Individual herbage intake estimation of grazing dairy cows, based only on behavioural characteristics

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Abstract

The objective of the study was to estimate individual herbage dry matter intake (hDMI) of grazing dairy cows based solely on eating and rumination behaviour characteristics as independent variables. Data from four rotational grazing experiments on multi-species pastures were available, including treatments relative to supplementation or herbage mass. Holstein cows of different types (428 to 718 kg body weight and 11.2 to 34.2 kg daily milk production) were grazed around 18 h d^{-1}. At least 105 seven-day measurements of hDMI using the n-alkane double indicator technique constituted the reference data, with an average hDMI of 12.9 kg d^{-1} (4.7 to 20.4 kg d^{-1}). Simultaneously, 27 behavioural characteristics were recorded using the RumiWatch System. For the predictor reduction, the best subset regression approach was applied and equations were validated using bootstrap validation. The following predictors related to grazing were retained in the models: eating time head up or head down, number of other chews, and rumination chews per bolus. Additionally, daily eating time, rumination time and number of other chews were used. Finally, rate of rumination chews were included. The root mean squared prediction errors for the different hDMI estimation models with 4 to 8 predictors were around 1.9 kg d^{-1}.

Keywords: herbage intake, dairy cows, behaviour, pasture

Introduction

The importance of efficient conversion of forage to food through animals is growing in environments where reasonable resource utilisation and significant lowering of emissions play a major role. An efficient conversion of pasture herbage to milk and meat requires a minimization of losses of available biomass at pasture as well as an improved feed efficiency of ruminants. In both cases the knowledge of feed intake is required. The measurement of individual dry matter intake (DMI) for dairy cows kept indoors is already challenging, but for grazing dairy cows it is even more expensive and laborious. Thus, individual herbage DMI (hDMI) measurements are not feasible for a large number of cows under on-farm conditions. As a result, many efforts have been made to indirectly estimate feed intake in general (de Souza *et al.*, 2019) or for grazing dairy cows (Lahart *et al.*, 2019; Rombach *et al.*, 2019).

Although the feeding and rumination behaviour of dairy cows, at first sight, appear promising for intake estimation, a single behavioural characteristic accounts for no more than 35% of hDMI variability (Rombach *et al.*, unpublished data). For a more accurate estimation of individual intake, performance, body size and other characteristics are therefore usually included in equations to estimate total DMI (Lahart *et al.,* 2019) or hDMI (Rombach *et al.,* 2019). The inclusion of performance data in intake estimations may cause interference, because performance (e.g. milk yield) is used in the determination of both input and output. Accordingly, estimation equations independent from output should be developed.

Therefore, in this evaluation, only eating and rumination behaviour data were employed for multivariable regressions for the estimation of hDMI.

Materials and methods

Four rotational grazing experiments on multi-species pastures constituted the data basis, including treatments relative to supplementation (0 to 7.9 kg d^{-1} whole-plant maize silage or 0 to 4 kg d^{-1} concentrate), herbage mass (589 to 2,333 kg DM ha^{-1}) and cow type. Experiments were conducted in western Switzerland in 2014 to 2016, between May and September, and involved a total of 94 dairy cows. Three different types of Holstein cows (body weight, 428 to 718 kg) were grazed around 18 h d^{-1} and produced between 11.2 and 34.2 kg d^{-1} of milk. At least 105 complete seven-day measurements of hDMI (average 12.9 kg d^{-1}, 4.7 to 20.4) with the n-alkane double indicator technique (Rombach *et al.*, 2019) as reference method were available. Behavioural data were collected simultaneously and processed using the RumiWatch System (RWS, Itin & Hoch GmbH, Liestal, Switzerland, Halter V 6.0, Converter 0.7.3.31). The RWS has been validated for grazing dairy cows by Rombach *et al.* (2018, 2019). Behaviour characteristics were averaged either over the day or over the daily length of stay on pasture.

In order to reduce the number of the initially observed 27 behavioural characteristics, the best subset regression approach was applied (R Core Team (2018), package 'leaps'). Finally, a maximum of eight predictors were considered for the hDMI estimation equations. As the sample size was too small to retain an independent validation dataset, the bootstrap cross-validation method was chosen (package 'rms').

Results and discussion

Predictors limited to the daily length of stay on pasture were included, like eating time head up (ETup, 7 to 174 min), eating time head down (ETdown, 348 to 680 min), rumination chews per bolus (RUcb, 37 to 68) and number of other chews (OCnp, 105 to 1,748). On the other hand behavioural characteristics averaged for the whole day were considered, like total eating time (ETtot, 441 to 742 min), number of other chews (OCnd, 189 to 2,816), rumination time (RUT, 303 to 601) and rate of rumination chews (RUrate, 57 to 85 min^{-1}). The root mean squared prediction errors (RMSPE) for the five different hDMI (kg DM d^{-1}) estimation equations with 4 to 8 predictors were similar with 1.93 to 1.89 kg d^{-1}, respectively. For this reason, only the two extreme equations in terms of the number of predictors are presented below:

$$\text{hDMI} = 5.2 + 0.0492 \cdot \text{ETup} + 0.0613 \cdot \text{ETdown} + 0.0017 \cdot \text{OCnp} - 0.0431 \cdot \text{ETtot}$$

$$\text{hDMI} = 4.7 + 0.0447 \cdot \text{ETup} + 0.0574 \cdot \text{ETdown} + 0.0068 \cdot \text{OCnp} + 0.0121 \cdot \text{RUT} - 0.0507 \cdot \text{RUcb} - 0.06 \cdot \text{RUrate} - 0.0029 \cdot \text{OCnd} - 0.0361 \cdot \text{ETtot}$$

These RMSPE correspond to a relative prediction error of around 15%. At best and depending on the approach chosen, Rombach *et al.* (2019) obtained a relative prediction error of 11 to 13%. A slightly lower relative prediction error of approximately 10% was reported by Lahart *et al.* (2019). Although error terms less than 10% would be desirable, these values are difficult to achieve and, depending on the objective, up to 20% can be tolerated. In contrast to Lahart *et al.* (2019), who determined total DMI (sum of hDMI and the amount of supplements fed in the barn), the present evaluation as well as Rombach *et al.* (2019) estimated hDMI.

Standardised coefficients (β) allow comparison of the weights of variables in multiple regressions. In both equations above, ETdown reached the highest β (1.24 or 1.70), followed by OCnp (equation with 8 predictors, 0.97) and ETtot (equation with 4 predictors, -0.87). The negative weight of ETtot is likely due to the supplements – maize silage and concentrates – eaten in the barn, which usually have a substitution effect. The significant weight of OCnp may be related to the individual variation in grazing behaviour or to incorrect classifications of chews by the RWS. Presumably, during ETup at pasture, dairy cows mainly process and swallow the grazed herbage. Therefore, even though ETdown and ETup are not sharply separated as cows may repeatedly raise or lower their head during a grazing bout, they are sufficiently independent to be kept in the equations. The inclusion of rumination characteristics like RUT, RUcb and RUrate in the estimation equations can be attributed to the influence of fibre and physical properties of the ration.

Intake estimation exclusively based on behavioural characteristics has the advantage that the input for subsequent efficiency calculations is not calculated on the base of energy sinks, like milk yield, growth or body weight. Further, the inclusion of behavioural characteristics may be beneficial if individual hDMI is impaired, caused for example by health problems, injuries, heat, and other unusual circumstances such as those produced by poor grazing management practice. Of course, the intake estimation should be more precise, accurate and supported by a broader database for individual feed efficiency evaluations.

Conclusions

One eating or rumination behaviour characteristic alone was not sufficient to estimate individual hDMI accurately, but the appropriate combination of several behavioural characteristics reduced the error term to around 15%. An hDMI estimation based exclusively on easily recorded behavioural characteristics has the benefit of an output independent input estimation for subsequent feed efficiency calculations. Other benefits would be the reduced need for measurements related to cows or grazed herbage and the possibility to automate hDMI estimation in future.

References

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