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Accuracy and precision in DM intake prediction models for lactating dairy cows

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ABSTRACT

Predicting the daily DM intake (**DMI**) of lactating dairy cows is an essential criterion for formulating diets according to requirements, which limits the application of safety margins in economically and environmentally sensitive nutrients, such as energy, protein, and phosphorus. An accurate estimation of nutrient excretion, which is necessary for good practice in crop fertilisation, is also highly dependent on DMI predictions. The study aimed to assess the accuracy and precision of the Swiss model developed in 1994 by Agroscope (2021), the North American model by National Research Council (NRC, 2001) and its update from National Academies of Sciences, Engineering, and Medicine (NASEM, 2021), the French model by Institut national de recherche agronomiques (INRA, 2018), the German model by Gesellschaft für Ernährungsphysiologie (GfE, 2023), and the Australian model by Commonwealth Scientific and Industrial Research Organization (CSIRO, 2007). The evaluation was based on routine Agroscope dairy herd data recorded between November 2015 and March 2021. The sample consisted of 138 primiparous (12.4 ± 9.7 weeks of lactation (**WOL**), 28.4 ± 5.5 kg/d milk yield (**MY**), 614 ± 57 kg BW) and 135 multiparous (16.3 ± 11.2 WOL, 32.8 ± 7.6 kg/d MY, 701 ± 63 kg BW) lactating Holstein cows, resulting in 413 partial lactations. Milk and diet composition were available on a monthly basis, and DMI, MY, and BW were collected on a daily basis. The models were assessed for RMSE of prediction, including its decomposition into error of central tendency (**ECT**), error of regression, and error due to disturbance. Moreover, the models were evaluated using the concordance correlation coefficient (**CCC**) analysis. Globally, DMI was overestimated by NRC and NASEM and underestimated by INRA and GfE. The accuracy of DMI prediction using the RMSE of prediction metric ranged from 2.50 to 4.37 kg/d in primiparous and from 3.02 to 4.98 kg/d in multiparous cows. In both cow groups, the highest precision values were obtained, with the Agroscope (ECT = 0.001 and 0.01%, respectively) model. The highest CCC was exhibited by the Agroscope model in primiparous cows (0.53) and by the INRA model in multiparous cows (0.70). Finally, the 30-year old Agroscope model emerged as the most accurate and precise in predicting DMI in lactating dairy cows fed a diet consisting of 90–95% of a mixed basal diet (dry and ensiled herbage and corn silage) and of 5–10% concentrates (DM basis).

Implications

Assessing models for predicting DM intake in lactating dairy cows is essential to formulating diets and minimising the excess use of economically and environmentally sensitive nutrients. Numerous prediction models are available, leading to the question of which is most suitable for the metric. A comparison of the measured data and prediction models shows that their accuracy is, in most cases, acceptable, with a relative error between 10 and 20%, but improvements that aim for an error of less than 10% (less than 1.8 kg DM/d) are necessary. The findings confirm that the 30-year-old Agroscope equation remains most suitable for lactating cows fed forage-based diets.

Introduction

There are several motivations for developing equations to predict DM intake (**DMI**). The main one is probably its role in diet formulation to determine the necessary nutrient concentration to cover the nutrient requirements of a cow or a group of cows according to numerous production parameters. For example, the

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production of large quantities of milk in high-yielding dairy cows requires vast amounts of energy (Allen, 2000), and 82% of the variation in milk yield (**MY**) is related to DMI (Huhtanen and Nousiainen, 2012). Other motivations are economical, as a realistic prediction of DMI allows cost-effective diet optimisation (Fuentes-Pila, 1996; Huhtanen et al., 2011) and environmental benefits, such as the limitation of methane emissions, a greenhouse gas dependent on DM and fibre intake (Niu et al., 2018). Finally, DMI plays an essential role in the estimation of nutrient excretion through a mass balance approach (excretion = intake – retention), a value necessary in crop fertilisation planning, and the estimation of potential in ammonia emissions dependent on urinary N (Schrade et al., 2023).

Numerous models have been developed to predict the DMI of dairy cows (e.g. de Souza et al., 2019; Gruber et al., 2004; Shah and Murphy, 2006). Such models have been adopted by institutes providing requirements and recommendations for dairy cow nutrition. The developed models can be classified according to their approach by solely considering animal characteristics, as done by the american national research council (NRC, 2001), the australian commonwealth scientific and industrial research organization (CSIRO, 2009), american national academies of sciences, engineering, and medicine (NASEM, 2021), and Agroscope (2021), or by considering both animal and dietary characteristics, as done by the German Gesellschaft für Ernährungsphysiologie (GfE, 2023) or the french institut national de recherche en agronomie (INRA, 2018) model.

Models predicting DMI are usually developed based on datasets obtained in specific conditions of production and reflecting regional practices. Therefore, assessing these models is crucial for validating the accuracy and precision of estimated values across diverse environmental conditions, genotypes, and management practices other than those for which they were developed (Souza et al., 2016). Moreover, evaluating DMI models using independent data can reveal the robustness of existing models and lead to a deeper understanding of the chosen parameter effects on DMI prediction (Fuentes-Pila, 1996; Jensen et al., 2015). Evaluating DMI models allows for the analysis of their strengths and weaknesses and eventual detection of knowledge gaps, as well as the impact of different datasets on predicting DMI, parameters used in the modelling approach, specific animal productive characteristic parameters (e.g. MY), and diet characteristic parameters (e.g. NDF) on the model performance. Several evaluations of DMI models in lactating dairy cows have been published. Faverdin et al. (1992) compared different models to predict DMI (multiple regression models, physical or energy limiting sensitive models, diet bulkiness, and concentrate substitution rate models) and concluded that no system was capable of correctly describing all the major factors of variation in DMI. Fuentes-Pila et al. (2003) evaluated models that include both dietary and animal parameters and concluded that they capture better the effects of increasing forage proportion in the total mixed ration by providing more accurate predictions of DMI. Clement et al. (2014) assessed an equation that included behavioural parameters (rumination time) to predict DMI and concluded that there was no gain in precision or accuracy using this approach. Krizsan et al. (2014) studied the specific impact of MY on the prediction of DMI and concluded that it better reflects the Scandinavian cow's productive potential when formulating diets aiming to sustain a given MY compared to energy corrected MY. Jensen et al. (2015) evaluated the model robustness of predicting DMI using all the above-mentioned modelling approaches in Scandinavian productive conditions to investigate the differences in DMI within and between different studies. They concluded that all models overpredicted DMI at high intakes and underpredicted DMI at low intakes.

The existing models for DMI estimation have previously undergone evaluation subsequent to their development process and had been evaluated with different breeds and management systems. Several studies (Krizsan et al., 2014; Clement et al., 2014; Jensen et al., 2015; Faverdin et al., 2017) on model development and evaluation were conducted using datasets with a concentrated proportion ranging from 25 to 42% in the total DMI. Therefore, there is currently a knowledge gap in evaluating the performance of these models using independent datasets, especially in the case of diets with high forage proportions, which are largely present in certain regions and countries, such as Switzerland. The objective of this study was to assess the precision and accuracy of six models predicting DMI in lactating dairy cows, utilising routinely collected data from the Agroscope herd in Posieux, Switzerland. In addition, the objective was to compare two evaluation methods: 1. RMSE of prediction (including its decomposition) and 2. the concordance correlation coefficients analysis of precision and accuracy, to assess the model fitness. Preliminary results from this study were previously communicated in Mehaba et al. (2022).

Material and methods

Dataset description

The dataset used for the model evaluation originated from the lactating dairy herd (Red Holstein and Holstein-Friesian), with a mean lactation yield (308 days) of 7 928 ± 1 106 kg for primiparous and 9 377 ± 1 206 kg for multiparous at Agroscope in Posieux, Switzerland. It contained values (between 1 and 308 days in milk) dating from 2015 to 2021, each year from November to March, the months when the cows were housed (cubicle housing) without any access to pasture. The animal information data, such as date of birth, lactation number, and calving date, were provided by the database from the associated breeding organisation (Holstein Switzerland, Posieux, Switzerland). The cows had *ad libitum* access to a mixed basal diet consisting of forages being hay and silage from mixed herbage swards and from alfalfa and whole-plant corn silage. The data for intake of the basal diet were provided from automatic records by access-controlled weighing bunks (Insentec RIC system, Hokofarm Group, Marknesse, Netherlands), allowing for individual recordings of intake at each visit. The intake data for the restrictively fed compound feed and mineral feed were provided by the automatic free access compound feed distributor (Hokofarm Group, Marknesse, Netherlands) at each visit. The nutrient content data of the on-site produced basal diets, concentrates, and mineral feeds were provided from the formulated recipes, which, for the basal diets, were based on the analysed nutrient

Table 1
Descriptive statistics of the chemical composition and nutritive values of diets fed to lactating dairy cows.

Characteristics	Mean	SD	CV, %
Dietary concentrate, % DMI	9.0	7.54	84.2
DM, g/kg	531	117.9	22.2
NEL_f, MJ/kg DM	6.3	0.53	8.5
NEL, MJ/kg DM	6.3	0.42	6.7
PDIE, g/kg DM	92.8	9.87	10.6
PDIN, g/kg DM	98.0	13.84	14.1
CP, g/kg DM	149.3	21.65	14.5
Crude fibre, g/kg DM	184.1	18.63	10.1
NDF, g/kg DM	365.9	45.51	12.4
ADF, g/kg DM	201.8	32.58	16.1

Abbreviations: DMI = DM intake; NEL_f = Net energy for lactation in the forage-based diet; NEL = Net energy for lactation in the diet; PDIE = Protein digestible in the small intestine when rumen fermentable energy is limiting; PDIN = Protein digestible in the small intestine when rumen fermentable nitrogen is limiting.

contents of each feedstuff batch (Table 1). The data for MY were provided from the automatic records obtained in the milking parlour, twice a day (0500 and 1600 h), and the data for BW were provided from an access-controlled walk-through scale (Hokofarm Group, Marknesse, Netherlands) following each milking (Table 2). Milk composition data were provided from the official milk controls occurring every 2–3 weeks for each individual cow.

Model description

Six models predicting the DMI evolution of lactating dairy cows were applied to each daily measured DMI in the dataset containing all required parameters, as summarised in Table 3.

Agroscope (2021): The Swiss model provides equations developed in 1994 to predict DMI for primiparous and multiparous cows (Table S1). The equations are multiple regression models that include week of lactation (**WOL**) as animal and energy-corrected milk as productive parameters, calculated according to the equation reported in Table S1. The model is based on a dataset including 599 partial lactations (25.2% primiparous, 74.8% multiparous) from Holstein, Swiss Fleckvieh, and Brown Swiss cows housed in a tied stall and recorded between 1985 and 1993. The basal diets used consisted of various conserved herbages with or without corn silage offered separately and *ad libitum*, and the amounts of provided concentrates were adjusted every week according to the individual previous weekly MY.

NRC (2001): The former US model valid until its update in 2021 (NASEM, 2021) consists of a multiple regression equation that includes metabolic $BW^{0.75}$, fat corrected MY as animal and productive parameters and an adjustment for WOL (Table S2). The model is based on a dataset including 17 087 WOL (34.9% primiparous, 65.1% multiparous) from Holstein cows, originating from publications in the Journal of Dairy Science (1988–1998) and data from Ohio State University and the University of Minnesota.

GfE (2023): The German model provides a multiple regression mixed model that includes two equations depending on feeding practices. The GfE model has an additive approach that sums up individually calculated values for the effects of BW, MY, DMI concentrate intake, and dietary metabolisable energy concentration, resulting in a predicted DMI. These equations originate from Gruber et al. (2004), and the used factor for net energy for lactation (**NEL**) was converted to metabolisable energy, and its impact was reduced. One equation is provided for a total mixed ration feeding system that includes concentrate proportion in %, and one equation is provided for a basal diet with an individual supply of concentrate feeds in kg per day. The equation based on the concentrate effect expressed in kg/day was chosen and includes day in milk (defined as WOL / 7), parity, BW, breed, and MY as productive parameters, the dietary concentrate quantity, and the metabolisable energy content of basal diet as diet parameters (Table S3). The model was developed using a dataset consisting of 77 experiments from 10 German, Austrian, and Swiss research institutions (Gruber et al., 2004). The Swiss data were based on published experiments from Agroscope (1995–2002) and from the Eidgenössische Technische Hochschule Zürich (ETHZ, 1995–2001). The dataset comprises data from 2151 Simmental, Brown Swiss, and Holstein cows representing 31 865 WOL (27.2% primiparous, 72.8% multiparous). The basal diets used consisted of various fresh and conserved herbages with or without corn silage offered mixed or separately and *ad libitum*, and the concentrates were offered restrictively according to individual MY. The GfE model did not provide information about the data quality used in the adaptation of the impact of dietary NEL content on DMI of the equations by Gruber et al. (2004).

CSIRO (2007): This Australian model was developed for growing sheep and beef cattle, with adaptations and corrections for dairy cattle. The equation is an empirical formula that includes standard mature reference BW, BW relative to the mature reference one, body condition score relative to the one at parturition, day in milk, days to the peak potential intake (animal parameters), and the ratio of actual MY to potential MY at peak of lactation (productive parameters) (Table S4). No information was provided about the data used to develop the equation.

INRA (2018): The French model provides an equation system that includes the interaction between a dietary (diet bulkiness), an animal (intake capacity), and a production parameter (productive indexes). Diet bulkiness is based on a fill unit, which is defined for each feedstuff. The intake capacity is expressed according to BW, potential MY for primiparous or multiparous cows, body condition score with adjustment indexes for WOL, week of gestation, age, and dietary protein concentration (Table S5). The intake capacity is intricately connected to the physical, chemical, and structural characteristics of the feeds, endowing them with specific digestibility traits and determining the time spent in the digestive tract (Faverdin et al., 2011). The proportional content of concentrates is also considered through the substitution rate between the basal diet and concentrate. The indexes corrected the intake capacity for lactation, gestation, and growth effects based on a time variable (i.e. WOL, week of gestation, and age). Each equation was validated separately, but the developmental performance of the model (i.e. performance of the model during its development phase) as a whole was not reported by INRA (2018).

NASEM (2021): The current US model provides two equations for predicting DMI. The first equation (Table S6) includes parameters related to parity, milk energy content, BW, and body condition score, which is an empirical equation provided by de Souza et al. (2019). The second equation focuses mainly on the physical rumen filling effect of the diet (NDF and ADF content) and MY. The model is based on a dataset including 31 635 WOL (46.5% primiparous, 53.5 multiparous) from Holstein cows collected from 2007 to 2016.

Table 2
Animal and dietary parameters required to estimate DM intake in lactating dairy cows by the evaluated models.

Models	Animal descriptive	Animal productive	Diet
Agroscope, 2021	WOL	ECM yield	
NRC, 2001	BW, WOL	FCM yield	
CSIRO, 2007	A, Z, CF	M	
INRA, 2018	BW, BCS, WOL, WOG, Age	MY	PDI, UFL, UE_f, UE_c
NASEM, 2021	BW, BCS, Parity, DIM	MilkE yield	
GfE, 2023	BW, Parity, DIM	MY	ME_f, DMI_c

Abbreviations: WOL = Week of lactation; ECM = Energy corrected milk; FCM = Fat corrected milk; MY = Milk yield; M = correction for lactating animals; MilkE = Milk energy content; Parity = Lactation number (GfE) or binary variable with 0 for primiparous, 1 for multiparous cows (NASEM); DIM = Days in milk; A =Standard mature reference weight; Z = The relative size the mature reference weight; CF = Condition factor compared to parturition; BCS = Body condition score; WOG = Week of gestation; Age = Age in months; ME_f = Metabolisable energy content of the basal diet; DMI_c = Concentrate offered in kg/d; PDI = Digestible protein in the small intestine; UFL = Forage unit for milk production; UE_f = Average of forage fill units; UE_c = Average of concentrate fill unit.

Dataset adaptation and calculations

Given the diverse modelling approaches and nutritional systems employed in the assessed models and the available data from the dataset, certain parameters were calculated according to the data in the dataset or were defined to allow calculation of DMI prediction and thus a model evaluation and comparison.

Table 3
Descriptive statistics of animal characteristics, DM intake, milk yield and composition in lactating dairy cows.

Characteristics	Primiparous			Multiparous		
	Mean	SD	CV, %	Mean	SD	CV, %
Lactation, number	1.0	0.00	0.0	3.3	1.50	44.4
Age, months	31.0	4.06	13.1	62.8	20.73	33.0
WOL	12.0	8.87	73.9	15.3	9.88	68.8
BW, kg	612	57.0	9	700	62.7	9
DMI, kg/d	18.5	3.03	16.4	22.5	3.54	15.7
DMI_f, kg/d	16.7	2.90	17.3	20.6	3.31	16.1
MY, kg/d	28.6	5.38	18.8	33.3	7.10	21.3
Energy corrected MY, kg/d	30.3	5.33	17.6	36.3	7.46	22.2
Milk fat, %	4.5	0.53	11.7	4.7	0.51	10.8
Milk protein, %	3.4	0.33	9.6	3.5	0.25	7.2
Milk lactose, %	4.8	0.18	3.8	4.7	0.13	2.7
Milk urea N, mg/dl	9.2	1.89	20.6	9.5	1.53	16.2

Abbreviations: WOL = Week of lactation; DMI = DM intake of the diet; DMI_f = DM intake of the forage-based diet; MY = Milk yield.

Productive parameters: The daily energy corrected (Agroscope, 2021; NASEM, 2021) and fat corrected (NRC, 2001) MY were calculated according to the equations in Supplementary Tables S1, S2, and S6, respectively, using the MY and monthly analysis of milk fat, protein, urea, and lactose contents. The values based on the monthly milk analysis were considered constant for each day until the next available milk analysis. The potential MY at the peak of lactation (INRA, 2018) was calculated according to Table S5, based on the sum of the mean daily MY from the dataset (7 738 kg/year for primiparous and 9 470 kg/year for multiparous) divided by 308 days.

Animal parameters: The body condition score (INRA, 2018; NASEM, 2021) was defined as 3.5 for the complete dataset. The standard mature reference BW (CSIRO, 2007) was defined according to the mean of the measured daily BW of multiparous cows over the third lactation, between 70 and 150 days in milk, resulting in 723 kg. This value was applied to the entire dataset. The BW relative to the standard mature reference BW was calculated on a daily basis and was, according to CSIRO (2007), defined as 1 when the value was superior to 1. The relative days to peak of lactation (CSIRO, 2007) were defined at 49 days (parameter *c*), corresponding to the maximum mean MY (34.9 kg/d and 45.2 kg for multiparous and primiparous cows, respectively) in the dataset.

Diet parameters: The fill unit (INRA, 2018) was calculated for each diet. The substitution rate, captured as the reduction in DMI of the basal diet (or forage) compared to concentrate intake, was defined at 0.55 (INRA, 2018; Table S5) as the dietary proportion of concentrates in the dataset was 9.1% (DM basis), which is relatively low compared to the maximal recommended 30% according to INRA (2018). The dietary metabolisable energy content was considered equal to NEL/0.635 (GfE, 2023). Moreover, the concentrate distribution was adjusted every week according to the individual previous weekly MY.

The descriptive statistics of the model input parameters for primiparous and multiparous cows in the dataset are presented in Table 4.

Statistical analysis

Data were analysed using R Statistical Software (v4.1.2; R-Core-Team, Vienna, Austria). The evaluation of prediction accuracy in the DMI models was conducted using the MSE and its RMSE of prediction approaches, as outlined in Jensen et al. (2015).

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(O_i - P_i)^2}{n}}$$

Where: O_i is the observed DMI for animal i, and P_i is the predicted DMI for animal i, and n is the number of pairs of O and P being compared and used for the model evaluation.

RMSE was decomposed into three types of errors (Bibby and Toutenberg, 1977): the errors attributable to central tendency (**ECT**), regression (**ER**), and disturbance (**ED**), relative to the MSE of prediction. The ECT describes the error due to the difference between the observed and predicted means of DMI. The ER is the error of unequal variation, measuring the deviation of the least square regression coefficient from 1; if the variance of the predicted DMI is the same as the variance of the observed DMI, then the ER is 0. Finally, the ED expresses the error due to disturbance, which is the variation in observed not accounted for by a least square regression of observed on predicted (Fuentes-Pila, 1996). ECT and ER are systematic errors and unwanted. The ED represents the part of the MSE that cannot be removed by linear correction of the prediction, and a desirable ED should account for most RMSE (Bibby and Toutenberg, 1977). The RMSE calculations were implemented using the goodness.of.fit function in the ZeBook package (v1.1; Brun et al., 2018). In addition, the decomposition of the MSPE across animals, as described above, can be recovered from a simple linear regression of the difference between observed and predicted on the difference between predicted and its mean using the lme4 package (v1.1–35.1; Bates et al., 2023) as follows:

$$O_i - P_i = \beta_0 + [\beta_1 \times (P_i - \bar{P})] + (1|Animal) + \varepsilon_i$$

where β_0 is the intercept, average deviation from the average prediction; O_i is the observed DMI on day i; P_i is the predicted DMI on day i; $\bar{P_i}$ is the mean predicted DMI; 1|Animal is the animal-specific random intercept; and ε_i is the residual error term. The RMSE result was interpreted according to Fuentes-Pila (1996) as satisfactory when < 10%, as acceptable when between 10 and 20%, and as unsatisfactory predictions when > 20% of mean DMI.

The concordance correlation coefficient (**CCC**) was calculated using the epi.ccc function in the epiR package (v0.9-99, Stevenson et al., 2022) and is defined by the following equation:

$$CCC = \frac{2\sigma_{xy}}{\sigma_x^2 + \sigma_y^2 + (\mu_y + \mu_x)^2}$$

where σ_x^2 is the variance of the observed DMI being compared, σ_y^2 is the variance of the predicted DMI, σ_{xy} is the SD in both observed and predicted DMI, μ_x is the mean observed DMI, and μ_y is the mean predicted DMI. The CCC combines measures of both precision and accuracy to determine how far the observed data deviate from the line of perfect concordance (Tedeschi, 2006), being a line at 45° on a square scatter plot, with values close to 1 indicating agreement between observed and predicted (Lin, 1989).

Similar to the RMSE of prediction, the CCC can be decomposed to estimate a scale or slope shift (υ), location bias (μ) relative to scale shift, and a bias correction factor (C_b) where values closer

Table 4
Descriptive statistics of input parameters used in models predicting DM intake of lactating dairy cows.

Equation	Primiparous			Multiparous		
	Mean	SD	CV, %	Mean	SD	CV, %
NRC, 2001						
Fat corrected MY, kg/d	30.7	5.38	17.5	36.8	7.71	20.9
$BW^{0.75}$, kg	123	8.6	7.0	136	9.2	6.7
CSIRO, 2007						
Relative size to mature BW	0.85	0.08	9.0	0.95	0.06	6.4
Relative condition	1.00	0.09	9.3	1.00	0.09	9.0
Condition factor	1.03	0.04	3.6	1.03	0.04	3.6
Correction relative d to lactation peak, M	1.85	1.32	71.3	2.25	1.41	62.7
Correction BCS at parturition, L	0.98	–	–	1.15	–	–
Current to potential MY ratio, D	0.82	0.15	18.8	0.74	0.16	21.3
Correction for lactating animal, m	1.36	0.15	10.8	1.35	0.17	12.5
INRA, 2018						
Gestation, week	7.83	7.84	100.1	8.68	7.62	87.8
Potential MY, kg/d	30.59	4.37	14.3	30.39	5.06	16.7
BCS	3.50	–	–	3.50	–	–
Diet energy content, UFL[3]	0.86	0.06	7.3	0.85	0.05	6.3
Diet PDI[4], g/kg	92.53	11.39	12.3	91.48	11.05	12.1
Diet fill unit, forage	1.06	0.19	18.3	0.95	0.16	16.9
Diet fill unit, concentrate	0.58	0.11	18.3	0.52	0.09	16.9
Effect of lactation	0.93	0.10	10.7	0.96	0.06	6.7
Effect of gestation	1.00	0.001	0.1	1.00	0.001	0.1
Effect of maturity	0.90	0.03	3.3	0.98	0.02	1.7
Effect of dietary protein	1.01	0.02	2.1	1.01	0.02	2.3
NASEM, 2021						
Energy corrected MY, Mcal/d	23.00	4.04	17.6	27.54	5.66	20.5
BCS	3.50	–	–	3.50	–	–
GfE, 2023						
Effect of days in milk	−1.81	1.31	72.6	−1.40	1.21	86.9
Effect of BW	0.014	0.002	12.3	0.01	0.002	13.1
Effect of MY	0.29	0.07	24.8	0.31	0.08	26.1
Effect of concentrate intake	0.08	0.01	18.1	0.09	0.02	19.1
Concentrate offered, kg/d	1.8	1.56	86.7	2.0	1.79	89.5

Abbreviations: MY = Milk yield; BCS = Body condition score; UFL = Milk forage unit expressed as net energy for lactation/7.36 (Agroscope, 2021); PDI = Digestible protein in the small intestine, considering the minimal PDI value between energy or nitrogen being limiting for rumen fermentation.

to 0 indicate less bias for v and μ and values close to 1 indicate little to no deviation of the best fit line from the 45° line. Interpretation of CCC was based on criteria defined by Hinkle et al. (2003) as follows: negligible = 0.0–0.3, low = 0.3–0.5, moderate = 0.5–0.7, high = 0.7–0.9, and very high = 0.9–1.0. The scale shift (υ) indicates that the variability in the predicted values is similar to the variability in the observed values, and the location shift (μ) indicates that, on average, there is no systematic difference.

To assess the effects of predictive variables on the difference between predicted and observed DMI (i.e. residual DMI), a selection of variables conducive to model comparison was made. Subsequently, a regression against residuals was performed, revealing a residual DMI explained by its correlation with MY, dietary NDF, dietary CP, and BW. The relationships were examined using linear mixed-effects models, incorporating a random effect for individual animals as follows:

$$ResDMI_{ij} = \beta_0 + (\beta_1 \times X_k) + (1|Amial) + \varepsilon_i$$

where $ResDMI_{ij}$ is the observed residual DMI for i^{th} animal on the j^{th} day; β_0 is the intercept, average values of the predictor variable (MY, NDF, CP, etc.); X_k is the predictor variable used to assess its effects on residuals; 1|Animal is the animal-specific random intercept; and ε_i is the residual error term.

Results

Accuracy of the predicted DM intake

The overall accuracy and precision estimates of the DMI, based on 29 280 daily observations, are shown in Table 5 and Fig. 1 and Fig. 2. The DMI of primiparous cows (observed mean of 18.45 kg/d) was overestimated by a mean bias ranging from 1.69 to 2.16 kg DM/d which represents a relative bias of 9.2–11.7% in the GfE, NASEM, NRC, and CSIRO models. It was underestimated by 3.86 kg/d (20.9%) in the INRA model and was equally predicted in the Agroscope model. According to RMSE and CCC, the predictions were considered to have unsatisfactory precision with low or negligible fit, except in the GfE and NASEM models, which considered them acceptable with low fit, and in the Agroscope model, which considered them acceptable with moderate fit. The error of prediction was mainly explained by the ED and 20–40% ECT, except in the INRA, GfE, and Agroscope models, in which the ECT was 78, 33%, and negligible, respectively. The ER also explained 10–20% of the prediction error in the NASEM, GfE, and Agroscope models. The Agroscope, NRC, GfE, and CSIRO models underestimated low DMI and overestimated high DMI (Fig. 1). The INRA model underestimated equally high and low DMI. On the contrary, the NASEM model overestimated equally high and low DMI.

The DMI of multiparous cows (observed mean of 22.53 kg/d) was overestimated by a mean bias ranging from 0.86 to 2.69 kg DM/d, representing 3.8–11.9% of the observed mean DMI in the NRC and NASEM models. It was underestimated by 2.38 kg (10.6%), 2.69 kg (11.9%), and 3.63 kg (16.1%) in the CSIRO, INRA, and GfE models, respectively, and was equally predicted in the Agroscope model. According to RMSE and CCC, the predictions reported acceptable precision with low or negligible fit, except in the CSIRO and GfE models, which showed unsatisfactory precision and low fit. The error of prediction was mainly explained by ED and 20–50% ECT, except in the INRA and Agroscope mod-

Table 5
Accuracy, error decomposition and concordance analysis of models predicting DM intake in lactating dairy cows.

Models	Mean DMI, kg/d		n	RMSE		Error distribution			CCC	υ	μ	C_b
	Observed	Predicted		kg DMI/d	%	ECT, %	ER, %	ED, %				
Primiparous												
Agroscope, 2021	18.45	18.44	10 912	2.50	13.5	0.001	17.23	82.77	0.53	0.66	−0.001	0.92
NRC, 2001	18.45	20.61	10 912	3.78	20.5	32.57	1.95	65.48	0.46	1.18	0.66	0.81
CSIRO, 2007	18.45	20.43	10 912	4.14	22.5	22.82	2.71	74.47	0.08	0.78	0.74	0.76
INRA, 2018	18.45	14.60	10 912	4.37	23.7	77.68	1.09	21.23	0.47	1.15	−1.19	0.58
NASEM, 2021	18.45	20.42	10 912	3.19	17.3	38.19	11.70	50.10	0.39	0.64	0.81	0.70
GfE, 2023	18.45	16.87	10 912	2.87	15.6	30.20	14.78	55.01	0.46	0.64	−0.66	0.76
Multiparous												
Agroscope, 2021	22.53	22.56	18 368	3.02	13.4	0.01	19.95	80.05	0.47	0.62	0.01	0.90
NRC, 2001	22.53	24.56	18 368	4.23	18.8	22.77	0.01	77.23	0.39	1.01	0.56	0.86
CSIRO, 2007	22.53	20.16	18 368	4.65	20.6	26.18	3.52	70.29	0.15	0.75	−0.77	0.75
INRA, 2018	22.53	19.84	18 368	3.23	14.3	69.45	0.76	29.79	0.70	1.08	−0.73	0.79
NASEM, 2021	22.53	23.40	18 368	3.17	14.1	7.44	11.19	81.37	0.48	0.70	0.29	0.90
GfE, 2023	22.53	18.90	18 368	4.98	22.1	53.44	11.60	34.95	0.15	0.52	−1.42	0.45

Abbreviations: DMI = DM intake; ECT = Error due to central tendency as proportion of mean square error; ER = Error due to regression as proportion of mean square error; ED = Error due to disturbance as proportion of mean square error; CCC = Concordance correlation coefficient; υ = location shift relative to the scale (squared difference of the means relative to the product of two SDs); μ = measure the scale shift (ratio of two SDs); C_b = Bias correction factor (accuracy).

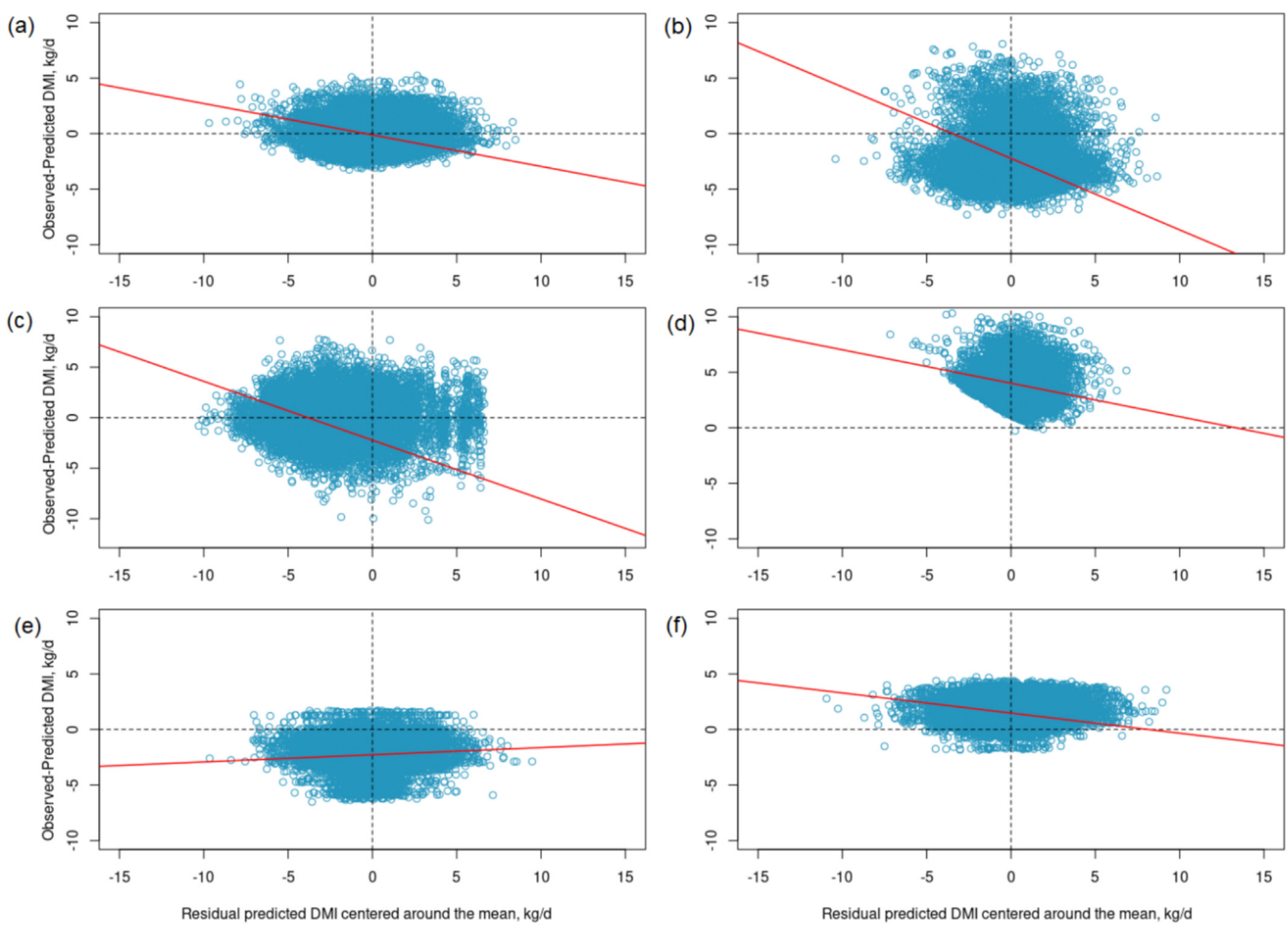

Fig. 1. Centralised residual plots of DM intake (DMI) in lactating primiparous cows predicted by (a) Agroscope, (b) NRC, (c) CSIRO, (d) INRA, (e) NASEM, (f) GfE. Dots represent individual values. Deviation of the regression line from intercept 0 indicates overall under- or overestimation. The slope reflects the error of regression (ER); the closer to zero, the smaller the ER, indicating equal accuracy at low or high DMI.

els, where this error was 70% and negligible, respectively. The ER also explained 10–20% of the prediction error in the NASEM, GfE, and Agroscope models. The Agroscope, NRC, GfE, CSIRO, and NASEM models underestimated low DMI and overestimated high DMI, whereas the INRA model underestimated equally high and low DMI (Fig. 1).

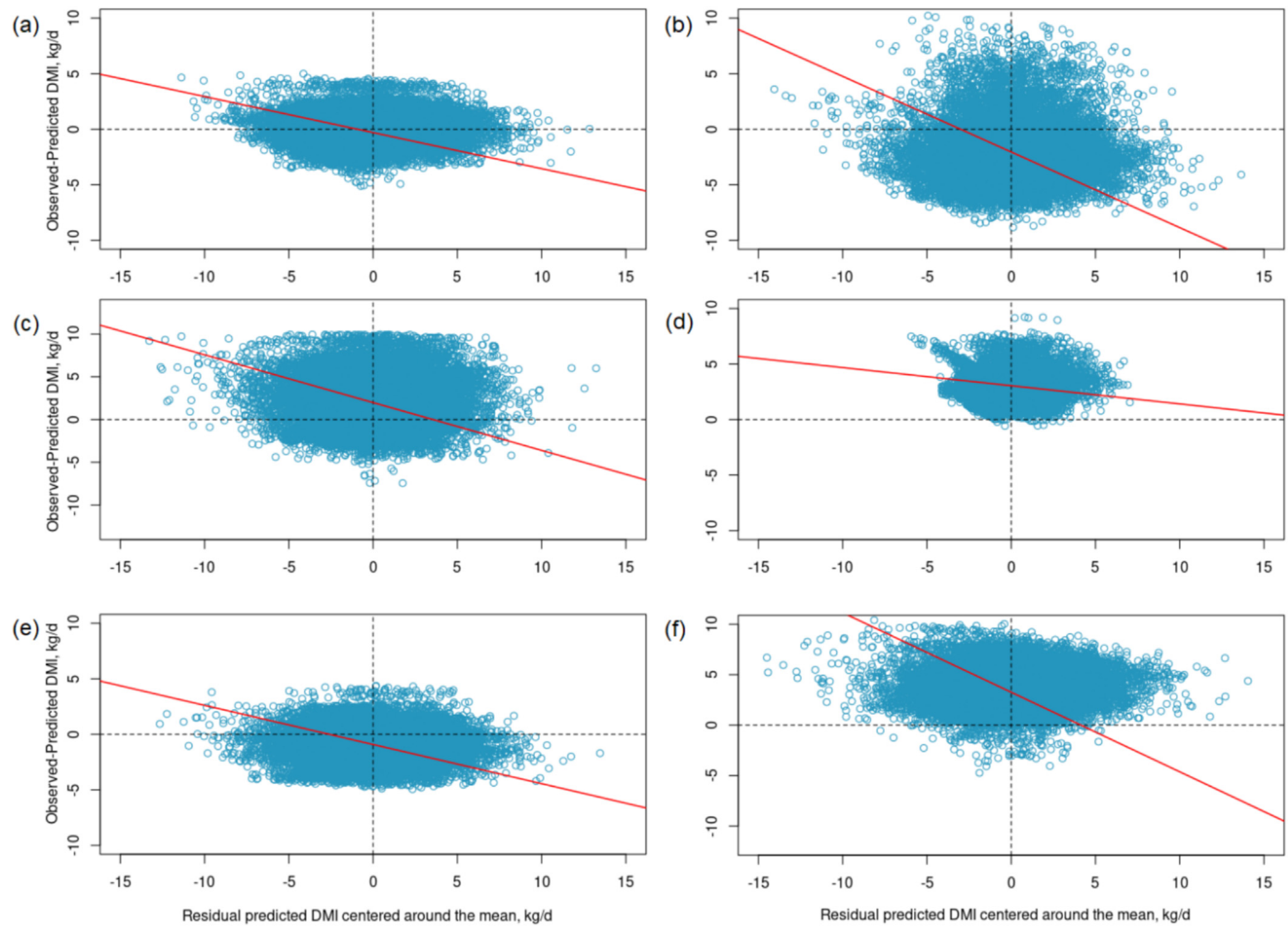

Fig. 2. Centralised residual plots of DM intake (DMI) in lactating multiparous cows predicted by (a) Agroscope, (b) NRC, (c) CSIRO, (d) INRA, (e) NASEM, (f) GfE. Dots represent individual values. Deviation of the regression line from intercept 0 indicates overall under- or overestimation. The slope reflects the error of regression (ER); the closer to zero, the smaller the ER, indicating equal accuracy at low or high DMI.

Effects of the main predictive parameters on residual DM intake

The relationship between the residual DMI and the common predictive variables among the six models evaluated is shown in Table 6. Overall, independent of lactation number and from each individual model, the residual DMI slope was negatively related to MY, BW, and dietary NDF and positively related to dietary CP. A negative and positive residual DMI slope was interpreted as an increasing overestimation and underestimation, respectively, of DMI with the increased unit of predictive parameters. The daily DMI was increasingly overestimated with increasing MY (P < 0.001) by 0.01–0.16 kg DMI/kg MY in all models and both groups of parities, except that it was the contrary in the GfE (primiparous and multiparous), NASEM (primiparous), and INRA (multiparous) models (P < 0.001) and that there was no effect in the NRC (multiparous) model. The daily DMI was increasingly overestimated with increasing BW (P < 0.001) by 0.3–2.7 kg DMI/100 kg BW, except that it was the contrary in the CSIRO model and for multiparous cows in the INRA model (P < 0.001). The daily DMI was increasingly overestimated with increasing dietary NDF (P < 0.001) from 0.8 to 3.2 kg DMI/100 g per kg DM of NDF and with decreasing dietary CP (P < 0.001) from 0.2 to 2.2 kg DMI/100 g per kg DM of protein, except in the INRA model, where it was the inverse for dietary CP (P < 0.05).

Discussion

Accuracy and precision of DM intake prediction models

The equation developmental performance of the models by Agroscope, CSIRO, and INRA was not reported; thus, a comparison with the present results was not possible. The reported developmental performance by the NRC, GfE, and NASEM models was 10.7, 2.8, and 12.6% kg/d lower on average than the respective RMSE values of the present study. Previous model evaluations also reported lower accuracies, with relative RMSE values of 8.9% for the NRC model (Jensen et al., 2015), 11.5% for the NRC model (Krizsan et al., 2014), and 14.3 and 12.1% for the NRC and NASEM models, respectively (de Souza et al., 2019). Lower accuracy can be expected when applying existing DMI models to independent datasets (Fuentes-Pila, 1996; Roseler et al., 1997a).

Management and environmental effects

The environmental conditions in which the data were collected have an important impact on the developed DMI equation. The location, as an environmental factor that affects the DMI of lactating cows, was attributed to differences in livestock management, feed presentation, or environment (Collier et al., 2006). Further-

Table 6
Effect of milk yield, BW and dietary parameters on model residuals for DM intake in lactating dairy cows[1].

Models	MY[2]	BW[3]	NDF[4]	CP[5]
Primiparous				
Agroscope, 2021	−0.040***	−0.4***	−1.6***	0.5***
NRC, 2001	−0.159***	−2.7***	−2.7***	0.4***
CSIRO, 2007	−0.019***	0.7***	−1.1***	0.9***
INRA, 2018	−0.066***	−0.3***	−1.0***	−0.2*
NASEM, 2021	0.054***	−1.1***	−1.0***	1.2***
GfE, 2023	0.140***	−1.1***	−1.6***	1.1***
Multiparous				
Agroscope, 2021	−0.081***	−0.8***	−2.1***	1.2***
NRC, 2001	−0.006	−1.3***	−3.2***	2.2***
CSIRO, 2007	−0.011***	1.3***	−1.9***	1.1***
INRA, 2018	0.056***	0.6***	−0.8***	−0.6***
NASEM, 2021	−0.070***	−2.2***	−2.1***	1.9***
GfE, 2023	0.166***	−0.3***	−2.8***	1.3***

Abbreviation: MY = Milk yield.
Values (slope of observed − predicted) are significant at *P < 0.05 and ***P < 0.001.
[1] Change in residual (slope of observed − predicted, P-value) DM intake kg/d per unit change of the predictive variable.
[2] per kg MY/d.
[3] per 100 kg BW.
[4] per 100 g NDF/kg DM.
[5] per 100 g CP/kg DM.

more, among the management factors, differences between the studies in feeding time or access to feed, also influenced by prepartum management, were mentioned for lactating cows (Huhtanen et al., 2011). Housing type (tie stalls vs. loose housing), temperature and photoperiod are environmental factors that affect DMI prediction (Ingvartsen et al., 1995; Mertens, 1987). It could be speculated that the differences in the accuracy and precision between the studied equations could partially be related to environmental and management effects, as none of them accounted for such parameters, but rather used different equations for different conditions. For example, the data set used in this study was collected by Agroscope as was the original data set used to develop the equations in the'80-'90, published in Agroscope (2021). However, conditions were different: Cows were tied vs. in loose housing, breed was multiple vs. 100% Holstein and energy–corrected MY was lower (7 776 vs. 9 470 kg/year for multiparous). Moreover, the basal diets were provided as separate feedstuffs vs. mixed, the dietary concentrate proportion was higher (19.8 vs. 8.7% DM) and the NEL content of the basal diet was lower (5.9 vs. 6.3 MJ/kg DM). The higher energy content probably reflects the progression made in herbage harvesting capacity (more surface conserved in less time and thus less dependent on weather conditions) and technique (use of conditioner and prewilting process for grass silage production).

The GfE proposed an equation for a total mixed ration or for a basal diet with individual feeding of concentrates, which was used in the present study. Agroscope proposed corrections based on feed access time and the use of specific feedstuffs, such as sugar beet pulp, when not mixing the basal diet, corrections that were not applied in this study, as cows had *ad libitum* access to a mixed basal diet. NRC considered that the effect of environmental temperature is encompassed in the MY parameter (i.e. a lowered MY will reflect the reduction in DMI). However, all equations had an expression of MY (fat or energy corrected) as a proxy parameter for environmental impact, highlighting the need for specific predictive variables to account for environmental effects on DMI. This is especially true under the climate change conditions that livestock production is experiencing.

Animal and dietary effects

The equations evaluated contained various levels of detail on animal and diet parameters. Among the equations evaluated, four contain only animal parameters (Agroscope, NRC, CISRO, and NASEM) and two contain, in addition to animal parameters, dietary parameters (GfE and INRA).

DMI models that included dietary parameters in addition to animal parameters offered no clear advantages or disadvantages, as these equations were not classified regarding the accuracy of prediction and goodness of fit in any particular way from the equations not including dietary parameters. This contradicts Ingvartsen's (1994) and NRC's (2001) observations that models entirely based on animal variables are not able to encompass the complexity of the factors affecting DMI in dairy cows. It can be argued that, in this study, the diets were mostly similar to each other, reducing the variability or representativeness needed to catch the broad effects of dietary parameters on the predictions (Cavallini et al., 2023). However, other studies reported similar variability of dietary parameters (e.g. CV of dietary NDF of 18.3% Fuentes-Pila et al., 2003; 12.0% in Krizsan et al., 2014; or 5.9% Jensen et al., 2015), validating the variability observed in this study in catching the effects of dietary effects on DMI predictions.

The animal parameter of MY, expressed as such or corrected according to milk nutrient contents, was included in all models as representing a major driver to predict DMI in lactating animals (Huhtanen and Nousiainen, 2012), with MY coefficients in the equations that vary from 0.11 to 0.37 kg DMI/kg MY. The overprediction of DMI with increasing MY and the negative relation between residual DMI and MY (0.01–0.16 kg DMI/kg MY), as found in the Agroscope, NRC, and CSIRO models, may be interpreted as an overemphasis on the MY parameter (Jensen et al., 2015). These results are in accordance with those of Huhtanen et al. (2011) and Jensen et al. (2015), who observed an overprediction of DMI with increasing MY in the NRC model, which includes animal parameters. However, the GfE model, which includes both animal and dietary parameters, underestimated DMI, suggesting different outcomes. In this study, no clear performance pattern between equations using MY or standardised MY expression was observed. This contrasts with the findings of Krizsan et al. (2014), who reported an improved prediction of DMI using standardised MY with a similar SD for energy corrected MY and MY.

Similar to the use of the breed parameter (GfE, 2023), the animal parameter of BW can be used in DMI prediction equations (Jensen et al., 2015). Within breed, changes in individual BW accounted for 5–10% of the variation associated with DMI, and BW was positively correlated with DMI (Roseler et al., 1997b), as confirmed by the findings of the present study, in which BW was mostly negatively correlated to the residual DMI. The MY is an important driver of DMI (NRC, 2001), and our comparison of the impact of MY and BW on DMI showed that BW had a lower impact on residual DMI. However, an increase in BW reduced residual DMI and improved the DMI prediction; therefore, including it in the DMI prediction models could reduce the intake prediction error associated with BW change (Huhtanen et al., 2010). The decrease in residual DMI (from 0.3 to 2.7 kg DMI/ 100 kg BW, except in the CSIRO model) with increasing BW is comparable with previously reported negative correlations (Jensen et al., 2015). The positive relationship in the CSIRO model is probably explained by the fact that this model was initially developed for growing meat-producing animals, in which BW gain is necessarily a pivotal predictive variable of DMI. The Agroscope was the only model that did not include BW as a parameter, and our results show that BW had a low impact on the residual DMI when applying that model.

The animal parameter of parity distinguished between primiparous and multiparous cows in the Agroscope, GfE, and NASEM models. Overall, the model error for DMI prediction was higher in multiparous cows than in primiparous cows, as observed in previous studies (Neal et al., 1984; Roseler et al., 1997a). These differences were attributed to lower variability in BW and MY for primiparous cows than for multiparous cows (Neal et al., 1984; Roseler et al., 1997a), which could not be confirmed in the present dataset, as the CV in MY, energy corrected MY, and BW was similar between primiparous and multiparous cows.

The dietary parameters of fibre content, such as NDF, could represent the rumen fill effect and thus adequately capture the dynamic nature of the intake regulation system (Mertens, 1987). The dietary NDF affected residual DMI in all models, exhibited as increasingly overpredicted DMI (values ranging from 0.8 to 3.2 kg DMI/100 g per kg DM). A more complex expression than dietary NDF, such as that applied by the INRA model, can also present certain limits. Faverdin et al. (1992) stated that the INRA equation using the *in vivo* method to determine the fill values of feedstuffs is impractical for determining fill values for new feeds or feeds obtained in particular climatic conditions, leading to inaccuracies in their fill value estimation and adding uncertainty to the prediction of DMI.

The effects of the dietary parameter of CP content on DMI estimation accuracy and precision are variable and likely from a combination of physical and metabolic mechanisms (Allen, 2000). The underprediction of DMI with increasing dietary CP is in accordance with the value reported by Allen (2000) (0.6 kg DMI/100 g CP per kg DM), except in the NRC, CSIRO, and GfE models for multiparous cows, in which the effect was above 1 kg DMI/100 g CP per kg DM. This underprediction was found even though the diets used contained lower CP concentrations (149.3 ± 21.65 g/kg DM) than the DMI-depressing threshold of >177 g CP/kg DM reported by Katongole and Yan (2020).

The concentrate proportion is a dietary parameter that could affect the substitution rate and, therefore, the overall DMI (Jensen et al., 2015). If the models were based on a high proportion of concentrates, such as up to 30% of the DM (Faverdin et al., 1992), the DMI estimation may become imprecise in diets with a low proportion of concentrates, such as in the present dataset (9.0% DM). There is probably a relationship between the dietary concentrate proportion and the dietary NDF and CP contents, leading to similar findings for these dietary parameters.

Modelling evaluation approach effects

The type of model, whether empirical or mechanistic, may play a role in the precision and accuracy of DMI prediction. Empirical models derived from observed data are data–dependent; when tested with different datasets, their precision and accuracy of prediction worsen (Jacob et al., 2023). It is also known that mechanistic models provide insight into the underlying mechanisms and can predict behaviour in unobserved conditions based on theoretical understanding, leading to unaltered model performance when evaluated under different conditions (Jacob et al., 2023). However, in this study, we found no clear difference in the precision of mechanistic (INRA and CSIRO) and empirical (Agroscope, NRC, GfE, and NASEM) equation performance based on RMSE and CCC.

The method used to evaluate the accuracy of a model to predict DMI, such as RMSE or CCC, may also play a role. RMSE is probably the most common and reliable estimate for measuring the predictive accuracy of a model (Tedeschi, 2006). However, it does not provide any information about model precision (Mitchell and Sheehy, 1997), which is covered by the error decomposition formulated by Bibby and Toutenburg (1977), given the ECT precision measure. Comparing the two evaluation methods (RMSE vs. CCC), we observed a decreased sensitivity and inconsistency of CCC, as a 74.1% difference in RMSE between the best (Agroscope, 13.5%) and worst (INRA, 23.7%) performing equation translated to a very low CCC change of 12.8% (Agroscope, 0.53 and INRA, 0.47). Classifying the models' precision according to RMSE was more consistent with the bias observed in primiparous and multiparous cows compared to a classification according to CCC. For example, the INRA model was least precise in primiparous cows according to RMSE of prediction but second-best according to CCC. However, the bias value (−3.85 kg/d) confirmed the RMSE classification of the model as the least precise.

These inconsistencies were also observed in multiparous cows in the CSIRO model, with both an unsatisfactory prediction and a negligible fit. These discrepancies could be explained by the nature of the CCC (Lin, 1989), also known as the reproducibility index, which uses the Pearson correlation coefficient times a bias-correction factor (C_b), therefore accounting simultaneously for accuracy and precision (Tedeschi, 2006; Li et al., 2019). However, this evaluation technique is not without drawbacks. CCC analysis assumes that each paired data point is interchangeable and, therefore, does not account for the variability of the compared sets of observations (Nickerson, 1997). Moreover, C_b accuracy measure is flawed, sometimes failing to give correct accuracy information and yielding unexplained results (Liao and Lewis, 2000). A model may be considered robust if its predictions are at least acceptable when applied to circumstances that differ from those represented in the developmental data (Fuentes-Pila, 1996). In this study, none of the equations evaluated reported RMSE below 10%; thus, none is deemed robust.

The use of daily DMI data might be the cause of the high variance due to the daily variation in intake, MY, and activity within cows. In an exploratory analysis, Martin et al. (2021) reported predictions of daily DMI with lower accuracy and precision than weekly DMI predictions. The use of weekly or group mean data, as in previous studies (Fuentes-Pila, 1996; Roseler et al., 1997a), could significantly reduce RMSE by erroneously removing important day-to-day and cow-to-cow variations in DMI (Ingvartsen et al., 1992). Greater differences between the observed and predicted DMI can also be attributed to the use of individual cow data rather than treatment mean data (Huhtanen et al., 2011). A comparison of equations using day in milk as a time scale (GfE, CSIRO, and NASEM equations) in equations using WOL (Agroscope, NRC, and INRA) did not confirm the reduction in RMSE (Table 5).

Conclusion

The study confirms the well-known notion that all models are wrong, but some are useful. All the evaluated models predicted

DMI with biased, but some with satisfactory precision. The observed RMSE of prediction was within the range observed under practical conditions. The interaction between environmental, diet, and animal factors seems to limit the use and affect the evaluation of any empirical and mechanistic intake model. The interaction of several factors that influence the prediction of DMI in ruminants makes it difficult to identify the single isolated factors that could be responsible for the observed errors. However, evaluation of the models helped identify the leverage parameters in the model performance and the gaps that need to be filled, namely, a periodical update of existing prediction equations and the use of easily measurable parameters as predictors (i e. Dietary NDF, CP, etc…). The study emphasises the importance of considering the specific context of each model and recognising potential limitations. This underscores the need for a nuanced interpretation of model performance, considering the unique characteristics of the studied population (high- vs. low-producing cows) through the analysis of the impact of predictive variables on residual DMI, including the nutritional system (animal parameters vs. animal plus dietary parameters) and broader environmental and management conditions (high forage vs. low forage-based diets). In essence, although certain models may demonstrate superior and consistent predictive accuracy based on RMSE of prediction or CCC, reported inconsistent contradicting results highlight RMSE of prediction as a reliable method for evaluating DMI. Researchers and practitioners should exercise caution in the application of these equations and be aware of their limitations in capturing the complexities of DMI in diverse and dynamic agricultural settings.

Supplementary material

Supplementary Material for this article (https://doi.org/10.1016/j.animal.2025.101535) can be found at the foot of the online page, in the Appendix section.

Ethics approval

As this study was conducted using existing datasets originating from routinely collected information in dairy herds, no ethical approval was necessary.

Data and model availability statement

None of the data were deposited in an official repository. The data/models that support the study findings are available upon request.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) did not use any AI and AI-assisted technologies.

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Declaration of interest

The authors report no conflicts of interest with any of the data presented.

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