Predicting manure volatile solid output of lactating dairy cows

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ABSTRACT

Organic matter (OM) in livestock manure consisting of biodegradable and nonbiodegradable fractions is known as volatile solids (VS). According to the Intergovernmental Panel on Climate Change (IPCC) Tier 2 guidelines, methane produced by stored manure is determined based on VS. However, only biodegradable OM generates methane production. Therefore, estimates of biodegradable VS (dVS; $dVS = VS - \text{lignin}$) would yield better estimates of methane emissions from manure. The objective of the study was to develop mathematical models for estimating VS and dVS outputs of lactating dairy cows. Dry matter intake, dietary nutrient contents, milk yield and composition, body weight, and days in milk were used as potential predictor variables. Multicollinearity, model simplicity, and random study effects were taken into account during model development that used 857 VS and dVS measurements made on individual cows (kg/cow per day) from 43 metabolic trials conducted at the USDA Energy and Metabolism laboratory in Beltsville, Maryland. The new models and the IPCC Tier 2 model were evaluated with an independent data set including 209 VS and dVS measurements (kg/cow per day) from 2 metabolic trials conducted at the University of California, Davis. Organic matter intake (kg/d) and dietary crude protein and neutral detergent fiber contents (% of dry matter) were significantly associated with VS. A new model including these variables fitted best to data. When evaluated with independent data, the new model had a root mean squared prediction error as a percentage of average observed value (RMSPE) of 12.5%. Mean and slope biases were negligible at <1% of total prediction bias. When energy digestibility of the diet was assumed to be 67%, the IPCC Tier 2 model had a RMSPE of 13.7% and a notable mean bias for VS to be

overpredicted by 0.4 kg/cow per day. A separate model including OM intake as well as dietary crude protein and neutral detergent fiber contents as predictor variables fitted best to dVS data and performed well on independent data (RMSPE = 12.7%). The Cornell Net Carbohydrate and Protein System model relying on fat-corrected milk yield and body weight more successfully predicted dry matter intake (DMI; RMSPE = 14.1%) than the simplified (RMSPE = 16.9%) and comprehensive (RMSPE = 23.4%) models to predict DMI in IPCC Tier 2 methodology. New models and the IPCC Tier 2 model using DMI from the Cornell Net Carbohydrate and Protein System model predicted VS (RMSPE = 17.7–19.4%) and dVS (RMSPE = 20%) well with small systematic bias (<10% of total bias). The present study offers empirical models that can accurately predict VS and dVS of dairy cows using routinely available data in dairy farms and thereby assist in efficiently determining methane emissions from stored manure.

Key words: dairy cow, manure, prediction model, volatile solid

INTRODUCTION

Despite a growing number of policies to reduce climate change, global emissions of greenhouse gases (GHG) have increased to unprecedented levels. Livestock manure management systems (MMS) are significant sources of GHG, particularly in regions where industrialized livestock farming takes place (Masse et al., 2008). For instance, MMS in the Americas and Europe account for 15 to 25% of total agriculture GHG emissions compared with 7 to 11% in Africa and Asia (Tubiello et al., 2013). Methane (CH₄) is the main GHG emitted, particularly from liquid-based MMS, common in North America. In the United States, on average 43% of total dairy cattle CH₄ emissions comes from MMS (Owen and Silver, 2015). Jayasundara et al. (2016) indicated the possibility of mitigating MMS emissions in Canadian dairy farms by up to 50%. Therefore, CH₄ from MMS is a primary target of programs and policies aiming at mitigating GHG emissions from agriculture.

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Quantifying CH₄ emissions from MMS is important in establishing national inventories and assessing the effect of mitigation programs (e.g., anaerobic digestors). Because measurement of CH₄ emissions is expensive and labor intensive, mathematical models can be used successfully to predict the emissions.

The Intergovernmental Panel on Climate Change (IPCC) Tier 2 methodology is widely used to estimate CH₄ emission factors (kg of CH₄/animal per year) of given MMS and relies primarily on OM or volatile solid (VS) output (kg/cow per day) and the maximum CH₄ producing potential of the manure (**B**₀; kg of CH₄/kg of VS). In IPCC Tier 2 methodology, VS is determined with a model requiring information such as gross energy (GE) intake (MJ/d) and dietary energy digestibility (DE; %), which are not routinely available at commercial farms. Therefore, default constants or population averages are generally used for those factors. The use of constant values can have considerable effect on the accuracy of VS estimates because factors, such as DE, are highly variable across diets (e.g., 49–81% in Hanigan et al., 2013). Alternatively, models including variables routinely measured on farms and that have significant relationships with OM digestibility or DE could be able to predict VS more efficiently and accurately. Nutrient composition of diets is routinely available in the majority of commercial dairy farms in the United States and has previously been shown to affect OM digestibility (Broderick et al., 2001; Colmenero and Broderick, 2006). Biodegradable VS (**dVS**; $dVS = VS - \text{fecal lignin output}$) undergoing anaerobic digestion produce CH₄ during manure storage (Petersen et al., 2016). Lignin is fully resistant to anaerobic digestion and increases the resistance of cellulose in lignocellulosic materials. Lignin content of VS could be as high as 14% and vary significantly [e.g., coefficient of variation (**CV**) >30%] across different diets (Hindrichsen et al., 2006). Therefore, CH₄ emissions from MMS determined with dVS would be more representative than those based on VS.

Dry matter intake is the most important information required by models predicting fresh manure nutrient output of dairy cows (Appuhamy et al., 2014), including the IPCC Tier 2 model. However, accurate measurements of feed intake of individual cows are challenging to obtain in most commercial farms (Vallimont et al., 2010). The IPCC Tier 2 methodology includes a separate set of models to predict DMI if actual feed intake measurements are not available. Other extant models for predicting DMI of lactating dairy cows are available. Appuhamy et al. (2016) evaluated several of those models, including the Cornell Net Carbohydrate and Protein System (**CNCPS**) model (Fox et al., 1992) and National Research Council model (NRC,

2001), using measured DMI of cows in North America and Europe. These models include variables such as dietary nutrient composition, milk yield and composition, week of lactation, and BW. Information on these variables is usually available in commercial farms or can be estimated with narrow uncertainty. The CNCPS model including fat-corrected milk and BW as predictor variables performed best and had small prediction error, which was only 8% of the average DMI of cows in the United States and Canada. Consequently, Appuhamy et al. (2016) demonstrated the possibility of accurately determining enteric CH₄ from North American cows using DMI estimated with the CNCPS model. The objectives of the present study were to (1) develop models to predict VS and dVS of lactating dairy cows using data routinely available in dairy farms and (2) evaluate the performance of these new models and the IPCC Tier 2 model using measured or estimated DMI by challenging them on an independent data set.

MATERIALS AND METHODS

Data for Model Development

A total of 857 measured fecal OM (**FOM**; kg/d) and urinary carbon (**UC**; kg/d) outputs of individual cows, as well as related DMI and dietary nutrient composition, milk yield and milk composition, DIM, BW, and age, were obtained from 43 energy balance trials conducted at the former Energy Metabolism Unit (**EMU**) at USDA Beltsville from 1962 to 1995. In each energy balance trial, feces and urine outputs of individual cows were measured daily over 5 to 7 d using a total collection method while animals were housed in respiration chambers for measurements of CH₄ and carbon dioxide production and oxygen consumption. Cows were catheterized to measure total urine volume in all trials (Wilkerson et al., 1997). Nutrient concentrations in diets, feces, and urine were measured with daily-collected samples composited over the trial period. Therefore, feed intake, milk yield, and manure output measurements were averaged over each trial period to be in line with the nutrient concentrations. All the trials used a total of 254 lactating Holstein cows, 226 of which were used in multiple trials and thus provided multiple manure output and other related measurements.

The forage content of the experimental diets varied from 0 to 100% with a mean of 53% of DM. Eighty percent of the diets included alfalfa hay or alfalfa silage. Almost half of those diets also included corn silage. Ground corn, soybean meal, and ground barley and oats were included in 71, 61, and 32% of the diets, respectively. Dried feed and fecal samples were analyzed

for ether extract, NDF, ADF, and permanganate lignin using the procedure described by Goering and Van Soest (1970). Feed, fecal, and urinary N and C were determined respectively using the Kjeldahl procedure and by combustion in an atmosphere of oxygen with volumetric determination of CO₂ produced (Smith et al., 1965). Urine OM output (UOM; kg/d) was calculated based on the measured UC output. Based on the calculations by Appuhamy et al. (2014) suggesting that nitrogenous compounds contributed to about 70% of total UC, it was assumed that 75 and 25% of UOM comprises nitrogenous and nonnitrogenous (e.g., sugars and fatty acid derivatives) compounds, respectively. The average molecular weight to C atom weight (MW:C) ratio of nonnitrogenous compounds was assumed to be 2.5. Based on Dijkstra et al. (2013), the average MW:C ratio of nitrogenous compounds in urine was calculated to be 4.4. This led to the average MW:C ratio of UOM to be approximately 4.0 ($2.5 \times 0.25 + 4.4 \times 0.75 = 3.93$). Therefore, 4 times the measured UC was taken as UOM (UOM = $4 \times$ UC), which was then added to measured FOM to determine VS (VS = FOM + UOM). A summary of measured and calculated variables is given in Table 1.

Data for Model Evaluation

A total of 209 feces and urine output measurements (kg/cow per day) recently made on lactating dairy cows were obtained from 2 independent experiments conducted at the University of California, Davis. In one experiment, 12 Holstein cows were randomly assigned to 2 dietary forage contents (37 or 53% of DM) and 2 dietary CP concentrations (16.2 or 19.7% of DM) over 4 periods, each providing repeated measures of fresh manure outputs (Niu et al., 2016). In the other experiment, 12 Holstein cows were assigned to 2 levels of a fibrolytic enzyme (plus control) over 3 periods, where repeated measures of feces and urine outputs were obtained (Tewoldebrhan et al., 2017). The measurements related to the enzyme dose that significantly changed OM digestibility were excluded from the data set. In both experiments at the University of California, Davis, urine and feces outputs (kg/d) were measured using a total collection method similar to that used in the energy metabolism trials of the EMU providing data for model development. Cows were housed in metabolic stalls in both experiments at the University of California, Davis, so the microenvironment of cows could

Table 1. Summary of data

Variable ¹	Data used for developing models (n = 857)				Independent data (n = 209)			
	Mean	SD	Minimum	Maximum	Mean	SD	Minimum	Maximum
Intake (kg/d)								
DM	16.4	4.2	7.1	28.7	21.2	3.4	14.7	32
OM	15.4	3.9	6.6	26.7	19.8	3.3	13.7	30
Gross energy intake (MJ/d)	312	84	126	558	397	69	271	608
Diet composition (% of DM)								
OM	93.7	1.1	90.6	96.5	83.4	0.5	92.3	94.2
CP	16.6	2.2	10.5	21.9	16.5	0.9	14.4	18.4
NDF	32.8	7.1	16.1	57.2	35.5	3.5	28	42.7
ADF	19.3	4.1	9.5	31	26.1	3.6	19.9	33.7
Lignin	4.5	1.3	1.8	8.4	5.7	1.1	4.2	7.6
Ether extract	2.6	0.8	0.6	4.9	3.8	0.1	3.6	4.1
Milk yield (kg/d)	23.6	10	5.2	49.1	32.4	6	16.8	46.4
Milk protein (%)	3.2	0.4	2.3	5.3	3.1	0.3	1.6	3.8
Milk fat (%)	3.5	0.7	1.2	7.5	3.7	0.8	1.8	8.9
DIM	163	83	11	488	188	41	107	269
BW (kg)	611	70	452	854	670	82	523	807
Fecal OM (kg/d)	4.8	1.53	1.12	9.6	6.3	1.6	3.2	10.8
Fecal lignin (kg/d)	0.6	0.24	0.05	1.46	0.88	0.18	0.46	1.47
Fecal ash content (% of DM)	9.52	1.77	4.85	17.8	8.91	0.97	6.73	11.7
Total urine (kg/d)	17.8	7.6	4.38	58.9	23.8	6.4	9.5	54.7
Urinary C output (kg/d)	0.23	0.07	0.02	0.5	ND ²	ND	ND	ND
Urinary OM output (kg/d)	0.93	0.29	0.08	2	1.31	0.37	0.54	3.12
Urinary energy (% of GE)	3.4	0.7	1.3	8.1	ND	ND	ND	ND
Fresh manure output (kg/d)								
VS	5.73	1.79	1.67	10.86	7.61	1.6	3.92	12.09
dVS	5.13	1.54	1.54	10.43	6.73	1.43	3.47	10.66
Digestibility (%)								
Energy	66.9	4.4	49.9	85	ND	ND	ND	ND
OM	69.2	4.4	53.9	86.7	68.62	4.71	55.68	80.92

¹VS = total volatile solids; dVS = biodegradable volatile solids (dVS = VS – fecal lignin output).

²ND = not determined.

be closer to that of cows in commercial dairy farms compared with that of cows in respiratory chambers at EMU. Moreover, the University of California, Davis, experiments provided daily measurements of VS and dVS of individual cows in each metabolic trial period, whereas the EMU database included average measurements of each cow over each period. Nonetheless, UOM and UC were not measured in both experiments at the University of California, Davis, so UOM was calculated assuming a constant UOM concentration of 0.055 kg/kg, which was the average concentration of cows in the EMU trials (Table 1). The UOM concentration was highly variable across cows in those 43 metabolic trials at EMU, with a CV of 28% (data not shown). This was likely attributable to highly variable N intake (CV = 32%; data not shown) predominantly determining the quantity of urea in urine and thus OM concentration in it. Variability of nitrogen intake in the experiments at the University of California, Davis, was much lower (CV = 18%; data not shown). Variability of nitrogen intake could even be lower among commercial herds. For instance, Jonker et al. (2002) reported a CV of 14% for nitrogen intake of lactating dairy cows across 372 commercial dairy farms. Also given the fact that UOM represents a small proportion of VS or dVS (<20%; Table 1), assuming a constant OM concentration in calculating UOM would not have a substantial effect on the model evaluation.

Model Development

Two linear models were constructed to separately predict VS and dVS. Selection of variables to develop the models began with a primary pool including DMI, OM intake (**OMI**), dietary CP, NDF, ADF, lignin, ether extract and total ash contents (% of DM), milk yield (kg/d), milk protein and fat percentages, BW (kg/cow), DIM, and the year that each experiment was conducted at EMU. Correlated variables ($|r| \geq 0.5$) were not regressed together to minimize multicollinearity issues such as inaccurate model parameters, decreased statistical power, and risk for excluding variables having significant effects during model construction (Graham, 2003). For instance, milk yield and DMI ($r = 0.76$), dietary ADF and NDF contents ($r = 0.83$), dietary ADF and lignin contents ($r = 0.64$), and milk yield and DIM ($r = -0.70$) were not regressed together (Table 2). Therefore, several secondary pools including uncorrelated candidate variables had to be formed. All possible combinations of variables in each secondary pool were regressed separately against VS or dVS. For example, one of the pools had 8 variables ($P = 8$), which led to 256 potential regression models ($2^P = 2^8$

= 256). Each regression was carried out accounting for random animal and study effects as shown in the following linear mixed-effects model:

$$Y_{ijk} = \beta_0 + \beta_1 X_{1ijk} + \dots + \beta_p X_{pijk} + \alpha_i + \gamma_j + \varepsilon_{ijk},$$

where Y_{ijk} = the k th measurement of the response of the i th cow in the j th study; β_0 = intercept; X_{1ijk} to X_{pijk} = the k th measurement of the explanatory variables (total number of the explanatory variables = p) pertaining to the i th cow in the j th study; β_1 to β_p = fixed effects (regression coefficients) of the explanatory variables; α_i = the random effect associated with the i th cow ($i = 1, \dots, 254$); γ_j = random effect associated with the j th study ($j = 1, \dots, 43$); and ε_{ijk} = random error. Interactions and polynomial effects of the explanatory variables were not included in the models to preserve model simplicity and avoid an effect of multicollinearity on model parameters (Shacham and Brauner, 1997). All the mixed models in each pool were first fitted to data using the lme4 package in R (version 2.12.2; R Foundation for Statistical Computing, Vienna, Austria) and then ranked by descending Bayesian information criterion (**BIC**; Schwarz, 1978) values. The absolute BIC value of a model has no interpretation but can be compared with the values of other models. Lower BIC values imply proper balance between model complexity and model fit (Myung, 2000). Models associated with the least BIC values were chosen as the final models to predict VS and dVS. A comprehensive description of the variable and model selection procedure is available in Appuhamy et al. (2014).

The IPCC Tier 2 Model to Predict VS

The IPCC Tier 2 model represents partitioning of dietary GE to fecal (**FGE**) and urinary (**UGE**) energy outputs (all in MJ/d). The FGE is represented as a function of GE and DE (%):

$$\text{FGE} = \left[\text{GE} \times \left(1 - \frac{\text{DE}}{100} \right) \right]. \quad [1]$$

The UGE is calculated as the product of GE and fraction of GE excreted in urine (**UE**):

$$\text{UGE} = \text{GE} \times \text{UE}. \quad [2]$$

The FGE plus UGE is eventually converted to VS (g/d) by taking into account the fraction of OM in the manure [$1 - \text{fraction of ash in manure (ASM)}$] and GE content of diet, assumed to be constant at 18.45 MJ/kg of DM:

$$VS = (FGE + UGE) \times \left[\frac{(1 - ASM)}{18.45} \right]. \quad [3]$$

The IPCC Tier 2 guidelines for national GHG inventories propose DE to range from 55 to 75% for ruminants fed grain-supplemented forage-based diets and default UE (0.04) and ASM (0.08) values for all livestock classes.

Predicting Feed Intake

The IPCC Tier 2 guidelines provide 2 models—a comprehensive model (**IPCC-CMP**) and a simplified model (**IPCC-SMP**)—to predict DMI or GE of cattle. The IPCC-CMP includes equations to calculate net energy requirements for maintenance, lactation, activity, pregnancy, tissue growth, and wool growth. The efficiencies that digestible energy is utilized for those functions are then applied to determine digestible energy intake (DEI) of the animal. Gross energy intake (e.g., GE in Equation 3) and DMI are subsequently determined with DE [$GE = DEI/(DE/100)$] and dietary gross energy content [$DMI = GE/\text{dietary gross energy content}$]. The IPCC-CMP is fully described in chapter 10 of *IPCC Guidelines for National Greenhouse Gas Inventories* (IPCC, 2006). In the IPCC-SMP, DMI is a function of BW and DE:

$$DMI = \frac{5.4 \times \frac{BW}{500}}{100 - \frac{DE}{100}}. \quad [4]$$

Appuhamy et al. (2016) previously evaluated a simplified form (Arnerdal, 2005) of the CNCPS model developed by Fox et al. (1992) along with 4 other models and

demonstrated that the CNCPS model best predicted DMI of lactating dairy cows in North America. In the present study, DMI and GE were predicted with the IPCC models and the CNCPS model (Equation 5, where FCM = fat-corrected milk yield).

$$DMI = 0.0185 \times BW + 0.305 \times FCM. \quad [5]$$

Model Evaluation

The IPCC Tier 2 model and new models to predict VS outputs as well as the IPCC Tier 2 models (IPCC-CMP and IPCC-SMP) and CNCPS model to predict DMI were evaluated using independent data described above. In applying IPCC-CMP to predict DMI, net energy requirements for tissue growth, activity, and wool growth were assumed to be zero. The IPCC Tier 2 model to predict VS (Equation 3) and new models to predict VS and dVS were evaluated first using measured DMI and then using the predicted DMI. In all cases, the overall agreement between model predictions and the observed values were determined by calculating the square root of mean squared prediction error expressed as a percentage of average observed value (**RMSPE**). Moreover, the mean squared prediction error was decomposed into systematic biases such as mean bias (**MB**) and slope bias (**SB**), and bias due to random causes to have insight into the magnitude of sources of prediction error. Those biases were calculated according to Bibby and Toutenburg (1977). The sources of errors can also be assessed using the observed versus predicted value plots, with unity and scatter regression lines indicating perfect and actual relationships between observed and predicted values, respectively (Figure 1). For example, the scatter regression line running notably away from the unity line indicates the presence of an MB.

Table 2. Correlations among candidate explanatory variables considered for developing models¹

Item	OMI	OM	CP	NDF	ADF	Lignin	EE	Milk yield	FCM	MilkPro	MilkFat	DIM	BW
DMI	0.99	-0.25	0.18	0.21	0.29	0.35	0.45	0.76	0.78	-0.08	0.17	-0.38	0.22
OMI		-0.21	0.16	0.21	0.28	0.35	0.44	0.76	0.77	-0.07	0.17	-0.38	0.23
OM			-0.49	-0.09	-0.32	-0.24	-0.11	-0.27	-0.29	0.12	-0.12	0.14	0.02
CP				-0.35	-0.20	-0.17	0.01	0.34	0.32	-0.06	-0.09	-0.24	0.03
NDF					0.83	0.43	0.22	0.13	0.20	-0.13	0.31	-0.12	-0.11
ADF						0.64	0.30	0.18	0.27	-0.15	0.38	-0.13	-0.09
Lignin							0.32	0.13	0.22	0.02	0.39	-0.04	0.03
EE								0.34	0.39	-0.03	0.20	-0.07	0.11
Milk yield									0.96	-0.48	0.00	-0.70	-0.02
FCM										-0.41	0.26	-0.67	0.01
MilkPro											0.22	0.52	0.27
MilkFat												0.01	0.09
DIM													0.16

¹OMI = OM intake; EE = ether extract; FCM = fat-corrected milk yield; MilkPro = milk protein percentage; MilkFat = milk fat percentage. Organic matter, CP, NDF, ADF, lignin, and EE represent dietary nutrient composition.

Figure 1. Observed versus predicted values of total volatile solid (VS) and biodegradable volatile solid (dVS) outputs of lactating dairy cows for new models and the Intergovernmental Panel on Climate Change (IPCC) Tier 2 model. Solid line = unity line; gray line = scatter regression.

RESULTS AND DISCUSSION

Data

Overall, data used for developing models show a wide range in both predictor (e.g., DMI) and response (e.g., VS) variables, allowing the models to capture well the true relationships between them. Dietary OM intake and composition (e.g., NDF and CP) potentially driving manure OM output (Broderick, 2003; Broderick et al., 2001; Colmenero and Broderick, 2006) were considerably variable with CV >20% (Table 1). The response variables such as VS and dVS output were even more variable with CV >30%. The average FOM output was 4.8 kg/d and related to average DMI and milk yield of 16.4 and 23.6 kg/d, respectively. Corresponding to the average UC output of 0.23 kg/d, the average urine OM output was calculated to be 0.93 kg/d. Overall, FOM and UOM outputs made 84 and 16% of VS, respectively, which was 5.73 kg/d (Table 1). The average urine energy (as % of GE) was 3.4% and close to the default constant of 4.0% used in the IPCC Tier 2 model. The average DE was 67% and within the range of 55 to 75% given in the IPCC Tier 2 guidelines. Data used for model evaluation also contained a wide range of values allowing for good assessment of predictive power of the models (Table 1). The average DMI and milk yield were 21.2 and 32.4 kg/d, respectively, and

similar to the average feed intake and milk production of modern dairy cows (NRC, 2001). The VS and dVS averaged at 7.61 and 6.73 kg/d and varied considerably (CV = 21%). Similar to those in data used for developing models, UOM and dVS contributed 17 and 93% of VS, respectively.

New Models

The new model to predict VS (kg/d) included OMI (kg/d) and dietary NDF and CP contents (% of DM) as predictor variables (Equation 6):

$$\text{VS} = -1.201 \pm 0.232 + 0.402 \pm 0.006 \times \text{OMI} + 0.036 \pm 0.003 \times \text{NDF} - 0.024 \pm 0.010 \times \text{CP}. \quad [6]$$

As expected, OMI was positively related to VS. Independent of OMI, dietary NDF content was positively related to VS, whereas CP content was negatively related to it. When evaluated with data used for model development, the model fitted the data well (RMSPE = 8.1% of the average observed value; data not shown) and had negligible MB and SB (1% of total error; data not shown), indicating a sound parameterization of the relationships of OMI, NDF, and CP with VS. Moreover, the relationships included in the model are consistent with the negative relationship of dietary NDF and posi-

tive relationship of dietary CP with apparent total-tract digestibility of OM (**dOM**) mainly driving VS in dairy cows (Broderick, 2003; Colmenero and Broderick, 2006; Huhtanen et al., 2009). The model should be capable of explaining well the heterogeneity of VS across different diets because OMI and dOM can vary significantly depending on forage type and quality (Bal et al., 1997; Ball et al., 2001). Benchaar et al. (2014) and Hassanat et al. (2013) increased corn silage content in a dairy cow diet replacing (0, 50, and 100%) barley silage and alfalfa silage and showed that corn silage content had a positive linear relationship with OMI and dOM. The linear increase in dOM was related to a notably decreasing NDF content in both cases (e.g., 37.8% to 32.4%). On the other hand, dietary CP content decreased (e.g., 16.7% to 15.9%) as corn silage content increased in those diets but did not appear to have a significant effect on dOM. This discrepancy is partly explained by the larger and more significant (e.g., smaller standard error estimate) coefficient of NDF compared with that of CP in the new model (Equation 6). Consistently, a meta-analysis conducted by Nousiainen et al. (2009) demonstrated that the effect size of dietary CP on dOM of dairy cows was not large even though the association was statistically significant. The authors also noted that it is hard to find significant CP effects on diet digestibility in single studies.

The new model developed to predict dVS also included positive relationships of OMI and dietary NDF content and a negative relationship of dietary CP content (Equation 7). When evaluated with data used for model development, the model fitted the data well (RMSPE = 8.7% of the average observed value; data not shown) and had minor mean and SB (1% of total error; data not shown):

$$\begin{aligned} \text{dVS} = & -1.017 \pm 0.221 + 0.364 \pm 0.006 \times \text{OMI} \\ & + 0.029 \pm 0.003 \times \text{NDF} - 0.023 \pm 0.010 \times \text{CP}. \quad [7] \end{aligned}$$

The VS and dVS predictions from the new models were in close agreement with the observed values (Figure 1) and thus had small RMSPE (12.5 and 12.7% of average observed value, respectively) when evaluated with the independent data set (Table 3). Given the wide range of VS and dVS in the data, the small RMSPE indicate that the models were able to explain much of the variability in VS and dVS and able to predict them with reasonable accuracy. Moreover, the minor systematic bias of the predictions (MB + SB <3% of total bias; Table 3) suggests that the models were parameterized properly and thereby able to capture the true relationships of feed intake and dietary nutrient composition with dVS. The minor systematic bias also suggests that those relationships are quite conserved over time given the fact that the data used for model development were overall 40 yr older than the data used for model evaluation.

Evaluation of the IPCC Tier 2 Model

Because DE values were not available in the evaluation data set, similar to what is expected in commercial dairy farms, a fixed DE of 67% was assumed along with the default UE (0.04) and ASM (0.08) values in predicting VS using the IPCC Tier 2 model (Equation 3). The 67% DE value was chosen because it was the average DE of lactating dairy (n = 857) cows in the data set used for model development (Table 1). Nonetheless, when evaluated with independent data, the IPCC Tier 2 model had a larger RMSPE compared

Table 3. Performance of the models to predict DMI, gross energy intake, total volatile solid output (VS), and biodegradable volatile solid output (dVS) of lactating dairy cows when evaluated with an independent data set¹

Response	Model	Prediction error estimate (%)			
		RMSPE	MB	SB	RB
DMI	CNCPS	14.1	3.6	4.5	91.9
	IPCC Tier 2 (simplified)	16.9	4.0	14.7	81.3
	IPCC Tier 2 (comprehensive)	23.4	56.3	6.8	36.9
	IPCC Tier 2 (comprehensive)	23.3	56.2	4.9	38.9
Gross energy intake					
With actual DMI					
VS	New model (Equation 6)	12.5	0.2	0.4	99.4
	IPCC Tier 2	13.7	13.9	0.7	85.4
dVS	New model (Equation 7)	12.7	2.44	0.4	97.2
With DMI estimates from CNCPS model					
VS	New model (Equation 6)	19.4	3.1	3.8	93.2
	IPCC Tier 2	17.7	1.0	0.1	98.9
dVS	New model (Equation 7)	20.0	5.8	4.1	90.1

¹RMSPE = root mean squared prediction error as a percentage of average observed value; MB, SB, and RB = mean bias, slope bias, and random bias, respectively, as a percentage of total bias; CNCPS = Cornell Net Carbohydrate and Protein System; IPCC = Intergovernmental Panel on Climate Change.

with the new model (13.7 vs. 12.5%). The IPCC model had a significant MB (13.9% of total bias), indicating a tendency to underpredict VS on average by about 0.4 kg/d (data not shown). This could possibly be attributable to the mean DE of dairy cows in the independent data set being less than 67%. The MB could have been worse (about 0.8 kg/d; data not shown) if a DE of 69% had been used. The US Environmental Protection Agency uses a DE of 69% in IPCC Tier 2 methodology to estimate enteric CH₄ emissions from dairy cows in California (Mangino et al., 2003). Reducing DE by 1, 2, and 3% (from 67 to 66.3, 65.7, and 65.0%, respectively) reduced the RMSPE to 13.1, 12.8, and 12.7%, respectively (data not shown). Reducing DE up to 65.0% cancelled out the MB (data not shown). Increasing or decreasing ASM or UGE (Equation 3) by the same percentages or more did not significantly change MB or RMSPE. For instance, decreasing ASM even by 10% (from 0.080 to 0.072) while DE and UGE were fixed respectively at 67% and 0.04 only slightly reduced RMSPE (13.4 vs. 13.7%; data not shown). Similarly, increasing UGE by 10% (from 0.040 to 0.044) while DE and ASM were fixed respectively at 67% and 0.08 did not change RMSPE much (13.7 vs. 13.3%; data not shown). These observations demonstrate clearly the critical importance of knowing actual DE or determining it accurately to predict VS accurately using the IPCC Tier 2 model. When analyzed using the EMU data, DMI and dietary CP, NDF, and lignin contents were significantly ($P < 0.001$) associated with DE (data not shown). Therefore, accounting for the differences in feed intake and diet composition is important in determining DE and thus predicting VS accurately.

Predictions with Estimated Feed Intake

When evaluated with independent data, the CNCPS model predicted DMI more accurately than both the comprehensive and simplified models in IPCC Tier 2 methodology. The CNCPS model had a smaller RMSPE (14.1% vs. 16.9 and 31.0%) and minor systematic bias (MB or SB <5% of total bias; Table 3). Consistently, Appuhamy et al. (2016) demonstrated that the CNCPS model predicted the DMI of dairy cows in North America with a small RMSPE of 8%. Overall, the satisfactory performance of the CNCPS model indicates the potential to predict DMI by using just milk yield, milk composition, and BW—information that is routinely available on commercial farms. When DMI estimates from the CNCPS model were used instead of actual DMI, the new and IPCC Tier 2 models still predicted VS and dVS with reasonable accuracy (e.g., RMSPE $\leq 20\%$; Table 3). Gross energy intake and DMI predictions from IPCC-CMP had large RMSPE (23.3

and 23.4%, respectively, in Table 3), the majority (56.2 and 56.3%, respectively) of which came from an MB for GE to be overpredicted. As mentioned before, predicting DMI with IPCC-CMP involves calculation of net energy requirements for various functions of the body. The average daily net energy requirement for maintenance was 0.47 MJ/kg of BW^{0.75} (data not shown) and in line with the estimates of Strathe et al. (2011) and Moraes et al. (2015; 0.48 and 0.52 MJ/kg of BW^{0.75}, respectively). The average net energy requirement for milk production was 95.2 MJ/d and close to that from the NRC (2001) model (97.4 MJ/d; data not shown). Net energy requirements of maintenance and milk production accounted for 96% of the total net energy requirement. The balance was net energy requirement for pregnancy, which was calculated as 10% of the net energy for maintenance (IPCC, 2006). Given that the energy requirement estimates were likely accurate, the prediction error appears to be related to the digestible energy utilization efficiency calculations. Calculation of the efficiency at which digestible energy was utilized for maintenance, lactation, and pregnancy heavily involves DE in the IPCC Tier 2 methodology (IPCC, 2006). Therefore, nonrepresentative DE constants recommended by IPCC can negatively affect VS predictions through its contribution to DMI prediction when actual DMI data are not available. Therefore, IPCC Tier 2 methodology needs to be revised basically to accurately represent DE to improve DMI, VS, and thus the CH₄ emission predictions. Such improvements could also be achieved with alternative models such as the new models developed in the present study.

Importance for CH₄ Emission Prediction from Stored Manure

In the dairy livestock system, VS is typically collected after excretion and stored in liquid or solid form until field application. Stored VS serves as a substrate for CH₄ production in stored manure and thus is an important variable for prediction of CH₄ emissions. In the Mangino et al. (2001) approach (the basis for the IPCC Tier 2 method for liquid manure), the monthly amount of VS excreted is multiplied by the maximum CH₄ producing potential (B_0 ; m³ of CH₄/kg of VS) and corrected for temperature effects to estimate CH₄ from manure storage. All VS is assumed to be available for methanogens, and the VS remaining in storage after 1 mo (i.e., not consumed) is carried over to the next month, when it can result in CH₄ production. This model overestimates measured CH₄ emission from stored liquid manure (kg/mo) often by more than 2 times unless VS was not carried over (VanderZaag et al., 2011), indicating that the biodegradability of VS

is an important factor for better CH₄ emission predictions. Indeed, Sommer et al. (2004) separated VS into degradable and nondegradable pools to model the temperature dependency of CH₄ production in stored manure. Assessment of GHG mitigation options for CH₄ emissions from MMS also requires estimates of dVS as treatments such as anaerobic digestion reduce the availability of this component in VS (Sommer et al., 2009). More accurate estimates of VS and a new model to predict dVS presented here can improve CH₄ emission estimates from stored manure in dairy farms. The extent of the improvement could be assessed successfully once data on measured VS and dVS and corresponding manure CH₄ emission measurements are available along with feed intake and diet composition information.

CONCLUSIONS

Organic matter intake and dietary nutrient composition such as NDF and CP concentrations were significantly related to total VS and biodegradable VS outputs of lactating dairy cows. New models using those relationships have the potential to predict VS outputs more accurately and perhaps efficiently than the IPCC Tier 2 recommended methodology, which requires accurate estimation of energy digestibility of feed. New models require actual DMI measurements to predict the VS outputs accurately (e.g., RMSPE <15%). However, we demonstrated that (1) DMI can be predicted more accurately using simple extant models (e.g., the CNCPS model) compared with the models in IPCC Tier 2 methodology and (2) new models predicted the VS outputs with reasonable accuracy (RMSPE ≤20%) using DMI predicted from those extant models. Therefore, new models would be considerably helpful in estimating CH₄ emissions from MMS in commercial dairy farms.

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