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Mohammed Benaouda, Cécile Martin, Xinran Li, Ermias Kebreab, Alexander Hristov, et al.. Evaluation of the performance of existing mathematical models predicting enteric methane emissions from ruminants: Animal categories and dietary mitigation strategies. *Animal Feed Science and Technology*, 2019, 255, pp.114207. 10.1016/j.anifeedsci.2019.114207 . hal-02569211

HAL Id: hal-02569211

<https://hal.inrae.fr/hal-02569211>

Submitted on 4 Sep 2024

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Article

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Benaouda, M., Martin, C., Li, X., Kebreab, E., Hristov, A. N., Yu, Z., Yáñez-Ruiz, D. R., Reynolds, C. K. ORCID: <https://orcid.org/0000-0002-4152-1190>, Crompton, L. A., Dijkstra, J., Bannink, A., Schwarm, A., Kreuzer, M., McGee, M., Lund, P., Hellwing, A. L. F., Weisbjerg, M. R., Moate, P. J., Bayat, A. R., Shingfield, K. J., Peiren, N. and Eugène, M. (2019) Evaluation of the performance of existing mathematical models predicting enteric methane emissions from ruminants: animal categories and dietary mitigation strategies. *Animal Feed Science and Technology*, 225. 114207. ISSN 0377-8401 doi: <https://doi.org/10.1016/j.anifeedsci.2019.114207> Available at <https://centaur.reading.ac.uk/84631/>

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To link to this article DOI: <http://dx.doi.org/10.1016/j.anifeedsci.2019.114207>

Publisher: Elsevier

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1 **Evaluation of the performance of existing mathematical models predicting enteric**
2 **methane emissions from ruminants: animal categories and dietary mitigation strategies**

3 Mohammed Benaouda ^{a,b}, Cécile Martin ^{a,b}, Xinran Li ^{a,b}, Ermias Kebreab ^c, Alexander N.
4 Hristov ^d, Zhongtang Yu ^e, David R. Yáñez-Ruiz ^f, Christopher K. Reynolds ^g, Les A. Crompton
5 ^g, Jan Dijkstra ^h, André Bannink ⁱ, Angela Schwarm ^{j,2}, Michael Kreuzer ^j, Mark McGee ^k, Peter
6 Lund ^l, Anne L. F. Hellwing ^l, Martin R. Weisbjerg ^l, Peter J. Moate ^m, Ali R. Bayat ⁿ, Kevin J.
7 Shingfield ^{†n}, Nico Peiren ^o and Maguy Eugène ^{a,b,1}.

8 ^aINRA, UMR1213 Herbivores, F-63122 Saint-Genès-Champanelle, France; ^bClermont
9 Université, VetAgro Sup, UMR1213 Herbivores, BP 10448, F-63000, Clermont-Ferrand,
10 France; ^cDepartment of Animal Science, University of California, Davis, Davis 95616, U.S.A.;
11 ^dDepartment of Animal Science, The Pennsylvania State University, University Park 16802,
12 U.S.A.; ^eDepartment of Animal Sciences, The Ohio State University, Columbus 43210, U.S.A.;
13 ^fEstacion Experimental del Zaidin, CSIC, Granada, Spain; ^gSchool of Agriculture, Policy, &
14 Development, University of Reading, Reading, RG6 6AR, UK; ^hAnimal Nutrition Group,
15 Wageningen University & Research, Wageningen, the Netherlands; ⁱWageningen Livestock
16 Research, Wageningen University & Research, Wageningen, The Netherlands; ^jETH Zurich,
17 Institute of Agricultural Sciences, 8092 Zurich, Switzerland; ^kTeagasc, Animal and Grassland
18 Research and Innovation Centre, Grange, Dunsany, Co. Meath, Ireland; ^lDepartment of Animal
19 Science, AU Foulum, Aarhus University, Blichers Allé 20, DK 8830 Tjele, Denmark;
20 ^mAgriculture Victoria, Ellinbank Centre, 1301 Hazeldean Road, Ellinbank, Victoria, 3820,
21 Australia; ⁿMilk Production, Production Systems, LUKE Natural Resources Institute Finland,
22 31600 Jokioinen, Finland; ^oAnimal Sciences Unit, Flanders research institute for agriculture,
23 fisheries and food, 9090 Melle, Belgium.

24 ¹**Corresponding author**

25 Maguy Eugène: maguy.eugene@inra.fr.

26 ²Present address: Department of Animal and Aquacultural Sciences, Norwegian University of
27 Life Sciences, PO Box 5003, 1432 Ås, Norway

28 **Abstract**

29 The objective of this study was to evaluate the performance of existing models predicting
30 enteric methane (CH₄) emissions, using a large database (3183 individual data from 103 *in vivo*
31 studies on dairy and beef cattle, sheep and goats fed diets from different countries). The impacts
32 of dietary strategies to reduce CH₄ emissions, and of diet quality (described by organic matter
33 digestibility (dOM) and neutral-detergent fiber digestibility (dNDF)) on model performance
34 were assessed by animal category. The models were first assessed based on the root mean
35 square prediction error (RMSPE) to standard deviation of observed values ratio (RSR) to
36 account for differences in data between models and then on the RMSPE. For dairy cattle, the
37 CH₄ (g/d) predicting model based on feeding level (dry matter intake (DMI)/body weight (BW)),
38 energy digestibility (dGE) and ether extract (EE) had the smallest RSR (0.66) for all diets, as
39 well as for the high-EE diets (RSR = 0.73). For mitigation strategies based on lowering NDF
40 or improving dOM, the same model (RSR = 0.48 to 0.60) and the model using DMI and neutral-
41 and acid-detergent fiber intakes (RSR = 0.53) had the smallest RSR, respectively. For diets with
42 high starch (STA), the model based on nitrogen, ADF and STA intake presented the smallest
43 RSR (0.84). For beef cattle, all evaluated models performed moderately compared with the
44 models of dairy cattle. The smallest RSR (0.83) was obtained using variables of energy intake,
45 BW, forage content and dietary fat, and also for the high-EE and the low-NDF diets (RSR =
46 0.84 to 0.86). The IPCC Tier 2 models performed better when dietary STA, dOM or dNDF
47 were high. For sheep and goats, the smallest RSR was observed from a model for sheep based
48 on dGE intake (RSR = 0.61). Both IPCC models had low predictive ability when dietary EE,
49 NDF, dOM and dNDF varied (RSR = 0.57 to 1.31 in dairy, and 0.65 to 1.24 in beef cattle). The
50 performance of models depends mostly on explanatory variables and not on the type of data

51 (individual vs. treatment means) used in their development or evaluation. Some empirical
52 models give satisfactory prediction error compared with the error associated with measurement
53 methods. For better prediction, models should include feed intake, digestibility and additional
54 information on dietary concentrations of EE and structural and nonstructural carbohydrates to
55 account for different dietary mitigating strategies.

56 **Keywords**

57 Model evaluation; methane emission; ruminant; dietary strategy

58 **Abbreviations**

59 ADF, acid-detergent fiber; ADFI, ADF intake; AU, Australia; BW, body weight; CCC,
60 concordance correlation coefficient; CH₄, enteric methane; CV, coefficient of variation; dGE,
61 digestibility of GE; DM, dry matter; DMI, DM intake; dNDF, digestibility of neutral-detergent
62 fiber; dOM, digestibility of organic matter; ECT, error in central tendency; ED, error due to the
63 disturbance; EE, ether extract; ER, error due to the regression; EUR, Europe; FA, fatty acids;
64 FPCM, fat and protein corrected milk; GE, gross energy; GEI, GE intake; GHG, greenhouse
65 gas; IPCC, Intergovernmental Panel on Climate Change; MSPE, mean square prediction error;
66 NDF, neutral-detergent fiber; NDFI, NDF intake; OM, organic matter; RMSPE, root MSPE;
67 RSR, RMSPE to standard deviation of observed values ratio; SF₆, Sulphur hexafluoride tracer;
68 STA, starch; US, United States of America; Y_m, percentage of GE converted into CH₄;

69 **1. Introduction**

70 Accurate estimation of enteric methane (CH₄) emissions from ruminants is important for
71 national greenhouse gas (GHG) inventories and for assessing dietary mitigating strategies. In
72 many countries, the IPCC (2006) Tier 1 or Tier 2 methodologies are used to report their national
73 inventories of GHG emissions. The IPCC Tier 2 model, although more detailed than Tier 1,
74 relies on gross energy intake (GEI) which can lead to inaccuracy in predicting CH₄ emissions
75 for diets of different nutrient composition (Ellis et al., 2010). The determination of CH₄

76 emissions from individual animals requires specialized equipment (Hammond et al., 2016) and
77 expensive methodologies (Kebreab et al., 2006). Many empirical models have been developed
78 for specific ruminant categories to estimate CH₄ emissions from dairy cattle (Charmley et al.,
79 2016; Niu et al., 2018), beef cattle (Ellis et al., 2009; Cottle and Eckard, 2018) and small
80 ruminants (Patra et al., 2016; Patra and Lalhriatpuii, 2016) or for all ruminants (Blaxter and
81 Clapperton, 1965; IPCC, 1997 and 2006; Sauvant et al., 2011; Ramin and Huhtanen, 2013).

82 Most prediction models are based on feed intake (dry matter intake (DMI) or GEI). However,
83 these models do not adequately account for the effect of other dietary factors such as lipid
84 supplementation (Bannink et al., 2006), neutral detergent fiber (NDF) content, organic matter
85 digestibility (dOM) (Archimède et al., 2011; Appuhamy et al., 2016), content of starch (STA)
86 and sugars (Hindrichsen et al., 2005) and the presence of plant secondary compounds
87 (Jayanegara et al., 2012). Consequently, alternative models that take into account feed
88 properties and animal characteristics to improve prediction of CH₄ emissions under different
89 nutritional mitigation strategies have been proposed. Some models can be applied across all
90 ruminant categories (Blaxter and Clapperton, 1965; IPCC, 2006; Ramin and Huhtanen, 2013;
91 Bell et al., 2016) whereas others are specific to one ruminant category (Charmley et al., 2016;
92 Escobar-Bahamondes et al., 2017a; Cottle and Eckard, 2018).

93 There is global interest in the use of nutrition and feeding management to decrease CH₄
94 emissions from ruminants (Knapp et al., 2014). Consequently, if the national inventory
95 calculations are based on empirical models, these should be assessed for their reliability under
96 different nutritional mitigation strategies and different production conditions. The objectives of
97 this study were to evaluate the performance of existing models using a large database of
98 individual records for specific 1) ruminant categories (dairy cattle, beef cattle, sheep or goats)
99 and 2) nutritional strategies that mitigate CH₄ emissions (lipid and STA supplementation, low
100 NDF content in the diet, or enhanced diet digestibility).

101 **2. Materials and methods**

102 *2.1. Database*

103 A database of 3183 individual observations from the GLOBAL NETWORK project
104 ([https://globalresearchalliance.org/research/livestock/collaborative-activities/global-research-](https://globalresearchalliance.org/research/livestock/collaborative-activities/global-research-project/)
105 [project/](https://globalresearchalliance.org/research/livestock/collaborative-activities/global-research-project/)) was used to evaluate the performance of models that predict CH₄ emissions from
106 ruminants. This individual database (Table 1) included 103 studies from three regions: Europe
107 (EUR; 2707 observations from 92 studies), United States of America (US; 198 observations
108 from 5 studies) and Australia (AU; 278 observations from 6 studies). Enteric CH₄ emissions
109 included in the present database were measured using respiration chambers (65% of data), SF₆
110 tracer technique (30%) and automated head chamber (GreenFeed™, C-Lock Inc., Rapid City,
111 SD, US; 5%), on different animal categories (dairy cattle, 67%; beef cattle, 18%; sheep, 13%;
112 goat, 2%), using various experimental designs (randomized block design (average adaptation
113 duration 47 days), latin square design (average adaptation duration 19 days), change-over or
114 switch-back design (average adaptation duration 15 days)).

115 *Data pre-processing*

116 Data pre-processing was performed, because the collected data were sometimes incomplete
117 (missing values or variables of interest), inconsistent (different names or units for the same
118 variable) and noisy (containing errors or outliers). We corrected the inconsistent data by using
119 the same name and unit across all studies. Outliers in the database were screened as described
120 by Niu et al. (2018). No data on gross energy content and chemical composition of the diets
121 were available for the AU dairy cattle data. All data on dietary composition for beef cattle,
122 sheep and goat subsets were from EUR. Finally, the dietary treatments were classified
123 according to the purpose of each study into four CH₄ mitigation strategies (A to D), as classified
124 by Martin et al., (2010) and Hristov et al., (2013). These were: (A) lipid supplementation (EE

125 content of the diet); (B) low fiber content in the diet (NDF content of the diet); (C) high STA
126 content in the diet, and (D) high-quality diet (in terms of dOM and dNDF).

127 **2.2. Selection of Models**

128 To select the models, we used web search online databases (Science Direct, Web of Science)
129 for articles written in English and published from 2000 to 2017 using the following key words:
130 “methane”, “*in vivo*”, “prediction”, “model” (or “equation”) and “ruminant” (or “cattle” or
131 “dairy” or “beef” or “sheep” or “goat”). Only models with predictor variables or required
132 information that were available in our database were selected (Table 2). Therefore, due to the
133 lack of information, the models of CH₄ emissions from ruminants fed plants rich of secondary
134 compounds were not evaluated. Some models were specific to one ruminant category (e.g.,
135 Charmley et al. (2016)), whereas others were applicable to more than one category. In addition
136 to the IPCC models, the models from Sauvant et al. (2011) were evaluated with data from all
137 ruminant categories. The models from Ramin and Huhtanen (2013) were evaluated with dairy
138 and beef cattle and sheep. The models containing variables associated with dietary lipid content
139 were used to evaluate their predictive ability for lipid supplementation mitigation strategy. The
140 models that take into account dietary NDF, dOM or dNDF were used to evaluate their ability
141 to predict CH₄ when ruminants are fed a high-quality diet (Low NDF content or high dOM and
142 dNDF). The models that use STA content or dietary concentrate content as variables, were
143 tested for their predictive ability when a large level of STA was used to reduce CH₄ emissions.
144 The published models were grouped based on the region of data origin (EUR, US or AU) and
145 the type of data used in their development (individual data or treatment means). All models
146 were used in their original version except one model from Nielsen et al. (2013) based on DMI,
147 EE and NDF contents, where we used the modified version of Appuhamy et al. (2016). Some
148 models are based on fatty acids (FA) instead of ether extract content, so the total FA content in
149 the diet was estimated using the adapted model of Giger-Reverdin et al. (2003):

150 $\%FA/EE = 100 - (32 - 5.86 \times EE + 0.261 \times EE^2 + 0.287 \times \text{forage})$

151 The unit of EE and forage proportion used in this equation is % DM.

152 The CH₄ unit used in the present evaluation is g/d; hence, when original equations used MJ/d,
153 a conversion factor (55.65 kJ per g of CH₄; Brouwer 1965) was used. When the equation was
154 reported in L/d, it was converted to g/d using the molar density of CH₄ (0.714 g/L).

155 *Choices of data for model evaluation*

156 Before model evaluation, data were checked to ensure there was no overlap between model
157 development and validation sets. Consequently, data originally used in model development by
158 the respective groups of researchers were excluded before evaluation of that particular model.
159 For example, the 154 observations used by Charmley et al. (2016) to develop their models were
160 removed before evaluating the performance of models from Charmley et al. (2016). For the
161 same reason, the models developed by Niu et al. (2018) were not tested, as these models were
162 derived from a large share of the database used in the present evaluation.

163 Next, we selected the data based on each model's specifications with respect to ruminant
164 category and CH₄ mitigation strategy. For instance, ruminant category-specific models were
165 evaluated only using the data from the respective ruminant category, whereas generic models
166 were evaluated first using the data from each ruminant category separately and then using the
167 data of all ruminant categories.

168 The evaluation of models by CH₄ mitigation strategies was carried out within each ruminant
169 category (dairy cattle, beef cattle, sheep and goats). Using the dietary content of EE, NDF and
170 STA values, the database was separated into two subsets for each strategy to assess, respectively,
171 the mitigation strategies of lipid supplementation, enhancement of diet quality by lowering
172 dietary fiber and the use of the high-STA diets. In addition, the performance of models was
173 assessed by variation in the diet quality (variations in dOM and in dNDF). The separation into
174 two subsets for lipid supplementation was set by mean of EE content. For the mitigation strategy

175 based on the use of STA, the two subsets were obtained from subtracting the standard deviation
176 from the mean of STA content. For NDF content in dairy cattle diets, the fixed threshold of 350
177 g/kg DM was used, due to the non-normal distribution of NDF data for this animal category.
178 Consequently, given the distribution of data the resulting thresholds were 39.3 g of EE/kg DM,
179 350 g of NDF/kg DM, and 101 g of STA/kg DM, for dairy cattle and 40 g of EE/kg DM, 338 g
180 of NDF/kg DM and 110 g of STA/kg DM for beef cattle. Within each strategy, the datasets
181 obtained were then qualified as low or high when dietary contents were lower or higher than
182 those thresholds, respectively. The existing models were originally developed from either
183 individual animal or treatment mean datasets. To test the effect of data type (individual vs.
184 means) on the performance of models, our individual database was transformed into a “means”
185 database by obtaining arithmetic means of the individual observations within the same
186 treatment and within each experiment. Four individual and four mean models with the smallest
187 RSR predicting CH₄ emissions from dairy cattle were evaluated using individual and mean
188 databases.

189 ***2.3. Criteria for model evaluation***

190 The CH₄ prediction models were evaluated using the following criteria. The prediction model
191 associated with the lowest root mean square prediction error (RMSPE) to standard deviation of
192 observed values ratio (RSR) and the lowest RMSPE is considered the best performing:

193 *Mean Square Prediction Error*

194 The mean square prediction error (MSPE) was calculated according to Bibby and Toutenburg
195 (1977):

$$196 \quad MSPE = \frac{1}{n} \sum_{i=1}^n (O_i - P_i)^2$$

197 Where n is the number of observations, O_i is the i^{th} observed value and P_i is the i^{th} predicted
 198 value. Usually, square root of the MSPE (RMSPE) is used to evaluate model prediction because
 199 it has the same unit as the observed values:

$$200 \quad RMSPE = \sqrt{\frac{1}{n} \sum_{i=1}^n (O_i - P_i)^2}$$

201 In the present research, RMSPE was also expressed as a percentage of mean observed CH₄
 202 emissions in order to compare models developed for different ruminant categories or CH₄
 203 mitigation strategies:

$$204 \quad RMSPE\% = \frac{\frac{1}{n} \sqrt{\sum_{i=1}^n (O_i - P_i)^2}}{\frac{1}{n} \sum_{i=1}^n O_i} \times 100$$

205
 206 A smaller value of RMSPE and RMSPE% indicates better performance of model prediction.
 207 The MSPE value is determined by three types of error: error in central tendency (ECT: measure
 208 of precision) or mean bias, error due the regression (ER; measure of accuracy) or slope bias,
 209 and error due to the disturbance (ED) or random error (Bibby and Toutenburg, 1977). These
 210 terms were calculated as:

$$211 \quad ECT = (\bar{P} - \bar{O})^2$$

$$212 \quad ER = (S_p - r \times S_o)^2$$

$$213 \quad ED = (1 - r^2) \times S_o^2$$

214 Where \bar{P} and \bar{O} are the predicted and observed mean values, S_p is the SD of predicted values,
 215 S_o is the SD of observed values, and r is the Pearson correlation coefficient.

216 *Concordance Correlation Coefficient*

217 The concordance correlation coefficient (CCC; Lin, 1989) was calculated as the product of r
 218 and a bias correction factor (C_b , measure of accuracy):

219
$$CCC = r \times C_b$$

220 where C_b indicates how far the best fit line deviates from the concordance or unity line of the
221 observed values versus predicted values plot. The C_b ranges from 0 to 1 with greater values
222 indicating less deviation from the concordance line. Large value of CCC indicates better
223 performance of model prediction.

224 *RMSPE to standard deviation of observed values ratio (RSR)*

225 When different data are used to compare the performance of models, the ratio of RMSPE and
226 SD, should be used because it takes into account the data variability (Moriassi et al., 2007).

227
$$RSR = RMSPE/SD \text{ of observed values of } CH_4$$

228 In this study, the performance of models with different numbers of data was ranked first by
229 RSR and then by RMSPE%.

230 **3. Results**

231 *3.1. Descriptive statistics of data*

232 The descriptive statistics of our database by ruminant category are presented in Table 1. Overall,
233 the database included a wide range in animal body weight, feed intake, diet composition, and
234 CH_4 emission. The dairy cattle included in the database produced, on average, 389 g of CH_4 /d
235 ($n = 2147$), 20.5 g of CH_4 /kg DMI ($n = 1975$) and 14.3 g of CH_4 /kg of fat and protein corrected
236 milk (FPCM; $n = 1733$). Enteric CH_4 emissions expressed as a percentage of GEI (Ym) was
237 6.12%. Only 14.5, 0 and 11.5% of the EUR, US and AU dairy diets were 100% forage-based,
238 respectively. On average, EUR, US and AU dairy cattle were fed diets with 37.4, 48.9 and 37.8
239 g of EE/kg DM, respectively.

240 Beef cattle produced 202 g CH_4 /d on average and the Ym was 6.99%. The forage proportion
241 was 0.70 of the diet resulting in an average DMI of 8.8 kg/d. Some high-grain diets (concentrate
242 proportion > 0.85) were included (6% of data). Most common ingredients in beef diets were
243 corn, wheat and grass silage (present in 60% of the observations) and cereal straw (32% of the

244 observations). The CH₄ emissions and Y_m value were 19.3 g/d and 5.45% for sheep, and 14.2
245 g/d and 4.20% for goats, respectively. The average proportion of forage in the diet was 0.76 for
246 sheep and 0.36 for goats. The contents of EE, NDF and dOM in diets for sheep and goats were
247 31 vs. 29 g/kg DM, 504 vs. 380 g/kg DM and 645 vs. 757g/kg DM, respectively.

248 **3.2. Performance of the models**

249 *3.2.1. Dairy Cattle*

250 Of the 40 existing equations evaluated using the dairy cattle data, only the 11 models with the
251 smallest RSR ($RSR \leq 1$) as well as the IPCC_1997 and IPCC_2006 Tier 2 models (used as
252 reference) are listed in Table 3. Overall, equations based on feed intake (DMI, GEI and feeding
253 level (DMI/BW)) had the smallest RSR of predicting CH₄ emissions from dairy cattle. All
254 models revealed a positive relationship between feed intake and daily CH₄ emissions. Two
255 models (Ramin_1 and Ramin_2) from Ramin and Huhtanen (2013) had low RSR (0.66 and
256 0.76, respectively) and RMSPE% (15.6 and 21.2%), and more than 90% of the prediction error
257 due to random error. These two models also showed small mean bias (0.70 and 6.30%,
258 respectively) with CCC values of 0.75 and 0.57, for Ramin_1 and Ramin_2 respectively.
259 Mills_3, a nonlinear equation from Mills et al. (2003; see Table 2), resulted in the third ranked
260 RSR (0.78), and in 21.8% of RMSPE%. A similar result was obtained by IPCC_1997, which
261 had the fourth ranked RSR (0.79) and the CCC value of 0.68. The mean bias obtained from the
262 prediction of IPCC_1997 was 0.10%, which was smaller than the mean bias observed in Mills_3
263 (11.7%), but the slope bias was greater (12.8 vs. 1.5%, respectively). Ellis et al. (2007) proposed
264 models with different levels of complexity for dairy cattle and one of those models (Ellis_3),
265 presented the fifth ranked RSR (RSR = 0.80, RMSPE% = 22.7% and CCC = 0.60).
266 Decomposition of the error indicated an 11.5% mean bias. This model included DMI, NDF
267 intake (NDFI) and acid detergent fiber intake (ADFI) and had smaller RSR than the three simple
268 models that only included one of the three predictors (models not shown in Table 3; RSR of

269 Ellis_3 vs. Ellis_1, Ellis_2 and Ellis_4 was 0.80 vs. 0.87, 1.06 and 1.28, respectively). In
270 addition, Ellis' simple models produced a larger mean bias than the complex model. The models
271 of Charmley et al. (2016) for dairy cattle based on GEI or DMI produced similar RSR (0.81),
272 which was similar to the RSR produced by IPCC_1997. The decomposition of RMSPE made
273 by the models of Charmley et al. (2016) showed that at least 81.0% of the error was due to
274 random effects. The linear models by Mills et al. (2003; Mills_2 and Mills_1) had the 9th and
275 10th ranked RSR and CCC values of 0.62 and 0.68, respectively. The Mills_2 model was
276 associated with the second smallest RMSPE% (17.8%) among all models, however it was
277 ranked 9th considering its greater RSR, due to the small variability of observed CH₄ values. The
278 11th and 12th ranked models in Table 3 are complex models from Ramin and Huhtanen (2013)
279 and Sauvant et al. (2011). They represent the only models including dOM in the diet. The
280 updated Tier 2 model of IPCC (IPCC_2006) relating GEI and CH₄ outputs was the last ranked
281 model with a RSR of 0.87.

282 The two subsets of low- and high-EE (under and over 39.3 g of EE/kg DM, respectively) diets
283 in the dairy cow data were created to enable assessment of the ability of the models to predict
284 difference in emissions caused by differences in concentrations of dietary lipids. These two data
285 subsets had mean dietary EE contents of 30.4 vs. 51.7 g/kg DM, respectively, and mean CH₄
286 yields and intensities of 20.9 vs. 18.8 g/kg DMI, and 15.7 vs. 12.4 g/kg of milk, respectively
287 (see Appendix A). A numerical difference in Y_m was also observed (6.42 vs. 5.68%, for the
288 low- vs. the high-EE subsets, respectively). Models that specifically included lipid content as
289 one of the variables showed the smallest RSR and RMSPE among all models tested with the
290 high-EE subset (Figure 1). The models Ramin_1 and Ramin_3 maintained their RSR and
291 RMSPE% (RSR = 0.73 and 0.83, respectively, and RMSPE% = 16.1 and 20.3%, respectively)
292 in the high-EE diets compared with their RSR and RMSPE% using all dairy diets, whereas the
293 RSR of IPCC_1997 increased from 0.79 to 1.05. The Moraes model showed large RSR (0.95),

294 with considerable mean bias (27.8%). All models gave larger CCC values using all dairy diets
295 than when only the high-EE diets were used.

296 The subsets of low-NDF and high-NDF diets (under and over 350 g NDF/kg DM, respectively)
297 of dairy cattle had mean NDF contents of 285 and 433 g/kg DM, respectively (Appendix B).
298 Other factors varied between the low- and the high-NDF subsets as CH₄ emissions (405 vs. 385
299 g/d), CH₄ yield (18.6 vs. 22.5 g/kg DMI), CH₄ intensity (12.9 vs. 16.2 g/kg of milk), Y_m (5.64
300 vs. 6.79%), DMI (22.2 vs. 17.4 kg/d) and GEI (409 vs. 331 MJ/d), respectively. Using the low-
301 NDF subset, Ramin_1 resulted in RSR of 0.48, RMSPE% of 10.1% and a CCC of 0.88. Using
302 the high-NDF subset, Ellis_3 had the smallest RSR (0.54) and RMSPE% (17.6%) (Figure 2).
303 Based on the obtained RSR and RMSPE%, the IPCC Tier 2 models performed better with the
304 high-NDF (RSR = 0.68 and 0.57, RMSPE% = 16.9 and 14.3%, for IPCC_1997 and IPCC_2006,
305 respectively) than with the low-NDF diets (RSR = 1.06 and 1.31, RMSPE% = 23.7 and 29.2%,
306 for IPCC_1997 and IPCC_2006, respectively). The existing models, except Ramin_1, had
307 smaller RSR at high NDF level in the diet (from 0.54 to 0.63) than at low NDF level (RSR >
308 0.95).

309 The two subsets representing low- and high-STA diets (under and over 101 g of STA/kg DM)
310 for dairy cattle are presented in Appendix C. The low- and the high-STA diets had average STA
311 concentrations of 56 and 215 g/kg DM of STA respectively. The CH₄ emissions, yields and
312 intensities in the low- and the high-STA subsets were 364 vs. 415 g/d, 22.7 vs. 20.4 g/kg DMI
313 and 17.1 vs. 14.1 g/kg of milk, respectively. The feed intakes (on DM basis) in the low- and the
314 high-STA subsets were 16.1 vs. 20.8 kg/d and the Y_m values were 6.73 vs. 6.17%, respectively.
315 In general, all models had smaller RMSPE% for the low-STA diets (RMSPE%: 11.9 to 16.4%)
316 than for the high-STA diets (RMSPE%: 18.2 to 26.1%). However, the RMSPE decomposition
317 revealed greater mean bias and smaller slope bias in the low- than the high-STA subsets (Figure
318 3). The ranking of models did not change between the low- and the high-STA subsets with the

319 exception of IPCC_2006, which had the smallest RSR (0.80) for the low-STA diets but the
320 greatest RSR (1.04) for the high-STA diets.

321 The two subsets representing the low- and the high-quality diets using either dOM (under and
322 over 720 g/kg DM, respectively) or dNDF (under and over 600 g/kg DM) are described in
323 Appendices D and E, respectively. At the low- and the high-dOM (mean: 679 and 767 g/kg DM,
324 respectively), Ellis_3 and Ramin_1 models had the smallest RSR and the greatest CCC for
325 predicting CH₄ emissions from dairy cattle (Figure 4; Table 4). At the low dNDF, the same two
326 models showed small RSR and RMSPE%, and greatest CCC (RSR = 0.67 and 0.78, RMSPE%
327 = 19.9 and 16.7%, CCC = 0.71 and 0.70, respectively). Ramin_1 had a smaller RMSPE%
328 compared with Ellis_3, but the adjustment of the RMSPE by the SD of observed values of CH₄
329 made Ellis_3 the highest ranked model. The evaluated models in both subsets (the low- and the
330 high-dNDF diets) generally showed acceptable RSR and RMSPE% and were more accurate for
331 the high-dNDF diets. All RSR obtained from the high-dNDF subset were smaller than those
332 obtained from the low-dNDF subset. The RMSPE% obtained by the best five models in the
333 high-dNDF subset had a small range (13.3 to 18.4%). Ellis_3 showed good predictive ability in
334 both subsets considering its small RSR (0.67 and 0.59 in the low- and the high-dNDF subsets,
335 respectively), RMSPE% < 20% and almost null mean and slope biases (Figure 5). Ramin_3
336 gave the smallest RSR for the high-dNDF subset, resulting in similar RSR with Ellis_3 (0.59)
337 but smaller RMSPE%. Mills_2 had 13.5% of RMSPE% and the third smallest RSR although it
338 had a 24.6% mean bias. The IPCC_2006 was associated with the fourth RSR for the high-dNDF
339 diets.

340 3.2.2. *Beef cattle*

341 For beef cattle, 21 models were evaluated using the beef cattle data. Table 5 presents the 10
342 models with the smallest RSR ($RSR \leq 1$) to predict CH₄ emissions from beef cattle. The model
343 from Escobar-Bahamondes et al. (2017a) resulted in the smallest RSR (0.83) and RMSPE%

344 (27.2%) among all models, with 93.6% of the RMSPE due to random errors and CCC value of
345 0.40. Among the feed intake-based models, Ramin_2, Yan_1, Yan_2 and IPCC_2006 had
346 similar results. The RSR of these models ranged from 0.84 to 0.87 and RMSPE% from 32.7 to
347 34.0%. The remaining models presented in Table 5 had low predictive ability considering the
348 large RMSPE% (> 33%) and the large mean bias (from 17.5 to 22.1%).

349 The descriptions of the low- and the high-EE subsets (under and over 40 g of EE/kg DM,
350 respectively) of beef cattle are shown in Appendix F. The average of EE content in each subset
351 was 25.3 and 58.4 g/kg DM, respectively. The emissions and yields of CH₄ in the low- and the
352 high-EE diets were 252 vs. 188 g/d, and 26.9 vs. 23.4, respectively. When models were
353 evaluated using each subset separately (Table 6), the ranking was the same, with the Escobar-
354 Bahamondes et al. (2017a) model having the smallest RSR followed by the models of Grainger
355 and Beauchemin (2011), IPCC_2006 and IPCC_1997. The RSR values of all models were
356 slightly smaller at the low- than at the high-EE diets. Large prediction errors were observed for
357 all models at high EE content (RMSPE% > 33%). The predictions by Tier 2 models of IPCC
358 are associated with large RMSPE% (from 33 to 37%) and large mean biases (from 31 to 45%)
359 in the high-EE subset. The CCC of all predicting models were smaller for the high-EE than for
360 the low-EE diets. Similar to lipid supplementation strategy, the models were evaluated when
361 low- or high-NDF diets were fed to beef cattle (under and over 338 g of NDF/kg DM,
362 respectively). In both the low- and the high-NDF diets (Appendix G), again the Escobar-
363 Bahamondes et al. (2017a) model showed the smallest RSR in the prediction of CH₄ emissions
364 from beef cattle. The RSR of this model was slightly smaller at high NDF than at low NDF
365 content (0.84 vs. 0.86, respectively). The IPCC_2006 and IPCC_1997 models were associated
366 with large RSR (from 0.88 to 0.98), RMSPE% (from 31 to 40.5%) and mean biases from 3.1
367 to 31.6%. When differences in dietary STA were taken into account (threshold = 110 g of
368 STA/kg DM; see Appendix H), the IPCC models presented the smallest RSR among all models,

369 although their prediction of CH₄ emissions was associated with large RSR (> 1) and RMSPE%
370 (> 32%); and small CCC (0.38). Diet composition and CH₄ emissions in each data subset of the
371 low- and the high-dOM or dNDF (under and over 745 and 600 g/kg DM, for dOM and dNDF
372 respectively) for the beef data are shown in Appendices I and J, respectively. The smallest RSR
373 was obtained by Ellis_5 model at the low-dOM and by IPCC_1997 at the high-dOM diets (RSR
374 = 0.71). However, using dNDF as an indicator of diet quality, the smallest RSR was obtained
375 by IPCC_2006 with both, the low- and the high-dNDF diets (Table 6).

376 *3.2.3. Small ruminants*

377 The six evaluated models with RSR < 1 using sheep data, ranked by RSR, are shown in Table
378 7. The Patra_3 model had the smallest RSR (0.61) with the RMSPE% being 19.2%, most of
379 which was due to random sources. The correlation coefficient (*r*) between observed and
380 predicted values by Patra_3 was 0.81, resulting in the largest CCC (0.75) in Table 7. The
381 IPCC_1997 and Patra_2 models were both based on GEI and were ranked 2nd and 3rd,
382 respectively. The RSR and RMSPE% obtained from IPCC_1997 and Patra_2 were similar (0.77
383 vs. 0.78; RMSPE% = 26.8 and 27.2%, respectively). In comparison to the IPCC_1997 and
384 Patra_2 models, the other models were all associated with greater RSR (0.85 on average) and
385 greater RMSPE% (around 30%). IPCC_1997 had greater precision and accuracy in predicting
386 CH₄ than IPCC_2006.

387 The evaluated models were less accurate at predicting CH₄ emissions for goats than they were
388 for sheep (Table 8). Three models from Patra and Lalhriatpuii (2016) resulted in large RSR
389 (from 0.86 to 0.98) and large RMSPE% (from 38 to 43%). The model from FAO reports (2010)
390 based on digestibility of dry matter was associated with a large RSR (1.22) and RMSPE%
391 (65.4%).

392 *3.2.4. Individual animal data vs. treatment means models*

393 Results of the comparison between models developed from individual records or treatment
394 means are shown in Table 9. The four models with the smallest RSR values based on individual
395 records in dairy cattle (all diets) were IPCC_1997, Charmley_2, Charmley_1, and IPCC_2006,
396 and the four models with the smallest RSR values based on treatment mean records were
397 Ramin_1, Ramin_2, Ellis_3, and Sauvant_1. The range in values of RSMPE% for individual
398 record models was smaller than that for mean record models (21.2 to 23.4% vs. 15.6 to 27.4%,
399 respectively). When both types of models (individual and treatment means) were evaluated
400 using the ‘treatment means’ database, the RMPSE% of individual and means models varied
401 from 16.9 to 18.7% and from 13.7 to 20.2%, respectively. Moreover, the values of RMSPE%
402 for each individual record and mean record model were decreased when evaluated using the
403 mean database compared with when evaluated using the individual database.

404 The SD of the observed values of CH₄ emissions in the ‘treatment means’ database was smaller
405 than that determined in the individual record database. In general, the ranking of the means
406 models was higher than that of individual record models when evaluated either by the individual
407 or ‘treatment means’ databases.

408 **4. Discussion**

409 In the current research, we aimed to identify the models that had the smallest prediction error
410 of CH₄ emissions and fitted our data, based on the smallest RSR and RMSPE%. We evaluated
411 a large number of published models to estimate CH₄ emissions for different ruminant categories
412 under diverse dietary regimes. The database generated by the GLOBAL NETWORK project
413 comprised > 3000 individual data from 103 studies and is the largest ever used in such model
414 evaluation. Previous studies have evaluated models for a single ruminant category (e.g., either
415 dairy cattle, beef cattle or feedlot cattle; Kebreab et al., 2008; Ellis et al., 2010; Escobar-
416 Bahamondes et al., 2017b) or models based on regional data obtained from the scientific
417 literature and based on treatment means (Appuhamy et al., 2016). This is the first evaluation of

418 models using a large database based on data from individual animals of all major livestock
419 species and breeds and the data were from experiments that have been conducted in various
420 countries in which diverse nutritional strategies to mitigate CH₄ emissions have been tested.
421 The domain of application of each model has been respected and the performance obtained
422 reflects the goodness of fit between the CH₄ predictions and CH₄ observed values in our
423 database. It should be pointed out that some dietary variables used by the evaluated model were
424 not measured in all included studies, therefore the models were evaluated against different
425 numbers of observations. In this study, we present the results of evaluations using maximal data
426 for each model and chose the statistical parameter “RSR” to compare models evaluated using
427 different datasets.

428 Some of the selected models are specific to certain ruminant categories, whereas others are
429 developed to estimate CH₄ emissions in different ruminant categories (IPCC, 1997 and 2006;
430 Sauvant et al., 2011; Ramin and Huhtanen, 2013). At the moment, although the IPCC Tier 2
431 models are primarily used to provide estimates of CH₄ emissions in national inventories of CH₄
432 emissions, their adequacy for dairy cattle (Appuhamy et al., 2016; Niu et al., 2018), as well as
433 for feedlot and beef cattle (Kebreab et al., 2008), and for small ruminants (Patra et al., 2016;
434 Patra and Lalhriatpuii, 2016) has been debated. In this research, we have compared the accuracy
435 of the IPCC Tier 2 models with those of other models from the scientific literature using data
436 for different nutritional strategies for CH₄ mitigation, as well as different ruminant categories.

437 *4.1. Dairy cattle*

438 The smallest error of prediction of CH₄ emissions from dairy cattle (by the smallest RSR and
439 RMSPE%) were obtained from the models developed in Ramin and Huhtanen (2013), Mills et
440 al. (2003), IPCC (1997) and Charmley et al. (2016). In general, they all use feed intake (DMI,
441 GEI or feeding level (DMI/BW)) as a predictor variable. This is in agreement with feed intake
442 being the key factor driving CH₄ emissions (Reynolds et al., 2011; Hristov et al., 2013; Niu et

443 al., 2018). Moreover, the DMI can explain at least 70% of variation in CH₄ emissions from
444 cattle (Ricci et al., 2013) through a positive linear relationship between DMI and the daily CH₄
445 emissions rate (g/d), using the slope to reflect the changes in CH₄ with DMI or the CH₄ yield
446 (g CH₄/kg DMI) with or without intercept (Dijkstra et al., 2011; Charmley et al., 2016).
447 However, Ramin_2 and Mills_3 performed better than other DMI-based models since it
448 included a curvilinear effect of DMI at large feed intake (Figure 6). The curvilinear effect may
449 be due to the high passage rate of solid matter out of the rumen (Knapp et al., 2014) and the
450 effect of a high proportion of concentrate which are hallmarks of diets associated with large
451 feed intake (Rotz et al., 2011). These two models also captured the effect of the shift in
452 fermentation pattern from more acetogenic to more propiogenic at increased DMI (Robinson et
453 al., 1986), especially for diets containing a large fraction of rapidly fermentable carbohydrates
454 by the indirect effect of pH on volatile fatty acids (Bannink et al., 2008). Janssen (2010)
455 discussed the negative effect of a large concentration of dissolved H₂ in the rumen on the CH₄
456 formation, especially in animals having a large intake of readily fermentable feed. However,
457 Ramin_2 resulted in smaller CCC than Mills_3 due to its under-prediction of CH₄ emissions
458 when emissions are greater than 600 g/d.

459 The overall smallest RSR and RMSPE, and the largest CCC and r were obtained from the
460 prediction made by the model Ramin_1. This performance can be explained by the inclusion of
461 three factors that affect ruminal CH₄ production: the feeding level (DMI/BW), energy
462 digestibility (dGE) and dietary lipid (EE) content. The importance of dGE as a key factor to
463 estimate CH₄ emissions has been long known (Blaxter and Clapperton, 1965). Other studies
464 have suggested that the use of dOM instead of energy digestibility to better predict CH₄
465 emissions from ruminants (Bell et al., 2016) because CH₄ is produced in the rumen by the
466 fermentation of OM (Sauvant et al., 2011). However, in the present evaluation, two models

467 include dOM (e.g., Ramin_3 and Sauvant_1) as a predictor, but they showed less precision and
468 accuracy than the model of Ramin_1 which is based on dGE.

469 In agreement with Niu et al. (2018), the Ym value of 6% of GEI being converted into CH₄ and
470 introduced in IPCC_1997 model, provided a more accurate prediction for dairy cattle across
471 regions than the Ym of 6.5% introduced in IPCC_2006 model. Kebreab et al. (2008) and
472 Appuhamy et al. (2016) pointed out that the Tier 2 model of the IPCC (2006) could over-
473 estimate CH₄ emissions in dairy cattle. The average Ym for dairy cattle in our database was
474 6.12%, which was closer to the IPCC_1997 value. More complex models based on Tier 3
475 methodology indicate that a Ym value of 6% is more realistic than a 6.5% (Bannink et al., 2011).
476 Both IPCC models are based on GEI only and do not capture the effect of changes in the
477 composition of the diet and therefore show a limited ability to estimate the difference in CH₄
478 emissions under different nutritional strategies (Ellis et al., 2010). Also, the present results
479 support this argument when the IPCC models were challenged against data from diets with
480 different concentrations of lipid, STA or digestible DM.

481 *Dietary lipid content*

482 The negative effect of high dietary EE concentration on the absolute CH₄ emissions (g/d) did
483 not become apparent from the data analysis because of the concomitantly greater feed intake in
484 the high- than in the low-EE subset (22.7 vs. 18.2 kg of DM/d, respectively). The daily CH₄
485 emissions are determined primarily by the amount of feed intake and, for this reason, the effect
486 of lipid supplementation is better assessed based on CH₄ yield. On this basis, the CH₄ yield for
487 the low- and the high-EE diets were 20.9 and 18.8 g/kg of DMI. In addition, a numerical effect
488 of EE on Ym was observed, with Ym about 12.5% smaller in the high- than in the low-EE
489 subsets (Ym = 5.68 vs. 6.42%). Moreover, the average of fiber intake (NDF intake, g/d) was
490 larger in the high-EE than in the low-EE subsets, which likely counterbalanced the effect of
491 lipid supplementation. Dietary lipids have been reported to reduce CH₄ emissions (Beauchemin

492 et al., 2008; Moate et al., 2011). Some authors reported that lipid sources (Knapp et al., 2014)
493 or fatty acids profile (Giger-Reverdin et al., 2003) have an effect as well, but this was not a
494 major source of variation based on the meta-analysis made by Beauchemin et al. (2008). In the
495 current research, the results related to lipid supplementation strategy are in agreement with the
496 results reported by Beauchemin et al. (2008), Martin et al. (2010) and Moate et al. (2011) who
497 showed that the addition of 10 g EE/kg DM led to 5.6% and 3.8% and 3.5% lower CH₄ yield
498 (g/kg DM), respectively. The negative effect of dietary lipids on daily CH₄ emissions (g/d) was
499 also reported in the meta-analysis of Eugène et al. (2008), where the average EE contents in the
500 low- and the high-EE subsets were 25 and 64 g/kg DM, respectively. However, that effect was
501 due to the lower DMI associated with the high dietary lipid content. The Ramin_1 model
502 includes both DMI and dietary lipid content (EE), and this may explain the small prediction
503 error (RSR and RMSPE %) of Ramin_1 with both the global dairy dataset and with the high-
504 EE subset. Some models from Grainger and Beauchemin (2011) and Nielsen et al. (2013)
505 performed well with the low-EE dataset but not the high-EE dataset. The model by Nielsen et
506 al. (2013) uses total fatty acid content instead of EE content. In the current research we
507 estimated in total fatty acid content from EE content using an equation from Giger-Reverdin et
508 al. (2003), and this may have introduced error and hence lower prediction performance by these
509 models.

510 The IPCC_1997 and IPCC_2006 models had small RSR (0.78 and 0.80, respectively), small
511 RMSPE% (17.1 and 17.6%, respectively) and large CCC (0.71) in the low-EE subset but large
512 RSR and RMSPE% and small CCC in the high-EE subset (RSR > 1, RMSPE% > 25% and
513 CCC < 0.50). Cows fed the low-EE diets (EE < 39.3 g/kg DM) had a Y_m value of 6.42% in our
514 database (n = 685 observations), which is close to the value of 6.5% adopted in IPCC (2006).
515 On the contrary, the Y_m of the high-EE diets was 5.68% (n = 490 observations) which is
516 substantially smaller than the value of 6% adopted in the IPCC_1997 model.

517 *Dietary NDF content*

518 When dairy cattle were fed high-quality diets (assessed by dOM or dNDF) or low-NDF diets,
519 the Ellis_3 model based on DMI, NDFI and ADFI, outperformed Ramin_1 by the smaller RSR,
520 which is based on DMI, dGE and EE. This result indicates the importance of including variables
521 associated with structural carbohydrates if the model is to predict the effect of NDF content on
522 CH₄ emissions from cattle. However, this effect may not depend only on structural carbohydrate,
523 as it can be often confounded by effects of DMI and the negative effect of dietary lipids on
524 dNDF, and the ratio of structural/non-structural carbohydrates in the diet (Moe and Tyrrell,
525 1979). Ramin_1 had a particularly good predictive ability for CH₄ emissions from dairy cattle
526 fed low NDF content diets indicated by a RMSPE of only 10.1% and CCC of 0.88. Both IPCC
527 models predicted CH₄ emissions for the high-NFD diets better than for the low-NDF diets.

528 *Dietary starch content*

529 The models were also assessed for predicting CH₄ emissions from dairy cow diets differing in
530 STA content, which mainly originated from either cereals or silages (corn or barley). To split
531 the database into the low- and the high-STA subsets, we chose to use dietary STA content as a
532 criterion and not the dietary concentrate content. Consequently, STA from the inclusion of
533 cereal in the diet, but also from corn or barley silages, which are largely present in the database,
534 were included. When substantial amounts of STA is fed to dairy cattle, it is more appropriate
535 to include information about feed composition or digestibility in the model as in Mills_2 and
536 Ramin_3 models, next to the feed intake. The Sauvart_1 model contains concentrate proportion
537 in the diet as a variable and its RSR was superior to 1 (not shown in Table 4) in predicting CH₄
538 emissions from cattle fed the high-STA diets in the present work. We surmise the proportion of
539 concentrate in the diet is not precise enough to explain variation in CH₄ emissions, and the
540 prediction models should introduce STA content. In addition, at the same content of STA in the
541 diet, the type of grain fed to dairy cattle has been reported to impact the CH₄ emissions (Moate

542 et al., 2017). However, more studies are required with direct comparisons between types of
543 starch. It is known that information about contents of dietary carbohydrate fractions (cellulose,
544 hemicellulose, lignin, STA and sugars) is useful to predict variation in CH₄ emissions (Moe and
545 Tyrrell, 1979; Hindrichsen et al., 2005; Ellis et al. 2009). However, because of the unavailability
546 of data on cellulose, hemicellulose, lignin and sugars in our database, these models could not
547 be evaluated. The IPCC_1997 and IPCC_2006 models, based on GEI, resulted in 20 to 22% of
548 RSMPE% for the high-STA diets. This can be explained by the capacity of GEI to capture STA
549 in the diet.

550 *Diet quality*

551 Feeding diets of high quality (i.e. digestibility) has been reported to reduce CH₄ intensity (g/kg
552 of milk) by increasing milk production per cow, diluting the amount of feed required per unit
553 of milk and changing rumen fermentation conditions (Knapp et al., 2014). The quality of diets
554 is partially determined by the cell-wall content and its digestibility (Jung and Allen, 1995).
555 However, at similar dietary NDF content, diet quality can still vary considerably (Broderick et
556 al., 2002), affecting feed intake, animal performance and CH₄ emissions, yield and intensity. In
557 the present evaluation, diet quality was assessed using dOM and dNDF of the diet. Under the
558 variation of both diet quality factors (dOM and dNDF), Ellis_3 and Ramin_1 showed the
559 smallest RSR. Only one of the two IPCC models had good predictions of CH₄ emissions with
560 small RSR and RMSPE for the high-quality diets depending on the criterion for diet quality
561 (the IPCC_1997 model for the high-dOM subset and the IPCC_2006 model for the high-dNDF
562 subset). In our database, dOM was affected by NDF, STA and EE contents in the diet. The
563 Ramin_3 model contains predictors that can account for effects associated with diet quality,
564 and it successfully reduced prediction error to 13%. A similar model, but expanded using more
565 parameters related to diet quality (i.e. dNDF), may be useful to better predict CH₄ emission.

566 The current research has mostly focused on predictive equations based on major nutrient
567 components in diets. Recently, research has shown that the inclusion of a small amount of 3-
568 nitrooxypropanol in the diet of cattle can result in a substantial, sustained reduction in CH₄
569 emissions (Hristov et al. 2015). We consider that if in the near future, 3-nitrooxypropanol is
570 registered for use in ruminants, predictive models that include 3-nitrooxypropanol as a predictor
571 will need to be developed.

572 *4.2.Beef cattle*

573 Models evaluated in the beef category were associated with considerable prediction error
574 (RMSPE > 34%). This suggests new equations need to be developed for beef cattle. Given that
575 all beef data in our study were from EUR, the effort of developing and updating equations
576 should be focused on including an evaluation for this specific region as well. Furthermore,
577 globally, the largest beef cattle herds are outside Europe and effort should also be directed
578 towards the development of improved predictive equations suited to these regions. The smallest
579 prediction error (considering RSR and RMSPE) with our beef data was obtained using the
580 model from Escobar-Bahamondes et al. (2017a). However, the CCC associated with this model
581 was not the largest among the evaluated models for beef cattle. Originally, the Escobar-
582 Bahamondes et al. (2017a) model was developed using data from both high-forage and high-
583 grain diets and it had a RMSPE% of 12.1% of the observed mean CH₄ emissions which was
584 much smaller than the RMSPE% of 27.2% obtained in the present evaluation. However,
585 Escobar-Bahamondes et al. (2017a) applied a cross-validation methodology using the same data
586 they used for the model development which may partly explain this observation. The DMI-
587 based model (Ramin_2) was less accurate for beef cattle than for dairy cattle, despite the fact
588 that it was developed from a general database including data from both dairy and beef cattle, as
589 well as sheep.

590 Similar to the dairy cattle category, there was not a single model that predicted CH₄ emissions
591 with small RSR and RMSPE in all nutritional mitigation strategies for beef cattle. The low
592 performance of models tested for the individual nutritional mitigation strategies may be because
593 all beef data were from EUR whereas the models were developed using data from US (Ellis et
594 al., 2007 and 2009; Grainger and Beauchemin, 2011). The CH₄ emissions (g/d) from beef cattle
595 fed diets with high EE content (average EE = 58.4 g/kg DM) was 25% smaller than CH₄
596 emissions from beef cattle fed the low-EE diets (average EE = 25.3 g/kg DM). Among all
597 models evaluated for this ruminant category, the model from Escobar-Bahamondes et al. (2017a)
598 achieved the most accurate prediction of CH₄ emissions from lipid supplemented diets, and
599 diets with different contents of NDF. This is in agreement with the results for dairy cattle where
600 complex models based on feed intake, digestibility and diet composition were also most
601 appropriate to predict CH₄ emissions under different nutritional conditions. The model of
602 Escobar-Bahamondes et al. (2017a) lacks a variable for digestibility (of energy, OM or NDF),
603 which probably explains its large RSR and RMSPE, and its small CCC compared with the
604 model Ramin_1 for dairy cattle.

605 *4.3. Small ruminants*

606 Few specific models for small ruminants were found in the scientific literature. In addition to
607 IPCC and global models (Sauvant et al., 2011; Ramin and Huhtanen, 2013), the equations
608 evaluated were obtained from Patra et al. (2016) and Patra and Lalhriatpuii (2016). For sheep,
609 the smallest prediction errors based on the values of RSR and RMSPE were obtained from
610 Patra_3, based on digestible energy intake (DEI, MJ/d). The Patra_3 model was also associated
611 with the largest CCC and largest correlation (r) between observed and predicted values. This is
612 probably because it considered the relationship between energy digestibility and CH₄
613 production in the rumen, first reported half a century ago (Blaxter and Clapperton, 1965). For
614 goats, all the evaluated models showed moderate predictions given the RSR > 0.85 and the

615 RMSPE% > 37% of the mean observed CH₄ emissions. In sheep, IPCC_1997 was better at
616 predicting CH₄ emissions than IPCC_2006. In a meta-analysis, IPCC_2006 was evaluated using
617 sheep data on 98 treatment means and the RMSPE was 23.1% of the mean CH₄ emissions (Patra
618 et al., 2016). In our evaluation, IPCC_2006 had a slightly larger prediction error (RMSPE =
619 30%, n = 111).

620 *4.4. Impact of the data source of models*

621 Models from Ramin and Huhtanen (2013) were applicable to different ruminant categories
622 (dairy and beef cattle, and sheep). They performed globally better than some category-specific
623 models such as those from Grainger and Beauchemin (2011), Nielsen et al. (2013) as well as
624 Moraes et al. (2014) in the dairy category. Grainger and Beauchemin (2011) proposed both
625 category-specific (Grainger_3 from cattle) and across categories models to estimate the effect
626 of dietary fat on CH₄ emissions from ruminants (Grainger_1 and Grainger_2). Similar RSR
627 were observed from across-categories and cattle-specific models when they were evaluated
628 using data from dairy and beef cattle fed lipid supplements. The present study only evaluated
629 models developed since 2000. However, it is acknowledged that the model of Blaxter and
630 Clapperton (1965) which was subsequently corrected by Wilkerson et al. (1995) as well as the
631 model of Moe and Tyrrell (1979) were developed using data from cattle with or without small
632 ruminants and their good predictive abilities have been well documented.

633 The use of databases containing either data from individual animals or treatment means in the
634 evaluation might lead to different conclusions about the performance of the same model (Ellis
635 et al., 2010). However, Ellis et al. (2010) used different sources to obtain their two evaluation
636 datasets, one for individual animal data and one for treatment mean data, and the difference in
637 the performance of one model when evaluated against these datasets may be due to the variation
638 in each dataset. Therefore, in the present study the treatment means database was created from
639 the original individual animal database to avoid such bias. The models developed on either

640 individual animal data or treatment means data had smaller RSR when challenged against data
641 from individual animals than when challenged against treatment means data, because of the
642 greater variability or standard deviation of observed CH₄ in individual animal data compared
643 with treatment means data (105 vs 74.3 g/d). Models derived from treatment means data had
644 smaller RSR than models derived from individual animal data. This might result from the
645 smoothing out of large individual variation when calculating means. Overall, our study
646 indicates that the performance of models (given by the RSR and RMSPE) does not as much
647 depend on the type of data used for the model development (individual animal records or
648 treatment means records), but essentially on the explanatory variables used in the model.

649 *4.5. Model prediction uncertainties*

650 Recent work from the GLOBAL NETWORK project (Hristov et al., 2018), reviewed the
651 uncertainties and discrepancies associated with the CH₄ measurement techniques, expressed as
652 coefficient of variation (CV). A significant CV was associated with all measurement methods
653 for CH₄ yield (g/kg of DMI): 21, 27 and 21% for respiration chambers, SF₆ tracer technique
654 and automated head chamber, respectively. This CV includes different sources of error
655 (Hammond et al., 2016). The range of the prediction errors (RMSPE%) obtained in this study
656 from the empirical models were 15.6 to 23.4% for dairy cattle (all diets), 27.2 to 36.7% for beef
657 cattle (all diets), 19.2 to 32.7% for sheep and 37.7 to 65.4% for goats. The different ranges of
658 prediction error between animal categories can be associated with the different amount of data
659 available for each category. Some evaluated models had smaller prediction error than the
660 uncertainty associated with the measurement techniques (see Tables 3, 5 and 7).

661 **5. Conclusions**

662 From the empirical CH₄ prediction models published since 2000, there is no unique model that
663 accurately predicts CH₄ emissions for all ruminant categories and for all nutritional strategies
664 designed to mitigate CH₄ emissions. With our database, the IPCC (1997) Tier 2 model generally

665 performed better than the updated IPCC (2006) model for the different ruminant categories and
666 nutritional strategies evaluated in this study. Using our database, both IPCC models performed
667 moderately under different mitigation strategies because they do not account for differences in
668 dietary lipid, NDF and STA contents, and the effects of diet quality (i.e., digestibility). The
669 models of Ramin and Huhtanen (2013) demonstrated a good predictive ability to estimate CH₄
670 emissions from dairy cattle. The model of Escobar-Bahamondes et al. (2017a) showed good
671 predictive performance when applied to beef cattle fed diets with different contents of EE and
672 NDF. The explanatory factors used in the model have more impact on its performance than the
673 type of data (individual data vs. treatment means) used in the development or in the evaluation.
674 Based on the results from our dataset, some empirical models give satisfactory predictions
675 compared with the error associated with CH₄ emissions measurement methods. More data and
676 modeling efforts are needed to better predict CH₄ emissions from beef cattle and small
677 ruminants. For future model development, it is recommended to take into account nutritional
678 strategies designed to mitigate CH₄ emissions.

679

680 **Acknowledgements**

681 This study is part of the Joint Programming Initiative on Agriculture, Food Security and Climate
682 Change (FACCE-JPI)'s "GLOBAL NETWORK" project and the "Feeding and Nutrition
683 Network" (<http://animalscience.psu.edu/fnn>) of the Livestock Research Group within the
684 Global Research Alliance for Agricultural Greenhouse Gases
685 (www.globalresearchalliance.org). Authors gratefully acknowledge funding for this project
686 from: USDA National Institute of Food and Agriculture Grant no. 2014-67003-21979)
687 University of California, Davis Sesnon Endowed Chair Program, USDA, and Austin Eugene
688 Lyons Fellowship (University of California, Davis); Funding from USDA National Institute of
689 Food and Agriculture Federal Appropriations under Project PEN 04539 and Accession number

690 1000803, DSM Nutritional Products (Basel, Switzerland), Pennsylvania Soybean Board
691 (Harrisburg, PA, USA), Northeast Sustainable Agriculture Research and Education (Burlington,
692 VT, USA), and PMI Nutritional Additives (Shoreview, MN, USA); the Ministry of Economic
693 Affairs (the Netherlands; project BO-20-007-006; Global Research Alliance on Agricultural
694 Greenhouse Gases), the Product Board Animal Feed (Zoetermeer, the Netherlands) and the
695 Dutch Dairy Board (Zoetermeer, the Netherlands); USDA National Institute of Food and
696 Agriculture (Hatch Multistate NC-1042 Project Number NH00616-R; Project Accession
697 Number 1001855) and the New Hampshire Agricultural Experiment Station (Durham, NH);
698 French National Research Agency through the FACCE-JPI program (ANR-13-JFAC-0003-01);
699 the Department of Agriculture, Food and the Marine, Ireland Agricultural GHG Research
700 Initiative for Ireland (AGRI-I) project; Academy of Finland (No. 281337), Helsinki, Finland;
701 Swiss Federal Office of Agriculture, Berne, Switzerland; the Department for Environment,
702 Food and Rural Affairs (Defra; UK); Defra, the Scottish Government, DARD, and the Welsh
703 Government as part of the UK's Agricultural GHG Research Platform projects
704 (www.ghgplatform.org.uk); INIA (Spain, project MIT01-GLOBALNET-EEZ); German
705 Federal Ministry of Food and Agriculture (BMBL) through the Federal Office for Agriculture
706 and Food (BLE); Swedish Infrastructure for Ecosystem Science (SITES) at Røob€acksdalen
707 Research Station; Comisi_ón Nacional de Investigaci_ón Cient_ífica y Tecnol_ógica, Fondo
708 Nacional de Desarrollo Cient_ífico y Tecnol_ógico (Grant Nos. 11110410 and 1151355) and
709 Fondo Regional de Tecnología Agropecuaria (FTG/RF-1028-RG); European Commission
710 through SMethane (FP7-SME-262270). The authors are thankful to all colleagues who
711 contributed data to the GLOBAL NETWORK project. All authors read and approved the final
712 manuscript. The authors declare that they have no competing interests.

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892

Table 1. Variable summary statistics of the database for different regions and ruminant categories

Variables	EUR					US					AU				
	Dairy cattle					Dairy cattle					Dairy cattle				
	n	Mean	SD	Min	Max	n	Mean	SD	Min	Max	n	Mean	SD	Min	Max
CH ₄ emission	1671	376	106	89.7	711	198	436	111	223	732	278	432	83.0	145	612
CH ₄ yield	1671	20.9	4.18	6.53	41.7	198	16.2	4.27	8.28	32.5	106	23.1	3.46	11.9	30.0
CH ₄ intensity	1441	14.1	4.48	3.22	59.3	198	11.1	3.84	4.68	31.7	94	24.1	7.82	13.0	66.2
Y _m	1599	6.28	1.23	2.14	11.3	198	4.91	1.27	2.55	9.79					
BW	1617	619	77.8	365	956	195	652	75.1	487	863	158	577	64.7	416	906
FPCM	1441	29.3	8.39	7.69	537	198	41.1	8.19	13.6	69.9	94	18.5	5.10	5.69	30.4
DMI	1671	18.3	4.54	4.17	33.5	198	27.3	3.49	19.6	37.2	106	19.5	2.84	9.09	24.9
GEI	1599	343	82.4	104	605	198	498	62.6	362	669					
forage	1141	0.68	0.18	0.35	1.00	198	0.61	0.03	0.56	0.65	278	0.75	0.11	0.57	1.00
CP	1570	165	30.7	81.0	274	198	165	6.11	152	177					
EE	977	37.4	13.1	17.0	80.1	198	48.9	5.73	38.0	55.0	108	37.8	16.5	16.9	65
ASH	1434	75.5	15.6	37.2	142	150	58.1	8.22	47.4	69.3					
NDF	1376	377	108	134	697	198	297	22.0	273	332					
ADF	1358	205	55.1	72.0	365	198	201	16.2	180	230					
STA	1209	183	89.4	10.0	566	111	249	19.5	239	298					
dOM	944	723	56.5	526	875	111	695	33.9	582	763					
dNDF	675	624	110	198	906	111	455	60.7	266	560					

Table 1 (continued)

Variables	EUR					EUR					EUR				
	Beef cattle					Sheep					Goats				
	n	Mean	SD	Min	Max	n	Mean	SD	Min	Max	n	Mean	SD	Min	Max
CH ₄ emission	577	202	90.9	27.5	566	399	19.3	7.76	3.69	55.2	60	14.2	6.44	4.67	36.3
CH ₄ yield	577	22.7	8.28	5.51	62.5	399	19.9	7.28	5.32	69.1	60	14.3	5.97	3.35	37.5
CH ₄ intensity	363	210	108	37.1	845	12	59.3	22.0	20.2	90.0	24	13.7	7.38	3.33	27.2
Ym	513	6.99	2.38	1.66	17.7	236	5.45	1.6	1.69	10.8	60	4.2	1.82	1.56	11
BW	577	509	144	129	857	399	46.5	16.3	19.3	98.7	60	45.4	6.51	29	57
FPCM											24	1.50	0.40	0.69	2.18
DMI	577	8.76	2.11	3.05	14.1	399	0.99	0.3	0.33	1.93	60	1.03	0.28	0.4	1.5
GEI	513	165	44.1	56.6	268	236	16.8	3.74	6.12	26.7	60	21.7	20.3	7.54	171
forage	529	0.7	0.21	0.1	1	399	0.76	0.34	0	1	60	0.36	0.32	0	1
CP	577	153	30.5	44	314	399	145	51.8	33.8	250	60	156	70	19.8	211
EE	273	46.9	26.3	24.4	165	81	30.6	23.2	12.1	67	60	28.6	17.1	10.2	52.6
ASH	577	95.6	58.2	29.5	114	351	89	29.6	27	155	60	102	31.9	63	150
NDF	513	346	107	203	754	399	504	127	261	797	60	380	55.1	292	509
ADF	365	201	76.3	86	453	363	288	70.9	129	472	60	225	84.1	144	467
STA	481	233	123	23.5	472	12	174	6.37	168	181					
dOM	137	745	55.6	563	820	342	645	75.6	455	831	36	757	52.5	654	837
dNDF	302	509	147	157	874	354	598	117	266	853	36	558	64.8	438	718

EUR = Europe; US = United States of America; AU = Australia; CH₄ emissions = methane emissions (g/d); CH₄ yield = methane emissions per kg of DMI; CH₄ intensity = methane emissions per kg of animal product (kg of fat and protein corrected milk for dairy cattle, sheep and goats; and kg of average daily gain for beef cattle); Ym = percentage of gross energy converted to CH₄ (%); BW = body weight (kg); FPCM = fat and protein corrected milk (kg/d) = milk yield (kg/d) × [0.337 + 0.116 × fat (%) + 0.06 × protein (%)] according to Gerber et al. (2011); DMI = dry matter intake (kg/d); GEI = gross energy intake (MJ/d); Forage = forage proportion in the diet; CP = dietary crude protein content (g/kg DM); EE = dietary ether extract content (g/kg DM); ASH: dietary ash content (g/kg DM); NDF = dietary neutral detergent fiber content (g/kg DM); ADF = Acid Detergent Fiber (g/kg DM); STA = Starch (g/kg DM); dOM = digestibility of organic matter (g/kg DM); dNDF = digestibility of NDF (g/kg DM); n = number of observations; SD = standard deviation; Min = minimum; Max = maximum.

Table 2: List of models evaluated in this study among animal category and mitigation strategy.

Source	Model	Prediction equation CH ₄ (g/d) =	Animal category ¹	Mitigation strategy ²	Origin ³
Charmley et al. (2016)	Charmley_1	$38 + 19.22 \times \text{DMI}$	Dairy	All diets	AU
Charmley et al. (2016)	Charmley_2	$(2.14 + 0.058 \times \text{GEI})/0.05565$	Dairy	All diets	AU
Mills et al. (2003)	Mills_1	$(5.93 + 0.92 \times \text{DMI})/0.05565$	Dairy	All diets	EUR
Mills et al. (2003)	Mills_3	$(56.27 \times (1 - \exp^{-0.028 \times \text{DMI}}))/0.05565$	Dairy	All diets	EUR
Nielsen et al. (2013)	Nielsen_1	$(1.23 \times \text{DMI} - 0.145 \times \text{FA} + 0.012 \times \text{NDF})/0.05565$	Dairy	Lip, DQ	EUR
Ellis et al. (2007)	Ellis_2	$(3.14 + 2.11 \times \text{NDFI})/0.05565$	Dairy	DQ	US
Ellis et al. (2007)	Ellis_3	$(2.16 + 0.493 \times \text{DMI} - 1.36 \times \text{ADFI} + 1.97 \times \text{NDFI})/0.05565$	Dairy	DQ	US
Moraes et al. (2014)	Moraes	$(0.225 + 0.042 \times \text{GEI} + 0.0125 \times \text{NDF} - 0.0329 \times \text{EE})/0.05565$	Dairy	Lip, DQ	US
Mills et al. (2003)	Mills_2	$(7.3 + 13.13 \times \text{NI} + 2.04 \times \text{ADFI} + 0.33 \times \text{STAI})/0.05565$	Dairy	DQ, STA	EUR
Escobar-Bahamondes et al. (2017a)	Escobar	$-35.0 + 0.08 \times \text{BW} + 120 \times \text{forage} - 69.8 \times \text{FA}^3 + 3.14 \times \text{GEI}$	Beef	All diets	EUR, US, AU
Yan et al. (2009)	Yan_1	$((35.1 \times \text{DMI}) + 14.7) \times 0.714$	Beef	All diets	EUR
Yan et al. (2009)	Yan_2	$(1.959 \times \text{GEI} + 8.8) \times 0.714$	Beef	All diets	EUR
Ellis et al. (2007)	Ellis_6	$(-1.02 + 0.681 \times \text{DMI} + 4.81 \times \text{forage})/0.05565$	Beef	DQ	US
Ellis et al. (2007)	Ellis_5	$(5.58 + 0.848 \times \text{NDFI})/0.05565$	Beef	DQ	US
Ellis et al. (2009)	Ellis_7	$(4.72 + 1.13 \times \text{STAI})/0.05565$	Beef	STA	US
Ellis et al. (2009)	Ellis_8	$(-1.01 + 2.76 \times \text{NDFI} + 0.722 \times \text{STAI})/0.05565$	Beef	DQ, STA	US
Ellis et al. (2009)	Ellis_9	$(2.5 - 0.367 \times \text{STAI}/\text{ADFI} + 0.766 \times \text{DMI})/0.05565$	Beef	DQ, STA	US
Charmley et al. (2016)	Charmley_3	$20.7 \times \text{DMI}$	Dairy and Beef	All diets	AU
Grainger and Beauchemin (2011)	Grainger_3	$(24.55 - 0.102 \times \text{FA}) \times \text{DMI}$	Dairy and Beef	Lip	EUR, US, AU
Moate et al. (2011)	Moate	$(\exp^{(3.15 - 0.0035 \times \text{FA})}) \times \text{DMI}$	Dairy and Beef	Lip	EUR, US
IPCC (1997) ⁴	IPCC_1997	$(0.060 \times \text{GEI})/0.05565$	All categories	All diets	EUR, US, AU

IPCC (2006) ⁴	IPCC_2006	$(0.065 \times \text{GEI}) / 0.05565$	All categories	All diets	EUR, US, AU
Ramin & Huhtanen (2013)	Ramin_2	$(20 + 35.8 \times \text{DMI} - 0.5 \times \text{DMI}^2) \times 0.714$	Dairy, Beef and Sheep	All diets	EUR, US, AU
Grainger and Beauchemin (2011)	Grainger_1	$(24.65 - 0.103 \times \text{FA}) \times \text{DMI}$	All categories	Lip	EUR, US, AU
Grainger and Beauchemin (2011)	Grainger_2	$(26.5 - (0.187 \times \text{FA}) + (0.0007 \times \text{FA}^2)) \times \text{DMI}$	All categories	Lip	EUR, US, AU
Ramin & Huhtanen (2013)	Ramin_1	$(49.7 - 0.63 \times \text{DMI}/\text{BW} + 0.59 \times \text{dGE} - 0.2 \times \text{EE}) \times \text{GEI} / 0.0555$	Dairy, Beef and Sheep	Lip, DQ	EUR, US, AU
Ramin & Huhtanen (2013)	Ramin_3	$(-0.6 - 0.7 \times \text{DMI}/\text{BW} + 0.076 \times \text{dOM} - 0.13 \times \text{EE} + 0.046 \times \text{NDF} + 0.044 \times \text{NFC}) \times \text{GEI} / 0.0555$	Dairy, Beef and Sheep	DQ, STA	EUR, US, AU
Sauvant et al. (2016)	Sauvant_1	$[45.42 - 6.66 \times \text{DMI}/\text{BW} + 0.75 \times \text{DMI}/\text{BW}^2 + 19.65 \times \text{pCO} - 35.0 \times \text{pCO}^2 - 2.69 \times (\text{DMI}/\text{BW}) \times \text{pCO}] \times \text{OMI} \times \text{dOM}$	All categories	DQ, STA	EUR, US, AU
Sauvant et al. (2016)	Sauvant_2	$(7.14 + 0.22 \times \text{dOM}) \times \text{DMI}$	All categories	DQ, STA	EUR, US, AU
Patra et al. (2016)	Patra_1	$(0.223 + 0.876 \times \text{DMI}) / 0.05565$	Sheep	All diets	
Patra et al. (2016)	Patra_2	$(0.208 + 0.049 \times \text{GEI}) / 0.05565$	Sheep	All diets	EUR, US, AU
Patra et al. (2016)	Patra_3	$(0.289 + 0.067 \times \text{DEI}) / 0.05565$	Sheep	All diets	EUR, US, AU
Patra & Lalhriatpuii (2016)	Patra_4	$(0.296 + 0.569 \times \text{DMI}) / 0.05565$	Goats	All diets	EUR, US, AU
Patra & Lalhriatpuii (2016)	Patra_5	$(0.507 + 0.573 \times \text{DMI} - 0.00074 \times \text{ADF}) / 0.05565$	Goats	All diets	EUR, US, AU
Patra & Lalhriatpuii (2016)	Patra_6	$(1.29 - 0.0011 \times \text{NDF}) / 0.05565$	Goats	All diets	EUR, US, AU
FAO 2010	FAO 2010	$((9.75 - 0.005 \times \text{DMD}) \times \text{GEI}) / 0.05565$	Goats	All diets	-

DMI = dry matter intake (kg/d), GEI = gross energy intake (MJ/d), FA = dietary fatty acids (g/kg DM), NDF = dietary neutral detergent fiber (g/kg DM), NDFI = NDF intake (kg/d), ADF = dietary acid detergent fiber (g/kg DM), ADFI = ADF intake (kg/d), EE = dietary extract ether (g/kg DM),

EEI = EE intake (kg/d), BW = body weight (kg), forage = forage proportion in the diet, NI = nitrogen intake (kg/d), STA = dietary starch (g/kg DM), STAI = STA intake (kg/d), dGE = digestibility of gross energy (g/kg DM), dOM = digestibility of organic matter (g/kg DM), NFC = non fibrous carbohydrates (g/kg DM), pCO = concentrate proportion in the diet, OMI = organic matter intake (kg/d), DEI = digestible energy intake (MJ/d).

¹ Animal category in which model is applied: Dairy = Dairy cattle, Beef = Beef cattle, All categories = dairy and beef cattle and small ruminants ² Mitigation strategy: All diets = Performance using all data of corresponding animal category, Lip = lipid supplementation, DQ = Diet quality, STA = Starch content. ³ origin of data used in the model development: EUR = Europe, US = United States of America, AU = Australia. ⁴ IPCC_1997 and IPCC_2006 are used for dairy cattle, beef cattle with forage proportion in the diet < 0.90 and mature sheep (> 1 year). For feedlot cattle (concentrate proportion > 0.90) and young sheep (< 1 year) Ym values of 3 and 4.5% were used.

Table 3. Evaluation of the performance of CH₄ emissions (g/d) prediction models for dairy cattle (ranked by RSR)

Rank	Model	n	RMSPE (g/d)	RMSPE %	ECT %	ER %	ED %	CCC	<i>r</i>	RSR
1	Ramin_1	463	61.0	15.6	0.70	2.90	96.4	0.75	0.76	0.66
2	Ramin_2	1958	82.1	21.2	6.30	3.30	90.4	0.57	0.69	0.76
3	Mills_3	1975	84.3	21.8	11.7	1.50	86.8	0.64	0.69	0.78
4	IPCC_1997	1797	82.3	21.2	0.10	12.8	87.1	0.68	0.68	0.79
5	Ellis_3	1034	88.7	22.7	11.5	0.80	87.7	0.60	0.66	0.80
6	Charmley_2	1797	84.5	21.8	7.60	9.60	82.8	0.66	0.68	0.81
7	Charmley_1	1869	87.0	22.8	8.10	9.80	82.0	0.66	0.68	0.81
8	Charmley_3	1869	87.6	22.9	3.00	16.0	81.0	0.67	0.68	0.81
9	Mills_2	1320	72.5	17.8	4.00	4.40	91.6	0.59	0.62	0.82
10	Mills_1	1975	89.3	23.1	18.4	1.80	79.8	0.61	0.68	0.83
11	Ramin_3	626	80.0	20.5	5.40	8.10	86.5	0.61	0.63	0.84
12	Sauvant_1	967	93.5	27.4	12.5	9.90	77.6	0.63	0.66	0.85
13	IPCC_2006	1797	90.8	23.4	11.0	17.4	71.6	0.65	0.68	0.87

Rank = rank of the performance based on the RSR, n = number of observations; RMSPE = Square root of the mean square prediction error, expressed in g/d and RMSPE% as a percentage of methane emissions mean; ECT% = error due to central tendency expressed as a percentage of RMSPE; ER% = error due to deviation of the regression slope expressed as a percentage of RMSPE; ED% = error due to the disturbance expressed as percentage of RMSPE; CCC = concordance correlation coefficient; *r* = correlation coefficient; RSR = RMSPE to standard deviation of observed values ratio.

Table 4. Evaluation of the performance of CH₄ emissions (g/d) prediction models for dairy cattle fed lipid supplements, diets with different contents of NDF and STA, and diets of different quality (ranked by RSR).

Mitigation strategy		Rank	Model	n	RMSPE (g/d)	RMSPE %	ECT %	ER %	ED %	CCC	<i>r</i>	RSR
Lipid supplementation	The low-EE diets (mean 30.4 g/kg DM)	1	IPCC_1997	685	64.0	17.1	7.68	15.2	77.1	0.71	0.73	0.78
		2	IPCC_2006	685	65.7	17.6	3.33	23.7	73.0	0.71	0.73	0.80
		3	Moate	609	66.2	17.9	10.7	17.3	72.0	0.70	0.72	0.81
		4	Grainger_3	609	72.4	19.6	23.7	16.6	59.7	0.67	0.73	0.89
		5	Grainger_1	609	73.2	19.8	25.1	16.5	58.4	0.66	0.73	0.90
		6	Nielsen_1	557	75.0	19.9	43.8	7.89	48.3	0.64	0.76	0.93
	The high-EE diets (mean 51.7 g/kg DM)	1	Ramin_1	391	70.6	16.1	8.57	7.53	83.9	0.72	0.74	0.73
		2	Ramin_3	314	87.2	20.3	0.66	8.03	91.3	0.60	0.61	0.83
		3	Moraes	490	95.3	22.9	27.8	0.87	71.3	0.47	0.59	0.95
		4	IPCC_1997	490	105	25.3	11.4	22.9	65.6	0.49	0.52	1.05
5		IPCC_2006	490	127	30.5	33.3	21.6	45.1	0.42	0.52	1.27	
Diet quality by NDF content	The low-NDF diets (mean 285 g/kg DM)	1	Ramin_1	67	41.9	10.1	2.31	1.96	95.7	0.88	0.88	0.48
		2	Ellis_3	414	89.9	21.7	6.78	5.10	88.1	0.40	0.45	0.95
		3	IPCC_1997	701	96.1	23.7	13.6	22.8	63.7	0.49	0.53	1.06
		4	IPCC_2006	701	118	29.2	37.3	20.6	42.1	0.41	0.53	1.31
	The high-NDF diets (mean 433 g/kg DM)	1	Ellis_3	514	63.4	17.6	6.26	1.76	92.0	0.82	0.85	0.54
		2	IPCC_2006	817	56.6	14.3	3.59	11.3	85.2	0.84	0.85	0.57
		3	Sauvant_2	562	65.2	18.0	10.9	24.3	64.9	0.86	0.89	0.58
		4	Nielsen_1	430	56.8	14.2	30.8	7.09	62.1	0.84	0.88	0.60
		5	Ramin_3	381	60.7	15.1	4.11	1.91	94.0	0.77	0.79	0.63
		6	IPCC_1997	817	67.0	16.9	36.5	2.73	60.8	0.78	0.85	0.68
STA content	The low-STA diets (mean 56.1 g/kg DM)	1	IPCC_2006	217	48.4	13.3	4.50	8.60	86.9	0.65	0.67	0.80
		2	Mills_2	217	53.2	14.6	14.5	1.42	84.1	0.52	0.59	0.87
		3	Ramin_3	144	40.3	11.9	26.7	10.4	63.0	0.58	0.65	0.95
		4	IPCC_1997	217	59.5	16.4	39.7	2.82	57.5	0.54	0.67	0.98
	The high-STA diets	1	Mills_2	1103	75.7	18.2	3.13	5.39	91.5	0.58	0.60	0.84
		2	Ramin_3	446	90.2	22.0	4.05	8.41	87.5	0.54	0.56	0.88

Diet quality by dOM	(mean 215 g/kg DM)	3	IPCC_1997	1102	83.9	20.2	0.05	22.8	77.2	0.58	0.58	0.93	
		4	IPCC_2006	1102	93.6	22.6	12.1	26.0	61.9	0.54	0.58	1.04	
	The low-dOM diets (mean 679 g/kg DM)	1	Ellis_3	323	82.4	21.8	0.01	0.31	99.7	0.72	0.76	0.65	
		2	Ramin_1	199	69.5	17.2	15.2	4.82	80.0	0.72	0.76	0.73	
		3	Ellis_2	323	103	27.2	13.4	2.93	83.7	0.52	0.67	0.81	
		4	Ramin_3	265	87.1	20.7	5.46	9.66	84.9	0.60	0.62	0.85	
	The high-dOM diets (mean 767 g/kg DM)	1	Ellis_3	290	55.6	15.6	1.02	0.01	99.0	0.84	0.85	0.53	
		2	Ramin_1	230	54.9	14.6	2.73	0.18	97.1	0.79	0.81	0.60	
		3	Ellis_2	290	73.3	20.6	25.0	5.55	69.5	0.68	0.81	0.70	
		4	IPCC_1997	479	71.1	20.5	2.85	17.6	79.6	0.72	0.72	0.77	
	Diet quality by dNDF	The low-dNDF Diets (mean 504 g/kg DM)	1	Ellis_3	337	78.8	19.9	1.39	0.02	98.6	0.71	0.74	0.67
			2	Ramin_1	179	71.6	16.7	17.3	7.14	75.5	0.70	0.74	0.78
3			Ellis_2	337	98.7	24.9	34.3	5.29	60.5	0.54	0.75	0.84	
4			Ramin_3	278	88.8	20.9	2.31	12.7	85.0	0.58	0.59	0.88	
5			Mills_2	352	103	25.1	19.9	7.70	72.4	0.47	0.53	0.99	
The high-dNDF diets (mean 700 g/kg DM)		1	Ramin_3	244	50.0	13.3	14.2	2.85	83.0	0.82	0.84	0.59	
		2	Ellis_3	307	62.6	18.4	0.31	0.00	99.7	0.78	0.80	0.59	
		3	Mills_2	287	52.2	13.5	24.6	0.78	74.6	0.75	0.83	0.65	
		4	IPCC_2006	345	59.2	16.2	1.03	26.0	73.0	0.82	0.83	0.65	
		5	Ramin_1	215	54.5	14.3	1.12	3.07	95.8	0.76	0.77	0.66	

EE = dietary ether extract (g/kg DM), NDF = neutral detergent fiber (g/kg DM), STA = dietary starch (g/kg DM), dOM = digestibility of organic matter (g/kg DM), dNDF = digestibility of NDF (g/kg DM), Rank = rank of the performance based on the RSR, n = number of observations; RMSPE = Square root of the mean square prediction error, expressed in g/d and RMSPE% as a percentage of methane emissions means; ECT% = error due to central tendency expressed as a percentage of RMSPE; ER% = error due to deviation of the regression slope expressed as a percentage of RMSPE; ED% = error due to the disturbance expressed as percentage of RMSPE; CCC = concordance correlation coefficient; r = correlation coefficient; RSR = RMSPE to standard deviation of observed values ratio.

Table 5. Evaluation of the performance of CH₄ emissions (g/d) prediction models for beef cattle (ranked by RSR).

Rank	Model	n	RMSPE (g/d)	RMSPE %	ECT %	ER %	ED %	CCC	<i>r</i>	RSR
1	Escobar	161	66.1	27.2	0.49	5.94	93.6	0.40	0.60	0.83
2	Ramin_2	419	75.3	33.3	0.77	1.92	97.3	0.42	0.56	0.84
3	Yan_1	419	76.3	33.8	5.07	0.06	94.9	0.48	0.56	0.85
4	Yan_2	403	78.0	34.0	9.29	0.77	89.9	0.49	0.57	0.87
5	IPCC_2006	380	76.6	32.7	15.0	0.43	84.6	0.46	0.60	0.87
6	Charmley_3	419	82.2	36.4	17.5	0.80	81.7	0.39	0.56	0.91
7	IPCC_1997	403	84.2	36.7	22.1	0.61	77.3	0.39	0.57	0.93
8	Grainger_2	177	77.1	32.9	18.6	0.43	81.0	0.40	0.52	0.95
9	Grainger_1	177	78.7	33.6	21.8	0.06	78.1	0.37	0.52	0.97

Rank = rank of the performance based on the RSR, n = number of observations; RMSPE = Square root of the mean square prediction error, expressed in g/d and RMSPE% as a percentage of methane emissions means; ECT% = error due to central tendency expressed as a percentage of RMSPE; ER% = error due to deviation of the regression slope expressed as a percentage of RMSPE; ED% = error due to the disturbance expressed as percentage of RMSPE; CCC = concordance correlation coefficient; *r* = correlation coefficient; RSR = RMSPE to standard deviation of observed values ratio.

Table 6. Evaluation of the performance of CH₄ emissions (g/d) prediction models for beef cattle fed lipid supplements or diets with different contents of NDF and STA and diets of different quality (ranked by RSR).

Mitigation strategy		Rank	Model	n	RMSPE (g/d)	RMSPE %	ECT %	ER %	ED %	CCC	<i>r</i>	RSR
Lipid supplementation	The low-EE diets (mean 25.3 g/kg DM)	1	Escobar	80	68.8	26.3	2.43	6.07	91.5	0.40	0.59	0.84
		2	Grainger_2	80	73.5	28.1	12.1	0.04	87.9	0.41	0.54	0.89
		3	Grainger_1	80	76.8	29.4	19.3	0.14	80.5	0.38	0.54	0.93
		4	Grainger_3	80	77.2	29.5	20.1	0.16	79.7	0.38	0.54	0.94
		5	IPCC_2006	95	78.0	31.0	33.2	0.17	66.6	0.40	0.59	0.98
		6	IPCC_1997	95	88.4	35.1	47.5	0.56	52.0	0.33	0.59	1.11
	The high-EE diets (mean 58.4 g/kg DM)	1	Escobar	81	63.3	28.1	0.05	3.99	96.0	0.33	0.53	0.86
		2	Grainger_2	145	72.1	39.0	3.18	0.08	96.7	0.16	0.29	0.97
		3	Grainger_1	145	73.0	39.5	2.49	0.58	96.9	0.13	0.24	0.98
		4	Grainger_3	145	73.1	39.5	2.72	0.58	96.7	0.13	0.24	0.98
		5	IPCC_2006	114	72.1	33.1	31.3	0.63	68.1	0.24	0.40	1.11
		6	IPCC_1997	114	80.4	36.9	45.1	0.17	54.8	0.19	0.40	1.24
Diet quality by NDF content	The low-NDF diets (mean 248 g/kg DM)	1	Escobar	79	62.6	27.6	0.09	4.21	95.7	0.40	0.55	0.86
		2	IPCC_2006	173	79.5	38.7	3.12	0.34	96.5	0.38	0.47	0.89
		3	IPCC_1997	173	83.2	40.5	11.9	0.02	88.0	0.34	0.47	0.94
		4	Ellis_6	173	95.5	46.4	42.2	7.03	50.8	0.28	0.64	1.07
	The high-NDF diets (mean 425 g/kg DM)	1	Escobar	78	66.2	25.9	2.07	5.56	92.4	0.44	0.61	0.84
		2	IPCC_2006	230	76.5	31.0	16.6	0.40	83.0	0.45	0.60	0.88
		3	IPCC_1997	230	84.9	34.4	31.6	0.99	67.4	0.38	0.60	0.98
		4	Ellis_6	230	107	43.3	51.6	2.52	45.9	0.20	0.55	1.23
STA content	The low-STA Diets (mean 60 g/kg DM)	1	IPCC_2006	128	85.5	34.9	30.4	0.74	68.9	0.36	0.57	0.99
		2	IPCC_1997	128	95.1	38.8	43.1	1.24	55.7	0.30	0.57	1.10
		3	Ellis_8	128	101	41.1	43.3	0.25	56.4	0.23	0.49	1.16
		4	Ellis_7	128	172	70.0	76.0	6.26	17.7	0.01	0.55	1.98
	The high-STA	1	IPCC_2006	289	74.4	32.1	10.5	1.37	88.1	0.38	0.47	0.94

	Diets (mean 296 g/kg DM)	2	IPCC_1997	289	80.7	34.8	24.7	0.41	74.9	0.33	0.47	1.02
		3	Ellis_7	353	107	49.9	47.8	0.71	51.5	0.10	0.36	1.30
		4	Ellis_8	289	109	47.1	25.7	27.7	46.6	0.28	0.34	1.38
Diet quality by dOM	The low-dOM diets (mean 672 g/kg DM)	1	Ellis_5	37	38.0	20.9	17.8	3.48	78.8	0.63	0.69	0.81
		2	IPCC_1997	37	41.8	23.0	0.69	26.6	72.7	0.64	0.64	0.89
		3	Ellis_9	37	42.5	23.4	40.4	0.01	59.6	0.54	0.71	0.90
	The high-dOM diets (mean 772 g/kg DM)	1	IPCC1997	36	48.5	28.0	0.89	0.09	99.0	0.66	0.70	0.71
		2	Ellis_2b	36	50.7	29.3	7.90	17.2	74.9	0.54	0.76	0.74
		3	Ellis_9	36	51.7	29.8	13.1	6.24	80.7	0.57	0.72	0.76
		4	IPCC_2006	36	52.3	30.2	13.8	1.11	85.1	0.64	0.70	0.77
Diet quality by dNDF	The low-dNDF diets (mean 440 g/kg DM)	1	IPCC_2006	223	66.7	34.9	0.11	11.0	88.9	0.68	0.79	0.65
		2	IPCC_1997	223	69.5	36.3	3.31	14.7	82.0	0.64	0.79	0.68
		3	Ellis_6	223	87.1	45.5	26.9	21.5	51.6	0.46	0.79	0.85
		4	Ellis_5	223	99.4	52.0	20.6	22.0	57.4	0.24	0.68	0.97
	The high-dNDF diets (mean 705 g/kg DM)	1	IPCC_2006	79	79.3	38.6	0.90	0.72	98.4	0.47	0.53	0.85
		2	IPCC_1997	79	81.9	39.8	7.72	0.09	92.2	0.43	0.53	0.88
		3	Ellis_5	79	98.1	47.7	22.7	0.81	76.5	0.16	0.38	1.05
		4	Ellis_6	79	99.1	48.2	32.0	0.47	67.5	0.25	0.48	1.06

EE = dietary ether extract (g/kg DM), NDF = neutral detergent fiber (g/kg DM), STA = dietary starch (g/kg DM), dOM = digestibility of organic matter (g/kg DM), dNDF = digestibility of NDF (g/kg DM), Rank = rank of the performance based on the RSR, n = number of observations; RMSPE = Square root of the mean square prediction error, expressed in g/d and RMSPE% as a percentage of methane emissions means; ECT% = error due to central tendency expressed as a percentage of RMSPE; ER% = error due to deviation of the regression slope expressed as a percentage of RMSPE; ED% = error due to the disturbance expressed as percentage of RMSPE; CCC = concordance correlation coefficient; r = correlation coefficient; RSR = RMSPE to standard deviation of observed values ratio.

Table 7. Evaluation of the performance of CH₄ emissions (g/d) prediction models for sheep (ranked by RSR).

Rank	Model	n	RMSPE (g/d)	RMSPE %	ECT %	ER %	ED %	CCC	<i>r</i>	RSR
1	Patra_3	90	3.33	19.2	3.45	5.31	91.2	0.75	0.81	0.61
2	IPCC_1997	111	4.35	26.8	2.30	3.82	93.9	0.64	0.66	0.77
3	Patra_2	111	4.41	27.2	8.69	0.00	91.3	0.59	0.66	0.78
4	Sauvant_1	229	6.73	31.1	1.82	10.8	87.4	0.61	0.62	0.84
5	Patra_1	274	6.71	32.7	0.64	2.18	97.2	0.51	0.55	0.85
6	IPCC_2006	111	4.86	29.9	18.1	6.45	75.4	0.61	0.66	0.86

Rank = rank of the performance based on the RSR, n = number of observations; RMSPE = Square root of the mean square prediction error, expressed in g/d and RMSPE% as a percentage of methane emissions means;; ECT% = error due to central tendency expressed as a percentage of RMSPE; ER% = error due to deviation of the regression slope expressed as a percentage of RMSPE; ED% = error due to the disturbance expressed as percentage of RMSPE; CCC = concordance correlation coefficient; *r* = correlation coefficient; RSR = RMSPE to standard deviation of observed values ratio.

Table 8. Evaluation of the performance of CH₄ emissions (g/d) prediction models for goats (ranked by RSR).

Rank	Model	n	RMSPE (g/d)	RMSPE %	ECT %	ER %	ED %	CCC	<i>r</i>	RSR
1	Patra_4	46	5.80	37.7	1.97	0.77	97.3	0.37	0.51	0.86
2	Patra_5	46	6.23	40.5	7.76	1.09	91.2	0.36	0.45	0.92
3	Patra_6	46	6.59	42.8	0.45	0.03	99.5	0.06	0.16	0.98
4	FAO 2010	30	10.1	65.4	48.5	5.15	46.4	0.37	0.54	1.22

Rank = rank of the performance based on the RSR, n = number of observations; RMSPE = Square root of the mean square prediction error, expressed in g/d and RMSPE% as a percentage of methane emissions means;; ECT% = error due to central tendency expressed as a percentage of RMSPE; ER% = error due to deviation of the regression slope expressed as a percentage of RMSPE; ED% = error due to the disturbance expressed as percentage of RMSPE; CCC = concordance correlation coefficient; *r* = correlation coefficient; RSR = RMSPE to standard deviation of observed values ratio.

Table 9. Evaluation of models using data from individual animals or treatment means.

Validation database	Model type	Model	n	RMSPE (g/d)	RMSPE %	ECT %	ER %	ED %	CCC	<i>r</i>	RSR
Individual	Individual	IPCC_1997	1797	82.3	21.2	4.10	12.8	87.1	0.68	0.68	0.79
		Charmley_2	1797	84.5	21.8	7.60	9.60	82.8	0.66	0.68	0.81
		Charmley_1	1869	87.0	22.8	8.10	9.80	82.0	0.66	0.68	0.81
		IPCC_2006	1797	90.8	23.4	11.0	17.4	71.6	0.65	0.68	0.87
	Mean	Ramin_1	463	61.0	15.6	0.71	2.92	96.4	0.75	0.76	0.66
		Ramin_2	1958	82.1	21.2	6.28	3.33	90.4	0.57	0.69	0.76
		Ellis_3	1034	88.7	22.7	11.5	0.80	87.7	0.60	0.66	0.80
		Sauvant_1	967	93.5	27.4	12.5	9.90	77.6	0.63	0.66	0.85
Means	Individual	Charmley_1	175	64.3	16.9	6.63	22.3	9.49	0.67	0.69	0.85
		Charmley_2	171	64.3	16.9	5.10	26.6	25.8	0.68	0.69	0.87
		IPCC_1997	171	65.2	17.1	3.03	30.6	21.1	0.68	0.69	0.88
		IPCC_2006	171	71.3	18.7	7.48	37.0	19.6	0.66	0.69	0.96
	Mean	Ramin_2	178	58.3	15.2	13.4	1.46	85.2	0.62	0.72	0.77
		Ramin_1	49	49.8	13.7	0.05	17.9	82.0	0.69	0.69	0.79
		Sauvant_1	81	70.9	20.2	6.66	24.2	69.1	0.62	0.64	0.92
		Ellis_3	117	74.1	19.3	29.5	1.50	69.0	0.54	0.64	0.92

n = number of observations; RMSPE = Square root of the mean square prediction error, expressed in g/d and RMSPE% as a percentage of methane emissions means;; ECT% = error due to central tendency expressed as a percentage of RMSPE; ER% = error due to deviation of the regression slope expressed as a percentage of RMSPE; ED% = error due to the disturbance expressed as percentage of RMSPE; CCC = concordance correlation coefficient; *r* = correlation coefficient; RSR = RMSPE to standard deviation of observed values ratio.

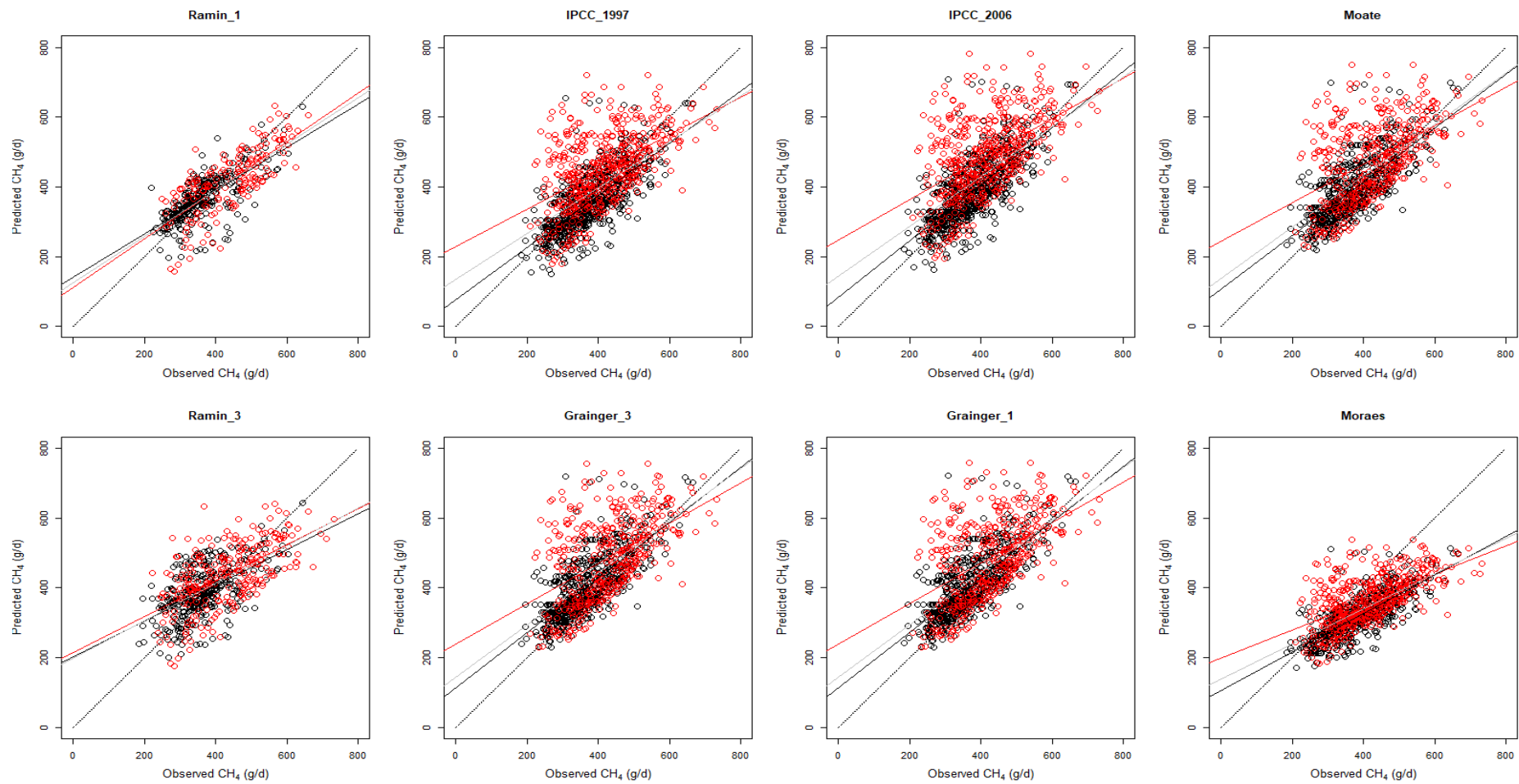


Figure 1. Observed vs. predicted values plots, using dairy cattle data, of 8 models with the smallest RSR for the low- (black points) and the high-EE (red points) diets. The black discontinued line is the identity line $y = x$, the gray, black and red lines are the fitted regression lines for all diets, the low- and the high-EE diets, respectively.

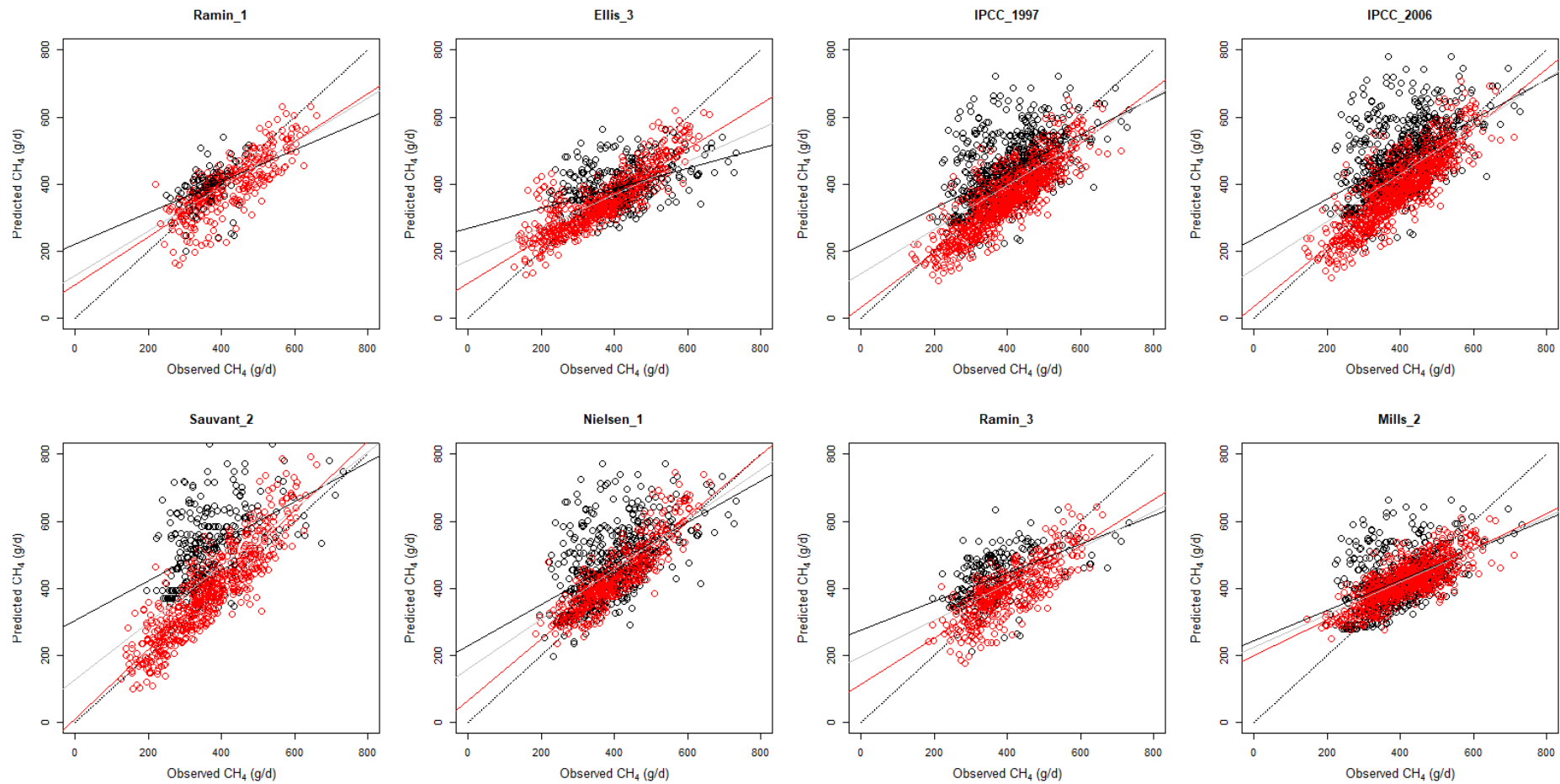


Figure 2. Observed vs. predicted values plots, using dairy cattle data, of 8 models with the smallest RSR for the low- (black points) and the high-NDF (red points) diets. The black discontinued line is the identity line $y = x$, the gray, black and red lines are the fitted regression lines for all diets, the low- and the high-NDF diets, respectively.

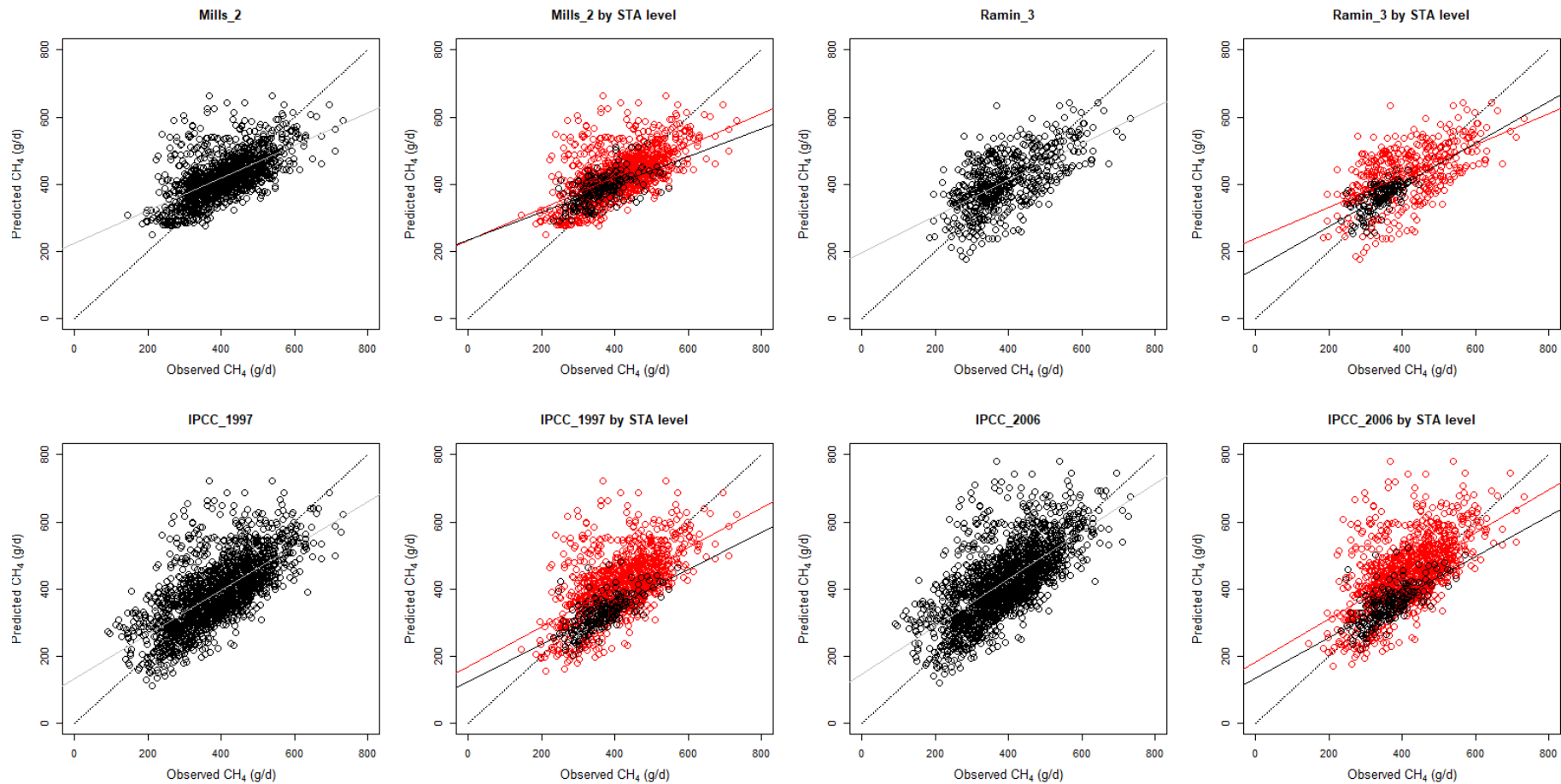


Figure 3. Observed vs. predicted values plots, using all dairy cattle data and for the low- (black points) and the high-STA (red points) diets, of the 4 models Mills_2, Ramin_3, and of IPCC_1997 and 2006. The black discontinued line is the identity line $y = x$, the gray, black and red lines are the fitted regression lines for all diets, the low- and the high-STA diets, respectively.

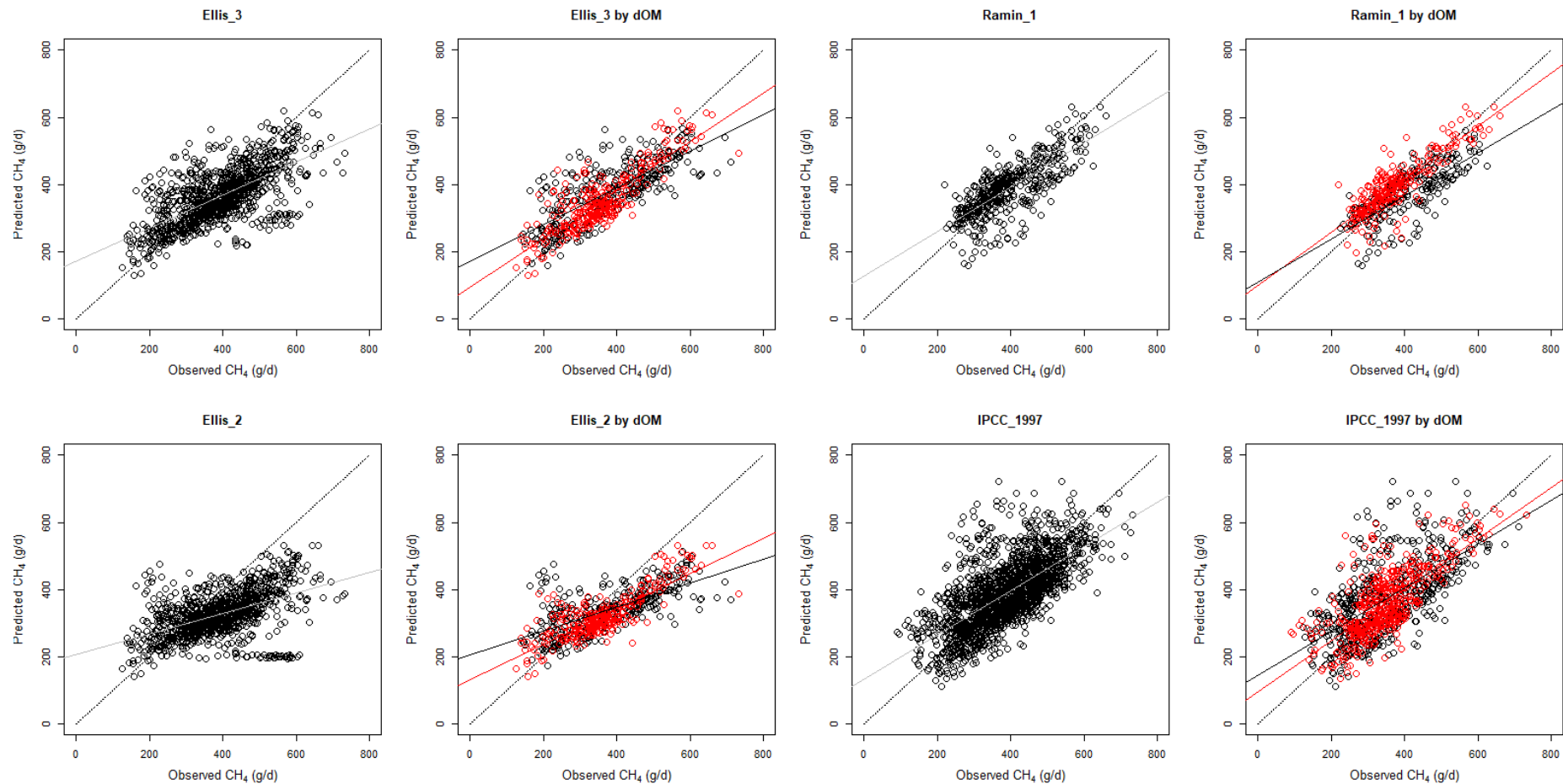


Figure 4. Observed vs. predicted values plots, using all dairy cattle data and for the low- (black points) and the high-dOM (red points), of the 4 models Ellis_3, Ramin_1, and of IPCC_1997 and 2006. The black discontinued line is the identity line $y = x$, the gray, black and red lines are the fitted regression lines for all diets, the low- and the high-dOM diets, respectively.

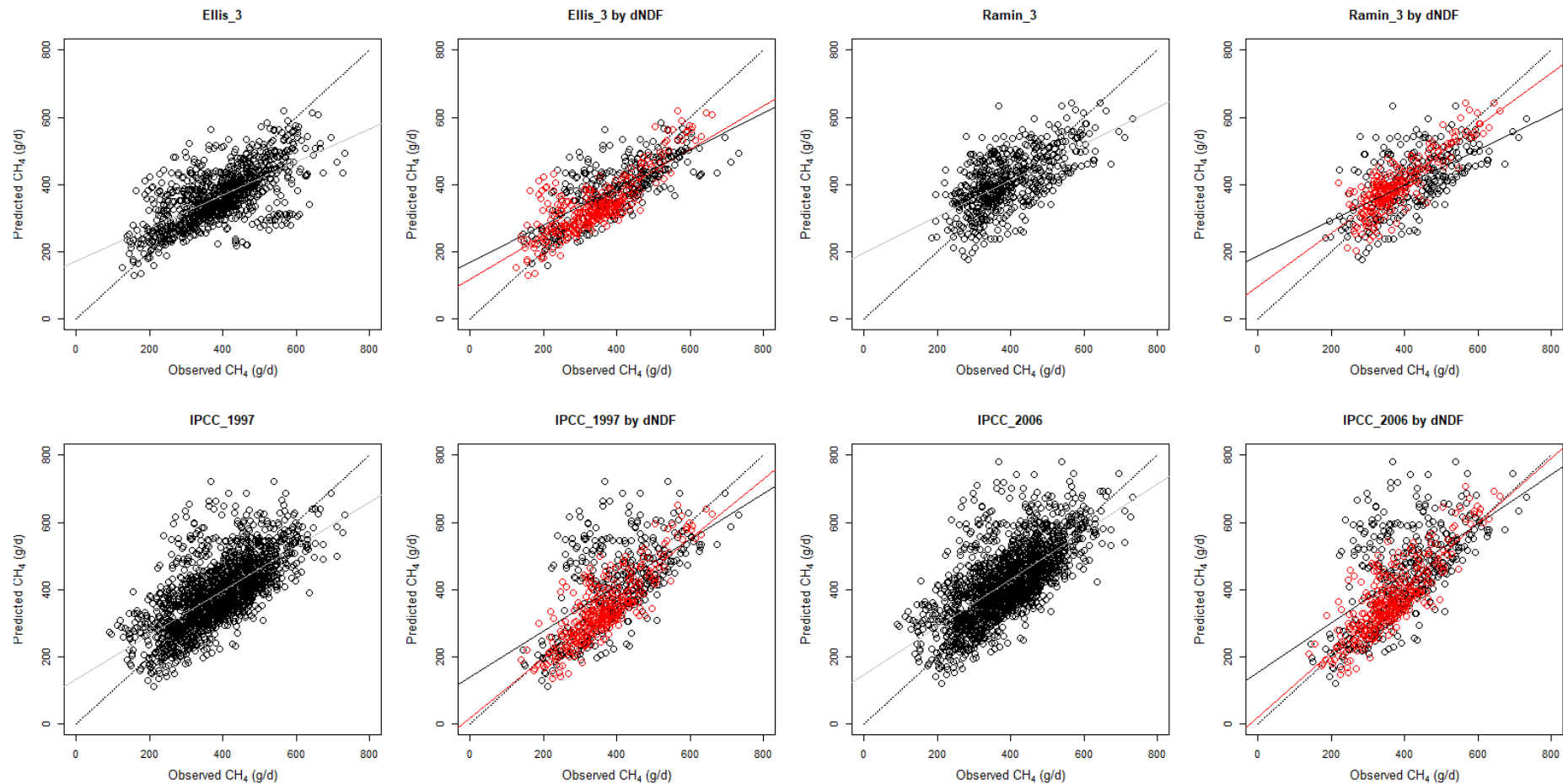


Figure 5. Observed vs. predicted values plots, using all dairy cattle data and for the low- (black points) and the high-dNDF (red points), of the 4 models Ellis_3, Ramin_3, and of IPCC_1997 and 2006. The black discontinued line is the identity line $y = x$, the gray, black and red lines are the fitted regression lines for all diets, the low- and the high-dNDF diets, respectively.

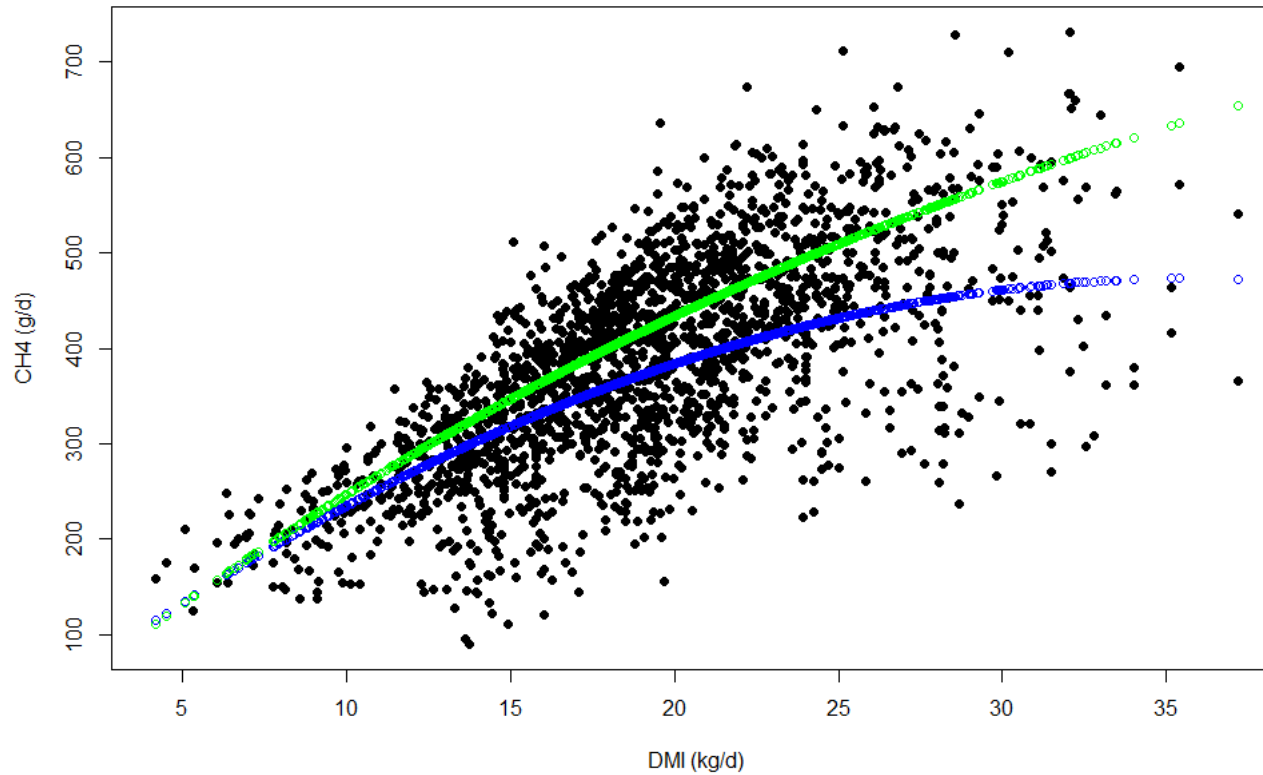


Figure 6. Relationship between DMI (kg/d) and CH₄ emissions (g/d) by dairy cattle in our database. The blue and green lines are two DMI-based models evaluated: Ramin_2 [$\text{CH}_4 \text{ (g/d)} = (20 + 35.8 \times \text{DMI} - 0.5 \times \text{DMI}^2) \times 0.714$] and Mills_3 [$\text{CH}_4 \text{ (g/d)} = (56.27 \times (1 - \exp^{-0.028 \times \text{DMI}}))/0.05565$], respectively.