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Improving the accuracy of beef cattle methane inventories in Latin America and Caribbean countries

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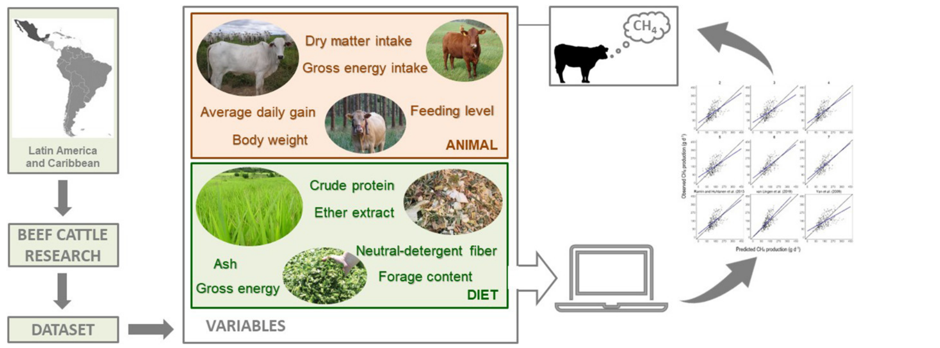
HIGHLIGHTS

- Intake and ADG were the key predictors of beef cattle CH_4 production.
- Separate models according to dietary forage content improved predictive ability.
- Developed models were more accurate than IPCC Tier 2 equations for all subsets.
- Developed models can allow LAC countries to improve the accuracy of their GHG inventories.

GRAPHICAL ABSTRACT



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ABSTRACT

On-farm methane (CH_4) emissions need to be estimated accurately so that the mitigation effect of recommended practices can be accounted for. In the present study prediction equations for enteric CH_4 have been developed in lieu of expensive animal measurement approaches. Our objectives were to: (1) compile a dataset from individual beef cattle data for the Latin America and Caribbean (LAC) region; (2) determine main predictors of CH_4 emission variables; (3) develop and cross-validate prediction models according to dietary forage content (DFC); and (4) compare the predictive ability of these newly-developed models with extant equations reported in literature, including those currently used for CH_4 inventories in LAC countries. After outlier's screening, 1100 beef cattle observations from 55 studies were kept in the final dataset (~ 50 % of the original dataset). Mixed-effects models were fitted with a random effect of study. The whole dataset was split according to DFC into a subset for all-forage (DFC = 100 %), high-forage (94 % ≥ DFC ≥ 54 %), and low-forage (50 % ≥ DFC) diets. Feed intake and average daily gain (ADG) were the main predictors of CH_4 emission (g d^{-1}), whereas this was feeding level [dry matter intake (DMI) as % of body weight] for CH_4 yield (g kg^{-1} DMI). The newly-developed models were more accurate than IPCC Tier 2 equations for all subsets. Simple and multiple regression models including ADG were accurate and a feasible option to predict CH_4 emission when data on feed intake are not available. Methane yield was not well predicted by any extant equation in contrast to the newly-developed models. The present study delivered new models that may be alternatives for the IPCC Tier 2 equations to improve CH_4 prediction for beef cattle in inventories of LAC countries based either on more or less readily available data.

1. Introduction

Sixty per cent of all global methane (CH_4) emissions are due to human-induced activities. Enteric CH_4 fermentation and manure management represent 32 % of global anthropogenic emissions, or 19.2 % of total global CH_4 emissions including non-anthropogenic sources (UNEP and CAC, 2021). Developing countries contribute about 70 % of livestock anthropogenic CH_4 emissions globally of which 25 % originates from Latin America and Caribbean (LAC) herds (UNEP and CAC, 2021). The short lifetime of CH_4 in the atmosphere, and its fast response to emission reduction, denotes that efforts to curb CH_4 emissions will have a prompt global warming mitigation effect (Saunois et al., 2020). Therefore, reducing anthropogenic CH_4 emissions in LAC countries, especially those from enteric fermentation, may have an important role in the global endeavors to restrain temperature rise to 1.5–2.0 °C (Congio et al., 2021; Arndt et al., 2022).

Prediction equations have been widely developed *in lieu* of expensive and laborious animal CH_4 measurement approaches (Hristov et al., 2018). Previous studies, based mainly on data from developed countries, already indicated that diet- or region-specific models are more accurate than universal equations to predict CH_4 emission, which seem to be related in particular to differences in animal diets (Niu et al., 2018; Benaouda et al., 2019). When accurate, these equations would be convenient to estimate CH_4 emissions under a range of conditions, and next to optimize the allocation of resources for research programs on enteric CH_4, which is particularly important for LAC developing countries (Congio et al., 2022a). Further, on-farm CH_4 emissions need to be estimated accurately so that mitigation of enteric CH_4 through better management practices is accounted for (Niu et al., 2018). Lastly, more accurate equations could aid LAC to improve the accuracy of their CH_4 inventories.

In 2018, beef cattle emitted 449 Mton of carbon dioxide equivalents due to ruminal CH_4 fermentation in the LAC region, or 39.5 % of beef cattle emissions globally (FAOSTAT, 2020). Recent studies already developed CH_4 prediction models from ruminants in the LAC region. However, they were either focused only on dairy cattle (Congio et al., 2022a) and sheep (Congio et al., 2022b), or they used a limited database (Benaouda et al., 2020). The development of models specifically for beef cattle is still necessary due to specifics regarding livestock production systems (*e.g.*, type and breed of animals) and diets (*e.g.*, sources and levels of forage inclusion). Therefore, the objectives of the present study were to: (1) compile a comprehensive LAC dataset for individual beef cattle data; (2) determine main predictors of CH_4 emission variables; (3) develop and cross-validate prediction models according to different dietary inclusion levels of forage (*i.e.*, the dietary forage content; DFC); and (4) compare the predictive ability of these newly-developed models with extant equations, including those currently used in CH_4 inventories in LAC countries (IPCC, 1997, 2006).

2. Material and methods

2.1. Dataset and data handling

The 'Latin America Methane Project' (LAMP) is a research initiative involving animal scientists from LAC countries studying *in vivo* CH_4 emission in ruminants and previous work was published by Congio et al. (2021, 2022a, 2022b). A comprehensive beef cattle dataset was compiled in LAMP which comprised 2194 individual beef cattle records from 67 studies (being 35 published and 32 unpublished). Studies performed from 2011 to 2021 by scientists from five LAC countries [Brazil, $n = 1656$ (records) from 39 (studies); Mexico, $n = 209$ from 11; Argentina, $n = 178$ from 7; Colombia, $n = 127$ from 9; Peru, $n = 24$ from 1]. The database included CH_4 emission (g d^{-1}) records along with corresponding dry matter intake (DMI; kg DM d^{-1}), body weight (BW; kg), average daily gain (ADG; kg d^{-1}), dietary forage content (DFC; % DM), crude protein (CP; % DM), ether extract (EE; % DM), neutral-detergent fiber (NDF; % DM), ash (% DM), and gross energy (GE; MJ kg^{-1} DM) concentration. Where not available, dietary variables were calculated as follows. Dietary GE ($n = 255$) according to Weiss and Tebbe (2019): {GE = [(CP (% DM) × 0.056) + (EE (% DM) × 0.094)] + [(100 - CP - EE - ash (% DM)) × 0.042] × 4.184}. Publications from the LAC region were used to derive dietary NDF ($n = 7$) and EE ($n = 369$). Methane yield [CH_4 yield (g kg^{-1} DMI) = CH_4 emission (g d^{-1}) ÷ DMI (kg DM d^{-1})], gross energy intake [GEI (MJ d^{-1}) = DMI (kg DM d^{-1}) × dietary GE (MJ kg^{-1} DM)),CH_4 conversion factor (Y_m) [Y_m (%) = CH_4 emission (g d^{-1}) × 0.05565 ÷ GEI (MJ d^{-1}) × 100)], and feeding level (FL) [FL (%) = DMI (kg DM d^{-1}) ÷ BW (kg) × 100], were computed for all observations.

Animal observations lacking CH_4 emission or DMI data were excluded from the dataset ($n = 359$). Studies in which CH_4 emission was negatively correlated with DMI were also excluded (12 studies totaling 376 individual animal records) following discussion in a review by Hristov et al. (2018). Additionally, records from treatments including anti-methanogenic additives or feed ingredients (*e.g.,* nitrate, tannins, lipid supplementation) were excluded ($n = 163$) (Niu et al., 2018). Next, the identification of outliers was performed using the interquartile range approach (Zwillinger and Kokoska, 2000) considering a factor of 1.5 for extremes (van Lingen et al., 2019). It was performed based on all animal variables (Congio et al., 2022a). As a result, 1100 beef cattle observations from 55 studies were kept in the final dataset (~ 50 % of the original dataset). This exclusion rate resembles that applied in previous meta-analyses for globally or regionally assembled databases where eventually also about 50 % of the original records were retained (van Lingen et al., 2019; Congio et al., 2022b). The complete list of references of the refined dataset used in the current analysis is included in Supplementary Material.

2.2. Model development

Mixed-effects models were fitted using the lme4 procedure (Bates et al., 2015) of R statistical package (R Core Team, 2020; version 4.0.2) according to:

$$Y_{ij} = \beta_0 + \beta_1 X_{ij1} + \beta_2 X_{ij2} + \ldots + \beta_k X_{ijk} + S_i + \varepsilon_{ij}$$

where Y_{ij} denotes the j^{th} response variable of CH_4 emission (g d^{-1}) or CH_4 yield (g kg^{-1} DMI) from the i^{th} study; β_0 denotes the fixed effect of intercept; X_{ij1} to X_{ijk} denote the fixed effects of predictor variables and β_1 to β_k are the corresponding slopes; S_i and ε_{ij} are the random effect of study and residual error, respectively.

Models were developed following a sequential approach with predictor variables being incrementally added (van Lingen et al., 2019). Simple CH_4 emission models were based on DMI, GEI, or ADG. Then, multiple regression models assessed combinations of the above variables with NDF, EE, or CP separately. Finally, models were tested with a selection of dietary variables, a selection of DMI or GEI together with dietary variables, and a selection of all available variables, as well as a selection of all available variables except DMI or GEI (Congio et al., 2022a). Methane yield models were developed considering ADG, FL, BW, GE, CP, EE, and NDF individually. Then, multiple CH_4 yield models were evaluated using a selection of dietary variables, and a selection of all available variables except DMI or GEI (as CH_4 yield is mathematically dependent on the latter variables). The backward multistep selection approach was used to select the most important variables to predict CH_4 emission and yield as described previously by van Lingen et al. (2019) and Congio et al. (2022a). The Bayesian information criterion was calculated for all fitted models, and those with the smallest values were chosen (James et al., 2014). The multi-collinearity among covariates in multiple regression models was verified considering the variance inflation factor (Zuur et al., 2010), and models were chosen when all covariates had a variance inflation factor lower than 3 (van Lingen et al., 2019).

2.3. Evaluation of developed models and extant equations

A leave-one-out cross-validation was performed to evaluate the predictive ability of fitted prediction models at different levels (James et al., 2014). Studies were sequentially taken as the testing set for model evaluation, whereas those remained were considered as the training set for model fitting (van Lingen et al., 2019). Also, thirteen extant equations, including those from IPCC (1997, 2006) were evaluated (but not cross-validated). The most accurate equations from Ellis et al. (2007, 2009), Yan et al. (2009), Hristov et al. (2013), Ramin and Huhtanen (2013), Moraes et al. (2014), Charmley et al. (2016), Patra (2017), van Lingen et al. (2019), Benaouda et al. (2020), and Ribeiro et al. (2020) were selected to be evaluated considering the availability of predictor variables in the present dataset (equations are detailed in Table S4). To ensure independent evaluation, studies used to develop the extant equations that overlapped the current dataset were not included in the evaluations of those extant equations corresponding to the method adopted by van Lingen et al. (2019) and Congio et al. (2022a). Next to the use of the complete dataset, the dataset was split into subsets according to DFC delivering subsets for data obtained with all-forage (DFC = 100 %), high-forage (94 % ≥ DFC ≥ 54 %), and low-forage (50 % ≥ DFC) diets, in order to derive separate prediction models for these subsets. These boundaries were defined to accommodate the wide range of beef cattle production systems from LAC region. A large proportion of beef cattle are raised in grazing systems with no supplement (*i.e.,* all-forage subset). The high-forage subset accommodates grazing animals receiving some level of concentrate and confined animals fed higher-forage diets, whereas the low-forage subset represents those are confined and fed higher levels of concentrate.

The all-forage subset comprised of mostly Angus (56 %), Nellore (16 %), and Brahman (10 %) breeds. On the other hand, Nellore (35 %), crosses including Zebu cattle (32 %), Holstein (7 %), Canchim (7 %), Gyr (7 %), Brahman (5 %), and Brangus (5 %) majorly composed the high-forage subset. Cattle fed low-forage diets were predominantly Nellore (72 %), Holstein × Charolais (7 %), Canchim (7 %), Holstein × Zebu (7 %). The main forage types for the all-forage subset were *Avena* spp. (33 %), *Megathyrsus maximus* (32 %), *Cynodon* spp. (9 %), *Urochloa* spp. (9 %), and *Pennisetum* spp. (6 %), whereas corn silage (47 %), *Urochloa* spp. (24 %), and *M. maximus* (16 %) were mostly represented in the high-forage subset. Corn silage (55 %), fresh-cut sugar cane (16 %), and *Urochloa* spp. (15 %) were the main forages for the low-forage subset. Respiration chambers, GreenFeed™ (C-Lock Inc., Rapid City, SD), and the tracer gas sulfur hexafluoride (SF_6) were used as CH_4 measurement techniques representing 8, 0 and 83 %, 41, 10 and 44 %, and 16, 41, and 44 % of the data in the all-forage, high-forage and low-forage subsets, respectively. Further, DMI was mostly estimated using markers (81 %) in the all-forage subset, whereas for the high-forage (80 %) and low-forage (100 %) subsets, the gravimetric technique was predominant.

Model performance was evaluated using a combination of statistic metrics including mean square prediction error (MSPE; Bibby and Toutenburg, 1977), mean bias (MB), slope bias (SB), root MSPE (RMSPE), ratio between RMSPE and standard deviation of observed values (RSR; Moriasi et al., 2007), and concordance correlation coefficient (CCC; Lin, 1989). In the present analysis, we considered unsuitable models with RSR ≥ 1.00 (van Lingen et al., 2019). Equations used to calculate all above metrics are detailed in Supplementary Material.

3. Results and discussion

Several models to predict enteric CH_4 emissions from beef cattle have been published already (*e.g.,* Ellis et al., 2009; Charmley et al., 2016; van Lingen et al., 2019). However, these models were developed from small datasets, some used published treatment means data (*vs.* individual animal observations in the current study), and/or based on a restricted geographic region, which did not comprise data from LAC (e.g., Ellis et al., 2007, 2009; Yan et al., 2009; Moraes et al., 2014; Charmley et al., 2016). Some studies included LAC data, but they either used limited databases (Benaouda et al., 2020) or included few data from LAC region (Escobar-Bahamondes et al., 2017). The 'Global Network' studies by Benaouda et al. (2019) and van Lingen et al. (2019) reported that regional equations are more accurate to predict CH_4 emissions, and that data from important beef-producing regions were essentially lacking. The current study is based on the largest database of individual animal data for beef cattle from the LAC region specifically including CH_4 measurements, and it therefore represents the greatest endeavour to date to establish accurate models for predicting CH_4 in beef cattle for this region.

3.1. Dataset

Summary variable statistics for the complete dataset, and the all-forage, high-forage, and low-forage subsets are shown in Table 1. The complete dataset mainly constituted data for high-forage (47 %) rather than all-forage (29.5 %) and low-forage (23.5 %) diets. The high- and low-forage subsets were composed only by data for growing cattle (100 %), whereas all-forage also included a small proportion of data for lactating beef cows (4 %). Feed intake and BW increased as the dietary forage content of subsets decreased.

Methane emission ranged from 38.2 from 364 g d^{-1} in the current study, whereas Escobar-Bahamondes et al. (2017) and van Lingen et al. (2019) reported mean values ranging from 37.0 to 372 g d^{-1} and from 37.4 to 322 g d^{-1}, respectively. Methane yield ranged from 19.3 (low-forage) to 27.3 (all-forage) g kg^{-1} DMI, whereas the Y_m varied from 5.97 (low-forage) to 8.79 % (all-forage) in the current study. Van Lingen et al. (2019) and Escobar-Bahamondes et al. (2017), both using data predominantly from the EU and North America, reported CH_4 yield and Y_m ranging from 20.0 to 22.1 g kg^{-1} DMI, and from 6.0 to 6.3 %, respectively. Further, Benaouda et al. (2020), using a smaller dataset from LAC, reported mean values of CH_4 yield and Y_m of 20.3 g kg^{-1} DMI and 6.2 %, respectively.

3.2. Methane emission

Developed CH_4 emission equations and metrics of model performance are shown in Table 2. Average daily gain (Eqs. 1, 8, and 10), DMI (Eqs. 2 and 3), GEI (Eqs. 4, 5, 9, and 11), and dietary GE content (Eq. 11) had a positive relationship with CH_4 emission, whereas FL (Eq. 11) and dietary contents of EE (Eqs. 3, 5, and 11) and CP (Eqs. 9, 10, and 11) had a negative relationship. A negative relationship between CH_4 emission and dietary EE concentration is in line with studies by Moraes et al. (2014) and Escobar-Bahamondes et al. (2017). Increased dietary lipid supplies non-fermentable energy to the rumen, whereas suppresses archaeal activity, and may cause a shift in the rumen fermentation profile as well decrease NDF digestibility at higher inclusion levels (Hristov et al., 2013). Finally, dietary CP being negatively related with CH_4 emission agrees with Blaxter et al. (1971), which showed a decrease in CH_4 emission when diet CP increases.

Feed intake variables were the main predictors of CH_4 emission in line with previous meta-analyses for beef cattle (van Lingen et al., 2019), dairy cattle (Niu et al., 2018), sheep (Congio et al., 2022b), and goats (Patra and Lalhriatpuii, 2016). In the present meta-analysis, DMI was significantly and positively related to CH_4 emission with slopes varying from 19.2 to 19.6 g CH_4 kg^{-1} DMI. This demonstrates that the greater the availability of substrate in the rumen, the greater the rate of formation CH_4 to be expected (Congio et al., 2022a). Furthermore, feed intake is a key covariate

Table 1
Summary statistics for the complete dataset, and the all-forage [dietary forage content (DFC) = 100 %], high-forage (94 % ≥ DFC ≥ 54 %), and low-forage (50 % ≥ DFC) subsets.

Item[a]	Complete					All-forage					High-forage					Low-forage				
	n[b]	Mean	Min[b]	Max[b]	SD[b]	n	Mean	Min	Max	SD	n	Mean	Min	Max	SD	n	Mean	Min	Max	SD
Animal variables																				
DMI (kg d^{-1})	1100	7.40	1.37	14.6	2.44	325	6.57	1.77	14.6	2.35	516	7.49	1.37	14.3	2.74	259	8.25	4.44	13.1	1.36
GEI (MJ d^{-1})	1100	130	24.8	263	43.2	325	113	24.8	238	38.6	516	131	25.1	263	49.0	259	148	78.6	229	24.3
BW (kg)	1100	345	106	657	103	325	300	122	534	92.3	516	351	106	657	99.8	259	389	110	643	101
FL (DMI as % BW)	1100	2.20	0.751	4.46	0.600	325	2.27	0.927	4.15	0.697	516	2.14	0.751	4.14	0.560	259	2.23	1.11	4.46	0.539
ADG (kg d^{-1})	825	1.01	0.092	2.79	0.431	254	1.01	0.357	2.00	0.360	368	0.915	0.092	2.31	0.475	203	1.17	0.333	2.79	0.379
Diet composition (% DM)																				
NDF	1100	49.9	17.2	85.7	14.2	325	60.1	41.1	85.7	11.0	516	50.1	28.3	73.4	12.1	259	36.6	17.2	63.4	10.2
EE	1100	2.97	0.670	6.99	1.18	325	2.82	0.670	4.00	1.08	516	2.90	0.730	6.99	1.25	259	3.31	1.24	6.46	1.10
CP	1100	14.3	4.09	25.1	3.44	325	15.2	4.09	25.1	5.08	516	13.7	7.08	21.2	2.41	259	14.2	9.85	20.0	2.13
Ash	1100	7.31	3.25	13.2	2.33	325	9.17	5.19	13.2	1.86	516	7.18	3.50	12.8	1.96	259	5.24	3.25	11.0	1.52
Forage	1100	72.6	17.3	100	23.7	325	100	100	100	0	516	72.1	53.9	94.4	10.8	259	39.1	17.3	50.0	10.0
GE (MJ kg^{-1} DM)	1100	17.6	14.0	21.3	0.948	325	17.3	14.0	19.9	0.655	516	17.6	14.5	20.0	1.07	259	18.0	16.5	21.3	0.857
Methane emissions																				
CH_4 (g d^{-1})	1100	153	38.2	364	48.7	325	171	57.3	347	59.1	516	139	38.2	364	44.4	259	156	71.4	298	31.6
CH_4 per DMI (g kg^{-1})	1100	22.1	8.78	49.5	7.80	325	27.3	13.0	48.1	8.04	516	20.2	8.78	49.5	7.41	259	19.3	9.97	37.0	4.50
Y_m (% GEI)	1100	7.01	2.66	15.0	2.50	325	8.79	4.20	15.0	2.60	516	6.42	2.66	15.0	2.31	259	5.97	3.14	12.0	1.32

[a] DMI = dry matter intake; GEI = gross energy intake; BW = body weight; FL = feeding level; NDF = dietary neutral-detergent fiber content; EE = dietary ether extract content; CP = dietary crude protein content; GE = dietary gross energy; ADG = average daily gain; Y_m = methane conversion factor.
[b] n = number of observations; Min = minimum; Max = maximum; SD = standard deviation.

Table 2
Methane emission (g d^{-1}) prediction equations and model evaluation metrics for the complete dataset, and for the all-forage [dietary forage content (DFC) = 100 %], high-forage (94 % ≥ DFC ≥ 54 %), and low-forage (50 % ≥ DFC) subsets.

Eq.	Prediction equation[a] Dataset or Subset	n[b]	RSR	RMSPE, %	MB, %	SB, %	CCC
	Complete						
(1)	114 (7.02) + 33.0 (4.17) × ADG	825	0.99	32.3	1.57	1.74	0.11
	All-forage						
(2)	20.0 (12.3) + 19.6 (1.32) × DMI	325	0.93	32.2	15.98	4.87	0.49
(3)	65.2 (23.7) + 19.2 (1.38) × DMI - 21.2 (8.37) × EE	325	0.92	32.0	7.28	7.33	0.48
(4)	19.6 (12.3) + 1.15 (0.077) × GEI	325	0.92	31.8	15.86	4.05	0.50
(5)	65.2 (23.6) + 1.12 (0.080) × GEI - 21.2 (8.36) × EE	325	0.91	31.4	6.65	6.33	0.49
(6)	- 83.9 (30.7) + 0.675 (0.093) × GEI + 0.358 (0.036) × BW + 6.53 (2.29) × ash	254	0.88	28.6	17.86	2.18	0.54
(7)	- 71.0 (20.9) + 0.570 (0.033) × BW + 27.9 (4.26) × FL	254	0.85	27.6	14.09	0.82	0.54
	High-forage						
(8)	80.8 (9.81) + 63.6 (4.66) × ADG	368	0.99	31.8	0.17	11.67	0.35
	Low-forage						
(9)	85.1 (28.3) + 0.655 (0.070) × GEI - 1.73 (1.76) × CP	259	0.99	20.1	0.29	6.01	0.22
(10)	207 (33.8) + 28.7 (5.59) × ADG - 6.21 (2.27) × CP	203	0.96	19.9	0.11	2.39	0.24
(11)	10.3 (68.8) + 0.739 (0.084) × GEI - 17.4 (5.99) × FL + 11.3 (3.73) × GE - 7.18 (1.97) × CP - 9.37 (2.33) × EE	203	0.91	18.9	0.13	1.79	0.37

[a] ADG = average daily gain (kg d^{-1}); DMI = dry matter intake (kg d^{-1}); EE = dietary ether extract content (% DM); GEI = gross energy intake (MJ d^{-1}); BW = body weight (kg); ash = dietary ash content (% DM); FL = feeding level (DMI as % BW); CP = dietary crude protein content (% DM); GE = dietary gross energy (MJ kg^{-1} DM).

[b] n = number of observations used to fit equations and for model evaluation; RSR = RMSPE-observations standard deviation ratio; RMSPE = root mean square prediction error (% of observed CH_4 production means); MB = mean bias (% of MSPE); SB = slope bias (% of MSPE); CCC = concordance correlation coefficient.

predicting CH_4 emissions because it is the consequence of certain dietary characteristics and animal nutritional requirements, both affecting the fermentative and digestive process (Charmley et al., 2016). Models based exclusively on feed chemical composition parameters did not perform well for the complete dataset as well as all subsets (results not shown), which is in line with Niu et al. (2018), reasserting also the key importance of DMI in determining CH_4 emission (Congio et al., 2022a).

Average daily gain (ADG) was positively related with CH_4 emission that agrees with previous results from Benaouda et al. (2020). This is probably due to the general positive relationship between feed intake and animal production variables (Hristov et al., 2005). Also, BW and CH_4 emission were positively corresponding to results of Moraes et al. (2014) and Benaouda et al. (2020). This is due to the proportionality between rumen volume and BW (Demment and Van Soest, 1985) as well as DMI. Heavier ruminants with higher requirements for maintenance energy are prone to consume extra feed and emit more CH_4 (Hristov et al., 2013).

Models including DMI, GEI, or ADG and dietary parameters (results not shown) were not more accurate than the one-variable models in the complete dataset and the high-forage subset. Nonetheless, the addition of EE (Eqs. 3 and 5) and CP (Eqs. 9 and 10) improved the model precision compared to those simple regressions in the all-forage and low-forage subsets, respectively. Models that included only dietary parameters were the least accurate considering developed models in all subsets (results not shown).

The ADG simple regression model (Eq. 1) was unique with a RSR < 1.00 (Table 2 and Fig. 1) in the complete dataset. For all-forage diets, the GEI model (Eq. 4) was slightly more accurate than the DMI model (Eq. 2), presenting smaller RSR (0.92 *vs.* 0.93) and RMSPE (31.8 *vs.* 32.2 %), but both had low precision (MB ~ 15.0 %). Inclusion of dietary EE content (Eqs. 3 and 5) improved the precision of these simple regression models (Table 2 and Fig. 2). The MB of those simple regressions including DMI (Eq. 2) or GEI (Eq. 4) averaged 15.92 %, whereas the correction for dietary EE decreased the MB to an average of 6.97 % (Eqs. 3 and 5). Both multiple regression models that allowed all variables (Eq. 6) and all variables except DMI (Eq. 7) for selection had the smallest RSR and RMSPE (Table 2), and included FL as well.

Similar to the complete dataset, the ADG simple regression (Eq. 8) was the unique model that had RSR < 1.00 in the high-forage subset; however, it had low accuracy (SB = 11.67 %) (Table 2 and Fig. 3). There were no simple regression models with RSR < 1.00 (results not shown) in the low-forage subset. Models including dietary CP content with GEI (Eq. 9) or ADG (Eq. 10) were associated with low RMSPE and good precision. The multiple regression model 11 selected GEI, FL, and dietary contents of GE, CP, and EE and had the best predictive accuracy (RMSPE = 18.9 %) with negligible bias (MB = 0.13 % and SB = 1.79 %) (Table 2 and Fig. 4).

Increasing complexity improved the predictive performance of CH_4 emission models only for the all-forage and low-forage subsets, but not for complete dataset and the high-forage subset. Usually, including dietary variables to feed intake simple models results in more accurate models (Niu et al., 2018; Congio et al., 2022b). However, Ribeiro et al. (2020) and

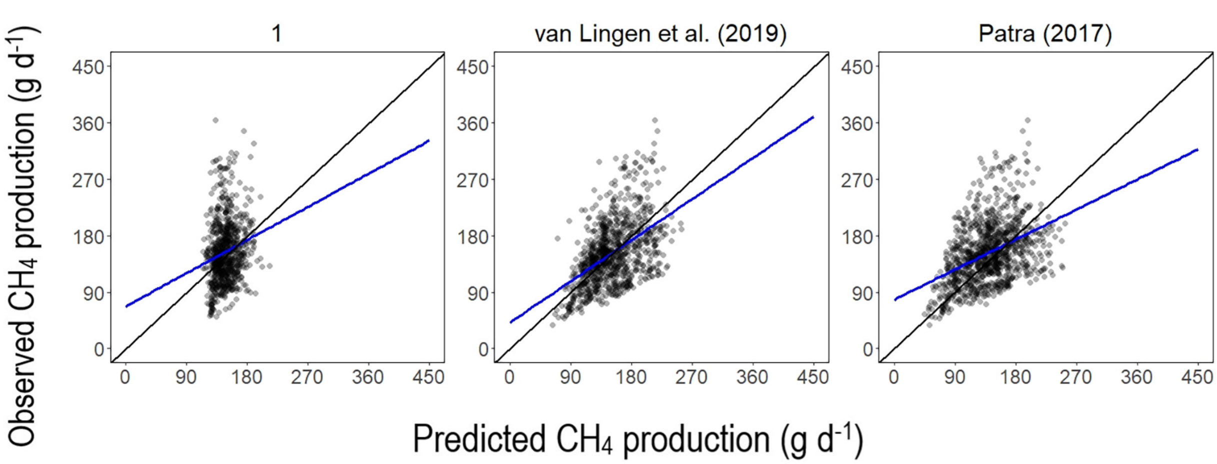

Fig. 1. Relationship between observed and predicted methane emission (g d^{-1}) using the complete dataset. The black solid line is the identity line (y = x), and the blue solid line is the fitted regression line for the relationship between observed and predicted values. For the interpretation of the references, the reader is referred to Table 2 (developed models), and Tables 3 and S1 (extant equations).

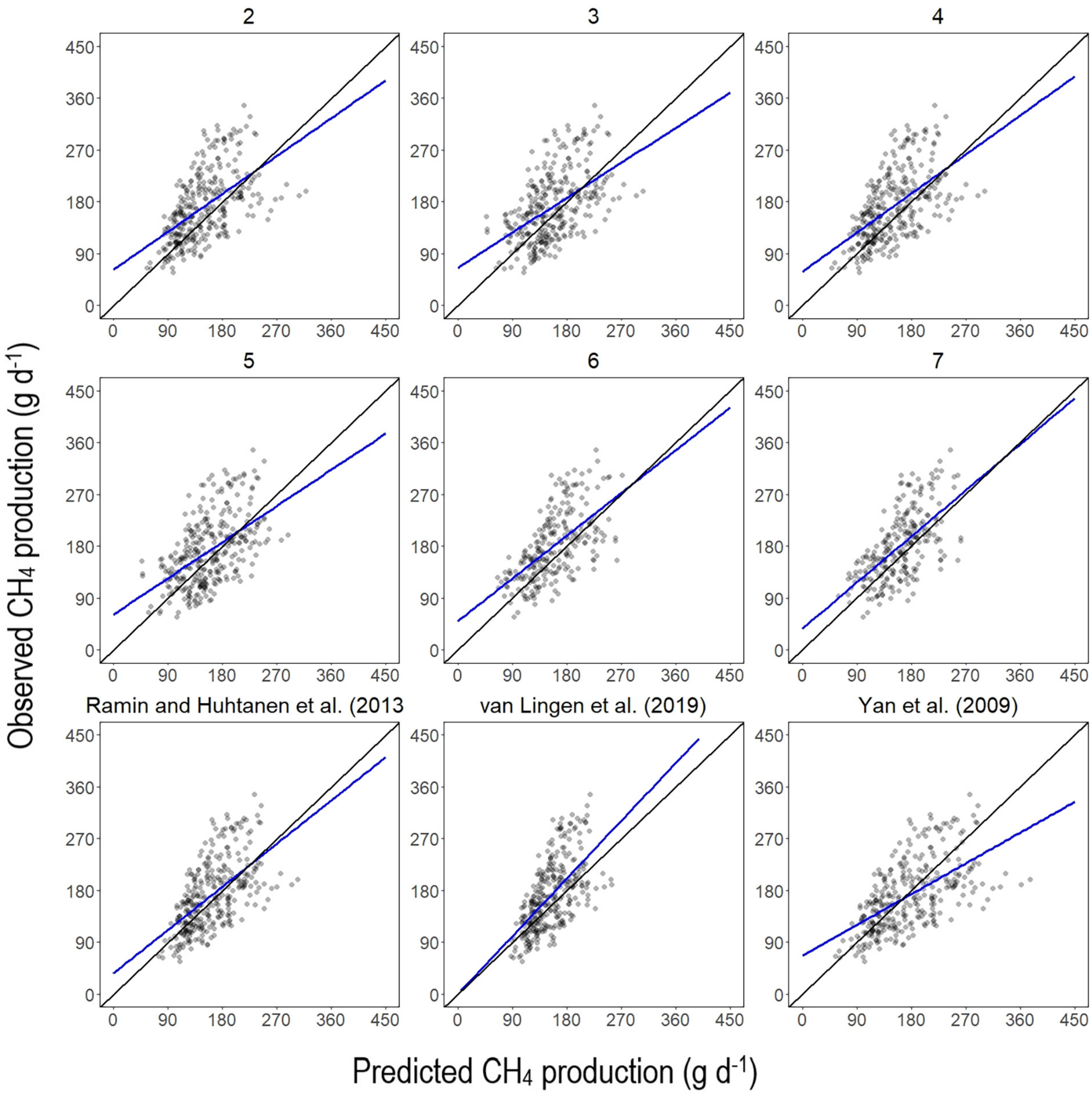

Fig. 2. Relationship between observed and predicted methane emission (g d^{-1}) using the all-forage (dietary forage content = 100 %) subset. The black solid line is the identity line (y = x), and the blue solid line is the fitted regression line for the relationship between observed and predicted values. For the interpretation of the references, the reader is referred to Tables 2 (developed models) and 3 (extant equations).

Congio et al. (2022a) also did not report more accurate equations comprising dietary variables using datasets containing LAC studies. The authors attributed those outcomes to a low variability of diets in terms of ingredients and nutrient contents (Ribeiro et al., 2020). Besides prediction potential, models with greater complexity might only be feasible in intensive beef cattle production systems. Extensive pasture-based systems are more common in LAC, however, and therefore simpler models based on easily available on-farm variables, such as ADG, probably are more practical to apply as discussed before by Congio et al. (2022a).

3.2.1. Performance of extant prediction equations

Prediction performances of extant equations using the complete dataset, and the all-forage, high-forage, and low-forage subsets are presented in Table 3. In the complete subset, the equation from van Lingen et al. (2019), including corrections for DFC and BW, was ranked first with a RMSPE of 29.4 %, good precision (MB = 0.02 %), and reasonable accuracy (SB = 4.46 %) (Table 3 and Fig. 1). This model was originally developed from a comprehensive global dataset. All remaining extant equations evaluated using the complete dataset had RSR > 1.00 (Table S1 and Fig. S1). In the all-forage subset, the equation from Ramin and Huhtanen (2013) was the best-performing (Table 3 and Fig. 2). The second-ranked equation was that of van Lingen et al. (2019), but it had low precision (MB = 12.18 %). The linear equation by Yan et al. (2009) was ranked third but had low accuracy (SB = 20.0 %). The equation from Ribeiro et al. (2020) was the ranked fourth, but it presented a large MB of 31.7 % (Table 3 and Fig. S2). All remaining extant equations were not suitable to predict CH_4 emission considering the all-forage subset including the IPCC (1997, 2006) Tier 2 equations (Table S2 and Fig. S2). The equation from Ellis et al. (2009) was the most accurate among extant equations for the high-forage subset (Table 3 and Fig. 3). The equation from Benaouda et al. (2020) that included both DMI and NDF, was ranked second by RSR, but it had a large MB of 25.7 %. The equation by van Lingen et al. (2019) also had RSR < 1.00 but also had larger systematic biases (MB = 12.54 % and SB = 12.63 %) (Table 3 and Fig. S3). All remaining extant equations evaluated using the high-forage subset had RSR > 1.00 (Table S3 and Fig. S3). No extant equations were suitable for predicting

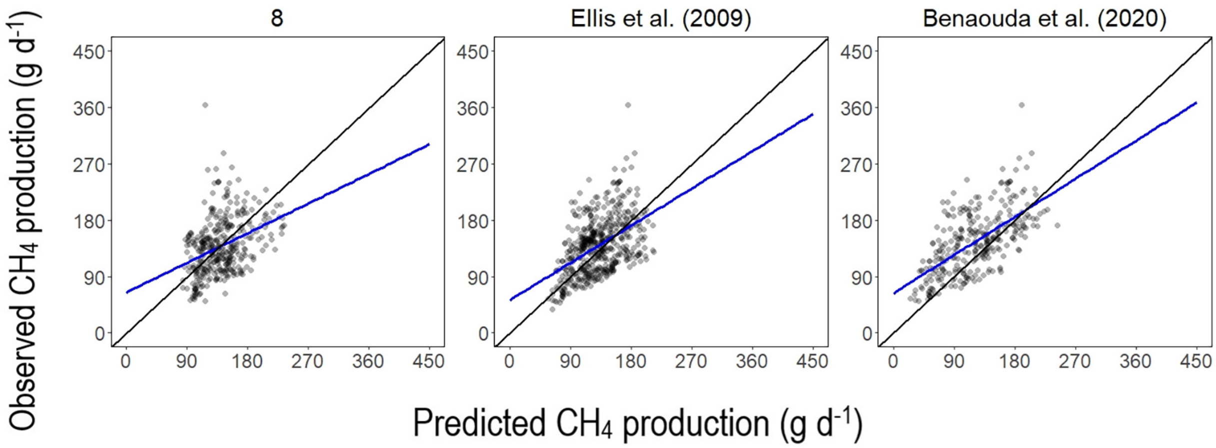

Fig. 3. Relationship between observed and predicted methane emission (g d^{-1}) using the high-forage (94 % ≥ dietary forage content ≥54 %) subset. The black solid line is the identity line (y = x), and the blue solid line is the fitted regression line for the relationship between observed and predicted values. For the interpretation of the references, the reader is referred to Tables 2 (developed models) and 3 (extant equations).

CH_4 emission in the low-forage subset with RSR > 1.00 (Table S4 and Fig. S4).

3.2.2. Comparison against extant prediction equations

Compared to the best extant equations, the most accurate CH_4 emission models derived in the present study had a comparable accuracy with the all-forage subset, were outperformed with the high-forage, and outperformed with the low-forage subset. The equation from van Lingen et al. (2019) performed better than our ADG simple model (Eq. 1) for the complete dataset. For all-forage diets, the developed model 7 including both BW and FL had similar overall performance compared with those from Ramin and Huhtanen (2013) and van Lingen et al. (2019). The equation by Ellis et al. (2009) was the first-ranked extant equation and it outperformed our ADG model (Eq. 8) in the high-forage subset. Considering the low-forage subset, all extant equations were outperformed by models developed in the current analysis (Eqs. 9–11). Tier 2 equations from IPCC (1997, 2006) appeared unsuitable for predicting CH_4 emission from beef cattle in the LAC region (Tables S1-S4). They had RSR > 1.00 and were outperformed by the models developed in the present study for all subsets, highlighting an opportunity to improve CH_4 inventories from LAC countries. Considering the fact that feed intake is barely obtainable in LAC beef ranches, the ADG simple or multiple regression models (Eqs. 1, 8, and 10) are good alternatives to predict CH_4 emission from beef cattle under different dietary regimes with respect to forage inclusion level.

3.3. Methane yield

Table 4 shows CH_4 yield equations and model performance metrics. Increasing model complexity did not result in more accurate models for the complete dataset and high-forage subset. The FL simple models (Eqs. 12 and 14) were best predicting CH_4 yield. There were no simple regression models with RSR < 1.00 for the all-forage and low-forage subsets. The multiple regression model including both FL and dietary EE (Eq. 13) was the most accurate for the all-forage forage subset, whereas for the low-forage subset Eq. 15, which included dietary contents of GE, CP, and EE along with FL, showed the best predictive performance. From the extant equations for prediction of CH_4 yield, that of van Lingen et al. (2019) had a RSR < 1.00 for only the complete dataset and the low-forage subset with a high and low RMSPE of 34.4 and 21.9 %, respectively (Table 5 and Fig. S5).

Similar to the results for CH_4 emission, the accuracy of newly-developed CH_4 yield models increased with model complexity for the all-forage and low-forage subsets, but not for the complete dataset and the high-forage subset. Most CH_4 modeling analyses have been focused on CH_4 emission rather than CH_4 yield (Congio et al., 2022a, 2022b). Our results indicate

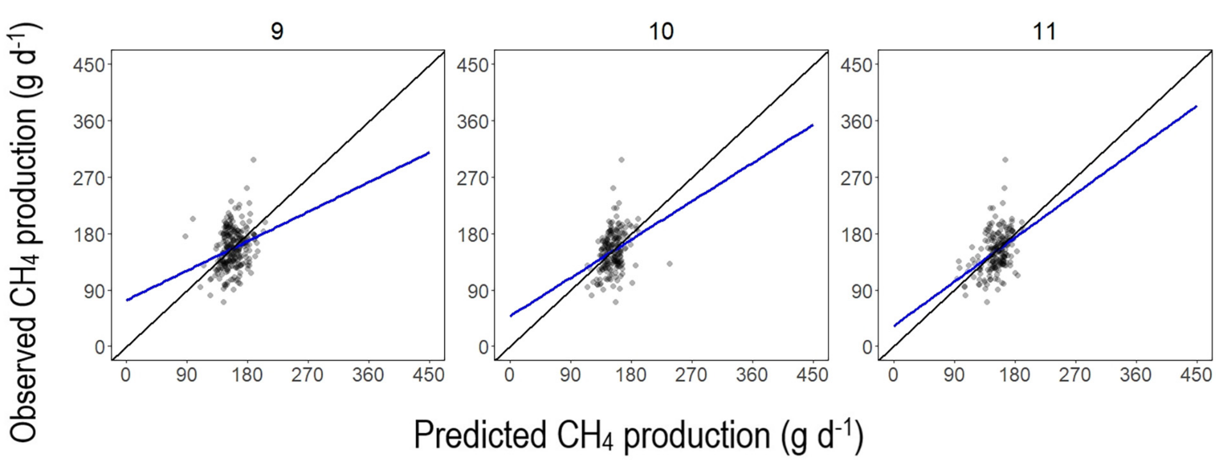

Fig. 4. Relationship between observed and predicted methane emission (g d^{-1}) using the low-forage (50 % ≥ dietary forage content) subset. The black solid line is the identity line (y = x), and the blue solid line is the fitted regression line for the relationship between observed and predicted values. For the interpretation of the references, the reader is referred to Table 2 (developed models).

Table 3
Performance evaluation of extant equations to predict enteric CH_4 emission (g d^{-1}) using the complete dataset, and the all-forage [dietary forage content (DFC) = 100 %], and high-forage (94 % ≥ DFC ≥ 54 %) subsets.

Rank	Reference	Equation[a]	n[b]	RSR[b]	RMSPE, %[b]	MB, %[b]	SB, %[b]	CCC[b]
Complete								
1	van Lingen et al. (2019)	- 6.41 + 11.3 × DMI + 0.557 × For +0.0996 × BW	975	0.88	29.4	0.02	4.46	0.47
All-forage								
1	Ramin and Huhtanen (2013)	(62 + 25 × DMI) × 0.714	325	0.83	28.7	3.51	2.03	0.55
2	van Lingen et al. (2019)	- 6.41 + 11.3 × DMI + 0.557 × For +0.0996 × BW	325	0.84	29.0	12.18	0.57	0.49
3	Yan et al. (2009)	(14.7 + 35.1 × DMI) × 0.714	325	0.90	31.3	0.70	20.04	0.59
4	Ribeiro et al. (2020)	(0.734 + 0.041 × GEI + 0.009 × BW - 0.04 × EE) ÷ 0.05565	289	0.95	31.7	31.75	0.30	0.49
High-forage								
1	Ellis et al. (2009)	(2.29 + 0.67 × DMI) ÷ 0.05565	516	0.92	29.4	3.59	7.48	0.46
2	Benaouda et al. (2020)	17.0 × DMI + 0.03 × NDF	301	0.96	32.9	25.69	9.97	0.56
3	van Lingen et al. (2019)	- 6.41 + 11.3 × DMI + 0.557 × For +0.0996 × BW	484	0.98	31.9	12.54	12.63	0.49

[a] DMI = dry matter intake (kg d^{-1}); BW = body weight (kg); GEI = gross energy intake (MJ d^{-1}); EE = dietary ether extract content (% DM); NDF = dietary neutral-detergent fiber content (% DM); For = dietary forage content (% DM).
[b] n = number of observations used for model evaluation; RSR = RMSPE-observations standard deviation ratio; RMSPE = root mean square prediction error (% observed CH_4 production means); MB = mean bias (% MSPE); SB = slope bias (% MSPE); CCC = concordance correlation coefficient.

however that CH_4 yield of beef cattle fed typical LAC diets can also be predicted reasonably well using FL as predictor (Eqs. 12 and 14), combining it with dietary EE (Eq. 13), or with dietary GE, CP, and EE (Eq. 15). The newly-developed models in the present study outperformed the extant equation of van Lingen et al. (2019) for the all-forage, high-forage, and low-forage subsets.

3.4. Research implications

Research on CH_4 emissions from ruminants is relatively novel in the LAC region as reviewed by Congio et al. (2021). The dataset used in the present study reflected diets typically used for feeding beef cattle in LAC production systems but adding further research could improve accuracy of the current models. A more complete dietary nutrient characterization in future research would eliminate the necessity to adopt table values from the literature to fill missing variables in dataset (Congio et al., 2022a).

Recently, meta-analysis studies also reported more accurate CH_4 prediction models when using digestibility variables as predictors (Benaouda et al., 2019, 2020; Ribeiro et al., 2020). We could not explore this kind of model in our study due to the absence of such data. Moreover, this poses a limitation to the applicability of such models in assisting CH_4 inventories in LAC countries because such observations are very scarce in livestock operations. For these reasons the newly-derived models in the present study may be more useful and feasible options to follow.

Ideally, the comparison of developed models and extant equations in this kind of meta-analysis should be based on equal number of observations. However, in the present study, the use of ADG as predictor variable, that was included in only 75 % of observations, as well as the evaluation of some equations, which presented overlapping of studies with our dataset, did not allow this ideal comparison scenario. As previously mentioned, these overlapped studies were removed from the evaluation of those extant equations in order to ensure independent evaluation. Moreover, we imagined that would be valuable to explore models including ADG because it is readily available on-farm. In cases of unequal amount of observations to compare model performances, the RSR is the most recommended statistic metric because it considers the data variability. This same approach was adopted by 'Global Network' studies by Benaouda et al. (2019) and van Lingen et al. (2019) in an attempt to maximize the number of observations to evaluate each model.

Table 4
Methane yield (g kg^{-1} DMI) prediction equations and model evaluation metrics for the complete dataset, and the all-forage [dietary forage content (DFC) = 100 %], high-forage (94 % ≥ DFC ≥ 54 %), and low-forage (50 % ≥ DFC) subsets.

Eq.	Prediction equation[a]	Model performance[b]					
	Dataset or Subset	n[b]	RSR	RMSPE, %	MB, %	SB, %	CCC
	Complete						
(12)	30.7 (1.04) - 4.35 (0.262) × FL	1100	0.97	34.2	1.65	0.21	0.16
	All-forage						
(13)	29.8 (2.64) - 6.31 (0.565) × FL + 4.03 (1.20) × EE	325	0.88	26.0	3.14	0.15	0.40
	High-forage						
(14)	27.4 (1.22) - 3.28 (0.324) × FL	516	0.92	33.5	0.08	5.54	0.21
	Low-forage						
(15)	1.19 (10.2) - 3.20 (0.676) × FL + 2.27 (0.547) × GE - 0.855 (0.269) × CP - 1.16 (0.292) × EE	203	0.90	19.9	1.24	0.58	0.37

[a] FL = feeding level (DMI as % BW); EE = dietary ether extract content (% DM); GE = dietary gross energy (MJ kg^{-1} DM); CP = dietary crude protein content (% DM).
[b] n = number of observations used to fit equations and for model evaluation; RSR = RMSPE-observations standard deviation ratio; RMSPE = root mean square prediction error (% observed CH_4 production means); MB = mean bias (% MSPE); SB = slope bias (% MSPE); CCC = concordance correlation coefficient.

4. Conclusions

The current study is based on the largest dataset of individual animal data including CH_4 measurements for beef cattle from the LAC region, and thus represents the greatest endeavour to date to establish accurate

Table 5
Performance evaluation of van Lingen et al. (2019) equation[a] to predict enteric CH_4 yield (g kg^{-1} DMI) using the complete dataset, and the all-forage [dietary forage content (DFC) = 100 %], high-forage (94 % ≥ DFC ≥ 54 %), and low-forage (50 % ≥ DFC) subsets.

Dataset or Subset	n[b]	RSR[b]	RMSPE, %[b]	MB, %[b]	SB, %[b]	CCC[b]
Complete	975	0.96	34.4	1.14	5.49	0.11
All-forage	325	1.13	33.4	22.51	2.28	0.01
High-forage	484	1.00	37.7	2.72	0.84	0.03
Low-forage	166	0.99	21.9	0.01	0.09	0.03

[a] CH_4 yield (g kg^{-1} DMI) = 17.3 + 0.0565 × For; where For = dietary forage content (% DM).
[b] n = number of observations used for model evaluation; RSR = RMSPE-observations standard deviation ratio; RMSPE = root mean square prediction error (% observed CH_4 production means); MB = mean bias (% MSPE); SB = slope bias (% MSPE); CCC = concordance correlation coefficient.

models for predicting CH_4 emissions for beef cattle in this region. Feed intake and ADG were the main predictors of CH_4 emission, whereas this was FL for CH_4 yield. Our most accurate CH_4 emission models outperformed IPCC (1997, 2006) Tier 2 equations, whereas the CH_4 yield models outperformed extant equations, for all subsets. Simple and multiple regression models including ADG were accurate and probably a more feasible option to predict CH_4 emission when feed intake data are not available. Different individual extant equations were evaluated to be good options as well to predict CH_4 emission from beef cattle for the complete dataset, and the all-forage and high-forage subsets, but not for low-forage subset. The current developed models can replace IPCC Tier 2 equations thus allowing LAC countries to estimate CH_4 more accurately in their inventories.

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2022.159128.

Ethical approval

Not applicable.

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CRediT authorship contribution statement

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Data availability

Data will be made available on request.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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