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Mathematical Models to Predict Dry Matter Intake and Milk Production by Dairy Cows Managed under Tropical Conditions

Antonio Leandro Chaves Gurgel [1,2,*], Geraldo Tadeu dos Santos [2], Luís Carlos Vinhas Ítavo [3], Camila Celeste Brandão Ferreira Ítavo [3], Gelson dos Santos Difante [3], Alexandre Menezes Dias [3], Vanessa Zirondi Longhini [3], Tairon Pannunzio Dias-Silva [1], Marcos Jácome de Araújo [1], João Virgínio Emerenciano Neto [4], Patrick Bezerra Fernandes [5] and Alfonso Juventino Chay-Canul [6]

1 Campus Professora Cinobelina Elvas, Federal University of Piauí, Bom Jesus 64900-000, Piauí, Brazil; tairon.mvet@gmail.com (T.P.D.-S.); jacome@ufpi.edu.br (M.J.d.A.)
2 Department of Animal Science, State University of Maringá, Maringá 87020-900, Paraná, Brazil
3 College of Veterinary Medicine and Animal Science, Federal University of Mato Grosso do Sul, Campo Grande 79070-900, Mato Grosso do Sul, Brazil; luis.itavo@ufms.br (L.C.V.Í.); camila.itavo@ufms.br (C.C.B.F.Í.); gelson.difante@ufms.br (G.d.S.D.); alexandre.menezes@ufms.br (A.M.D.); vanessa.longhini@ufms.br (V.Z.L.)
4 Academic Unit Specialized in Agricultural Sciences, Federal University of Rio Grande do Norte, Macaíba 59280-000, Rio Grande do Norte, Brazil; joao.emerenciano@ufrn.br
5 Goiás Federal Institute, Campus Rio Verde, Rio Verde 75901-970, Goiás, Brazil; zoo.patrick@hotmail.com
6 División Académica de Ciencias Agropecuarias, Universidad Juárez Autónoma de Tabasco, Villahermosa 86298, Tabasco, México; aljuch@hotmail.com
* Correspondence: antonio.gurgel@ufpi.edu.br or antonioleandro09@gmail.com; Tel.: +55-(81)-9944-9752

Abstract: This study aimed to create an equation to predict dry matter intake (DMI) and milk production and N-ureic in the milk of dairy cows managed in tropical conditions in Brazil. We used 113 observations from three experiments using lactating Jersey, Girolando, and Holstein cows. The goodness of fit of the developed equations was evaluated using the coefficients of determination (r^2) and root mean square error (RMSE). There was a positive correlation between body weight and milk yield (MY) of r = 0.73. The equation considered DMI to be the most important variable to estimate the MY (r^2 = 0.65). Four equations were adjusted to estimate the DMI, where, by a stepwise procedure, the first variable included in the equation was the neutral detergent fibre intake, which explained 92% of the DMI of the cows. However, when the variables BW, MY, and milk fat were included in the equation, there was a reduction of 0.06 in RMSE and an increase in precision (r^2 = 0.94). The nutrient intake, milk production, and characteristics prediction equations present satisfactory precision and accuracy for dairy cows managed in tropical conditions in Brazil.

Keywords: fat; intake; milk composition; milk yield; milk urea nitrogen; protein

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1. Introduction

The composition of milk can be influenced by various factors, such as the rearing system, breed, age, lactation stage, and animal health, as well as the time of year [1–3]. Nonetheless, the most significant factors that can affect milk composition are diet and the amount of food intake, especially with regard to its fat content [4–6]. In a study conducted by Wanderley et al. [7], the researchers investigated the impact of different lipid sources on milk yield and composition. Their findings revealed that certain oilseeds, such as whole soybeans, can modify the fatty acid profile in milk and result in higher daily milk and fatty acid yields.

In modern dairy farming, milk urea nitrogen (MUN) content plays a crucial role in regulating crude protein intake and monitoring protein utilization efficiency and energy–protein balance for cows [8]. However, the reported MUN values in the literature can be highly variable. The variation in MUN is strongly correlated with several nutritional factors, such as dietary crude protein, soluble protein, starch, non-fibrous carbohydrates, the ratio of crude protein to starch, and the availability of ammonia in the rumen, which depends on the capacity of rumen bacteria to capture it [9].

According to Imaizumi et al. [10], including urea in diets consisting of soybean meal and corn silage to increase the dietary protein of dairy cows has the potential to raise MUN levels, with reported values reaching up to 16.5 mg/dL. Similarly, Kozerski et al. [11] investigated the effects on nutrient intake of replacing soybean meal protein with non-protein nitrogen using extruded urea and observed a positive and linear correlation between MUN and the extruded urea level, with a maximum MUN content of 16.7 (mg/dL). Furthermore, MUN is positively associated with plasma urea nitrogen [8] and urinary nitrogen excretion, which may be more strongly influenced by dietary crude protein content than the lactation stage [12]; moreover, the type and proportion of fermentable carbohydrates influence MUN quantity [13].

Dietary fibre content is a crucial factor that can limit intake, particularly in diets with high levels of neutral detergent fibre (NDF) and acid detergent fibre (ADF), which can physically restrict intake [14,15]. As noted by Van Soest [16], fibre is a limiting component of intake because NDF and ADF are slow to degrade in the rumen and tend to remain in the digestive tract for a longer period, causing physical filling and, in turn, reducing intake. Additionally, the National Research Council [1] has indicated that factors such as diet, lactation stage, and energy balance can significantly influence the response to milk production.

Milk cattle farming in tropical regions remains a traditional activity, and most producers rely on management practices that have been passed down for generations without much change. However, as noted by Chico-Alcudia et al. [17], the lack of sophisticated infrastructure, such as measurement equipment to evaluate milk production and composition, and nutrient intake, is one of the primary limitations to increasing profitability in dairy farms. This lack of advanced technology hinders farmers' ability to accurately measure and monitor the various factors that affect milk production, thereby limiting their capacity to make informed decisions that can improve their operations.

Equations for predicting nutrient intake and milk characteristics have been developed for dairy herds to increase accuracy and precision. In Brazil, most scientific studies on dairy cows use equations developed by international research committees, particularly the prediction equations reported by the National Research Council. However, research on beef cattle and sheep has shown that these equations may lead to underestimation or overestimation of results when used under conditions different from those in which they were developed [18,19]. Therefore, while these equations can be useful tools for predicting nutrient intake and milk characteristics, caution must be exercised when applying them to different conditions, as they may not accurately reflect the actual situation.

Most of the prediction models published by international committees are based on research conducted in temperate countries and are therefore designed specifically for the environmental characteristics, breeds, and feed compositions found in those regions [20]. These factors can be very different from the reality of tropical regions, highlighting the need for research in Brazil to develop mathematical models specifically for predicting the nutrient intake and milk characteristics of dairy cows in tropical conditions. Our goal was to create an equation that accurately predicts dry matter intake, milk yield, and milk ureic nitrogen in dairy cows managed under tropical conditions in Brazil.

2. Materials and Methods

This study utilised data from three experiments involving cows of varying frames. The dataset comprised 113 observations from lactating Jersey [11], Girolando [7], and Holstein cows [21].

The research was conducted with Holstein cows (100.0 ± 7 days in milk and 550.0 ± 41.5 kg BW) at the State University of Maringá dairy cattle research facilities in Maringá, Paraná, Brazil (23°25′ S; 51°57′ W) [21]. Additionally, studies with Jersey cows

(148 ± 8 days in milk and 409.10 ± 17.13 kg BW) and Girolando cows (35 ± 8 days in milk and 410 ± 7.15 kg BW) were conducted on a dairy farm located in Campo Grande, Mato Grosso do Sul State, Brazil (20°26′37″ S; 54°38′52″ O) [7,11].

In a study conducted by Durman et al. [21], cows were fed different diets consisting of corn-based meals with varying levels of okara replacing soybean meal. The diets included a control diet without okara, a diet with 35 g/kg of okara on a DM basis, a diet with 65 g/kg DM okara, and a diet with 95 g/kg DM okara mixed with a roughage concentrate in a total ratio of 60:40. Meanwhile, Wanderley et al. [7] investigated the effects of different lipid sources on cow diets. The control group received no additional lipid source, while the other four diets contained different lipid sources, such as cottonseed, sunflower seed, whole soybean, and soybean oil, which were included to provide 70 g/kg of lipid. Finally, Kozerski et al. [11] formulated a diet based on concentrate, corn silage, and Tifton grass that provided 1.013 kg/day of crude protein from concentrate. Soybean meal was replaced with starea at doses of 0, 125, 250, 375, and 500 g/kg in the diet.

Several prediction models were developed for dry matter (DMI), neutral detergent fibre (NDFI), crude protein (CPI) intake, milk yield (MY), milk fat (MFat), and milk urea nitrogen (MUN). To create these models, various predictive variables such as body weight (BW), metabolic body weight ($BW^{0.75}$), DMI, NDFI, CPI, acid detergent fibre intake (ADFI), total digestible nutrient intake (TDNI), milk yield (MY), fat-corrected milk yield (FCMY), milk protein (MProt), milk fat (MFat), milk lactose (MLac), milk total solids (MTS), and milk urea nitrogen (MUN) were tested.

Descriptive statistical analysis was carried out using the PROC SUMMARY procedure in SAS, while the PROC CORR procedure in SAS was used to estimate Pearson correlation coefficients between variables [22]. The PROC REG in SAS (SAS University Edition, SAS Institute Inc., Cary, CA, USA) was used to adjust the models and select variables. The variables were selected using the STEPWISE option and Mallow's C(p). To test the outliers, studentised residuals were evaluated with respect to the values predicted by the equations, and residues outside the range of −2.5 to 2.5 were removed. The developed equations' goodness of fit was evaluated using coefficients of determination (r^2) and root mean square error (RMSE) [23].

An external evaluation of the developed equations was conducted using an independent dataset, which consisted of information from four experiments involving lactating dairy cows [24–27]. To assess the adequacy of the equations, several criteria were used [28], including the coefficient of determination (r^2). The concordance correlation coefficient (CCC) was also employed as an indicator of deviation from the identity line [23]. Additionally, the mean square error (MSE), root mean square error (RMSE), and square root mean square of the prediction error (RQMEP) were calculated using the Model Evaluation System version 3.2.2 program. All statistical analyses were performed using a significance level of 5%.

3. Results

The average body weight (BW) of cows in this study from different frames was 440.52 ± 90.49, with milk yield (MY) of 14.26 ± 5.35 kg/day. The average dry matter, crude protein, and neutral detergent acid fibre intakes were, respectively, 13.13 ± 3.87; 1.90 ± 0.63; and 5.79 ± 1.42 kg/day. The milk protein and fat contents were 3.68 ± 0.53, and 4.07 ± 1.32%, respectively. The MUN showed a mean of 18.06 ± 7.35 mg/dL (Table 1). In this way, we adjusted four equations to estimate the DMI, where, in a stepwise procedure, the first variable included in this model was NDFI, which explained 92% of the DMI of cows. Nonetheless, when the BW, MY, and MFat variables were included in the DMI equation (Equation (4)), there was a 0.06 reduction in the root mean square error (RMSE), and an increase in the precision (r^2 = 0.94).

The NDFI showed a high positive correlation with BW (r = 0.79), MY (r = 0.81), and CPI (r = 0.96) (Table 2). Thus, when included in the NDFI equation, these variables showed a better adjustment to estimate NDFI (Equation (8), Table 3). Similarly, the CPI showed a high positive correlation with BW (r = 0.77), MY (r = 0.80), and FCMY (r = 0.55) (Table 2), which resulted in the CPI equation (Equation (12)) with $r^2 = 0.84$ (Table 3).

Table 1. Descriptive statistics of the nutrient intake and productive parameters of lactating Jersey, Girolando, and Holstein cows managed in tropical conditions.

Variables	N	Average ± SD	Minimum	Maximum	SEM
Body weight (BW, kg)	113	440.52 ± 90.49	312.25	704.00	8.51
Metabolic body weight ($BW^{0.75}$, kg)	113	95.81 ± 14.45	74.28	136.67	1.36
Dry matter intake (DMI, kg/day)	113	13.13 ± 3.87	9.47	27.11	0.36
Crude protein intake (CPI, kg/day)	113	1.90 ± 0.63	1.19	4.54	0.06
Neutral detergent fibre intake (NDFI, kg/day)	113	5.79 ± 1.42	4.37	11.89	0.13
Acid detergent fibre intake (ADFI, kg/day)	97	3.16 ± 0.39	2.64	4.48	0.04
Total digestible nutrients intake (TDNI, kg/day)	97	9.12 ± 1.05	6.34	13.06	0.11
Milk yield (MY, kg/day)	113	14.26 ± 5.35	4.50	34.93	0.50
Fat-corrected milk yield (FCMY, kg/day)	113	14.14 ± 5.15	4.82	34.56	0.48
Milk protein (MProt, %)	113	3.68 ± 0.53	2.68	4.77	0.49
Milk fat (MFat, %)	113	4.07 ± 1.32	1.04	7.50	0.12
Milk lactose (MLac, %)	113	4.48 ± 0.25	3.79	4.92	0.02
Milk total solids (MTS, %)	113	13.22 ± 1.65	9.95	16.76	0.15
Milk urea nitrogen (MUN, mg/dL)	113	18.06 ± 7.35	6.85	38.49	0.69

N, number of observations; SD, standard deviation; SEM, standard error of the mean.

Table 2. Pearson's correlation coefficients between intake and productive parameters of lactating Jersey, Girolando, and Holstein cows managed in tropical conditions.

	BW	$BW^{0.75}$	DMI	CPI	NDFI	ADFI	TDNI	MY	FCMY	MFat	MLac	MProt	MTS	MUN
BW	1.00	0.99 **	0.81 **	0.77 **	0.79 **	0.15	0.15	0.73 **	0.58 **	−0.23 *	0.19 *	−0.42 **	−0.29 *	−0.06
$BW^{0.75}$		1.00	0.80 **	0.76 **	0.78 **	0.15	0.14	0.72 **	0.58 **	0.22 *	0.19 *	−0.41 **	0.29 *	0.06
DMI			1.00	0.98 **	0.96 **	0.80 **	0.81 *	0.81 *	0.56 **	−0.44 **	0.33 *	−0.56 **	−0.47 **	0.05
CPI				1.00	0.96 **	0.77 **	0.69 **	0.80 **	0.55 **	−0.44 **	0.37 **	−0.57 **	−0.48 **	0.11
NDFI					1.00	0.93	0.58 **	0.81 *	0.56 **	−0.40 **	0.32 *	−0.52 **	−0.44 **	0.02
ADFI						1.00	0.45 **	0.10	−0.35 **	−0.58 **	0.38 **	−0.48 **	−0.55 **	0.45 **
TDNI							1.00	0.12	−0.08	−0.21 *	0.26 *	−0.12	0.18 *	0.21 *
MY								1.00	0.86 **	−0.26 *	0.34 *	−0.55 **	−0.32 *	−0.12
FCMY									1.00	0.23 *	0.05	−0.19 *	0.14	−0.41 *
MFat										1.00	−0.60 **	0.74 **	0.94 **	−0.58 **
MLac											1.00	−0.62 **	−0.52 **	0.41 **
MProt												1.00	0.83 **	−0.42 **
MTS													1.00	−0.53 **
MUN														1.00

Correlations followed by no superscripts indicate non-significance; * $p < 0.05$; ** $p < 0.001$.

There was a positive correlation between BW and milk yield (MY) of r = 0.73 (Table 2). MY showed a positive correlation with all variables of intake (DMI, CPI, NDFI, ADFI, and TDNI), and a negative correlation with the variables of milk composition (MFat, MProt, MTS, and MUN), except with MLac (r = 0.26). The first equation considered DMI the most important variable to estimate the MY ($r^2 = 0.65$). Likewise, when BW, MFat, and MLac were included in the adjustment of this equation (Equation (16)), there was a reduction in error and C(p), with an increase of 12% on the determination coefficient (Table 4).

Regarding milk composition, there were negative correlations of MFat with BW (r = −0.23), DMI (r = −0.44), NDFI (r = −0.44), and TDNI (r = −0.21). Likewise, MUN showed a positive correlation ($p < 0.05$) with ADFI (r = 0.45), TDNI (r = 0.21), and MLac (r = 0.41), whereas MUN presented a negative correlation with FCMY (r = −0.41), MFat (r = −0.58), MProt (r = −0.42), and MTS (r = −0.53).

Table 3. Regression equations to predict the nutrient intake of lactating Jersey, Girolando, and Holstein cows managed under tropical conditions.

Equation		RMSE	r^2	C(p)	*p*-Value
Dry matter intake (DMI, kg/day)					
1	$Y_{DMI} = -2.06483 + 2.62252.NDFI$	1.03	0.92	14.38	0.0001
2	$Y_{DMI} = -2.77526 + 0.00480.BW + 2.37990.NDFI$	1.00	0.93	8.29	0.0001
3	$Y_{DMI} = -1.52619 + 0.00557.BW + 0.25994.NDFI - 0.21927.MFat$	0.97	0.94	2.34	0.0001
4	$Y_{DMI} = -1.22245 + 0.00494.BW + 0.04608.MY + 2.14859.NDFI - 0.22863.MFat$	0.97	0.94	2.03	0.0001
Neutral detergent fibre intake (NDFI, kg/day)					
5	$Y_{NDFI} = 2.73423 + 0.21464.MY$	0.84	0.65	39.64	0.0001
6	$Y_{NDFI} = 3.63559 + 0.00000654.BW^2 + 0.00361.MY^2$	0.69	0.77	10.78	0.0001
7	$Y_{NDFI} = 1.16600 + 1.92445.CPI + 0.00217.BW$	0.39	0.93	4.95	0.0001
8	$Y_{NDFI} = 1.46183 + 1.78164.CPI + 0.00175.BW + 0.0007125.MY^2$	0.38	0.93	2.47	0.0001
Crude protein intake (CPI, kg/day)					
9	$Y_{CPI} = 0.56512 + 0.09414.MY$	0.38	0.64	84.38	0.0001
10	$Y_{CPI} = 0.09150 + 0.00234.BW + 0.12265.MY - 0.06824.FCMY$	0.29	0.78	10.11	0.0001
11	$Y_{CPI} = 2.11775 + 0.00454.MY^2 - 0.08930.FCMY$	0.28	0.81	21.60	0.0001
12	$Y_{CPI} = 1.81163 + 0.00371.MY^2 + 0.000002.BW^2 - 0.08015.FCMY$	0.26	0.84	6.07	0.0001

RMSE, root mean square error; r^2, coefficient of determination.

The MFat was estimated by DMI, MY, MProt, and BW variables, and the better adjustment showed an RMSE of 0.60 and r^2 of 0.76 (Equation (20)). Likewise, the MUN equation with better adjustment (Equation (23)) showed an RMSE of 5.21 and r^2 of 0.92, estimated by the MY, CPI, and MLac variables (Table 4).

Table 4. Regression equations to predict the milk yield and composition of lactating Jersey, Girolando, and Holstein cows managed in tropical conditions.

Equation		RMSE	r^2	C(P)	*p*-Value
Milk Yield (MY, kg/day)					
13	$Y_{MY} = -0.35370 + 1.11265.DMI$	3.19	0.65	22.02	0.0001
14	$Y_{MY} = -2.98665 + 0.85514.DMI + 0.01365.BW$	3.11	0.67	3.83	0.0001
15	$Y_{MY} = 31.07583 + 0.77530.CPI^2 - 0.10347.BW + 0.00012679.BW^2$	2.86	0.72	1.89	0.0001
16	$Y_{MY} = -6.95912 + 0.02140.DMI^2 - 0.07114.BW + 0.0000904.BW^2 + 4.85942.\ MFat - 0.50981.\ MFat^2 + 4.42102.MLac$	2.61	0.77	5.26	0.0001
Milk Fat (MFat, %)					
17	$Y_{MFat} = 8.11644 - 1.70280.DMI + 1.23601.NDFI + 1.04077.TDNI$	0.93	0.51	7.15	0.0001
18	$Y_{MFat} = 7.79626 – 1.66251.DMI + 1.36044.NDFI - 0.06672.MY + 0.00333.BW + 1.02753.TDNI$	0.91	0.54	5.16	0.0001
19	$Y_{MFat} = 0.84993 - 0.15719.DMI + 0.00186.BW - 0.11913.MY + 1.66848.MProt - 0.77230.MLac$	0.62	0.75	4.39	0.0001
20	$Y_{MFat} = 2.41143 - 0.51728.DMI + 0.01024.DMI^2 + 0.10335.MY - 1.58625.MProt + 0.00000285.BW^2 - 0.07149.MLac^2$	0.60	0.76	1.68	0.0001
Milk urea nitrogen (MUN, mg/dL)					
21	$Y_{MUN} = 42.83429 + 13.39994.CPI - 18.57076.NDFI + 18.89071.ADFI - 2.16292.MFat$	4.52	0.62	11.93	0.0001
22	$Y_{MUN} = 37.89993 + 13.68839.CPI - 20.88952.NDFI + 20.58141.ADFI + 0.02893.BW - 2.26930.MFat$	4.35	0.65	5.84	0.0001
23	$Y_{MUN} = -0.80896.MY + 1.03405.CPI^2 + 1.22163.MLac^2$	5.21	0.92	34.91	0.0001

RMSE, root mean square error; r^2, coefficient of determination.

In the external evaluation, Equations (4), (8), (12), (15), (20) and (23) (Table 5) showed high coefficients of the determination of the regression. Based on the CCC analysis, these models displayed accuracy and precision, with a CCC greater than 0.55. Considering RMSEP, the DMI model (Equation (4)) best predicted the value of DMI, with an RMSEP value of 1.70 kg. This value indicates an error of only 12.9%, on average, in the predictions. The NDFI and CPI models (Equations (8) and (12)) best predicted the value of intake, with an RMSEP value of 1.19 and 0.56 kg, respectively. The MY (Equation (16)), MFat (Equation (20)), and MUN (Equation (23)) presented RMSEP values of 1.25, 0.44, and 0.99, respectively (Table 5).

Table 5. External validation of the equations for predicting the milk yield and composition of lactating Jersey, Girolando, and Holstein cows managed in tropical conditions.

	Y	r^2	CCC	MSE	RMSE	RMSEP
Equation (4)	DMI	0.94	0.89	0.68	0.82	1.70
Equation (8)	NDFI	0.87	0.64	0.62	0.79	1.19
Equation (12)	CPI	0.92	0.60	0.03	0.18	0.56
Equation (15)	MY	0.79	0.55	28.60	5.54	1.25
Equation (20)	MFat	0.71	0.63	0.18	0.43	0.44
Equation (23)	MUN	0.82	0.71	0.37	0.61	0.99

r^2, coefficient of determination; CCC, concordance correlation coefficient; MSE, mean square error; RMSE, root mean square error; RMSEP, root mean square of the error prediction.

4. Discussion

The variability observed in the data of this study can be attributed to the different breeds used in three separate experiments with lactating Jersey [11], Girolando [7], and Holstein cows [21]. Furthermore, it is important to note that the cows used in the three experiments had different diets, which could lead to varying intake levels. Factors such as hay quality [29], feed additive usage [30], and forage quality [31] have been shown to potentially alter the intake patterns of production animals. It is widely recognized that a diverse database can enhance the predictive capacity and comprehensiveness of the generated equations, as noted in recent studies [32–36]. Therefore, the inclusion of multiple breeds in this study is beneficial for improving the accuracy of the developed prediction models [37–39].

The best predictor of DMI (kg/day) was found to be NDFI (kg/day). It is a reliable parameter for expressing the action of physical and chemical mechanisms that control dry matter intake in ruminant animals, as it positively correlates with rumen filling and rumination time, while inversely relating to the energy concentration of the diet. Although NDFI was found to be a strong predictor of DMI, the combination of NDFI, MY, MFat, and BW variables resulted in more accurate predictions than a model with only one variable. Previous research has also shown that MY and BW are highly correlated with DMI and are crucial predictors of DMI in dairy cows, regardless of breed or frame. Milk fat percentage (MFat) had a negative and moderate correlation with DMI (–0.44). Madilindi et al. [40] found a similar result, demonstrating a moderate antagonistic association between milk fat and DMI (–0.55). The inclusion of MFat in the DMI prediction equation was based on this correlation between milk fat percentage and DMI. Other studies have also emphasised the importance of MFat in DMI prediction models in dairy cows. Rumen digestibility problems, especially with low-fibre diets, can cause an increase in food in the cow's rumen, leading to a reduction in milk fat content.

The NDFI showed a high positive correlation with BW, such as DMI. Likewise, for DMI, NDFI was predicted using BW, MY, and CPI. An NDF intake of close to 1.8% of BW can be achieved by grazing animals [41,42]. According to Mertens [35], the maximum intake of NDF is 1.2% of BW. Our NDFI results showed an average of 1.46% BW. It is noteworthy that NDF intake is highly correlated with body size and ruminal capacity; thus, the greater the BW, the greater the absolute intake of fibre.

Initially, the estimation of CPI was based on milk yield, requiring 94 g/L of CP, which is consistent with NRC recommendations [1]. However, further analysis revealed that CPI also had a strong positive correlation with BW, resulting in a more accurate CPI equation (Equation (12)). As per NRC guidelines, the amount of crude protein required in the diet is influenced by various factors, such as milk yield, milk protein percentage, growth rate, and body size [1]. Therefore, incorporating BW as a predictor variable in the CPI equation can enhance the accuracy of estimating CPI in dairy cows.

The importance of body weight as a predictor of nutrient intake (DM, NDF, and CP) cannot be overstated. The significant role of body weight in predicting DMI, NDFI, and CPI highlights its importance in improving nutrient intake estimates. The relationship between animal weight and DMI is well documented, as an animal's requirements increase in response to an increase in BW [43]. This relationship has been reported in various species, such as sheep [18,44,45], beef cattle [20,41,46], and dairy cattle [40]. Previous studies have used BW and/or $BW^{0.75}$ or empty body weight to predict DMI, and these variables have been shown to be significant predictors of nutrient intake. Thus, it is important to consider body weight when predicting nutrient intake to improve the accuracy of estimates.

Milk yield showed a positive correlation with all variables of intake. We observed that 65% of the variation in MY can be explained by DMI (Equation (13)). The greater the DMI capacity, the greater the supply of nutrients for milk synthesis and MY capacity, since these variables are highly correlated. Despite this, with the insertion of the BW, MFat, and MLac variables in the MY prediction model, there were improvements in the adjustment of the prediction. Thus, the higher the fat content in milk, the lower the total production, inversely to the lactose content, which has a positive correlation with milk production [1,47].

Regarding milk composition, MFat was estimated by DMI, MY, MProt, and BW variables. According to NRC [47], milk fat has a very high variation in its composition, with many factors affecting this milk content. Thus, MFat is a difficult variable to predict. The NRC [47] did not present a prediction model for milk fat content. However, this information has commercial value, since there is a commercial interest of the industry and the producer in knowing the fat content that is being produced by the dairy herd, since the productive yield of derivatives is dependent on this nutrient in the milk.

The greater the milk production, the greater the protein requirement [1]. Thus, a high intake of nitrogenous compounds will determine a greater release of ammonia in the rumen, which can increase MUN concentrations [11,48]. The negative correlations between MUN and the variables MFat ($r = -0.58$) and Mprot ($r = -0.42$) are consistent with the results of Johnson and Young [49]. In contrast, MUN and MLac showed a positive correlation ($r = 0.41$), similar to the results of Meyer et al. [50].

An evaluation to validate the selected equations (Table 5) was carried out using an external dataset [24–27], as recommended by Tedeschi [28] and Steyerberg and Harrell [51]. This is an important step in confirming that the developed models can be extrapolated to other production systems [52].

Table 5 shows that Equations (4), (8), (12), (15), (24), and (27) had high r^2 values and were found to be accurate and precise according to CCC analysis, which had a value greater than 0.55. Although various statistical techniques can assess the precision and accuracy of mathematical models, no single technique can provide an adequate evaluation of the models' performance. In the present study, a combination of statistical methods was used to evaluate the predictive performance of the equations. It should be noted that r^2 criteria measure precision and not accuracy; hence, their interpretation can often be misleading. On the other hand, RMSE and RMSEP values provide information on the level of error between predicted and observed values and help identify the best-performing model. Among the evaluated models, the DMI model (Equation (4)) had the smallest RMSEP value, indicating that it was the most accurate in predicting DMI. The NDFI and CPI models (Equations (8) and (12)) had RMSEP values of 1.19 and 0.56 kg, respectively, and were found to be the best predictors of intake. The MY (Equation (16)), MFat (Equation (24)), and MUN (Equation (27)) had RMSEP values of 1.25, 0.44, and 0.99, respectively (Table 5).

The present study successfully developed models for predicting DMI, NDFI, CPI, MY, MFat, and MUN utilizing data from lactating Jersey, Girolando, and Holstein cows. Validation of the models revealed reasonable prediction accuracies, indicating their potential practical application. However, it is important to note that the models were developed using data from specific breeds and production systems. Therefore, further studies using data from other breeds and different production systems are necessary to improve the accuracy and precision of these models for predicting nutrient intake and milk production characteristics. External validation of the equations is crucial to ensuring their robustness and generalisability to other situations or production systems. Ultimately, the development of accurate and precise models for nutrient intake and milk production characteristics will help farmers optimise feed management and improve animal productivity and health.

5. Conclusions

The prediction equations for nutrient intake and milk production and characteristics demonstrate satisfactory precision and accuracy for dairy cows managed under tropical conditions in Brazil. Milk fat can be estimated using variables such as DMI, milk yield, milk protein, and BW, while MUN can be estimated using variables such as MY, CP intake, and milk lactose. However, further research is necessary to develop and validate prediction models for other breeds and frame sizes.

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