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Miller, G A; Mitchell, MA; Barker, ZE; Giebel, Katharina ; Codling, Edward; Amory, Jonathan; Michie, C; Davison, Chris; Tachtatzis, Christos; Andonovic, Ivan; Duthie, C-A

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

3 G.A. Miller¹, M. Mitchell², Z.E. Barker³, K. Giebel³, E.A. Codling⁴, J.R. Amory³, C.
4 Michie⁵, C. Davison⁵, C. Tachtatzis⁵, I. Andonovic⁵, and C-A. Duthie¹

5 ¹ *Future Farming Systems, SRUC, Peter Wilson Building, West Mains Road, King's*
6 *Buildings, Edinburgh, EH9 3JG, UK*

7 ² *Animal and Veterinary Science, SRUC, Peter Wilson Building, West Mains Road,*
8 *King's Buildings, Edinburgh, EH9 3JG, UK*

9 ³ *Writtle University College, Lordship Road, Writtle, Chelmsford, CM1 3RR, UK*

10 ⁴ *Department of Mathematical Sciences, University of Essex, Wivenhoe Park,*
11 *Colchester, CO4 3SQ, UK*

12 ⁵ *University of Strathclyde, Glasgow, Royal College Building, 204 George Street,*
13 *Glasgow, G1 1XW, UK*

14 Corresponding author: Dr Gemma Miller. Email: gemma.miller@sruc.ac.uk

15 Running head: Predict calving with sensors and machine learning

16 **Abstract**

17 Worldwide, there is a trend towards increased herd sizes and the animal to
18 stockman ratio is increasing within the beef and dairy sectors, thus the time available
19 to monitoring individual animals is reducing. The behaviour of cows is known to
20 change in the hours prior to parturition, e.g. less time ruminating and eating, and
21 increased activity level and tail raise events. These behaviours can be monitored
22 non-invasively using animal mounted sensors. Thus behavioural traits are ideal
23 variables for the prediction of calving. This study explored the potential of two sensor
24 technologies for their capabilities in predicting when calf expulsion should be
25 expected. Two trials were conducted at separate locations: i) beef cows (n = 144)
26 and (ii) dairy cows (n = 110). Two sensors were deployed on each cow: 1) Afimilk
27 Silent Herdsman (SHM) collars monitoring time spent ruminating (RUM), eating
28 (EAT) and the relative activity level (ACT) of the cow and 2) tail mounted Axivity
29 accelerometers to detect tail-raise events (TAIL). The exact time the calf was
30 expelled from the cow was determined by viewing closed-circuit television camera
31 footage. Machine learning random forest (RF) algorithms were developed to predict
32 the when calf expulsion should be expected using single sensor variables and by
33 integrating multiple sensor data-streams. The performance of the models were
34 tested by the Matthew's Correlation Coefficient (MCC), the area under the curve and
35 the sensitivity and specificity of predictions. The TAIL model was slightly better at
36 predicting calving within a five hour window for beef cows (MCC = 0.31) than for
37 dairy cows (MCC = 0.29). The TAIL+RUM+EAT models were equally as good at
38 predicting calving within a five hour window for beef and dairy cows (MCC = 0.32 for
39 both models). Combining data-streams from SHM and tail sensors did not
40 substantially improve model performance over tail sensors alone therefor hour-by-

41 hour algorithms for the prediction of the time of calf expulsion were developed using
42 tail sensor data. Optimal classification occurred at two hours prior to calving for both
43 beef (MCC = 0.29) and dairy cows (MCC = 0.25). This study has shown that tail
44 sensors alone are adequate for the prediction of parturition and that the optimal time
45 for prediction is two hours before expulsion of the calf.

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

48

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

57 **Introduction**

58 There is a global trend towards increased herd sizes. For instance, in the UK, the
59 average dairy herd size has increased 2.7% since 2014 and the average beef herd
60 size by 1.2% (AHDB, 2018). If available labour does not increase in line with herd
61 size, this can result in the cow to stockman ratio increasing and in less time being
62 available for monitoring of individual animals. In order to optimise the production
63 efficiency of the UK livestock sector there is a requirement for the development and
64 use of cost-effective animal monitoring solutions to inform on the health and
65 productive status of individual animals.

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

75 The costs associated with mild and severe cases of dystocia in the dairy sector are
76 estimated at between £110 and £400 due to milk loss (McGuirk *et al*, 2007).

77 Dystocia can lead to increased days open, increased numbers of services,
78 premature culling and poor calf health, performance and survival (McGuirk *et al*,
79 2007; López de Maturana *et al*, 2007; Lombard *et al*, 2007; Gaafar *et al*, 2011;
80 Barrier *et al*, 2013). Thus the development of methods to automatically predict the

81 onset of parturition and identify problematic calvings is important to facilitate timely
82 and appropriate interventions to prevent the losses associated with dystocia.

83 A number of physiological and behavioural changes occur around calving which offer
84 opportunities to predict the onset of parturition. Characterisation of maternal
85 hormonal profiles is able to predict calving times with limited accuracy (Shah *et al*,
86 2006) and the process is invasive and retrospective. Reductions in body temperature
87 occur on the day of calving and can be used to predict parturition onset within a 24
88 hour window, but variations in temperature change between individual animals limit
89 the predictive power of temperature alone (Saint-Dizier and Chastant-Maillard,
90 2015). Behavioural indicators, such as lying and standing, eating and rumination
91 (Kovács, *et al*, 2016) patterns, social behaviour and tail raising events are known to
92 change in the 24 hours prior to calving (Huzzey *et al*, 2005; Miedema *et al*, 2011a,b;
93 Jensen, 2012). Advances in animal mounted sensor capable of monitoring these
94 behaviours provide the opportunity to develop an automated system for prediction of
95 parturition.

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

102 **Methods**

103 *Animals*

104 Two studies were conducted, one with beef cows at the Beef and Sheep Research
105 Centre at Scotland's Rural College (SRUC), UK, and one at a commercial dairy farm
106 in Essex, UK. In the beef trial, a total of 144 pregnant spring-calving cows which
107 calved between March and June 2017 were monitored. The animals were a mixture
108 of breeds (51 Limousin sired; 59 Aberdeen Angus sired, 34 Luing), with 78, 54 and
109 12 calving to the first, second and third artificial insemination (AI) respectively. At the
110 beginning of the trial the average liveweight was 662 ± 91 kg and the average body
111 condition score was 2.8 ± 0.3 (using the system described in Lowman *et al*, 1976).
112 Cows ranged in age from 2-16 years and parity number from 0-13. Cows were
113 allocated to one of two group-housed straw-bedded pens prior to calving (Pen 1:
114 32m x 6.4m housing up to 24 cattle; Pen 2: 27.4m x 6.4m housing up to 20 cattle).
115 Animals entered the study based on anticipated date of calving, with those calving to
116 the first AI entering the trial first. Throughout the study, all beef cows were fed a total
117 mixed ration comprising of (per head/day on a fresh weight basis) whole crop barley
118 silage (27.7%), grass silage (41.0%), barley straw (25.6%), maize dark grains (5.1%)
119 and minerals (0.6%).

120 In the dairy trial, a total of 110 Holstein Friesian dairy cows which calved between
121 July and October 2017 were monitored. Cows ranged in age from 1-10 years and
122 parity ranged from 0-6. All dairy cows were served using AI and estimated calving
123 dates were available from the Cattle Information Service records. Cows were housed
124 in a 41 cubicle dry-cow shed (30m x 12m) from 14 or more days pre-calving, where
125 they remained loose housed until showing signs of calving (determined visually by
126 the farm staff). At which point they were moved to a smaller (6m x 10m) loose straw

127 bedded yard for calving and until approximately 24 hours post calving. Cows were
128 fed a dietary cation-anion balanced total mixed ration which was delivered once a
129 day at approximately 9am. To allow scraping and bedding up cows were removed
130 from the cubicle house once a day and held in the adjacent collecting yard (10-
131 11am).

132 *Experimental design and sensors*

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

- 135 1. Silent Herdsman (SHM) collars (Afimilk Ltd., Israel), neck mounted
136 accelerometers originally designed to detect oestrus based on cow activity,
137 rumination and eating patterns (Konka *et al*, 2014). Data from the collars was
138 downloaded to a base station in real time and classified into behaviours by
139 proprietary algorithms (hourly eating and rumination and relative activity per 1.5
140 hours).
- 141 2. Tail mounted tri-axial accelerometers (TTA) (AX3 3-Axis logging accelerometer,
142 Axivity, Newcastle upon Tyne, UK) measuring acceleration at a frequency of 12.5
143 Hz. The TTAs have an internal battery which is rechargeable. Data is downloaded
144 manually to a computer in comma separated values format. Previous work from
145 SRUC and the University of Edinburgh has characterised tail-raise signatures and
146 demonstrated that this information may be important to predict time-to-calving during
147 the immediate pre-calving period (Miedema *et al*, 2011a). The TTAs were housed in
148 synthetic pouches and mounted on cow tails using hook and loop straps (Figure 1).
149 The angle of the tail at any point in time can be determined by calculating the pitch of

150 the TTA (Figure 1). An approximation to this is obtained from the magnitude of the
151 gravitational acceleration measured on the x-axis of the TTA:

$$152 \quad Acc_x = g \sin(\theta)$$

153 where θ is the angle of the TTA orientation with respect to gravity (Figure 1). Using
154 this approach, the orientation of the TTA was determined for a period of 10 minutes
155 following attachment, thereafter deviations of more than 20° from this position were
156 deemed to be when the tail was in a raised position.

157 Continuous 24 hour video data was collected for the duration of the calving period.
158 Twenty five dome cameras were mounted above the beef calving pens and footage
159 recorded continuously using GeoVision software (EZCCTV, Letchworth, UK). In the
160 dairy study 2 cameras were installed at positions which ensured that there was full
161 coverage of the calving pen. Shed lights were left on at night to ensure that calving
162 time could be recorded for animals calving during the night, Videos were manually
163 reviewed to ascertain the exact time of calf expulsion (calf completely expelled from
164 the cow) for each cow.

165 *Data Analysis*

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

170 For the development of the prediction models, sensor variables (TAIL, RUM, EAT
171 and ACT) were combined with non-sensor variables. The non-sensor variables used
172 in the beef models were as follows: time of day, parity, breed, weight at beginning of

173 trial (kg), body condition score at beginning of trial, age (years) and AI status
174 (conceived on the first, second or third AI). For dairy cows the variables were: time of
175 day, parity (multiparous or primiparous), number of lactations and age.

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

181 The data from individual sensor variables were plotted to visually assess changes in
182 behaviour in the week prior to calving. The five hours prior to calving was statistically
183 compared to a control period which was the corresponding five hour period 24 hours
184 before using a Wilcoxon signed-rank test. The data was then randomly divided into
185 training and validation data sub-sets (70:30), using the createDataPartition function
186 in the R package caret (Kuhn, 2018), with no animal allowed to be in both the
187 training and validation sub-sets.

188 Random forest (RF) models were developed to predict when an animal was within 5
189 hours of calving using single variables and then combined variables. Random forest
190 classifiers are ensemble machine learning algorithms which are considered to be
191 more accurate than single classifiers, and more robust to noise (Agjee *et al*, 2018).

192 Ensemble algorithms construct a set of independent classifier models (decision
193 trees), with each model having a 'vote' on how to classify each new data point. RFs
194 were developed for each individual sensor variable (TAIL, RUM, EAT and ACT), and
195 then for multiple sensor variables, and finally - for the best model - hourly time points
196 leading up to calf expulsion. The algorithm creates i bootstrapped samples from the

197 training data sub-set, where i is the number of independent decision trees (ntree). A
198 decision tree is then fitted to each bootstrap sample. To overcome the unbalanced
199 nature of the data (fewer target time points than non-target) the bootstrapping,
200 resampling during parameter tuning and model evaluation were down sampled i.e. if
201 there were 100 time points of interest then only 100 other data points were included.
202 Each tree was then tested with the out-of-bag (oob) data points. At each branch in
203 each decision tree, only a random subset of variables are considered (mtry), this
204 parameter and ntree were optimised during tuning of the algorithm. All possible
205 values of mtry were tested and ntree was increased (by 500 trees) until increasing
206 the number of trees further no longer reduced the model error (i.e. the oob error
207 stabilised).

208 The final models were tested on the validation data sub-set. The binary class
209 variable 'calving' and the model predictions (class probabilities) were used to create
210 Receiver Operator Characteristic (ROC) curves and to estimate the area under the
211 ROC curve (AUC). Based on the ROC curves, a threshold for the probability that a
212 cow was within 5 hours of calf expulsion was chosen that resembled the optimum
213 balance between sensitivity (true positives divided by true positives plus false
214 negatives) and specificity (true negatives divided by true negatives plus the false
215 positives). The Matthew's Correlation Coefficient (MCC) was also calculated. The
216 MCC is a metric which assesses the performance of a binary classifier and is less
217 sensitive to imbalanced data sets (such as the test sub-sets in this case) and is
218 calculated using the following equation:

219

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

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

224 All data analyses were undertaken in R (version 3.4.1, R core team, 2017) using the
225 caret (Kuhn, 2018) and pROC (Robin *et al*, 2011) packages.

226 **Results**

227 *Data inclusion*

228 Table 1 gives a summary of the success of data capture for the tail sensors and
229 SHM collars in the beef and dairy trials, and the reasons for excluding animals from
230 the data analysis. Supplementary Table 1 shows how the number of animals
231 included in the analysis changed with hours prior to calving. For the beef trial, a total
232 of 124 animals were included in the eating/rumination dataset, 112 in the activity
233 dataset and 75 in the tail sensor dataset. The corresponding numbers for the dairy
234 animals were 81, 101 and 53, respectively.

235 *Changes in behaviour measured by animal mounted sensors*

236 *Tail raising.*

237 Mean time spent with the tail in a raised position per hour in the week prior to calving
238 was 2.1 ± 0.04 min/hr in beef cows (Figure 2a) and 3.2 ± 0.07 min/hr for dairy cows
239 (Figure 2b). In the five hours prior to calving time spent with the tail raised was
240 significantly higher than in the control period for both beef (increase from 4.7 ± 0.80
241 to 22.8 ± 1.66 min/hr, $p < 0.01$) and dairy cows (increase from 6.6 ± 1.29 to $26.2 \pm$
242 2.48 min/hr, $p < 0.01$).

243 *Time spent ruminating.*

244 In the week prior to calving, the mean time spent ruminating by beef cows was 21.9
245 ± 0.12 min/hr (Figure 3a). Time spent ruminating decreased significantly in the five
246 hours prior to calving compared to the control period (from 23.8 ± 0.67 to 12.0 ± 0.59
247 min/hr, $p < 0.001$). For dairy cows the mean time spent ruminating in the week prior
248 to calving was 16.6 ± 0.10 min/hr (Figure 3b). Time spent ruminating decreased
249 significantly in the five hours prior to calving when compared to the control period
250 (from 14.9 ± 0.73 to 8.8 ± 0.73 min/hr, $p < 0.001$).

251 *Time spent eating.*

252 The mean time spent eating by beef cows was 21.1 ± 0.15 min/hr (Figure 4a) in the
253 week prior to calving. During the control period, mean time spent eating was $19.1 \pm$
254 0.76 min/hr, which increased significantly in the five hours prior to calving ($23.0 \pm$
255 0.74 min/hr, $p < 0.001$). For dairy cows the mean time spent eating in the week prior
256 to calving was 19 ± 0.1 min/hr (Figure 4b). The five hours prior to calving was $24 \pm$
257 0.9 min/hr, which was significantly higher ($p < 0.05$) than the control period (22 ± 1.0
258 min/hr).

259 *Relative activity level.*

260 In the week prior to calving, the mean relative activity by beef cows was 4.2 ± 0.06
261 (Figure 5a). Relative activity significantly increased compared to the control period in
262 the five hours prior to calving (from 5.9 ± 0.54 to 13.6 ± 1.12 , $p < 0.01$). For dairy
263 cows the mean relative activity was 2.9 ± 0.04 in the week prior to calving (Figure
264 5b). There was also a significant increase in relative activity in the five hours prior to
265 calving compared to the control period in dairy cows (from 4.3 ± 0.53 to 9.1 ± 0.81).

266 *Predictive models*

267 The model performance statistics for individual and integrated sensor variables are
268 shown in Table 2. Note that data in the integrated sensor models containing ACT
269 had to be aggregated into 3 hour blocks to resolve the differences in resolution
270 without making the assumption that behaviours were being displayed evenly
271 throughout the reported time periods. The TAIL and TAIL+RUM+EAT models were
272 found to be the most robust models in both the beef and dairy cow data sets. The
273 TAIL model was slightly better at predicting calving within a five hour window for beef
274 cows (MCC = 0.31) than for dairy cows (MCC = 0.29). The TAIL+RUM+EAT models
275 were equally as good at predicting calving within a five hour window for beef and
276 dairy cows (MCC = 0.32 for both models).

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

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

291 *Predicting time to calving*

292 As TAIL was identified as the most important sensor variable for prediction of
293 parturition, and as a one sensor system is more desirable than a multiple sensor
294 system, it was selected to develop models for prediction of discreet time points prior
295 to calf expulsion. Model parameters and performance metrics are shown for hours 0-
296 12 prior to calving in Table 3. Within the beef cows, the predictive performance of
297 TAIL increases after four hours prior to calf expulsion (MCC increases from 0.07 at
298 four hours prior to 0.17 at three hours prior). A similar increase was observed in the
299 dairy cows (MCC increased from 0.06 four hours prior to calf expulsion to 0.14 at
300 three hours prior to calf expulsion).

301 **Discussion**

302 *Behavioural changes*

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

307 The beef cows displayed an increase in the EAT variable in the hour prior to calf
308 expulsion and in the hour in which the calf was born which was not observed in the
309 dairy cows. This is contrary to other studies which report decreases when
310 measurements were made by visual observation (Miedema *et al*, 2011a) and by
311 recording the time the cow spends with its head in a feed bin (Braun *et al*, 2014;
312 Büchel and Sundrum, 2014). The hour in which the calf was born includes the whole
313 hour, regardless of when the cow calved within that hour – e.g. if the cow calved at
314 quarter past the hour, the next 45 minutes are also included. The apparent observed

315 increase in eating may actually be misclassification of licking behaviour, this
316 behaviour has been shown to peak in the hour proceeding birth of the calf (Jensen,
317 2012). The same trend was not observed in the dairy cows as their collars were
318 removed directly after calving. In the hour prior to calf expulsion it is possible that the
319 cow is displaying ground licking or nesting behaviours (Miedema *et al*, 2011a) which
320 are being misclassified as eating by the accelerometer algorithms.

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

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

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

343 *Predictive models*

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

357 A variety of multi-sensor systems have been used to integrate data streams
358 monitoring different behaviours. Rutten *et al* (2017) achieved a very low false
359 positive rate of 1% within three hours of calf expulsion using two sensors to measure
360 activity level, rumination time, feeding time and temperature; however the sensitivity
361 was only 42.4%. Borchers *et al* (2017) were able to predict parturition eight hours
362 prior to calf expulsion with a sensitivity of 82.8% and a specificity of 80.4% using two
363 sensors (neck mounted for rumination time and leg mounted for time spent standing

364 or lying and step count). Ouellet *et al* (2016) achieved sensitivity of 77% and
365 specificity of 77% within a 24 hour window using three sensors to record four
366 variables (vaginal temperature, rumination time, lying time and lying bouts). In the
367 present study, similar results were achieved with a single sensor (TTA: sensitivity =
368 78.6%, specificity = 83.5% for dairy cows).

369 **Conclusions**

370 In this study it was possible to predict when beef or dairy cows were within five hours
371 of calf expulsion using animal mounted technologies. Of the variables measured by
372 the sensors used in this study, time spent with the tail in a raised position was found
373 to be the best predictor of parturition, and had optimal predictive power at two hours
374 prior to calf expulsion.

375 **Declaration of Interest**

376 The authors declare no conflict of interest.

377 **Ethics statement**

378 The animal trials described below were approved by the Animal Experiment
379 Committee of SRUC and were conducted in accordance with the requirements of the
380 UK Animals (Scientific Procedures) Act 1986.

381 **Software and data repository resources**

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

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392 which improved this paper.

393 **References**

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495

496 Table 1: Success of data recording (robust data collected) for variables collected
 497 using neck mounted accelerometers (Silent Herdsman collars): time spent eating,
 498 time spent ruminating and relative activity level, and tail mounted accelerometers
 499 (tail raise) on beef and dairy cows

	Beef			Dairy		
	Eating / Rumination	Activity	Tail raise	Eating / Rumination	Activity	Tail raise
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 hours	4	15	3	4	2	0
Animals in analysis	124	111	75	81	101	53

500

501

502 Table 2: Model parameter tuning and performance statistics for single and combined
503 sensor variable random forest models to predict calving in beef and dairy cows. mtry
504 = number of variables used at each split in each independent decision tree, ntree =
505 number of independent decision trees oob error = out of bag error, AUC = area
506 under the curve, CI = confidence interval, Se = sensitivity, Sp = specificity, MCC =
507 Matthew's Correlation Coefficient, TAIL = number of tail raise events per hour, EAT =
508 time spent eating per hour (minutes), RUM = time spent ruminating per hour
509 (minutes), ACT = relative level of activity per 1.5 hours (minutes).

	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

510

511 ¹ ACT models have a 1.5 hour time step due to the resolution of data collection for
512 this sensor variable.

513 ² Combined models containing ACT have a 3 hour time step to resolve differences in
514 the resolution of data collection between ACT and other sensor variables.

515

516 Table 3: Model parameter tuning and performance statistics for random forest
 517 models using number of tail raise events to predict parturition at discreet time points
 518 prior to calf expulsion in beef and dairy cows. Mtry = number of variables used at
 519 each split in each tree, ntree = number of independent decision trees, oob error = out
 520 of bag error, AUC = area under the curve, Se = sensitivity, Sp = specificity, MCC =
 521 Matthew's Correlation Coefficient

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

522

523 Figure 1: Tail mounted tri-axial accelerometer (TTA) attachment to cow tail and
524 orientation

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

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

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

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