Sensor-based parturition detection in ewes: towards autonomous welfare assessment for sheep

by

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Abstract

The livestock industry is facing one of its biggest challenges to date: to increase productivity and meet the world's growing demand for protein, yet at the same time improve sustainability outcomes, particularly those related to social license and animal welfare. This is not a simple challenge to overcome, with the demands of increased production and animal welfare often seen as competing. However, there is one suite of technologies which may hold the answer to this problem: on-animal sensors. Many of these systems are in their commercial infancy and research is required to provide guidance on how they may be applied to solve critical industry problems linked to production and welfare. A key component of this research is exploring how the raw outputs from these sensors can be converted from large complex data to meaningful information so that a producer is alerted to a problem and can implement an intervention strategy.

This thesis examines the potential for on-animal sensor technology for autonomous detection of a key event in grazing sheep production systems: parturition. Parturition (or lambing) can be considered one of the most important periods in the breeding animal's life. It is a period of vulnerability for the mother and newborn, requiring specific physical, physiological and behavioural changes to ensure survival. Parturition is also a period of significant welfare risk both to the ewe (in the form of disease, particularly dystocia) and the lamb (from mismothering and a range of other issues).

Chapter 1 is a general introduction and briefly introduces the major concepts that will be addressed. Chapter 2 is a published manuscript and provides a general review of the use of sensor technology in sheep research. It provides an understanding of which sensors have been applied to sheep and the likely best candidates for use in my research. Chapter 3 extends this knowledge and explores how sensor technologies might be employed in welfare assessment. This chapter has also been published.

Through this scoping work (Chapters 2 and 3), Global Navigation Satellite System (GNSS) tracking and accelerometers were identified as two key sensor systems. Both are readily available and likely to provide the required information for detecting parturition-related behaviours. Since the experimental chapters (Chapters 5 - 9) were developed with the intention of publication, it was not possible to provide in-depth information on the complete data analysis process. Consequently, an additional chapter (Chapter 4) was included prior to the experimental chapters to provide more background and context for the thesis reader. This chapter outlines the data analysis methods used throughout the thesis.

Chapters 5, 6 and 7 explore how data from GNSS and accelerometers can be interpreted and related to the behavioural changes expressed by sheep around parturition. Chapter 5 is a published manuscript and reports on the value of GNSS tracking for the detection of lambing-related behaviours. This research demonstrated the value of GNSS data to monitor daily changes in movement, social activity and landscape utilisation associated with parturition. However, at the time of publication, limitations in the ability of GNSS to detect hourly changes in behaviour were evident, and so the data from accelerometer sensors were also explored. Contrasting with the results of this chapter, later analysis uncovered further potential of GNSS to detect hourly changes in behaviour using novel metrics.

To understand the potential for accelerometers to detect parturition activity, basic behavioural algorithms were first developed using machine learning (ML) classification techniques (Chapter 6). These results have been published and indicate the ability of ML to detect common behaviours from accelerometer data with an accuracy of 76.9 – 98.1 %. These algorithms were then applied in Chapter 7 to explore if the accelerometer data could be linked to parturition-related activities. Similar to Chapter 5, measurable changes in behaviour were identified and associated with parturition. In particular, ewes significantly increased their walking behaviour and the number of posture changes in the hour of parturition. This chapter has also been published.

The ultimate goal of this thesis was to determine if a near-real-time sensor-based system might be developed to detect parturition in ewes, specifically via remote monitoring of typical parturition behaviours. Chapter 8 integrates the knowledge gained in Chapters 5 and 7, building a simulated near-real-time parturition detection model that integrates the two sensor types. Overall, the final model successfully identified between 81.8% and 90.9 % of lambing events within ± 3 h of known birth, with accuracy depending on the use of different alert criteria.

Chapter 9 has been prepared as a short communication. This chapter applies the model developed in Chapter 8 and investigates the value of the model for the assessment of welfare at lambing using data gathered from an adverse lambing event (prolapsed animal). The results suggest that ewes with repeated lambing alerts that are not followed by parturition may be at-risk of an adverse event and should be closely inspected by the producer.

The final chapter (Chapter 10) is the synthesis chapter, reporting research conclusions, limitations and recommendations for future research.

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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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Declaration of co-authorship and co-contribution

Publications by the candidate relevant to this thesis

I declare that all publications included in this manuscript have not been submitted for an award by another research degree candidate or co-Author, either at CQUniversity or elsewhere.

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Abbreviations

ACC: Accelerometer

AIC: Akaike information criteria

BCS: Body condition score

CART: Classification and Regression Trees

CL: Contact logger

CP: Closest peer

CV: Cross validation

CWT: Continuous wavelet transformation

EBV: Estimated Breeding Value

EM: Environmental management

FD: Five Domains

FF: Five Freedoms

FFT: Fast Fourier transform

FN: False negative

FP: False positive

GDP: Gross Domestic Product

GNSS: Global Navigation Satellite Systems

GPS: Global Positioning System

Ha: Hectares

HDOP: Horizontal dilution of precision

HR: Heart rate monitors and echocardiograms (Chapter 2)

HR: Heart rate (Chapter 3)

Hz: Hertz

IMU: Inertial monitoring unit

IoT: Internet of Things

JB: Jaw and bite sensors

LDA: Linear Discriminant Analysis

LOOCV: Leave one out cross validation

Max_X: Maximum X

Max_Y: Maximum Y

Max_Z: Maximum Z

MCC: Mathews correlation coefficient

MCP: Minimum convex polygon

MDP: Mean distance to peers

$Mean_X$: Mean X-axis

$Mean_Y$: Mean Y-axis

$Mean_Z$: Mean Z-axis

$Mean_{XYZ}$: Mean all-axis

MEMS: Micro-electromechanical systems

MI: Movement intensity

Min_X: Minimum X

Min_Y: Minimum Y

Min_Z: Minimum Z

ML: Machine learning

MS: Motion sensors

MUAEC: Massey University Animal Ethics Committee

MV (Chapter 2 only): Methods validation

MV: Movement variation

NCL: Neuronal ceroid lipofuscinosis

PC: Posture change

PLM: Precision livestock management

QDA: Quadratic Discriminant Analysis

QoL: Quality of Life

RF: Random Forest

RFID: Radio frequency identification

RHD: Research Higher Degree

ROC: Receiver operating characteristics

SD_X: Standard deviation X

SD_Y: Standard deviation Y

SD_Z: Standard deviation Z

SD_{XYZ}: Average standard deviation (all axes)

SE: Standard error

SMA: Signal magnitude area

SOB: Store-on-board

SV: Sensor validation

SVM: Support Vector Machine

TN: True negative

TP: True positive

VHF: Very-high frequency

WLAN: Wireless local area network

WoW: Walk-over-weigh

Chapter 1. Introduction

1.1 Background

It is no secret that sheep and wool production plays a significant role in both the economies and cultures of Australia and New Zealand. The adage of "riding on the sheep's back" refers to Australia's early dependence on the wool industry and the resulting period of economic prosperity throughout the 19th and 20th centuries (Parsonson, 2000). In New Zealand, it is often quoted that there are more sheep than people, and in fact, with populations of 27.5 and 4.7 million for sheep and humans, respectively (FAO, 2017), it is actually closer to six sheep for every person. Sheep production also plays a significant economic role in both countries. In Australia, the sheep sector contributes approximately 7% (AUD$ 4.1 billion) to the gross value of agricultural production and 5% ($2.6 billion) to agricultural export income (Australian Bureau of Statistics, 2019). In New Zealand, this story is much the same. Beef and sheep production contribute approximately 3% (NZ$ 7.0 billion) to the Gross Domestic Product (GDP) (Beef and Lamb and Meat Industry Association, 2017), and wool and lamb provide NZ$ 3.4 billion in export value (Beef and Lamb, 2018). What both countries contribute on a global scale is also significant. When combined, Australia and New Zealand provide 87% of sheep meat exports (FAO, 2018) and constitute the largest (Australia) and third largest (New Zealand) suppliers of wool (Beef and Lamb, 2018, Department of Agriculture and Water Resources, 2018b). It is therefore easy to see why the continued prosperity of the sheep industry is so important, not just locally, but globally. However, this may not be as simple as it seems. As we move through the 21st century, livestock producers are being challenged with conflicting pressures: to increase production efficiency while also improving environmental sustainability. Furthermore, producers have to deal with another key challenge: social concern for animal welfare. A contributing solution to this may be the application of sensor technology.

This chapter provides a brief introduction to sensor technology, animal welfare and the integration of these two areas of research for improved welfare monitoring in pasture-based sheep. More thorough reviews of the above topics are presented later in the thesis in both the systematic review chapters (Chapters 2 and 3) and in the introduction and discussion of experimental chapters (Chapters 5 to 9).

1.2 A brief introduction to sensor technology

Sensors are devices that detect or measure data from an observable element (e.g. movement, temperature), recording the input or otherwise responding in a certain way (AgriFutures Australia, 2016). Driven largely by the rise of small, cost-effective electronics (Watanabe et al., 2008) and the Internet of Things (IoT) (Smith et al., 2015), sensors are now being used for a multitude of purposes (Ahmad et al., 2017). One purpose is for the remote monitoring of animals. Remote monitoring of animals is far from a novel concept. First adopted in the 1950s, tracking technologies such as very-high frequency (VHF) transmitters were used for observational wildlife research (Turner et al., 2000). Later, location technologies such as the Global Navigation Satellite System (GNSS) were introduced (Swain et al., 2011), followed closely by other sensor types including accelerometers, magnetometers, audio, proximity, heart rate monitors and cameras (Fogarty et al., 2018, Wilmers et al., 2015). In livestock production, research involving the application of remote monitoring technology has been conducted in a number of species, including sheep (Broster et al., 2010, Broster et al., 2017, Fogarty et al., 2020a, Fogarty et al., 2018, Dobos et al., 2014, Dobos et al., 2015, Fogarty et al., 2015, Fogarty et al., 2020b), cows (Finger et al., 2014, Guo et al., 2009, Handcock et al., 2009, Huzzey et al., 2005, Manning et al., 2017) and pigs (Cornou and Lundbye-Christensen, 2012, Pastell et al., 2016, Thompson et al., 2016).

In addition to research, sensor technologies are increasingly being developed for application in the commercial livestock sector (Trotter et al., 2018). In intensive livestock production systems, technologies have also been embraced by producers, for example: automated egg counting and bird weighing in poultry systems (Cronin et al., 2008); and automated feed systems, environment control and growth data in piggeries (Banhazi et al., 2012). The dairy industry uses wearable health monitors (Neethirajan, 2017) and collection of detailed production and milk quality data is a common practice (Banhazi et al., 2012). In contrast, extensive animal industries are yet to fully embrace these technologies, although investment from companies [e.g. Herddogg (HerdDogg, 2019), Allflex (Allflex, 2018)] and levy agencies [e.g. Australian Wool Innovation (Australian Wool Innovation, 2015)] is growing (Trotter, 2013, Trotter et al., 2018).

1.2.1 Types of sensors

Sensors for the livestock industries can be categorised into three main groups: (i) on-animal sensors; (ii) off-animal sensors; and (iii) in-animal sensors. On-animal sensors are those that are attached to the animal, e.g. ear tag or collar attachment. These devices collect information on the animal itself, including movement, function or measurable behaviour patterns (Fogarty et al., 2018). Off-animal sensors, including walk-over-weigh (WoW), automated drafting and low-cost cameras (Trotter, 2013, Wathes et al., 2008), do not physically attach to the animal, but still record various features of the animal being examined, e.g. body weight (via WoW). In-animal sensors such as rumen bolus or implantable devices collect data on the internal state of an animal (Rose-Dye et al., 2011). An additional group of sensors not previously identified are environmental sensors. These sensors are more applicable to wider agricultural enterprises rather than livestock in particular and include technologies such as soil moisture probes, pasture sensors and weather stations (Trotter, 2013). Environmental sensors can be attached to a number of platforms including motor vehicles, unmanned aerial vehicles (i.e. drones), satellites, water pumps and irrigation systems (AgriFutures Australia, 2016). As a whole, sensors provide increased surveillance and monitoring capacity and support for decision-making processes.

1.2.2 Communicating, managing and analysing the data from sensors

It is essential that the information captured by sensors be adequately interpreted and conveyed to the livestock producer. Furthermore, due to the volume of data that can be collected, data transfer and communication is a critical issue (Smith et al., 2015). This is particularly important for remote sensing devices, where the sensor itself may be physically distant from a central server and/or from the producer themselves (AgriFutures Australia, 2016). Current options for data transfer include wireless Bluetooth and ZigBee (Wathes et al., 2008), mobile communications (e.g. 3G, 4G, 5G) and long-range area networks (WLAN) (AgriFutures Australia, 2016). Since data transmission requires a large amount of power, compression of data or embedded processing is generally recognised as being important (Handcock et al., 2009).

1.3 A brief introduction to animal welfare

Animal welfare refers to the sentient individual's perception of its own physical and emotional state, including its ability to cope and quality of life (Webster, 2016). Public concern and the request for high welfare standards has increased in recent years (Kaurivi et al., 2019), with the widespread belief that increased farming intensity leads to poor welfare outcomes (Dawkins, 2017). In one survey conducted with the Australian public, 71 % of respondents considered farm animal welfare to be a moderate to serious issue (Department of Agriculture and Water Resources, 2018a). In New Zealand, when asked "have you ever had concerns about the way farm animals are typically treated in New Zealand?", 60 % of veterinarian and 50 % livestock officers indicated that they have had concerns. Forty-one percent of the general public and 34 % of farmers also indicated they had concerns (Loveridge, 2013). In a survey by the European Commission, the majority of respondents noted that animal welfare was of great importance (average score of 7.8 out of 10) and 62 % indicated that they would be willing to change their shopping habits to buy more welfare-friendly products (European Commission, 2007). In the United States, 36 % of respondents considered animal welfare 'somewhat important', with a further 22 % indicating 'very important' and 11 % as 'extremely important' (Grimshaw et al., 2014). These surveys highlight global animal welfare concern, emphasising the substantial challenge being faced by the sheep industry and wider animal agriculture.

1.3.1 Welfare in sheep production systems

In Australia and New Zealand, the majority of sheep production based on extensive grazing landscapes (Beef and Lamb, 2017, Australian Bureau of Statistics, 2012). This means that large flock numbers are run over sizeable pasture or rangeland environments, typically with low producer input (Petherick, 2006). In the previously referenced survey of the Australian public (Department of Agriculture and Water Resources, 2018a), 25 % of respondents identified overcrowding and space restriction as a significant welfare issue. This was closely followed by concern for intensive farming (22 %) and indoor confinement (21 %). Of the 24 concerns identified, only three are exclusive to extensive (beef or sheep) production (dehorning, mulesing and branding). Thus, it is clear that extensive systems are of less concern to the public, which is very likely due to their perception as being more "natural" (Dwyer, 2009,

Goddard et al., 2006). Although extensive production provides animals with considerably more behavioural freedom (Lynch et al., 1992), this does not mean that they are exempt from any welfare challenges (Dwyer, 2009, Bailey, 2016, Waterhouse, 2019). In fact, one of the major problems in extensive sheep systems is the stockperson's ability to regularly inspect the animals (Petherick and Edge, 2010), which is ironically due to this provision of 'freedom' and space. The inability to inspect animals can impact early detection of problems and is a significant welfare issue that should not be overlooked (Dwyer, 2009, Petherick and Edge, 2010). As consumers' concerns for animal welfare continue to rise, it seems likely that the focus will eventually turn to extensive production systems. It is this prospect, in addition to the general ethics associated with producing animals for human use, that is encouraging the industry to find methods of improving welfare.

Further to bracing for requested increases in welfare standards (Kaurivi et al., 2019), welfare improvement should also be considered from a productivity and profitability standpoint. There are a number of financial benefits associated with good welfare, including reduced morbidity and mortality, resistance to disease and improved product quality (Dawkins, 2017). For example, maternal undernutrition and inadequate shelter are known contributors to lamb mortality in Australia (Hinch and Brien, 2014). This clearly also contributes to lowered reproductive efficiency and results in economic losses (Dawkins, 2017). Conversely, improved overall health can improve farm profits through reduction of medication and treatment requirements, and increase in animal growth and condition (Green et al., 2012). While it is incorrect to assume that all welfare improvements will result in commercial gain (Dawkins, 2017), these benefits should not be overlooked and may actually help to encourage producer uptake of welfare-positive changes.

1.3.2 How do we monitor animal welfare?

Animal welfare, and our ability to adequately measure and monitor it, has remained a topic for research and debate for decades (Green and Mellor, 2011). Over the years, various principles of animal welfare have been developed, including the Five Freedoms (FF) (Webster, 2016), the Five Domains Model (FD) (Mellor and Reid, 1994) and concepts of Quality of Life (QoL) (Green and Mellor, 2011, FAWC, 2009). These ideas encompass three major orientations of animal welfare: biological functioning, affective states and natural living

(Hemsworth et al., 2015) and have provided foundational knowledge for the development of welfare guidelines, for instance the World Organisation for Animal Health's 'General Principles for the Welfare of Animals in Livestock Production Systems' (Fraser et al., 2013) and the European Union's 'Welfare Quality® Project' (Welfare Quality Network, 2018). While the various guidelines may differ in application, the overall goal is arguably similar: to minimise negative welfare and maximise positive welfare through adequate monitoring and assessment programs.

1.4 Sensor technology for welfare assessment

Current welfare assessments generally provide a 'snapshot' of the animal's state at a particular point in time (Rushen and de Passille, 2012). However, as welfare varies over time this approach is limited and may result in inadequate consideration of chronic stress (Webster, 2016). In contrast, 'lifelong' animal welfare monitoring refers to the continued assessment of welfare throughout the duration of the animal's life, not just during times of potential elevated stress. As availability of sensor technology for extensive animal industries continues to expand, the use of devices for animal welfare monitoring are becoming more important. Automatically assessing welfare could improve both the quality of assessment, by reducing inter-observer differences, and also the quantity of data used to make a decision through constant (or near constant) data recording (Rushen and de Passille, 2012).

1.5 Thesis context

The ability to quantify animal welfare for the life of the animal has value for livestock managers. This thesis was undertaken as a component of a larger research program led by The New Zealand Merino Company. The broad concept of this program was to evaluate the potential for sensors to provide an objective means of assessing lifelong welfare in sheep. While the initial intent of this thesis was to research a similarly broad area of animal welfare, it was soon discovered that the notion of lifelong monitoring was far too extensive for a single PhD to undertake. Thus, the specific scope of this PhD was refined to focus on a single critical event that impacts on the welfare of sheep from birth, specifically the parturition event itself.

1.5.1 Parturition and welfare

Parturition (or lambing in sheep) can be considered one of the most important periods of time in the breeding animal's life, particularly in a welfare context. It is a time when both the mother and newborn are vulnerable; the birth process itself is physically demanding, the behavioural and physiological changes associated with lambing and lactation are numerous, and the ewe and lamb must form an immediate and lasting bond to ensure survival (Jensen, 2012, Bickell et al., 2010). In Australia, death of lambs is a significant issue with reported losses ranging between 6% and 63% (Hinch and Brien, 2014). In New Zealand, losses are also considerable, ranging from 13% up to 30% (Dalton et al., 1980, Kerslake et al., 2005, Nicoll et al., 1999). Cause of death is often multifactorial, with starvation, mismothering and cold exposure considered to have the greatest impact on survival (Hinch and Brien, 2014). Dystocia, or difficult labour, is another major cause of neonatal mortality, often resulting in physical damage due to malpresentation or damage to the central nervous system (Hinch and Brien, 2014, Schmoelzl et al., 2015). Given that the success of parturition impacts not only the lamb's welfare, but the ewe's as well, this aspect of the sheep lifecycle was chosen as the focus for the PhD program. Welfare at lambing can also be considered to be the very first part of lifelong welfare assessment for the offspring.

1.5.2 Research questions

The research reported in this thesis focuses on the application of sensor technologies for sheep behaviour monitoring in extensive grazing environments. More specifically, on-animal sensors have been applied for sensor-based parturition detection in pasture-based ewes, with an extension of this knowledge to help develop a novel lambing alert system. Due to the importance of devising strong analytical processes, much of the thesis focuses on the data management and analytics of sensor data. This has then been contextualised across welfare assessment, with a short application of the research findings for welfare assessment at the end of the thesis.

The research questions to be answered in this thesis are:

(i) How are on-animal sensors used in sheep research and for what purpose?

(ii) How can on-animal sensors be applied to facilitate the assessment of animal welfare?

(iii) Can we detect changes in sheep behaviour at parturition using on-animal sensors?

(iv) Can we develop a simulated online model for parturition detection using data collected from both on-animal and weather sensors?

(v) Can the developed model be applied to detect an adverse welfare event during parturition?

1.6 Thesis structure

The structure of the thesis is outlined Figure 1.1. For the purpose of readability, each chapter has been treated as a distinct unit and written with the intention for publication. Though separate, each chapter is linked to form part of the overall narrative.

Chapters 2, 3, 5, 6 and 7 are published manuscripts. Chapters 8 and 9 have been prepared for publication. All published manuscripts have been reproduced in their published format. The remaining experimental chapters have been prepared in the format and referencing style requested by the journal where their submission will occur. The use of published manuscripts as thesis chapters is in accordance with CQUniversity's Policy 'Research Higher Degree Theses Policy and Procedure'.

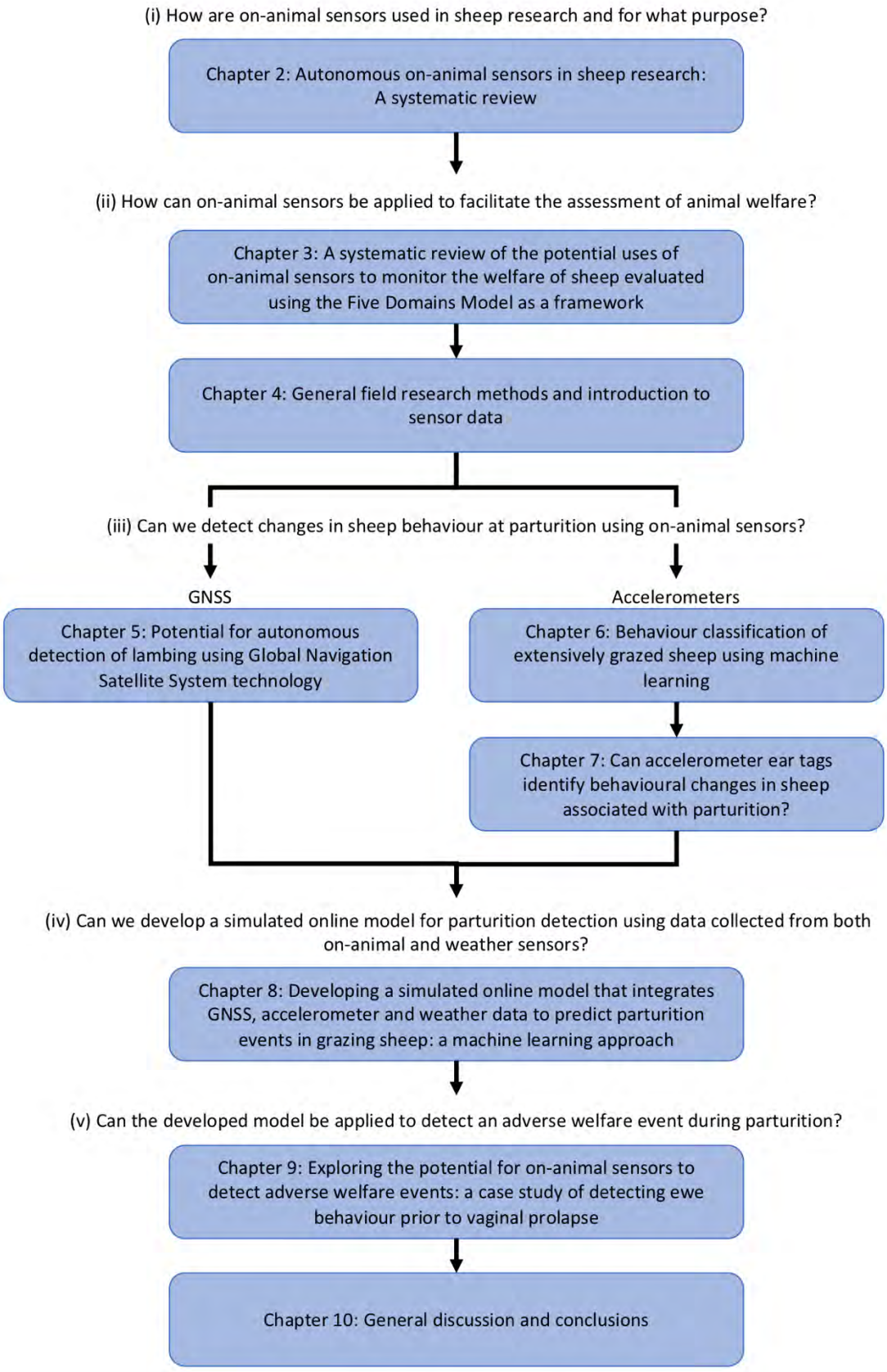

Figure 1.1 Schematic outline of the thesis structure

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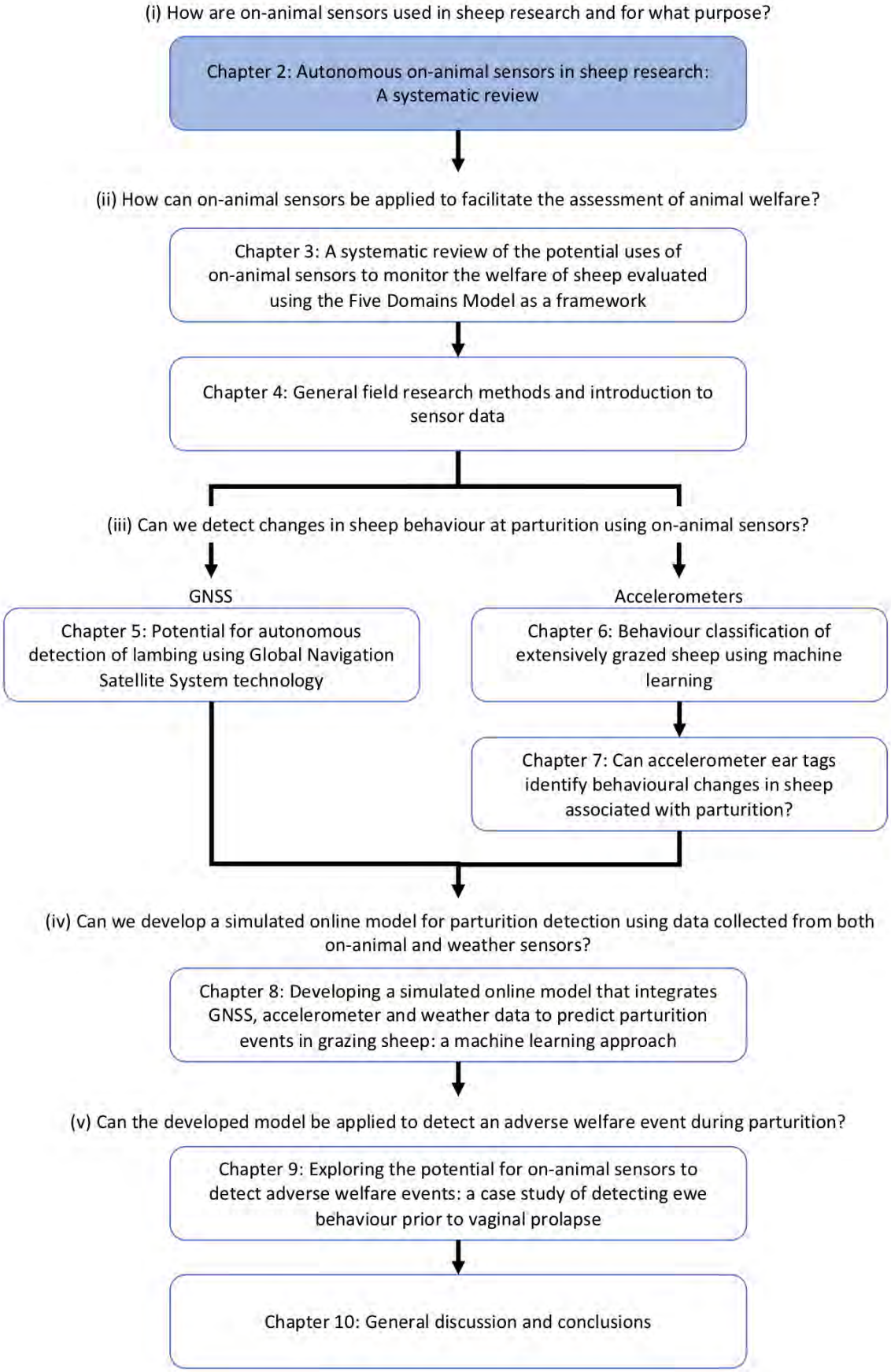
(i) How are on-animal sensors used in sheep research and for what purpose?
Chapter 2: Autonomous on-animal sensors in sheep research: A systematic review
(ii) How can on-animal sensors be applied to facilitate the assessment of animal welfare?
Chapter 3: A systematic review of the potential uses of on-animal sensors to monitor the welfare of sheep evaluated using the Five Domains Model as a framework
Chapter 4: General field research methods and introduction to sensor data
(iii) Can we detect changes in sheep behaviour at parturition using on-animal sensors?
GNSS
Accelerometers
Chapter 5: Potential for autonomous detection of lambing using Global Navigation Satellite System technology
Chapter 6: Behaviour classification of extensively grazed sheep using machine learning
Chapter 7: Can accelerometer ear tags identify behavioural changes in sheep associated with parturition?
(iv) Can we develop a simulated online model for parturition detection using data collected from both on-animal and weather sensors?
Chapter 8: Developing a simulated online model that integrates GNSS, accelerometer and weather data to predict parturition events in grazing sheep: a machine learning approach
(v) Can the developed model be applied to detect an adverse welfare event during parturition?
Chapter 9: Exploring the potential for on-animal sensors to detect adverse welfare events: a case study of detecting ewe behaviour prior to vaginal prolapse
Chapter 10: General discussion and conclusions

Chapter 2. Autonomous on-animal sensors in sheep research: A systematic review

Fogarty E.S., Swain D.L., Cronin G.M., Trotter M. 2018. Autonomous on-animal sensors in sheep research: A systematic review. *Computers and Electronics in Agriculture,* 150, 245-256.

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Overview

To understand how autonomous sensors may be used for behavioural monitoring and ultimately welfare assessment, it is first important to understand how they have been previously applied. This chapter explores the use of autonomous sensors in sheep research, including the type of sensors used, the application method and focus of the research. This review was conducted for two key reasons: firstly, to explore what research had been implemented to date using on-animal sensors and sheep; and secondly, to clarify which particular sensors have the most potential for use in this research program. This review was conducted as a systematic review to ensure maximum breadth of knowledge.

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Review

Autonomous on-animal sensors in sheep research: A systematic review

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ABSTRACT

This systematic review explores the use of on-animal sensor technology in sheep research. A total of 71 peer-reviewed articles reporting on 82 independent experiments were reviewed, ranging in publication date from 1983 to 2017 and distributed across all populated continents. The findings demonstrate increasing numbers of published studies that validate the application of sensor technology to categorise and quantify sheep behaviour. The studies also used sheep sensors for environmental management, validation of data analysis methods and for health and welfare research. Whilst historically many applications of sensors in sheep research have been conducted over a short period with small numbers of experimental animals, this trend appears to be changing as technology develops and access improves. The literature suggests that many applications of sensors have already or are currently moving through a proof-of-concept stage, allowing future applications to focus on commercialisation of technology and potential integration with other technologies already in use (e.g. weather data).

1. Introduction

Location technology was first used to study animal movement in the 1960s, when very-high frequency (VHF) transmitters revolutionised our ability to monitor complex animal behaviour (Kochanny et al., 2009). Two decades later, the satellite-based system ARGOS was employed for wildlife observation (Swain et al., 2011), followed by Global Positioning System (GPS), which was first applied to monitor moose (*Alces alces*) in 1994 (Rempel et al., 1995). Whilst these location technologies were being established, concurrent development of body movement monitoring technology was also occurring, including pressure sensors to monitor standing and lying in cattle (Canaway et al., 1955), pedometers to measure walking behaviour in sheep (Powell, 1968) and mercury tilt switches to indicate cattle and sheep body posture (Champion et al., 1997; Rutter et al., 1997a). More recently, accelerometers have been used to measure linear acceleration along one or multiple reference axes (Yang and Hsu, 2010). Inertial Monitoring Units (IMUs) extend this and include gyroscopes and/or magnetometers for additional measurements of angular motion and gravitational force (Andriamandroso et al., 2017). Other sensor developments include: contact loggers for the study of pair interactions in sheep (Broster et al., 2010; Broster et al., 2012; Freire et al., 2012); and heart rate monitors (Goddard et al., 2000; Simitzis et al., 2009; Destrez et al., 2012; Simitzis et al., 2012; Coulon et al., 2015) and oxygen sensors (Barkai et al., 2002) to help understand physiological change.

According to the FAO, overall food production needs to increase by 70% to meet growth projections of the world population by 2050 (FAO, 2009). This will require technologies that improve current efficiency standards. Whilst the use of sensors in livestock research has shown promise, their application in existing farming systems is still in its infancy (King, 2017). The exception to this is the dairy industry, where commercial sensors such as the GEA CowView System (GEA Farm Technologies, Bönen, Germany) and Afimilk Silent Herdsman (Afimilk, Kibbutz Afikim, Israel) are among several commercial offerings used to monitor health and oestrous behaviour (Tullo, 2016; King, 2017). In contrast, the use of digital technologies to measure extensive livestock performance and behaviour is lacking. This is considered an untapped area for development, particularly in countries such as Australia and New Zealand where nearly half of all agricultural businesses (including cropping) indicate a main agricultural activity of beef and/or sheep farming (Australian Bureau of Statistics, 2012; Statistics New Zealand, 2012).

Small ruminants, particularly sheep, are hugely important in many regions of the world, providing both food and fibre. According to the FAO, Asia is the largest global producer of sheep products contributing 52.6% of sheep meat and 45.6% of sheep milk production in 2016 (FAO, 2017). In addition, they are the world's leading producer of greasy wool, providing over 900,000 tonnes in 2013 (FAO, 2017). Whilst Asia remains dominant across the three major industries, the regions providing the next largest production value differs between commodities, with Africa the second largest sheep meat producer (18.8%), Europe the second largest sheep milk producer (29%) and

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Oceania the second largest greasy wool producer (24.2%) (FAO, 2017). This global contribution to sheep production highlights the importance of the industry and indicates how collective improvements in production efficiency could significantly improve the outlook for future food security.

The aim of this review was to use a quantitative systematic methodology to review how sensors have been applied in sheep research and trends for their application. The focus was on commercially relevant technologies. To the best of the authors' knowledge, this current review is the first for on-animal sensors used in sheep research.

2. Materials and methods

2.1. Search strategy

The method for this review was based on that used in Higgins and Green (2011) and Williams et al. (2016). A search of electronic databases was conducted in February 2017 and May 2017 for literature concerning the use sensors in sheep production systems. Searches were performed in the following databases: Scopus, ScienceDirect, CAB Abstracts and ProQuest. Search terms used were 'sheep', 'ovine', '*Ovis aries*', 'ewe*', 'ram' and 'lamb' in conjunction with 'gps', 'global positioning system*', 'gnss', 'global navigation satellite system*', 'accelerometer*', 'proximity log*', 'contact log*', 'rumen sensor', 'rumen bolus', 'body temperature monitor', 'body temperature AND sensor', 'blood pressure monitor' 'blood pressure AND sensor', 'heart rate monitor' and 'heart rate AND sensor'. Search terms were not case-sensitive. Initial searches including 'ram*' and 'lamb*' returned many irrelevant results and thus the truncation option was not used. Searches were restricted to titles, abstracts and keywords. The Boolean search term 'AND' was used in each search to join the sheep-related and sensor-related terms, respectively (e.g. sheep AND GPS, ewe* AND accelerometer). When searching Scopus, if irrelevant results were still found (e.g. RAM computer memory), the search was limited to the 'agricultural and biological sciences' subject area. However, this option was not available when searching the other databases.

Articles were required to meet the following criteria for inclusion: (i) written in English; (ii) included domestic sheep (*Ovis aries*) as subjects (some studies involved additional species and were also included); and (iii) included at least one type of on-animal autonomous sensor attached to at least one sheep subject. Books and book chapters were not included. If a paper was not peer-reviewed or missing data (e.g. conference papers), a comprehensive search for peer-reviewed articles presenting the data was made. If no peer-reviewed article could be found, the paper was excluded. If an article was unavailable online, a comprehensive search through affiliated networks and interlibrary loan services was conducted before the article was discarded. Articles that involved invasive animal procedures such as implantation of sensors into the abdominal cavity (Faurie et al., 2004) or skull (Bishai et al., 2003) of an unborn foetus or measuring brain wave activity at slaughter (Rodríguez et al., 2012), were excluded as these were considered to have minimal commercial relevance. Similarly, articles involving monitoring of animals in oxygen chambers (Aharoni et al., 2003) or metabolism cages (López and Fernández, 2013) were excluded as irrelevant as were those monitoring the stress response during transport (Fisher et al., 2010; Hall et al., 2010; de la Fuente et al., 2012; Santurtun et al., 2014; Santurtun et al., 2015). Other studies that were excluded included those that involved manual measurements e.g. heart rate measured once daily (Piccione et al., 2007) and studies that employed radio-frequency identification (RFID) as a data management tool (Ait-Saidi et al., 2014). For all articles that met the above criteria, a comprehensive bibliographic search was conducted to identify other relevant literature. A search for literature that had cited the original paper was also conducted using Google Scholar.

2.2. Data collection and extraction

Once a complete list of articles meeting the criteria was established, the bibliographic details including author, title and year of publication were listed. If multiple experiments were presented in one article, they were treated as a single study unless explicitly separated with results independently analysed and reported. Details of each experiment were then recorded, including the location of each experiment site by country and then more broadly by continent: Africa, Antarctica, Asia, Europe, Oceania, North America and South America. If no details on experiment site were documented, the location of the First Author's institution was used. Climate details (e.g. tropical, arid, temperate, cold, polar) were based on the Köppen-Geiger system detailed in Peel et al. (2007). Further details including the year of experiment initiation and conclusion and the season in which the experiment was conducted was also recorded. Seasons were based on standard quarterly grouping of months for the northern and southern hemispheres i.e. December to February, March to May, June to August and September to November corresponding to winter, spring, summer and autumn for the northern hemisphere and summer, autumn, winter, spring for the southern hemisphere. Experiments were then classified as 'grazing' or 'intensive'. A 'grazing' experiment was one in which animals were managed in outdoor paddocks and grazed forage for either all or part of the day (Williams et al. 2016). In comparison, an 'intensive' experiment was one where animals were housed in small pens or barns for the duration of the study. Experiments in which animals were grazed during the day and kept indoors at night were still considered 'grazing' if sensors were removed overnight. If however the sensors remained on the animals whilst indoors, this was recorded as a 'combination'. Duration of experiments was then determined using three criteria: (i) the period of time between first sensor attachment and last sensor removal; (ii) the maximum period of sensor deployment used throughout the experiment; and (iii) the total length of time sensors were deployed, even if this was done over multiple deployments. Durations were 'clustered' based on defined periods of time (i.e. 1–2 weeks, 2–4 weeks) and clusters were always classified to the smaller cluster group (i.e. a 14-day study was classified as 1–2 weeks, not 2–4 weeks). When determining experiment duration, a month was considered to be four weeks. The number of repeat deployments per experiment was also recorded.

Animal details were recorded for each experiment, including sheep breed, class (ewe, ram, wether, hogget, lamb) and number used. Details of additional species co-monitored with the sheep were also recorded. Sensor information was then extracted, including the sensor type (GPS, accelerometer etc.), attachment method and programmed data collection interval. Finally, the broad focus of the study based on the objectives of each experiment, was determined to be up to two of the following: (i) behaviour; (ii) health; (iii) methods validation; (iv) environment management; (v) sensor validation; (vi) welfare; and (vii) other (Table 1).

3. Results

3.1. Database and bibliographic search results

Database searches identified 2294 unique documents containing the relevant search terms. Approximately 11.6% (n = 266) and 6.5% (n = 149) of articles were excluded as they related to sheep but not sensors, or sensors but not sheep, respectively. A further 11.3% (n = 260) were not relevant to either subject area. Due to the large number of results returned, a large proportion of documents (51.9%; n = 1191) were excluded as soon as their non-relevance to sheep was determined without examining their relevance to sensors. Approximately 8.4% (n = 192) of articles were excluded based on the document type (e.g. book, book chapter, review, conference paper) and 1.2% (n = 27) as non-English language. Of the remaining 209 articles, a further 42 were excluded as they involved invasive medical procedures,

Table 1
Defining criteria used for establishing the broad focus of studies.

Broad focus	Definition
(1) Behaviour	Use sensor data to analyse various behaviour patterns, usually associated with a particular context e.g. lambing, grazing
(2) Health	Experiments that aim to identify various attributes associated with the onset of existing or potential clinical/subclinical disease and/or general indication of good health
(3) Methods validation	Focus on the sensor output data and validating methods for analysis, usually with field data
(4) Environment management	Focus on sheep production in a broader context to understand the impact of production on the environment
(5) Sensor validation	Experiments that aim to endorse the use of sensors for various research purposes, including those that confirm that the attachment of sensors does not impact behaviour
(6) Welfare	Use of sensors to specifically measure a particular aspect of animal welfare (sometimes termed 'animal wellbeing'). Experiments that attempted to measure emotional states in sheep were also included in this category
(7) Other	Unable to be defined by another category

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37 were excluded as they related to wild sheep (e.g. Bighorn sheep, mouflon etc.), 25 were removed as the sensor used in the study was not attached to the animal (e.g. handheld GPS used to identify locations of interest) and 14 related to carcass traits. A further 18 were removed for other reasons (e.g. using sensors for identification purposes or using chamber sensors). Twenty-one articles were unable to be retrieved.

The bibliographic search identified 226 unique documents related to sheep and/or sensors. Upon close examination, only 25 of these met the required criteria. Nearly half were rejected as they related to sheep but not sensors (46.0%; n = 104). A further 18.6% (n = 42) were rejected as relevant to sensors but not sheep and 16.8% (n = 38) were the incorrect document type. Five articles were rejected as the sensor was not attached to the animal, two were rejected as non-English and one was rejected as it involved invasive medical procedures. Nine articles were unable to be retrieved.

Overall, a total of 2520 articles were examined through both database and bibliographic searches, resulting in 77 articles that met the selection criteria. Six articles were excluded from further analyses due to incomplete methodology. For the remaining 71 articles, 82 independent experiments were reported (Table 2). The year of study conduct (if known) and publication are shown in Fig. 1. If experiments were conducted over multiple years, this was categorised based on the first year only. The year of study conduct was unknown for 35 of the 82 reviewed experiments (Table 2). Thus, any further reference to year of the experiment refers to publication year only. It is acknowledged that due to the inevitable lag between study conduct and publication, the use of publication date may impact the accuracy of extrapolated time patterns discussed. However, it was conceded that consideration of all publications was necessary for a comprehensive review. To help mitigate potential inaccuracies, publication dates were grouped in five-year windows to allow a more general assessment of time patterns (Fig. 1).

3.2. Study site location, climate and environment data

The 82 independent experiments were distributed across six continents (Fig. 2). The majority of experiments were conducted in temperate climates (n = 56), followed by cold (n = 15) and arid (n = 10) climates. One experiment (Zampaligré and Schlecht, 2017), was conducted over three locations spanning both arid-steppe and a tropical-savannah climates. Experiments were conducted across all seasons, most commonly in summer (n = 28) and autumn (n = 28), followed by spring (n = 24) and winter (n = 21). The season was not recorded for 31 experiments. Approximately 72.0% of experiments (n = 59) were conducted under grazing conditions. In comparison, only 24.4% (n = 20) were conducted in intensive, pen-style conditions, with the remaining 3.6% of experiments (n = 3) conducted in a combination of grazing and housed environments.

3.3. Animal data

The majority of experiments (80.5%; n = 66) were conducted solely on domestic sheep (*Ovis aries*) with the remainder involving one (15.9%; n = 13) or two (3.7%; n = 3) additional species integrated into the experiment. In most cases, cattle were the most common addition (n = 9), followed by goats (n = 4). Other species included dogs (n = 2), kangaroos (n = 2), deer (n = 1) and yaks (n = 1). A total of 17 different sheep breeds were used across all experiments. Of these, Merinos were the most common (n = 25), followed by crossbreds (n = 11) and a mixture of breeds (n = 9). Breed was not recorded for nine experiments. The majority of experiments were conducted in ewes, either individually (n = 37) or with another animal class (n = 12). Animal class was not recorded for ten experiments. The number of sheep used per sensor deployment and the total number that carried a sensor throughout the experiment is shown in Fig. 3.

3.4. Experimental design and methodology

Approximately 80.5% of experiments (n = 66) were conducted using one sensor, with the remaining conducted using two (n = 12) or three (n = 4) sensors. GPS was by far the most common sensor, being used in 40 experiments (48.8%). Motion sensors including accelerometers, IMUs, inclinometers, pitch and roll sensors and mercury tilt devices were the next most commonly used sensor type (25.6%; n = 21) followed by heart rate monitors and echocardiograms (19.5%; n = 16). Jaw and bite sensors and contact loggers were used in ten and five experiments, respectively. Other sensors that were used in small numbers include oestrus detectors (n = 3), urine sensors (n = 3), temperature loggers (n = 2), oxygen sensors (n = 1) and respiration sensors (n = 1). The majority of multi-sensor experiments involved GPS (31.3%; n = 5), motion sensors (18.8%; n = 3), or a combination of the two (31.3%; n = 5). Of the three remaining multi-sensor experiments, a combination of heart rate monitors, temperature loggers and jaw/bite sensors were utilised. Fig. 4 shows how the use of the different sensor types has changed over time.

Sensor attachment was most commonly done through the use of collars (n = 41) followed by a harness, backpack or girth strap (n = 37). Other methods of attachment included being strapped to a head collar or nose band (n = 10), being directly attached to the fleece or skin (n = 5) or by attachment to the leg (n = 3). Other attachments (e.g. attached to horn, facemask) were used in the remaining 5 experiments. Attachment manner was not stated for one experiment. When deploying sensors, a variety of intervals for data capture were programmed across all sensors types. The majority were programmed to record continuously (n = 35) or between intervals of one to 10 min (n = 22) or less than one minute (n = 17). Only a small number of sensors were programmed at intervals of 11 to 30 min (n = 4) and over 30 min (n = 3). The programmed interval was recorded as 'other' for 16 sensors and unknown for five. 'Other' included those that were not programmed at set intervals e.g. an oestrus detector recording mounts or contact loggers recording when animals come within a specified distance. When examing the timed programmed intervals for the two most common sensors, GPS and motion sensors, there is a clear

Table 2
Summary of the reviewed experiments.

Publication	No. of Exp.[a]	Year of Exp.[a]	Continent	Climate[b]	Species	Animal Class	Sensor (s)	Exp.[a] Type[c]	Major Focus[d]
Alhamada et al. (2016)	2	Unknown	Europe	Csa	Sheep	Ewe, ram	Oestrus detector	I	5
Alhamada et al. (2017)	1	Unknown	Europe	Csa	Sheep	Ewe, ram	Oestrus detector	G	1
Alvarenga et al. (2016)	1	2015	Oceania	Cfb	Sheep	Ewe	Motion sensor (accelerometer)	C	5
Animut et al. (2005)	1	2002–03	North America	Cfa	Sheep, Goat	Wether	Jaw/bite	G	1
Ares et al. (2007)	1	2003–04	South America	BWk	Sheep	Ewe	GPS	G	1, 3
Barkai et al. (2002)	1	Unknown	Asia	BSh	Sheep	Lamb	HR Monitor, jaw/bite, oxygen sensor	C	5
Betteridge et al. (2010a)	1	2009	Oceania	Cfb	Sheep, Cattle	Hogget	GPS, jaw/bite, urine sensor	G	4, 5
Betteridge et al. (2010b)	2	2006	Oceania	Cfb	Sheep, Cattle	Ewe	GPS, urine sensor	G	4, 5
Broster et al. (2010)	1	2008	Oceania	Cfa	Sheep	Ewe, lamb	Contact Logger	G	1
Broster et al. (2012)	1	2008	Oceania	Cfa	Sheep	Ewe	GPS	G	1
Broster et al. (2017)	1	2010	Oceania	Cfa	Sheep	Ewe, lamb	Contact Logger, GPS	G	1
Champion et al. (1997)	2	Unknown	Europe	Cfb	Sheep, Cattle	Ewe	Motion sensor (mercury tilt)	G	5
Coulon et al. (2015)	1	Unknown	Europe	Dfc	Sheep	Lamb	HR Monitor	I	1
Cronin et al. (2016)	1	2011	Oceania	Cfb	Sheep	Lamb	Motion sensor (accelerometer)	G	2
Désiré et al. (2004)	3	Unknown	Europe	Dfc	Sheep	Lamb	Echocardiogram	I	1
Destrez et al. (2012)	1	Unknown	Europe	Dfc	Sheep	Lamb	HR Monitor	I	1
Destrez et al. (2013)	2	Unknown	Europe	Dfc	Sheep	Lamb	HR Monitor	I	1, 6
di Virgilio and Morales (2016)	1	2014–15	South America	Csb	Sheep	Ewe, hogget, wether	GPS	G	1, 4
Dobos et al. (2014)	1	2012	Oceania	Cfb	Sheep	Ewe	GPS	G	1, 5
Dobos et al. (2015)	1	2009	Oceania	Cfb	Sheep	Ewe	GPS	G	1
Donovan et al. (2013)	1	Unknown	Oceania	Cfb	Sheep	Hogget	GPS	G	1, 2
Doyle et al. (2016)	2	2012 & 2014	Oceania	Cfa	Sheep	Ewe	Contact Logger	G	1, 3
Falú et al. (2014)	1	2009–11	South America	Cfa	Sheep, Cattle	Ewe	GPS	G	1, 4
Falzon et al. (2013)	1	2010	Oceania	Cfb	Sheep	Ewe	GPS	G	2
Fogarty et al. (2015)	1	2013	Oceania	Cfb	Sheep	Ewe, ram	GPS	G	1, 5
Freire et al. (2012)	1	Unknown	Oceania	Cfa	Sheep	Ewe	Contact Logger, GPS	G	1
Giovanetti et al. (2017)	1	2013–14	Europe	Csa	Sheep	Ewe	Motion sensor (accelerometer)	G	5
Gipson et al. (2012)	1	2002–03	North America	Cfa	Sheep, Goat, Dog	Not recorded	GPS	G	1
Goddard et al. (2000)	1	1995–96	Europe	Cfb	Sheep	Lamb	HR Monitor	I	1
Greiveldinger et al. (2007)	1	Unknown	Europe	Dfc	Sheep	Lamb	HR Monitor	I	1, 6
Haddadi et al. (2011)	1	2010	Oceania	Csb	Sheep	Not recorded	GPS, motion sensor (IMU)	G	3
Hargreaves and Hutson (1990)	1	Unknown	Oceania	Cfb	Sheep	Wether	HR Monitor	I	1, 6
Harris et al. (2016)	1	2010–12	Asia	BSk	Sheep, Yak	Not recorded	GPS	G	4
Hobbs-Chell et al. (2012)	1	Unknown	Oceania	Csb	Sheep	Ewe	GPS, motion sensor (IMU)	I	5
Hulbert et al. (1998)	1	1997	Europe	Cfb	Sheep	Ewe	GPS	G	5
Jørgensen et al. (2016)	1	2013–14	Europe	Dfc	Sheep	Ewe	GPS	G	1
Kaur et al. (2016)	1	2015	Oceania	Csa	Sheep	Lamb	GPS	G	1, 2
Kawamura et al. (2005)	1	2002	Asia	BSk	Sheep	Not recorded	GPS	G	3, 5
Kuźnicka and Gburzyński (2017)	1	Unknown	Europe	Dfb	Sheep	Lamb	Motion sensor (accelerometer)	I	3, 5
Lin et al. (2011)	1	2008	Asia	BSk	Sheep	Ewe	GPS	G	1
Lowe et al. (2001)	1	2000	Oceania	Cfb	Sheep	Lamb	Echocardiogram, Temperature logger	G	7
Manning et al. (2014)	1	2013	Oceania	Cfb	Sheep	Ewe	GPS	G	1, 5
McLennan et al. (2015)	1	Unknown	Europe	Cfb	Sheep	Ewe	Motion sensor (accelerometer)	G	5
Morgan-Davies et al. (2016)	1	2013	Europe	Cfb	Sheep	Ewe	GPS	G	7
Morton et al. (2014)	2	2012 & 2013	Europe	Cfb	Sheep	Ewe, wether	Motion sensor (accelerometer)	G	2
Munn et al. (2013)	1	2008	Oceania	BWh	Sheep, Kangaroo	Not recorded	GPS	G	4
Munn et al. (2016)	1	2009	Oceania	BWh	Sheep, Kangaroo	Ewe	GPS	G	4
Mysterud et al. (2014)	1	2007–08	Europe	Dfc	Sheep	Not recorded	GPS	G	3, 4
Nadimi et al. (2012)	1	Unknown	Europe	Dfb	Sheep	Not recorded	Motion sensor (accelerometer)	G	5
Ormaechea and Peri (2015)	1	2008–10	South America	Cfb	Sheep	Not recorded	GPS	G	1, 4
Penning (1983)	5	Unknown	Europe	Cfb	Sheep	Ewe, ram, wether	Jaw/bite, motion sensor (mercury tilt & accelerometer)	G	5
Pérez-Barbería et al. (2015)	1	2008	Europe	Cfb	Sheep, Deer	Ewe	GPS	G	1, 3
Putfarken et al. (2008)	1	2003	Europe	Cfb	Sheep, Cattle	Not recorded	GPS	G	1, 4
Radeski and Ilieski (2017)	1	Unknown	Europe	Cfa	Sheep	Ewe, ram	Motion sensor (accelerometer)	I	5
Reefmann et al. (2009)	1	2007	Europe	Dfb	Sheep	Ewe	Echocardiogram, respiration sensor, temperature logger	I	1, 6

(*continued on next page*)

Table 2 (*continued*)

Publication	No. of Exp.[a]	Year of Exp.[a]	Continent	Climate[b]	Species	Animal Class	Sensor (s)	Exp.[a] Type[c]	Major Focus[d]
Rurak et al. (2008)	1	Unknown	North America	Cfb	Sheep	Ewe, lamb	Motion sensor (accelerometer)	I	5
Rusch et al. (2009)	1	2002	Europe	Dfc	Sheep	Ewe	GPS	G	4
Rutter et al. (1997a)	1	Unknown	Europe	Cfb	Sheep	Ewe	GPS, jaw/bite, motion sensor (mercury tilt)	G	5
Rutter et al. (1997b)	1	Unknown	Europe	Cfb	Sheep	Ewe	Jaw/bite	G	5
Schlecht et al. (2006)	1	1998	Africa	BSh	Sheep, Cattle, Goat	Not recorded	GPS	G	4
Simitzis et al. (2009)	1	Unknown	Europe	Csa	Sheep	Lamb	HR Monitor	I	1, 2
Simitzis et al. (2012)	1	Unknown	Europe	Csa	Sheep	Lamb	HR Monitor	I	1
Tallet et al. (2006)	1	Unknown	Europe	Dfc	Sheep	Lamb	Echocardiogram	I	1
Taylor et al. (2011)	1	2008–09	Oceania	Cfb	Sheep	Ewe	GPS	G	1
Thomas et al. (2008)	1	2007	Oceania	BWh	Sheep	Ewe	GPS, motion sensor (inclinometer)	G	1
Umstätter et al. (2008)	1	Unknown	Europe	Cfb	Sheep	Ewe	GPS, motion sensor (pitch & roll sensor)	C	3, 5
Verbeek et al. (2012)	1	Unknown	Oceania	Cfb	Sheep	Lamb	Motion sensor (accelerometer)	G	1
Webber et al. (2015)	1	2010	North America	BSk	Sheep, Dog	Ewe	GPS	G	1
Williams et al. (2011) & Williams et al. (2009)	1	2004–06	Europe	Cfb	Sheep	Ewe	GPS	G	1, 4
Zampaligré and Schlecht (2017)	1	2009–10	Africa	Aw, BSh	Sheep, Cattle, Goat	Ewe	GPS	G	1, 4

[a] Exp. = Experiment.
[b] As per Peel et al. (2007).
[c] I = Intensive; G = Grazing; C = Combination.
[d] As per Table 1; See Fig. 7.

preference for motion sensors to record continuously (Fig. 5). In comparison, GPS was most often programmed to record at intervals of one to ten minutes (n = 18), with no studies using GPS intervals of less than one second.

As shown in Fig. 6 maximum continuous deployment tended to be short in duration, with the majority of experiments either using sensors for ≤ 48 h (n = 36) or between 2 and 7 days (n = 22). The longest single deployment, used in a total of three experiments, was 3–6 months. Total deployment also tended to be short, with periods of ≤48 h (n = 24), 2–7 days (n = 18) and 2–4 weeks (n = 13) the most common. The longest total deployment was 1–2 years, seen in just one experiment (di Virgilio and Morales 2016). In contrast to the first two characteristics, total experimental duration (calculated from first sensor attachment to last sensor removal) showed a relatively even distribution (Fig. 6); with the most common duration being ≤48 h (n = 14), 1–2 weeks (n = 10) and 6–12 months (n = 10). Total sensor deployment and experiment length was unknown for two and five experiments, respectively. Approximately 61.0% (n = 50) of experiments involved repeat sensor deployment, with the number of deployments ranging from 1 to 40, with a mean of 4.2 and a median of 2.

Most experiments were conducted to autonomously categorise and quantify animal behaviour, including both spatial behaviour (e.g. location within a given area or relative to resources and other individuals) and general behaviour (e.g. grazing, drinking, walking etc.; 52.4%; n = 43) or to validate the use of sensors (35.4%; n = 29; Fig. 7). Following this, experiments focused on environment management (17.1%; n = 14), methods validation (11.0%; n = 9), health (8.5%; n = 7) or welfare (6.1%; n = 5). Only two experiments fell into the "other" category; Lowe et al. (2001) who examined the impact of climate on body temperature in sheep and Morgan-Davies et al. (2016) who studied the impact of an animal's origin on their ability to thrive in mountainous regions of Scotland. The majority of studies (67.1%; n = 55) had a singular focus, with the remaining having a focus over two areas (32.9%; n = 27). Of those with two major focal areas, most involved GPS (n = 18) or heart rate monitors (n = 6), followed by four experiments for 'other' sensors, two experiments each for motion sensors and contact loggers and one for jaw and bite sensors. Four of these experiments involved multiple sensors hence discrepancies in totals

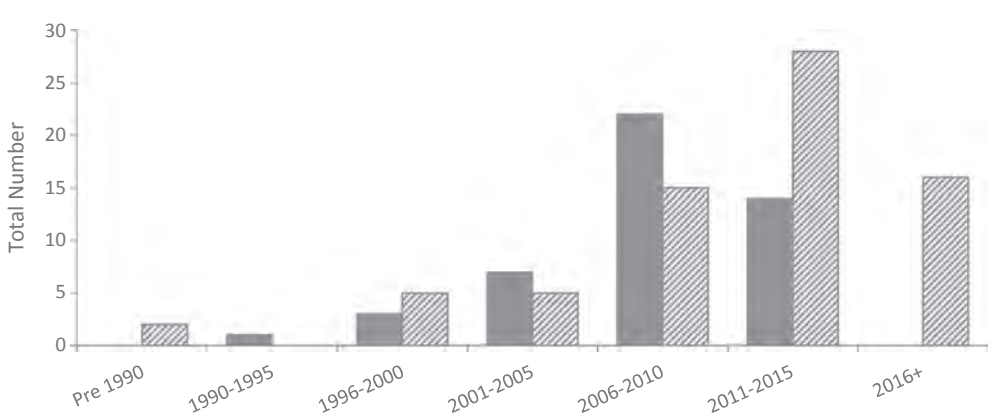

Fig. 1. The year of experiment conduct (solid) and year of study publication (diagonal striped). The year of experiment conduct was unknown for 35 experiments and is not included.

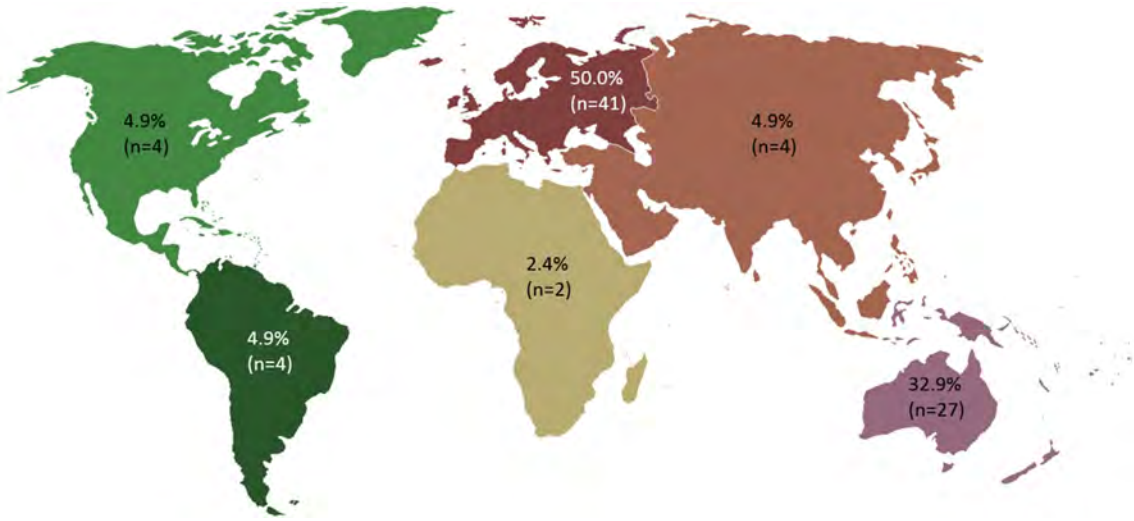

Fig. 2. Distribution of experiments across continents. Map source (Wikimedia Commons).

listed. The proportion of each sensor type's application to the seven major focus areas is shown in Fig. 8. The values are based on the total number of focal areas listed for each sensor type i.e. 58 focal areas for GPS (40 experiments with at least one focus plus an additional 18 with a dual focus); 22 focal areas for heart rate monitors (16 experiments with at least a single focus plus six with a second focal area).

4. Discussion

4.1. General trends

The results of this systematic review show that there is a growing application of the use of sensors in sheep research. This rising interest is evident in Fig. 1 where the number of peer-reviewed papers published in the 17 months between 2016 and the date of this review (n = 16) surpasses those published between 2006 and 2010 (n = 15) and is already more than half of those published between 2011 and 2015 (n = 28). The global interest of this research area is also evident from Fig. 2, particularly in Europe and Oceania. When considering these results, the use of the first author's institution where no direct reference to study location was provided should be noted as a potential limitation. In addition, the restriction to English language publications may also be considered a potential source of bias. However, removal of those articles where the author's institution was used still indicates Europe and Oceania as leaders in this area of research (n = 20 and n = 23, respectively). Furthermore, of those publications discarded as non-English, 16 were from Europe, ten were from Asia and one was from South America. Thus, the high level of interest from Europe and Oceania is likely correct, potentially reflecting the interest for production efficiency gains in these two developed regions and the corresponding value of sheep production (The European Sheep Meat Forum 2016; Australian Bureau of Statistics 2017). However, the low number of studies from Asia is likely under representative considering the value of the industry in this region (FAO 2017). In this case, Asia will likely continue to emerge as a dominant player in this field, particularly considering the rapidly growing Asian economies evident today (FAO, 2009).

4.2. The impact of sensor capabilities on experimental design

This review highlighted the impact of sensor capabilities on how studies have been designed and undertaken. For example, a preference for shorter continuous deployment is evident (Fig. 6). This is also shown for period of total deployment, which follows a similar yet less pronounced pattern (Fig. 6). In contrast, total experiment duration does not follow this trend, ranging from less than 48 h to over 2 years in

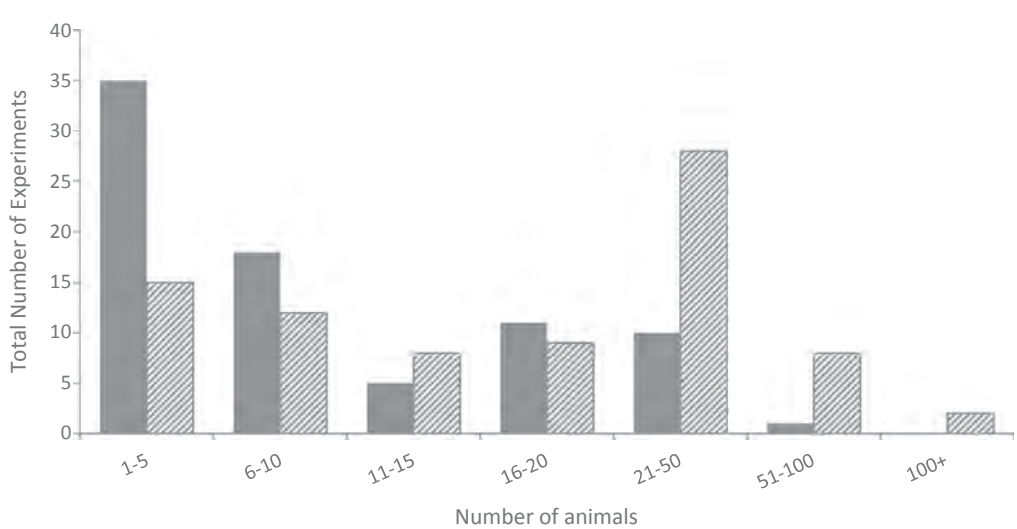

Fig. 3. The total number of animals used in a single deployment (solid) or that had a sensor attached at some point during the experiment (diagonal striped).

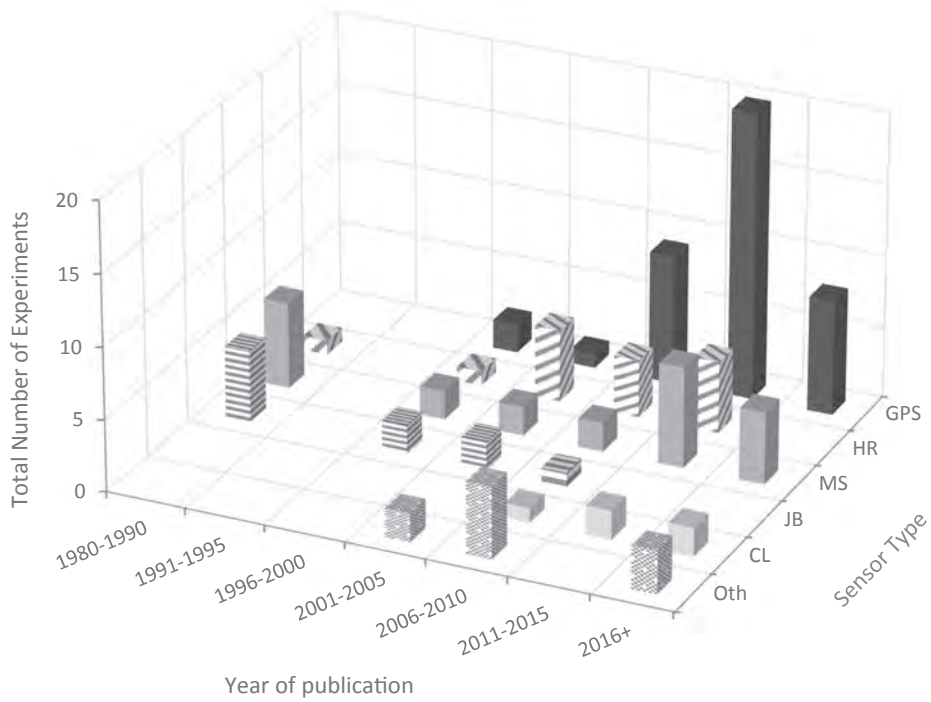

Fig. 4. The use of sensors over time. Sensor types include GPS (dark grey), heart rate monitors and echocardiograms (HR; diagonal stripe), motion sensors (MS; mid-grey), jaw and bite sensors (JB; horizontal stripe), contact loggers (CL; light grey) and other sensors (spotted).

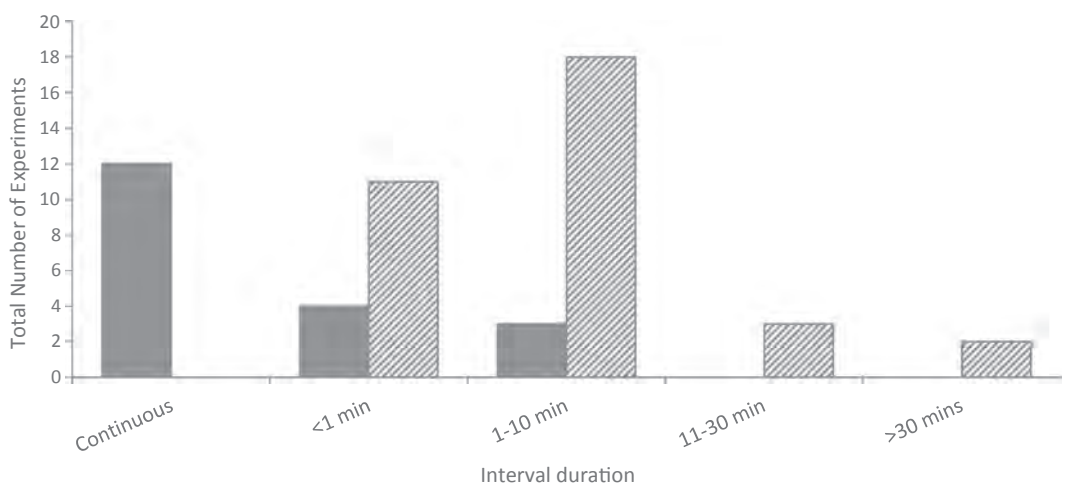

Fig. 5. The most commonly programmed timed intervals for the two most common sensors, motion sensors (solid) and GPS (diagonal striped). Not shown on the graph were three GPS experiments that used intervals classified as 'other', three GPS experiments with 'unknown' intervals and two motion sensor experiments with 'unknown' intervals.

length. Overall, these results suggest that sensors are being deployed for short periods of time, removed and then re-deployed multiple times within a single experiment. This is reinforced in Fig. 6, which shows that while nine experiments had a total duration of over one year, only one of the experiments had a total deployment period of this length. In this case, these experiments involved long periods of time during which the sensors were not attached or were not collecting data. An inclination for shorter programmed time intervals for data collection is also apparent. As shown in Fig. 5, the majority of sensors were programmed to capture data at less than one-minute intervals, with this number falling progressively as interval length increased.

The aforementioned trend for shorter experiment duration and programmed data capture interval likely reflect the impact of battery constraints and memory capacity on study design (Schwager et al., 2007; Swain et al., 2011). Due to these limitations, sensor intervals are often recommended to be short enough for high-resolution data, but long enough to allow for an adequate study length, depending on the objective of the study (Schwager et al., 2007). In this current review, studies with continuous sensor deployment of 3–6 months generally employed longer intervals of 30 (Mysterud et al., 2014) to 60 min (Pérez-Barbería et al., 2015). The exception was di Virgilio and Morales (2016), who used an interval of 5 min for a maximum of 164 days. In contrast, experiments where deployment was less than 48 h generally collected data continuously (64.4%; n = 29) or at intervals of less than one minute (17.8%; n = 8). The exceptions were Falzon et al. (2013) and Barkai et al. (2002) where intervals of 12 and 20 min were used when collecting GPS and heart rate data, respectively. Of note, Barkai et al. (2002) also used jaw movement and oxygen concentration sensors which were set to record continuously. This compromise between the need to collect detailed datasets within the limitation of sensor

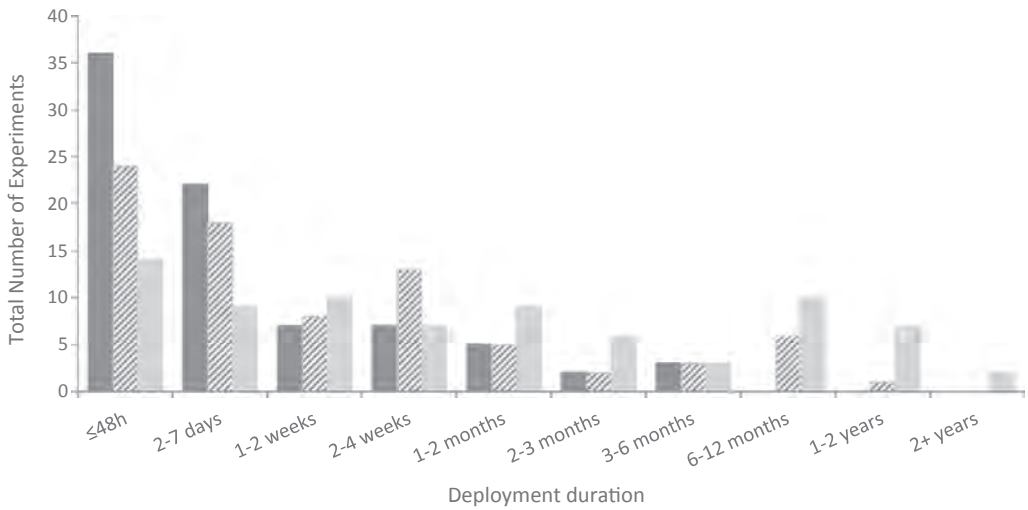

Fig. 6. The maximum length of the deployment period (dark grey solid), total deployment period (diagonal striped) and total length of experiment (light grey solid).

capabilities has changed over time. That is, of those studies published before the 21st century, the longest continuous deployment was only 1–2 weeks (Hulbert et al., 1998). In contrast, experiments with continuous deployments in excess of this were not published until 2008 when Thomas et al. (2008) deployed GPS and motion sensors for 19 days. Since then, deployments have continued to grow with the three longest being 91 days (Mysterud et al., 2014), 164 days (di Virgilio and Morales, 2016) and 6 months (Pérez-Barbería et al., 2015). Thus as sensor technologies and capabilities have matured over the last two decades (Ruiz-Garcia et al., 2009; Swain et al., 2011), the corresponding impact on sensor use in a research capacity and experimental design is evident. From here, it is expected that deployment durations will continue to grow, even as programmed intervals for data collection remain consistent.

Another impact of sensor functionality on experimental design is shown in the trend for smaller numbers of experimental subjects in each study; mostly commonly one to five (42.7%; n = 35) or six to ten animals (22.0%; n = 18; Fig. 3). This contrasts the total number of sheep with a sensor attached at some point throughout the experiment, which indicates no clear pattern of use. In this case, it appears researchers are using the same sensors deployed across multiple periods within the one experiment. A reason for this may be the economic cost of sensors, which has remained high despite the falling cost of many electronic components such as GPS chip sets and wireless sensor technologies (Ruiz-Garcia et al., 2009; Trotter et al., 2010; Swain et al., 2011; Banhazi et al., 2012). Furthermore, when the high cost per unit is multiplied by the number of animals involved in the study, the motivation for smaller groups becomes clear. Again, examination of this trend over time indicates growth in the number of experimental subjects being used. Between 1980 and 2000 the maximum number of animals used per deployment was 12 (Champion et al., 1997). From there, group sizes per deployment remained under 20 until 2008 when Rurak et al. (2008) attached accelerometers to 33 newborn lambs. This was followed by experiments involving 40 animals in 2012 and 2014 (Verbeek et al., 2012; Morton et al., 2014) and 49 animals in 2016 (Doyle et al., 2016). Only one experiment has involved over 50 animals, with Alhamada et al. (2017) attaching oestrus detectors to five rams and sixty ewes to monitor mounting behaviour. Thus, whilst earlier research appears to have been more focused towards data interpretation based on smaller groups, falling technology prices and improved access to technology has impacted experimental design, resulting in more sensors (and more experimental subjects) being studied within a

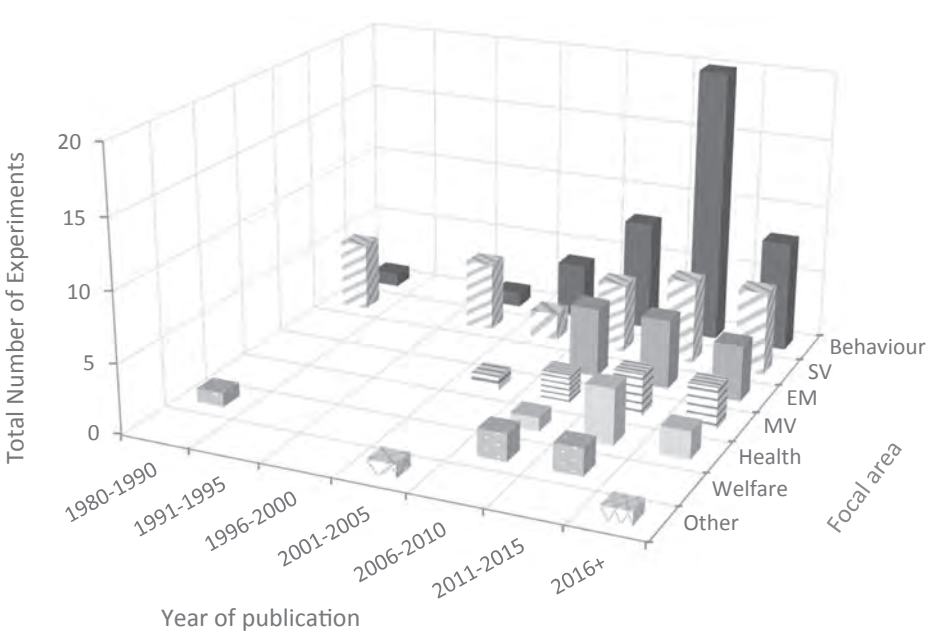

Fig. 7. The broad focus of experiments as defined in Table 1.Experiments could have up to two focal areas. Focal areas include behaviour (dark grey), sensor validation (SV; diagonal striped), environmental management (EM; mid-grey), methods validation (MV; horizontal strip), health (light grey), welfare (spotted) or other (cross hatch).

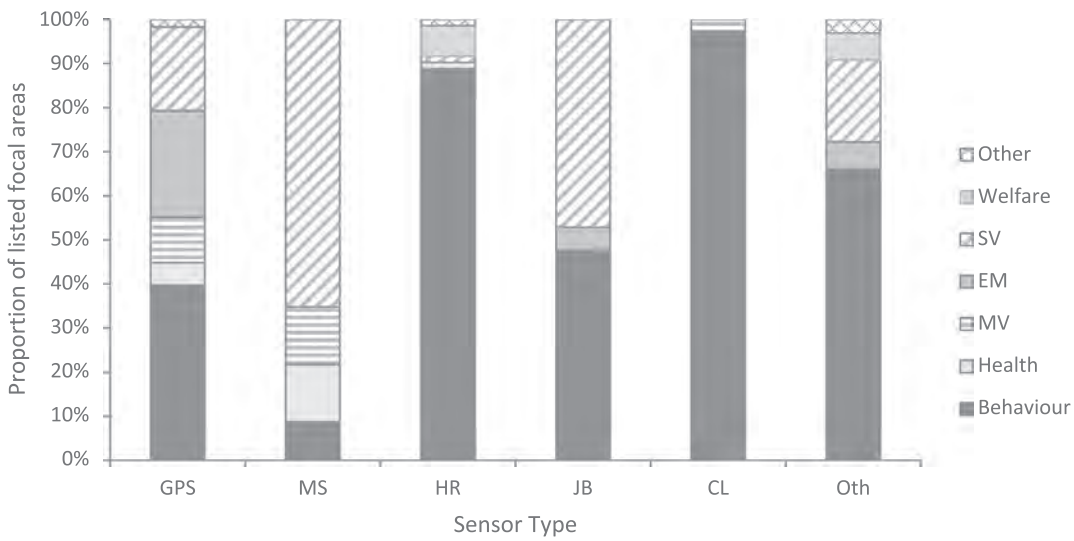

Fig. 8. The proportion of each sensor type and their application within the major focal areas listed in Table 1. Sensor types include GPS, motion sensors (MS), heart rate monitors and echocardiograms (HR), jaw and bite sensors (JB), contact loggers (CL) and other sensors (oth). Major focal areas include behaviour (dark grey), health (light hatch), methods validation (MV; horizontal stripe), environmental management (EM; mid grey), sensor validation (SV; diagonal striped), welfare (spotted) and other (cross hatch).

single deployment period. As the cost of sensor units continues to fall, it is possible that devices will be applied even more broadly, facilitating the commercialisation of cost-efficient research devices and leading to overall expansion of precision livestock farming in the sheep industry.

4.3. Application of sensors

The reviewed literature highlights a change in sensor use over time (Fig. 4). For example, the popularity of GPS for tracking animal movement appears to have increased since the mid-1990s, with a peak of 20 experiments published between 2011 and 2015. Similarly, contact loggers though less popular overall, have only been used in the last decade, the first of which being Broster et al. (2010). In contrast, the use of motion sensors and heart rate monitors has remained relatively stable since the 1980s. However, further examination of this reveals a change in the type of motion sensor used. For example, the last experiments to use mercury tilt sensors were conducted in the late 1990s (Champion et al., 1997; Rutter et al., 1997a). Since then accelerometers have increased in popularity with a total of ten experiments since 2011. Later use of other types of motion sensors is also noted for inclinometers and pitch and roll sensors (Thomas et al., 2008; Umstätter et al., 2008), and the more advanced IMUs (Haddadi et al., 2011; Hobbs-Chell et al., 2012). Of interest, Hobbs-Chell et al. (2012) did not use the IMUs to their capacity in their study, instead focusing on confirmation that the sensor attached to a sheep harness does not impact behaviour. This change in sensor use highlights the impact of technology improvements and sensor capabilities on experimental design, allowing more detailed datasets to be gathered using smaller and more discrete devices.

The results of this review also demonstrate the broad application of technologies in sheep production research, covering all seven focal areas defined in Table 1. As outlined in Section 3.4, for the majority of studies the objective was to apply sensors to enable quantification of sheep behaviour or to validate the sensor-generated data. As sensor-based livestock monitoring using digital technologies is relatively new, this may reflect basic 'proof-of-concept' research with a focus on 'finding' sensors that are appropriate for both research and industry to derive reliable and meaningful information. This focus on proof-of-concept is supported by the fact that of the 12 experiments published between 1980 and 2000, ten were classified as 'sensor validation' (Fig. 7). Since the start of the 21st century, other applications of the technology have been explored including experiments focused on method validation emerging between 2001 and 2005, and health and environmental management from 2006. Despite this rise in other applications, behaviour monitoring has remained a dominant objective, with more experiments published since 2001 than any other field. This concentration of activity toward sensor validation and behaviour monitoring suggests commercial applications will likely focus on identification of different aspects of behaviour and behavioural change, at least in the early stages. Indeed much of the research has already confirmed the ability of sensors to identify and monitor broad aspects of behaviour e.g. grazing, posture, walking (Radeski and Ilieski, 2017; Penning, 1983; Champion et al., 1997; Rutter et al., 1997b; Umstätter et al., 2008; Nadimi et al., 2012; McLennan et al., 2015; Alvarenga et al., 2016; Giovanetti et al., 2017), with a recent shift toward identification of more unique and discrete behaviours e.g. sexual behaviour (Fogarty et al., 2015; Alhamada et al., 2016, 2017) and suckling events (Kuźnicka and Gburzyński, 2017). Thus, as the foundation of knowledge from these more mature focus areas becomes further established, it is likely that future research will move toward broader and possibly innovative sensor application methods, including those already emerging as focal areas.

The impact of sensor type on the ability to research particular objectives can be seen in Fig. 8, where the proportions of all major focal areas for each sensor type is shown. Across all technologies, with the exception of motion sensors, behaviour is considered the major focus for the majority of studies. At the other end of the spectrum, health and welfare show the lowest level of application, in addition to 'other' studies. GPS was the most widely applied sensor type, used in all types of studies except for welfare. This wide application reflects the technology's unique capacity to provide information on the location of the animal and also allow derivation of various movement metrics (de Weerd et al., 2015). In contrast, jaw and bite sensors were the least widely applied, reflecting the limitations of solely measuring feeding activity. Motion sensors were most often applied in sensor validation studies with only a small number used to study behaviour, health and method validation. This result is expected given the use of multiple types of motion sensors that all require independent validation. Furthermore, as the inherent nature of motion sensors is to measure movement only, their application in an environmental focused study is unlikely given the expected requirement to monitor animals in relation to their surroundings. As we move forward, it is possible that sensors that have already been widely applied in sensor validation studies (GPS,

motion sensors, jaw and bite sensors, other sensors) will become more widely seen in other experiment types. However, this doesn't automatically exclude sensors that have not be widely validated (i.e. heart rate monitor and contact loggers), as these are more focused on measuring objective criteria rather than inferring patterns from a data set and thus do not require as intensive validation. Thus, it is likely that research will continue to utilise different sensor types, chosen based on the research question at hand. Further development of integrated technologies in a single device may provide a further step in the development of a 'gold-standard' for sensor application, allowing measurement of a number of different criteria for a broader monitoring potential.

5. Conclusion

The results of this current review highlight the broad application of sensor technologies in sheep production research, and the increasing interest in this area. As shown, sensors have been applied under a broad range of contexts, highlighting the potential for precision technologies to revolutionise livestock management. As further developments in sensor technology continue, the number of commercial applications is expected to increase. However, to ensure on-animal sensors are used to the best of their capabilities, it is likely further research expanding the existing application of technologies will be required. This is likely to be achieved through integration of both on-animal and external sensors. There is a unique opportunity to apply this integrated sensor approach to meet several industry needs as this technology matures.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.compag.2018.04.017.

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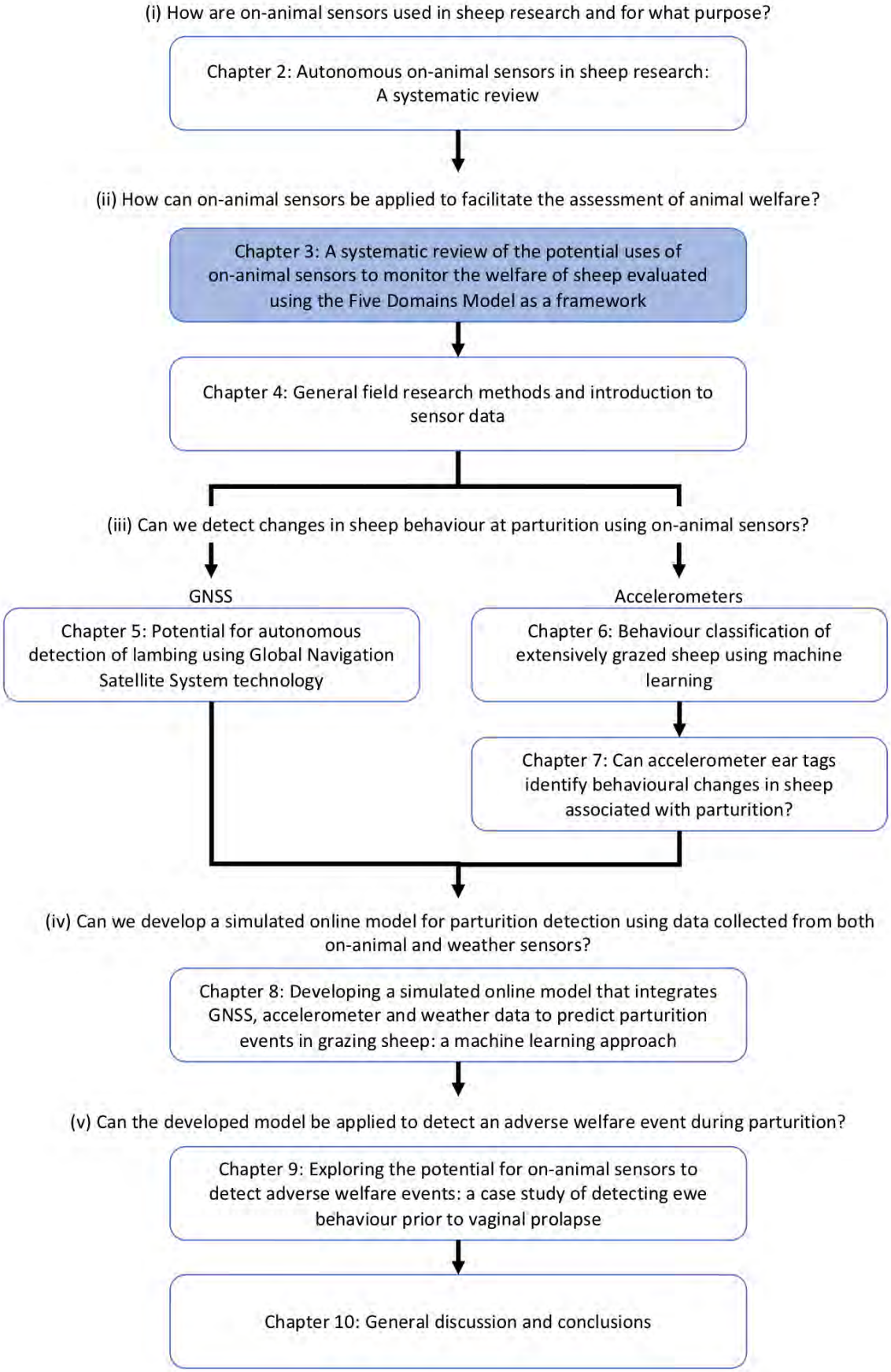
(i) How are on-animal sensors used in sheep research and for what purpose?
Chapter 2: Autonomous on-animal sensors in sheep research: A systematic review
(ii) How can on-animal sensors be applied to facilitate the assessment of animal welfare?
Chapter 3: A systematic review of the potential uses of on-animal sensors to monitor the welfare of sheep evaluated using the Five Domains Model as a framework
Chapter 4: General field research methods and introduction to sensor data
(iii) Can we detect changes in sheep behaviour at parturition using on-animal sensors?
GNSS
Accelerometers
Chapter 5: Potential for autonomous detection of lambing using Global Navigation Satellite System technology
Chapter 6: Behaviour classification of extensively grazed sheep using machine learning
Chapter 7: Can accelerometer ear tags identify behavioural changes in sheep associated with parturition?
(iv) Can we develop a simulated online model for parturition detection using data collected from both on-animal and weather sensors?
Chapter 8: Developing a simulated online model that integrates GNSS, accelerometer and weather data to predict parturition events in grazing sheep: a machine learning approach
(v) Can the developed model be applied to detect an adverse welfare event during parturition?
Chapter 9: Exploring the potential for on-animal sensors to detect adverse welfare events: a case study of detecting ewe behaviour prior to vaginal prolapse
Chapter 10: General discussion and conclusions

Chapter 3. A systematic review of the potential uses of on-animal sensors to monitor the welfare of sheep evaluated using the Five Domains Model as a framework

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Overview

As is evident from the systematic review conducted in Chapter 2, specific sensor-based research conducted for the purpose of welfare assessment is limited. This chapter expands on the findings of Chapter 2, exploring how on-animal sensors may be applied for welfare assessment. This assessment was conducted using the Five Domains (FD) Model as a framework. Initially the publications were also assessed under the Five Freedoms (FF) paradigm. However, this approach resulted in an unintended comparison between the two frameworks, opening up the review to debate on the relative merits of the FF and FD, rather than focusing on the merits of sensor technology in welfare assessment. Thus, in the published manuscript, only the FD Model was reported and discussed.

The intention of this chapter was to provide clarity around the potential for on-animal sensor application for welfare assessment, including the relative strengths and weaknesses of using different sensor types. This knowledge would then be applied during fieldwork planning to assess welfare in pasture-based sheep.

This manuscript has been published in Animal Welfare and appears in this thesis in its published form. Supplementary material for this chapter can be found in Appendix A.

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A systematic review of the potential uses of on-animal sensors to monitor the welfare of sheep evaluated using the Five Domains Model as a framework

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Abstract

This systematic review explores the use of on-animal sensors in sheep and their potential application in objective welfare monitoring. The key questions posed were: To what extent can current scientific knowledge inform a sensor-based approach to welfare evaluations? And, how might this knowledge shape development of commercial monitoring systems? These questions were explored through retrospective classification of published sensor applications using The Five Domains (FD) Model as a framework for animal welfare assessment. A total of 71 studies were reviewed. The results indicate studies specifically evaluating the use of sensors for welfare assessment are limited, though many experiments could still be related to some aspect of welfare. The assessment of sensor utilisation revealed the greatest proportion of applications within the 'Behaviour' Domain (90.1%; n = 64), and the lowest within the 'Health' (25.4%; n = 18) and 'Mental state' Domains (25.4%; n = 18). The review also highlights how different sensor types (location, motion or physiological) differ in their applicability for welfare assessment. This paper is the first to classify published sensor applications using the FD Model as a framework and highlights the potential for sensor technology in sheep welfare monitoring. The results suggest that any attempt to create a commercial sensor-based system for objective welfare assessment will require the integration of more than one sensor type, particularly if multiple Domains are to be addressed.

Keywords: *animal welfare, Five Domains Model, remote monitoring, sensor, sheep, systematic review*

Introduction

Issues surrounding animal welfare are faced by all livestock industries. Whilst it can be argued that this is not a novel problem, a recent increase in community and political scrutiny is evident (Webster 2016; Australian Farm Institute 2017; Dawkins 2017). Animal welfare impacts consumer purchasing behaviour, with studies indicating a growing ethical concern for animal welfare standards, particularly in western countries (Coleman 2007; European Commission 2007; Napolitano *et al* 2010). Whilst many developed nations, including Australia, New Zealand, the United Kingdom and many countries in Europe, already have relatively high standards of animal welfare (Mellor & Bayvel 2008; Webster 2008; Blokhuis *et al* 2010; Australian Farm Institute 2017), rising awareness among citizens has resulted in an increased prominence of animal protection as a broader societal issue (Napolitano *et al* 2010). In a review by Poletto and Hötzel (2012), implementation of 'clean, green and ethical' animal production systems that still guarantee high animal welfare standards, was cited as a significant global challenge. Coupled with the increased demand for food and fibre for the expanding human population, the risk for declining welfare standards in response to greater farm intensification is amplified (Dawkins 2017).

To assist livestock industries in responding constructively to changing societal views, it will be important for welfare standards to be based on objective scientific measures (Poletto & Hötzel 2012). Objective measures are also necessary to improve animal welfare for the sake of the animal itself and should be strived for in all production systems. However, the development of these measures is often not straightforward. Fraser and Broom (1990) define animal welfare as "the state of an animal as it attempts to cope with its environment", encompassing both physiological and psychological aspects of an animal's life (Tilbrook & Ralph 2018). This definition or similar, whilst commonly accepted by welfare scientists, provides little in the way of measurable criteria for welfare assessment. Added to this difficulty is the problem that the key features of objective welfare assessment systems need to be reliably recorded, quantified and reported.

The Five Freedoms (FF) paradigm was one of the first attempts to develop a comprehensive 'check list' upon

Table 1 The FD Model for welfare assessment; key features and examples.

Physical/Functional Domains							
Survival-related factors						Situation-related factors	
1 Nutrition		2 Environment		3 Health		4 Behaviour	
Restrictions on:	Opportunities to:	Unavoidable/ Imposed conditions:	Available conditions:	Presence of:	Presence of:	Exercise of 'agency' impeded by:	'Agency' exercised by:
Water or food intake	Drink enough water	Thermal extremes	Thermally tolerable	Disease	Appropriate body condition score	Choices markedly restricted	Available engaging choices
Food quality and variety	Eat a balanced/varied diet	Close confinement	Space for freer movement	Injury			Bonding
Voluntary over-eating		Unpredictable events	Normal environment variation	Functional impairment	Good fitness level	Constraints on animal-animal interaction	Play
Affective experience Domain							
5 Mental state							
Negative:	Positive:	Negative:	Positive:	Negative:	Positive:	Negative:	Positive:
		Forms of discomfort:	Forms of comfort:				Calmness
Thirst	Quenching thirst	Thermal	Thermal	Pain	Comforts of good health and high functional capacity	Anger	Engaged
Hunger	Pleasure of different tastes/smells	Respiratory, eg breathlessness	Respiratory	Debility		Boredom	Maternally rewarded
		Auditory, eg impairment	Auditory	Sickness		Helplessness	Playfulness

Table adapted from Mellor and Beausoleil (2015).

which the strengths and weaknesses of a given husbandry system could be judged (Webster 2008). Largely unchanged since the early 1990s (Webster 2008), the FF has achieved worldwide recognition and continues to be incorporated into many legislative, policy and corporate documents (FAWC 2009; McCulloch 2013). Despite this clear and lasting impact, the FF is often critiqued by contemporary animal welfare scientists due to perceived limitations of encouraging unattainable welfare goals and its focus on removing negative welfare aspects (McCulloch 2013; Mellor 2016a,b). This has led to the development of new models for welfare assessment, including the Five Domains (FD) Model (Mellor & Reid 1994; Mellor & Beausoleil 2015; Mellor 2016b, 2017), the Welfare Quality Project® (Blokhuis *et al* 2010; Welfare Quality® Network 2018) and three conceptual frameworks for understanding welfare; 'biological functioning', 'affective states' and 'natural living' (Fraser *et al* 1997; Hemsworth *et al* 2015).

The FD Model was developed in the 1990s to facilitate complete systematic welfare assessment (Mellor 2017). The FD Model incorporates five areas in which welfare can be either compromised or enhanced; three internal survival-related factors (Domains 1–3), one external situation-related factor (Domain 4) and an overarching assessment of how Domains 1–4 impact the affective experience of the animal (Domain 5) (Table 1; see Mellor and Beausoleil [2015] for an in-depth review). The FD Model supports a dual focus for assessment, the first by encouraging correction of negative welfare and the second through promotion of positive welfare states (Mellor & Beausoleil 2015). This incorporation of positive welfare mirrors the shift in contemporary welfare science, where animals are now expected to 'thrive' in their environment and not simply 'survive' (Hemsworth *et al* 2015; Mellor 2016a,b).

Precision livestock management (PLM) and the application of remote automated monitoring technologies have been proclaimed as a method of improving productivity of existing farm systems (Tullo *et al* 2016; King 2017). Whilst there are proponents for the use of PLM for welfare monitoring (Umstätter *et al* 2008; Morris *et al* 2012; Nadimi *et al* 2012; McLennan *et al* 2015; Radeski & Ilieski 2017), there are few practical examples of this in the literature. The broad aim of this review was to evaluate how research reporting the use of on-animal sensors might be related to animal welfare assessment, and in particular to consider how the use of sensors might further enhance such assessment using the FD Model as a framework. Sheep were chosen as a case-study to provide focus for the review. The specific objectives were to: (i) understand how on-animal sensors can be applied to facilitate the assessment of animal welfare by reference to the FD Model, even if this was not the original intent of the study; (ii) explore how different sensor types impact our ability to monitor particular features of the Domains; and (iii) identify gaps in the

current literature to direct future research efforts and better inform commercial sensor development. This review is the first to assess existing literature under an established welfare framework as a way of determining the potential value of on-animal sensors for welfare assessment.

Materials and methods

Initial literature search

The methods used for this systematic review have been described in depth by Fogarty *et al* (2018). Briefly, four electronic databases (Scopus, ScienceDirect, CAB Abstracts and ProQuest) were searched for relevant literature between February and May 2017. Search terms used were 'sheep', 'ovine', 'ovis aries', 'ewe*', 'ram' and 'lamb' in conjunction with 'GPS', 'Global Positioning System*', 'GNSS', 'Global Navigation Satellite System*', 'accelerometer*', 'proximity log*', 'contact log*', 'rumen sensor', 'rumen bolus', 'body temperature monitor', 'body temperature AND sensor', 'blood pressure monitor' 'blood pressure AND sensor', 'heart rate monitor' and 'heart rate AND sensor'. To be included in this review, articles needed to be written in English, conducted on domestic sheep (*Ovis aries*) and use at least one type of on-animal sensor attached to at least one sheep. Only peer-reviewed articles were retained. If a paper was not peer-reviewed or missing data (eg abstract only or conference paper), a thorough search for the relevant peer-reviewed paper presenting this information was conducted. If this could not be sourced, the paper was excluded. Books, book chapters and review papers were also excluded. The reference list of each publication was also searched to ensure comprehensive coverage of the subject area.

Potential use of on-animal sensors to monitor welfare

Experiment overview and objectives

General information including the location and duration of the study, number and type of animals used and sensor application were recorded for each reviewed experiment. In addition, the broad focus of each experiment was determined to include up to two of the following categories: (i) behaviour; (ii) health; (iii) method validation; (iv) environment management; (v) sensor validation; (vi) welfare; or (vii) other (see Fogarty *et al* [2018] for details). A focus on 'welfare' was defined as studies in which sensors were used to measure a particular aspect of animal welfare (either positive or negative).

Application to the Five Domains Model

To explore potential relationships between the reviewed studies and key features of the FD Model, a comprehensive list of keywords was developed (Table 2). These keywords were based on the descriptions presented in Table 1. Each study was then evaluated based on the presence or absence of these keywords in either the aims, objectives or conclusion sections. If a keyword was present, the study was considered 'applicable' to that particular Domain. If studies did not include an overt statement of aims or conclusions then the entire last paragraph of the introduction and/or discussion were assessed. When assessing the presence of keywords, some level of scientific judgment was necessary to ensure inclusion was contextually relevant (eg 'grazing' referring to the act of grazing *per se* [Domain 1 and 4] or as a general descriptor of the type of production system which would not be considered relevant to any Domain). Each publication was assessed as a whole, even if multiple independent experiments were included within a single paper. This contrasts with the approach of Fogarty *et al* (2018), who presented results for each independent experiment. The present approach was considered necessary to minimise repetition and inflation of results due to similar experiments within a single publication.

The use of different sensor types for welfare assessment

Once the welfare assessment had been conducted, each study was then reviewed to determine the broad 'family' of sensors: (i) location; (ii) motion; and (iii) physiological. Each 'family' was then subdivided based on the type of data collected (see Table 3 for definitions).

Results and Discussion

Search results

The results of the database and bibliographic searches identified 2,294 and 226 unique documents, respectively, relevant to the search terms. Of these, a total of 71 studies reporting on 82 independent experiments were included in this review. An in-depth summary of results can be found in Fogarty *et al* (2018).

The Five Domains

The outcomes of aligning published sensor applications in each study to the FD Model are shown in Table 4 (supplementary material to papers published in *Animal Welfare*: https://www.ufaw.org.uk/the-ufaw-journal/supplementary-material) and summarised in Figure 1. The assessment of sensor utilisation revealed the greatest proportion of applications within the 'Behaviour' Domain (90.1%; n = 64), and the lowest within the 'Health' (25.4%; n = 18) and 'Mental state' Domains (25.4%; n = 18).

Location sensors were utilised in 64.8% of reviewed studies (n = 46), followed by motion sensors (33.8%; n = 24) and physiological sensors (28.2%; n = 20). Fourteen of the 71 reviewed studies used multiple sensors and thus reported percentages do not sum to 100. The distribution of sensor type under each Domain is shown in Figure 2. Location sensors were dominant across all Domains, with the exception of 'Mental state', where physiological sensors were widely utilised.

Nutrition

The results of this review suggest sensors may have some relevance for assessing the nutritional aspects of welfare (Figure 1, Figure 2[a]). At a basic level, many of the studies were focused on grazing or bite behaviour, satisfying the fundamental assessment of 'food intake'. In initial experiments by Penning (1983) and Rutter *et al* (1997b), jaw movement was successfully measured by a change in conductivity of a fitted noseband, with 91.0 and 95.0% agreement between visual observations and sensor output,

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Table 2 The specific keywords or phrases used for categorisation into the FD Model.

Domain	Keywords or phrases
1 Nutrition	Feeding, grazing, ruminating, suckling, foraging, drinking or similar
	Water
	Food, diet
	Jaw movement, bite rate or similar
	Undernutrition, malnutrition, starvation or similar
	Nutritional status, nutritional condition or similar
	Metabolisable energy (ME)
	Energy expenditure (EE)
	Food availability, herbage mass or similar
	Food variety, eg preferred/unpreferred vegetation, varied foraging opportunity, vegetation type
	Food quality
2 Environment	Environment
	Exposure/thermal stress
	Weather, temperature, wind, chill, rainfall or similar
	Shelter
	Housing conditions
	Space for free movement (eg stocking rate/similar, spatial/grazing distribution/similar, confinement, home range, roaming)
	Environmental variability, eg landscape heterogeneity, seasonal patterns
	Predictability or unpredictability, novel changing conditions
3 Health	Disease or reference to a specific disease, eg Huntington's disease, NCL disease
	Walking, locomotion (only if discussed in the context of normal vs abnormal)
	Parasite burden, eg faecal egg count
	Functional impairment including restricted growth/function
	Immunology
	Core temperature
	Death/survival
	Reduced physical activity
	Body condition score, body mass, liveweight, weight gain/loss or similar
4 Behaviour	Behaviour
	Feeding behaviour, eg grazing
	Social behaviour, eg affiliative behaviour, mother-offspring interaction
	Movement behaviour, eg walking, running, standing, ambulation, number of steps, distance travelled, speed of travel
	Spatial behaviour, eg foraging paths, spatial utilisation, sheltering
	Vigilance behaviour, eg hide from predators
	Sexual behaviour, eg mountings
	Agency, eg site selection/preference, judgement bias
	Sleep, rest, lying
	Specific behaviours, eg urination, faecal excretion
5 Mental state	Affective state(s)
	Emotion, eg calm, relaxed, optimism, optimistic
	Positive/negative perception
	Fear, fearfulness or similar
	Distress, stress or similar
	Temperament
	Hunger/satiated
	Libido
	Boredom
	Isolation
	Cognitive

Table 3 Sensor family and broad measurement definitions.

Sensor family	Sub-family	Definition	Broad measurement	Definition
Location	Absolute	Location information based on the absolute location of the animal in space and time (ie GPS)	Distance/Speed	Using the distance and/or time between consecutive locations to calculate distance travelled or speed of movement
			Social interaction	Comparison of GPS positions to determine how close in space animals are
			Spatial data	GPS positions related to the environment, including resource use, spatial map visualisation, etc
	Relative	Location information based on the sensor's relative location to another sensor (ie contact logger)	Social interaction	Time and duration of contacts
Motion	Acceleration	Movement based on the acceleration the of animal (ie accelerometer)	Raw and/or derived metrics	Use of raw axis (x, y, z) data and/or derived calculations
			Proprietary metrics	Output from proprietary programme providing summary data
	Body or body-part position	Sensors that determine a change in body position or orientation (ie mercury tilt sensors, jaw/bite sensors or similar)	Body movement	Some measure of body movement eg jaw movements
			Body orientation	Some measure of orientation usually through a tilt sensor
			Proprietary metrics	Output from proprietary programme providing summary data
Physiological		Group of sensors that measure various aspects of an animals' physiology (ie HR monitor, oxygen sensor, respiratory sensor, temperature sensor, urine sensor)	General HR	Basic measures of heart rate eg beat per minute (bpm), mean/min/max bpm
			Complex HR	Complex derivations from heart rate eg beat-to-beat intervals; root-mean-square of successive beat-to-beat differences
			Oxygen concentration	Concentration of oxygen in breathed air via face mask system
			Respiration rate	Rate of respiration via extensible belt
			Body temperature	Various measures of body temperature, eg ear
			Body humidity	A measure of perspiration
			Urination	Urination events

respectively. More recently, accelerometers (a type of motion sensor) have emerged as a replacement, perhaps due to limitations of jaw sensors in terms of skills required for precise attachment for accurate readings, the miniaturisation of acceleration sensors and/or the greater range of application for accelerometers across multiple types of behaviours (Watanabe *et al* 2008).

Attempts to identify grazing from data signatures, either as a separate behaviour (Nadimi *et al* 2012; Alvarenga *et al* 2016; Giovanetti *et al* 2017) or as part of a class of 'active' behaviours (Nadimi *et al* 2012; McLennan *et al* 2015) have yielded variable results both between and even within experiments. For example, when grouped with 'standing' and 'standing ruminating', McLennan *et al* (2015) found 'grazing' could only be detected in 3.4% of cases. However, when joined with 'walking' to form an 'active' behaviour group, accuracy increased to 80.0%. In contrast, Alvarenga *et al* (2016) found high levels of precision (85.0 to 92.9%) when distinguishing 'grazing' from other behaviours ('lying', 'running', 'standing' or 'walking'), depending on the method of analysis. While these experiments indicate that sensors can detect feeding to some degree, performance is inconsistent and will need to be further refined before successful implementation in a commercial system.

The quality and variety of feed available to animals should also be considered when assessing animal welfare. This is particularly important in extensive production systems where pasture quality can vary considerably (Rutter 2014). For improved welfare standards, managing the survival-critical aspect of having enough food would simply minimise negative welfare, whereas encouraging exploration and acquisition of varied foods would improve it, along with other relevant aspects of welfare, such as health status and body condition (Mellor 2016b). In this review, only three experiments addressed this area of welfare using varied application of location (GPS) sensors (Ares *et al* 2007; Pérez-Barbería *et al* 2015; Jørgensen *et al* 2016). Ares *et al* (2007) found sheep travelled at different speeds depending on grass or shrub density. Similarly, Pérez-Barbería *et al* (2015) found vegetation type impacted intra-

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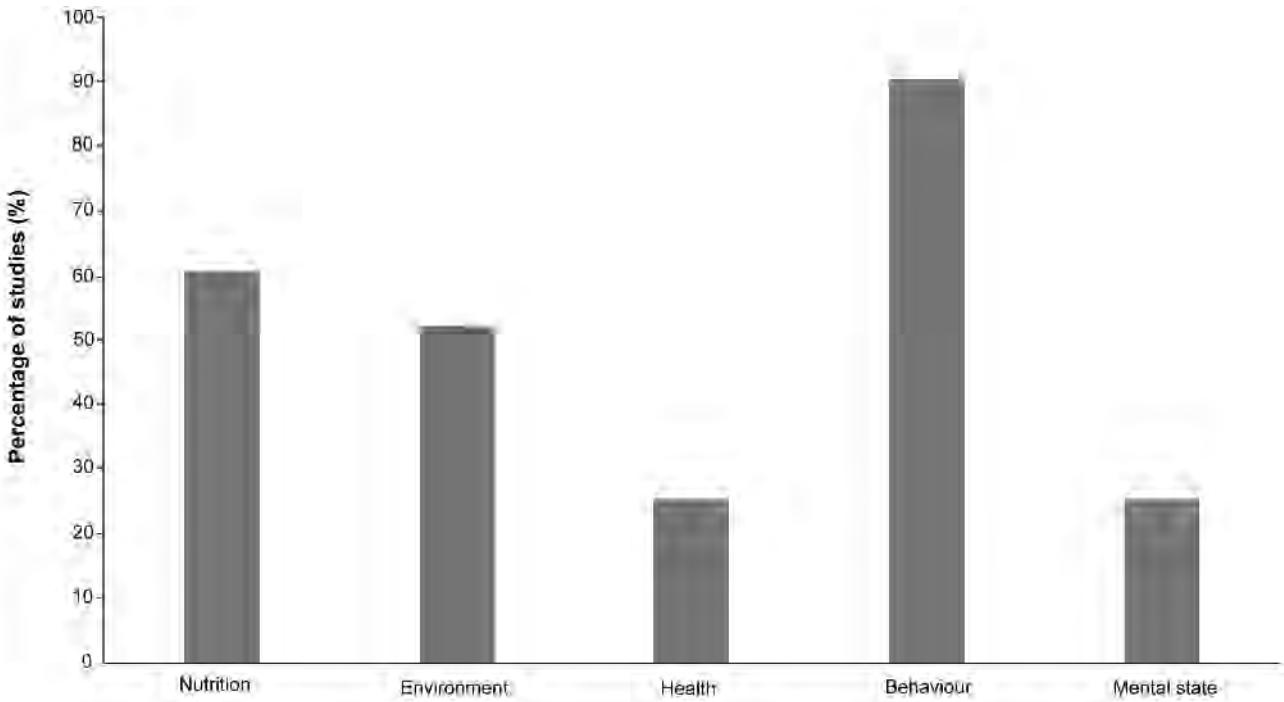
Figure 1



Alignment of the reviewed studies to the FD Model.

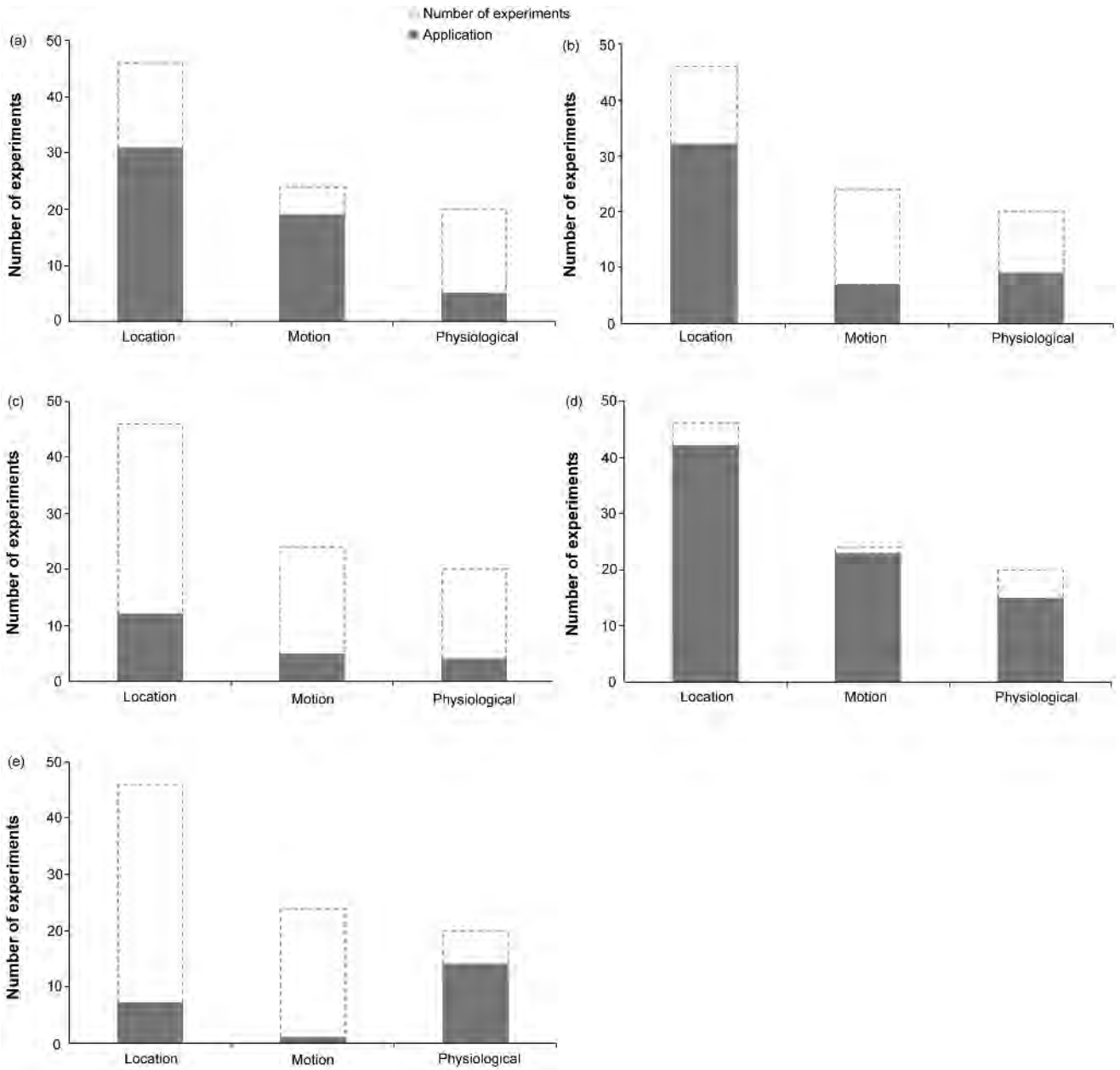
species interaction but did not impact inter-species contact between sheep and deer. Jørgensen *et al* (2016) did not find any impact of habitat quality on ranging behaviour of two sheep breeds in alpine Norway. Whilst detectable influences of food quality on grazing behaviour were inconsistent, this aspect of welfare, as highlighted in the FD model, should be explored further. This could then be combined with simpler measurements of food intake, extending welfare assessment to include both negative welfare minimisation and positive welfare promotion.

Comprehensive welfare assessment should also consider the influence of other factors on feeding behaviour. Several other factors were explored in a number of studies where various impacts on grazing were examined: social behaviour (di Virgilio & Morales 2016); stocking density (Lin *et al* 2011); food availability (Freire *et al* 2012); weather (Thomas *et al* 2008); and overall spatiotemporal patterns (Kawamura *et al* 2005; Schlecht *et al* 2006; Ares *et al* 2007; Putfarken *et al* 2008; Williams *et al* 2009, 2011; Falú *et al* 2014; Mysterud *et al* 2014; Ormaechea & Peri 2015; Zampaligré & Schlecht 2018). Given that sheep exist in a dynamic environment, the ability to address context-specific impacts would provide additional value in a welfare monitoring system. In the experiment by di Virgilio and Morales (2016), GPS was able to confirm the impact of social hierarchy on food choice, with dominant individuals more likely to graze preferred areas compared to low-ranked animals. Whilst provision of a 'yes/no' indicator of whether an animal has eaten is useful, extrapolation to known contextual parameters (in this case social grouping) would ensure a more holistic assessment of welfare, ie is the animal eating more or less due to underlying social interactions or is this an indicator of a larger health issue.

Environment

Similar to 'Nutrition', the application of sensors to monitor the 'Environment' Domain shows merit (Figure 1, Figure 2[b]). Many of these studies addressed aspects of the animal's physical environment, including provision of a thermally comfortable setting (Lowe *et al* 2001; Thomas *et al* 2008; Broster *et al* 2010; Taylor *et al* 2011; Falú *et al* 2014; Pérez-Barbería *et al* 2015; Doyle *et al* 2016; Harris *et al* 2016; Broster *et al* 2017; Zampaligré & Schlecht 2018). All studies were conducted using location sensors, with the exception of Lowe *et al* (2001) who used a heart-rate (HR) monitor and temperature sensor to monitor changes in body temperature based on weather fluctuations. This widespread use of location sensors is not particularly surprising, given an animal's absolute (GPS) or relative (contact logger) position can provide valuable information on complex animal-environment relationships. For example, Thomas *et al* (2008) found sheep travelled faster and further from water on cooler days, evidenced by speed of movement between consecutive GPS points and interaction with paddock resources. Similarly, Doyle *et al* (2016) noted daily contact time between animals increased on hotter and wetter days, measured by the number and duration of contact logger interactions. As sheep often live in fluctuating environments, the ability to monitor animal welfare in such changeable conditions would be hugely beneficial. This also suggests a deeper level of complexity for welfare assessment: that it is not only the individual itself but many contextual factors that impact welfare.

Figure 2



Alignment of major sensor families to the FD Model for (a) Nutrition, (b) Environment, (c) Health, (d) Behaviour and (e) Mental state. Families include location sensors (GPS and contact loggers), motion sensors (accelerometers, jaw/bite sensors, mercury tilt sensors or similar) and physiological sensors (HR monitors, temperature sensors, urine sensors or similar). The dotted line represents the total number of studies conducted using that particular sensor family.

Provision of a thermally comfortable setting is often achieved through adequate shelter. This was studied by Broster *et al* (2010, 2012, 2017) and Taylor *et al* (2011) who used GPS and/or contact loggers to monitor sheltering behaviour in lambing ewes. Each experiment explored different aspects of this behaviour, noting increased sheltering on high chill days (Taylor *et al* 2011), altered mother-offspring interaction in different shelter types (Broster *et al* 2010), increased crossing of sheltered areas at low stocking rates (Broster *et al* 2012) and preference for shelter at parturition (Broster *et al* 2017). Given wind, rain and low air temperatures are known to increase lamb mortality (Alexander *et al* 1980; Mellor & Stafford 2004), the use of on-animal sensors during this critical period is a good example of how sensors may be used to improve welfare monitoring. Further integration of these animal-based indicators with environment-based sensors (eg adverse weather reporting from an external weather station), would extend welfare assessment further, ensuring animals are more effectively managed in extensive production systems.

Another aspect of the 'Environment' Domain is the animal's 'space for freer movement'. In extensive animal production,

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space availability can be determined through stocking rate. This aspect was studied in a number of the experiments, usually with one of two motivations: (i) understanding the impact of changing stocking rate on sheep behaviour (Animut *et al* 2005; Putfarken *et al* 2008; Williams *et al* 2009; Lin *et al* 2011; Broster *et al* 2012); or (ii) understanding the impact of stocking rate on the environment (Kawamura *et al* 2005; Rusch *et al* 2009; Mysterud *et al* 2014; Harris *et al* 2016). The former has an obvious impact on welfare, with increased stocking rate found to increase the number of steps taken and time spent eating, even at the expense of rest (Animut *et al* 2005; Lin *et al* 2011). However, inclusion of the second group highlights a potential limitation of the review, with the method of accepting studies based on the presence or absence of keywords introducing research with minimal application to welfare. In the case of these studies, whilst the health of the environment would have some indirect impact on the animal's welfare, the sensor technology has ultimately been applied with a very different focus in mind. Despite this, there does appear to be some crossover between welfare assessment and environmental sustainability assessment which is also an emerging area for commercial sensor systems (Handcock *et al* 2009).

Health

One of the lowest levels of sensor alignment across all studies was with the 'Health' Domain (Figure 1, Figure 2[c]). Many of these experiments were concerned with identification of impaired growth and/or function. For example, Donovan *et al* (2013) and Simitzis *et al* (2009) used location (GPS) or physiological (HR monitor) sensors, respectively, to examine the effects of maternal undernutrition on offspring development. Other relevant studies were those with a specific disease or disease-related focus: Cronin *et al* (2016) on neuronal ceroid lipofuscinosis (NCL), Morton *et al* (2014) on Huntington's disease, Goddard *et al* (2000) on immunological response to human contact and Falzon *et al* (2013) on measurable impacts of worm burden. Due to the variability of disease states and shared clinical signs of functional impairment, identification of sensors dedicated to single diseases may prove difficult. For example, Cronin *et al* (2016) found NCL-affected animals showed high levels of walking behaviour compared to unaffected animals. Falzon *et al* (2013) found sheep with higher faecal egg counts travelled greater distances in a 24-h period compared to animals with a lower worm burden. Whilst completely unrelated, these studies present similar symptoms for detection (increased walking) and highlight potential limitations for technology application.

When conducting this review, distinguishing between a study's 'relevance' or 'non-relevance' was often difficult. This was particularly the case for this Domain, with reference to the required inclusion of 'abnormal movement' (Table 2). Given that the FD Model extends the definition of 'health' to include 'general activity' and 'physical fitness' as a sign of positive welfare, this decision may have falsely limited the results and contributed to the apparent low level of application. However, this demarcation was considered important to minimise confusion over what would be included under 'general' activity. Furthermore, given that these aspects of welfare would often be included under another Domain (eg distance travelled included in the 'Behaviour' Domain), this distinction prevented inflation of the results from aspects that would be considered relevant across these other Domains.

Behaviour

Sensor technology allows for recording of numerous behaviours: eg anti-predator (Manning *et al* 2014), urination (Betteridge *et al* 2010a,b), feeding (Penning 1983; Rutter *et al* 1997b; Nadimi *et al* 2012; Alvarenga *et al* 2016; Giovanetti *et al* 2017) and sexual behaviour (Fogarty *et al* 2015; Alhamada *et al* 2016, 2017). This was supported in this review, with the majority of studies aligned with this Domain (Figure 1, Figure 2[d]). At first glance, this suggests great potential for on-animal sensors as a method of quantitative data collection for behavioural welfare assessment. However, as previously stated, many behaviours are non-specific and may be altered due to a number of factors. On the one hand, this can be beneficial, allowing use of sensor data across a variety of purposes (eg measuring increased or decreased walking to indicate disease, foraging due to hunger or engagement in play). On the other hand, this generalised presentation makes it difficult to pinpoint causative factors, requiring human operator judgment as to whether a behaviour represents 'good' or 'bad' welfare. Of course, where behaviours are unique to a specific event, eg centripedal rotation during predation (Manning *et al* 2014), on-animal behaviour monitoring has an obvious and easy application. For the most part, however, commercial welfare monitoring from a behavioural standpoint will require ample thought before implementation. Furthermore, as behaviour is plastic and can easily be modified based on the perceived stimuli at any time, systems will need to be adaptable (Ralph *et al* 2018), with the presence of a particular behaviour and the resulting impact on welfare often dependent on the context under which it is being expressed.

Mental state

There was a generally low level of alignment of the reviewed studies with the 'Mental state' Domain (Figure 1). This reflects the subjective nature of affective states and difficulty in 'measuring' an emotional response (Hemsworth *et al* 2015; Tilbrook & Ralph 2018). In a review by Hemsworth *et al* (2015), historical focus of welfare science has been on detection of negative welfare states using physiological or behavioural measurements. Similar results were found in this review (Figure 2[e]), with all experiments examining negative affects (ie 'stress', 'isolation', 'fear' etc) using physiological sensors (Hargreaves & Hutson 1990; Goddard *et al* 2000; Lowe *et al* 2001; Tallet *et al* 2006; Destrez *et al* 2012; Simitzis *et al* 2012; Destrez *et al* 2013) or 'behavioural' measures from GPS (Webber *et al* 2015) or accelerometers (Verbeek *et al* 2012). Of those using physiological sensors, all were conducted with HR monitors, either exclusively

(Hargreaves & Hutson 1990; Goddard *et al* 2000; Tallet *et al* 2006; Destrez *et al* 2012; Simitzis *et al* 2012; Destrez *et al* 2013) or in conjunction with another physiological sensor (temperature sensor; [Lowe *et al* 2001]). This is unsurprising given elevated heart rate is often related to stimulation of the sympathetic (ie fight or flight) nervous system (Hargreaves & Hutson 1990).

In addition to measuring negative affects, a number of experiments addressed the positive aspects of mental state (Freire *et al* 2012; Gipson *et al* 2012; Coulon *et al* 2015; Alhamada *et al* 2016, 2017) or general emotions (Désiré *et al* 2004; Greiveldinger *et al* 2007; Reefmann *et al* 2009). Many of these experiments also utilised HR monitors (Désiré *et al* 2004; Greiveldinger *et al* 2007; Reefmann *et al* 2009; Coulon *et al* 2015) with inter-heartbeat interval and heart-rate variability indicative of parasympathetic (ie rest and digest) activation.

One aspect lacking in the reviewed papers was the use of sensors to measure internal (ie mental) stressors. In experiments involving race car drivers (Taelman *et al* 2016) and horses (Norton *et al* 2018), heart-rate modelling can be used to indicate mental stress by decoupling the recorded heart rate into its fundamental components: basal metabolism, thermoregulation and physical activity. In both studies, once these fundamental components have been accounted for, any further change in heart rate is thought to reflect a quantifiable measure of the organism's stress level. This represents a novel approach to objectively measure stress (specifically acute stress response) using wearable technology and could be applied in future sheep research to quantify mental aspects of welfare. This would undoubtedly improve overall welfare assessment and allow for continuous objective monitoring of an aspect of welfare that has remained difficult to measure thus far.

Limitations of the review

This review indicates the potential for animal sensor systems to monitor welfare through reliable quantitative behavioural and physiological measures that can then be mapped to welfare frameworks. However, there are a number of limitations that should be considered. First, there is a measure of subjectivity when determining 'application' to each Domain. The development of keywords has attempted to mitigate this, though some level of scientific judgement was still required. For example, 'grazing' can be used to indicate food intake (Domain 1 and 4) or as a method of describing an extensive production system (not relevant to any Domain). In this case, contextual use has significant impact on the relevance of the study and needs to be assessed accordingly. Furthermore, inclusion of a contextually relevant word did not necessarily equate to relevance either, with some papers including keywords when recommending future scientific work, not discussing the research at hand.

Another limitation of this review is the tendency to include studies as relevant based on presence of a keyword, with no option to determine relevance if a keyword is not used. For example, if a keyword was present the paper was automatically assessed to determine application to a Domain. On the other hand, missing keywords meant the article was never assessed under that Domain, even if they should have been. For example, Manning *et al* (2014) used location sensors (GPS) to study sheep behaviour during predation. Whilst this could be considered relevant to 'Health' (injury from a predation event) and 'Mental state' (fear associated with the event), it was not included under either Domain due to the absence of relevant keywords in the aims and/or conclusions. Furthermore, as some studies did not include overt statements of objectives or conclusions, there was some discrepancy between assessment based on concise statements (eg Dobos *et al* 2014) or assessment on entire paragraphs (eg Freire *et al* 2012; Donovan *et al* 2013; Munn *et al* 2013). This may have led to under or over estimation of relevance, respectively, and should be considered when interpreting these results.

Since the inclusion criteria did not relate to the quality of the study, this should also be considered when interpreting results. For example, of the 71 publications reviewed, only 19.7% (n = 14) referred to previously validated accuracy of the sensors, with a further 21.1% (n = 15) including the validation as part of the publication methods. An additional 18.3% (n = 13) of publications that did not include reference to sensor accuracy, all used GPS and employed some method of *post hoc* data 'cleaning': exclusion based on speed/distance values (Dobos *et al* 2014; Falú *et al* 2014; Webber *et al* 2015); removal of location points outside of a paddock boundary (Gipson *et al* 2012; Harris *et al* 2016); rejection based on a given horizontal dilution of precision (HDOP) value (or similar) (Schlecht *et al* 2006; Williams *et al* 2009, 2011; Jørgensen *et al* 2016; Broster *et al* 2017); and/or other methods (Haddadi *et al* 2011; Gipson *et al* 2012; Donovan *et al* 2013; Falú *et al* 2014). Forty-one percent (n = 29) of publications did not include validated accuracy measures or post-processing cleaning. Thus, when considering how technology might enhance welfare assessment, consideration of study design and quality of work is also important.

Finally, this review provided a comprehensive assessment of how sensors can be used to monitor various components of welfare. However, there was no exploration of the thresholds or limits around which an objective measure of welfare might be based. For this reason, this review should not be used as a definitive ranking of studies based on their perceived merit for welfare assessment, but as a benchmark that establishes what has been published in this space and where further studies are required. Furthermore, the review provides a scaffold upon which technology developers may better understand the requirements for welfare assessment and how their system may contribute to this.

Animal welfare implications

The results of this review highlight the low number of studies that have been conducted with an explicit focus on sensor technology for welfare assessment. In most cases it is clear that the reviewed literature was never intended to relate to welfare, with the majority of publications (59.2%; n = 42)

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having no mention of 'welfare' in the main body of text. Perhaps the reason for this low level of application is the complexity of welfare *per se*. Welfare encompasses physiological and psychological aspects (Tilbrook & Ralph 2018), with the focus for assessment invariably depending on the context in which welfare is being viewed (Hemsworth *et al* 2015; Mellor & Beausoleil 2015; Littlewood & Mellor 2016; Mellor 2017). For this reason, it is likely that the reviewed studies, given that they are using relatively novel technology that first needs to be proven as a useful tool in an agricultural context, chose not to focus on such a complex issue in the first instance. Despite this apparent low level of deliberate application, the retrospective classification of the reviewed literature under the FD Model highlights how sensors can often be applied to welfare assessments, even if this was not the authors' original intent.

When choosing a sensor type for commercial development, those sensors with broad application across multiple Domains would be beneficial. Location information would be valuable in extensive livestock systems, where animals are often dispersed over large distances. This information could also be used to locate an individual, enabling swift intervention for animals that fall outside the welfare standards. However, as some location sensors (GPS) have high power requirements, this could be a significant barrier for implementation (Swain *et al* 2011). Motion sensors can detect a number of behaviours which can then be extrapolated to infer many aspects of welfare, eg disease state, injury, time spent lying or daily activity patterns. However, practicalities of fitting the sensor, data accuracy, download and interpretation are still being determined (Watanabe *et al* 2008; Barwick *et al* 2018). Finally, physiological sensors appear uniquely able to measure aspects of mental state and should not be discounted for inclusion in a commercial device. Again, practicalities associated with attachment will need to be researched further.

Given the benefits of each sensor type, perhaps the development of on-animal sensors for welfare assessment should focus on the integration of more than one sensor. Though issues such as large device size and common attachment points will still need to be overcome, integration will allow broad welfare assessment. As the current rate of technology development continues to rise, further miniaturisation of existing technologies and improved battery capacity will increase the relevance of appropriate sensor technologies. In the meantime, the use of sensors in a research capacity will provide fundamental knowledge upon which commercial welfare systems will be able to be built.

Despite the clear benefit of sensor technology for welfare assessment, careful consideration of a number of factors is still required before implementation. Firstly, regardless of the model chosen for assessment, every system will still need to adequately consider the physical, biotic and social context of the animal in question. The apparent numerical objectivity of technological sensors may hinder this, as it will be tempting for commercial business to develop arbitrary welfare 'scores' in order to rank different animals/farms/production systems etc. Furthermore, given that use of technological sensors will inevitably result in reliance on indices that can actually be measured or observed in every situation, there is the potential to miss important aspects of the animal's life that may still impact their welfare status. This may result in assessment being based on incomplete 'snapshots' of the animal's life at a given point in time rather than constant monitoring of welfare. It is important to note that these considerations are not limited to sensor technology, but rather common amongst welfare assessments in general. Thus, whilst these aspects still require consideration, as long as the final welfare assessment is based on cautious inference from scientifically informed best judgment (Mellor 2017), sensor technology has the potential to enhance current monitoring systems.

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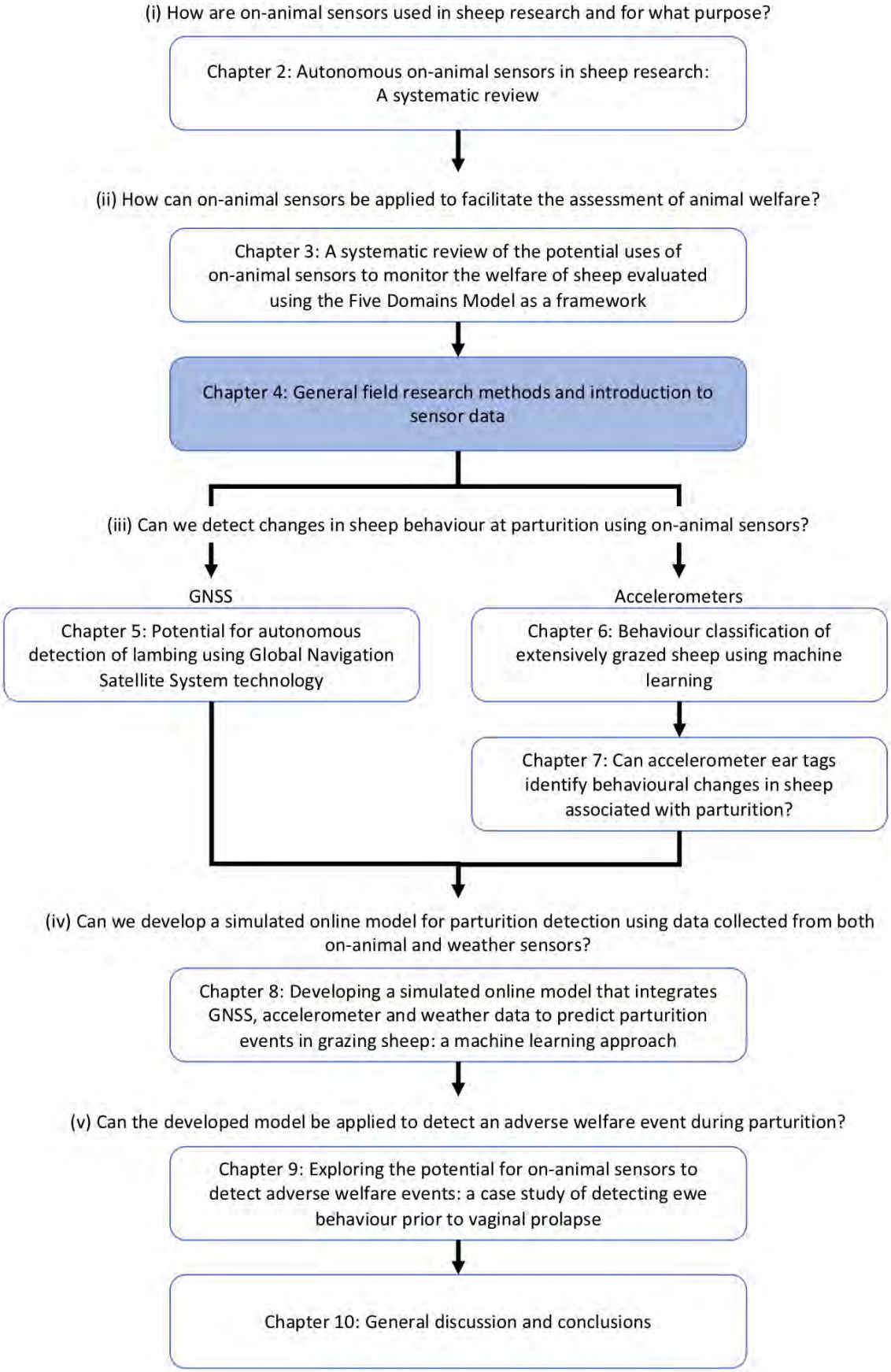
(i) How are on-animal sensors used in sheep research and for what purpose?
Chapter 2: Autonomous on-animal sensors in sheep research: A systematic review
(ii) How can on-animal sensors be applied to facilitate the assessment of animal welfare?
Chapter 3: A systematic review of the potential uses of on-animal sensors to monitor the welfare of sheep evaluated using the Five Domains Model as a framework
Chapter 4: General field research methods and introduction to sensor data
(iii) Can we detect changes in sheep behaviour at parturition using on-animal sensors?
GNSS
Accelerometers
Chapter 5: Potential for autonomous detection of lambing using Global Navigation Satellite System technology
Chapter 6: Behaviour classification of extensively grazed sheep using machine learning
Chapter 7: Can accelerometer ear tags identify behavioural changes in sheep associated with parturition?
(iv) Can we develop a simulated online model for parturition detection using data collected from both on-animal and weather sensors?
Chapter 8: Developing a simulated online model that integrates GNSS, accelerometer and weather data to predict parturition events in grazing sheep: a machine learning approach
(v) Can the developed model be applied to detect an adverse welfare event during parturition?
Chapter 9: Exploring the potential for on-animal sensors to detect adverse welfare events: a case study of detecting ewe behaviour prior to vaginal prolapse
Chapter 10: General discussion and conclusions

Chapter 4. General field research methods and introduction to sensor data

Overview

This section has been included to provide clarity around how data has been managed and its presentation across Chapters 5 to 9. As these chapters have been written for the purpose of publication, it was not possible to thoroughly explain the process of data management, analysis and other thesis-scale background detail in the individual manuscripts themselves. It is the intent of this section to provide the reader with a synoptic view of the methodology used in the PhD program, the sensors applied and how each field trial and data analysis process has been undertaken. Details on dataset distribution between each chapter are also provided.

4.1 Context

The original focus of the PhD was to assess sensor application for lifelong welfare monitoring (as directed by the agency funding the research). However, throughout the development of Chapter 2, it was decided that this concept was too large and complex to address within a single PhD program. Hence, the research focus shifted to parturition as a time of potential adverse welfare. Parturition can be considered as a period of considerable welfare risk (Bickell et al., 2010, Hinch and Brien, 2014). For the ewe, it is a period of physical discomfort (Jensen, 2012), especially if the birth process has complications such as dystocia. For the lamb, parturition is the first experience of the newborn, and can be considered the first aspect of 'lifelong' welfare monitoring.

The systematic literature reviews reported in Chapters 2 and 3 indicate merit in the use of sensors for autonomous welfare assessment. The three major sensor types most appropriate for assessment are location technologies, motion sensors and physiological sensors (Chapter 3). In this program, two technologies were chosen for further analysis, namely GNSS (location sensor) and accelerometers (motion sensor). These were selected for two reasons: the first being that they showed potential for detection of key behaviours of interest; and the second being that they are readily available as research tools. These sensors are also being developed into commercial platforms (Trotter, 2018). Though physiological sensors such as a heart rate monitor would also provide great information, especially for the 'Mental State' domain, operational versions of this technology are not readily available in either a research or commercial context.

4.2 Field work

The PhD research program was based on two separate field campaigns involving fitting of on-animal sensor systems and observational data recording. Both field campaigns were conducted at a commercial mixed enterprise property in North Canterbury, New Zealand (43.0°S and 173.2°E). The following information has been reported in detail in Chapter 5 and Chapter 7. However, a summary is provided here to better understand how the data from each trial was handled.

4.2.1 2017 field trial

The first field trial was conducted from 29 September to 13 October 2017. Mixed-aged Merino and Merino-cross ewes (n = 40; 20 twin-bearing and 20 single-bearing) were selected based on an expected lambing date within the experimental period and number of expected lambs (confirmed by ultrasound assessments as per normal farm practice). Prior to the study's commencement, ewes were fitted with i-gotU GT-600 GNSS loggers (Mobile Action, Taiwan) attached to neck collars and programmed to obtain locations at 3 min intervals. Total weight of the GNSS collar was approximately 500 g (Figure 4.1) The animals were also fitted with tri-axial accelerometers (Axivity AX3, Axivity Ltd, Newcastle, UK) attached to ear tags and configured at 12.5 Hz. Total weight of the accelerometer ear tag was 20 g (Figure 4.2). An in-situ photograph of sensor attachment is shown in Figure 4.3. The accelerometers were fixed with orientation of the X-, Y- and Z-axis along the dorso-ventral (up-down), lateral (side-to-side) and anterior-posterior (forward-backward) axes, respectively (Figure 4.4). Animals were kept in a 3.09 ha experimental paddock for the entire study duration. Forage and water were supplied *ad libitum* and shelter was provided by the natural sloping topography. The devices remained on the animals until 25 October 2017 (total attachment period 26 days), after which they were removed, and the data downloaded.

Figure 4.1 i-gotU GT-600 GNSS loggers enclosed in a neck collar

Figure 4.2 Axivity AX3 tri-axial accelerometer attached to a standard ear tag

Figure 4.3 In-situ photograph of attached GNSS collar and accelerometer ear tag

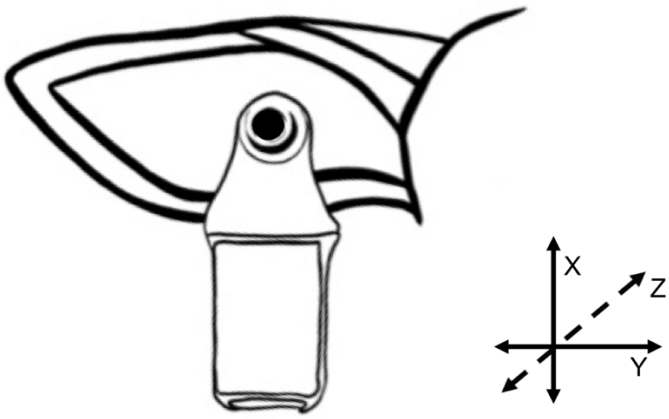

Figure 4.4 Schematic drawing of the ear tag attachment site including device orientation

Throughout the experimental period (30 September 2017 to 13 October 2017: 14 days in total), ewes were observed from a neighbouring paddock using binoculars and a Nikon Coolpix B500 camera with a 40x optical zoom (Nikon, Japan). However, due to technical issues associated with time stamping, the videos were unable to be used during data analysis. *Ad libitum* behaviour observations (Martin and Bateson, 2007) were conducted from 0630 h – 1230 h and 1530 h – 1800 h ± 30 min to record lambing events. Where possible, the exact time of lambing was recorded (to the nearest minute). Lambing was considered the time in which the first lamb was expelled fully. If this was not achievable, lambing time was estimated to the nearest hour. For ewes that lambed overnight or during periods where the observer was not present, only the day of lambing was recorded. In this situation, day of lambing was noted as the day the newborn was first identified.

4.2.2 2018 field trial

The second field trial was conducted from 8 September to 23 September 2018. Mixed-age ewes (n = 39; Merino or Merino-cross) were selected from the main commercial flock based on them having an expected lambing date during the experimental period and number of expected lambs (confirmed by ultrasound assessments as per normal farm practice). Again, prior to study commencement, ewes were fitted with GNSS collars and accelerometer ear tags as per the 2017 trial. The accelerometers were configured at the same rate as 2017 (12.5 Hz). However, the GNSS collars were configured to collect locations at 2 min intervals. Following device attachment, animals were moved to the planned study paddock. However, on the morning of Study Day 1 it was noted that this paddock did not allow adequate observation of the animals. Hence the flock were moved to an adjoining paddock at 1100 h on Study Day 1, where they remained for the rest of the study. This second paddock was 4.4 ha. Forage and water were supplied *ad libitum* and shelter was provided by tree breaks along the east and west paddock boundaries. The north side of the paddock followed a major farm road. The devices were removed on the morning of 24 September 2018 (total attachment period 16 days) and data was subsequently downloaded.

Similar to the 2017 trial, ewes were visually observed throughout the experimental period (9 September to 23 September 2018: 15 days in total). *Ad libitum* behaviour observations (Martin and Bateson, 2007), assisted by binoculars, were conducted from 0730 h – 1230 h

and 1330 h – 1730 h (± 30 min) to record lambing events. Video observations were also acquired during these times using a Nikon Coolpix B500 camera with a 40x optical zoom (Nikon, Japan) and a Sony HDR-PJ410 Camcorder (Sony, Japan). Both cameras were synchronised with the "time.is" website (https://time.is/) at the start of each day before any recordings.

Again, where possible the exact time of lambing was recorded. If this was not possible, lambing was estimated to the nearest hour or day (for those that lambed overnight or during periods where the observer was not present).

4.3 Data management and analysis

As detailed previously, two types of sensors were selected for evaluation: GNSS and accelerometers. The following section provides a basic description of each sensor and chosen methods of data processing.

4.3.1 GNSS

GNSS tracking of animal movement was first conducted in 1994 and applied to Moose (*Alces alces*) to understand the impact of forest cover on accuracy (Rempel et al., 1995). Today, GNSS tracking is widely used in both wildlife (see Wilmers et al. (2015) and Hofman et al. (2019) for a review) and livestock (see Swain et al. (2011) for a review) research. As detailed in Chapter 2, GNSS is widely reported in sheep research (48.8% of reviewed literature), usually for the purpose of monitoring behaviour or environment-related analysis.

4.3.1.1 Raw GNSS data

At a basic level, raw GNSS data provides three important pieces of information: a timestamp and the corresponding latitude and longitude (Figure 4.5). Other information such as altitude and horizontal dilution of precision (HDOP) is also provided, but this was not considered in the current analysis. In the majority of publications, raw GNSS data is processed into more meaningful metrics e.g. speed or distance travelled (Dobos et al., 2014, Dobos et al., 2015, Fogarty et al., 2015, Broster et al., 2012, Falzon et al., 2013, Thomas et al., 2008), social metrics (Dobos et al., 2014), or general interactions with the environment, e.g. distance from

shelter (Broster et al., 2012, Taylor et al., 2011), distance from water (Thomas et al., 2008), preferred grazing locations (Falú et al., 2014, Ormaechea and Peri, 2015).

a)

A	B	C
timestamp	Longitude	Latitude
9/9/18 0:01	173.167435	-42.970711
9/9/18 0:03	173.167175	-42.970608
9/9/18 0:05	173.16713	-42.970627
9/9/18 0:07	173.167221	-42.97065
9/9/18 0:10	173.16716	-42.970581
9/9/18 0:12	173.167145	-42.970634
9/9/18 0:14	173.167068	-42.970547
9/9/18 0:16	173.166824	-42.970482

b)

Figure 4.5 Example of raw GNSS data: a) tabular and b) graphical

In this project, three major GNSS metrics were calculated: (i) speed of movement; (ii) distance to peers; and (iii) use of space. Processing and analysis was conducted using a combination of ArcGIS Version 10.3.1 (ESRI, 2016) and the statistical software R (R Core Team, 2018). This work has been presented in detail in Chapter 5. For contextual purposes, the following sections provide further details of each metric.

4.3.1.2 Speed of movement

Distance, time and speed between consecutive locations was calculated using the raw GNSS data. Speed of movement was calculated as distance between consecutive GNSS locations divided by the time interval between the readings (Dobos et al., 2014, Schlecht et al., 2004, Trotter et al., 2010) (Figure 4.6). For the 2017 field trial, speeds over 3 m/s and distances over 540 m (calculated as the maximum distance that could be travelled at 3 m/s for the 3 min interval between GNSS fixes) were removed, as these are commonly associated with GNSS error (Swain et al., 2011, Taylor et al., 2011, Dobos et al., 2015). For the 2018 field trial, speeds over 3 m/s and distances over 360 m (the maximum distance that could be travelled at 3 m/s for the 2 min interval between GNSS fixes) were removed (Dobos et al., 2015). Once these erroneous points had been excluded, movement metrics were recalculated. A moving window average for speed was also applied, based on the two locations prior to and following the point of interest. This was done to smooth out inaccuracies in the uncorrected dataset

and was considered particularly important for maximum and minimum speed calculation where inaccurate GNSS data may be falsely interpreted as erratic movement.

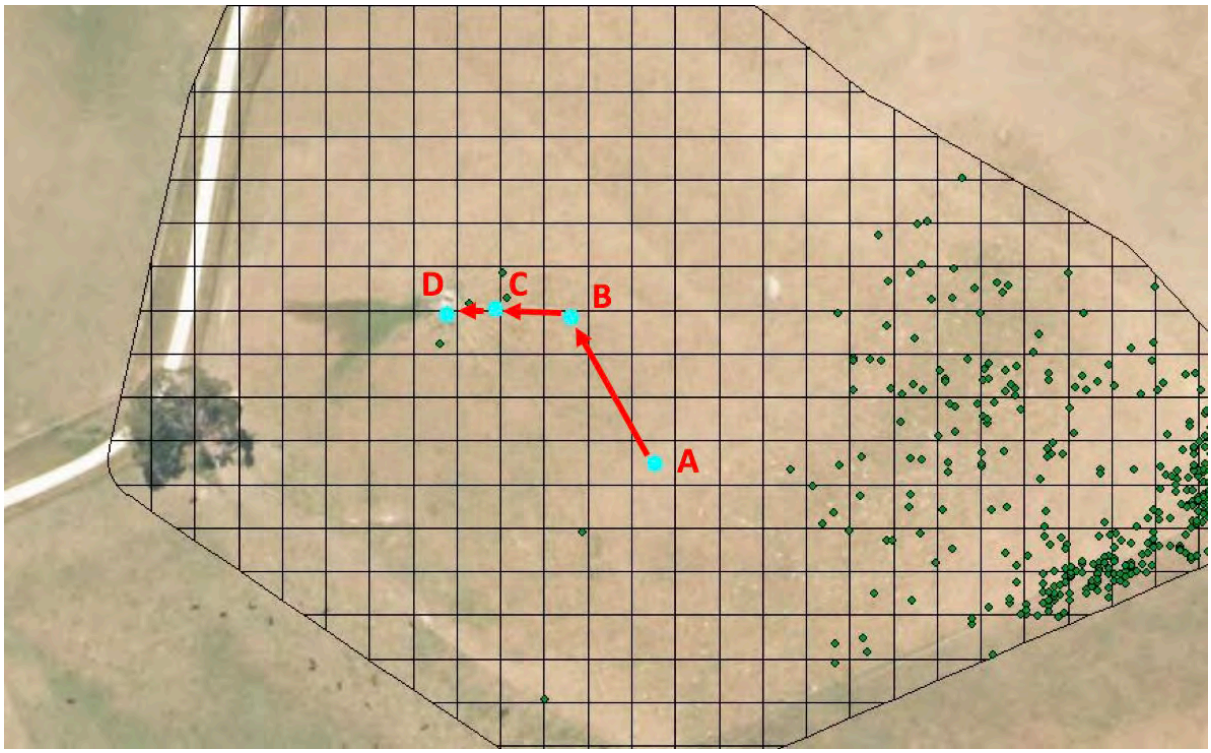

Figure 4.6 Calculation of speed of movement between consecutive GNSS locations. Arrows show direction of movement. Speed calculation is based on the straight-line distance between consecutive locations, divided by the time interval between locations. For example, distance between Point A and Point B is 100 m and the time interval between the points is 3 min (180 s). Calculated speed is 0.56 m/s.

4.3.1.3 Distance from peers

The distance of each ewe to her peers served as a measure of ewe isolation. The method for calculation was: (i) for each GNSS point of a reference ewe, find the closest point in time for every other ewe in the paddock; (ii) calculate the straight-line distance between the reference ewe and each comparison ewe; and (iii) remove points where the time difference between the 2 GNSS points was over 5 min (300 s). This interval was chosen to ensure animals that were consistently on asymmetric GNSS fix timings would still be included in analysis.

As per the discussion section in Chapter 5, an additional calculation of distance to 'closest peer' was suggested for future research. This was calculated for later analysis and applied in Chapter 8. Figure 4.7 provides a schematic diagram of how mean distance to peers and distance to closest peer metrics are calculated.

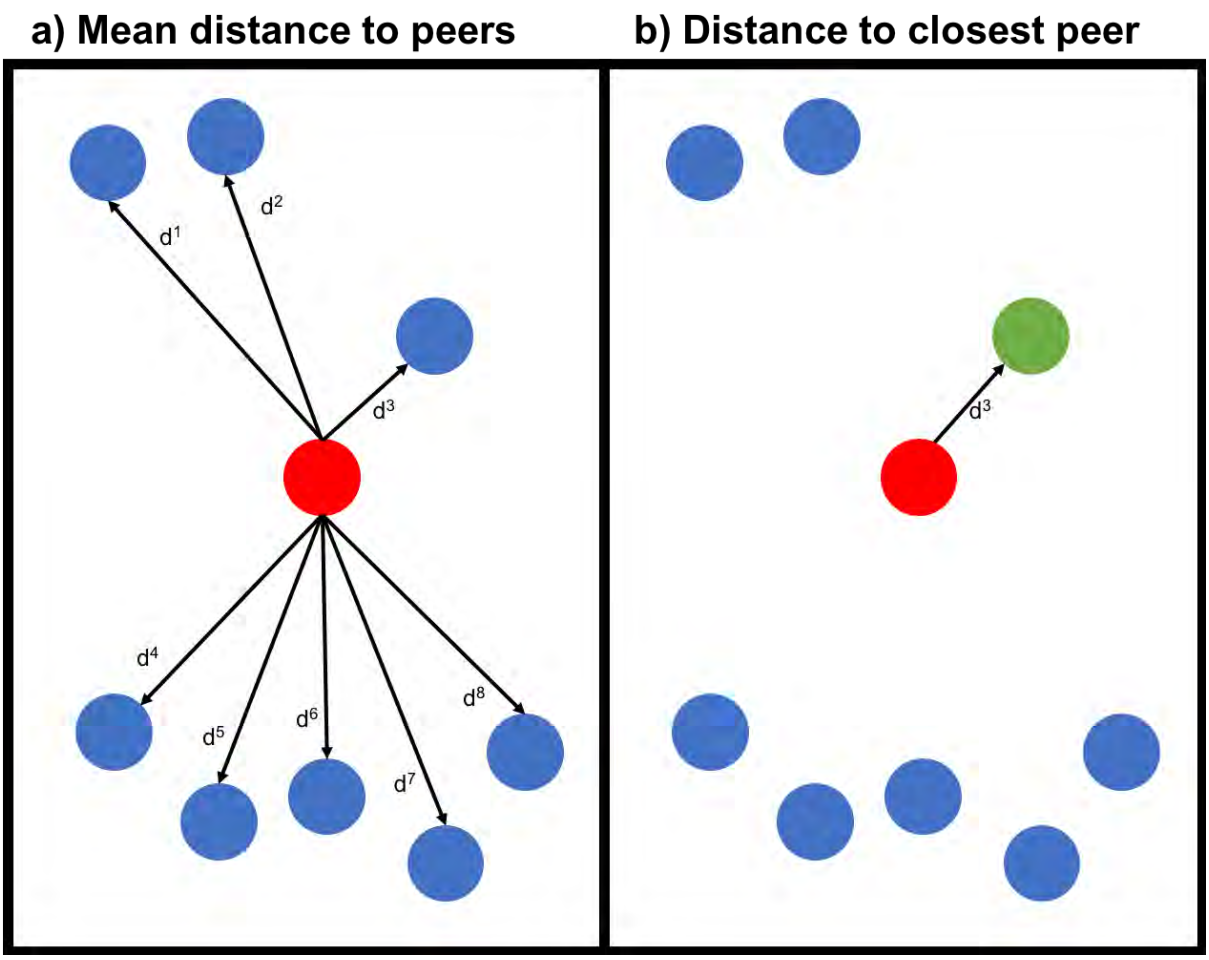

Figure 4.7 Schematic diagram of calculation of distance to peers. a) Mean distance to peers is calculated by averaging the straight-line distance of the sheep of interest (red circle) from all other sheep in the flock (blue circles). b) Distance to closest peer is the straight-line distance from the sheep of interest (red circle) to the closest animal in the flock (green circle). In this situation, the straight-line distance to all other ewes in the flock is discarded.

4.3.1.4 Use of space by minimum convex polygon (MCP)

To determine how much of the paddock each ewe utilised, a 95% minimum convex polygon (MCP) was calculated. MCP is calculated by drawing a polygon around the outermost points in a dataset and measuring the area within the polygon (Burgman and Fox, 2003). For calculation of 95 % MCP, 5 % of outlying locations furthest from the centroid are discarded before calculation, improving the accuracy of the estimate (Calenge, 2006). The 95 % MCP was calculated for each ewe on each day of the study. Due to normal inaccuracies that occur in GNSS data (Trotter and Lamb, 2008), the data was trimmed to the paddock boundaries (+10 m buffer) prior to MCP calculation. This was done to prevent overestimate of the animal's spatial utilisation where the location estimates were seemingly outside of the

paddock. The buffer size (+10 m) was chosen based on the mean location error of < 10 m for the i-gotU device (Morris and Conner, 2017)

Figure 4.8 shows an example of a 95 % MCP calculated for two different sheep on Day 5 of the 2017 field trial.

Figure 4.8 The 95 % MCP calculated for two different animals: a) Red 7; b) Black 2. Data represents a single day (Day 5) of the 2017 field trial. Calculated MCP: a) 0.43 ha; b) 1.67 ha.

4.3.1.5 Use of GNSS-derived metrics

Once the GNSS-derived metrics were calculated, changes in these behaviours in the period surrounding parturition were examined. The objective of this research was to identify potential metrics that could be used in later algorithm development for parturition detection. Analysis was conducted using linear mixed-effects models with a first order autoregressive correlation structure. Metrics were summarised on a daily and hourly basis and the results of this work are presented in Chapter 5.

4.3.2 Accelerometer data

Similar to GNSS, raw accelerometer data provides four basic pieces of information: a timestamp and a corresponding acceleration on the X-, Y- and Z-axis. As detailed in Chapter 2, the use of accelerometers has increased in recent years, allowing researchers to interpret animal movements through discernible changes in acceleration (Bidder et al., 2014). In many cases, accelerometers provide information on broad categories of animal behaviour. In sheep, the three behaviours most prominent in terms of time budget are grazing, travelling and rest (either standing or lying) (Barwick, 2016). These behaviours, and subsequent changes to the normal patterns of these behaviours, can be used to identify important changes in the animal, e.g. parturition (Jensen, 2012, Krieger et al., 2018, Krieger et al., 2017), lameness (Barwick et al., 2018a) or disease (Cronin et al., 2016, Morton et al., 2014).

In the current work, the initial focus for accelerometer data analysis involved identification of methods that make adequate differentiation between these main behaviours possible. The finalised results are presented in Chapter 6. For context, the following sections have been included to explain the data handling process behind this work and to provide a justification for particular methodological decisions.

4.3.2.1 Raw accelerometer data

Figures 4.9 – 4.12 illustrate the raw data signatures from four behaviours (grazing, lying, standing and walking) for a 60 s duration. Note walking behaviour is only displayed for a 40 s period as this was the longest duration of consistent walking visually observed.

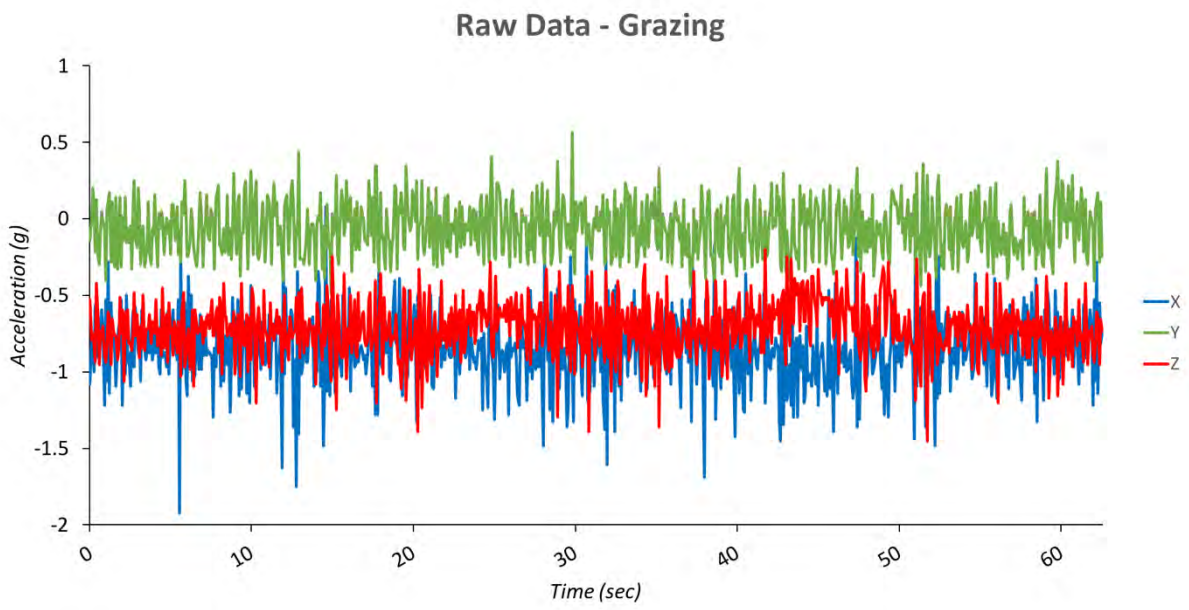

Figure 4.9 Acceleration signal from the ear-borne accelerometer while the animal was grazing (60 s).

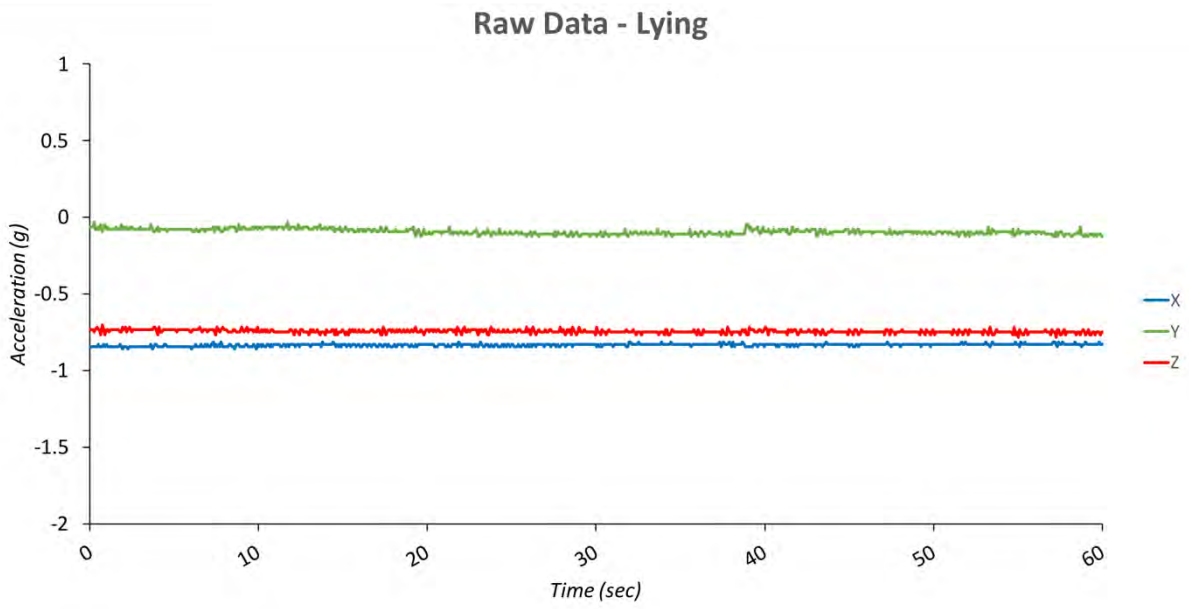

Figure 4.10 Acceleration signal from the ear-borne accelerometer while the animal was lying (60 s).

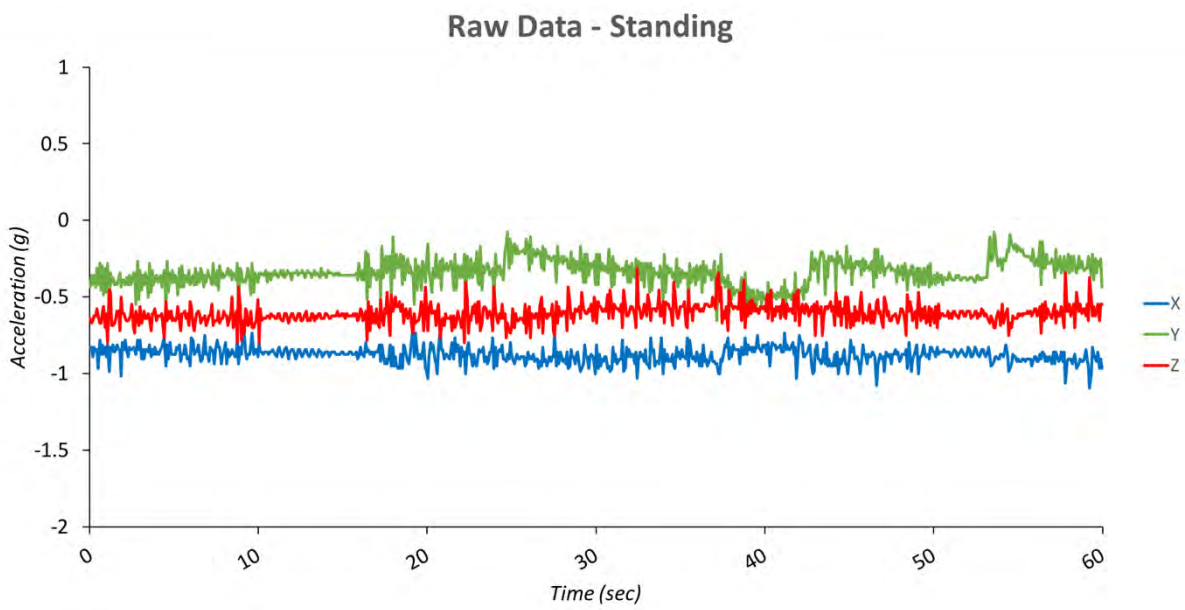

Figure 4.11 Acceleration signal from the ear-borne accelerometer while the animal was standing (60 s).

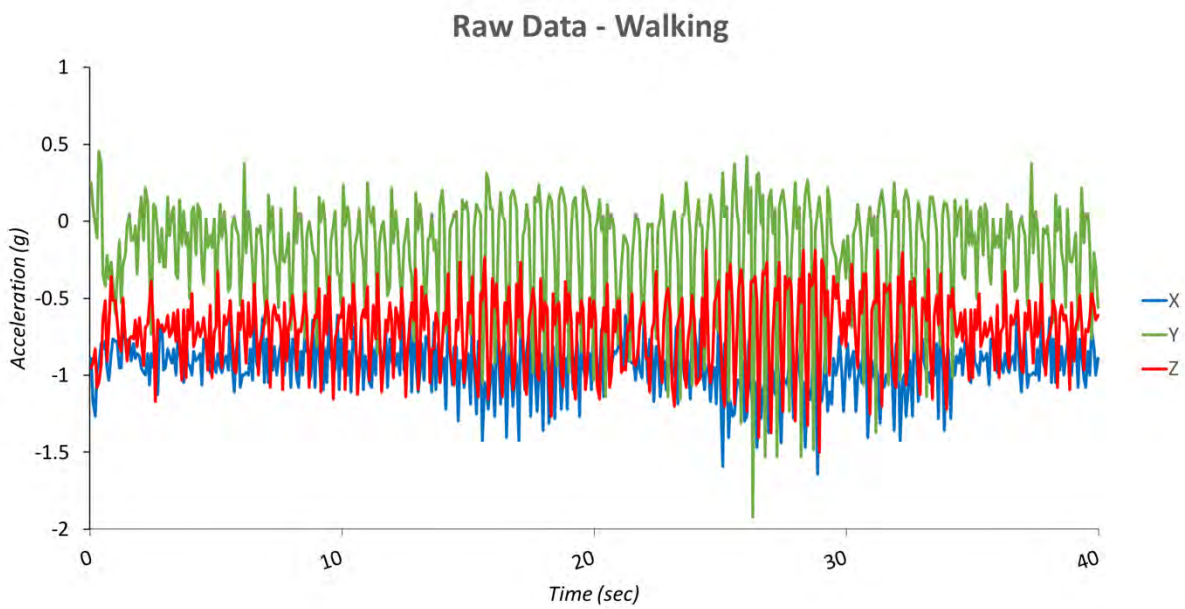

Figure 4.12 Acceleration signal from the ear-borne accelerometer while the animal was walking (40 s).

As shown in Figures 4.9 – 4.12, there are some obvious differences in the raw data signatures between the behaviours. However, analysing these raw signals is not simple. Due to the high sampling frequency of accelerometers (usually multiple readings per second), raw accelerometer datasets can be large if collected over extended periods of time (Brown et al., 2013). This results in datasets that are difficult to manage due to their high processing

requirements. Furthermore, as we move toward sensor application in a commercial setting, consideration of infrastructure requirements for data transfer is crucial. For example, data transmission is an extremely power-intensive process (Handcock et al., 2009), and therefore optimal sampling size and algorithm selection is essential to prevent transfer of surplus data (Vázquez-Diosdado et al., 2019). This is particularly important if initial analysis is conducted on the device itself (embedded processing) or close to the device (edge computing; see Chapter 8 for details). For this reason, research with a commercial application focus, which is the case in this thesis, should concentrate on discovering the best analysis processes.

One method of reducing the complexity of accelerometer datasets is by summarising the data over a set time period (termed 'epoch'). This results in the calculation of numerous summary 'features' that represent the overall intensity of activity during each time period (Barwick, 2016, Chen and Bassett, 2005, Yang and Hsu, 2010). Features can be summarised over any epoch length, with published literature ranging from 3s (Alvarenga et al., 2016) to 300s (Decandia et al., 2018). In specific studies of sheep, epoch durations of 3 to 10 s are common (Alvarenga et al., 2016, Barwick et al., 2018a, Barwick et al., 2018b, Radeski and Ilieski, 2017, Walton et al., 2018, Mansbridge et al., 2018), though there is also merit in examining a 30 s epoch (Decandia et al., 2018, Umstätter et al., 2008). In the current program, multiple epoch lengths (5, 10 and 30 s) were evaluated. Epochs were calculated as a discrete unit of time based on actual time of day, with no overlap (Table 4.1). Further detail is provided in Chapters 6 and 7.

Table 4.1 Example epoch classification based on consecutive periods of time

Time range (hh:mm:ss)	10s epoch	30s epoch
00:00:00 – 00:00:10	1	1
00:00:10 – 00:00:20	2	
00:00:20 – 00:00:30	3	
00:00:30 – 00:00:40	4	2
00:00:40 – 00:00:50	5	
00:00:50 – 00:01:00	6	

4.3.2.2 Feature calculation

During the feature calculation process, numerous metrics are computed to provide more information on the raw acceleration waveforms (Brown et al., 2013, Barwick, 2016). These features can be calculated for a single axis (e.g. mean or standard deviation of the X-axis) or all three axes can be evaluated simultaneously. The features used in this research program have been reported in the literature (Barwick et al., 2018b, Alvarenga et al., 2016, Barwick et al., 2018a, Campbell et al., 2013, Marais et al., 2014). A summary is provided in Table 4.2.

Table 4.2 Features calculated for each epoch (5, 10, 30s) based on raw X, Y and Z acceleration values.

Feature	Description	Reference
$Mean_X$ $Mean_Y$ $Mean_Z$	Mean value for each axis over the epoch	Barwick et al. (2018a); Barwick et al. (2018b); Marais et al. (2014)
Min_X Min_Y Min_Z	Minimum (Min) value for each axis over the epoch	Barwick et al. (2018a); Barwick et al. (2018b); Marais et al. (2014)
Max_X Max_Y Max_Z	Maximum (Max) value for each axis over the epoch	Barwick et al. (2018a); Barwick et al. (2018b); Marais et al. (2014)
SD_X SD_Y SD_Z	Standard deviation (SD) for each axis over the epoch	Campbell et al. (2013); Marais et al. (2014)
Movement Intensity (MI)	Measurement of the instantaneous intensity of movements, averaged over an epoch. MI is independent of device orientation (Zhang and Sawchuk, 2011)	Barwick et al. (2018a); Barwick et al. (2018b)
Signal Magnitude Area (SMA)	The average magnitude of acceleration over an epoch (Zhang and Sawchuk, 2011)	Alvarenga et al. (2016); Barwick et al. (2018a); Barwick et al. (2018b); Campbell et al. (2013)

Energy	Sum of the squared signal components from each axis (Zhang and Sawchuk, 2011)	Alvarenga et al. (2016); Barwick et al. (2018a); Barwick et al. (2018b); Marais et al. (2014)
Entropy	A measure of the freedom of motion whereby smooth motion is more predictable than random motion and therefore has lower entropy (Smith et al., 2016)	Alvarenga et al. (2016); Barwick et al. (2018a); Marais et al. (2014)
Movement Variation (MV)	Total variance of signal vibration within an epoch (Barwick, 2016)	Alvarenga et al. (2016); Barwick et al. (2018a); Barwick et al. (2018b)

Two commonly used techniques for accelerometer data analysis are fast Fourier transformation (FFT) and continuous wavelet transformation (CWT). FFT decomposes the acceleration signal, making it possible to identify individual frequencies and amplitudes (Shuert et al., 2018). CWT generates a spectrum of acceleration signals, allowing for documentation of when and where a frequency occurs (Sakamoto et al., 2009, Brown et al., 2013). While these two techniques have potential, they can be complicated and are often not essential for adequate analysis (Shephard et al., 2008, Laich et al., 2009). In contrast, simpler statistics and machine learning (ML) are more intuitive and widely accessible to a range of users (Shephard et al., 2008, Brown et al., 2013). For this reason, the more complex FFT and CWT were not pursued as part of this analysis.

4.3.2.2.1 Preliminary results

The following section provides summary statistics for some of the key features identified through the analysis process. This data was not presented in the published papers because it would have resulted in these manuscripts being excessively long. However, it is presented in this thesis to provide the reader with a more in-depth understanding of the results. The data presented below was collected from 12 ewes in the 2018 field trial (see Chapter 6 for details).

Each data point represents the calculated features for one discrete epoch. Epochs have also been labelled with the known behaviour according to video observations.

To visualise the data, density plots were generated (Figures 4.13 – 4.15). For brevity, only data for the three most important features for behaviour discrimination are presented: movement variation (MV; Figure 4.13), standard deviation of X (SD_X; Figure 4.14) and standard deviation of Y (SD_Y; Figure 4.15). In addition, only the 10 s epoch is presented, as this was the most valuable epoch duration for classification of the four mutually exclusive behaviours (see Chapter 6 for details).

As shown, there appears to be some ability to differentiate between the four mutually exclusive behaviours using the calculated features. For example, lower activity behaviours (i.e. lying) are generally represented by smaller feature values. Conversely, higher activity behaviours (i.e. grazing) generally display larger feature values. This is particularly true for MV, where the clear distinction between inactive (lying and standing) and active behaviours (grazing and walking) is apparent for the majority of animals. Given that each of the presented features provides a measure of signal variance within an epoch, the distinction between low- and high-level activity is unsurprising and can be attributed to the low inertia of the sheep's ear, resulting in higher velocity as the sensor is moved (Barwick et al., 2018b). These findings are also consistent with published literature, with features that consider signal variation often identified as the most important predictors, for example variance of single and combined axes (Giovanetti et al., 2017), inverse coefficient of variation (Giovanetti et al., 2017) and movement variation (Alvarenga et al., 2016, Barwick et al., 2018b).

Although broad patterns for behaviour differentiation are evident, there is still considerable overlap between the behaviours, particularly lying/standing and grazing/walking. This represents a limitation for behaviour discrimination using a single metric, with a combination of metrics potentially more appropriate. To explore this further, 3D plots were generated for a number of feature combinations. Again, for brevity, plots have been only been included for the most important predictor features (MV, SD_X and SD_Y) for each 10 s epoch (Figure 4.16).

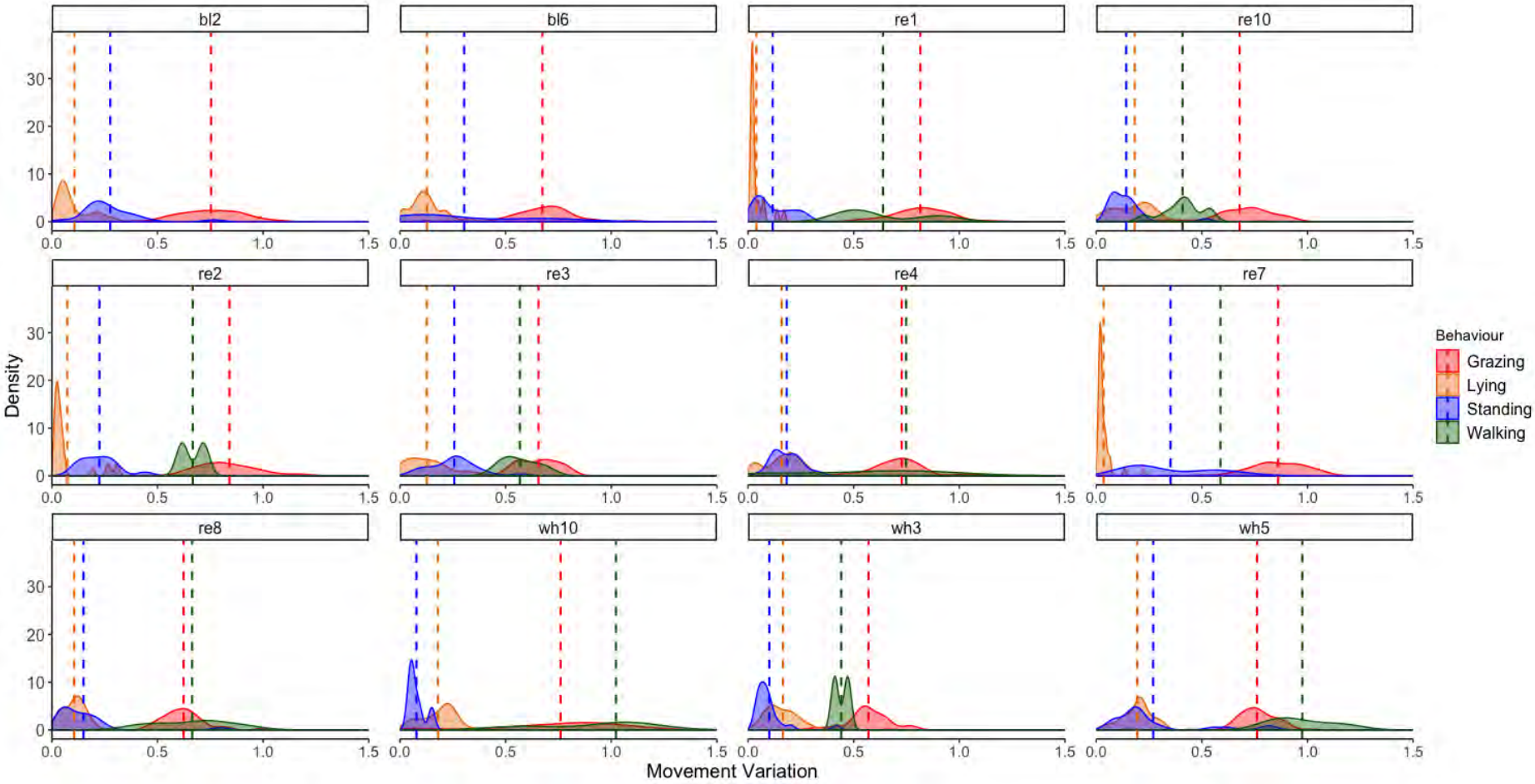

Figure 4.13 Density plots of movement variation (MV) for four mutually exclusive behaviours: grazing (red), lying (orange), standing (blue) and walking (green). Mean lines for each behaviour are also included (dashed lines). Plots are presented for individual sheep (see Section 4.4 and Chapter 6 for more details). Note, observed walking behaviour was not available for animals bl2 and bl6.

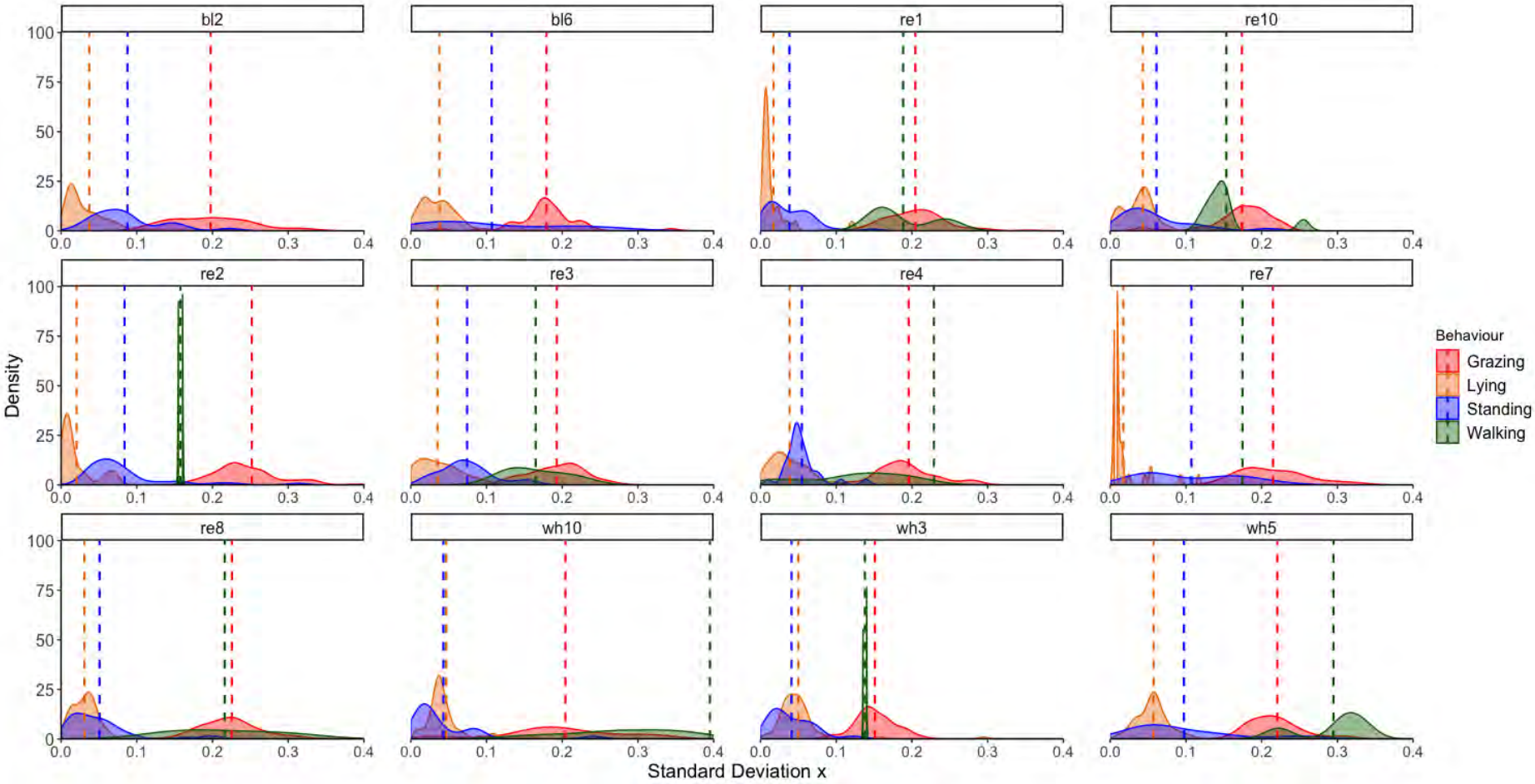

Figure 4.14 Density plots of standard deviation for the x-axis (SD_X) for four mutually exclusive behaviours: grazing (red), lying (orange), standing (blue) and walking (green). Mean lines for each behaviour are also included (dashed lines). Plots are presented for individual sheep (see Section 4.4 and Chapter 6 for more details). Note, observed walking behaviour was not available for animals bl2 and bl6.

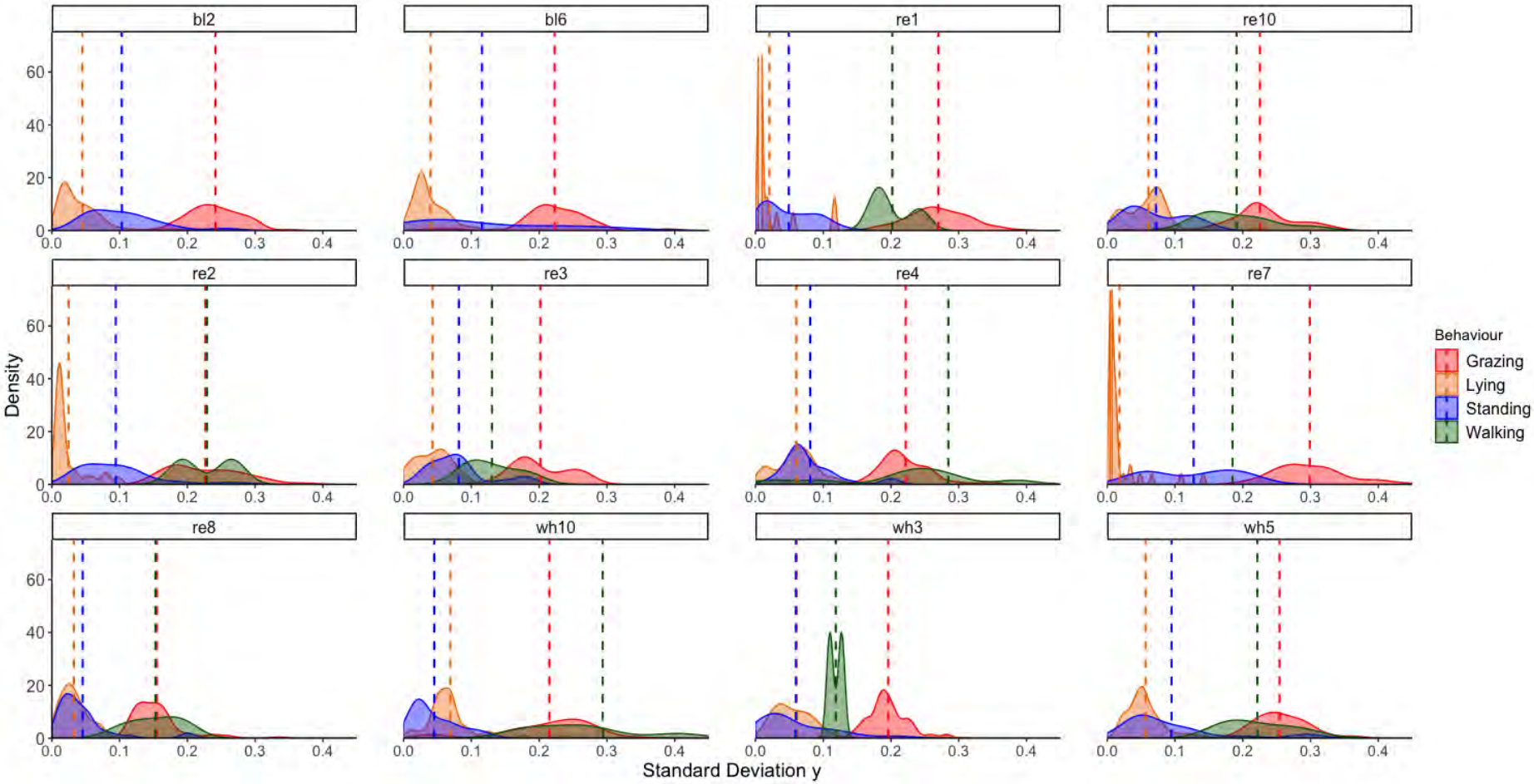

Figure 4.15 Density plots of standard deviation for the y-axis (SD_Y) for four mutually exclusive behaviours: grazing (red), lying (orange), standing (blue) and walking (green). Mean lines for each behaviour are also included (dashed lines). Plots are presented for individual sheep (see Section 4.4 and Chapter 6 for more details). Note, observed walking behaviour was not available for animals bl2 and bl6.

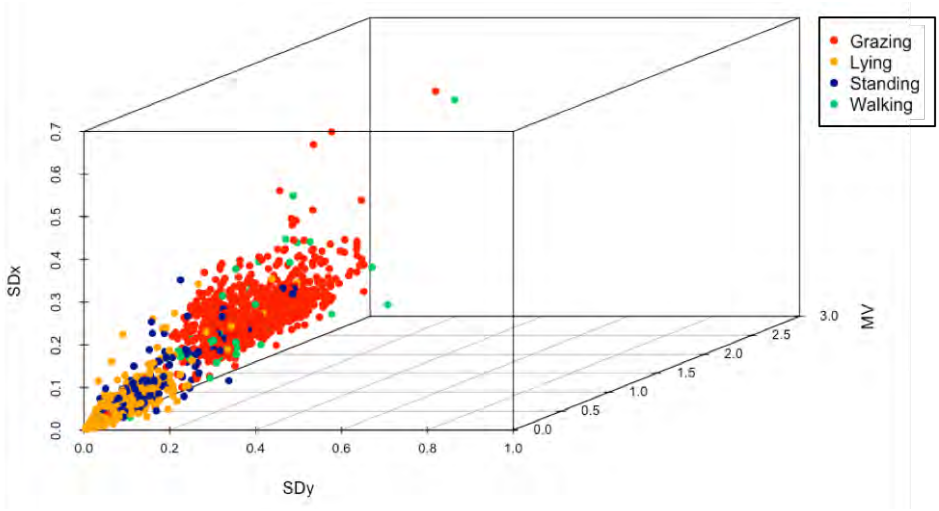

Figure 4.16 3D scatterplot of four mutually exclusive behaviours: grazing (red), lying (orange), standing (blue) and walking (green). Data represents features calculated for discrete 10 s epochs: MV SD_X and SD_Y.

Similar to the density plots (Figures 4.13 – 4.15), there appears to be some capacity for behaviour differentiation using a combination of the top three features (MV, SD_X and SD_Y). To clarify this further, Figure 4.16 has been reproduced below with an isolated scale to show the majority of the data (Figure 4.17). As indicated, classification of behaviours could be based on the approximate boundaries provided, allowing differentiation of behaviours based on where they fall in 3D space. Furthermore, the boundaries indicate potential for different groupings of behaviours to improve classification accuracy, for instance active (grazing/walking) vs inactive (lying/standing) behaviours; or lying posture vs upright posture (grazing, standing, walking). This is explored further in Chapter 6. It is important to note that the boundaries included in Figure 4.17 are estimates of the actual boundaries, and have been included to show how classification might work. In practice, the true boundaries are likely to be more complex, even occurring across more than three dimensions, highlighting the potential for more sophisticated measures of behaviour classification such as ML.

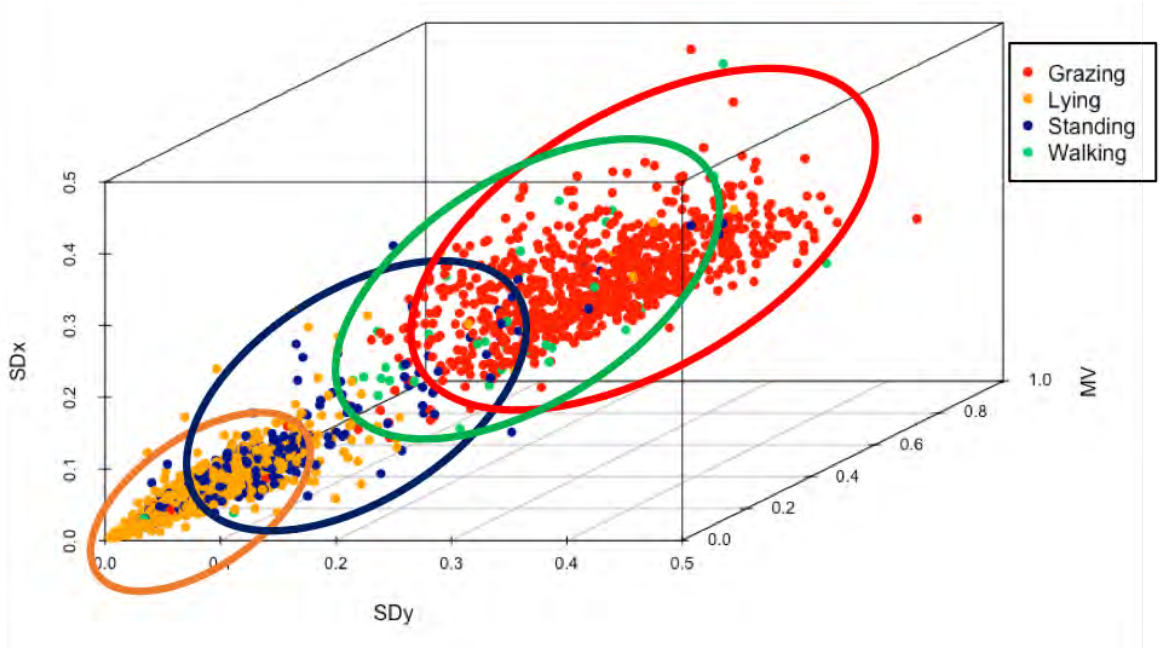

Figure 4.17 Reproduction of Figure 4.13 with different axis scales for ease of visualisation. Four mutually exclusive behaviours are shown: grazing (red), lying (orange), standing (blue) and walking (green). Note that the figure has been annotated with ovals representing the approximate boundaries of each behaviour class.

4.3.2.3 Machine Learning

Basic graphing and inspection of accelerometer data provides interesting insights during preliminary analysis. However, to explore the full potential of accelerometer data, advanced statistical classification techniques are commonly employed. This is usually conducted after feature calculation, with the metrics applied to various ML algorithms. ML algorithms can be either supervised [e.g. Classification and Regression Trees (CART); Support Vector Machines (SVM); Linear Discriminant Analysis (LDA), Quadratic Discriminant Analysis (QDA), Random Forest (RF)] or unsupervised (Cluster Analysis, Hidden Markov Model) (Brown et al., 2013). Supervised ML uses data from a period of time where the behaviour is known (known as 'labelled'). This labelled data is used to 'train' the algorithm, with the objective of subsequent classification of the remaining data (Shuert et al., 2018). Unsupervised ML does not require labelled data, instead forming its own method of classification based on previously unknown patterns in the data (Sakamoto et al., 2009). ML has been criticised for being a "black box" method of classification, as the internal rules of classification are often difficult to interpret (Bidder et al., 2014, Nathan et al., 2012). Nevertheless, they are widely used for behaviour classification, and have been used with success in sheep (Barwick et al., 2018a, Barwick et al.,

2018b, Walton et al., 2018). In this project, four types of ML were evaluated for behaviour classification: CART, SVM, LDA and QDA. This work is presented in Chapter 6.

4.3.2.4 Use of ML-classified behaviours from accelerometer data

Similar to the GNSS data, once the accelerometer data was classified into more meaningful information (i.e. corresponding behaviours), changes in the pattern of behaviour in the period around parturition were examined. Again, the intent of this work was to identify changes in ewe behaviour at parturition that can be measured using an ear tag accelerometer. The results of this work are presented in Chapter 7.

4.3.2.5 A note on individual animal variability

As shown throughout Section 4.3.2, whilst broad patterns of behaviour differentiation are evident, there is also variability between individual animals. For example, in Figures 4.13 – 4.15, of the 10 animals where all four behaviours were observed, the majority of animals (n = 7) displayed a pattern of increasing feature values in the order of lying, standing, walking and grazing for at least one of the reported features. The exception to this was animals re4, wh10 and wh3 which consistently displayed a different pattern of behaviour. Disparities in the data signatures for individual animals are expected (Miriam et al., 2013) and have been explored in dynamic modelling systems for dairy cows (Jensen et al., 2018, Jensen et al., 2016). Causes of disparities may occur for a number of reasons; for example, differences between individual accelerometers, time-drift and the resulting incongruence between observed and recorded behaviours or shifting orientation of a device during deployment. Differences may also result from individuality of ewes, including differences in movement or other patterns of behaviour that develop over time.

Although the impact of individuality is an important consideration for improved model accuracy, development of more 'generalised' models has been deliberately conducted in this thesis. In a commercial situation, model training for each individual is likely to be unfeasible, as it would require considerable producer input to observe and record behaviours for each individual animal. In contrast, the application of generalised models would allow producers to immediately use a commercial sensor for their advertised purpose. Although the use of individual models should not be discounted in the future, for the purposes of this thesis a

more generalised approach was considered key, particularly in the model training processes in Chapters 6 and 8. The impact of individuality has also been discussed further in these chapters, and in Chapter 9.

4.3.3 Integrative use of GNSS and accelerometer data for predictive algorithm development

Using the knowledge of sheep parturition behaviour gained in Chapter 5 and Chapter 7, a second ML model was developed for the purpose of detecting parturition in a simulated real-time scenario. This model was then applied to detect an adverse birth event using the single ewe that experienced vaginal prolapse as a case study. This work is discussed in-depth in Chapters 8 and 9.

4.4 How was the field data used within each chapter?

As stated previously, the original intent of this project was to examine the potential of on-animal sensors for lifelong welfare monitoring. However, this scope was too great for a single PhD thesis to undertake. Parturition was consequently chosen as the focussed research topic since this event represents a key point of risk for both ewe and lamb in terms of welfare. To study this, a field program was developed with the hope of capturing as many 'adverse' (i.e. dystocic) parturition events as possible. This information was then going to be compared to typical birth events to determine if the adverse event could be differentiated. In 2017 this was carried out by selecting equal numbers of twin- and single-bearing ewes, with the hope of comparing higher-risk twin births (Hinch and Brien, 2014, Alexander et al., 1983) with their single-bearing counterparts. However, throughout the 2017 trial, only one adverse birth event occurred (ewe prolapse and subsequent euthanasia). Thus, the focus of the research shifted to discovering an appropriate sensor-based method for detecting the parturition event itself. Throughout the data analysis process, it also emerged that the scope of data analysis for parturition detection was extensive enough without the added complexities of an exploration of dystocia. As a result of this shift toward detection of the birth event itself (either typical or adverse), ewes were selected differently in the 2018 trial to assist in observation (all selected ewes were single-bearing).

To provide clarity regarding the use of data throughout the thesis, summary tables have been provided (Tables 4.3 and 4.4). As shown, in addition to the small number of adverse birth events, failure of video observation in the 2017 field trial severely restricted the use of the accelerometer data, with requirements to wait until the 2018 trial to collect adequate observations for ML analysis. For detailed summaries of the use data collection from individual animals, see Appendix B and C.

Table 4.3 Summary of the available datasets at study conclusion. Device failure refers to devices that either did not turn on at study commencement and therefore were not attached, or those that failed to record for the entire duration of the experiment.

Year	Sensor	Complete datasets at trial conclusion	Failed device
2017	GNSS	37	3
	Accelerometer	38	2
	Total (Integrated dataset)	**35**	**5**
2018	GNSS	35	4
	Accelerometer	38	2[1]
	Total (Integrated dataset)	33	6

[1]One accelerometer from 2018 failed to record past Day 9 but was still used in Chapter 7 as a large proportion of the required data (see Chapter 7 for details). The animal was then removed in Chapter 8.

Table 4.4. Summary of the datasets used in each chapter of the thesis. Note: Animals that were used in Chapter 6 for ML algorithm development were removed from any further analysis.

Chapter	Year	Sensor	Total number of datasets analysed	Day of lambing identified only	Day + hour of lambing identified	Did not lamb (DNL)	Animal died	Use in data analysis
5	2017	GNSS	36	14	8	14	NA[1]	Statistical analysis GNSS-derived behaviour at lambing
6	2018	Accelerometer	12[2]	NA	NA	NA	NA	ML algorithm training and validation to identify basic behaviours
7	2018	Accelerometer	25	14	11	NA	NA	Statistical analysis ML-derived behaviour (from accelerometer data) at lambing
8	2017	Accelerometer & GNSS	8	NA	8	NA	NA	ML algorithm training to identify hours of lambing activity
	2018	Accelerometer & GNSS	9	NA	9	NA	NA	Independent validation of the ML algorithm
9	2017	Accelerometer & GNSS	14	14	NA	NA	1	Use of the model in Chapter 8 to compare alert profiles of typical and 'adverse' parturition events

[1]One animal died during the 2017 trial. However, this dataset was not analysed until Chapter 9.
[2]Animals in this chapter were used for initial ML algorithm development and subsequently removed from any further analysis.

4.5 References

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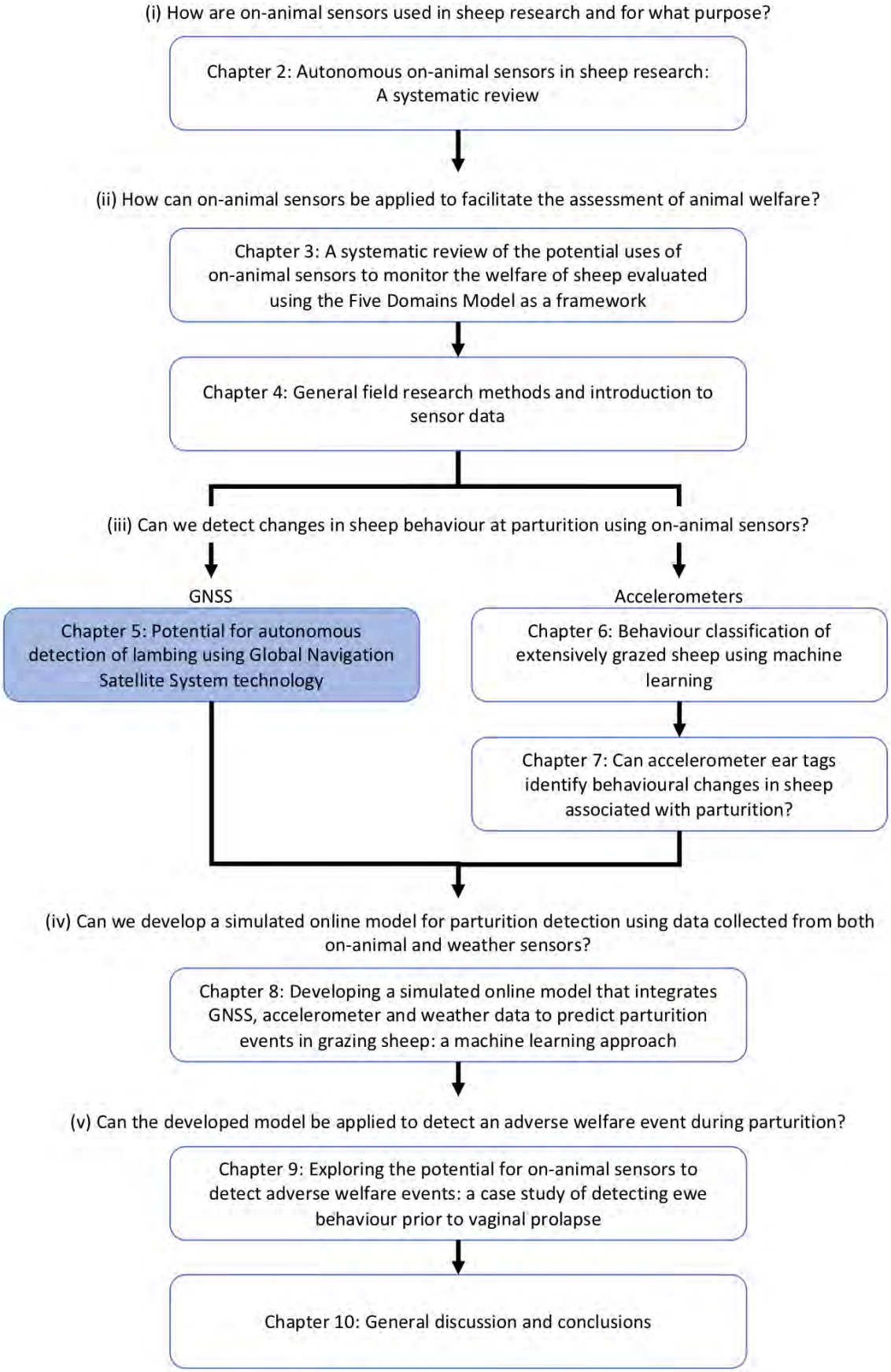
(i) How are on-animal sensors used in sheep research and for what purpose?
Chapter 2: Autonomous on-animal sensors in sheep research: A systematic review
(ii) How can on-animal sensors be applied to facilitate the assessment of animal welfare?
Chapter 3: A systematic review of the potential uses of on-animal sensors to monitor the welfare of sheep evaluated using the Five Domains Model as a framework
Chapter 4: General field research methods and introduction to sensor data
(iii) Can we detect changes in sheep behaviour at parturition using on-animal sensors?
GNSS
Accelerometers
Chapter 5: Potential for autonomous detection of lambing using Global Navigation Satellite System technology
Chapter 6: Behaviour classification of extensively grazed sheep using machine learning
Chapter 7: Can accelerometer ear tags identify behavioural changes in sheep associated with parturition?
(iv) Can we develop a simulated online model for parturition detection using data collected from both on-animal and weather sensors?
Chapter 8: Developing a simulated online model that integrates GNSS, accelerometer and weather data to predict parturition events in grazing sheep: a machine learning approach
(v) Can the developed model be applied to detect an adverse welfare event during parturition?
Chapter 9: Exploring the potential for on-animal sensors to detect adverse welfare events: a case study of detecting ewe behaviour prior to vaginal prolapse
Chapter 10: General discussion and conclusions

Chapter 5. Potential for autonomous detection of lambing using Global Navigation Satellite System technology

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Overview

Lambing (parturition) was selected as a focus for this PhD program because it represents a key point of risk for both the ewe and the lamb. As shown in Chapter 3, a holistic welfare assessment system will likely require integrating a number of sensors. However, an understanding of each technology separately provides important foundational knowledge. Furthermore, in order to monitor welfare at parturition, it is imperative that the actual parturition event itself can be accurately detected. Hence, Chapters 5 to 8 will focus on the detection of parturition only. This chapter explores GNSS and measurable parameters that are able to identify lambing. Data presented in this paper was collected during the 2017 field trial.

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Potential for autonomous detection of lambing using global navigation satellite system technology

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Abstract

Context. On-animal sensing systems are being promoted as a solution to the increased demand for monitoring livestock for health and welfare. One key sensor platform, global navigation satellite system (GNSS) positioning, provides information on the location and movement of sheep. This information could be used to detect partition in sheep, a key period of time when both ewes and lambs are at risk. The development of algorithms based on key behavioural features could provide alerts to sheep managers to enable intervention when problems arise.

Aims. To investigate the use of GNSS monitoring as a method for detecting behavioural changes in sheep in the period around parturition.

Methods. GNSS collars were attached to 40 late gestation ewes grazing a 3.09 ha paddock in New Zealand. Several metrics were derived: (i) mean daily speed, (ii) maximum daily speed, (iii) minimum daily speed, (iv) mean daily distance to peers, and (v) spatial paddock utilisation by 95% minimum convex polygon. Speed metrics and distance to peers were also evaluated at an hourly scale for the 12 h before and 12 h after lambing.

Key results. Minimum daily speed peaked on the day of parturition ($P < 0.001$), suggesting animals may have been expressing more agitation and did not settle. Isolation was also evident during this time, with postpartum ewes located further from their peers than pre-partum ewes ($P < 0.001$). Day of lambing was also evident by reduced spatial paddock utilisation ($P < 0.001$).

Conclusions. This study demonstrates that GNSS technology can be used to detect parturition-related behaviours in sheep at a day scale; however, detection at the hour scale using GNSS is not possible.

Implications. This research highlights the opportunity to develop predictive models that autonomously detect behavioural changes in ewes at parturition using GNSS. This could then be extended to identify ewes experiencing prolonged parturition, for example dystocic birth enabling intervention which would improve both production and welfare outcomes for the sheep industry.

Additional keywords: behaviour monitoring, ewe, GNSS, GPS, *Ovis aries*.

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Introduction

Livestock monitoring has historically relied on direct human observation of animal behaviour (Turner *et al*. 2000; Watanabe *et al*. 2008). However, issues associated with observer error (especially at night), an inability to observe during extreme weather events and high labour costs may limit its use (Turner *et al*. 2000; Dobos *et al*. 2015). Since the advent of remote monitoring tools, for example global navigation satellite system (GNSS), their use in livestock research has increased dramatically, allowing the study of animal behaviour at an intensity not previously possible by visual observation alone (Swain *et al*. 2011; Dobos *et al*. 2015; Fogarty *et al*. 2018). As the cost of electronics continues to decrease, commercialisation of sensor technologies, such as GNSS, for real-time or near-real time monitoring are becoming more prevalent (Bailey *et al*. 2018). In order to ensure maximum benefit from the use of this technology, accurate interpretations of GNSS data are required. In the case of extensive sheep production, remote monitoring and identification of lambing events could provide a previously unattainable level of surveillance, allowing for closer supervision to safeguard against ewe and lamb mortality or for postpartum selection of higher performing ewes (Dobos

et al. 2014). Close supervision at parturition often results in lower lamb mortality (Holmøy *et al*. 2012).

To understand how a sensor system might detect a birth event, it is necessary to understand what behaviours a ewe may exhibit. In general, parturition is seen as a period of restlessness in the ewe, with increasingly frequent changes in body position as labour approaches (Owens *et al*. 1985). Although the first signs of parturition have been noted from as early as 15 days prior (Holmes 1976), overt behaviours are more commonly identified on the actual day of lambing (Owens *et al*. 1985; Echeverri *et al*. 1992; Schmoelzl *et al*. 2018). In a study by Echeverri *et al*. (1992), ewes spent more time standing during the 8 h before birth and increased their number of steps during the 6 h prior. Ground sniffing and pawing also increased during this time (Owens *et al*. 1985; Echeverri *et al*. 1992), possibly reflecting the ewe's attraction to birth fluid and/or nesting behaviour (Arnold and Morgan 1975; Echeverri *et al*. 1992). In a report by Schmoelzl *et al*. (2018), average time from first sign of parturition to lamb expulsion was 163 min ± 22 (s.e.m.). Similarly, Owens *et al*. (1985) found abdominal straining was evident from 1 h before delivery, followed by appearance of the chorio-allantoic sac 33–55 min before lamb expulsion. Once the lamb is born, ewes generally stand within 4 min of delivery (Owens *et al*. 1985), after which the ewe grooms the lamb to facilitate bonding (Alexander 1988).

Many livestock species also display isolation at birth, facilitating the development of the mother–offspring bond (Alexander 1988; Lidfors *et al*. 1994). Although documented in cattle (*Bos taurus*) (Vitale *et al*. 1986; Lidfors *et al*. 1994), mouflon (*Ovis orientalis*) (Langbein *et al*. 1998; Ciuti *et al*. 2009) and bighorn sheep (*Ovis canadensis*) (Bangs *et al*. 2005; Karsch *et al*. 2016), this behaviour is not always observed in domestic sheep. In a study by Alexander *et al*. (1979), the proportion of ewes that lambed in isolation (defined as having no other ewe within 10 m of the birth site) ranged from 27.3 to 64.6%, depending on the size of the paddock, presence of shelter and whether the ewe had been recently shorn. Similarly, Arnold and Morgan (1975) found 46% of ewes isolated themselves before birth, with a further 20% alienated when the flock moved on without the new mother. In contrast, Fraser (1968) (as cited in Arnold and Morgan (1975)) found only 12% of ewes were isolated at lambing. Stevens *et al*. (1981) also noted less than 10% of Merino ewes displayed this behaviour. Despite this inconsistency, isolation as an indicator of parturition shows merit and should be evaluated further.

A change in the ewe's spatial landscape utilisation can also indicate onset of parturition (Dobos *et al*. 2012). New mothers decrease their rate of travel and amount of space used, due to the immobility associated with the birth event or a need to remain at the birth site for several hours (Alexander 1980; Alexander *et al*. 1983). Furthermore, sheep are considered 'followers', where young remain with the mother after birth, as compared with 'hiders' where the young lie concealed while the mother grazes (Alexander 1988). Thus, the limited physical capabilities of the newborn lamb also limit how far the ewe can travel, particularly during the neonate's first few days of life (Alexander 1980).

The use of GNSS technologies to investigate ewe characteristics around parturition has been reported by several authors (Taylor *et al*. 2011; Broster *et al*. 2012; Dobos *et al*. 2012, 2014, 2015; Broster *et al*. 2017). Dobos *et al*. (2014, 2015) relied on speed of movement to identify lambing. Mean distance to peers has also been used to indicate isolation (Dobos *et al*. 2014) and minimum convex polygon (MCP) calculated to estimate a ewe's use of space (Dobos *et al*. 2012). The work undertaken to date has proposed and applied several different metrics (Dobos *et al*. 2012, 2014, 2015). The objective of the present study was to assess all of these metrics in a commercial flock of ewes to determine the feasibility of GNSS to detect behavioural change at parturition. It is hypothesised that GNSS will be able to detect broad scale patterns of behaviour and identify changes in these patterns associated with lambing. Once these parameters have been identified, it is proposed that they could then be used in the future development of a predictive model to autonomously detect a lambing event. However, in order to ensure adequate model development, validation of the appropriate predictors is essential.

Materials and methods

Location and use of animals

The study was conducted at a commercial mixed enterprise farm in North Canterbury, New Zealand (43.0°S, 173.2°E), over a 2-week period from 29 September to 13 October 2017. Temperatures ranged from 3.8 to 22.3°C and total rainfall was 85.6 mm, as recorded by the on-farm weather station.

As part of this farm's normal practice, an experienced operator used an ultra-sound scanner to confirm pregnancy in the total ewe flock (n = 9200), and to estimate lambing date and parity status (singles or twins). Forty ewes were then selected from a subflock of ~175 Merino and Merino-cross animals, all of which had an expected lambing date within the experimental period. Of the 40 ewes selected, 20 were twin-bearing and 20 were single-bearing.

These 40 ewes were placed in a 3.09 ha experimental paddock and provided *ad libitum* access to forage and water. Shelter was provided by the natural sloping topography. The experimental paddock was slightly smaller than average for this property (mean size 5–8 ha) but could otherwise be considered a normal commercial size for this region. The paddock was selected as it allowed visual observation from a neighbouring paddock with minimal flock disturbance. The impact of the reduced paddock size was mitigated by using a smaller number of ewes (n = 40) compared with normal subflock sizes for this property (65–100 ewes per paddock). This ensured stocking rates used in this study were similar to the normal practices of this commercial farm.

All research procedures and use of animals were approved by the Massey University Animal Ethics Committee (approval number MUAEC 17/59).

Data collection

On the morning of 29 September 2017, experimental ewes were separated from the larger commercial flock and moved into the yards. Animals were fitted with i-gotU GT-600 GNSS loggers (Mobile Action Technology Inc., Taipei, Taiwan) attached to

neck collars. The GNSS devices were programmed to obtain locations at 3-min intervals. Ewes were also fitted with identification 'bibs', which were numbered (1–10) and coloured (black, green, orange, red) to allow for 40 unique colour and number combinations. Upon fitting GNSS collars and bibs, ewes were observed for at least 30 min to monitor for signs of distress before being moved to the experimental paddock at 15:30 hours.

Ewes were observed from a neighbouring paddock using binoculars and a Nikon Coolpix B500 camera with a 40× optical zoom (Nikon, Tokyo, Japan), from 30 September to 13 October 2017 (14 days in total). *Ad libitum* behaviour observations (Martin and Bateson 2007) were conducted from 06:30 to 12:30 and 15:30 to 18:00 hours to record lambing events and ewe-lamb interactions. Collars and bibs were removed on 25 October 2017.

GNSS data analysis

The GNSS tracking data were processed and analysed using a combination of ArcGIS ver. 10.3.1 (ESRI 2016) and R statistical software (R Core Team 2018). After the tracking data were downloaded, erroneous locations were detected (e.g. locations with a latitude and longitude of zero) and removed. Distance, time and speed between successive locations was then calculated. Speed of movement was calculated as distance between consecutive GNSS locations divided by the time interval between the readings (Schlecht *et al*. 2004; Trotter *et al*. 2010; Dobos *et al*. 2014). Speeds over 3 m/s and distances over 540 m (calculated as the maximum distance that could be travelled at 3 m/s for the 3-min interval between GNSS fixes) were also removed, as these are commonly associated with GNSS error (Swain *et al*. 2011; Taylor *et al*. 2011). Once these erroneous points had been excluded, movement metrics were recalculated. A moving window average for speed was also determined based on the two locations before and following the point of interest (i.e. an average over five GNSS points or 12 min).

Visualisation of the data in ArcGIS showed many of the GNSS points were outside the paddock boundaries (mean location error of i-gotU device <10 m (Morris and Conner 2017)). Previous studies (Trotter and Lamb 2008; Mullen *et al*. 2013; Fogarty *et al*. 2015) have automatically excluded these points as GNSS error, but this was not initially conducted on this dataset to minimise processing requirements. The exception to this were the data for MCP calculation which was trimmed to the paddock boundaries to prevent overestimation of the animal's spatial utilisation where GNSS locations were apparently outside of the paddock.

Daily and hourly speed metrics

Calculation of speed metrics was based on the methodology proposed by Dobos *et al*. (2014). That is, the mean daily speed of ewes was calculated for each calendar day of the study based on a 24-h period from midnight to midnight. In addition, the maximum daily speed and the minimum daily speed were also determined. Metrics were calculated using a moving window average to smooth out inaccuracies in the uncorrected dataset (moving window average was calculated for each position using the preceding and following two locations, i.e. 5 GNSS points or 12 min). This was especially important for calculation of minimum and maximum speed values where inaccurate data may be incorrectly interpreted as erratic sheep movement. For ewes that lambed during the trial, daily metrics were based on day of lambing (Day 0) to allow comparison of speed values in the 4 days leading up to and following parturition (Day ± 4). Due to the relatively short length of the trial, a 4-day period was chosen to maximise the number of animals with a complete set of days for analysis.

Mean hourly speed was also determined for the 12 h before and after lambing, where 'Hour 0' represented the hour in which the lambing occurred (i.e. if a birth was recorded at 16:30 hours, then 16:00 to 16:59 hours was determined as Hour 0 with 15:00 to 15:59 and 17:00 to 17:59 hours representative of Hour – 1 and Hour + 1 respectively). Only animals with known birth time were included in these analyses and birth time was classified by hour of the day. Again, hourly speed values were based on a moving window average of five values for each time point.

Daily and hourly isolation at lambing

The mean distance of each ewe to her peers was calculated for each study day to determine isolation behaviour at parturition. This approach mirrors Dobos *et al*. (2014), where ewe isolation was also identified by monitoring the spatial distance (in metres) of each individual ewe to her peers. Previous work (Alexander *et al*. 1979) has defined 'isolation' as a categorical variable based on a defined distance (e.g. 10 m). However, this approach applies an arbitrary threshold and is unable to account for differences in individual ewe behaviour. Furthermore, as distance from peers can be considered as existing on a continuum and subject to normal variability, the chosen approach allows application across a broader range of contexts and periods of time. The method for calculation was: (i) for each GNSS point of a reference ewe, find the closest point in time for every other ewe in the paddock; (ii) calculate the straight-line distance between the reference ewe and each comparison ewe; and (iii) remove points where the time difference between the two GNSS points was over 5 min (300 s). This interval was chosen to ensure animals that were consistently on asymmetric GNSS fix timings would still be included in analysis. For ewes that lambed during the trial, daily metrics were aligned based on day of lambing (Day 0) to allow comparison between the 4 days before and after parturition. The mean distance to peers was also calculated on an hourly basis in the 12 h leading up to and after parturition.

Daily spatial paddock utilisation

To determine changes in spatial utilisation of the paddock throughout the study, the 95% MCP for each animal was calculated in the software R using the 'adehabitatHR' package (Calenge 2006). MCP is normally calculated by drawing a polygon around the outer most points in a dataset ensuring no internal angle exceeds 180 degrees and measuring the area within the polygon (Burgman and Fox 2003). It is considered a standard method for estimating home range (van Beest *et al*. 2011). In the case of the 95% MCP, 5% of outlying locations furthest from

the centroid are discarded before calculation, improving the accuracy of the estimate (Calenge 2006). The 95% MCP was calculated for each ewe on each day of the study and aligned around day of lambing (Day 0) for animals that lambed during the study.

MCP was not calculated at an hourly level as it is considered a coarse-scale metric, used to provide overall patterns of movement on a minimum of a daily basis.

Statistical analyses

All statistical analyses were conducted using R software with linear mixed-effects models using the 'nlme' package (Pinheiro *et al.* 2018) and a significance level of $P < 0.05$. Separate analyses were conducted using daily or hourly data. For the daily speed analysis, the model contained day around birth as a fixed effect and individual animals as random effects. A first order autoregressive structure was specified for the errors to account for the repeated-measures nature of the experiment. For these day scale analyses, dependent variables included mean, maximum and minimum speed, mean distance to peers and 95% MCP in the 4 days leading up to and following parturition. Maximum daily speed was log-transformed to ensure normality of errors. For assessment at an hourly scale, the model contained hour as a fixed effect and individual animals as a random effect. A first order autoregressive correlation structure was specified for the errors. Only speed (mean, maximum and minimum) and mean distance to peers were used as dependent variables. Mean and maximum hourly speed were log-transformed to ensure normality of errors. Least square means and standard errors were generated for each model using the 'lsmeans' package within R software (Lenth 2016). Pairwise comparisons were also computed with the 'lsmeans' package with the Tukey adjustment for multiple comparisons.

Results

Lambing and records collected

Of the 40 ewes, 25 lambed during the observation period including 12 twin-bearing (24 lambs) and 13 singles (13 lambs) for a total of 37 lambs. Of these animals, eight ewes (four twin-bearing and four singles) had the exact time of birth recorded (within a 60-min period). The remaining animals (eight twin-bearing and nine singles) either lambed overnight or during periods when the observer was not present. For these animals, day of lambing was recorded as the day in which the newborn was first identified.

Of the 37 lambs in this experiment, four died before the end of the experimental period. Two of these lambs were from a twin-bearing ewe that prolapsed during labour and was subsequently euthanised as per normal farm practice. This ewe was excluded from analysis. The remaining two lambs died during the trial. The first was born alive to a twin-bearing ewe (confirmed through observation of maternal behaviour towards both lambs) and died during the first 24 h. The second was found dead upon arrival to the paddock. The mother of the lamb, and whether the lamb was stillborn or died shortly after birth, were not known. Three GNSS collars failed during the experiment; one twin-bearing, one singleton and one animal that did not give birth during the observation period. These animals were excluded from analysis.

To summarise, daily GNSS data was available for 36 ewes: 22 that lambed (10 twin-bearing, 12 singletons) and 14 that did not lamb. Hourly GNSS data was available for eight ewes: four twin-bearing and four singletons.

GNSS data analyses

Daily and hourly speed metrics

No differences in mean daily speed ($P = 0.07$) or maximum daily speed ($P = 0.15$) were detected in the 4 days before and following parturition (Day ± 4). Minimum daily speed of animals differed between the 4 days surrounding parturition ($P < 0.001$). As shown in Fig. 1, minimum daily speed was the highest on the day of parturition.

No differences ($P = 0.51$) were detected in the mean hourly speeds of ewes around parturition. Also no difference in mean hourly speed for pre- and postpartum animals were detected ($P = 0.06$). Similarly, no difference in the minimum hourly speeds around parturition ($P = 0.50$) or between pre- and postpartum animals ($P = 0.87$) were detected. Maximum hourly speed in the 12 h before and following parturition differed ($P = 0.04$), with an apparent spike at Hour –9 (Fig. 2*a*). Pre- and postpartum maximum hourly speed (shown as dotted and dashed lines, respectively, in Fig. 2*a*) differed ($P = 0.001$). Upon closer examination of the data contributing to the spike at Hour –9, this result reflects a single outlying value for one particular animal where the recorded location was 400 m outside out of paddock boundaries, and then immediately back inside the paddock within a 3-min interval. Although this error did not exceed the speed threshold that would have resulted in its removal from the analyses in the initial data cleaning process, exploring the impact of removing it is warranted. If this animal is removed completely from the dataset, no differences ($P = 0.08$) in maximum hourly speed around parturition can be detected. Nevertheless, the general decline in maximum hourly speed is still evident between pre- and postpartum animals ($P = 0.005$; Fig. 2*b*).

Daily and hourly isolation at lambing

Mean distance to peers differed in the days surrounding lambing ($P < 0.001$). As shown in Fig. 3, this metric exhibited

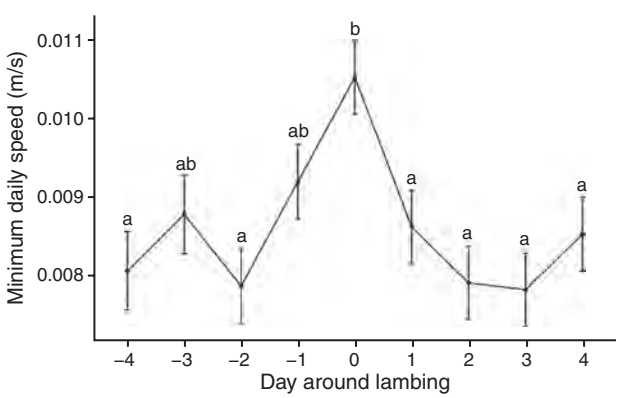

Fig. 1. Daily minimum speed of movement ($P < 0.001$; $n = 22$). The values presented are least square means ± s.e. Different letters above error bars indicate significant differences between days ($P < 0.05$).

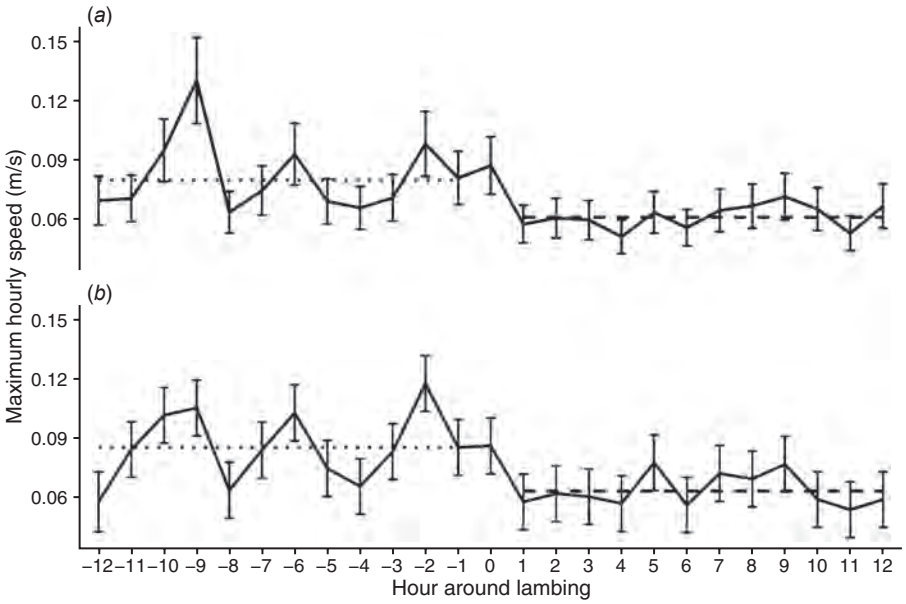

Fig. 2. Maximum hourly speed (m/s) in the 12 h leading up to and following parturition ($n = 8$). (*a*) Least square means ± s.e for all animals, including the outlier at Hour –9 ($P = 0.0382$); (*b*) least square means ± s.e after omission of the outlier ($P = 0.0757$). Pre-partum maximum speeds (dotted) and postpartum maximum speeds (dashed) are also shown: (*a*) $P = 0.001$; (*b*) $P = 0.0049$

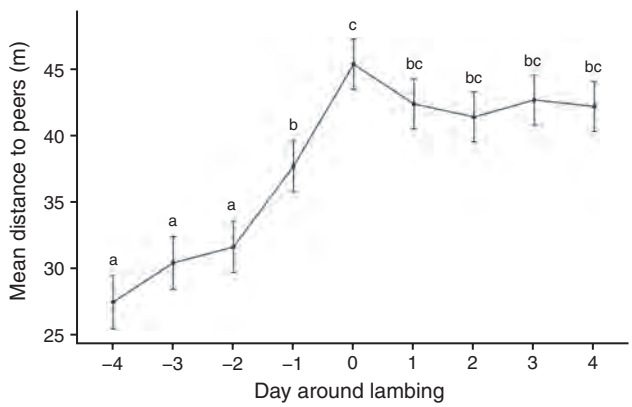

Fig. 3. The mean distance of ewes to peers (m) in the days surrounding lambing ($P < 0.0001$; $n = 22$). The values presented are least square means ± s.e. Different letters above error bars indicate significant differences between days ($P < 0.05$).

an almost linear increase from Day –4 to Day 0, followed by a plateau through to 4 days post lambing. No differences in mean distance to peers in the 12 h leading up to or after parturition were detected ($P = 0.11$), though a potential trend for increased isolation before lambing is suggested between Hour –4 and Hour –1 (Fig. 4).

Daily spatial paddock utilisation

Differences in the 95% MCP in the days surrounding lambing were detected ($P < 0.001$). As shown in Fig. 5, ewes decreased their degree of spatial utilisation of the paddock from 2 days before birth, with a minimum at Day 0. After parturition, ewes increased their spatial utilisation in a linear fashion. To compare this trend at parturition with the more general pattern over time, the 95% MCP for animals that did not lamb during the study was also calculated. This analysis showed important changes over the days of the study ($P < 0.001$) with a general increasing trend over time (Fig. 6).

Discussion

This research supports the hypothesis that GNSS technology can detect broad scale patterns in ewe activity associated with lambing, including change in speed of movement, distance to peers and spatial utilisation of the paddock. Validation of these measurable variables is an essential step before the development of autonomous lambing detection models, providing fundamental knowledge for model construction and scope.

Change in daily patterns of behaviour

The ability to detect the day of parturition or provide an indicator that this event was about to occur would be valuable to the sheep industry, allowing both targeted monitoring of ewes during this critical period and ensuring accurate recording of birth date. In this study, ewes displayed a significantly higher minimum daily speed on the day of parturition compared with all other days (Fig. 1). Importantly, this increase in minimum daily speed was followed by a decline, returning to previous levels in the days following parturition. This suggests the day of parturition was characterised by heightened agitation in the ewe, likely reflecting a level of restlessness as she seeks a suitable birth site or manages physical discomfort (Holmes 1976; Owens *et al*. 1985; Echeverri *et al*. 1992). In Dobos *et al*. (2014, 2015), day of lambing was identified by a decrease in

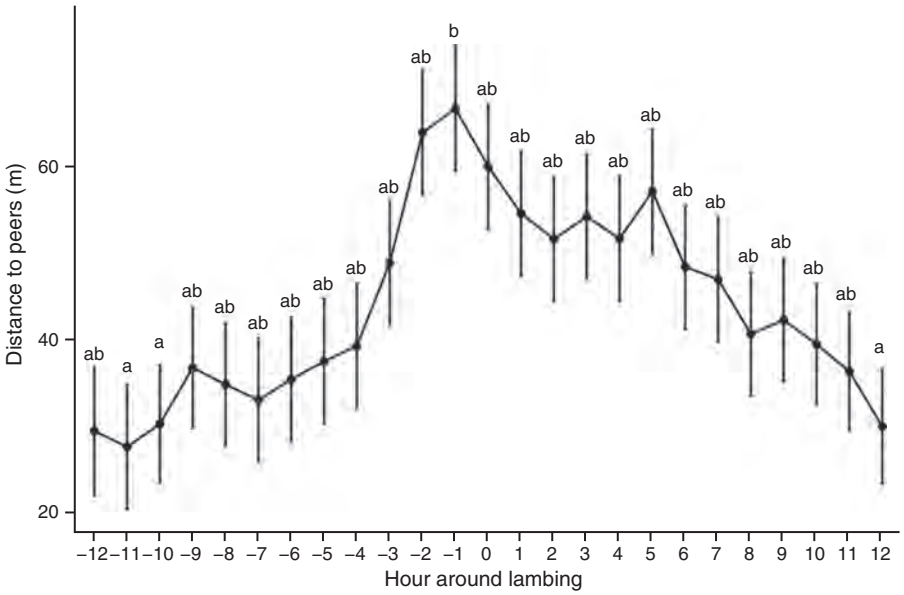

Fig. 4. The mean distance of ewes to peers (m) 12 h before and 12 h post-lambing ($P = 0.11$; $n = 8$). Values presented are least square means ± s.e.

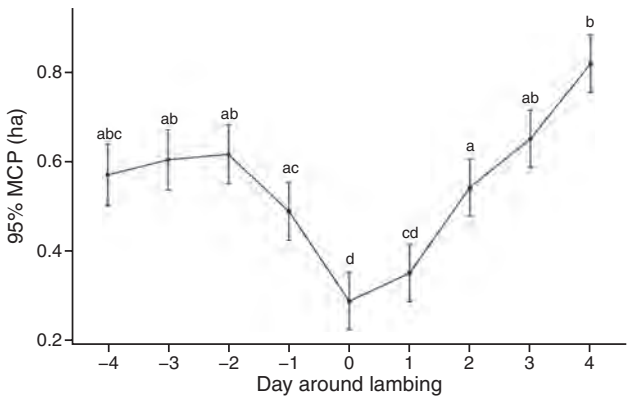

Fig. 5. Differences in daily use of space as indicated by the 95% minimum convex polygon (MCP) ($P < 0.0001$; $n = 22$). Values presented are least square means ± s.e. Different letters above error bars indicate significant differences between days ($P < 0.05$).

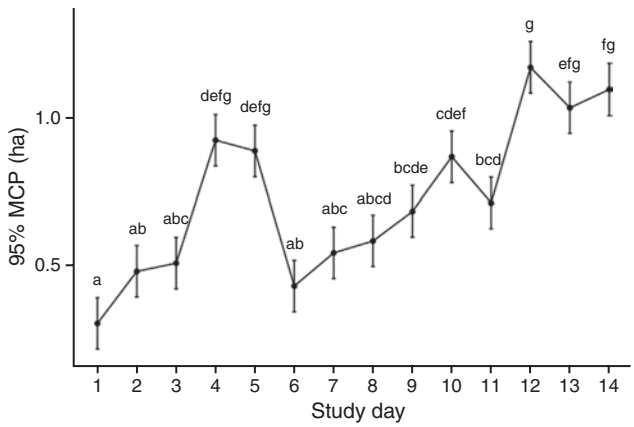

Fig. 6. Daily means of the 95% minimum convex polygon (MCP) for ewes that did not lamb during the study ($P < 0.0001$; $n = 14$). Values presented are least square means ± s.e. Different letters above error bars indicate significant differences between days ($P < 0.05$).

mean daily speed. However, this was not supported in the present study. This may reflect differences in data analysis, with Dobos *et al*. (2014, 2015) using a 7-day window for investigation, compared with only 4 days in this study. Although necessary to maximise the number of complete datasets for analysis, the use of a smaller window is considered a limitation of this study. Given that the first signs of parturition have been noted to occur from as early as 15 days prior (Holmes 1976), comparison with days even more temporally distant is warranted in future research. Despite this, as the intensity of periparturient behaviour is widely reported to increase closer to the birth event (Arnold and Morgan 1975; Owens *et al*. 1985; Echeverri *et al*. 1992), the methodology used in the present study should have been sufficient to identify changes in daily speed if present.

Increasing levels of isolation from Day –4 were evident in this study, with mean distance to peers reaching a maximum on the day of lambing and remaining high during the 4 days post-birth (Fig. 4). Dobos *et al*. (2014) also reported an increase in mean distance to peers on day of lambing, although extension of this behaviour beyond parturition was not seen. These inconsistencies may reflect differences in the size of the paddock used in the two studies (3.09 ha in the present study compared with 1.6 ha), with ewes in the present study able to disperse more broadly in the days following lambing. Curiously however, the extent to which the ewes in Dobos *et al*. (2014) separated themselves on lambing day (83.6 ± 14.6 m) was much higher compared with the current study (45.7 ± 1.86 m), thus highlighting the strong desire for isolation at lambing, even in paddocks of smaller size. Given paddocks in commercial

enterprises may vary greatly in size and shape, further research that examines this behaviour in paddocks of even larger scale is warranted. Future research should also attempt to expand on the current findings and determine if the extent of ewe isolation can be used to indicate maternal investment or her ability to successfully deliver and raise a newborn through to weaning. As lamb survival is impacted by many interconnecting factors and lambing conditions are rarely comparable (Murphy *et al*. 1994), further research may only be able to infer correlation between ewe isolation and survival. Nevertheless, lamb survival is known to increase when ewes remain in close contact with the newborn for at least 6 h (Murphy *et al*. 1994). Thus, distance from peers may be indicative of close contact of the mother and its newborn and could potentially be useful to identify ewes more likely to lose offspring.

In addition to a sustained level of isolation (Fig. 4), ewes in this study increased their spatial utilisation of the paddock during the 4 days following birth (Fig. 5). This may reflect the ewe's change in physiological state as she moves from late gestation into early lactation. Lactation has large energetic costs, requiring females maintain a higher plane of nutrition to meet metabolic needs (Ciuti *et al*. 2009). In bighorn sheep, lactating animals have been found to increase time spent grazing by 57% compared with dry ewes (Ruckstuhl and Festa-Bianchet 1998). This is similar to dairy cattle and wild red deer (*Cervus elaphus*), where total time spent grazing increased by 105 min (Gibb *et al*. 1999) and 2 h (Clutton-Brock *et al*. 1982) respectively. In domestic sheep, heightened pasture intake is generally managed through increased time spent grazing or rate of consumption (Arnold and Dudzinski 1967; Arnold 1975; Penning *et al*. 1995). Increased spatial utilisation of the paddock over the following days after lambing also likely reflects the increased ability of lambs to walk, nurse and follow their mother (Dwyer 2003). In the present study, postpartum ewes appeared to increase their use of the paddock at the expense of close social contact, possibly reflecting this reported need for increased foraging activity and increased mobility of the lamb.

When interpreting the ewe's change in spatial paddock utilisation around parturition, patterns should be inferred with caution. In the present study, animals were moved to a new paddock upon commencement of the trial and thus the tendency for reduced spatial utilisation in the initial days of the study may actually reflect a period of habituation rather than true pre-partum behaviour (Thomas and Revell 2011). Likewise, the increase in use of space in the latter stages may reflect declining dry matter availability over time (Arnold 1960; Forbes and Hodgson 1985), requiring animals expand their foraging area irrespective of changes to nutritive requirements due to lactation. This is somewhat supported by data shown in Fig. 6, where the animals that did not lamb during the course of the study still showed an increasing trend for spatial utilisation of the paddock over time. However, given that the degree of spatial utilisation of new mothers 4 days post-parturition (0.81 ha $\pm$ 0.06) was still less than that covered by ewes that did not lamb (1.10 ha $\pm$ 0.08 on Day 14), there still appears to be an impact of parturition status on ewe behaviour, even if this is confounded by time. It is possible that if the analysis was extended past Day 4, postpartum ewes may have maintained these lower levels of overall spatial paddock utilisation compared with animals yet to lamb. Further research should focus on confirming this behavioural change over a wider period of time and in paddocks of varying size and forage availability.

Change in hourly patterns of behaviour

In addition to identifying the day of parturition, the ability to detect the hour of birth and particularly the onset of lambing before it commences, could improve current management practice and allow direct intervention by producers if required (Dobos *et al*. 2014). However, in our study, the use of GNSS technology to monitor hourly changes in ewe behaviour was largely unsupported. This outcome is similar to Dobos *et al*. (2014), who was also unable to identify changes in ewe behaviour that could be used as a reliable warning signal for lambing. One reason for this may be due to the tendency for ewes to give birth at different hours of the day, with normal diurnal patterns making it difficult to discern changes in behaviour due to parturition alone. Once the values are averaged over the coarser daily metric, subtle changes in diurnal pattern do not appear to confound the results. Although the tracking interval used in this study was at a slightly finer resolution to that of Dobos *et al*. (2014) (3 vs 5 min), this does not appear sufficient to mitigate the effects of normal diurnal patterns. Further assessment of GNSS at a subday scale should be attempted using even finer resolution tracking or through integration with another sensor type. For example, accelerometers, which provide a measure of three-dimensional movement and have already been applied in sheep to identify lambing (Schmoelzl *et al*. 2016), suckling (Kuźnicka and Gburzyński 2017) and other general behaviours (Alvarenga *et al*. 2016; Giovanetti *et al*. 2017; Radeski and Ilieski 2017; Barwick *et al*. 2018) and could be used to detect more subtle changes associated with parturition.

In the present study, a ewe's level of isolation was not predictive of the hour of lambing (P = 0.11). However, as seen in Fig. 4, there was a trend for increased isolation before lambing, followed by a decrease post-birth, even if this was not significant. Although somewhat expected given the inconsistencies of this behaviour in domestic sheep (Fraser 1968; Arnold and Morgan 1975; Alexander *et al*. 1979; Stevens *et al*. 1981), the method for assessment should also be discussed. In Alexander *et al*. (1979), ewes were visually confirmed as 'isolated' when there was no other ewe within 10 m of the birth site. However, in our study, the mean distance to peers at either an hourly (Fig. 3) or daily scale (Fig. 4) never decreased below 25 m. In this instance, estimating an animal's level of isolation based on her distance to all others within the flock may be considered a limitation, with assessment based on the distance to the nearest neighbour a potentially superior method. Using the former calculation, a ewe located at an intermediate distance from all others in the flock (i.e. truly isolated) would exhibit a similar mean distance compared with one distant from the majority but still within close contact with a smaller subflock (i.e. not isolated). Thus, although the approach of Alexander *et al*. (1979) to define isolation based on a fixed distance was considered arbitrary and

limited, the approach in this study could also be refined. Further research should consider this to ensure subflocking behaviour is not being masked. This will also be important for application of these metrics in a commercial sensor-based system, where some threshold level will be required to determine if an 'alert' of parturition should be delivered.

Conclusions

Changes in ewe speed of movement, isolation and spatial paddock utilisation occur at parturition and can be detected using GNSS sensors. Using a day-scale resolution, minimum daily speed increases on the day of lambing, potentially indicating a level of restlessness in the ewe. In addition, ewes isolate themselves and limit their spatial utilisation of the paddock. Although some change in hourly maximum speed was identified in this study, GNSS technology alone is not sufficient to detect the onset of lambing or actual time of birth.

In the present study we identified measurable variables for detection of parturition in sheep using GNSS. With the methodology applied in this study, behavioural changes related to lambing were detected at a daily scale. Ideally, GNSS or other similar sensor technology should be further developed for lambing detection at a much finer scale (e.g. hourly) to maximise benefits of real-time monitoring. Despite this limitation, the patterns identified in this study could still be used to inform a model that identifies if a ewe has given birth in the preceding 24 h based on a deviation from 'normal' baseline patterns. If this were extended to include a measure of parturition success (e.g. dystocia), the use of the model in a commercial setting would allow producers to effectively manage their animals during this period, improving welfare standards and increasing economic returns from rapid intervention and increased survival rates. However, in order to ensure adequate model development, validation of appropriate variables such as a universal change in speed of movement, isolation or use of space, as has been attempted in this study, is an essential first step. A variety of mathematical and statistical models are currently used for detecting a variety of phenomena in the animal sciences. For example, for the autonomous detection of mastitis (de Mol and Ouweltjes 2001) and oestrus in dairy cows (Chung *et al*. 2013) and diseases on different livestock species (Fernández-Carrión *et al*. 2017). Thus, the identification of variables that are significantly altered around birth events would enable the development of predictor variables that could be used in time series and machine learning models for the detection of birth events in sheep.

Conflict of interest

The authors declare no conflicts of interest.

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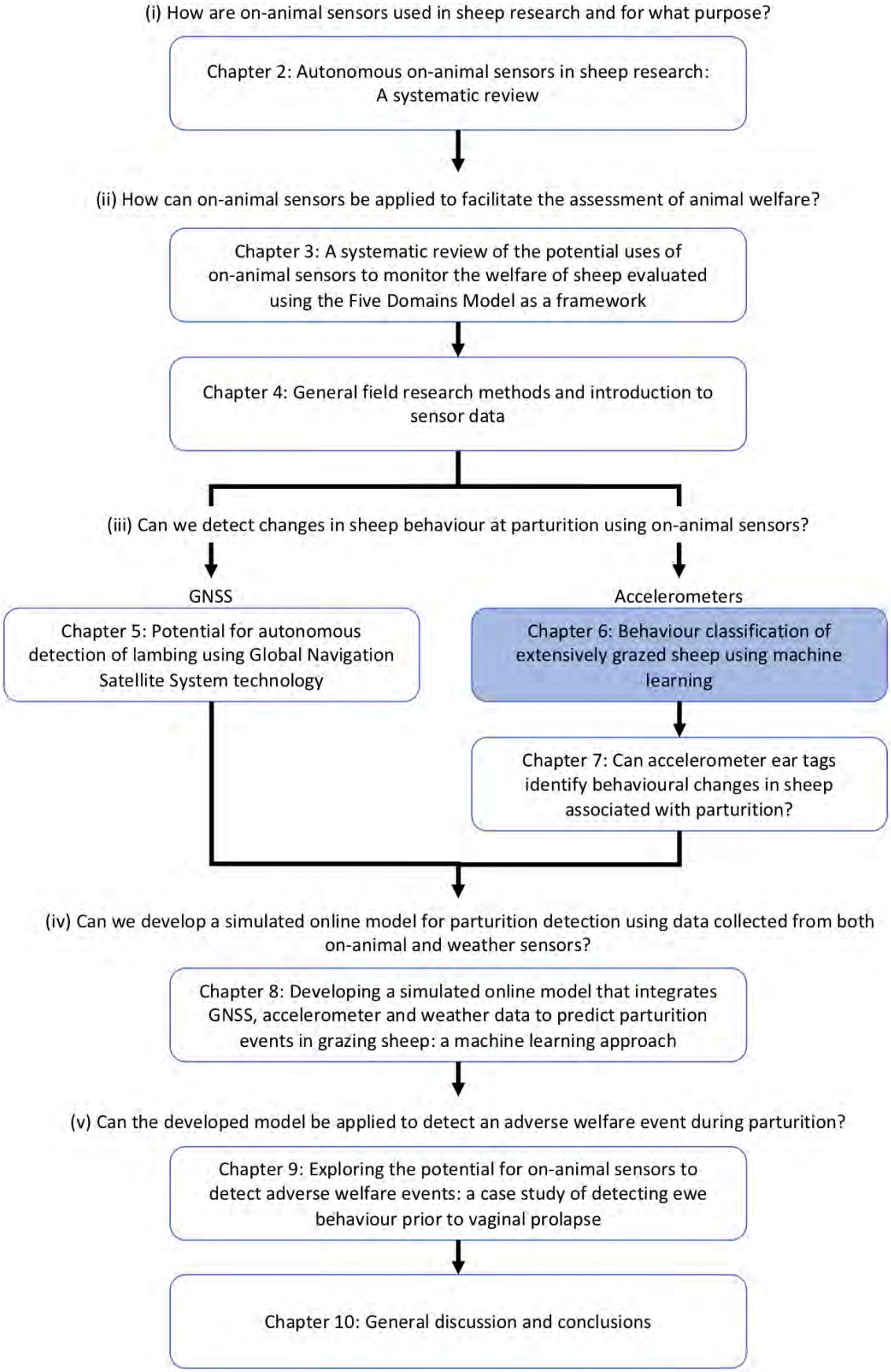
(i) How are on-animal sensors used in sheep research and for what purpose?
Chapter 2: Autonomous on-animal sensors in sheep research: A systematic review
(ii) How can on-animal sensors be applied to facilitate the assessment of animal welfare?
Chapter 3: A systematic review of the potential uses of on-animal sensors to monitor the welfare of sheep evaluated using the Five Domains Model as a framework
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GNSS
Accelerometers
Chapter 5: Potential for autonomous detection of lambing using Global Navigation Satellite System technology
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Chapter 7: Can accelerometer ear tags identify behavioural changes in sheep associated with parturition?
(iv) Can we develop a simulated online model for parturition detection using data collected from both on-animal and weather sensors?
Chapter 8: Developing a simulated online model that integrates GNSS, accelerometer and weather data to predict parturition events in grazing sheep: a machine learning approach
(v) Can the developed model be applied to detect an adverse welfare event during parturition?
Chapter 9: Exploring the potential for on-animal sensors to detect adverse welfare events: a case study of detecting ewe behaviour prior to vaginal prolapse
Chapter 10: General discussion and conclusions

Chapter 6. Behaviour classification of extensively grazed sheep using machine learning

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Overview

Accelerometers have increased in popularity in recent years (Chapter 2). However, despite the growing number of studies in this area, there is still no established method of data analysis appropriate for sheep behaviour classification. Thus, this chapter provides supporting evidence to determine the most appropriate method of accelerometer data analysis to detect sheep behaviour. Machine learning was selected as the method of analysis due to its promising application in previous sheep research (Barwick, 2016, Alvarenga et al., 2016). The chosen ML models [Classification and Regression Trees (CART)], Support Vector Machine (SVM), Linear Discriminant Analysis (LDA) and Quadratic Discriminant Analysis (QDA) were based on previous use of these models in sheep (Alvarenga et al., 2016, Marais et al., 2014, Umstätter et al., 2008, Barwick et al., 2018) and cattle (Robert et al., 2009, Hokkanen et al., 2011, Nadimi et al., 2012, Watanabe et al., 2008).

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Behaviour classification of extensively grazed sheep using machine learning

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ABSTRACT

The application of accelerometer sensors for automated animal behaviour monitoring is becoming increasingly common. Despite the rapid growth of research in this area, there is little consensus on the most appropriate method of data summation and analysis. The objective of this current study was to explore feature creation and machine learning (ML) algorithm options to provide the most accurate behavioural classification from an ear-borne accelerometer in extensively grazed sheep. Nineteen derived movement features, three epochs (5, 10 and 30 s) and four ML-algorithms (Classification and Regression Trees (CART), Linear Kernel Support-Vector Machines (SVM), Linear Discriminant Analysis (LDA) and Quadratic Discriminant Analysis (QDA)) were assessed. Behaviour classification was also evaluated using three different ethograms, including detection of (i) grazing, lying, standing, walking; (ii) active and inactive behaviour; and (iii) body posture. Detection of the four mutually-exclusive behaviours (grazing, lying, standing and walking) was most accurately performed using a 10 s epoch by an SVM (76.9%). Activity was most accurately detected using a 30 s epoch by a CART (98.1%). LDA and a 30 s epoch was superior for detecting posture (90.6%). Differentiation relied on identification of disparities between behaviours rather than pattern recognition within a behaviour. The choice of epoch and ML algorithm will be dependent on the application purpose, with different combinations of each more accurate across the different ethograms. This study provides a crucial foundation for development of algorithms which can identify multiple behaviours in pasture-based sheep. This knowledge could be applied across a number of contexts, particularly at times of change in physiological or mental state e.g. during parturition or stress-inducing husbandry procedures.

1. Introduction

Behaviour is often used by researchers to better understand an animal's interaction with their environment and physiological state (Frost et al., 1997; Barwick et al., 2018a). However, behaviour is often difficult to consistently monitor, especially when animals are in large numbers or spread over vast distances (Dobos et al., 2015). The development of sensor technologies has improved our ability to remotely monitor livestock in a broad range of contexts and on scales not previously possible (Brown et al., 2013; Schmoelzl et al., 2016). Of these sensors, one type that has increased in popularity is the accelerometer (Fogarty et al., 2018). Accelerometers measure both gravitational and inertial acceleration associated with movement, usually on three different axes (called tri-axial) (Brown et al., 2013; Alvarenga et al., 2016; Barwick et al., 2018b). Recent advances in miniaturisation of technology has increased accelerometer uptake, with reduced size, mass and power consumption making attachment to the animal easier and less invasive (Watanabe et al., 2008; Alvarenga et al., 2016; Walton et al., 2018). Extensive beef and sheep industries are now exploring the potential for these systems to optimise production, reduce costs and enhance sustainability (Trotter, 2018).

In sheep, accelerometers have previously been used to detect basic behaviours (specifically, behavioural states rather than behavioural events) such as high- and low-level general activity (McLennan et al., 2015), gait and posture (Radeski and Ilieski, 2017) or some combination of grazing, lying, standing, ruminating, running and/or walking (Nadimi et al., 2012; Alvarenga et al., 2016; Giovanetti et al., 2017; Barwick et al., 2018b; Decandia et al., 2018; Mansbridge et al., 2018; Walton et al., 2018). More specific applications have included the detection of suckling (Kuźnicka and Gburzyński, 2017) and lameness (Barwick et al., 2018a). These studies vary in their approach, with differences in study purpose, design, sensor attachment and data sample rate. Some have also been conducted in controlled pen environments, either wholly (Alvarenga et al., 2016; Giovanetti et al.,

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2017; Barwick et al., 2018a) or in part (Radeski and Ilieski, 2017). As these sensors evolve into commercially affordable systems, further evaluation in sheep kept under normal grazing conditions is warranted. This is particularly important for behaviour signatures that may subtly differ between pen and pasture environments (e.g. differences in biting signatures of animals eating a total mixed ration compared to those actively tearing pasture (Martz and Belyea, 1986)) or behaviours that may arise due to extensive management conditions (e.g. increased insect-defence behaviours such as ear-flicking or head shaking (Dougherty et al., 1993; Mooring et al., 2003)).

In addition to differing study design, there has also been a number of ways in which behaviour states have been interpreted and classified. For example, Alvarenga et al. (2016) used accelerometers to classify five mutually-exclusive sheep behaviours (grazing, lying, running, standing and walking). Similarly, Barwick et al. (2018b) and Walton et al. (2018) classified lying, standing and walking behaviours, with Barwick et al. (2018b) including an additional classification of grazing. Other approaches include Mansbridge et al. (2018), where classification was focused on grazing, ruminating and other non-eating behaviours and Rurak et al. (2008) and Umstätter et al. (2008) where behaviours were classified as either 'active' or 'inactive'. While a higher degree of resolution in behavioural observation might be desirable from a research perspective, it is entirely feasible that simple bivariate classifications (e.g. active/inactive) may prove reliable enough to be applied in commercial contexts and should not be immediately dismissed.

The first step in most accelerometer-based data analysis involves the process of feature extraction. There have been a large number of features proposed in the literature, ranging from simple averages of a single accelerometer axis (Hokkanen et al., 2011) to more complex metrics designed to capture the variability of signal magnitude across all three axes (Alvarenga et al., 2016; Barwick et al., 2018b; Walton et al., 2018). Most features are created using a fixed time segment commonly referred to as the 'epoch' (Decandia et al., 2018). Epochs help to reduce both the amount and complexity of data and reduce noise in the dataset (Chen and Bassett, 2005; Barwick, 2016). However, choosing an optimal epoch length can be challenging, as epochs are required to be both short enough to maximise the likelihood of capturing a single behaviour yet sufficient in duration to allow adequate differentiation between behaviours (Chen and Bassett, 2005). While this method of data summation is common, there is not yet a consensus on the most appropriate epoch length for behaviour detection.

Once the features have been created, these are then analysed using any one of a number of machine learning (ML) algorithms e.g. discriminant analysis (Giovanetti et al., 2017; Barwick et al., 2018a; Barwick et al., 2018b; Decandia et al., 2018); classification trees (Alvarenga et al., 2016); random forest (Barwick et al., 2018a; Barwick et al., 2018b; Mansbridge et al., 2018; Walton et al., 2018); support vector machine (Mansbridge et al., 2018). Whilst some studies have compared the value of different epochs and ML algorithms, none have comprehensively evaluated the many different combinations in parallel and the resulting ability to classify multiple behaviour states in extensively grazed sheep.

The objective of this current study was to explore how a range of ML algorithms (Classification and Regression Trees (CART), Linear Kernel Support Vector Machine (SVM), Linear Discriminant Analysis (LDA) and Quadratic Discriminant Analysis (QDA)) can be used to predict behavioural states in sheep. Algorithms were assessed using three epoch lengths (5, 10, 30 s). Assessment of calculated features was also conducted to determine the best features for behaviour prediction. Analysis was applied to three different ethograms: (i) detection of four mutually-exclusive behavioural states (grazing, lying, standing, walking); (ii) detection of general activity (active – grazing, walking; inactive – standing, lying); and (iii) detection of body posture (upright – grazing, standing, walking; prostrate – lying). Though similar aspects of accelerometer application have been studied in sheep (Umstätter et al., 2008; Alvarenga et al., 2016; Giovanetti et al., 2017; Barwick et al., 2018b; Decandia et al., 2018; Mansbridge et al., 2018; Walton et al., 2018) and cattle (Martiskainen et al., 2009; Robert et al., 2009; Smith et al., 2016; Abell et al., 2017), the focus of this study was to assess multiple combinations of analysis protocols, with the objective of identifying algorithms appropriate for commercial application in extensively grazed sheep. Further to this, while comparable applications are already present in the dairy industry (Trotter, 2013), there is still a requirement to study these aspects in sheep given the differences between the two species e.g. bio-mechanical differences related to common behaviours and the resulting difference in acceleration signatures (Chambers et al., 1981; Barwick et al., 2018b).

2. Materials and methods

2.1. Animals, location and instrumentation

All procedures were approved by the Massey University Animal Ethics Committee (MUAEC 18-67).

This study was conducted at a commercial mixed enterprise property on the South Island of New Zealand (43.0°S and 173.2°E). Twelve pregnant mixed-aged ewes (Merino or Merino cross) were selected for observation and fitted with ear-borne accelerometers (Axivity AX3, Axivity Ltd, Newcastle, UK). These animals were part of a larger flock (39 ewes in total) also fitted with ear tag accelerometers being monitored for the purposes of parturition detection. All ewes (n = 39) were selected from the main commercial flock on the basis of being ultrasound scanned as single-bearing with an expected lambing date from early to mid-September 2018. The experimental paddock was 4.4 ha. Animals were provided with *ad libitum* access to forage and water. Shelter was provided by tree breaks along the east and west boundaries. The north side of the paddock followed a major farm road (Fig. 1).

The accelerometers were configured to collect data at 12.5 Hz (12.5 records/second). The internal clock was synced with the time.is website (https://time.is) prior to deployment. The accelerometers were attached to ear tags and fixed to the ewe's ear by an experienced operator using a commercial Allflex applicator (Allflex Australia Pty Ltd, Australia). Tags were fixed with orientation of the X, Y and Z axis along the dorso-ventral, lateral and anterior-posterior axes, respectively. A schematic drawing of the tag and attachment site is shown in Fig. 2. Tags were attached on the morning of 8 September 2018 with animals observed for at least 30 min to monitor for signs of distress. Animals were then moved to the experimental paddock with data collection starting at midnight on 9 September 2018 (Day 1). Tags were removed by 1200 on 23 September 2018 (Day 16). Accelerometer data were then downloaded using the proprietary software (OMGUI, Axivity Ltd, Newcastle, UK).

2.2. Observations

To facilitate observation, ewes were fitted with unique identification 'bibs'. Ewes were observed from 0730 h to 1230 h and 1330 h to 1730 h (± 30 min) for the duration of the study. Visual observations were conducted for the purpose of recording lambing behaviour and time of birth. For the purpose of the current study *ad libitum* video recordings were acquired during these times using a Nikon Coolpix B500 camera with a 40x optical zoom (Nikon, Japan) and a Sony HDR-PJ410 Camcorder (Sony, Japan). Both cameras were synced with the time.is website at the start of each day before any recordings. Video recordings were usually conducted from the roadside at the northern end of the paddock. The exception to this was when the entire flock was located at the southern end of the paddock and recordings were collected from within the paddock at an appropriate distance to minimise flock disturbance (Fig. 1).

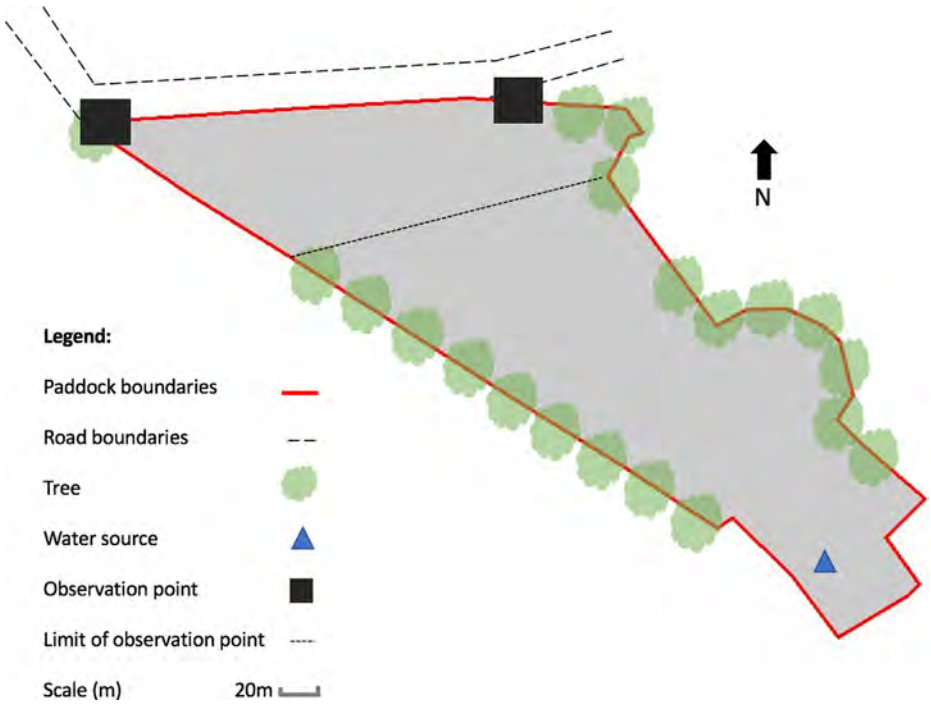

Fig. 1. Schematic diagram of the experimental paddock.

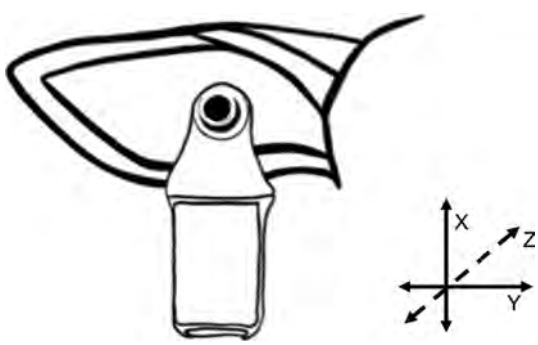

Fig. 2. Schematic drawing of the tag and attachment site including device orientation.

2.3. Behavioural annotation of video files

Video files were downloaded and annotated by a single observer (first author) to record the exact time and duration of each behaviour state. Observations were *ad libitum and* classified as per Table 1. Behaviours were only recorded if they were continuously performed for at least ten seconds (for the 5 and 10 s epochs) or 30 s (for the 30 s epoch). This was conducted to ensure each discrete epoch only contained the accelerometer data from a single behaviour. If an animal transitioned to another behaviour within an epoch, this was discarded. If the observer was unsure of the animal's behaviour (e.g. if they were partially concealed by another animal), the observation was discarded. Due to the difficulties in differentiating between grazing and standing behaviours, grazing was only recorded when clear jaw movements were evident and standing was only recorded when the head was upright with no jaw movements. Again, if the observer was unsure of the behaviour, the observation was discarded.

Behaviours recorded on the day of lambing were excluded from analysis because of the potential impact of parturition behaviour on the accelerometer data. Days either side of this were still included in analysis as overt behavioural changes are usually only evident on the actual day of lambing (Wallace, 1949; Owens et al., 1985; Echeverri et al., 1992; Schmoelzl et al., 2016).

2.4. Ethogram development

To facilitate assessment using different methods of behaviour classification, further annotations were made to reclassify each behaviour based on activity and posture (Table 1). Put simply, three different ethograms were used for assessment, with each ethogram representing different groupings of similar behaviours: (i) detection of four mutually-exclusive behaviours (grazing, lying, standing, walking); (ii) detection of active (grazing, walking) and inactive (lying, standing) behaviours and (iii) detection of upright (grazing, walking, standing) and prostrate (lying) body posture.

2.5. Calculation of movement metrics

The raw accelerometer data that corresponded to individual behaviours were then extracted and partitioned into epochs of 5 s, 10 s and

Table 1
Recorded behaviour definitions (Barwick et al., 2018b).

Behaviour description	Ethogram classification 1. Behaviour	2. Activity	3. Posture
Animals are grazing with their head down or chewing with head up. Grazing animals still or moving.	Grazing	Active	Upright
Animals are recumbent and inactive with minor head movements.	Lying	Inactive	Prostrate
Animals are idle and standing upright. Only standing behaviour with head up was recorded.	Standing	Inactive	Upright
Animals are travelling using progressive steps in a forward direction. Head position can be up or down.	Walking	Active	Upright

Table 2
Nineteen features calculated for each epoch (5, 10, 30 s) based on raw X, Y and Z acceleration values. Equations adapted from Campbell et al. (2013); Marais et al. (2014); Alvarenga et al. (2016); Barwick et al. (2018a); Barwick et al. (2018b).

Feature	Equation
Average X-axis (A_x)	$A_x = \frac{1}{T}\sum_{t=1}^{T} x(t)$ Where T is the total number of counts in the epoch
Average Y-axis (A_y)	As above for the Y-axis
Average Z-axis (A_z)	As above for the Z-axis
Average all-axis (A_{xyz})	$A_{xyz} = \frac{1}{T}\sum_{t=1}^{T}(x(t) + y(t) + z(t))$ Where T is the total number of counts in the epoch
Minimum X (Min_X)	The minimum X-axis acceleration value for the epoch
Minimum Y (Min_Y)	The minimum Y-axis acceleration value for the epoch
Minimum Z (Min_Z)	The minimum Z-axis acceleration value for the epoch
Maximum X (Max_X)	The maximum X-axis acceleration value for the epoch
Maximum Y (Max_Y)	The maximum Y-axis acceleration value for the epoch
Maximum Z (Max_Z)	The maximum Z-axis acceleration value for the epoch
Standard Deviation (SD_X)	$SD_X = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(x(t) - \bar{x})^2}$
Standard Deviation (SD_Y)	As above for the Y-axis
Standard Deviation (SD_Z)	As above for the Z-axis
Average Standard Deviation (SD_{XYZ})	$SD_{XYZ} = \frac{1}{T}\sum_{t=1}^{T}(SDX + SDY + SDZ)$
Movement Intensity (MI)	$\frac{1}{T}(\sum_{t=1}^{T}\sqrt{x(t)^2 + y(t)^2 + z(t)^2})$ Where T is the total number of counts in the epoch
Signal Magnitude Area (SMA)	$\frac{1}{T}\sum_{t=1}^{T}(\lvert x(t)\rvert + \lvert y(t)\rvert + \lvert z(t)\rvert)$ Where T is the total number of counts in the epoch
Energy	$\frac{1}{T}\sum_{t=1}^{T}(x(t)^2 + y(t)^2 + z(t)^2)^2$ Where T is the total number of counts in the epoch
Entropy	$\frac{1}{T}\sum_{t=1}^{T}(1 + (x(t) + y(t) + z(t))^2 \ln(1 + (x(t) + y(t) + z(t))^2)$ Where T is the total number of counts in the epoch
Movement Variation (MV)	$\frac{1}{T}(\sum_{t=1}^{T}(\lvert x_{t-1} - x_t\rvert + \lvert y_{t-1} - y_t\rvert + \lvert z_{t-1} - z_t\rvert))$ Where T is the total number of counts in the epoch

30 s. Again, epochs were only included if they contained data from a single behaviour for the entire epoch (e.g. a 15 s observation of a single behaviour would provide three 5 s epochs, one 10 s epoch and no 30 s epochs). Nineteen movement features were calculated for each epoch (Table 2). These were the most commonly applied and reported in previous research (Campbell et al., 2013; Marais et al., 2014; Alvarenga et al., 2016; Barwick et al., 2018a; Barwick et al., 2018b).

To summarise, nine separate datasets were developed through this process, representing the three epoch durations and three ethograms to be assessed. Each row of the datasets contained data for a single epoch, including the calculated movement metrics, animal ID and the corresponding behaviour (Table 1).

2.6. Training and test data sets

All ML model development and validation was conducted in R (R Core Team, 2018) using the 'caret' (Kuhn, 2018) and 'randomForest' packages (Liaw and Wiener, 2002). Leave one out cross validation (LOOCV) was used to train and subsequently test the performance of each ML algorithm. This process was based on Smith et al. (2016), and involves training the ML on all but one of the available datasets (11 of the 12 individual animal datasets), with the remaining animal's dataset used for performance evaluation. This process was repeated 12 times across all individual animals.

Within each training progression, a 10-fold CV was also used to split the training data into non-overlapping secondary training and test sets for parameter selection. This process ensures optimal parameter selection during the training process, whilst retaining a completely independent dataset (from the animal that had been 'left out') for final model validation. Again, this process was based on (Smith et al., 2016).

The use of unbalanced datasets has been shown to provide sub-optimal classification, particularly for the minority class (Weiss and Provost, 2003; Amrine et al., 2014). To account for this, the training dataset was under-sampled by randomly removing observations from the majority class(es) to make the dataset more balanced. This was conducted for Ethogram One only, where the disparity between behaviour frequencies was most obvious (particularly for walking data). For Ethogram Two and Three the training sets were kept in their original (unbalanced) form. This decision was made to maximise the number of available observations for training and to minimise handling of the dataset. The method of under-sampling was adapted from Smith et al. (2016) and Abell et al. (2017).

2.7. ML classifiers

Models for classification of each ethogram were developed using ML algorithms (CART, SVM, LDA and QDA) from the 'caret' package (Kuhn, 2018).

CART is a simple and intuitive process, resulting in a single decision tree based on simple yes/no questions (Valletta et al., 2017). These algorithms are easy to train and can manage unbalanced data; however, they are prone to overfitting (Nathan et al., 2012; Valletta et al., 2017).

SVM is a type of non-probabilistic classifier (Mansbridge et al., 2018). The model works by creating a hyperplane to separate observations, maximising the distance of observations from the hyperplane (Nathan et al., 2012; Wang, 2019). SVM is primarily a binary classifier, though multiclass classifications can be implemented by comparing one class to all other classes (Nathan et al., 2012). SVMs have relatively high computational costs (Vázquez-Diosdado et al., 2015).

LDA reduces dimensionality of the data by applying linear boundaries between groups; maximising the distance between the classes whilst simultaneously minimising the variance within each class (Nathan et al., 2012). The use of the linear boundaries can minimise the

risk of overfitting but may also reduce accuracy. QDA is an extension of LDA where the decision boundary between classes is quadratic (Marais et al., 2014). LDA is often considered a baseline algorithm, though still performs relatively well (Nathan et al., 2012; Marais et al., 2014).

Though these methods can be considered 'black box', with the internal rules with each algorithm difficult to determine (Nathan et al., 2012), the above MLs were chosen for inclusion as they are relatively easy to apply and interpret. There is also precedence for their use based on previous applications in sheep (Marais et al., 2014; Alvarenga et al., 2016; Barwick et al., 2018b; Mansbridge et al., 2018) and cattle (Martiskainen et al., 2009; Robert et al., 2009; Smith et al., 2016).

2.8. Feature evaluation

For CART and SVM, all 19 features were used in model development. A Receiver Operating Characteristics (ROC) curve analysis was then conducted to determine the dominant features for prediction using each algorithm. For LDA and QDA, variable selection of the top three features was performed before model development using random forest (RF). This prior selection of features was conducted to allow direct comparison with previous protocols established by Barwick et al. (2018b) and to explore if the application of numerous features (as per protocols used in CART and SVM) improved classification accuracy. The feature selection process involved development of a RF using the 'randomForest' package (Liaw and Wiener, 2002), then calculation of the average Gini Index of each variable. Gini Index provides a measure of error across the forest (Alvarenga et al., 2016; Barwick et al., 2018b). The RF was calculated using an mtry (approximately equal to the square root of the number of variables used for classification) of 4.4 and ntree (number of trees in the random forest) of 500 (Barwick et al., 2018b).

2.9. ML evaluation

Once prediction models for each ethogram had been developed, the average accuracy and Kappa value was calculated. Accuracy was calculated using the following equation:

$$accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)}$$

where true positive (TP) refers to the number of instances where the behaviour of interest was correctly identified, false negative (FN) is the number of instances where the behaviour of interest was incorrectly identified as another behaviour, true negative (TN) where the behaviour of interest was correctly classified as not being observed and false positive (FP) is the number of instances where the behaviour of interest was incorrectly identified as not being observed. The Kappa value compares the observed accuracy with an expected (random) accuracy, providing a value between 0.00 and 1.00 where higher scores indicate higher performance (Alvarenga et al., 2016). This metric is particularly useful in unbalanced samples such as in this current study (Santegoeds, 2016).

Average sensitivity, specificity and precision was then calculated for the highest performing algorithms per ethogram, using the following equations:

$$sensitivity = \frac{TP}{(TP + FN)}$$

$$specificity = \frac{TN}{(TN + FP)}$$

$$precision = \frac{TP}{(TP + FP)}$$

The entire workflow for ethogram development is summarised in Fig. 3.

3. Results

3.1. Sensor and observation results

A summary of the total number of epoch observations collected for each behaviour is presented in Table 3.

The proportion of available data for the 5 s and 10 s epoch was 40% grazing, 45% lying, 13% standing and 2% walking. This equates to 42% active compared to 58% inactive behaviour and 55% upright compared to 45% prostrate posture. The low amount of walking data resulted in the development and application of the under-sampling protocol described in Section 2.6.

The proportion of available data for the 30 s epoch was 29% grazing, 64% lying and 7% standing. Walking was excluded due to the very low levels of data. This equates to 29% active compared to 71% inactive behaviour and 36% upright compared to 64% prostrate posture.

3.2. Ethogram One: Detection of grazing, lying, standing and walking behaviour

The results of the CART, SVM, LDA and QDA for detecting grazing, lying, standing and walking behaviour are shown in Table 4. The highest performing algorithm that was able to detect all four behaviours was SVM using a 10 s epoch (Table 5).

3.3. Ethogram Two: Detection of activity

The results for the ML algorithms for detecting active or inactive behaviour is shown in Table 6. For 5 and 10 s epochs, active behaviour was trained using grazing and walking data. For the 30 s epoch, active behaviour was trained using grazing data only. Inactive behaviour was trained using standing and lying behaviours for all epochs. Accuracy and kappa values were high for all ML and epoch combinations, with the highest for CART using 30 s epochs (Table 7).

3.4. Ethogram Three: Detection of posture

The results for the ML algorithms for detecting posture are shown in Table 8. The highest performing epoch was 30 s, especially for LDA which showed 90.6% accuracy and 0.8 kappa value. The performance statistics for the LDA model are shown in Table 9.

3.5. Feature evaluation

One objective of this study was to explore which features might be most valuable to the ML analysis. This was achieved separately for the CART/SVM and LDA/QDA algorithms. The relative importance of the nineteen features for CART and SVM development was calculated using ROC curve analysis after model development (Table 10). For LDA and QDA, feature selection was conducted before model development using the RF Gini Index (Barwick et al., 2018b) (Table 11). As shown in Tables 10 and 11, MV, SD_Y, SD_X and Min_X were consistently identified as the most important features for classification, particularly for the RF calculation where only one other metric was identified ($Mean_Y$; Table 11). Max_Y was also identified by the SVM algorithm as important for walking (5 s epoch and 10 s epoch) and standing (30 s epoch) differentiation (Table 10).

4. Discussion

In this study, a number of features, epoch lengths and ML algorithms were used to successfully classify various behaviour states in extensively grazed sheep using an ear-borne accelerometer. Given the value of the ear-tag form and its application in current husbandry practice (Barwick et al., 2018b), this research provides valuable insight

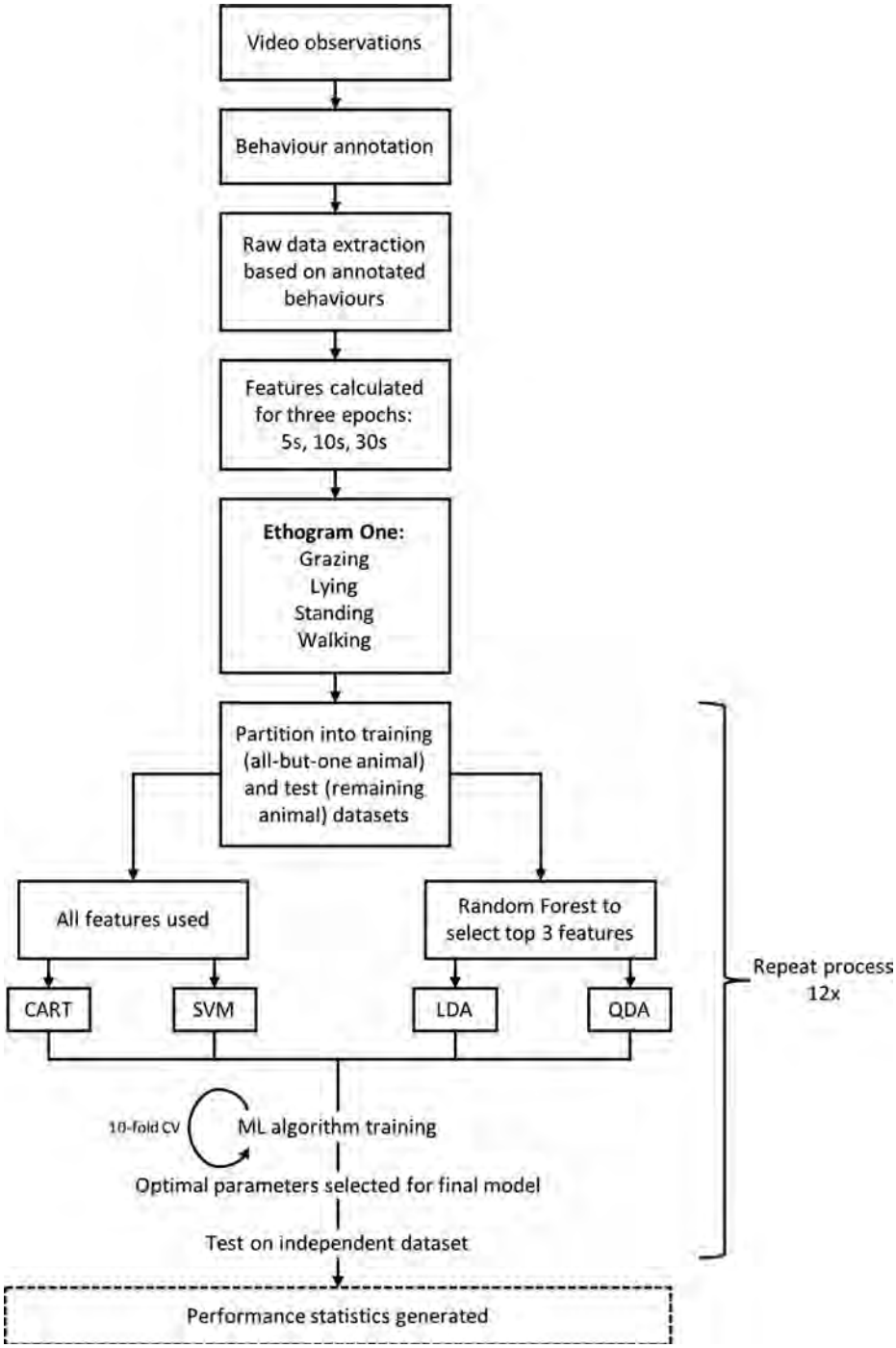

Fig. 3. Workflow for development of Ethogram One using ML-algorithms. This process was repeated for Ethogram Two and Ethogram Three.

of the behaviour assessments that can be conducted using this attachment method.

The results indicate that the ear attachment method is able to distinguish between four basic behaviours with reasonable accuracy. In general, longer epochs reported greater accuracy overall. However, due to lack of available training data, the 30 s epochs models could not be applied to classify walking (Table 4). As shown in Table 5, standing and walking classification had relatively low sensitivity (62.9% and 65.6%, respectively). This means that of those available data points, only a small proportion were correctly identified in the test dataset (true positive), with the rest being misclassified as another behaviour (false negative). Specificity was also low for these behaviours, particularly walking (45.2%), and reflects a lower true negative rate (i.e. higher false positives). This contrasts with Barwick et al. (2018b), where standing had 98% and 95% and walking had 96% and 100% sensitivity and specificity, respectively, using the same attachment method. Curiously, the sensitivity of lying classification was also low in the current study (55.5%). This contrasts Walton et al. (2018) where lying classification had over 92% for all performance metrics. In this study, the amount of walking data collected was significantly lower than the other behaviours (Table 3). Though we attempted to mitigate this by undersampling the remaining behaviours, the results of the current study should be interpreted with caution. It should also be noted that undersampling may have impacted the results for the other behaviours such as lying by discarding potentially useful information which may have assisted in algorithm development. Further research should be

Table 3
Total number of epoch observations available for each animal and behaviour.

	Total number of epoch observations										
	Grazing			Lying			Standing			Walking	
Animal	5	10	30	5	10	30	5	10	30	5	10
1	176	88	12	536	268	83	44	22	4		
2	82	41	6	506	253	75	18	9			
3	186	93	12	46	23	5	74	37	3	6	3
4	144	72	11	94	47	12	42	21	1	18	9
5	192	96	20	56	28	8	80	40	4	4	2
6	96	48	7	18	9	1	48	24	1	8	4
7	182	91	10	124	62	18	56	28	5	22	11
8	128	64	9	78	39	12	30	15	4	2	1
9	182	91	14	26	13	2	82	41	1	10	5
10	140	70	9	96	48	15	44	22	6	14	7
11	74	37	5	132	66	20	42	21	2	4	2
12	196	98	18	304	152	45	44	22	4	8	4
TOTAL	**1778**	**889**	**133**	**2016**	**1008**	**296**	**604**	**302**	**35**	**96**	**48**

Table 4
Accuracy and kappa values for ML prediction of grazing, lying, standing and walking at 5, 10 and 30 s epochs. Bold indicates the highest accuracy/kappa combination.

Epoch	ML	Accuracy (%)	Kappa	No.[1] of behaviours detected
5 s	CART	54.0	0.4	4
	SVM	64.6	0.5	4
	LDA	53.8	0.3	4
	QDA	64.3	0.4	4
10 s	CART	63.4	0.4	4
	SVM	**76.9**	**0.6**	**4**
	LDA	56.6	0.4	4
	QDA	65.9	0.5	4
30 s	CART	71.4	0.6	3
	SVM	75.6	0.6	3
	LDA	74.6	0.6	3
	QDA	71.5	0.5	3

[1] No. = Number.

Table 5
Performance statistics for the 10 s epoch SVM test dataset for Ethogram One. Metrics reflect the average values for all iterations of the model (i.e. mean of all 12 test sets).

	Grazing	Lying	Standing	Walking
Metrics used	***All***			
Accuracy (%)	76.9			
	Range (54.8[1] – 90.8[2])			
Sensitivity (%)	90.3	55.5	62.9	65.6
Specificity (%)	98.1	93.3	84.0	45.2
Precision (%)	96.8	69.8	45.2	25.1

[1] Animal ID: 11.
[2] Animal ID: 8.

conducted to improve this result, ensuring adequate training data is collected for behaviour differentiation. Researchers should note that obtaining adequate amounts of data for some behaviours (e.g. walking and running) in extensive grazing environments may be challenging as animals may only spend a small amount of time in this behaviour state compared to grazing and resting. Observation of these behaviours in extensive environments may also be difficult if animals are ranging over large areas or hilly terrain. For this reason, it may be necessary to manage the animals in such a way that large amounts of data can be easily collected for these behaviours that are less frequent but still highly significant.

In situations where it is not necessary to determine the exact behaviour of the animal, discrimination between activity levels may be sufficient. This reduces the complexity of the ethogram and decreases the computational burden of data processing. For example, if

Table 6
Accuracy and kappa values for ML prediction of active or inactive behaviours at 5, 10 and 30 s epochs. Bold indicates the highest accuracy/kappa combination.

Epoch	ML	Accuracy (%)	Kappa
5 s	CART	95.2	0.9
	SVM	95.5	0.9
	LDA	90.7	0.8
	QDA	92.4	0.8
10 s	CART	96.6	0.9
	SVM	96.9	0.9
	LDA	96.0	0.9
	QDA	96.2	0.9
30 s	**CART**	**98.1**	**1.0**
	SVM	97.8	0.9
	LDA	96.8	0.9
	QDA	98.0	0.9

Table 7
Performance statistics for the 30 s epoch CART test dataset for Ethogram Two. Metrics reflect the average values for all iterations of the model (i.e. mean of all 12 test sets).

	Active	Inactive
Metrics used	***All***	
Accuracy (%)	98.1	
	Range (86.7[1]–100.0[2])	
Sensitivity (%)	97.4	98.5
Specificity (%)	98.5	97.4
Precision (%)	96.9	98.6

[1] Animal ID: 10.
[2] Animal ID: 1, 2, 3, 4, 5, 6, 7, 11.

Table 8
Accuracy and kappa values for ML prediction of upright and prostrate postures at 5, 10 and 30 s epochs. Bold indicates the highest accuracy/kappa combination.

Epoch	ML	Accuracy (%)	Kappa
5 s	CART	83.3	0.6
	SVM	81.1	0.5
	LDA	82.8	0.6
	QDA	81.6	0.6
10 s	CART	85.3	0.6
	SVM	82.7	0.6
	LDA	84.4	0.6
	QDA	84.1	0.6
30 s	CART	89.4	0.7
	SVM	88.0	0.7
	LDA	**90.6**	**0.8**
	QDA	89.0	0.7

Table 9
Performance statistics for the 30 s epoch LDA for Ethogram Three. Metrics reflect the average values for all iterations of the model (i.e. mean of all 12 test sets). The LDA algorithm used the top three ranked metrics from the training data, identified using RF.

	Upright	Prostrate
Metrics used	***MV, Min_X, SD_X***	
Accuracy (%)	90.6	
	Range (80.0[1]–100.0[2])	
Sensitivity (%)	80.7	100
Specificity (%)	100	80.8
Precision (%)	100	79.0

[1] Animal ID: 10.
[2] Animal ID: 2.

Table 10
The top three features for each ethogram using 5, 10 and 30 s epochs. Importance was calculated after CART and SVM model development using a ROC curve analysis. Values in parentheses are alternative dominant features for one particular behaviour (S = standing; W = walking).

Epoch	Ethogram One		Ethogram Two		Ethogram Three	
	CART	SVM	CART	SVM	CART	SVM
5 s	SD_Y	SD_Y	SD_Y	SD_Y	SD_Y	SD_X
	MV	MV	MV	MV	MV	SD_Y
	SD_X	SD_X $(Max_Y)^W$	SD_X	SD_X	SD_X	MV
10 s	MV	MV	MV	MV	Min_X	Min_X
	SD_X	SD_Y	SD_X	SD_Y	SD_Y	Energy
	Max_Y	SD_X $(Max_Y)^W$	Min_X	SD_X	MV	SD_Y
30 s	MV	MV	MV	MV	MV	SD_Y
	SD_X	SD_Y $(Mean_Y)^S$	Min_X	SD_Y	Min_X	MV
	Min_X	SD_X $(Max_Y)^S$	SD_X	SD_X	SD_Y	SD_X

Table 11
The top three features for each ethogram using 5, 10 and 30 s epochs training dataset. Importance was calculated based on the Gini index from RF calculation.

Epoch	Ethogram One	Ethogram Two	Ethogram Three
5 s	MV	MV	MV
	SD_Y	SD_Y	SD_Y
	SD_X	SD_X	SD_X
10 s	MV	MV	MV
	SD_X	SD_X	SD_X
	Min_X	Min_X	SD_Y
30 s	MV	MV	MV
	SD_Y	Min_X	Min_X
	$Mean_Y$	SD_X	SD_X

accelerometers are being used for the sole purpose of measuring feed intake, the ability to distinguish grazing from other behaviours is crucial. In contrast, if it is enough to know that an animal is alive and moving, then a more general indication of activity may be adequate. This may be the case for some commercial applications where variations in day-to-day activity provide useful information; for example detection of oestrus behaviour in sheep using a sensor-based approach (Fogarty et al., 2015). Detection of active or inactive behaviours in this current study had over 90% accuracy for all epoch durations. The highest performing ML was CART (98.1%), closely followed by QDA (98.0%), both using the 30 s epoch. This was similar, if not slightly better than related studies (Umstätter et al., 2008) where pitch (vertical head movement) and tilt (lateral head movement) collected at 30 s increments was able to detect active and inactive behaviours with 94.4% and 96.6% accuracy, respectively. Adding to the benefit of higher model accuracy, classification of activity may also be applicable across a wider range of contexts because of the clear and distinct differences between the two states. In contrast, unless identification of a specific behaviour is absolutely crucial, such explicit classification may actually be detrimental in some situations. This is because ML classification requires the algorithm to be 'taught' a finite spectrum of behaviours, which might not necessarily be relevant to the behaviour being performed. Furthermore, the ML is inherently required to make a classification regardless of whether the behaviour completely 'fits' into one of the pre-defined groups. This is problematic for behaviours which may not be commonly trained, but are still relevant e.g. licking behaviour of a ewe to clean placenta off a newborn lamb may be incorrectly classified as grazing; scratching behaviour of sheep infested with lice maybe be incorrectly classified as walking. While there may be a motivation for development of commercial algorithms that provide as much detail as possible, more basic ethograms may actually be more appropriate in some situations.

Another method of reducing ethogram complexity is to detect the animal's posture. For example, lying behaviour in sheep is known to change with biomass availability (Arnold, 1984), parasite burden (Berriatua et al., 2001) and stress from surgical husbandry procedures (Fell and Shutt, 1989). Changes in lying and standing behaviour may also indicate an altered physiological status, including the onset of parturition (Echeverri et al., 1992). In this current study, the ability to differentiate between postures varied with epoch length and ML algorithm (81.1%–90.6%). The highest overall accuracy was evident using a 30 s epoch and LDA (90.6%), followed closely by the other ML algorithms also using 30 s epochs. This is superior to McLennan et al. (2015), where detection of lying and lying-ruminating behaviours had an accuracy of 74.6%. In the current study, upright posture was more difficult to classify than prostrate posture, with sensitivity of 80.7% compared to 100%, respectively. This contrasts the results for Ethogram One (Table 5) where standing behaviour had a higher sensitivity (62.9%) compared to lying (55.5%). The reasons for this may be twofold. Firstly, it may simply reflect the impact of under-sampling in Ethogram One. Secondly, it may reflect differences in the method of ML behaviour classification, with differentiation of lying from all other behaviours (grazing, standing and walking) potentially easier than differentiation from the three separate behaviours. This is supported by the results of Ethogram One, with lying most often misclassified as standing (data not presented). Given that the orientation of the ear would not significantly change between standing and lying behaviours, this difficulty in differentiating between the two exclusive behaviours is expected (Barwick et al., 2018b). Leg-mounted devices may offer a solution to this issue (Radeski and Ilieski, 2017), however their use and maintenance in the field is difficult (McLennan et al., 2015) and possibly impractical in a commercial situation (Barwick et al., 2018b). As ear-borne sensors could be easily integrated with current ear tag identifiers (Barwick et al., 2018b; Walton et al., 2018), there is merit in exploring the commercial development in this form, even if more simple methods of behaviour differentiation (i.e. posture) are required. Another potential method of improving this accuracy could be through identification of the transition event itself (i.e. the change between lying and standing behaviour) rather than the established state, as has been explored in dairy cattle (Vázquez-Diosdado et al., 2015). This warrants further research.

As part of the model development process, key features were assessed either post-model development (CART and SVM) or pre-model development (LDA and QDA). Across all ethograms and epochs, MV, SD_Y, SD_X and Min_X were consistently identified amongst the top features (Tables 10 and 11). Interestingly, most of these features relate to some measure of variation across a given epoch. MV calculates total variation as a cumulative measure of amplitude, frequency and duration (Campbell et al., 2013), providing information on the total amount of movement (Barwick, 2016). Similarly, SD_X and SD_Y measure variance of a particular axis, in this case the dorso-ventral (up-down) and lateral (side-to-side) movement, respectively. Thus, behaviour discrimination appears to rely on detecting differences between behaviours rather than identifying specific movement patterns within a behaviour. This was also concluded by Barwick et al. (2018b), with MV also identified as the most important predictor for the ear-borne accelerometer. This was associated this with the tendency of the ear tag to experience a higher degree of movement compared to collar or leg attachment methods, due to the less rigid fixation point for the device and the small size of the ear resulting in lower inertia and higher acceleration values when the animal moves (Barwick et al., 2018b). Though beneficial in some aspects, this susceptibility to movement may also be problematic, potentially causing a shift in axis orientation and/or inconsistencies between the orientation of the device between individual animals. This is particularly important for features that are dependent on deployment orientation (e.g. SD_Y and SD_X).

In the context of developing commercially efficient ear-borne sensor systems, it is important to consider how the algorithms will actually be deployed. In this study, the devices used were "store-on-board", with

the data stored on the tag and downloaded at the conclusion of the trial. This is obviously not appropriate for a commercial setting, where real-time or near-real-time information is required (Bailey et al., 2018). As data transmission is considered one of the most power intensive activities (Handcock et al., 2009), consideration of the amount and type of data to be transferred is important. When seeking to optimise the power management of commercial ear tag systems, it will be necessary to run embedded processing systems where the algorithms are processed on the device itself. This has important implications, as complex algorithms may take longer to compute and therefore reduce energy efficiency. In the current study, CART and SVM performed slightly better than the LDA and QDA models across all ethograms and epochs. However, this came at the expense of requiring more input feature variables for adequate training. In contrast, the simpler LDA used only three input features and was consistently only marginally lower in accuracy compared to the more complex ML's. Whilst more computationally intensive ML's may prove relevant in the future, the simplest solution (LDA) appears to be the most useful in this situation.

Though not the focus of the current study, it is also important to consider the impact of individual animal behaviour on the development of general algorithms for commercial application. As shown in Tables 5, 7 and 9, model accuracy varied between the highest and lowest performing animals for each ethogram, ranging from a 36% difference in Ethogram One, to 13% difference in Ethogram Two. Interestingly, the results did not demonstrate a consistent performance of individuals, with the animal scoring the lowest accuracy in Ethogram One (Animal 11; Table 5), amongst the highest performers in Ethogram Two (Table 7). The exception to this was Animal 10, which was lowest performing animal for Ethograms Two and Three, and the third lowest performing animal in Ethogram One (accuracy 69.39%). As previously mentioned, ear tag accelerometers experience a higher degree of movement compared to other attachment methods (Barwick et al., 2018b). This may result in changing orientation of a single device, leading to systematic inaccuracies of an individual dataset. Other causes of inaccuracies may be due to changes in the physical movement of individuals. An extreme example of this would be animals experiencing lameness (Barwick et al., 2018a), and although this was not the case for animals in this study, even subtle variations in gait may have influenced the results. Finally, differences in individual animals may reflect just that, differences in individuals and the idiosyncrasies that may develop over time. Regardless of the cause, given that individuality of results is present in the current study, this represents an important factor impacting generic commercial application, and should be considered in future work.

5. Conclusion

Accelerometers allow for fine-scale monitoring of animal movement and behaviour, and are becoming increasingly used in animal behaviour research (Fogarty et al., 2018). Despite the technology's growing popularity, there is still no consistent protocol for data analysis, particularly for sheep behaviour classification using ear-borne accelerometers. The current study found that ear-borne accelerometers are able to distinguish between four main behaviours, two activity states and two postures in pasture-based ewes. Accuracy varied depending on the method of behaviour classification, with the highest performing ML for each ethogram having over 75% accuracy (Ethogram One) and 90% accuracy (Ethogram Two and Three). Overall, epochs of 10 s and 30 s appear the most appropriate across a range of contexts.

Future research should consider the use of dynamic epochs and features for best-practice behaviour detection; for example, a 30 s epoch for detection of activity and 10 s epoch for detection of mutually-exclusive behavioural states or 30 s epoch of MV and 5 s epoch of SD_X. Application of these findings should then be used to identify changes in overall behaviour patterns, particularly at times where these patterns would be expected to change e.g. during parturition or stress-inducing husbandry procedures.

CRediT authorship contribution statement

Eloise S. Fogarty: Conceptualization, Methodology, Investigation, Data curation, Writing - original draft, Writing - review & editing. **David L. Swain:** Supervision. **Greg M. Cronin:** Supervision. **Luis E. Moraes:** Validation. **Mark Trotter:** Conceptualization, Methodology, Supervision, Writing - review & editing.

Declaration of Competing Interest

The authors declare no conflicts of interest.

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Appendix A. Supplementary material

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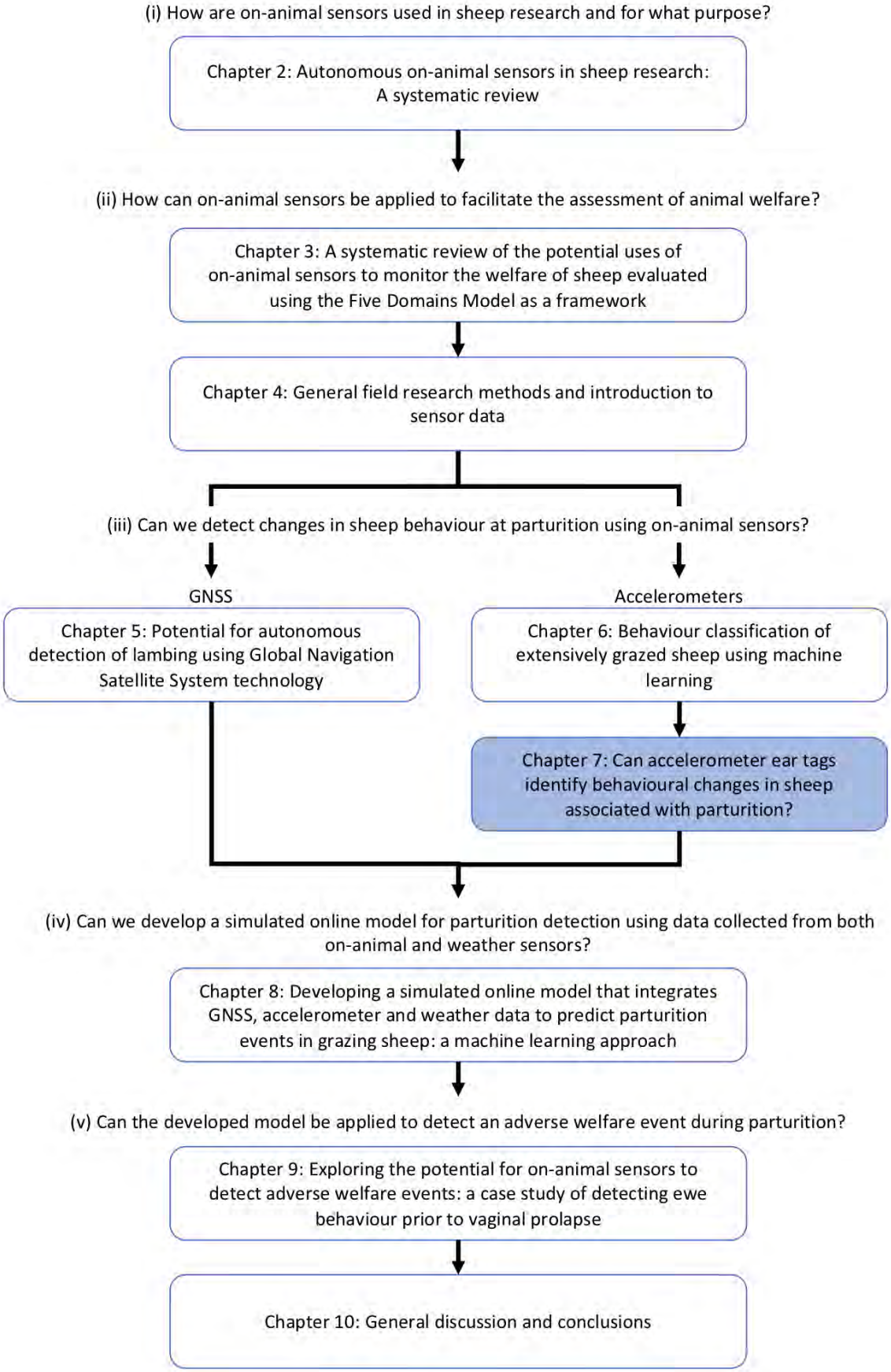
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Chapter 7. Can accelerometer ear tags identify behavioural changes in sheep associated with parturition?

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Overview

This chapter builds on Chapter 6, applying the highest performing ML algorithms to monitor changes in behaviour at lambing as measured by accelerometer-based behaviour classification. Methods applied in this chapter are similar to Chapter 5, with a focus on detecting daily and hourly changes in behaviour. These findings are intended to facilitate the development of a parturition detection model using machine learning.

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Can accelerometer ear tags identify behavioural changes in sheep associated with parturition?

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ABSTRACT

On-animal sensor systems provide an opportunity to monitor ewes during parturition, potentially reducing ewe and lamb mortality risk. This study investigated the capacity of machine learning (ML) behaviour classification to monitor changes in sheep behaviour around the time of lambing using ear-borne accelerometers. Accelerometers were attached to 27 ewes grazing a 4.4 ha paddock. Data were then classified based on three different ethograms: (i) detection of grazing, lying, standing, walking; (ii) detection of active behaviour; and (iii) detection of body posture. Proportion of time devoted to performing each behaviour and activity was then calculated at a daily and hourly scale. Frequency of posture change was also calculated on an hourly scale. Assessment of each metric using a linear mixed-effects model was conducted for the 7 days (day scale) or 12 h (hour scale) before and after lambing. For all physical movements, regardless of the ethogram, there was a change in the days surrounding lambing. This involved either a decrease (grazing, lying, active behaviour) or peak (standing, walking) on the day of parturition, with most values returning to either pre-partum or near-pre-partum levels (all $P < 0.001$). Hourly changes also occurred for all behaviours (all $P < 0.001$), the most marked being increased walking behaviour and frequency of posture change. These findings indicate ewes were more restless around the time of parturition. Further application of this research should focus on development of algorithms that can be used to identify onset of lambing and/or time of parturition in pasture-based ewes.

1. Introduction

Extensive sheep production refers to animals raised on large pasture or rangeland conditions and typically requires small amounts of producer input (Petherick, 2006). Traditionally, concern for animal welfare in extensive systems has been largely overlooked, due to the perception of it being more 'natural' than intensive systems (Goddard et al., 2006). Although extensively-raised animals have considerably more behavioural freedom than their intensively-raised counterparts (Dwyer, 2009), managing animals in these conditions can result in welfare challenges (Bailey, 2016). For example, extensively-raised sheep are maintained outside year-around, often in rugged environments (Munoz et al., 2018). Consequently, sheep are subject to variable climatic conditions, inconsistent food and water availability (Goddard et al., 2006) and increased risk of predation (Manning et al., 2014). Furthermore, animals are often

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managed in large groups at a low stocking density, often with considerable dispersal over the landscape (Petherick and Edge, 2010). This can make close inspection of animals difficult, restricting the stockperson's capacity to identify and manage adverse welfare events (Munoz et al., 2018). Topography and natural landforms (e.g. rivers) may also limit the close inspection of animals (Petherick and Edge, 2010), meaning that animals that become ill or injured may not be identified and treated as quickly as those in intensive systems (Bailey et al., 2018). Remote on-animal sensing technologies could benefit extensive sheep production, improving the frequency with which the animals are effectively observed. This increased surveillance will enable earlier detection of issues than is currently possible, improving decision-making capabilities and potentially allowing timely intervention to improve animal welfare and farm profitability (Trotter, 2010, 2013; Neethirajan, 2017; Bailey et al., 2018; Vázquez-Diosdado et al., 2019).

One of the key periods of time in which this increased surveillance would be of benefit is during lambing (parturition). Parturition is a critical period for the ewe and lamb, and mortality at this time affects productivity and welfare (Alexander, 1980, 1988; Hinch and Brien, 2014). Previous applications of sensor technology to detect parturition-related behaviours in sheep has mostly been conducted using Global Navigation Satellite System (GNSS). While these techniques can be used for identification of lambing-related behaviour on a day scale, GNSS has not yet been found to have the capacity for detecting hourly changes in behaviour (Dobos et al., 2014; Fogarty et al., 2020a). Alternative sensor technologies such as accelerometers have been proposed to address this limitation (Dobos et al., 2014), due to the capacity of this instrumentation to monitor behaviour on a finer scale. Accelerometers have previously been used for parturition detection in cows (Huzzey et al., 2005; Jensen, 2012; Krieger et al., 2017, 2018) and sows (Cornou and Lundbye-Christensen, 2012; Pastell et al., 2016; Thompson et al., 2016). The application of these technologies for lambing detection, particularly in pasture-based sheep, however, has not yet been fully explored. A single study has been published in which there was examination of parturition duration using accelerometer technology (Schmoelzl et al., 2016). Ewes, however, were only assessed for a 24 h period, and thus a comprehensive analysis of temporal changes in behaviour was not possible. Furthermore, these animals were monitored using leg-attached accelerometers, which have arguably limited commercial application because these devices are more difficult to attach and maintain (McLennan et al., 2015). As commercially affordable sensor-based systems become more widely available for sheep production, evaluation of the use of sensors in normal grazing conditions is essential (Fogarty et al., 2020a).

In this study we have applied behaviour classification machine learning (ML) algorithms to accelerometer data to monitor changes in sheep behaviour around the time of lambing. It is hypothesised that accelerometer data will have the capacity for identification of changes in daily and hourly patterns of behaviour associated with lambing. This knowledge is intended to faciliate the future development of algorithms based on ear tag accelerometer data for the detection of behavioural changes around the time of lambing in real-time or near-real-time.

2. Materials and methods

2.1. Location and animals

All procedures were approved by the Massey University Animal Ethics Committee (MUAEC 18–67). The study was conducted at a commercial mixed enterprise on the South Island of New Zealand (43.0 °S and 173.2 °E) from 8 September to 23 September 2018. Mixed-age ewes (n = 39: Merino or Merino cross) were selected from the main commercial flock and fitted with accelerometer ear tags (Axivity AX3, Axivity Ltd, Newcastle, UK). Selection was based on ewes having an expected lambing date during the experimental period and being single-bearing (confirmed through ultrasonic assessments as per normal farm practice). Of the 39 ewes selected, 12 ewes were used for observation (via *ad libitum* video recordings acquired between 0730 h – 1230 h and 1330 h–1730 h (± 30 min.) of each day of the study) and subsequent development of ML behaviour algorithms (Fogarty et al., 2020a). The current study extends this research, and reports on the application of the algorithms on the remaining animals (n = 27). The experimental paddock was 4.4 ha and animals were provided *ad libitum* access to forage and water.

2.2. Accelerometers

Accelerometers were configured at 12.5 Hz, attached to ear tags and fixed to the ewe's ear by an experienced operator. The total tag weight was 18.5 g and battery life is 30 days as per manufacturer's guidelines (Axivity AX3, Axivity Ltd, Newcastle, UK). Tags were fixed with orientation of the X, Y and Z axis along the dorso-ventral (up-down), lateral (side-to-side) and anterior-posterior (forward-backward) axes, respectively. The accelerometers were attached on the morning of 8 September 2018, with animals observed for at least 30 min to monitor for signs of distress. Animals were then returned to the paddock, with data collection commencing at midnight on 9 September 2018 (Study Day 1). On the morning of Study Day 1, it was noted that in the experimental paddock there was not allowance for adequate observation of the animals. Thus, the flock were moved to an adjoining paddock at 1100 h on Study Day 1, where the flock remained for the rest of the study. These early data were not removed as it was thought to reflect commercial conditions where movement of animals prior to parturition may be necessary. Data collection ceased at 2359 h on 23 September (Study Day 15) and tags were removed by 1300 h on 24 September 2018 (Study Day 16). Accelerometer data were then downloaded using the proprietary software (OMGUI, Axivity Ltd, Newcastle, UK) and analysed using R-Studio (R Core Team, 2018).

2.3. Observations

Throughout the experiment, ewe behaviour was observed *ad libitum* (Martin and Bateson, 2007) for the purpose of recording the

Table 1
Summary of the ML algorithms developed for each ethogram as per Fogarty et al. (2020a).

Ethogram	ML algorithm	Epoch length	Possible classification	Accuracy (Fogarty et al., 2020a)
One	Linear kernel Support Vector Machine (SVM)	10 s	Grazing Lying Standing Walking	76.9 %
Two	Classification tree (CART)	30 s	Active Inactive	98.1 %
Three	Linear discriminant analysis (LDA)	30 s	Upright Prostrate	90.6 %

time of birth. Observations were conducted from 0730 h – 1230 h and 1330 h–1730 h (± 30 min.) on each day of the study. A single observer (the first author) remained at the paddock during these times and recorded the time of lambing when observed. To facilitate visual observations, ewes were fitted with unique identification 'bibs' that could be easily distinguished through binoculars or by visual observation alone.

Where possible, the exact time of lambing (to the nearest minute) was recorded. If this was not achievable, lambing time was estimated to the nearest hour. For ewes that lambed overnight or during periods where the observer was not present, only the day of lambing was recorded. In this situation, day of lambing was noted as the day in which the newborn was first identified.

2.4. Machine learning algorithm development

The development of ML algorithms applied in this study has been previously published (Fogarty et al., 2020a). Three different ethograms were examined, including: (i) detection of four mutually-exclusive behaviours (grazing, lying, standing, walking); (ii) detection of active (or inactive) behaviour; and (iii) detection of body posture (upright or prostrate). A summary of the ethograms and most effectively performing ML algorithms as reported in Fogarty et al. (2020a) are shown in Table 1.

2.5. Behaviour classification

Using the algorithms developed and reported in Fogarty et al. (2020a) (Table 1), behaviour classification was conducted on the complete accelerometer dataset for the entire experimental period. Classification was based on a calculated epoch of 10 s (Ethogram One) or 30 s (Ethograms Two and Three). Epochs were determined based on actual time of day using consecutive 10 s (Ethogram One) or 30 s (Ethograms Two and Three) time periods. This resulted in a behaviour classification for each ewe and calculated epoch for the entire 15-day period.

2.6. Change in sheep behaviour at parturition

After the ML classification for each 10 s or 30 s epoch was determined for all three ethograms, the proportion of time devoted to performing each behaviour was calculated on a daily and hourly basis. Daily metrics were centred around the day of lambing (Day 0) and calculated for the 7 days before and 7 days after parturition (Day ± 7; 15 days in total). Individual ewe datasets were still included in the analysis even if there were missing days [e.g., parturition occurred on Study Day 4 would have an individual dataset of Day -3 through to Day +7 (11 days in total)].

Hourly metrics were centred around the hour of lambing (Hour 0) and calculated for the 12 h before and 12 h after parturition (Hour ± 12; 25 h in total). Hourly metrics were only calculated for those ewes where the hour of birth was known ($n = 11$). Hour of birth was classified by hour of the day, regardless of when the birth occurred within that hour (i.e., a birth at 1201 h and 1259 h would both have an hour of birth (i.e., Hour 0) of 1200 h). The number of posture changes was also calculated on an hourly basis. A posture change was defined as the change in classification from upright to prostrate or vice versa for consecutive epochs. For example, if the data were classified as prostrate for 5 min, then upright for the next 30 s epoch, then prostrate again, this would be noted as two posture changes (prostrate to upright and upright to prostrate).

2.7. Statistical analysis

All statistical analyses were conducted using R-Studio (R Core Team, 2018). Linear mixed-effects models were developed using the 'nlme' package (Pinheiro et al., 2018). Significance was $P \leq 0.05$. Separate analysis was conducted for day and hour data and for each method of behaviour classification. Day or hour around birth was treated as a fixed effect. Individual animals were treated as random effects and the subject of the repeated measures analysis. As this experiment involved repeated measures, either a first-order autoregressive AR(1) structure or first-order heterogenous autoregressive ARH(1) structure was specified. Selection of the structure was based on the lowest Akaike Information Criteria (AIC) score. These structures were selected considering the mathematical properties that assume an exponential decay of the correlation on the errors of observation on the same animal over time. That is,

errors on pairs of observations closer in time are more correlated than errors on pairs of observation more distant in time. The selection between AR(1) and ARH(1) allowed for examination of potential model improvement when there was allowance for the error variances to be different at the different time points. Day scale metrics did not require transformation. All hour scale metrics were square root transformed to ensure normality of errors. The exception to this was hourly posture change (± 12 h) which did not require transformation. Least-square means and upper and lower 95 % confidence intervals were generated using the 'lsmeans' package (Lenth, 2016). Pairwise comparisons with Tukey adjustment were also computed using this package.

Additional analyses were conducted to compare differences in behaviour for the three possible behaviour states (pre-partum (Days -7 to -1; Hours -12 to -1); lambing (Day 0; Hour 0) or post-partum (Days +1 to +7; Hours +1 to +12)). In this case, the behaviour state (a factor with three categorisations) was treated as a fixed effect and individual animals were treated as random effects. Again, all hour scale metrics (except posture change ± 12 h) were square root transformed to ensure normality of errors and autoregressive structure was based on AIC score. Day scale metrics did not require transformation. Least-square means, upper and lower 95 % confidence intervals and pairwise comparisons with Tukey adjustment were also calculated.

3. Results

3.1. Animal data and lambing records

Of the 27 ewes used in this study, 26 lambed during the observation period (Study Day 1 to Study Day 15), with the earliest birth on Study Day 3 and the latest on Study Day 14. The remaining ewe did not give birth before the accelerometers were removed and was excluded from analysis. Of the 26 ewes that lambed, 12 ewes had the time of birth recorded within a 60 min time period. The remaining 14 animals lambed overnight or during periods when observation was not being conducted. In these cases, day of lambing was recorded as the day the lamb was first observed.

With one accelerometer, attached to a ewe with a known hour of birth, there was failure to record throughout the entire experimental duration and data were excluded from the analysis. With another accelerometer, also attached to a ewe with the hour of birth documented, there was failure to record past Study Day 9. The data for this animal were still included in analysis up until Study Day 8 because the ewe lambed early in the experiment (Study Day 3) and thus there was still a relatively large dataset for this ewe to analyse (Day -2 to Day +5; 8 days in total).

To summarise, from the 27 ewes in the study, 25 datasets were available for day scale analysis. The average number of days analysed per animal (from a maximum of 15 days) was 12.5 (range 8–15). Of the 12 animals where hour of birth was recorded, 11 datasets were available for hour scale analysis. All had a complete hourly dataset of 25 h (Hour 0 ± 12).

3.2. Daily changes in behaviour derived from the accelerometers

3.2.1. Grazing, lying, standing and walking behaviour

The proportion of time devoted to grazing, standing, walking and lying varied among the 7 days before and 7 days after parturition (all $P < 0.001$; Fig. 1). Values for time devoted for grazing decreased from Day -2, decreasing to a minimum on lambing day before increasing to pre-lambing values by Day +1 (Fig. 1a). When grouped by behaviour state, the average daily proportion [± 95 % CI] of time devoted to grazing was 25.7 % [23.1; 28.3] and 28.0 % [25.4; 30.6] for pre- and post-partum animals, respectively, compared with 21.5 % [18.3; 24.7] on the day of lambing. For standing and walking behaviour, there was an inverse trend in time values compared to grazing, with both behaviours increasing from Day -2, reaching a peak on lambing day and returning to pre-partum values by Day +1 (Fig. 1b; c). When grouped by behaviour state, the daily proportion of standing behaviour in pre- and post-partum animals was 34.9 % [28.1; 41.7] and 36.6 % [29.7; 43.4], respectively, compared with 40.2 % [33.3, 47.2] on the day of lambing. For walking behaviour, the daily proportions were 10.1 % [7.5; 12.7] pre-partum, 14.4 % [11.4; 17.4] at lambing and 10.2 % [7.5; 12.9] post-partum.

The proportion of time ewes devoted to lying did not follow the trend of the other behaviours (Fig. 1d). Instead, lying behaviour was consistent pre-partum (29.3 % [21.4; 37.2]), before decreasing on the day of parturition (25.4 % [17.2; 33.6]), with a sustained lesser value for lying behaviour during the 7 days post-partum (25.4 % [17.4; 33.4]). Though lying behaviour varied during the entire 15-day period ($P < 0.001$), the values at Day 0 did not differ from those on any other day ($P > 0.05$).

3.2.2. Active and inactive behaviour

The proportion of time devoted to active behaviours varied among the 7 days before and 7 days after parturition ($P = 0.004$; Fig. 2). Note that data for inactive behaviours are not displayed because these values were the inverse to active behaviour data. Similar to grazing (Fig. 1a), ewes had decreased values for active behaviour from 2 days prior to parturition, decreasing to a minimum on the day of lambing. Values for active behaviour then increased rapidly, returning to pre-lambing values by Day +1. When grouped by behaviour state, the average proportion of time devoted to active behaviour prior to and after lambing was 34.2 % [32.2; 36.1] and 34.5 % [32.5; 36.5] ($P = 0.90$), respectively, compared with 30.2 % [27.0; 33.3] on the day of lambing (both pairs $P < 0.01$). A summary of the daily changes in behaviour can be found in Table 2.

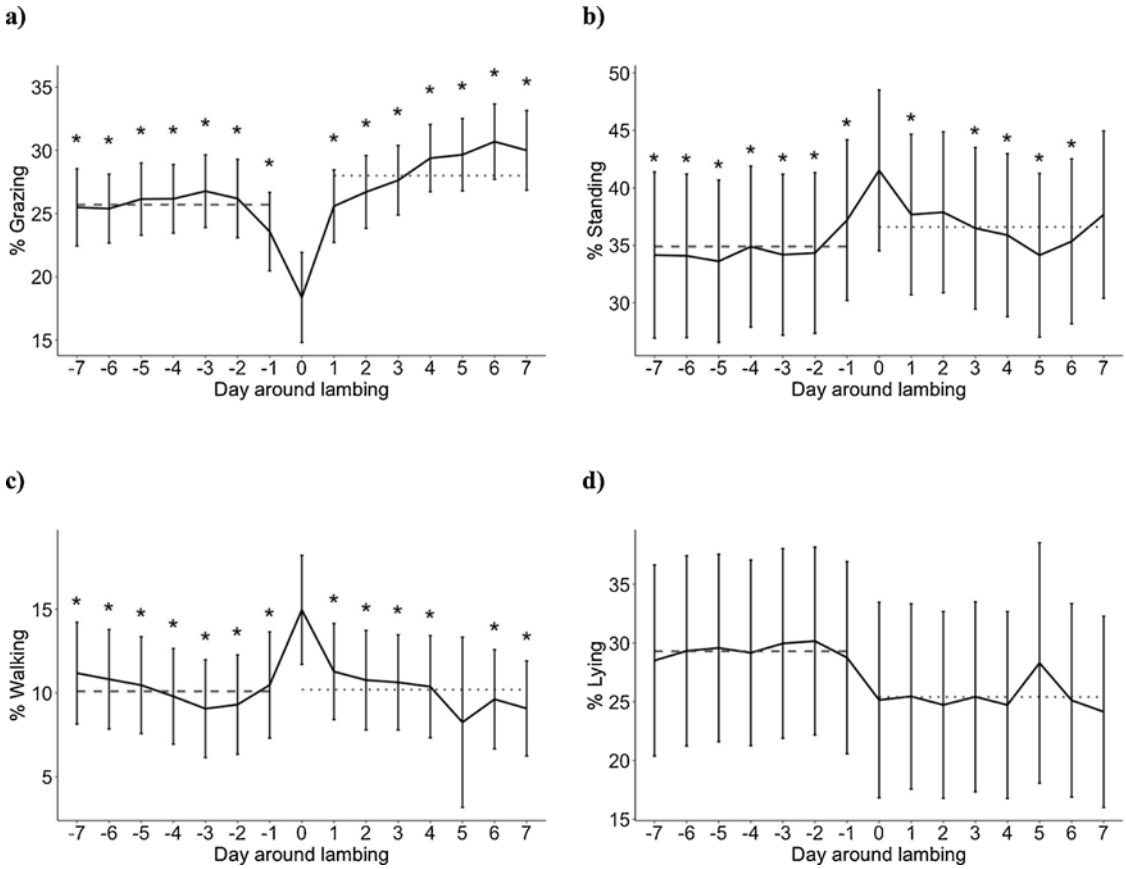

Fig. 1. Proportion of time devoted to performing four mutually-exclusive behaviours from 7 days before to 7 days after lambing (n = 25); Values represent least-square means ± 95 % CI where a) grazing; b) standing; c) walking; d) lying (all P < 0.001); Days marked '*' were different (P ≤ 0.05) to the day of birth (Day 0); Mean pre-partum (dashed line) and post-partum (dotted line) behaviour are also depicted where a) P = 0.004; b) P = 0.13; c) P = 0.97; d) P < 0.001.

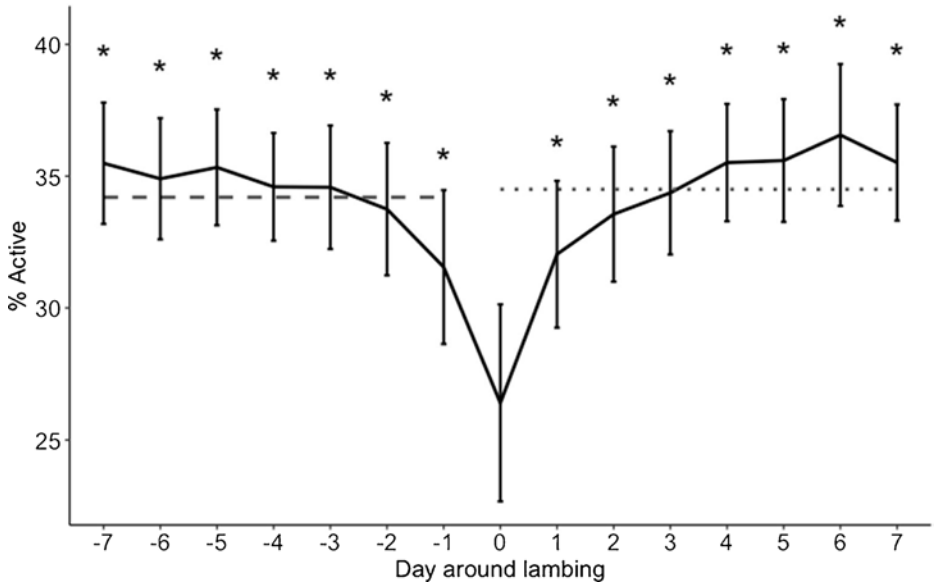

Fig. 2. Proportion of time devoted to active behaviours from 7 days before to 7 days after lambing (P = 0.004; n = 25); Values represent least-square means ± 95 % CI; Days marked '*' were different (P ≤ 0.05) to the day of birth (Day 0); Mean pre-partum (dashed line) and post-partum (dotted line) active behaviour are also depicted (P = 0.90).

Table 2
Difference in daily behaviour for pre-partum (Pr), lambing (L) and post-partum (Po) ewes; NS = Not significant.

Behaviour	Pairs	*P*-value	Description of overall trend	Reference
Grazing	Pr – L	< 0.001	Minimum on day of lambing; Increased overall in post-partum animals compared to pre-partum	Fig. 1a
	L – Po	< 0.001		
	Pr – Po	0.004		
Standing	Pr – L	< 0.001	Peak on day of lambing; Return to pre-partum levels by Day +1	Fig. 1b
	L – Po	< 0.001		
	Pr – Po	NS		
Walking	Pr – L	< 0.001	Peak on day of lambing; Return to pre-partum levels by Day +1	Fig. 1c
	L – Po	< 0.001		
	Pr – Po	NS		
Lying	Pr – L	0.004	Decreased on day of lambing; Remained low post-partum	Fig. 1d
	L – Po	NS		
	Pr – Po	< 0.001		
Active behaviour	Pr – L	0.004	Minimum on day of lambing; Return to pre-partum values by Day +1	Fig. 2
	L – Po	0.002		
	Pr – Po	NS		

3.3. Hourly changes in behaviour

3.3.1. Grazing, lying, standing and walking behaviour

The proportion of time devoted to grazing varied in the 12 h period before and 12 h period after parturition ($P < 0.001$; Fig. 3a). When values collected during the hour of lambing (Hour 0) were compared with values during the hours preceding or hours following parturition, there were no differences ($P > 0.05$). When pre- and post-partum hours were grouped together, ewes had less grazing

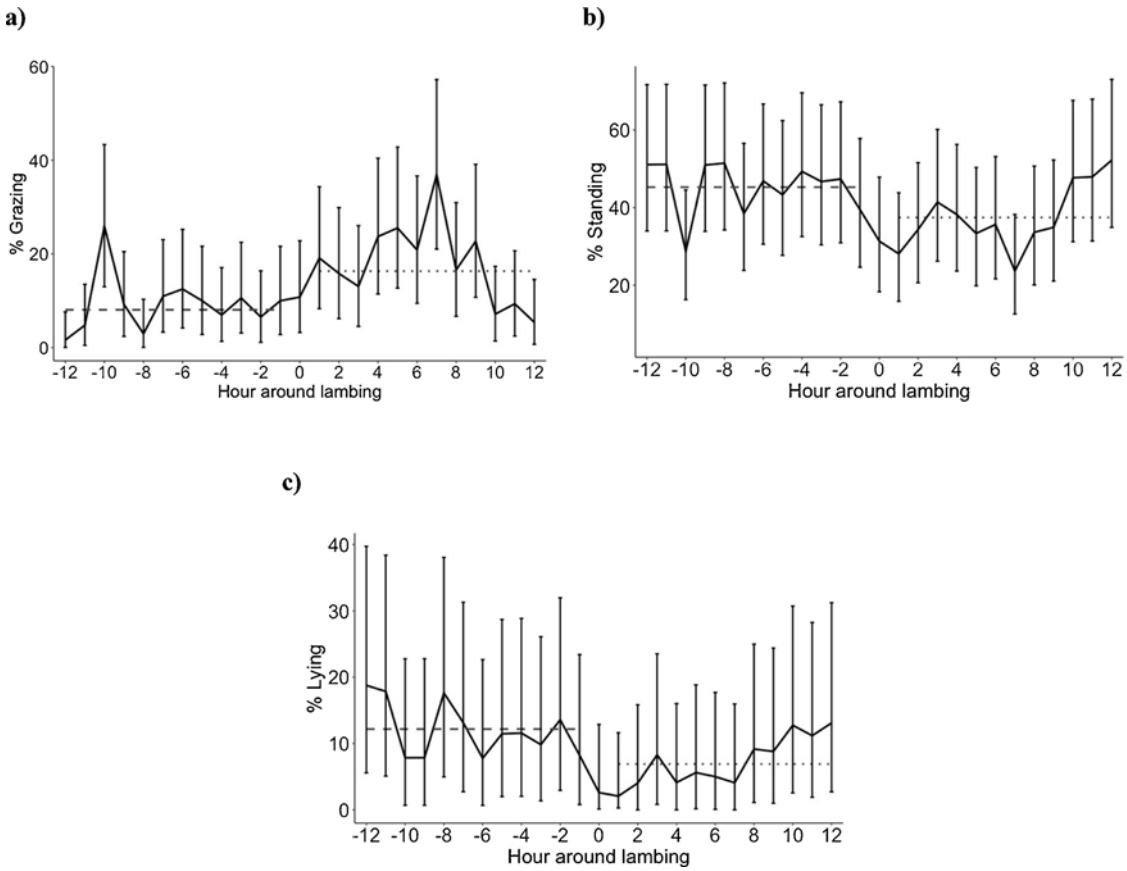

Fig. 3. Hourly proportion of time devoted a) grazing (P < 0.001), b) standing (P < 0.001) and c) lying (P = 0.005) from 12 h before to 12 h after lambing (n = 11); Values represent backtransformed least-square means ± 95 % CI; Hours marked '*' were different (P ≤ 0.05) to the hour of birth (Hour 0); Backtransformed mean pre-partum (dashed line) and post-partum (dotted line) behaviour are also depicted where a) P = 0.007; b) P = 0.04; c) P = 0.02.

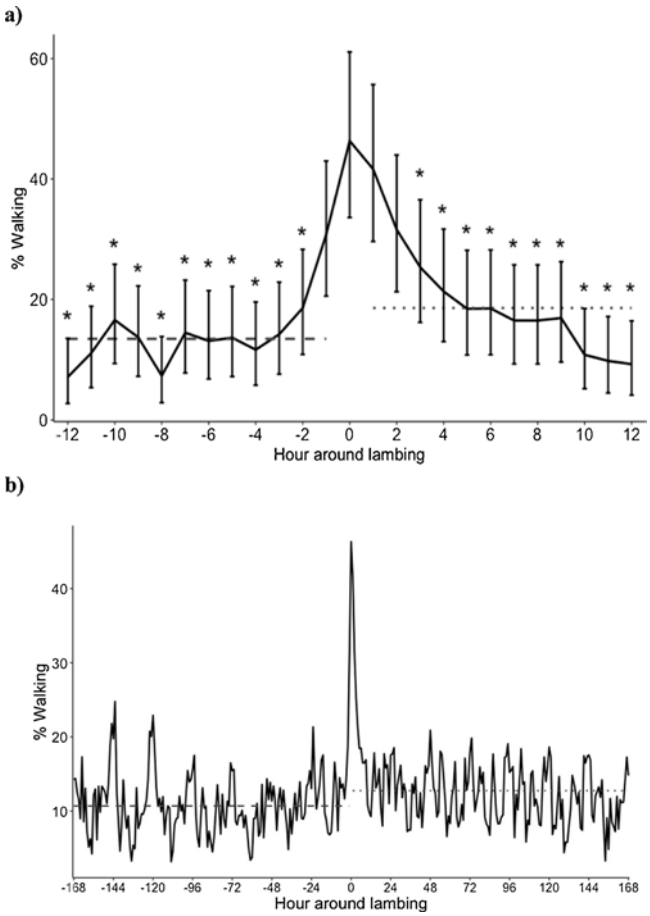

Fig. 4. Proportion of walking behaviour a) 12 h before to 12 h after lambing; b) 168 h (7 days) before to 168 h (7 days) after lambing (both P < 0.001; n = 11); In a) values represent backtransformed least-square means ± 95 % CI; In b) only backtransformed least-squares mean are depicted for ease of visualisation; In a) hours marked '*' were different (P ≤ 0.05) to the hour of birth (Hour 0); Backtransformed mean pre-partum (dashed line) and post-partum (dotted line) walking behaviour are also depicted a) P = 0.05; b) P < 0.001.

activity in the hours preceding the time of lambing (8.1 % [4.8; 12.3]) compared to after lambing (16.3 % [11.4; 22.2]; $P = 0.007$).

The proportion of time devoted to standing ($P < 0.001$; Fig. 3b) and lying ($P = 0.005$; Fig. 3c) also varied in the 12 h before and 12 h after parturition. When compared to the hour of lambing (Hour 0), there were no specific hours either preceding or subsequent to parturition for which the values for time devoted to standing or lying were different ($P > 0.05$ for all pairs). There was a trend for lesser time devoted to standing ($P = 0.04$) and lying behaviour ($P = 0.02$) post-partum compared to pre-partum.

Walking behaviour also varied in the 12 h before and 12 h after parturition ($P < 0.001$). As depicted in Fig. 4a, the proportion of time devoted to walking increased in the hours surrounding parturition, particularly between Hour -1 and Hour +2. This pattern is even more pronounced when the hours surrounding lambing were extended to 7 days (± 168 h; $P < 0.001$; Fig. 4b). As depicted in Fig. 4b, there are also two apparent peaks in walking behaviour around Hour -143 and Hour -120. These are the result of increased pattern of walking of two ewes and corresponds to the time when animals were moved between paddocks on Study Day 1.

3.3.2. Active and inactive behaviours

Values for hourly activity varied among the 12 h before and 12 h after parturition ($P < 0.001$; Fig. 5). The overall pattern for active behaviour was very similar to grazing (Fig. 3a). Although there was a trend for increased active behaviour from Hour -2 to Hour +1, the values for a majority of hours surrounding parturition were not different from Hour 0 ($P > 0.05$).

3.3.3. Posture change

The number of posture changes per hour varied in the 12 h prior to and following parturition ($P < 0.001$). As depicted in Fig. 6a, the number of hourly posture changes increased from Hour -4, reaching a maximum at Hour 0, before returning to values similar to the pre-partum period by Hour +5. When data analyses were conducted on individual hours, the number of posture changes during the hour of lambing (Hour 0) was 32.4 [25.5; 39.2]. Values for pre-partum posture change ranged from 7.8 [1.0; 14.7] (Hour -12) to 28.5 [21.6; 35.3] (Hour -1). Conversely, values for post-partum posture change ranged from 30.9 [24.1; 37.8] (Hour +1) to 7.0 [0.2; 13.8] (Hour +11). When grouped by behaviour state, the average number of posture changes in pre- and post-partum ewes was 14.3

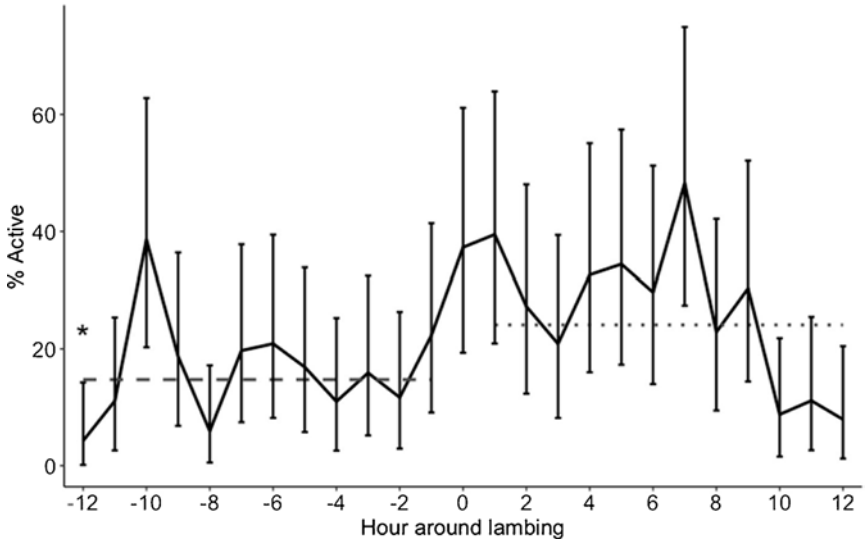

Fig. 5. Proportion of time devoted to active behaviours 12 h before to 12 h after lambing (P < 0.001; n = 11); Values represent backtransformed least-square means ± 95 % CI; Hours marked '*' were different (P ≤ 0.05) to the hour of birth (Hour 0); Backtransformed mean pre-partum (dashed line) and post-partum (dotted line) active behaviour are also depicted (P = 0.05).

[10.2; 18.5] and 17.1 [13.0; 21.2], respectively. Similar to walking behaviour, when the hours surrounding lambing were extended to 7 days (± 168 h), this increase in posture change at lambing becomes even more pronounced ($P < 0.001$; Fig. 6b). A summary of the data for hourly changes in behaviour can be found in Table 3.

4. Discussion

The results from this research support the hypothesis that ML classification of accelerometer data can be used to detect daily and hourly behaviour changes associated with parturition. While there have been similar applications in other livestock species (Huzzey et al., 2005; Cornou and Lundbye-Christensen, 2012; Jensen, 2012; Pastell et al., 2016; Thompson et al., 2016; Krieger et al., 2017, 2018), this is the first known application of ML-derived behaviour classification for monitoring parturition behaviour in pasture-based ewes using an ear tag accelerometer.

4.1. Detectable changes in daily and hourly ewe behaviour at parturition

In the present study, all behaviour metrics, regardless of classification method, were different in the 7 days prior to and 7 days following lambing. For the majority of behaviours, this involved either a decrease (grazing, active behaviour) or peak (standing, walking) on Day 0, before returning to either pre-partum or near-pre-partum values. The exception was lying, for which there was not a return to pre-partum values after lambing. Previous studies regarding the earliest observable change in ewe maternal behaviour are inconsistent. In a study by Holmes (1976), hind-leg stamping was recorded from as early as 15 days prior, though the majority of behaviours were only evident from 4 h pre-partum. In contrast, Alexander (1960) reported that the majority of ewes did not have any behavioural changes until labour was imminent. These inconsistencies in findings may reflect differences in breed (Arnold and Morgan, 1975; Holmes, 1976), litter size (Owens et al., 1985), ewe age (Alexander, 1960; Arnold and Morgan, 1975) and previous experience (Bickell et al., 2010), or simply differences among individuals (Safar and Kor, 2014). There, however, is an overall consensus that overt behavioural change manifests on the actual day of lambing (Wallace, 1949; Owens et al., 1985; Echeverri et al., 1992; Schmoelzl et al., 2016). This pattern of behavioural change also occurs in cattle, with the greatest changes in calving behaviour in the 24 h before and after parturition (Rice et al., 2017).

Of the maternal behaviours associated with lambing, increased ewe restlessness is widely reported to occur (Wallace, 1949; Arnold and Morgan, 1975; Owens et al., 1985; Echeverri et al., 1992; Ceyhan et al., 2012). In the present study, restlessness peaked on the day of parturition (Fig. 1c) and between Hour -1 to Hour +2 (Fig. 4a), as evidenced by an increased walking behaviour. Increased walking and walking in a circling pattern have previously been reported to occur on the day of lambing, potentially reflecting discomfort or nesting behaviour (Arnold and Morgan, 1975; Echeverri et al., 1992). As depicted in Fig. 1c, the proportion of walking behaviour per day increased from approximately 10 % in pre-partum animals to 15 % on the day of parturition. At an hourly scale, walking increased from 19 % at Hour -2 to 46 % by Hour 0 (Fig. 4a). This pattern is even more evident when values for this variable were compared to values at hours more temporally distant (Fig. 4b), with no other hour during the 7 days before or 7 days after parturition (± 168 h) having values greater than those at Hour 0. The values at the only other hours where there was an increase in walking behaviour were those at Hours -143 and -120, which were the result of increased pattern of walking of two particular ewes and corresponded to the transfer of animals between experimental paddocks on Study Day 1. Considering that the

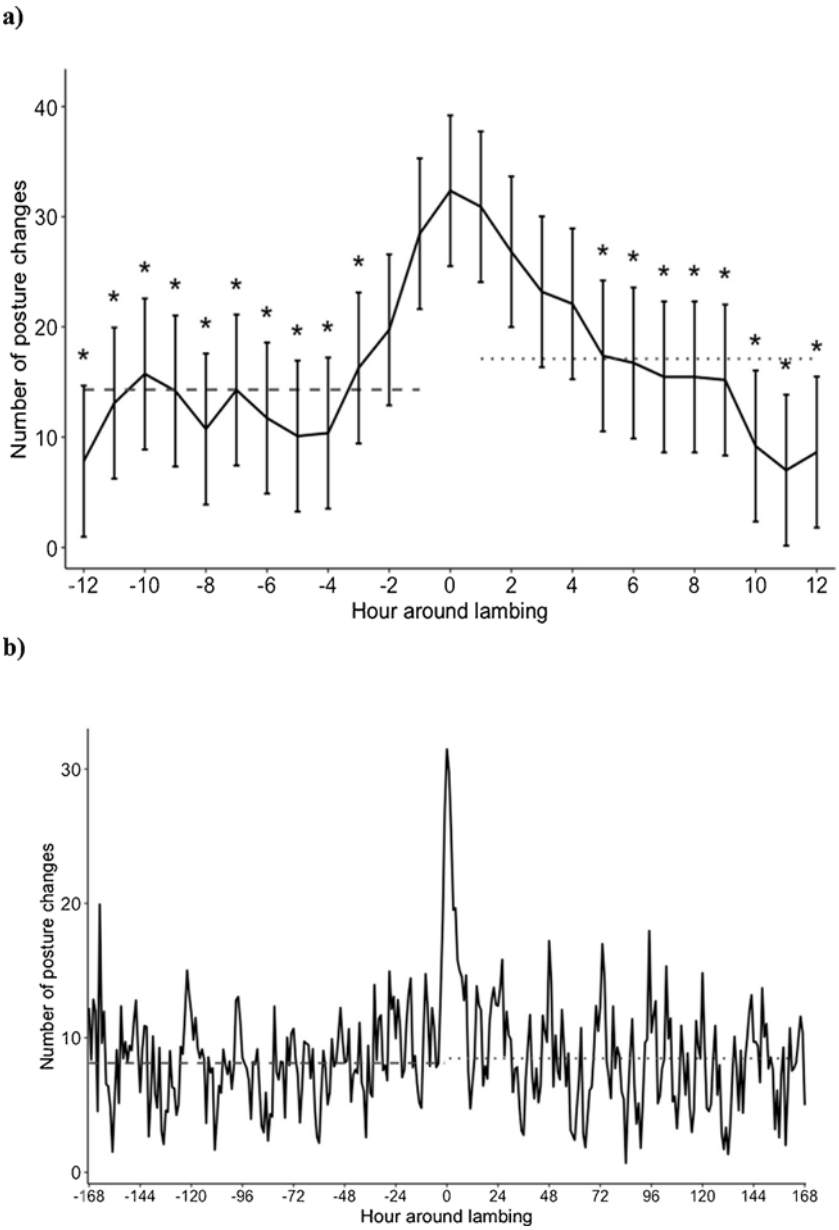

Fig. 6. Number of posture changes per hour a) 12 h before to 12 h after lambing; b) 168 h (7 days) before to 168 h (7 days) after lambing (both $P < 0.001$; $n = 11$); In a) values represent least-square means ± 95 % CI; In b) values represent least-square means only for ease of visualisation; In a) hours marked '*' were different ($P \leq 0.05$) to the hour of birth (Hour 0); Mean posture changes pre-partum (dashed line) and post-partum (dotted line) are also depicted a) $P = 0.40$; b) $P = 0.73$.

change associated with lambing could still be distinguished from all other hours, even those where animals had been considerably disturbed, this behaviour change may represent one of the more reliable metrics for predicting a lambing event using accelerometer sensors.

Ewe restlessness was also evident as a result of the increased frequency of posture change, particularly from Hour -2 to Hour +4 (Fig. 6a). This pattern was similar to that reported by Echeverri et al. (1992), where there was an increased frequency of posture change starting 4 h prior to birth. In the present study, the average number of posture changes more than doubled during the lambing period, increasing from approximately 14 changes per hour in pre-partum animals to 32 changes in Hour 0. In contrast, Echeverri et al. (1992) noted a considerably lesser number of posture changes, ranging from only 3.2–10.7 per 2 h period. This may reflect differences in animal management (pasture-based in the present study compared to pen-based in the Echeverri et al. (1992) study). More likely, however, are differences associated with the data collection method (ML algorithm in the present study compared to video observation in the Echeverri et al. (1992) study). In the present study, the epoch used for posture determination was 30 s,

Table 3
Difference in hourly behaviour for pre-partum (Pr), lambing (L) and post-partum (Po) ewes; NS = Not significant.

Behaviour	Pairs			*P*-value	Description of overall trend	Reference
Grazing	Pr	–	L	NS	Increased overall in post-partum animals compared to pre-partum	Fig. 3a
	L	–	Po	NS		
	Pr	–	Po	0.007		
Standing	Pr	–	L	NS	Decreased overall in post-partum animals compared to pre-partum	Fig. 3b
	L	–	Po	NS		
	Pr	–	Po	0.04		
Lying	Pr	–	L	0.03	Decreased overall in post-partum animals compared to pre-partum	Fig. 3c
	L	–	Po	NS		
	Pr	–	Po	0.02		
Walking	Pr	–	L	< 0.001	Peak at Hour 0; Returned to pre-partum values by Hour +3	Fig. 4a
(± 12 h)	L	–	Po	0.05		
	Pr	–	Po	0.05		
Walking	Pr	–	L	< 0.001	Peak at Hour 0	Fig. 4b
(± 168 h)	L	–	Po	< 0.001		
	Pr	–	Po	< 0.001		
Active behaviour	Pr	–	L	NS	Increased physical activity in post-partum animals compared to pre-partum	Fig. 5
	L	–	Po	NS		
	Pr	–	Po	0.05		
Posture changes (± 12 h)	Pr	–	L	0.04	Increased between Hour -2 to Hour +4; Returned to pre-partum levels by Hour +5	Fig. 6a
	L	–	Po	NS		
	Pr	–	Po	NS		
Posture change (± 168 h)	Pr	–	L	0.002	Peak at Hour 0 before returning to pre-partum values	Fig. 6b
	L	–	Po	0.003		
	Pr	–	Po	NS		

equating to a maximum of 120 possible posture changes per hour (i.e., total number of 30 s epochs in 1 h). At Hour 0, ewes had an average of 32 posture changes, equating to one change every 3.8 epochs, or approximately every 2 min. In a study on castration response, lambs had postural changes 59 times in the first 2 h following the procedure, compared to 21 times in control animals (Jongman and Hemsworth, 2014). Thus, while the frequency of postural changes that occurred in the present study is feasible, it is also possible that the results have been inflated by sensitivity of the ML classification. This was also supported during algorithm development (Fogarty et al., 2020a), where an accuracy of 90.6 % meant that misclassifications of postural positions were still occurring (Table 1). When using this metric for lambing prediction, it may be more appropriate to focus on detection of overall trends and pattern changes, rather than strict thresholds for posture change frequency. Nevertheless, this metric, along with walking behaviour, appear to be particularly reliable for detecting hourly changes in behaviour, and are clear candidates for integration into predictive algorithms.

In contrast to walking and posture change, for daily active behaviour there was a decrease prior to lambing, and a minimum value at parturition (Fig. 2). Considering the large number of studies in which restlessness at lambing has been evaluated (Wallace, 1949; Arnold and Morgan, 1975; Owens et al., 1985; Echeverri et al., 1992), the result from the present study was initially unexpected. Further exploration, however, led to the observation that the majority of previous research concentrated on the time immediately surrounding lambing, usually within the last 12–24 h prior to birth (Wallace, 1949; Arnold and Morgan, 1975; Owens et al., 1985; Echeverri et al., 1992). In contrast, in studies by Dobos et al. (2014) and Dobos et al. (2015), the use of behaviour tracking technologies utilising GNSS indicated there was a decreased speed of movement and distance travelled on the day of parturition, compared to the occurrences 7 days before or after parturition. Thus, while restlessness may increase on the day of lambing, the relative value for this activity still appears to be less when compared to the values on the days before or after parturition. This highlights the importance of considering multiple time scales for parturition detection, with there being different patterns of behavioural change ascertained depending on the scale of the assessment.

Differences in daily and hourly patterns of behaviour also occurred for the time devoted for grazing. On a day scale, values for grazing behaviour decreased from Day -2 to Day 0, with values returning to those pre-partum after parturition (Fig. 1a). On an hourly scale this pattern was reversed, with values increasing from approximately 8% prior to lambing to 16 % post-partum (Fig. 3a). Though previous descriptions of pre-parturition feeding in sheep are limited, decreased feeding behaviour in the 24 h period before and after parturition has been reported in cows (Miedema et al., 2011; Jensen, 2012; Schirmann et al., 2013). This substantiates the daily patterns that were detected to occur in the present study, however the increased grazing in the hours after parturition is inconsistent with what occurred with cattle. In the present study, behaviour classification was limited to only four possible behaviours: grazing, lying, standing and walking. Considering that for ewes and lambs there is a 'bonding' period after birth (Dwyer and Lawrence, 2000), after which returning to grazing is usually gradual (Alexander et al., 1983; Bickell et al., 2010), it is possible that this behaviour increase actually reflects maternal grooming (Alexander, 1988). This is further reinforced when there is consideration that the lowered head position and movements of grazing animals would likely be analogous to those performed when a ewe is licking her lamb. Maternal grooming is an intensive bonding behaviour that helps to clean away placenta and improve thermal insulation of the newborn offspring (Alexander, 1988). As the mother-offspring bond has such a large effect on lamb survival, further research should be conducted to confirm if this movement pattern would allow for identification of post-parturition grooming, after

which a potential measure of lamb survivability and/or welfare status may be possible.

4.2. Implications for future algorithm development

The research conducted in the present study has allowed for identification of changes in ewe behaviour that can be quantified using an accelerometer fitted to the ear. These findings could be applied in future research to develop an algorithm that can be used for identification of parturition in pasture-based sheep based on the expected behaviour changes identified in the current study. For simplicity, development of a univariate model may be tempting, particularly for behaviours for which there are marked changes at parturition (e.g., hourly walking behaviour and number of posture changes). As, however, behaviour is known to be influenced by a number of factors other than parturition [e.g., husbandry practices (Jongman and Hemsworth, 2014), parasite burden (Falzon et al., 2013), climate (Thomas et al., 2008; Taylor et al., 2011)], reliance on a single feature for algorithm development is discouraged. For example, as depicted in Fig. 4b, in addition to the change at parturition, increased walking behaviour due to management activity (i.e., stock movement between paddocks) was also identified as a deviation from "normal". If a predictive model was developed to simply detect an increase in walking behaviour, it is likely that this would be falsely identified as a behaviour associated with parturition. In contrast, if a model was developed with the requirement that both an increase in walking behaviour and increased number of posture changes occur, this would likely reduce the number of false-positives in detecting the time of ewe parturition.

In addition to a multivariate approach, assessment of changes at both an individual and flock level may be appropriate. Using the previous example, if an increase in walking behaviour was identified for the majority of the flock at the same time, it is likely that this would reflect disruption to the entire flock (e.g., stock movement). In contrast, if the majority of the flock was relatively inactive, and the walking behaviour of a single ewe rapidly increased, this would indicate an individual change, and would be more likely reflective of parturition behaviour.

Parturition is reported as occurring at different times throughout the day (Alexander, 1988). Thus, a similar consideration for diurnal pattern should also be incorporated into algorithm development. In previous studies by Fogarty et al. (2020a) and Dobos et al. (2014), hourly changes in GNSS tracking data could not be effectively used to identify time of parturition, with the conclusion being that this was due to confounding effects of diurnal patterns. In the current study, though with the use of accelerometer data there were differences in hourly behavioural patterns, variability within the hours was still evident. This may reflect an underlying effect of a diurnal pattern and should still be considered in future studies. Though the capacity to detect the day of lambing after it has occurred is arguably less valuable for producers because it provides no benefit of forewarning and potential intervention, detection at a day scale removes the confounding effect of diurnal patterns and should not be immediately dismissed as a possible approach.

One limitation of the current study is that the behaviours classified through the ML approach were restricted to only four possible outcomes: grazing, lying, standing and walking. While this may encompass a large proportion of common sheep behaviours, it does not allow for classification of all possible behaviours from an animal's entire behavioural repertoire. For example, there are behaviours that are less commonly expressed (e.g., ground pawing) or expressed at a finer scale (e.g., ruminating) that warrant further investigation and input into a parturition detection model (Owens et al., 1985; Echeverri et al., 1992; Saint-Dizier and Chastant-Maillard, 2015). This may be more simple for more common behaviours or those easier to observe (e.g., ruminating), compared to those which are less frequently expressed or more difficult to observe (e.g., ground pawing or maternal grooming). For these behaviours, it may be necessary to manage the animals to facilitate observation, or even generate contrived situations where observations are more easily collected. In the context of developing an online model for parturition detection, there is also a case to be made for direct sensor data [e.g., movement variation, energy, signal magnitude area (Fogarty et al., 2020b)] to be used in the place of ML-classified behaviours. This would obviously reduce the computational power required, however, it also reduces interpretability and the capacity to compare model outputs against known behaviour patterns. This area of data handling and management needs to be investigated further, with consideration to the likely processing power and data transfer limitations emerging in the industry.

5. Conclusion

The results of the present study support the use of ML classification of accelerometer data as a method of monitoring of sheep behaviour associated with parturition. In particular, the results from the present study indicate that with the use of ear tag accelerometers there is the capacity to detect daily and hourly changes in sheep behaviour at parturition. Application of this knowledge in development of an online model for detection of parturition is a logical next objective for researchers, with the challenge being to detect changes in behaviour in real-time or near-real-time. Once developed, the models could be integrated with commercial-grade sensors, improving the capacity to make timely operational decisions. This would have particular application in the sheep industry, where lamb mortality is not only a significant welfare issue, but a substantial contributor to reproductive inefficiency (Hinch and Brien, 2014).

CRediT authorship contribution statement

E.S. Fogarty: Conceptualization, Methodology, Investigation, Data curation, Writing - original draft. **D.L. Swain:** Supervision. **G.M. Cronin:** Supervision. **L.E. Moraes:** Validation. **M. Trotter:** Conceptualization, Methodology, Supervision, Writing - review & editing.

Declaration of Competing Interest

The authors declare no competing interest.

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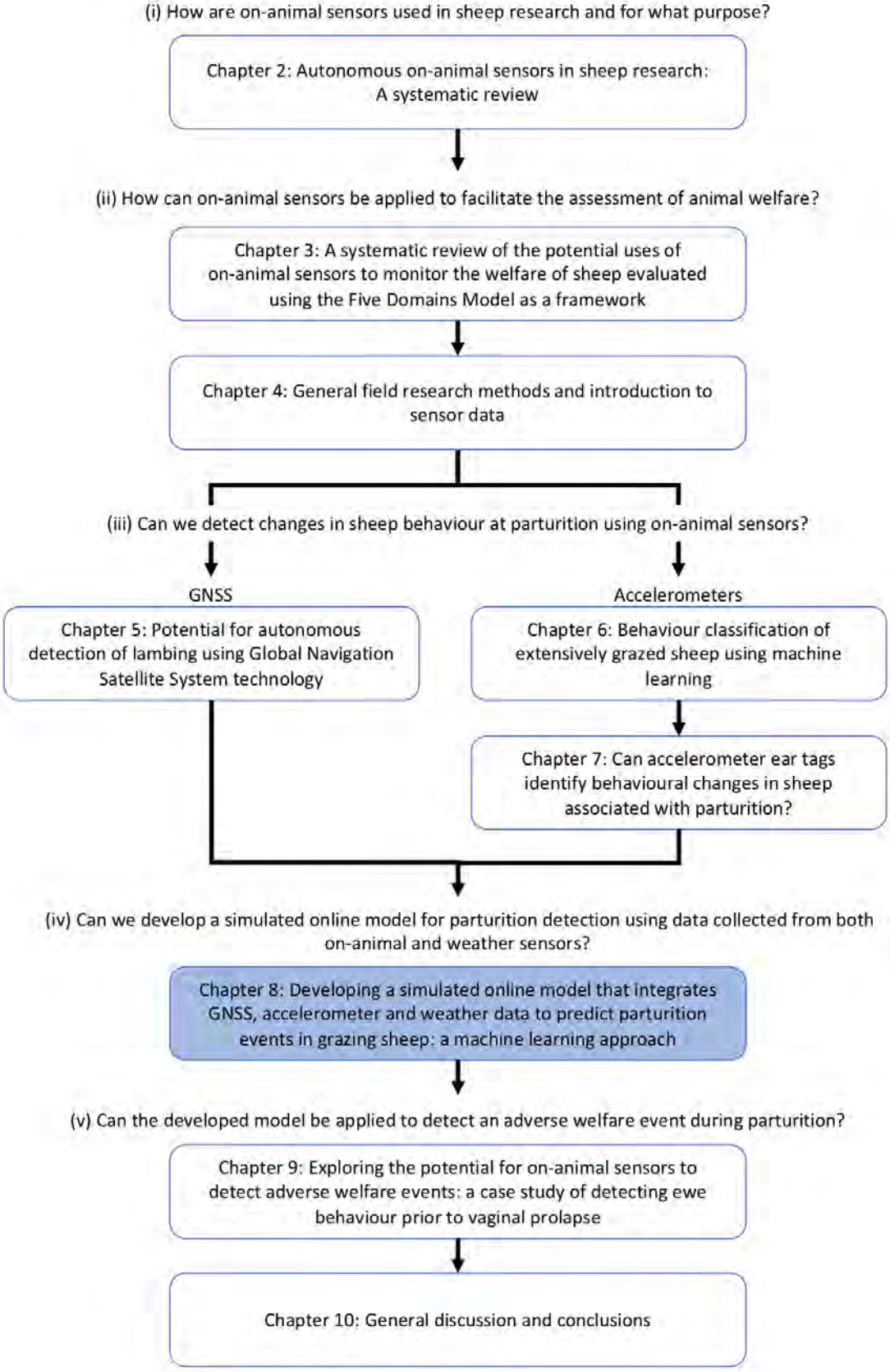
(i) How are on-animal sensors used in sheep research and for what purpose?
Chapter 2: Autonomous on-animal sensors in sheep research: A systematic review
(ii) How can on-animal sensors be applied to facilitate the assessment of animal welfare?
Chapter 3: A systematic review of the potential uses of on-animal sensors to monitor the welfare of sheep evaluated using the Five Domains Model as a framework
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GNSS
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Chapter 5: Potential for autonomous detection of lambing using Global Navigation Satellite System technology
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Chapter 8. Developing a simulated online model that integrates GNSS, accelerometer and weather data to detect parturition events in grazing sheep: a machine learning approach

Fogarty E.S., Swain D.L., Cronin G.M., Moraes L.E., Bailey D.W., Trotter M. Developing a simulated online model that integrates GNSS, accelerometer and weather data to detect parturition events in grazing sheep: a machine learning approach.

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Overview

The research presented in Chapters 5-7 has been analysed post-hoc. That is, the data was downloaded and subsequently processed well after the parturition events occurred, and in some cases, the analysis also explored the behaviour changes that occur in the days following lambing. However, if we want to explore the potential for sensors to monitor parturition in a commercial context, the way in which data arrives for processing is very different. For a sensor system's practical application, an analytical framework must be developed so that it can process data as it becomes available (so that only current and historical data is known). This is known as 'online' processing. In addition, the detection algorithm needs to alert to an event within a reasonable time frame (known as 'real-time' or 'near-real-time').

This chapter takes the learnings from previous chapters and explores the potential for near-real-time lambing detection using a simulated online ML approach. To consider a commercially applicable case, the algorithm was developed for near-real-time parturition detection using the previous hour of data. Sensor integration is also explored, utilising GNSS, accelerometer and weather data.

This manuscript has been prepared for submission to Computers and Electronics in Agriculture. It appears in this thesis in the format required by the journal. Data presented in this chapter is as follows: animals from the 2017 field trial were used to train and subsequently test the ML algorithm. Once a final model was developed, animals from the 2018 field trial were used as an independent validation dataset. Only animals where the hour

of birth was recorded were used in this chapter. Furthermore, only complete datasets were utilised (i.e. no sensor failure for the entire duration of the trials).

Developing a simulated online model that integrates GNSS, accelerometer and weather data to detect parturition events in grazing sheep: a machine learning approach

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Abstract

Near-real-time monitoring of livestock has the potential to improve animal welfare and productivity through increased surveillance and improved decision-making capabilities. This could be achieved through integrated application of on-animal sensor technologies with other external data sources, e.g. local weather stations. One potentially valuable application of these integrated systems is for monitoring of parturition events in sheep. In the current study, a simulated online parturition detection model is developed and reported. Using a machine learning (ML)-based approach, the model incorporates data from Global Navigation Satellite System (GNSS) tracking collars, accelerometer ear tags and local weather data, with the aim of detecting parturition events in pasture-based sheep. The specific objectives were two-fold: (i) determine which sensor systems and features provide the most useful information for lambing detection; and (ii) evaluate how these data might be integrated using ML classification to alert to a parturition event as it occurs. Two independent field trials were conducted during the 2017 and 2018 lambing seasons in New Zealand, with the data from each used for ML training and independent validation, respectively. Based on objective (i), four features were identified as exerting the greatest importance for lambing detection: mean distance to peers (MDP), MDP compared to the flock mean (MDP.Mean), closest peer (CP) and posture change (PC). Using these four features, the final ML was able to detect 27.3 % and 54.5 % of lambing events within ±3 h of birth with no prior false positives. If earlier false positives were allowed, this detection increased to 90.9 % and 81.8 % depending on the requirement for a single alert, or two consecutive alerts occurring. To identify the potential causes of model failure, the data of three animals were investigated further. Lambing detection appeared to rely on increased social isolation behaviour in addition to increased PC behaviour. The results of the study support the use of integrated sensor data for ML-based prediction of parturition events in grazing sheep. This is the first known application of ML classification for the detection of lambing in pasture-based sheep. Application of this knowledge could have significant impacts on the ability to remotely monitor animals in commercial situations, with a logical extension of the information for remote monitoring of animal welfare.

8.1 Introduction

There is increased interest in the development of sensing technologies to improve animal management in the extensive grazing industries (Fogarty et al., 2018). Much of the research to date has been conducted using individual on-animal sensors such as Global Navigation Satellite System (GNSS) tracking, motion sensors (e.g. accelerometers, inertial monitoring units, pitch and roll sensors), jaw or bite sensors and physiological sensors (Fogarty et al., 2018, Wathes et al., 2008). In specific studies of sheep, on-animal sensor technologies have been applied to monitor various behaviours of interest, either within a particular context [e.g. lambing (Dobos et al., 2014, Dobos et al., 2015, Fogarty et al., 2020a); predation (Manning et al., 2014); oestrus (Fogarty et al., 2015)] or more generally for basic behaviour recognition (Barwick et al., 2018b, Fogarty et al., 2020b, Alvarenga et al., 2016, Decandia et al., 2018, Giovanetti et al., 2017).

In the majority of sensor-based sheep research, single sensor types are applied in isolation (Fogarty et al., 2018). However, given the number of available technologies and the benefits each can provide, there is merit in exploring the use of integrated monitoring systems. This is likely to be particularly valuable when a single sensor is unable to collect all the desired information, or when the use of multiple sensors improves accuracy. For example, in work by Spink et al. (2013), joint GNSS and accelerometer tracking of Canada geese (*Branta canadensis canadensis*) found the combination of the two sensor types improved the ability to distinguish behaviours of interest, compared to GNSS alone. In Dewhirst et al. (2016), integration of GNSS, accelerometers and magnetometers improved the accuracy of location and distance travelled estimates of domestic dogs. The use of integrated sensors has also been explored in cattle production systems. For example, Barker et al. (2018) found integrated local positioning data and accelerometers could detect changes in dairy cow feeding behaviour associated with lameness. González et al. (2014) also reported on an integrated GNSS and accelerometer behaviour monitoring system, incorporating additional live weight data from remote weighing systems, to demonstrate the value for beef cattle grazing systems. One key gap in the literature is the lack of reported use of weather data in an integrated sensor approach. Weather has obvious implications for animal behaviour (Thomas et al., 2008), particularly in extensive grazing systems (Goddard et al., 2006), and so its exploration as a component of an overall behavioural monitoring systems is also warranted.

While the application of sensors in a research context is important, there is growing interest in the development of these systems for commercial application. In this context, sensors will require real-time or near-real-time data processing and information transfer to ensure timely operational decisions (Bailey et al., 2018). Within this near-real-time requirement sit additional concepts of online processing and edge computing. Online processing refers to the analysis of each data point as they become available, with the aim of identifying the nonconformities as soon as possible after they occur (Aminikhanghahi and Cook, 2017). Edge computing refers to the capacity to perform some level of processing either at or near the device, without the reliance of data transfer to the cloud (ur Rehman et al., 2016). Although many advances have been made in near-real-time sensor systems, there are a number of practical challenges associated with their implementation (Vázquez-Diosdado et al., 2019). For example, data transmission is an extremely power-intensive activity and selection of data deemed most relevant to analysis may be necessary (Handcock et al., 2009). Sensor type can also impact on power requirements [e.g. GNSS receivers require significant amounts of power (Swain et al., 2011)] and computational requirements can greatly impact the power supply (Vázquez-Diosdado et al., 2019). Given these limitations, most applications of on-animal sensors, particularly in a research context, are still conducted using 'store-on-board' (SOB) devices, where the data are saved on the sensor itself and only accessible after the device has been removed (Bailey et al., 2018, Trotter, 2010). In this case, the entire dataset is usually viewed as a whole (known as 'offline' processing), with previously occurring patterns detected after they occur through an examination of historical data (Aminikhanghahi and Cook, 2017). Although obviously not directly applicable to commercial settings, SOB devices can serve as a proxy to collect sensor data for later use in simulated online scenarios, which serve to evaluate the potential for developing commercially viable products.

One potentially valuable application of sensor technology is for monitoring of parturition (lambing) events in sheep. Lambing is a critical period for the ewe and lamb, with lasting impacts on productivity and welfare (Alexander, 1980, Alexander, 1988, Hinch and Brien, 2014). Detection of lambing has implications for two key welfare outcomes for the sheep industry. Firstly, it provides an indication of ewe welfare, particularly if applied to detect abnormal parturition-related behaviour (e.g. detection of prolapse or dystocia). Secondly, welfare of the newborn can also be inferred, given experience of dystocia or even selection

of an appropriate lambing site can indicate quality of mothering and early experience of the lamb (Alexander, 1988). Previous sensor-based research of lambing behaviour has focused on two main technologies: firstly, GNSS (Dobos et al., 2014, Dobos et al., 2012, Dobos et al., 2015, Fogarty et al., 2020a); and secondly and to a lesser extent, accelerometers (Schmoelzl et al., 2016, Fogarty et al., 2020c). These studies have broadly proven the ability of each sensor type to detect changes in behaviour associated with lambing. However, the application of these sensors to detect a lambing event under commercial conditions in simulated 'near-real-time' is yet to be explored. This process has been examined in other livestock industries including calving beef and dairy cattle (Miller et al., 2020), farrowing pigs (Traulsen et al., 2018, Cornou and Lundbye-Christensen, 2012) and for detection of stress in police horses (Norton et al., 2018).

In this paper, a simulated online machine learning (ML) classification algorithm for detection of parturition events in commercial grazing ewes is developed and evaluated. SOB data were used as a substitute for near-real-time sensor data and allowed for sequential processing of each data point to simulate an online processing scenario. The algorithm uses data from GNSS tracking collars, accelerometer ear tags and local weather data and hence explores the benefits of an integrated sensor approach. The specific objectives were to: (i) determine which sensor systems and features provide the most useful information for lambing detection; and (ii) evaluate how this data might be integrated using ML classification to alert to a parturition event as it occurs. Within this last objective, the concept of adjusting detection criteria post-classification is explored in the context of applying the model in situations where false positives are more or less acceptable. This knowledge is intended to contribute to the development of commercially feasible lambing detection systems for improved surveillance of animals, ultimately improving methods of monitoring during this critical period.

8.2 Materials and methods

8.2.1 Location and animals

Two independent field trials were conducted at a commercial mixed enterprise on the South Island of New Zealand (43.0°S and 173.2°E) over consecutive years. Trial One was conducted from 29 September to 13 October 2017. Trial Two was conducted from 9 September to 23

September 2018. All procedures were approved by the Massey University Animal Ethics Committee (MUAEC 17/59; MUAEC 18/67).

In Trial One, 40 mixed-age Merino or Merino-cross ewes were selected from the main commercial flock. Selection was based on ewes having an expected lambing date during the experimental period (determined via ultrasound scanning as per normal farm practice). The experimental paddock was 3.1 ha and provided *ad libitum* access to forage and water.

In Trial Two, 39 mixed-age Merino or Merino-cross ewes were selected from the main commercial flock. Again, selection was based on ewes having an expected lambing date during the experimental period. Of the 39 animals selected, 12 ewes have been previously used for development of ML behaviour algorithms (Fogarty et al., 2020b) that are applied for prediction of animal behaviour in the current study. For this reason, these animals were excluded and their data subsequently removed from the validation dataset. The experimental paddock was 4.4 ha and provided *ad libitum* access to forage and water.

Throughout each trial, weather data were collected by an on-farm weather station for later incorporation into the dataset. Weather data included average air temperature, average wind speed and average solar radiation recorded hourly. Total rainfall was also recorded as a cumulative value per day.

8.2.2 Instrumentation

In both trials, experimental ewes were fitted with devices on the morning prior to study commencement. Each animal was fitted with a GNSS logger (i-gotU GT-600, Mobile Action Technology Inc., Taiwan) attached to a neck collar and an accelerometer (Axivity AX3, Axivity Ltd, Newcastle, UK) attached to an ear tag. GNSS loggers were programmed to obtain locations at 3 min (Trial One) or 2 min (Trial Two) intervals. Accelerometers were configured at 12.5 Hz and fixed with an orientation of the X-, Y- and Z-axis along the dorso-ventral (up-down), lateral (side-to-side) and anterior-posterior (forward-backward) axes, respectively.

In Trial One, ewes were moved to the experimental paddock after instrument attachment and remained in this location for the entire experiment duration.

In Trial Two, animals were also moved to a paddock after instrument attachment. However, on the first day of the experiment, it was noted that the original paddock did not allow for adequate observation of the animals. Thus, the ewes were moved to an adjoining paddock at 1100 h on Study Day One, where they remained for the duration of the trial. In this case, early sensor data (from midnight to 1100 h on Study Day One) were discarded, as the animals were not in the experimental paddock.

8.2.3 Observation

For Trial One, ewes were observed from 0630 h – 1230 h and 1530 h – 1800 h (± 30 min) for the entire experimental period (14 days). For Trial Two, observations were conducted between 0730 h – 1230 h and 1330 h – 1730 h (± 30 min) for the entire experimental period (15 days). Observations were conducted for the purpose of recording lambing time, via the use of binoculars. Ewes were also fitted with identification 'bibs' with unique colour/number combinations to allow the observer to differentiate individual ewes from a distance.

Time of lambing was recorded to the nearest hour where possible. Lambing was defined as the time in which the lamb was fully expelled. Hour records were rounded down, i.e. lambing events at 1301 h and 1359 h would both be recorded within 1300 h. If ewes lambed during the observational period, but the actual birth was not able to be observed (e.g. if ewes were hidden from view), the hour of birth was recorded within a maximum 2 h window. If this could not be determined, the record was discarded. Ewes that lambed overnight were also excluded due to uncertainty of exact lambing time.

8.2.4 Data management and analysis

After each experiment, the devices were removed, and data downloaded. GNSS tracking data were downloaded using the proprietary software (@Trip PC, Mobile Action Technology Inc., Taipei, Taiwan). Accelerometer data were downloaded using the proprietary software (OMGUI, Axivity Ltd, Newcastle, UK). All data were processed and analysed using the statistical software R (R Core Team, 2018). Weather data from the on-farm weather station were also downloaded for the study period. The datasets for each trial were kept separate at all times.

8.2.4.1 GNSS data

After download, the GNSS data were checked for fidelity. Any locations that had not been correctly logged (i.e. locations with a latitude and longitude of zero) were removed. Due to differences in the logging intervals between the trials (3 min Trial One; 2 min Trial Two), the GNSS data were interpolated to 5 min intervals. This interval was chosen as it was considered a more reasonable frequency for commercial application where battery life may be limited (Anderson et al., 2013) and has been previously applied in sheep (Dobos et al., 2014, McGranahan et al., 2018) and cattle (Trotter et al., 2010, Turner et al., 2000). This process was conducted by interpolating the existing GNSS tracks to a common time interval (5 min) using the *redisltraj* function in the R package *adehabitatLT* (Calenge, 2006).

After interpolation, the distance and speed between successive locations were then calculated (Dobos et al., 2014, Fogarty et al., 2020a). Speeds over 3 m/s were removed because these positions were likely inaccurate (Fogarty et al., 2020a). The distance, time and speed between successive GNSS locations were then recalculated and a moving window average of speed based on the two locations prior to and following the point of interest (i.e. five locations in total) were calculated.

To determine the extent of each ewe's social activity, the distance between each ewe and each of her peers was determined (Fogarty et al., 2020a). The straight-line distance between the GNSS locations for each ewe-pair was calculated using the 'Vincenty (ellipsoid)' method (Hijmans, 2019). Once the distance between each ewe-pair was calculated, values were averaged to calculate the mean distance to peers (MDP). The closest peer (CP; i.e. the smallest distance between ewes) was also recorded.

To calculate the spatial landscape utilisation of each ewe, the minimum convex polygon (MCP) was calculated for each ewe for every hour of the trial. MCP is a standard method for home range estimation (Burgman and Fox, 2003). To ensure MCP was not overestimated, the GNSS data were further processed to remove any locations outside of the paddock boundaries + 10m (mean location error of i-gotU device < 10m (Morris and Conner, 2017)).

8.2.4.2 Accelerometer data

After download, raw accelerometer data were processed according to the methods outlined in Fogarty et al. (2020b) and Fogarty et al. (2020c). Briefly, a number of features were extracted from the raw X-, Y- and Z-axis values (see Fogarty et al. (2020b) for details). Features were calculated using two epoch lengths (10 s and 30 s). After feature extraction, previously developed ML algorithms (Fogarty et al., 2020b) were used to classify the animal's behaviours. Classification was conducted in three ways: (i) detection of specific behaviour (grazing, standing, lying and walking); (ii) detection of general activity (active or inactive); and (iii) detection of posture (prostrate or upright).

8.2.4.3 Integrating GNSS, accelerometer and weather data

Following raw data processing, the GNSS and accelerometer data sets were each summarised on an hourly basis and then integrated together with the weather data (Table 8.1). These summaries, and the selected features, are discussed in detail in the following sections (Sections 8.2.4.3.1 - 8.2.4.3.3). Hourly summaries were chosen to minimise data processing requirements while still allowing for detection at a relatively fine temporal scale. The use of hourly summaries also reflects previous work (Dobos et al., 2014, Fogarty et al., 2020a, Fogarty et al., 2020c). In the context of simulating a commercially relevant online model, hourly detection was also thought to represent a reasonable time frame in which a producer might be made aware and respond to any alerts developed.

8.2.4.3.1 Features derived from prior research

A number of key features for the GNSS and accelerometer data were selected due to their performance in previous research (Fogarty et al., 2020a, Dobos et al., 2014, Fogarty et al., 2020c) or hypothesised as having potential in an integrated approach.

For the GNSS data, key features were: (i) mean speed (MeanSp); (ii) minimum speed (MinSp); (iii) maximum speed (MaxSp); (iv) MDP; (v) CP and (vi) MCP. These features were based on previous work conducted by Dobos et al. (2014) and Fogarty et al. (2020a).

For the accelerometer data, key features were as follows: (i) the proportion of each hour spent performing mutually exclusive behaviours (grazing, standing, lying and walking); (ii) the proportion of each hour spent active; and (iii) the number of times each individual changed

their posture (i.e. upright to prostrate and vice versa) within an hour. These features were based on previous work (Fogarty et al., 2020c).

8.2.4.3.2 Peer-based features comparing the individual to the flock

Given the gregarious nature of sheep (Lynch et al., 1992), additional metrics were included in the integrated dataset to allow for concurrent assessment at an individual and flock-level. In an example outlined in Fogarty et al. (2020c), ewe walking behaviour was not only shown to increase at parturition, but also during periods of normal flock management (e.g. movement between paddocks). Based on this, it was decided that monitoring at both an individual and flock-level was necessary, noting that changes in behaviour of a single ewe would more likely indicate parturition, whereas broader changes to the flock would suggest a whole-flock change (Fogarty et al., 2020c). Thus, additional features were included comparing each ewe's individual feature values at a given point in time to the mean value of all other animals at this time. These features were calculated as a percentage difference from the mean (i.e. percentage increase or decrease) and denoted "Name.Mean", where "Name" refers to the feature of interest (see Table 8.1 for details).

8.2.4.3.3 Temporal comparison of features

To enable temporal comparison of features, the percentage increase or decrease in each feature was compared at key time intervals. Specifically, the percentage change between the current hour and the previous hour (Hour -1: denoted "Name.1h") or the current hour and 24 h previous (Hour -24: "Name.24h") were calculated. Inclusion of these time-based calculations was considered important to ensure temporal associations in behaviour were accounted for in the model. These calculations also allowed for a comparison of each individual against their own 'baseline' to determine if significant changes in behaviour over time became evident (see Table 8.1 for details).

Due to similarities between some derived features, a test for collinearity was conducted. Features with a correlation ± 0.8 were removed from further analysis (see Table 8.1 for details).

Table 8.1. Features provided from each sensor type, including the unit of measurement. Derived features are reported as absolute values per hour. Peer-based features are calculated as the percentage difference between the individual ewe and the mean of all other ewes in the flock. Temporal features are calculated as the percentage difference between the current hour and the previous hour (1 h) or 24 hours previous (24 h). Features removed due to collinearity are in italics. FNP = Feature not progressed. NA = Not applicable.

Sensor type	Derived features	Unit	Peer-based features	Unit	Temporal features	Unit
GNSS	Mean speed (MeanSp)	m/s	MeanSp.Mean	%	MeanSp.1h / .24h	%
	Minimum speed (MinSp)	m/s	*MinSp.Mean*[1]	-	MinSp.1h / .24h	%
	Maximum speed (MaxSp)[2]	-	*FNP*[2]	-	*FNP*[2]	-
	Mean distance to peers (MDP)	m	MDP.Mean	%	MDP.1h / .24h	%
	Closest peer (CP)	m	*CP.Mean*[3]	-	CP.1h / .24h	%
	MCP	%	MCP.Mean	%	MCP.1h / .24h	%
Accelerometer	Time spent grazing (Grazing)	%	Grazing.Mean	%	Grazing.1h / .24h	%
	Time spent lying (Lying)	%	Lying.Mean	%	Lying.1h / .24h	%
	Time spent standing (Standing)	%	*Standing.Mean*[4]	-	Standing.1h / .24h	%
	Time spent walking (Walking)	%	Walking.Mean	%	Walking.1h / .24h	%
	Time spent active[5]	-	*FNP*[5]	-	*FNP*[5]	-
	Posture changes (PC)	Count	PC.Mean	%	PC.1h / .24h	%
Weather data	Average air temperature (AirTemp)	°C	NA	NA	NA	NA
	Total rainfall (Rainfall)	mm	NA	NA	NA	NA
	Average wind speed (WindSp)	kph	NA	NA	NA	NA
	Average solar radiation (SolarRad)	w/m^2	NA	NA	NA	NA

[1]Removed from analysis due to collinearity with MinSp
[2]Removed from analysis due to collinearity with MeanSp (no additional features calculated)
[3]Removed from analysis due to collinearity with CP
[4]Removed from analysis due to collinearity with S
[5]Removed from analysis due to collinearity with time spent grazing (no additional features calculated)

8.2.5 Development of a simulated online parturition detection model using machine learning

ML algorithms are commonly used for pattern recognition and classification tasks (Nathan et al., 2012) and have been successfully used in sheep behaviour research (Barwick et al., 2018a, Barwick et al., 2018b, Walton et al., 2018, Fogarty et al., 2020b). This process involves developing the algorithm with a training dataset and then testing it against an independent validation dataset.

8.2.5.1 Training dataset

Data collected from Trial One were used as the training dataset and will henceforth be referred to as such. Once collated, the dependent variable on the training dataset was 'labelled' to represent the behaviour state of the ewe (considered a binary state of either 'lamb' or 'non-lamb'). The process of labelling was as follows: the hour of birth (Hour 0) and one hour either side (Hour ± 1) were labelled as 'lamb' (3 hours in total). This was done to ensure that those animals that lambed earlier or later within the hour would still have an adequate representation of 'lambing' behaviour included in the training dataset. Furthermore, the inclusion of multiple 'lamb' hours per animal was important to increase the amount of training data for this behaviour state for a more balanced dataset. Conversely, 'non-lamb' hours were represented by the 24-hour period for the third day prior to (Day -3) and third day after parturition (Day +3; 48 hours in total). Only these days were selected to reduce the number of 'non-lamb' hours for a more balanced training dataset, whilst also ensuring that normal diurnal patterns were represented. The use of data from three days prior to and following lambing was based on previous work (Fogarty et al., 2020a, Fogarty et al., 2020c) which suggests that most lambing-related behaviours do not commence until the day before (Day -1) or day of (Day 0) actual lambing.

8.2.5.2 Validation dataset

Data collected from Trial Two were used as the validation dataset and will henceforth be referred to as such. The process of labelling the validation dataset was different and intentionally more specific compared to the training dataset. The hour of birth was labelled as Hour 0 and the hours surrounding Hour 0 were labelled numerically (± x hours) to represent the temporal association to the parturition event. For ewes where the hour of birth was

known within a maximum 2 h window, the hour of birth was designated as the middle hour within the window, and the hours either side labelled as per the previous (i.e. a window of 1200 h – 1400 h would designate 1300 h as Hour 0 (hour of birth), 1400 h as Hour +1, etc.). If the middle hour fell on a part-hour, the hour was rounded down (i.e. 1330 h would round down to 1300 h).

8.2.5.3 Part A: Simulated online parturition detection ML development and evaluation

Support Vector Machine (SVM) classification was used to predict the binary ewe status ("lamb" or "non-lamb"). SVMs generate a hyperplane between observations to separate distinct classes (Nathan et al., 2012), with the aim of maximising the distance between the observations and the hyperplane (Joo et al., 2013). This ML algorithm has become popular in recent years due to its relative ease of application and high performance in real-world applications (Martiskainen et al., 2009, Joo et al., 2013).

Leave-one-animal-out cross validation (LOOCV) was used to train and test the SVM. This process involved using all but one of the datasets to train the algorithm, with subsequent performance evaluation using the remaining dataset. During each training iteration, the data were pre-processed to 'centre' and 'scale'. The tuning cost ('C') parameter was also adjusted using a grid-based search. This process was repeated for all animals to enable selection of the best C value.

Based on the first objective of this study, to determine which sensor systems and features provide the most useful information for lambing detection, feature selection was also conducted throughout this training process. To do this, a Receiver Operating Characteristics (ROC) curve analysis was conducted using the *varImp* function from the *caret* package (Kuhn, 2018). This function applies ROC curve analysis to each feature, calculates the resulting area under the curve and uses this area as a measure of feature importance between 0 and 100 (Kuhn, 2007). Only features with an importance 'score' over 75 were retained for algorithm training to reduce the complexity and computational requirements of the SVM as this is considered a limiting factor to commercial application. A similar approach has previously reported in Vázquez-Diosdado et al. (2019), where a single feature was incorporated into an online algorithm to minimise energy consumption. In that paper, the authors state that while including additional features can improve accuracy, their inclusion should be conducted

under a cost-benefit approach given the computational costs of complex models (Vázquez-Diosdado et al., 2019).

Once trained, performance statistics for the SVM were calculated including: Kappa value, precision, recall (sensitivity) and the Matthews Correlation Coefficient (MCC). The Kappa value compares the observed accuracy with random accuracy and is considered informative in unbalanced samples such as in the current study (Santegoeds, 2016). Precision and recall are also useful for unbalanced samples where the focus is on detection of the smaller class (Tang et al., 2009). MCC is widely used in bioinformatics for unbalanced classification (Boughorbel et al., 2017), providing a score between -1 and 1 where 1 indicates prefect prediction, 0 indicates random prediction and -1 indicates total disagreement. Precision, recall and MCC were calculated using the following equations:

$$precision = \frac{TP}{(TP + FP)}$$

$$recall = \frac{TP}{(TP + FN)}$$

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}$$

where TP, TN, FP and FN refer to true positive (correct classification of ‘lamb’), true negative (correct classification of ‘non-lamb’), false positive (incorrect classification of ‘non-lamb’ as ‘lamb’) and false negative (incorrect classification of ‘lamb’ as ‘non-lamb’), respectively. Accuracy was not calculated due to the imbalanced nature of the dataset (Yap et al., 2014).

8.2.5.4 Part B: Validation of the parturition detection model

Based on the second objective of this study, the final algorithm was applied to the independent validation dataset to detect the day and hour of lambing. To simulate an online situation, the first hour where lambing detection occurred was recorded and compared to the known time of birth. Detection success was assessed across two timeframes: firstly, if it was within ± 1 h of the recorded hour of birth; and secondly, if it was within ± 3 h of recorded hour of birth. These two different levels were implemented to make it possible to identify both pre- and post-parturient behaviours, which are known to change in the hours just prior to or following lambing (Fogarty et al., 2020c). For example, in a study by Arnold and Morgan (1975), pre-lambing maternal interest and behavioural changes associated with parturition were found to increase most significantly between 180 and 120 min prior to birth. A broader detection window was also important to allow for the complete length of labour [approximately 65.4 ± 9.6 mins (Echeverri et al., 1992)], and detection of early post-parturient behaviour such as the tendency to remain at the birth site for up to 5 h (mean of 2 h) (Alexander et al., 1983). If lambing detection occurred within ±3 h of known birth, the predictions ceased, and the model was no longer applied to that animal. If ewes did not have a correct detection within ±3 h, predictions continued until the known day of birth, after which predictions were also ceased. This enabled the evaluation of the likely number of false positives that were generated.

8.3 Results

8.3.1 Data and lambing records

A summary of the sensor and lambing records is presented in Table 8.2. In each year, a number of devices failed to record data and were excluded. In addition, one ewe prolapsed during the 2017 trial and was removed from the data set. Ewes that gave birth overnight or did not give birth during the experimental period were also excluded due to uncertainty of the exact time of birth.

Table 8.2. Data and lambing records for the training (Trial One) and validation (Trial Two) datasets.

	Training	Validation
Animals at trial initiation	40	39
Animals with one or more failed devices	5	6
Complete datasets at trial conclusion	35	33
Excluded datasets	27[1]	22[2]
Day and hour of birth identified	8	9
Hour of birth known within a maximum 2 h window	0	2
TOTAL	**8**	**11**

[1]Exclusion based on prolapse (n = 1) or unknown lambing time (overnight or outside of the experimental period; n = 26)

[2]Exclusion based on previous use in ML algorithm development [n = 12; Fogarty et al. (2020b)] or unknown lambing time (overnight or outside of the experimental period; n = 10)

8.3.2 Weather records

During Trial One (training dataset), temperatures ranged from 3.8°C to 22.3°C and total rainfall was 85.6 mm. Average daily wind speed was 9.2 km/h with an average gust speed of 21.7 km/h. Average solar radiation was 104.9 w/m^2.

During Trial Two (validation dataset), temperatures ranged from 0.7°C to 21.6°C. Average daily wind speed was 7.1 km/h with an average gust speed of 18.0 km/h. Average solar radiation was 176.0 w/m^2. There was no rainfall during this period.

8.3.3 Part A: Simulated online parturition detection ML development and evaluation

8.3.3.1 Feature importance

Using the ROC curve analysis (Figure 8.1), the feature with the highest importance for differentiation between lambing and non-lambing animals was MDP.Mean (i.e. the MDP of the ewe compared to the average MDP of all others in the flock, expressed as a percentage).

This was closely followed by CP and MDP (both expressed in metres). These features are all GNSS-derived. The most important accelerometer-derived features were PC, followed by PC.Mean (i.e. PC of the ewe compared to the average PC of all others in the flock, expressed as a percentage) and PC.24h (i.e. PC of the ewe in the hour of interest compared to the same hour in the previous day, expressed as a percentage). Three weather features (wind speed, air temperature and solar radiation) were within the top 10 most important features. Hour of the day was not an important feature for the purposes of differentiation.

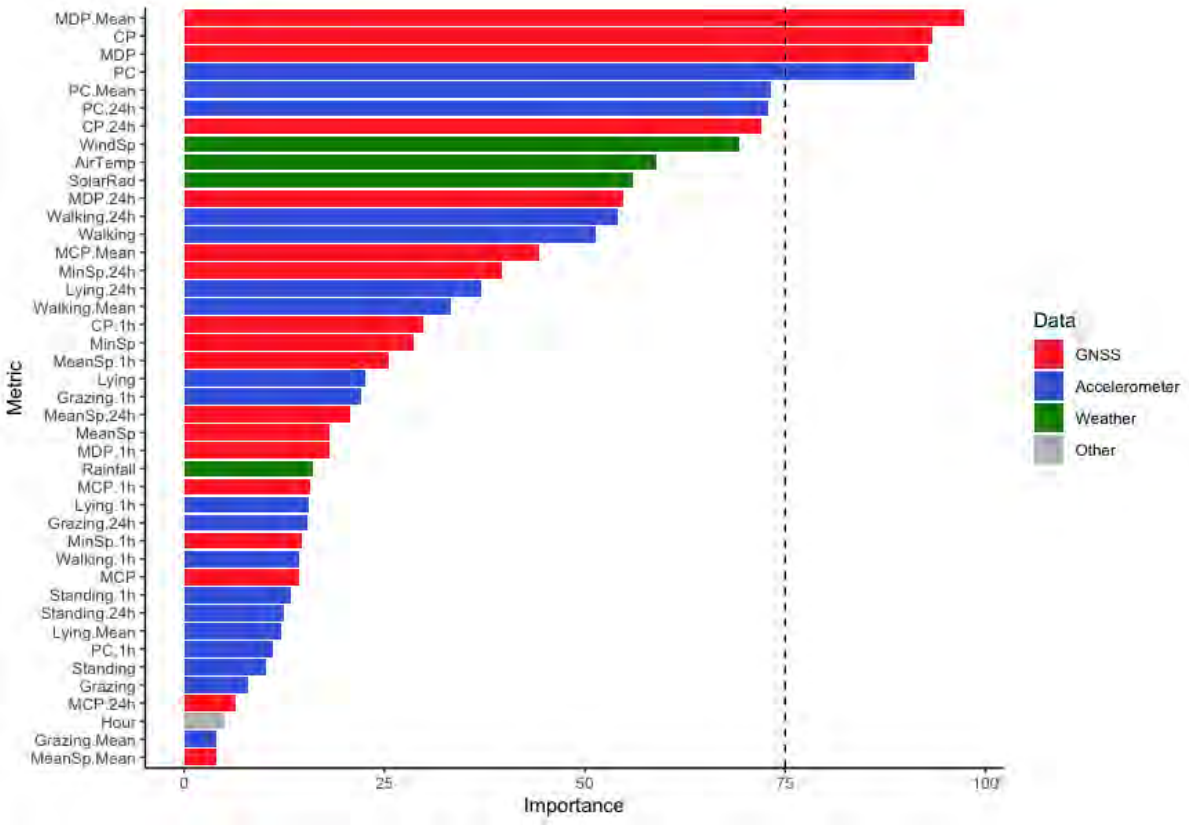


Figure 8.1. Feature importance for the integrated dataset determined by ROC curve analysis. Data types are: GNSS-derived (red); accelerometer-derived (blue); weather (green) and other (grey). Only those metrics with an importance 'score' above the chosen threshold (dashed line) were used in the ML.

As depicted in Figure 8.1, it is clear that both GNSS and accelerometer sensors provide the most useful information for identification of lambing. Specifically, four features emerged as having an importance 'score' over 75 and were retained in the final model: MDP.Mean, CP, MDP and PC. Although the original objective of the study was to examine an integrated sensor approach for parturition detection, due to the apparent importance of the GNSS metrics in the ROC curve analysis, a second SVM was developed at this stage to examine the benefits of using GNSS data alone.

8.3.3.2 ML evaluation

The two SVM models (the integrated SVM and GNSS SVM) were evaluated by LOOCV using the training dataset from Trial One. The integrated SVM performed slightly better than the GNSS SVM, with a higher Kappa (0.4), recall (47.6 %) and MCC (0.6) compared to the single sensor dataset (Kappa: 0.3; recall: 33.3 %; and MCC: 0.5). The GNSS SVM demonstrated a higher precision (83.3 %) compared to the integrated model (71.1 %). Overall, the integrated SVM demonstrated a higher number of true positives (n = 10) compared to the single sensor (n = 7 true positives). Based on the performance of the integrated model, and due to the original objectives of understanding the value of integrated sensor systems, only the integrated model was selected for later validation using the Trial Two data.

Prior to validation, summary statistics (Table 8.3) and density plots (Figure 8.2) were generated for the training dataset to assist in understanding of the SVM classification process. As shown in Table 8.3, lambing animals displayed an increased level of social isolation compared to non-lambing animals, both in terms of actual distance (MDP) and when this distance was compared to the mean of the flock (MDP.Mean). This pattern was also evident for CP, with lambing animals being a mean distance of 8 m from their closest peer compared to non-lamb animals at 1.5 m. Frequency of changing posture also increased at lambing (mean 26.2 and 9.7 changes per hour for lambing and non-lambing animals, respectively).

Table 8.3. Summary statistics for the top four features of the training dataset (determined by ROC curve analysis)

	Lamb			**Non-lamb**		
Features	Mean	Min	Max	Mean	Min	Max
MDP.Mean (%)	51.3	-3.8	118.9	4.1	-28.6	191.5
CP (m)	8.0	0.6	26.1	1.5	0	11.5
MDP (m)	66.5	37.6	114.4	35.0	9.5	87.5
PC (count)	26.2	6	48	9.7	0	38

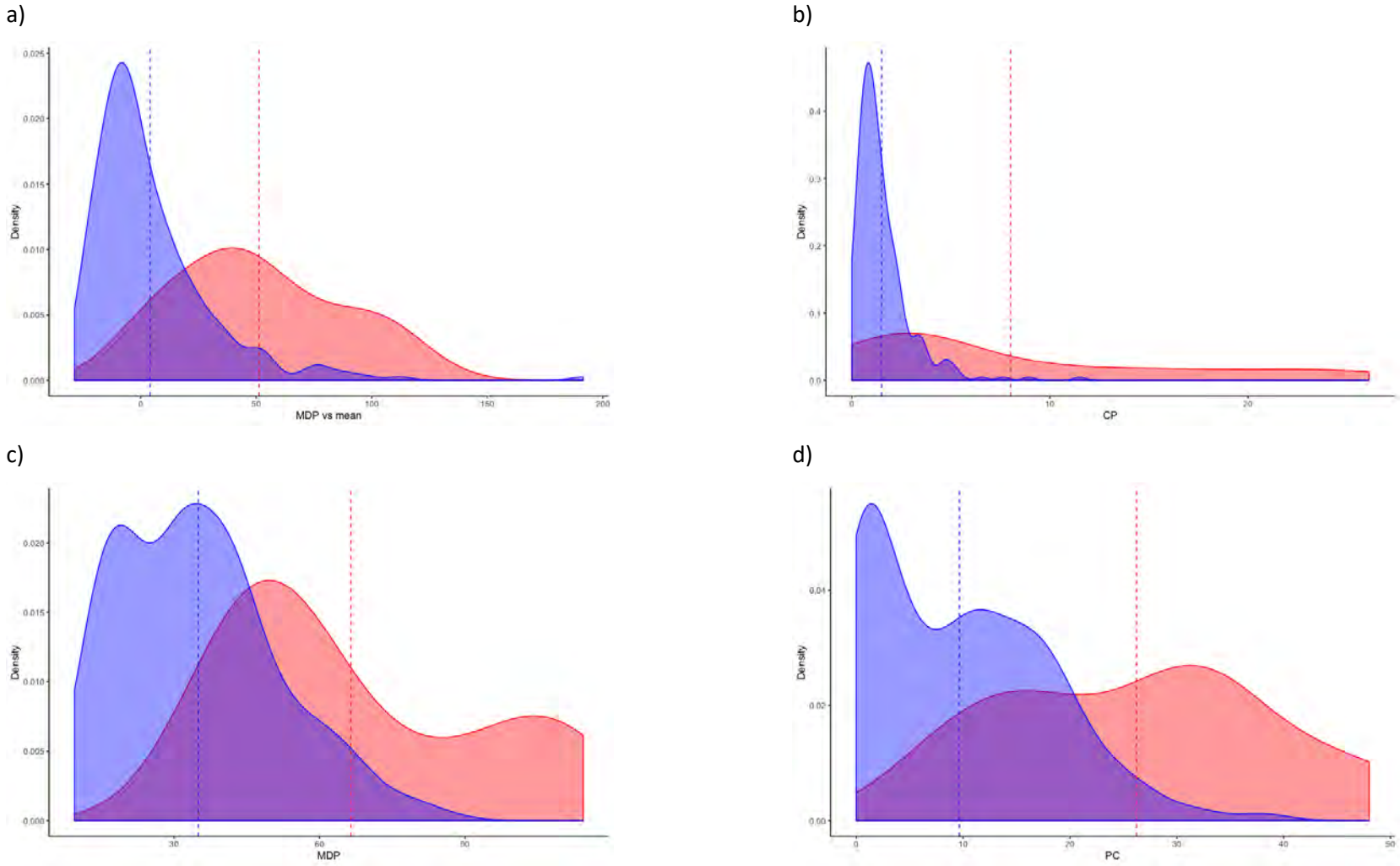


Figure 8.2. Density plots of the four most important features (determined by ROC curve analysis) for differentiation between lambing (red) and non-lambing (blue) animals using the training dataset. Features are: a) MDP.Mean; b) CP; c) MDP; d) PC. Mean lines are also shown (lambing: red dashed line; non-lambing: blue dashed line)

Although all four features are dominant predictors for lambing, there is still some obvious overlap between the two behaviour states (Figure 8.2). For example, across all features, the maximum non-lamb values were consistently higher than the mean lambing values for each particular feature. This may contribute to inaccuracies in detection and highlights the potential to further refinement. This is explored further in Section 8.3.4.

8.3.4 Part B: Validation of the parturition detection model

To explore if the integrated SVM could alert for parturition events as they occurred sequentially over time, the final model was tested against the independent validation dataset from Trial Two (Table 8.4). To simulate a near-real-time system where data would be made available in an incremental fashion, only the first hour of lambing detection was recorded and compared to the known time of birth. If this initial detection alerted too early (i.e. false positives before the actual birth event), the model was applied up until the actual day of birth to determine if later detection of the event would still occur.

Three animals (from a total of 11; 27.3 %) had the first lambing alert within ±1 h of the known lambing hour. No additional animals had the first lambing alert within ±3 h. Seven ewes (63.6 %) had a number of false positives (range: 1-28; mean: 8) prior to correct detection. One animal (Animal 6) did not have any alerts within ±3 h of known lambing hour. The closest alerts for this animal were Hour -6 and Hour +4.

Table 8.4. Application of the integrated SVM to the validation dataset. Hour of first alert is expressed relative to the recorded hour of birth. Notations 'X' and 'X+' indicate the animal meets the criteria.

Animal	Hour of first alert	False positives (prior to actual lambing)	First alert within ±1 h (X) or ±3 h (X+)	Early false positives with later accurate alert ±3 h	Failed (no alerts ±3 h)
1	-67	1		X	
2	-21	6		X	
3	0	0	X		
4	-1	0	X		
5	-43	1		X	
6	-114 (4.8 days)	28			X
7	-118 (4.9 days)	3		X	
8	-169 (7.0 days)	18		X	
9	-1	0	X		
10	-56	6		X	
11	-68	1		X	
TOTAL		**64**	**3 (+ 0)**	**7**	**1**

While this model was able to alert to all but one parturition event, this high rate of detection comes at the cost of numerous false positive alerts (n = 64). To explore a second scenario under which false positives were less acceptable, a simple modification was applied. This basic change required identification of at least two consecutive 'lamb' hours before an alert was generated. The results of this process are presented in Table 8.5.

Table 8.5. Application of the integrated SVM to the validation dataset with the additional criteria of requiring identification of at least two consecutive 'lamb' hours before an alert was generated. Hour of first alert is expressed relative to the recorded hour of birth. Notations 'X' and 'X+' indicate the animal meets the criteria.

Animal	Hour of first alert	False positives (prior to actual lambing)	First alert within ±1 h (X) or ±3 h (X+)	Early false positives with later accurate alert ±3 h	Failed (no alerts ±3 h)
1	+2	0	X+		
2	-20	3		X	
3	+1	0	X		
4	0	0	X		
5	0	0	X		
6	-110 (4.6 days)	12			X
7	+9	0			X
8	-141 (5.9 days)	6		X	
9	0	0	X		
10	-16	1		X	
11	+3	0	X+		
TOTAL		**22**	**4 (+ 2)**	**3**	**2**

Four animals (from a total of 11; 36.4 %) had the first alert within ±1 h of the known lambing hour. An additional two animals had the first alert within ±3 h of the known lambing hour (6 in total within ±3 h; 54.5 %). Three ewes had false positives (range 1-12; mean 5.5) with an accurate later prediction within ±3 h of birth. Two ewes did not have any alerts occur within ±3 h of birth (Animals 6, 7). For these animals, the closest alerts Hour -16 and Hour +5 (Animal 6) and Hour +9 (Animal 7).

8.3.4.1 Misclassification – why is it occurring?

To further explore reasons for misclassifications and to understand how the SVM used the data for lambing event detection, the individual datasets of three animals in the validation

dataset were plotted (Figure 8.3). Lambing alerts and the period of the actual birth event were also plotted. The three chosen animals represent those which were consistently correct (Animal 9), consistently incorrect (Animal 6) or had early false positives but were later correct (Animal 2).

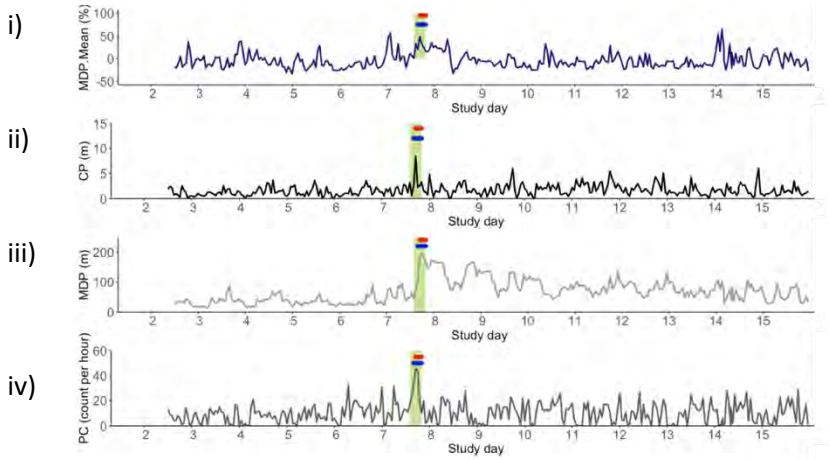
8.4 Discussion

This study represents the first reported attempt to integrate data from multiple sensors for the purpose of parturition detection in sheep. A number of studies have reported on the relationship between individual sensors and parturition (Dobos et al., 2014, Dobos et al., 2015, Fogarty et al., 2020a, Broster et al., 2010, Broster et al., 2017, Fogarty et al., 2020c). However, none have attempted to explore how this data might be used in the context of developing an online lambing detection system that might be of value in commercial production systems.

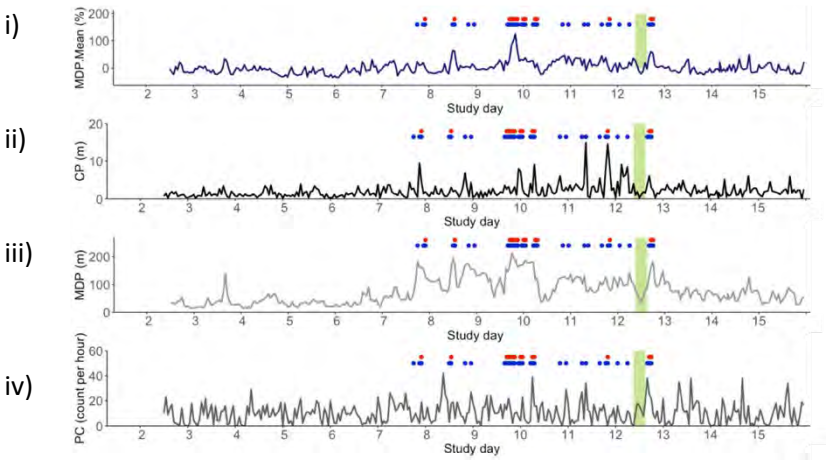
8.4.1 Feature importance for lambing prediction

The four features most important for lambing prediction were derived from GNSS (MDP.Mean, CP, MDP) and accelerometers (PC) and highlight the importance of these sensor types for lambing detection. Overall, ewes demonstrated an increased level of social isolation at lambing compared to non-lambing animals (Table 8.3; Figure 8.2). This was evidenced by an increase in MDP.Mean, MDP and CP and supports published reports of ewe social isolation at parturition (Fogarty et al., 2020a, Dobos et al., 2014, Arnold, 1975, Alexander et al., 1979). Increased frequency of changing posture was also exhibited by lambing ewes, with the mean number of hourly changes increasing almost 3-fold, from 9.7 to 26.2 (Table 8.3; Figure 8.2). Again, this is consistent with published literature (Echeverri et al., 1992, Owens et al., 1985), and may indicate the onset of general restlessness associated with lambing.

a) Animal 9 (consistently correct alerts)



b) Animal 6 (consistently incorrect alerts)



c) Animal 2 (Early false positives with later correct alerts)

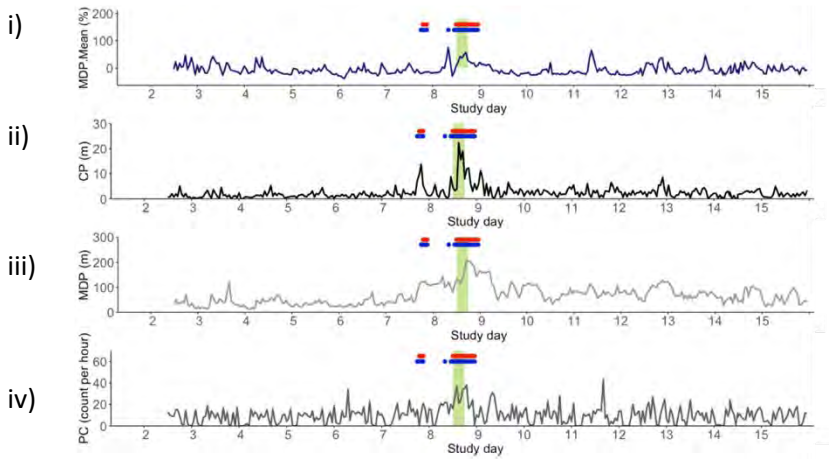


Figure 8.3. Individual datasets for a) Animal 9, b) Animal 6, and c) Animal 2. Features include: i) MDP.Mean (blue); ii) CP (black); iii) MDP (light grey); and iv) PC (dark grey). Though the model was applied as a simulated online scenario, data is presented for all study days to enable visualisation of broader patterns. Alerts are shown for two scenarios: hour of alert (blue circles) and two consecutive 'lamb' hours required before alert (red circles). Alerts are included up to the day of birth for both scenarios. The hours of known lambing (Hours ±3) are included as pale green shading.

Based on previously reported limitations of GNSS behaviour monitoring at an hourly scale (Dobos et al., 2014, Fogarty et al., 2020a), the reported importance of many of the GNSS-derived variables was initially unexpected. In Fogarty et al. (2020a), no significant difference in hourly MDP were found in the 12 h surrounding lambing. However, in the current study, this feature was ranked as the third most important for discrimination between lambing and non-lambing animals. In addition, in Fogarty et al. (2020a) GNSS was only shown capable of detecting the day but not the hour of lambing, whereas in the current study, GNSS-derived metrics were amongst the most important features identified (Figure 8.1). This disparity may reflect a difference in the methodologies of the two studies. In Fogarty et al. (2020a), the statistical comparison at an hourly scale was restricted to only 12 h around parturition. In contrast, in the current study the training dataset used values at lambing and compared them to non-lambing values collected 3 days either side of parturition. Indeed, in a second analysis in Fogarty et al. (2020a), broader changes in daily behaviour were found to indicate parturition, including MDP which increased from two days prior to birth. Thus, it appears that when compared to hours closer in time [as in Fogarty et al. (2020a)], there is a limited capacity to detect broader changes in behaviour that may occur over many days. Conversely, when behaviour is compared to hours more distance in time (as in the current study), the behaviour of ewes is detectably different.

In addition to the differences in methodology, the remaining GNSS features applied in the final model (MDP.Mean and CP) are novel features that to the best of our knowledge, have not yet been reported for sheep using GNSS data. As previously noted, given the gregarious nature of sheep (Lynch et al., 1992), measurements that assess flock-level behaviour change are important to differentiate individual changes in behaviour from the group. In contrast to previous literature that does not support the use of GNSS to detect hourly behaviour changes associated with parturition (Dobos et al., 2014, Fogarty et al., 2020a), the results of the current study suggests GNSS has notable monitoring ability, either in isolation or when integrated with an accelerometer. In the current study, the addition of Mean.MDP adjusts for changes in MDP that are the result of herd behaviour, which may be impacted by a number of factors, for example weather (Alexander et al., 1979, Thomas et al., 2008), forage quality (Arnold, 1984, Arnold, 1960) and social dynamics (Doyle et al., 2016). It is important to note that measurements of social activity using on-animal sensors are not limited to GNSS.

Proximity loggers represent another sensor type that can provide this information, often in a smaller size with lower power requirements (Handcock et al., 2009, Paganoni et al., 2020, Fogarty et al., 2019). Referring to commercial platforms seeking to operationalise this research, it may be worthwhile exploring the substitution of a proximity sensor for a GNSS. However, this substitution may introduce limitations, given that it will result in the loss of some key functionality, particularly where the location data from the GNSS may be critical for the producer to actually respond to a lambing alert and find a ewe in an extensive landscape.

The reduced importance of accelerometer features in this analysis was also unexpected. This was particularly true for features related to walking behaviour which have been previously reported as a powerful predictor of lambing (Fogarty et al., 2020c). The key accelerometer features identified were those related to posture change (PC, PC.Mean, PC.24h), although only PC met the required threshold for inclusion. Given accelerometers are generally small devices that can be easily applied to an animal (Watanabe et al., 2008), their integration into a commercial-grade device warrants further investigation. It should be noted that the method of detecting PC in this study required a significant level of data handling prior to the ML classification. More explicitly, the raw data had to be classified using previously developed ML models (Fogarty et al., 2020b), after which hourly summaries of PC could be calculated and applied in the current model. This was considered to be essential as the actual process of ewes changing their posture was not adequately observed for ML training (Fogarty et al., 2020b), and thus classification into two distinct postures was required before frequency of PC could be determined. Furthermore, classification into explicit behaviour allowed for comparison with known changes in parturition and assisted in the interpretability of the model. However, given the constraints of battery life and processing power in commercial situations (Vázquez-Diosdado et al., 2019), further exploration of posture change detection should be undertaken. For example, using metrics derived from the raw data such as movement variation (MV) or standard deviation of an accelerometer axis [SD_X; SD_Y; SD_Z; (Fogarty et al., 2020b, Barwick et al., 2018b)]. In previous work by Fogarty et al. (2020b), MV, SD_X and SD_Y were consistently identified amongst the most important predictors for classification of behaviour, general activity and posture. Thus, it is possible that use of these metrics may have similar predictive power when applied for parturition detection and should be considered in future studies.

The ROC curve analysis found weather features had only moderate importance for detection of parturition, particularly wind speed, air temperature and solar radiation. Sheep are known to have two major grazing episodes which are highly correlated to sunrise and sunset (Gonyou, 1984). Weather is known to disrupt these patterns such as; for example reduced grazing range in hot weather (Thomas et al., 2008). Weather is also known to impact social activity, particularly rising temperature and rainfall which both result in increased social contact (Doyle et al., 2016). It is likely that the findings of the current study reflect the relatively mild weather conditions experienced, which may not have been extreme enough to have an impact on the ewe's behaviour. Despite not playing an important role in the current study, inclusion of weather features in future models may still be warranted, particularly where more extreme weather events are experienced.

8.4.2 Detection of parturition and implications for commercial application

The use of sensor technology in a commercial environment necessitates the development of near-real-time information transfer. As the challenges associated with implementation are still widespread, SOB devices have been applied in the current study as a proxy for simulated online application. In the current study, 27.3 % (n = 3) and 54.5 % (n = 6) of animals had an accurate prediction of lambing within ±3 h of birth with no prior false positives, depending on the detection criteria used [i.e. first hour of alert (Table 8.4) compared to two consecutive hours of alert (Table 8.5)]. In a real-life scenario, it is unlikely that the model would automatically terminate as soon as the first alert occurs, instead requiring direct confirmation (or rejection) from the producer that lambing has (or has not) occurred. For this reason, inclusion of animals with initial false positives and later accurate alerts is also reasonable. Based on the latter, the results of the current study are encouraging, with 90.9 % (n = 10; Table 8.4) and 81.8 % (n = 9; Table 8.5) of lambing events successfully detected. The models applied in the current study are not true real-time detection algorithms, as they require the collection of an entire hour's worth of data before summary and prediction can occur. However, current methods of lambing detection are usually based on visual observation which may increase the risk of mismothering (Alexander, 1980). Thus, despite not being a true real-time model, successful remote detection of lambing within ± 3 h could significantly increase the efficacy of ewe surveillance and may be useful for improving both production and welfare outcomes.

When considering the end-use of these models, it is important to understand how they may be applied in a real-life setting. For example, though the results of Table 8.4 indicate the ability to detect approximately 90.9 % of birth events within a 3 h window using the first hour of alert, the high rate of detection was also accompanied by a high rate of false positives (n = 64). If this were applied directly in a commercial situation, it would correspond to a large number of false alarms for every correct alert. In situations where the animals represent a higher economic value (e.g. seed stock breeding animals), an increase in false positives may be tolerable if all events of interest are identified. In contrast, in most commercial production systems where the value of individual animals is lower, producers may prefer to reduce the number of false positives at the expense of potentially missing some events of interest (Dominiak and Kristensen, 2017).

As shown in Table 8.5, inclusion of the simple requirement for two consecutive lambing alerts decreased the number of false positives from 64 to 22. This scenario also narrowed the window of detection, with a further one and two animals having the first alert within ±1 (Animal 5) or ± 3 h (Animals 1 and 11), respectively. However, the restriction did increase the overall failure to detect a lambing event from one (Table 8.4) to two (Table 8.5). Practical application of the latter model might be found in a commercial production system where individual animal monitoring is less valuable and where refining flock-scale management brings economic return. For example, a producer may choose to be alerted when the flock has commenced lambing, applying this knowledge to initiate a flock-wide physical monitoring program (i.e. visual observation). This may be useful for flocks without adequate breeding records or if the flock are at known risk of adverse parturition events such as dystocia and/or prolapse (Hinch and Brien, 2014). Another example application might be the use of flock-level alerts for warning of increased lambing numbers, especially if the lambing events are occurring during periods of increased predation or adverse weather. In the current study, we have modified the model to sit at the end of two extremes and there is likely a mid-point where the applications are optimised. Exactly how the model sensitivity should be refined requires ample thought and should be contemplated in further research. This has also been discussed by Dominiak and Kristensen (2017) where customisation of detection models is advised depending on two things: firstly, the priorities of the producer; and secondly, the purpose of the model application (e.g. cost optimisation vs health or welfare improvement).

8.4.3 Understanding the limitations and reasons for model failure

A key consideration for successful commercial application, is the ability of a detection model to generalise across a number of individuals. However, based on the results of the current study and our understanding of the variability between individual animal behaviour (Holmes, 1976, Bickell et al., 2010, Lynch et al., 1992), this remains a challenge. One of the major limitations of many ML algorithms is the inability to interpret their internal 'rules' used to categorise data (Nathan et al., 2012). In the case of the current SVM, although the model has a relatively high accuracy for differentiation between lambing and non-lambing animals, the requirements for classification, including thresholds and/or the required number of features for alert cannot be easily determined. To explore the ML models further, three of the animals' feature traces are reported in detail (Figure 8.3). Through this we can make inferences as to how the ML might be working and identify potential reasons for model failure.

As an example of an individual animal for which the classification algorithm worked well, Animal 9 (Figure 8.3a) shows obvious peaks in the data at the time of lambing, particularly for CP and MDP. This suggests Animal 9 was distant from the main flock at the time of parturition (peak CP 8.4 m at Hour 0; peak MDP 194.9 m at Hour +1). In contrast, the classification algorithm did not work well for Animal 6 (Figure 8.3b), and CP and MDP actually fell at the hour of lambing, suggesting the ewe was not separate from the flock at this time (peak CP 4.0 m at Hour -3; peak MDP 85.2 m at Hour +3). Given that isolation behaviour was evident in the training dataset (Table 8.3), the ML appears to rely on this expected behaviour for correct alerts (Animal 9) and hence cannot identify lambing when this expected behaviour does not occur (Animal 6). This is further supported by the earlier peaks in CP and MDP for Animal 6 which correspond to early false positives. Of note, given that the MDP.Mean did not peak for Animal 9 at lambing, it appears that the ML does not require all three social metrics to increase for an alert to occur.

Examination of the PC feature reveals a similar scenario. That is, for Animal 9 (Figure 8.3a), an increase in PC behaviour at lambing was evident, and was accompanied by correct lambing detection. In contrast, Animal 6 (Figure 8.3b) demonstrated decreased PC at the time of lambing, which again contributed to the model missing the event detection. For both Animal 9 and Animal 6, earlier peaks in PC behaviour were evident prior to parturition. However, for

Animal 9 these were not accompanied by peaks in the remaining features whereas for Animal 6, the increased PC behaviour was also accompanied by peaks in social isolation, ultimately resulting in a number of false positive alerts. Thus, while is appears that the model may not require all three measurements of social isolation for an alert to occur, the algorithm appears to be sensitive to changes in behaviour when they occur at the same time as other key fluctuations. Although the introduction of the stricter detection criteria did reduce these false positives somewhat, it does not mean that the more 'unexpected' patterns of behaviour for individual ewes can be mitigated.

Animal 2 is an example of a ewe that displays early false positives followed by correct lambing alert. As shown in Figure 8.3c, false positives were evident on the day prior to birth (Study Day 7) due to a peak in both CP and MDP. This may reflect variable social activity of this ewe or it may demonstrate early social isolation and/or a time of birth site selection or nesting behaviour (Echeverri et al., 1992, Alexander, 1988). If this could be isolated, this behaviour could be used as a powerful predictor of impending parturition, providing producers with the opportunity to act on an alert prior to the event occurring. However, as isolation at parturition is inconsistent in domestic sheep (Alexander, 1988), the ability to generalise this behaviour across numerous individuals is unlikely.

8.4.4 Recommendations for future research

In this study, the method of data labelling was fixed for the training dataset (i.e. Hours ± 1 labelled as 'lambing'; 3h in total). However, as parturient behaviour is known to vary between animals (Holmes, 1976, Bickell et al., 2010), this labelling protocol may have been too rigid for the natural inconsistencies that exist. Although the impact of labelling protocol is valid, it should also be noted that the variation in lambing behaviour may also be a product of normal diurnal changes (e.g. normal grazing patterns). For example, parturition records in this study were collected at various times throughout the observation period, depending on when the animals lambed. This means that ewes that gave birth during the normal peak morning or evening grazing periods were labelled identically (and thus indistinguishable), to those that lambed during normal periods of resting or rumination. Given that spatial behaviour is known to change throughout the day (Gonyou, 1984), it is possible lambing behaviour in this study is confounded by time itself, thus resulting in higher variability (and wider density plots) for

the lambing day data (Figure 8.2). In contrast, the non-lamb data are represented by two 24-h periods, one 3 days prior to lambing and one 3 days after lambing, and thus will naturally contain data that are representative of the entire diurnal pattern. Further research should be conducted to determine the impact of the labelling protocol, potentially using detailed individual observations as a method of identifying the commencement of lambing behaviour. In addition, research should also be conducted using data from ewes that lamb overnight, to ensure the patterns in behaviour are consistent across a number of contexts.

Although this study has presented an adequate method of simulating online parturition detection, application of this knowledge in commercial systems still requires further thought. For example, the use of embedded processing and edge computing has been suggested for commercial application, given the energetic costs of data transmission (Vázquez-Diosdado et al., 2019). However, in the current study, the most valuable features for parturition detection were those that compared the individual ewe's behaviour within the wider flock context (i.e. MDP, MDP.Mean, CP, PC.Mean) or relative to its own past behaviour (PC.24h). In the latter instance, edge computing is valid as previous data could be stored on the device and used as a comparative metric to current readings. In the former example, however, comparison with other ewes is necessary and would require transfer of data to a central repository for parallel processing with all other devices. Given this, future research should investigate how the data can be condensed prior to transmission and still be useful for comparison to other ewes.

8.5 Conclusion

The outcomes support the use of integrated sensor data for ML-based prediction of parturition events in grazing sheep using SOB data as a proxy for near-real-time detection. This is the first known application of ML classification for the detection of lambing in pasture-based sheep. Four main features generated from GNSS and accelerometer data were identified as the most useful for lambing prediction: MDP.Mean, CP, MDP and PC. Using these features, information on ewe social activity and frequency of changing posture is used to detect if a lambing event has occurred within the previous hour. Though weather data were not used in the final model, all sensor types were well represented across the ROC curve analysis, thus highlighting the benefits of sensor integration. A surprising outcome of the current study was the success of applying the GNSS data for parturition detection in isolation,

without the added integration of the accelerometer data. This suggests the that application of GNSS over a longer time period and with novel comparisons to flock-level behaviour are important to adequately represent the value of this sensor type.

In the current study, the ML models were able to detect lambing events with reasonable accuracy. This success depended on variation in individual animal behaviour and highlights the sensitivity of the ML model for detecting a change in key behaviours. Further research should consider the use of this model (or similar) for detection of adverse lambing events. This would have significant impacts on the ability to remotely monitor animal welfare using on-animal sensors and is a logical extension of the information presented in this paper.

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Conflicts of interest

The authors declare there are no conflicts of interest.

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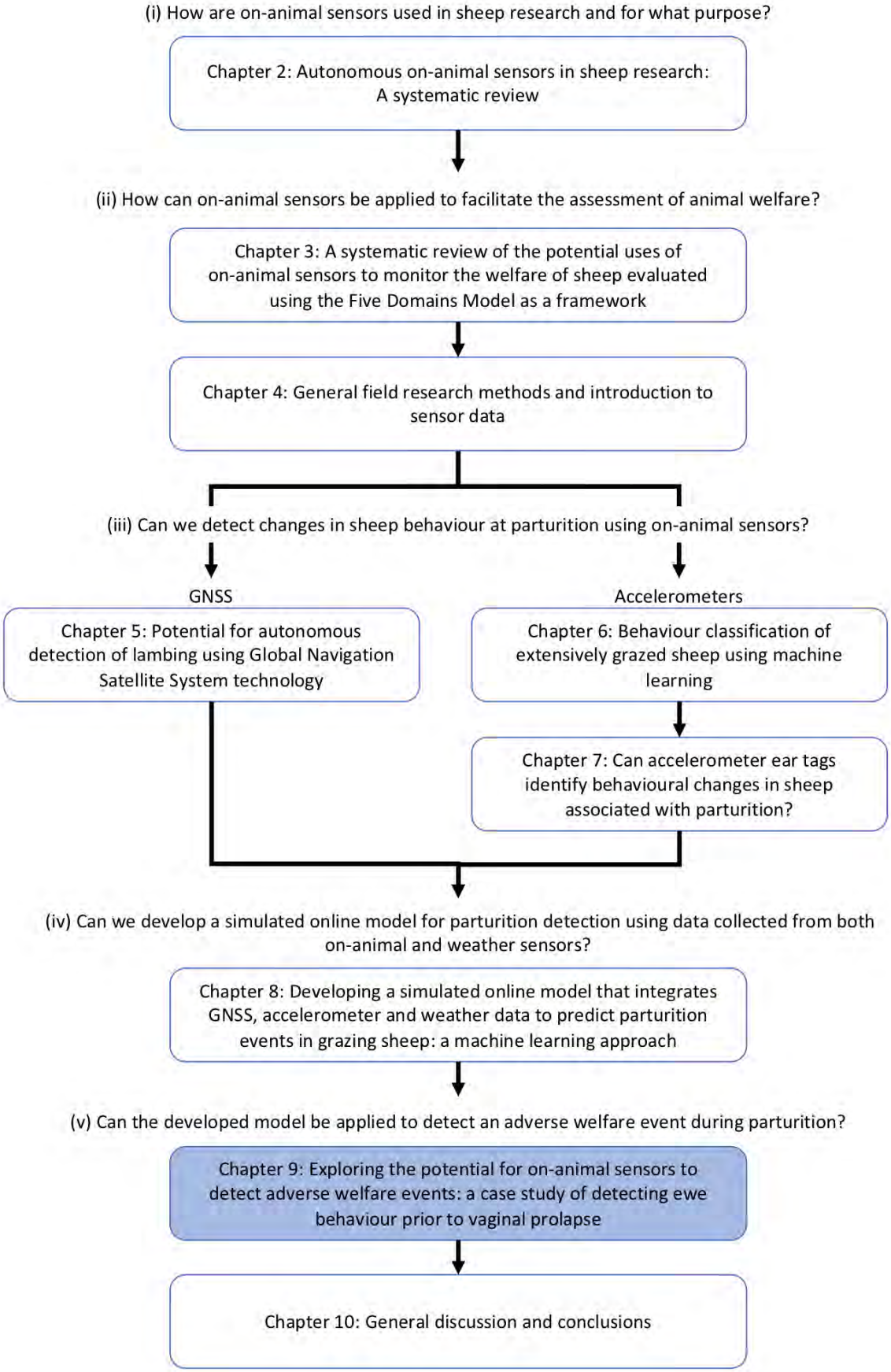
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Chapter 9. Exploring the potential for on-animal sensors to detect adverse welfare events: a case study of detecting ewe behaviour prior to vaginal prolapse

Fogarty E.S., Swain D.L., Cronin G.M., Trotter M. Exploring the potential for on-animal sensors to detect adverse welfare events: a case study of detecting ewe behaviour prior to vaginal prolapse.

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Overview

The focus of this thesis so far has been on detecting the parturition event as a necessary component of any welfare monitoring system. This chapter explores how a sensor system might be applied to detect an adverse lambing event with associated impacts on animal welfare. Data was available for two parturition scenarios: (i) an adverse birth event (vaginal prolapse); and (ii) typical birth events where labour progressed with no issues. As data were only available for a single ewe that experienced prolapse, the chapter has been prepared as a proof of concept paper. The objective of this chapter was to explore if the ewe that experienced vaginal prolapse exhibited common precursor parturition behaviours to ewes that progressed through a 'normal' birth event, to compare the alert profiles of each and then explore how this might be practically applied in an animal monitoring protocol utilised in a commercial environment.

This manuscript has been prepared as a short communication for submission to Animal Welfare. It appears in this thesis in the format required by the journal. Data presented in this chapter was collected during the 2017 field trial.

Exploring the potential for on-animal sensors to detect adverse welfare events: a case study of detecting ewe behaviour prior to vaginal prolapse

Running Title: Autonomous detection of prolapse in grazing ewes

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Abstract

Parturition is a critical period for the ewe and lamb, and the incidence of dystocia has known impacts on lamb and ewe welfare and productivity. Current methods of dystocia monitoring are mostly conducted through visual observation. Novel approaches for monitoring have also been suggested, including the application of on-animal sensor technologies for remote surveillance of parturition success. This short communication explores how the use of sensor-based parturition detection models can be applied for detection of adverse and successful parturition events, respectively, in pasture-based sheep. Specifically, the alert profile of a single ewe that experienced vaginal prolapse is reported, and compared with the alert profiles of 13 ewes that experienced typical birth events. Though the ewe that experienced vaginal prolapse exhibited some common precursor alerts similar to ewes that progressed through a typical birth event, the overall alert profile was markedly different for the prolapsed animal, with an increased number of alerts occurring from five days prior to the prolapse event. As successful parturition has significant welfare and productivity outcomes, application of these research findings in a commercial system could greatly improve current methods of welfare monitoring at lambing.

Keywords

Accelerometers, animal welfare, GNSS, machine learning, on-animal sensors, sheep

9.1 Introduction

Parturition is a critical period for the ewe and lamb, with implications for welfare and productivity (Alexander 1980, 1988). It is during this high-risk period that ewes may experience dystocia (abnormal or difficult birth), which is a known cause of lamb mortality (Hinch & Brien 2014; Refshauge et al 2016). Dystocia can also impact on the ewe, with adverse consequences such as pregnancy toxaemia and physical trauma, including vaginal or uterine prolapse (Scott 2015).

Current techniques for dystocia monitoring in commercial systems are limited to periodic visual assessment, usually from a distance (Welch & Kilgour 1970). However, large flock sizes, limited labour and extensive terrain may make inspection challenging (Waterhouse 1996). In addition, as human presence can increase the risk of mismothering (Alexander 1980), many sheep producers may minimise the time spent closely observing their animals to reduce interference. Sheep are also characteristically stoic, tending to hide signs of pain and discomfort (Doyle 2017). Thus, the ability of the producer to successfully identify adverse parturition events such as dystocia may be limited using visual observation alone.

A potential solution to this issue is to deploy on-animal sensor systems for remote surveillance of animals (Waterhouse 2019). While the application of sensors for parturition detection has been reported for sheep (Chapter 8) there are few, if any, publications exploring how sensors might be used to detect adverse parturition events such as dystocia. Furthermore, there has been no consideration of how these might be integrated into a sensor-based system for commercial application.

This short communication reports a case study of a single ewe that experienced an adverse parturition event (vaginal prolapse) and explores how behavioural data from on-animal sensors might be integrated with routine visual inspections to optimise intervention and improve livestock welfare and production outcomes. Although a formal comparison of the behavioural differences between adverse and typical parturition events would be ideal, data were only available for a single prolapsed ewe, and thus the results are presented as a proof of concept. The early-warning symptoms of vaginal prolapse are consistent with the early signs of labour (Scott 2015). Therefore, we applied a previously developed parturition

detection model (Chapter 8) to explore if the ewe that experienced vaginal prolapse exhibited common precursor parturition behaviours to ewes that progressed through a typical birth event. We hypothesised that ewes experiencing prolapse will exhibit heightened parturition behaviours such as restlessness, and that these will appear as outlier data compared to ewes progressing through a typical birth event.

9.2 Materials and methods

A complete explanation of the materials and methods is available in Chapter 8.

9.2.1 Location and use of animals

All research procedures and use of animals were approved by the Massey University Animal Ethics Committee (approval number MUAEC 17/59). The study was conducted at a commercial mixed enterprise farm in North Canterbury, New Zealand (42°56’47’’S, 173°11’43’’E) from 30 September (Study Day 1) to 13 October 2017 (Study Day 14). Mixed-age ewes (n = 40; Merino and Merino-cross) were selected from the larger commercial flock based on estimated lambing date (confirmed by ultrasound as per normal farm practice). Ewes were kept in a 3.09 ha paddock with *ad libitum* access to pasture and water.

Of the 40 ewes, 26 were excluded from the current study due to sensor failure (n = 5), failure to lamb during study period (n = 13), or previous use in model development (n = 8). The remaining 14 ewes are the focus of this study with one of these being the subject of the adverse event and 13 acting as examples of typical parturition. The case study ewe was identified as prolapsed between 0700 h – 0730 h on Day 14. Once identified, the farm manager was alerted and the animal was humanely euthanised at 0900 h. This was conducted according to normal farm practice. The lambs were not able to be recovered.

9.2.2 Instrumentation and observation

Ewes were fitted with GNSS loggers (Mobile Action, Taiwan) attached to neck collars and accelerometers (Axivity AX3, Axivity Ltd, Newcastle, UK).

Visual observations were carried out on each day of the trial from 0730 h – 1230 h and 1330 h – 1730 h (± 30 min) for the purpose of recording parturition-related activities.

9.2.3 Data management and analysis

A full description of the data management and analysis is reported in Chapter 8. Briefly, selected features from GNSS and accelerometer data were integrated and analysed using a Support Vector Machine (SVM) to classify each animal as expressing either lambing or non-lambing behaviour on an hourly basis. This analysis was undertaken in the context of a simulated online parturition detection model with the proposed system able to detect 90.9 % of lambing events within ± 3 h (Chapter 8).

The SVM was applied to the 13 ewes that progressed through typical parturition and a single ewe that experienced an adverse parturition experience (vaginal prolapse). This ewe was the only animal to experience an adverse parturition event during the trial period.

9.3 Results and discussion

9.3.1 Comparison of parturition alerts for the case study ewe compared to typical animals

The results of the parturition detection model application are presented in Table 9.1. As shown, the algorithm correctly alerted to the day of lambing for 12 of the 13 ewes that experienced a typical birth process. The remaining animal (Animal N) did not report any lambing alerts. Three ewes that experienced a typical birth process also reported a false positive on the day prior to recorded lambing (Animals B, C and D), followed by the subsequent accurate alert on the day of lambing.

The case study ewe (Animal A) demonstrated a markedly different alert profile compared to the other sheep. This individual reported an alert on both Days -5 and -4 and then again on Days -2, -1 and 0. The alerts on Days -2 and -1 were consistent with the other sheep that experienced typical parturition (particularly Animals B, C and D), and are likely to reflect typical pre-partum behaviours (Scott 2015; Fogarty et al 2020a; Fogarty et al 2020b). In contrast, the alerts generated on Days -5 and -4 are less obviously related to the observed prolapse event. Although false positive alerts have been reported from 7 days prior to birth using this same model (Chapter 8), it is feasible that these behaviours were indicative of impending prolapse. It is possible that the ewe began experiencing difficulties up to 4 or 5

days prior to actual prolapse, however, this cannot be confirmed. Future research is required to determine if this pattern of behaviour is consistent.

Table 9.1. The timeline of alerts reported for parturition for the case study ewe experiencing prolapse (Animal A) and 13 other ewes experiencing typical birthing events (Animals B – N). For Animal A, Day 0 refers to the day when prolapse was identified. For Animals B – N, Day 0 refers to the day of recorded lambing. Alerts are noted as 'X'. Lack of alerts are noted as '-'.

ID	Type of birth	Day around lambing						Notes
		-5	-4	-3	-2	-1	0	
A	Prolapse	X	X	-	X	X	X	Alerts on five days. Prolapse identified and animal euthanised on Day 0
B	Typical	-	-	-	-	X	X	False positive on the day prior to lambing. Subsequent correct detection on Day 0
C	Typical	-	-	-	-	X	X	False positive on the day prior to lambing. Subsequent correct detection on Day 0
D	Typical	-	-	-	-	X	X	False positive on the day prior to lambing. Subsequent correct detection on Day 0
E	Typical	-	-	-	-	-	X	Correct detection of day of lambing
F	Typical	-	-	-	-	-	X	Correct detection of day of lambing
G	Typical	-	-	-	-	-	X	Correct detection of day of lambing
H	Typical	-	-	-	-	-	X	Correct detection of day of lambing
I	Typical	-	-	-	-	-	X	Correct detection of day of lambing
J	Typical	-	-	-	-	-	X	Correct detection of day of lambing
K	Typical	-	-	-	-	-	X	Correct detection of day of lambing
L	Typical	-	-	-	-	-	X	Correct detection of day of lambing
M	Typical	-	-	-	-	-	X	Correct detection of day of lambing
N	Typical	-	-	-	-	-	-	Detection failure – no alerts provided

9.3.2 Application for improved animal management

The results of the current study indicate the ability to detect parturition-related behaviour in pasture-based sheep, and the capacity to extend this application for an indication of prolapse. However, while the alert to parturition and prolapse is an important proof of concept, it is of little value if it cannot be integrated into a viable management system.

To explore this further, a conceptual flowchart was developed (Figure 9.1) to demonstrate how the individual alerts could be interpreted to enhance the likelihood of observing and/or intervening in an adverse event. As depicted in (Figure 9.1), once an alert is triggered, the producer would inspect the flock within a reasonable timeframe (e.g. within 24 h), visually confirming the presence or absence of new lambs and thus designating the alert as 'true positive' or 'false positive'. If a parturition event was confirmed (i.e. true positive), application of the model for this ewe would cease, and no further action would be required. Conversely, if the alert was a false positive, this information would be integrated into the system for further analysis. If an alert was generated for two days but the producer was unable to identify a lamb for the ewe in question, this would escalate the ewe to a potential-risk status, and subsequently continued observation in the paddock is recommended. Once a third alert was generated without the presence of a lamb, the ewe's risk status would be escalated further to encourage separation for closer inspection.

In the instance of the case study ewe, the ewe would have been identified for closer inspection after Day -4 (Escalation One) and then again after Day -2 (Escalation Two). If this process was applied and if the escalation status was genuine, it is feasible that the ewe could have been targeted for separation and close monitoring, potentially allowing intervention and/or prevention of prolapse progression. At the very least, the escalation after Day -2 would have enabled rapid detection of the prolapse condition and reduced the animal's suffering. It is also worth noting that the case study animal received early treatment in this study due to the presence of the observer. Under normal commercial conditions where observation is less frequent, it is possible that the ewe would not have been identified for a longer period and therefore suffered for a longer period of time.

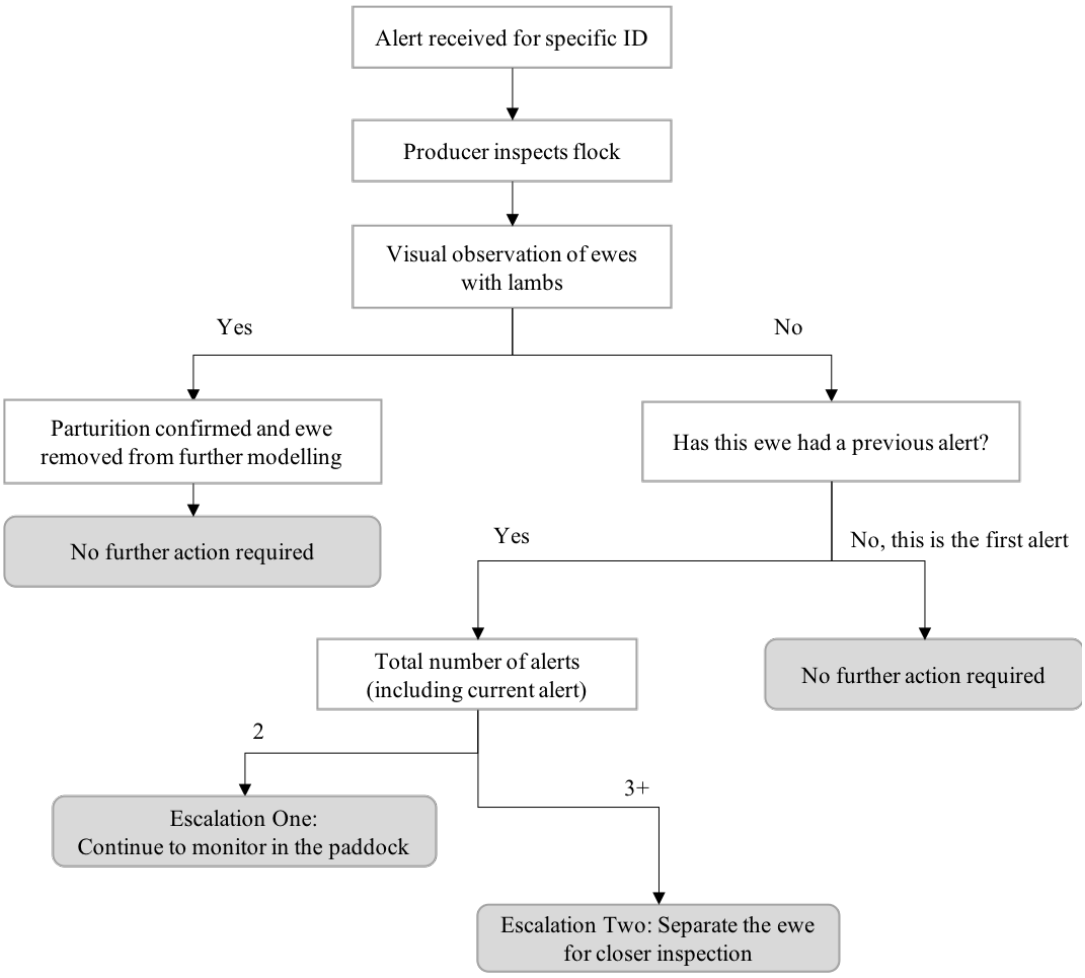

Figure 9.1. Conceptual flowchart detailing commercial application of predictive type models for improved surveillance of ewes during parturition and identification of at-risk ewes

9.4 Animal welfare implications

Successful parturition has a significant and lasting impact on animal welfare and productivity outcomes in sheep production systems (Brien & Hinch 2010). Identification of animals either before or during a disease state could greatly improve survival, allowing producers to address areas of concern before they become an issue. This would not only improve on-farm welfare, it would also result in increased productivity and cost-benefits for the farmer (Trotter 2013; Trotter et al 2018). Similarly, when animals are detected to be in an untreatable disease state, the length of time spent suffering could be reduced through earlier detection. As public concern for animal welfare continues to rise (Dawkins 2017), it is also possible that a push for autonomous welfare assessment will come from outside the industry, increasing the current requirements for transparency and adequate documentation (Smith et al 2015). There is

already a shift in business behaviour, for example targeted marketing of “certified ethical” wool (ZQ Natural Fibre 2019), promoting animal welfare and traceability as major company values.

As with any novel monitoring system, a number of critical issues remain which need to be considered. For example, using the proposed method, the model of response requires additional investment in time to undertake closer individual inspections, and where necessary, invoke management actions. Furthermore, knowledge of negative welfare status changes the duty of care of producers, effectively increasing their responsibility to act on an alert once they become aware of any issues (Waterhouse 2019). Considering this, further research into how sensor-based welfare systems can be practically applied across livestock production systems is required, including ways that satisfy all parties involved.

Although the use of a single animal may be regarded as a limitation of this study, it is feasible that the outcomes of this research could be further applied to other adverse welfare events including abortion, neonate death or predation. Furthermore, as the parturition detection model applied in this study only uses measures of social behaviour and posture change to detect parturition events, it is possible that a model that incorporates more features would also be valuable. This warrants further investigation using a larger sample number.

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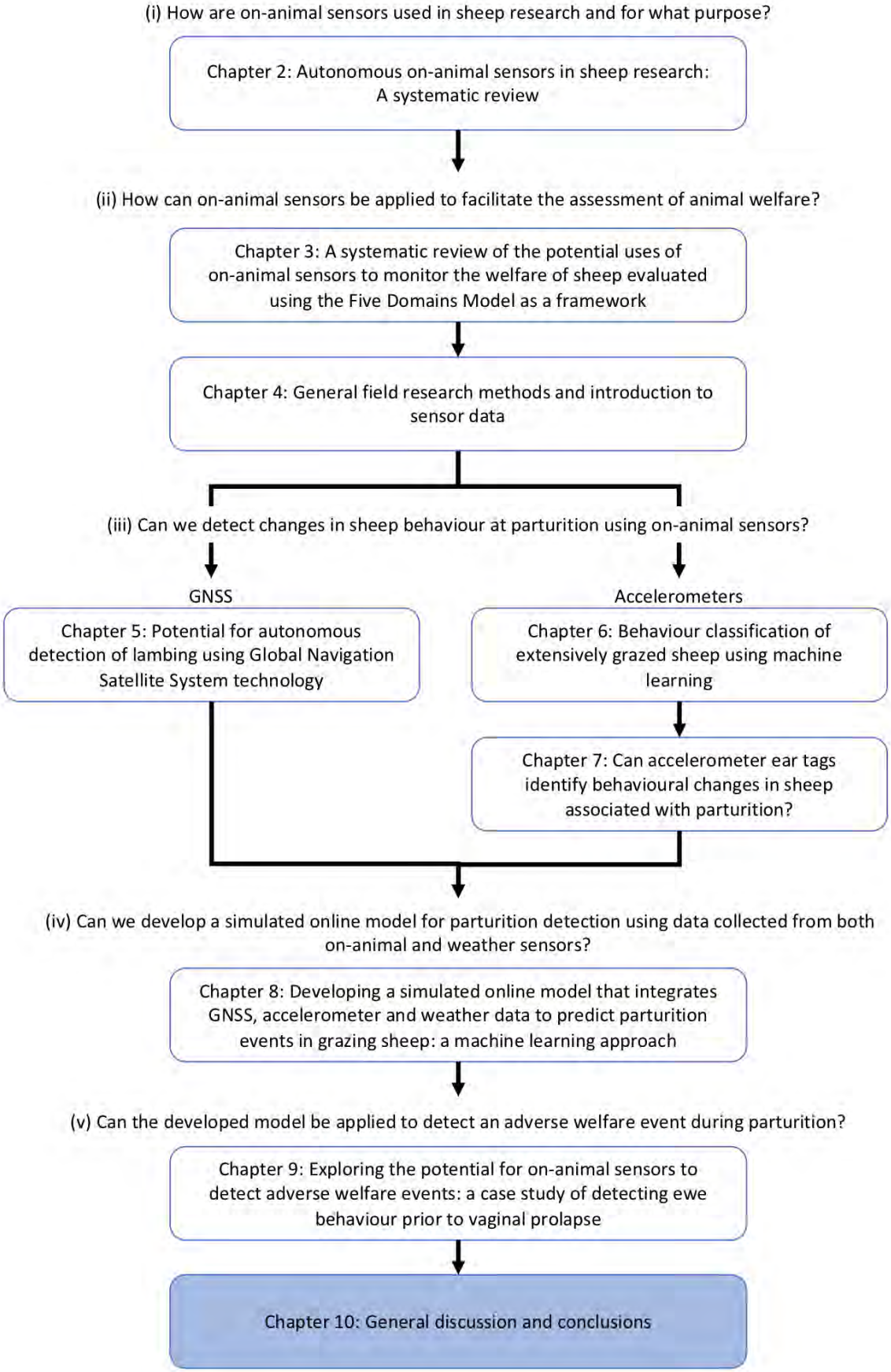
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Chapter 10. General discussion and conclusions

10.1 Research summary

This thesis reports on the application of GNSS and accelerometer sensor technologies and explores their value for autonomous monitoring of sheep in grazing systems. Focussing on parturition as a period of critical welfare risk, this thesis has: firstly, highlighted the ability of each technology to detect changes in ewe behaviour associated with lambing; and secondly, explored how these technologies' integration might be used for near-real-time detection of both successful and adverse lambing events. The specific research questions explored in this thesis were as follows:

(i) How are on-animal sensors used in sheep research and for what purpose?

(ii) How can on-animal sensors be applied to facilitate the assessment of animal welfare?

(iii) Can we detect changes in sheep behaviour at parturition using on-animal sensors?

(iv) Can we develop a simulated online model for parturition detection using data collected from both on-animal and weather sensors?

(v) Can the developed model be applied to detect an adverse welfare event during parturition?

A brief summary of how each piece of research has contributed to these original objectives follows.

10.1.1 The use of on-animal sensors in sheep research

As detailed in Chapter 2, a number of different technologies have demonstrated application for sheep research, including location sensors (e.g. GNSS, contact loggers), motion sensors (e.g. accelerometers, pitch and roll sensors, mercury tilt devices) and physiological sensors (e.g. HR monitors, oxygen sensors, respiration sensors). The most common research objectives of papers using these technologies were to quantify sheep behaviour and/or to validate the sensor data itself. Other more minor applications included environmental management and health monitoring. Of interest, the use of on-animal sensors specifically for welfare assessment was not commonly reported. This was attributed to the prerequisite need to validate the use of sensors for sheep research, before extending their use to more complex

applications such as welfare assessment. Overall, this represented a large gap in the literature and highlighted a need for further research.

Of note, this paper contains publications up to and including May 2017. However, a number of other relevant publications have been produced since this time. To quantify this, a count of references made throughout this thesis from June 2017 until 2020 was conducted. For consistency with Chapter 3, websites, software and general reports were excluded. A total of 24 additional references were counted throughout the thesis. Of these, 12 publications were focused on sheep, four were focused on cattle and three focused on other species (i.e. pigs, horses). Four publications were referenced for analytical or methodological purposes and one concentrated on general concepts of animal welfare.

10.1.2 On-animal sensors for assessment of animal welfare

On-animal sensors have been advocated as a potential method of improving on-farm animal welfare monitoring (King, 2017, Morris et al., 2012). However, based on the results of the initial review, there were few practical examples of this in the literature. Hence, in the second literature review (Chapter 3), the potential for welfare monitoring by on-animal sensors using the Five Domains (FD) Model as a reference framework was explored. The review identified three types of sensors that are able to address the major aspects of welfare [Nutrition, Environment, Health, Behaviour, Mental State (Mellor and Beausoleil, 2015): location sensors, motion sensors and physiological sensors. Of the five welfare domains, Behaviour was the most easily monitored using sensor technology, followed by Nutrition, Environment, Health and Mental State. Based on the outcomes of Chapters 2 and 3, two sensor types were selected for use in this PhD program; GNSS and accelerometers. These were selected based on the availability of research-grade forms and the technology's proven potential for detecting key behaviours of interest. While physiological sensors also demonstrated obvious potential for application, operational versions of these sensors were ultimately considered too difficult to access for this program. These would benefit from further research, particularly as they appear uniquely able to monitor aspects of the Mental State Domain.

10.1.3 Detecting changes in sheep behaviour at parturition using on-animal sensors

To facilitate welfare monitoring at parturition, it is essential to understand each of the selected technologies in isolation, before attempting an integrated sensor-based approach. Hence, the research presented in Chapters 5 to 7 focused on the detection of parturition using each sensor type independently.

In Chapter 5, the feasibility of GNSS for detecting behaviour change at parturition was presented. Overall, GNSS derived data was able to monitor daily changes in behaviour, including increased minimum daily speed, increased mean distance to peers and reduced spatial utilisation of the paddock. Despite trends for behaviour change at an hourly scale, GNSS derived data did not appear sufficient to detect sub-day changes in behaviour associated with lambing at the time of publication. This was later contradicted in Chapter 8, where novel GNSS metrics (CP and MDP.Mean) were amongst the most important features for lambing detection at this time scale. This suggests that the benefits of GNSS lie in the comparison between individual ewe data and the rest of the flock, rather than more simple metrics collected from each ewe in isolation (Chapters 4 and 8). It is worth noting that these novel features were developed as a direct consequence of an in-depth exploration of the raw data, coupled with an improved understanding of animal behaviour developed throughout the project. There are likely to be other novel features that may become important in other environments or when exploring other applications of sensors. This is an area ripe for further research.

To assess the viability of accelerometer-based behaviour monitoring at parturition, a similar study was conducted in Chapter 7. Prior to this however, the accelerometer data was processed using ML to classify the data into known behaviours. This was important to ensure interpretability and to allow for comparison with published behaviour patterns. Presented in Chapter 6, ML classification was able to detect four common behaviours (grazing, lying, standing, walking), with an accuracy of 76.9% using a 10 s epoch. When the behaviours were grouped by activity (i.e. active or inactive) and posture (i.e. upright or prostrate), accuracy increased to 98.1% and 90.6%, respectively, using a 30 s epoch. Based on the differences in epoch performance across different behaviours, application of dynamic epochs may represent a method for improved ML classification. For example, use of 30 s epoch to detect

overall activity and a 10 s epoch to detect the specific behaviour. This would be particularly important for short-duration behaviours (e.g. standing up, lying down, head shake) which are often misclassified as an intermediate activity when averaged over longer epochs (Chen and Bassett, 2005). Dynamic epochs could also be used to combine features summarised over different lengths (e.g. 30 s epoch of MV and a 5 s epoch of SD_x) and represents another area of novel research.

Using the ML-classified data, accelerometers demonstrated a capacity for detecting daily and hourly changes in sheep behaviour at parturition. On a day scale, grazing and lying behaviours decreased in favour of standing and walking. On an hourly scale, changes in behaviour were also detected. This was particularly marked for walking behaviour and frequency of posture change, which both significantly increased in the hours immediately surrounding parturition. Although the predictive value of the latter two features was significant, the research concluded that application of these findings for lambing detection should still incorporate a multivariable approach. This was considered particularly important since behaviour is impacted by a number of factors outside of parturition [e.g. walking behaviour may be impacted by husbandry practices (Jongman and Hemsworth, 2014)]. Assessment of changes at both an individual and flock level was also a recommendation for further investigation. As this technology continues to be developed, the demonstrated ability to monitor behaviour on a finer temporal scale makes this sensor type an obvious contender for integration into a commercial system. Of note, this research has highlighted the challenges associated with accelerometer data interpretation, with this approach requiring transformation into useful behaviour categories prior to interpretation. It is possible that further development of algorithms may not require this intermediate step to produce alerts for the human end-user. However, this work has highlighted the significant difficulties associated with data interpretation that often requires some measure of 'ground-truthing' to ensure correct interpretation.

10.1.4 Development of a simulated online model for parturition detection using integrated sensor data

Using the knowledge gained in Chapters 5 and 7, it is clear that GNSS and accelerometers have potential for monitoring sheep behaviour at parturition. However, to ensure commercially-relevant application, it was important to develop an analytical framework that

processes the data as it becomes available for near-real-time alerts. The outcomes of this work are detailed in Chapter 8, and successfully demonstrate the use of ML-based detection of parturition using integrated GNSS and accelerometer data. Although the integration of weather data were also explored, this was not incorporated into the final model. This was likely reflective of the relatively mild weather conditions experienced throughout the field program and underplays the potential impact of climate on animal behaviour. Considering the known impact of weather on many aspects of behaviour, e.g. sheltering (Broster et al., 2012, Alexander et al., 1979), social activity (Doyle et al., 2016), and grazing behaviour (Thomas et al., 2008), further investigation of weather data integration into event detection models is recommended.

Overall, the final model was able to identify 90.9% and 81.8% of lambing events within ± 3 h of known birth, with accuracy depending on the use of different alert criteria. Accuracy also differed between individuals, with some ewes having consistently correct or consistently incorrect lambing alerts occurring. Based on the results documented in Chapter 5 and the previous limitations identified in GNSS monitoring of parturition, a surprising outcome of this chapter was the model's performance when trained using GNSS data alone. This highlights the benefit of GNSS application when individual ewe metrics are compared to the flock.

This chapter raised an interesting issue with regard to the requirements of reporting events and the need for balancing sensitivity (true positive rate) and specificity (true negative rate) in model application. In normal commercial situations, generation of the right alert at the correct time is crucial. Conversely, false positives are time-consuming and reduce trust in the system (Dominiak and Kristensen, 2017). Somewhat frustratingly, however, the definition of 'allowable' false positives is usually on a case-by-case scenario, for instance higher-value seed stock animals compared to lower-value production stock. 'Allowable' false positives are also impacted by welfare impacts, such as possible detection of adverse parturition events (like dystocia) requiring immediate action, compared to detection of reduced feed intake requiring less urgent investigation. In this chapter, including the requirement for two consecutive lambing predictions resulted in a substantial decline in the number of false positive alerts generated. However, the number of failed alerts also increased. Refinement of model criteria should be researched further, including the potential application of a 'sliding scale' to tune the model to each particular circumstance. The application of a multi-stage decision process

is another possibility, where the combination of machine-prediction and human validation could be of value. This was explored further in Chapter 9.

10.1.5 Application of the developed model for detection of an adverse welfare event

To explore the feasibility of monitoring parturition success as a measure of animal welfare, the model developed in Chapter 8 was applied to another group of animals in Chapter 9. The results suggest that ewes with repeated alerts that are not followed by parturition may be at-risk of an adverse event and should be inspected. As data was only available for a single animal, this chapter represents a proof of concept for remote monitoring of welfare at parturition.

This chapter raised another key issue with reference to the use of on-animal sensors for welfare monitoring, whereby true autonomous application may not be possible if the model requires producer input in the form of visual inspection, confirmation of an event occurring and subsequent management action. The potential change in the producer's duty of care is another important consideration for commercial application; requiring collaborative input by producers, commercial companies, levy agencies and lawmakers alike.

10.2 Study limitations

There were a number of limitations of the research presented in this thesis. First, due to the use of sensors in a commercial pasture-based setting, there was limited ability to collect detailed observations of the animals either during lambing or at other times. Other similar issues included technical difficulties around time stamp matching of video which was a particular problem in the 2017 field campaign. Conduct of the field campaigns on a commercial property (as opposed to a research station with purpose-built facilities), also meant that it was impossible to view the animals overnight, leading to a number of 'missed' lambing events (See Appendix B and C). This restricted the later use of these datasets.

A major theme presented throughout this thesis is the development of analytical processes suitable for commercial exploit. As such, a key research focus was the development of generalised models that can be used across a number of animals. As previously identified in Chapter 4, although broad patterns of behaviour are evident for the majority of animals,

differences between individuals were also evident. This is further discussed in Chapter 6, where ML accuracy for the highest and lowest performing animals ranged between 54.8 % and 90.8% for Ethogram One. To account for this, subsequent model development in Chapter 8 utilised completely independent groups of animals to train and test the model. This made it possible to examine common behaviour patterns associated with parturition, even when using animals from different lambing seasons. Although the results in Chapter 8 broadly support generalisation across different animal groups, a larger proportion of false positives (n = 64) was evident, suggesting some incongruence between the two flocks. By comparison, when the model was applied to another group of animals within the same lambing season (Chapter 9), this resulted in a considerably smaller number of false positives (n = 3), which only occurred for the prolapsed animal. Based on this, the approach used in the current research can be considered limited, with potential improvements if model training is conducted using data from a similar context (e.g. the same lambing season). The commercial feasibility of this is still unknown, however, as it would require the producer to collect detailed observations of each individual animal.

One final limitation is the focus on sensor-based detection of parturition behaviour, with minimal discussion on the importance of other welfare Domains. Arguably, we have used behaviour monitoring not only for assessment under the Behaviour Domain, but as a means of collecting information on the ewe for application across the other Domains [e.g. detection of functional impairment (i.e. prolapse) as an example of the Health Domain; the inferred presence of pain or debility or being maternally rewarded as an example of the Mental State Domain; (Mellor and Beausoleil, 2015)]. Furthermore, we attempted to address aspects of the Environment Domain by including weather data in Chapter 8, although this was not incorporated into the final model. Based on the results of Chapter 3, the use of sensor data for autonomous welfare monitoring is complex. This is similarly reported in published literature, whereby the integrative nature of body functions means that the animal's state, their affective experience and the external circumstances they experience inevitably interact across a number of Domains (Mellor, 2017, Mellor and Beausoleil, 2015). The results presented in this thesis, although somewhat limited, can also be considered as important foundational knowledge for on-animal sensor-based welfare assessment using parturition as a case study.

10.3 Application of this research

The use of parturition detection models developed throughout this thesis have potential production implications. For example, individual lambing alerts (either during or after birth) could serve to facilitate targeted inspection of ewes and lambs following birth, particularly for high value production systems (e.g. seed stock breeding animals). Alternatively, flock-level alerts could be used to initiate a physical monitoring program by visual observation, particularly if flocks are at known risk of dystocia, prolapse or other adverse scenarios. Other production applications may include early inspection tagging of neonate lambs, movement of ewe/lambs from high-risk locations e.g. near cliffs, or for identification of potential mismothering if multiple ewes are lambing in the same area. Valuable breeding information could also be collected, including identification of ewes with desirable maternal behaviour e.g. ewes that remain at the birth site, the intensity and duration of maternal grooming and reduced time to first suckling event (Hinch and Brien, 2014). This could then be applied more broadly to Estimated Breeding Values (EBVs) for faster genetic gain.

In addition to use in a direct production sense, it is possible that the ability to detect lambing events may be used for entirely different reasons. That is, producers may make use of real-time tracking records to market their products for a higher dollar premium. Animal welfare and the push for improved welfare standards is a mounting pressure for 21st century producers (Dawkins, 2017). Thus, increasing transparency and adequate documentation of the industry through early adoption of technologies could enable producers to safeguard themselves against public backlash and the perception that they are not satisfying adequate welfare standards. This shift in business behaviour is already evident in the sheep industry, for example 'ZQ Natural Fibre™' (ZQ). ZQ is a leading wool brand developed by The New Zealand Merino Company (and co-funders of this research). The brand is marketed as a 'certified ethical' product, and lists 'animal welfare', 'environmental sustainability', 'traceability' and 'social responsibility' as major brand values (ZQ Natural Fibre, 2019). ZQ is a prime example of the integration of animal welfare, on-farm productivity and marketing, encouraging consumer demand for ethically-produced fibre.

Of interest, this particular work has been conducted using neck collar and ear tag sensor attachment methods, with the purpose of providing supporting evidence for the

establishment of commercial devices. It has been stated in the literature that ear tag form factors will likely be the most appropriate due to the easy integration with existing husbandry procedures (Barwick et al., 2018). However, it should be noted that ear tag attachment can be considered a welfare issue in its own right, due to issues associated with pain of attachment and the potential for ear damage (Awad, 2016). Collar attachment should therefore also be considered for initial commercial development. Leg attachment is unlikely to be appropriate due to difficulties associated with on-farm maintenance (McLennan et al., 2015). Further consideration is also required for development of a completely integrated device. In this research, the two devices were attached using different methods (neck collar and ear). However, in a commercial context, it will be necessary for both sensors to be located on the same device. This may have limitations associated with power supply and/or on-sensor data analysis and should be explored in further research.

10.4 Recommendations for future research

This project has identified a number of aspects that should be explored in future research. These range from discrete packages of technical work related to sensor analysis through to conceptual research and the need for hardware development to support commercialisation.

10.4.1 Technical work related to sensor analysis

Refinement of behaviour models is an important consideration for future research. In the context of parturition detection, exploration of fine-scale behaviours associated with lambing is of particular interest. For example, during the field campaigns it was observed that the ewes approaching lambing would 'toss' their heads up and to the side whilst in lateral recumbency. This behaviour appeared to correspond to the period of active labour and was initially considered for further investigation. However, due to limitations in gathering detailed observations in a commercial setting, and the technical issues associated with video collection, this was unable to be conducted. Future research should attempt to capture this behaviour, potentially in a confined pen trial with continuous video recording.

Further research should also investigate the ability to detect other maternal behaviours, such as grooming and suckling. Chapter 7 noted a trend for increased grazing behaviour in the hours following lambing. Given that post-partum return to grazing is usually gradual

(Alexander et al., 1983, Bickell et al., 2010), it was concluded that this behaviour increase was reflective of maternal grooming (Alexander, 1988). Further research should be conducted to identify this behaviour, especially given the impact of maternal grooming on lamb survivability (Alexander, 1988). Similar research should also be conducted to identify suckling behaviour, particularly the initial suckling event where delivery of colostrum is important (Alexander, 1988). Suckling could also be utilised to infer information about the welfare of the lamb from the ewe sensor data, as continued suckling would suggest the lamb has survived, whereas initial suckling followed by a cessation would suggest lamb death.

Refinement of study methodology could also be addressed in future work. For example, in this work, the GNSS speed data was averaged over a moving window of five location estimates. This process was done to smooth out the uncorrected dataset, although the actual choice of the five locations was arbitrary. Further work could be conducted to determine the impact of this decision, if any.

Finally, further work should also be conducted to incorporate a broader range of behaviours into the initial ML classification model. In Chapter 6, behaviour classification was limited to only grazing, lying, standing and walking, with further reclassification into activity and posture. However, sheep obviously have a wider behavioural repertoire that should also be considered. For example, decreased rumination is a known indicator of calving (Saint-Dizier and Chastant-Maillard, 2015). This highlights limitations of ML as the model is only able to classify behaviours within the constraints of its training. Given this, further development of ML classification models should incorporate a larger number of behaviours, for example rumination, maternal grooming and suckling. Consideration for mixed behaviour epochs should also be conducted; for example, classification of epochs based on the 'majority' behaviour performed. Alternatively, simple classification as a 'mixed behaviour' epoch could also be used. Limitations associated with mixed behaviour epochs could be addressed through shorter epoch durations or a moving window classification. This has only recently been addressed in the literature (Barwick et al., 2020).

10.4.2 Conceptual research of sensor-based welfare assessment

This thesis has explicitly examined how GNSS and accelerometer technologies can be used for improved monitoring and welfare assessment of lambing ewes. However, if the ultimate

industry objective is for lifelong sensor-based welfare monitoring, then the presented research represents only a small aspect of a much larger picture. To explain this further, a schematic diagram has been included below (Figure 10.1). This figure illustrates the type of sensors and/or data sources that may be available on farms, and the potential use of this data for application across the FD framework. Using the research presented in this thesis as an example (shown in colour), sensor data can be readily applied across the four physical Domains: Nutrition, Environment, Health and Behaviour. As shown, GNSS is applicable across all four Domains, illustrating the importance of location-based data, particularly for grazing animals. Accelerometer data is also applicable across these Domains; the exception being the Environment Domain due to the limited capacity of motion sensors to contextualise movement within the external environment when used in isolation. In contrast, weather data has an obvious application to the Environment Domain, with limited representation across the remaining Domains. It should be noted that in the current research, environment data was provided by on-farm weather stations only. Further use of regional weather stations and/or weather warnings would also be of benefit and should be explored further.

As depicted in Figure 10.1, the use of other sources of data not included in this thesis also has merit for holistic welfare assessment. For example, off-animal sensors (e.g. Walk over Weigh) and external sensors (e.g. pasture biomass sensors) which can provide further information on the animal or environment, respectively. Management data (e.g. shearing, drenching or joining records) may also be useful in identifying at-risk animals. Also depicted in Figure 10.1 is the generally limited application of sensor technologies for the direct assessment of the Mental State Domain. The exception to this, as previously discussed in Chapter 3, are physiological sensors including HR monitors, which can be used to objectively measure the stress-response. This limitation is consistent with published literature, where the animal's affective experience is often inferred from the internal state and external circumstances of the animal (Mellor, 2017), and may represent a subjective aspect of welfare assessment that continues to remain elusive to scientific research.

Realistically, an on-farm welfare monitoring system may also be applied purely during periods of higher welfare risk, particularly in the earlier stages of commercialisation where targeted application may be more achievable. Irrespective of the final application (i.e. lifelong or targeted), it is important to understand where the current research applies within the broader

scope of welfare assessment and its purpose as an initial step towards realising the full possibilities that sensors will provide for animal management.

10.4.3 Hardware development to support application

Further to considering where this research fits into the broader concept of sensor-based welfare monitoring, it is important to reflect on how the results presented in this thesis may actually work in a commercial on-farm environment. Figure 10.2 provides a graphical representation of the likely design of an on-farm commercial system. Of course, there are likely to be differences as commercial systems evolve, but emerging systems [e.g. Australian Wool Innovation (2015), HerdDogg (2019)] follow a similar pattern. One of the key considerations for commercial application is how large amounts of data generated by sensors might be managed across these systems, particularly with regard to energy efficiency. The research in this thesis was undertaken, wherever possible, with this in mind. This is particularly evident throughout Chapters 6, 8 and 9 where aspects of analytics and data transfer, and the broader potential for embedded processing (Vázquez-Diosdado et al., 2019) and edge computing (ur Rehman et al., 2016) are discussed. In addition to this work, however, other areas of research including transfer infrastructure and the integration of multiple data sources are required. As illustrated in Figures 10.1 and 10.2, the current research represents a small aspect of the overall narrative, with considerable research and development still necessary. Nevertheless, the concepts presented throughout this thesis provide strong foundational knowledge for the continued research and development of sensor-based welfare monitoring systems.

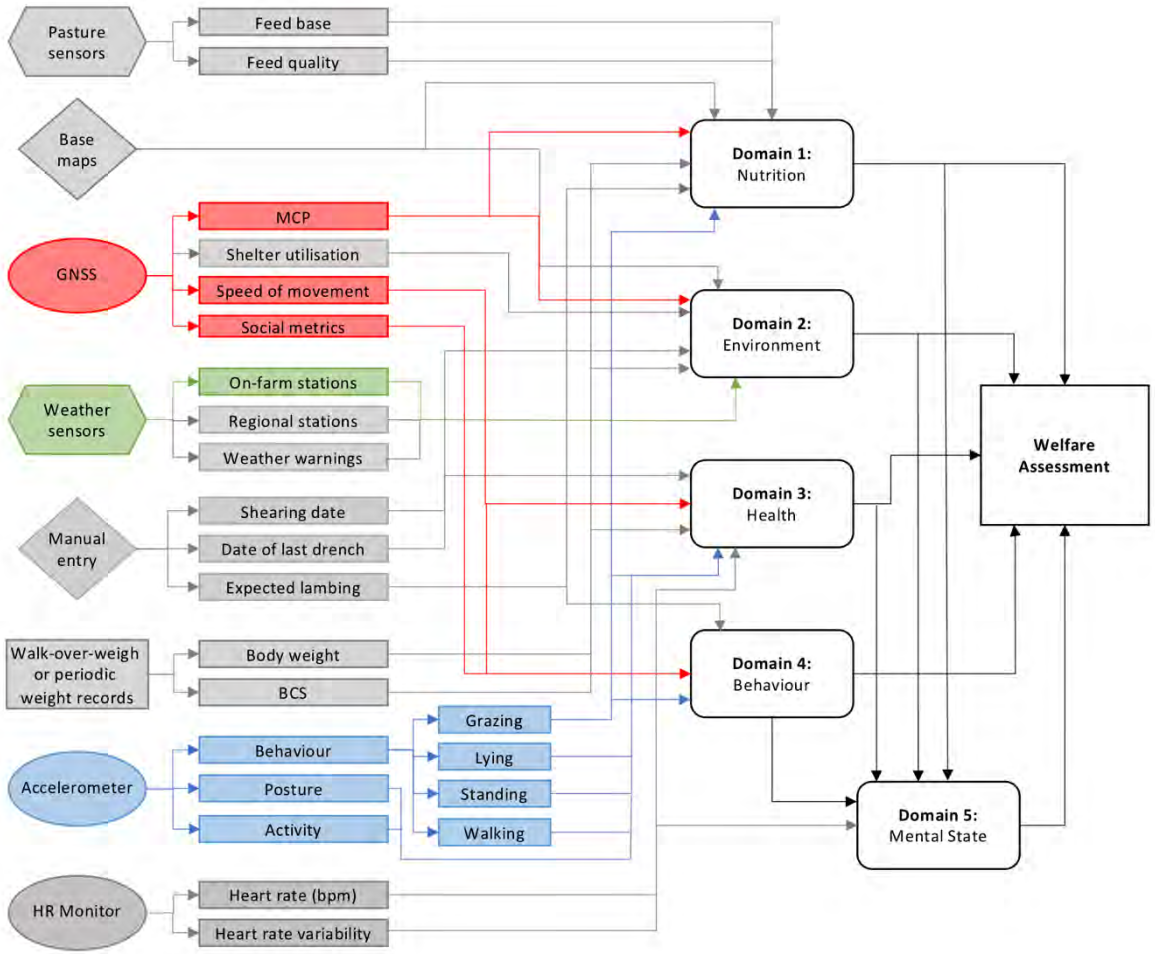

Figure 10.1 Schematic diagram indicating required inputs for holistic welfare assessment under the FD Model. Research aspects presented in this thesis are shown in colour (GNSS: red; Accelerometer: blue; Weather sensors: green). Shapes indicate sensor types: on-animal sensors (circle); off-animal sensors (rectangle); external sensors (hexagon) and other (diamond)

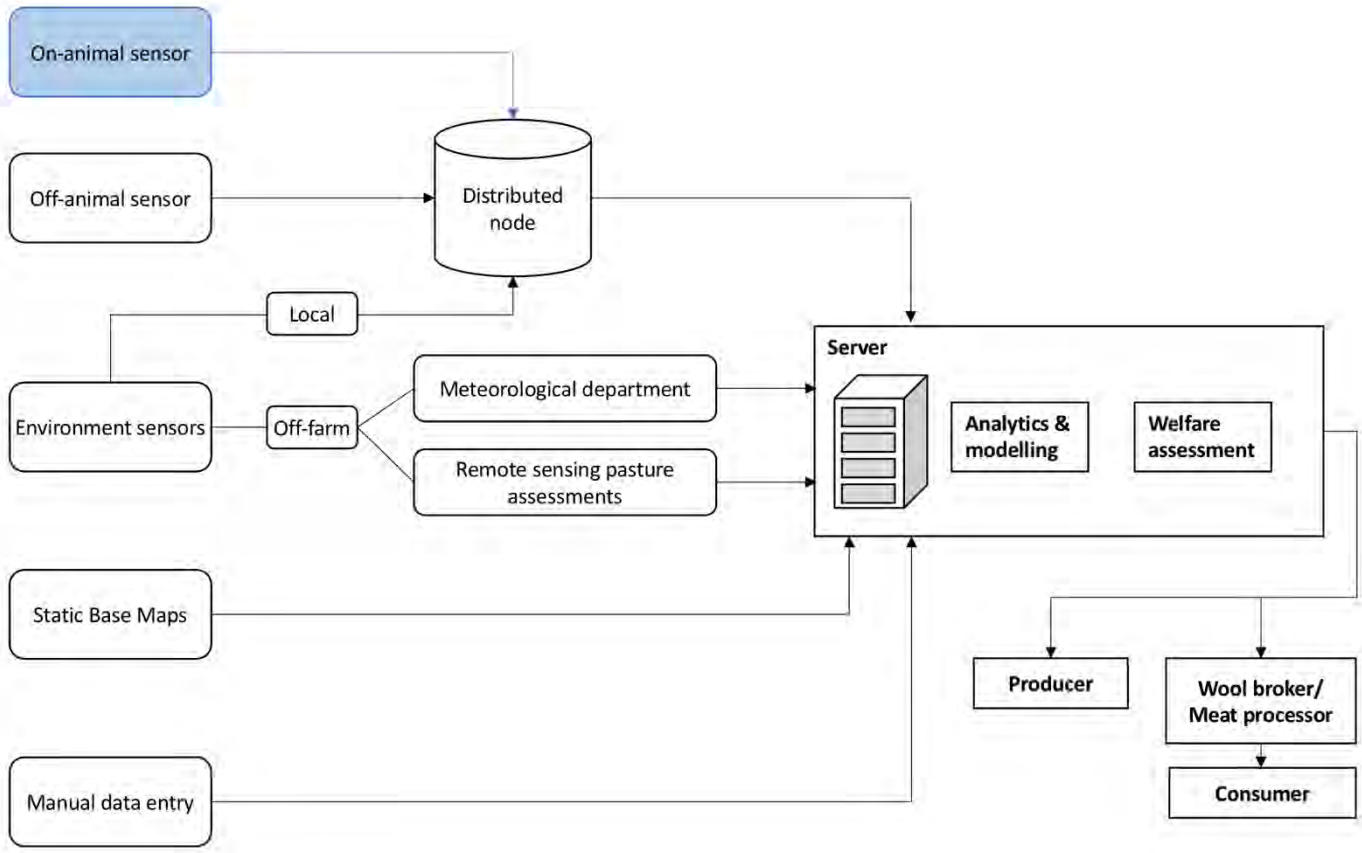

Figure 10.2 Proposed structure and data flow of a remote welfare monitoring system. Research aspects presented in this thesis are shown in blue

10.5 Final conclusions

The application of sensor technologies in livestock production has many potential benefits. They offer the potential for improved animal welfare, particularly in extensive systems where adequate monitoring may be difficult. Good animal welfare has both ethical and economic advantages, the former allowing production under a social license, and the latter resulting from on-farm gains. Conversely, poor welfare constitutes a moral quandary and impacts on social acceptance of the agriculture industry. Ultimately, as we continue to produce animals and use their products for our own gain, it is our responsibility to work within the ethical production requirements and ensure quality of life for these animals. Sensor technologies may offer part of the solution to this, allowing a level of surveillance that was not previously possible. This thesis has focused on welfare at parturition and serves as a proof of concept that this application is possible. From here, continued research and development is essential to ensure that the benefits of these sensor technologies can be easily applied in commercial settings.

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Appendices

Appendix A: Chapter 2. Supplementary material.

Appendix B: Chapter 4. Summary of the 2017 fieldwork data and its use in the thesis.

Appendix C: Chapter 4. Summary of the 2018 fieldwork data and its use in the thesis

Appendix A: Chapter 2 – Supplementary material

Assessment of each experiment's application to the FD Model. Application marked with a 'X'

Experiments	Sensor family	Sub-family	Sensor(s)	Broad measurement	Nutrition	Environment	Health	Behaviour	Mental State
Alhamada et al (2016)	Location	Relative	RFID (oestrus sensor)	Social interaction	X	-	-	X	X
Alhamada et al (2017)	Location	Relative	RFID (oestrus sensor)	Social interaction	-	-	-	X	X
Alvarenga et al (2016)	Motion	Acceleration	Accelerometer	Raw and/or derived metrics	X	X	-	X	-
Animut et al (2005)	Motion	Body or body-part position	Jaw/bite	Proprietary metrics	X	X	-	X	-
	Physiological	-	HR monitor	General HR					
Ares et al (2007)	Location	Absolute	GPS	Distance/speed & Spatial data	X	X	-	X	-
Barkai et al (2002)	Motion	Body or body-part position	Jaw/bite	Proprietary metrics	X	X	-	-	-
	Physiological	-	HR monitor	General HR					
	Physiological	-	Oxygen Sensor	Oxygen concentration					
Betteridge et al (2010a)	Location	Absolute	GPS	Spatial data	X	X	-	X	-
	Motion	Body or body-part position	Pendulum with magnetic reed switch	Body orientation & Body movement					
	Physiological	-	Urine sensor	Urination events					
Betteridge et al (2010b)	Location	Absolute	GPS	Spatial data	-	-	-	X	-
	Physiological	-	Urine sensor	Urination events					
Broster et al (2010)	Location	Relative	Contact Logger	Social interaction	X	X	X	X	-

Experiments	Sensor family	Sub-family	Sensor(s)	Broad measurement	Nutrition	Environment	Health	Behaviour	Mental State
Broster et al (2012)	Location Location	Absolute Relative	GPS Contact Logger	Distance/speed & Spatial data Social interaction	-	X	X	X	-
Broster et al (2017)	Location	Absolute	GPS	Distance/speed & Spatial data	X	X	X	X	-
Champion et al (1997)	Motion	Body or body-part position	Mercury tilt sensor	Body orientation & Body movement	X	-	-	X	-
Coulon et al (2015)	Physiological	-	HR monitor	Complex HR	-	-	-	X	X
Cronin et al (2016)	Motion	Acceleration	Accelerometer	Proprietary metrics	X	-	X	X	-
Désiré et al (2004)	Physiological	-	HR monitor	Complex HR	-	X	-	X	X
Destrez et al (2012)	Physiological	-	HR monitor	General HR	-	-	-	X	X
Destrez et al (2013)	Physiological	-	HR monitor	General HR	-	X	-	X	X
di Virgilio and Morales (2016)	Location	Absolute	GPS	Social interaction & spatial data	X	X	-	X	-
Dobos et al (2014)	Location	Absolute	GPS	Distance/speed & social interaction	-	-	-	X	-
Dobos et al (2015)	Location	Absolute	GPS	Distance/speed	X	-	-	X	-
Donovan et al (2013)	Location	Absolute	GPS	Distance/speed	X	-	X	X	-
Doyle et al (2016)	Location	Relative	Contact Logger	Social interaction	-	X	-	X	X
Falú et al (2014)	Location	Absolute	GPS	Distance/speed & spatial data	X	X	-	X	-
Falzon et al (2013)	Location	Absolute	GPS	Distance/speed	-	-	X	X	-
Fogarty et al (2015)	Location	Absolute	GPS	Distance/speed	-	-	-	X	-
Freire et al (2012)	Location Location	Absolute Relative	GPS Contact Logger	Distance/speed Social interaction	X	X	-	X	X
Giovanetti et al (2017)	Motion	Acceleration	Accelerometer	Raw and/or derived metrics	X	-	-	X	-

Experiments	Sensor family	Sub-family	Sensor(s)	Broad measurement	Nutrition	Environment	Health	Behaviour	Mental State
Gipson et al (2012)	Location	Absolute	GPS	Distance/speed & spatial data & social interaction	-	X	-	X	X
Goddard et al (2000)	Physiological	-	HR monitor	General HR	-	-	X	X	X
Greiveldinger et al (2007)	Physiological	-	HR monitor	Complex HR	-	X	-	X	X
Haddadi et al (2011)	Location Motion	Absolute Multiple	GPS IMU	Social interaction NA[1]	-	-	-	X	-
Hargreaves and Hutson (1990)	Physiological	-	HR monitor	General HR	-	-	-	-	X
Harris et al (2016)	Location	Absolute	GPS	Spatial data	X	X	-	-	-
Hobbs-Chell et al (2012)	Location Motion	Absolute Multiple	GPS IMU	NA[1] NA[1]	-	-	-	X	-
Hulbert et al (1998)	Location	Absolute	GPS	NA[1]	X	-	X	X	-
Jørgensen et al (2016)	Location	Absolute	GPS	Spatial data	X	X	-	X	-
Kaur et al (2016)	Location	Absolute	GPS	Distance/speed	-	-	X	X	-
Kawamura et al (2005)	Location	Absolute	GPS	Distance/speed & spatial data	X	X	-	-	-
Kuźnicka and Gburzyński (2017)	Motion	Acceleration	Accelerometer	Raw and/or derived metrics	X	-	-	X	-
Lin et al (2011)	Location	Absolute	GPS	Distance/speed & spatial data	X	X	X	X	-
Lowe et al (2001)	Physiological Physiological	- -	HR monitor Temperature sensor	General HR Body temperature	-	X	X	-	X
Manning et al (2014)	Location	Absolute	GPS	Distance/speed	-	-	-	X	-

Experiments	Sensor family	Sub-family	Sensor(s)	Broad measurement	Nutrition	Environment	Health	Behaviour	Mental State
McLennan et al (2015)	Motion	Acceleration	Accelerometer	Proprietary metrics	X	-	X	X	-
Morgan-Davies et al (2016)	Location	Absolute	GPS	Distance/speed & spatial data	X	X	X	X	-
Morton et al (2014)	Motion	Acceleration	Accelerometer	Proprietary metrics	-	-	X	X	-
Munn et al (2013)	Location	Absolute	GPS	Distance/speed & spatial data	X	X	-	X	-
Munn et al (2016)	Location	Absolute	GPS	Distance/speed	X	X	-	X	-
Mysterud et al (2014)	Location	Absolute	GPS	Spatial data	X	X	-	-	-
Nadimi et al (2012)	Motion	Acceleration	Accelerometer	Raw and/or derived metrics	X	-	-	X	-
Ormaechea and Peri (2015)	Location	Absolute	GPS	Distance/speed & spatial data	X	X	-	X	-
Penning (1983)	Motion	Acceleration	Accelerometer	Raw and/or derived metrics	X	-	-	X	-
	Motion	Body or body-part position	Mercury tilt sensor	Body orientation					
	Motion	Body or body-part position	Jaw/bite	Body movement					
Pérez-Barbería et al (2015)	Location	Absolute	GPS	Distance/speed & social interaction	X	X	-	X	-
Putfarken et al (2008)	Location	Absolute	GPS	Distance/speed & spatial data	X	X	-	X	-
Radeski and Ilieski (2017)	Motion	Acceleration	Accelerometer	Raw and/or derived metrics	-	-	-	X	-
Reefmann et al (2009)	Physiological	-	HR monitor	Complex HR	-	-	-	X	X
	Physiological	-	Respiratory sensor	Respiration rate					
	Physiological	-	Temperature sensor	Body temperature & humidity					
Rurak et al (2008)	Motion	Acceleration	Accelerometer	Proprietary metrics	-	-	X	X	-
Rusch et al (2009)	Location	Absolute	GPS	Distance/speed & spatial data	-	X	-	-	-

Experiments	Sensor family	Sub-family	Sensor(s)	Broad measurement	Nutrition	Environment	Health	Behaviour	Mental State
Rutter et al (1997a)	Location	Absolute	GPS	Spatial data	X	X	-	X	-
	Motion	Body or body-part position	Mercury tilt sensor	Body orientation					
	Motion	Body or body-part position	Jaw/bite	NA[1]					
Rutter et al (1997b)	Motion	Body or body-part position	Jaw/bite	Proprietary metrics	X	-	-	X	-
Schlecht et al (2006)	Location	Absolute	GPS	Distance/speed & spatial data	X	X	-	X	-
Simitzis et al (2009)	Physiological	-	HR monitor	General HR	X	-	X	X	-
Simitzis et al (2012)	Physiological	-	HR monitor	General HR	-	-	-	X	X
Tallet et al (2006)	Physiological	-	HR monitor	General HR	-	-	-	X	X
Taylor et al (2011)	Location	Absolute	GPS	Distance/speed & spatial data	-	X	-	X	-
Thomas et al (2008)	Location	Absolute	GPS	Distance/speed & spatial data	X	X	X	X	-
	Motion	Body or body-part position	Inclinometer	Body orientation					
Umstätter et al (2008)	Location	Absolute	GPS	NA[1]	X	-	-	X	-
	Motion	Body or body-part position	Pitch-Roll sensor	Body orientation					
Verbeek et al (2012)	Motion	Acceleration	Accelerometer	Proprietary metrics	X	-	-	X	X
Webber et al (2015)	Location	Absolute	GPS	Distance/speed	X	X	X	X	X
Williams et al (2009)	Location	Absolute	GPS	Spatial data	X	X	-	X	-
Williams et al (2011)	Location	Absolute	GPS	Spatial data	X	X	-	X	-
Zampaligré and Schlecht (2017)	Location	Absolute	GPS	Distance/speed & spatial data	X	X	-	X	-

[1]Sensor data not presented

Appendix B: Chapter 4 - Summary of the 2017 fieldwork data and its use in the thesis.

Use of the animals within each chapter is included in parentheses where: D = day scale analysis only; D & H = day and hour scale analysis; Train = included in training dataset; and ID refers to relevant chapter ID (where applicable)

Study ID	GNSS	Acc	Status	Chapter (ID)	Additional Chapter (ID)	Study ID	GNSS	Acc	Status	Chapter	Additional Chapter (ID)
B9	✓	✓	HoB	5 (D & H)	8 (Train)	B4	✓	×	DoB	5 (D)	NA
B10	✓	✓	HoB	5 (D & H)	8 (Train)	B1	✓	✓	DNL	5	NA
G8	✓	✓	HoB	5 (D & H)	8 (Train)	B2	✓	✓	DNL	5	NA
O4	✓	✓	HoB	5 (D & H)	8 (Train)	B3	✓	✓	DNL	5	NA
R2	✓	✓	HoB	5 (D & H)	8 (Train)	B5	✓	✓	DNL	5	NA
R4	✓	✓	HoB	5 (D & H)	8 (Train)	B6	✓	✓	DNL	5	NA
R7	✓	✓	HoB	5 (D & H)	8 (Train)	B7	✓	✓	DNL	5	NA
R9	✓	✓	HoB	5 (D & H)	8 (Train)	G1	✓	✓	DNL	5	NA
G9	✓	✓	Prolapse	9 (ID A)	NA	G3	✓	✓	DNL	5	NA
G4	✓	✓	DoB	5 (D)	9 (ID B)	G5	✓	✓	DNL	5	NA
G7	✓	✓	DoB	5 (D)	9 (ID C)	G6	✓	✓	DNL	5	NA
O6	✓	✓	DoB	5 (D)	9 (ID D)	O8	✓	✓	DNL	5	NA
O9	✓	✓	DoB	5 (D)	9 (ID E)	O10	✓	✓	DNL	5	NA
R3	✓	✓	DoB	5 (D)	9 (ID F)	R5	✓	✓	DNL	5	NA
G10	✓	✓	DoB	5 (D)	9 (ID G)	R8	✓	×	DNL	5	NA
G2	✓	✓	DoB	5 (D)	9 (ID H)	B8	×	✓	Sensor Failure	NA	NA
O1	✓	✓	DoB	5 (D)	9 (ID I)	O3	×	✓	Sensor Failure	NA	NA
O2	✓	✓	DoB	5 (D)	9 (ID J)	O7	×	✓	Sensor Failure	NA	NA
O5	✓	✓	DoB	5 (D)	9 (ID K)						
R1	✓	✓	DoB	5 (D)	9 (ID L)						
R10	✓	✓	DoB	5 (D)	9 (ID M)						
R6	✓	✓	DoB	5 (D)	9 (ID N)						

Status:		
	HoB	Hour of birth recorded
	DoB	Day of birth recorded
	DNL	Did not lamb

Appendix C: Chapter 4 - Summary of the 2018 fieldwork data and its use in the thesis

Use of the animals within each animal is included in parentheses where: D = day scale analysis only; D & H = day and hour scale analysis; and ID refers to relevant chapter ID (where applicable)

Study ID	GNSS	Acc	Status	Chapter (ID)	Additional Chapter (ID)
Bl2	✓	✓	NA	6	NA
Bl6	✓	✓	NA	6	NA
Re1	✓	✓	NA	6	NA
Re10	✓	✓	NA	6	NA
Re2	✓	✓	NA	6	NA
Re3	✓	✓	NA	6	NA
Re4	✓	✓	NA	6	NA
Re7	✓	✓	NA	6	NA
Re8	✓	✓	NA	6	NA
Wh10	✓	✓	NA	6	NA
Wh3	✓	✓	NA	6	NA
Wh5	✓	✓	NA	6	NA
Bl1	✓	✓	HoB	7 (D & H)	8 (ID 1)
Bl10	✓	✓	HoB	7 (D & H)	8 (ID 2)
Bl3	✓	✓	HoB	7 (D & H)	8 (ID 3)
Bl4	✓	✓	HoB	7 (D & H)	8 (ID 4)
Bl9	✓	✓	HoB	7 (D & H)	8 (ID 5)
Gr1	✓	✓	HoB	7 (D & H)	8 (ID 6)
Gr6	✓	✓	HoB	7 (D & H)	8 (ID 7)
Wh6	✓	✓	HoB	7 (D & H)	8 (ID 8)
Wh8	✓	✓	HoB	7 (D & H)	8 (ID 9)

Study ID	GNSS	Acc	Status	Chapter (ID)	Additional Chapter (ID)
Gr9	×	✓	HoB	7 (D & H)	NA
Bl5	✓	✓[1]	HoB	7 (D & H)	NA
Wh7	✓	✓	HoB[2]	7 (D)	8 (ID 10)
Wh9	✓	✓	HoB[2]	7 (D)	8 (ID 11)
Bl7	✓	✓	DoB	7 (D)	NA
Bl8	✓	✓	DoB	7 (D)	NA
Gr3	✓	✓	DoB	7 (D)	NA
Gr4	✓	✓	DoB	7 (D)	NA
Gr5	✓	✓	DoB	7 (D)	NA
Re5	✓	✓	DoB	7 (D)	NA
Re6	✓	✓	DoB	7 (D)	NA
Re9	✓	✓	DoB	7 (D)	NA
Wh4	✓	✓	DoB	7 (D)	NA
Gr10	×	✓	DoB	7 (D)	NA
Gr2	×	✓	DoB	7 (D)	NA
Gr8	×	✓	DoB	7 (D)	NA
Wh1	✓	✓	DNL	NA	NA
Gr7	✓	×	Sensor failure	NA	NA

Status:	HoB	Hour of birth recorded
	DoB	Day of birth recorded
	DNL	Did not lamb