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Beef cattle methane emission estimation using the eddy covariance technique in combination with geolocation

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ABSTRACT

Methane emissions of a grazing herd of Belgian Blue cattle were estimated per individual on the field by combining eddy covariance measurements with geolocation of the cattle and a footprint model. This method allows the measurement of outdoor non-invasive methane emissions but is complex and subject to methodological issues. Estimated emissions were 220 $\pm$35 g CH_4 LU^{-1} day^{-1} (grams of methane per livestock unit per day), where the uncertainty corresponds to the random error and does not include any possible systematic error. Cattle behavior was also monitored and presented a clear daily pattern of activity with more intense grazing after sunrise and before sunset. However, no significant methane emission pattern could be associated with it, the diurnal emission variation being lower than the measurement precision.

Introduction

Ruminants are able to digest cellulose which makes them incredibly apt to transform raw forage, like grass, into high quality products. This digestive characteristic is due to an association with a very specific microbial flora present in the rumen or hindgut which allows the transformation of complex plant material into digestible fatty acids (acetate, lactate, propionate or butyrate). However, this transformation is accompanied by the co-production of methane, a potent greenhouse gas, which is mostly released through eructation (Broucek, 2014).

The current standard measurement method for cattle methane emissions is the metabolic chamber. This method calculates a mass balance between methane entering and leaving a sealed ventilated chamber containing an animal. Tracer methods are the major alternative for grazing ruminants; they involve the use of an external (e.g., SF_6 released by an ingested canister) or internal (e.g., metabolic CO_2 emissions) tracer released at a known rate from the animal's rumen. Measuring tracer and methane concentration ratios in excreted gases allows the computation of methane fluxes. Both techniques are accurate with a precision commonly higher than 90%, but require lots of animal handling (Storm et al., 2012), are rather invasive and could impact the natural grazing behavior of cattle. Emerging methods rely on the use of proxies; they are based on the relationship between methane emissions and the composition of matrices that are easy to sample such as feces or milk (Dehareng et al., 2012; Vanlierde et al., 2018). This method is valid as long as the composition of the proxies and the characteristics of the sampled animals (i.e., breed, intake level, physiological status, etc.) remain within the range of variability of the database that was used to develop the relationship. In addition to these animal-centered approaches, measurement methods have been developed that work at the scale of the environment in which the animals evolve. Some of these techniques simply reproduce lower scale methods (i.e., by considering the barn or the feeding trough as a chamber or by adding a tracer gas in a ventilated barn at a known rate and measuring the methane/tracer ratio) while others involve micro-meteorological methods (Johnson and Johnson, 1995; Storm et al., 2012). The latter are promising because they allow measurements to be recorded of the emission rate of the whole herd, on the field, with a half-hour time resolution, little animal handling and without disturbing the cow's natural behavior. Among micrometeorological methods, eddy-covariance (EC) is well suited for measurements in a pasture with low cattle density over large areas, and has become more affordable with the release of fast and precise optical methane analyzers. Nevertheless, applying this measurement method to grazed pastures is challenging due to a combination of source complexity (i.e., spatial and temporal variation in animal locations and emission intensities) and limitations in methodology specific to EC (Dumortier et al., 2017; Wohlfahrt et al., 2012).

Cattle emissions are not constant over time. Most of the CH_4

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produced escapes through the mouth, with 83% of emissions associated with eructation and 15% associated with respiration (Hammond et al., 2016). Cattle eruct 15 to 28 times each hour (every 130 to 230 s) according to the composition of their diet, feed intake levels and physiology (Blaise et al., 2018). Moreover, methane emissions vary throughout the day, peaking approximately 2 hours after feeding followed by a decrease until the next feeding event (Blaise et al., 2018). Cattle methane emissions thus present a 24-hour emission pattern which can be related to their feeding behavior (Hammond et al., 2016; Hegarty, 2013).

When using EC, the measured covariance corresponds to the vertical flux at one specific point that is representative of exchanges within the footprint, the area "sensed" by the flux measurement device. This footprint can be modeled through a set of functions that weight the respective contribution of each element of the surface to the measured vertical flux (Rannik et al., 2012), known as a footprint model. However, animals act as moving CH_4 sources which may wander in or out of the footprint. Therefore, fluxes measured through eddy covariance must be combined with a footprint model as well as information about the cattle's location on the pasture in order to estimate the animals' contribution to the measured flux. The ability of this approach to provide reliable emission estimates was previously tested using artificial sources (Dumortier et al., 2019). Previous investigations by Heidbach et al. (2017) showed that the FFP (Flux Footprint Prediction) model presented by Kljun et al. (2015) was the most efficient of the four tested models as long as the artificial source was located further from the mast carrying the sensors than the footprint peak (maximum of the footprint function). One of the main drawbacks of this model is that sources are assumed to be at ground level, while cattle emissions are emitted at muzzle height (i.e., up to 1 m height). To tackle this issue, Coates et al. (2017) simulated free-range cattle with artificial methane sources scattered on a field at a height of 0.8 m. They were able to estimate artificial source emissions with an error of 10% regardless of the distance between the source and the mast by using a Lagrangian stochastic model which could consider source heights. Because stochastic approaches require high computational power, Dumortier et al. (2019) tried to assess to what extent ready-to-use footprint models, that do not consider source height, could be stretched beyond the conditions for which they were designed in order to estimate methane emissions from elevated artificial sources. They concluded that emissions could be correctly estimated (error of less than 15%) using the analytical Kormann & Meixner (2001) footprint model when the artificial source was located further from the mast than the footprint peak.

These results strengthen the idea that EC can be used to estimate point source emissions of methane from cattle in field conditions. Felber et al. (2015) were the first to put this idea into practice. They calculated an emission per dairy cow by combining EC with cow geolocation data and the Kormann & Meixner (2001) footprint model. The experiment was run on a 3.6 ha pasture divided into 6 paddocks which were either very close to or distant from the mast. Every few days animals were transferred from one paddock to another (rotational grazing). This resulted in high stocking densities at the pasture level (5.5 LU ha^{-1}; LU, livestock unit) but very high stocking densities in the occupied paddock (up to 33 LU ha^{-1}). For paddocks close to the mast (less than 60 m), measured methane emission levels compared reasonably well (difference of less than 5%) with those obtained from metabolic chambers hosting dairy cows with similar milk production levels and body weights. However, for paddocks more distant from the mast, measured emissions per animal were lower and compared poorly to metabolic chambers, suggesting an imprecision of the footprint model. Other authors have successfully used a similar approach in different contexts (Prajapati and Santos, 2017), researching different gases (Gourlez de la Motte et al., 2019) or using different footprint tools (Coates et al., 2018).

In this work, free ranging cattle methane emissions on the pasture are estimated by combining eddy covariance with geolocation. This approach provides a variety of situations with the herd at rest, gathered at various distances from the mast, and cows more dispersed on the pasture during grazing. Moreover, we are able to rely on a methane emission estimation method previously validated on the same site with an artificial tracer (Dumortier et al., (2019). Our main objectives are:

- To adapt an existing method combining the EC technique and a footprint model (Dumortier et al., 2019) with cattle geolocation data in order to estimate mean enteric emissions per livestock unit (LU). The validity of this approach is estimated by the internal consistency of the results (stability of emissions, uncertainties and impact of meteorological conditions).
- To estimate methane emissions of Belgian Blue cattle on a typical Belgian commercial farm and to compare these with existing estimates (including IPCC default values).
- To investigate the relation between methane emissions and cattle behavior.

Materials and Methods

Experimental site

The ICOS-candidate Dorinne Ecosystem Station (BE-Dor) is a 4.2 ha pasture located in Dorinne, Belgium (location: 50̊18'42.84"N; 4̊58'4.8"E; 248 m above sea level). The site is the location of previous investigations and is fully described in Dumortier et al. (2017) and in Gourlez de la Motte et al. (2019). The pasture is situated on a loamy plateau with a calcareous and/or clay substrate. Its species composition is: 66% grasses, 16% legumes and 18% other species. The dominant species are perennial ryegrass (Lolium perenne L.) and white clover (Trifolium repens L.). The pasture is used for cow-calf grazing operations with Belgian Blue cattle with a mean annual stocking density in the pasture (SD_p) of 2.0 LU ha^{-1} (livestock unit per ha). An eddy-covariance measuring mast is located in the center of the pasture (Fig. 1). Wind speed and direction are measured on this mast using a sonic anemometer (CSAT3, Campbell Scientific Ltd, UT, USA) at a height of 2.6 m. Air sampled near the anemometer (0.216 m N, 0.125 m E and 0.23 cm below) is carried through a 2 μm filter (SS-4FW4-2, Swagelok Company, OH, USA) and a heated PTFE tube (inner diameter 3.18 mm, length 6.85 m, flow rate 9 10^{-5} m^3 s^{-1}) to the fast methane analyzer (G2311-f, Picarro, Inc, CA, USA).

Four measurement campaigns were organized involving 8 to 19 cows weighing between 700 and 850 kg, up to one breeding bull (±1300 kg) and up to 19 calves (Table 1). During each of these campaigns, cattle positions and behavior were monitored as described in §2.2, fluxes were measured as described in §2.3, and cattle emissions were computed as described in §2.4.

Position and behavior monitoring

During the four measurement campaigns, the position and behavior of each adult cow were monitored using a homemade tracking device consisting of a GPS unit and an accelerometer which was located on the top of the cow's neck (Fig. 2). Data were collected by a GPS antenna module (Fastrax UP 501, Fastrax Ltd., Finland) and a low power 3 axis accelerometer (ADXL335, Analog Devices Inc., MA, USA) and were stored on a micro SD card. Power was supplied by four batteries (3.8 V, 4 × 2000 mAH). The tracker could work for approximately 30 days on a single charge, avoiding too frequent handling of cows for battery replacement. In order to reach this autonomy, the data collection had to be discontinuous. Every 5 minutes, the tracker would wake up, wait for the acquisition of at least 3 satellite signals (which typically took about 30 s), record the position and acceleration components (used to detect behavior) in 3 dimensions at 20 Hz for 20 s, and then return to sleep mode. Neither the calves nor the bull were equipped with tracking devices. The GPS module precision was assessed by leaving the device motionless at a known position in the pasture for 41 days. During this

Fig. 1. Satellite view from the Dorinne Ecosystem Station. The pasture is highlighted in white, the red cross indicates the mast and the black ellipse indicates the location of the barn.

Table 1
Description of the four measurement campaigns.

Campaign	Start and end date	Number of cows /calves	Stocking density [LU ha^{-1}]	Main wind direction
Spring 2014	27 May 2014 – 25 Jun 2014	17-19 /17-19	6	N-E
Spring 2015	14 Apr 2015 – 7 May 2015	12 /0	2.8	S-W
Summer 2015	14 Aug 2015 – 2 Sept 2015	12 /10	3.8	S-W
Autumn 2015	19 Oct 2015 – 2 Nov 2015	8 /0	1.9	S-E

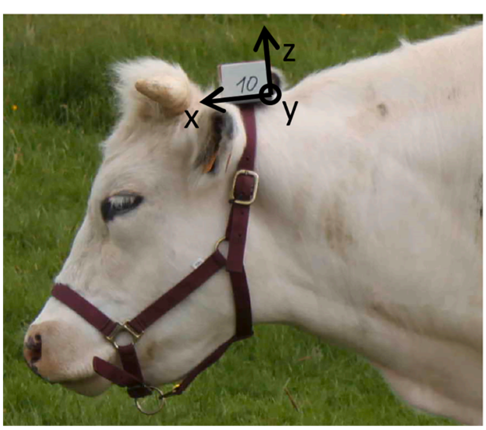

Fig. 2. Position and activity tracking device represented with the three axis system of the accelerometer.

period, 50% of the points were found within 3 m of the true location, 76% within 5 m and 95% within 11 m.

For animals which were not correctly geolocated (GPS malfunctions, representing 3.7 to 18.8% of the dataset from one campaign to another, or calves), their contribution to the footprint had to be estimated, resulting in an additional correction. Cattle footprint contributions were corrected by a geolocation correction factor (GCF) using Eq. (1), with a cow corresponding to 1 LU and a calf (4 to 10 months) to 0.4 LU. Data were excluded from the dataset when the GCF was larger than 1.5 (up to 56% of the dataset for the Spring 2014 campaign). The calves' conversion factor of 0.4 is based on the Walloon region criteria for the Common Agriculture Policy ("Arrêté ministériel exécutant l'arrêté du Gouvernement wallon du 3 septembre 2015 relatif aux aides agro-environnementales et climatiques") and is in agreement with the estimated emission levels of calves which should be between 30 and 40% of an adult cow (Basarab et al., 2012; Dämmgen et al., 2013; Lockyer, 1997).

$$GCF = \frac{\sum LU \ on \ the \ pasture}{\sum Detected \ LU} \tag{1}$$

Cattle behavior was sorted into three categories (grazing, ruminating and other) on the basis of the acceleration mean value and standard deviation along the x-axis as represented in Fig. 2. The use of the x-axis was selected because it was discriminating and had a physical interpretation. The measured acceleration can be divided into two terms: a low frequency component which corresponds to gravity projection along each axis and allows identification of the cattle's neck position, and a high frequency component due to the cattle's movements (Andriamandroso et al., 2016). During grazing, the cow's neck is oriented downward (positive values of a_x, the mean x acceleration component) and is moving abruptly for each bite (high σ_{ax}, the standard deviation of this value), while during rumination the cow's neck is horizontal or raised slightly upwards (a_x, values close to 0 ms^{-2} or slightly negative) with small movements related to mastication (low σ_{ax}). Other behaviors are characterized by a large array of a_x and σ_{ax} values, which sometimes overlap with rumination or grazing characteristic values (Andriamandroso et al., 2017). Attributing a behavior using universal absolute thresholds of a_x and σ_{ax} was not possible due to the specific positioning of the device on each cow. However, as cattle spend approximately 60% of their time grazing and 15% ruminating (Braghieri et al., 2011), these behaviors were detected by an algorithm which was looking for combinations of a_x and σ_{ax} occurring more frequently. For each cow-collar combination, a 2D histogram was created with 20 categories of a_x and 20 categories of σ_{ax}. For each of these 400 categories (20 × 20), the ones with the highest occurrence (threshold set at 3 times the average occurrence) were considered as rumination or grazing according to a_x and σ_{ax} (Fig. 3).

The precision of the behavior detection method was assessed by comparison to the behavior of cows which were visually observed for

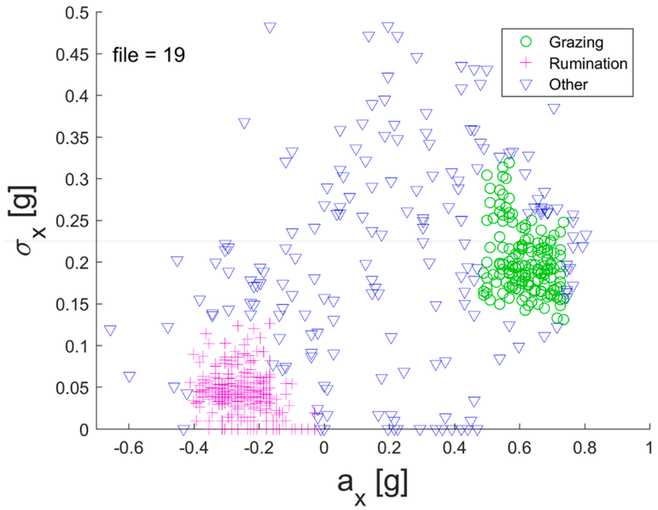

Fig. 3. Scatterplot of acceleration characteristics along the x-axis for a single cow and during a single measurement campaign. The horizontal axis corresponds to the mean acceleration and the vertical axis corresponds to the standard deviation. Each point represents a 20 s sample and is automatically associated with a behavior by an algorithm.

two hours, resulting in the acquisition of 115 5-minute measures. Those results are presented in Table 2. Detected behaviors agreed with observations in 85, 80 and 23% of the time for grazing, rumination and other behaviors respectively, while observations agreed with detections 96, 45 and 38% of the time for grazing, rumination and other behaviors respectively. This means that the grazing behavior was well characterized, while rumination and other behaviors where poorly distinguished.

Flux measurement and processing

Turbulent methane fluxes were calculated using EddyPro® version 6.2.2 open source software (Li-Cor Inc., NE, USA). The computation was the same as the method used by Dumortier et al. (2019) with the exception of the averaging period (30 minutes instead of 15 minutes) due to the presence of outliers that could not be filtered for the 15-minute averaging interval. The main differences from the default calculation method were the use of a running mean with a 120 s time constant, and the absence of stationarity filtering because animals could cause sudden fluctuations in the methane dry mixing ratio.

Time lags between measured vertical velocity and methane dry mixing ratio were calculated using a covariance maximization method with a default value of 2.3 s and a window size of 1 s (79% of the records were found within this time window for methane). A correction for high-frequency losses was applied using an in situ spectral correction method (Fratini et al., 2012). Data were also filtered on the basis of friction velocity, using a u_* threshold of 0.13 m s^{-1} (Dumortier et al., 2017; Gourlez de la Motte et al., 2016). Among the statistical tests for raw data screening proposed by Vickers and Mahrt (1997), some choices were made. The spike filtering, drop-out, absolute limit and discontinuities tests were applied using the default settings proposed in EddyPro®. These tests removed less than 3% of the dataset. Amplitude resolution, skewness and kurtosis tests were disabled as in a previous artificial source campaign (Dumortier et al., 2019); they induced a removal of almost all periods involving the artificial source in the footprint, although these signal characteristics were obviously generated by a real phenomenon.

An additional filter was added to remove data associated with poorly defined footprint functions (z/L>0.05). Moreover, as cattle muzzles are not found solely at ground level but at a height ranging from ground level to approximately 0.8 m high, a minimum distance between the source and the mast was defined. The impact of the source height had been tested using FIDES (Loubet et al., 2010), a pseudo Gaussian footprint model which includes the height of the source as an input variable. The conclusion was that for a source located further than 12 m from the mast for unstable conditions and 16 m from the mast for neutral conditions, the source height impact on the footprint function was below 15% if the source is found below 0.8 m. These distances were therefore selected for data filtering.

The footprint function extended well beyond the pasture borders (Fig. 4) which means that events occurring outside of the pasture could be unintentionally detected. This was the case during the Spring 2015 campaign which started early in the season (14 April), resulting in contaminated fluxes originating from the barn (Fig. 1) which was a strong methane source when cattle were still housed indoors, and from a manure heap located 500 m south-west from the mast. For this campaign, contaminated wind directions (5 to 50 and 200 to 230° N, clockwise) were thus removed from the dataset. Other campaigns were not affected by these issues as, for later dates, no (or only a few) cows were present in the barn and the manure had been used for crop

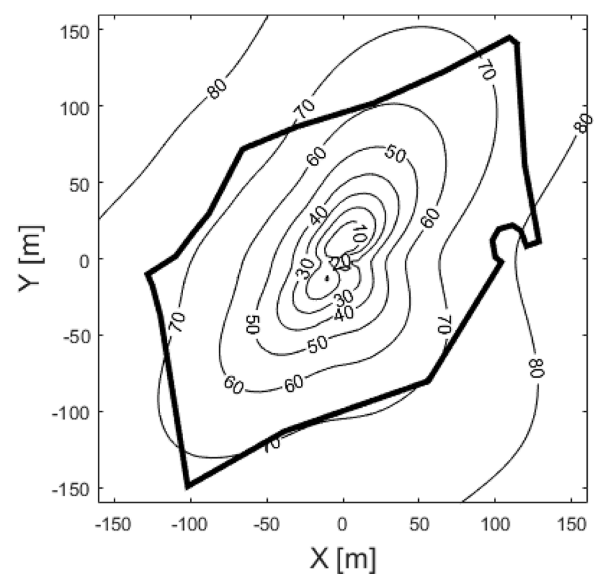

Fig. 4. Mean cumulative footprint during the whole measurement period using the Kormann & Meixner footprint model. The isopleths represent the area responsible for x% of the measured flux (proportion of the footprint found inside a specific area). The bold line corresponds to the pasture limits.

Table 2
Confusion matrix of the behavior detection algorithm. Each row of the matrix represents the instances in a predicted class while each column represents the instances in an observed class.

ObservationPrediction	Grazing	Rumination	Other	Total	Observation corresponding to prediction
Grazing	48	0	2	50	96%
Rumination	0	20	24	44	45%
Other	8	5	8	21	38%
Total	56	25	34	115	
Prediction corresponding to observation	86%	80%	24%		

fertilization.

Applied filters and associated data loss are described in Table 3. According to this table, the proportion of high quality flux data (meaning data without instrument malfunctions and with u_* above 0.13) was between 40 and 67% from one period to another. Moreover, 60 to 80% of the remaining dataset was eliminated due to poorly defined cattle contribution to the footprint (which corresponds to a z/L ratio above 0.05), unavailable cattle positions (GCF above the threshold), presence of cattle too close to the mast (12 to 16 m according to meteorological conditions) or wind coming from a strong and undesired methane source (barn or manure heap) for the Spring 2015 campaign. The remaining high quality dataset was used for this study. No filter was associated to a minimum cattle contribution to the footprint.

Enteric emission estimation

Methane emissions per LU (f_{CH4}) were estimated according to the method described by Dumortier et al. (2019), which is equivalent to the method proposed by Felber et al. (2015). f_{CH4} were computed by combining turbulent flux measurements with cattle positions through the use of a footprint function using Eq. (2), where F_{CH4} is the measured methane flux (nmole m^{-2} s^{-1}), i corresponds to the cow identification number and ϕ_i the value of the footprint function at the i cow location (m^{-2}). As cattle locations were recorded every 5 minutes, the one sixth ratio allows the calculation of an average ϕ_i for each 30-minute interval as each animal occupied 6 locations during an averaging interval.

$$f_{CH_4} = \frac{F_{CH4}}{GCF \times \frac{1}{6}\sum_i \phi_i} \tag{2}$$

where $GCF \times \frac{1}{6}\sum_i \phi_i$ corresponds to the stocking density in the footprint (SD_f). The footprint function (ϕ) was calculated according to the footprint model described by Kormann & Meixner (2001)(KM) on a 30-minute averaging period. However, f_{CH4} values estimated through this method were subject to high variations, especially for low SD_f. A method more robust than a division was therefore considered.

Equation (2) implies a direct relationship between measured methane fluxes and cattle density in the footprint. In other words, f_{CH4} can be calculated as the slope of the linear regression associated with the relation between SD_f and the measured methane flux. Different regression methods can be used to infer the slope of the linear regression. The most common one, the Linear Least Square regression (LLS) minimizes residues associated with the vertical axis and supposes no uncertainty associated with the horizontal axis. However, when uncertainties are associated with both axes, as was the case here, functional relations must be used (Webster, 1997). The Reduced Major Axis method (RMA, Matlab code provided by Trujillo-Ortiz, 2020 & Hernandez-Walls, 2020) minimizes residues along the normalized horizontal and vertical axis, this method is therefore able to deal with uncertainties on both axes. Another way to estimate the slope of the regression is the Median-Median Regression (MMR) which is obtained by dividing the dataset into two groups (based on the median value of the x axis). For each group the central point is calculated as the median value along horizontal and vertical axes. The regression line then corresponds to the line passing through the center of each group. The main advantage of the MMR method is that it doesn't involve a hypothesis about the distribution shape or the uncertainty associated with each axis. We applied these last two methods (RMA and MMR) to our dataset, resulting in two f_{CH4} estimates. Both methods were far more robust than a simple division. For both options, the confidence interval of the slope was estimated through a bootstrapping method. This resampling method is adapted to almost any distribution and allows numerical estimation of the uncertainty of the parent population and not only of the sample. The 95% confidence interval was computed as the 2.5 and 97.5 percentile of the slope distribution after 5000 draws, and the 95% uncertainty range corresponded to the half of this confidence interval.

Table 3
Number (and percentage) of half-hours remaining after the application of each filtering step for each measurement campaign.

	Spring 2014	Spring 2015	Summer 2015	Autumn 2015
Measurement period	1385	1097	913	669
High quality flux data	859 (62%)	730 (67%)	415 (45%)	267 (40%)
+ Well defined cattle contribution to the footprint	299 (22%)	136 (12%)	156 (17%)	171 (26%)

Results

Cattle behavior and distribution

For each campaign, cattle were found to be well spread over the whole pasture when grazing, while they gathered near the water troughs and the trees bordering the pasture when ruminating or idling (Fig. 5). We also observed that grazing behaviors followed a diurnal pattern; animals grazed mainly during the day with peak activities just after

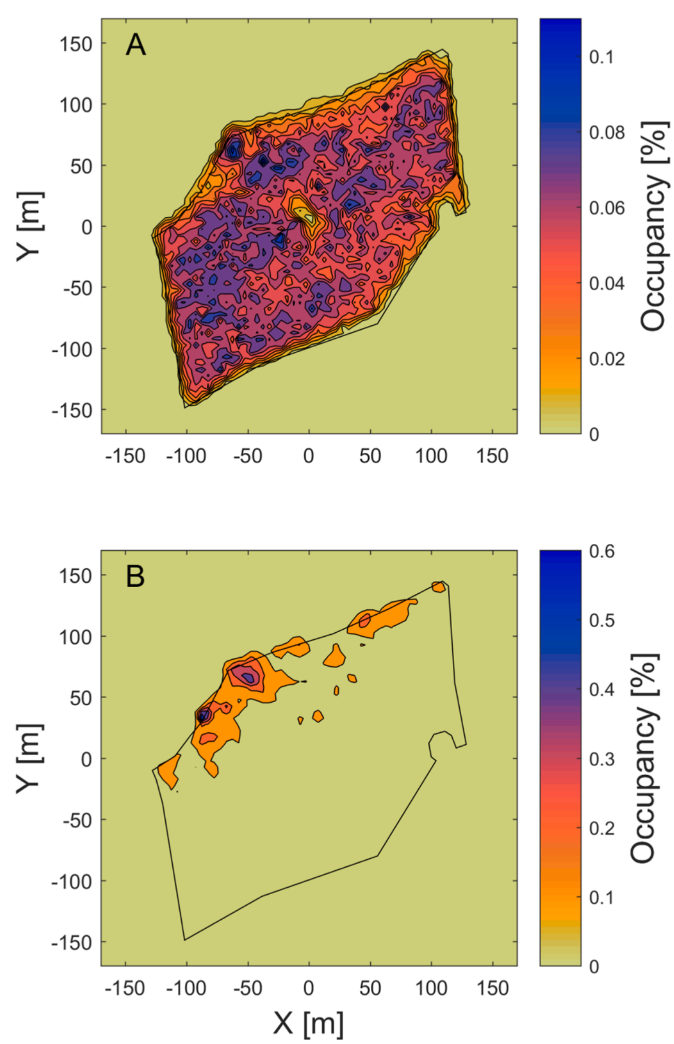

Fig. 5. Density maps of cows' positions when grazing (A) or expressing other behaviors (B) for all four campaigns combined. The black line represents the limits of the pasture. The occupancy is calculated as the percentage of the time spent by cattle in each square meter. A homogeneous cattle distribution would result in a 0.06% occupancy over the whole pasture.

sunrise and before sunset (Fig. 6). This behavior was confirmed by GPS trackers which revealed a strong correlation between cattle movement and grazing behavior. Cows were covering larger distances during the 5-minute interval between two consecutive measurements when they were grazing (Fig. 6). These results confirm the validity of the animal behavior detection method presented in §2.2.

One might wonder if cattle geolocation was really necessary in order to estimate f_{CH4}. Without information about cattle's location, f_{CH4} could be estimated for each campaign considering a homogeneous cattle disposition in the pasture as done by Dumortier et al. (2017). However, as showed in Fig. 5, cattle disposition on the pasture is generally heterogeneous. The only notable exception is during grazing events which are observed at sunrise and sunset. These periods could thus be used to estimate cattle emissions without requiring any knowledge about cattle location.

Enteric methane emissions

Enteric methane emissions were estimated by the slope of the linear regression associated with the relation between SD_f and measured methane fluxes. In Fig. 7, the two selected regression lines are drawn for the Spring 2014 campaign, along with the LLS regression line for comparison purposes. The slope of these regression lines were used to estimate f_{CH4}. For each campaign, f_{CH4} values are represented in Table 4. As slopes estimated using the RMA method were more stable and associated with smaller confidence intervals, this method was selected for the rest of the paper. Over the course of all four campaigns, f_{CH4} obtained using RMA was found to be between 184 and 255 (95% confidence intervals) which corresponds to 220 ±35 g CH_4 LU^{-1} day^{-1}. This indicates an estimated random error of 16%. No significant differences in methane emission levels were observed between campaigns (overlapping confidence intervals).

The uncertainty associated to a measurement method is critical when assessing its ability to quantify emissions and, more importantly, to identify the impact of any mitigation of this emission. The error associated with f_{CH4} estimates can be divided into two categories: the precision, which can be dealt with by increasing the size of the dataset, and the accuracy, which is associated with the method and was previously analyzed at the same site by Dumortier et al. (2019). In order to investigate the impact of the size of the dataset on the random error associated with cattle CH_4 emissions estimates, a bootstrapping method was used (a random part of the dataset was sub-sampled) (Fig. 8). Using this method, we observed that at least 480 valid half-hours are needed in order to obtain a 95% uncertainty range below 20%, while only 190 measures are needed in order to obtain an uncertainty range below 30%.

Quantifying the relation between the uncertainty range and the size of the dataset allows an estimation to be made of the amount of data required when designing an experiment. If one wishes to be able to

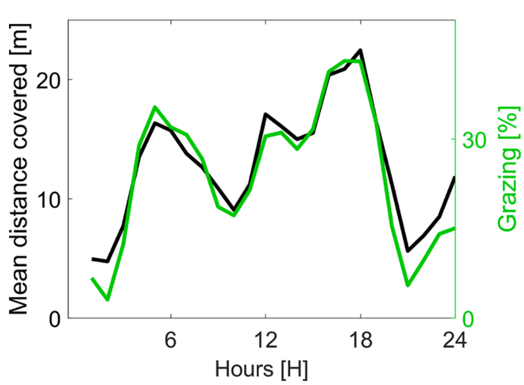

Fig. 6. Average percentage of the herd grazing (green) and distance covered between each measurement (black; each 5 minutes) according to the time of day for all four campaigns combined.

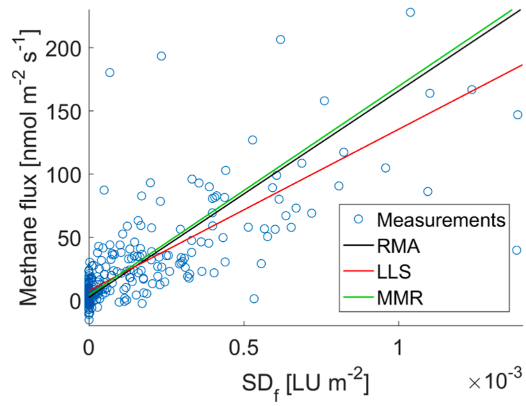

Fig. 7. Relation between measured methane flux and stocking density in the footprint (SD_f) calculated according to the Kormann & Meixner footprint model for the Spring 2014 campaign with each point corresponding to a 30-minute measurement interval. The different regression lines correspond to the reduced major axis method (RMA), the linear least square (LLS) and the median-median regression method (MMR) (see §2.3.1 for more details about each method).

Table 4
Estimated cattle emissions per livestock unit (f_{CH4}) for each campaign using two different methods: reduced major axis regression (RMA) and median-median regression (MMR). All estimations are presented through a 95% confidence interval and a 95% uncertainty range.

Campaign	RMA [g CH_4 LU^{-1} day^{-1}]	MMR [g CH_4 LU^{-1} day^{-1}]
Spring 2014	188 – 268	168 – 266
	228 ± 40	217 ± 49
Spring 2015	158 – 237	93 – 415
	197.5 ± 39.5	254 ± 161
Summer 2015	137 – 321	125 – 426
	229 ± 92	275.5 ± 150.5
Autumn 2015	172 – 270	166 – 409
	221 ± 49	287.5 ± 121.5
All seasons	185 – 255	183 – 254
	220 ± 35	218.5 ± 35.5

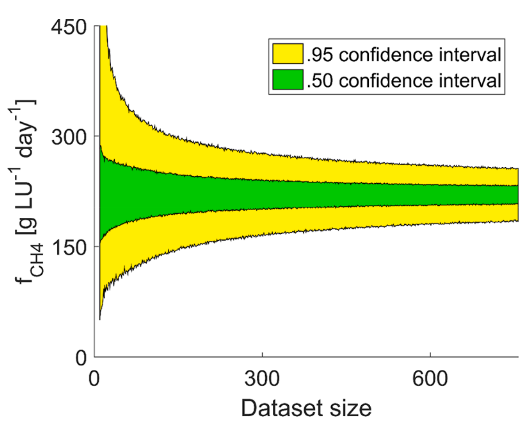

Fig. 8. Impact of the size of the dataset on methane emissions per livestock unit (f_{CH4}) confidence intervals estimated using a bootstrapping method. For each possible size of the dataset, 5000 sub-samples were analyzed in order to compute associated f_{CH4} estimates. For x% of those runs, estimated f_{CH4} values were found within the .x confidence interval, x corresponding to 95 (yellow) or 50 (green).

distinguish a significant impact of a specific mitigation action, the amount of data required to observe differences above a certain threshold can be estimated. However, this uncertainty estimation method is numeric and only based on our dataset. Other sites may provide different relations between methane fluxes and stocking densities in the footprint, leading to different curves. This result is thus difficult to extrapolate to other datasets.

Relations between cattle behavior and emissions

During each campaign cattle mainly grazed after sunrise and before sunset, with intermediate grazing events during the day when the photoperiod was long or during the night on shorter days (Fig. 9). However, significant f_{CH4} variations throughout the day were only observed for the Spring 2014 and Spring 2015 campaigns where emissions were significantly lower for one 4-hour period (2 to 6 pm and 6 to 10 am respectively). Due to this very weak f_{CH4} diurnal variation, no detection of any significant impact of cattle behaviors on methane emissions was possible.

An impact of the time since grazing peak was assessed when all campaigns were grouped together (Fig. 10). However, no significant impact of this time on cattle methane emissions was observed.

Cattle methane emissions bias analysis

Atmospheric conditions or cattle movements on the pasture should not have any impact on estimated f_{CH4}. Nevertheless, in order to detect possible biases, such relations were examined. We observed no significant impact (largely overlapping confidence intervals) of the distance between the closest cow and the mast, atmospheric stability, u_*, average distance covered by animals and wind direction on estimated f_{CH4}. For each variable and when using the complete dataset (all four campaigns grouped together), significant relations were assessed after dividing the dataset into 3 equal size categories of the selected variable. The absence of an impact of u_* (even for values below 0.13 m s^{-1}), of the distance between cattle and the mast (even when below 12 m) or atmospheric conditions (even for z/L values above 0.05) does not indicate the absence of bias from any of the previously listed variables on f_{CH4} but rather that the bias is lower than the uncertainty range associated with the measurements (relative 95% uncertainty ranges around 27% when the dataset was subdivided into 3 categories).

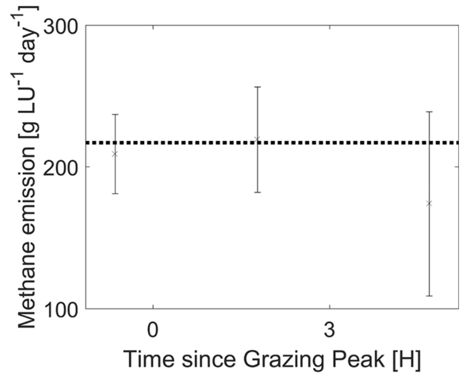

Fig. 10. Methane emissions per livestock unit (f_{CH4}) according to time since grazing peak for all campaigns together. Times since grazing peak were organized into 3 categories containing the same number of samples and plotted as the category mean. The error bars correspond to the 95% confidence intervals of f_{CH4} (bootstrapping method). The dotted line indicates the f_{CH4} estimated using all data. All values have been computed with the RMA regression method and the KM footprint model.

Discussion

Validity of the method

The first objective was to provide estimates of the mean enteric CH_4 emissions per livestock unit by combining the EC technique with a footprint model and cattle geolocation data. The combination of EC with geolocation allows stable and realistic estimations of cattle methane emissions to be made with measurement campaigns as short as one month (197 to 229 g CH_4 LU^{-1} day^{-1}). Obtained methane emissions were realistic and the regression slope 95% uncertainty range was estimated between 18 and 40% for each campaign, despite the heterogeneous distribution of cattle on the pasture. As already highlighted by Gourlez de la Motte et al. (2019), cattle were not homogeneously dispersed on the pasture at all times (Fig. 5). Therefore the use of GPS trackers was a great improvement compared with the homogeneous

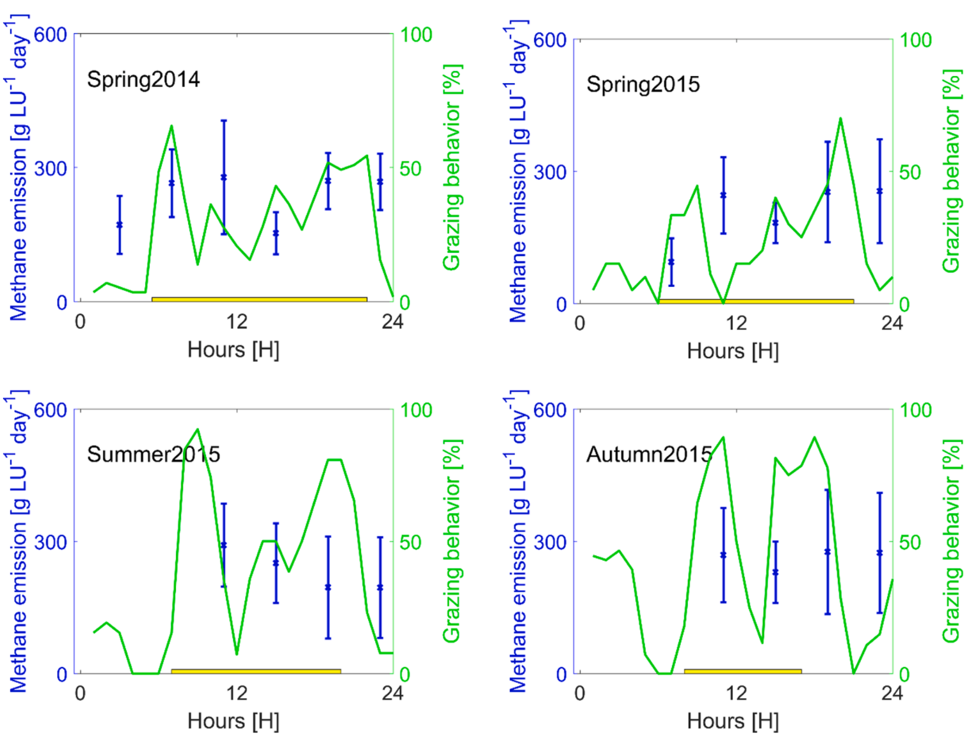

Fig. 9. Methane emission per livestock unit (f_{CH4}) evolution throughout the day for each measurement campaign computed with the reduced major axis (RMA) regression method and the Kormann & Meixner footprint model. The whiskers indicate the 95% uncertainty range of f_{CH4} for each 4-hour period (bootstrapping). The green line indicates the percentage of animal grazing and the yellow strip indicates the photoperiod for this specific time of year. Whiskers are only represented when more than 10 points were available for a given interval.

cattle distribution hypothesis. As a result, the assumption used in Dumortier et al. (2017) that cattle are spread homogeneously over the pasture is only valid when cattle are grazing. This might explain why the homogeneous cattle distribution hypothesis can lead to good results if cattle are confined in a delimited area, upwind from the mast, whose average footprint contribution is known (Dengel et al., 2011; Dumortier et al., 2017; Felber et al., 2015).

Belgian Blue CH_4 emissions

The second objective was to estimate methane emissions for the Belgian Blue breed on a typical Belgian commercial farm and to compare these values with existing estimates. When averaging all four campaigns, estimated emissions were 220 ±35 g CH_4 LU^{-1} day^{-1} or 80 ±13 kg CH_4 LU^{-1} yr^{-1}. These values are very close to tier 2 IPCC emission estimates (IPCC, 2006) of 205 ±41 g CH_4 LU^{-1} day^{-1}, considering a measured average dry matter ingestion of 9.5 kg per day (Gourlez de la Motte et al., 2016), a default raw energy content of 18.45 MJ kg^{-1}, a default methane conversion factor of 6.5% and a default uncertainty range of 20%. The values are also very close to a previous measurement of 223 ±16 g CH_4 LU^{-1} day^{-1} obtained by De Mulder et al. (2018) on the same breed using metabolic chambers (indoor-housed Belgian Blue heifers). On the whole, the random error associated with f_{CH4} estimates was 16% (35 g CH_4 LU^{-1} day^{-1}).

The random error associated with emission estimates does not give any information about the measurement accuracy. Our best estimate of this accuracy is obtained from the artificial source experiment run on the same site (Dumortier et al., 2019). A recovery rate between 90% and 113% was obtained, according to the distance between the source and the mast. For comparison, a 13% systematic error on f_{CH4} estimates would translate to approximately 30 g CH_4 LU^{-1} day^{-1}.

Impact of cattle behavior on CH_4 emissions

The third objective was to investigate the relation between methane emissions and cattle behavior. The 95% confidence interval of f_{CH4} estimates depends on the number of observations. Therefore, when the dataset was subdivided, uncertainty on binned estimations increased, making it difficult to demonstrate the dependency of emissions on the cattle's behavior. For instance, when averaged over 4-hour periods, f_{CH4} uncertainty ranges were estimated between 20 to 60% according to the time of the day and the campaign. The confidence interval was thus simply too large to detect any link between f_{CH4} and cattle behavior. This high uncertainty might be due to the fact that we were working with relatively low stocking densities (1.9 to 6 LU ha^{-1}) in a real production environment where cattle do not always exhibit the same behavior simultaneously. In these conditions about 480 valid half-hours were needed in order to limit the 95% relative uncertainty range to 20%.

No significant differences in f_{CH4} appeared between campaigns, with 95% confidence intervals largely overlapping. Therefore, no impact of the season or of grass intake, both in terms of quantity or quality, can be inferred from the present dataset. We can say that the impact of the season on cattle methane emissions at our site was lower than the uncertainty range associated with our measurements. Moreover, cattle methane emissions might be relatively stable as the farmer adjusts cattle stocking density according to grass availability and quality variations throughout the year.

Cattle positions in the pasture as well as micro-meteorological variables like the minimal distance from the mast, atmospheric stability, u_* or wind direction variation had no significant impact on estimated methane emissions. This means that the precision associated with the measures was insufficient for their detection. Filters (u_* and z/L) were nevertheless applied to reduce the variability associated with f_{CH4} as these filters were theoretically justified.

Conclusions

Estimated methane emissions from cattle raised at the BE-Dor site were 220 ±35 g CH_4 LU^{-1} day^{-1}, where the uncertainty corresponds to the random error and does not include any possible systematic error. This figure corresponds to previous estimates and should be representative of common rearing practices in south Belgium.

The present technique is not limited to methane and, provided the appropriate analyzers are available, can be used to estimate other gaseous animal emissions like CO_2 (Felber et al., 2016; Gourlez de la Motte et al., 2019). Some European pastures are already monitored using eddy covariance (Flechard et al., 2007; Hörtnagl et al., 2018), most of them without tracking the cattle's location on the pasture. However, measured fluxes on a pasture (CO_2, CH_4, volatile organic compounds, N_2O, etc.) are intrinsically biased as these fluxes are impacted by cattle. As cattle distribution on the pasture is fundamentally heterogeneous, the use of geolocation can greatly help in the interpretation of the measurements. Alternatively, CH_4 fluxes could be used as proxies of cattle presence in the footprint (Gourlez de la Motte et al., 2019). Altogether, the combination of eddy covariance with a footprint model has the advantages of working outdoors with minimal impacts on cattle raising conditions, but is costly and labor intensive.

Several improvements could be brought to the technique. The most labor-intensive step of the work was to equip cattle with GPS trackers in order to obtain their positions. More easily automatable solutions could be developed with the help of active RFID tags or infra-red cameras. Eddy covariance footprint models could also be improved by considering source height using a 3D footprint model or by working with backward stochastic Lagrangian models. Additionally, individual fluxes measured through eddy covariance are often discarded due to stationarity issues. The use of recently explored alternative flux calculation methods such as a wavelet transform (Göckede et al., 2019; Schaller et al., 2017) could increase methane flux measurement accuracy in non-stationary conditions, which is of great importance at the half-hour scale. In conclusion, the combination of a methane flux quantification method with cattle geolocation is a promising way to measure cattle methane emissions on the field in real commercial conditions, but substantial improvements are still required for optimal efficiency.

Declaration of Competing Interest

None.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.agrformet.2020.108249.

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