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Enteric methane emission estimates for Kenyan cattle in a nighttime enclosure using a backward Lagrangian Stochastic dispersion technique

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Abstract

This study provides methane (CH_4) emission estimates for mature female African beef cattle in a semi-arid region in Southern Kenya using open-path laser spectroscopy together with a backward Lagrangian Stochastic (bLS) dispersion modeling technique. We deployed two open-path lasers to determine 10-min averages of line-integrated CH_4 measurements upwind and downwind of fenced enclosures (so-called bomas: a location where the cattle are gathered at night) during 14 nights in September/October 2019. The measurements were filtered for wind direction deviations and friction velocity before the model was applied. We compared the obtained emission factors (EFs) with the Intergovernmental Panel on Climate Change (IPCC) Tier 1 estimates for the Sub-Saharan African (SSA) countries, which were mostly derived from studies carried out in developed countries and adapted to the conditions in Africa. The resulting EF of 75.4 ± 15.99 kg year^{-1} and the EFs calculated from other studies carried out in Africa indicate the need for the further development of region-specific EFs depending on animal breed, livestock systems, feed quantity, and composition to improve the IPCC Tier 1 estimates.

Abbreviations

AFOLU	Agriculture, Forestry, and Other Land Use
bLS	Backward Lagrangian Stochastic
EC	Eddy covariance
EF	Emission factor
FAO	Food and Agriculture Organization of the United Nations
IDM	Inverse dispersion model
ILRI	International Livestock Research Institute
LW	Live weight
MOST	Monin–Obukhov similarity theory
SSA	Sub-Saharan Africa

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1 Introduction

At present, anthropogenic greenhouse gas (GHG) emissions are the highest in history and are still on the rise (IPCC 2019b). Although global methane (CH_4) emissions constitute only 4% of the global anthropogenic carbon dioxide (CO_2) emissions in units of carbon mass flux, they contribute 20% to the additional radiative forcing in the lower atmosphere (Ciais et al. 2013). The Agriculture, Forestry, and Other Land Use (AFOLU) sector accounted for 44% of the anthropogenic CH_4 emissions during the period between 2007 and 2016, representing 23% of the total net anthropogenic GHG emissions (IPCC 2019b). In absolute numbers, global methane emissions from the AFOLU sector were 162 ± 49 Mt CH_4 year^{-1} (4.5 ± 1.4 Gt CO_2-equivalents (eq) year^{-1}) between 2007 and 2016 (IPCC 2019b) with livestock accounting for almost two-thirds of those emissions

(Saunois et al. 2020). Cattle dominate the CH_4 emissions from the livestock sector, accounting for 64–78% (Herrero et al. 2013; Milich 1999). Patra (2014) projects an increase of enteric fermentation CH_4 emissions from cattle of 26% until 2050 compared to 2010 due to the expected population increase and the corresponding increase in animal-derived food demand (Dangal et al. 2017; van den Pol et al. 2016).

National GHG inventories are used to monitor national annual GHG emissions and help them to achieve the goals set by the Paris Climate Agreement (Horowitz 2016). According to the good practice guidance outlined by the IPCC (Penman 2000), emission factors (EF) are fundamental parameters to calculate national inventories. EFs are the average emission rate of a given source, relative to units of activity or processes (Mareddy 2017). The IPCC suggests three different approaches (Tier 1–Tier 3) to derive national GHG inventories for individual components within the agricultural sector. The Tier 1 approach is the most basic method and based on default values of methane emissions per head which are then multiplied by the number of animals (Gavrilova et al. 2019). In the specific case of Sub-Saharan Africa (SSA), the default value is 41 kg CH_4 head^{-1} for free-grazing mature female African beef cattle (Dong et al. 2006). Up to date, even though it is the most straight forward approach, this value causes large uncertainties in national GHG inventories since cattle contribute with around 50% to countries' AFOLU GHG emissions and, therefore, with around 12% to the total net anthropogenic GHG emissions (IPCC 2019b). Reasons for lifestock CH_4 emission uncertainties are for instance inaccuracies in the livestock census data and the fact that the default EFs for SSA were derived from former studies almost exclusively carried out in developed Western countries and adapted to developing countries based on expert knowledge. To date, only little localized empirical data are available to verify the default tier. While some new information (Tier 2) has become available, this information has only recently been taken up by the IPCC (2019a) (Goopy et al. 2018, 2020; Ndung'u et al. 2019). Tier 2 approaches provide advanced GHG inventories necessary to achieve countries' goals set by the Paris Climate Agreement (Horowitz 2016) by helping to understand the impact of different productivity measures on GHG emissions to find ways to mitigate those without necessarily decreasing the animal numbers. The Tier 2 approach is based on country-specific livestock data (i.e., live weight (LW) as well as detailed feed basket information) to derive region-specific emission factors (Gavrilova et al. 2019). Available studies that have developed and/or used Tier 2 EFs in SSA countries show substantial differences to the Tier 1 estimates (Du Toit et al. 2013; Goopy et al. 2018; Kouazounde et al. 2015; Ndung'u et al. 2019; Tongwane and Moeletsi 2020). Tier 2 values are expected to be superior to the Tier 1 values by taking more data into account and have so far been developed for smallholder farming systems and/or dairy systems in SSA but not yet for pastoral livestock systmes. Such rangeland/grazing systems are completely different from the smallholder farming systems as livestock (e.g., cattle) graze during the day and are kept in enclosures (so-called bomas or kraals) throughout the night to avoid theft or predation (Butterbach-Bahl et al. 2020). As a consequence, feed is often unavailable throughout the night (Nicholson 1987). Additionally, the movement and feeding patterns of such grazing animals in SSA are further affected by feed shortages during the dry seasons or distinct droughts (Norman 1965) and thus also affect CH_4 emissions from enteric fermentation.

Methane EFs from enteric fermentation from cattle can be derived via indirect approaches, e.g., through activity data (Goopy et al. 2018), or direct approaches, e.g., via eddy covariance (EC) flux, via cattle respiration chambers, with different tracer-ratio techniques, via mass balance techniques, the flux-gradient technique, the here proposed backward Lagrangian Stochastic (bLS) methodology (overview, e.g., in: Harper et al. 2011), or the GreenFeed (C-lock Inc., Rapid City, USA) system (Waghorn et al. 2016). Here, we aim at deriving region-specific EFs in rangeland/dryland systems in SSA through methane concentration measurements using two open-path laser spectrometers (GasFinder2.0, Boreal Laser Inc., Edmonton, AB, Canada). This method is based on the bLS technique described by Flesch et al. (1995) that has not been used in Africa before for estimating EFs for enteric methane production but has been demonstrated to be feasible in multiple other locations in developed countries (e.g., Flesch et al. (2014), Gao et al. (2009), Laubach et al. (2013)). Hence, the goals of this study were to test the applicability of the bLS technique for Kenyan cattle in night-time bomas (1), to adapt data filtering methods to our specific location (2), to determine EFs for free-grazing mature female African beef cattle in SSA-countries using the bLS inverse dispersion model (IDM) method (3), and to compare the calculated EFs with the IPCC Tier 1 values and existing literature for improving the greenhouse gas inventories of SSA countries (4).

2 Methods

2.1 Backward Lagrangian Stochastic model

The bLS technique as described by Flesch et al. (2014) is an IDM that generates trajectories backwards from the sensor to locations within the defined source area allowing the calculation of emission per unit time.

For this study, we used the IDM software WindTrax (Thunder Beach Scientific, Halifax, Canada) that was successfully compared to other methods (Bonifacio et al. 2016;

Yang et al. 2017) as well as gas release experiments (Flesch et al. 2004; Gao et al. 2009), and that has been applied for the quantification of CH_4 emissions from cattle in multiple studies (Bai et al. 2015, 2020; Flesch et al. 2007; Laubach et al. 2014; McGinn et al. 2019; Prajapati and Santos 2018; Rhoades et al. 2010; Todd et al. 2014; van Haarlem et al. 2008). The underlying bLS model is based on the Monin–Obukhov similarity theory (MOST) and assumes that friction velocity $u*$, the Obukhov length L, the surface roughness length z_0, and the wind direction β sufficiently describe the wind properties in a horizontally homogenous surface layer (Monin and Obukhov 1954). Besides horizontally homogeneous turbulence, the model assumes stationary atmospheric conditions at every location in the measured area.

The bLS model calculates the emission rate Q [mg s^{-1} m^{-2}] from the simulated ratio between the concentration, C [mg m^{-3}], increase at the sensor's location due to the source (C_L- C_B) and the source-strength-normalized concentration change $S = ((C_L—C_B)/Q)_{sim}$. The latter is a function of the flowfield variables determined numerically for each run, and the measured concentration increase due to the source with C_L and C_B representing the downwind and background concentration, respectively:

$$Q = \frac{C_L - C_B}{S} \tag{1}$$

In this study, downwind concentration increase was determined using a line-averaging open-path laser absorption spectrometer. To obtain the simulated ratio of concentration increase and source strength, 50,000 (N) trajectories each were simulated from 30 points (P) along the laser light path and the average inverse vertical wind speed w_0 at each touchdown location within the source area for each particle set and release location was calculated as shown in Eq. (2):

$$S = \frac{1}{P} \sum_{j=1}^{P} \left(\frac{1}{N} \sum \left| \frac{2}{w_0} \right| \right) \tag{2}$$

2.2 Calibration of the laser spectrometers

We used two GasFinder2.0 open-path tunable diode laser absorption spectrometers for the methane concentration measurements. The lasers record an absorption spectrum between 1.3 and 1.7 µm (Boreal Laser Inc. 2017). Multiple studies verified the usability of one or two open-path lasers together with the WindTrax software for estimating methane concentrations (Flesch et al. 2004, 2005a, 2005b, 2014; Gao et al. 2009; Hofschreuder et al. 2004; Laubach and Kelliher 2005).

We calibrated the two laser instruments in the laboratory before and after the field deployment, with 2.5 months lying

between the two calibrations, using four different standard gases (Air Liquide) with CH_4 mixing ratios of 200 ± 4 ppm, 400 ± 8 ppm, 600 ± 12 ppm, and 800 ± 16 ppm together with a one-meter long calibration tube. Data were stored every second with a runtime of two times 15 min after reaching a stable concentration. We found a good linear relationship between measured and actual standard gas concentration using linear regression with R^2 for quality analysis (Fig. 1).

Both laser instruments underestimated the CH_4 concentrations resulting in the usage of the mean correction factors of 1.325 and 1.665 and mean detection limits of 0.045 ppm v and 0.015 ppm v for Laser 1 and Laser 2, respectively (for further information see Table 1).

2.3 Site characteristics

Our field campaign took place in South Central Kenya at Kapiti Research Station managed by the International Livestock Research Institue (ILRI) (Rivero et al. 2021). The Research Station can be identified as a ranching system located in the semi-arid region of Southern Kenya (1°37′49.908″S, 37°8′43.195″E). The climate is typical for semi-arid savannas, with the annual precipitation being lower than the potential evapotranspiration. The mean annual precipitation is 550 mm, with rainfall being distributed in a bimodal precipitation regime (Berliner and Kioko 1999; McCown and Jones 1992). Approximately 80% of the annual precipitation occurs during the two rainy seasons (Mar–Jun and Oct–Dec). The mean annual temperature is 20.2 °C, with 4 °C of annual variation.

Livestock management on the farm is typical for pastoral systems, where herders graze animals during the day and keep them in enclosures (bomas in East Africa) during the night. There are bomas distributed in different areas of the farm, and each area is used for a few months (2–3) every year until cattle are moved when the pasture in the area surrounding the bomas is exhausted. Some of the bomas are subject to occasional extraction of manure by local farmers.

2.4 Field experiment

The measurements took place during a 1-month period in 2019 (27th of September till 23rd of October). During this time, we recorded measurements over 14 nights with the rainy season starting on the 8th of October 2019. Methane emission measurements from cattle were only possible during the night since the cattle are only then located in the bomas. We used two open-path laser spectrometers together with two retroreflectors to carry out the field measurements (Fig. 2 and Fig. 3). The different wind and turbulence parameters which are essential inputs for the EF calculation have been provided by the Mazingira Centre, International Livestock Research Institute (ILRI), observed by their eddy
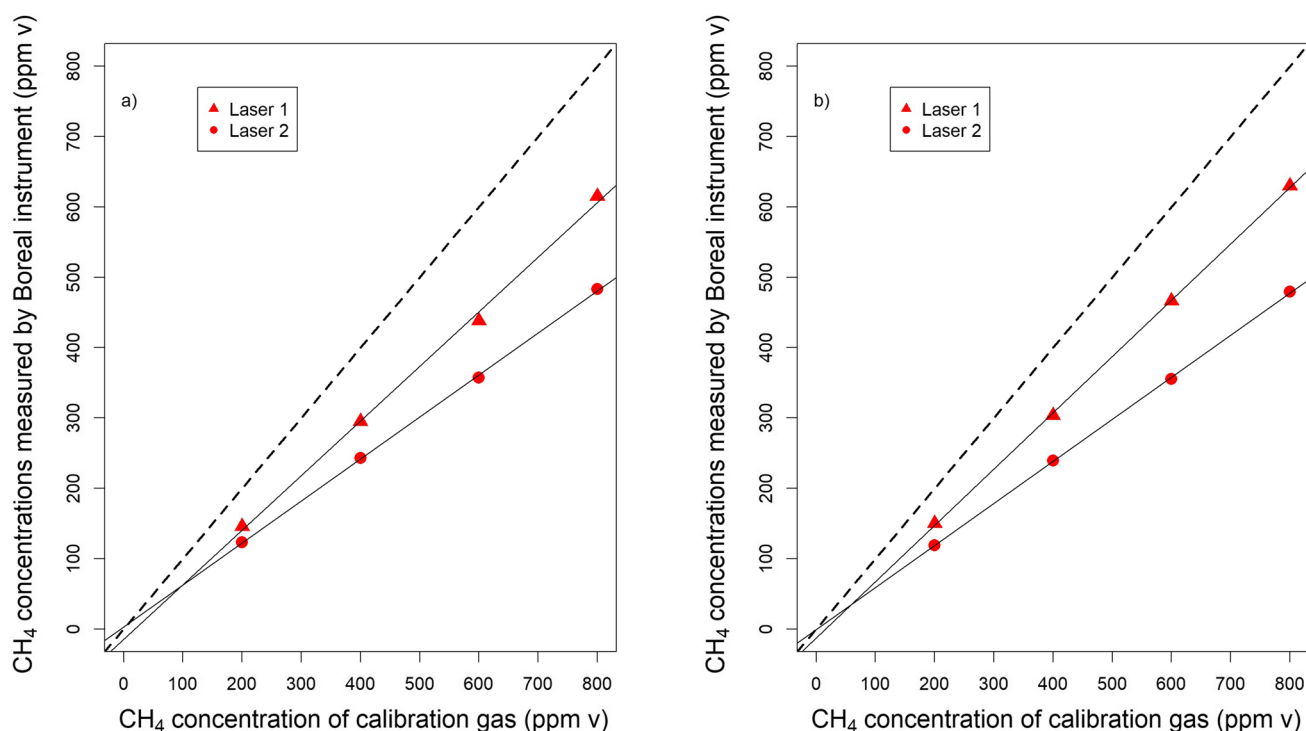
Fig. 1 Calibration results for the open-path methane lasers 1 and 2 before (**a**) and after (**b**) the field deployment where the dotted line represents the identity line

Table 1 Calibration results for the both laser spectrometers 1 and 2 before and after the field deployment with R^2, the resulting correction factors (Cor. fac.), the slopes of the linear regression lines, the stand-ard errors (SE) of the y-estimates of the regression analysis and the resulting detection limits (Det. l.)

Laser	R^2		Cor. fac		Slope		SE (ppm v)		Det. l. (ppm v)	
No	Before	After	Before	After	Before	After	Before	After	Before	After
1	0.998	0.999	1.35	1.30	0.776	0.801	4.11	1.33	0.07	0.02
2	0.999	0.999	1.65	1.68	0.597	0.599	1.22	0.85	0.02	0.01

covariance (EC) tower located approximately 200 m away. The eddy covariance systems encompassed a Gill WindMaster Pro (Gill Instruments Ltd. Lymington, Hampshire, S041 9EG, UK) which was mounted at a height of 4.2 m above the soil surface. Data were collected at a rate of 10 Hz.

The lasers were erected up- and downwind of the bomas with the laser path being perpendicular to the main wind direction of 112.5° from North to measure background and elevated methane concentrations, respectively.

We took the measurements at two different enclosure locations. Location 1, called Kilahani, consists of three connected bomas (Ø ~ 20 m) with around 140 animals in each boma. Location 2, called Potha, consists of four connected bomas (Ø ~ 18 m) with around 100 animals in each boma. We then excluded pre-ruminant calves (0–3.5 months old) from the EF calculations since they produce negligible methane emissions (Reed et al. 1990) which were around 15% of

the animals at Location 1 and 10% at Location 2. The herds between the two sites differed, and still consisted of > 50% female adult animals which is why we assumed that the herd only consisted of female adult animals after excluding pre-ruminant calves by using Eq. 3:

$$n_{total} = n_{cows} + n_{heifers}\frac{m_{heifers}}{m_{cows}} + n_{bulls}\frac{m_{bulls}}{m_{cows}} + n_{calves}\frac{m_{calves}}{m_{cows}}$$

(3)

where n represents the number of animals and m (kg) the mean LW. The observed herds are weighted regularly and average LW values were 420 kg for cows, 380 kg for heifers, 500 kg for bulls, and 115 kg for ruminating calves, respectively.

To reduce potential disturbances induced by obstacles in the bLS dispersion model we set up our measurements in approx. 17 m distance of the enclosure. This is ten times the

Fig. 2 Typical field setup, with one of the laser spectrometers on the right-hand side and bomas in the background

Fig. 3 Schematic drawing of the typical field set up, where the grey boxes represent the GasFinders (bottom side) and the retroreflectors (top side)
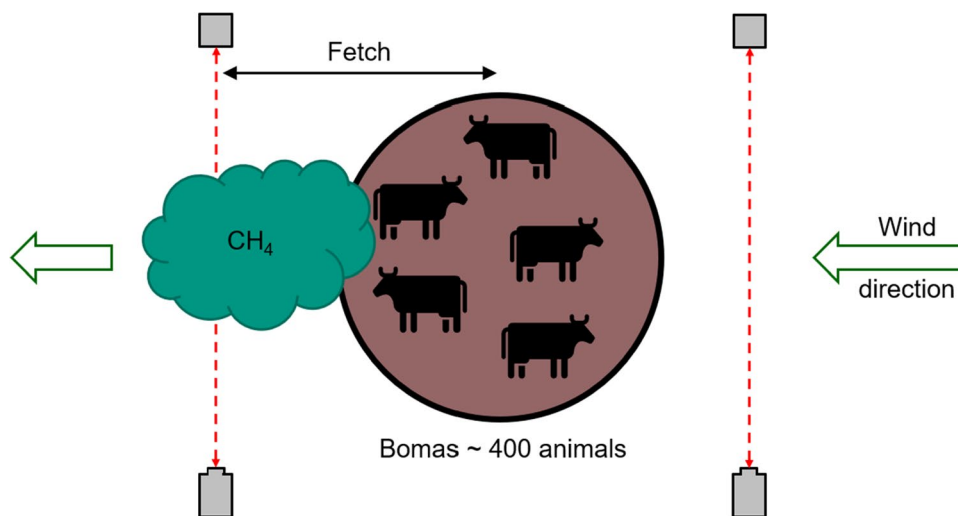
height of the enclosure fence (1.7 m), following the suggestion of Flesch et al. (2005a) to minimize possible measurement errors due to wind perturbation caused by the enclosure itself. Besides that, we chose a measurement height of around 1.7 m, staying lower than the maximum of 0.1 times of the available fetch, after Flesch et al. (2004) for a homogenous surface layer, where fetch is the distance between the center of the source and the laser path (Fig. 3), to avoid making measurements at the edge of the tracer plume.

To receive reliable results, unrealistic and erroneous measurements have to be filtered from the collected laser absorption spectrometer data. Following the

suggestion of Boreal Laser Inc. (2017), we kept those data with a light value output by the instruments between 3000 and 11,000 units to avoid gas concentration misreadings caused by either not enough returning light or by a saturation of the receiver, whereas the full range is between 1 and 16,368 units. Since the wind direction was with 112.5° from north generally very consistent during our measurement period, we filtered out data with deviations from the main wind direction of $\pm 22.5°$. Additional data filtering criteria followed the findings from Gao et al. (2009) and Flesch et al. (2014) who reported strong over-/underestimations of the emission rates for extremely stable/unstable conditions,

respectively, which is why we chose the friction velocity $u* > 0.15$ m s^{-1} as a threshold. After filtering, 67.7% of the data remained with no discernible influence of the field site (Table 2). Other proposed filtering methods like Obhukov length $|L| > 10$ m (Flesch et al. 2014) or discarding the data when the standard deviation exceeding 2/3 of the mean EF (Gao et al. 2009) showed no effect in our specific location and were, therefore, not applied.

2.5 Results

The CH$_4$ emission estimates per head ranged from 1.30 to 3.77 mg s^{-1} with a mean value of 2.39 ± 0.18 mg s^{-1} which resulted from averaging ten-minute measurement periods (Fig. 4). Those estimates resulted in a CH$_4$ EF per head of 75.4 ± 5.69 kg year^{-1} using Eq. (4) on the mean emission rate.

$$EF = \frac{Emission \quad rate * 60 * 60 * 24 * 365}{10^6} \qquad (4)$$

During the measurement period, the mean wind direction was stable during the course of the night, whereas the friction velocity showed a decreasing trend. The same trend was observed for the nighttime methane emissions data (Fig. 5).

3 Discussion

3.1 Methodology

The bLS technique is well suited for measuring gas concentrations from well-defined area sources, if the size of the area does not exceed the maximum path length of the open-path laser, which is the case for the bomas under study. For our setup, the path length was limited to 60 to 80 m depending on the kind of retroreflector used. Denmead (2008) reports maximum path lengths of 1000 m but suggests to only use lengths of 100 to 300 m for more reliable results. The technique requires sufficiently strong wind speeds and steady wind directions to maximize the yield of high-quality single measurements. It can be improved by mounting the laser instruments on pan-tilt scanning units with multiple retroreflectors to be able to react to changing wind directions and by adding small silicone heaters and electrical fans to prevent condensation on the reflector's surface overnight as done by Gao et al. (2009) and Flesch et al. (2014), or by using a multi-path system which would allow to accept a wider range of wind directions. Such complex setups were not required for our measurements due to the optimal site conditions.

Our calculated values might have been biased since the source strength calculated using the bLS method applied in this study has been reported to systematically vary with height-to-fetch ratio. McBain and Desjardins (2005) confirmed the results of Flesch et al. (2004) that the measurement height should not exceed 0.1 times of the available fetch and that smaller ratios improved the quality of the data. Furthermore, Laubach (2010) found the best height to fetch ratio to be 0.080 for unstable and 0.067 for stable stratifications. Since the ratio of ~ 0.10 that was predominantly used in our study is close to the reported optimal ratios, we classify the data quality as high. Flesch et al. (2014) reported that the bLS technique overestimated the release rate at night by about 8–12% depending on the chosen filtering method in their gas release experiment while it underestimated the

Table 2 Total number of measured 10-min periods for every observed night before and after data filtering, nights when precipitation occurred are marked and the field site is shown

| Night	No. of periods	No. after filtering	Percentage (remaining)	Precipitation (X = yes)	Location
28.09.–29.09	41	33	80.5		Kilahani
30.09. –01.10	50	45	90.0		Potha
02.10. –03.10	60	39	65.0		Potha
03.10. –04.10	53	45	84.9		Potha
05.10. –06.10	36	27	75.0		Kilahani
06.10. –07.10	55	47	85.5		Kilahani
08.10. –09.10	56	19	33.9	X	Potha
09.10. –10.10	35	31	88.6	X	Potha
11.10. –12.10	46	41	89.1	X	Potha
14.10. –15.10	39	22	56.4		Potha
15.10. –16.10	56	37	66.1		Potha
18.10. –19.10	43	26	60.5	X	Potha
19.10. –20.10	58	39	67.2		Potha
22.10. –23.10	47	6	12.8	X	Potha
Total	675	457	67.7		
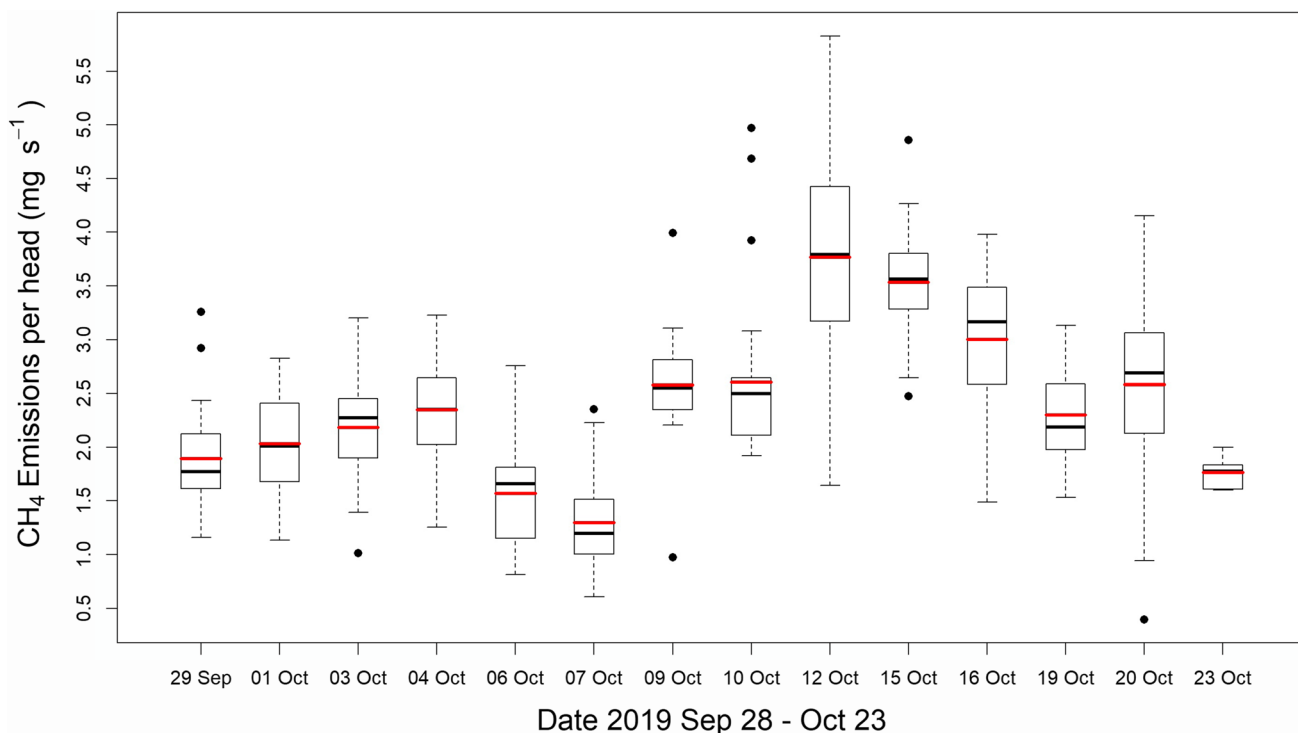
Fig. 4 Boxplots of single livestock CH_4 emissions determined each night during the period September 28th to October 23rd. Boxes indicate the range from the first quartile (Q1) to the third quartile (Q3) after applying the data filtering methods and the error bars represent the minimum/maximum values. Data are defined as outliers (black dots) when lower/higher than Q1 − 1.5/Q3 + 1.5 times the interquartile range (Q3–Q1), respectively. Red and black lines represent the nighttime median and mean values, respectively
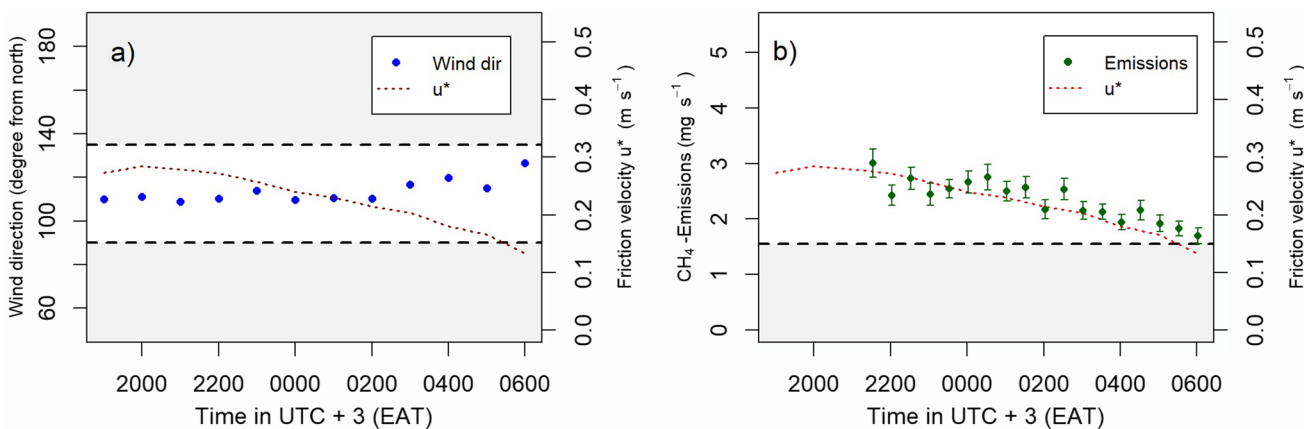
Fig. 5 Mean wind direction and friction velocity in the observed nights (**a**) together with the mean nightly course of the methane emissions per head with included error bars and the friction velocity u* (**b**), the critical values (black dashed lines) used for data filtering of emission rate during the day. Gao et al. (2009) reported GHG overestimations during typical stable nighttime conditions and underestimations during unstable conditions. Furthermore, the authors suggested that it might be caused by an uncertainty in the parameterization of the turbulent kinetic energy dissipation rate, which is the rate at which turbulence

90° clockwise from north and 135° clockwise from north for the wind direction and of 0.15 m s^{-1} for the friction velocity are shown and the parts where data are filtered are grayed out

energy is absorbed by breaking turbulent air fluxes down into smaller and smaller fluxes until it is converted into heat by viscous forces. Flesch et al. (2014) suspected that the bias might be caused by problems with the laser temperature sensitivity of the instruments. They based their suspicion on the work from Laubach et al. (2013) who found out that at least

for their instruments the temperature sensitivity was greater than the value given by Boreal Laser Inc. and also reported sensitivity differences between their lasers.

3.2 Data filtering

The bLS technique worked generally well for our site during nighttime in most of the dry nights until around 0300–0500 EAT and until 0100–0300 EAT in the rainy nights until the friction velocity decreased or condensation occurred on the retroreflector. The latter can also be seen in the smaller number of measurements remaining after data filtering (Table 2). We chose the relatively restrictive filter that only allowed for data with deviations of 22.5° from the mean wind direction since the wind was coming from the same direction for almost all the time. Using the Obhukov length as filter criterion showed no results since it was always inside the proposed range of Gao et al. (2009). The same applies for a filter using integral turbulence characteristics (Foken and Wichura 1996) and for one using a threshold of the standard deviation reported by WindTrax (Gao et al. 2009). Only the friction velocity filter criterion resulted in some rejected data points mainly at the end of the night when the turbulence intensity declined. This shows that it is important to adapt the filtering methods to the measurement location in order to retain as much high quality data as possible. Due to the very homogenous wind conditions, 67.7% of the data passed the filtering criteria. In comparison, Gao et al. (2009) retained 40% and Flesch et al. (2014) 63% of the nighttime data after applying their filters, indicating that the conditions at the site were beneficial for the bLS approach in general and specifically for a setup that cannot be adjusted to changes in the main wind direction.

3.3 Diurnal/seasonal variations

We took measurements during daytime in order to determine methane emissions from manure which showed no significant concentration increases indicating that the manure emissions were below the detection limit of the two open-path laser absorption spectrometers. Latest research has shown that methane emissions from manure in semiarid landscape are considerably lower than suggested by the IPCC EFs (Pelster et al. 2016; Zhu et al. 2018).

As expected, the CH_4 production in animals decreases over the course of the night due to the absence of feed inside the bomas and the resulting decrease in the rumination process. This decrease leads to the conclusion that our results might underestimate the total annual emissions since the animals are free-grazing during the day, indicating that the actual methane emissions are in the range of the values of the first hours of the night or higher. Our measurements took place at the end of the dry season and went on into the

beginning of the rainy season. Feed availability increases in the rainy season due to plant growth which is leading to increases in beef (milk) production and, therefore, also methane production. As a consequence, highest productivity of animals is usually observed toward the end of the rainy season (Demarchi et al. 2016). The animals experience a clear seasonal effect of feed restriction through LW losses in productive females and reduced gains in other cattle classes mainly during the dry season and/or droughts. This results in a lower daily methane production since they have to meet their energy requirements by mobilization of their endogenous tissue rather than through consumption and fermentation of feed (Goopy et al. 2020).

3.4 Combined uncertainty of per head methane emissions

We considered additional uncertainty sources which go beyond the temporal variability of methane (ut = 5.69 kg year^{-1} resulting in a value of 7.55%, see Sect. 3) and include the precision of the methane measurement, uncertainty of the flow model and uncertainty due to limitation to night time measurements. The combined uncertainty of per head emissions $u_{combined}$ was calculated as follows (5):

$$u_{combined} = \sqrt{u_t^2 + u_p^2 + u_{FlowModel}^2 + u_{Day/Night}^2} \quad (5)$$

where $u_{FlowModel}$ characterizes the uncertainty value of the bLS model which we assumed to be 10% of the average value following the suggestion of Flesch et al. (2014). Since we could only carry out our measurements at night, we added an uncertainty value $u_{Day/Night}$ to account for the potential effect of substituting day time values with night time values (Eq. (6)).

$$u_{Day/Night} = 1 - rQ \text{ with } rQ = \frac{Q_N}{\left(Q_N * \frac{9}{24} + Q_D * \frac{15}{24}\right)} \quad (6)$$

The underlying assumption is that animals have reduced feed intake during the night, and that predominantly early night time emission rates are representative for daytime emission rates. Consequently, we used the mean emission rate of the first three measured hours of every night (21:00–24:00) Q_D as a value representing the daytime emissions and assumed that this value is viable for 15 h each day since the animals are locked in the bomas for around 9 h each night. We compared that with the nightly mean emission rate Q_D and calculated the share rQ of the nightly emission rate on the daily emission rate with resulted in a value for $u_{Day/Night}$ of 10%.

To address the precision of the instruments, we first calculated the one-sigma standard deviation of the background

measurements based on all determined 10-min background measurements. Based on this value and S (Eq. (1)), the uncertainty due to the instrument precision u_p was calculated. This resulted in a value for u_p of 13.89% which leads to a value of 21.21% for $u_{combined}$ using Eq. (5) and an EF of 75.4 ± 15.99 kg year^{-1}.

Considering these factors in our uncertainty calculations, we are confident that our observations meet the expected values approximately for methane emissions per head and year. Yet, we suggest undertaking additional investigations during the whole day to verify or correct our calculated mean methane emission values in the future. Places such as Kapiti Research Station could provide a well-suited platform to carry out such measurements. In addition, more repetitions of similar measurements as ours could potentially reduce the uncertainty of the mean EF estimates since we only observed a total of 14 nights. Our measurements took place during a period of 1 month, which restricts the usability of the calculated emission estimates on an annual scale because we observed the animals during a period of relatively low emissions leading to a potential underestimation of the actual EFs.

3.5 Comparison with other studies

The predicted methane emission factors of the IPCC are based on measurements from the Organization for Economic Cooperation and Development (OECD) countries and thus may not be representative of the African livestock systems, breeds, soil, and climate conditions (i.e., Goopy et al. 2020; Pelster et al. 2016). The Tier 1 EFs for cattle in Africa were largely adjusted by expert knowledge depending on countries' national inventories. Due to a scarcity of data

on GHG sources and sinks, most developing countries currently quantify agricultural GHG emissions and reductions using IPCC Tier 1 emission factors with few exceptions such as Kenya for its dairy sector. However, conducting in-situ measurements leads to more accurate measurements and can be used to validate the IPCC values at the same time (Dong et al. 2006) while simultaneously providing an opportunity to track GHG mitigation actions. At the moment, the lack of reliable information on agricultural GHG emissions for developing economies limits the possibility for low-carbon agricultural development and also the opportunities for livestock keepers to benefit from carbon markets and the negotiating position of developing countries in the global climate policy discussions (Rosenstock et al. 2013).

Our calculated mean value of 75.4 ± 15.99 kg year^{-1} head^{-1} is considerably higher than the IPCC Tier 1 value. As shown in Table, six other studies also calculated their own methane EFs for enteric fermentation of cattle in SSA countries. The observed LWs range from 162.3 kg in the IPCC values (Dong et al. 2006) to up to 440 kg in the study from Tongwane and Moeletsi (2020). The LW dependent comparison of our results with those other studies improves our confidence in our results further (Fig. 6).

Nevertheless, each of the studies mentioned here, based their EF estimates on different methodologies causing further difficulties when comparing results. Kouazounde et al. (2015) collated the data they used for their EF calculations from different sources of country-specific data as proposed by the IPCC (Dong et al. 2006) without collecting data themselves. The authors made several assumptions as some (often crucial) data such as the average LW per day for the Borgou and Lagune cattle were sparse or simply not available. They derived that information from expert opinions and

Fig. 6 Comparison of LW to CH$_4$ EFs from the different studies of Table 3 (blue dots) with our observed value (red triangle) and a trend line (blue dotted line)
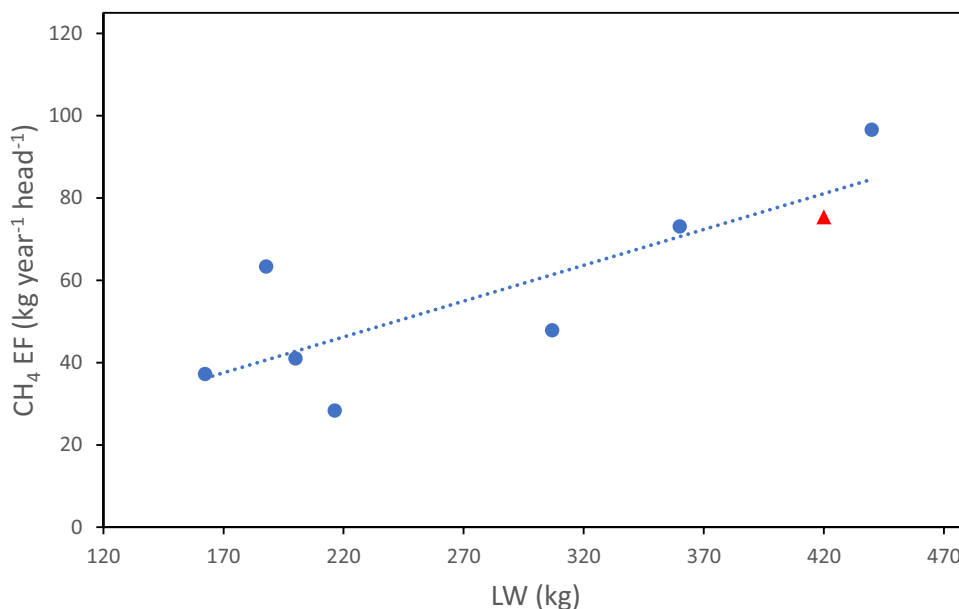
Table 3 Comparison of the calculated methane emission factors for mature female cattle with other publications located in Africa

Author	Cattle type	Mean LW (kg)	CH$_4$ EF (kg year^{-1} head^{-1})	Location	Cattle breed
Dong et al. (2006)	Beef	200.0	41.0	IPCC Tier 1 (SSA)	
Goopy et al. (2018)	Dairy	216.3	28.3	Kenya	Zebu, Bos Taurus
Goopy et al. (2020)	Beef steers	162.3	37.2	Kenya	Boran
Ndung'u et al. (2019)	Dairy	306.9	47.8	Kenya	Zebu, Bos Taurus
Du Toit et al. (2013)	Beef	360.0	73.1	South Africa	Holstein, Jersey
Tongwane and Moeletsi (2020)	Beef	440.0	96.6	South Africa	Bonsmara, Zebu, Bos Taurus
Kouazounde et al. (2015)	Multi-purpose	187.8	63.3	Benin	Borgou, Somba, Lagune
Present study	Beef	420.0	75.4	Kenya	

reported data from Togo, an adjacent West African country. Tongwane and Moeletsi (2020) obtained and used data from the South African Department of Environmental Affairs and the Department of Agriculture, Forestry and Fisheries to calculate their EFs.

Du Toit et al. (2013) based their calculations on methods from the Australian National Inventory Report which includes Australian country-specific and IPCC default methodologies. They adapted them to South African conditions and management systems where possible. The authors report much higher EFs than the IPCC Tier 1 default values, which is not surprising since the breeds they used for their calculations are around twice as heavy as the ones used by the IPCC.

While the studies of Kouazounde et al. (2015), Tongwane and Moeletsi (2020), and Du Toit et al. (2013) are relying on other literature without knowing the accuracy of those studies, Goopy et al. (2018) and Ndung'u et al. (2019) improved the IPCC Tier 2 methodology for SSA countries by adapting it to smallholder livestock systems (1–19 animals per household) with no access to feed overnight and reduced feed availability during the dry season. Even though the two studies expected to gain similar results since they used the same method in a similar region in the western Kenyan highlands, their results show substantial differences. This may have been caused by slightly different climatic conditions leading to greater LWs in the study by Ndung'u et al. (2019) than the study by Goopy et al. (2018).

The other study cited here, Goopy et al. (2020), tested the relationship between feed intake and enteric CH$_4$ production to simulate the influence of the dry seasons by feeding different maintenance energy requirement levels. Their mean EF is higher than the one from Goopy et al. (2018) despite lower LW. However, Goopy et al. (2020) did not observe female nor mature animals and the experiment aimed at simulating extreme conditions in terms of feed scarcity.

The values reported in this study are even higher than those from the two studies in Kenyan smallholder farms—dominated by dairy cattle—who also sampled data in the dry and the rainy season. It needs to be noted that both Goopy et al. (2018) and Ndung'u et al. (2019) collected data over a full year covering rainy and dry seasons. In comparison, we measured during a very short period of 14 nights only, and with an entirely different method. The existing studies used additional data including daily weight increase, locomotion, and milk yield to indirectly calculate methane emissions from energy expenditure, whereas we directly measured the methane concentrations. Our mean EF value is close to the EFs in the South African studies (Kouazounde et al. 2015; Tongwane and Moeletsi 2020) which seems plausible since the mean LW in our study was similar to the ones in their studies. Furthermore, the observed livestock system—cattle ranching—was also similar to the South African studies (Fig. 6). This shows the need for developing not only country—but even region-specific and/or livestock system-specific emission factors. It also needs to be noted that the statistical data required for such disaggregation must then be collected since those EFs have a big influence on national GHG inventories.

Methane EFs from African cattle are generally lower than those from cattle in developed countries. Ominski et al. (2007) reported EFs of 90 kg CH$_4$ year^{-1} head^{-1} and 94 kg CH$_4$ year^{-1} head^{-1} for beef cows and bulls in Canada; Castelán-Ortega et al. (2014) reported 82.5 kg CH$_4$ year^{-1} head^{-1} for the tropical regions and 70.5 kg CH$_4$ year^{-1} head^{-1} for the temperate regions in Mexico as mean values for calves, heifers, steers, and bulls; and Basarab et al. (2005) reported 102.5 kg CH$_4$ year^{-1} head^{-1} for beef cows in Alberta, Canada. All of the available studies no matter from which continent urge for country and/or even region-specific EFs for the different cattle breeds since one or few EFs cannot reliably predict the methane emissions for cattle breeds in all of the 51 SSA countries.

4 Conclusions

In this study, we determined the CH_4 emissions from free-grazing mature female African beef cattle using an IPCC Tier 2 approach for Kenya. The measurements were conducted for a herd of 300 to 400 animals during 14 nights in 10-min intervals resulting in a mean EF of 75.4 ± 15.99 kg year^{-1} head^{-1}. Our results, together with the to our best knowledge six other publications available for Africa, express the need for the continued development of country-specific or ideally region-specific EFs since the estimates differ depending on the region, animal breed, livestock systems, feed quantity, and composition. However, for that to work, a lot of more of these variables have to be observed and made available by the different nations.

In the course of most nights, methane emissions showed a decreasing trend due to the lack of feed in the bomas and, therefore, reduced rumination (Fig. 5). Improved EF estimates could be obtained if measurements based on the bLS technique were carried out together with a modeling approach that quantifies EFs from field measurements of LW, milk production, locomotion, etc., similar to the study by Ndung'u et al. (2019). Differences in the methodologies could be investigated, which would help to improve the accuracy of a range of methods. Additionally, observing a herd for an entire diurnal cycle would help to detect and characterize regular CH_4-emission patterns. Furthermore, measurements distributed over the whole year, especially at the end of the rainy season, could help to verify or improve the calculated EFs.

Availability of data and material The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Code availability Not applicable.

Declarations

Ethics approval Not applicable.

Consent to participate Not applicable.

Consent for publication Not applicable.

Conflict of interest The authors declare no conflict of interests.

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