Identification of discriminating behavioural and movement variables in lameness scores of dairy cows at pasture from accelerometer and GPS sensors using a Partial Least Squares Discriminant Analysis

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Abstract

The behaviour and movement of lame dairy cows at pasture have been studied little, yet they could be relevant to improve the automatic detection of lameness in cows in pasture-based systems. Our aim in this study is to identify behavioural and movement variables of dairy cows at pasture that could discriminate lameness scores. Individual cow behaviours were predicted from accelerometer data and movements measured using GPS data. Sixty-eight dairy cows from three pasture-based commercial farms were equipped with a 3-D accelerometer and a GPS sensor fixed on a neck collar for 1 to 5 weeks, depending on the farm, in spring and summer 2018. A lameness score was assigned to each cow by a trained observer twice a week. Behaviours were predicted every 10 seconds based on accelerometer data, and then combined with the GPS position. Segmentation on behavioural time series was used to delineate each behavioural bout within each outdoor period. Thirty-seven behavioural and movement variables were then calculated from the behavioural bouts for each cow . A partial least square discriminant analysis was performed to identify the variables that best discriminate lameness scores. Time spent grazing, grazing bout duration, duration before lying down in the pasture, time spent resting, number of resting bouts, distance travelled during grazing, and dispersion were the most discriminant variables in the PLS-DA (VIP > 1). Severely lame cows spent 4.5 times less time grazing and almost twice as much time resting as their sound congeners, especially in the lying

position. Exploratory behaviour was also reduced for both moderately and severely lame cows, resulting in 1.2 and 1.7 times less distance travelled respectively, especially during grazing, These variables could be used as additional variables to improve the performance of existing lameness detection devices in pasture-based systems.

Keywords

Behaviour and movement, dairy cow lameness, pasture, accelerometer, GPS, PLS-DA

Highlights

- Behavioural and movement variables can discriminate lameness scores using PLS-DA
- Lame cows spend more time resting and less time grazing and exploring
- Accelerometer combined with GPS could help lameness detection in grazing systems

Abbreviations

- AHDB: Agriculture and Horticulture Development Board
- AMS: Automatic Milking System
- ANOVA: Analysis of Variance
- GPS: Global Positioning System
- HMM: Hidden Markov Model
- LS: Lameness Score
- PLS-DA: Partial Least Squares Discriminant Analysis
- VIP: Variable Importance in Projection

1. Introduction

Lameness is one of the main health disorders in dairy cattle (Huxley, 2013), affecting animal welfare (Whay and Shearer, 2017) and inducing economic losses for farmers (Willshire and Bell, 2009). Lameness detection is usually done by visual inspection by the farmer, and lameness prevalence is often underestimated by farmers (Cutler et al., 2017), leading to delayed treatment of lame cows. For these reasons, automatic lameness detection tools could be a relevant way to improve the early identification of lame cows in dairy farms in order to reduce associated costs (Green et al., 2002) and to increase chances of recovery (Leach et al., 2012).

Automatic detection tools are being developed for indoor systems. The main systems are based on gait change determined using 2D and 3D cameras, pressure mats or pedometers, or on changes in behaviour determined using accelerometers on the neck, feeding data or automatic milking system (AMS) data (Van Nuffel et al., 2015). The performance of these systems is promising, although their sensitivity and specificity should be improved in order to increase their use in commercial dairy farms (O'Leary et al., 2020).

Agroecology promotes the return of pasture-based systems for dairy cows (Dumont et al., 2013). Although lameness is less common in grazing systems, its prevalence in dairy farming remains non-negligible (Haskell et al., 2006). Furthermore, lameness may be favoured by certain grazing conditions, such as grazing on moist soils during periods of heavy rainfall (Politiek et al., 1986; Vermunt and Greenough, 1995), alternate grazing with sheep (Barker et al., 2010), or when cows have to walk on roads or concrete tracks between the parlour and grazing (Barker et al., 2009). In addition, dairy cows usually graze for only part of the year and are housed during the winter season (van den Pol-van Dasselaar et al., 2020), possibly leading to lameness prevalence similar to indoor-based systems in early spring. For these reasons, the development of automatic tools for lameness detection in dairy cows would also be relevant for pasture-based systems.

Previous studies have shown that the amount of time spent in standing and lying positions by dairy cows at pasture changed with lameness (Navarro et al., 2013), suggesting that behaviour could be a relevant indicator to help lameness detection at pasture, in the same way as in indoor systems (Almeida et al., 2008; Blackie et al., 2011; Weigele et al., 2018). A wide range of behaviours on pasture can now be collected using accelerometer sensors (Riaboff et al., 2020a), a technology already used in dairy farming for heat detection (Kamphuis et al., 2012), and one that is quite affordable for farmers (Delagarde and Lamberton, 2015). Furthermore, indicators evaluating the movement of dairy cows at grazing obtained with embedded Global Positioning System (GPS) sensors (Feldt and Schlecht, 2016; Riaboff et al., 2020b) could also be interesting for lameness detection, although this has not yet been studied. The identification of behavioural variables (time-budget, duration and number of bouts) and movement variables (distance, dispersion, distance travelled during grazing, etc.) that discriminate lameness scores on pasture would thus be a first step in the development of a lameness prediction model for pasture-based systems.

In two previous studies, a methodology was developed to predict a wide range of behaviours in dairy cows at pasture from accelerometer data every 10 seconds, including grazing, walking, resting and ruminating both in lying and standing position (Riaboff et al., 2019; Riaboff et al., 2020a). These predicted behaviours can be combined with the cow position using GPS data collected on animals (Riaboff et al., 2020b). Behavioural and movement variables can then be calculated from the predicted behaviours and GPS position. In this study, we propose to identify behavioural variables predicted from accelerometer data as well as movement variables computed from GPS data that could be used to discriminate lameness scores in pasture-based systems, using a Partial Least Squares Discriminant Analysis (PLS-DA).

2. Materials and methods

An overview of the main steps in the Materials and methods section is provided in Figure 1. First, accelerometer and GPS data were obtained from 68 dairy cows from three pasture-based farms. For each cow, a lameness score was collected twice a week over the course of the experiment (*section 2.1*). Prediction of behaviours was carried out using accelerometer data and combined with the position of dairy cows using GPS data (*section 2.2*). For each cow, a lameness score was assigned for each day the cow was fitted with the accelerometer and GPS device. For each day the cow was fitted, the lameness score was the score from the closest scoring session. Behavioural and movement variables were then computed for each cow on each day she was equipped after identifying behavioural bouts within each outdoor period (*section 2.3*). Finally, the identification of discriminant behavioural and movement variables was done using a PLS-DA (*section 2.4*).

< Figure 1.>

2.1 <u>Data collection</u>

2.1.1 Description of farms and animals

The experiment was carried out on three commercial dairy farms successively, with herd size ranging from 54 to 71 Holstein cows, located in the Pays-de-la-Loire region (France) from April to July of 2018. Dairy cows were milked using an AMS (milking count per day (mean ± SD): 2.7 ± 0.8; 2.4 ± 0.7 and 2.0 ± 0.8). Cows were housed from November to March and had access to pasture continuously from April to October. During the grazing season, cows were free to stay in the barn. Barns were equipped with straw cubicles in all three farms. Cows received supplementation with maize silage and concentrates in the first and the third farm (theoretical supplementation: 40 %), and supplementation with hay and concentrates in the second farm (theoretical supplementation: 20 %). Most of the concentrates were delivered during milking with the AMS. Details on each farm are provided in Appendix 1.

Cows with less than 50 or more than 250 days in milk at the start of the experiment were not included in order to avoid animals leaving the herd or being dried off during the experiment. Animals were then selected so that both lame cows (lameness score ≥ 2; Agriculture and Horticulture Development Board, Stoneleigh Park, Kenilworth, Warwickshire, CV8 2TL, 2020) and sound cows (lameness score ≤ 1; Agriculture and Horticulture Development Board, Stoneleigh Park, Kenilworth, Warwickshire, CV8 2TL, 2020) were equipped in each farm. For this purpose, each cow in the herd was scored three days before the start of the experiment in each farm according to the methodology described in *section 2.1.3.1*. The distribution of lameness scores in each farm is provided in Appendix 1. As parity may impact behaviour, we tried to balance the dataset in terms of parity. For this purpose, we chose the animals so that each lame cow had an equivalent sound cow with the same parity (1, 2 or ≥ 3) and with a difference in days in milk of less than 20 days. Based on these criteria, 13/54 cows were equipped in the first farm, 27/71 cows in the second farm, and 26/61 in the last one, giving a total of 68 different cows used for the study. Among the equipped cows, one cow in Farm 1 and eight cows in Farm 3 showed signs of heat on one day each during the experiment (AMS data). Details on the animals selected in each farm are provided in Table 1.

< Table 1>

2.1.2 Description of sensors

An RF-Track datalogger (RF-Track, Rennes, France) comprising an LSM9DS1 three-axis accelerometer (STMicroelectronics, Geneva, Switzerland) ± 2 g and a GPS sensor (part number EVA-7M-0, μ-Blox, Thalwil, Switzerland) with a static position error estimated at ± 1.72 m was used. The sampling rate was 59.5 Hz and 1 Hz for the accelerometer and GPS data, respectively. Sensors were powered with two 3.7 V lithium batteries (2.6 Ah). A secure digital card was used for data storage. The dataloggers were 98.2 mm x 51.60 mm x 36.0 mm in size and weighed 250 g. The dataloggers were attached to a collar and positioned on the right side of the cow's neck. A counter-weight of 500 g was added to prevent the collars from turning around and they were tightly adjusted. The x-axis detected the up-down direction, the y-axis detected the backward-forward direction and the z-axis detected the left-right direction. The device used is shown in Figure 2.

2.1.3 Experiment design

The experiment was carried out from April 2018 to July 2018 using 68 cows from three pasture-based commercial farms. The course of the experiment is shown in Figure 2.

< Figure 2>

2.1.3.1 Lameness score collection

Equipped cows were scored twice a week for the duration of the experiment. Each scoring session was carried out in the barn after supplementation delivery. Cows were made to walk along a 3 m x 30 m path marked with a tape. A camera was positioned near the path so that each animal was filmed as it walked along it. The videos were used to check intra-observer consistency. If necessary, a handler would stand behind the cows to encourage them to walk. Lameness scores (LS) were assigned to each cow by a single experimenter (C.E. Petiot, 5th year veterinary student at the time of the experiment) trained in the methodology developed by the Agriculture and Horticulture Development Board (Agriculture and Horticulture Development Board, Stoneleigh Park, Kenilworth, Warwickshire, CV8 2TL, 2020). The AHDB method classifies lameness using a four-point scale (0 = good mobility (not lame), 1 = imperfect mobility, 2 = impaired mobility (lame), and 3 = severely impaired mobility (severely lame); Table 2). The Cohen’s Kappa was computed to evaluate the intra-reliability of observer scoring. An intra-observer Cohen’s Kappa of 0.66 was obtained by scoring 50 cows from the three farms using videos watched twice several months apart, suggesting a strong agreement between the scoring sessions (Cohen, 1960). We did not interfere in the management of lameness by the farmers during the experiment. At the end of the data collection process, each farmer was provided with a detailed report on the prevalence of lameness on their farm, along with a list of recommendations to reduce this prevalence.

< Table 2>

2.1.3.2 Accelerometer and GPS data collection

In each farm, the selected cows were continuously equipped with the device for a minimum of two days and a maximum of six days, the latter corresponding to the battery life of the sensors. Data were downloaded after each continuous period and batteries were recharged for eight hours before equipping the cows for the next period. Four, two and five continuous periods were carried out, leading to 21, 12 and 25 days of experiment in the first, the second and the third farm, respectively. In this way, accelerometer and GPS data were collected on a total of 58 different days (Table 1).

2.2 Prediction of dairy cow behaviour and combination with GPS data

This step aimed to (i) predict the behaviours successively expressed every 10 seconds by the cows from accelerometer data over the course of the experiment, and to then (ii) combine the predicted behaviours with GPS data. For this purpose, we used a methodology described in two previous studies (Riaboff et al., 2019; Riaboff et al., 2020a), which ensures the prediction of six behaviours in dairy cows on pasture from accelerometer data with high performance (accuracy: 98 %; Cohen’s Kappa: 0.96). We refer to Riaboff et al. (2020a, 2019) for a detailed explanation of the methodology. The six predicted behaviours are the following:

- Grazing: biting, taking frequent bites or chewing and searching without raising the head.
- Walking: moving from one location to another without lowering the head to ground level.

- Ruminating while lying: lying down with regurgitating ruminal bolus before chewing and then re-swallowing.
- Ruminating while standing: standing with regurgitating ruminal bolus before chewing and then re-swallowing.
- Resting while lying: lying down without rumination.
- Resting while standing: standing without movement or rumination.

The methodology developed was thus applied in this study to predict the behaviours as illustrated in Figure 3. Raw signal accelerometer sequences collected on the 68 cows over the 58 days of the experiment were divided into segments (*windows*) of 10 s, without data in common between two consecutive windows (without *overlap*). Sixty-one features were then calculated in each window. This pre-processing step was performed in Matlab R2018a. The eXtreme Gradient Boosting model fitted by Riaboff et al. (2020a) was then directly used to predict the behaviours from the calculated features using the xgboost package (Chen et al., 2018) in R 4.0.0 (*R Core Team*, 2020). The Hidden Markov Model (HMM)-based Viterbi algorithm reported by Riaboff et al. (2020a) was then applied with the R package HMM (Himmelmann, 2010) to smooth the predicted behaviours in successive windows from the same cow over the entire experiment. Each 10 s window of behaviour was finally associated with the position (longitude and latitude) of the cow, based on the time of the GPS and the accelerometer, which was previously synchronised. In this way, each 10 s window of behaviour was associated with the GPS coordinates of the first sample of the window and those of the last sample of the window. At the end of this step, we obtained the sequences of the 10 s windows of behaviour for each cow over time, with the associated GPS coordinates.

< Figure 3>

2.3 Creation of the dataset with behavioural and movement variables and the associated lameness score

The aim of this step was to gather in the same dataset the variables calculated from the predicted behaviours and the movement of the cows and the corresponding lameness scores for each cow on each of the days she was equipped with the device.

2.3.1 Lameness score assignment for each cow on each of the days she was equipped

As explained in section *2.1.3.1*, scoring sessions were carried out twice a week. The score assigned to each observation (cow X day) corresponded to the score obtained for a given cow in the scoring session closest to the day of the observation. If the scoring session was more than three days away from the day considered (i.e. if the cow missed a scoring session), a missing value was assigned for that observation. For 10 of the 58 days of the experiment, the number of days between the two successive scoring sessions was the same. If the cow was scored in both sessions, we chose to assign the lameness score from the second session as the default value.

2.3.2 Behavioural and movement variables for each cow on each of the days she was equipped

2.3.2.1 Identification of behavioural bouts within outdoor periods

The aim of this step was to identify behavioural bouts within each outdoor period, i.e. sessions during which an animal expressed the same behaviour continuously, with only brief interruptions. The principle used to identify behavioural bouts within each outdoor period is illustrated in Figure 4. For this purpose, we first identified periods spent outdoors for each cow from GPS data and the coordinates of the barn (French National Geographic Institute; "Géoportail," 2006), using the R package sp (Pebesma and Bivan, 2005). We then applied Lavielle segmentation (Lavielle, 1999) on the "indoor-outdoor" periods time series in order to smooth potential GPS errors (Figure 4 a) using the R package adehabitatLT (Calenge, 2006). This method finds the best segmentation of a time series given a fixed maximum number of segments by minimising a contrast function (contrast between the actual time series and the segmented time series). Finally, the sequence of 10 s windows of predicted behaviour for each cow within each outdoor period was smoothed, also using Lavielle segmentation

(Figure 4 b). A more in-depth explanation of the use of this method and the parameters chosen is provided in Appendix 2.

Each segment resulting from the segmentation was considered as a bout. The behaviour associated with each bout was the behaviour most represented. It should be noted that in some segments, no behaviour could be identified as the most represented. In this case, the bout was annotated “heterogeneous bout” (16 % of the bouts). As the “heterogeneous bouts” were difficult to interpret from a behavioural point of view (Appendix 3), they were not considered in the rest of the analysis.

< Figure 4>

2.3.2.2 Calculation of movement and behavioural variables

The behavioural bouts previously obtained and the corresponding positions of dairy cows on pasture were used to compute different variables. These variables are presented in Table 3. The following behavioural variables were computed for each cow on each day she was equipped: the overall time spent on pasture (1), the time-budgets (2), the number of bouts (3), and the mean duration of bouts (4). The variables (2) to (4) were calculated for the six predicted behaviours described in section 2.2, as well as for the following grouped behaviours:

- Ruminating: grouping of “ruminating while lying” and “ruminating while standing” behaviours
- Resting: grouping of “resting while lying” and “resting while standing” behaviours
- Lying: grouping of behavioural variables from “ruminating while lying” and “resting while lying”
- Standing: grouping of behavioural variables from “ruminating while standing” and “resting while standing”

The following movement variables were also computed from the GPS data and behavioural bouts: the number of round-trips between the pasture and the barn (5), the overall distance travelled (6), the overall dispersion (7), the distance travelled during grazing (8), the distance travelled during walking (9), the ratio of the distance travelled during grazing over the distance travelled during grazing and walking (10), the speed of walking (11), and the mean duration between the time the cow enters the pasture and the time she lies down (12). It should be noted that behavioural and movement variables were recorded as a missing value when no outdoor period was detected over a whole day for a given cow.

< Table 3>

2.3.2.3 Weighting and standardisation

As explained in section *2.1*, 68 cows from three commercial farms were used in this study, and data were collected over 58 days, which resulted in a considerable variation between cows (time spent outdoors, etc.) and between days (pasture access, area of pasture, etc.), thus preventing comparison of the behavioural variables from one cow to another and from one day to the next. Consequently, both behavioural and movement variables were corrected to make the observations comparable thereafter. A weighting was thus applied depending on the variable, using:

- The time spent outside by the cow on a given day ($Time_{out}$).
- The maximum $time_{out}$ recorded on a given day among all the cows equipped on that day ($Time_{out,max}$).
- The distance travelled by the cow on a given day (Distance).
- The maximum distance travelled on a given day among all the cows equipped on that day ($Distance_{max}$).
- The maximum dispersion on a given day among all the cows equipped on that day ($R2n_{max}$).

The weighting applied to each variable is provided in Table 3. A more detailed explanation of the weighting is provided in Appendix 4. Finally, the behavioural and movement variables were standardised.

2.3.3 Dataset cleaning

The resulting dataset was then cleaned to avoid including unusable observations and highly correlated variables in the analysis to follow. First, observations for which the nearest scoring session was more than three days away (the cow having missed a scoring session; section *2.3.1*) were removed from the dataset, corresponding to 14 observations (1.5 % of the dataset). Missing values corresponding to observations in which the cow did not go to the pasture on a given day (section 2.3.2.2) were also removed from the dataset. This corresponded to the deletion of 88 observations (9.3 % of the dataset). Details on the observations removed are provided in Appendix 5 a. This resulted in a dataset of 863 observations (Appendix 5 b). The coefficient of correlations between each behavioural and movement variable were calculated using the R package corrplot (Wei, 2017). No variable was highly correlated with another (correlation > 0.95; see Appendix 6), and the 37 quantitative variables were therefore retained.

2.4 Identification of discriminating variables in lameness score with a PLS-DA

A one-way Analysis of Variance followed by a Tukey test was applied in a preliminary step, and showed that the group LS=0 was never significantly different from the group LS=1 for any of the variables studied (Appendix 7). For this reason, we combined LS=0 and LS=1 within the same group "LS0-1" before applying the PLS-DA.

We applied a PLS-DA model because (i) it is a Machine Learning method adapted to perform a first analysis on a large dataset about which we have limited *a priori* knowledge, and (ii) it is particularly relevant to identify the variables that have contributed to discrimination between groups using the Variable Importance in Projection (VIP) metric (Tenenhaus, 1998).

PLS-DA is a multivariate projection method for modelling a relationship between the quantitative variables X and a dummy matrix Y (Barker and Rayens, 2003). The target is to find PLS-components which both restore the variance of the matrix X and maximise the separation between the classes of Y. In this study, the independent variables X were the behavioural and movement variables, and the dummy matrix Y was a three-column matrix, representing the groups "LS0_1", "LS2" and "LS3". For each column in Y, each sample was assigned to 0 or 1 depending on the group to which it belonged. VIPs were then used to identify variables of X which are important in determining class membership of Y, also called discriminant variables (Chong and Jun, 2005). A more detailed description of the PLS-DA and the definition of VIP are provided in Appendix 8. The PLS-DA and VIP analysis were performed with the R package plsdeplot (Sanchez, 2016).

3. Results

Means and standard deviations obtained for the three lameness groups (LS0_1, LS2 and LS3) for each variable are provided in Table 4. Plots of the included cow X day observations on the first two PLS-components with the associated performance metrics of the PLS-DA model, as well as the circle of correlations and the VIP of variables in descending order, are displayed in Figure 5. It should be noted that the VIPs used were those computed only on the first component, because it was the only significant component in the discrimination model.

< Table 4>

< Figure 5>

Three PLS-components were kept in the model as the Q2cum (predictive coefficient) continued to increase until the third component (Appendix 9 a), but only the first one was significant based on the Tenenhaus criteria (Tenenhaus, 1998; Appendix 9 b). The PLS-DA model using the first two components led to a Q2cum of 0.11, a R2Xcum of 0.42 and a R2Ycum of 0.11. Plots of observations (Figure 5 a) showed a discrimination between each LS on the first PLS component (R2X: 20%), although there is an overlap between the 95 % confidence ellipses. The circle of correlations on the first two components between the most important variables (VIP > 0.8) and lameness scores is provided in Figure 5 b. The discrimination was explained by both the behavioural and movement variables. The LS0_1 group was associated with higher “distance”, “R2n”, “distance grazing”, “distance ratio” and “duration before lying” and with longer “$\text{time}_{\text{grazing}}$” and “duration $\text{bout}_{\text{grazing}}$” than the two other groups (Figure 5 b; Table 4). The LS2 group was associated with longer “$\text{time}_{\text{ruminating\_standing}}$”, “$\text{time}_{\text{standing}}$” and “duration $\text{bout}_{\text{standning}}$” (Figure 5 b; Table 4). The LS3 group was associated with an increase in resting behaviour (“$\text{time}_{\text{resting}}$”, “number $\text{bouts}_{\text{resting}}$”, “duration bouts$_{resting}$”), especially in the lying position (“time$_{resting_lying}$”, “duration bout$_{resting_lying}$”, “number bouts$_{resting_lying}$”) (Figure 5 b; Table 4).

Among the 37 variables tested, 17 contributed to discriminate the lameness scores (VIP > 0.8), among which 14 were very important for discrimination (VIP>1) (Figure 5 c). The most important behavioural variables (VIP > 1) included grazing behaviour (“time$_{grazing}$”), resting behaviour (“time$_{resting}$”, “duration bout$_{resting}$”, “number bouts$_{resting}$”) especially while lying (“time$_{resting_lying}$”, “duration bout$_{resting_lying}$”, “duration before lying”), and ruminating both while standing (“time$_{ruminating_standing}$”) and lying (“time$_{ruminating_lying}$”). The most important movement variables (VIP > 1) were the distance travelled (“distance grazing”, “distance”, “distance ratio”) and the dispersion (“dispersion R2n”). Other variables that contributed to discrimination (VIP > 0.8) were “number bouts$_{resting}$” , “number bouts$_{resting_lying}$”, “duration bouts$_{grazing}$” and “duration bouts$_{resting}$”.

4. Discussion

4.1 <u>Behavioural and movement variables to discriminate lameness scores</u>

Instances where cows did not go out to pasture a given day (missing outdoor periods; *section 2.3.2.2*) occurred for both lame and sound cows (Appendix 5 a). Furthermore, the PLS-DA showed that the time spent outdoors (time$_{out}$) was not a discriminating variable. Consequently, lame and sound cows spent a similar amount of time on pasture but the expressed behaviours and movement patterns are altered with the lameness score.

4.1.1 Discriminating variables related to grazing behaviour

The time spent grazing was the variable that best discriminated the lameness scores (Figure 5 c). LS0_1 (sound cows) spent 4.5 times longer grazing than LS3 (severely lame) and 1.6 times longer than LS2 (moderately lame), which was explained by longer grazing bouts (Figure 5 b; Table 4). These results contrast with those obtained in the study by Walker et al. (2008), where no difference was observed in grazing behaviour between lame and sound cows at pasture. It should be noted that the latter study was carried out on animals after oestrus synchronisation, whereas only nine cows showed signs of heat on one day each during the experiment in our study (AMS data; section *2.1.1*), which could explain this difference in results, as feeding behaviour is also modified during heat events (Dolecheck et al., 2015). Furthermore, our results are in accordance with the studies conducted in indoor-based systems, as reductions in feeding time (Weigele et al., 2018) and the duration of feeding bouts (Norring et al., 2014) have already been shown.

4.1.2 Discriminating variables related to resting behaviour

Time spent resting was the second most discriminating variable between lameness scores (Figure 5 c). Severely lame cows spent almost twice as much time resting as their sound congeners, especially in the lying position, which was explained by both more and longer resting while lying bouts (Figure 5 b; Table 4). These results are consistent with those obtained in indoor-based systems, as Weigele et al. (2018) found a decrease in activity in lame cows, while Blackie et al. (2011) observed an increase in lying bouts. The increase in the number of lying bouts was also noted by Navarro et al. (2013), while the increase in resting bout duration has already been observed in indoor-based systems (Weigele et al., 2018).

In our study, the duration before lying down was also one of the most important variables (Figure 5 c) and contributed to discriminating the sound group from the other two (Figure 5 b; Table 4). Indeed, sound cows or those with a slight asymmetry in their gait lie down twice as late once they enter the pasture as lame cows (Table 4). Yunta et al., (2012) also showed that lame cows lay down earlier than sound cows once the ration had been distributed in indoor based-systems. Similarly, lame cows probably shortened their first grazing bout once on the pasture in our study. It is also possible that severely lame cows avoid lying down in the barn and therefore lie down more quickly once on pasture.

4.1.3 Discriminant variables related to exploratory behaviour

The total distance travelled contributes to the discrimination between lameness scores (Figure 5 c). Indeed, sound cows travelled about 1.5 times further than their lame congeners (Figure 5 b; Table 4). This finding is in agreement with the study by Blackie et al. (2011) in indoor-based systems. In our study, the distance travelled during grazing as well as the distance ratio were also 1.6 times and 2.3

times greater for the sound and slightly asymmetric gait cows than for the moderately and severely lame cows, respectively (Figure 5 b; Table 4), explaining why these variables were also important in discriminating between lameness scores (Figure 5 c). Similarly, the dispersion of the sound group was 1.6 times greater than for the severely lame cows, and also slightly greater than for the moderately lame cows (Figure 5 b; Table 4). All of these results suggest a more pronounced exploratory dynamic in sound and slightly asymmetric gait cows than in lame animals, especially during grazing behaviour. Nevertheless, walking time did not discriminate between lameness scores (Figure 5 c), which is in accordance with the study by Beer et al. (2016) in indoor-based systems. However, speed has not emerged as a discriminant variable in our study, contrary to what was observed in indoor-based systems (Beer et al., 2016; Blackie et al., 2011). It should be noted that in our study, speed was measured by averaging the distances travelled calculated from the GPS data across all the 10 s windows in which the walking behaviour was predicted. It is therefore possible that the chosen window size was too small to calculate a representative walking speed.

4.1.4 Discriminant variables related to ruminating and standing position

The moderately lame group was associated with a slightly longer time ruminating while in standing position than sound cows (Figure 5 b; Table 4). These results differ from those obtained by Walker et al. (2008) on pasture, as lame cows spent more time ruminating while lying down and less time ruminating while standing compared to sound cows. However, the results are difficult to compare, as the latter study was carried out with cows after oestrus synchronization, contrary to our study (section *2.1.1*), and rumination may be modified during this period (Dolecheck et al., 2015). It would be interesting to conduct our experiment again with other cows in order to confirm the results observed on the standing and lying positions adopted by lame cows while ruminating. The moderately lame group also spent 1.7 times longer standing than the sound group (Figure 5 b; Table 4). This result is quite unexpected, as time spent standing on pasture is somewhat reduced in lame cows in other studies (Walker et al., 2008; Navarro et al., 2013). This could be explained by the difference in the grazing systems used (size of the herd, duration of pasture access, milking system, etc.). In particular, it should be noted that in the second and the third farm, a single AMS was used for 71 and 61 cows, respectively. This led to AMS saturation at certain times, forcing animals to wait on the access road from the pasture to the AMS before being milked. As it has already been shown that lame cows avoid aggressive behaviours with others (Galindo and Broom, 2002) and move to the back of the herd (Walker et al., 2008), it is possible that moderately lame animals waited longer than sound animals, explaining the increase in the total time spent standing. In contrast, severely lame cows may postpone milking and wait lying down in the pasture as long as possible before being milked, which could also explain why they spend more time lying down. Experiments in farms using a milking parlour rather than an AMS should be done to confirm the discriminatory status of the standing position between the moderately lame group and the other two groups.

4.2 Behavioural and movement variables as relevant indicators to improve the performance of existing lameness detection devices in pasture-based systems

4.2.1 Variables providing additional information in pasture-based systems

Most existing lameness detection systems use data collected from housed cows, such as computer vision based on digital cameras (Van Hertem et al., 2014) or the indoor behaviour of dairy cows from accelerometer data (Beer et al., 2016). In this regard, combining different types of data is often a means to obtain better performance of prediction, whatever the classification problem (Wang et al., 2018). Especially for lameness prediction, Beer et al. (2016) combined data from leg-attached accelerometers and from a noseband sensor to detect lameness in indoor-based systems, and reached good performance of prediction (sensitivity: 90.2 %; specificity: 91.7 %). In the same way, de Mol et al. (2013) combined activity data from accelerometers, milking data and data from computerised concentrate feeders, and obtained satisfactory performance of lameness prediction (sensitivity: 85.5 %; specificity: 88.8 %). Use of discriminant behavioural and movement variables is therefore certainly a potential way to enhance the performance of lameness prediction in pasture-based systems. However, it should be noted that lameness scores 0 and 1 cannot be discriminated (Appendix 7), probably because it is difficult for the observer to distinguish between a cow with a lameness score 0 (not lame) and a cow with a lameness score 1 (slight asymmetry, unidentifiable affected leg) during the scoring sessions. Furthermore, as explained in the previous section, discriminating variables between lameness scores 2 and 3 should be confirmed by carrying out experiments in other farms that do not use an AMS. On the basis of this study, it thus seems possible to discriminate sound cows or cows with a slight asymmetry from severely lame cows using behavioural and movement variables at pasture, but the relevance of these variables for discriminating moderately lame cows from the other two groups has yet to be confirmed.

4.2.2 A potentially transferable approach in the field

Behavioural and movement variables were obtained from (1) the collection of accelerometer and GPS data from dairy cows on commercial farms, (2) the application of a robust methodology to predict a wide range of behaviours every 10 seconds (Riaboff et al., 2019; Riaboff et al., 2020a) and then combination with the GPS position (Riaboff et al., 2020b), (3) an unsupervised segmentation on time series (Lavielle, 1999) to first isolate the outdoor periods and then to identify the behavioural bouts within each of these, and (4) a weighting of variables per cow or per day. Steps (1) and (2) provide automatic monitoring of cattle behaviour at pasture every 10 s. Step (3) ensures smoothing of the predicted behaviours to obtain continuous behavioural bouts without the need to set arbitrary criteria, as are often applied in commercial systems (Hendriks et al., 2020; Werner et al., 2018). Step (4) is a way of adapting these variables to each animal, each day of grazing and each farm, which is necessary for use in commercial farms. The combination of these four steps thus ensures a robust collection of behavioural and movement variables, which is easily transferable to the field.

In addition, neck-mounted accelerometer sensors are already used for other applications ("Medria Solutions," 2020), which could facilitate transfer to the field if a centralised collection of raw accelerometer data is produced to respond to several issues (heat detection, welfare monitoring, lameness detection, etc.). In the same way, embedded GPS sensors can be used for several applications in pasture-based systems, including the development of targeted preventive treatments based on the identification of risk areas visited by cows (Agoulon et al., 2012), or the reduction of environmental impacts at farm level based on the identification of overused areas (Lush et al., 2018). It should therefore be possible to integrate the overall methodology used in our study into automatic lameness detection devices for pasture-based systems.

4.3 Limits and perspectives

The discriminant behavioural and movement variables identified can be used to enhance the performance of lameness detection systems in pasture-based farming, but the creation of a high-performance prediction model based exclusively on these variables seems difficult to achieve at the moment. The two main reasons for this are (i) the poor performance of the PLS-DA model (Q2cum: 0.11; criterion of validity of the predictive model: Q2cum > 0.5 (Tenenhaus, 1998)), and (ii) the need for the animals to go on pasture to collect data. Concerning the first point (i), other statistical models should be used to confirm our results. In our study, we chose a machine learning method (PLS-DA) to identify discriminant variables because (i) we had a large dataset of 863 observations (Appendix 5 b) and 37 innovative variables for which we had limited *a priori* knowledge, and (ii) cows were not followed long enough to ensure sufficient transitions between scores, especially for lameness score 3, nor were there enough animals (Appendix 5 b) to be able to distinguish the random cow effect from the fixed lameness effect in a probabilistic model. As this study has highlighted the relevance of 17 behavioural and movement variables at pasture to discriminate between lameness scores, it would now be interesting to carry out this experiment again with an adapted protocol to apply a statistical model, such as an ordinal logistic regression, in order to conclude on the significance of these 17 variables, and to assess their ability to predict lameness scores at pasture. The second point (ii) is a key limitation because we can only predict behaviours on pasture, since the model developed in Riaboff et al. (2020a, 2019) was fitted on behaviours observed for grazing exclusively. Consequently, additional data on cows in the barn is needed to monitor lameness throughout the year if (1) cows only have access to pasture for part of the year, and (2) cows could have access to pasture but prefer to remain in the barn, as observed in our study with farms using AMS (9.3 % of the data were discarded for this reason; *section 2.3.3*). The behavioural and movement variables calculated in this way are therefore relevant in addition to other variables measured on the animals in the barn, but are not sufficient to develop a prediction model based solely on these variables.

Furthermore, from a technological point of view, the device used to automatically report GPS and accelerometer data is not usable in its current state for a field application. The major drawback is the battery life, limited to six days, which requires the sensors to be removed every six days for recharging. As the sampling rate of both the GPS (1 Hz) and the accelerometer (59.5 Hz) sensors are high, a possible solution is to (i) reduce the sampling rate of the GPS sensor to compute the movement variables with the desired minimum precision, and (ii) to reduce the sampling rate of the accelerometer sensor to find an appropriate trade-off between battery life and the performance of the prediction of behaviours. Another solution would be using solar energy, as recently proposed for virtual fences (Acosta et al., 2020). Data extraction is also a key concern, as it is currently done manually. Automatic data transfer is also required for field use. In view of the relevance of such an approach for the diagnosis of lameness in pasture, these technological limitations are certainly worth removing to make the developed system functional.

5. Conclusion

This study aimed to identify behavioural and movement variables for dairy cows at pasture, calculated automatically from a methodology based on accelerometer and GPS sensors, to discriminate between lameness scores. To the authors' knowledge, this is one of the most comprehensive studies focusing on the relationship between the behaviour and the movement of dairy cows on pasture and lameness. We found that grazing and resting behaviours and the position (standing/lying) adopted by the cows while ruminating were modified with lameness, as were the exploratory dynamics of the cows. Therefore, 17 variables derived from these behaviours (time spent grazing and resting, duration of grazing and resting bouts, duration before lying down, etc.) and related to the exploratory dynamics (distance, dispersion, distance travelled during grazing, etc.) may be relevant additional indicators to improve the performance of automatic lameness detection devices in pasture-based systems, although methodological and technological challenges still need to be addressed.

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Ethical considerations: This study did not require approval from an ethics committee under French legislation. The only procedures performed on the cows consisted in visual locomotion scoring and fitting and removing the collars on the cows twice a week. Farmers were informed about lameness prevalence just after the experiment carried out in their farm, and a list of recommendations was provided to reduce the lameness prevalence in their farm.

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Figures

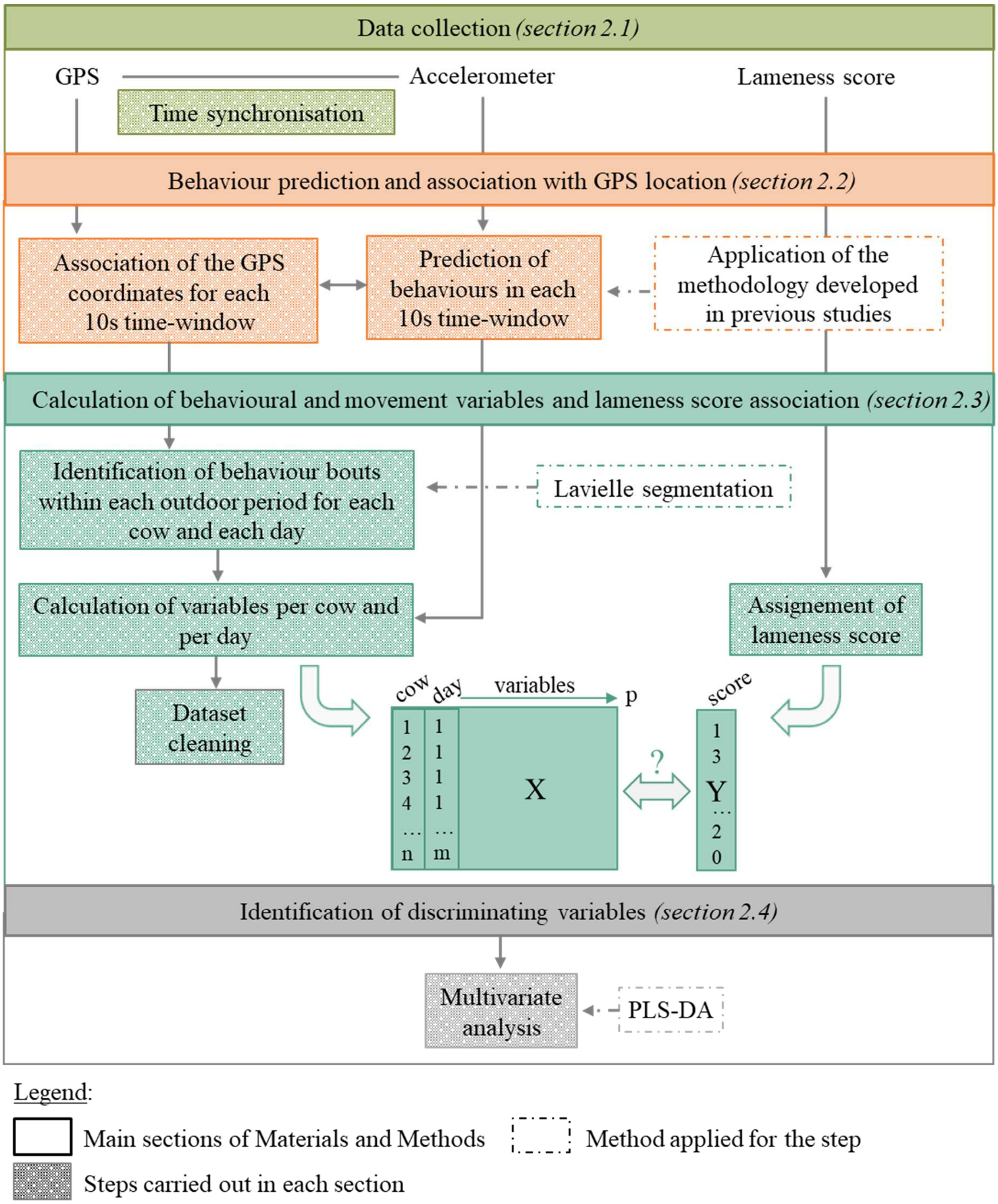


Figure 1. Overview of the main steps applied in the Material and methods section.

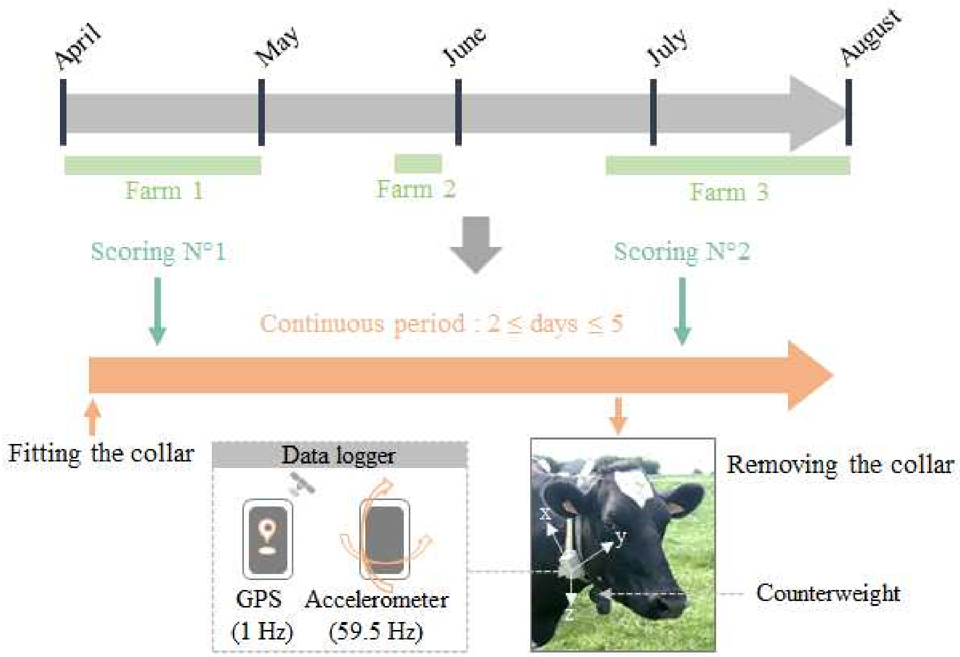
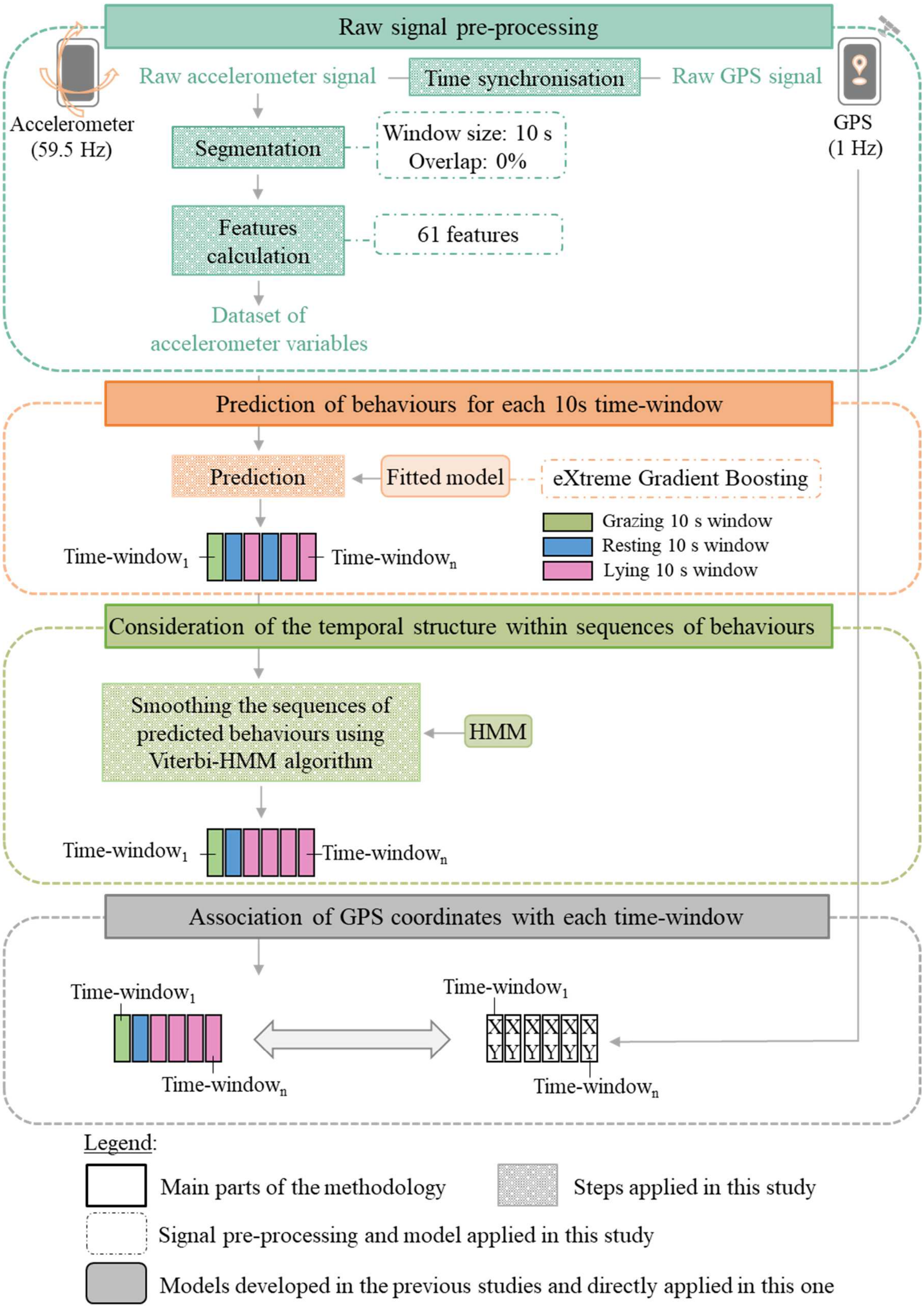


Figure 2. Time sequence of the experiment carried out to collect sensor data from dairy cows and the associated lameness score. The device used to obtain accelerometer and GPS data is displayed.



701 Figure 3. Description of the successive steps carried out to obtain the predicted behaviours for every
702 10 s time-window and the corresponding GPS coordinates.

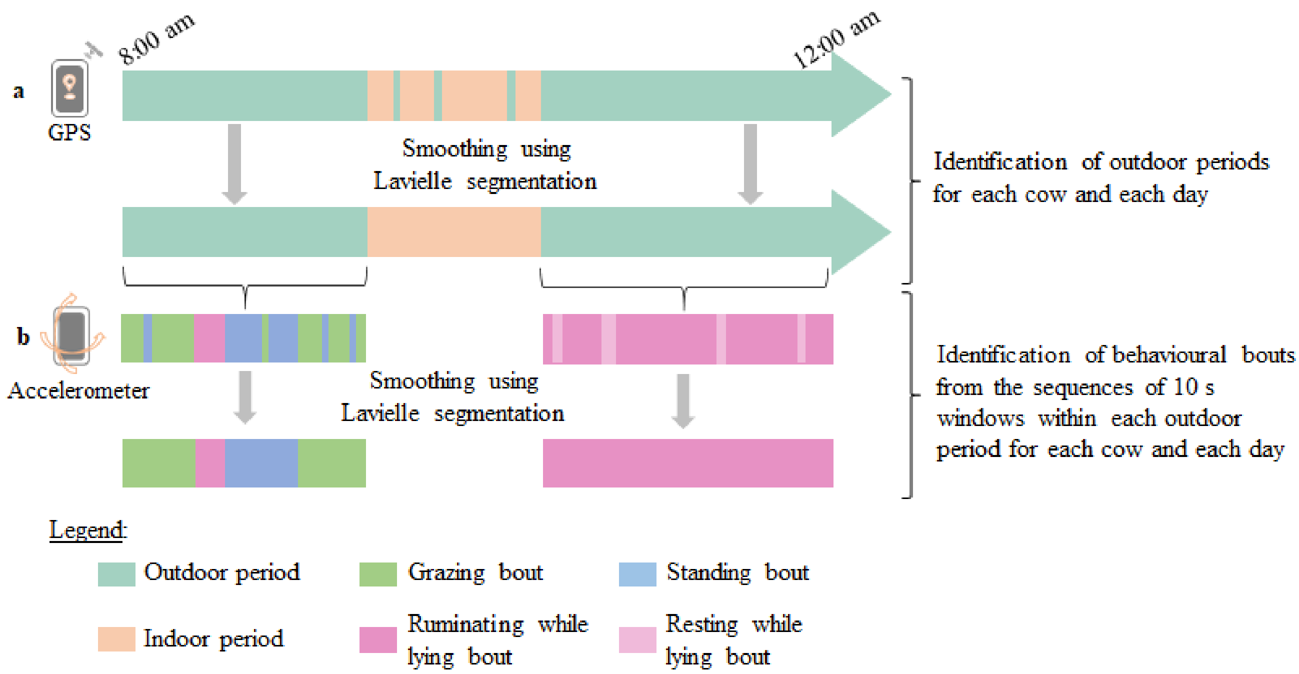


Figure 4. Principle of the identification of (a) outdoor periods for each cow on each day she was equipped and (b) bouts of behaviours within each outdoor period using Lavielle segmentation.

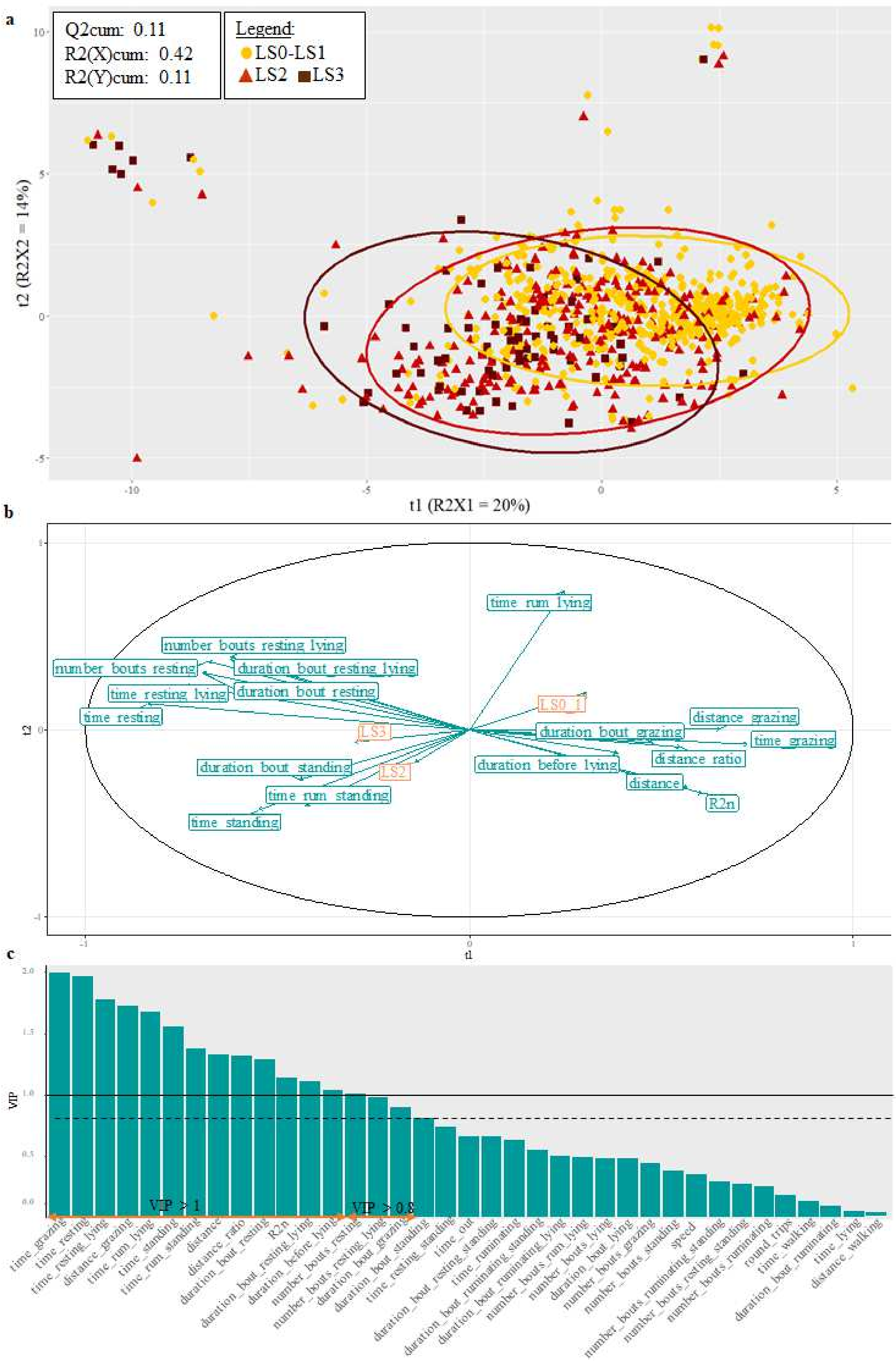


Figure 5. PLS-DA score plot with performance of the model (a), circle of correlations with important variables (i.e. with VIP > 0.8) (b) and VIP on the first component for each variable (c).

Tables

	Farm 1	Farm 2	Farm 3	Total
Number of equipped cows / Herd size	15/54	27/71	26/61	68
Parity (mean ± sd)	1.7 ± 0.7	2.3 ± 1.2	1.5 ± 0.6	
Days in milk (mean ± sd)	145 ± 56	151 ± 63	176 ± 92	
Average milk yield	14,066 kg	9,912 kg	8,542 kg	
Number of days of experiment	21	12	25	58
Lameness score at the start of the experiment[1]				
Lameness score 0	1 (6%)	6 (22%)	0 (0%)	7 (10%)
Lameness score 1	7 (46%)	17 (63%)	12 (44%)	36 (53%)
Lameness score 2	6 (40%)	4 (15%)	12 (44%)	22 (32%)
Lameness score 3	1 (6%)	0 (0%)	2 (7.4%)	3 (4%)

Table 1. Dairy cows under study and duration of animal monitoring

[1] Number of equipped cows (percentage of the herd)

Table 2. Criteria to assign lameness score using the Agriculture and Horticulture Development Board

Lameness score (LS)	Clinical description	Decision criteria
LS 0	Satisfactory mobility	Walking has an even distribution of weight and rhythm is regular between the four legs. The back is straight.
LS 1	Imperfect mobility	Asymmetric strides (rhythm or weight transfer) or shorter. The affected member is not identifiable.
LS 2	Altered mobility	The lame leg is identifiable and/or the strides are clearly shorter. The back is usually arched.
LS 3	Severely altered mobility	The speed is lower than those of the herd. The lame leg is clearly identifiable as the cow hardly stands on this member. The back is arched both when standing and walking.

method.

Table 3. Variables calculated from the behavioural bouts and movement of cows on pasture.

Variable	Definition	Calculation	Weighting	Additional explanation
$Time_{out}$ (1)	Time spent outside	$\sum_{k=1}^{n} Time_{k\,(c,d)}$ for each outdoor period *k* for the cow *c* on day *d*..	$Time_{out,max}$	
$Time_{b}$ (2)	Time spent expressing behaviour *b*	$\sum_{k=1}^{n}\sum_{j=1}^{m} Time_{j,k_{(c,d)}}$ for any bout *j* of the behaviour *b* within the outdoor period *k*, for the cow *c* on day *d*.	$Time_{out}$	$Time_{b}$ was computed for each predicted and grouped behaviour.
Number bouts$_{b}$ (3)	Number of bouts with the behaviour *b*	$\sum_{k=1}^{n}\sum_{j=1}^{m} \mathbb{1}_{B}\{Bout_{j,k_{(c,d)}}\}$ where $\mathbb{1}_{B} = 1$ if $bout_{j,k(c,d)}$ is associated with the behaviour b, 0 otherwise, for any bout *j* of the behaviour *b* within the outdoor period *k*, for the cow *c* on day *d*.	$Time_{out}$	Number_bouts$_{b}$ was computed for each predicted and grouped behaviour except for *walking*, as the number of occurrences was very low and not representative.
Duration bouts$_{b}$ (4)	Average bout duration for behaviour *b*	$\frac{Time_{b}}{Number\_Bouts_{b}}$ with $Time_{b}$ and Number_Bouts$_{b}$ defined in N°2 and N°3.	$Time_{out}$	Duration_bouts$_{b}$ was computed for each predicted and grouped behaviour defined in section 2.2 except for *walking*, as the number of occurrences was too low to calculate a representative average duration.
Round trips (5)	Number of round trips between pasture and farm	*s*-1 for the *s outdoor/indoor* segments obtained with the Lavielle function for the cow *c* on day *d*.	$Time_{out}$	
Distance (6)	Total Euclidean distance travelled	$\sum_{k=1}^{n}\sum_{t=1}^{T} Distance_{t,k_{(c,d)}}$ [1]for any 10 s time-window *t* within the outdoor period *k*, for the cow *c* on day *d*.	$Distance_{max}$	The distance within each 10 s time-window was calculated using the first and last GPS coordinates of the window. The GPS error was considered by (i) replacing by 0 the distance of time windows with stationary behaviour, and (ii) removing time windows with a speed greater than 25 $m.s^{-1}$ to avoid considering aberrant GPS coordinates in the distance calculation.
Dispersion (R2n) (7)	Sum of net squared displacement between each location and the	$\sum_{k=1}^{n}\sum_{t=1}^{T} R2n_{t,k_{(c;d)}}$	$R2n_{max}$	R2n was strongly related to the dispersion. The more a cow explored the pasture from the pasture entrance, the higher the R2n was. We refer to Calenge et al. (2009) for a more detailed

	first location in the pasture	[1]for any 10s time-window t within the outdoor period k, for the cow c on day d.		explanation. The GPS error was considered by (i) replacing by 0 the R2n in time windows with stationary behaviour, and (ii) removing time windows with a speed greater than 25 $m.s^{-1}$ to avoid considering aberrant GPS coordinates in the distance calculation.
Distance Grazing (8)	Euclidean distance travelled during grazing bouts	$\sum_{k=1}^{n}\sum_{j=1,b=Grazing}^{m}\sum_{t=1}^{T}\text{Distance}_{t,k_{(b;c;d)}}$ for any 10s time-window t within the bout j with the behaviour $b = Grazing$ within the outdoor period k, for the cow c on day d.	Distance	Distance Grazing was calculated in the same way as the distance (6) considering only the grazing bouts.
Distance Walking (9)	Euclidean distance travelled during walking	$\sum_{k=1}^{n}\sum_{t=1,b=Walking}^{T}\text{Distance}_{t,k_{(b;c;d)}}$ for any 10s time-window t where the behaviour b = *Walking* has been predicted, within the outdoor period k, for the cow c on day d.	Distance	Distance Walking was calculated in the same way as the distance (6) considering only windows where the walking behaviour was predicted. The distance travelled during each walking time window was only considered if the animal's movement corresponded to a minimum speed of 2 $m.s^{-1}$.
Distance ratio (10)	Distance travelled during grazing over the distance travelled during grazing and walking	$\frac{\text{Distance\_Grazing}}{\text{Distance\_Grazing} + \text{Distance\_Walking}}$ with Distance_Grazing and Distance_Walking defined in (8) and (9), respectively.		
Speed (11)	Average speed during walking	$\frac{\text{Distance\_Walking}}{\text{Time\_Walking}}$ with Distance Walking and Time Walking defined in (9) and (2), respectively.		When no walking was predicted during an outdoor period, the missing speed for the cow c on day d was replaced by the average speed of the group of cows with the same lameness score as the cow c.
Duration before lying (12)	Average duration before lying down after entrance to pasture	$\frac{\sum_{k=1}^{n}\text{Time\_first\_lying}_{,k_{(c,d)}} - \text{Time\_entrance}_{k_{(c,d)}}}{\sum_{k=1}^{n}\mathbb{1}_{B}\{\text{Period}_{k_{(c,d)}}\}}$ where $\text{Time\_first\_lying}_{,k(c,d)}$ is the GPS time when the cow c first lay down in the outdoor period k on day d. $\text{Time\_entrance}_{k(c,d)}$ is the time recorded with the GPS when the cow c entered the pasture in the outdoor period k on day d. $\mathbb{1}_{B} = 1$ if there is at least one lying bout over the outdoor period k for the cow c on day d.		When no lying down was predicted during an outdoor period, the missing duration before lying down for the cow c on day d was replaced by the average duration before lying down of the group of cows with the same lameness score as the cow c. It should be noted that the information "absence of lying" has already been provided by the behavioural variables.

717 [1]Distances and R2n were calculated for each 10s time-window using the function *as.ltraj* of the R package *adehabitatLT* (Calenge, 2006)

Table 4. Mean and standard errors obtained for each weighted behavioural and movement variable before standardisation according to lameness score (LS). Notations are those used in Table 3.

	LS = 0_1 (mean ± se)	LS = 2 (mean ± se)	LS = 3 (mean ± se)
Time$_{\text{out}}$	0.76 ± 0.01	0.73 ± 0.01	0.69 ± 0.03
Round trips	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00
Time$_{\text{grazing}}$	0.27 ± 0.01	0.17 ± 0.01	0.06 ± 0.01
Time$_{\text{ruminating lying}}$	0.29 ± 0.01	0.22 ± 0.01	0.16 ± 0.02
Time$_{\text{resting lying}}$	0.18 ± 0.01	0.22 ± 0.01	0.34 ± 0.03
Time$_{\text{walking}}$	0.01 ± 0.00	0.01 ± 0.00	0.00 ± 0.00
Time$_{\text{ruminating standing}}$	0.06 ± 0.00	0.11 ± 0.01	0.13 ± 0.02
Time$_{\text{resting standing}}$	0.04 ± 0.00	0.06 ± 0.01	0.07 ± 0.02
Time$_{\text{lying}}$	0.47 ± 0.01	0.44 ± 0.02	0.50 ± 0.03
Time$_{\text{standing}}$	0.10 ± 0.01	0.17 ± 0.01	0.20 ± 0.02
Time$_{\text{ruminating}}$	0.35 ± 0.01	0.33 ± 0.01	0.29 ± 0.03
Time$_{\text{resting}}$	0.22 ± 0.01	0.28 ± 0.01	0.41 ± 0.03
Nb bouts$_{\text{grazing}}$	0.01 ± 0.00	0.00 ± 0.00	0.00 ± 0.00
Nb bouts$_{\text{ruminating lying}}$	0.01± 0.00	0.008 ± 0.00	0.007 ± 0.00
Nb bouts$_{\text{resting lying}}$	0.01 ± 0.00	0.01 ± 0.00	0.03 ± 0.01
Nb bouts$_{\text{ruminating standing}}$	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00
Nb bouts$_{\text{resting standing}}$	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00
Nb bouts$_{\text{lying}}$	0.02 ± 0.00	0.02 ± 0.00	0.03 ± 0.01
Nb bouts$_{\text{standing}}$	0.01 ± 0.00	0.01 ± 0.00	0.01 ± 0.00
Nb bouts$_{\text{ruminating}}$	0.01 ± 0.00	0.01 ± 0.00	0.01 ± 0.00
Nb bouts$_{\text{resting}}$	0.01 ± 0.00	0.02 ± 0.00	0.03 ± 0.01
Duration bouts$_{\text{grazing}}$	0.11 ± 0.01	0.08 ± 0.01	0.04 ± 0.01
Duration bouts$_{\text{ruminating lying}}$	0.10 ± 0.00	0.08 ± 0.01	0.08 ± 0.01
Duration bouts$_{\text{resting lying}}$	0.06 ± 0.00	0.07 ± 0.01	0.15 ± 0.03
Duration bouts$_{\text{ruminating standing}}$	0.02 ± 0.00	0.04 ± 0.01	0.04 ± 0.01
Duration bouts$_{\text{resting standing}}$	0.01 ± 0.00	0.02 ± 0.00	0.03 ± 0.01
Duration bouts$_{\text{lying}}$	0.08 ± 0.00	0.02 ± 0.0	0.12 ± 0.01
Duration bouts$_{\text{standing}}$	0.02 ± 0.00	0.03 ± 0.00	0.04 ± 0.01
Duration bouts$_{\text{ruminating}}$	0.06 ± 0.00	0.06± 0.00	0.06 ± 0.01
Duration bouts$_{\text{resting}}$	0.04 ± 0.00	0.04 ± 0.00	0.09 ± 0.03
Distance	0.50 ± 0.01	0.43 ± 0.02	0.30 ± 0.03
R2n	0.48 ± 0.01	0.43 ± 0.02	0.29 ± 0.03
Distance Walking	0.13 ± 0.01	0.13 ± 0.01	0.13 ± 0.03
Distance Grazing	0.49 ± 0.02	0.34 ± 0.02	0.21 ± 0.03
Distance Ratio	0.55 ± 0.02	0.43 ± 0.03	0.30 ± 0.05
Speed	3.42 ± 0.10	3.43 ± 0.08	3.10 ± 0.05
Duration Before Lying	63.5 ± 2.08	55.4 ± 3.56	34.6 ± 4.13