# Using animal-mounted sensor technology and machine learning to predict time-to-calving in beef and dairy cows

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# Using animal-mounted sensor technology and machine learning to predict time-to-calving in beef and dairy cows

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*Worldwide, there is a trend towards increased herd sizes, and the animal-to-stockman ratio is increasing within the beef and dairy sectors; thus, the time available to monitoring individual animals is reducing. The behaviour of cows is known to change in the hours prior to parturition, for example, less time ruminating and eating and increased activity level and tail-raise events. These behaviours can be monitored non-invasively using animal-mounted sensors. Thus, behavioural traits are ideal variables for the prediction of calving. This study explored the potential of two sensor technologies for their capabilities in predicting when calf expulsion should be expected. Two trials were conducted at separate locations: (i) beef cows (n = 144) and (ii) dairy cows (n = 110). Two sensors were deployed on each cow: (1) Afimilk Silent Herdsman (**SHM**) collars monitoring time spent ruminating (**RUM**), eating (**EAT**) and the relative activity level (**ACT**) of the cow, and (2) tail-mounted Axivity accelerometers to detect tail-raise events (**TAIL**). The exact time the calf was expelled from the cow was determined by viewing closed-circuit television camera footage. Machine learning random forest algorithms were developed to predict when calf expulsion should be expected using single-sensor variables and by integrating multiple-sensor data-streams. The performance of the models was tested using the Matthew's correlation coefficient (**MCC**), the area under the curve, and the sensitivity and specificity of predictions. The TAIL model was slightly better at predicting calving within a 5-h window for beef cows (MCC = 0.31) than for dairy cows (MCC = 0.29). The TAIL + RUM + EAT models were equally as good at predicting calving within a 5-h window for beef and dairy cows (MCC = 0.32 for both models). Combining data-streams from SHM and tail sensors did not substantially improve model performance over tail sensors alone; therefore, hour-by-hour algorithms for the prediction of time of calf expulsion were developed using tail sensor data. Optimal classification occurred at 2 h prior to calving for both beef (MCC = 0.29) and dairy cows (MCC = 0.25). This study showed that tail sensors alone are adequate for the prediction of parturition and that the optimal time for prediction is 2 h before expulsion of the calf.*

**Keywords:** precision livestock farming, parturition, bovine, random forest, animal-mounted sensors

## Implications

The availability of non-invasive sensors to monitor cattle behaviour provides opportunities for the translation of current behaviour and technology validation research into a multi-sensor platform to predict when a cow will calf. Four behaviours were monitored in this trial: time spent ruminating, time spent eating, relative activity and tail raising. Using machine learning techniques, tail raising was found to be the best single predictor of time-to-calving with optimum prediction 2 h prior to calving. Combining tail raising with time spent eating and time spent ruminating slightly increased the predictive performance of the model.

## Introduction

There is a global trend towards increased herd sizes. For instance, in the UK, the average dairy herd size has increased 2.7% since 2014 and the average beef herd size by 1.2% (Agriculture and Horticulture Development Board, Beef and

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Lamb, 2018). If available labour does not increase in line with herd size, this can result in the cow-to-stockman ratio increasing and less time being available for monitoring of individual animals. To optimise the production efficiency of the UK livestock sector, there is a requirement for the development and use of cost-effective animal monitoring solutions to inform on the health and productive status of individual animals.

Dystocia is a considerable problem within beef and dairy systems. Internationally, the prevalence of dystocia in dairy cows typically varies between 2% and 7% of calvings, but is as high as 14% in the USA (Mee, 2008). In the UK, 6.9% of dairy heifers experience serious difficulties during calving (Rumph and Faust, 2006). Reports of assisted calvings range from 10% to 50% (Mee, 2008), with primiparous cows more commonly experiencing difficulties (Lombard *et al.*, 2007). In the beef sector, between 1% and 8% of cows experience difficult calvings, require surgical intervention or have stillbirths (Nix *et al.*, 1998; Phocas and Laloë, 2003; Eriksson *et al.*, 2004; De Amicis *et al.*, 2018).

The costs associated with mild and severe cases of dystocia in the dairy sector are estimated at between £110 and £400 due to milk loss (McGuirk *et al.*, 2007). Dystocia can lead to increased days open, increased numbers of services, premature culling and poor calf health, performance and survival (McGuirk *et al.*, 2007; López de Maturana *et al.*, 2007; Lombard *et al.*, 2007; Gaafar *et al.*, 2011; Barrier *et al.*, 2013). Thus, the development of methods to automatically predict the onset of parturition and identify problematic calvings is important to facilitate timely and appropriate interventions to prevent the losses associated with dystocia.

A number of physiological and behavioural changes occur around calving, which offer opportunities to predict the onset of parturition. The characterisation of maternal hormonal profiles is able to predict calving times with limited accuracy (Shah *et al.*, 2006) and the process is invasive and retrospective. Reductions in body temperature occur on the day of calving and can be used to predict parturition onset within a 24-h window, but variations in temperature change between individual animals limit the predictive power of temperature alone (Saint-Dizier and Chastant-Maillard, 2015). Behavioural indicators, such as lying and standing, eating and rumination (Kovács *et al.*, 2016) patterns, social behaviour and tail-raising events are known to change in the 24 h prior to calving (Huzzey *et al.*, 2005; Miedema *et al.*, 2011a and 2011b; Jensen, 2012). Advances in animal-mounted sensors capable of monitoring these behaviours provide the opportunity to develop an automated system for the prediction of parturition.

The objectives of this study were to determine if integrating data-streams from accelerometers mounted at two locations on the animal could be used to develop machine learning algorithms to predict when calf expulsion should be expected to occur. The novelty of the study lies in the integration of accelerometer data-streams into a machine learning algorithm to predict time-to-calf expulsion in both beef and dairy cows.

## Methods

### *Animals*

Two studies were conducted, one with beef cows at the Beef and Sheep Research Centre at Scotland's Rural College (**SRUC**), UK, and one at a commercial dairy farm in Essex, UK. In the beef trial, a total of 144 pregnant spring-calving cows which calved between March and June 2017 were monitored. The animals were a mixture of breeds (51 Limousin sired; 59 Aberdeen Angus sired; 34 Luing), with 78, 54 and 12 calving to the first, second and third artificial insemination (**AI**), respectively. At the beginning of the trial, the average liveweight was $662 \pm 91$ kg, and the average body condition score was $2.8 \pm 0.3$ (using the system described in Lowman *et al.*, 1976). Cows ranged in age from 2 to 16 years, and parity number from 0 to 13. Cows were allocated to one of two group-housed straw-bedded pens prior to calving (pen 1: $32 \times 6.4$ m housing up to 24 cattle; pen 2: $27.4 \times 6.4$ m housing up to 20 cattle). Animals entered the study based on anticipated date of calving, with those calving to the first AI entering the trial first. Throughout the study, all beef cows were fed a total mixed ration comprising of (per head per day on a fresh weight basis) whole crop barley silage (27.7%), grass silage (41.0%), barley straw (25.6%), maize dark grains (5.1%) and minerals (0.6%).

In the dairy trial, a total of 110 Holstein Friesian dairy cows which calved between July and October 2017 were monitored. Cows ranged in age from 1 to 10 years, and parity ranged from 0 to 6. All dairy cows were served using AI, and estimated calving dates were available from the Cattle Information Service records. Cows were housed in a 41-cubicle dry cow shed ($30 \times 12$ m) from 14 or more days pre-calving, where they remained loose-housed until showing signs of calving (determined visually by the farm staff), at which point they were moved to a smaller ($6 \times 10$ m), loose, straw-bedded yard for calving and until approximately 24 h post-calving. Cows were fed a dietary cation–anion balanced, total mixed ration which was delivered once a day at approximately 0900 h. To allow scraping and bedding, cows were removed from the cubicle house once a day and held in the adjacent collecting yard (1000 to 1100 h).

### *Experimental design and sensors*

All cows in both studies were fitted with two sensors, and data collection was started immediately:

(1) Silent Herdsman (**SHM**) collars (Afimilk Ltd., Israel), neck-mounted accelerometers originally designed to detect oestrus based on cow activity, rumination and eating patterns (Konka *et al.*, 2014). Data from the collars were downloaded to a base station in real time and classified into behaviours by proprietary algorithms (hourly eating and rumination and relative activity per 1.5 h).

(2) Tail-mounted tri-axial accelerometers (**TTA**) (AX3 3-Axis logging accelerometer; Axivity, Newcastle upon Tyne, UK) measuring acceleration at a frequency of 12.5 Hz. These have an internal battery which is rechargeable. Data are downloaded manually to a computer in comma-separated value format. Previous work from SRUC and the University of Edinburgh has characterised

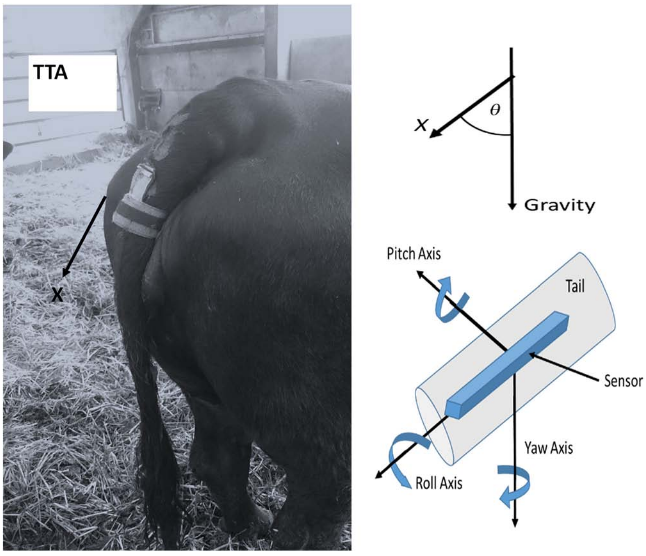


**Figure 1** (colour online) Tail-mounted tri-axial accelerometer (TTA) attachment to cow tail and orientation.

tail-raise signatures and demonstrated that this information may be important to predict time-to-calving during the immediate pre-calving period (Miedema *et al.*, 2011a). The TTAs were housed in synthetic pouches and mounted on cow tails using hook and loop straps (Figure 1). The angle of the tail at any point in time can be determined by calculating the pitch of TTA (Figure 1). An approximation to this is obtained from the magnitude of gravitational acceleration measured on the *x*-axis of TTA:

$$Acc_x = g \sin(\theta)$$

where $\theta$ is the angle of TTA orientation with respect to gravity (Figure 1). Using this approach, the orientation of TTA was determined for a period of 10 min following attachment; thereafter deviations of >20° from this position were deemed to be when the tail was in a raised position.

Continuous, 24-h video data were collected for the duration of the calving period. Twenty-five dome cameras were mounted above the beef calving pens and footage recorded continuously using GeoVision software (EZCCTV, Letchworth, UK). In the dairy study, two cameras were installed at positions which ensured that there was full coverage of the calving pen. Shed lights were left on at night to ensure that calving time could be recorded for animals calving during the night. Videos were manually reviewed to ascertain the exact time of calf expulsion (calf completely expelled from the cow) for each cow.

*Data analysis*

The SHM collars use proprietary algorithms to convert raw accelerometer data into minutes per hour spent eating (**EAT**), minutes per hour spent ruminating (**RUM**) and a relative numeric level of activity per 1.5 h (**ACT**). Raw TTA data were expressed as minutes per hour with the tail in a raised position (**TAIL**).

For the development of prediction models, sensor variables (TAIL, RUM, EAT and ACT) were combined with non-sensor variables. The non-sensor variables used in beef models were: time of day, parity, breed, weight at beginning of trial (kg), body condition score at beginning of trial, age (years) and AI status (conceived on the first, second or third AI). For dairy cows, the variables were: time of day, parity (multiparous or primiparous), number of lactations and age.

The hour in which a calf was completely expelled from the cow was deemed 'hour 0' for that cow, and all previous data points were assigned a value according to the number of hours relative to hour 0. For each sensor variable, only animals which had at least 48 h prior to calf expulsion were included, and all data up to 196 h (1 week) were considered.

Data from individual sensor variables were plotted to visually assess changes in behaviour in the week prior to calving. The 5 h prior to calving was statistically compared to a control period which was the corresponding 5-h period 24 h before, using a Wilcoxon signed-rank test. Data were then randomly divided into training and validation data subsets (70:30), using the createDataPartition function in the R package caret (Kuhn, 2018), with no animal allowed to be in both training and validation subsets.

Random forest (**RF**) models were developed to predict when an animal was within 5 h of calving using single variables and then combined variables. Random forest classifiers are ensemble machine learning algorithms which are considered to be more accurate than single classifiers, and more robust to noise (Agjee *et al.,* 2018). Ensemble algorithms construct a set of independent classifier models (decision trees), with each model having a 'vote' on how to classify each new data point. Random forests were developed for each individual sensor variable (TAIL, RUM, EAT and ACT) and then for multiple sensor variables, and finally – for the best model – hourly time points leading up to calf expulsion. The algorithm creates *i* bootstrapped samples from the training data subset, where *i* is the number of independent decision trees (ntree). A decision tree is then fitted to each bootstrap sample. To overcome the unbalanced nature of the data (fewer target time points than non-target), bootstrapping, resampling during parameter tuning and model evaluation were down-sampled, that is, if there were 100 time points of interest, then only 100 other data points were included. Each tree was then tested with the out-of-bag (**oob**) data points. At each branch in each decision tree, only a random subset of variables was considered (mtry); this parameter and ntree were optimised during tuning of the algorithm. All possible values of mtry were tested and ntree was increased (by 500 trees) until increasing the number of trees further no longer reduced the model error (i.e. oob error stabilised).

The final models were tested on the validation data subset. The binary class variable 'calving' and the model predictions (class probabilities) were used to create receiver operator characteristic (**ROC**) curves and to estimate the area under the ROC curve (**AUC**). Based on the ROC curves, a threshold for the probability that a cow was within 5 h of calf expulsion was chosen that resembled the optimum balance between sensitivity (true positives divided by true positives plus false negatives) and specificity (true negatives divided by true negatives plus false positives). The Matthew's correlation coefficient (**MCC**) was also calculated. It is a metric which assesses the performance of a binary classifier and is less sensitive to imbalanced datasets (such as the test subsets in this case) and is calculated using the following equation:

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

where TP = true positive, TN = true negative, FP = false positive and FN = false negative. These values were derived from the optimum model identified by the ROC curve. The MCC values are between −1 and +1, with +1 being a perfect classifier, 0 being no better than random, and −1 being a completely inversed classification.

All data analyses were undertaken in R (v3.4.1; R Core Team, 2017) using the caret (Kuhn, 2018) and pROC (Robin *et al*., 2011) packages.

## Results

### *Data inclusion*

Table 1 gives a summary of the success of data capture for tail sensors and SHM collars in the beef and dairy trials, and the reasons for excluding animals from data analysis. Supplementary Table S1 shows how the number of animals included in the analysis changed with hours prior to calving. For the beef trial, a total of 124 animals were included in the eating/rumination dataset, 111 in the activity dataset and 78 in the tail sensor dataset. The corresponding numbers for dairy animals were 81, 101 and 53, respectively.

### *Changes in behaviour measured by animal-mounted sensors*

*Tail raising.* Mean time spent with the tail in a raised position per hour in the week prior to calving was 2.1 ± 0.04 min/h in beef cows (Figure 2a) and 3.2 ± 0.07 min/h for dairy cows (Figure 2b). In the 5 h prior to calving, time spent with the tail raised was significantly higher than in the control period for both beef (increase from 4.7 ± 0.80 to 22.8 ± 1.66 min/h, $P < 0.01$) and dairy cows (increase from 6.6 ± 1.29 to 26.2 ± 2.48 min/h, $P < 0.01$).

*Time spent ruminating.* In the week prior to calving, the mean time spent ruminating by beef cows was 21.9 ± 0.12 min/h (Figure 3a). Time spent ruminating decreased significantly in the 5 h prior to calving compared to the control period (from 23.8 ± 0.67 to 12.0 ± 0.59 min/h, $P < 0.001$). For dairy cows, the mean time spent ruminating in the week prior to calving was 16.6 ± 0.10 min/h (Figure 3b). Time spent ruminating decreased significantly in the 5 h prior to calving compared to the control period (from 14.9 ± 0.73 to 8.8 ± 0.73 min/h, $P < 0.001$).

**Table 1** *Success of data recording (robust data collected) for variables collected using neck-mounted accelerometers (Silent Herdsman collars) (time spent eating, time spent ruminating and relative activity level) and tail-mounted accelerometers (tail raising) from beef and dairy cows*

| | Beef | | | Dairy | | |
|---|---|---|---|---|---|---|
| | Eating/rumination | Activity | Tail raising | Eating/rumination | Activity | Tail raising |
| Total animals | 144 | 144 | 144 | 110 | 110 | 110 |
| Successful recording | 137 | 128 | 93 | 85 | 103 | 55 |
| Not attached | – | – | 3 | – | – | 2 |
| No calving time | 9 | 9 | 9 | – | – | – |
| Less than 48 h | 4 | 15 | 3 | 4 | 2 | 0 |
| Animals in analysis | 124 | 111 | 78 | 81 | 101 | 53 |

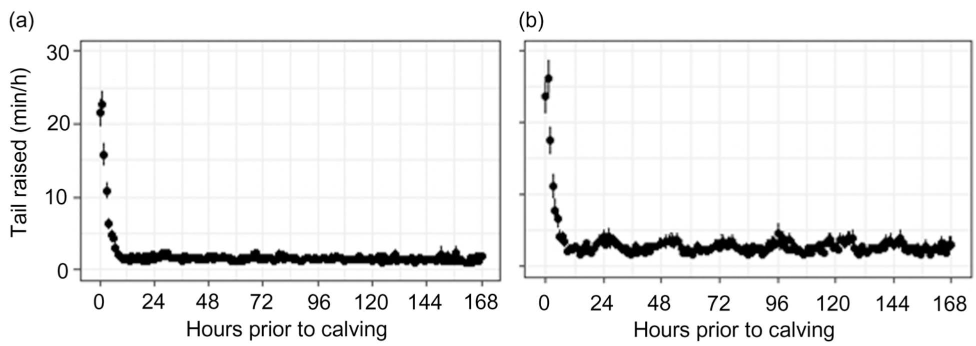


**Figure 2** Average time spent with the tail in a raised position (minutes per hour) 1 week prior to calf expulsion for (a) beef and (b) dairy cows measured using tail-mounted accelerometers. Standard errors are given by vertical bars.

*Time spent eating.* The mean time spent eating by beef cows was 21.1 ± 0.15 min/h (Figure 4a) in the week prior to calving. During the control period, mean time spent eating was 19.1 ± 0.76 min/h, which increased significantly in the 5 h prior to calving (23.0 ± 0.74 min/h, $P < 0.001$). For dairy cows, the mean time spent eating in the week prior to calving was 19 ± 0.1 min/h (Figure 4b). The 5 h prior to calving was 24 ± 0.9 min/h, which was significantly higher ($P < 0.05$) than the control period (22 ± 1.0 min/h).

*Relative activity level.* In the week prior to calving, the mean relative activity by beef cows was 4.2 ± 0.06 (Figure 5a). Relative activity significantly increased compared to the control period in the 5 h prior to calving (from 5.9 ± 0.54 to 13.6 ± 1.12, $P < 0.01$). For dairy cows, the mean relative activity was 2.9 ± 0.04 in the week prior to calving (Figure 5b). There was also a significant increase in relative activity in the 5 h prior to calving compared to the control period in dairy cows (from 4.3 ± 0.53 to 9.1 ± 0.81).

### *Predictive models*

The model performance statistics for individual and integrated sensor variables are shown in Table 2. Note that data in the integrated sensor models containing ACT had to be aggregated into 3-h blocks to resolve the differences in resolution without making the assumption that behaviours were

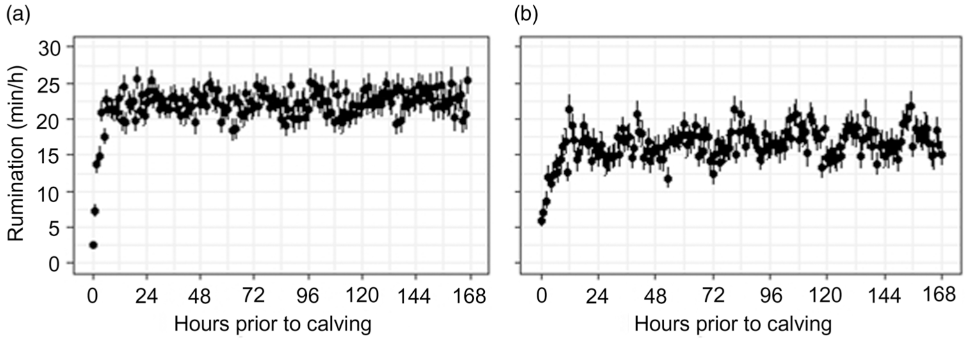


**Figure 3** Average time spent ruminating (minutes per hour) 1 week prior to calf expulsion for (a) beef and (b) dairy cows measured using neck-mounted accelerometers (Silent Herdsman collars). Standard errors are given by vertical bars.

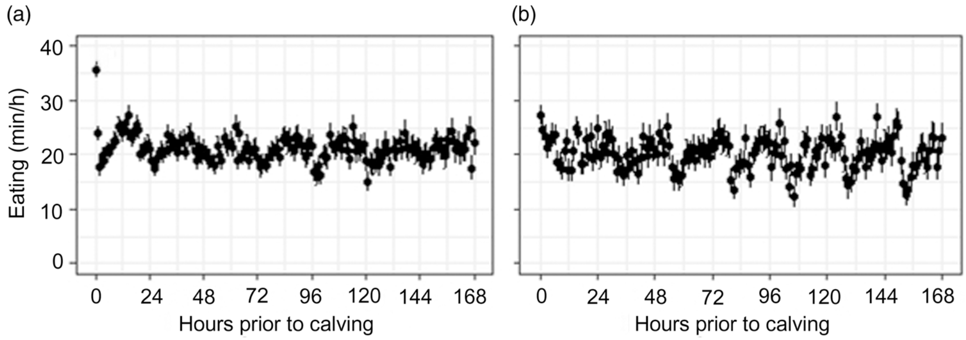


**Figure 4** Average time spent eating (minutes per hour) 1 week prior to calf expulsion for (a) beef and (b) dairy cows measured using neck-mounted accelerometers (Silent Herdsman collars). Standard errors are given by vertical bars.

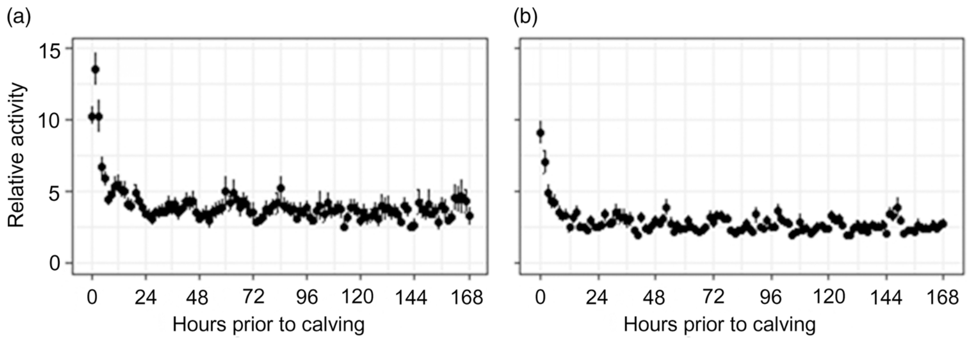


**Figure 5** Average relative activity (per hour) 1 week prior to calf expulsion for (a) beef and (b) dairy cows measured using neck-mounted accelerometers (Silent Herdsman collars). Standard errors are given by vertical bars.

**Table 2** *Model parameter tuning and performance statistics for single- and combined-sensor variable random forest models to predict calving in beef and dairy cows*

| | mtry | ntree | obb error | AUC (95% CI) | Se (%) | Sp (%) | MCC |
|---|---|---|---|---|---|---|---|
| Beef | | | | | | | |
| TAIL | 3 | 1000 | 0.187 | 86.7 (83.1, 90.4) | 76.1 | 83.3 | 0.31 |
| RUM | 4 | 2500 | 0.376 | 69.5 (65.1, 73.9) | 69.6 | 62.3 | 0.13 |
| EAT | 4 | 2500 | 0.386 | 71.7 (67.5, 75.9) | 63.8 | 70.2 | 0.15 |
| ACT[1] | 3 | 2500 | 0.296 | 78.1 (73.8, 82.4) | 70.9 | 71.5 | 0.18 |
| TAIL + RUM + EAT | 2 | 2500 | 0.187 | 86.7 (83.1, 90.3) | 75.4 | 84.6 | 0.32 |
| RUM + EAT + ACT[2] | 5 | 2500 | 0.526 | 46.7 (55.3, 62.5) | 62.5 | 55.3 | 0.07 |
| TAIL + RUM + EAT + ACT[2] | 6 | 1500 | 0.526 | 72.9 (60.5, 85.3) | 81.3 | 69.7 | 0.22 |
| Dairy | | | | | | | |
| TAIL | 2 | 2000 | 0.267 | 87.9 (81.5, 90.1) | 78.6 | 83.5 | 0.29 |
| RUM | 1 | 1000 | 0.491 | 64.0 (58.5, 69.5) | 69.8 | 59.3 | 0.12 |
| EAT | 3 | 500 | 0.463 | 62.4 (56.4, 68.5) | 59.3 | 61.7 | 0.09 |
| ACT[1] | 5 | 2000 | 0.421 | 68.2 (63.7, 72.7) | 66.7 | 62.3 | 0.11 |
| TAIL + RUM + EAT | 3 | 2000 | 0.226 | 85.2 (80.5, 89.8) | 76.7 | 85.1 | 0.32 |
| RUM + EAT + ACT[2] | 4 | 1500 | 0.345 | 51.4 (68.8, 75.0) | 75 | 68.8 | 0.18 |
| TAIL + RUM + EAT + ACT[2] | 5 | 1000 | 0.242 | 86.9 (78.8, 95.1) | 79.2 | 81.3 | 0.3 |

mtry = number of variables used at each split in each independent decision tree; ntree = number of independent decision trees; oob error = out-of-bag error; AUC = area under the curve; CI = confidence interval; Se = sensitivity; Sp = specificity; MCC = Matthew's correlation coefficient; TAIL = number of tail-raise events per hour; EAT = time spent eating per hour (minutes); RUM = time spent ruminating per hour (minutes); ACT = relative level of activity per 1.5 h (minutes).
[1]ACT models have a 1.5-h time step due to the resolution of data collection for this sensor variable.
[2]Combined models containing ACT have a 3-h time step to resolve differences in the resolution of data collection between ACT and other sensor variables.

being displayed evenly throughout the reported time periods. The TAIL and TAIL + RUM + EAT models were found to be most robust in both beef and dairy cow datasets. The TAIL model was slightly better at predicting calving within a 5-h window for beef cows (MCC = 0.31) than for dairy cows (MCC = 0.29). The TAIL + RUM + EAT models were equally as good at predicting calving within a 5-h window for beef and dairy cows (MCC = 0.32 for both models).

Variables recorded by SHM collars alone (RUM, EAT and ACT) were not good predictors of the onset of parturition, with the RUM and EAT variables performing the worst in both beef (MCC of 0.13 and 0.15 for RUM and EAT, respectively) and dairy cows (MCC of 0.12 and 0.09 for RUM and EAT, respectively). Combining these variables resulted in a poorer performing model (MCC = 0.07), likely due to the lower resolution of data.

When assessing the relative importance of sensor variables (calculated by determining the drop in prediction accuracy after shuffling the values of a given predictor variable in the oob samples, rendering them random and with no predictive power – data not shown) within the TAIL + RUM + EAT dairy model, the TAIL variable was by far the most important. Scaled (0 to 100, with 0 being redundant and 100 being the most important) importance for TAIL was 100 in both, with RUM and EAT models having substantially less influence (scaled importance of 22.1 and 21.7, respectively, for beef cows and 26.2 and 29.1 for dairy cows).

*Predicting time-to-calving.* As TAIL was identified as the most important sensor variable for the prediction of parturition, and as a one-sensor system is more desirable than a multiple-sensor system, it was selected to develop models for the prediction of discreet time points prior to calf expulsion. Model parameters and performance metrics are shown for hours 0 to 12 prior to calving in Table 3. Within beef cows, the predictive performance of TAIL increases after 4 h prior to calf expulsion (MCC increases from 0.07 at 4 h prior to 0.17 at 3 h prior). A similar increase was observed in dairy cows (MCC increased from 0.06 at 4 h prior to calf expulsion to 0.14 at 3 h prior to calf expulsion).

## Discussion

*Behavioural changes*

Changes in rumination behaviour observed in this study are in line with those found in previous studies. Reductions in time spent ruminating of 30% to 50% on the day of calving have been observed in dairy cows (Soriani *et al.*, 2012; Calamari *et al.*, 2014; Braun *et al.*, 2014; Büchel and Sundrum, 2014; Pahl *et al.*, 2014).

Beef cows displayed an increase in the EAT variable in the hour prior to calf expulsion and in the hour in which the calf was born, which was not observed in dairy cows. This is contrary to other studies which report decreases when measurements were made by visual observations (Miedema *et al.*, 2011a) and by recording the time the cow spends with its head in a feed-bin (Braun *et al.*, 2014; Büchel and Sundrum, 2014). The hour in which the calf was born includes the whole hour, regardless of when the cow calved within that hour – for example, if the cow calved at quarter past the hour, the next 45 min is also included. The apparent increase in eating may actually be a misclassification of licking behaviour; this behaviour has been shown to peak

**Table 3** *Model parameter tuning and performance statistics for random forest models using number of tail-raise events to predict parturition at discreet time points prior to calf expulsion in beef and dairy cows*

| Hours prior to calf expulsion | mtry | ntree | oob error | AUC | Se (%) | Sp (%) | MCC |
|---|---|---|---|---|---|---|---|
| Beef | | | | | | | |
| 0 | 6 | 2000 | 0.14 | 88.5 (79.9, 97.1) | 79.2 | 93.3 | 0.25 |
| 1 | 8 | 500 | 0.11 | 89.8 (80.0, 99.6) | 90.9 | 90.9 | 0.23 |
| 2 | 6 | 2000 | 0.23 | 95.4 (92.2, 98.6) | 91.3 | 93.5 | 0.29 |
| 3 | 6 | 1000 | 0.25 | 84.1 (74.6, 93.7) | 78.3 | 87.0 | 0.17 |
| 4 | 8 | 2500 | 0.32 | 59.2 (45.4, 73.1) | 47.8 | 82.2 | 0.07 |
| 5 | 8 | 1000 | 0.54 | 47.8 (35.7, 59.9) | 52.2 | 53.9 | 0.01 |
| 6 | 6 | 2000 | 0.51 | 56.4 (44.9, 67.9) | 53.1 | 70.5 | 0.05 |
| 7 | 8 | 1500 | 0.57 | 57.6 (44.1, 71.0) | 68.4 | 60.8 | 0.05 |
| 8 | 7 | 1500 | 0.59 | 53.8 (40.6, 67.1) | 57.9 | 58.1 | 0.03 |
| 9 | 7 | 2500 | 0.52 | 54.2 (43.1, 65.3) | 57.7 | 51.1 | 0.02 |
| 10 | 8 | 500 | 0.44 | 63.4 (50.8, 69.7) | 63.2 | 64.2 | 0.05 |
| 11 | 6 | 2000 | 0.64 | 59.5 (49.3, 69.7) | 62.5 | 56.4 | 0.03 |
| 12 | 8 | 2500 | 0.69 | 65.3 (52.1, 78.5) | 55.6 | 66.5 | 0.04 |
| Dairy | | | | | | | |
| 0 | 5 | 500 | 0.21 | 88.2 (71.9, 100) | 87.5 | 89.7 | 0.16 |
| 1 | 5 | 1500 | 0.13 | 93.2 (88.5, 97.9) | 81.3 | 89.7 | 0.20 |
| 2 | 5 | 2500 | 0.34 | 92.0 (86.0, 98.0) | 86.7 | 92.4 | 0.25 |
| 3 | 4 | 1500 | 0.31 | 85.4 (75.5, 95.3) | 70.0 | 90.3 | 0.14 |
| 4 | 2 | 1500 | 0.59 | 68.3 (48.6, 87.9) | 88.9 | 54.1 | 0.06 |
| 5 | 3 | 1000 | 0.50 | 56.4 (38.2, 74.7) | 58.3 | 61.4 | 0.03 |
| 6 | 5 | 1500 | 0.58 | 65.5 (51.8, 79.1) | 80.0 | 59.0 | 0.06 |
| 7 | 1 | 2000 | 0.68 | 56.9 (43.7, 70.0) | 50.0 | 61.2 | 0.02 |
| 8 | 5 | 500 | 0.83 | 54.5 (38.6, 70.4) | 61.1 | 55.6 | 0.03 |
| 9 | 5 | 500 | 0.60 | 58.8 (41.8, 75.8) | 71.4 | 54.1 | 0.04 |
| 10 | 5 | 500 | 0.48 | 57.5 (42.3, 72.8) | 47.4 | 69.3 | 0.04 |
| 11 | 5 | 1500 | 0.42 | 52.7 (38.0, 67.4) | 71.4 | 41.4 | 0.02 |
| 12 | 5 | 1000 | 0.56 | 50.2 (34.6, 65.9) | 72.7 | 40.2 | 0.02 |

mtry = number of variables used at each split in each tree; ntree = number of independent decision trees; oob error = out-of-bag error; AUC = area under the curve; Se = sensitivity; Sp = specificity; MCC = Matthew's correlation coefficient.

in the hour proceeding the birth of the calf (Jensen, 2012). The same trend was not observed in dairy cows as their collars were removed directly after calving. In the hour prior to calf expulsion, it is possible that the cow is displaying ground-licking or nesting behaviours (Miedema *et al.*, 2011a) which are being misclassified as eating by the accelerometer algorithms.

Activity levels are known to increase in cows in the hours prior to calf expulsion when measured by visual observations (Miedema *et al.*, 2011a, 2011b) and leg-mounted accelerometers (Titler *et al.*, 2015). In this study, neck-mounted accelerometers detected an increase in activity prior to calf expulsion, particularly in the final 2 h; however, Clark *et al.* (2015) did not detect any increase in activity prior to calf expulsion in dairy cows using similar neck-mounted accelerometers. As different animal-mounted sensors have different algorithms to define behaviours, and have undergone different validation exercises, it may be expected that there will be substantial differences in behavioural measurements between them.

An increase in tail-raising behaviour, particularly in the 2 h prior to calving, has previously been observed in dairy cows (Miedema et al., 2011a, 2011b; Jensen, 2012). Data capture from tail sensors was lower than would be practical for a commercial system. There were two related reasons for this: (1) the sensors were designed for data-gathering purposes and are not sufficiently robust enough for commercial deployment. (2) Some sensor data could not be processed into tail-raise events as the orientation of the accelerometer could not be determined. Robust housing for the accelerometer would need to be engineered before this system could be considered for commercialisation.

There are no studies which use animal-mounted sensors to detect changes in rumination time, eating time, relative activity and tail raising prior to calf expulsion in suckler beef cows. This study has shown that patterns of behaviours leading up to calf expulsion are very similar in suckler beef and dairy cows.

*Predictive models*

Interest in developing real-time predictive models to alert farmers to when cows will calve using animal-mounted sensors is increasing. The majority of published studies using sensors to monitor various behaviours have been on dairy cows. Some studies simply use threshold changes in behaviours to define the onset of parturition. Titler *et al.* (2015) were able to predict parturition on average 6 h in advance by a 50% increase in activity. Krieger *et al.* (2018) used threshold values for frequency and duration of tail-raise events to predict parturition in five cows and detected calving between 6 and 121 min prior to expulsion of the calf. In reality, the results of Krieger *et al.* (2018) are similar to those found here, where increases in the predictive accuracy of algorithms were observed 1 to 2 h prior to calf expulsion in hour-by-hour models. The rationale behind exploring the use of a more complex algorithm than simple threshold algorithms was to allow variables which are risk factors for dystocia (e.g. age, parity) to be included in the model.

A variety of multi-sensor systems have been used to integrate data-streams monitoring different behaviours. Rutten *et al.* (2017) achieved a very low false positive rate of 1% within 3 h of calf expulsion using two sensors to measure activity level, rumination time, feeding time and temperature; however, the sensitivity was only 42.4%. Borchers *et al.* (2017) were able to predict parturition 8 h prior to calf expulsion with a sensitivity of 82.8% and a specificity of 80.4% using two sensors (neck-mounted for rumination time and leg-mounted for time spent standing or lying and step count). Ouellet *et al.* (2016) achieved a sensitivity of 77% and a specificity of 77% within a 24-h window using three sensors to record four variables (vaginal temperature, rumination time, lying time and lying bouts). In the present study, similar results were achieved with a single sensor (TTA: sensitivity = 78.6%, specificity = 83.5% for dairy cows).

## Conclusions

In this study, it was possible to predict when beef or dairy cows were within 5 h of calf expulsion using animal-mounted technologies. Of the variables measured by the sensors, time spent with the tail in a raised position was found to be the best predictor of parturition, and had an optimal predictive power at 2 h prior to calf expulsion.

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## Declaration of interest

The authors declare no conflict of interest.

## Ethics statement

Animal trials were approved by the Animal Experiment Committee of SRUC and were conducted in accordance with the requirements of the UK Animals (Scientific Procedures) Act 1986.

## Software and data repository resources

None of the data or models were deposited in an official repository.

## Supplementary material

To view supplementary material for this article, please visit https://doi.org/10.1017/S1751731119003380

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