |
| Prob(F-statistic) | 0.007797 | | |

**Unit root test of residual:**

Null Hypothesis: R has a unit root

Exogenous: Constant

Lag Length: 1 (Automatic - based on SIC, maxlag=4)

| | | t-Statistic | Prob.* |
|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | -4.889217 | 0.0011 |
| Test critical values: | 1% level | -3.831511 | |
| | 5% level | -3.029970 | |
| | 10% level | -2.655194 | |

*MacKinnon (1996) one-sided p-values.

Warning: Probabilities and critical values calculated for 20 observations and may not be accurate for a sample size of 19

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(R)

Method: Least Squares

Date: 03/16/21 Time: 00:42

Sample (adjusted): 1995 2013

Included observations: 19 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| R(-1) | -1.919530 | 0.392605 | -4.889217 | 0.0002 |
| D(R(-1)) | 0.393760 | 0.235464 | 1.672270 | 0.1139 |
| C | 0.000962 | 0.002298 | 0.418682 | 0.6810 |

| | | | |
|---|---|---|---|
| R-squared | 0.718992 | Mean dependent var | -0.000938 |
| Adjusted R-squared | 0.683866 | S.D. dependent var | 0.017645 |
| S.E. of regression | 0.009921 | Akaike info criterion | -6.244416 |
| Sum squared resid | 0.001575 | Schwarz criterion | -6.095294 |
| Log likelihood | 62.32195 | Hannan-Quinn criter. | -6.219179 |
| F-statistic | 20.46897 | Durbin-Watson stat | 1.939250 |

| Prob(F-statistic) | 0.000039 |
|---|---|

The residual has no unit root.

**Serial correlation test:** EViews

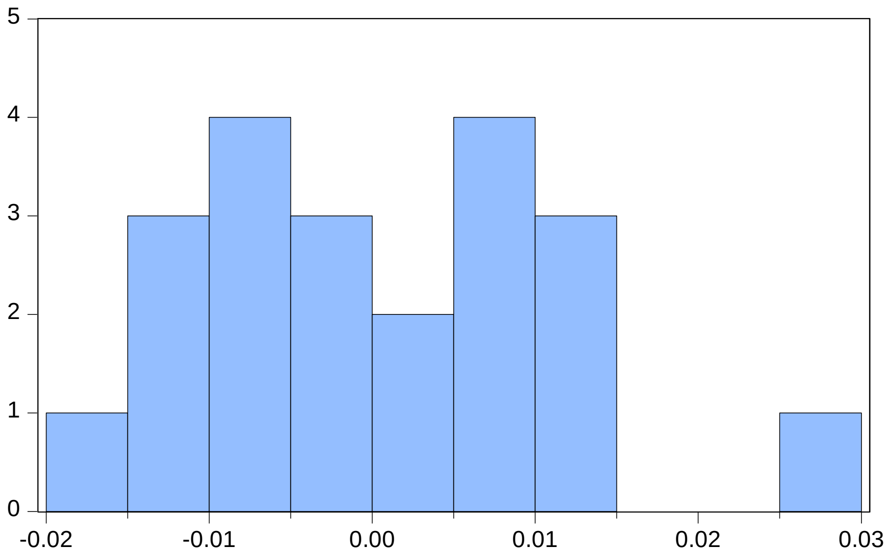
Date: 03/16/21 Time: 00:43
Sample: 1992 2013
Included observations: 21

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|---|---|
| | | 1 | -0.352 | -0.352 | 2.9984 | 0.083 |
| | | 2 | -0.187 | -0.356 | 3.8902 | 0.143 |
| | | 3 | 0.219 | 0.006 | 5.1790 | 0.159 |
| | | 4 | 0.130 | 0.223 | 5.6603 | 0.226 |
| | | 5 | -0.166 | 0.077 | 6.4879 | 0.262 |
| | | 6 | -0.126 | -0.172 | 7.0002 | 0.321 |
| | | 7 | 0.255 | 0.037 | 9.2403 | 0.236 |
| | | 8 | -0.110 | -0.053 | 9.6896 | 0.287 |
| | | 9 | -0.317 | -0.333 | 13.726 | 0.132 |
| | | 10 | 0.322 | 0.051 | 18.284 | 0.050 |
| | | 11 | -0.156 | -0.197 | 19.461 | 0.053 |
| | | 12 | -0.134 | -0.134 | 20.423 | 0.059 |

The residuals are flat and no serial correlation.

**Diagnostic checking:**

**Normality test of residuals:**



Series: Residuals
Sample 1993 2013
Observations 21

| | |
|---|---|
| Mean | 1.65e-19 |
| Median | -0.001082 |
| Maximum | 0.027357 |
| Minimum | -0.016693 |
| Std. Dev. | 0.010583 |
| Skewness | 0.627142 |
| Kurtosis | 3.266498 |
| Jarque-Bera | 1.438717 |
| Probability | 0.487065 |

**Breusch-Godfrey Serial Correlation LM Test:**

Lag(2)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 2.984950 | Prob. F(2,17) | 0.0774 |
| Obs*R-squared | 5.457921 | Prob. Chi-Square(2) | 0.0653 |

Lag(4)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 1.544180 | Prob. F(4,15) | 0.2400 |
| Obs*R-squared | 6.125175 | Prob. Chi-Square(4) | 0.1900 |

Lag (8)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.706639 | Prob. F(8,11) | 0.6822 |
| Obs*R-squared | 7.128717 | Prob. Chi-Square(8) | 0.5228 |

## Heteroscedasticity test:

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 0.012439 | Prob. F(1,19) | 0.9124 |
| Obs*R-squared | 0.013739 | Prob. Chi-Square(1) | 0.9067 |
| Scaled explained SS | 0.012745 | Prob. Chi-Square(1) | 0.9101 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/16/21 Time: 00:44
Sample: 1993 2013
Included observations: 21

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.000107 | 3.69E-05 | 2.897855 | 0.0092 |
| DSTREAMFLOW | -4.48E-11 | 4.02E-10 | -0.111529 | 0.9124 |

| | | | |
|---|---|---|---|
| R-squared | 0.000654 | Mean dependent var | 0.000107 |
| Adjusted R-squared | -0.051943 | S.D. dependent var | 0.000165 |
| S.E. of regression | 0.000169 | Akaike info criterion | -14.44568 |
| Sum squared resid | 5.41E-07 | Schwarz criterion | -14.34620 |
| Log likelihood | 153.6796 | Hannan-Quinn criter. | -14.42409 |
| F-statistic | 0.012439 | Durbin-Watson stat | 1.825009 |
| Prob(F-statistic) | 0.912367 | | |

Probability is greater than 5%, so the model is not heteroscedastic.

**ARIMAX (0,1,0) Forecasting**: Extend workfile size (from 1994-2016) by double clicking the range> provide original values in dstreamflow from 2013-2016>Quick >estimate equation> dcpue c dstreamflow> Forecast> Forecast sample (1994-2016)>ok>

Associated excel file to determine MAPE, RAMSE, MAE etc. of the year 2014-2016.

**Sample 1994-2016:**

**Unit root test:** All variables have unit root, 1st difference of the series made them stationary.

**Lag selection**: Lag 4 selected for the granger causality test for granger causality test.

**Granger causality test:**

Pairwise Granger Causality Tests
Date: 03/16/21 Time: 00:56
Sample: 1994 2016
Lags: 4

| Null Hypothesis: | Obs | F-Statistic | Prob. |
|---|---|---|---|
| DLICENCES does not Granger Cause DCPUE | 18 | 1.08410 | 0.4197 |
| DCPUE does not Granger Cause DLICENCES | | 1.40041 | 0.3089 |
| DPRICE does not Granger Cause DCPUE | 18 | 0.41049 | 0.7971 |
| DCPUE does not Granger Cause DPRICE | | 0.39272 | 0.8090 |
| DRAINFALL does not Granger Cause DCPUE | 18 | 1.77072 | 0.2187 |
| DCPUE does not Granger Cause DRAINFALL | | 1.33435 | 0.3291 |
| DTEMPERATURE does not Granger Cause DCPUE | 18 | 0.53177 | 0.7160 |
| DCPUE does not Granger Cause DTEMPERATURE | | 0.37096 | 0.8237 |
| DSTREAMFLOW does not Granger Cause DCPUE | 18 | 0.69933 | 0.6115 |
| DCPUE does not Granger Cause DSTREAMFLOW | | 5.96860 | 0.0625 |
| DSTREAMWATERLEVEL does not Granger Cause DCPUE | 18 | 0.86469 | 0.5206 |
| DCPUE does not Granger Cause DSTREAMWATERLEVEL | | 4.95671 | 0.0617 |

No reverse causality was found.

**Test for multicollinearity**:

**Coefficients[a]**

| Model | | Collinearity Statistics Tolerance | VIF |
|---|---|---|---|
| 1 | dlicence | .843 | 1.186 |
| | dprice | .548 | 1.825 |
| | drainfall | .401 | 2.496 |
| | dtemperature | .501 | 1.996 |
| | dstreamflow | .214 | 4.673 |
| | dstreamwaterlevel | .168 | 5.955 |

a. Dependent Variable: dcpue

**Collinearity Diagnostics[a]**

| Model | Dimension | Eigenvalue | Condition Index | Variance Proportions (Constant) | dlicence | dprice | drainfall | dtemperature | dstreamflow | dstreamwaterlevel |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 2.643 | 1.000 | .00 | .00 | .02 | .04 | .00 | .03 | .02 |
| | 2 | 1.535 | 1.312 | .04 | .01 | .11 | .00 | .16 | .00 | .01 |
| | 3 | 1.136 | 1.525 | .25 | .44 | .01 | .01 | .02 | .00 | .00 |
| | 4 | .893 | 1.720 | .68 | .28 | .00 | .01 | .01 | .00 | .00 |
| | 5 | .397 | 2.580 | .00 | .04 | .50 | .14 | .29 | .12 | .01 |
| | 6 | .299 | 2.972 | .01 | .16 | .35 | .65 | .25 | .07 | .01 |
| | 7 | .097 | 5.226 | .01 | .08 | .01 | .14 | .27 | .79 | .95 |

a. Dependent Variable: dcpue

Here, multicollinearity is absent among variables. Tolerance is more than 0.1, VIF is less than 10.

**Regression Test:**

Forward Stepwise:

**Coefficients**[a]

| Model | | Unstandardized Coefficients B | Std. Error | Standardized Coefficients Beta | t | Sig. |
|---|---|---|---|---|---|---|
| 1 | (Constant) | .000 | .002 | | .101 | .920 |
| | dstreamflow | 6.706E-8 | .000 | .517 | 2.702 | .014 |

a. Dependent Variable: dcpue

**Excluded Variables**[a]

| Model | | Beta In | t | Sig. | Partial Correlation | Collinearity Statistics Tolerance |
|---|---|---|---|---|---|---|
| 1 | dlicence | -.366[b] | -2.064 | .053 | -.428 | 1.000 |
| | dprice | .341[b] | 1.700 | .106 | .363 | .833 |
| | drainfall | -.150[b] | -.595 | .559 | -.135 | .596 |
| | dtemperature | -.084[b] | -.424 | .676 | -.097 | .979 |
| | dstreamwaterlevel | .036[b] | .105 | .917 | .024 | .320 |

a. Dependent Variable: dcpue

b. Predictors in the Model: (Constant), dstreamflow

**Regression Test** : Eviws: dcpue c dstreamflow

Dependent Variable: DCPUE
Method: Least Squares
Date: 03/16/21 Time: 01:02
Sample (adjusted): 1995 2016
Included observations: 22 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.000234 | 0.002315 | 0.101242 | 0.9204 |
| DSTREAMFLOW | 6.71E-08 | 2.48E-08 | 2.702179 | 0.0137 |

| | | | |
|---|---|---|---|
| R-squared | 0.267447 | Mean dependent var | 0.000301 |
| Adjusted R-squared | 0.230819 | S.D. dependent var | 0.012380 |
| S.E. of regression | 0.010858 | Akaike info criterion | -6.121410 |
| Sum squared resid | 0.002358 | Schwarz criterion | -6.022224 |

| | | | |
|---|---|---|---|
| Log likelihood | 69.33551 | Hannan-Quinn criter. | -6.098045 |
| F-statistic | 7.301770 | Durbin-Watson stat | 2.751696 |
| Prob(F-statistic) | 0.013712 | | |

**Unit root test of residual:**

Null Hypothesis: R has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=4)

| | | t-Statistic | Prob.* |
|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | -5.650542 | 0.0002 |
| Test critical values: | 1% level | -3.808546 | |
| | 5% level | -3.020686 | |
| | 10% level | -2.650413 | |

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(R)
Method: Least Squares
Date: 03/16/21 Time: 01:04
Sample (adjusted): 1997 2016
Included observations: 20 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| R(-1) | -2.030113 | 0.359277 | -5.650542 | 0.0000 |
| D(R(-1)) | 0.455057 | 0.220224 | 2.066334 | 0.0544 |
| C | 0.000658 | 0.002124 | 0.309650 | 0.7606 |

| | | | |
|---|---|---|---|
| R-squared | 0.763506 | Mean dependent var | -4.34E-05 |
| Adjusted R-squared | 0.735683 | S.D. dependent var | 0.018454 |
| S.E. of regression | 0.009488 | Akaike info criterion | -6.340176 |
| Sum squared resid | 0.001530 | Schwarz criterion | -6.190816 |
| Log likelihood | 66.40176 | Hannan-Quinn criter. | -6.311020 |
| F-statistic | 27.44169 | Durbin-Watson stat | 2.106158 |
| Prob(F-statistic) | 0.000005 | | |

Residuals do not have unit root.

**Serial correlation test:** EViews

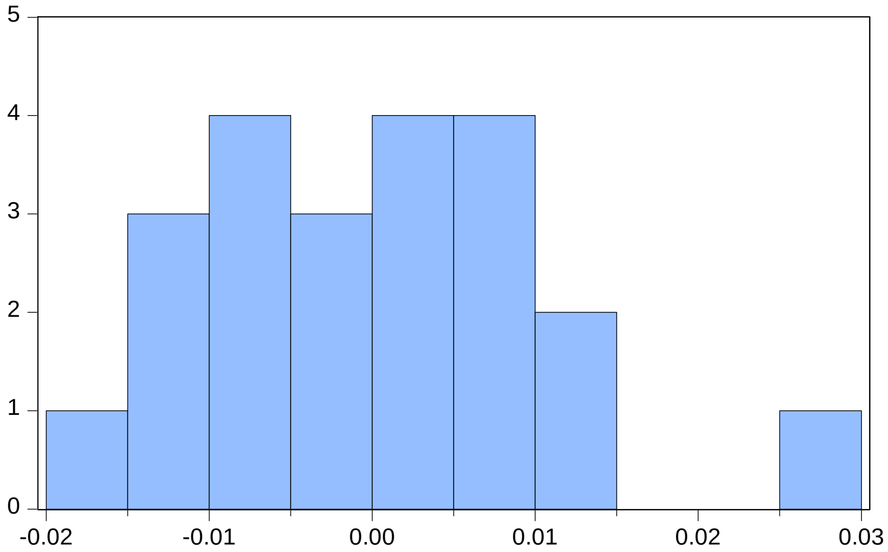
Date: 03/16/21   Time: 01:05
Sample: 1994 2016
Included observations: 22

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|---|---|
| | | 1 | -0.390 | -0.390 | 3.8150 | 0.051 |
| | | 2 | -0.215 | -0.433 | 5.0397 | 0.080 |
| | | 3 | 0.236 | -0.077 | 6.5828 | 0.086 |
| | | 4 | 0.090 | 0.141 | 6.8203 | 0.146 |
| | | 5 | -0.182 | 0.034 | 7.8529 | 0.165 |
| | | 6 | -0.064 | -0.136 | 7.9885 | 0.239 |
| | | 7 | 0.258 | 0.092 | 10.326 | 0.171 |
| | | 8 | -0.150 | -0.022 | 11.170 | 0.192 |
| | | 9 | -0.262 | -0.301 | 13.953 | 0.124 |
| | | 10 | 0.167 | -0.279 | 15.173 | 0.126 |
| | | 11 | 0.163 | -0.008 | 16.442 | 0.126 |
| | | 12 | -0.293 | -0.106 | 20.964 | 0.051 |

**Selection of MA and AR term:**

The residuals are flat and no serial correlation i.e. in white noise.

Normality test of residuals:




| | |
|---|---|
| Series: Residuals | |
| Sample 1995 2016 | |
| Observations 22 | |
| Mean | 5.91e-19 |
| Median | -0.000110 |
| Maximum | 0.027778 |
| Minimum | -0.017766 |
| Std. Dev. | 0.010596 |
| Skewness | 0.543659 |
| Kurtosis | 3.378571 |
| Jarque-Bera | 1.215110 |
| Probability | 0.544681 |

**Breusch-Godfrey Serial Correlation LM Test:**

Lag(2)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 4.159628 | Prob. F(2,18) | 0.0627 |
| Obs*R-squared | 6.953982 | Prob. Chi-Square(2) | 0.0609 |

Lag (4)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 2.090823 | Prob. F(4,16) | 0.1296 |
| Obs*R-squared | 7.552036 | Prob. Chi-Square(4) | 0.1094 |

Lag(8)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.908262 | Prob. F(8,12) | 0.5403 |
| Obs*R-squared | 8.297173 | Prob. Chi-Square(8) | 0.4050 |

## Heteroscedasticity test:

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 0.000290 | Prob. F(1,20) | 0.9866 |
| Obs*R-squared | 0.000319 | Prob. Chi-Square(1) | 0.9857 |
| Scaled explained SS | 0.000314 | Prob. Chi-Square(1) | 0.9859 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/16/21 Time: 01:05
Sample: 1995 2016
Included observations: 22

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.000107 | 3.70E-05 | 2.899401 | 0.0089 |
| DSTREAMFLOW | 6.75E-12 | 3.96E-10 | 0.017034 | 0.9866 |

| | | | |
|---|---|---|---|
| R-squared | 0.000015 | Mean dependent var | 0.000107 |
| Adjusted R-squared | -0.049985 | S.D. dependent var | 0.000169 |
| S.E. of regression | 0.000173 | Akaike info criterion | -14.39603 |
| Sum squared resid | 6.01E-07 | Schwarz criterion | -14.29684 |
| Log likelihood | 160.3563 | Hannan-Quinn criter. | -14.37266 |
| F-statistic | 0.000290 | Durbin-Watson stat | 1.808781 |
| Prob(F-statistic) | 0.986578 | | |

**ARIMAX (0,1,0) Forecasting**: Extend workfile size (from 1996-2019) by double clicking the range> provide original values in dstreamflow from 2017-2019>Quick >estimate equation> dcpue c dstreamflow> Forecast> Forecast sample (1996-2019)>ok>

Associated excel file to determine MAPE, RAMSE, MAE etc. of the year 2017-2019.

**Regression model:** 3 years lag of Env. variables

**Sample 1990-2010:**

**Multicollinearity test:**

**Coefficients[a]**

| Model | | Collinearity Statistics Tolerance | VIF |
|---|---|---|---|
| 1 | licence | .547 | 1.828 |
| | price | .664 | 1.505 |
| | rainfall | .258 | 3.873 |
| | temperature | .839 | 1.192 |
| | streamflow | .033 | 30.067 |
| | streamwaterlevel | .069 | 14.529 |

a. Dependent Variable: cpue

Here, multicollinearity is present between streamflow and Stream water level. Tolerance is less than 0.1, VIF is more than 10.

So, run the analysis two-times: first time, with all the variables excluding stream water level and for the second time, with all the variable excluding streamflow. Then compared results of the two models, specifically R squares and P values. Model including all other variables excluding streamflow showed improved result than the other. So, I deleted streamflow from the model.

Result of including streamflow and excluding stream water level in the model:

**Model Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | .865[a] | .748 | .643 | .007554832 |

a. Predictors: (Constant), streamflow, price, licence, temperature, rainfall

Result of including stream water level and excluding streamflow in the model:

**Model Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | .878[a] | .770 | .675 | .007212650 |

a. Predictors: (Constant), streamwaterlevel, price, temperature, licence, rainfall

**MLR:**

cpue licences price rainfall temperature streamwaterlevel c

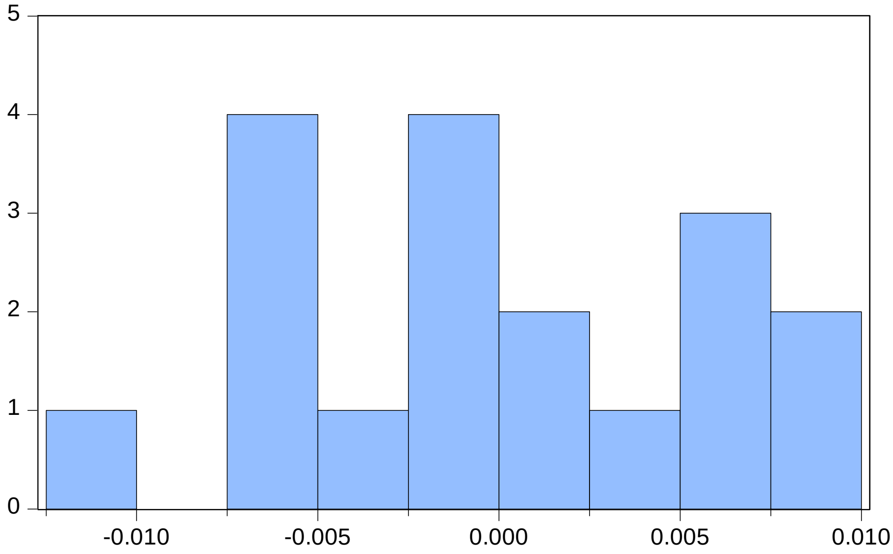
Dependent Variable: CPUE
Method: Least Squares
Date: 03/24/21 Time: 11:49
Sample: 1993 2010
Included observations: 18

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| LICENCES | -0.002269 | 0.000640 | -3.545158 | 0.0040 |
| PRICE | 2.65E-08 | 2.17E-08 | 1.221125 | 0.2455 |
| RAINFALL | -1.16E-05 | 5.46E-06 | -2.117556 | 0.0558 |
| TEMPERATURE | -0.003364 | 0.005120 | -0.656991 | 0.5236 |
| STREAMWATERLEVEL | 0.034699 | 0.028132 | 1.233444 | 0.2410 |
| C | 0.152382 | 0.128897 | 1.182197 | 0.2600 |

| | | | |
|---|---|---|---|
| R-squared | 0.770416 | Mean dependent var | 0.043609 |
| Adjusted R-squared | 0.674756 | S.D. dependent var | 0.012647 |
| S.E. of regression | 0.007213 | Akaike info criterion | -6.764759 |
| Sum squared resid | 0.000624 | Schwarz criterion | -6.467968 |
| Log likelihood | 66.88283 | Hannan-Quinn criter. | -6.723836 |
| F-statistic | 8.053699 | Durbin-Watson stat | 3.254106 |
| Prob(F-statistic) | 0.001546 | | |

**Diagnostic checking:**

**Normality test:**




Series: Residuals
Sample 1993 2010
Observations 18

| | |
|---|---|
| Mean | -1.98e-17 |
| Median | -0.000233 |
| Maximum | 0.009890 |
| Minimum | -0.011388 |
| Std. Dev. | 0.006060 |
| Skewness | -0.021416 |
| Kurtosis | 2.045050 |
| Jarque-Bera | 0.685324 |
| Probability | 0.709878 |

## Breusch-Godfrey Serial Correlation LM Test:

Lag(2)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 5.091855 | Prob. F(2,10) | 0.0699 |
| Obs*R-squared | 9.081917 | Prob. Chi-Square(2) | 0.0607 |

Lag(4)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 2.244109 | Prob. F(4,8) | 0.1536 |
| Obs*R-squared | 9.517654 | Prob. Chi-Square(4) | 0.0694 |

Lag(8)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 1.646816 | Prob. F(8,4) | 0.3312 |
| Obs*R-squared | 13.80774 | Prob. Chi-Square(8) | 0.0869 |

## Heteroscedasticity test:

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 0.228993 | Prob. F(5,12) | 0.9426 |
| Obs*R-squared | 1.567850 | Prob. Chi-Square(5) | 0.9051 |
| Scaled explained SS | 0.364107 | Prob. Chi-Square(5) | 0.9963 |

Test Equation:

Dependent Variable: RESID^2
Method: Least Squares
Date: 03/24/21 Time: 11:50
Sample: 1993 2010
Included observations: 18

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | -0.000179 | 0.000741 | -0.241990 | 0.8129 |
| LICENCES | 1.77E-07 | 3.68E-06 | 0.048201 | 0.9623 |
| PRICE | 3.58E-11 | 1.25E-10 | 0.286516 | 0.7794 |
| RAINFALL | -2.26E-08 | 3.14E-08 | -0.720869 | 0.4848 |
| TEMPERATURE | 7.43E-06 | 2.95E-05 | 0.252408 | 0.8050 |
| STREAMWATERLEVEL | 5.97E-05 | 0.000162 | 0.369234 | 0.7184 |

| | | | |
|---|---|---|---|
| R-squared | 0.087103 | Mean dependent var | 3.47E-05 |
| Adjusted R-squared | -0.293271 | S.D. dependent var | 3.65E-05 |
| S.E. of regression | 4.15E-05 | Akaike info criterion | -17.08113 |
| Sum squared resid | 2.07E-08 | Schwarz criterion | -16.78434 |
| Log likelihood | 159.7302 | Hannan-Quinn criter. | -17.04021 |
| F-statistic | 0.228993 | Durbin-Watson stat | 1.804265 |
| Prob(F-statistic) | 0.942621 | | |

**Sample 1992-2013:**

**Multicollinearity test:**

**Coefficients[a]**

| Model | | Collinearity Statistics Tolerance | VIF |
|---|---|---|---|
| 1 | licence | .359 | 2.788 |
| | price | .415 | 2.407 |
| | rainfall | .199 | 9.133 |
| | temperature | .577 | 1.732 |
| | streamflow | .049 | 20.225 |
| | streamwaterlevel | .050 | 19.843 |

a. Dependent Variable: cpue

Here, multicollinearity is present between streamflow and Stream water level. Tolerance is less than 0.1, VIF is more than 10.

So, run the analysis two-times: first time, with all the variables excluding stream water level and for the second time, with all the variable excluding streamflow. Then compared results of the two models, specifically R squares and P values. Model including all other variables excluding streamwaerlevel showed improved result than the other. So, I deleted streamwaterlevel from the model.

Result of including streamflow and excluding stream water level in the model:

**Model Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | .889[a] | .790 | .710 | .006518051 |

a. Predictors: (Constant), streamflow, price, licence, temperature, rainfall

Result of including stream water level and excluding streamflow in the model:

**Model Summary**

| Model | R | R Square | Adjusted R Square | Std. Error of the Estimate |
|---|---|---|---|---|
| 1 | .883[a] | .780 | .695 | .006682584 |

a. Predictors: (Constant), streamwaterlevel, temperature, price, licence, rainfall

**MLR:**

cpue licences price rainfall temperature streamflow c

Dependent Variable: CPUE
Method: Least Squares
Date: 03/24/21 Time: 12:09
Sample: 1995 2013
Included observations: 19

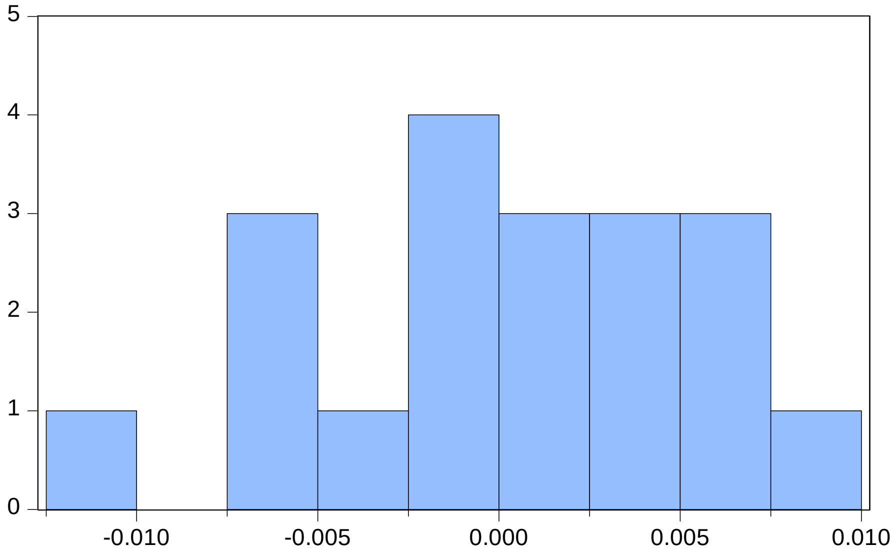
| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|

| | | | | |
|---|---|---|---|---|
| LICENCES | -0.002499 | 0.000620 | -4.029664 | 0.0014 |
| PRICE | 6.76E-08 | 1.98E-08 | 3.411510 | 0.0046 |
| RAINFALL | -8.60E-06 | 7.00E-06 | -1.228484 | 0.2410 |
| TEMPERATURE | 0.002230 | 0.004112 | 0.542347 | 0.5968 |
| STREAMFLOW | 4.80E-08 | 4.89E-08 | 0.982521 | 0.3438 |
| C | 0.037856 | 0.099065 | 0.382127 | 0.7085 |

| | | | |
|---|---|---|---|
| R-squared | 0.790462 | Mean dependent var | 0.046093 |
| Adjusted R-squared | 0.709871 | S.D. dependent var | 0.012101 |
| S.E. of regression | 0.006518 | Akaike info criterion | -6.976393 |
| Sum squared resid | 0.000552 | Schwarz criterion | -6.678150 |
| Log likelihood | 72.27574 | Hannan-Quinn criter. | -6.925919 |
| F-statistic | 9.808273 | Durbin-Watson stat | 2.579445 |
| Prob(F-statistic) | 0.000465 | | |

## Diagnostic Checking:

## Normality test:




| | |
|---|---|
| Series: Residuals | |
| Sample 1995 2013 | |
| Observations 19 | |
| Mean | -4.70e-18 |
| Median | 0.001709 |
| Maximum | 0.008392 |
| Minimum | -0.011956 |
| Std. Dev. | 0.005539 |
| Skewness | -0.428011 |
| Kurtosis | 2.403374 |
| Jarque-Bera | 0.861917 |
| Probability | 0.649886 |

## Breusch-Godfrey Serial Correlation LM Test:

Lag(2)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 1.082700 | Prob. F(2,11) | 0.3722 |
| Obs*R-squared | 3.125055 | Prob. Chi-Square(2) | 0.2096 |

Lag(4)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.778219 | Prob. F(4,9) | 0.5665 |
| Obs*R-squared | 4.882790 | Prob. Chi-Square(4) | 0.2995 |

Lag(8)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.852908 | Prob. F(8,5) | 0.6003 |
| Obs*R-squared | 10.96499 | Prob. Chi-Square(8) | 0.2037 |

## Heteroscedasticity Test:

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 0.742122 | Prob. F(5,13) | 0.6056 |
| Obs*R-squared | 4.218973 | Prob. Chi-Square(5) | 0.5183 |
| Scaled explained SS | 1.385893 | Prob. Chi-Square(5) | 0.9259 |

Test Equation:

Dependent Variable: RESID^2

Method: Least Squares

Date: 03/24/21 Time: 12:11

Sample: 1995 2013

Included observations: 19

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | -0.000198 | 0.000558 | -0.354658 | 0.7285 |
| LICENCES | 5.51E-06 | 3.49E-06 | 1.577030 | 0.1388 |
| PRICE | -7.29E-11 | 1.12E-10 | -0.653652 | 0.5247 |
| RAINFALL | -3.28E-08 | 3.94E-08 | -0.832723 | 0.4200 |
| TEMPERATURE | 7.12E-06 | 2.32E-05 | 0.307569 | 0.7633 |
| STREAMFLOW | 1.59E-10 | 2.75E-10 | 0.577281 | 0.5736 |

| | | | |
|---|---|---|---|
| R-squared | 0.222051 | Mean dependent var | 2.91E-05 |
| Adjusted R-squared | -0.077160 | S.D. dependent var | 3.54E-05 |
| S.E. of regression | 3.67E-05 | Akaike info criterion | -17.33446 |
| Sum squared resid | 1.75E-08 | Schwarz criterion | -17.03621 |
| Log likelihood | 170.6774 | Hannan-Quinn criter. | -17.28398 |
| F-statistic | 0.742122 | Durbin-Watson stat | 1.772631 |
| Prob(F-statistic) | 0.605642 | | |

## Sample 1994-2016:

**Multicollinearity test:**

**Coefficients[a]**

| Model | | Collinearity Statistics Tolerance | VIF |
|---|---|---|---|
| 1 | licence | .573 | 1.745 |
| | price | .533 | 1.876 |
| | rainfall | .182 | 5.503 |
| | temperature | .772 | 1.295 |
| | streamflow | .133 | 7.541 |
| | streamwaterlevel | .148 | 6.760 |

a. Dependent Variable: cpue

Here, multicollinearity is absent among variables.

**MLR:**

cpue licences price rainfall temperature streamflow streamwaterlevel c

Dependent Variable: CPUE
Method: Least Squares
Date: 03/24/21 Time: 12:14
Sample: 1997 2016
Included observations: 20

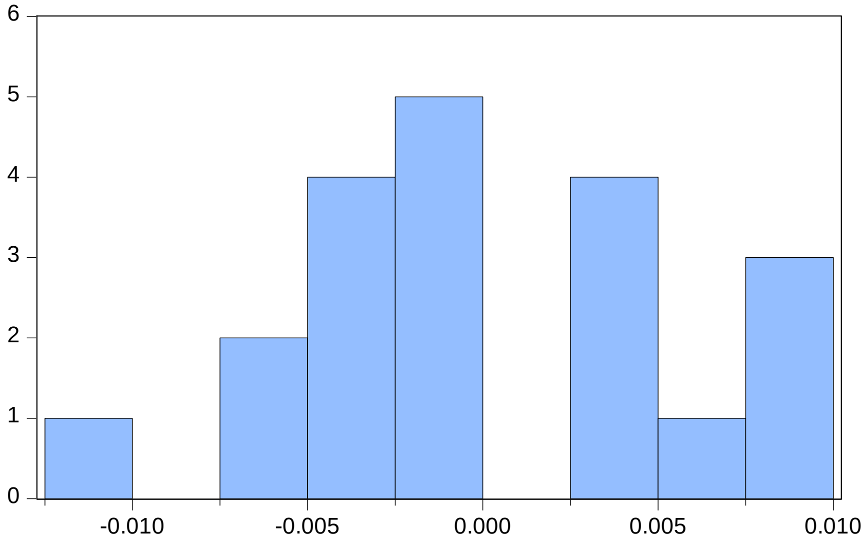
| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| LICENCES | -0.001103 | 0.000580 | -1.902094 | 0.0795 |
| PRICE | 4.96E-08 | 2.15E-08 | 2.309141 | 0.0380 |
| RAINFALL | -9.80E-06 | 5.20E-06 | -1.885543 | 0.0819 |
| TEMPERATURE | -0.002017 | 0.003977 | -0.507039 | 0.6206 |
| STREAMFLOW | -6.45E-08 | 3.96E-08 | -1.625997 | 0.1279 |
| STREAMWATERLEVEL | 0.079889 | 0.026666 | 2.995922 | 0.0103 |
| C | 0.045559 | 0.091691 | 0.496875 | 0.6276 |

| | | | |
|---|---|---|---|
| R-squared | 0.736196 | Mean dependent var | 0.047273 |
| Adjusted R-squared | 0.614440 | S.D. dependent var | 0.010095 |
| S.E. of regression | 0.006268 | Akaike info criterion | -7.037415 |
| Sum squared resid | 0.000511 | Schwarz criterion | -6.688909 |

| | | | |
|---|---|---|---|
| Log likelihood | 77.37415 | Hannan-Quinn criter. | -6.969383 |
| F-statistic | 6.046495 | Durbin-Watson stat | 2.427172 |
| Prob(F-statistic) | 0.003288 | | |

## Diagnostic Checking:

## Normality Test:




Series: Residuals
Sample 1997 2016
Observations 20

| | |
|---|---|
| Mean | 4.38e-18 |
| Median | -0.001380 |
| Maximum | 0.008561 |
| Minimum | -0.010620 |
| Std. Dev. | 0.005185 |
| Skewness | 0.078658 |
| Kurtosis | 2.270458 |
| Jarque-Bera | 0.464150 |
| Probability | 0.792887 |

## Breusch-Godfrey Serial Correlation LM Test:

Lag(2)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 1.013345 | Prob. F(2,11) | 0.3945 |
| Obs*R-squared | 3.111595 | Prob. Chi-Square(2) | 0.2110 |

Lag(4)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.429314 | Prob. F(4,9) | 0.7843 |
| Obs*R-squared | 3.204656 | Prob. Chi-Square(4) | 0.5242 |

Lag(8)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.181238 | Prob. F(8,5) | 0.9829 |
| Obs*R-squared | 4.495891 | Prob. Chi-Square(8) | 0.8098 |

## Heteroscedasticity test:

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 1.078685 | Prob. F(6,13) | 0.4235 |
| Obs*R-squared | 6.647571 | Prob. Chi-Square(6) | 0.3547 |
| Scaled explained SS | 1.784103 | Prob. Chi-Square(6) | 0.9384 |

Test Equation:

Dependent Variable: RESID^2

Method: Least Squares

Date: 03/24/21 Time: 12:15

Sample: 1997 2016

Included observations: 20

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 9.89E-05 | 0.000427 | 0.231702 | 0.8204 |
| LICENCES | 4.01E-06 | 2.70E-06 | 1.486250 | 0.1611 |
| PRICE | 7.10E-11 | 9.99E-11 | 0.710441 | 0.4900 |
| RAINFALL | 7.71E-09 | 2.42E-08 | 0.318982 | 0.7548 |
| TEMPERATURE | -2.57E-06 | 1.85E-05 | -0.138729 | 0.8918 |
| STREAMFLOW | 1.81E-10 | 1.85E-10 | 0.981697 | 0.3442 |
| STREAMWATERLEVEL | -0.000139 | 0.000124 | -1.121741 | 0.2823 |

| | | | |
|---|---|---|---|
| R-squared | 0.332379 | Mean dependent var | 2.55E-05 |
| Adjusted R-squared | 0.024246 | S.D. dependent var | 2.95E-05 |
| S.E. of regression | 2.92E-05 | Akaike info criterion | -17.77736 |
| Sum squared resid | 1.11E-08 | Schwarz criterion | -17.42886 |
| Log likelihood | 184.7736 | Hannan-Quinn criter. | -17.70933 |
| F-statistic | 1.078685 | Durbin-Watson stat | 2.032282 |
| Prob(F-statistic) | 0.423494 | | |

## 2. Hervey Bay:

**Data cleaning and processing:** Box plot shows no outlier is detected.

Treatment for missing values:

Tsset time

ipolate streamflow time, gen (newstreamflow) epolate

ipolate streamwaterlevel time, gen (newstreamwaterlevel) epolate

**Year: 1990-2010**

Check for seasonality and trend: Line diagram showing no seasonality pattern but a steady positive secular trend for the dependent variable "cpue".

**Unit root test:**

All variable has unit root, so I took1st difference of all the series. Now the series is stationary.

**Lag selection:**

Lag 4 was selected for the granger causality test.

**Granger Causality test:**

Pairwise Granger Causality Tests

Date: 03/16/21 Time: 23:22

Sample: 1990 2010

Lags: 4

| Null Hypothesis: | Obs | F-Statistic | Prob. |
|---|---|---|---|
| DLICENCES does not Granger Cause DCPUE | 16 | 0.72192 | 0.6037 |
| DCPUE does not Granger Cause DLICENCES | | 0.45794 | 0.7651 |
| DPRICE does not Granger Cause DCPUE | 16 | 1.54804 | 0.2876 |
| DCPUE does not Granger Cause DPRICE | | 1.58041 | 0.2798 |
| DRAINFALL does not Granger Cause DCPUE | 16 | 1.47314 | 0.3066 |
| DCPUE does not Granger Cause DRAINFALL | | 1.44439 | 0.3143 |
| DTEMPERATURE does not Granger Cause DCPUE | 16 | 1.16339 | 0.4027 |
| DCPUE does not Granger Cause DTEMPERATURE | | 1.32197 | 0.3497 |
| DSTREAMFLOW does not Granger Cause DCPUE | 16 | 0.33695 | 0.8451 |
| DCPUE does not Granger Cause DSTREAMFLOW | | 0.25565 | 0.8973 |
| DSTREAMWATERLEVEL does not Granger Cause DCPUE | 16 | 0.33225 | 0.8481 |
| DCPUE does not Granger Cause DSTREAMWATERLEVEL | | 1.06545 | 0.4401 |

No reverse causality was found.

**Test for multicollinearity**:

**Coefficients[a]**

| | Collinearity Statistics | |
|---|---|---|
| Model | Tolerance | VIF |

| | | | |
|---|---|---|---|
| 1 | dlicence | .696 | 1.438 |
| | dprice | .297 | 3.367 |
| | drainfall | .313 | 3.199 |
| | dtemperature | .527 | 1.897 |
| | dstreamflow | .282 | 3.552 |
| | dstreamwaterlevel | .233 | 4.288 |

a. Dependent Variable: dcpue

**Collinearity Diagnostics[a]**

| | | | | Variance Proportions | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Model | Dimension | Eigenvalue | Condition Index | (Constant) | dlicence | dprice | drainfall | dtemperature | dstreamflow | dstreamwaterlevel |
| 1 | 1 | 2.940 | 1.000 | .00 | .00 | .02 | .03 | .01 | .02 | .02 |
| | 2 | 1.386 | 1.456 | .00 | .08 | .07 | .00 | .15 | .02 | .00 |
| | 3 | 1.100 | 1.635 | .32 | .30 | .00 | .00 | .04 | .00 | .01 |
| | 4 | .971 | 1.740 | .53 | .16 | .00 | .00 | .10 | .00 | .00 |
| | 5 | .257 | 3.382 | .08 | .01 | .16 | .49 | .35 | .07 | .18 |
| | 6 | .207 | 3.769 | .06 | .40 | .08 | .41 | .26 | .53 | .05 |
| | 7 | .138 | 4.616 | .02 | .05 | .67 | .07 | .09 | .35 | .75 |

a. Dependent Variable: dcpue

Here, multicollinearity is absent among variables. Tolerance is more than 0.1 and VIF is less than 10.

**Multiple Regression Test**: SPSS

Stepwise (backward) regression in SPSS

**Coefficients[a]**

| | | Unstandardized Coefficients | | Standardized Coefficients | | |
|---|---|---|---|---|---|---|
| Model | | B | Std. Error | Beta | t | Sig. |
| 1 | (Constant) | .001 | .002 | | .563 | .583 |
| | dlicence | .001 | .001 | .287 | .996 | .337 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | dprice | 1.997E-9 | .000 | .033 | .074 | .942 |
| | drainfall | 9.314E-6 | .000 | .455 | 1.060 | .309 |
| | dtemperature | 4.729E-7 | .006 | .000 | .000 | 1.000 |
| | dstreamflow | 1.427E-9 | .000 | .013 | .029 | .978 |
| | dstreamwaterlevel | -.025 | .019 | -.677 | -1.361 | .197 |
| 2 | (Constant) | .001 | .002 | | .600 | .558 |
| | dlicence | .001 | .001 | .287 | 1.096 | .292 |
| | dprice | 1.995E-9 | .000 | .033 | .090 | .929 |
| | drainfall | 9.314E-6 | .000 | .455 | 1.111 | .285 |
| | dstreamflow | 1.425E-9 | .000 | .013 | .031 | .976 |
| | dstreamwaterlevel | -.025 | .018 | -.677 | -1.428 | .175 |
| 3 | (Constant) | .001 | .002 | | .625 | .542 |
| | dlicence | .001 | .000 | .289 | 1.164 | .263 |
| | dprice | 2.266E-9 | .000 | .037 | .115 | .910 |
| | drainfall | 9.441E-6 | .000 | .462 | 1.334 | .202 |
| | dstreamwaterlevel | -.025 | .015 | -.670 | -1.708 | .108 |
| 4 | (Constant) | .001 | .002 | | .677 | .508 |
| | dlicence | .001 | .000 | .299 | 1.325 | .204 |
| | drainfall | 9.365E-6 | .000 | .458 | 1.372 | .189 |
| | dstreamwaterlevel | -.026 | .012 | -.692 | -2.090 | .053 |
| 5 | (Constant) | .001 | .002 | | .567 | .578 |
| | drainfall | 6.926E-6 | .000 | .339 | 1.031 | .317 |
| | dstreamwaterlevel | -.022 | .012 | -.588 | -1.789 | .091 |
| 6 | (Constant) | .001 | .002 | | .657 | .520 |
| | dstreamwaterlevel | -.013 | .008 | -.337 | -1.521 | .046 |

a. Dependent Variable: dcpue

**Excluded Variables[a]**

| Model | | Beta In | t | Sig. | Partial Correlation | Collinearity Statistics Tolerance |
|---|---|---|---|---|---|---|
| 2 | dtemperature | .000[b] | .000 | 1.000 | .000 | .527 |
| 3 | dtemperature | -.003[c] | -.009 | .993 | -.003 | .582 |
| | dstreamflow | .013[c] | .031 | .976 | .008 | .311 |
| 4 | dtemperature | -.018[d] | -.078 | .939 | -.020 | .922 |
| | dstreamflow | .028[d] | .075 | .941 | .019 | .367 |
| | dprice | .037[d] | .115 | .910 | .030 | .483 |
| 5 | dtemperature | -.014[e] | -.060 | .953 | -.015 | .922 |
| | dstreamflow | .170[e] | .481 | .637 | .120 | .410 |
| | dprice | .167[e] | .546 | .593 | .135 | .548 |
| | dlicence | .299[e] | 1.325 | .204 | .314 | .925 |
| 6 | dtemperature | -.062[f] | -.268 | .792 | -.065 | .964 |
| | dstreamflow | .267[f] | .817 | .425 | .194 | .469 |
| | dprice | .105[f] | .347 | .733 | .084 | .568 |
| | dlicence | .215[f] | .967 | .347 | .228 | .997 |
| | drainfall | .339[f] | 1.031 | .317 | .243 | .455 |
| 7 | dtemperature | .004[g] | .015 | .988 | .004 | 1.000 |
| | dstreamflow | -.121[g] | -.516 | .612 | -.121 | 1.000 |
| | dprice | .281[g] | 1.244 | .230 | .281 | 1.000 |
| | dlicence | .197[g] | .850 | .406 | .197 | 1.000 |
| | drainfall | -.095[g] | -.406 | .689 | -.095 | 1.000 |
| | dstreamwaterlevel | -.337[g] | -1.521 | .146 | -.337 | 1.000 |

a. Dependent Variable: dcpue

b. Predictors in the Model: (Constant), dstreamwaterlevel, dlicence, drainfall, dprice, dstreamflow

c. Predictors in the Model: (Constant), dstreamwaterlevel, dlicence, drainfall, dprice

d. Predictors in the Model: (Constant), dstreamwaterlevel, dlicence, drainfall

e. Predictors in the Model: (Constant), dstreamwaterlevel, drainfall

f. Predictors in the Model: (Constant), dstreamwaterlevel

**Regression Test**: Eviws: dcpue c dstreamwatrelevel

Dependent Variable: DCPUE
Method: Least Squares
Date: 03/16/21 Time: 23:43
Sample (adjusted): 1991 2010
Included observations: 20 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.001229 | 0.001871 | 0.656761 | 0.5196 |
| DSTREAMWATERLEVEL | -0.012688 | 0.008342 | -1.521058 | 0.0456 |

| | | | |
|---|---|---|---|
| R-squared | 0.113895 | Mean dependent var | 0.001104 |
| Adjusted R-squared | 0.064667 | S.D. dependent var | 0.008641 |
| S.E. of regression | 0.008357 | Akaike info criterion | -6.636720 |
| Sum squared resid | 0.001257 | Schwarz criterion | -6.537146 |
| Log likelihood | 68.36720 | Hannan-Quinn criter. | -6.617282 |
| F-statistic | 2.313617 | Durbin-Watson stat | 2.672896 |
| Prob(F-statistic) | 0.145618 | | |

**Unit root test for the residuals of regression model** (including dcpue c dstreamwaterlevel):

Null Hypothesis: R has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=4)

| | | t-Statistic | Prob.* |
|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | -6.289033 | 0.0001 |
| Test critical values: | 1% level | -3.831511 | |
| | 5% level | -3.029970 | |
| | 10% level | -2.655194 | |

*MacKinnon (1996) one-sided p-values.
Warning: Probabilities and critical values calculated for 20 observations and may not be accurate for a sample size of 19

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(R)
Method: Least Squares
Date: 03/17/21 Time: 00:19

Sample (adjusted): 1992 2010

Included observations: 19 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| R(-1) | -1.437167 | 0.228520 | -6.289033 | 0.0000 |
| C | -5.30E-05 | 0.001769 | -0.029978 | 0.9764 |

| | | | |
|---|---|---|---|
| R-squared | 0.699391 | Mean dependent var | -0.000875 |
| Adjusted R-squared | 0.681709 | S.D. dependent var | 0.013634 |
| S.E. of regression | 0.007692 | Akaike info criterion | -6.798020 |
| Sum squared resid | 0.001006 | Schwarz criterion | -6.698606 |
| Log likelihood | 66.58119 | Hannan-Quinn criter. | -6.781195 |
| F-statistic | 39.55194 | Durbin-Watson stat | 2.261752 |
| Prob(F-statistic) | 0.000008 | | |

The residual has no unit root.

**Serial correlation test**: EViews

The probability of Q stat (Ljung-Box test) is more than .05. So, I should accept the null hypothesis. (Null: there is no serial correlation).

Correlogram plot:

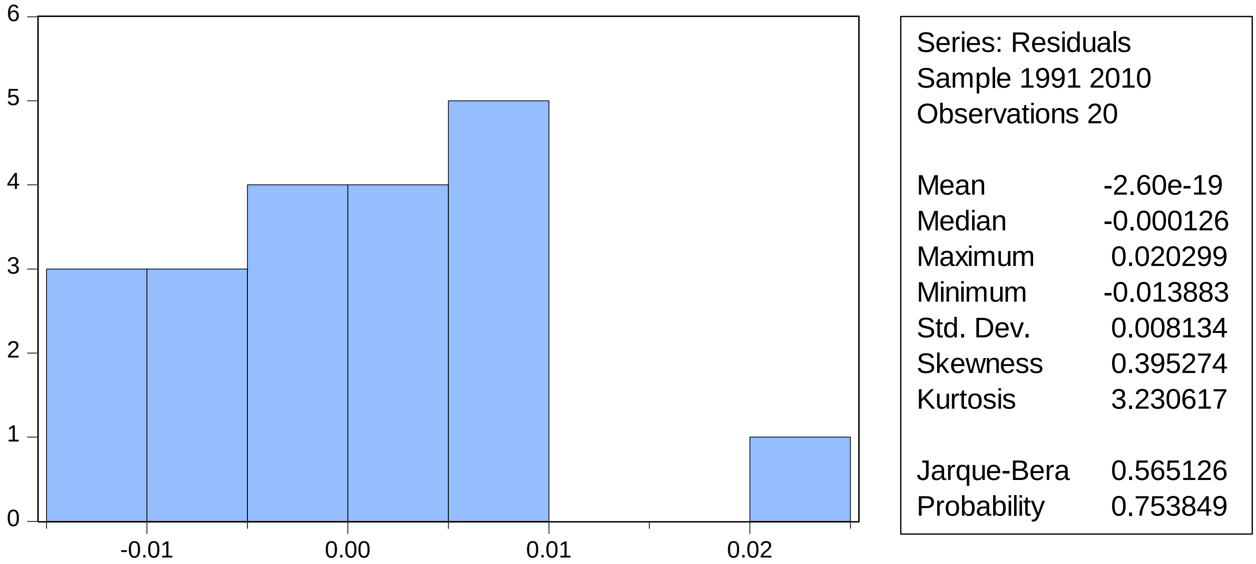
Date: 03/17/21 Time: 00:09
Sample: 1990 2010
Included observations: 20

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|---|---|
| | | 1 | -0.397 | -0.397 | 3.6421 | 0.056 |
| | | 2 | -0.118 | -0.326 | 3.9800 | 0.137 |
| | | 3 | -0.014 | -0.272 | 3.9848 | 0.263 |
| | | 4 | -0.046 | -0.312 | 4.0431 | 0.400 |
| | | 5 | 0.171 | -0.076 | 4.9005 | 0.428 |
| | | 6 | -0.190 | -0.282 | 6.0381 | 0.419 |
| | | 7 | 0.093 | -0.177 | 6.3307 | 0.502 |
| | | 8 | -0.099 | -0.366 | 6.6893 | 0.571 |
| | | 9 | 0.107 | -0.305 | 7.1443 | 0.622 |
| | | 10 | 0.176 | -0.052 | 8.5132 | 0.579 |
| | | 11 | -0.212 | -0.109 | 10.714 | 0.468 |
| | | 12 | -0.006 | -0.143 | 10.716 | 0.553 |

The residuals are not flat and no serial correlation i.e. in white noise.

**Diagnostic reports:**

**Normality test of residuals:**




The probability of Jarque-Bera test in more than 5%, so the residual series follows normal distribution

**Breusch-Godfrey Serial Correlation LM Test:**

Lag(2)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 3.129899 | Prob. F(2,16) | 0.0713 |
| Obs*R-squared | 5.624308 | Prob. Chi-Square(2) | 0.0601 |

Lag(4)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 2.628733 | Prob. F(4,14) | 0.0793 |
| Obs*R-squared | 8.578391 | Prob. Chi-Square(4) | 0.0725 |

Lag(8)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 3.383234 | Prob. F(8,10) | 0.0376 |
| Obs*R-squared | 14.60420 | Prob. Chi-Square(8) | 0.0673 |

**Heteroscedasticity test:**

Quick>estimate equation> dcpue c dstreamwaterlevel >ok>view tab> residual diagnostics>Breusch-Pagan-Godfrey test>ok

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 0.169956 | Prob. F(1,18) | 0.6850 |
| Obs*R-squared | 0.187073 | Prob. Chi-Square(1) | 0.6654 |
| Scaled explained SS | 0.169002 | Prob. Chi-Square(1) | 0.6810 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/17/21 Time: 00:21
Sample: 1991 2010
Included observations: 20

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 6.25E-05 | 2.20E-05 | 2.833205 | 0.0110 |
| DSTREAMWATERLEVEL | 4.05E-05 | 9.83E-05 | 0.412257 | 0.6850 |

| | | | |
|---|---|---|---|
| R-squared | 0.009354 | Mean dependent var | 6.29E-05 |
| Adjusted R-squared | -0.045682 | S.D. dependent var | 9.63E-05 |
| S.E. of regression | 9.85E-05 | Akaike info criterion | -15.51844 |
| Sum squared resid | 1.75E-07 | Schwarz criterion | -15.41886 |
| Log likelihood | 157.1844 | Hannan-Quinn criter. | -15.49900 |
| F-statistic | 0.169956 | Durbin-Watson stat | 1.381554 |
| Prob(F-statistic) | 0.685019 | | |

Probability is greater than 5%, so the model is not heteroscedastic.

**ARIMAX (0,1,0) Forecasting:**

Extend workfile size (from 1990-2013) by double clicking the range> provide actual value in dstreamwaterlevel from 2010-2013>Quick >estimate equation> dcpue c dstreamwaterlevel > Forecast> Forecast sample (1990-2013)>ok>

Associated excel file to determine MAPE, RAMSE, MAE etc. of the year 2011-2013.

**Year 1992-2013:**

**Unit root test**: The series has unit root; hence 1$^{st}$ difference of the series has taken and the final series has no unit root

**Lag selection**: Lag 4 was selected.

**Granger Causality test:**

Pairwise Granger Causality Tests
Date: 03/17/21 Time: 12:13
Sample: 1992 2013
Lags: 4

| Null Hypothesis: | Obs | F-Statistic | Prob. |
|---|---|---|---|
| DLICENCES does not Granger Cause DCPUE | 17 | 1.02843 | 0.4486 |
| DCPUE does not Granger Cause DLICENCES | | 1.15691 | 0.3972 |
| DPRICE does not Granger Cause DCPUE | 17 | 1.02008 | 0.4522 |
| DCPUE does not Granger Cause DPRICE | | 1.73673 | 0.2346 |
| DRAINFALL does not Granger Cause DCPUE | 17 | 0.30859 | 0.8645 |
| DCPUE does not Granger Cause DRAINFALL | | 0.51081 | 0.7302 |
| DTEMPERATURE does not Granger Cause DCPUE | 17 | 0.40489 | 0.8005 |
| DCPUE does not Granger Cause DTEMPERATURE | | 1.46621 | 0.2984 |
| DSTREAMFLOW does not Granger Cause DCPUE | 17 | 1.92379 | 0.1999 |
| DCPUE does not Granger Cause DSTREAMFLOW | | 0.47461 | 0.7540 |
| DSTREAMWATERLEVEL does not Granger Cause DCPUE | 17 | 1.22786 | 0.3716 |
| DCPUE does not Granger Cause DSTREAMWATERLEVEL | | 1.15293 | 0.3987 |

No reverse causality detected.

**Test for multicollinearity:**

**Coefficients**[a]

| Model | | Collinearity Statistics | |
|---|---|---|---|
| | | Tolerance | VIF |
| 1 | dlicence | .623 | 1.606 |
| | dprice | .287 | 3.481 |
| | drainfall | .353 | 2.831 |
| | dtemperature | .552 | 1.811 |
| | dstreamflow | .565 | 1.771 |
| | dstreamwaterlevel | .225 | 4.438 |

a. Dependent Variable: dcpue

**Collinearity Diagnostics[a]**

| Model | Dimension | Eigenvalue | Condition Index | Variance Proportions (Constant) | dlicence | dprice | drainfall | dtemperature | dstreamflow | dstreamwaterlevel |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 2.813 | 1.000 | .00 | .01 | .02 | .03 | .00 | .04 | .02 |
| | 2 | 1.291 | 1.476 | .02 | .07 | .03 | .00 | .22 | .04 | .01 |
| | 3 | 1.099 | 1.600 | .28 | .24 | .01 | .01 | .09 | .00 | .00 |
| | 4 | .972 | 1.701 | .57 | .14 | .00 | .01 | .03 | .05 | .00 |
| | 5 | .419 | 2.592 | .06 | .12 | .02 | .07 | .03 | .86 | .07 |
| | 6 | .283 | 3.155 | .00 | .01 | .30 | .64 | .24 | .00 | .04 |
| | 7 | .124 | 4.770 | .07 | .40 | .62 | .24 | .38 | .02 | .85 |

a. Dependent Variable: dcpue

Here, multicollinearity is absent among variables. Tolerance is more than 0.1, VIF is less than 10.

**Regression Test**: SPSS

Backward stepwise regression:

**Coefficients[a]**

| Model | | Unstandardized Coefficients B | Std. Error | Standardized Coefficients Beta | t | Sig. |
|---|---|---|---|---|---|---|
| 1 | (Constant) | .001 | .002 | | .527 | .606 |
| | dlicence | .001 | .001 | .351 | 1.303 | .214 |
| | dprice | 6.886E-9 | .000 | .106 | .268 | .792 |
| | drainfall | 1.452E-5 | .000 | .577 | 1.613 | .129 |
| | dtemperature | -.004 | .006 | -.215 | -.752 | .464 |
| | dstreamflow | -3.953E-8 | .000 | -.337 | -1.193 | .253 |
| | dstreamwaterlevel | -.020 | .019 | -.473 | -1.056 | .309 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 2 | (Constant) | .001 | .002 | | .620 | .544 |
| | dlicence | .001 | .001 | .383 | 1.647 | .120 |
| | drainfall | 1.450E-5 | .000 | .576 | 1.663 | .117 |
| | dtemperature | -.005 | .004 | -.266 | -1.290 | .217 |
| | dstreamflow | -3.965E-8 | .000 | -.338 | -1.236 | .236 |
| | dstreamwaterlevel | -.023 | .015 | -.541 | -1.523 | .149 |
| 3 | (Constant) | .001 | .002 | | .510 | .617 |
| | dlicence | .001 | .001 | .354 | 1.504 | .152 |
| | drainfall | 1.297E-5 | .000 | .515 | 1.478 | .159 |
| | dtemperature | -.005 | .004 | -.260 | -1.240 | .233 |
| | dstreamwaterlevel | -.031 | .014 | -.716 | -2.159 | .046 |
| 4 | (Constant) | .001 | .002 | | .440 | .666 |
| | dlicence | .001 | .001 | .351 | 1.466 | .161 |
| | drainfall | 1.285E-5 | .000 | .510 | 1.443 | .167 |
| | dstreamwaterlevel | -.030 | .014 | -.695 | -2.066 | .054 |
| 5 | (Constant) | .001 | .002 | | .278 | .784 |
| | dlicence | .000 | .000 | .192 | .879 | .391 |
| | dstreamwaterlevel | -.014 | .009 | -.319 | -1.456 | .163 |
| 6 | (Constant) | .000 | .002 | | .182 | .858 |
| | dstreamwaterlevel | -.014 | .009 | -.319 | -1.466 | .045 |

a. Dependent Variable: dcpue

**Excluded Variables[a]**

| Model | | Beta In | t | Sig. | Partial Correlation | Collinearity Statistics Tolerance |
|---|---|---|---|---|---|---|
| 2 | dprice | .106[b] | .268 | .792 | .072 | .287 |
| 3 | dprice | .113[c] | .280 | .783 | .072 | .287 |
| | dstreamflow | -.338[c] | -1.236 | .236 | -.304 | .565 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 4 | dprice | .303[d] | 1.028 | .319 | .249 | .517 |
| | dstreamflow | -.330[d] | -1.180 | .255 | -.283 | .565 |
| | dtemperature | -.260[d] | -1.240 | .233 | -.296 | .995 |
| 5 | dprice | .297[e] | .975 | .343 | .230 | .518 |
| | dstreamflow | -.266[e] | -.918 | .371 | -.217 | .577 |
| | dtemperature | -.257[e] | -1.184 | .253 | -.276 | .995 |
| | drainfall | .510[e] | 1.443 | .167 | .330 | .361 |
| 6 | dprice | .348[f] | 1.269 | .221 | .287 | .610 |
| | dstreamflow | -.255[f] | -.887 | .387 | -.205 | .578 |
| | dtemperature | -.255[f] | -1.183 | .252 | -.269 | .995 |
| | drainfall | .272[f] | .840 | .412 | .194 | .457 |
| | dlicence | .192[f] | .879 | .391 | .203 | 1.000 |

a. Dependent Variable: dcpue

b. Predictors in the Model: (Constant), dstreamwaterlevel, dlicence, dtemperature, dstreamflow, drainfall

c. Predictors in the Model: (Constant), dstreamwaterlevel, dlicence, dtemperature, drainfall

d. Predictors in the Model: (Constant), dstreamwaterlevel, dlicence, drainfall

e. Predictors in the Model: (Constant), dstreamwaterlevel, dlicence

f. Predictors in the Model: (Constant), dstreamwaterlevel

**Eviws:** dcpue c dstreamwaterlevel

Dependent Variable: DCPUE
Method: Least Squares
Date: 03/17/21 Time: 12:21
Sample (adjusted): 1993 2013
Included observations: 21 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| DSTREAMWATERLEVEL | -0.013646 | 0.009311 | -1.465652 | 0.1591 |
| C | 0.000365 | 0.002008 | 0.181857 | 0.0446 |

| | | | |
|---|---|---|---|
| R-squared | 0.101576 | Mean dependent var | 0.000432 |
| Adjusted R-squared | 0.054290 | S.D. dependent var | 0.009459 |
| S.E. of regression | 0.009199 | Akaike info criterion | -6.449042 |
| Sum squared resid | 0.001608 | Schwarz criterion | -6.349564 |

| | | | |
|---|---|---|---|
| Log likelihood | 69.71494 | Hannan-Quinn criter. | -6.427453 |
| F-statistic | 2.148136 | Durbin-Watson stat | 2.530464 |
| Prob(F-statistic) | 0.159097 | | |

**Unit root test of residual:**

Null Hypothesis: R has a unit root

Exogenous: Constant

Lag Length: 0 (Automatic - based on SIC, maxlag=4)

| | | t-Statistic | Prob.* |
|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | -6.307707 | 0.0000 |
| Test critical values: | 1% level | -3.808546 | |
| | 5% level | -3.020686 | |
| | 10% level | -2.650413 | |

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(R)

Method: Least Squares

Date: 03/17/21 Time: 12:23

Sample (adjusted): 1994 2013

Included observations: 20 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| R(-1) | -1.416072 | 0.224499 | -6.307707 | 0.0000 |
| C | 0.000781 | 0.001883 | 0.414665 | 0.6833 |

| | | | |
|---|---|---|---|
| R-squared | 0.688512 | Mean dependent var | -0.000224 |
| Adjusted R-squared | 0.671207 | S.D. dependent var | 0.014632 |
| S.E. of regression | 0.008390 | Akaike info criterion | -6.628966 |
| Sum squared resid | 0.001267 | Schwarz criterion | -6.529393 |
| Log likelihood | 68.28966 | Hannan-Quinn criter. | -6.609528 |
| F-statistic | 39.78717 | Durbin-Watson stat | 2.080607 |
| Prob(F-statistic) | 0.000006 | | |

The residual has no unit root.

**Serial correlation test:** EViews

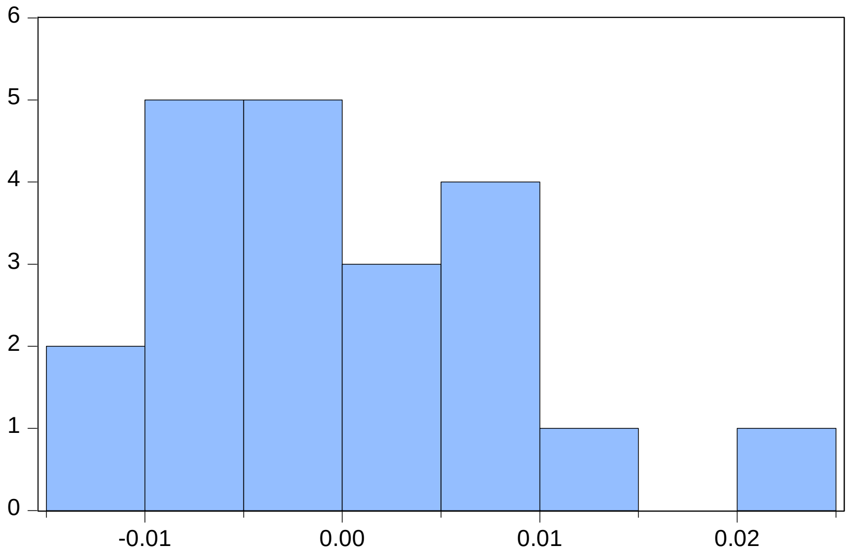
Date: 03/17/21 Time: 12:21
Sample: 1992 2013
Included observations: 21

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|---|---|
| | | 1 | -0.357 | -0.357 | 3.0801 | 0.079 |
| | | 2 | -0.076 | -0.233 | 3.2251 | 0.199 |
| | | 3 | 0.108 | -0.010 | 3.5392 | 0.316 |
| | | 4 | -0.118 | -0.111 | 3.9336 | 0.415 |
| | | 5 | 0.095 | 0.033 | 4.2033 | 0.521 |
| | | 6 | -0.249 | -0.281 | 6.2056 | 0.401 |
| | | 7 | 0.207 | 0.040 | 7.6798 | 0.362 |
| | | 8 | -0.116 | -0.149 | 8.1812 | 0.416 |
| | | 9 | -0.059 | -0.098 | 8.3216 | 0.502 |
| | | 10 | 0.215 | 0.073 | 10.360 | 0.410 |
| | | 11 | -0.150 | -0.021 | 11.450 | 0.406 |
| | | 12 | 0.060 | -0.035 | 11.644 | 0.475 |

The residuals are flat and no serial correlation.

**Diagnostic checking:**

**Normality test of residuals:**




Series: Residuals
Sample 1993 2013
Observations 21

| | |
|---|---|
| Mean | 1.65e-19 |
| Median | -0.000425 |
| Maximum | 0.021173 |
| Minimum | -0.014183 |
| Std. Dev. | 0.008966 |
| Skewness | 0.426691 |
| Kurtosis | 2.756194 |
| Jarque-Bera | 0.689239 |
| Probability | 0.708490 |

**Breusch-Godfrey Serial Correlation LM Test:**

Lag(2)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 2.915319 | Prob. F(2,17) | 0.0815 |
| Obs*R-squared | 5.363118 | Prob. Chi-Square(2) | 0.0685 |

Lag(4)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 1.619574 | Prob. F(4,15) | 0.2209 |
| Obs*R-squared | 6.334033 | Prob. Chi-Square(4) | 0.1756 |

Lag(8)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 1.088380 | Prob. F(8,11) | 0.4361 |
| Obs*R-squared | 9.278303 | Prob. Chi-Square(8) | 0.3194 |

## Heteroscedasticity test:

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 0.070380 | Prob. F(1,19) | 0.7936 |
| Obs*R-squared | 0.077501 | Prob. Chi-Square(1) | 0.7807 |
| Scaled explained SS | 0.055708 | Prob. Chi-Square(1) | 0.8134 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/17/21 Time: 12:25
Sample: 1993 2013
Included observations: 21

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 7.67E-05 | 2.32E-05 | 3.300470 | 0.0038 |
| DSTREAMWATERLEVEL | 2.86E-05 | 0.000108 | 0.265292 | 0.7936 |

| | | | |
|---|---|---|---|
| R-squared | 0.003691 | Mean dependent var | 7.66E-05 |
| Adjusted R-squared | -0.048747 | S.D. dependent var | 0.000104 |
| S.E. of regression | 0.000106 | Akaike info criterion | -15.36699 |
| Sum squared resid | 2.15E-07 | Schwarz criterion | -15.26751 |
| Log likelihood | 163.3534 | Hannan-Quinn criter. | -15.34540 |
| F-statistic | 0.070380 | Durbin-Watson stat | 1.555680 |
| Prob(F-statistic) | 0.793641 | | |

Probability is greater than 5%, so the model is not heteroscedastic.

**ARIMAX (0,1,0) Forecasting**: Extend workfile size (from 1994-2016) by double clicking the range> provide original values in dstreamwaterlevel from 2013-2016>Quick >estimate equation> dcpue c dstreamwaterlevel> Forecast> Forecast sample (1994-2016)>ok>

Associated excel file to determine MAPE, RAMSE, MAE etc. of the year 2014-2016.

**Sample 1994-2016:**

**Unit root test:** All variables have unit root, 1st difference of the series made them stationary.

**Lag selection**: Lag 4 was selected for the granger causality test

**Granger causality test:**

Pairwise Granger Causality Tests

Date: 03/17/21 Time: 12:50

Sample: 1994 2016

Lags: 4

| Null Hypothesis: | Obs | F-Statistic | Prob. |
|---|---|---|---|
| DLICENCES does not Granger Cause DCPUE | 18 | 3.86507 | 0.0427 |
| DCPUE does not Granger Cause DLICENCES | | 1.50627 | 0.2794 |
| DPRICE does not Granger Cause DCPUE | 18 | 0.42931 | 0.7843 |
| DCPUE does not Granger Cause DPRICE | | 0.41099 | 0.7967 |
| DRAINFALL does not Granger Cause DCPUE | 18 | 0.92562 | 0.4904 |
| DCPUE does not Granger Cause DRAINFALL | | 0.50237 | 0.7354 |
| DTEMPERATURE does not Granger Cause DCPUE | 18 | 0.78294 | 0.5639 |
| DCPUE does not Granger Cause DTEMPERATURE | | 1.57044 | 0.2631 |
| DSTREAMFLOW does not Granger Cause DCPUE | 18 | 1.48093 | 0.2862 |
| DCPUE does not Granger Cause DSTREAMFLOW | | 1.08359 | 0.4199 |

No reverse causality was found.

**Test for multicollinearity:**

**Coefficients[a]**

| | Collinearity Statistics | |
|---|---|---|
| Model | Tolerance | VIF |

| | | | |
|---|---|---|---|
| 1 | dlicence | .682 | 1.467 |
| | dprice | .256 | 3.911 |
| | drainfall | .379 | 2.636 |
| | dtemperature | .377 | 2.654 |
| | dstreamflow | .406 | 2.461 |
| | dstreamwaterlevel | .165 | 6.045 |

a. Dependent Variable: dcpue

**Collinearity Diagnostics[a]**

| | | | | Variance Proportions | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Model | Dimension | Eigenvalue | Condition Index | (Constant) | dlicence | dprice | drainfall | dtemperature | dstreamflow | dstreamwaterlevel |
| 1 | 1 | 2.686 | 1.000 | .00 | .01 | .02 | .04 | .00 | .03 | .02 |
| | 2 | 1.401 | 1.385 | .04 | .05 | .04 | .00 | .12 | .03 | .01 |
| | 3 | 1.143 | 1.533 | .03 | .34 | .00 | .02 | .08 | .03 | .00 |
| | 4 | .969 | 1.665 | .88 | .03 | .01 | .00 | .00 | .01 | .00 |
| | 5 | .418 | 2.534 | .01 | .33 | .09 | .02 | .06 | .47 | .03 |
| | 6 | .296 | 3.013 | .00 | .06 | .15 | .77 | .11 | .04 | .05 |
| | 7 | .087 | 5.565 | .04 | .18 | .70 | .14 | .63 | .39 | .90 |

a. Dependent Variable: dcpue

Here multicollinearity is absent among variables. Tolerance is more than 0.1, VIF is less than 10.

**Regression Test:**

Forward Stepwise:

**Coefficients[a]**

| | Unstandardized Coefficients | | Standardized Coefficients | | |
|---|---|---|---|---|---|
| Model | B | Std. Error | Beta | t | Sig. |

| | | | | | | |
|---|---|---|---|---|---|---|
| 1 | (Constant) | .001 | .002 | | .520 | .609 |
| | dstreamflow | -5.776E-8 | .000 | -.531 | -2.801 | .011 |

a. Dependent Variable: dcpue

**Excluded Variables[a]**

| Model | | Beta In | t | Sig. | Partial Correlation | Collinearity Statistics Tolerance |
|---|---|---|---|---|---|---|
| 1 | dlicence | .175[b] | .911 | .374 | .205 | .983 |
| | dprice | .372[b] | 2.046 | .055 | .425 | .937 |
| | drainfall | .095[b] | .424 | .676 | .097 | .752 |
| | dtemperature | -.176[b] | -.922 | .368 | -.207 | .997 |
| | dstreamwaterlevel | -.059[b] | -.219 | .829 | -.050 | .517 |

a. Dependent Variable: dcpue

b. Predictors in the Model: (Constant), dstreamflow

**Regression Test** : Eviws: dcpue c dstreamflow

Dependent Variable: DCPUE
Method: Least Squares
Date: 03/17/21 Time: 12:54
Sample (adjusted): 1995 2016
Included observations: 22 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.000912 | 0.001755 | 0.519958 | 0.6088 |
| DSTREAMFLOW | -5.78E-08 | 2.06E-08 | -2.800667 | 0.0110 |

| | | | |
|---|---|---|---|
| R-squared | 0.281706 | Mean dependent var | 0.000899 |
| Adjusted R-squared | 0.245791 | S.D. dependent var | 0.009477 |
| S.E. of regression | 0.008231 | Akaike info criterion | -6.675407 |
| Sum squared resid | 0.001355 | Schwarz criterion | -6.576222 |
| Log likelihood | 75.42948 | Hannan-Quinn criter. | -6.652042 |
| F-statistic | 7.843736 | Durbin-Watson stat | 2.935148 |
| Prob(F-statistic) | 0.011041 | | |

**Unit root test of residual:**

Null Hypothesis: R has a unit root

Exogenous: Constant

Lag Length: 1 (Automatic - based on SIC, maxlag=4)

| | | t-Statistic | Prob.* |
|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | -5.650542 | 0.0002 |
| Test critical values: | 1% level | -3.808546 | |
| | 5% level | -3.020686 | |
| | 10% level | -2.650413 | |

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(R)

Method: Least Squares

Date: 03/16/21 Time: 01:04

Sample (adjusted): 1997 2016

Included observations: 20 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| R(-1) | -2.030113 | 0.359277 | -5.650542 | 0.0000 |
| D(R(-1)) | 0.455057 | 0.220224 | 2.066334 | 0.0544 |
| C | 0.000658 | 0.002124 | 0.309650 | 0.7606 |

| | | | |
|---|---|---|---|
| R-squared | 0.763506 | Mean dependent var | -4.34E-05 |
| Adjusted R-squared | 0.735683 | S.D. dependent var | 0.018454 |
| S.E. of regression | 0.009488 | Akaike info criterion | -6.340176 |
| Sum squared resid | 0.001530 | Schwarz criterion | -6.190816 |
| Log likelihood | 66.40176 | Hannan-Quinn criter. | -6.311020 |
| F-statistic | 27.44169 | Durbin-Watson stat | 2.106158 |
| Prob(F-statistic) | 0.000005 | | |

Residuals do not have unit root.

**Serial correlation test:** EViews

Date: 03/17/21 Time: 12:56
Sample: 1994 2016
Included observations: 22

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|---|---|
| | | 1 | -0.478 | -0.478 | 5.7434 | 0.017 |
| | | 2 | 0.085 | -0.186 | 5.9339 | 0.051 |
| | | 3 | -0.068 | -0.146 | 6.0620 | 0.109 |
| | | 4 | -0.102 | -0.260 | 6.3674 | 0.173 |
| | | 5 | 0.197 | 0.017 | 7.5783 | 0.181 |
| | | 6 | -0.116 | -0.025 | 8.0221 | 0.236 |
| | | 7 | 0.051 | -0.022 | 8.1126 | 0.323 |
| | | 8 | -0.095 | -0.113 | 8.4550 | 0.390 |
| | | 9 | -0.040 | -0.173 | 8.5194 | 0.483 |
| | | 10 | 0.066 | -0.126 | 8.7114 | 0.560 |
| | | 11 | 0.131 | 0.137 | 9.5307 | 0.573 |
| | | 12 | -0.120 | -0.005 | 10.297 | 0.590 |

**Selection of MA and AR term:**

dcpue c dstreamflow ar(1) ma(1)

Dependent Variable: DCPUE
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 03/17/21 Time: 13:28
Sample: 1995 2016
Included observations: 22
Failure to improve objective (non-zero gradients) after 18 iterations
Coefficient covariance computed using outer product of gradients

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.001281 | 0.000311 | 4.117772 | 0.0007 |
| DSTREAMFLOW | -3.98E-08 | 3.16E-08 | -1.258616 | 0.2252 |
| AR(1) | 0.034914 | 0.315984 | 0.110494 | 0.9133 |
| MA(1) | -0.999999 | 11698.23 | -8.55E-05 | 0.9999 |
| SIGMASQ | 3.29E-05 | 0.011209 | 0.002931 | 0.9977 |

| | | | |
|---|---|---|---|
| R-squared | 0.616834 | Mean dependent var | 0.000899 |
| Adjusted R-squared | 0.526677 | S.D. dependent var | 0.009477 |
| S.E. of regression | 0.006520 | Akaike info criterion | -6.891603 |
| Sum squared resid | 0.000723 | Schwarz criterion | -6.643639 |
| Log likelihood | 80.80763 | Hannan-Quinn criter. | -6.833190 |
| F-statistic | 6.841803 | Durbin-Watson stat | 1.988422 |
| Prob(F-statistic) | 0.001796 | | |

| | |
|---|---|
| Inverted AR Roots | .03 |
| Inverted MA Roots | 1.00 |

Removed the MA term as the MA coefficient is nearly -1. Then re-estimated the model:

dcpue c dstreamflow ar(1)

Dependent Variable: DCPUE
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 03/17/21 Time: 13:52
Sample: 1995 2016
Included observations: 22
Convergence achieved after 9 iterations
Coefficient covariance computed using outer product of gradients

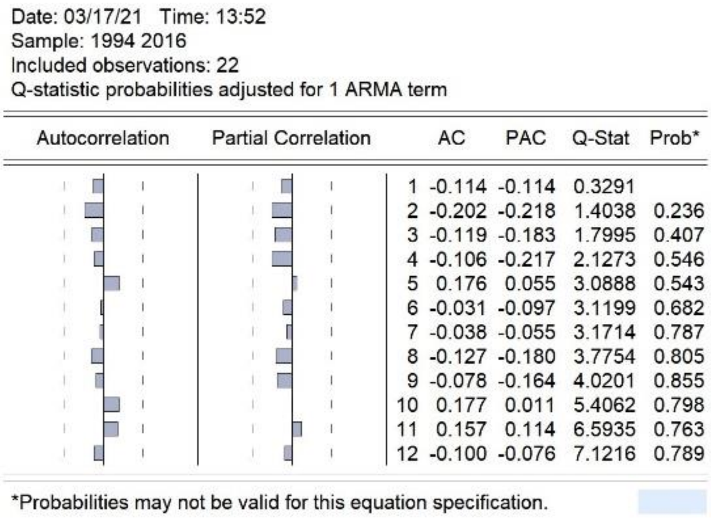
| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.001016 | 0.001310 | 0.775351 | 0.4482 |
| DSTREAMFLOW | -5.47E-08 | 2.64E-08 | -2.072434 | 0.0529 |
| AR(1) | -0.469464 | 0.200188 | -2.345121 | 0.0307 |
| SIGMASQ | 4.72E-05 | 1.68E-05 | 2.805102 | 0.0117 |

| | | | |
|---|---|---|---|
| R-squared | 0.449863 | Mean dependent var | 0.000899 |
| Adjusted R-squared | 0.358174 | S.D. dependent var | 0.009477 |
| S.E. of regression | 0.007593 | Akaike info criterion | -6.748985 |
| Sum squared resid | 0.001038 | Schwarz criterion | -6.550613 |
| Log likelihood | 78.23883 | Hannan-Quinn criter. | -6.702254 |
| F-statistic | 4.906377 | Durbin-Watson stat | 2.213251 |
| Prob(F-statistic) | 0.011544 | | |

| | |
|---|---|
| Inverted AR Roots | -.47 |

**Serial correlation test:**

The residuals are flat and no serial correlation i.e. in white noise.



Date: 03/17/21 Time: 13:52
Sample: 1994 2016
Included observations: 22
Q-statistic probabilities adjusted for 1 ARMA term

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob* |
|---|---|---|---|---|---|---|
| | | 1 | -0.114 | -0.114 | 0.3291 | |
| | | 2 | -0.202 | -0.218 | 1.4038 | 0.236 |
| | | 3 | -0.119 | -0.183 | 1.7995 | 0.407 |
| | | 4 | -0.106 | -0.217 | 2.1273 | 0.546 |
| | | 5 | 0.176 | 0.055 | 3.0888 | 0.543 |
| | | 6 | -0.031 | -0.097 | 3.1199 | 0.682 |
| | | 7 | -0.038 | -0.055 | 3.1714 | 0.787 |
| | | 8 | -0.127 | -0.180 | 3.7754 | 0.805 |
| | | 9 | -0.078 | -0.164 | 4.0201 | 0.855 |
| | | 10 | 0.177 | 0.011 | 5.4062 | 0.798 |
| | | 11 | 0.157 | 0.114 | 6.5935 | 0.763 |
| | | 12 | -0.100 | -0.076 | 7.1216 | 0.789 |

*Probabilities may not be valid for this equation specification.

**Unit root test of residual:**

Null Hypothesis: R has a unit root

Exogenous: Constant

Lag Length: 0 (Automatic - based on SIC, maxlag=4)

| | | t-Statistic | Prob.* |
|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | -4.873619 | 0.0009 |
| Test critical values: | 1% level | -3.788030 | |
| | 5% level | -3.012363 | |
| | 10% level | -2.646119 | |

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(R)

Method: Least Squares

Date: 03/17/21 Time: 13:54

Sample (adjusted): 1996 2016

Included observations: 21 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| R(-1) | -1.116235 | 0.229036 | -4.873619 | 0.0001 |
| C | 6.73E-05 | 0.001600 | 0.042060 | 0.9669 |

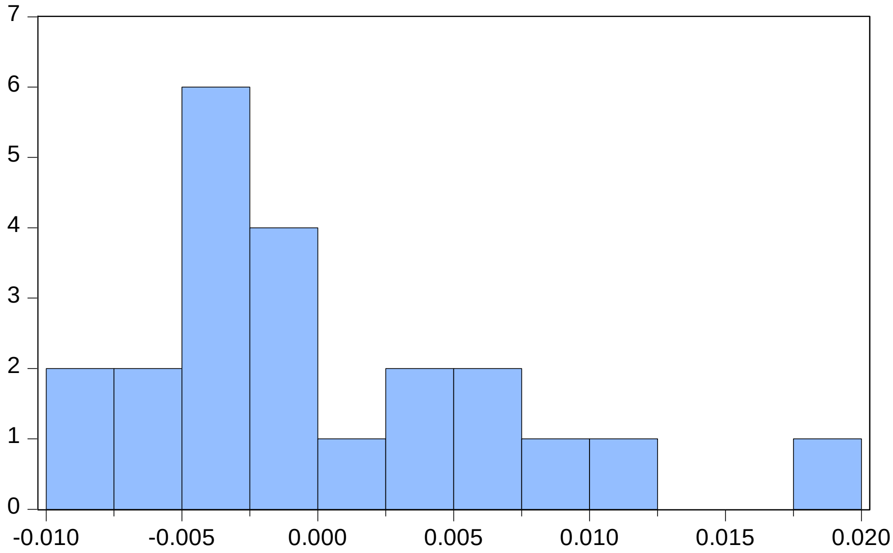
| | | | |
|---|---|---|---|
| R-squared | 0.555578 | Mean dependent var | -8.86E-05 |
| Adjusted R-squared | 0.532187 | S.D. dependent var | 0.010716 |

| | | | |
|---|---|---|---|
| S.E. of regression | 0.007329 | Akaike info criterion | -6.903532 |
| Sum squared resid | 0.001021 | Schwarz criterion | -6.804053 |
| Log likelihood | 74.48708 | Hannan-Quinn criter. | -6.881942 |
| F-statistic | 23.75216 | Durbin-Watson stat | 2.035144 |
| Prob(F-statistic) | 0.000105 | | |

There is no unit root in the residuals of new model.

**Diagnostic checking:**

**Normality test of residuals:**




| | |
|---|---|
| Series: Residuals | |
| Sample 1995 2016 | |
| Observations 22 | |
| Mean | -3.24e-05 |
| Median | -0.001889 |
| Maximum | 0.019320 |
| Minimum | -0.009654 |
| Std. Dev. | 0.007029 |
| Skewness | 1.060325 |
| Kurtosis | 3.790346 |
| Jarque-Bera | 4.694987 |
| Probability | 0.095609 |

**Breusch-Godfrey Serial Correlation LM Test:**

Lag(2)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 3.286881 | Prob. F(2,18) | 0.0607 |
| Obs*R-squared | 5.885251 | Prob. Chi-Square(2) | 0.0627 |

Lag(4)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 2.232129 | Prob. F(4,16) | 0.1113 |
| Obs*R-squared | 7.879625 | Prob. Chi-Square(4) | 0.0961 |

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.965461 | Prob. F(8,12) | 0.5038 |
| Obs*R-squared | 8.615081 | Prob. Chi-Square(8) | 0.3758 |

**Heteroscedasticity test:**

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 0.514169 | Prob. F(1,20) | 0.4816 |
| Obs*R-squared | 0.551410 | Prob. Chi-Square(1) | 0.4577 |
| Scaled explained SS | 0.511298 | Prob. Chi-Square(1) | 0.4746 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/17/21 Time: 13:56
Sample: 1995 2016
Included observations: 22

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 4.71E-05 | 1.73E-05 | 2.719229 | 0.0132 |
| DSTREAMFLOW | 1.46E-10 | 2.04E-10 | 0.717056 | 0.4816 |

| | | | |
|---|---|---|---|
| R-squared | 0.025064 | Mean dependent var | 4.72E-05 |
| Adjusted R-squared | -0.023683 | S.D. dependent var | 8.04E-05 |
| S.E. of regression | 8.13E-05 | Akaike info criterion | -15.91036 |
| Sum squared resid | 1.32E-07 | Schwarz criterion | -15.81117 |
| Log likelihood | 177.0139 | Hannan-Quinn criter. | -15.88699 |
| F-statistic | 0.514169 | Durbin-Watson stat | 1.791815 |
| Prob(F-statistic) | 0.481631 | | |

**ARIMAX (1,1,0) Forecasting**: Extend workfile size (from 1995-2019) by double clicking the range> provide original values in dstreamflow from 2017-2019>Quick >estimate equation> dcpue c dstreamflow ar(1) > Forecast> Forecast sample (1996-2019)>ok>

Associated excel file to determine MAPE, RAMSE, MAE etc. of the year 2017-2019.

**Regression model:** 3 years lag of Env. variables

**Sample 1990-2010:**

**Multicollinearity test:**

**Coefficients**[a]

| Model | | Collinearity Statistics Tolerance | VIF |
|---|---|---|---|
| 1 | licence | .457 | 2.186 |
| | price | .619 | 1.615 |
| | rainfall | .457 | 2.190 |
| | temperature | .751 | 1.332 |
| | streamflow | .397 | 2.522 |
| | streamwaterlevel | .366 | 2.729 |

a. Dependent Variable: cpue

Here, multicollinearity is absent among variables.

**MLR:**

cpue licences price rainfall temperature streamflow streamwaterlevel c

Dependent Variable: CPUE
Method: Least Squares
Date: 03/24/21 Time: 12:24
Sample: 1993 2010
Included observations: 18

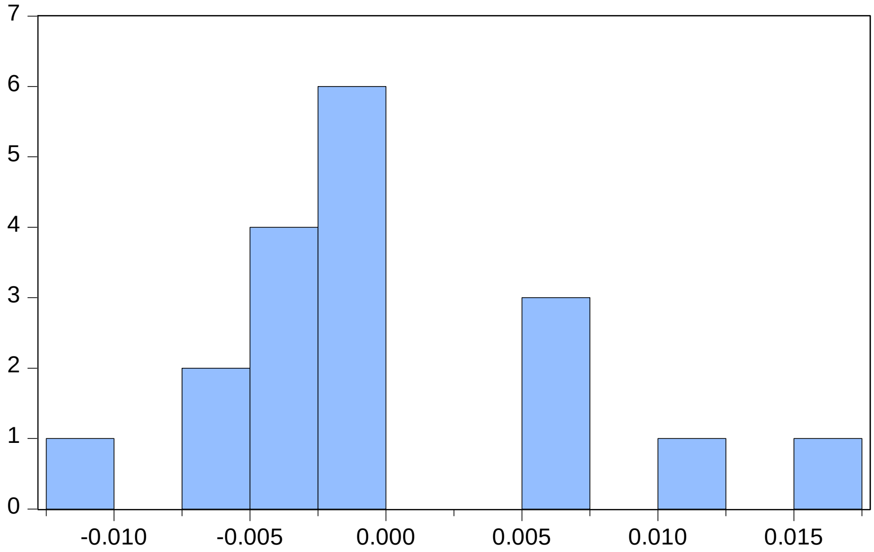
| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| LICENCES | -0.000958 | 0.000499 | -1.918913 | 0.0413 |
| PRICE | 2.84E-08 | 2.54E-08 | 1.119018 | 0.2870 |
| RAINFALL | 5.88E-06 | 1.12E-05 | 0.525690 | 0.6095 |
| TEMPERATURE | 0.002942 | 0.006752 | 0.435672 | 0.6715 |
| STREAMFLOW | 1.65E-09 | 6.92E-08 | 0.023909 | 0.9814 |
| STREAMWATERLEVEL | -0.008797 | 0.019386 | -0.453776 | 0.6588 |
| C | 0.005335 | 0.143429 | 0.037197 | 0.9710 |

| | | | |
|---|---|---|---|
| R-squared | 0.567718 | Mean dependent var | 0.040633 |
| Adjusted R-squared | 0.331929 | S.D. dependent var | 0.009822 |

| | | | |
|---|---|---|---|
| S.E. of regression | 0.008028 | Akaike info criterion | -6.526410 |
| Sum squared resid | 0.000709 | Schwarz criterion | -6.180154 |
| Log likelihood | 65.73769 | Hannan-Quinn criter. | -6.478666 |
| F-statistic | 2.407730 | Durbin-Watson stat | 2.102909 |
| Prob(F-statistic) | 0.098092 | | |

**Diagnostic checking:**

**Normality test:**




| | |
|---|---|
| Series: Residuals | |
| Sample 1993 2010 | |
| Observations 18 | |
| Mean | -4.00e-18 |
| Median | -0.001333 |
| Maximum | 0.015622 |
| Minimum | -0.011804 |
| Std. Dev. | 0.006458 |
| Skewness | 0.730489 |
| Kurtosis | 3.464135 |
| Jarque-Bera | 1.762408 |
| Probability | 0.414284 |

**Breusch-Godfrey Serial Correlation LM Test:**

Lag(2)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.050264 | Prob. F(2,9) | 0.9512 |
| Obs*R-squared | 0.198834 | Prob. Chi-Square(2) | 0.9054 |

Lag(4)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.284381 | Prob. F(4,7) | 0.8792 |
| Obs*R-squared | 2.516174 | Prob. Chi-Square(4) | 0.6417 |

Lag(8)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.667967 | Prob. F(8,3) | 0.7124 |
| Obs*R-squared | 11.52808 | Prob. Chi-Square(8) | 0.1735 |

## Heteroscedasticity test:

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 0.302726 | Prob. F(6,11) | 0.9227 |
| Obs*R-squared | 2.550994 | Prob. Chi-Square(6) | 0.8627 |
| Scaled explained SS | 1.173773 | Prob. Chi-Square(6) | 0.9782 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/24/21 Time: 12:27
Sample: 1993 2010
Included observations: 18

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 2.24E-05 | 0.001309 | 0.017075 | 0.9867 |
| LICENCES | -6.91E-07 | 4.56E-06 | -0.151699 | 0.8822 |
| PRICE | 1.48E-10 | 2.32E-10 | 0.639187 | 0.5358 |
| RAINFALL | -4.12E-08 | 1.02E-07 | -0.403444 | 0.6944 |
| TEMPERATURE | -4.81E-06 | 6.16E-05 | -0.078029 | 0.9392 |
| STREAMFLOW | -2.75E-10 | 6.32E-10 | -0.435154 | 0.6719 |
| STREAMWATERLEVEL | 0.000103 | 0.000177 | 0.580077 | 0.5736 |

| | | | |
|---|---|---|---|
| R-squared | 0.141722 | Mean dependent var | 3.94E-05 |
| Adjusted R-squared | -0.326430 | S.D. dependent var | 6.36E-05 |
| S.E. of regression | 7.33E-05 | Akaike info criterion | -15.91946 |
| Sum squared resid | 5.91E-08 | Schwarz criterion | -15.57321 |
| Log likelihood | 150.2752 | Hannan-Quinn criter. | -15.87172 |
| F-statistic | 0.302726 | Durbin-Watson stat | 2.070841 |
| Prob(F-statistic) | 0.922703 | | |

## Sample 1992-2013:

## Multicollinearity test:

**Coefficients[a]**

| Model | | Collinearity Statistics Tolerance | VIF |
|---|---|---|---|
| 1 | licence | .640 | 1.564 |
| | price | .878 | 1.139 |
| | rainfall | .383 | 2.613 |
| | temperature | .839 | 1.191 |
| | streamflow | .216 | 4.625 |
| | streamwaterlevel | .193 | 5.177 |

a. Dependent Variable: cpue

Here, multicollinearity is absent among variables.

**MLR:**

cpue licences price rainfall temperature streamflow streamwaterlevel c

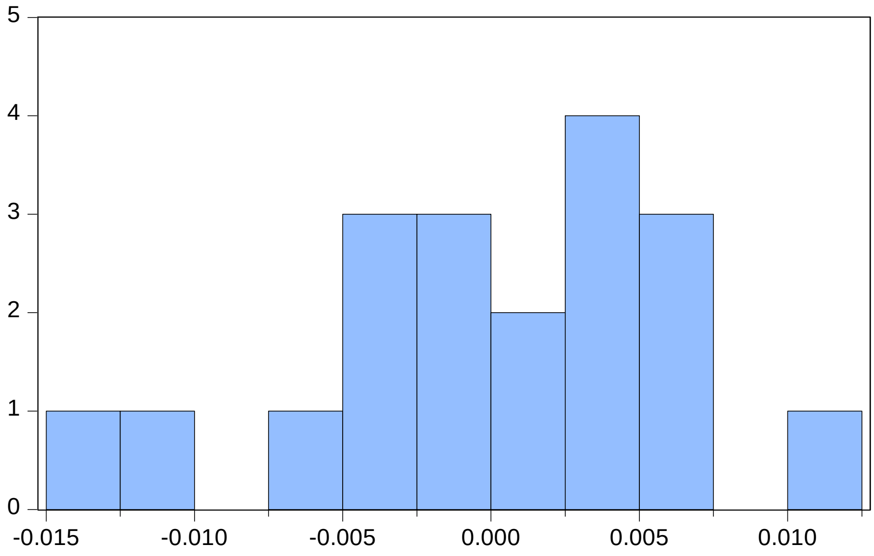
Dependent Variable: CPUE
Method: Least Squares
Date: 03/24/21 Time: 12:32
Sample: 1995 2013
Included observations: 19

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| LICENCES | -0.000853 | 0.000461 | -1.850083 | 0.0891 |
| PRICE | 6.25E-08 | 1.70E-08 | 3.680259 | 0.0031 |
| RAINFALL | 3.70E-06 | 1.02E-05 | 0.362720 | 0.7231 |
| TEMPERATURE | 0.001810 | 0.005637 | 0.321128 | 0.7536 |
| STREAMFLOW | -6.04E-08 | 5.88E-08 | -1.028408 | 0.3240 |
| STREAMWATERLEVEL | 0.018203 | 0.020982 | 0.867561 | 0.4027 |
| C | -0.017038 | 0.127388 | -0.133747 | 0.8958 |

| | | | |
|---|---|---|---|
| R-squared | 0.645014 | Mean dependent var | 0.043639 |
| Adjusted R-squared | 0.467522 | S.D. dependent var | 0.009880 |
| S.E. of regression | 0.007210 | Akaike info criterion | -6.749463 |
| Sum squared resid | 0.000624 | Schwarz criterion | -6.401512 |
| Log likelihood | 71.11990 | Hannan-Quinn criter. | -6.690576 |
| F-statistic | 3.634031 | Durbin-Watson stat | 1.840055 |
| Prob(F-statistic) | 0.027229 | | |

**Diagnostic Checking:**

**Normality test**:




Series: Residuals
Sample 1995 2013
Observations 19

| | |
|---|---|
| Mean | 1.30e-18 |
| Median | 0.001158 |
| Maximum | 0.011900 |
| Minimum | -0.014051 |
| Std. Dev. | 0.006235 |
| Skewness | -0.478141 |
| Kurtosis | 3.095064 |
| Jarque-Bera | 0.731114 |
| Probability | 0.693810 |

**Breusch-Godfrey Serial Correlation LM Test:**

Lag(2)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.177095 | Prob. F(2,10) | 0.8403 |
| Obs*R-squared | 0.649941 | Prob. Chi-Square(2) | 0.7225 |

Lag(4)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.225246 | Prob. F(4,8) | 0.9167 |
| Obs*R-squared | 1.923237 | Prob. Chi-Square(4) | 0.7499 |

Lag(8)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.688050 | Prob. F(8,4) | 0.6981 |
| Obs*R-squared | 11.00371 | Prob. Chi-Square(8) | 0.2015 |

**Heteroscedasticity Test:**

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 2.014624 | Prob. F(2,16) | 0.1658 |
| Obs*R-squared | 3.822196 | Prob. Chi-Square(2) | 0.1479 |
| Scaled explained SS | 2.839311 | Prob. Chi-Square(2) | 0.2418 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/24/21 Time: 12:34
Sample: 1995 2013
Included observations: 19

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | -0.000151 | 9.57E-05 | -1.582304 | 0.1331 |
| LICENCES | 5.16E-06 | 2.66E-06 | 1.937121 | 0.0706 |
| PRICE | 7.79E-11 | 1.15E-10 | 0.677109 | 0.5080 |

| | | | |
|---|---|---|---|
| R-squared | 0.201168 | Mean dependent var | 3.68E-05 |
| Adjusted R-squared | 0.101314 | S.D. dependent var | 5.48E-05 |
| S.E. of regression | 5.19E-05 | Akaike info criterion | -16.74989 |
| Sum squared resid | 4.31E-08 | Schwarz criterion | -16.60077 |
| Log likelihood | 162.1239 | Hannan-Quinn criter. | -16.72465 |
| F-statistic | 2.014624 | Durbin-Watson stat | 1.719435 |
| Prob(F-statistic) | 0.165822 | | |

## Sample 1994-2016:

## Multicollinearity test:

**Coefficients[a]**

| Model | | Collinearity Statistics Tolerance | VIF |
|---|---|---|---|
| 1 | licence | .880 | 1.137 |
| | price | .903 | 1.107 |
| | rainfall | .454 | 2.201 |

| | | | |
|---|---|---|---|
| | temperature | .775 | 1.290 |
| | streamflow | .305 | 3.282 |
| | streamwaterlevel | .200 | 4.997 |

a. Dependent Variable: cpue

**MLR:**

cpue licences price rainfall temperature streamflow streamwaterlevel c

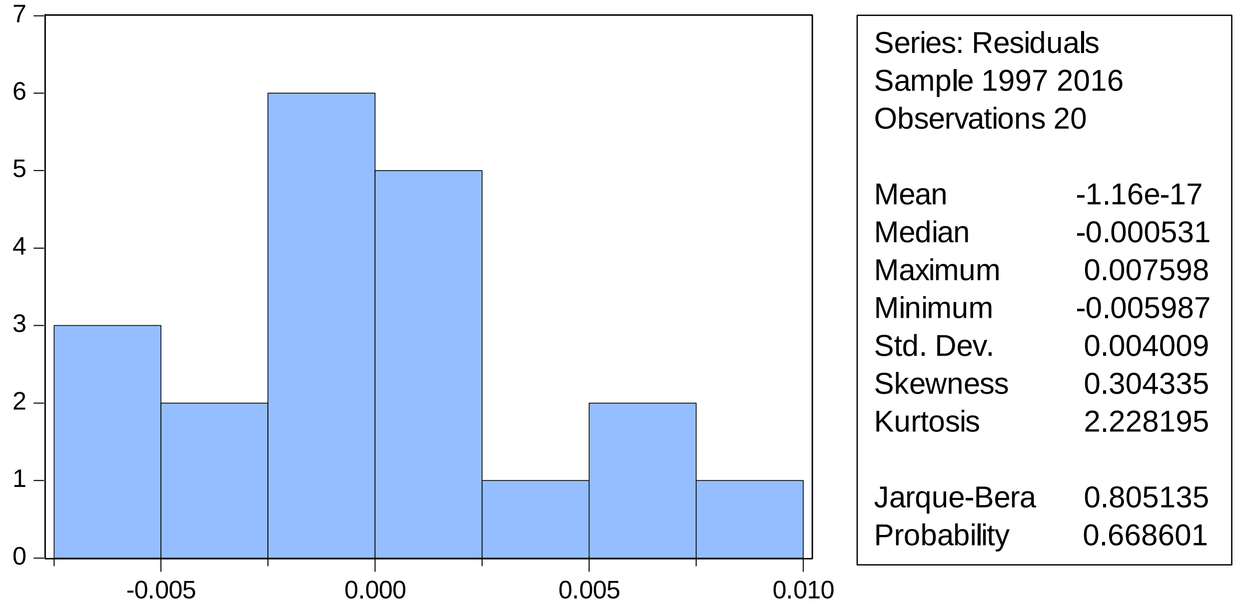
Dependent Variable: CPUE
Method: Least Squares
Date: 03/24/21 Time: 12:36
Sample: 1997 2016
Included observations: 20

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| LICENCES | -0.000850 | 0.000251 | -3.382898 | 0.0049 |
| PRICE | 6.48E-08 | 1.19E-08 | 5.461766 | 0.0001 |
| RAINFALL | -6.99E-06 | 6.39E-06 | -1.093815 | 0.2939 |
| TEMPERATURE | 0.006312 | 0.003566 | 1.769962 | 0.1002 |
| STREAMFLOW | -6.97E-08 | 2.91E-08 | -2.397746 | 0.0322 |
| STREAMWATERLEVEL | 0.038942 | 0.012931 | 3.011470 | 0.0100 |
| C | -0.130502 | 0.085685 | -1.523038 | 0.1517 |

| | | | |
|---|---|---|---|
| R-squared | 0.784782 | Mean dependent var | 0.046810 |
| Adjusted R-squared | 0.685450 | S.D. dependent var | 0.008641 |
| S.E. of regression | 0.004846 | Akaike info criterion | -7.551936 |
| Sum squared resid | 0.000305 | Schwarz criterion | -7.203430 |
| Log likelihood | 82.51936 | Hannan-Quinn criter. | -7.483904 |
| F-statistic | 7.900627 | Durbin-Watson stat | 2.700827 |
| Prob(F-statistic) | 0.000973 | | |

**Diagnostic Checking:**

**Normality Test:**




## Breusch-Godfrey Serial Correlation LM Test:

Lag(2)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 3.709256 | Prob. F(2,11) | 0.0687 |
| Obs*R-squared | 8.055495 | Prob. Chi-Square(2) | 0.0678 |

Lag(4)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 3.049939 | Prob. F(4,9) | 0.0760 |
| Obs*R-squared | 11.50934 | Prob. Chi-Square(4) | 0.0614 |

Lag(8)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 1.540810 | Prob. F(8,5) | 0.3291 |
| Obs*R-squared | 14.22849 | Prob. Chi-Square(8) | 0.0760 |

## Heteroscedasticity test:

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 0.496497 | Prob. F(6,13) | 0.8001 |
| Obs*R-squared | 3.728623 | Prob. Chi-Square(6) | 0.7133 |
| Scaled explained SS | 0.967414 | Prob. Chi-Square(6) | 0.9868 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/24/21 Time: 12:38
Sample: 1997 2016
Included observations: 20

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.000525 | 0.000335 | 1.568115 | 0.1409 |
| LICENCES | 1.27E-07 | 9.82E-07 | 0.129080 | 0.8993 |
| PRICE | -4.07E-11 | 4.63E-11 | -0.878271 | 0.3957 |
| RAINFALL | 1.71E-08 | 2.50E-08 | 0.684707 | 0.5056 |
| TEMPERATURE | -2.00E-05 | 1.39E-05 | -1.433422 | 0.1753 |
| STREAMFLOW | 1.19E-10 | 1.14E-10 | 1.045207 | 0.3150 |
| STREAMWATERLEVEL | -6.69E-05 | 5.05E-05 | -1.323660 | 0.2084 |

| | | | |
|---|---|---|---|
| R-squared | 0.186431 | Mean dependent var | 1.53E-05 |
| Adjusted R-squared | -0.189062 | S.D. dependent var | 1.74E-05 |
| S.E. of regression | 1.89E-05 | Akaike info criterion | -18.64253 |
| Sum squared resid | 4.66E-09 | Schwarz criterion | -18.29402 |
| Log likelihood | 193.4253 | Hannan-Quinn criter. | -18.57450 |
| F-statistic | 0.496497 | Durbin-Watson stat | 1.866501 |
| Prob(F-statistic) | 0.800095 | | |

## 3. Pooled Reference sites:

**Data Preparation:** Average value of all the variables were extracted from the three NFZs.

**Year: 1990-2010**

**Check for seasonality and trend:** Line diagram showing no seasonality pattern but a steady positive secular trend for the dependent variable "cpue".

**Unit root test:**

All variable has unit root, so I took 1st difference of all the series. Now the series is stationary.

**Lag selection**: Stata

Lag 4 was selected for the granger causality test.

**Granger Causality test**:

Pairwise Granger Causality Tests

Date: 03/18/21 Time: 13:22

Sample: 1990 2010

Lags: 4

| Null Hypothesis: | Obs | F-Statistic | Prob. |
|---|---|---|---|
| DLICENCES does not Granger Cause DCPUE | 16 | 0.07266 | 0.9883 |
| DCPUE does not Granger Cause DLICENCES | | 0.85684 | 0.5330 |
| DPRICE does not Granger Cause DCPUE | 16 | 3.39722 | 0.0759 |
| DCPUE does not Granger Cause DPRICE | | 1.66554 | 0.2606 |
| DRAINFALL does not Granger Cause DCPUE | 16 | 1.15702 | 0.4051 |
| DCPUE does not Granger Cause DRAINFALL | | 0.55838 | 0.7005 |
| DTEMPERATURE does not Granger Cause DCPUE | 16 | 1.15594 | 0.4054 |
| DCPUE does not Granger Cause DTEMPERATURE | | 0.53828 | 0.7132 |
| DSTREAMFLOW does not Granger Cause DCPUE | 16 | 0.62819 | 0.6578 |
| DCPUE does not Granger Cause DSTREAMFLOW | | 0.14417 | 0.9599 |

No reverse causality was found.

**Test for multicollinearity**:

**Coefficients[a]**

| Model | | Collinearity Statistics | |
|---|---|---|---|
| | | Tolerance | VIF |
| 1 | dlicence | .700 | 1.428 |
| | dprice | .525 | 1.904 |
| | drainfall | .447 | 2.236 |
| | dtemperature | .588 | 1.701 |
| | dstreamflow | .254 | 3.930 |
| | dstreamwaterlevel | .189 | 5.279 |

a. Dependent Variable: dcpue

**Collinearity Diagnostics[a]**

| Model | Dimension | Eigenvalue | Condition Index | Variance Proportions (Constant) | dlicence | dprice | drainfall | dtemperature | dstreamflow | dstreamwaterlevel |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 2.538 | 1.000 | .00 | .03 | .03 | .04 | .01 | .02 | .02 |
| | 2 | 1.437 | 1.329 | .01 | .02 | .11 | .00 | .16 | .02 | .02 |
| | 3 | 1.071 | 1.539 | .44 | .20 | .03 | .02 | .02 | .01 | .00 |
| | 4 | .982 | 1.608 | .37 | .16 | .00 | .05 | .04 | .04 | .01 |
| | 5 | .586 | 2.082 | .00 | .21 | .12 | .31 | .18 | .04 | .00 |
| | 6 | .279 | 3.016 | .18 | .37 | .72 | .15 | .55 | .05 | .00 |
| | 7 | .107 | 4.873 | .00 | .01 | .00 | .43 | .04 | .82 | .95 |

a. Dependent Variable: dcpue

Here, multicollinearity is absent among variables. Tolerance is more than 0.1 and VIF is less than 10.

**Multiple Regression Test:** SPSS

Stepwise (backward) regression in SPSS

Analyse> regression>Linear>Provide variables> Method (backward)> Statistics (select Confidence interval, R square change and descriptives)>continue>ok

**Coefficients[a]**

| Model | | Unstandardized Coefficients B | Std. Error | Standardized Coefficients Beta | t | Sig. |
|---|---|---|---|---|---|---|
| 1 | (Constant) | .000 | .002 | | .287 | .779 |
| | dlicence | -.001 | .001 | -.294 | -1.199 | .252 |
| | dprice | 2.361E-8 | .000 | .325 | 1.148 | .271 |
| | drainfall | 1.682E-5 | .000 | .803 | 2.618 | .021 |
| | dtemperature | .006 | .005 | .296 | 1.106 | .289 |
| | dstreamflow | 1.720E-9 | .000 | .914 | 2.246 | .043 |
| | dstreamwaterlevel | -.042 | .018 | -1.100 | -2.333 | .036 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 2 | (Constant) | .001 | .002 | | .544 | .595 |
| | dlicence | -.001 | .001 | -.236 | -.978 | .344 |
| | dprice | 1.018E-8 | .000 | .140 | .609 | .552 |
| | drainfall | 1.502E-5 | .000 | .718 | 2.398 | .031 |
| | dstreamflow | 1.641E-9 | .000 | .872 | 2.136 | .051 |
| | dstreamwaterlevel | -.039 | .018 | -1.008 | -2.155 | .049 |
| 3 | (Constant) | .001 | .002 | | .657 | .521 |
| | dlicence | -.001 | .001 | -.193 | -.854 | .406 |
| | drainfall | 1.534E-5 | .000 | .733 | 2.511 | .024 |
| | dstreamflow | 1.774E-9 | .000 | .943 | 2.461 | .026 |
| | dstreamwaterlevel | -.041 | .017 | -1.060 | -2.355 | .033 |
| 4 | (Constant) | .001 | .002 | | .798 | .436 |
| | drainfall | 1.331E-5 | .000 | .636 | 2.385 | .030 |
| | dstreamflow | 1.748E-9 | .000 | .929 | 2.448 | .026 |
| | dstreamwaterlevel | -.040 | .017 | -1.031 | -2.316 | .034 |

a. Dependent Variable: dcpue

**Excluded Variables[a]**

| Model | | Beta In | t | Sig. | Partial Correlation | Collinearity Statistics Tolerance |
|---|---|---|---|---|---|---|
| 2 | dtemperature | .296[b] | 1.106 | .289 | .293 | .588 |
| 3 | dtemperature | .114[c] | .524 | .608 | .139 | .903 |
| | dprice | .140[c] | .609 | .552 | .161 | .806 |
| 4 | dtemperature | .114[d] | .527 | .606 | .135 | .903 |
| | dprice | .074[d] | .336 | .741 | .087 | .883 |
| | dlicence | -.193[d] | -.854 | .406 | -.215 | .803 |

a. Dependent Variable: dcpue

b. Predictors in the Model: (Constant), dstreamwaterlevel, dlicence, dprice, drainfall, dstreamflow

c. Predictors in the Model: (Constant), dstreamwaterlevel, dlicence, drainfall, dstreamflow

d. Predictors in the Model: (Constant), dstreamwaterlevel, drainfall, dstreamflow

**Regression Test** : Eviws: dcpue c drainfall dstreamflow dstreamwaterlevel

Dependent Variable: DCPUE
Method: Least Squares
Date: 03/18/21 Time: 13:28
Sample (adjusted): 1991 2010
Included observations: 20 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.001254 | 0.001572 | 0.798118 | 0.4365 |
| DRAINFALL | 1.33E-05 | 5.58E-06 | 2.385144 | 0.0298 |
| DSTREAMFLOW | 1.75E-09 | 7.14E-10 | 2.447887 | 0.0263 |
| DSTREAMWATERLEVEL | -0.039676 | 0.017128 | -2.316474 | 0.0341 |

| | | | |
|---|---|---|---|
| R-squared | 0.355229 | Mean dependent var | 0.001502 |
| Adjusted R-squared | 0.234335 | S.D. dependent var | 0.007992 |
| S.E. of regression | 0.006993 | Akaike info criterion | -6.910924 |
| Sum squared resid | 0.000782 | Schwarz criterion | -6.711777 |
| Log likelihood | 73.10924 | Hannan-Quinn criter. | -6.872048 |
| F-statistic | 2.938342 | Durbin-Watson stat | 2.468034 |
| Prob(F-statistic) | 0.064984 | | |

**Unit root test for the residuals of regression model** (including dcpue c drainfall dstreamflow dstreamwaterlevel):

Null Hypothesis: R has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=4)

| | | t-Statistic | Prob.* |
|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | -5.391547 | 0.0004 |
| Test critical values: | 1% level | -3.857386 | |
| | 5% level | -3.040391 | |
| | 10% level | -2.660551 | |

*MacKinnon (1996) one-sided p-values.
Warning: Probabilities and critical values calculated for 20 observations and
may not be accurate for a sample size of 18

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(R)
Method: Least Squares
Date: 03/18/21 Time: 13:31
Sample (adjusted): 1993 2010
Included observations: 18 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| R(-1) | -1.959029 | 0.363352 | -5.391547 | 0.0001 |
| D(R(-1)) | 0.531378 | 0.227935 | 2.331268 | 0.0341 |
| C | 0.000184 | 0.001401 | 0.131428 | 0.8972 |

| | | | |
|---|---|---|---|
| R-squared | 0.725976 | Mean dependent var | -0.000552 |
| Adjusted R-squared | 0.689439 | S.D. dependent var | 0.010617 |
| S.E. of regression | 0.005917 | Akaike info criterion | -7.271028 |
| Sum squared resid | 0.000525 | Schwarz criterion | -7.122633 |
| Log likelihood | 68.43925 | Hannan-Quinn criter. | -7.250566 |
| F-statistic | 19.86985 | Durbin-Watson stat | 2.146930 |
| Prob(F-statistic) | 0.000061 | | |

The residual has no unit root.

**Serial correlation test**: EViews

The probability of Q stat (Ljung-Box test) is more than .05. So, I should accept the null hypothesis. (Null: there is no serial correlation).

**Correlogram plot:**

Date: 03/18/21 Time: 13:32
Sample: 1990 2010
Included observations: 20

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|---|---|
| | | 1 | -0.266 | -0.266 | 1.6401 | 0.200 |
| | | 2 | -0.387 | -0.493 | 5.2989 | 0.071 |
| | | 3 | 0.139 | -0.208 | 5.7957 | 0.122 |
| | | 4 | 0.125 | -0.124 | 6.2246 | 0.183 |
| | | 5 | -0.186 | -0.254 | 7.2427 | 0.203 |
| | | 6 | 0.103 | -0.030 | 7.5774 | 0.271 |
| | | 7 | 0.101 | 0.011 | 7.9249 | 0.339 |
| | | 8 | -0.148 | -0.056 | 8.7227 | 0.366 |
| | | 9 | -0.121 | -0.187 | 9.3076 | 0.409 |
| | | 10 | 0.279 | 0.084 | 12.736 | 0.239 |
| | | 11 | -0.112 | -0.117 | 13.347 | 0.271 |
| | | 12 | -0.123 | -0.072 | 14.182 | 0.289 |

The residuals are not flat and no serial correlation i.e. in white noise.

**Selection of AR and MA term:**

dcpue c drainfall dstreamflow dstreamwaterlevel ar(2)

Dependent Variable: DCPUE
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 03/18/21 Time: 13:34
Sample: 1991 2010
Included observations: 20
Convergence achieved after 9 iterations
Coefficient covariance computed using outer product of gradients

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.001326 | 0.000939 | 1.412066 | 0.1798 |
| DRAINFALL | 1.63E-05 | 4.55E-06 | 3.575057 | 0.0030 |
| DSTREAMFLOW | 1.32E-09 | 7.59E-10 | 1.740505 | 0.0337 |
| DSTREAMWATERLEVEL | -0.039680 | 0.014764 | -2.687704 | 0.0177 |
| AR(2) | -0.519450 | 0.332248 | -1.563441 | 0.1403 |
| SIGMASQ | 3.02E-05 | 1.35E-05 | 2.243039 | 0.0416 |

| | | | |
|---|---|---|---|
| R-squared | 0.502672 | Mean dependent var | 0.001502 |
| Adjusted R-squared | 0.325054 | S.D. dependent var | 0.007992 |
| S.E. of regression | 0.006566 | Akaike info criterion | -6.939120 |
| Sum squared resid | 0.000604 | Schwarz criterion | -6.640401 |
| Log likelihood | 75.39120 | Hannan-Quinn criter. | -6.880807 |
| F-statistic | 2.830082 | Durbin-Watson stat | 2.616022 |
| Prob(F-statistic) | 0.057074 | | |

| | | |
|---|---|---|
| Inverted AR Roots | -.00+.72i | -.00-.72i |

**Unit root test of residual:**

Null Hypothesis: R has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=4)

| | t-Statistic | Prob.* |
|---|---|---|

| | | | |
|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | -5.900899 | 0.0001 |
| Test critical values: | 1% level | -3.831511 | |
| | 5% level | -3.029970 | |
| | 10% level | -2.655194 | |

*MacKinnon (1996) one-sided p-values.

Warning: Probabilities and critical values calculated for 20 observations and may not be accurate for a sample size of 19

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(R)

Method: Least Squares

Date: 03/18/21 Time: 13:37

Sample (adjusted): 1992 2010

Included observations: 19 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| R(-1) | -1.373563 | 0.232772 | -5.900899 | 0.0000 |
| C | 1.57E-05 | 0.001267 | 0.012362 | 0.9903 |

| | | | |
|---|---|---|---|
| R-squared | 0.671945 | Mean dependent var | -0.000488 |
| Adjusted R-squared | 0.652648 | S.D. dependent var | 0.009352 |
| S.E. of regression | 0.005512 | Akaike info criterion | -7.464536 |
| Sum squared resid | 0.000516 | Schwarz criterion | -7.365121 |
| Log likelihood | 72.91309 | Hannan-Quinn criter. | -7.447711 |
| F-statistic | 34.82061 | Durbin-Watson stat | 2.092451 |
| Prob(F-statistic) | 0.000017 | | |

**Serial correlation test:**

**Correlogram plot:**

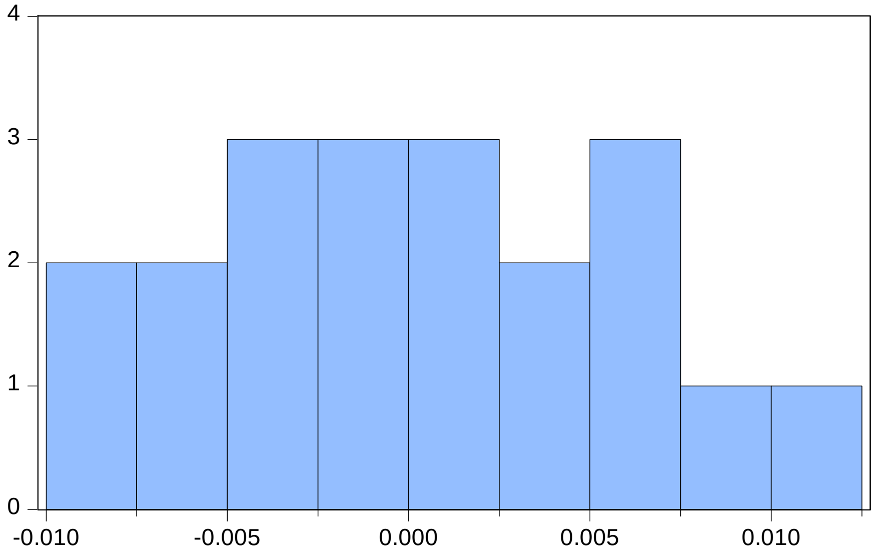
Date: 03/18/21   Time: 13:38
Sample: 1990 2010
Included observations: 20
Q-statistic probabilities adjusted for 1 ARMA term

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob* |
|---|---|---|---|---|---|---|
| | | 1 | -0.349 | -0.349 | 2.8154 | |
| | | 2 | -0.060 | -0.207 | 2.9038 | 0.088 |
| | | 3 | 0.069 | -0.034 | 3.0267 | 0.220 |
| | | 4 | -0.007 | -0.003 | 3.0282 | 0.387 |
| | | 5 | -0.120 | -0.132 | 3.4519 | 0.485 |
| | | 6 | -0.027 | -0.152 | 3.4753 | 0.627 |
| | | 7 | 0.037 | -0.078 | 3.5216 | 0.741 |
| | | 8 | 0.096 | 0.090 | 3.8594 | 0.796 |
| | | 9 | -0.246 | -0.211 | 6.2828 | 0.616 |
| | | 10 | 0.189 | 0.011 | 7.8562 | 0.549 |
| | | 11 | -0.102 | -0.134 | 8.3651 | 0.593 |
| | | 12 | -0.152 | -0.264 | 9.6373 | 0.563 |

*Probabilities may not be valid for this equation specification.

**Diagnostic reports:**

**Normality test of residuals:**




| Series: Residuals | |
|---|---|
| Sample 1991 2010 | |
| Observations 20 | |
| Mean | 3.09e-05 |
| Median | -0.000399 |
| Maximum | 0.011908 |
| Minimum | -0.008993 |
| Std. Dev. | 0.005636 |
| Skewness | 0.232677 |
| Kurtosis | 2.300477 |
| Jarque-Bera | 0.588239 |
| Probability | 0.745187 |

The probability of Jarque-Bera test in more than 5%, so the residual series follows normal distribution

**Breusch-Godfrey Serial Correlation LM Test:**

Lag(2)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 3.564892 | Prob. F(2,14) | 0.0661 |
| Obs*R-squared | 6.748563 | Prob. Chi-Square(2) | 0.0642 |

Lag(4)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 2.154734 | Prob. F(4,12) | 0.1363 |
| Obs*R-squared | 8.360215 | Prob. Chi-Square(4) | 0.0792 |

lag(8)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 1.004447 | Prob. F(8,8) | 0.4976 |
| Obs*R-squared | 10.02219 | Prob. Chi-Square(8) | 0.2635 |

## **Heteroscedasticity test**:

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 0.194232 | Prob. F(3,16) | 0.8988 |
| Obs*R-squared | 0.702775 | Prob. Chi-Square(3) | 0.8726 |
| Scaled explained SS | 0.224825 | Prob. Chi-Square(3) | 0.9735 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/18/21 Time: 13:39
Sample: 1991 2010
Included observations: 20

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 2.96E-05 | 8.51E-06 | 3.478964 | 0.0031 |
| DRAINFALL | 1.89E-08 | 3.02E-08 | 0.624439 | 0.5411 |
| DSTREAMFLOW | -6.04E-13 | 3.87E-12 | -0.156193 | 0.8778 |
| DSTREAMWATERLEVEL | -4.24E-06 | 9.27E-05 | -0.045741 | 0.9641 |

| | | | |
|---|---|---|---|
| R-squared | 0.035139 | Mean dependent var | 3.02E-05 |
| Adjusted R-squared | -0.145773 | S.D. dependent var | 3.54E-05 |
| S.E. of regression | 3.79E-05 | Akaike info criterion | -17.34800 |
| Sum squared resid | 2.29E-08 | Schwarz criterion | -17.14885 |
| Log likelihood | 177.4800 | Hannan-Quinn criter. | -17.30912 |
| F-statistic | 0.194232 | Durbin-Watson stat | 2.007564 |
| Prob(F-statistic) | 0.898782 | | |

Probability is greater than 5%, so the model is not heteroscedastic.

**ARIMAX (2,1,0) Forecasting:**

Extend workfile size (from 1990-2013) by double clicking the range> provide actual value in drainfall, dstreamflow, dstreamwaterlevel from 2010-2013>Quick >estimate equation> dcpue c drainfall dstreamflow dstreamwaterlevel ar(2) Forecast> Forecast sample (1990-2013)>ok>

Associated excel file to determine MAPE, RAMSE, MAE etc. of the year 2011-2013.

**Year 1992-2013:**

Unit root test: The series has unit root, 1st difference removed unit root from the series and the final series has no unit root.

**Lag selection**:

Lag 4 selected for the granger causality test for granger causality test.

**Granger Causality test:**

Pairwise Granger Causality Tests
Date: 03/19/21 Time: 12:36
Sample: 1992 2013
Lags: 4

| Null Hypothesis: | Obs | F-Statistic | Prob. |
|---|---|---|---|
| DLICENCES does not Granger Cause DCPUE | 17 | 0.93217 | 0.4917 |
| DCPUE does not Granger Cause DLICENCES | | 0.72492 | 0.5990 |
| DPRICE does not Granger Cause DCPUE | 17 | 1.17317 | 0.3912 |
| DCPUE does not Granger Cause DPRICE | | 0.62499 | 0.6579 |
| DRAINFALL does not Granger Cause DCPUE | 17 | 3.56155 | 0.0696 |
| DCPUE does not Granger Cause DRAINFALL | | 0.61662 | 0.6631 |
| DTEMPERATURE does not Granger Cause DCPUE | 17 | 0.27989 | 0.8830 |
| DCPUE does not Granger Cause DTEMPERATURE | | 0.46977 | 0.7572 |
| DSTREAMFLOW does not Granger Cause DCPUE | 17 | 0.29041 | 0.8763 |
| DCPUE does not Granger Cause DSTREAMFLOW | | 0.29186 | 0.8753 |
| DSTREAMWATERLEVEL does not Granger Cause DCPUE | 17 | 3.97021 | 0.0661 |
| DCPUE does not Granger Cause DSTREAMWATERLEVEL | | 0.09259 | 0.9821 |

No reverse causality detected.

**Test for multicollinearity:**

**Coefficients**[a]

| Model | | Collinearity Statistics Tolerance | VIF |
|---|---|---|---|
| 1 | dlicence | .732 | 1.365 |
| | dprice | .482 | 2.075 |
| | drainfall | .512 | 1.953 |
| | dtemperature | .543 | 1.840 |
| | dstreamflow | .374 | 2.673 |
| | dstreamwaterlevel | .307 | 3.260 |

a. Dependent Variable: dcpue

**Collinearity Diagnostics**[a]

| Dimension | Eigenvalue | Condition Index | Variance Proportions (Constant) | dlicence | dprice | drainfall | dtemperature | dstreamflow | dstreamwaterlevel |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 2.595 | 1.000 | .00 | .01 | .03 | .03 | .03 | .03 | .03 |
| 2 | 1.328 | 1.398 | .00 | .00 | .10 | .08 | .14 | .00 | .04 |
| 3 | 1.193 | 1.475 | .13 | .34 | .00 | .03 | .00 | .05 | .01 |
| 4 | .970 | 1.636 | .82 | .07 | .00 | .01 | .01 | .02 | .00 |
| 5 | .436 | 2.439 | .00 | .34 | .02 | .46 | .24 | .16 | .01 |
| 6 | .300 | 2.943 | .03 | .24 | .84 | .06 | .55 | .04 | .00 |
| 7 | .179 | 3.806 | .01 | .00 | .01 | .33 | .03 | .70 | .91 |

a. Dependent Variable: dcpue

Here, multicollinearity is absent among variables. Tolerance is more than 0.1, VIF is less than 10.

**Regression Test** : SPSS

Backward stepwise regression:

**Coefficients[a]**

| Model | | Unstandardized Coefficients B | Unstandardized Coefficients Std. Error | Standardized Coefficients Beta | t | Sig. |
|---|---|---|---|---|---|---|
| 1 | (Constant) | .000 | .002 | | .177 | .861 |
| | dstreamflow | 1.938E-9 | .000 | .499 | 2.512 | .021 |

a. Dependent Variable: dcpue

**Excluded Variables[a]**

| Model | | Beta In | t | Sig. | Partial Correlation | Collinearity Statistics Tolerance |
|---|---|---|---|---|---|---|
| 1 | dlicence | .007[b] | .035 | .972 | .008 | .998 |
| | dprice | .276[b] | 1.301 | .210 | .293 | .848 |
| | drainfall | .139[b] | .656 | .520 | .153 | .901 |
| | dtemperature | -.187[b] | -.874 | .394 | -.202 | .874 |
| | dstreamwaterlevel | -.114[b] | -.392 | .700 | -.092 | .490 |

a. Dependent Variable: dcpue

b. Predictors in the Model: (Constant), dstreamflow

**Regression Eviws:** dcpue c dstreamflow

Dependent Variable: DCPUE

Method: Least Squares

Date: 03/19/21 Time: 14:13

Sample (adjusted): 1993 2013

Included observations: 21 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.000321 | 0.001811 | 0.177239 | 0.8612 |
| DSTREAMFLOW | 1.94E-09 | 7.72E-10 | 2.512013 | 0.0212 |

| | | | |
|---|---|---|---|
| R-squared | 0.249315 | Mean dependent var | 0.000418 |

| | | | |
|---|---|---|---|
| Adjusted R-squared | 0.209805 | S.D. dependent var | 0.009334 |
| S.E. of regression | 0.008297 | Akaike info criterion | -6.655392 |
| Sum squared resid | 0.001308 | Schwarz criterion | -6.555914 |
| Log likelihood | 71.88162 | Hannan-Quinn criter. | -6.633803 |
| F-statistic | 6.310207 | Durbin-Watson stat | 2.620444 |
| Prob(F-statistic) | 0.021196 | | |

## Unit root test of residual:

Null Hypothesis: R has a unit root

Exogenous: Constant

Lag Length: 3 (Automatic - based on SIC, maxlag=4)

| | | t-Statistic | Prob.* |
|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | -3.541518 | 0.0197 |
| Test critical values: | 1% level | -3.886751 | |
| | 5% level | -3.052169 | |
| | 10% level | -2.666593 | |

*MacKinnon (1996) one-sided p-values.

Warning: Probabilities and critical values calculated for 20 observations and may not be accurate for a sample size of 17

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(R)

Method: Least Squares

Date: 03/19/21 Time: 14:14

Sample (adjusted): 1997 2013

Included observations: 17 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| R(-1) | -3.023875 | 0.853836 | -3.541518 | 0.0041 |
| D(R(-1)) | 1.384575 | 0.713204 | 1.941345 | 0.0761 |
| D(R(-2)) | 0.829549 | 0.506548 | 1.637652 | 0.1274 |
| D(R(-3)) | 0.466852 | 0.273517 | 1.706845 | 0.1136 |
| C | 0.001889 | 0.001919 | 0.984321 | 0.3444 |

| | | | |
|---|---|---|---|
| R-squared | 0.779753 | Mean dependent var | -0.000229 |
| Adjusted R-squared | 0.706337 | S.D. dependent var | 0.013922 |
| S.E. of regression | 0.007544 | Akaike info criterion | -6.696118 |

| | | | |
|---|---|---|---|
| Sum squared resid | 0.000683 | Schwarz criterion | -6.451055 |
| Log likelihood | 61.91700 | Hannan-Quinn criter. | -6.671758 |
| F-statistic | 10.62106 | Durbin-Watson stat | 1.898510 |
| Prob(F-statistic) | 0.000648 | | |

The residual has no unit root.

**Serial correlation test:** EViews

Date: 03/19/21 Time: 14:15
Sample: 1992 2013
Included observations: 21

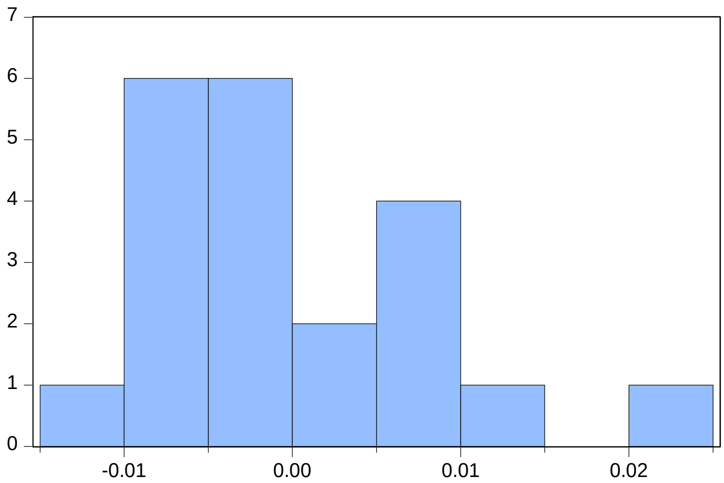
| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|---|---|
| | | 1 | -0.377 | -0.377 | 3.4359 | 0.064 |
| | | 2 | -0.110 | -0.294 | 3.7439 | 0.154 |
| | | 3 | 0.122 | -0.055 | 4.1428 | 0.246 |
| | | 4 | -0.248 | -0.310 | 5.8884 | 0.208 |
| | | 5 | 0.305 | 0.123 | 8.7003 | 0.122 |
| | | 6 | -0.178 | -0.128 | 9.7149 | 0.137 |
| | | 7 | 0.230 | 0.332 | 11.536 | 0.117 |
| | | 8 | -0.102 | -0.023 | 11.923 | 0.155 |
| | | 9 | -0.277 | -0.135 | 15.002 | 0.091 |
| | | 10 | 0.287 | -0.054 | 18.630 | 0.045 |
| | | 11 | -0.224 | -0.165 | 21.044 | 0.033 |
| | | 12 | 0.028 | -0.283 | 21.086 | 0.049 |

**Serial correlation test:**

The residuals are flat and no serial correlation.

**Diagnostic checking:**

**Normality test of residuals:**




Series: Residuals
Sample 1993 2013
Observations 21

| | |
|---|---|
| Mean | -1.65e-19 |
| Median | -0.002077 |
| Maximum | 0.020904 |
| Minimum | -0.010649 |
| Std. Dev. | 0.008087 |
| Skewness | 0.844835 |
| Kurtosis | 3.118554 |
| Jarque-Bera | 2.510412 |
| Probability | 0.285017 |

## Breusch-Godfrey Serial Correlation LM Test:

Lag (2)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 2.847379 | Prob. F(2,17) | 0.0858 |
| Obs*R-squared | 5.269495 | Prob. Chi-Square(2) | 0.0717 |

Lag(4)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 1.986096 | Prob. F(4,15) | 0.1484 |
| Obs*R-squared | 7.271149 | Prob. Chi-Square(4) | 0.1222 |

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 1.648051 | Prob. F(8,11) | 0.2173 |
| Obs*R-squared | 11.44839 | Prob. Chi-Square(8) | 0.1776 |

## Heteroscedasticity test:

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 0.026290 | Prob. F(1,19) | 0.8729 |
| Obs*R-squared | 0.029018 | Prob. Chi-Square(1) | 0.8647 |
| Scaled explained SS | 0.025162 | Prob. Chi-Square(1) | 0.8740 |

Test Equation:

Dependent Variable: RESID^2

Method: Least Squares

Date: 03/19/21 Time: 14:17

Sample: 1993 2013

Included observations: 21

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 6.24E-05 | 2.08E-05 | 2.999575 | 0.0074 |
| DSTREAMFLOW | -1.44E-12 | 8.86E-12 | -0.162143 | 0.8729 |

| | | | |
|---|---|---|---|
| R-squared | 0.001382 | Mean dependent var | 6.23E-05 |
| Adjusted R-squared | -0.051177 | S.D. dependent var | 9.29E-05 |
| S.E. of regression | 9.52E-05 | Akaike info criterion | -15.58979 |

| | | | |
|---|---|---|---|
| Sum squared resid | 1.72E-07 | Schwarz criterion | -15.49031 |
| Log likelihood | 165.6928 | Hannan-Quinn criter. | -15.56820 |
| F-statistic | 0.026290 | Durbin-Watson stat | 2.186797 |
| Prob(F-statistic) | 0.872905 | | |

Probability is greater than 5%, so the model is not heteroscedastic.

**ARIMAX (0,1,0) Forecasting**: Extend workfile size (from 1992-2016) by double clicking the range> provide original values in dstreamflow from 2013-2016>Quick >estimate equation> dcpue c dstreamflow> Forecast> Forecast sample (1994-2016)>ok>

Associated excel file to determine MAPE, RAMSE, MAE etc. of the year 2014-2016.

**Sample 1994-2016:**

**Unit root test:** All variables have unit root, 1st difference of the series made them stationary.

**Lag selection:** Lag 4 was selected for the granger causality test.

**Granger causality test:**

Pairwise Granger Causality Tests
Date: 03/20/21 Time: 15:03
Sample: 1994 2016
Lags: 4

| Null Hypothesis: | Obs | F-Statistic | Prob. |
|---|---|---|---|
| DLICENCES does not Granger Cause DCPUE | 18 | 1.51967 | 0.2759 |
| DCPUE does not Granger Cause DLICENCES | | 1.01552 | 0.4489 |
| DPRICE does not Granger Cause DCPUE | 18 | 0.72566 | 0.5962 |
| DCPUE does not Granger Cause DPRICE | | 0.66273 | 0.6334 |
| DRAINFALL does not Granger Cause DCPUE | 18 | 3.29953 | 0.0632 |
| DCPUE does not Granger Cause DRAINFALL | | 0.91962 | 0.4933 |
| DTEMPERATURE does not Granger Cause DCPUE | 18 | 0.50759 | 0.7320 |
| DCPUE does not Granger Cause DTEMPERATURE | | 1.22525 | 0.3657 |
| DSTREAMFLOW does not Granger Cause DCPUE | 18 | 0.52745 | 0.7189 |
| DCPUE does not Granger Cause DSTREAMFLOW | | 0.13090 | 0.9671 |

| | | | |
|---|---|---|---|
| DSTREAMWATERLEVEL does not Granger Cause DCPUE | 18 | 3.73089 | 0.0468 |
| DCPUE does not Granger Cause DSTREAMWATERLEVEL | | 0.11613 | 0.9734 |

No reverse causality was found.

**Test for multicollinearity**:

### Coefficients[a]

| Model | | Collinearity Statistics Tolerance | VIF |
|---|---|---|---|
| 1 | dlicence | .657 | 1.521 |
| | dprice | .470 | 2.128 |
| | drainfall | .491 | 2.036 |
| | dtemperature | .564 | 1.773 |
| | dstreamflow | .357 | 2.801 |
| | dstreamwaterlevel | .296 | 3.376 |

### Collinearity Diagnostics[a]

| Model | Dimension | Eigenvalue | Condition Index | Variance Proportions (Constant) | dlicence | dprice | drainfall | dtemperature | dstreamflow | ds w el |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 2.652 | 1.000 | .00 | .02 | .03 | .03 | .03 | .03 | .0 |
| | 2 | 1.390 | 1.381 | .06 | .01 | .07 | .05 | .12 | .01 | .0 |
| | 3 | 1.153 | 1.516 | .11 | .26 | .00 | .05 | .03 | .06 | .0 |
| | 4 | .927 | 1.691 | .78 | .05 | .02 | .01 | .01 | .03 | .0 |
| | 5 | .411 | 2.541 | .02 | .30 | .07 | .43 | .36 | .10 | .0 |
| | 6 | .297 | 2.987 | .02 | .32 | .74 | .15 | .44 | .03 | .0 |
| | 7 | .169 | 3.957 | .00 | .03 | .06 | .28 | .02 | .75 | .9 |

a. Dependent Variable: dcpue

a. Dependent Variable: dcpue

Here multicollinearity is absent among variables. Tolerance is more than 0.1, VIF is less than 10.

**Regression Test:**

**Forward Stepwise:**

**Coefficients[a]**

| Model | | Unstandardized Coefficients | | Standardized Coefficients | t | Sig. |
|---|---|---|---|---|---|---|
| | | B | Std. Error | Beta | | |
| 1 | (Constant) | .001 | .002 | | .401 | .692 |
| | dstreamflow | 1.847E-9 | .000 | .492 | 2.525 | .020 |

a. Dependent Variable: dcpue

**Excluded Variables[a]**

| Model | | Beta In | t | Sig. | Partial Correlation | Collinearity Statistics |
|---|---|---|---|---|---|---|
| | | | | | | Tolerance |
| 1 | dlicence | .027[b] | .134 | .895 | .031 | 1.000 |
| | dprice | .341[b] | 1.675 | .110 | .359 | .837 |
| | drainfall | .096[b] | .459 | .651 | .105 | .904 |
| | dtemperature | -.191[b] | -.927 | .366 | -.208 | .895 |
| | dstreamwaterlevel | -.160[b] | -.570 | .575 | -.130 | .497 |

a. Dependent Variable: dcpue

b. Predictors in the Model: (Constant), dstreamflow

**Regression Test:** Eviws: dcpue c dstreamflow

Dependent Variable: DCPUE
Method: Least Squares
Date: 03/20/21 Time: 15:19
Sample (adjusted): 1995 2016
Included observations: 22 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.000673 | 0.001678 | 0.401268 | 0.6925 |
| DSTREAMFLOW | 1.85E-09 | 7.31E-10 | 2.525061 | 0.0201 |

| | | | |
|---|---|---|---|
| R-squared | 0.241733 | Mean dependent var | 0.000642 |
| Adjusted R-squared | 0.203820 | S.D. dependent var | 0.008821 |
| S.E. of regression | 0.007871 | Akaike info criterion | -6.764688 |
| Sum squared resid | 0.001239 | Schwarz criterion | -6.665502 |
| Log likelihood | 76.41157 | Hannan-Quinn criter. | -6.741323 |
| F-statistic | 6.375931 | Durbin-Watson stat | 2.802370 |
| Prob(F-statistic) | 0.020125 | | |

Unit root test of residual

Null Hypothesis: R has a unit root

Exogenous: Constant

Lag Length: 0 (Automatic - based on SIC, maxlag=4)

| | | t-Statistic | Prob.* |
|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | -6.685114 | 0.0000 |
| Test critical values: | 1% level | -3.788030 | |
| | 5% level | -3.012363 | |
| | 10% level | -2.646119 | |

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation

Dependent Variable: D(R)

Method: Least Squares

Date: 03/20/21 Time: 15:20

Sample (adjusted): 1996 2016

Included observations: 21 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| R(-1) | -1.403130 | 0.209889 | -6.685114 | 0.0000 |
| C | 9.04E-05 | 0.001611 | 0.056101 | 0.9558 |

| | | | |
|---|---|---|---|
| R-squared | 0.701684 | Mean dependent var | 1.02E-05 |
| Adjusted R-squared | 0.685983 | S.D. dependent var | 0.013177 |
| S.E. of regression | 0.007384 | Akaike info criterion | -6.888645 |
| Sum squared resid | 0.001036 | Schwarz criterion | -6.789167 |
| Log likelihood | 74.33078 | Hannan-Quinn criter. | -6.867056 |
| F-statistic | 44.69075 | Durbin-Watson stat | 2.233790 |
| Prob(F-statistic) | 0.000002 | | |

Residuals do not have unit root.

**Serial correlation test:**

Date: 03/20/21 Time: 15:21
Sample: 1994 2016
Included observations: 22

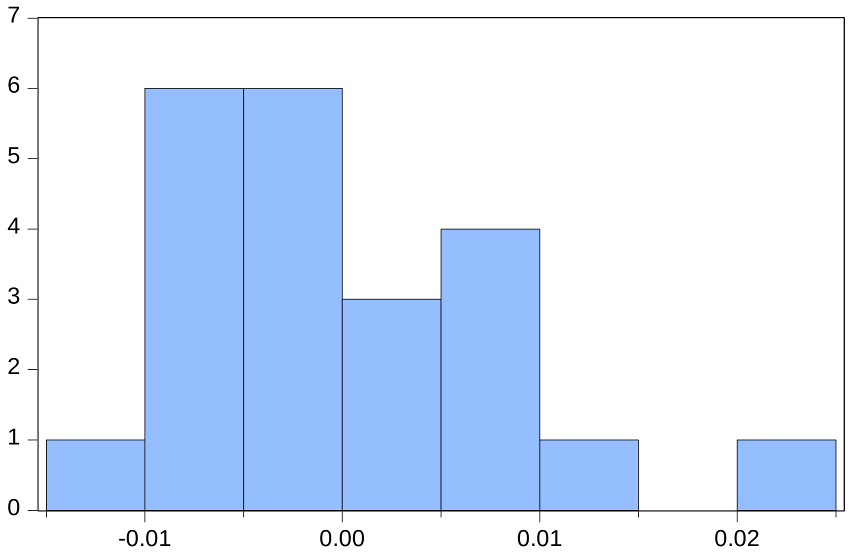
| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob |
|---|---|---|---|---|---|---|
| | | 1 | -0.403 | -0.403 | 4.0748 | 0.044 |
| | | 2 | -0.118 | -0.334 | 4.4414 | 0.109 |
| | | 3 | 0.159 | -0.052 | 5.1423 | 0.162 |
| | | 4 | -0.355 | -0.446 | 8.8457 | 0.065 |
| | | 5 | 0.357 | 0.033 | 12.798 | 0.025 |
| | | 6 | -0.109 | -0.140 | 13.193 | 0.040 |
| | | 7 | 0.158 | 0.352 | 14.075 | 0.050 |
| | | 8 | -0.122 | -0.126 | 14.640 | 0.067 |
| | | 9 | -0.291 | -0.171 | 18.088 | 0.034 |
| | | 10 | 0.265 | -0.249 | 21.175 | 0.020 |
| | | 11 | -0.068 | 0.000 | 21.400 | 0.029 |
| | | 12 | -0.011 | -0.351 | 21.406 | 0.045 |

Selection of MA and AR term:

Residual is flat and in white noise.

**Diagnostic Reports:**

**Normality test of residuals:**




Series: Residuals
Sample 1995 2016
Observations 22

| | |
|---|---|
| Mean | -4.44e-19 |
| Median | -0.001555 |
| Maximum | 0.020535 |
| Minimum | -0.011371 |
| Std. Dev. | 0.007682 |
| Skewness | 0.836403 |
| Kurtosis | 3.426433 |
| Jarque-Bera | 2.731779 |
| Probability | 0.255154 |

**Breusch-Godfrey Serial Correlation LM Test:**

Lag(2)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 3.161272 | Prob. F(2,18) | 0.0666 |

| | | | |
|---|---|---|---|
| Obs*R-squared | 5.718809 | Prob. Chi-Square(2) | 0.0673 |

Lag(4)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 2.923140 | Prob. F(4,16) | 0.0644 |
| Obs*R-squared | 9.289005 | Prob. Chi-Square(4) | 0.0643 |

Lag(8)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 1.772319 | Prob. F(8,12) | 0.1791 |
| Obs*R-squared | 11.91541 | Prob. Chi-Square(8) | 0.1550 |

## Heteroscedasticity test:

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 0.062369 | Prob. F(1,20) | 0.8053 |
| Obs*R-squared | 0.068393 | Prob. Chi-Square(1) | 0.7937 |
| Scaled explained SS | 0.068574 | Prob. Chi-Square(1) | 0.7934 |

Test Equation:

Dependent Variable: RESID^2

Method: Least Squares

Date: 03/20/21 Time: 15:23

Sample: 1995 2016

Included observations: 22

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 5.63E-05 | 1.96E-05 | 2.873502 | 0.0094 |
| DSTREAMFLOW | -2.13E-12 | 8.54E-12 | -0.249738 | 0.8053 |

| | | | |
|---|---|---|---|
| R-squared | 0.003109 | Mean dependent var | 5.63E-05 |
| Adjusted R-squared | -0.046736 | S.D. dependent var | 8.98E-05 |
| S.E. of regression | 9.19E-05 | Akaike info criterion | -15.66576 |
| Sum squared resid | 1.69E-07 | Schwarz criterion | -15.56658 |
| Log likelihood | 174.3234 | Hannan-Quinn criter. | -15.64240 |
| F-statistic | 0.062369 | Durbin-Watson stat | 2.098835 |
| Prob(F-statistic) | 0.805337 | | |

**ARIMAX (0,1,0) Forecasting**: Extend workfile size (from 1995-2019) by double clicking the range> provide original values in dstreamflow dprice from 2017-2019>Quick >estimate equation> dcpue c dstreamflow > Forecast> Forecast sample (1996-2019)>ok>

Associated excel file to determine MAPE, RAMSE, MAE etc. of the year 2017-2019.

**Regression model:** 3 years lag of Env. variables

**Sample 1990-2010:**

**Multicollinearity test:**

**Coefficients**[a]

| Model | | Collinearity Statistics Tolerance | VIF |
|---|---|---|---|
| 1 | licence | .405 | 2.468 |
| | price | .648 | 1.542 |
| | rainfall | .230 | 4.353 |
| | temperature | .749 | 1.336 |
| | streamflow | .101 | 9.947 |
| | streamwaterlevel | .051 | 19.646 |

a. Dependent Variable: cpue

Here, multicollinearity is present in stream water level, so I will delete this variable from the equation.

**MLR:**

cpue licences price rainfall temperature streamflow c

Dependent Variable: CPUE

Method: Least Squares

Date: 03/24/21 Time: 13:45

Sample: 1993 2010

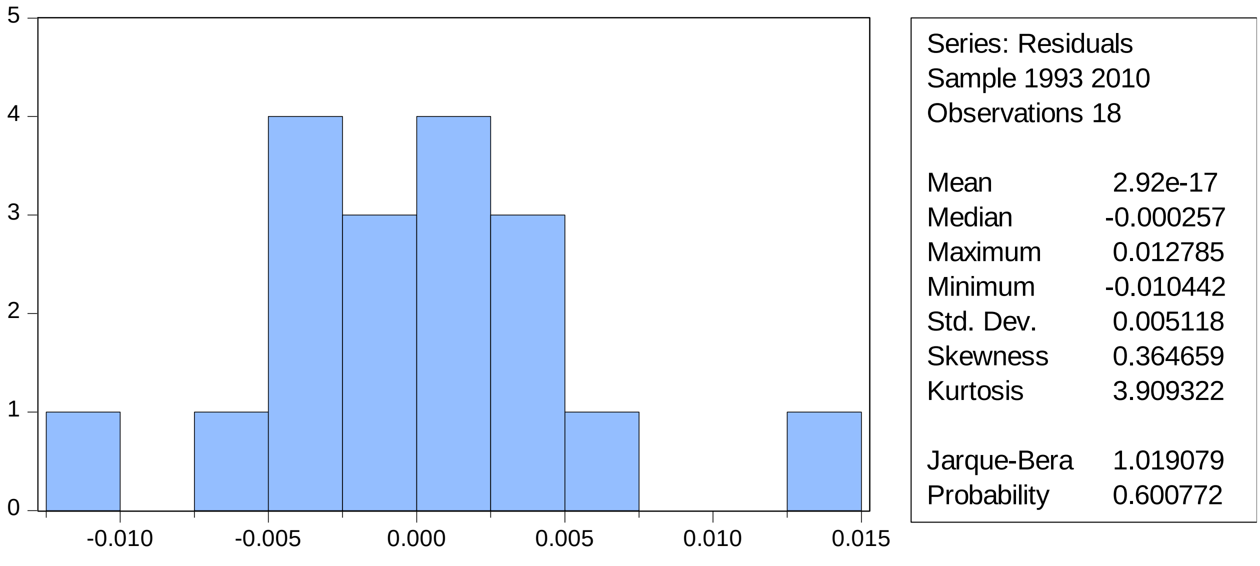
Included observations: 18

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| LICENCES | -0.001849 | 0.000456 | -4.057837 | 0.0016 |
| PRICE | 7.71E-08 | 2.10E-08 | 3.667858 | 0.0032 |
| RAINFALL | 3.00E-07 | 5.14E-06 | 0.058457 | 0.9543 |
| TEMPERATURE | 0.004562 | 0.006043 | 0.754854 | 0.4649 |
| STREAMFLOW | -1.10E-09 | 6.46E-10 | -1.709984 | 0.1130 |
| C | -0.038104 | 0.150727 | -0.252800 | 0.8047 |

| | | | |
|---|---|---|---|
| R-squared | 0.806071 | Mean dependent var | 0.043067 |
| Adjusted R-squared | 0.725267 | S.D. dependent var | 0.011622 |
| S.E. of regression | 0.006092 | Akaike info criterion | -7.102528 |
| Sum squared resid | 0.000445 | Schwarz criterion | -6.805737 |
| Log likelihood | 69.92275 | Hannan-Quinn criter. | -7.061604 |
| F-statistic | 9.975651 | Durbin-Watson stat | 1.763493 |
| Prob(F-statistic) | 0.000594 | | |

**Diagnostic checking:**

**Normality test:**




**Breusch-Godfrey Serial Correlation LM Test:**

Lag(2)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.390286 | Prob. F(2,10) | 0.6867 |

| | | | |
|---|---|---|---|
| Obs*R-squared | 1.303299 | Prob. Chi-Square(2) | 0.5212 |

Lag(4)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.163302 | Prob. F(4,8) | 0.9511 |
| Obs*R-squared | 1.358772 | Prob. Chi-Square(4) | 0.8513 |

Lag(8)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 2.166733 | Prob. F(8,4) | 0.2373 |
| Obs*R-squared | 14.62508 | Prob. Chi-Square(8) | 0.0669 |

## Heteroscedasticity test:

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 1.546926 | Prob. F(5,12) | 0.2478 |
| Obs*R-squared | 7.054774 | Prob. Chi-Square(5) | 0.2166 |
| Scaled explained SS | 4.561024 | Prob. Chi-Square(5) | 0.4718 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/24/21 Time: 13:46
Sample: 1993 2010
Included observations: 18

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | -0.000108 | 0.000997 | -0.108244 | 0.9156 |
| LICENCES | 5.69E-06 | 3.01E-06 | 1.888662 | 0.0833 |
| PRICE | 8.15E-11 | 1.39E-10 | 0.586187 | 0.5686 |
| RAINFALL | -4.92E-08 | 3.40E-08 | -1.445669 | 0.1739 |
| TEMPERATURE | 1.12E-06 | 4.00E-05 | 0.028074 | 0.9781 |
| STREAMFLOW | -1.68E-12 | 4.27E-12 | -0.394084 | 0.7004 |

| | | | |
|---|---|---|---|
| R-squared | 0.391932 | Mean dependent var | 2.47E-05 |
| Adjusted R-squared | 0.138570 | S.D. dependent var | 4.34E-05 |
| S.E. of regression | 4.03E-05 | Akaike info criterion | -17.13915 |
| Sum squared resid | 1.95E-08 | Schwarz criterion | -16.84236 |

| | | | |
|---|---|---|---|
| Log likelihood | 160.2523 | Hannan-Quinn criter. | -17.09822 |
| F-statistic | 1.546926 | Durbin-Watson stat | 1.460536 |
| Prob(F-statistic) | 0.247776 | | |

**Sample 1992-2013:**

**Multicollinearity test:**

**Coefficients[a]**

| Model | | Collinearity Statistics Tolerance | VIF |
|---|---|---|---|
| 1 | licence | .685 | 1.459 |
| | price | .474 | 2.110 |
| | rainfall | .192 | 5.222 |
| | temperature | .787 | 1.271 |
| | streamflow | .150 | 6.675 |
| | streamwaterlevel | .079 | 12.640 |

a. Dependent Variable: cpue

Here, multicollinearity is present in stream water level, so I will remove the variable from the equation.

**MLR:**

cpue licences price rainfall temperature streamflow c

Dependent Variable: CPUE
Method: Least Squares
Date: 03/24/21 Time: 13:48
Sample: 1995 2013
Included observations: 19

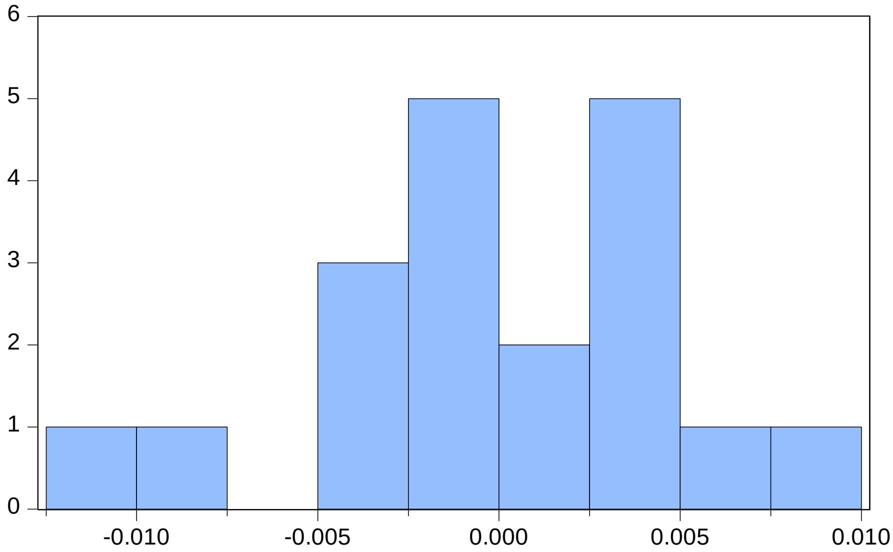
| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| LICENCES | -0.001719 | 0.000457 | -3.764358 | 0.0024 |
| PRICE | 7.70E-08 | 1.92E-08 | 4.015642 | 0.0015 |
| RAINFALL | -5.40E-06 | 4.57E-06 | -1.179837 | 0.2592 |

| | | | | |
|---|---|---|---|---|
| TEMPERATURE | 0.004413 | 0.004751 | 0.928926 | 0.3699 |
| STREAMFLOW | 8.39E-10 | 7.84E-10 | 1.069954 | 0.3041 |
| C | -0.033425 | 0.117908 | -0.283482 | 0.7813 |

| | | | |
|---|---|---|---|
| R-squared | 0.838115 | Mean dependent var | 0.046513 |
| Adjusted R-squared | 0.775851 | S.D. dependent var | 0.011853 |
| S.E. of regression | 0.005612 | Akaike info criterion | -7.275819 |
| Sum squared resid | 0.000409 | Schwarz criterion | -6.977575 |
| Log likelihood | 75.12028 | Hannan-Quinn criter. | -7.225345 |
| F-statistic | 13.46077 | Durbin-Watson stat | 2.226022 |
| Prob(F-statistic) | 0.000094 | | |

## Diagnostic Checking:

### Normality test:




| Series: Residuals | |
|---|---|
| Sample 1995 2013 | |
| Observations 19 | |
| Mean | -1.13e-17 |
| Median | -0.000202 |
| Maximum | 0.009424 |
| Minimum | -0.010267 |
| Std. Dev. | 0.004769 |
| Skewness | -0.277042 |
| Kurtosis | 2.996758 |
| Jarque-Bera | 0.243057 |
| Probability | 0.885566 |

### Breusch-Godfrey Serial Correlation LM Test:

Lag(2)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.444115 | Prob. F(2,11) | 0.6524 |
| Obs*R-squared | 1.419586 | Prob. Chi-Square(2) | 0.4917 |

Lag(4)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.500120 | Prob. F(4,9) | 0.7369 |
| Obs*R-squared | 3.455226 | Prob. Chi-Square(4) | 0.4847 |

Lag(8)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.612838 | Prob. F(8,5) | 0.7439 |
| Obs*R-squared | 9.406661 | Prob. Chi-Square(8) | 0.3092 |

## Heteroscedasticity Test:

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 3.405117 | Prob. F(5,13) | 0.0784 |
| Obs*R-squared | 7.77368 | Prob. Chi-Square(5) | 0.0661 |
| Scaled explained SS | 5.035461 | Prob. Chi-Square(5) | 0.4116 |

Test Equation:

Dependent Variable: RESID^2

Method: Least Squares

Date: 03/24/21 Time: 13:49

Sample: 1995 2013

Included observations: 19

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 4.03E-06 | 0.000509 | 0.007918 | 0.9938 |
| LICENCES | 6.25E-06 | 1.97E-06 | 3.169815 | 0.0074 |
| PRICE | 5.44E-12 | 8.27E-11 | 0.065716 | 0.9486 |
| RAINFALL | -2.64E-08 | 1.97E-08 | -1.336764 | 0.2042 |
| TEMPERATURE | -4.44E-06 | 2.05E-05 | -0.216294 | 0.8321 |
| STREAMFLOW | -1.88E-12 | 3.38E-12 | -0.556524 | 0.5873 |

| | | | |
|---|---|---|---|
| R-squared | 0.567036 | Mean dependent var | 2.15E-05 |
| Adjusted R-squared | 0.400511 | S.D. dependent var | 3.13E-05 |
| S.E. of regression | 2.42E-05 | Akaike info criterion | -18.16667 |
| Sum squared resid | 7.63E-09 | Schwarz criterion | -17.86843 |
| Log likelihood | 178.5834 | Hannan-Quinn criter. | -18.11620 |
| F-statistic | 3.405117 | Durbin-Watson stat | 1.442125 |
| Prob(F-statistic) | 0.034778 | | |

## Sample 1994-2016:

**Multicollinearity test:**

**Coefficients**[a]

| Model | | Collinearity Statistics Tolerance | VIF |
|---|---|---|---|
| 1 | licence | .932 | 1.073 |
| | price | .602 | 1.662 |
| | rainfall | .358 | 2.797 |
| | temperature | .890 | 1.123 |
| | streamflow | .143 | 6.970 |
| | streamwaterlevel | .117 | 8.534 |

a. Dependent Variable: cpue

**MLR:**

cpue licences price rainfall temperature streamflow streamwaterlevel c

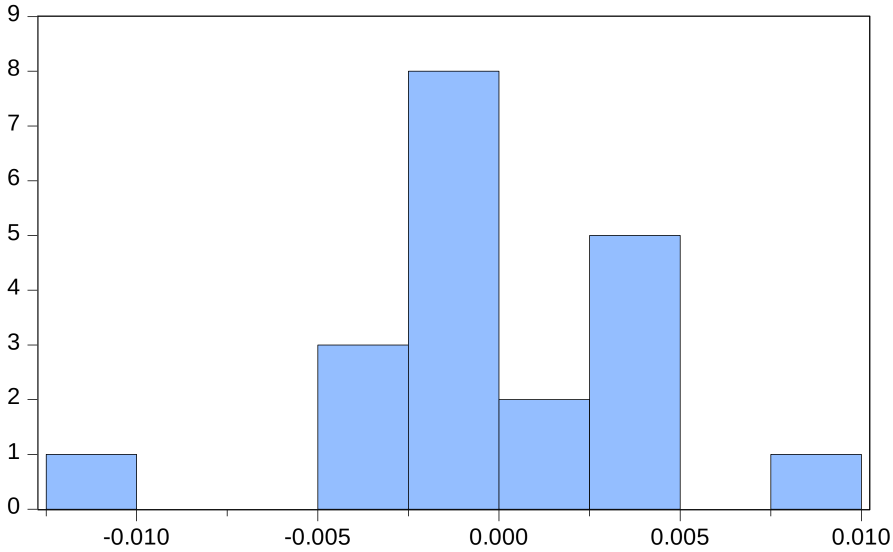
Dependent Variable: CPUE
Method: Least Squares
Date: 03/24/21 Time: 13:53
Sample: 1997 2016
Included observations: 20

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| LICENCES | -0.001380 | 0.000310 | -4.447552 | 0.0007 |
| PRICE | 8.18E-08 | 1.52E-08 | 5.397004 | 0.0001 |
| RAINFALL | -5.26E-06 | 4.33E-06 | -1.215744 | 0.2457 |
| TEMPERATURE | 0.005381 | 0.003457 | 1.556614 | 0.1436 |
| STREAMFLOW | 1.00E-09 | 9.32E-10 | 1.074720 | 0.3020 |
| STREAMWATERLEVEL | -0.005337 | 0.013907 | -0.383768 | 0.7074 |
| C | -0.059318 | 0.085722 | -0.691980 | 0.5011 |

| | | | |
|---|---|---|---|
| R-squared | 0.848108 | Mean dependent var | 0.048447 |
| Adjusted R-squared | 0.778004 | S.D. dependent var | 0.009922 |
| S.E. of regression | 0.004675 | Akaike info criterion | -7.624004 |
| Sum squared resid | 0.000284 | Schwarz criterion | -7.275498 |
| Log likelihood | 83.24004 | Hannan-Quinn criter. | -7.555972 |
| F-statistic | 12.09787 | Durbin-Watson stat | 2.135663 |
| Prob(F-statistic) | 0.000115 | | |

## Diagnostic Checking:

## Normality Test:




Series: Residuals
Sample 1997 2016
Observations 20

| | |
|---|---|
| Mean | 1.26e-18 |
| Median | -0.000256 |
| Maximum | 0.007950 |
| Minimum | -0.010315 |
| Std. Dev. | 0.003867 |
| Skewness | -0.441325 |
| Kurtosis | 4.147016 |
| Jarque-Bera | 1.745599 |
| Probability | 0.417780 |

## Breusch-Godfrey Serial Correlation LM Test:

Lag(2)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.524695 | Prob. F(2,11) | 0.6058 |
| Obs*R-squared | 1.741814 | Prob. Chi-Square(2) | 0.4186 |

Lag(4)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 0.243911 | Prob. F(4,9) | 0.9063 |
| Obs*R-squared | 1.956052 | Prob. Chi-Square(4) | 0.7438 |

Lag(8)

Breusch-Godfrey Serial Correlation LM Test:

| | | | |
|---|---|---|---|
| F-statistic | 1.249326 | Prob. F(8,5) | 0.4208 |
| Obs*R-squared | 13.33094 | Prob. Chi-Square(8) | 0.1010 |

## Heteroscedasticity test:

Heteroscedasticity Test: Breusch-Pagan-Godfrey

| | | | |
|---|---|---|---|
| F-statistic | 3.457318 | Prob. F(6,13) | 0.0688 |
| Obs*R-squared | 8.29491 | Prob. Chi-Square(6) | 0.0657 |
| Scaled explained SS | 8.173742 | Prob. Chi-Square(6) | 0.2256 |

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 03/24/21 Time: 13:56
Sample: 1997 2016
Included observations: 20

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.000282 | 0.000356 | 0.791730 | 0.4427 |
| LICENCES | 4.37E-06 | 1.29E-06 | 3.395883 | 0.0048 |
| PRICE | 1.72E-11 | 6.29E-11 | 0.273339 | 0.7889 |
| RAINFALL | -4.08E-08 | 1.80E-08 | -2.275356 | 0.0405 |
| TEMPERATURE | -1.96E-05 | 1.43E-05 | -1.363201 | 0.1960 |
| STREAMFLOW | -6.93E-12 | 3.87E-12 | -1.791960 | 0.0964 |
| STREAMWATERLEVEL | 0.000106 | 5.77E-05 | 1.843137 | 0.0882 |

| | | | |
|---|---|---|---|
| R-squared | 0.614745 | Mean dependent var | 1.42E-05 |
| Adjusted R-squared | 0.436935 | S.D. dependent var | 2.59E-05 |
| S.E. of regression | 1.94E-05 | Akaike info criterion | -18.59328 |
| Sum squared resid | 4.89E-09 | Schwarz criterion | -18.24478 |
| Log likelihood | 192.9328 | Hannan-Quinn criter. | -18.52525 |
| F-statistic | 3.457318 | Durbin-Watson stat | 1.508628 |
| Prob(F-statistic) | 0.028832 | | |

Table B 4: Result of independent sample t-test

**For comparison between the models:**

Analyze> compare Means> Independent Sample T test> Provide variable and groups> ok

If the significance level is less than .05 then reject null hypothesis of equal mean.

**Group Statistics**

| | Models | N | Mean | Std. Deviation | Std. Error Mean |
|---|---|---|---|---|---|
| MAE | ARIMAX | 24 | .01258 | .009207 | .001879 |
| | MLR | 24 | .08300 | .050367 | .010281 |

| | | | | | |
|---|---|---|---|---|---|
| MAPE | ARIMAX | 24 | 27.05492 | 26.966631 | 5.504541 |
| | MLR | 24 | 167.60633 | 135.466005 | 27.651883 |
| RMSE | ARIMAX | 24 | .01417 | .009494 | .001938 |
| | MLR | 24 | .08355 | .049815 | .010168 |

**Independent Samples Test**

| | | Levene's Test for Equality of Variances | | t-test for Equality of Means | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | 95% Confidence Interval of the Difference | |
| | | F | Sig. | t | df | Sig. (2-tailed) | Mean Difference | Std. Error Difference | Lower | Upper |
| MAE | Equal variances assumed | 35.493 | .000 | -6.737 | 46 | .000 | -.070417 | .010452 | -.091455 | -.049379 |
| | Equal variances not assumed | | | -6.737 | 24.535 | .000 | -.070417 | .010452 | -.091963 | -.048871 |
| MAPE | Equal variances assumed | 18.245 | .000 | -4.985 | 46 | .000 | -140.551417 | 28.194442 | -197.303885 | -83.798948 |
| | Equal variances not assumed | | | -4.985 | 24.820 | .000 | -140.551417 | 28.194442 | -198.640319 | -82.462514 |
| RMSE | Equal variances assumed | 34.283 | .000 | -6.702 | 46 | .000 | -.069379 | .010351 | -.090216 | -.048543 |
| | Equal variances not assumed | | | -6.702 | 24.669 | .000 | -.069379 | .010351 | -.090713 | -.048045 |

Since *p* value is less than the significance level 0.05, hence the null hypothesis of equal mean is rejected. So, the mean of two different population is statistically different.

**For comparison between the sites:**

**ARIMAX model:**

**Group Statistics**

| | Models | N | Mean | Std. Deviation | Std. Error Mean |
|---|---|---|---|---|---|
| MAE | NFZs | 12 | .01600 | .011045 | .003189 |
| | Reference | 12 | .00917 | .005458 | .001576 |
| MAPE | NFZs | 12 | 36.55733 | 35.470055 | 10.239323 |
| | Reference | 12 | 17.55250 | 8.085379 | 2.334048 |
| RMSE | NFZs | 12 | .01750 | .011374 | .003283 |
| | Reference | 12 | .01083 | .005906 | .001705 |

**Independent Samples Test**

| | | Levene's Test for Equality of Variances | | t-test for Equality of Means | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | 95% Confidence Interval of the Difference | |
| | | F | Sig. | t | df | Sig. (2-tailed) | Mean Difference | Std. Error Difference | Lower | Upper |
| MAE | Equal variances assumed | 4.308 | .050 | 1.921 | 22 | .068 | .006833 | .003557 | -.000542 | .014209 |
| | Equal variances not assumed | | | 1.921 | 16.069 | .073 | .006833 | .003557 | -.000704 | .014370 |
| MAPE | Equal variances assumed | 4.869 | .038 | 1.810 | 22 | .084 | 19.004833 | 10.501977 | -2.774933 | 40.784600 |
| | Equal variances not assumed | | | 1.810 | 12.140 | .095 | 19.004833 | 10.501977 | -3.847763 | 41.857430 |
| RMSE | Equal variances assumed | 4.509 | .045 | 1.802 | 22 | .085 | .006667 | .003700 | -.001006 | .014339 |
| | Equal variances not assumed | | | 1.802 | 16.530 | .090 | .006667 | .003700 | -.001156 | .014489 |

In ARIMAX model, since *p* value is more than the significance level 0.05, hence the null hypothesis of equal mean is accepted. So, the mean of two different population is statistically same.

**MLR model:**

**Group Statistics**

| | Models | N | Mean | Std. Deviation | Std. Error Mean |
|---|---|---|---|---|---|
| MAE | NFZs | 12 | .08108 | .056452 | .016296 |
| | Reference | 12 | .08492 | .045930 | .013259 |
| MAPE | NFZs | 12 | 170.73633 | 173.692733 | 50.140773 |
| | Reference | 12 | 164.47633 | 90.442318 | 26.108448 |
| RMSE | NFZs | 12 | .08175 | .055746 | .016093 |
| | Reference | 12 | .08534 | .045540 | .013146 |

**Independent Samples Test**

| | | Levene's Test for Equality of Variances | | t-test for Equality of Means | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | 95% Confidence Interval of the Difference | |
| | | F | Sig. | t | df | Sig. (2-tailed) | Mean Difference | Std. Error Difference | Lower | Upper |
| MAE | Equal variances assumed | .266 | .611 | -.182 | 22 | .857 | -.003833 | .021009 | -.047403 | .039736 |
| | Equal variances not assumed | | | -.182 | 21.126 | .857 | -.003833 | .021009 | -.047507 | .039841 |
| MAPE | Equal variances assumed | 2.243 | .148 | .111 | 22 | .913 | 6.260000 | 56.530949 | -110.978013 | 123.498013 |
| | Equal variances not assumed | | | .111 | 16.556 | .913 | 6.260000 | 56.530949 | -113.253757 | 125.773757 |
| RMSE | Equal variances assumed | .252 | .621 | -.173 | 22 | .864 | -.003592 | .020780 | -.046686 | .039503 |
| | Equal variances not assumed | | | -.173 | 21.158 | .864 | -.003592 | .020780 | -.046786 | .039603 |

In MLR model, since *p* value is more than the significance level 0.05, hence the null hypothesis of equal mean is accepted. So, the mean of two different population is statistically same.

**Appendix C**

Table C 1: Identification of zones for this study

Zone 1: South East Queensland

Zone 2: Darling Downs South West

Zone 3: Wide Bay-Burnett

Zone 4: Mackay, Isaac & Whitsunday

Zone 5: Rockhampton

Zone 6: Capricorn Coast

Zone 7: Rest of the Central Queensland

Zone 8: Townsville

Zone 9: Rest of the North Queensland

Zone 10: Far North

Zone 11: New South Wales (NSW)

Zone 12: Victoria (VIC)

Zone 13: Northern Territory (NT)

Zone 14: South Australia (SA)

Zone 15: Western Australia (WA)

Zone 16: Tasmania (TAS)

Table C 2: Analysis of travel cost method

## Model 1: Postcode model

## Postcode model 100 km

### Mackay (Postcode model 100 km):

Table: Regression statistics for four functional forms of the TGF for Mackay (Postcode model 100 km)

| Model | Coefficients | | | Test statistics | |
|---|---|---|---|---|---|
| | Constant (t statistic) | Travel cost (t statistic) | Personal income (t statistic) | $R^2$ | F (*P*-value) |
| Linear | .1045477** (2.90) | -.0007267*** (-3.97) | -.0000493 (-1.18) | 0.6061 | 8.46 (0.0060) |
| Semi-log independent | .2244538** (4.07) | -.0412443*** (-4.51) | -.0000506 (-1.32) | 0.6639 | 10.87 (0.0025) |
| Semi-log Dependent | -.2633003* (-0.09) | -.0463015** (-3.00) | -.002115* (-0.60) | 0.4854 | 5.19 (0.0259) |
| Double log | 5.877769* (1.12) | -2.35807** (-2.71) | -.0016175* (-0.44) | 0.4380 | 4.29 (0.0420) |

Note- *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Breusch-Pagan test for heteroscedasticity

| Heteroscedasticity test result for semi- log dependent model |
|---|
| Null hypothesis ($H_o$): Constant variance (no heteroscedasticity in residual) |
| Variables: fitted values of ln_visit rate |
| $Chi^2(1)$ = 0.65 |
| Prob > $chi^2$ = 0.4194 |

Table: Predicted number of fishers for four functional forms of TGF

| Model | Predicted no. of fishers |
|---|---|
| Linear | 3295 |
| Semi-log (I) | 154136 |
| Semi-log (D) | 1838 |
| Double log | 2074 |
| Actual | 1984 |

Table 6 6: Demand schedules for Mackay (Postcode model 100 km)

| Increase in travel cost in ($) (P) | Number of visits |
|---|---|
| 0 | 1838 |
| 50 | 181 |
| 100 | 17 |
| 300 | 0 |

Table: Regression statistics for four functional forms of demand for Mackay (Postcode model 100 km)

| Model | Coefficients | | Test statistics | |
|---|---|---|---|---|
| | Constant (t statistic) | Increase in travel cost (t statistic) | $R^2$ | F (*P*- value) |
| Linear | 969.7308*** (4.91) | -7.895299*** (-3.70) | 0.5778 | 13.69 (0.0041) |
| Semi-log independent | 1863.97*** (18.89) | -393.4136*** (-16.07) | 0.9627 | 258.17 (0.0000) |
| Semi-log dependent | 7.440689*** (48.93) | -.0451355*** (-27.45) | 0.9869 | 753.27 (0.0000) |
| Double log | 9.599424*** (7.84) | -1.467346 *** (-4.83) | 0.6999 | 23.33 (0.0007) |

Note: *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Predicted number of fishers for four functional forms of demand function

| Model | Predicted no. of fishers |
|---|---|
| Linear | 969 |
| Semi-log (I) | 0 |
| Semi-log (D) | 1703 |
| Double log | 14756 |
| Actual | 1984 |

The double-log demand function can be written as:

Log Q = 7.440689 - 0.0451355 P

After the inversion of equation, it becomes:

P = 164.81 - 22.15 Log Q

**Rockhampton (Postcode model 100 km):**

Table: Regression statistics for four functional forms of the TGF for Rockhampton (Postcode model 100 km)

| Model | Coefficients | | | Test statistics | |
|---|---|---|---|---|---|
| | Constant (t statistic) | Travel cost (t statistic) | Personal income (t statistic) | $R^2$ | F (*P*-value) |
| Linear | .1392637 (1.23) | -.0004383 (-0.96) | -.0001527 (-0.91) | 0.1907 | 0.59 (0.5893) |
| Semi-log independent | .0892185 (0.64) | -.0031977 (-0.19) | -.0000843 (-0.49) | 0.0467 | 0.12 (0.8873) |

| | | | | | |
|---|---|---|---|---|---|
| Semi-log | -.3624732* | -.0131938* | -.005443* | 0.1037 | 0.29 |
| Dependent | (-0.07) | (-0.62) | (-0.69) | | (0.7605) |
| Double log | -3.101724* | .1105269* | -.002578* | 0.0393 | 0.10 |
| | (-0.49) | (0.14) | (-0.34) | | (0.9047) |

Note- *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Breusch-Pagan test for heteroscedasticity

| Heteroscedasticity test result for semi- log dependent model |
|---|
| Null hypothesis ($H_o$): Constant variance (no heteroscedasticity in residual) |
| Variables: fitted values of ln_visit rate |
| $Chi^2(1) = 0.86$ |
| Prob > $chi^2$ = 0.3537 |

Table: Predicted number of fishers for four functional forms of TGF

| Model | Predicted no. of fishers |
|---|---|
| Linear | 4016 |
| Semi-log (I) | 124677 |
| Semi-log (D) | 2064 |
| Double log | 1532 |
| Actual | 2799 |

Table 6 6: Demand schedules for Rockhampton (Postcode model 100 km)

| Increase in travel cost in ($) (P) | Number of visits |
|---|---|
| 0 | 2064 |
| 50 | 1067 |
| 100 | 551 |
| 300 | 39 |
| 500 | 2 |

Table: Regression statistics for four functional forms of demand for Rockhampton (Postcode model 100 km)

| Model | Coefficients | | Test statistics | |
|---|---|---|---|---|
| | Constant (t statistic) | Increase in travel cost (t statistic) | $R^2$ | F (*P*-value) |
| Linear | 1324.475*** (6.99) | -2.724979*** (-4.25) | 0.6440 | 18.09 (0.0017) |
| Semi-log independent | 2457.28 *** (14.59) | -391.4943*** (-10.81) | 0.9212 | 116.85 (0.0000) |
| Semi-log dependent | 7.492952 *** (45.93) | -.0119947*** (-21.75) | 0.9793 | 473.16 (0.0000) |
| Double log | 10.22028*** (8.36) | -1.195436 *** (-4.55) | 0.6741 | 20.68 (0.0007) |

Note: *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Predicted number of fishers for four functional forms of demand function

| Model | Predicted no. of fishers |
|---|---|
| Linear | 1324 |
| Semi-log (I) | 0 |
| Semi-log (D) | 1795 |
| Double log | 27454 |
| Actual | 2799 |

The Semi-log dependent demand function can be written as:

Log Q = 7.492952 - 0.0119947 P

After the inversion of equation, it becomes:

P = 624.68 - 83.37 Log Q

**Townsville (Postcode model 100 km):**

Table: Regression statistics for four functional forms of the TGF for Townsville (Postcode model 100 km)

| Model | Coefficients | | | Test statistics | |
|---|---|---|---|---|---|
| | Constant (t statistic) | Travel cost (t statistic) | Personal income (t statistic) | $R^2$ | F (*P*-value) |
| Linear | -.0074464 (-0.63) | -.0001273 (-1.42) | .0000286* (1.84) | 0.6634 | 6.90 (0.0221) |
| Semi-log independent | .0003439 (0.02) | -.0031514 (-1.07) | .0000262 (1.34) | 0.6272 | 5.89 (0.0316) |
| Semi-log Dependent | -6.603373 * (-4.05) | -.0360969* (-2.90) | .0035569* (1.66) | 0.7957 | 13.63 (0.0039) |
| Double log | -4.778443* (-1.42) | -.8323552* (-1.72) | .0031977* (0.99) | 0.6838 | 7.57 (0.0178) |

Note- *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Breusch-Pagan test for heteroscedasticity

Heteroscedasticity test result for semi- log dependent model

Null hypothesis ($H_o$): Constant variance (no heteroscedasticity in residual)

Variables: fitted values of ln_visit rate

$Chi^2(1) = 0.52$

Prob > $chi^2$ = 0.4712

Table: Predicted number of fishers for four functional forms of TGF

| Model | Predicted no. of fishers |
|---|---|
| Linear | 1948 |

| | |
|---|---|
| Semi-log (I) | 192995 |
| Semi-log (D) | 1872 |
| Double log | 1838 |
| Actual | 2002 |

Table 6 6: Demand schedules for Townsville (Postcode model 100 km)

| Increase in travel cost in ($) (P) | Number of visits |
|---|---|
| 0 | 1872 |
| 50 | 307 |
| 100 | 50 |
| 300 | 0 |

Table: Regression statistics for four functional forms of demand for Townsville (Postcode model 100 km)

| Model | Coefficients | | Test statistics | |
|---|---|---|---|---|
| | Constant (t statistic) | Increase in travel cost (t statistic) | $R^2$ | F ($P$-value) |
| Linear | 1069.107*** (5.40) | -6.750701*** (-3.87) | 0.6243 | 14.96 (0.0038) |
| Semi-log independent | 1968.211*** (17.99) | -390.9949*** (-14.71) | 0.9600 | 216.24 (0.0000) |
| Semi-log dependent | 7.554326*** (174.70) | -.0366867*** (-96.16) | 0.9990 | 9246.37 (0.0000) |
| Double log | 9.750001*** (7.41) | -1.420914*** (-4.44) | 0.6870 | 19.75 (0.0016) |

Note: *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Predicted number of fishers for four functional forms of demand function

| Model | Predicted no. of fishers |
|---|---|
| Linear | 1069 |

| | |
|---|---|
| Semi-log (I) | 0 |
| Semi-log (D) | 908 |
| Double log | 17154 |
| Actual | 2002 |

The Semi-log dependent demand function can be written as:

Log Q = 7.554326 -.0366867 P

After the inversion of equation, it becomes:

P = 205.85 - 27.25 log Q

**Hinchinbrook (Postcode model 100 km):**

Table: Regression statistics for four functional forms of the TGF for Hinchinbrook (Postcode model 100 km)

| Model | Coefficients | | | Test statistics | |
|---|---|---|---|---|---|
| | Constant (t statistic) | Travel cost (t statistic) | Personal income (t statistic) | $R^2$ | F (*P*-value) |
| Linear | .0228915 (1.48) | -.0000349 (-0.24) | -.0000261* (-1.17) | 0.0236 | 0.69 (0.5068) |
| Semi-log independent | .0213443 (1.28) | .0001932 (0.07) | -.0000254 (-1.14) | 0.0227 | 0.66 (0.5201) |
| Semi-log Dependent | -7.994606* (-7.21) | .4196994* (2.19) | -.0010328* (-0.70) | 0.0888 | 2.78 (0.0705) |
| Double log | -7.994606* (-7.21) | .4196994* (2.19) | -.0010328* (-0.70) | 0.0888 | 2.78 (0.0705) |

Note- *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Breusch-Pagan test for heteroscedasticity

| Heteroscedasticity test result for semi- log dependent model |
| --- |
| Null hypothesis ($H_o$): Constant variance (no heteroscedasticity in residual) |
| Variables: fitted values of ln_visit rate |
| $Chi^2(1) = 0.04$ |
| $Prob > chi^2 = 0.8428$ |

Table: Predicted number of fishers for four functional forms of TGF

| Model | Predicted no. of fishers |
| --- | --- |
| Linear | 7210 |
| Semi-log (I) | 1284975 |
| Semi-log (D) | 608 |
| Double log | 582 |
| Actual | 1484 |

Table 6 6: Demand schedules for Townsville (Postcode model 100 km)

| Increase in travel cost in ($) (P) | Number of visits |
| --- | --- |
| 0 | 608 |
| 50 | 390 |
| 100 | 150 |
| 300 | 30 |
| 500 | 0 |

Table: Regression statistics for four functional forms of demand for Hinchinbrook (Postcode model 100 km)

| Model | Coefficients | Test statistics |
| --- | --- | --- |

| | Constant (t statistic) | Increase in travel cost (t statistic) | $R^2$ | F (*P*-value) |
|---|---|---|---|---|
| Linear | 434.0722*** (8.86) | -1.185121*** (-5.21) | 0.6932 | 27.11 (0.0002) |
| Semi-log independent | 776.2138*** (12.24) | -123.4659*** (-8.85) | 0.8670 | 78.25 (0.0000) |
| Semi-log dependent | 6.449168*** (38.68) | -.0109279*** (-14.11) | 0.9432 | 199.15 (0.0000) |
| Double log | 8.149657*** (9.11) | -.7958822*** (-4.04) | 0.5765 | 16.34 (0.0016) |

Note: *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Predicted number of fishers for four functional forms of demand function

| Model | Predicted no. of fishers |
|---|---|
| Linear | 157 |
| Semi-log (I) | 0 |
| Semi-log (D) | 230 |
| Double log | 1463 |
| Actual | 1484 |

The Semi-log dependent demand function can be written as:

Log Q = 6.449168 -.0109279 P

After the inversion of equation, it becomes:

P = 590.09 -91.5 Log Q

**Hervey Bay (Postcode model 100 km):**

Table: Regression statistics for four functional forms of the TGF for Hervey Bay (Postcode model 100 km)

| Model | Coefficients | | | Test statistics | |
|---|---|---|---|---|---|
| | Constant (t statistic) | Travel cost (t statistic) | Personal income (t statistic) | $R^2$ | F (*P*-value) |
| Linear | .0838172 (0.59) | -.0003122 (-1.02) | -.0001291* (-0.46) | 0.3770 | 0.61 (0.6230) |
| Semi-log independent | .1678623 (1.47) | -.0183444 (-2.07) | -.0001986 (-1.04) | 0.6978 | 2.31 (0.3022) |
| Semi-log Dependent | 5.729908* (0.31) | -.035289 * (-0.91) | -.0210638* (-0.58) | 0.2930 | 0.41 (0.7070) |
| Double log | 13.16709* (0.73) | -1.881016* (-1.34) | -.0260026* (-0.86) | 0.4755 | 0.91 (0.5245) |

Note- *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Breusch-Pagan test for heteroscedasticity

| Heteroscedasticity test result for double log model |
|---|
| Null hypothesis ($H_o$): Constant variance (no heteroscedasticity in residual) |
| Variables: fitted values of ln_visit rate |
| $Chi^2(1)$ = 0.04 |
| Prob > $chi^2$ = 0.8391 |

Table: Predicted number of fishers for four functional forms of TGF

| Model | Predicted no. of fishers |
|---|---|
| Linear | 1209 |

| | |
|---|---|
| Semi-log (I) | 108422 |
| Semi-log (D) | 528 |
| Double log | 940 |
| Actual | 2013 |

Table 6 6: Demand schedules for Hervey Bay (Postcode model 100 km)

| Increase in travel cost in ($) (P) | Number of visits |
|---|---|
| 0 | 940 |
| 50 | 70 |
| 100 | 28 |
| 300 | 5 |
| 500 | 2 |
| 1000 | 0 |

Table: Regression statistics for four functional forms of demand for Hervey Bay (Postcode model 100 km)

| Model | Coefficients | | Test statistics | |
|---|---|---|---|---|
| | Constant (t statistic) | Increase in travel cost (t statistic) | $R^2$ | F (*P*-value) |
| Linear | 187.8943 (2.64) | -.4070015** (-1.51) | 0.1396 | 2.27 (0.1539) |
| Semi-log independent | 646.1581*** (7.59) | -123.9608*** (-6.58) | 0.7555 | 43.26 (0.0000) |
| Semi-log dependent | 4.714192*** (15.85) | -.0074844*** (-6.64) | 0.7588 | 44.04 (0.0000) |
| Double log | 8.071375*** (21.67) | -1.081957*** (-13.13) | 0.9249 | 172.37 (0.0000) |

Note: *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Predicted number of fishers for four functional forms of demand function

| Model | Predicted no. of fishers |
|---|---|
| Linear | 187 |
| Semi-log (I) | 0 |
| Semi-log (D) | 111 |
| Double log | 3201 |
| Actual | 2013 |

The Double-log dependent demand function can be written as:

Log Q = 8.071375 -1.081957 Log P

After the inversion of equation, it becomes:

Log P = 7.42 - 0.92 Log Q

## Postcode model 300 km

### Cairns (Postcode model 300 km):

Table: Regression statistics for four functional forms of the TGF for Cairns (Postcode model 300 km)

| Model | Coefficients | | | Test statistics | |
|---|---|---|---|---|---|
| | Constant (t statistic) | Travel cost (t statistic) | Personal income (t statistic) | $R^2$ | F (*P*-value) |
| Linear | -.0019281 (-0.34) | -.0000443** (-2.75) | .0000119 (1.47) | 0.7491 | 16.42 (0.0005) |
| Semi-log independent | .0102822* (1.90) | -.002741*** (-5.08) | 4.31e-06 (0.71) | 0.8736 | 38.03 (0.0000) |

| | | | | | |
|---|---|---|---|---|---|
| Semi-log | -11.12237*** | -.017889** | .0088817** | 0.8500 | 31.16 |
| Dependent | (-5.20) | (-2.94) | (2.92) | | (0.0000) |
| Double log | -7.587371** | -.950748 ** | .0071597** | 0.8823 | 41.21 |
| | (-2.97) | (-3.74) | (2.49) | | (0.0000) |

Note- *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

able: Breusch-Pagan test for heteroscedasticity

| Heteroscedasticity test result for double log model |
|---|
| Null hypothesis ($H_o$): Constant variance (no heteroscedasticity in residual) |
| Variables: fitted values of ln_visit rate |
| $Chi^2(1) = 2.24$ |
| $Prob > chi^2 = 0.1345$ |

Table: Predicted number of fishers for four functional forms of TGF

| Model | Predicted no. of fishers |
|---|---|
| Linear | 909 |
| Semi-log (I) | 211110 |
| Semi-log (D) | 878 |
| Double log | 1054 |
| Actual | 1045 |

Table 6 6: Demand schedules for Cairns (Postcode model 300 km)

| Increase in travel cost in ($) (P) | Number of visits |
|---|---|
| 0 | 1054 |
| 50 | 231 |
| 100 | 136 |
| 300 | 53 |
| 500 | 33 |

| | |
|---|---|
| 1000 | 17 |
| 3000 | 6 |
| 5000 | 3 |
| 10000 | 2 |
| 30000 | 0 |

Table: Regression statistics for four functional forms of demand for Cairns (Postcode model 300 km)

| Model | Coefficients | | Test statistics | |
|---|---|---|---|---|
| | Constant (t statistic) | Increase in travel cost (t statistic) | $R^2$ | F ($P$-value) |
| Linear | 246.9864*** (3.75) | -.0167472 (-1.45) | 0.1155 | 2.09 (0.1676) |
| Semi-log independent | 662.484*** (8.34) | -87.71773*** (-6.33) | 0.7147 | 40.08 (0.0000) |
| Semi-log dependent | 4.828109 *** (13.45) | -.0002911*** (-4.61) | 0.5710 | 21.30 (0.0003) |
| Double log | 8.279693*** (35.59) | -.7947134 *** (-19.58) | 0.9599 | 383.35 (0.0000) |

Note: *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Predicted number of fishers for four functional forms of demand function

| Model | Predicted no. of fishers |
|---|---|
| Linear | 246 |
| Semi-log (I) | 0 |
| Semi-log (D) | 124 |
| Double log | 3942 |
| Actual | 1045 |

The double-log demand function can be written as:

Log Q = 8.279693 -.7947134 Log P

After the inversion of equation, it becomes:

Log P= 10.35 - 1.25 Log Q

**Mackay (Postcode model 300 km):**

Table: Regression statistics for four functional forms of the TGF for Mackay (Postcode model 300 km)

| Model | Coefficients | | | Test statistics | |
|---|---|---|---|---|---|
| | Constant (t statistic) | Travel cost (t statistic) | Personal income (t statistic) | $R^2$ | F (*P*-value) |
| Linear | .0180296 (1.08) | -.0001289** (-2.41) | .0000177 (0.72) | 0.2582 | 2.96 (0.0790) |
| Semi-log independent | .1035887*** (4.44) | -.0218061*** (-4.33) | .0000144 (0.78) | 0.5276 | 9.49 (0.0017) |
| Semi-log Dependent | -6.343177*** (-4.50) | -.0117782** (-2.60) | .0031303 * (1.50) | 0.2897 | 3.47 (0.0546) |
| Double log | .5637332* (0.26) | -1.754016*** (-3.77) | .0025813* (1.51) | 0.4592 | 7.22 (0.0054) |

Note- *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Breusch-Pagan test for heteroscedasticity

| Heteroscedasticity test result for double log model |
|---|
| Null hypothesis ($H_o$): Constant variance (no heteroscedasticity in residual) |
| Variables: fitted values of ln_visit rate |
| $Chi^2(1) = 0.46$ |
| Prob > $chi^2$ = 0.4984 |

Table: Predicted number of fishers for four functional forms of TGF

| Model | Predicted no. of fishers |
|---|---|
| Linear | 3426 |
| Semi-log (I) | 192142 |
| Semi-log (D) | 1366 |
| Double log | 2469 |
| Actual | 2038 |

Table 6 6: Demand schedules for Mackay (Postcode model 300 km)

| Increase in travel cost in ($) (P) | Number of visits |
|---|---|
| 0 | 2469 |
| 50 | 528 |
| 100 | 256 |
| 300 | 66 |
| 500 | 31 |
| 1000 | 10 |
| 3000 | 1 |
| 5000 | 0 |

Table: Regression statistics for four functional forms of demand for Mackay (Postcode model 300 km)

| Model | Coefficients | | Test statistics | |
|---|---|---|---|---|
| | Constant (t statistic) | Increase in travel cost (t statistic) | $R^2$ | F (*P*-value) |
| Linear | 700.7327** (3.04) | -.2086762 (-1.51) | 0.1714 | 2.27 (0.1597) |

| | | | | |
|---|---|---|---|---|
| Semi-log independent | 1937.42*** (9.34) | -284.6575*** (-7.52) | 0.8371 | 56.53 (0.0000) |
| Semi-log dependent | 5.708544*** (11.65) | -.0014757*** (-5.01) | 0.6955 | 25.12 (0.0004) |
| Double log | 9.618768*** (17.33) | -1.039212*** (-10.26) | 0.9054 | 105.32 (0.0000) |

Note: *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Predicted number of fishers for four functional forms of demand function

| Model | Predicted no. of fishers |
|---|---|
| Linear | 700 |
| Semi-log (I) | 0 |
| Semi-log (D) | 301 |
| Double log | 15044 |
| Actual | 2038 |

The Semi-log dependent demand function can be written as:

Log Q = 5.708544 -.0014757P

After the inversion of equation, it becomes:

P= 3868.33 - 677.64 Log Q

**Rockhampton (Postcode model 300 km):**

Table: Regression statistics for four functional forms of the TGF for Rockhampton (Postcode model 300 km)

| Model | Coefficients | | | Test statistics | |
|---|---|---|---|---|---|
| | Constant (t statistic) | Travel cost (t statistic) | Personal income (t statistic) | $R^2$ | F (*P*-value) |

| | | | | | |
|---|---|---|---|---|---|
| Linear | .0410049 | -.0000883* | -.0000176 | 0.2759 | 2.29 |
| | (1.66) | (-1.91) | (-0.48) | | (0.1441) |
| Semi-log independent | .0666077** | -.0084715 | -.0000187 | 0.2179 | 1.67 |
| | (2.14) | (-1.58) | (-0.48) | | (0.2289) |
| Semi-log Dependent | -5.420695*** | -.011253*** | .0025933* | 0.5502 | 7.34 |
| | (-3.45) | (-3.83) | (1.10) | | (0.0083) |
| Double log | -2.33799* | -1.025014 ** | .0023532* | 0.3660 | 3.46 |
| | (-1.03) | (-2.63) | (0.84) | | (0.0650) |

Note- *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Breusch-Pagan test for heteroscedasticity

| Heteroscedasticity test result for semi- log dependent model |
|---|
| Null hypothesis ($H_o$): Constant variance (no heteroscedasticity in residual) |
| Variables: fitted values of ln_visit rate |
| $Chi^2(1) = 1.46$ |
| Prob > $chi^2$ = 0.2272 |

Table: Predicted number of fishers for four functional forms of TGF

| Model | Predicted no. of fishers |
|---|---|
| Linear | 3970 |
| Semi-log (I) | 277962 |
| Semi-log (D) | 2376 |
| Double log | 3634 |
| Actual | 2888 |

Table 6 6: Demand schedules for Rockhampton (Postcode model 300 km)

| Increase in travel cost in ($) (P) | Number of visits |
|---|---|
| 0 | 2376 |
| 50 | 1353 |
| 100 | 771 |
| 300 | 81 |
| 500 | 8 |
| 1000 | 0 |

Table: Regression statistics for four functional forms of demand for Rockhampton (Postcode model 300 km)

| Model | Coefficients | | Test statistics | |
|---|---|---|---|---|
| | Constant (t statistic) | Increase in travel cost (t statistic) | $R^2$ | F (*P*-value) |
| Linear | 1459.942** (6.87) | -2.876537*** (-4.10) | 0.5839 | 16.84 (0.0015) |
| Semi-log independent | 2897.205*** (14.48) | -458.4523*** (-10.90) | 0.9083 | 118.84 (0.0000) |
| Semi-log dependent | 7.642508*** (86.83) | -.0102264*** (-35.20) | 0.9904 | 1239.31 (0.0000) |
| Double log | 10.15256*** (9.27) | -1.043069*** (-4.53) | 0.6310 | 20.52 (0.0007) |

Note: *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Predicted number of fishers for four functional forms of demand function

| Model | Predicted no. of fishers |
|---|---|
| Linear | 1459 |
| Semi-log (I) | 0 |
| Semi-log (D) | 2084 |

| | |
|---|---|
| Double log | 25656 |
| Actual | 2888 |

The Semi-log dependent demand function can be written as:

Log Q=7.642508 -.0102264 P

After the inversion of equation, it becomes:

P= 747.28 - 97.78 Log Q

**Townsville (Postcode model 300 km):**

Table: Regression statistics for four functional forms of the TGF for Townsville (Postcode model 300 km)

| Model | Coefficients | | | Test statistics | |
|---|---|---|---|---|---|
| | Constant (t statistic) | Travel cost (t statistic) | Personal income (t statistic) | $R^2$ | F (*P*-value) |
| Linear | -.0163843* (-2.05) | -.0000175 (-1.58) | .0000382*** (3.25) | 0.7043 | 11.91 (0 .0023) |
| Semi-log independent | -.0033349 (-0.27) | -.0021812* (-1.90) | .0000278* (1.95) | 0.7288 | 13.43 (0.0015) |
| Semi-log Dependent | -7.651391*** (-5.37) | -.0130627*** (-6.60) | .0044048* (2.11) | 0.8904 | 40.62 (0.0000) |
| Double log | -.2167622* (-0.09) | -1.378634** (-5.95) | -.0011512* (0.40) | 0.8707 | 33.67 (0.0000) |

Note- *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Breusch-Pagan test for heteroscedasticity

| Heteroscedasticity test result for double log model |
|---|

| |
|---|
| Null hypothesis ($H_o$): Constant variance (no heteroscedasticity in residual) |
| Variables: fitted values of ln_visit rate |
| $Chi^2(1) = 0.53$ |
| $Prob > chi^2 = 0.4646$ |

Table: Predicted number of fishers for four functional forms of TGF

| Model | Predicted no. of fishers |
|---|---|
| Linear | 1893 |
| Semi-log (I) | 225975 |
| Semi-log (D) | 1695 |
| Double log | 1902 |
| Actual | 2018 |

Table 6 6: Demand schedules for Townsville (Postcode model 300 km)

| Increase in travel cost in ($) (P) | Number of visits |
|---|---|
| 0 | 1902 |
| 50 | 214 |
| 100 | 100 |
| 300 | 26 |
| 500 | 14 |
| 1000 | 5 |
| 3000 | 1 |
| 5000 | 0 |

Table: Regression statistics for four functional forms of demand for Townsville (Postcode model 300 km)

| Model | Coefficients | | Test statistics | |
|---|---|---|---|---|
| | Constant (t statistic) | Increase in travel cost (t statistic) | $R^2$ | F (*P*-value) |

| | | | | |
|---|---|---|---|---|
| Linear | 361.1299** (2.29) | -.1433922 (-1.31) | 0.1173 | 1.73 (0.2114) |
| Semi-log independent | 1256.037*** (6.68) | -190.319*** (-5.85) | 0.7245 | 34.18 (0.0001) |
| Semi-log dependent | 4.719281*** (10.17) | -.0015756*** (-4.91) | 0.6498 | 24.13 (0.0003) |
| Double log | 8.830447*** (24.73) | -1.019893*** (-16.49) | 0.9544 | 272.00 (0.0000) |

Note: *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Predicted number of fishers for four functional forms of demand function

| Model | Predicted no. of fishers |
|---|---|
| Linear | 361 |
| Semi-log (I) | 0 |
| Semi-log (D) | 112 |
| Double log | 6839 |
| Actual | 2018 |

The Semi-log dependent demand function can be written as:

Log Q = 4.719281 -.0015756 P

After the inversion of equation, it becomes:

P = 2995.23 -634.68 Log Q

**Hinchinbrook (Postcode model 300 km):**

Table: Regression statistics for four functional forms of the TGF for Hinchinbrook (Postcode model 300 km)

| Model | Coefficients | Test statistics |
|---|---|---|

| | Constant (t statistic) | Travel cost (t statistic) | Personal income (t statistic) | $R^2$ | F (*P*-value) |
|---|---|---|---|---|---|
| Linear | .0210532 (1.66) | -.00002 (-0.74) | -.0000237 (-1.26) | 0.0261 | 0.98 (0.3806) |
| Semi-log independent | .0218785 (1.58) | -.0008127 (-0.50) | -.0000234 (-1.24) | 0.0222 | 0.83 (0.4400) |
| Semi-log Dependent | -7.002618*** (-7.63) | .0029519* (1.50) | -.0012548* (-0.92) | 0.0448 | 1.71 (0.1875) |
| Double log | -7.647277*** (-7.80) | .255711** (2.22) | -.0011095* (-0.83) | 0.0778 | 3.08 (0.0400) |

Note- *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Breusch-Pagan test for heteroscedasticity

| Heteroscedasticity test result for double log model |
|---|
| Null hypothesis ($H_o$): Constant variance (no heteroscedasticity in residual) |
| Variables: fitted values of ln_visit rate |
| $Chi^2(1) = 0.53$ |
| Prob > $chi^2$ = 0.4685 |

Table: Predicted number of fishers for four functional forms of TGF

| Model | Predicted no. of fishers |
|---|---|
| Linear | 7027 |
| Semi-log (I) | 1515403 |
| Semi-log (D) | 753 |
| Double log | 752 |
| Actual | 1669 |

Table 6 6: Demand schedules for Hinchinbrook (Postcode model 300 km)

| Increase in travel cost in ($) (P) | Number of visits |
|---|---|
| 0 | 752 |
| 50 | 564 |
| 100 | 410 |
| 300 | 306 |
| 500 | 200 |
| 1000 | 50 |
| 3000 | 0 |

Table: Regression statistics for four functional forms of demand for Hinchinbrook (Postcode model 300 km)

| Model | Coefficients | | Test statistics | |
|---|---|---|---|---|
| | Constant (t statistic) | Increase in travel cost (t statistic) | $R^2$ | F (*P*-value) |
| Linear | 553.2277*** (10.84) | -.372747*** (-5.16) | 0.7272 | 26.66 (0.0004) |
| Semi-log independent | 922.1196*** (16.24) | -114.2276*** (-10.11) | 0.9108 | 102.15 (0.0000) |
| Semi-log dependent | 6.601658*** (68.13) | -.0030862*** (-22.52) | 0.9807 | 507.23 (0.0000) |
| Double log | 8.166217*** (8.75) | -.6190047*** (-3.33) | 0.5262 | 11.11 (0.0076) |

Note: *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Predicted number of fishers for four functional forms of demand function

| Model | Predicted no. of fishers |
|---|---|
| Linear | 553 |

| | |
|---|---|
| Semi-log (I) | 0 |
| Semi-log (D) | 736 |
| Double log | 3520 |
| Actual | 1669 |

The Semi-log dependent demand function can be written as:

Log Q=6.601658 -.0030862 P

After the inversion of equation, it becomes:

P= 2143.9 - 324.02 Log Q

**Hervey Bay (Postcode model 300 km):**

Table: Regression statistics for four functional forms of the TGF for Hervey Bay (Postcode model 300 km)

| Model | Coefficients | | | Test statistics | |
|---|---|---|---|---|---|
| | Constant (t statistic) | Travel cost (t statistic) | Personal income (t statistic) | $R^2$ | F (*P*-value) |
| Linear | .0048848* (1.85) | -.000024** (-3.24) | 4.84e-06 (0.89) | 0.2311 | 6.61 (0.0031) |
| Semi-log independent | .0243164*** (6.40) | -.0048796*** (-6.08) | 5.74e-06 (1.46) | 0.4831 | 20.56 (0.0000) |
| Semi-log Dependent | -6.159047*** (-8.93) | -.0091347*** (-4.69) | .0003053* (0.21) | 0.4553 | 18.39 (0.0000) |
| Double log | -.6213533* (-0.56) | -1.380572*** (-5.88) | -.0005687* (-0.49) | 0.5419 | 26.02 (0.0000) |

Note- *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Breusch-Pagan test for heteroscedasticity

| Heteroscedasticity test result for double log model |
|---|
| Null hypothesis ($H_o$): Constant variance (no heteroscedasticity in residual) |
| Variables: fitted values of ln_visit rate |
| $Chi^2(1) = 1.90$ |
| $Prob > chi^2 = 0.1683$ |

Table: Predicted number of fishers for four functional forms of TGF

| Model | Predicted no. of fishers |
|---|---|
| Linear | 1168 |
| Semi-log (I) | 976318 |
| Semi-log (D) | 358 |
| Double log | 831 |
| Actual | 2127 |

Table 6 6: Demand schedules for Hervey Bay (POSTCODE MODEL300 km)

| Increase in travel cost in ($) (P) | Number of visits |
|---|---|
| 0 | 831 |
| 50 | 209 |
| 100 | 138 |
| 300 | 62 |
| 500 | 39 |
| 1000 | 19 |
| 3000 | 5 |
| 5000 | 2 |
| 10000 | 1 |
| 30000 | 0 |

Table: Regression statistics for four functional forms of demand for Hervey Bay (Postcode model 300 km)

| Model | Coefficients | | Test statistics | |
|---|---|---|---|---|
| | Constant (t statistic) | Increase in travel cost (t statistic) | $R^2$ | F (*P*-value) |
| Linear | 217.8879*** (3.96) | -.0271315** (-2.22) | 0.2348 | 4.91 (0.0416) |
| Semi-log independent | 554.6474*** (9.94) | -69.86538*** (-8.00) | 0.8001 | 64.03 (0.0000) |
| Semi-log dependent | 4.762578*** (13.80) | -.0005369*** (-6.99) | 0.7533 | 48.86 (0.0000) |
| Double log | 8.254781*** (24.68) | -.8371668*** (-15.99) | 0.9411 | 255.71 (0.0000) |

Note: *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Predicted number of fishers for four functional forms of demand function

| Model | Predicted no. of fishers |
|---|---|
| Linear | 217 |
| Semi-log (I) | 0 |
| Semi-log (D) | 117 |
| Double log | 3845 |
| Actual | 2127 |

The Double log dependent demand function can be written as:

Log Q=8.254781 -.8371668 Log P

After the inversion of equation, it becomes:

Log P = 9.82 -1.19 Log Q

## Model 2: Zoned model

## Zoned model 100 km

### Cairns (Zoned model 100 km):

Table: Regression statistics for four functional forms of the TGF for Cairns (Zoned model 100 km)

| Model | Coefficients | | | Test statistics | |
|---|---|---|---|---|---|
| | Constant (t statistic) | Travel cost (t statistic) | Personal income (t statistic) | $R^2$ | F (*P*-value) |
| Linear | .024** (2.13) | -.0001** (-2.14) | -0.000023 (-.135) | 0.125 | 3.775 (0.007) |
| Semi-log independent | 0.20 (1.58) | -.002 (-.945) | -1.596E-5 (-.973) | 0.095 | 2.767 (0.031) |
| Semi-log Dependent | -5.648803*** (-6.08) | -.0087265* (-1.44) | .0000315* (0.03) | 0.3438 | 11.00 (0.0000) |
| Double log | -8.007627* (-8.14) | .2183* (1.45) | .0000363* (0.03) | 0.3228 | 10.01 (0.0000) |

Note- *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Breusch-Pagan test for heteroscedasticity

| Heteroscedasticity test result for semi- log dependent model |
|---|
| Null hypothesis ($H_o$): Constant variance (no heteroscedasticity in residual) |
| Variables: fitted values of ln_visit rate |
| $Chi^2(1) = 3.19$ |
| Prob > $chi^2$ = 0.0828 |

Table: Predicted number of fishers for four functional forms of TGF

| Model | Predicted no. of fishers |
|---|---|
| Linear | 2591 |
| Semi-log (I) | 210843 |
| Semi-log (D) | 580 |
| Double log | 142 |
| Actual | 1045 |

Table 6 6: Demand schedules for Cairns (Zoned model 100 km)

| Increase in travel cost in ($) (P) | Number of visits |
|---|---|
| 0 | 580 |
| 50 | 370 |
| 100 | 235 |
| 300 | 38 |
| 500 | 6 |
| 1000 | 0 |

Table: Regression statistics for four functional forms of demand for Cairns (Zoned model 100 km)

| Model | Coefficients | | Test statistics | |
|---|---|---|---|---|
| | Constant (t statistic) | Increase in travel cost (t statistic) | $R^2$ | F (*P*-value) |
| Linear | 426.8649*** (13.04) | -.6490789*** (-5.49) | 0.7510 | 30.16 (0.0003) |
| Semi-log independent | 717.329*** (14.33) | -99.4623 *** (-8.37) | 0.8752 | 70.13 (0.0000) |
| Semi-log dependent | 6.310482*** (118.26) | -.0082113*** (-42.62) | 0.9945 | 1816.23 (0.0000) |

| | | | | |
|---|---|---|---|---|
| Double log | 8.578601*** (8.57) | -.8955436*** (-3.77) | 0.5871 | 14.22 (0.0037) |

Note: *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Predicted number of fishers for four functional forms of demand function

| Model | Predicted no. of fishers |
|---|---|
| Linear | 426 |
| Semi-log (I) | 0 |
| Semi-log (D) | 550 |
| Double log | 5316 |
| Actual | 1045 |

The semi-log dependent demand function can be written as:

Log Q = 6.310482 - .0082113 P

After the inversion of equation, it becomes:

P= 768.49 -121.78 Log Q

**Mackay (Zoned model 100 km):**

Table: Regression statistics for four functional forms of the TGF for Mackay (Zoned model 100 km)

| Model | Coefficients | | | Test statistics | |
|---|---|---|---|---|---|
| | Constant (t statistic) | Travel cost (t statistic) | Personal income (t statistic) | $R^2$ | F (*P*-value) |
| Linear | .029934** (2.39) | -.0001285* (-1.63) | -.0000168 (-1.00) | 0.0505 | 1.90 (0.1342) |

| | | | | | |
|---|---|---|---|---|---|
| Semi-log independent | .0286122* (1.96) | -.0012542 (-0.58) | -.000012 (-0.72) | 0.0600 | 1.69 (0.1576) |
| Semi-log Dependent | -5.015125*** (-5.47) | -.0046199* (-0.80) | .000419* (0.34) | 0.3479 | 14.14 (0.0000) |
| Double log | -5.752703*** (-5.43) | .0778043* (0.50) | .0007705* (0.64) | 0.3454 | 13.98 (0.0000) |

Note- *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Breusch-Pagan test for heteroscedasticity

| Heteroscedasticity test result for linear model |
|---|
| Null hypothesis ($H_0$): Constant variance (no heteroscedasticity in residual) |
| Variables: fitted values of ln_visit rate |
| $Chi^2(1) = 2.19$ |
| $Prob > chi^2 = 0.0921$ |

Table: Predicted number of fishers for four functional forms of TGF

| Model | Predicted no. of fishers |
|---|---|
| Linear | 1749 |
| Semi-log (I) | 77135 |
| Semi-log (D) | 357 |
| Double log | 1341 |
| Actual | 1984 |

Table 6 6: Demand schedules for Mackay (Zoned model 100 km)

| Increase in travel cost in ($) (P) | Number of visits |
|---|---|
| 0 | 1749 |
| 50 | 994 |

| | |
|---|---|
| 100 | 238 |
| 300 | 0 |

Table: Regression statistics for four functional forms of demand for Mackay (Zoned model 100 km)

| Model | Coefficients | | Test statistics | |
|---|---|---|---|---|
| | Constant (t statistic) | Increase in travel cost (t statistic) | $R^2$ | F (*P*-value) |
| Linear | 1745.21*** (376.63) | -15.00222*** (-228.09) | 0.9998 | 52025.60 (0.0000) |
| Semi-log independent | 2221.216*** (8.20) | -375.1949*** (-5.36) | 0.7234 | 28.77 (0.0002) |
| Semi-log dependent | 8.413868*** (11.72) | -.0394352*** (-3.87) | 0.5766 | 14.98 (0.0026) |
| Double log | 8.885992*** (5.78) | -.7734674*** (-1.95 ) | 0.2566 | 3.80 (0.0473) |

Note: *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Predicted number of fishers for four functional forms of demand function

| Model | Predicted no. of fishers |
|---|---|
| Linear | 1745 |
| Semi-log (I) | 0 |
| Semi-log (D) | 4509 |
| Double log | 7229 |
| Actual | 1984 |

The semi-log dependent demand function can be written as:

Log Q=8.413868 -.0394352P

After the inversion of equation, it becomes:

P= 213.29 -25.35 Log Q

**Rockhampton (Zoned model 100 km):**

Table: Regression statistics for four functional forms of the TGF for Rockhampton (Zoned model 100 km)

| Model | Coefficients | | | Test statistics | |
|---|---|---|---|---|---|
| | Constant (t statistic) | Travel cost (t statistic) | Personal income (t statistic) | $R^2$ | F (*P*-value) |
| Linear | .0328913** (2.63) | -.0001197 (-1.53) | -.0000165 (-0.99) | 0.0772 | 2.22 (0.0719) |
| Semi-log independent | .0286122* (1.96) | -.0012542 (-0.58) | -.000012 (-0.72) | 0.0600 | 1.69 (0.1576) |
| Semi-log Dependent | -5.015125*** (-5.47) | -.0046199* (-0.80) | .000419* (0.34) | 0.3479 | 14.14 (0.0000) |
| Double log | -5.752703*** (-5.43) | .0778043* (0.50) | .0007705* (0.64) | 0.3454 | 13.98 (0.0000) |

Note- *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Breusch-Pagan test for heteroscedasticity

| Heteroscedasticity test result for semi-log dependent model |
|---|
| Null hypothesis ($H_o$): Constant variance (no heteroscedasticity in residual) |
| Variables: fitted values of ln_visit rate |
| $Chi^2(1) = 4.47$ |
| Prob > $chi^2$ = 0.0834 |

Table: Predicted number of fishers for four functional forms of TGF

| Model | Predicted no. of fishers |
|---|---|

| | |
|---|---|
| Linear | 2456 |
| Semi-log (I) | 123866 |
| Semi-log (D) | 761 |
| Double log | 260 |
| Actual | 2799 |

Table 6 6: Demand schedules for Rockhampton (Zoned model 100 km)

| Increase in travel cost in ($) (P) | Number of visits |
|---|---|
| 0 | 761 |
| 50 | 593 |
| 100 | 461 |
| 300 | 169 |
| 500 | 62 |
| 1000 | 5 |
| 3000 | 0 |

Table: Regression statistics for four functional forms of demand for Rockhampton (Zoned model 100 km)

| Model | Coefficients | | Test statistics | |
|---|---|---|---|---|
| | Constant (t statistic) | Increase in travel cost (t statistic) | $R^2$ | F (*P*-value) |
| Linear | 580.4754*** (11.01) | -.5608709 *** (-5.85) | 0.7568 | 34.24 (0.0001) |
| Semi-log independent | 996.1427*** (13.01) | -132.9376*** (-8.59) | 0.8703 | 73.79 (0.0000) |
| Semi-log dependent | 6.609176*** (212.39) | -.0048634*** (-85.96) | 0.9985 | 7389.53 (0.0000) |
| Double log | 8.853109*** (9.05) | -.8527719*** (-4.31) | 0.6284 | 18.60 (0.0012) |

Note: *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Predicted number of fishers for four functional forms of demand function

| Model | Predicted no. of fishers |
|---|---|
| Linear | 580 |
| Semi-log (I) | 0 |
| Semi-log (D) | 741 |
| Double log | 6996 |
| Actual | 2799 |

The semi-log dependent demand function can be written as:

Log Q =6.609176 -.0048634 P

After the inversion of equation, it becomes:

P=1358.97 -205.62 Log Q

**Townsville (Zoned model 100 km):**

Table: Regression statistics for four functional forms of the TGF for Townsville (Zoned model 100 km)

| Model | Coefficients | | | Test statistics | |
|---|---|---|---|---|---|
| | Constant (t statistic) | Travel cost (t statistic) | Personal income (t statistic) | $R^2$ | F (*P*-value) |
| Linear | .0244637** (2.13) | -.0001612* (-2.14) | -.0000231 (-1.41) | 0.1247 | 3.78 (0.0065) |
| Semi-log independent | .0142887* (1.10) | .0000562 (0.03) | -.0000111 (-0.67) | 0.0462 | 1.73 (0.1657) |
| Semi-log Dependent | -5.015125*** (-5.47) | -.0046199* (-0.80) | .000419* (0.34) | 0.3479 | 14.14 (0.0000) |

| | | | | | |
|---|---|---|---|---|---|
| Double log | -5.752703*** | .0778043* | .0007705* | 0.3454 | 13.98 |
| | (-5.43) | (0.50) | (0.64) | | (0.0000) |

Note- *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Breusch-Pagan test for heteroscedasticity

Heteroscedasticity test result for semi-log dependent model

Null hypothesis ($H_o$): Constant variance (no heteroscedasticity in residual)

Variables: fitted values of ln_visit rate

$Chi^2(1) = 4.47$

$Prob > chi^2 = 0.0834$

Table: Predicted number of fishers for four functional forms of TGF

| Model | Predicted no. of fishers |
|---|---|
| Linear | 1172 |
| Semi-log (I) | 192320 |
| Semi-log (D) | 2346 |
| Double log | 1510 |
| Actual | 2002 |

Table 6 6: Demand schedules for Townsville (Zoned model 100 km)

| Increase in travel cost in ($) (P) | Number of visits |
|---|---|
| 0 | 2346 |
| 50 | 1827 |
| 100 | 1422 |
| 300 | 523 |
| 500 | 192 |
| 1000 | 15 |
| 3000 | 0 |

Table: Regression statistics for four functional forms of demand for Townsville (Zoned model 100 km)

| Model | Coefficients | | Test statistics | |
|---|---|---|---|---|
| | Constant (t statistic) | Increase in travel cost (t statistic) | $R^2$ | F (*P*-value) |
| Linear | 1588.777*** (6.32) | -1.183442*** (-3.49) | 0.5749 | 12.17 (0.0068) |
| Semi-log independent | 2931.808*** (12.02) | -395.7242*** (-8.48) | 0.8887 | 71.86 (0.0000) |
| Semi-log dependent | 7.545879*** (48.79) | -.0040925*** (-19.60) | 0.9771 | 384.06 (0.0000) |
| Double log | 9.8673*** (8.29) | -.8791885*** (-3.86) | 0.6234 | 14.90 (0.0038) |

Note: *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Predicted number of fishers for four functional forms of demand function

| Model | Predicted no. of fishers |
|---|---|
| Linear | 1588 |
| Semi-log (I) | 0 |
| Semi-log (D) | 1892 |
| Double log | 19289 |
| Actual | 2002 |

The semi-log dependent demand function can be written as:

Log Q= 7.545879 - .0040925 P

After the inversion of equation, it becomes:

P = 1243.83 -244.35 Log Q

**Hinchinbrook (Zoned model 100 km):**

Table: Regression statistics for four functional forms of the TGF for Hinchinbrook (Zoned model 100 km)

| Model | Coefficients | | | Test statistics | |
|---|---|---|---|---|---|
| | Constant (t statistic) | Travel cost (t statistic) | Personal income (t statistic) | $R^2$ | F (*P*-value) |
| Linear | .0244637** (2.13) | -.0001612* (-2.14) | -.0000231 (-1.41) | 0.1247 | 3.78 (0.0065) |
| Semi-log independent | .0204902* (1.58) | -.001871 (-0.94) | -.000016 (-0.97) | 0.0945 | 2.77 (0.0312) |
| Semi-log Dependent | -7.680069*** (-8.61) | -.0058919* (0.347) | .000124* (0.10) | 0.3647 | 8.45 (0.0000) |
| Double log | -8.007627*** (-8.14) | .2183* (1.45) | .0000363* (0.03) | 0.3228 | 10.01 (0.0000) |

Note- *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Breusch-Pagan test for heteroscedasticity

| Heteroscedasticity test result for semi-log dependent model |
|---|
| Null hypothesis ($H_o$): Constant variance (no heteroscedasticity in residual) |
| Variables: fitted values of ln_visit rate |
| $Chi^2(1)$ = 3.40 |
| Prob > $chi^2$ = 0.0920 |

Table: Predicted number of fishers for four functional forms of TGF

| Model | Predicted no. of fishers |
|---|---|
| Linear | 11483 |

| | |
|---|---|
| Semi-log (I) | 1285021 |
| Semi-log (D) | 514 |
| Double log | 677 |
| Actual | 1484 |

Table 6 6: Demand schedules for Hinchinbrook (Zoned model 100 km)

| Increase in travel cost in ($) (P) | Number of visits |
|---|---|
| 0 | 514 |
| 50 | 380 |
| 100 | 282 |
| 300 | 84 |
| 500 | 25 |
| 1000 | 1 |
| 3000 | 0 |

Table: Regression statistics for four functional forms of demand for Hinchinbrook (Zoned model 100 km)

| Model | Coefficients | | Test statistics | |
|---|---|---|---|---|
| | Constant (t statistic) | Increase in travel cost (t statistic) | $R^2$ | F (*P*-value) |
| Linear | 352.1185*** (9.91) | -.4134008*** (-5.45) | 0.6644 | 29.70 (0.0001) |
| Semi-log independent | 675.9219*** (14.85) | -95.28298*** (-10.55) | 0.8812 | 111.31 (0.0000) |
| Semi-log dependent | 6.185011*** (86.46) | -.005696*** (-37.29) | 0.9893 | 1390.69 (0.0000) |
| Double log | 8.676396*** (9.31) | -.8948035*** (-4.84) | 0.6096 | 23.42 (0.0002) |

Note: *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Predicted number of fishers for four functional forms of demand function

| Model | Predicted no. of fishers |
|---|---|
| Linear | 352 |
| Semi-log (I) | 0 |
| Semi-log (D) | 485 |
| Double log | 5862 |
| Actual | 1484 |

The semi-log dependent demand function can be written as:

Log Q= 6.185011 -.005696 P

After the inversion of equation, it becomes:

P = 1085.84 -175.56 Log Q

**Hervey Bay (Zoned model 100 km):**

Table: Regression statistics for four functional forms of the TGF for Hervey Bay (Zoned model 100 km)

| Model | Coefficients | | | Test statistics | |
|---|---|---|---|---|---|
| | Constant (t statistic) | Travel cost (t statistic) | Personal income (t statistic) | $R^2$ | F (*P*-value) |
| Linear | .024** (2.13) | -.0001** (-2.14) | -0.000023 (-.135) | 0.125 | 3.775 (0.007) |
| Semi-log independent | 0.20 (1.58) | -.002 (-.945) | -1.596E-5 (-.973) | 0.095 | 2.767 (0.031) |
| Semi-log Dependent | -7.208*** (-8.064) | .001* (.133) | .000124* (0.282) | 0.310 | 9.416 (0.000) |

| | | | | | |
|---|---|---|---|---|---|
| Double log | -5.752703*** | .0778043* | .0007705* | 0.3454 | 13.98 |
| | (-5.43) | (0.50) | (0.64) | | (0.0000) |

Note- *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Breusch-Pagan test for heteroscedasticity

Heteroscedasticity test result for double log model

Null hypothesis ($H_o$): Constant variance (no heteroscedasticity in residual)

Variables: fitted values of ln_visit rate

$Chi^2(1) = 2.17$

Prob > $chi^2$ = 0.1411

Table: Predicted number of fishers for four functional forms of TGF

| Model | Predicted no. of fishers |
|---|---|
| Linear | 1817 |
| Semi-log (I) | 107527 |
| Semi-log (D) | 86 |
| Double log | 703 |
| Actual | 2013 |

Table 6 6: Demand schedules for Hervey Bay (Zoned model 100 km)

| Increase in travel cost in ($) (P) | Number of visits |
|---|---|
| 0 | 703 |
| 50 | 388 |
| 100 | 287 |
| 300 | 93 |
| 500 | 0 |

Table: Regression statistics for four functional forms of demand for Hervey Bay (Zoned model 100 km)

| Model | Coefficients | | Test statistics | |
|---|---|---|---|---|
| | Constant (t statistic) | Increase in travel cost (t statistic) | $R^2$ | F (*P*-value) |
| Linear | 477.0808*** (12.69) | -1.132205*** (-6.55) | 0.8111 | 42.93 (0.0001) |
| Semi-log independent | 791.87 *** (18.69) | -115.9516 *** (-12.30) | 0.9380 | 151.29 (0.0000) |
| Semi-log dependent | 6.636753*** (23.79) | -.010154*** (-7.92) | 0.8625 | 62.73 (0.0000) |
| Double log | 8.011977*** (7.26) | -.6934619*** (-2.82) | 0.4436 | 7.97 (0.0181) |

Note: *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Predicted number of fishers for four functional forms of demand function

| Model | Predicted no. of fishers |
|---|---|
| Linear | 477 |
| Semi-log (I) | 0 |
| Semi-log (D) | 762 |
| Double log | 3016 |
| Actual | 2013 |

The semi-log dependent demand function can be written as:

Log Q= 6.636753 -.010154 P

After the inversion of equation, it becomes:

P = 653.58 -98.48 Log Q

## Zoned model 300 km

**Cairns (Zoned model 300 km):**

Table: Regression statistics for four functional forms of the TGF for Cairns (Zoned model 300 km)

| Model | Coefficients | | | Test statistics | |
|---|---|---|---|---|---|
| | Constant (t statistic) | Travel cost (t statistic) | Personal income (t statistic) | $R^2$ | F (*P*-value) |
| Linear | .014** (2.27) | -2.685E-5** (-2.68) | -1.024E-5 (-.112) | 0.103 | 5.165 (0.001) |
| Semi-log independent | 0.20** (2.93) | -.002* (-2.505) | -1.362E-5 (-1.495) | 0.099 | 4.919 (0.001) |
| Semi-log Dependent | -6.512*** (-11.459) | -.006** (-6.217) | .0001* (0.135) | 0.328 | 17.509 (0.0000) |
| Double log | -5.699** (-7.384) | -.162* (-1.699) | -.001* (-.798) | .318 | 11.77 (0.0000) |

Note- *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Breusch-Pagan test for heteroscedasticity

| Heteroscedasticity test result for linear model |
|---|
| Null hypothesis ($H_o$): Constant variance (no heteroscedasticity in residual) |
| Variables: fitted values of ln_visit rate |
| $Chi^2(1) = 1.27$ |
| Prob > $chi^2$ = 0.2616 |

Table: Predicted number of fishers for four functional forms of TGF

| Model | Predicted no. of fishers |
|---|---|

| | |
|---|---|
| Linear | 1341 |
| Semi-log (I) | 211166 |
| Semi-log (D) | 505 |
| Double log | 224 |
| Actual | 1045 |

Table 6 6: Demand schedules for Cairns (Zoned model 300 km)

| Increase in travel cost in ($) (P) | Number of visits |
|---|---|
| 0 | 1341 |
| 50 | 1059 |
| 100 | 777 |
| 300 | 0 |

Table: Regression statistics for four functional forms of demand for Cairns (Zoned model 300 km)

| Model | Coefficients | | Test statistics | |
|---|---|---|---|---|
| | Constant (t statistic) | Increase in travel cost (t statistic) | $R^2$ | F (*P*-value) |
| Linear | 1334.294*** (173.23) | -5.453776 *** (-81.08) | 0.9989 | 6573.28 (0.0000) |
| Semi-log independent | 1730.954 *** (6.93) | -232.8606*** (-3.61) | 0.6501 | 13.01 (0.0087) |
| Semi-log dependent | 7.833457*** (13.83) | -.0228036*** (-4.61) | 0.7523 | 21.25 (0.0025) |
| Double log | 8.892809*** (5.36) | -.8036683* (-1.87) | 0.3336 | 3.50 (0.0134) |

Note: *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Predicted number of fishers for four functional forms of demand function

| Model | Predicted no. of fishers |
|---|---|
| Linear | 1334 |
| Semi-log (I) | 0 |
| Semi-log (D) | 2523 |
| Double log | 7279 |
| Actual | 1045 |

The semi-log dependent demand function can be written as:

Log Q= 7.833457 - 0.0228036 P

After the inversion of equation, it becomes:

P = 343.497 -43.85 Log Q

**Mackay (Zoned model 300 km):**

Table: Regression statistics for four functional forms of the TGF for Mackay (Zoned model 300 km)

| Model | Coefficients | | | Test statistics | |
|---|---|---|---|---|---|
| | Constant (t statistic) | Travel cost (t statistic) | Personal income (t statistic) | $R^2$ | F (*P*-value) |
| Linear | .019** (2.971) | -4.320E-5* (-3.715) | -5.457E-6 (-.598) | 0.081 | 3.944 (0.004) |
| Semi-log independent | .036*** (4.158) | -.002*** (-2.318) | -1.362E-5* (-1.492) | 0.102 | 3.36 (0.004) |
| Semi-log Dependent | -5.026*** (-8.41) | -.004*** (-3.749) | -6.484E-5* (-.079) | 0.355 | 19.66 (0.0000) |

| | | | | | |
|---|---|---|---|---|---|
| Double log | -4.582*** | -.146* | -.001* | 0.313 | 16.316 |
| | (-6.255) | (-1.550) | (-.721) | | (0.0000) |

Note- *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Breusch-Pagan test for heteroscedasticity

| Heteroscedasticity test result for semi-log dependent model |
|---|
| Null hypothesis ($H_o$): Constant variance (no heteroscedasticity in residual) |
| Variables: fitted values of ln_visit rate |
| $Chi^2(1)$ = 1.46 |
| Prob > $chi^2$ = 0.2268 |

Table: Predicted number of fishers for four functional forms of TGF

| Model | Predicted no. of fishers |
|---|---|
| Linear | 2022 |
| Semi-log (I) | 191828 |
| Semi-log (D) | 826 |
| Double log | 498 |
| Actual | 2038 |

Table 6 6: Demand schedules for Mackay (Zoned model 300 km)

| Increase in travel cost in ($) (P) | Number of visits |
|---|---|
| 0 | 826 |
| 50 | 676 |
| 100 | 553 |
| 300 | 248 |
| 500 | 111 |
| 1000 | 15 |
| 3000 | 0 |

Table: Regression statistics for four functional forms of demand for Mackay (Zoned model 300 km)

| Model | Coefficients | | Test statistics | |
|---|---|---|---|---|
| | Constant (t statistic) | Increase in travel cost (t statistic) | $R^2$ | F (*P*-value) |
| Linear | 563.0205*** (6.66) | -.272254*** (-3.09) | 0.4880 | 9.53 (0.0115) |
| Semi-log independent | 1065.482*** (12.22) | -136.8104*** (-8.08) | 0.8671 | 65.22 (0.0000) |
| Semi-log dependent | 6.329598*** (29.85) | -.0023554*** (-10.65) | 0.9190 | 113.46 (0.0000) |
| Double log | 8.637374*** (9.68) | -.7468761*** (-4.31) | 0.6501 | 18.58 (0.0015) |

Note: *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Predicted number of fishers for four functional forms of demand function

| Model | Predicted no. of fishers |
|---|---|
| Linear | 563 |
| Semi-log (I) | 0 |
| Semi-log (D) | 560 |
| Double log | 5638 |
| Actual | 2038 |

The semi-log dependent demand function can be written as:

Log Q= 6.329598 -.0023554 P

After the inversion of equation, it becomes:

P= 2687.29 - 424.56 Log Q

**Rockhampton (Zoned model 300 km):**

Table: Regression statistics for four functional forms of the TGF for Rockhampton (Zoned model 300 km)

| Model | Coefficients | | | Test statistics | |
|---|---|---|---|---|---|
| | Constant (t statistic) | Travel cost (t statistic) | Personal income (t statistic) | $R^2$ | F (*P*-value) |
| Linear | .019*** (2.971) | -4.320E-5*** (-3.715) | -5.457E-6 (-.598) | 0.081 | 3.944 (0.004) |
| Semi-log independent | .036*** (4.158) | -.002** (-2.318) | -1.362E-5 (-1.492) | 0.102 | 3.36 (0.004) |
| Semi-log Dependent | -5.026*** (-8.411) | -.004* (-3.749) | -6.484E-5* (-.079) | 0.355 | 19.66 (0.0000) |
| Double log | -4.582*** (-6.255) | -.146* (-1.550) | -.001* (-.721) | 0.313 | 16.316 (0.0000) |

Note- *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Breusch-Pagan test for heteroscedasticity

| Heteroscedasticity test result for semi-log dependent model |
|---|
| Null hypothesis ($H_o$): Constant variance (no heteroscedasticity in residual) |
| Variables: fitted values of ln_visit rate |
| $Chi^2(1)$ = 1.46 |
| Prob > $chi^2$ = 0.2268 |

Table: Predicted number of fishers for four functional forms of TGF

| Model | Predicted no. of fishers |
|---|---|
| Linear | 2188 |

| | |
|---|---|
| Semi-log (I) | 278327 |
| Semi-log (D) | 1009 |
| Double log | 801 |
| Actual | 2888 |

Table 6 6: Demand schedules for Rockhampton (Zoned model 300 km)

| Increase in travel cost in ($) (P) | Number of visits |
|---|---|
| 0 | 1009 |
| 50 | 826 |
| 100 | 676 |
| 300 | 304 |
| 500 | 136 |
| 1000 | 18 |
| 3000 | 0 |

Table: Regression statistics for four functional forms of demand for Rockhampton (Zoned model 300 km)

| Model | Coefficients | | Test statistics | |
|---|---|---|---|---|
| | Constant (t statistic) | Increase in travel cost (t statistic) | $R^2$ | F (*P*-value) |
| Linear | 721.6052*** (10.14) | -.6018774*** (-4.97) | 0.6384 | 24.71 (0.0002) |
| Semi-log independent | 1342.058*** (13.72) | -174.7019*** (-9.16) | 0.8569 | 83.85 (0.0000) |
| Semi-log dependent | 6.892557*** (446.67) | -.0038887 *** (-148.09) | 0.9994 | 21931.22 (0.0000) |
| Double log | 8.931727*** (9.86) | -.7164157*** (-4.06) | 0.5404 | 16.46 (0.0012) |

Note: *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Predicted number of fishers for four functional forms of demand function

| Model | Predicted no. of fishers |
|---|---|
| Linear | 721 |
| Semi-log (I) | 0 |
| Semi-log (D) | 984 |
| Double log | 7568 |
| Actual | 2888 |

The semi-log dependent demand function can be written as:

Log Q= 7.073234-0.0089995 P

After the inversion of equation, it becomes:

P=785.907 – 111.11 Log Q

**Townsville (Zoned model 300 km):**

Table: Regression statistics for four functional forms of the TGF for Townsville (Zoned model 300 km)

| Model | Coefficients | | | Test statistics | |
|---|---|---|---|---|---|
| | Constant (t statistic) | Travel cost (t statistic) | Personal income (t statistic) | $R^2$ | F (*P*-value) |
| Linear | .014** (2.269) | -2.685E-5* (-2.683) | -1.024E-5 (-1.119) | 0.103 | 5.165 (0.001) |
| Semi-log independent | .020* (2.933) | -.002 (-2.505) | -1.362E-5 (-1.495) | 0.099 | 4.919 (0.001) |
| Semi-log Dependent | -5.026*** (-8.411) | -.004* (-3.749) | -6.484E-5* (-.079) | 0.355 | 19.66 (0.0000) |

| | | | | | |
|---|---|---|---|---|---|
| Double log | -4.582*** | -.146* | -.001* | 0.313 | 16.316 |
| | (-6.255) | (-1.55) | (-.721) | | (0.0000) |

Note- *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Breusch-Pagan test for heteroscedasticity

Heteroscedasticity test result for semi-log dependent model

Null hypothesis ($H_o$): Constant variance (no heteroscedasticity in residual)

Variables: fitted values of ln_visit rate

$Chi^2(1) = 1.46$

$Prob > chi^2 = 0.2268$

Table: Predicted number of fishers for four functional forms of TGF

| Model | Predicted no. of fishers |
|---|---|
| Linear | 1261 |
| Semi-log (I) | 225060 |
| Semi-log (D) | 1190 |
| Double log | 739 |
| Actual | 2018 |

Table 6 6: Demand schedules for Townsville (Zoned model 300 km)

| Increase in travel cost in ($) (P) | Number of visits |
|---|---|
| 0 | 1190 |
| 50 | 974 |
| 100 | 798 |
| 300 | 358 |
| 500 | 161 |
| 1000 | 21 |
| 3000 | 0 |

Table: Regression statistics for four functional forms of demand for Townsville (Zoned model 300 km)

| Model | Coefficients | | Test statistics | |
|---|---|---|---|---|
| | Constant (t statistic) | Increase in travel cost (t statistic) | $R^2$ | F (*P*-value) |
| Linear | 822.5864*** (7.80) | -.6758266 *** (-4.39) | 0.5974 | 19.29 (0.0007) |
| Semi-log independent | 1570.368*** (13.41) | -211.2421*** (-9.68) | 0.8781 | 93.66 (0.0000) |
| Semi-log dependent | 6.984521*** (132.67) | -.0036537*** (-47.56) | 0.9943 | 2261.91 (0.0000) |
| Double log | 8.967069*** (10.01) | -.7276056*** (-4.35) | 0.5932 | 18.96 (0.0008) |

Note: *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Predicted number of fishers for four functional forms of demand function

| Model | Predicted no. of fishers |
|---|---|
| Linear | 822 |
| Semi-log (I) | 0 |
| Semi-log (D) | 1079 |
| Double log | 7840 |
| Actual | 2018 |

The semi-log dependent demand function can be written as:

Log Q = 6.984521 -.0036537P

After the inversion of equation, it becomes:

P= 1911.59-273.69 Log Q

**Hinchinbrook (Zoned model 300 km):**

Table: Regression statistics for four functional forms of the TGF for Hinchinbrook (Zoned model 300 km)

| Model | Coefficients | | | Test statistics | |
|---|---|---|---|---|---|
| | Constant (t statistic) | Travel cost (t statistic) | Personal income (t statistic) | $R^2$ | F (*P*-value) |
| Linear | .014** (2.269) | -2.685E-5* (-2.683) | -1.024E-5 (-1.12) | 0.103 | 5.165 (0.001) |
| Semi-log independent | .020* (2.93) | -.002 (-2.505) | -1.362E-5 (-1.495) | 0.099 | 4.919 (0.001) |
| Semi-log Dependent | -7.197*** (-13.32) | -.005* (-5.085) | .000124* (0.138) | 0.361 | 16.76 (0.0000) |
| Double log | -6.594*** (-10.345) | -.247* (-3.258) | -.001* (-.764) | 0.309 | 13.29 (0.0000) |

Note- *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Breusch-Pagan test for heteroscedasticity

| Heteroscedasticity test result for semi-log dependent model |
|---|
| Null hypothesis ($H_o$): Constant variance (no heteroscedasticity in residual) |
| Variables: fitted values of ln_visit rate |
| $Chi^2(1) = 1.46$ |
| Prob > $chi^2$ = 0.2268 |

Table: Predicted number of fishers for four functional forms of TGF

| Model | Predicted no. of fishers |
|---|---|
| Linear | 8961 |

| | |
|---|---|
| Semi-log (I) | 1517332 |
| Semi-log (D) | 1004 |
| Double log | 608 |
| Actual | 1669 |

Table 6 6: Demand schedules for Hinchinbrook (Zoned model 300 km)

| Increase in travel cost in ($) (P) | Number of visits |
|---|---|
| 0 | 1004 |
| 50 | 782 |
| 100 | 609 |
| 300 | 224 |
| 500 | 82 |
| 1000 | 6 |
| 3000 | 0 |

Table: Regression statistics for four functional forms of demand for Hinchinbrook (Zoned model 300 km)

| Model | Coefficients | | Test statistics | |
|---|---|---|---|---|
| | Constant (t statistic) | Increase in travel cost (t statistic) | $R^2$ | F (*P*-value) |
| Linear | 750.7339 *** (8.50) | -.6974937*** (-4.91) | 0.7280 | 24.09 (0.0008) |
| Semi-log independent | 1270.638 *** (11.85) | -171.6926*** (8.18) | 0.8814 | 66.86 (0.0000) |
| Semi-log dependent | 6.855158*** (113.82) | -.0047674*** (-49.20) | 0.9963 | 2420.56 (0.0000) |
| Double log | 8.945032*** (8.25) | -.8579596*** (-4.04) | 0.6447 | 16.33 (0.0029) |

Note: *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Predicted number of fishers for four functional forms of demand function

| Model | Predicted no. of fishers |
|---|---|
| Linear | 750 |
| Semi-log (I) | 0 |
| Semi-log (D) | 948 |
| Double log | 7669 |
| Actual | 1669 |

The semi-log dependent demand function can be written as:

Log Q=6.855158 - 0.0047674 P

After the inversion of equation, it becomes:

P= 1437.86 -209.75 Log Q

**Hervey Bay (Zoned model 300 km):**

Table: Regression statistics for four functional forms of the TGF for Hervey Bay (Zoned model 300 km)

| Model | Coefficients | | | Test statistics | |
|---|---|---|---|---|---|
| | Constant (t statistic) | Travel cost (t statistic) | Personal income (t statistic) | $R^2$ | F (*P*-value) |
| Linear | .014** (2.27) | -2.685E-5** (-2.68) | -1.024E-5 (-1.12) | 0.103 | 5.165 (0.001) |
| Semi-log independent | 0.20 (2.933) | -.002 (-2.505) | -1.362E-5 (-1.495) | 0.099 | 4.919 (0.001) |
| Semi-log Dependent | -7.054*** (-13.12) | -.005* (5.46) | -.000124* (-0.171) | 0.350 | 19.28 (0.000) |

| | | | | | |
|---|---|---|---|---|---|
| Double log | -6.594*** | -.247* | -.001* | 0.309 | 13.29 |
| | (-10.34) | (3.258) | (-0.764) | | (0.0000) |

Note- *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Breusch-Pagan test for heteroscedasticity

Heteroscedasticity test result for semi-log dependent model

Null hypothesis ($H_o$): Constant variance (no heteroscedasticity in residual)

Variables: fitted values of ln_visit rate

$Chi^2(1) = 1.46$

Prob > $chi^2 = 0.2268$

Table: Predicted number of fishers for four functional forms of TGF

| Model | Predicted no. of fishers |
|---|---|
| Linear | 12082 |
| Semi-log (I) | 975700 |
| Semi-log (D) | 264 |
| Double log | 197 |
| Actual | 2127 |

Table 6 6: Demand schedules for Hervey Bay (Zoned model 300 km)

| Increase in travel cost in ($) (P) | Number of visits |
|---|---|
| 0 | 264 |
| 50 | 206 |
| 100 | 160 |
| 300 | 59 |
| 500 | 21 |
| 1000 | 1 |
| 3000 | 0 |

Table: Regression statistics for four functional forms of demand for Hervey Bay (Zoned model 300 km)

| Model | Coefficients | | Test statistics | |
|---|---|---|---|---|
| | Constant (t statistic) | Increase in travel cost (t statistic) | $R^2$ | F (*P*-value) |
| Linear | 180.7148*** (8.22) | -.1895888*** (-5.13) | 0.6690 | 26.27 (0.0002) |
| Semi-log independent | 341.7533*** (12.90) | -47.63511*** (-9.71) | 0.8788 | 94.29 (0.0000) |
| Semi-log dependent | 5.385463*** (30.72) | -.0043903*** (14.88) | 0.9446 | 221.54 (0.0000) |
| Double log | 7.569573*** (8.60) | -.7967879*** (-4.89) | 0.6475 | 23.88 (0.0003) |

Note: *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Predicted number of fishers for four functional forms of demand function

| Model | Predicted no. of fishers |
|---|---|
| Linear | 180 |
| Semi-log (I) | 0 |
| Semi-log (D) | 218 |
| Double log | 1938 |
| Actual | 2127 |

The semi-log dependent demand function can be written as:

Log Q= 5.385463 - 0.0043903 P

After the inversion of equation, it becomes:

P= 1370.64 -227.77 Log Q

## Model 3: Geographic model

**Cairns (Geographic model):**

Table: Regression statistics for four functional forms of the TGF for Cairns (Geographic model)

| Model | Coefficients | | | Test statistics | |
|---|---|---|---|---|---|
| | Constant (t statistic) | Travel cost (t statistic) | Personal income (t statistic) | $R^2$ | F (*P*-value) |
| Linear | .0023358 (0.34) | -7.08e-07 ** (-2.75) | -1.86e-06 (-1.47) | 0.8541 | 16.42 (0.0005) |
| Semi-log independent | .0027674 * (1.90) | -.0003328*** (-5.08) | -4.80e-07 (-0.71) | 0.8736 | 37.09 (0.0000) |
| Semi-log Dependent | 4.403845 *** (5.20) | -.0043442 ** (-2.94) | -.0173035 ** (-2.92) | 0.9080 | 31.16 (0.0000) |
| Double log | 7.05026 ** (2.97) | -2.041023** (-3.74) | -.0088182** (-2.49) | 0.9123 | 41.21 (0.0000) |

Note- *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Breusch-Pagan test for heteroscedasticity

| Heteroscedasticity test result for double log model |
|---|
| Null hypothesis ($H_o$): Constant variance (no heteroscedasticity in residual) |
| Variables: fitted values of ln_visit rate |
| $Chi^2(1) = 1.50$ |
| Prob > $chi^2 = 0.1573$ |

Table: Predicted number of fishers for four functional forms of TGF

| Model | Predicted no. of fishers |
|---|---|
| Linear | 212 |
| Semi-log (I) | 3669948 |
| Semi-log (D) | 200 |
| Double log | 200 |
| Actual | 201 |

Table 6 6: Demand schedules for Cairns (Geographic model)

| Increase in travel cost in ($) (P) | Number of visits |
|---|---|
| 0 | 200 |
| 50 | 59 |
| 100 | 29 |
| 300 | 8 |
| 500 | 4 |
| 1000 | 2 |
| 3000 | 0 |

Table: Regression statistics for four functional forms of demand for Cairns (Geographic model)

| Model | Coefficients | | Test statistics | |
|---|---|---|---|---|
| | Constant (t statistic) | Increase in travel cost (t statistic) | $R^2$ | F (*P*-value) |
| Linear | 65.25489*** (4.18) | -.035962 ** (-2.20) | 0.2445 | 4.85 (0.0436) |
| Semi-log independent | 182.7499 *** (13.32) | -28.90276*** (-10.73) | 0.8847 | 115.06 (0.0000) |
| Semi-log dependent | 3.617642 *** (10.98) | -.0017222*** (-5.00) | 0.6249 | 24.99 (0.0002) |
| Double log | 6.817123 *** | -.8713376*** | 0.8960 | 129.19 (0.0000) |

| | | |
|---|---|---|
| | (17.47) | (-11.37) |

Note: *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Predicted number of fishers for four functional forms of demand function

| Model | Predicted no. of fishers |
|---|---|
| Linear | 65 |
| Semi-log (I) | 0 |
| Semi-log (D) | 37 |
| Double log | 913 |
| Actual | 201 |

The double-log demand function can be written as:

Log Q= 6.817123-.8713376 Log P

After the inversion of equation, it becomes:

Log P= 7.84 - 1.15 Log Q

**Mackay (Geographic model):**

Table: Regression statistics for four functional forms of the TGF for Mackay (Geographic model)

| Model | Coefficients | | | Test statistics | |
|---|---|---|---|---|---|
| | Constant (t statistic) | Travel cost (t statistic) | Personal income (t statistic) | $R^2$ | F (*P*-value) |
| Linear | -.0228953 (1.78) | -1.82e-06** (-0.92) | .000042 (1.87) | 0.4324 | 2.67 (0.1377) |
| Semi-log independent | .0056142*** (0.819) | -.0031705*** (-1.69) | .0000273 (1.21) | 0.5479 | 4.24 (0.0621) |

| | | | | | |
|---|---|---|---|---|---|
| Semi-log | -15.55069*** | -.0020208** | .011259 * | 0.6945 | 7.96 |
| Dependent | (-3.21) | (-3.23) | (1.58) | | (0.0158) |
| Double log | 5.438618* | -2.511396*** | .0010916* | 0.8590 | 21.32 |
| | (0.96) | (-5.55) | (0.20) | | (0.0011) |

Note- *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Breusch-Pagan test for heteroscedasticity

Heteroscedasticity test result for double log model

Null hypothesis ($H_o$): Constant variance (no heteroscedasticity in residual)

Variables: fitted values of ln_visit rate

$Chi^2(1) = 4.24$

Prob > $chi^2$ = 0.0873

Table: Predicted number of fishers for four functional forms of TGF

| Model | Predicted no. of fishers |
|---|---|
| Linear | 238 |
| Semi-log (I) | 17771375 |
| Semi-log (D) | 251 |
| Double log | 531 |
| Actual | 2094 |

Table 6 6: Demand schedules for Mackay (Geographic model)

| Increase in travel cost in ($) (P) | Number of visits |
|---|---|
| 0 | 531 |
| 50 | 262 |
| 100 | 164 |
| 300 | 59 |
| 500 | 35 |
| 1000 | 17 |

| | |
|---|---|
| 3000 | 3 |
| 5000 | 1 |
| 10000 | 0 |

Table: Regression statistics for four functional forms of demand for Mackay (Geographic model)

| Model | Coefficients | | Test statistics | |
|---|---|---|---|---|
| | Constant (t statistic) | Increase in travel cost (t statistic) | $R^2$ | F (*P*-value) |
| Linear | 196.8739** (4.84) | -.0401172 (-2.48) | 0.2661 | 6.16 (0.0238) |
| Semi-log independent | 517.0425*** (14.85) | -67.85065*** (-11.64) | 0.8885 | 135.51 (0.0000) |
| Semi-log dependent | 4.83744*** (17.00) | -.0008411*** (-7.43) | 0.7648 | 55.27 (0.0000) |
| Double log | 8.296586*** (18.21) | -.8327836*** (-10.92) | 0.8752 | 119.19 (0.0000) |

Note: *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Predicted number of fishers for four functional forms of demand function

| Model | Predicted no. of fishers |
|---|---|
| Linear | 196 |
| Semi-log (I) | 0 |
| Semi-log (D) | 126 |
| Double log | 4010 |
| Actual | 2094 |

The double log dependent demand function can be written as:

Log Q=8.296586 - 0.8327836 Log P

After the inversion of equation, it becomes:

Log P= 9.95 - 1.2 Log Q

**Rockhampton (Geographic model):**

Table: Regression statistics for four functional forms of the TGF for Rockhampton (Geographic model)

| Model | Coefficients | | | Test statistics | |
|---|---|---|---|---|---|
| | Constant (t statistic) | Travel cost (t statistic) | Personal income (t statistic) | $R^2$ | F (*P*-value) |
| Linear | .0338864 (1.13) | -1.81e-06 (-0.68) | -.0000377 (-0.79) | 0.1721 | 1.04 (0.3890) |
| Semi-log independent | .0560817** (2.67) | -.0077859 (-3.10) | 2.25e-06 (0.06) | 0.5584 | 6.32 (0.0168) |
| Semi-log Dependent | -7.157001*** (-1.08) | -.0011981*** (-2.05) | -.0021034 * (-0.20) | 0.3748 | 3.00 (0.0055) |
| Double log | 2.612668* (0.77) | -2.553089** (-6.33) | .0058684* (1.03) | 0.8224 | 23.15 (0.0002) |

Note- *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Breusch-Pagan test for heteroscedasticity

| Heteroscedasticity test result for double log model |
|---|
| Null hypothesis ($H_o$): Constant variance (no heteroscedasticity in residual)<br>Variables: fitted values of ln_visit rate<br>$Chi^2(1) = 1.25$<br>Prob > $chi^2$ = 0.2638 |

Table: Predicted number of fishers for four functional forms of TGF

| Model | Predicted no. of fishers |
|---|---|
| Linear | 101158 |
| Semi-log (I) | 20506643 |
| Semi-log (D) | 730 |
| Double log | 6165 |
| Actual | 2998 |

Table 6 6: Demand schedules for Rockhampton (Geographic model)

| Increase in travel cost in ($) (P) | Number of visits |
|---|---|
| 0 | 1009 |
| 50 | 826 |
| 100 | 676 |
| 300 | 304 |
| 500 | 136 |
| 1000 | 18 |
| 3000 | 0 |

Table: Regression statistics for four functional forms of demand for Rockhampton (Geographic model)

| Model | Coefficients | | Test statistics | |
|---|---|---|---|---|
| | Constant (t statistic) | Increase in travel cost (t statistic) | $R^2$ | F (*P*-value) |
| Linear | 1078.947** (2.47) | -.2333352*** (-1.44) | 0.1141 | 2.06 (0.1705) |
| Semi-log independent | 3509.494*** (6.06) | -495.7472*** (-5.25) | 0.6329 | 27.59 (0.0001) |
| Semi-log dependent | 5.55114 *** (11.18) | -.0009837*** (-5.32) | 0.6387 | 28.29 (0.0001) |

| | | | | |
|---|---|---|---|---|
| Double log | 9.772588*** (14.75) | -1.022751*** (-9.47) | 0.8487 | 89.73 (0.0000) |

Note: *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Predicted number of fishers for four functional forms of demand function

| Model | Predicted no. of fishers |
|---|---|
| Linear | 1078 |
| Semi-log (I) | 0 |
| Semi-log (D) | 257 |
| Double log | 17546 |
| Actual | 2998 |

The Semi-log dependent demand function can be written as:

Log Q= 5.55114 - 0.0009837 P

After the inversion of equation, it becomes:

P= 5643.12 - 1016.57 Log Q

**Townsville (Geographic model):**

Table: Regression statistics for four functional forms of the TGF for Townsville (Geographic model)

| Model | Coefficients | | | Test statistics | |
|---|---|---|---|---|---|
| | Constant (t statistic) | Travel cost (t statistic) | Personal income (t statistic) | $R^2$ | F (*P*-value) |
| Linear | .0002546* (0.02) | -1.21e-06 (-0.97) | 3.72e-06*** (0.25) | 0.1787 | 0.65 (0.5540) |
| Semi-log independent | .017639* (2.66) | -.0020856* (-4.68) | -4.57e-06* (-0.60) | 0.7288 | 13.43 (0.0015) |

| | | | | | |
|---|---|---|---|---|---|
| Semi-log | -12.14391* | -.0024462*** | .0058403* | 0.6367 | 5.26 |
| Dependent | (-1.67) | (-2.82) | (0.56) | | (0.0480) |
| Double log | -.6285831* | -1.966402** | .0032238* | 0.7674 | 9.90 |
| | (-0.09) | (-3.98) | (0.38) | | (0.0126) |

Note- *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Breusch-Pagan test for heteroscedasticity

| Heteroscedasticity test result for double log model |
|---|
| Null hypothesis ($H_o$): Constant variance (no heteroscedasticity in residual) |
| Variables: fitted values of ln_visit rate |
| $Chi^2(1) = 0.01$ |
| Prob > $chi^2$ = 0.9678 |

Table: Predicted number of fishers for four functional forms of TGF

| Model | Predicted no. of fishers |
|---|---|
| Linear | 1765 |
| Semi-log (I) | 17475351 |
| Semi-log (D) | 184 |
| Double log | 4252 |
| Actual | 2034 |

Table 6 6: Demand schedules for Townsville (Geographic model)

| Increase in travel cost in ($) (P) | Number of visits |
|---|---|
| 0 | 4252 |
| 50 | 206 |
| 100 | 120 |
| 300 | 37 |
| 500 | 24 |
| 1000 | 13 |

| | |
|---|---|
| 3000 | 4 |
| 5000 | 2 |
| 10000 | 0 |

Table: Regression statistics for four functional forms of demand for Townsville (Geographic model)

| Model | Coefficients | | Test statistics | |
|---|---|---|---|---|
| | Constant (t statistic) | Increase in travel cost (t statistic) | $R^2$ | F (*P*-value) |
| Linear | 610.1154** (2.16) | -.1008319 (-1.08) | 0.0683 | 1.17 (0.2949) |
| Semi-log independent | 2212.745*** (5.31) | -323.165*** (-4.60) | 0.5693 | 21.15 (0.0003) |
| Semi-log dependent | 5.020444*** (11.80) | -.0007226*** (-5.16) | 0.6242 | 26.58 (0.0001) |
| Double log | 9.379304*** (46.64) | -1.005954*** (-29.66) | 0.9821 | 879.49 (0.0000) |

Note: *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Predicted number of fishers for four functional forms of demand function

| Model | Predicted no. of fishers |
|---|---|
| Linear | 610 |
| Semi-log (I) | 0 |
| Semi-log (D) | 151 |
| Double log | 11840 |
| Actual | 2034 |

The Semi-log dependent demand function can be written as:

Log Q=5.020444 - 0.0007226 P

After the inversion of equation, it becomes:

P= 6947.74 -1383.89 Log Q

**Hinchinbrook (Geographic model):**

Table: Regression statistics for four functional forms of the TGF for Hinchinbrook (Geographic model)

| Model | Coefficients | | | Test statistics | |
|---|---|---|---|---|---|
| | Constant (t statistic) | Travel cost (t statistic) | Personal income (t statistic) | $R^2$ | F (*P*-value) |
| Linear | -.0124044 (-0.59) | -1.44e-06 (-0.97) | .0000275 (0.86) | 0.1014 | 0.73 (0.4992) |
| Semi-log independent | .0218785 (1.58) | -.0008127 (-0.50) | -.0000234 (-1.24) | 0.0222 | 0.83 (0.4400) |
| Semi-log Dependent | -7.002618*** (-7.63) | .0029519* (1.50) | -.0012548* (-0.92) | 0.0448 | 1.71 (0.1875) |
| Double log | -7.647277*** (-7.80) | .255711** (2.22) | -.0011095* (-0.83) | 0.0778 | 3.08 (0.0400) |

Note- *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Breusch-Pagan test for heteroscedasticity

| Heteroscedasticity test result for semi- log dependent model |
|---|
| Null hypothesis ($H_o$): Constant variance (no heteroscedasticity in residual)<br>Variables: fitted values of ln_visit rate<br>$Chi^2(1)$ = 3.17<br>Prob > $chi^2$ = 0.0751 |

Table: Predicted number of fishers for four functional forms of TGF

| Model | Predicted no. of fishers |
|---|---|
| Linear | 25904 |
| Semi-log (I) | 22716994 |
| Semi-log (D) | 1206 |
| Double log | 797 |
| Actual | 1908 |

Table 6 6: Demand schedules for Hinchinbrook (Geographic model)

| Increase in travel cost in ($) (P) | Number of visits |
|---|---|
| 0 | 1206 |
| 50 | 1145 |
| 100 | 1088 |
| 300 | 886 |
| 500 | 721 |
| 1000 | 432 |
| 3000 | 55 |
| 5000 | 7 |
| 10000 | 0 |

Table: Regression statistics for four functional forms of demand for Hinchinbrook (Geographic model)

| Model | Coefficients | | Test statistics | |
|---|---|---|---|---|
| | Constant (t statistic) | Increase in travel cost (t statistic) | $R^2$ | F (*p*-value) |
| Linear | 1008.895*** (11.14) | -.1678365*** (-5.33) | 0.7397 | 28.42 (0.0003) |
| Semi-log independent | 1612.365 *** (12.02) | -166.755*** (-7.17) | 0.8371 | 51.37 (0.0000) |

| | | | | |
|---|---|---|---|---|
| Semi-log dependent | 7.036556***<br>(99.85) | -.0009271***<br>(-37.85) | 0.9931 | 1432.74<br>(0.0000) |
| Double log | 9.110952***<br>(9.15) | -.6756549***<br>(-3.91) | 0.6047 | 15.30<br>(0.0029) |

Note: *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Predicted number of fishers for four functional forms of demand function

| Model | Predicted no. of fishers |
|---|---|
| Linear | 1032 |
| Semi-log (I) | 0 |
| Semi-log (D) | 1197 |
| Double log | 91118 |
| Actual | 1908 |

The Semi-log dependent demand function can be written as:

Log Q=7.036556 -.0009271 P

After the inversion of equation, it becomes:

P= 7589.84 -1078.63 Log Q

**Hervey Bay (Geographic model):**

Table: Regression statistics for four functional forms of the TGF for Hervey Bay (Geographic model)

| Model | Coefficients | | | Test statistics | |
|---|---|---|---|---|---|
| | Constant<br>(t statistic) | Travel cost<br>(t statistic) | Personal income<br>(t statistic) | $R^2$ | F<br>(*p*-value) |
| Linear | .0186052*<br>(5.08) | -4.30e-07* | -.0000276 *** | 0.8131 | 13.05<br>(0.0065) |

| | | | | | |
|---|---|---|---|---|---|
| | | (-0.99) | (-4.65) | | |
| Semi-log independent | .0202329*** (5.34) | -.0005285 (-1.07) | -.0000254*** (-3.83) | 0.8175 | 13.44 (0.0061) |
| Semi-log Dependent | 2.469161 (0.53) | -.0016917*** (-3.08) | -.0179484 * (-2.39) | 0.7657 | 9.80 (0.0129) |
| Double log | 8.662176* (1.86) | -1.991114*** (-3.28) | -.0097627* (-1.20) | 0.5419 | 26.02 (0.0000) |

Note- *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Breusch-Pagan test for heteroscedasticity

| Heteroscedasticity test result for linear model |
|---|
| Null hypothesis ($H_o$): Constant variance (no heteroscedasticity in residual) |
| Variables: fitted values of ln_visit rate |
| $Chi^2(1) = 0.33$ |
| Prob > $chi^2$ = 0.5651 |

Table: Predicted number of fishers for four functional forms of TGF

| Model | Predicted no. of fishers |
|---|---|
| Linear | 3065 |
| Semi-log (I) | 19195377 |
| Semi-log (D) | 1091 |
| Double log | 1168 |
| Actual | 2259 |

Table 6 6: Demand schedules for Hervey Bay (Geographic model)

| Increase in travel cost in ($) (P) | Number of visits |
|---|---|

| | |
|---|---|
| 0 | 3065 |
| 50 | 2653 |
| 100 | 2240 |
| 300 | 590 |
| 500 | 0 |

Table: Regression statistics for four functional forms of demand for Hervey Bay (Geographic model)

| Model | Coefficients | | Test statistics | |
|---|---|---|---|---|
| | Constant (t statistic) | Increase in travel cost (t statistic) | $R^2$ | F (*p*-value) |
| Linear | 3058.256 *** (415.99) | -8.17515 ** (-220.02) | 0.9998 | 48410.30 (0.0000) |
| Semi-log independent | 4004.301*** (8.19) | -506.3903*** (-4.84) | 0.6612 | 23.42 (0.0004) |
| Semi-log dependent | 8.851896 *** (14.42) | -.0129262 *** (-4.17) | 0.5912 | 17.35 (0.0013) |
| Double log | 9.505462*** (6.26) | -.6089762*** (-1.87) | 0.2262 | 3.51 (0.0857) |

Note: *** significant at 1% level, ** significant at 5% level, and * significant at 10% level

Table: Predicted number of fishers for four functional forms of demand function

| Model | Predicted no. of fishers |
|---|---|
| Linear | 3058 |
| Semi-log (I) | 0 |
| Semi-log (D) | 6987 |
| Double log | 13432 |
| Actual | 2259 |

The semi- log dependent demand function can be written as:

$$\text{Log } Q = 8.851896 - .0129262\, P$$

After the inversion of equation, it becomes:

$$P = 684.78 - 77.36 \text{ Log } Q$$