Modelling restricted feeding conditions on cows' feeding behaviour on pasture-based milk production systems to develop a Decision Support System

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Abstract

The aim of this study was to identify a set of feeding behaviour and activity related variables that could potentially detect a shortage of available feed for the individual cow on pasture. A group of lactating cows was offered 100% of their intake capacity as herbage allowance throughout a 10-week experimental period, while another group was offered 60% of their intake allowance, either for a two week or six week period in springtime. Each cow was equipped with an automated noseband sensor. The data were analysed by using a binomial generalized lineal model (GLM). The GLM was examined for the classification of full or restricted herbage allowance as a function of a previously identified set of characteristics. The model was further refined by including additional characteristics, which achieved higher prediction performance. For the combined data, the refined model achieved 77% accuracy, 75% sensitivity, 78% specificity and F-score 0.76 towards a decision support system for grass utilisation in pasture based milk production.

Keywords: feeding behaviour, generalized linear model, classification performance

Introduction

In precision dairy farming, one of the key factors for farmers to recognise biosensor technologies is the scope of utilising biosensor data to develop a reliable pasture-based grazing system (French *et al.*, 2015). In this context, the current study aims to identify a set of feeding behaviour and activity related characteristics of milking cows recorded by the RumiWatchSystem (Alsaaod *et al.*, 2015) and quantify their relationship with insufficient grass allowance, so that the study findings can be further used as guidance for developing a decision support system. The efficacy of such a support system depends mainly on its ability to identify the correct grass allowance per cow. This study, therefore, considered the association between grazing behaviour and activity with grass allowance as means of identifying one of the groups for grazing cows: access to sufficient or insufficient grass.

Werner *et al.* (2019) suggested that bite frequency (BITEFREQ), rumination time per day (RUMINATETIME), rumination chews per bolus (RUMICHEWBOLUS) and frequency of standing or laying (STANDLAY) were significantly affected by restricted grass allowance. Therefore, this study first considered only these variables to examine their predictive performance using a GLM with logit link, i.e. logistic regression (LR) model. The model was further refined by incorporating additional characteristics using a stepwise method (Efroymson, 1960). Thus, a refined set of feeding behaviour and activity related variables was proposed for which the LR model increased the classification performance indices.

Material and methods

Data collection and cleaning

Data for this study came from a larger overall experiment at Teagasc, Moorepark Dairy Research Farm, Animal & Grassland Research and Innovation Centre, Fermoy, Co.

Cork, Ireland (Claffey, 2018). The experiment was conducted in springtime using 105 calving cows to examine the effects of restricted pasture allowance on milk production, immunology and indicators of reproductive health of grazing dairy cows. Ethical approval was received from Teagasc Animal Ethics Committee (TAEC; TAEC100/2015) and procedure authorisation was granted by the Irish Health Products Regulatory Authority (HPRA).

For the current study, 40 focal cows were selected for recording the feeding behaviour and activities using the RumiWatch System. Out of these, 10 cows were randomly assigned to a group where cows were offered 100% of their intake allowance and the remaining 30 cows were assigned to the restricted allowance groups where cows were offered 60% of their intake allowance. The 60% group was further divided into six sub-groups based on the duration of restriction, i.e. two-week (2) or six-week (6) period and three time points of (early) lactation at the commencement of restricted allowance: *start* (S: restriction starts at the beginning of experiment), *mid* (M: two weeks after the S restriction commenced) or *late* (L: four weeks after the S restriction commenced). The behaviour of the cows in the 100% group was monitored over 10-week period. The three cow groups on the two-week restricted pasture allowance (PA) had their behaviour recoded during the full two-week periods whereas the behaviour of the three groups on the six-weeks restricted PA was recorded during the last two-week period due to limited sensor device resources (Werner *et al.*, 2019). Throughout this paper, the notions S2, M2, L2, S6, M6 and L6 denote the six treatment sub-groups as well as the subsets of combined data, which included the records of the respective cows from the insufficient and sufficient grass allowance groups.

In total 1,221 records were collected during the experimental period. For the safety and strictness, all records with missing values were removed. The combined data included 629 records for cows that had 100% intake allowance and 592 records for cows with 60% of the intake allowance. However, the subsets of the combined data S2, M2, L2, S6, M6 and L6 were unbalanced.

Research design

The research design comprised three parts for this study. The first part was data exploring, and fitting univariate logistic regression models with one exposure variable at a time. At this stage, all the feeding and activity related variables recorded by the RumiWatch System were considered for screening. Based on the results of univariate analyses, a set of nine candidate variables was selected for further analysis using multivariate models.

The candidate set identified in the first part included the four previously identified characteristics (Werner *et al.*, 2019). These variables were used in Model 1 as follows.

$$\log\left(\frac{\pi_i}{1-\pi_i}\right)=\beta_0+\beta_1 BITEFREQ_i + \beta_2 RUMINATETIME_i + \beta_3\, RUMICHEWBOLUS_i + \beta_4 STANDLAY_i \quad (1)$$

The second part was data classifications using Model 1. Given the recorded values of the predictor variables, the fitted model estimates the log of odds, $\log\left(\frac{\pi_i}{1-\pi_i}\right)$ where π_i=P(Y=1), i.e. the probability that the cow had insufficient (60%) PA and $(1-\pi_i)$=P(Y=0) i.e. the probability that it had sufficient (100%) PA. The regression coefficients β's are the instantaneous change in *log(odds)* for one unit change of the independent variable, holding all other variables constant (Kabacoff, 2015). For each data set, the estimated coefficients of *Model 1* were exponentiated to obtain *odds ratio* (*OR*) which described the relationship between each characteristic and the odds of insufficient grass allowance in a multivariate framework.

The third part of the study was model refinement based on stepwise regression. The procedure identified the best set of characteristics from the nine candidates for which the exploratory analysis showed significant association with the pasture allowance groups. Thus, a refined classification model was proposed. The classification performance of Model

1 and the refined models was compared based on accuracy, sensitivity, specificity, and F-score. These indices were estimated form the cross validation study as follows. Given data, a random sampling divided the rows into a training set and a testing set such that each row had 70% chance of being included in the training set and 30% chance of being included in the testing set. Both the models were estimated from the training set and applied to classify the grass allowance for each cow in the testing set. Based on the true and predicted classes, a confusion matrix was created for estimating the classification indices. The procedure was repeated 1,000 times and the indices were summarised by the means. The statistical analyses were performed by using *glm, step, acf* (R core Team, 2019) and *lrm* (Frank & Harrell, 2019) functions and the codes for repeated cross validations were written in R3.5.3.

Results and discussion

Estimation of Model 1

Table 1 presents the estimated coefficients of Model 1 and the odds ratios (in brackets) for the subsets and combined data. While the results for combined data demonstrate that each characteristic was significantly associated with the odds of insufficient grass allowance, separate analyses show that the magnitude of effects were different for different duration of restriction and the stages of lactation. For example, using S2, the odds of insufficient grass was expected to increase by a factor of 1.2 for every unit increase in the 'bite-frequency' (holding other characteristics fixed). The remaining variables had insignificant negative effects on the odds.

Table 1. Estimated coefficients with odds ratios (in brackets) for Model 1 based on the subsets and combined data

Variables	S2	M2	L2	S6	M6	L6	Combined
BITEFREQ	0.18*** (1.20)	0.083** (1.09)	0.09* (1.09)	0.105*** (1.11)	0.177*** (1.19)	0.094** (1.09)	0.12*** (1.12)
RUMINATETIME	-0.003 (0.99)	-0.012*** (0.99)	-0.012*** (0.99)	-0.012** (0.99)	-0.009*** (0.99)	-0.009*** (0.99)	-0.008*** (0.99)
RUMICHEWBOLUS	-0.039 (0.96)	-0.006 (0.99)	-0.135** (0.87)	-0.317*** (0.73)	-0.109** (0.90)	-0.14** (0.87)	-0.12*** (0.89)
STANDLAY	-0.17*** (0.84)	-0.25*** (0.78)	-0.086 (0.92)	-0.056 (0.95)	-0.122*** (0.88)	-0.05 (0.95)	-0.107*** (0.87)

P-value: *** < 0.001; ** < 0.01; * < 0.05

However, the magnitude of the effects and corresponding *P-values* for significance tests were different across the data sets, though the direction of effects was the same in all cases. One possible reason for the differences in results is that the combined data were obtained from the six blocks of cows that were attributed to different level combinations of restriction period and lactation stage factors. This implies that the between group variation of each characteristics among the treatment cows was not assumed to be equal. As a result, Model 1 did not fit all data sets equally well. For example, the pseudo R^2 for S2 (R^2=0.62), M2 (R^2=0.51), L2 (R^2=0.62), S6 (R^2=0.87), M6 (R^2=0.47), L6 (R^2=0.43) and the combined data (R^2=0.54) reveal that Model 1 best explained the percent of variation in *log (odds)* for S6 group. Comparing S2 and S6 this is reasonable since intuitively, cows with longer periods of insufficient feed intake are expected to show relatively greater difference in certain behavioural characteristics from the control cows than those with shorter period of insufficient feed intake. Based on this assumption, given lactation stage, it was expected that the pseudo would be higher for six-week restriction data than two-week restriction data. However, Model 1 achieved lower pseudo R^2 for six-week restriction for both M and L groups.

Table 2. Estimated coefficients with odds ratios (in brackets) for the refined models based on the subsets and combined data

Variables	S2	M2	L2	S6	M6	L6	Combined
BITEFREQ	0.20*** (1.22)	0.124*** (1.13)	0.237*** (1.27)	.301*** (1.35)	0.303*** (1.35)	0.514*** (1.67)	0.13*** (1.14)
RUMINATETIME	0.004 (1.004)	-0.009** (0.99)	-0.007* (0.99)	-0.004 (0.99)	0.002 (1.00)	-0.007 (0.99)	-0.002 (0.99)
RUMICHEWBOLUS	0.131* (1.14)	0.105 (1.10)	-0.029 (0.97)	-0.204** (0.82)	-0.047 (0.95)	0.158** (1.17)	-0.064*** (0.94)
STANDLAY	-0.14** (0.87)	-0.271*** (0.76)	-0.093 (0.91)	-0.134* (0.87)	-0.154*** (0.86)	-0.153** (0.86)	-0.12*** (0.89)
CHEWPBOLUS	-0.353*** (0.70)	-0.118* (0.88)	-0.325*** (0.72)	-0.312*** (0.73)	-0.136** (0.87)	-0.595*** (0.55)	-0.14*** (0.87)
RUMIBOUTLENGTH	-0.091* (0.91)	-0.090* (0.91)	-0.074* (0.93)	-0.126** (0.88)	-0.17*** (0.84)	-0.109** (0.90)	-0.084*** (0.92)
HACTIVITY.mean	0.031* (1.03)	-0.007 (0.99)	-0.012 (0.99)	-0.019 (0.98)	-0.0002 (0.99)	0.052** (1.05)	0.013*** (1.01)

P-value: *** < 0.001; ** < 0.01; * < 0.05

Model refinement

Apart from the four characteristics in Werner *et al.* (2019), the exploratory analysis of this study identified the candidate variables: number of rumination chews per day (RUMINATECHEW), number of bolus per day (BOLUS), number of chews per bolus (CHEWPBOLUS), mean rumination bout length per day (RUMIBOULENTH) and number of head activities (up or down) per hour of the day (HACTIVITY.mean). In order to increase the goodness of fit (and classification performance), Model 1 was refined by using the additional variables.

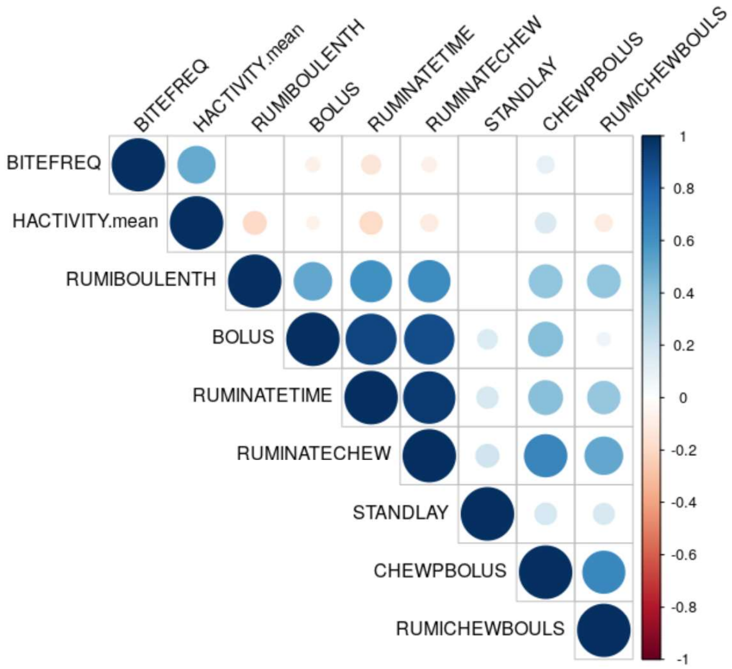

Figure 1. Correlation plots among the feeding behaviour and activity related variables

However, based on the combined data, the correlation plots in Figure 1 indicate that there would be a concern with GLM using all (nine) variables since some of the variables were highly collinear. As a result, a sequential strategy, i.e. stepwise procedure was adapted, through which the less significant variables were trimmed using backward search direction. Similarly, a refined set of characteristics was obtained by applying the stepwise regression to S2, M2, L2, S6, M6 and L6 data sets. Table 2 presents the estimated coefficients and the odds ratios for the refined models. The estimated effects of the common characteristics were slightly different from Model 1. For example, unlike Model 1 the effect of 'rumination, time' was insignificant in most cases. Also, using the combined data, the OR of 'bite frequency', 'rumination chews per bolus' and 'standing or laying frequency' in the refined model were slightly higher than Model 1. In all cases, bite-frequency had strong positive relationship and chews per bolus and rumination bout length had negative relationship with the odds of insufficient grass allowance. Conversely, rumination time had significant negative effect for S2 and M2 and rumination chew per bolus had significant negative effects for S6 and L6 data sets. Head activity per hour had a small effect and the relationship was significant for S2, S6 and combined data. The effect of standing or laying frequency was highly significant for all cases except L2.

Table 2 further reveals that unlike Model 1, for each lactation stage the OR of bite frequency was relatively higher for six-week restriction period than two-week restriction period. Similarly, the effects of rumination bought length and chews per bolus had negative effects across the subsets and combined data. The pseudo R^2 of S2 (R^2=0.66), M2 (R^2=0.57), L2 (R^2=0.62), S6 (R^2=0.90), M6 (R^2=0.61) and L6 (R^2=0.80) and combined data (R^2=0.60) clearly indicate that the refined model achieved higher explanatory power than Model 1 in all cases. Moreover, unlike Model 1, the refined model achieved higher explanatory power for

M6 than M2 and L6 than L2. Thus, the refined model validates the assumption that the characteristics could explain the variation in *log(odds)* better for longer period of restricted PA than shorter period. Thus, the refined model should be preferred to Model 1.

Classification performance

In this section, the predictive performance of Model 1 and the refined models was compared separately for S2, M2, L2, S6, M6, L6 and combined data. In each case, the performance was evaluated based on accuracy, sensitivity, specificity, and F-score. Table 3 presents the estimates of these indices based on the cross validation study.

Clearly, the refined models performed better than Model 1 with respect to all indices. In addition, the restriction period affected the predictive performances. Accuracy is a popular performance measure of classifiers, since it reflects the overall prediction performance. Given lactation stage, estimated accuracy was higher for six-week restriction data than two-week restriction data.

For example, Model 1 achieved 77% accuracy for S2 and 84% accuracy for S6 data. The corresponding figures for the refined model are 80% and 88%, respectively. This implies that in general cows were more apt to be correctly classified in case of longer duration of insufficient feed allowance.

Table 3. Performance of Model 1 and the refined models based on cross validation study

Models	Indices	S2	M2	L2	S6	M6	L6	Combined
Model 1	Accuracy	0.77	0.79	0.75	0.83	0.79	0.84	0.73
	Sensitivity	0.62	0.63	0.48	0.72	0.45	0.33	0.74
	Specificity	0.85	0.88	0.87	0.89	0.91	0.95	0.73
	F-score	0.64	0.67	0.52	0.73	0.49	0.44	0.73
Refined model	Accuracy	0.80	0.82	0.80	0.87	0.81	0.88	0.77
	Sensitivity	0.68	0.70	0.61	0.80	0.54	0.63	0.75
	Specificity	0.88	0.88	0.88	0.91	0.91	0.94	0.78
	F-score	0.70	0.71	0.64	0.81	0.58	0.64	0.76

Since the data were unbalanced, further comparisons based on sensitivity and specificity scores suggest that for L6 Model 1 achieved 84% accuracy due to high specificity *(0.95)*. Here, specificity refers to the proportion of 100% intake allowances that were correctly predicted. However, in this case the rate of correct classification of insufficient grass allowance was not reliable due to very low sensitivity (0.33). Conversely, the refined model, in this case achieved 60% sensitivity while maintaining specificity at the high level (0.94). The refined model had a concern of lower sensitivity (0.54) for M6 data, though the estimate was relatively higher than Model 1 (0.45). For the combined data, both models maintained a good balance in all indices while refined model having higher scores than Model 1.

Since the current study aimed to contribute to the development of a pasture-based decision support system, identifying insufficient grass allowance may be often more important than full intake allowance. In such cases, the F-score is a better performance measure since it maintains a balance between the precision (proportion of predicted insufficient allowance that were actually insufficient) and sensitivity of the classifiers. As with other indices, the F-score of the refined models was higher than Model 1 in all cases. However, the low sensitivity resulted low F-score for M6. Future studies need to address this issue and focus on further improvement of the classification models.

Conclusion

This study explored the performance of a set of previously identified feeding behaviour and activity related variables and refined the set in the context of classification. Seven characteristics of lactating spring cows were identified which were significantly associated with the odds of insufficient grass allowance. No unique set of characteristics was found to be the best indicators for all cases. The model adequacy and prediction performance depended on the duration of insufficient feeding: in general, cows with longer period of insufficient allowance were more apt to be correctly identified than those with shorter restriction period. The results of Table 2 can be used as guidance for heuristic estimation of the likelihood of insufficient grass allowance, given that other factors are similar to the underlying experimental conditions. However, since the sensitivity of the refined model was still less than 0.8 in most cases, care should be taken while using the models for future prediction. Further study should address this issue and also focus on thresholding the important characteristics towards developing a decision support system.

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