Benefits of behavioural characteristics in herbage intake estimation models for grazing dairy cows

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Take home message The inclusion of behavioural characteristics to estimate herbage dry matter intake brings some benefits, however behavioural characteristics alone are not sufficient to estimate individual herbage intake accurately.

Introduction Information about herbage dry matter intake (hDMI) is a core element of dairy cow management, even more pronounced in pasture-based feeding systems. Its knowledge helps to monitor the nutritional status and consequently to adapt the optional supplementation in accordance to the cow nutritional requirements. Furthermore, it enables the ranking of dairy cows in relation to their feed efficiency as well as to improve pasture and livestock management. Reliable routine estimation of the individual hDMI is not an easy task. Often the methods used for individual hDMI estimation are either expensive, time-consuming or impracticable at farm level. Estimation of hDMI using recorded ingestive behaviour data might be an elegant method, even more so as a variety of behavioural recorders exist and are more and more used at farm level.

The objective of this study was to develop models for individual hDMI estimation of grazing dairy cows and to quantify the estimation error of these models as well as the benefits of behavioural characteristics for hDMI estimation.

Materials & methods Data from four rotational grazing experiments on multi-species pastures, including treatments relative to supplementation, herbage mass and cow type, constituted the basis. These experiments took place in the western part of Switzerland from 2014 to 2016 between May and September and involved at all 94 dairy cows. Red Holstein and two different types of Holstein cows grazed between 16 and 19 h d^{-1} in these experiments. In total 130 seven-day measurements of hDMI (average 12.4 kg d^{-1}, 4.7 to 20.4) with the n-alkane double indicator technique (Heublein *et al.*, 2017) 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). In addition to the behavioural elements mentioned by Rombach *et al.* (2018) the used evaluation software (converter) allowed a differentiation of prehension bites and mastication chews during grazing. Due to technical issues 21 (16 %) records from the RWS could not be utilised for further evaluation.

The 53 variables available, describing pasture characteristics (e.g. herbage mass 589 to 2333 kg DM ha^{-1}), supplementation (e.g. amounts of chopped whole-plant maize silage 0 to 7.9 kg d^{-1} or concentrate 0 to 4 kg d^{-1}), cows (e.g. body weight 428 to 719 kg), cow performance (e.g. milk yield 14 to 38 kg d^{-1}) and behaviour (e.g. total eating time 441 to 742 min d^{-1}, total eating chews 31668 to 54174 n d^{-1}, grazing time 355 to 691 min d^{-1}, prehension bites 11037 to 40304 n d^{-1}, total eating chews at pasture 26225 to 48710 n d^{-1}) were thinned out based on statistical and nutritional-linked criteria. For the final reduction of predictors in the models the best subset regression approach was applied (R Core Team (2016), package leaps). As the sample size was too small to retain an independent validation dataset, the bootstrap cross-validation method was chosen (package rms).

Results & discussion Unfortunately, behavioural characteristics like number of prehension bites or grazing time, explained only 26 % or 35 %, respectively, of the hDMI variability. Thus, they are alone not sufficient for an accurate hDMI estimation. The variability in bite size (0.26 to 1.04 g DM) and intake rate (11.5 to 40.8 g min^{-1} grazing) between individual grazing dairy cows is too large. Consequently, other predictors than behavioural characteristics have to be included in the models for hDMI estimation. The root mean squared prediction errors (RMSPE) for different hDMI estimation models with 4 to 12 predictors were calculated. Models without information about supplementation and grazing behaviour exhibit a RMSPE between 2.1 to 2.3 kg d^{-1} depending on the number of predictors in the model. Inclusion of behavioural characteristics per day or during grazing like eating time or chews, prehension bites or rates, or eating chews head down reduced the error term by about 0.5 kg d^{-1}. If quantities of supplemental feed in the barn are available for modelling hDMI, the error term decreased again about 0.2 kg d^{-1}, to end at 1.4 to 1.6 kg d^{-1}. In this case, inclusion of behavioural information did not additionally improve the estimation accuracy. On the other hand, the inclusion of behavioural characteristics may be beneficial if individual hDMI is outside of the norm, caused for example by health problems, injuries, heat or other unusual circumstances.

Conclusion Eating behaviour characteristics alone are not sufficient to estimate individual hDMI accurately but combined with other predictors they bring some improvements. Prospectively, a larger dataset in terms of number of animals and herds, covering more breeds, different grazing systems, management patterns as well as behaviour recorders easier to handle at farm level would potentially increase the accuracy and robustness of the estimation models for individual hDMI.

References

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