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Abstract

Measuring enteric methane (CH_4) produced by cattle is central for the construction of national greenhouse gas inventories and for devising strategies to mitigate the environmental footprint of ruminant livestock. Efforts to estimate or measure enteric CH_4 emissions in cattle include techniques such as the Green-Feed system, laser detectors, respiration chambers, and the SF6 technique. However, using these tools on a large scale is complicated and expensive. Therefore, it is necessary to develop alternative methods to estimate CH_4 emissions from cattle. The objective of this work was to evaluate the potential use of intake time (IT) to estimate enteric CH_4 emissions in cattle. The CH_4 emissions of seven steers were measured in respiration chambers. A computer vision technique, called Object Detection (OD), was used to estimate IT. The images recorded from the top of the feeder were used for OD. Additionally, the dry matter intake (DMI) was measured by the difference between the offered and rejected food each day. CH_4 emissions were predicted by two linear equations using DMI or IT as explanatory variables. The equation using IT versus that one using DMI presented lower root mean square error (RMSE, 13.8 *vs.* 20.2 g/d), relative prediction error (RPE, 9.1% *vs.* 13.3%) and RMSE to standard deviation of observed values ratio (RSR, 0.38 *vs.* 0.56), respectively. Our results indicated that, under our experimental conditions, IT is a potential predictor of enteric CH_4 emissions in cattle. However, more experimental data are needed to validate our findings.

Keywords*:* Greenhouse gasses inventories, modelling, Object Detection technique, Precision Livestock Farming

1. Introduction

Methane (CH_4) emitted from livestock contributes substantially to global warming (Gerber et al., 2013). To establish the amount of CH_4 emitted from livestock, and specifically from cattle, several methods have been developed: open-circuit respiration chambers (Pinares and Waghorn, 2012), sulfur hexafluoride tracer (SF6) (Zimmerman, 1993) and GreenFeed (C-Lock Inc. Rapid City, SD, USA). Unfortunately, the implementation of those methods on a large scale is hampered by their high cost and the need for advanced equipment. Farms and animal lab facilities around the world, with few exceptions, are not equipped to measure cattle CH_4 emissions because these devices require advanced instrumentation, expensive maintenance, and highly skilled labor.

Complementary to experimental-based techniques, mathematical models have been accepted by IPCC (Shukla et al., 2019) to estimate the total amount of CH_4 emitted by cattle. Predictive models of enteric CH_4 emissions are mainly based on feed intake and chemical composition (Sauvant et al., 2011; Ramin and Huhtanen, 2013; Benaouda et al., 2019). Under the assumption that food composition is well known, the estimation accuracy of the models will depend mainly on the accuracy of feed intake determination.

Dry Matter Intake (DMI) is the primary predictor of enteric CH_4 emissions (Appuhamy et al., 2016; Charmley et al., 2016; Hristov et al., 2018). However, the individualized measurement of DMI, especially for grazing animals or in group-housing systems, is an expensive task (Seymour, et al., 2019). As an alternative to the direct measurement of DMI, new technologies based on sensors and Machine Learning algorithms allow the DMI to be inferred satisfactorily using the time that animals spend eating (Intake Time, IT), both indoors (Barker et al., 2018) and grazing (Mattachini et al., 2016).

Taking into account that IT has a close relationship with DMI, and that this in turn has a close relationship with CH_4 emissions, it is possible to infer that

IT has the potential to infer CH_4 emissions in a similar way as DMI. Based on this premise, Muñoz-Tamayo et al. (2019) evaluated theoretically the use of IT as CH_4 emissions predictor. The authors found that the accuracy of enteric CH_4 predictions using IT was similar to the accuracy obtained when DMI is used as a predictor in a dynamic model. The application of mathematical models using IT as predictors can be useful to improve the ruminant's enteric CH_4 inventories, in particular in countries lacking advanced experimental infrastructures. The objective of this work was to evaluate the potential of IT as a predictor of CH_4 emission.

2. Material and methods

2.1. Location and animals

Seven Angus x Brahman crossbreed steers (body weight: 240.7 +/- 23.1 kg; age: 477 +/- 42 days) were housed at the calorimetry laboratory of Universidad de Antioquia (Antioquia, Colombia). This laboratory is located at an altitude of 2480 m, with 16ºC average temperature and coordinates 6°26'43.1"N 75°32'43.0"W. During 60-days before the measurement of CH_4 emissions, the animals were individually housed in 2.5-m^2 covered pens (Figure 1) and adapted to the diet and to the respiration chamber facility.

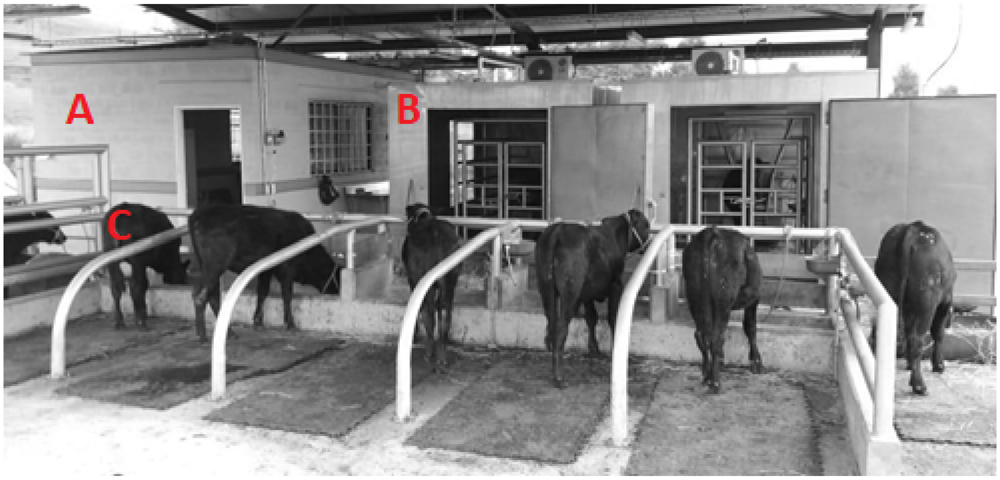

Figure 1. Calorimetry laboratory, Universidad de Antioquia. A. Monitoring room. B. Two respiration chambers for CH_4 measurements. C. Individual pens.

2.2. Diet and feeding

The diet consisted of hay grass (*Digitaria decumbens* Stent.) and supplement (corn-cottonseed-soybean meal) in a 60:40 ratio. Animals were fed *ad libitum* twice a day, at 09:00 and 15:00 h, throughout the experimental period. The daily amount offered was adjusted such that the rejected food was 10% of the offer. Diet composition is presented in Table 1.

2.3. CH_4 emissions

The calorimetry laboratory has two respiration chambers made in galvanized steel (Figure. 1). Internal dimensions of the chambers were 2.6 m wide, 3.7 m length, 2.3 m height, resulting in 22.1 m^3 total volume. The chambers have side windows (1.40 x 1.30 m) to allow visual contact between animals, and are provided with feeder, automatic drinker, fan to ensure gas mixing, air conditioning and dehumidifier to guarantee thermoneutrality and welfare conditions.

Table 1. Chemical composition of hay grass *(Digitaria decumbens* Stent*)* and supplement.

Nutrient (%)[1]	**Hay**	**Concentrate supplement**[2]
DM	89.0	87.8
CP	6.0	24.5
NDF	59.0	13.8
Ash	8.7	10.6
GE (kcal/kg DM)	4200	4450

[1] Composition expressed as percentage of the dry matter (DM); CP= Crude protein; NDF= Neutral detergent fiber; Ash= Inorganic matter; GE= Gross energy (kcal/kg DM).

[2] Supplement: corn (35.4%), soybean meal (35%), cotton seed (15%), urea (0.6%) molasses (8%) and mineralized salt (6%).

During the measurement of CH_4 emissions, the air was removed from the chambers at 500 L/min using a mass-flow system (Flowkit 2000, Sable Systems International, Las Vegas, NV, USA). CH_4 concentration in the extracted air column was measured every second with an infrared analyzer (MA-10, Sable Systems International, Las Vegas, NV, USA). The Expedata-UI2 software (Sable Systems International, Las Vegas, NV, USA) automatically calculated CH_4 emissions as liters per minute . The results were corrected for standard temperature and pressure. Figure 2 shows the respiration chamber design and the sampling for CH_4 quantification.

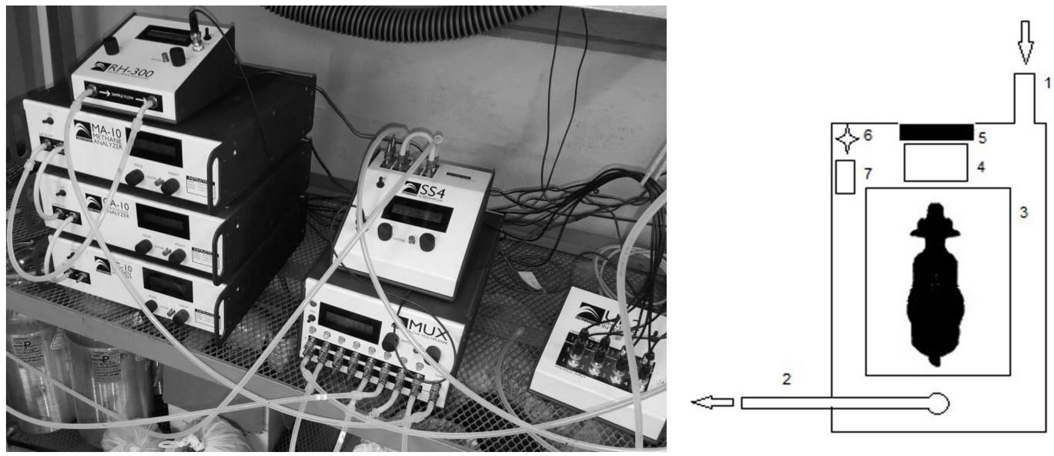

Figure 2: Methane analyzer and respiration chamber design: 1. Air inlet. 2. Air outlet. 3. Metallic pen. 4. Feeder and drinker. 5. Air conditioning. 6. Fan. 7. Dehumidifier

Before measuring the CH_4 produced by the animals, the analyzer was calibrated with commercially prepared gas of known concentration (0.098%). The animal's CH_4 emissions were adjusted according to the Recovery Factors (RF) of each chamber. To estimate the RF in each chamber, pure CH_4 was injected at a known rate (0.25 L/min) for 2 h. The amount of gas injected was determined gravimetrically. RF were 0.87 and 0.90 for chamber 1 and 2, respectively. CH_4 emissions from each animal were measured for three consecutive days.

2.4. Intake time (IT) measurements

To identify eating activity, a video camera was placed over the feeder inside each chamber (Figure 3). It was assumed that animals only visit the feeder to eat. To establish if the animal was eating or not, the object detection model YOLOv5x was used (Jocher et al., 2020). This model is a convolutional neural network (CNN, or ConvNet), based on the YOLO model (AlexeyAB/darknet) that, in simple terms, divides an input image into multiples grids, and use some of these cells for object detection if the center of an object falls into a grid cell. In general, the YOLO-based models have been trained using several image databases (e.g COCO dataset) to detect 80 different classes of objects, including horse, sheep, and cow. Given that in this work just one object class was necessary (i.e. cow), the model was fine-tuned to increase the cow detection accuracy.

Considering that all the video monitoring was taken under the same environmental conditions (e.g. illumination, distance from the feeder), the images data set extracted from the videos (>2 million) was visually inspected to find 1000 images with eating animals. This image sub-set was randomly selected from both chambers and all measured days. In each selected image, the software LabelImg (Tzutalin, 2018) was used to find the area where the object of interest (steer head) is located. This process is named “Image Labelling” and as result, 1000 text files with the object coordinates were obtained. The images, their corresponding labeling information, and the free resources in Google Colab were used to re-train the YOLOv5x following the Jocher et al. (2020) instructions. Finally, the re-trained YOLOv5x was used to calculate the IT per animal per day in the 2 chambers.

Figure 3: Example of eating activity detection in the chamber.

2.5. Dry matter intake (DMI)

Simultaneously with the quantification of CH_4 emissions, the DMI was determined. The DMI was daily calculated as the difference between the feed offered and rejected. Samples of food offered and refused were collected daily, and stored at -10^{o}C for subsequent dry matter analysis (AOAC 930.15, 1990).

2.6. Model equations and performance indicators

We developed two linear equations to estimate CH_4 emission. The impact of the feed intake was either represented by the DMI or IT. The model performance was assessed by the calculation of the following statistical indicators:

The root mean square error $RMSE$:

$$RMSE = \sqrt{\frac{1}{n}\left(\frac{\sum_{i=1}^{n}\left(O_i - P_i\right)^2}{n}\right)}$$

where n is the number of observations, O_i is the *i*th observed value and P_i is the *i*th model predicted value.

The relative prediction error RPE:

$$RPE = \left(\frac{RMSE}{\mathrm{X}o}\right) * 100$$

where $\mathrm{X}o$ is the mean of the observations.

The mean absolute error MAE:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|O_i - P_i\right|$$

The mean absolute percent error $MAPE$:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{O_i - P_i}{O_i}\right| * 100$$

The RMSE to standard deviation of observed values ratio RSR:

$$RSR = \frac{RMSE}{So}$$

where So is the standard deviation of the observed values.

The coefficient of determination R^2:

$$R^2 = \frac{\sum_{i=1}^{n}\left(O_i - P_i\right)^2}{\sum_{i=1}^{n}\left(O_i - \mathrm{X}o\right)^2}$$

The Lin's concordance correlation coefficient CCC (Lin, 1989):

$$CCC = \frac{2\sigma_{xp}}{\sigma_x^2 + \sigma_p^2 + (\mathrm{X}o - Po)^2}$$

where Po is the mean of the model predictions, and σ_x^2, σ_p^2 are the variances for the observations and the model predictions. The covariance σ_{xp} is calculated as:

$$\sigma_{xp} = \frac{1}{n}\sum_{i=1}^{n}\left(O_i - \mathrm{X}o\right)\left(P_i - Po\right)$$

3. Results and discussion

Table 2 shows the summary of the experimental data used for model construction. The mean DMI was 6.3 kg/d and the average CH_4 emissions per animal was 152.0 g/d. The mean IT recorded by image analysis was 5.4 h/animal/day. We observed that some animals eat food that falls outside the image area, which can have a negative impact on the precision of IT determination with image analysis in our experimental framework.

Table 2. Dry matter intake (DMI), intake time (IT) and CH_4 emissions data used for model construction.

Animal	DMI (kg/d)	IT (h/d)	CH_4 (g/d)
1	6.3	6.3	179.1
2	5.9	3.7	132.7
3	6.1	5.6	148.3
4	6.7	6.5	189.3
5	6.0	5.0	141.6
6	8.6	7.0	184.8
7	4.6	3.7	88.3
Mean±SD[1]	6.3±1.2	5.4±1.3	152.0±36

[1]SD= standard deviation

3.1. CH_4 emission

Figure 4 shows a typical pattern of the IT and CH_4 emission for an animal in our facility. CH_4 emission starts to increase when feed is offered. Compared with other studies reporting experimental data on the dynamic emissions of CH_4 (Crompton et al., 2011; Troy et al., 2015; Moate et al., 2018; Muñoz-Tamayo et al., 2019), our data suggest a possible buffer effect of the respiration chamber that hampers to capture the fluctuation pattern of CH_4 missions.

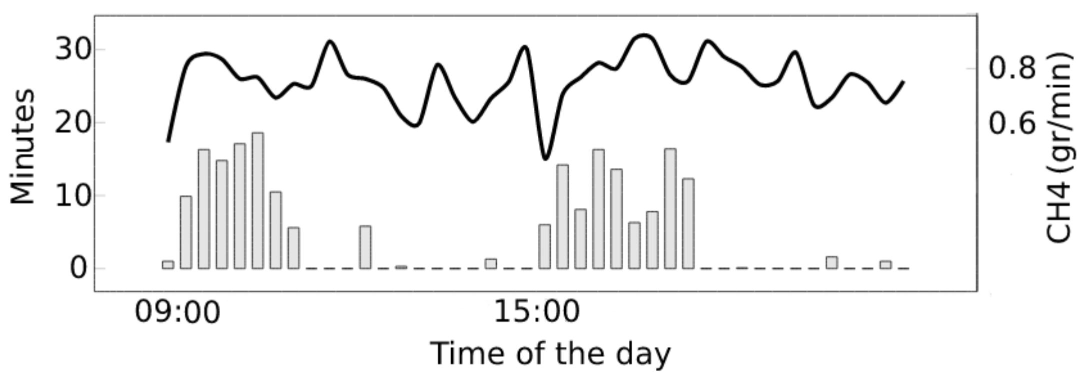

Figure 4. Example of intake time and CH_4 emission patterns. The line represents CH_4 emissions pattern (gr per minute) and the bars represent intake time pattern (minutes in 20 minutes intervals)

3.3. Performance of mathematical models

Table 3 shows the resulting linear equations obtained when using DMI and IT as predictors and the respective statistical performance indicators. For the model with DMI as predictor, the estimated slope is 12% higher than the slope estimated for Angus steers and 23% higher than the slope estimated for Brahman steers in the work of Charmley et al. (2016).

As observed, IT is a better predictor than DMI under our experimental conditions for all statistical performance indicators. Models with higher CCC and lower RPE, MAPE and RSR present better predictive performance. The RPE for IT (9.1) indicates satisfactory predictability (Fuentes-Pila et al., 1996). Likewise, the MAPE value for IT (8.2) is associated with a high predictive capacity (Mayer and Butler, 1993). Based on these parameters, it is observed that the model that incorporates IT for CH_4 estimations presents superior performance compared with DMI.

Table 3. Statistical indicators of model performance.

Statistical indicator[1]	Models[2]	
	CH_4 = 24.07*DMI	CH_4 = 27.95*IT
RMSE	20.2	13.8
RPE	13.3	9.1
MAE	16.9	10.9
MAPE	11.5	8.2
RSR	0.56	0.38
R^2	0.63	0.84
CCC	0.78	0.92

[1] $RMSE$: root mean square error; RPE: relative prediction error, MAE: mean absolute error; $MAPE$: mean absolute percent error; RSR: RMSE to standard deviation of observed values ratio; R^2: coefficient of determination; CCC: Lin's concordance correlation coefficient.

[2] CH_4: methane (g/d); DMI: dry matter intake (kg/d); IT: Intake time (h/d).

Hristov et al. (2018), using DMI as an independent variable, obtained CCC between 0.69 and 0.74 and RSR between 0.64 and 0.67. In the present work, both models resulted in higher CCC and lower RSR. McBride's (2005) indicated that CCC values lower than 0.90 and fluctuating between 0.90 and 0.95 are associated with poor and moderate predictive capacity, respectively. Accordingly, the model with IT had a better predictive capacity than the model with DMI.

Although it is widely accepted that DMI can be used to predict CH_4 emissions, the association between these variables depends on the DMI range used to establish the relation. Higher ranks are associated with higher coefficients of determination (R^2) (Hristov and Melgar 2020). Hristov et al. (2018) revealed that the relationship was higher for the respirometric chamber (R^2 = 0.58), with DMI ranges between 3.9 and 33.5 kg/d.

Benaouda et al. (2019) evaluated the performance of various CH_4 prediction models in dairy cattle, including the Charmley et al. (2016) model, which includes DMI as predictor. This model occupied a medium position, with root mean square prediction error (RMSPE), RSR and CCC of 22.8%, 0.81 and 0.68, respectively. In the present work, the best performance parameters for the model including IT are explained by the lower RMSE and the higher Pearson correlation coefficient between CH_4 emissions and IT (R = 0.92), with respect to DMI (R = 0.80).

Figure 5 displays the comparison of the experimental data against the model predictions and the respective residuals. Determination of IT in the field fulfills the characteristics of low cost and individual level accuracy discussed by Negussie et al. (2017). Accordingly, our work suggests that IT is a potential proxy of CH_4 emissions on a large scale. However, more experimental data are needed to validate our findings.

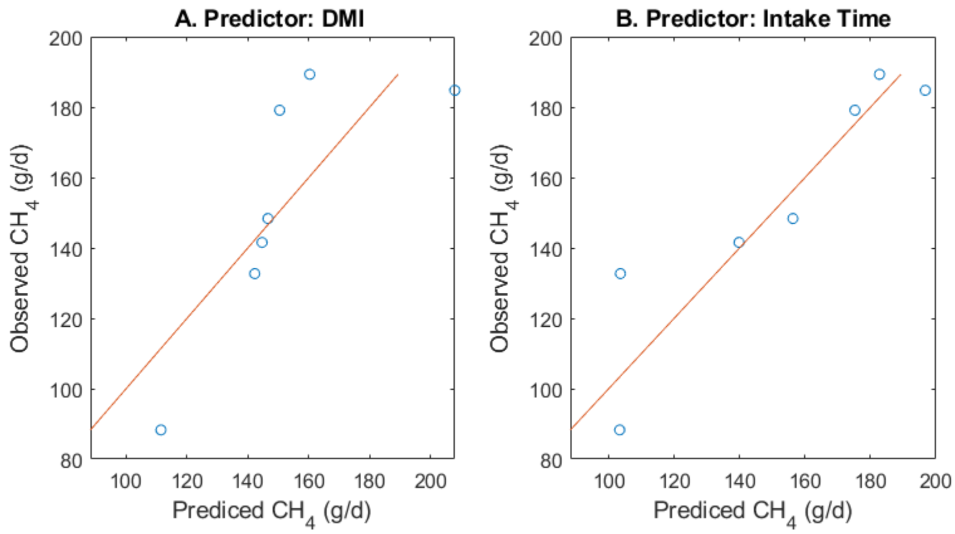

Figure 5: Experimental data of CH_4 emissions are compared against the predictive CH_4 production when using DMI (A) and IT (B) as predictor variables. The solid line is the isocline.

4. Conclusion

Our work indicated the potential of using IT as a predictor of CH_4 emissions, since IT can be estimated using different technologies (e.g. computer vision). Our result is of great relevance for estimation of CH_4 emissions at large scale, in particular for conditions when accurate estimations of DMI are not feasible.

Ethical considerations

This study was approved by the Ethics Committee for Animal Experimentation at Universidad de Antioquia (act 76, May 2012, Medellín-Colombia).

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Author contributions

J.F. Ramirez-Agudelo: Conceptualization, Methodology, Software, Investigation, Data Curation, Writing - Original Draft,; **C.S. Escobar-Restrepo:** Conceptualization, Methodology, Investigation, Writing - Original Draft; **R. Muñoz-Tamayo:** Formal analysis, Methodology, Writing - Review & Editing, Funding acquisition; **S.L. Posada-Ochoa:** Conceptualization, Methodology , Supervision, Writing - Review & Editing; **R. Rosero-Noguera:** Conceptualization, Methodology, Supervision, Project administration, Funding acquisition.

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