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Using Walk-over-Weighing technology for parturition date determination in beef cattle

Don Menzies[A,B], *Kym P. Patison*[A], *Nick J. Corbet*[A] *and Dave L. Swain*[A]

[A]CQUniversity, School of Health, Medical and Applied Sciences, Precision Livestock Management Research Group, Rockhampton, Qld 4702, Australia.
[B]Corresponding author. Email: d.menzies@cqu.edu.au

Abstract. The northern Australian beef industry is dominated by cow-calf operations where reproductive efficiency is a major profit driver. The postpartum anoestrus interval is a major contributor to an animal's reproductive efficiency and is influenced by genetic selection. The genetic trait that measures an animal's postpartum anoestrus interval is the days to calving estimated breeding value and a key requirement is knowledge of the cow's calving date. Traditionally calving date is recorded using laborious and costly methods that are impeding the recording and hence the accuracy of genetic predictions for this trait by the northern Australian seedstock industry. The present experiment used Walk-over-Weighing technology to automatically record animal weights as cattle enter a restricted area where they access water. With the use of a novel method to accurately assess weights, the growth paths of cows were tracked from late gestation to post-calving. The calving date was visualised in the growth paths of most cows (78.3%) and a custom algorithm was able to automatically detect the calving date within 10 days of the observed calving period for 63% of cows. The use of Walk-over-Weighing to record calving date provides the opportunity to increase the recording of the days to calving estimated breeding value in the northern seedstock industry, thereby increasing reproductive efficiency and improving the profitability of northern beef producers.

Additional keywords: autonomous data collection, calving, reproductive efficiency.

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Introduction

The northern Australian beef industry comprises ~60% of the total cattle numbers (Gleeson *et al*. 2012). Numerous reports have listed reproductive efficiency as the major profit driver of the industry (McCosker *et al*. 2010; McLean *et al*. 2014). The major components of reproductive efficiency are: the age at which a heifer reaches puberty, the length of a cow's postpartum anoestrus interval (PPAI) and the total weight of calves weaned in a cow's lifetime (Burns *et al*. 2010). The PPAI is the number of days from a cow calving to returning to oestrus and it is the most variable component of a cow's calving interval. Extended PPAI result in cows failing to conceive in restricted mating systems or calving out of season or in alternate years in continuous mating systems (Entwistle 1983; Burns *et al*. 2010). The productivity of a beef enterprise is therefore directly affected by the PPAI, which is a heritable trait that can be improved by genetic selection (Johnston *et al*. 2014).

Within the Australian seedstock industry an animal's genetic merit for a particular trait is measured in terms of an estimated breeding value (EBV). The trait that relates to an animal's calving interval is the days to calving EBV, where lesser or negative values indicate a short PPAI and are, therefore, more favourable (BREEDPLAN 2011*b*). Schatz *et al*. (2010) demonstrated that selection for fertility, which included using sires with low days to calving EBV, successfully increased pregnancy rates in yearling-mated heifers. It is, however, recognised that female fertility traits, such as calving date, are difficult to measure and this is impeding the recording and submission of data (Johnston 2007), thereby reducing the amount of recording and accuracy of fertility EBV.

The major data required to record the days to calving EBV are the date the bull entered the herd and the calving date (BREEDPLAN 2011*a*). Obtaining an accurate calving date is difficult in an extensive beef production system as it is a laborious and costly process. Traditionally, calving date or birth date are recorded by daily or weekly observations when cows are observed to ascertain if they have calved, or by estimation based on the size of a calf at some future date such as at branding or weaning.

Autonomous methods of recording calving date without physically sighting the calf have been researched to reduce the reliance on labour and provide a management alert. Products either measure tail movement (Moocall 2016) or vaginal temperature (Medria 2016) in order to predict onset of parturition but are more suited to intensive production systems where devices can be attached/inserted close to the predicted calving date. For an autonomous method of recording calving date to be applicable to extensive production systems, it would need to fit within current management practices thereby not requiring additional labour, and provide at least the same accuracy as traditional methods.

The monitoring of animal weight change associated with the birthing process at the end of gestation could define the date of calving. O'Rourke *et al*. (1991) determined that the weight of the gravid uterus in late gestation was ~57.5 kg for *Bos indicus* and 74.5 kg for *Bos taurus* cows. By extrapolation of their results, the mean weight of all components expelled at calving for a *Bos taurus* cow would be ~62.5 kg (O'Rourke *et al*. 1991).

Walk-over-Weighing (WoW) technology, which autonomously records an animal's identity and weight, could potentially detect the calving event. The use of WoW data to derive liveweight change has been extensively researched in the sheep industry. Results have been variable with some authors concluding that WoW lacks repeatability for decision making (Brown *et al*. 2014), whereas others advocate for its use to provide regular information on animal weight change across an entire flock (Morris *et al*. 2012). Within the dairy industry, WoW has been used to detect small individual animal weight changes (Alawneh 2011; Dickinson *et al*. 2013). In an extensive beef enterprise, Aldridge *et al*. (2017) were able to detect calving date based on changes in weight profiles in 59% of cows in their study.

The present study expands on the research of Aldridge *et al*. (2017) to determine if the calving date of cows can be automatically derived from WoW data by assessing a novel method to remove erroneous data and algorithms to automatically assign the calving date. The working hypothesis of the present study, that changes in cow weight throughout gestation and after calving can provide data that enables the identification of calving date, was tested.

Materials and methods

Animals and data collection

This study was conducted at Belmont Research Station (150°13′E, 23°8′S), ~26 km north of Rockhampton, in Central Queensland with all procedures approved by the CQUniversity Animal Ethics Committee (approval number A14/09–315). A group of 40 tropical composite (*Bos taurus*) cows were allocated to the experimental group following confirmation the cows were pregnant on 6 August 2015. The group comprised 28 cows that were previously conditioned to use the WoW system and 12 introduced cows. The introduced cows were trained over a 2-week period to pass through the WoW system. Data collection began on 21 August 2015 and continued until 5 March 2016.

The WoW system comprised a fenced area around the water trough and a race leading into the compound. As the cows walked through the race and over the weigh platform their radio frequency identification (RFID) tag was read and weight recorded. They then passed through a set of spear gates (one-way gates) to access the water trough and exited the confined area through a separate set of spear gates. Further details on the hardware configuration of the WoW system are presented in Menzies *et al*. (2017).

Each month the cows were walked to cattle handling facilities to be weighed (referred to as a static weight) and pregnancy was confirmed via transrectal palpation with ultrasonic assessment (Honda HS-2000V using a 10-MHz linear array transducer, Honda Electronics Co Ltd, Toyohashi, Japan). There was ~2 h between the cows exiting the paddock and being weighed on each occasion.

Cows began calving in mid-October and the last cow calved on 9 February 2016. Throughout the calving season observations were conducted every day to locate and record date of birth of newborn calves. When a calf was located it was captured and the date, identity of the presumed mother, cow description, calf description, calf sex and calf weight was recorded. The calf was identified using a management and RFID tag. It is estimated that the greatest period between the time of a calf being born and the time when it was tagged was 48 h.

Central Queensland has a summer-dominant rainfall pattern with the majority occurring between November and April (Rudder *et al*. 1985) and to illustrate the effect of precipitation on the growth paths of the cows, daily rainfall totals were recorded. Negligible rainfall (17 mm) was received in the 4 months before the start of the calving season. In mid-November there were two rainfall events that totalled 131 mm. This was followed by 46 mm of rainfall in December, 20 mm in January and 77 mm in February. The rain events throughout the experimental period were not however substantial enough to result in surface water accumulating. The total rainfall for the calendar year of 2015 was 687 mm, which is much less than the yearly average for Rockhampton of slightly greater than 800 mm (Bureau of Meteorology 2016).

Data processing and analyses

On 5 March 2016 the data were downloaded from the Tru-Test XR3000 indicator as a CSV file. Code was written in R Foundation for Statistical Computing software (R Core Team 2014) to import the CSV file, generate graphs and perform the analysis. All data not related to the study period or experimental animals, including data that were not associated with an RFID number or a weight, were removed from the dataset. The original dataset, which included a bull, the calves and test tags, had 8694 records. There were 7346 records for the 40 cows, which was reduced to 7151 records once rows without weights were removed.

There were some periods during which the WoW data were not available. Three cows were removed from the data analysis due to missing data: Cow 4944 died while calving and, therefore, had no weights recorded postpartum; the calves from Cows 1958 and 1975 were never found and the cows, therefore, did not have calving dates recorded. An issue with the RFID reader cable not being correctly attached to the weigh indicator meant no data was collected between 14 and 23 October 2015. In addition, two cows (1977 and 1989) lost their RFID devices and had missing data until they were retagged.

To test whether the newborn calf was being weighed with their mother in the early postpartum period the WoW records were analysed to assess the length of time from calving until the calf's identity was recorded. There were 34 live calves tagged from the 37 cows. The original dataset was searched to identify the first recording for each calf. This data were then used to calculate the mean length of time from the calving date until the calves were recorded.

Cows are known to isolate themselves from the herd during parturition and select an area in which to calve (von Keyserlingk and Weary 2007). The duration of this isolation could potentially impact on the ability of the WoW system to detect the weight loss associated with parturition. To ascertain whether the frequency with which cows accessed the WoW system decreased, the number of RFID reads per day during the parturition period was compared with the rest of the data collection period. Data was selected from 2 days either side of the observed calving date (4 days in total). The eight cows that calved within the period that the WoW system malfunctioned were excluded from the analysis as they would have none or fewer RFID reads within that period. The number of RFID reads within the parturition period was divided by four to give the reads per day. Similarly, the number of RFID reads during the rest of the data collection period was divided by the number of days outside the parturition period (data collection – 4 days) to derive reads per day. The RFID reads per day within and outside the parturition period were compared statistically using a Welch Two Sample *t*-test ($P < 0.05$).

Rolling mean filter method

A method was designed to filter erroneous weights, which often occur when two animals are weighed at once or an animal only has two feet on the weigh platform when the weight is recorded (Brown *et al*. 2014). To identify the occurrence of an erroneous weight, the recorded weight was compared with the rolling mean and rolling standard deviation. The R function 'rollmean' from the Zoo package was used to process each individual animal's dataset and calculate the rolling mean using a window of five consecutive weights. The first rolling mean weight was calculated at the point of the third recorded weight by including the previous two weights, the current weight and the following two weights. The rolling mean was then subtracted from the actual weight as an absolute value. The rolling standard deviation was calculated using the same method as the rolling mean. If the absolute value was greater than the rolling standard deviation it was deemed that the weight was erroneous. The rolling mean window then shifted to the next weight and continued to the end of the dataset at which point all rows of data that contained erroneous weights were removed from the dataset. This resulted in 4674 total records for the 37 cows in the dataset. The pattern of change in bodyweights of the whole herd filtered dataset was graphed and a generalised additive model regression line used to determine the overall weight trajectory.

To illustrate the change in bodyweight trajectory of each individual cow, R code was written to graph the cow filtered WoW and static weights, with the observed calving date shown as a 48-h period before the recorded calving date (hereafter referred to as the calving period). The Local Polynomial Regression Fitting function from the Stats package within R was used to fit a smoothing line to the plot.

Statistical methods to derive the date of calving from the WoW dataset

Using the rolling mean filtered dataset, four different methods were tested to automatically detect the date of calving based on the weight loss of individual cows associated with calving.

(1) Difference in rolling means. A custom designed model was developed to identify when calving occurred based on the greatest weight difference between pre- and post-calving weights. The model identified the optimal number of weights before and after calving that were required to detect the greatest weight change. To develop the model, a portion of the cows from the filtered dataset and their known calving dates were used, whereas the remaining portion were used to test the accuracy of the model (described below). Eighteen of the 37 cows were randomly selected and between 1 and 25 weights per cow were used either side of the known calving period. The weights were averaged and the difference between the pre- and post-calving weights was calculated by subtracting the mean post-calving weight from the mean pre-calving weight. The mean difference was then graphed to ascertain the optimum number of weights that gave the greatest difference. The means of the optimum range were analysed and the results deemed statistically significant at $P < 0.05$.

The model was then applied to the remaining animals to assess accuracy at determining calving date. Model application occurred in two stages: with the first stage, the optimum range derived from the model above was used as the window size (described as 'n'), to calculate rolling means before and after calving. The forward rolling mean (xbrollfwd) started at the first WoW weight for each animal and calculated the mean for the weights within the window and continued this process until the window reached the end of the dataset. The backward rolling mean (xbrollback) started at the nth weight and calculated the mean for all weights within the window and continued this process until the last weight. The difference between the backward and forward rolling means was calculated by subtracting the nth^{+1} xbrollfwd value from the nth xbrollback value and working through to the nth last xbrollfwd value. The rows of data before the xbrollback mean started (nth – 1) and after the xbrollfwd mean finished (nth – 1 row from the end of the dataset) were given NA values and removed from the dataset.

The second stage of the model compared the rolling mean difference with the expected weight loss for each cow to determine the calving date. An algorithm was written to iterate through the rolling mean difference data, comparing whether each value was greater than one-thirteenth of the mean weight of the cow. Rather than using a standard weight for the expected weight loss (e.g. 62.5 kg) for all cows that had varying weights, this method was chosen to assess for a significant weight loss relative to the cow's weight and account for some variance in WoW data. The average static weight of the cows at the final static weighing was 557.3 kg, with one-ninth of that being 61.9 kg and one-13th being 42.9 kg, therefore, by choosing one-thirteenth this allowed for a 19.1 kg variance in the WoW data. The date corresponding with the greatest weight loss for each cow, greater than one-thirteenth of the animal's WoW weight, was assigned as the cow's derived calving date, and compared with the calving period to determine the model's accuracy.

(2) Breakpoint analyses. The purpose of the 'Breakpoint' package within R is to estimate both the number and the corresponding locations of breakpoints in biological measurements. The particular function tested searched the

dataset for a single breakpoint for each cow. The date relative to that breakpoint was then extracted and compared with the calving period.

(3) Changepoint analyses. The 'changepoint' package within R is designed to provide a multiple changepoint search method to use on time series data. Although the 'changepoint' package can be used to select multiple changepoints, the 'at most one change' method was used for the analysis. The function tested whether there was a change in mean in the growth path of each cow. The weights were extracted for each individual animal, a changepoint derived and the corresponding date calculated. The date derived from the 'changepoint' analysis was then compared with the calving period.

(4) Strucchange analyses. The 'strucchange' package within R is designed to assess a dataset for structural changes. It provides numerous breakpoints and confidence intervals associated with each breakpoint. The weights for each cow were extracted and the 'strucchange' analysis was used to calculate the break points. The date related to the breakpoint with the smallest confidence interval was extracted and compared with the calving period.

Results

Over the 198 days of the study, there was variation in the frequency that the cows were recorded, with the minimum number of records being 118 and the maximum being 243. The mean number of data points recorded for each cow was 178.78 ± 33.45 s.d.

The average WoW weight, s.d. and average static weight for each cow are illustrated in Fig. 1. There were large differences in the average weights, from a minimum of 403.92 kg to a maximum of 723.84 kg, which reflects differences in age and phenotype of the cows used in the study. In addition, there were differences in the WoW variance, observed by the differences in the standard deviations, but in all cases the static weights were within one standard deviation of the WoW data.

The analysis of the time from birth to the calves first accessing the WoW system showed that only 11 of the 34 calves were recorded. The mean number of days from calving until calves accessed the WoW system was 36.8 days ± 31.1 s.d. with a range from 7.5 to 97.7 days.

The analysis of the frequency with which cows accessed the WoW system within the parturition period showed a mean 0.78 ± 0.39 s.d. compared with 0.92 ± 0.13 s.d. throughout the rest of the data collection period. Although there was a tendency towards cows coming to water less frequently during the parturition period it was not significant ($P = 0.08$).

Rolling mean filter method

When viewing the growth paths for the whole herd certain trends related to seasonally conditions and rainfall were evident. The weight of cows decreased from the start of the data collection in August through to the rainfall event in mid-November, when animals began to gain weight until January when weights plateaued. There was a small increase in the weight trajectories from mid-February to the end of the trial (Fig. 2).

The rolling mean filter method removed 2059 records from the 37 cows. Although the mean weight of the cows did not vary following the filter method (561.0 kg ± 68.5 s.d. before filtering vs 560.5 kg ± 69.8 s.d. after filtering) the filtering process decreased the range of weights from between 253 and 1010 kg before filtering to between 330 and 812 kg after filtering. The minimum and maximum weights following the filtering were consistent with the static recordings, which ranged between 321 kg and 776 kg.

There was an obvious decrease in weights of some cows with the decrease being associated with calving whereas the use of animal weight changes to assess calving date was not as obvious

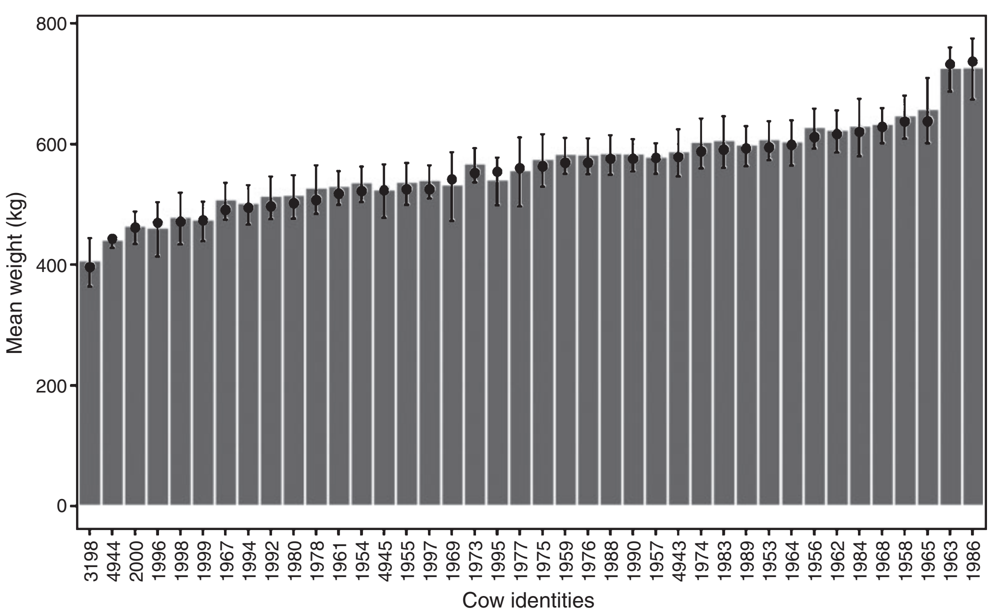

Fig. 1. Average Walk-over-Weighing weight for each cow from lightest to heaviest over the trial period with error bars showing s.d. and dots showing the average of the static weights.

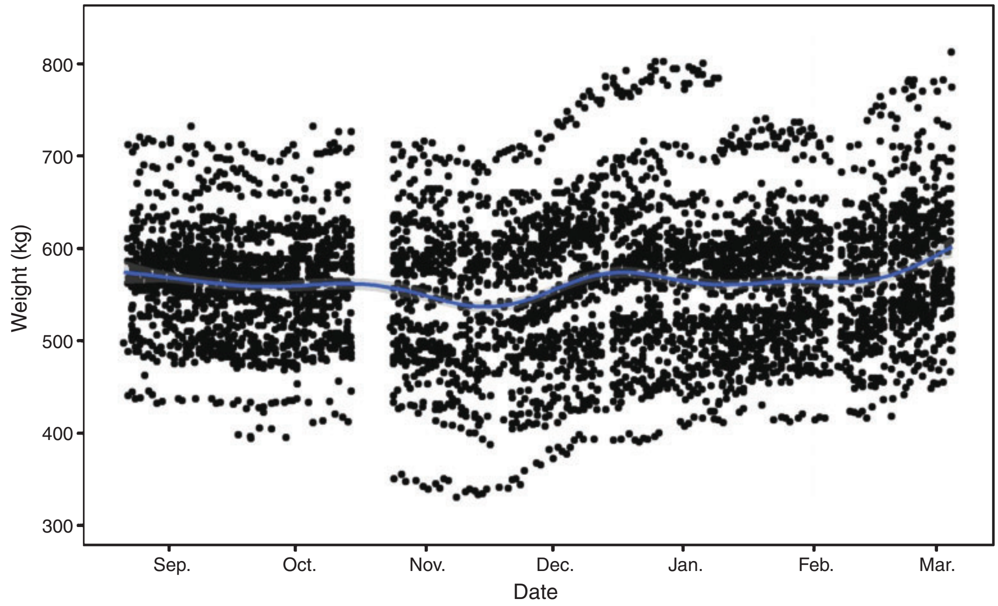

Fig. 2. Whole herd filtered Walk-over-Weighing data with a generalised additive model regression line. Note the 9-day period where no data were recorded in mid-October, and the increase in weight after rainfall events in mid-November and early February.

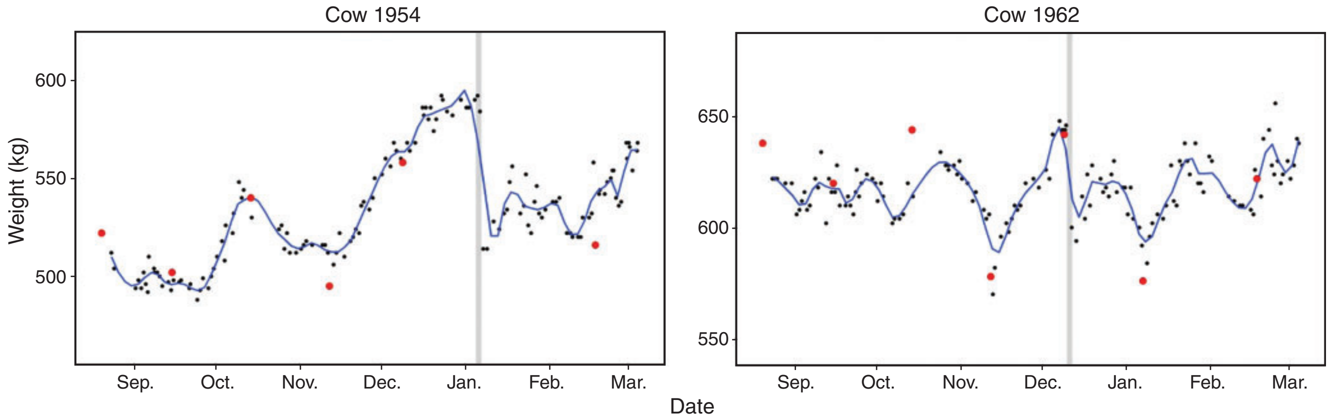

Fig. 3. Growth paths of two cows showing an ideal weight profile (Cow 1954) and a weight profile that is too variable to easily distinguish the calving event (Cow 1962). Note that the red dots are the static weights, the grey vertical bar is the 48-h calving period and the blue line is the smoothing line using the Local Polynomial Regression Fitting function.

in other individuals (Fig. 3). Based on the visual appraisal of the change in weight trajectories, 29 cows (78.3%) had an obvious weight loss around calving whereas for eight cows (21.6%) the day of calving was more difficult to detect. The reasons for the difficulty in detecting the weight loss associated with calving were either due to the trajectory of weight changes in these individuals being too variable or due to there not being enough weight loss at the time of parturition.

Statistical methods to derive date of calving from WoW dataset

(1) Difference in rolling means. When developing the custom designed model to identify calving date using the known birth dates of 18 randomly selected cows, the graph of the mean difference in weights pre- and post-calving indicated the greatest difference occurred when using 16 weights before and after the calving period (Fig. 4). The mean pre- and post-calving weights were 582.0 kg ± 4.9 s.e.m. and 516.7 kg ± 5.3 s.e.m., respectively. This equated to a weight difference of 65.3 kg and when the means were analysed using a Welch Two Sample *t*-test it indicated that they were different ($P < 0.001$).

Having assigned the model parameter ‘n’ as 16, the model was applied to the remaining 19 cows to assess the accuracy to detect the calving date autonomously. Once the difference between the pre- and post-calving means was calculated, compared with one-thirteenth of the mean cow weight and the greatest value for each cow retained, there were 13 of the 19

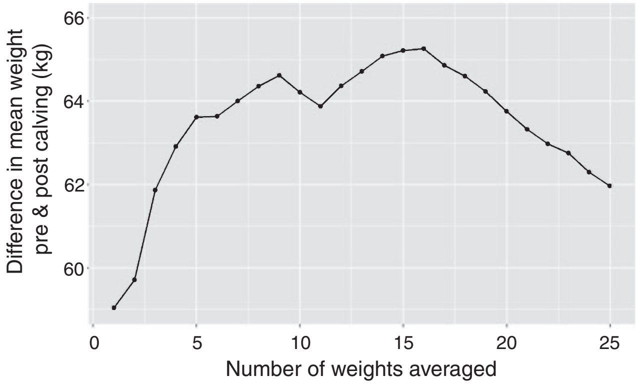

Fig. 4. The difference in mean weight pre- and post-calving, using a window of between 1 and 25 weights, to identify the optimal number of weights that generates the greatest weight change. The greatest change occurs at 16 weights; this number is used as a variable in the model to determine calving date from Walk-over-Weighing data.

cows (68%) that had a potential calving date. Of these, four (21%) were within the recorded calving period; two (10.5%) were within 1 day of the calving period; two (10.5%) were within 2 days of the calving period; four (21%) were within 10 days of the calving period and one cow's assigned calving date was 15 days from the calving period. The four cows that were within 10 days of the calving period all calved around the period when the WoW system did not record any data in mid-October. From the sample of 19 cows, the algorithm was able to detect the calving date to within 10 days of the calving period for 63% of cows and within 2 days of the calving period for 42% of cows.

Of the six cows for which a calving date was not calculated, when assessing their weight trajectories, five had an obvious change in weight associated with calving. Therefore, it would appear the reason that the algorithm could not detect the calving date was that the weight loss was not sufficient to be detected.

(2) Breakpoint analyses. The breakpoint analysis resulted in 34 of the 37 cows being assigned a single breakpoint. Of those, only six cows (16.2%) had the date correctly assigned based on the observed calving period. Another four cows (10.8%) had the breakpoint assigned within 5 days of the calving period. It would appear that in two of the three cows not assigned a breakpoint it was due to the weight loss associated with parturition not being sufficient to be detected.

(3) Changepoint analyses. The mean changepoint analysis derived changepoints for all 37 cows, however, only four of the cows (10.8%) had a date allocated within the recorded calving period. Six cows (16.2%) were within 1 day of the calving period and five cows (13.5%) were within 1 week.

(4) Strucchange analyses. The strucchange analysis derived structural changes in the data for all 37 cows. Seven cows (18.9%) were allocated dates within the recorded calving period, six cows (16.2%) were within 1 day of the calving period and six cows (16.2%) were within 10 days of the calving period. In summary, the use of the strucchange analysis allowed for detection of the calving date to within 10 days of the calving period for 51.4% of cows and within 1 day of the calving period in 35.1% of cows.

Discussion

The authors are only aware of one other publication that has automatically calculated a calving date using WoW. Coventry (2014) achieved a similar result to those of the present experiment with a similar sized group of animals. Over two breeding seasons, 79% (30/38) and 100% (12/12) of calving events were detected to within ± 2 days of calving. The WoW data were collected using a prototype Remote Livestock Management System (Precision Pastoral Pty Ltd, Alice Springs, NT, Australia) unit that had a patented algorithm to calculate the birth date. The patent describes several possible methods of calculating the birth date including using between 5 and 20 weights to average the cow weight pre- and post-calving; using a weight difference between pre- and post-calving weights greater than an expected value and using a weight difference between pre- and post-calving weights that is greater than 0.04 and less than 0.12 of the cow weight (Driver and Christian 2015), however, the actual method used is not clearly described. With the present study, the optimum weight difference was achieved by using 16 weights pre- and post-calving and rather than assessing an expected weight difference (e.g. 45 kg) a weight loss difference relative to the cow weight was evaluated (e.g. greater than 0.077).

Aldridge *et al.* (2017) is the only publication that the authors are aware of that used the weight profiles of cows, derived from a WoW system, to determine the calving date. Calving date was determined in 59% of cows when using an observed calving period of 1 week. To remove spurious weights from the weight trajectory data, Aldridge *et al.* (2017) tested various methods with the most desirable result achieved by removing weights ± 60 kg from the mean cow weight. A similar result was achieved when removing weights based on the individual cow mean and 1 s.d. or using a running median. Aldridge *et al.* (2017), however, did not test a running mean and 1 s.d. for assessments as occurred in the present study. There was also a major difference with the hardware configuration between the previous and present WoW studies that resulted in cows entering and exiting through the WoW system rather than the system being one directional. In addition, cows only had 5 days from the introduction of the WoW system to the time the first cow calved in the previous study meaning they had limited time to become conditioned to the environment of the WoW system. These differences may account for the fact that in the present study the calving date was able to be ascertained from the weight trajectory data in 19% more cows that Aldridge *et al.* (2017) achieved.

In the present study, the rolling mean method was used to identify erroneous weights and removed a considerable amount of the variability in the range of weights; however, the ability to effectively use this methodology is affected by the relative variance. For example, if an animal has little variance in in their WoW data, then a weight that deviates slightly from the mean will be removed. Whereas an animal that has large variance, for example ± 25 kg between weights (Cow 1962 – Fig. 3), the variation needs to be much greater for removal to occur.

An important component of using WoW to derive calving date is to have an adequate number of weights pre- and post-calving to extrapolate the weight loss. Without the post-calving growth path, as was the case for Cow 4944 that died while calving, there is no way of determining how much weight is lost when delivering the calf. Similarly numerous weights before calving are required to extrapolate the loss in weight at calving. For those animals that calved around the time that no data were recorded (14–23 October) it was more difficult to determine an accurate calving date. For example, even though Cow 1977 had a large loss in weight associated with parturition between 22 and 24 October, because there were no weights for the previous week the algorithm detected the change in weight as 14 October when the last weights were recorded. Of the eight cows that calved within that period or 2 days before when data collection did not occur, the loss of weight was visualised in six cows. Of the five cows that had the difference in the rolling means algorithm applied to ascertain calving date, one date was 15 days later than the calving period and the other four all had the calving dates estimated 7 days prior or 7 days after the calving period. Also, as the algorithm was used to calculate the rolling mean pre- and post-calving based on 16 weights, there is obviously a need for the data recordings to extend for 16 weights on either side of the calving period. This finding in the present study emphasises the importance of having cows conditioned for use of the WoW system well before the start of the calving season so that numerous weights can be recorded to generate a pre-calving growth path.

Previous research within the sheep industry to decipher the weight loss at parturition has proved difficult due to the lamb crossing the WoW system at the same time as the ewe (J. S. Richards, pers. comm.). The analysis in the present study showed that only a subset of calves crossed the WoW system within the data collection period. With a mean of 37 days post-calving before calves accessed the WoW system it is assumed that calves were ‘hidden’ in the paddock or left in a crèche while the cow went to water in the early postpartum period. Similarly, if the frequency with which cows came to water in the parturition period was considerably reduced it may impact on the ability to extrapolate the growth paths of cows. Although our results showed that the frequency was reduced, which concurs with the review of cow maternal behaviour conducted by von Keyserlingk and Weary (2007), the difference in visits to water was not significant and did not impact on the ability to plot the trajectory of the cows’ growth path. Ideally the result of 63% of cows having an assigned calving date within 10 days would be refined with further adjustments to the system. This includes ensuring that data is captured each time an animal crosses the WoW platform, as data not recorded in mid-October due to technical problems affected the present results. Additionally, more research is required on a larger herd and in different environments to assess whether the 16 weight rolling average provides for optimal accuracy. The application of the current system is dependent on increasing the number of cows getting an assigned birth date and potentially increasing the accuracy of the birth date. It could however, be argued that having the birth date calculated to within 10 days of the actual date would be as accurate as beef producers estimating the date based on the size of the calf at branding or weaning.

Currently no calving dates derived from WoW systems have been submitted to BREEDPLAN. The research and development team at the Animal Genetics and Breeding Unit, who are responsible for the development of BREEDPLAN, will investigate the utility of WoW for enhancing genetic evaluation of several traits requiring date of birth when sufficient data are available on recorded herds (D. J. Johnston, pers. comm., 22 August 2016). However, WoW data are expected to be accepted as valid animal weight data from 2016 by New Zealand Animal Evaluation Limited, through which the Dairy New Zealand national database is managed (Dirks *et al*. 2015).

A recent survey of the northern Australian seedstock industry identified the main reasons for not using BREEDPLAN are the perceived lack of financial return and that the costs of collecting and submitting data are too great (Agricultural Business Research Institute 2015). The use of genomic technology has been suggested as a possible solution. However, recent research indicates that a genomic-derived EBV will only be relevant for animals less than two generations from the animal which provided the phenotype. The report lists ‘smart data acquisition applications’ as possibly reducing the cost of phenotype collection (Meat and Livestock Australia 2015). The present study provides evidence that the use of WoW data with an automated algorithm is a viable alternative to traditional phenotypic-based methods of recording calving date in a far less labour intensive manner.

This experiment has demonstrated that WoW can autonomously derive the calving date of cows in extensive pastoral zones. Further research will be required to assess the rolling mean function to remove erroneous weights and evaluate the algorithm to automatically assign calving date on larger herds and in various environments. The results from this experiment, however, indicate that WoW could be a potential solution to the cost and labour required to manually record calving dates, thereby increasing the recording of days to calving EBV and consequently increasing reproductive efficiency in the northern Australian beef industry.

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