Adequacy of equations used to calculate the contribution of urinary nitrogen to total nitrogen excreted by ruminants

Ronaldo VIBART[1*] and David PACHECO[1]

[1]AgResearch, Grasslands Research Centre, Tennent Drive, Private Bag 11008, Palmerston North 4442, New Zealand

*Corresponding author: Ronaldo.vibart@agresearch.co.nz

Abstract

This study was undertaken to assess the adequacy of the current equation used in OverseerFM™ to predict the contribution of urinary nitrogen (N) to total N excreted. Comparison with observed data has shown that dietary N concentration was the best sole predictor of the contribution of urinary N to total N excreted. A large database was compiled containing feed and excreta variables from dairy cattle (n = 184), beef cattle (n = 70), sheep (n = 143) and deer (n = 33) to evaluate the predictive ability of five linear models and four non-linear models to calculate the contribution of urinary N. Livestock class-specific linear models for beef cattle and sheep did not result in better predictions than those obtained from a generic linear model developed for all ruminant classes. The predictive ability of a non-linear dairy cattle model was noticeably better than that of a linear model. The poor performance of a linear model along with a smaller number of observations from deer studies points to the need for the construction of a new deer-specific model. This study provides support for the robustness of N partitioning towards urinary N in the animal sub-model of OverseerFM™ for a comprehensive range of diets with varying N concentration for beef cattle and sheep, but not so for dairy cattle and deer. In the future, the use of more sophisticated modelling approaches that involve partitioning of data for model development and evaluation may be required.

Keywords: lactating dairy cattle, nitrogen in excreta, nitrogen in urine, non-linear models, sheep and cattle

Introduction

Nitrogen (N) excreted in the urine is the single largest contributor to N losses to the environment from grazed forages (e.g., de Klein et al. 2014; Woods et al. 2018), and the quantity of N excreted in urine varies widely (e.g., Selbie et al. 2015), affected by diet and animal. Increasing or maintaining dietary energy intake while reducing the proportion of N-rich forages tends to improve milk yield and N use efficiency, and decrease the excretion of labile urinary N (e.g., Broderick 2003). In practice, much effort has been devoted to reducing N intake, often via the use of low N feeds (e.g., maize silage, fodder beet) because of the well-established relationships between N intake and N excreted in urine, which have been described as either linear (e.g., Vibart et al. 2009) and/or exponential (Castillo et al. 2000). The use of low N diets runs the risk of shifting from a metabolisable energy (ME)-limiting to a metabolisable protein (MP)-limiting diet (e.g., Kyamanywa et al. 2021). Therefore, N in diets can only be reduced to a certain extent without affecting animal performance.

It is important that the ruminant N-algorithms in OverseerFM (OVERSEER 2018) are reviewed to ensure that the relationships between N intake and urinary N excretion appropriately capture the partitioning of N between product (growth, milk, wool, velvet) and excreta (dung and urine) as diets may become increasingly limited by MP rather than by ME in the future. The objective of this study was to assess the adequacy of the existing equation used in OverseerFM to predict the percentage contribution of urinary N to the total amount of N excreted, by comparison with observed data.

Materials and Methods

Database construction and criteria for inclusion

A large database (n = 430 treatment means from 108 studies) comprising dairy cattle (n = 184 from 49 studies), beef cattle (n = 70 from 15 studies), sheep (n = 143 from 36 studies) and deer studies (n = 33 from 8 studies) was constructed (Figure 1 and Table 1). Relevant data on daily feed and excreta variables were compiled, including N intake and N concentration of the diet (expressed as a percentage of dry matter offered; Ndiet), as well as daily amounts of N in faeces and urine, and the contribution of urinary N to total N excreted (UN%exN) (Figure 1).

Studies that included the measurement of total or partial collection of urine and faeces were used in the evaluation of the models. Studies in which UN was estimated (e.g., using creatinine concentrations from spot-samples) were not included. For the purpose of this model evaluation, N partitioning within an animal was calculated on a daily basis, and daily N intake in the database was partitioned into UN and FN, which were added to calculate total N in excreta. The database was based on studies in which temperate

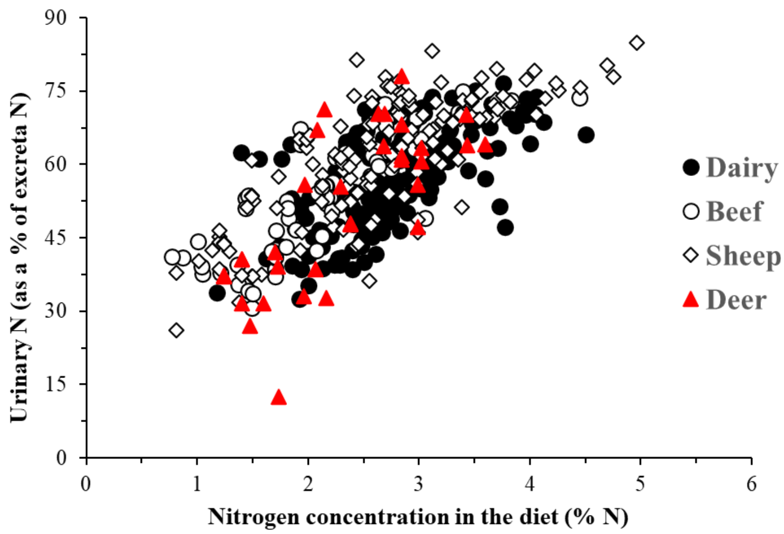

Figure 1 Nitrogen (N) concentration in the diet (expressed as a percentage of dry matter offered) and urinary N (expressed as a percentage of total N excreted) across all four ruminant classes.

Table 1 Studies with dairy cattle, beef cattle, sheep and deer included in the database. For a complete set of references, see Pacheco et al. (2018).

Dairy cattle	Brookes 1984; Van Vuuren et al. 1993; Valk 1994; Petit & Tremblay 1995; Mackle et al. 1996; Carruthers & Neil 1997; Carruthers et al. 1997; Delagarde et al. 1997; Peyraud et al. 1997; Aston et al. 1998; Keady et al. 1998; Keady & Murphy 1998; Kolver et al. 1998; Miller et al. 1999; Moorby & Theobald 1999; Kebreab et al. 2000; Miller et al. 2000; Moorby et al. 2000; Castillo et al. 2001a, b; Estermann et al. 2001; Miller et al. 2001; Ohtani et al. 2001; Reynolds et al. 2001; Ruiz et al. 2001; Astigarraga et al. 2002; Bargo et al. 2002; Jonker et al. 2002; Pacheco et al. 2003; Rearte et al. 2003; Mulligan et al. 2004; Moorby et al. 2006; Tas et al. 2006; Burke et al. 2008; Woodward et al. 2009; Zanton & Heinrichs 2009; Cheng et al. 2011; Whelan et al. 2011; Whelan et al. 2012; Woodward et al. 2012; Higgs et al. 2013; Cheng et al. 2014; Arndt et al. 2015; Hynes et al. 2016; Sánchez-Chopa et al. 2016; Bertilsson et al. 2017; Moate et al. 2017.
Beef cattle	Betteridge et al. 1986; Rouzbehan et al. 1996; Fiems et al. 1997; Terada et al., 1998; Archibeque et al., 2001; Estermann et al., 2001; Archibeque et al., 2002; Estermann et al. 2002; Browne et al. 2005; Wickersham et al. 2008a; Wickersham et al. 2008b; Taylor-Edwards et al. 2009; Waggoner et al. 2009; Drewnoski & Poore 2012; Wei et al. 2016; Shreck et al. 2017.
Sheep	Rattray & Joyce 1969; Maloy & Kay 1971; Joyce et al. 1972; Offer et al. 1978; Nolan & Stachiw 1979; Ulyatt et al. 1984; Barry et al. 1986; McCutcheon et al. 1987; Thomson 1987; Bremmers et al. 1988; Dellow et al. 1988; Domingue et al. 1991; Sun et al. 1994; Masuko et al. 1997; van der Walt et al. 1999; Simpson 2000; Yu et al. 2001; Hoskin et al. 2002; Min et al. 2002; Pinares-Patiño et al. 2003a; Pinares-Patiño et al. 2003b; Bermingham 2004; Mouro et al. 2007; Vranić et al. 2007; Vranić et al. 2009; Dias 2010; Cheng et al. 2013; Sun et al. 2013; Recavarren & Milano 2014; Jonker et al. 2015; Luo et al. 2015; Sun et al. 2016; Van Emon et al. 2017; Zhao et al. 2017.
Deer	Maloy & Kay 1971; Domingue et al. 1991; Freudenberger et al. 1994; Kim et al. 1996; Masuko et al. 1997; Puttoo & Dryden 1998; Jeon et al. 2003.

forages represented a majority of the ration offered. Initially, it was intended to only have studies in which fresh grasses were offered as the experimental diet. However, the number of observations in the database was too small for some of the ruminant classes under study. Therefore, the definition of forage was expanded to include conserved forages (hay and silage) and their derivatives (e.g., dry grass pellets). Data from studies in which forages other than grasses, such as legumes, herbs and forage crops, were also included.

Models evaluated

Generic linear models for multiple livestock classes

Data from all four ruminant classes (dairy cattle, beef cattle, sheep, and deer) were used to assess the current equation used in OverseerFM (OVERSEER 2018)

(Model 1), along with two other generic (i.e., for multiple ruminant classes) models reported in previous reviews of the literature: Ledgard et al. (2003) (Model 2) and Luo and Kelliher (2010) (Model 3).

$$UN\%exN = (11.9 \times Ndiet) + 29.9 \quad \text{(Model 1)}$$

$$UN\%exN = (11.0 \times Ndiet) + 31.8 \quad \text{(Model 2)}$$

$$UN\%exN = (10.5 \times Ndiet) + 34.4 \quad \text{(Model 3)}$$

where UN%exN is urinary N as a percentage of total N excreted and Ndiet is the N concentration in the feed dry matter (g N/100 g DM).

Linear models for specific livestock classes or physiological stage

Model 2 provided the best predictions (as described in the Results section) and was compared with previously published models developed to predict UN%exN for specific livestock classes or physiological stage (i.e., lactating vs non-lactating). A model for predicting excretion from lactating dairy cattle (Model 4; Ledgard et al. 2003) and a model built specifically for non-lactating cattle and sheep (Model 5; Ledgard et al. 2003) were used for this comparison.

$$UN\%exN = (10.1 \times Ndiet) + 34.2 \quad \text{(Model 4)}$$

$$UN\%exN = (11.9 \times Ndiet) + 29.9 \quad \text{(Model 5)}$$

Can a non-linear model improve UN%exN predictions?

Data from all four ruminant classes were used to assess the adequacy of a fitted generic polynomial model (Model 6), along with the assessment of livestock-specific polynomial models [dairy (Model 7; n = 184), beef (Model 8; n = 70) and sheep (Model 9; n = 143)].

$$UN\%exN = (-0.533 \times Ndiet^3) + (3.3394 \times Ndiet^2) + (6.0964 \times Ndiet) + 28.973 \quad \text{(Model 6)}$$

$$UN\%exN = (-3.6096 \times Ndiet^3) + (30.096 \times Ndiet^2) + (-68.963 \times Ndiet) + 94.172 \quad \text{(Model 7)}$$

$$UN\%exN = (-1.9565 \times Ndiet^3) + (13.347 \times Ndiet^2) + (-13.876 \times Ndiet) + 41.28 \quad \text{(Model 8)}$$

$$UN\%exN = (0.4603 \times Ndiet^3) + (-5.589 \times Ndiet^2) + (30.465 \times Ndiet) + 12.509 \quad \text{(Model 9)}$$

Model evaluation

The predictive ability of the different equations was evaluated using several model performance parameters derived from the comparison of observed (O) and predicted (P) values. The association between O and P values was measured by the coefficient of determination (r^2), an indication of how much of the variability in the observed values is accounted for by the models. A concordance correlation coefficient (CCC) (Lin 1989) was also calculated to assess the agreement between the O and P values (i.e., a measure of deviation from a 1:1 agreement; observed = predicted). Values of R^2 and CCC closer to one suggest a better prediction.

Prediction error was assessed via the root-mean-squared prediction error (RMSPE), which represents the mean difference between O and P values. To allow for comparisons of models, RMSPE is often expressed as a percentage of the observed mean (relative prediction error; RPE). RPE values <10% indicate that the model predictions are robust, RPE values between 10-20% suggest a reasonable prediction, and RPE values >20% are indicative of poor prediction (Vetharaniam et al. 2018). A ratio of RMSPE to standard deviation of observed values (RSR) was also calculated to assess the error associated with the model predictions relative to the inherent variation in observed values. With this statistic, RSR values closer to zero are considered better than those closer to one; RSR values <0.5 and <0.75 are indicative of a very good and good predictive ability of the model, respectively, whereas RSR values >1 suggest that the model predictions have greater variation than the variation in the observed data (Moriasi et al. 2007).

The RMSPE was also partitioned to assess systematic biases (i.e., errors in central tendency, errors due to regression and random errors) in the prediction error (Bibby and Toutenburg 1977). A robust model should have small biases, with most of the error in prediction being random. Finally, a modelling efficiency (MEF) parameter was added to the suit of modelling performance parameters. This parameter can be used as a good indicator of goodness-of-fit as it reflects the proportion of variation explained by the line $Y = f(Xi)$. The upper and lower limits to MEF are 1 and (potentially) negative infinity; a MEF value < 0 indicates that the model-predicted values are worse than the observed mean. All the above model evaluations were conducted using the Model Evaluation System v. 3.2.2 (Texas A&M University; available at https://nutritionmodels.com/mes.html).

Results

Generic linear models for multiple ruminant classes

All three linear models showed very similar model performance parameters derived from the comparison of Observed and Predicted values (Table 2). Coefficient of determination (r^2; a measure of precision), CCC (a measure of both precision and accuracy), RPE and RSR values were similar across models. Based on the slightly lesser RMSPE (8.9), RPE (14.7) and RSR (0.74) values, along with a slightly greater RMSPE partitioning towards random error (91.5%), Model 2 (Ledgard et al. 2003) is deemed to provide the best fit relative to observed data.

Table 2 Results of the comparison between observed and predicted values from three models on the percentage of urinary nitrogen (UN) in total N excreted (UN%exN) of all ruminant classes. Details in the text and as a footnote.

Item	Model 1	Model 2	Model 3
Mean observed (O)	58.1	58.1	58.1
Mean predicted (P)	61.1	60.6	61.9
Mean bias (O – P)	-3.0	-2.5	-3.8
No. of observations	430	430	430
r^2	0.50	0.50	0.50
CCC	0.65	0.63	0.60
MSPE	81.7	79.4	88.1
RMSPE	9.0	8.9	9.4
RPE	15.6	15.3	16.2
RSR	0.75	0.74	0.77
RMSPE decomposition (% RMSPE)			
ECT	11.0	8.1	16.6
Slope bias	0.02	0.35	0.91
Random error	89.0	91.5	82.5
MEF	0.44	0.46	0.40

While the linear Model 2 is marginally better than the other two equations tested, a mean bias was observed; Model 2 consistently overpredicts the mean value of UN%exN in the database of observed values (60.6 vs. 58.1 for observed vs. predicted UN%exN, respectively). When comparing O and P values across the range of ruminant classes using the coefficient of determination, Model 2 predictions can only explain 50% of the variability in the observed values (Table 2).

The models evaluated are the current model used in OverseerFM (Model 1), and the models proposed by Ledgard et al. (2003) (Model 2) and Luo and Kelliher (2010) (Model 3). Evaluation includes coefficient of determination (r^2), concordance correlation coefficient (CCC), root-mean-squared prediction error (RMSPE), relative prediction error (RPE), ratio of RMSPE to standard deviation of observed values (RSR), RMSPE decomposition (error in central tendency ECT, slope bias and random error) and modelling efficiency (MEF).

Results of the evaluation of the linear Model 2 for different animal classes is presented in Table 3. The generic equation is less suitable to predict UN%exN for dairy cattle and deer than for beef cattle and sheep, as illustrated by the lower measures of accuracy (e.g., CCC, mean bias) and precision (e.g., r^2) and the lower modelling efficiency (MEF statistic).

The poor predictive performance of Model 2 for deer can be expected due to the original equation not including deer data. The poor model performance for dairy cattle, however, indicates that while N concentration of the diet might be useful to determine UN%exN for ruminant classes that are either growing or have reached mature liveweight (beef cattle and sheep), the amount of feed N secreted in milk reduces the proportion of feed N excreted in urine.

Generic vs ruminant class-specific models

For lactating dairy cattle, both the generic and the equation derived using lactating dairy cattle data only, had poor to moderate measures for accuracy and precision (Table 4). Equations for non-lactating cattle and sheep provided greater accuracy and precision than those used to predict UN%exN from lactating dairy cattle (Table 4). This suggests that using dietary N concentration as the sole predictor of UN%exN is not appropriate for a lactating animal.

Evaluation of non-linear models

Data from all four ruminant classes were used to assess the adequacy of the polynomial function Model 6 (generic) and models 7 to 9 (animal class specific; dairy, beef and sheep, respectively) (Table 5). Reduced mean bias, RMSPE, RPE and RSR values, along with increased CCC and MEF values, are a reflection of model improvement for dairy cattle.

Discussion

Evaluating the robustness of linear generic models

The evaluation of model adequacy (or model robustness) is a key step in the assessment of models

Table 3 Results of the comparison between observed and predicted values from Model 2 on the percentage of urinary nitrogen (N) in total N excreted (UN%exN) for different ruminant classes. See footnote on Table 2 for abbreviations.

Item	Dairy cattle	Beef cattle	Sheep	Deer
Mean observed (O)	57.1	54.1	61.5	51.2
Mean predicted (P)	62.2	55.8	61.2	57.4
Mean bias (O – P)	-5.1	-1.7	-0.3	-6.2
No. of observations	184	70	143	33
r^2	0.38	0.66	0.57	0.52
CCC	0.47	0.75	0.73	0.52
MSPE	86.5	51.8	65.1	168.3
RMSPE	9.3	7.2	8.1	13.0
RPE	14.9	12.9	13.2	22.6
RSR	0.92	0.87	0.80	0.95
RMSPE decomposition (% RMSPE)				
ECT	29.9	5.4	0.13	23.2
Slope bias	0.01	5.4	0.11	36.4
Random error	70.1	89.1	99.8	40.4
MEF	0.12	0.63	0.58	0.33

Table 4 Results of the comparison between observed and predicted values from two models that predict the percentage of urinary nitrogen (N) in total N excreted (UN%exN) by lactating dairy cows (Model 2 vs Model 4) and non-lactating cattle and sheep (Model 2 vs Model 5). See footnote on Table 2 for abbreviations.

	Dairy cattle		Non-lactating cattle and sheep	
Item	Model 2	Model 4	Model 2	Model 5
Mean observed (O)	56.8	56.8	58.6	58.6
Mean predicted (P)	62.8	62.7	59.2	59.5
Mean bias (O – P)	-6.0	-5.9	-0.62	-0.96
No. of observations	165		256	
r^2	0.48	0.48	0.57	0.57
CCC	0.48	0.46	0.70	0.72
MSPE	90.0	89.5	73.9	73.5
RMSPE	9.5	9.5	8.6	8.6
RPE	15.1	15.1	14.5	14.4
RSR	0.95	0.95	0.67	0.67
RMSPE decomposition (% RMSPE)				
ECT	40.1	38.5	0.51	1.2
Slope bias	1.1	2.4	1.3	0.1
Random error	58.8	59.1	98.1	98.7
MEF	0.11	0.12	0.56	0.57

Table 5 Results of the comparison between observed and predicted values from a generic polynomial model (Model 6), and livestock class-specific polynomial models (Model 7 for dairy, Model 8 for beef, Model 9 for sheep) on the percentage of urinary nitrogen (N) in total N excreted (UN%exN). See footnote on Table 2 for abbreviations.

Item	Model 6 All classes	Model 7 Dairy cattle	Model 8 Beef cattle	Model 9 Sheep
Mean observed (O)	57.7	57.2	54.4	61.5
Mean predicted (P)	57.6	57.2	53.9	61.5
Mean bias (O – P)	0.11	0.001	0.49	-0.008
No. of observations	430	184	70	143
r^2	0.48	0.41	0.59	0.60
CCC	0.66	0.58	0.76	0.75
MSPE	76.2	58.4	58.9	61.9
RMSPE	8.7	7.6	7.7	7.9
RPE	15.1	13.4	14.1	12.8
RSR	0.72	0.77	0.63	0.63
RMSPE decomposition (% RMSPE)				
ECT	0.02	0.00	0.41	0.00
Slope bias	0.17	0.00	0.68	0.00
Random error	99.82	100.00	98.9	100.00
MEF	0.48	0.41	0.59	0.60

because it indicates both the level of precision and accuracy of the model predictions. The three linear, generic models evaluated were similar in their predictive performance. Model 2 was slightly more accurate (i.e., slightly lower RMSPE, RPE and RSR values) and provided a better overall goodness of fit (i.e., slightly higher MEF value), but the negative mean bias (mean observed minus mean predicted) meant that Model 2 consistently overpredicted the mean value of UN%exN (58.1 vs 60.6%, O vs P respectively; Table 2). This bias (about 4% of the mean observed value, with an error of prediction scaled as a proportion of the mean equivalent to 15% of the mean value), along with Model 2 predictions explaining only 50% of the variability in the observed values (r^2 = 0.50) shows that the model precision is moderate at best. Although Model 2 provided a reasonable estimate of the mean UN%exN, the model tends to overestimate UN%exN in cases of low Ndiet and underestimate UN%exN in cases of high Ndiet (i.e. slope bias).

Applying a generic linear model to specific animal classes

Model 2 performed differently when applied to specific animal classes (Table 3). The model performed better (i.e., lower mean bias, RMSPE, and RPE, and higher MEF values) for beef cattle and sheep, compared with dairy cattle and deer. Consistent with our findings, Pacheco et al. (2018) reported that the equation developed by Luo and Kelliher (2010) (Model 3 in Table 2) provided adequate predictions of UN%exN for beef cattle and sheep, but the model was inadequate (reduced precision and accuracy) for dairy cattle and deer using a similar dataset to that used here.

The different model performances across animal classes could be attributable, at least partly, to dairy cattle having a distinct pattern in dietary N concentration (Figure 2; top) and a larger sink of N as animal product (proportionally more of the N intake is directed to milk) compared with beef cattle and sheep. Along with these characteristics, the patterns of predicted and observed UN%exN for dairy cattle are very different. Because dietary N concentration is the only predictor in the model, the predicted N concentrations will follow the same distribution as the observed N concentrations. However, the resulting distribution of predicted UN%exN for dairy cattle is different to the distribution of observed UN%exN values, which partly explains the poorer model performance for lactating dairy cattle. In addition to having dietary N intake directed to milk production, the difference between lactating cattle and growing cattle is most likely a reflection of differences in both maintenance requirements (ME and N) and the dynamics of N metabolism in the rumen, as suggested by Reynolds and Kristensen (2008).

The relevance of Ndiet in predicting UN%exN is

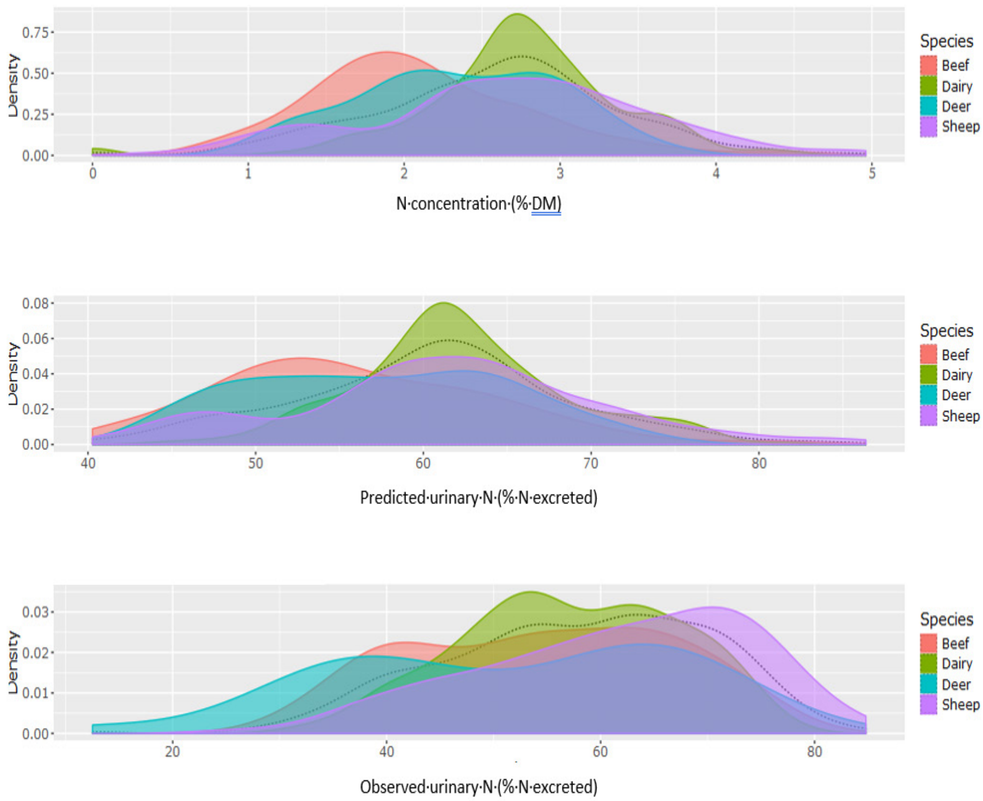

Figure 2 Density curves of dietary N concentration (top), predicted percentage of urinary nitrogen (UN) in total N excreted (UN%exN) (centre) and observed UN%exN (bottom) of all ruminant classes. The frequency density curves allow for a comparison of different ruminant classes; the total area under the individual curves is equal to 1.

undeniable. But we could be asking too much from a sole predictor. Predictions of UN%exN that included Ndiet, a measure of ME intake and the ratio of N-to-ME in the diet (N:MEdiet) (dairy cattle), Ndiet and DM intake (beef cattle), Ndiet alone (sheep) and Ndiet and N:MEdiet (deer) improved the linear predictions of UN%exN by reducing mean biases and increasing precision of the predictions (Pacheco et al. 2018).

The distributions in feed N concentration for dairy and beef cattle observations suggest a statistical normal distribution, but N concentrations are higher for dairy cattle. Feed data from sheep and deer studies show an almost bimodal pattern with two distinct quality of diets (Figure 2; top). The distributions of observed UN%exN do not follow a normal distribution, which is possibly the result of having many different mobs of animals within classes (adults, growing, lactating, pregnant) for which a given N concentration is likely to lead to different partitioning of N in excreta.

The varying distribution in feed N concentration and O vs P patterns of UN%exN in lactating dairy cows might have contributed both to the relatively poor model performance of dairy cattle when Model 2 was used for specific animal classes (MEF = 0.12 in Table 3) and the lack of response when the generic Model 2 was compared with a model built specifically for lactating dairy cattle (Model 4 in Table 4).

Evaluating non-linear models

The same database was used to explore the model adequacy of non-linear equations. Using cattle data, the non-linear relationship between the dietary N concentration and the proportion of total urea produced by the ruminant that is excreted in urine (Reynolds and Kristensen 2008) led us to believe that models other than linear (but still with Ndiet as the sole predictor) could offer improved predictive solutions, especially for dairy cattle. The smooth 'S' shape from the relationship between dietary N [from crude protein CP = N concentration × 6.25, expressed as a percentage] and the proportion of total urea production by cattle that ended up in urine was represented by an order 3 polynomial function [fraction of urea in urine = $-0.0004 \times CPdiet^3 + 0.016 \times CPdiet^2 - 0.1326 \times CPdiet + 0.3268$] (Reynolds and Kristensen 2008). As dietary N concentration increases, the proportion of urea production that ends up in urine increases, leading to the increasing part of the S curve, and at high N concentrations, the excess of urea reaches saturation and the proportion of urinary N, driven by the amount of urea excreted, tends to flatten (Reynolds and Kristensen 2008). These patterns are particularly relevant to lactating dairy cattle, as they are often fed diets high in CP in response to lactation requirements, and a large proportion of N intake is secreted in milk as an additional sink of N compared with beef cattle, sheep and deer. Capturing this in Model 7 (dairy cattle) resulted in improvements in model predictive ability. But using an order 3 polynomial function approach for beef cattle and sheep only resulted in minimal improvements (lower mean biases and RSR values in Model 8 and Model 9) compared with the linear approach (Model 2) applied to these livestock classes.

While the improvement in the predictive ability of the nonlinear models can be attributed to a better representation of the underlying biological principles, we acknowledge that the non-linear model improvements reported here could be due to the fact that the same data was used to construct and evaluate the model. A way to deal with this issue would be to use more sophisticated modelling approaches that involve partitioning of data for model development and evaluation (e.g., Pacheco et al. 2018), taking advantage of the larger dataset assembled.

Conclusions

This study provides support for the predictive robustness of N partitioning towards urinary N in the animal sub-model of OverseerFM for a range of pasture-based diets for beef cattle and sheep, but not so for dairy cattle and deer. We have demonstrated that the use of a non-linear approach can result in a better predictive model for dairy cattle, if a sole predictor variable such as N concentration of the diet (expressed as a percentage of dry matter offered) continues to be used in Overseer. Also, the use of more sophisticated modelling approaches that involve distinct data for model development and model evaluation may be required.

ACKNOWLEDGEMENTS

The authors thank Alexander Hunt-Painter (Overseer Limited) for the valuable discussions on the modelling aspects of the work, and Alec Mackay (AgResearch) for a comprehensive review of a prior version of the manuscript.

REFERENCES

Bibby J, Toutenburg H. 1977. *Prediction and improved estimation in linear models*. John Wiley & Sons, London, UK.

Broderick GA. 2003. Effects of varying dietary protein and energy levels on the production of lactating dairy cows. *Journal of Dairy Science 86*: 1370-1381. https://doi.org/10.3168/jds.s0022-0302(03)73721-7

Castillo AR, Kebreab E, Beever DE, France J. 2000. A review of efficiency of nitrogen utilisation in lactating dairy cows and its relationship with environmental pollution. *Journal of Animal and Feed Sciences 9*: 1-32. https://doi.org/10.22358/jafs/68025/2000

de Klein CAM, Shepherd MA, van der Weerden TJ. 2014. Nitrous oxide emissions from grazed grasslands: interactions between the N cycle and climate change — a New Zealand case study. *Current Opinion in Environmental Sustainability* 9-10: 131-139. https://doi.org/10.1016/j.cosust.2014.09.016

Kyamanywa N, Tait IM, Mitchell CM, Hedley MJ, Pacheco D, Bishop P. 2021. Effect of a late summer diet change from pasture to brassica crop and silages on dairy cow milk production and urinary nitrogen excretion. *New Zealand Journal of Agricultural Research* 64: 36-55. https://doi.org/10.1080/00288233.2020.1713176

Ledgard SF, Luo J, Monaghan R. 2003. Partitioning of excreta nitrogen from grazing animals into urine and dung nitrogen. Report prepared for MAF (currently MPI), Wellington, New Zealand. 16 pages.

Lin LIK. 1989. A concordance correlation coefficient to evaluate reproducibility. *Biometrics 45*: 255-268. https://doi.org/10.2307/2532051

Luo J, Kelliher F. 2010. Partitioning of animal excreta N into urine and dung and developing the N_2O inventory (MAF POL 0910-11528, 09-03). AgResearch Report to MAF. 24 pages.

Moriasi DN, Arnold JG, Van Liew MW, Bingner RL, Harmel RD, Veith TL. 2007. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. *Transactions of the ASABE 50*: 885-900. http://dx.doi.org/10.13031/2013.23153

OVERSEER. 2018. Animal model. OVERSEER® Technical Manual for the description of the OVERSEER® Nutrient Budgets engine ISSN: 2253-461X. Prepared by D. M. Wheeler, AgResearch Ltd.

Pacheco D, Waghorn GC, Rollo M. 2018. Methodology for splitting nitrogen between livestock dung and urine. MPI Technical Paper No: 2018/72. Prepared for the Ministry for Primary Industries, Wellington, New Zealand. Available at: http://www.mpi.govt.nz/news-and-resources/publications/

Reynolds CK, Kristensen NB. 2008. Nitrogen recycling through the gut and the nitrogen economy of ruminants: An asynchronous symbiosis. *Journal of Animal Science 86*: E293-305. https://doi.org/10.2527/jas.2007-0475

Selbie DR, Buckthought LE, Shepherd MA. 2015. The challenge of the urine patch for managing nitrogen in grazed pasture systems. *Advances in Agronomy 129*: 229-292. http://dx.doi.org/10.1016/bs.agron.2014.09.004

Vetharaniam I, Vibart RE, Pacheco D. 2018. Evaluation of a sheep rumen model with fresh forages of diverse chemical composition. *Journal of Animal Science 96*: 5287-5299. https://doi.org/10.1093/jas/sky354

Vibart RE, Barrett BA, Pacheco D. 2009. Prediction of nitrogen utilization efficiency from plant constituents in lactating cows fed pasture-based diets. *Journal of Dairy Science 92*: 2.

Woods RR, Cameron KC, Edwards GR, Di HJ, Clough TJ. 2018. Reducing nitrogen leaching losses in grazed dairy systems using an Italian ryegrass-plantain-white clover forage mix. *Grass and Forage Science 73*: 878-887. https://doi.org/10.1111/gfs.12386