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Adaptation and evaluation of the GrazeIn model of grass dry matter intake and milk yield prediction for grazing dairy cows

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The prediction of grass dry matter intake (GDMI) and milk yield (MY) are important to aid sward and grazing management decision making. Previous evaluations of the GrazeIn model identified weaknesses in the prediction of GDMI and MY for grazing dairy cows. To increase the accuracy of GDMI and MY prediction, GrazeIn was adapted, and then re-evaluated, using a data set of 3960 individual cow measurements. The adaptation process was completed in four additive steps with different components of the model reparameterised or altered. These components were: (1) intake capacity (IC) that was increased by 5% to reduce a general GDMI underprediction. This resulted in a correction of the GDMI mean and a lower relative prediction error (RPE) for the total data set, and at all stages of lactation, compared with the original model; (2) body fat reserve (BFR) deposition from 84 days in milk to next calving that was included in the model. This partitioned some energy to BFR deposition after body condition score nadir had been reached. This reduced total energy available for milk production, reducing the overprediction of MY and reducing RPE for MY in mid and late lactation, compared with the previous step. There was no effect on predicted GDMI; (3) The potential milk curve was reparameterised by optimising the rate of decrease in the theoretical hormone related to secretory cell differentiation and the basal rate of secretory cell death to achieve the lowest possible mean prediction error (MPE) for MY. This resulted in a reduction in the RPE for MY and an increase in the RPE for GDMI in all stages of lactation compared with the previous step; and (4) finally, IC was optimised, for GDMI, to achieve the lowest possible MPE. This resulted in an IC correction coefficient of 1.11. This increased the RPE for MY but decreased the RPE for GDMI compared with the previous step. Compared with the original model, modifying this combination of four model components improved the prediction accuracy of MY, particularly in late lactation with a decrease in RPE from 27.8% in the original model to 22.1% in the adapted model. However, testing of the adapted model using an independent data set would be beneficial and necessary to make definitive conclusions on improved predictions.

Keywords: dairy cow, grass dry matter intake, milk yield, model, adaptation

Implications

The adapted GrazeIn model predicts grass dry matter intake (GDMI) and milk yield (MY) for spring calving grazing dairy cows with increased prediction accuracy compared with the original model. The adapted model can be used as a decision support tool to provide dairy farmers with more accurate estimates of the GDMI and MY of cows in their herds. The use of GrazeIn as a decision support tool could lead to reduced costs of milk production and increased profitability through increased accuracy in the grazing management decision-making process, increased grass utilisation, increased stocking rates and reductions in concentrate and forage supplementation.

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Introduction

In 2015, the EU milk quota system will be removed and with this, there is expected to be increased volatility in milk prices (Shalloo *et al.*, 2011). Grazed grass is the cheapest feed source available to dairy farmers with a relative cost ratio of grazed grass to concentrate of 1 : 2.4 (Finneran *et al.*, 2010). There is a strong inverse relationship between the total cost of production and the grazed grass proportion in the dairy cow diet (Dillon *et al.*, 2005). The average milk production cost is reduced by €0.025/l with a 10% increase in the proportion of grazed grass in the dairy cow diet (Dillon *et al.*, 2005). Thus, increasing the grazed grass proportion also reduces dependence on purchased feed, which is also subject to substantial price volatility. Grass dry matter intake (GDMI) also has a major effect on the production performance of grazing dairy cows (Dillon *et al.*, 2005) and dairy farm profitability (Shalloo, 2009). Increasing the grazed grass proportion in the dairy cow diet results in lower milk production costs and increased profitability (Shalloo, 2009).

The prediction of DMI in dairy cows has received much attention through the years owing to the impact that DMI has on cow performance (Ingvartsen, 1994). Accurate prediction models simulating dairy cow GDMI are useful as decision support tools with regard to the feeding and management of grazing dairy cows. Inaccurate prediction models limit the ability to anticipate the technical consequences of adopting different strategies for GDMI and milk yield (MY) management on individual dairy farms (Shah and Murphy, 2006). Model evaluation is an important process to establish the accuracy of model predictions and to identify weaknesses that need to be addressed in the model (Tedeschi, 2006).

Using a tested and well-parameterised model to predict the GDMI and MY of grazing dairy cows would provide valuable information, aiding the decision-making process around grazing management, to optimise the grazed grass proportion in the dairy cow diet and to increase farm profitability. The GrazeIn model (Delagarde *et al.*, 2011a; Faverdin *et al.*, 2011) predicts GDMI and MY of individual cows using individual cow data. GrazeIn accounts for the variation in GDMI and MY by including cow, sward, grazing management and supplementation input variables in its calculations. Thus, GrazeIn could be an extremely useful decision support tool for dairy farmers and advisors as the input variables used by GrazeIn are readily available on farms.

Previous studies (O'Neill *et al.*, 2013a and 2013b) evaluated GrazeIn at both a herd level and an individual cow level using an independent database. The detailed evaluations of GrazeIn by O'Neill *et al.* (2013a and 2013b) highlighted the large error with which MY in autumn/late lactation was predicted, compared with spring and summer/early and mid lactation. As a result, it was necessary to adapt GrazeIn. The objective of this study was to adapt GrazeIn to improve the prediction accuracy of the model for GDMI and MY prediction for spring calving grazing dairy cows. The prediction accuracy was measured/assessed using parameters such as the relative prediction error (RPE).

Material and methods

Model description

GrazeIn (Delagarde *et al.*, 2011a; Faverdin *et al.*, 2011) is a semi-mechanistic prediction model that simulates the GDMI and MY of grazing dairy cows using easily obtainable cow, sward, grazing management and supplementation variables. Cow variables include age, parity, week of lactation (WOL), potential peak milk yield (PMY_{peak}), milk fat concentration, milk protein concentration, BW, body condition score (BCS), week of conception, BCS at calving and calf birth weight. Sward variables include grass fill value (FV; an inverse function of its 'ingestibility'), grass energy concentration (unité fourragère lait (UFL); 1 UFL is equal to the net energy for lactation of 1 kg of standard air-dry barley) and grass protein value (true protein absorbable in the small intestine when rumen fermentable energy is limiting microbial protein synthesis in the rumen; PDIE). Grazing management variables include pre-grazing herbage mass and daily herbage allowance. Supplementation variables include quantity of supplementation offered and nutritive value (UFL, FV and PDIE) of supplementation offered. Once all inputs have been entered, the model uses these in the sub-models (GDMI and MY) (Figure 1). The sub-models in GrazeIn are linked such that outputs from one sub-model are being used automatically as inputs in the other sub-model and vice-versa through a process of iterative calculations focused on convergence to predict GDMI and MY.

GrazeIn is capable of calculating GDMI and MY for each individual cow or for the grazing herd (all cows grazing in the same paddock, managed identically and receiving a sward of equal quality and composition) using cow, sward, grazing management and supplementation input variables.

Brief descriptions of the sub-models are provided below, and more detailed descriptions are provided by Delagarde *et al.* (2011a) and Faverdin *et al.* (2011).

Intake model, grazing model and interactions

The GrazeIn model (Figure 1) is based on the French fill unit system (Dulphy *et al.*, 1989). The fill unit system predicts the intake capacity (IC) of the cow and FV of the feed in the same units, namely, fill units (FU).

GrazeIn uses the additive effects of BW, BCS and PMY and the multiplicative effects of the age of the cow (index of maturity; IM) and physiological state of the cow (index of lactation; IL and index of gestation; IG) to calculate IC (Faverdin *et al.*, 2011). GrazeIn uses age (months), WOL (weeks) and week of conception (expressed in terms of WOL that conception occurred) to calculate these indices:

$$\begin{aligned}\text{Intake capacity (FU)} &= (9.4 + 0.0015\,\text{BW (kg)} - 1.5\ \text{BCS (scale 0}-5)\\ &\quad + 0.15\ \text{PMY (kg/cow per day)}) \times \text{IL} \times \text{IG} \times \text{IM} \qquad (1)\end{aligned}$$

The prediction of GDMI occurs in two steps. The first step is the calculation of theoretical GDMI. This assumes that the cow was offered fresh cut grass *ad libitum* indoors and takes into account the cow, sward and supplementation characteristics (Faverdin *et al.*, 2011). GrazeIn calculates the FV of the grass consumed and the concentrate fed separately. The second step amends the theoretical GDMI obtained indoors by taking into account the factors that limit intake at grazing (Faverdin *et al.*, 2011). The grazing model accounts for the restrictions placed on DMI when cows are grazing in rotational or continuous stocked systems.

GrazeIn accounts for the interactions between the cow, sward, grazing management and supplementation input variables using intermediate values calculated by iterative processes in the model (Delagarde *et al.*, 2011a; Faverdin *et al.*, 2011).

A full description of the GDMI sub-model used in GrazeIn can be found in Faverdin *et al.* (2011).

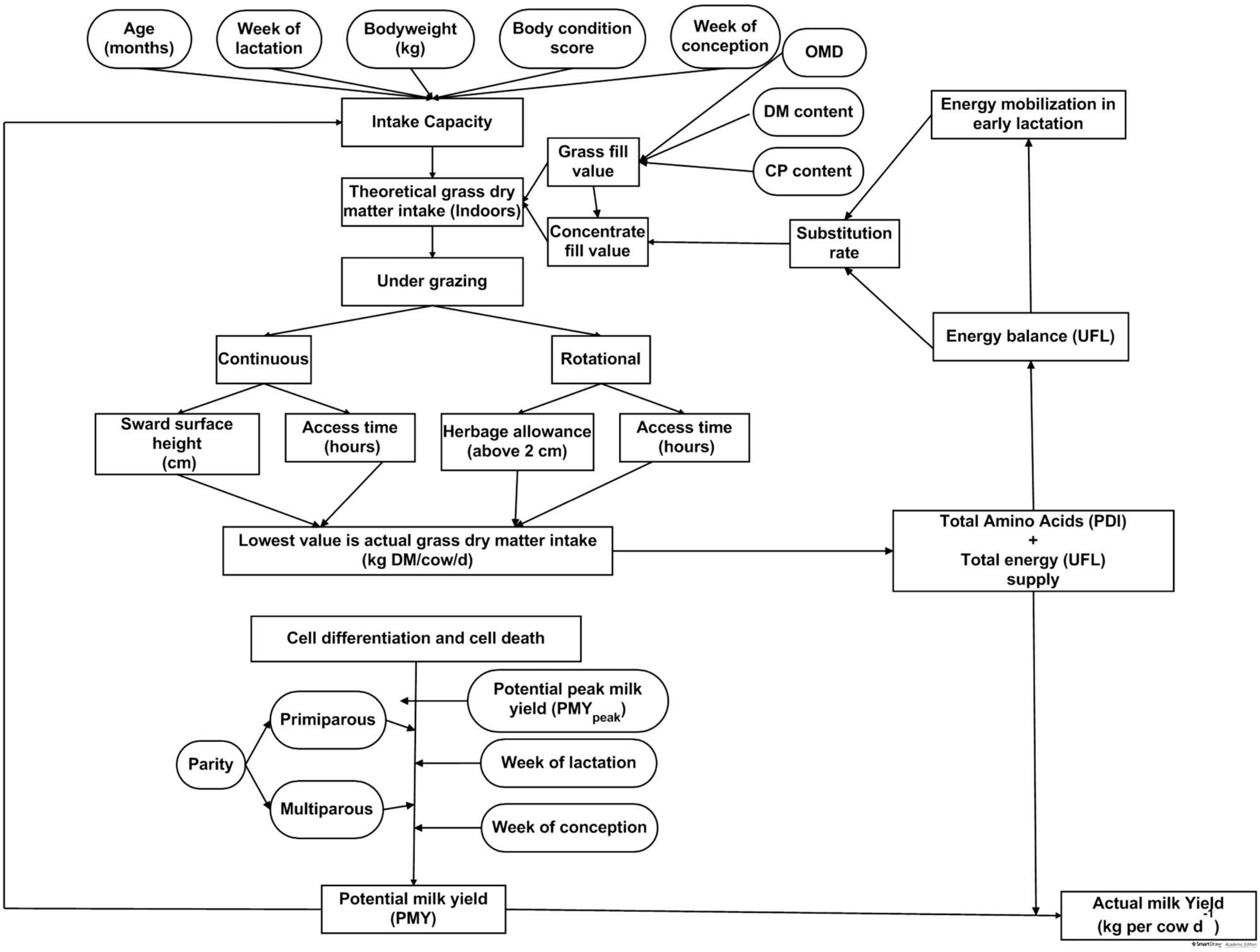

Figure 1 Structure of the GrazeIn model of grass dry matter intake (GDMI) and milk yield (Delagarde *et al.*, 2011a; Faverdin *et al.*, 2011).

MY model

The daily MY is predicted using the response of MY to energy and protein supply as described by Faverdin *et al.* (2011). The predicted MY is dependent on the requirements of the mammary gland (PMY) and the quantities of energy and protein supplied to the mammary gland by the feed consumed by the cow. GrazeIn simulates a lactation curve based on theoretical modelling of a dynamic population of secretory cells in the mammary gland. The number of secretory cells is used to simulate the shape of the PMY curve. The dynamics of production during lactation are modelled on secretory cell differentiation and secretory cell death. The genetic potential of the cow to produce milk does not affect the number of secretory cells in the mammary gland but influences the ability of the secretory cells to synthesise milk. This is reflected in the PMY of the cow. GrazeIn can predict different MY responses to similar energy supplies according to the genetic merit of the cow using the PMY. The PMY of the cow is a function of parity (multiparous or primiparous), WOL, PMY_{peak} and stage of gestation (Faverdin *et al.*, 2011). The GrazeIn model thus requires PMY_{peak} as an input variable.

Moorepark database description

To carry out the adaptation and evaluation of GrazeIn, data from the Moorepark database (O'Neill *et al.*, 2013b) were used as model input data to simulate GDMI and MY. From an original database of 8787 individual cow measurements, a data set of 4514 cows with measured data for all required input variables was selected. From this data set, 554 cows were removed, as these were cows in herds where >30% of the herd had been removed owing to lack of complete measured data. This resulted in a data set of 3960 individual cow measurements available for use from 11 published studies spanning the years 2004 to 2009 (Table 1). A description of the cow, sward, grazing management and supplementation variables for the data set can be found in Tables 2 and 3. All cows in the data set were from spring calving herds resulting in stage of lactation and season being confounded. Cows in the data set had a mean PMY_{peak} of 32.7 kg/cow per day (Table 2) and a mean actual daily GDMI of 15.9 kg DM/cow per day. The mean actual MY was 20.4 kg/cow per day (Table 2). Cows in the data set received concentrate supplementation ranging from 0.0 kg to 6.2 kg DM/cow per day (Table 3).

Table 1 *The 11 grass-based lactating dairy cow studies included in the data set of 3960 individual cow measurements, which was used to adapt the GrazeIn model and to evaluate the adapted model*

Studies in data set	Number of individual cow measurements[1]	Year of study	Description of study
O'Neill *et al.* (2011)	42	2009	Grazing compared with total mixed ration diet
Wims *et al.* (2010)	262	2009	Pre-grazing herbage mass by daily herbage allowance
Curran *et al.* (2010)	255	2008	Pre-grazing herbage mass by daily herbage allowance
Coleman *et al.* (2010)	1336	2006 to 2008	Strain of dairy cow by feeding system
Prendiville *et al.* (2010)	575	2006 to 2007	Dairy cow breed comparison
Kennedy *et al.* (2009)	12	2007	Restricting pasture access time
McEvoy *et al.* (2009)	291	2007	Pre-grazing herbage mass by daily herbage allowance
Kennedy *et al.* (2008)	196	2005	Daily herbage allowance by concentrate supplementation
McEvoy *et al.* (2008)	359	2006	Daily herbage allowance by concentrate supplementation
McCarthy *et al.* (2007)	476	2004 to 2005	Strain of dairy cow by feeding system
Kennedy *et al.* (2006)	156	2004	Early spring grazing by stocking rate

[1]Total number of individual cow measurements in each study.

Table 2 *Mean, standard deviation and range of the cow, grass dry matter intake (GDMI) and milk yield variables for the total data set (*$n = 3960$*) and the mean values in early (0 to 16 weeks), mid (17 to 25 weeks) and late lactation (>26 weeks)*

Parameters	Cows	Mean	s.d.	Minimum	Maximum	Stage of lactation Early	Mid	Late
Cow (during measurement period)								
Parity[1]	3960	2.5	1.64	1.0	10.0	2.6	2.4	2.5
Potential peak milk yield (kg/cow per day)[1]	3960	32.7	7.29	17.4	66	33.4	32.4	32.3
Week of lactation[1]	3960	20	9.8	1	42	11	21	32
Milk fat concentration (g/kg)[1]	3960	41.4	7.79	17.5	82.0	38.3	39.9	46.6
Milk protein concentration (g/kg)[1]	3960	35.4	3.98	23.7	54.0	33.1	34.7	39.0
Week of conception (expressed in terms of week of lactation that conception occurred)[1,2]	2986	15	4.7	5	39	14	15	15
Calf birth weight (kg)[1]	2986	39	6.0	20	64	39	39	38
Age (months)[1]	3960	47	20.4	22	135	45	46	49
BW (kg)[1]	3960	521	73.0	303	786	509	517	540
BCS[1,3]	3960	2.81	0.311	1.50	4.50	2.81	2.77	2.84
BCS at calving[1,3]	3960	3.19	0.432	2.00	5.00	3.17	3.20	3.19
Actual GDMI and milk yield								
GDMI (kg DM/cow per day)	3960	15.9	3.28	4.98	26.3	16.3	16.9	15.6
Milk yield (kg/cow per day)	3960	20.4	7.20	3.1	44.6	26.1	19.7	13.9

[1]Variable used as input variable in the GrazeIn model.
[2]Only includes cows that were pregnant in the lactation during which the GDMI measurement took place.
[3]Body condition score (BCS) (scale 0 to 5) (Lowman *et al.*, 1976).

Model adaptation

GrazeIn was rebuilt using the C++ programming language with the equations from Delagarde *et al.* (2011a) and Faverdin *et al.* (2011). Data from the Moorepark data set were used as input variables in both the original and the rebuilt GrazeIn model. The predicted GDMI and MY from both simulations were compared to test the reconstructed model. Following this, the adaptation was carried out, with each step in the adaptation process being additive to the adaptation steps before it. The objective of the adaptation was to increase the prediction accuracy through (1) the inclusion and optimisation of an IC correction coefficient (for GDMI), (2) the inclusion of a body fat reserve (BFR) deposition calculation from 84 days in milk (DIM) onwards and (3) the optimisation of the persistency of the potential lactation curve (for MY). The adaptation process was carried out and evaluated step-by-step with each step including the adaptations described in the previous steps.

Inclusion of IC correction coefficient

Adaptation of the IC was undertaken to reduce the underprediction of GDMI by GrazeIn during lactation. This was achieved by introducing a 5% correction coefficient to increase the IC calculated and used by GrazeIn. This value was derived as follows. The original model accounted for the increase in the maintenance energy requirements of a grazing cow compared with a stall-fed cow by increasing the maintenance energy requirements by 20% (Coulon *et al.*, 1989).

Table 3 *Mean, standard deviation and range of the sward, grazing management and supplementation variables for the total data set (*n *= 3960) and the mean values in early (0 to 16 weeks), mid (17 to 25 weeks) and late lactation (>26 weeks)*

						Stage of lactation		
Parameters	Cows	Mean	s.d.	Minimum	Maximum	Early	Mid	Late
Sward								
Fill value (FU/kg DM)[1]	3960	0.96	0.030	0.89	1.04	0.95	0.96	0.99
UFL (UFL/kg DM)[1,2]	3960	0.95	0.077	0.76	1.10	0.99	0.93	0.91
PDIE (g/kg DM)[1,3]	3960	100	5.2	88	115	103	99	98
Pre-grazing sward height (cm)	3960	12.0	2.64	5.7	19.2	11.2	11.7	13.4
Post-grazing sward height (cm)	3960	4.9	1.08	2.7	8.3	4.6	5.0	5.1
Pre-grazing herbage mass (kg DM/ha) above 4 cm[1]	3960	1,696	547	664	4257	1656	1614	1822
Daily herbage allowance (kg DM/cow per day) above 4 cm	3960	16.6	5.14	6.5	36.9	16.3	17.6	16.1
Offered grass composition								
Dry matter (g/kg)	3563	175	30.7	110	258	189	184	148
Organic matter (g/kg DM)	3563	893	25.5	804	938	897	891	890
CP (g/kg DM)	3563	223	30.2	165	321	230	218	218
ADF (g/kg DM)	3563	268	39.0	182	392	249	275	286
Organic matter digestibility (g/kg DM)	3563	788	41.1	645	857	810	787	764
Selected grass composition								
Dry matter (g/kg)	3200	179	30.4	131	258	191	187	153
Organic matter (g/kg DM)	3200	915	16.8	834	941	918	913	912
CP (g/kg DM)	3200	222	28.7	155	290	227	221	215
ADF (g/kg DM)	3200	242	28.2	190	359	229	241	261
Organic matter digestibility (g/kg DM)	3200	846	18.0	775	874	857	845	831
Supplementation								
Concentrate fed (kg DM/cow per day)[1]	3960	1.0	1.46	0.0	6.2	1.4	0.6	0.93
Concentrate UFL (UFL/kg DM)[1]	3960	1.10	0.027	1.04	1.16	1.10	1.09	1.10
Concentrate PDIE (g/kg DM)[1]	3960	124	6.7	102	144	125	123	124

[1]Variable used as input variable in the GrazeIn model.
[2]Unité Fourragère Lait (UFL) (feed unit for milk).
[3]True protein absorbable in the small intestine when rumen fermentable energy is limiting microbial protein synthesis in the rumen.

In the original model, the increased energy requirements of grazing dairy cows were not matched by an increased IC. A 20% increase in maintenance energy requirements equates to 1 UFL/day for a 600 kg grazing cow compared with the same cow if stall-fed (Coulon *et al.*, 1989). Assuming the energy concentration of grazed grass was 1.00 UFL/kg DM, this equates to a requirement of an extra 1 kg of grazed grass. Assuming a GDMI of 20 kg DM/cow per day, the cow would have to increase GDMI by 5%.

BFR deposition

The original model accounted for mobilisation of BFR in the first 84 DIM, expressed in UFL/day and calculated based on PMY_{peak}, BCS at calving and WOL. The original model did not account for the deposition of BFR after 84 DIM. In reality, the cow regains BFR lost in early lactation, from nadir BCS to the next calving (Friggens *et al.*, 2004). Including the deposition of BFR in the energy requirements would reduce the amount of energy available for milk production and ultimately reduce predicted MY. The new BFR deposition calculation in the model includes the deposition of BFR from 84 DIM to next calving. This was achieved by calculating the BFR mobilised by the cow from calving to nadir BCS (DIM 84) and then setting that to equal the BFR deposited from 84 DIM to next calving (set at 365 days after previous calving) (Figure 2).

The energy mobilised in the first 84 DIM was calculated using equation (2) for the average daily mobilisation of BFR over the course of the lactation week in early lactation (Faverdin *et al.*, 2007 and 2011):

$$\begin{aligned}&\text{Average daily mobilisation of BFR over the course of the}\\&\text{lactation week in early lactation (UFL/day)}\\&\quad = -1 + [(1.33\times(a + (0.47\times\text{potential peak milk yield})\\&\qquad + (1.89\times\text{BCS at calving}))]\\&\qquad \times\left(e^{-0.25\times\text{week of laction}} - e^{-\text{week of lactation}}\right)\end{aligned}\qquad(2)$$

where a is −9.54 for primiparous cows and −13.24 for multiparous cows.

If the value obtained was negative then the value for mobilisation was zero.

The total BFR mobilised in the first 84 DIM was calculated using the equation (3):

$$\text{Total BFR mobilised in early lactation (UFL)} = 7\text{ days per week}\times\sum_{k=1}^{12}\begin{array}{c}\text{average daily mobilisation of BFR}\\\text{over the course of the lactation}\\\text{week in early lactation (UFL/day)}\end{array}\qquad(3)$$

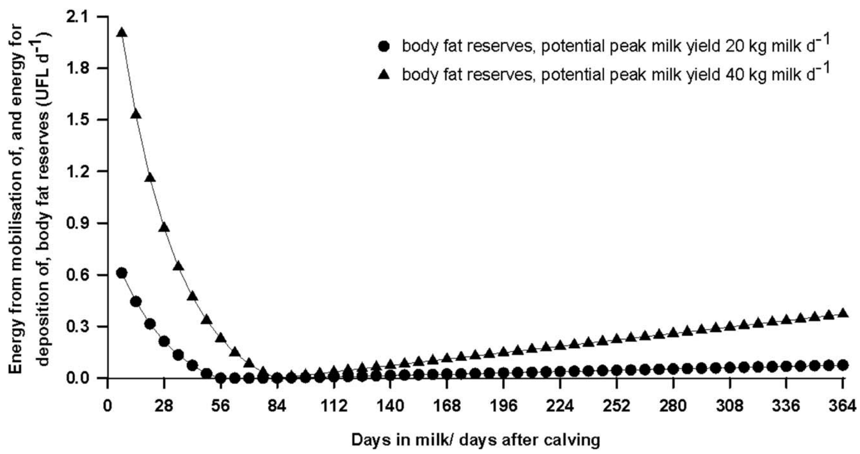

Figure 2 The energy mobilised in early lactation and the energy used for body fat reserve deposition from 84 days in milk to next calving (365 days after previous calving), for a cow with a potential peak milk yield of 20 kg milk/cow per day and a cow with a potential peak milk yield of 40 kg milk/cow per day, both with a body condition score at calving of 2.75 (scale 0 to 5) (Lowman *et al.*, 1976).

It was assumed that the cow regained the total BFR mobilised in early lactation between 84 DIM and the next calving (365 days after previous calving). The linear rate of BFR deposition from 84 DIM to the next calving was calculated using equation (4):

$$\text{Rate of increase in BFR deposition (UFL/day)} = \text{Total BFR mobilised in early lactation (UFL)} \times \frac{2}{280 \times 281\ \text{days}} \quad (4)$$

The daily energy partitioned towards the BFR deposition from 84 DIM to next calving (365 days after previous calving) was calculated using equation (5):

$$\text{Daily BFR deposition (UFL/day)} = \text{Rate of increase in BFR deposition (UFL/day)} \times [(7\ \text{days} \times \text{lactation week}) - (365\ \text{days after previous calving} - 280\ \text{DIM})] \quad (5)$$

Optimisation of the potential lactation curve (for MY)
Previous evaluations of GrazeIn (O'Neill *et al.*, 2013a and 2013b) highlighted problems with the prediction of MY in late lactation. MY is predicted by the model using the PMY and the MY response to nutrient intake. To reduce the overprediction of late lactation MY, the potential lactation curve used to estimate MY by GrazeIn was reparameterised. This process was carried out by optimising, for MY, the coefficients for the rate of decrease in the theoretical hormone related to secretory cell differentiation (*kh*) and for the basal rate of secretory cell death (*ks*). The objective function was set to minimise the overall mean prediction error (MPE) for MY by adjusting the coefficients *kh* and *ks*.

$$\text{MPE} = \sqrt{\frac{\sum_{\text{cow}} ((\text{actual milk yield}_{\text{cow}} - \text{predicted milk yield}_{\text{cow}})^2)}{\text{Number of cows}}} \quad (6)$$

A limit was placed on the range within which the coefficients could be optimised. All combinations within this range were tested using the 3960 individual cow measurements in the data set. The optimal combination of coefficients were the coefficients that achieved the lowest overall MPE for the prediction of MY.

If in the optimal combination, one or more of the coefficients reached the upper or lower limit value, then the limits were widened to increase the range and the optimisation was rerun. The coefficients in the original model for the rate of decrease in the theoretical hormone related to secretory cell differentiation were 0.08/day for primiparous and 0.13/day for multiparous cows, and the coefficients for the basal rate of secretory cell death were 0.0015/day for primiparous and 0.0025/day for multiparous cows. There was no change in the optimised coefficient for kh for primiparous or multiparous cows (0.08/day and 0.13/day, respectively). The optimised coefficients ks were 0.0023/day for primiparous and 0.0035/day for multiparous cows.

Optimisation of the IC correction coefficient (for GDMI)
The final step in the adaptation process was optimising the IC for GDMI. This was undertaken to ensure that the previous steps, carried out to improve MY, had not decreased the prediction accuracy of GDMI. The objective function was set to minimise the overall MPE for GDMI by optimising the IC correction coefficient. A limit was placed on the range within which the coefficient could be optimised. The different coefficients within this range were tested using the 3960 individual cow measurements in the data set. The optimal coefficient was the coefficient that achieved the lowest overall MPE for the prediction of GDMI.

$$\text{MPE} = \sqrt{\frac{\sum_{\text{cow}} ((\text{actual GDMI}_{\text{cow}} - \text{predicted GDMI}_{\text{cow}})^2)}{\text{Number of cows}}} \quad (7)$$

If the optimal coefficient reached the upper or lower limit value, then the limits were widened to increase the range and the optimisation was run again.

Following each step of the adaptation process, the prediction accuracy of the adapted model (including all previous adaptation steps) was evaluated using the total data set of 3960 individual cow measurements and using sub-data sets for early, mid and late lactation.

Statistical analysis

Predicted GDMI and MY were simulated by GrazeIn and the adapted models using data from the data set of 3960 individual cow measurements and input variables. The actual values from the data set and the predicted values from the model for GDMI and MY were compared using linear regression of the actual on the predicted values. The accuracies of the original model and the adapted models were determined using the origin, slope and r^2 of the relationships between the actual and the predicted values (Hayirli *et al.*, 2003). The statistical analysis carried out in this paper is similar to the analysis carried out by O'Neill *et al.* (2013a and 2013b) and uses the common deviance measures proposed by Rook *et al.* (1990), namely, mean square prediction error (MSPE), MPE and RPE (Hayirli *et al.*, 2003).

$$\mathrm{MSPE} = (A_\mathrm{m} - P_\mathrm{m})^2 + S_\mathrm{p}^2(1-b)^2 + S_\mathrm{A}^2(1-r^2) \quad (8)$$

where A_m and P_m are the means of the actual and predicted GDMI/MY, respectively, S_A^2 and S_p^2 are the variances of the actual and predicted GDMI/MY, respectively, b is the slope of the regression of actual on predicted, and r is the correlation coefficient of actual and predicted. The MSPE is the sum of the mean bias, line bias and random variation (Bibby and Toutenburg, 1977).

The MPE is the square root of the MSPE (Rook *et al.*, 1990).

$$\mathrm{MPE} = \sqrt{\mathrm{MSPE}} \quad (9)$$

The RPE is the expression of the MPE as a percentage of the actual measured GDMI/MY.

$$\mathrm{RPE} = \left(\frac{\sqrt{\mathrm{MSPE}}}{A_\mathrm{m}}\right) \times 100 \quad (10)$$

where A_m is the mean of the actual measured GDMI/MY.

Ideally, models are considered robust for practical use if they have a satisfactory level of accuracy for most data sets (RPE $\leqslant$ 10%) rather than high accuracy for some data sets and poor accuracy for others (Fuentes-Pila *et al.*, 1996; Keady *et al.*, 2004). An RPE of $\leqslant$10% is achievable for models predicting DMI of dairy cows in confined systems of milk production (Zom *et al.*, 2012) but is very difficult to achieve for models predicting GDMI of grazing dairy cows (Delagarde and O' Donovan, 2005).

The concordance correlation coefficient (CCC; Lin (1989)) was used to evaluate the extent of agreement between the actual and predicted values. The CCC is calculated as CCC = $\rho \times C_\mathrm{b}$, with ρ being the Pearson correlation coefficient and C_b the bias correction factor. The Pearson correlation coefficient reflects precision, that is, the degree to which the predicted against actual values cluster about the regression line. The bias correction factor reflects accuracy, that is, the degree to which the regression line adheres to the 45° line through the origin. The scale of Landis and Koch (1977) has been used here to describe the degree of concordance, with 0.21 to 0.40 being 'fair'; 0.41 to 0.60 being 'moderate'; 0.61 to 0.80 being 'substantial'; and 0.81 to 1.00 being 'almost perfect'.

Results

Original GrazeIn model

Total data set. The model predicted GDMI with an RPE of 15.8% (Table 4). The majority of the MSPE was attributed to random variation (0.85). The model had a CCC for GDMI of 0.69 with a Pearson correlation coefficient of 0.70 and a bias correction factor of 0.98.

GrazeIn predicted MY with an RPE of 18.9% (Table 4). The majority of the MSPE was attributed to random variation (0.95). The model had a CCC for MY of 0.84 with a Pearson correlation coefficient of 0.86 and a bias correction factor of 0.97.

By stage of lactation. Investigating GDMI by stage of lactation, the RPE ranged from 15.2% to 16.4% (Tables 5, 6 and 7). The bias between predicted and actual values was consistently negative indicating the model on average underpredicted GDMI during all stages of lactation. The mean average bias ranged from −1.4 kg to −0.6 kg DM/cow per day. In early lactation, the majority of the MSPE was attributed to random variation (0.95). This majority reduced to 0.73 for mid lactation and 0.77 for late lactation.

GrazeIn predicted MY in early lactation with an RPE of 15.9% (Table 5) but predicted MY of cows in mid and late lactation with an RPE of 17.4% and 27.8%, respectively (Tables 6 and 7). The mean average bias was −1.0 kg in early lactation and was +1.3 kg and +2.5 kg in mid and late lactation. This indicated that the model on average underpredicted MY in early lactation and overpredicted MY in mid and late lactation. The bias increased as stage of lactation increased. The proportion of the MSPE attributed to the mean bias, line bias and random variation was 0.41, 0.07 and 0.52 for late lactation.

Inclusion of IC correction coefficient in the model

Total data set. Grass DMI was predicted with an RPE of 15.0%. The majority of the MSPE was attributed to random variation (0.95) (Table 4).

GrazeIn predicted a mean daily MY of 21.8 kg/cow per day with an RPE of 19.6% (Table 4). The majority of the MSPE was attributed to random variation (0.87).

By stage of lactation. Investigating GDMI by stage of lactation the RPE ranged from 13.9% to 16.0% (Tables 5, 6 and 7). The majority of the MSPE was attributed to random variation (1.00, 0.87 and 0.89 in early, mid and late lactation, respectively).

GrazeIn predicted MY in early lactation with an RPE of 15.4% (Table 5) but predicted MY of cows in mid and late lactation with an RPE of 18.9% and 30.5%, respectively (Tables 6 and 7). The proportion of the MSPE for MY attributed to the mean bias was 0.01 for early lactation, 0.27 for mid lactation and 0.50 for late lactation.

Table 4 *Prediction accuracy of the GrazeIn model for grass dry matter intake (GDMI) (kg DM/cow per day) and milk yield (kg/cow per day) prediction of grazing dairy cows for the total data set (*n *= 3960) investigating the original model and the model adapted to include (1) intake capacity correction coefficient, (2) body fat reserve deposition, (3) optimised potential lactation curve and (4) intake capacity correction coefficient optimisation*

					Regression of *A* upon *P*						Proportion of MSPE				
Category	Actual (*A*)	s.d.	Predicted (*P*)	s.d.	Origin	Slope	R^2	Model residuals (s.d.)	Bias (*P* – *A*)	MSPE (kg^2)	Mean bias	Line bias	Random	RPE (%)	CCC
GDMI															
Original	15.9	3.3	14.9	2.4	1.74	0.95	0.50	2.31	−1.0	6.33	0.15	0.00	0.85	15.8	0.69
Model 1	15.9	3.3	15.5	2.6	1.98	0.90	0.50	2.32	−0.4	5.68	0.04	0.01	0.95	15.0	0.68
Model 2	15.9	3.3	15.5	2.6	1.97	0.90	0.50	2.32	−0.4	5.67	0.04	0.01	0.95	15.0	0.68
Model 3	15.9	3.3	15.1	2.5	1.92	0.93	0.49	2.35	−0.8	6.17	0.10	0.01	0.89	15.6	0.65
Model 4	15.9	3.3	15.7	2.6	2.24	0.87	0.48	2.36	−0.2	5.71	0.01	0.02	0.97	15.0	0.68
Milk yield															
Original	20.4	7.2	21.2	6.5	0.33	0.95	0.73	3.76	0.8	14.90	0.04	0.01	0.95	18.9	0.84
Model 1	20.4	7.2	21.8	6.6	−0.09	0.94	0.73	3.73	1.4	16.03	0.12	0.01	0.87	19.6	0.83
Model 2	20.4	7.2	21.5	6.7	0.33	0.93	0.74	3.65	1.1	14.85	0.09	0.01	0.90	18.9	0.85
Model 3	20.4	7.2	20.6	7.0	1.48	0.92	0.79	3.31	0.2	11.31	0.00	0.03	0.97	16.5	0.89
Model 4	20.4	7.2	21.0	7.2	1.16	0.92	0.79	3.30	0.6	11.65	0.03	0.03	0.94	16.7	0.89

MSPE = mean square prediction error; RPE = relative prediction error; CCC = concordance correlation coefficient.

Table 5 *Prediction accuracy of the GrazeIn model for grass dry matter intake (GDMI) (kg DM/cow per day) and milk yield (kg/cow per day) prediction of grazing dairy cows for early lactation (0 to 16 weeks) (*n *= 1557) investigating the original model and the model adapted to include (1) intake capacity correction coefficient, (2) body fat reserve deposition, (3) optimised potential lactation curve and (4) intake capacity correction coefficient optimisation*

					Regression of *A* upon *P*						Proportion of MSPE				
Category	Actual (*A*)	s.d.	Predicted (*P*)	s.d.	Origin	Slope	R^2	Model residuals (s.d.)	Bias (*P* – *A*)	MSPE (kg^2)	Mean bias	Line bias	Random	RPE (%)	CCC
GDMI															
Original	15.5	3.7	14.9	2.7	0.66	1.00	0.54	2.47	−0.6	6.45	0.05	0.00	0.95	16.4	0.69
Model 1	15.5	3.7	15.4	2.8	0.83	0.95	0.54	2.47	−0.1	6.14	0.00	0.00	1.00	16.0	0.71
Model 2	15.5	3.7	15.4	2.8	0.83	0.95	0.54	2.47	−0.1	6.14	0.00	0.00	1.00	16.0	0.71
Model 3	15.5	3.7	15.2	2.8	0.68	0.98	0.54	2.49	−0.3	6.28	0.02	0.00	0.98	16.2	0.70
Model 4	15.5	3.7	15.8	2.9	0.92	0.93	0.54	2.49	0.3	6.31	0.01	0.01	0.98	16.2	0.71
Milk yield															
Original	26.1	5.9	25.1	6.6	8.05	0.72	0.64	3.58	−1.0	17.18	0.05	0.20	0.74	15.9	0.79
Model 1	26.1	5.9	25.8	6.7	7.59	0.72	0.65	3.54	−0.3	16.12	0.01	0.22	0.77	15.4	0.80
Model 2	26.1	5.9	25.8	6.7	7.59	0.72	0.65	3.53	−0.3	16.10	0.01	0.22	0.77	15.4	0.80
Model 3	26.1	5.9	25.8	6.7	7.39	0.72	0.68	3.39	−0.3	14.98	0.01	0.23	0.76	14.8	0.81
Model 4	26.1	5.9	26.2	6.7	6.98	0.73	0.68	3.37	0.1	14.70	0.00	0.23	0.77	14.7	0.82

MSPE = mean square prediction error; RPE = relative prediction error; CCC = concordance correlation coefficient.

Table 6 *Prediction accuracy of the GrazeIn model for grass dry matter intake (GDMI) (kg DM/cow per day) and milk yield (kg/cow per day) prediction of grazing dairy cows for mid lactation (17 to 25 weeks) (*n *= 1153) investigating the original model and the model adapted to include (1) intake capacity correction coefficient, (2) body fat reserves deposition, (3) optimised potential lactation curve and (4) intake capacity correction coefficient optimisation*

					Regression of *A* upon *P*						Proportion of MSPE				
Category	Actual (*A*)	s.d.	Predicted (*P*)	s.d.	Origin	Slope	R^2	Model residuals (s.d.)	Bias (*P* – *A*)	MSPE (kg^2)	Mean bias	Line bias	Random	RPE (%)	CCC
GDMI															
Original	16.9	3.0	15.5	2.3	2.85	0.90	0.48	2.18	−1.4	6.53	0.27	0.01	0.73	15.2	0.60
Model 1	16.9	3.0	16.1	2.4	3.12	0.85	0.47	2.20	−0.8	5.52	0.10	0.02	0.87	13.9	0.65
Model 2	16.9	3.0	16.1	2.4	3.11	0.85	0.47	2.20	−0.8	5.50	0.10	0.02	0.87	13.9	0.65
Model 3	16.9	3.0	15.7	2.3	2.98	0.88	0.47	2.21	−1.2	6.21	0.20	0.01	0.78	14.8	0.61
Model 4	16.9	3.0	16.4	2.5	3.35	0.82	0.45	2.23	−0.5	5.40	0.04	0.03	0.92	13.8	0.65
Milk yield															
Original	19.7	4.7	21.0	4.6	3.28	0.78	0.59	3.01	1.3	11.80	0.15	0.09	0.77	17.4	0.74
Model 1	19.7	4.7	21.7	4.7	2.92	0.78	0.59	3.01	2.0	13.87	0.27	0.08	0.65	18.9	0.71
Model 2	19.7	4.7	21.4	4.7	3.06	0.78	0.60	3.00	1.7	12.99	0.23	0.08	0.69	18.3	0.72
Model 3	19.7	4.7	20.1	4.2	2.21	0.87	0.60	2.98	0.4	9.26	0.01	0.03	0.96	15.4	0.78
Model 4	19.7	4.7	20.5	4.2	1.97	0.87	0.59	3.00	0.8	9.91	0.06	0.03	0.91	16.0	0.75

MSPE = mean square prediction error; RPE = relative prediction error; CCC = concordance correlation coefficient.

Table 7 *Prediction accuracy of the GrazeIn model for grass dry matter intake (GDMI) (kg DM/cow per day) and milk yield (kg/cow per day) prediction of grazing dairy cows for late lactation (>25 weeks) (*n *= 1250) investigating the original model and the model adapted to include (1) intake capacity correction coefficient, (2) body fat reserve deposition, (3) optimised potential lactation curve and (4) intake capacity correction coefficient optimisation*

					Regression of *A* upon *P*						Proportion of MSPE				
Category	Actual (*A*)	s.d.	Predicted (*P*)	s.d.	Origin	Slope	R^2	Model residuals (s.d.)	Bias (*P* – *A*)	MSPE (kg^2)	Mean bias	Line bias	Random	RPE (%)	CCC
GDMI															
Original	15.6	2.8	14.4	2.0	2.98	0.87	0.41	2.15	−1.2	6.01	0.22	0.01	0.77	15.7	0.55
Model 1	15.6	2.8	14.9	2.2	3.32	0.82	0.40	2.16	−0.7	5.26	0.08	0.03	0.89	14.7	0.59
Model 2	15.6	2.8	14.9	2.2	3.31	0.82	0.40	2.16	−0.7	5.23	0.08	0.03	0.89	14.7	0.59
Model 3	15.6	2.8	14.5	2.0	3.07	0.86	0.40	2.17	−1.1	5.98	0.20	0.01	0.79	15.7	0.55
Model 4	15.6	2.8	15.0	2.2	3.52	0.80	0.39	2.19	−0.6	5.26	0.06	0.04	0.91	14.7	0.59
Milk yield															
Original	13.9	4.1	16.4	4.0	1.72	0.74	0.54	2.78	2.5	14.92	0.41	0.07	0.52	27.8	0.62
Model 1	13.9	4.1	16.9	4.1	1.49	0.73	0.53	2.79	3.0	17.90	0.50	0.06	0.43	30.5	0.57
Model 2	13.9	4.1	16.4	4.0	1.84	0.74	0.53	2.78	2.5	15.00	0.41	0.08	0.52	27.9	0.62
Model 3	13.9	4.1	14.6	3.4	1.17	0.87	0.52	2.81	0.7	8.64	0.06	0.02	0.92	21.2	0.70
Model 4	13.9	4.1	15.0	3.4	1.01	0.86	0.51	2.84	1.1	9.46	0.12	0.02	0.85	22.1	0.68

MSPE = mean square prediction error; RPE = relative prediction error; CCC = concordance correlation coefficient.

Inclusion of IC correction coefficient and BFR deposition in the model

Total data set. The prediction accuracy results of GrazeIn for GDMI were identical to the previous step (Table 4).

GrazeIn predicted a mean daily MY of 21.5 kg/cow per day (Table 4). MY was predicted with an RPE of 18.9%. The majority of the MSPE was attributed to random variation (0.90).

By stage of lactation. The prediction accuracy results of GrazeIn for GDMI were identical to the previous step (Tables 5, 6 and 7).

GrazeIn predicted MY in early lactation with an RPE of 15.4% (Table 5) but predicted MY of cows in mid and late lactation with an RPE of 18.3% and 27.9%, respectively (Tables 6 and 7). The proportion of the MSPE attributed to the mean bias and line bias was 0.01 and 0.22 for early lactation, 0.23 and 0.08 for mid lactation and 0.41 and 0.08 for late lactation.

Inclusion of IC correction coefficient and BFR deposition in the model and optimisation of the potential lactation curve

Total data set. The model predicted GDMI with an RPE of 15.6% (Table 4). The majority of the MSPE was attributed to random variation (0.89).

MY was predicted with an RPE of 16.5% (Table 4). The majority of the MSPE was attributed to random variation (0.97).

By stage of lactation. Investigating GDMI by stage of lactation the RPE ranged from 14.8% to 16.2% (Tables 5, 6 and 7). The majority of the MSPE was attributed to random variation (0.98, 0.78 and 0.79 in early, mid and late lactation, respectively).

GrazeIn predicted MY in early lactation with an RPE of 14.8% (Table 5) but predicted MY of cows in mid and late lactation with an RPE of 15.4% and 21.2%, respectively (Tables 6 and 7). The majority of the MSPE was attributed to random variation (0.76, 0.96 and 0.92 in early, mid and late lactation, respectively).

Inclusion of IC correction coefficient and BFRs deposition in the model and optimisation of the potential lactation curve and the IC correction coefficient

Total data set. The model predicted GDMI with an RPE of 15.0% (Table 4). The majority of the MSPE was attributed to random variation (0.97). The model had a CCC for GDMI of 0.68 with a Pearson correlation coefficient of 0.69 and a bias correction factor of 0.97, which was similar to the original model.

MY was predicted with an RPE of 16.7% (Table 4). The majority of the MSPE was attributed to random variation (0.94). The model had a CCC for MY of 0.89 with a Pearson correlation coefficient of 0.89 and a bias correction factor of 1.00.

By stage of lactation. Investigating GDMI by stage of lactation the RPE ranged from 13.8% to 16.2% (Tables 5, 6 and 7). The majority of the MSPE was attributed to random variation (0.98, 0.92 and 0.91 in early, mid and late lactation, respectively).

GrazeIn predicted MY in early lactation with an RPE of 14.7% (Table 5) but predicted MY of cows in mid and late lactation with an RPE of 16.0% and 22.1%, respectively (Tables 6 and 7). The proportion of the MSPE attributed to random variation was 0.77, 0.91 and 0.85 in early, mid and late lactation, respectively.

Discussion

Various models have been developed for the prediction of GDMI and MY of grazing dairy cows (Baudracco *et al*., 2010; Delagarde *et al*., 2011a; Faverdin *et al*., 2011). One of these models, GrazeIn (Delagarde *et al*., 2011a; Faverdin *et al*., 2011), was identified by Delagarde and O' Donovan (2005) as being suitable for predicting the GDMI and MY of grazing dairy cows. They evaluated GrazeIn using Irish and French databases containing 190 and 114 grazing herds, respectively. They found that GrazeIn predicted GDMI with a lower level of error for Irish (RPE = 10%), French (RPE = 12%) and combined databases (RPE = 11%) than three other published GDMI models (Sepatou: Cros *et al.* (2003); Pâtur'IN: Delaby *et al.* (2001); Diet-Check: Heard *et al.* (2004)). In addition, with GrazeIn, more of the variation was attributable to random variation than was the case for the other three models. GrazeIn predicted more accurately than the other three models because of its utilising more input factors and estimating more interactions than those of other models (Delagarde and O' Donovan, 2005).

Numerous evaluations of GrazeIn have been carried out using data from different countries (Delagarde and O' Donovan, 2005; Delagarde *et al*., 2011b; O'Neill *et al*., 2013a and 2013b). O'Neill *et al.* (2013a) evaluated GrazeIn at a herd level using an independent database, not only for the database as a whole, but also by season and by grazing management input variable. For the total database (522 grazing herds), GrazeIn predicted GDMI with an RPE of 12.2% and MY with an RPE of 12.8%. Investigation by season and input variable revealed that GrazeIn predicted MY in autumn with a large level of error compared with spring and summer and predicted MY less accurately for herds offered grass with a low FV, high UFL and high PDIE concentration compared with herds offered grass of lower quality (higher FV, lower UFL and lower PDIE concentration).

In the study by O'Neill *et al.* (2013b), GrazeIn was evaluated at a cow level using 8787 individual cow measurements from Irish studies. GrazeIn predicted GDMI with an RPE of 15.5% and MY with an RPE of 16.7% for the total database. There were large differences in prediction accuracies between stages of lactation. GrazeIn predicted MY in late lactation with a large level of error (RPE = 22.9%) compared with early and mid lactation (RPE = 13.9% and 15.4%).

The detailed evaluations of GrazeIn by O'Neill *et al.* (2013a and 2013b) highlighted the large error with which MY in autumn/late lactation was predicted compared with spring/early and summer/mid lactation. As a result, it was necessary to adapt GrazeIn.

Inclusion of IC correction coefficient

In the evaluation of the original model in the current paper, GrazeIn predicted GDMI with an RPE of 15.8%. Stage of lactation did not appear to have a significant effect on RPE for GDMI prediction. The RPE values are within the range reported by Keady *et al.* (2004) and Fuentes-Pila *et al.* (1996) as acceptable (RPE 10% to 20%). As a result, the prediction of GDMI by the original model was within acceptable limits, but given the importance of GDMI it was deemed important to try to improve it further. The absence of a line bias for the total data set, and for the different stages of lactation, indicated that the general structure of GrazeIn for the prediction of GDMI was acceptable with the majority of the MSPE attributed to random variation (Rook *et al.*, 1990). At grazing, the maintenance energy requirements of the cow are 20% higher than the maintenance energy requirements of a stall-fed cow indoors (Coulon *et al.*, 1989). The original model takes account of this, but does not include a similar correction coefficient for the IC of the grazing cow. Kaufmann *et al.* (2011) demonstrated that the higher energy requirements of grazing cows in comparison with stall-fed cows might be because of the increased level of physical activity required to graze. Grazing cows spent more time walking and eating than their counterparts indoors. The increased maintenance energy requirements of the grazing cow are not accounted for in the calculation of IC in GrazeIn but are accounted for in a similar model for predicting DMI in Nordic countries (Volden *et al.*, 2011). Increasing the IC of the grazing cow by 5% in the model reduced the RPE for GDMI and the bias between predicted and actual GDMI for the total data set and for GDMI prediction in the different stages of lactation. As the GDMI and MY sub-models are linked, the increased IC resulted in an increase in energy intake with the extra energy partitioned into MY. In early lactation, this resulted in an improved MY prediction owing to the underprediction of MY at this time. In mid and late lactation, however, there was an increase in the RPE of MY because of an increase in the overprediction of MY.

Inclusion of IC correction coefficient and BFR deposition

Following the inclusion of the IC correction coefficient, the deposition of BFR was included in the model. Cows generally mobilise BFR in early lactation and regain these reserves during the subsequent pregnancy (Friggens *et al.*, 2004). The mobilisation of BFR in early lactation and the deposition of BFR during pregnancy are natural components of the reproductive cycle of the cow (Friggens *et al.*, 2004). This increase in BFR in late lactation is observed as an increase in BCS in late lactation and late pregnancy (Roche *et al.*, 2006). One approach to dealing with BCS change and the mobilisation/deposition of BFR is that of Baudracco *et al.* (2010) who used a BCS model proposed by Friggens *et al.* (2004) to predict the genetically driven pattern of BCS change throughout lactation. The model of Friggens *et al.* (2004) is based on the concept that at any given time in pregnancy or lactation there is an optimal BCS that the cow is genetically driven to achieve. It assumes that the cow is genetically driven to achieve a target level of BCS at or around conception and at next calving. Cows in early lactation will adjust the partitioning of energy to achieve the target BCS at conception. After conception, the cow will gradually increase BCS to achieve the target BCS at next calving. An alternative approach, used in the present study, was to include BFR deposition from 84 DIM to the next calving. The total BFR deposited during this period was equal to the BFR mobilised from calving to 84 DIM. The calculation attempts to simulate what occurs during lactation, namely, the partitioning of energy in mid and late lactation into BFR deposition (Roche *et al.*, 2006) and away from MY. Including BFR deposition in the model therefore reduced the overprediction of MY in mid and late lactation. The reduction in the RPE was larger in late lactation than in mid lactation because of the incremental increase in energy partitioned towards BFR deposition later in lactation (Figure 2) (Roche *et al.*, 2006). Including BFR deposition in the model had no effect on predicted GDMI as the energy partitioned towards BFR deposition is not used in the iterative calculation of GDMI. As a result, the prediction accuracy for GDMI remained unchanged.

Inclusion of IC correction coefficient and BFR deposition and optimisation of the potential lactation curve

GrazeIn includes a potential lactation curve model based on the mammary gland model of Neal and Thornley (1983) to simulate the PMY of the dairy cow, which is the functional capacity of the mammary gland to produce milk (Faverdin *et al.*, 2011). The PMY lactation curve is simulated based on the variation in an arbitrary number of secretory cells (fixed number initially). The number of secretory cells varies because of secretory cell differentiation and secretory cell death (Neal and Thornley, 1983; Faverdin *et al.*, 2011).

Secretory cell differentiation in the model is directly related to a theoretical lactation hormone. The rate of exponential decrease in this hormone, and thus a decrease in the secretory cell differentiation rate, differs between primiparous and multiparous cows. This agrees with Paliser *et al.* (2001) who also found that the rate of decrease in the theoretical hormone related to secretory cell differentiation was higher in multiparous compared with primiparous cows. In the original model, the coefficient for the rate of decrease in the theoretical hormone related to secretory cell differentiation was 0.08/day for primiparous and 0.13/day for multiparous cows (Faverdin *et al.*, 2011). The optimised coefficients were identical to those used in the original model. This suggests that the values used in the original model were accurate for MY predictions for grazing dairy cows.

In GrazeIn, secretory cell death is a function of the number of secretory cells and the cow's stage of pregnancy. The death of secretory cells is proportional to the number of secretory cells (Faverdin *et al.*, 2011). The basal rate of secretory cell death is different for primiparous and multiparous cows. The original model had basal rate of secretory cell death coefficients of 0.0015/day for primiparous cows and 0.0025/day for multiparous cows. The optimised basal rate of secretory cell death coefficients were 0.0023/day for primiparous and 0.0035/day for multiparous cows. The basal rate of secretory cell death coefficient was larger for multiparous than for primiparous cows and this agrees with the frequently made observation of lower lactation curve persistency for multiparous compared with primiparous cows (Stanton *et al*., 1992). Optimising the basal rate of secretory cell death coefficients resulted in an increase in the coefficients for both primiparous and multiparous cows compared with those used in the original model. This leads to a decrease in the persistency of the potential lactation curve used by the model. It is difficult to validate the PMY persistency as the PMY curve is theoretical and assumes that MY is not limited by nutrient intake. The persistency of cows in the literature is the persistency of actual MY and is limited by the nutrient supply available to the mammary gland (Faverdin *et al*., 2011).

Optimising the basal rate of secretory cell death coefficients resulted in an improvement in the prediction accuracy of the model for MY in all stages of lactation compared with the previous step. There was a small reduction in the RPE for MY prediction in early lactation, a larger reduction in mid lactation and the largest reduction in late lactation. As a result, MY prediction improved throughout lactation.

Optimising the basal rate of secretory cell death coefficients for primiparous and multiparous cows resulted in a decrease in the prediction accuracy of GDMI compared with the previous step. This was owing to a decrease in the PMY persistency leading to a decrease in predicted GDMI and an increase in the underprediction of GDMI by GrazeIn.

Inclusion of IC correction coefficient and BFR deposition and optimisation of the potential lactation curve and IC correction coefficient

The second step of the adaptation process improved the MY prediction in late lactation as energy was diverted towards BFR deposition and MY. The third step optimised the potential lactation curve for MY, which also increased the prediction accuracy of the model for MY, especially in late lactation. This latter step, however, also changed IC through adaptations to the PMY curve. It was then necessary to reoptimise the model for GDMI to deal with the fact that the previous two steps were carried out to improve MY irrespective of GDMI. This was carried out by optimising the correction coefficient for IC, resulting in a new correction coefficient for IC of 1.11. This final optimisation succeeded in improving the prediction accuracy of GDMI compared with the original model and maintained the improvements in the prediction accuracy of MY. The increase in the correction coefficient may be owing to the fact that not all factors that affect IC are accounted for by the original IC equation. The Nordic feed evaluation system contains a similar model to GrazeIn for predicting feed intake of dairy cows using IC and FV (Volden *et al*., 2011). In their calculation of IC, the increased maintenance energy requirements of loose-housed and grazing cows compared with stall-fed cows are accounted for. Season may affect IC as grazing lactating dairy cows consumed 10% less grass in autumn than in spring, even though cows were at the same stage of lactation and grazing grass of the same digestibility (Corbett *et al*., 1963). The lower intake in autumn may be attributed to the greater proportion of dead material in the sward (Le Du *et al*., 1981), increased area rejected because of excreta contamination (Greenhalgh and Reid, 1969) and shorter day length affecting grazing intensity (Linnane *et al*., 2001). Including extra factors such as these to calculate IC could reduce or remove the IC correction coefficient. In addition or alternatively, the coefficients for the existing input variables in the calculation of IC could be reparameterised to increase their effect on IC giving rise to a greater IC, thus reducing or removing the requirement for an IC correction coefficient.

Conclusion

The adaptation of GrazeIn improved the GDMI and MY prediction accuracy by using the original input variables, adding new equations to the model and optimising some coefficients in the model. The adaptations not only improved the prediction accuracy of GDMI and MY prediction across the total data set but also in each stage of lactation, particularly MY in late lactation. Future work on GrazeIn should aim to test whether using new input variables not previously included would increase the prediction accuracy of GDMI and MY. Further testing of the adapted model, using an independent data set, would be beneficial.

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