

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

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1 Abstract

2 This study provides methane (CH₄) emission estimates for mature female African beef cattle in
3 a semi-arid region in Southern Kenya using open-path laser spectroscopy together with a
4 backward Lagrangian Stochastic (bLS) dispersion modeling technique. We deployed two open-
5 path lasers to determine 10-minute averages of line-integrated CH₄ measurements upwind and
6 downwind of fenced enclosures (so-called bomas: a location where the cattle are gathered at
7 nighttime) during 14 nights in September/October 2019. The measurements were filtered for
8 wind direction deviations and friction velocity before the model was applied. We compared the
9 obtained emission factors (EFs) with the Intergovernmental Panel on Climate Change (IPCC)
10 Tier 1 estimates for the Sub-Saharan African (SSA) countries, which were mostly derived from
11 studies carried out in developed countries and adapted to the conditions in Africa. The resulting
12 mean EF of 75.4 ± 5.69 kg yr⁻¹ and the EFs calculated from other studies carried out in Africa
13 differ considerably from each other, which indicates the need for the further development of
14 region-specific EFs to improve the IPCC Tier 1 estimates.

15 Acknowledgments

16 The authors wish to thank Ilona Glücks, Geroge Wanyama and all the other people from the
17 Mazingira Centre and the ILRI Kapiti Research Station for their help in organizing the field
18 measurements and for providing the eddy covariance tower wind data. We also like to thank
19 Alexandra Bierer, Peter Nickolaus, and Luise Wanner for their constructive criticism on the
20 manuscript. LM and SL acknowledge financial support of the CGIAR Fund Council, Australia
21 (ACIAR), Irish Aid, European Union, International Fund for Agricultural Development
22 (IFAD), the Netherlands, New Zealand, UK, USAID, and Thailand for funding to the CGIAR
23 Research Program on Livestock. We acknowledge the support provided by the Programme for
24 Climate-Smart Livestock (PCSL) implemented by GIZ and commissioned by the Federal
25 Ministry for Economic Cooperation and Development (BMZ), Germany.

26 Abbreviations

27	AFOLU	Agriculture, Forestry and Other Land Use
28	bLS	backward Lagrangian Stochastic
29	EC	Eddy Covariance
30	EF	Emission Factor
31	FAO	Food and Agriculture Organization of the United Nations
32	IDM	Inverse Dispersion Model
33	ILRI	International Livestock Research Institute
34	LW	Live Weight
35	MOST	Monin-Obukhov Similarity Theory

37

1 Introduction

38 At present anthropogenic greenhouse gas (GHG) emissions are the highest in history and are
39 still on the rise (IPCC 2019b). Although global methane (CH₄) emissions constitute only 4 %
40 of the global anthropogenic carbon dioxide (CO₂) emissions in units of carbon mass flux, they
41 contribute 20 % to the additional radiative forcing in the lower atmosphere (Ciais et al. 2013).
42 Methane has a global warming potential of 28 on a per mass basis over a time horizon of 100
43 years without the inclusion of feedback cycles (IPCC 2014), making it the second most
44 important greenhouse gas contributing to human-induced climate change. The main
45 contributors to anthropogenic CH₄ emissions are energy production and agriculture via rice
46 cultivation and enteric fermentation of ruminants (Thorpe 2009). More specifically, the
47 Agriculture, Forestry and Other Land Use (AFOLU) sector accounted for 44 % of the
48 anthropogenic CH₄ (and 82 % of the nitrous oxide) emissions during the period between 2007
49 and 2016, representing 23 % of the total net anthropogenic GHG emissions (IPCC 2019b). In
50 absolute numbers global these methane emissions from the AFOLU sector were 162 ± 49 Mt
51 CH₄ yr⁻¹ (4.5 ± 1.4 Gt CO₂-equivalents (eq) yr⁻¹) between 2007 and 2016 (IPCC 2019b) with
52 livestock accounting for almost two thirds of those emissions (Saunois et al. 2020). Cattle
53 dominate the CH₄ emissions from the livestock sector, accounting for 64 – 78 % (Herrero et al.
54 2013; Milich 1999). Patra (2014) projects an increase of enteric fermentation CH₄ emissions
55 from cattle of 26 % until 2050 compared to 2010 due to the expected population increase and
56 the corresponding increase in animal-derived food demand (Dangal et al. 2017; van den Pol et
57 al. 2016).

58 National GHG inventories are used to monitor countries' annual GHG emissions and help them
59 to achieve the goals set by the Paris Climate Agreement (Horowitz 2016). According to the

60 good practice guidance outlined by the IPCC (Penman 2000), emission factors (EF) are used to
61 derive those national inventories. EFs are the average emission rate of a given source, relative
62 to units of activity or processes (Mareddy 2017). The IPCC suggests three different approaches
63 (Tier 1 – Tier 3) to derive national GHG inventories for individual components within the
64 agricultural sector. The Tier 1 approach is the most basic method and based on default values
65 of methane emissions per head which are then multiplied by the number of animals (Gavrilova
66 et al. 2019). In the specific case of Sub-Saharan Africa (SSA), the default value is
67 41 kg CH₄ head⁻¹ for free-grazing mature female African beef cattle (Dong et al. 2006). Up to
68 date, even though it is the most straight forward approach, this value causes large uncertainties
69 in national GHG inventories. Reasons for the uncertainties are for instance inaccuracies in the
70 livestock census data and the fact that the default EFs for SSA were derived from former studies
71 almost exclusively carried out in developed Western countries and adapted to developing
72 countries based on expert knowledge. To date, only little localized empirical data are available
73 to verify the default Tier. While some new information (Tier 2) has become available, this
74 information has only recently been taken up by the IPCC (2019a) (Goopy et al. 2018; Goopy
75 et al. 2020; Ndung'u et al. 2019). Tier 2 approaches provide advanced GHG inventories
76 necessary to achieve countries' goals set by the Paris Climate Agreement (Horowitz 2016) by
77 helping to understand the impact of different productivity measures on GHG emissions to find
78 ways to mitigate those without necessarily decreasing the animal numbers. The Tier 2 approach
79 is based on country-specific livestock data (i.e. live weight (LW) as well as detailed feed basket
80 information) to derive region-specific emission factors (Gavrilova et al. 2019). Available
81 studies that have developed and/or used Tier 2 EFs in SSA countries show substantial
82 differences to the Tier 1 estimates (Du Toit et al. 2013; Goopy et al. 2018; Kouazounde et al.
83 2015; Ndung'u et al. 2019; Tongwane and Moeletsi 2020). Tier 2 values are expected to be
84 superior to the Tier 1 values by taking more data into account and have so far been developed
85 for smallholder farming systems and/or dairy systems in SSA but not yet for pastoral livestock

86 systems. Such rangeland/grazing systems are completely different from the smallholder
87 farming systems as livestock (e.g. cattle) graze during the day and are kept in enclosures (so-
88 called bomas or kraals) throughout the night to avoid theft or predation (Butterbach-Bahl et al.
89 2020). As a consequence, feed is often unavailable throughout the night (Nicholson 1987).
90 Additionally, the movement and feeding patterns of such grazing animals in SSA are further
91 affected by feed shortages during the dry seasons or distinct droughts (Norman 1965) and thus
92 also affect CH₄ emissions from enteric fermentation.

93 Methane EFs from enteric fermentation from cattle can be derived via indirect approaches, e.g.
94 through activity data (Goopy et al. 2018), or direct approaches, e.g. via a combination of eddy
95 covariance (EC) flux and GPS data (Felber et al. 2015), via cattle respiration chambers
96 (Charmley et al. 2016; Goopy et al. 2020), with the sulfur hexafluoride (SF₆) tracer technique
97 (Goopy et al. 2016; Storm et al. 2012), or the proposed backward Lagrangian Stochastic (bLS)
98 methodology. Here, we aim at deriving region-specific EFs in rangeland/dryland systems in
99 SSA through methane concentration measurements using two open-path laser spectrometers
100 (GasFinder2.0, Boreal Laser Inc., Edmonton, AB, Canada). This method is based on the bLS
101 technique described by Flesch et al. (1995) that has not been used in Africa before for estimating
102 EFs for enteric methane production but has been demonstrated to be feasible in multiple other
103 locations in developed countries (e.g.: Flesch et al. (2014), Gao et al. (2009), Laubach et al.
104 (2013)). Hence, the goals of this study were to test the applicability of the bLS technique for
105 Kenyan cattle in nighttime bomas (1), to adapt data filtering methods to our specific location
106 (2), to determine EFs for free-grazing mature female African beef cattle in SSA-countries using
107 the bLS inverse dispersion model (IDM) method (3), and to compare the calculated EFs with
108 the IPCC Tier 1 values and existing literature for improving the greenhouse gas inventories of
109 SSA countries (4).

110 2 Methods

111 2.1 Backward Lagrangian Stochastic (bLS) model

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

115 For this study, we used the IDM software WindTrax, (Thunder Beach Scientific, Halifax,
116 Canada) that was successfully compared to other methods (Bonifacio et al. 2016; Yang et al.
117 2017) as well as gas release experiments (Flesch et al. 2004; Gao et al. 2009), and that has been
118 applied for the quantification of agricultural emissions (Bai et al. 2015; Bai et al. 2020; Flesch
119 et al. 2007; Laubach et al. 2014; McGinn et al. 2019; Prajapati and Santos 2018; Rhoades et al.
120 2010; Todd et al. 2014; van Haarlem et al. 2008). The underlying bLS model is based on the
121 Monin-Obukhov Similarity Theory (MOST) and assumes that friction velocity u^* , the Obukhov
122 length L , the surface roughness length z_0 , and the wind direction β sufficiently describe the wind
123 properties in a horizontally homogenous surface layer (Monin and Obukhov 1954). Besides
124 horizontally homogeneous turbulence, the model assumes stationary atmospheric conditions at
125 every location in the measured area.

126 The emission rate Q [M T⁻¹L⁻²] is calculated by the bLS model from the simulated ratio
127 between the concentration, C [M L⁻³], increase at the sensor's location due to the source (C_L -
128 C_B) and the source emission rate $((C_L - C_B)/Q)_{sim}$, and the measured concentration increase due
129 to the source with C_L and C_B representing the downwind and background concentration,
130 respectively:

$$Q = \frac{C_L - C_B}{\left(\frac{C_L - C_B}{Q}\right)_{sim}}. \quad (1)$$

131 In this study, downwind concentration increase was determined using a line-averaging open-
 132 path laser absorption spectrometer. To obtain the simulated ratio of concentration increase and
 133 source strength, 50000 (N) particles each were released from 30 points (P) along the laser light
 134 path and the average inverse vertical wind speed w_0 at each touchdown location within the
 135 source area for each particle set and release location was calculated as shown in equation
 136 (2):

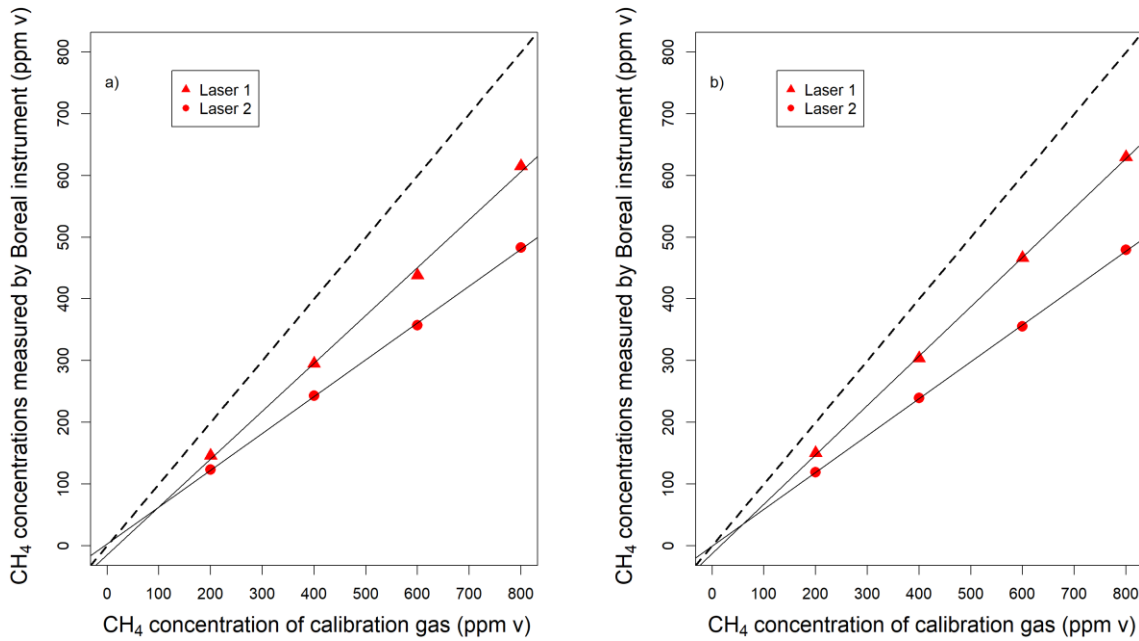
$$\left(\frac{C_L - C_B}{Q}\right)_{sim} = \frac{1}{P} \sum_{j=1}^P \left(\frac{1}{N} \sum \left|\frac{2}{w_0}\right|\right). \quad (2)$$

137 2.2 Calibration of the laser spectrometers

138 We used two GasFinder2.0 open-path tunable diode laser absorption spectrometers for the
 139 methane concentration measurements. The lasers record an absorption spectrum between 1.3
 140 and 1.7 μm (Boreal Laser Inc. 2017). Multiple studies verified the usability of one or two open-
 141 path lasers together with the WindTrax software for estimating methane concentrations
 142 (Denmead 2008; Flesch et al. 2004; Flesch et al. 2005a; Flesch et al. 2005b; Flesch et al. 2014;
 143 Gao et al. 2009; Hofschreuder et al. 2004).

144 We calibrated the two laser instruments in the laboratory before and after the field deployment,
 145 with 2.5 months lying between the two calibrations, using four different standard gases (Air
 146 Liquide) with the mixing ratios of 200 ± 4 ppm, 400 ± 8 ppm, 600 ± 12 ppm, and 800 ± 16 ppm
 147 together with a one-meter long calibration tube. Data were stored every second with a runtime
 148 of two times 15 minutes after reaching a stable concentration. We found a good linear

149 relationship between measured and actual standard gas concentration using linear regression
 150 with R^2 for quality analysis (**Fig. 1**).



151
 152 **Fig. 1** Calibration results for the open-path methane lasers 1 and 2 before (a) and after (b) the field deployment where the
 153 dotted line represents the identity line

154 Both laser instruments underestimated the CH₄ concentrations resulting in the usage of the
 155 mean correction factors of 1.325 and 1.665 and mean detection limits of 0.045 ppm v and
 156 0.015 ppm v for Laser 1 and Laser 2, respectively (for further information see **Table 1**).

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

Laser No.	R^2		Cor. fac.		Slope		SE (ppm v)		Det. l. (ppm v)	
	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

160
 161 **2.3 Site characteristics**
 162 Our field campaign took place in South Central Kenya at Kapiti Research Station managed by
 163 the International Livestock Research Institute (ILRI) (Rivero et al. 2021). The Research Station

164 can be identified as a ranching system located in the semi-arid region of Southern Kenya
165 (1° 37' 49.908"S, 37° 8' 43.195" E). The climate is typical for semi-arid savannas, with the
166 annual precipitation being lower than the potential evapotranspiration. The mean annual
167 precipitation is 550 mm, with rainfall being distributed in a bimodal precipitation regime
168 (Berliner and Kioko 1999; McCown and Jones 1992). Approximately 80 % of the annual
169 precipitation occurs during the two rainy seasons (Mar-Jun and Oct-Dec). The mean annual
170 temperature is 20.2 °C, with 4 °C of annual variation.

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

176 2.4 Field experiment

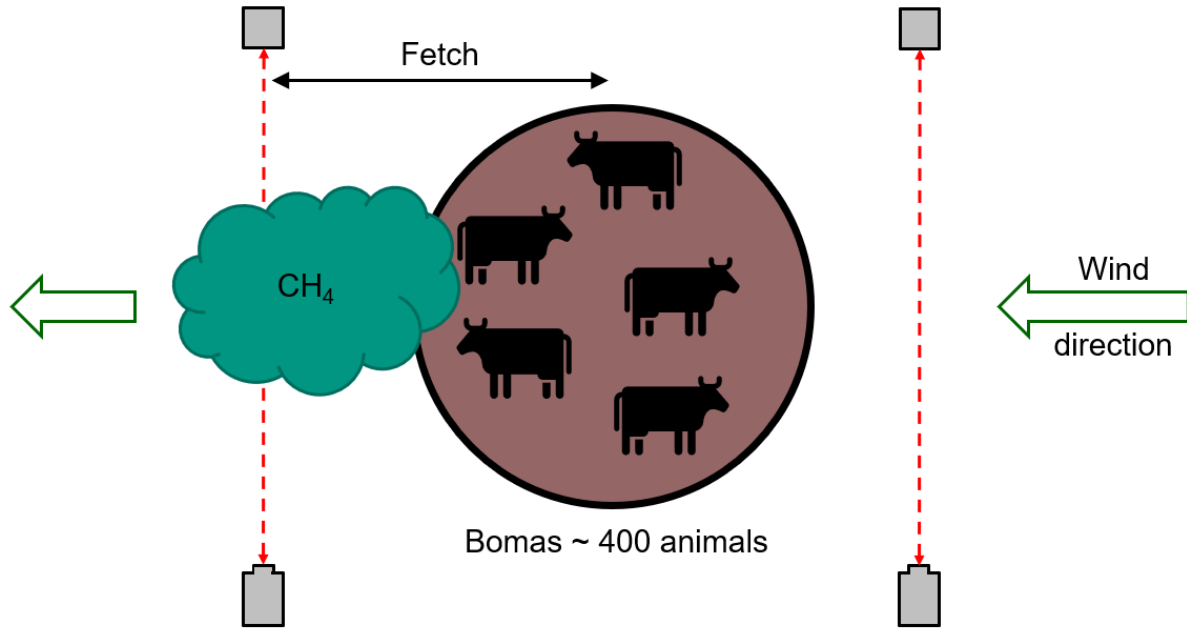
177 The measurements took place during a one-month period in 2019 (27th of September till 23rd
178 of October). During this time, we recorded measurements over 14 nights with the rainy season
179 starting on the 8th of October 2019. Methane emission measurements from cattle were only
180 possible during the night since the cattle are only then located in the bomas. We used two open-
181 path laser spectrometers together with two retroreflectors to carry out the field measurements
182 (Fig. 2, Fig. 3).



183

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

185 The lasers were erected up- and downwind of the bomas with the laser path being perpendicular
186 to the main wind direction of 112.5 degrees from North to also measure background methane
187 concentrations.



188

189 **Fig. 3** Scheme of the typical field set up, where the gray boxes represent the GasFinders (bottom side) and the retroreflectors
 190 (top side)

191 We took the measurements at two different enclosure locations. Location 1, called Kilahani,
 192 consists of three connected bomas ($\varnothing \sim 20$ m) with around 140 animals in each boma. Location
 193 2, called Potha, consists of four connected bomas ($\varnothing \sim 18$ m) with around 100 animals in each
 194 boma. We then excluded pre-ruminant calves (0 – 3.5 months old) from the EF calculations
 195 since they produce negligible emissions which were around 15 % of the animals at Location 1
 196 and 10 % at Location 2 (Reed et al. 1990). Since the herds mainly consisted of female adult
 197 animals (> 50 %) and we could only measure the emissions of the entire herd we decided to
 198 assume that the herd only consisted of female adult animals after excluding pre-ruminant calves
 199 by using equation 3:

$$n_{total} = n_{cows} + n_{heifers} \frac{m_{heifers}}{m_{cows}} + n_{bulls} \frac{m_{bulls}}{m_{cows}} + n_{calves} \frac{m_{calves}}{m_{cows}}, \quad (3)$$

200 where n represents the number of animals and m (kg) the mean LW.

201 To reduce potential disturbances induced by obstacles in the bLS dispersion model we set up
202 our measurements in approx. 17 m distance of the enclosure fence. This is ten times the height
203 of the fence (1.7 m), following the suggestion of Flesch et al. (2005b) to minimize measurement
204 errors. Besides that, we chose a measurement height of around 1.7 m, staying lower than the
205 maximum of 0.1 times of the available fetch, after Flesch et al. (2004) for a homogenous surface
206 layer, where fetch is the distance between the center of the source and the laser path (**Fig. 3**), to
207 avoid making measurements at the edge of the tracer plume. The different wind and turbulence
208 parameters necessary for the EF calculation have been provided by the Mazingira Centre,
209 International Livestock Research Institute (ILRI), observed by their eddy covariance (EC)
210 tower located approximately 200 m away.

211 To receive reliable results, unrealistic and erroneous measurements have to be filtered from the
212 collected laser absorption spectrometer data. Following the suggestion of Boreal Laser Inc.
213 (2017) we kept those data with a light value output by the instruments between 3,000 and
214 11,000 units to avoid gas concentration misreadings caused by either not enough returning light
215 or by a saturation of the receiver, whereas the full range is between 1 and 16,368 units. Since
216 the wind direction was with 112.5 degrees from north generally very consistent during our
217 measurement period we filtered out data with deviations from the main wind direction
218 of $\pm 22.5^\circ$. Additional data filtering criteria followed the findings from Gao et al. (2009) and
219 Flesch et al. (2014) who reported strong over-/underestimations of the emission rates for
220 extremely stable/unstable conditions, respectively, which is why we chose the friction velocity
221 $u^* > 0.15 \text{ m s}^{-1}$ as a threshold. The presented data show the remaining values after applying the
222 different filters resulting in 67.7 % remaining data (**Table 2**). Other proposed filtering methods
223 like Obukhov length $|L| > 10 \text{ m}$ (Flesch et al. 2014) or discarding the data when the standard
224 deviation exceeding $2/3$ of the mean EF (Gao et al. 2009) showed no effect in our specific
225 location and were, therefore, neglected.

226
227

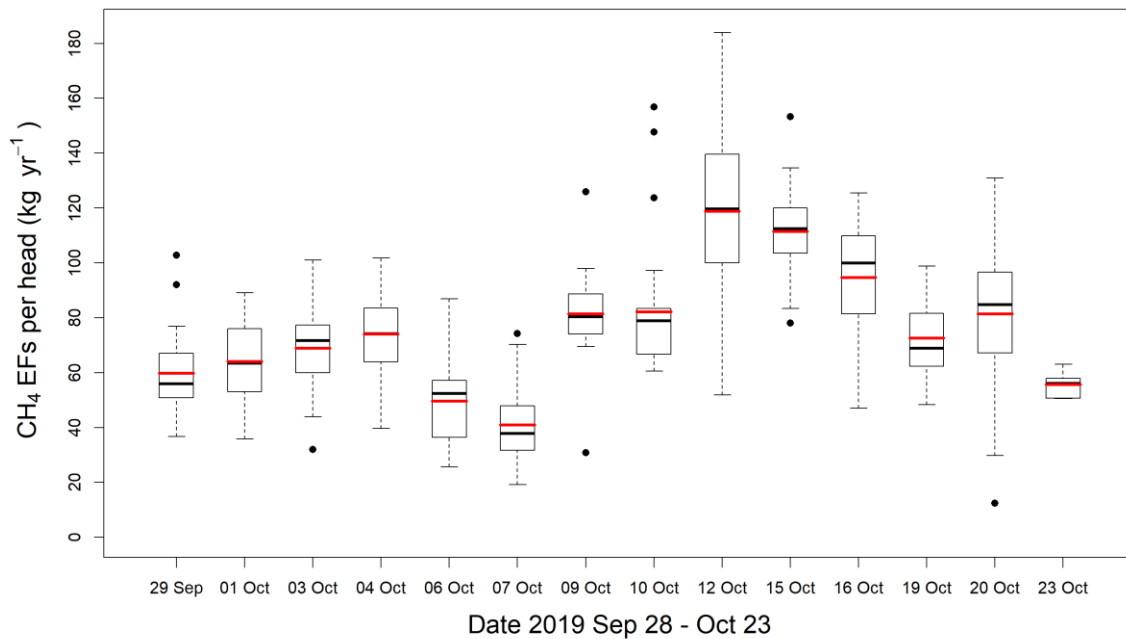
Table 2 Total number of measured 10-minute periods for every observed night before and after data filtering, nights when precipitation occurred are marked

Night	No. of periods	No. after filtering	Percentage (remaining)	Precipitation (X = yes)
28.09.-29.09.	41	33	80.5	
30.09.-01.10.	50	45	90.0	
02.10.-03.10.	60	39	65.0	
03.10.-04.10.	53	45	84.9	
05.10.-06.10.	36	27	75.0	
06.10.-07.10.	55	47	85.5	
08.10.-09.10.	56	19	33.9	X
09.10.-10.10.	35	31	88.6	X
11.10.-12.10.	46	41	89.1	X
14.10.-15.10.	39	22	56.4	
15.10.-16.10.	56	37	66.1	
18.10.-19.10.	43	26	60.5	X
19.10.-20.10.	58	39	67.2	
22.10.-23.10.	47	6	12.8	X
Total	675	457	67.7	

228

229 3 Results

230 The CH₄ EFs per head estimates ranged from 41.0 kg yr⁻¹ to 119.0 kg yr⁻¹ which resulted from
231 averaging ten-minute measurement periods (**Fig. 4**).

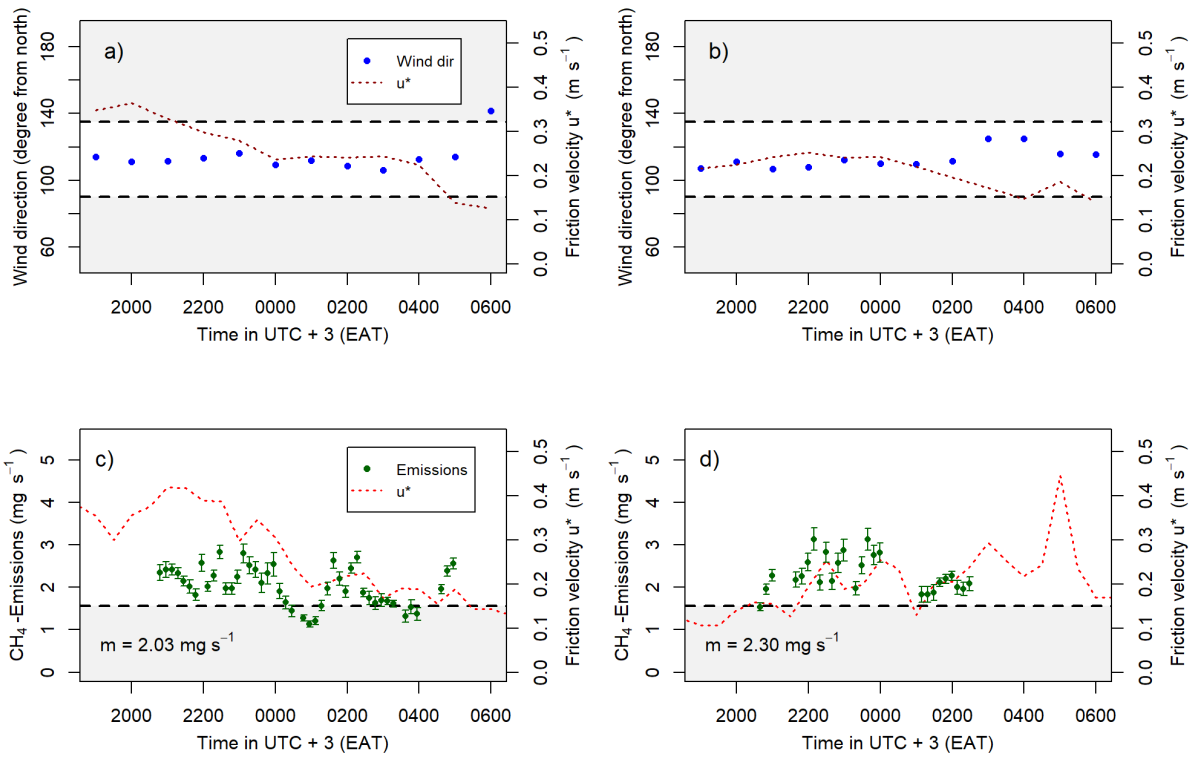


232

233 **Fig. 4** Boxplots of single livestock CH₄ emission rates determined each night during the period September 28th to October 23rd.
234 Boxes indicate the range from the first quartile (Q1) to the third quartile (Q3) after applying the data filtering methods and the
235 error bars represent the minimum/maximum values. Data are defined as outliers (black dots) when lower/higher than $Q1 - 1.5(Q3 - Q1)$
236 $+ 1.5$ times the interquartile range ($Q3 - Q1$), respectively. Red and black lines represent the nighttime median and
237 mean values, respectively

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

241 **Table 3** shows the nightly mean methane emissions together with the nightly extrapolated
242 annual EFs. Methane emissions are shown in the different units mg s⁻¹, g d⁻¹ and the EFs in
243 kg yr⁻¹ to facilitate comparability with other publications.



244

245 **Fig. 5** Mean wind direction and friction velocity in the observed nights before (a) and after (b) the first rain fell together with
 246 an example of the course of the methane emissions per head with included error bars and the friction velocity u^* for a typical
 247 dry (c) and rainy (d) night together with the mean (m) emissions calculated with the WindTrax software. The critical values
 248 (black dotted lines) used for data filtering of 90 ° clockwise from north and 135 ° clockwise from north for the wind direction
 249 and of 0.15 m s^{-1} for the friction velocity are shown and the parts where data are filtered are grayed out

250

251
252

Table 3 Methane emissions \pm S.E.M. calculated with WindTrax in different units, where every value represents a single female adult animal together with its methane EF \pm S.E.M

Night	CH₄ emissions (mg s⁻¹)	CH₄ emissions (g d⁻¹)	CH₄ EF (kg yr⁻¹)
28.09.-29.09.	1.89	163.3	59.6
30.09.-01.10.	2.03	175.4	64.1
02.10.-03.10.	2.19	189.2	69.1
03.10.-04.10.	2.35	203.0	74.2
05.10.-06.10.	1.57	135.6	49.5
06.10.-07.10.	1.30	112.3	41.0
08.10.-09.10.	2.58	222.9	81.4
09.10.-10.10.	2.61	225.5	82.4
11.10.-12.10.	3.77	325.7	119.0
14.10.-15.10.	3.53	305.0	111.4
15.10.-16.10.	3.00	259.2	94.7
18.10.-19.10.	2.30	198.7	72.6
19.10.-20.10.	2.58	222.9	81.4
22.10.-23.10.	1.77	152.9	55.9
Mean	2.39 \pm 0.18	206.6 \pm 15.58	75.4 \pm 5.69

253

254 4 Discussion

255 4.1 Methodology

256 The main advantage of the bLS technique is that methane fluxes can be determined with only
257 one concentration measurement as long as the background methane concentration is known.
258 Moreover, it is very useful for measuring gas concentrations from well-defined area sources, if
259 the size of the area does not exceed the maximum path length of the open-path laser, which is
260 the case for the bomas under study. For our setup, the path length was limited to 60 to 80 m
261 depending on the kind of retroreflector used. Denmead (2008) reports maximum path lengths
262 of 1000 m but suggests to only use lengths of 100 to 300 m for more reliable results. The
263 technique requires sufficiently strong wind speeds and steady wind directions to maximize the
264 yield of high quality single measurements. It can be improved by mounting the laser instruments
265 on pan-tilt scanning units with multiple retroreflectors to be able to react to changing wind
266 directions and by adding small silicone heaters and electrical fans to prevent condensation on
267 the reflector's surface overnight as done by Gao et al. (2009) and Flesch et al. (2014). Such a
268 complex setup was not required for our measurements due to the optimal site conditions.

269 Our calculated values might have systematically overestimated the EFs by around 10 % since
270 other studies also recognized similar overestimations. Flesch et al. (2014) reported that the bLS
271 technique overestimated the release rate at night by about 8 - 12 % depending on the chosen
272 filtering method in their gas release experiment while it underestimated the emission rate during
273 the day. Gao et al. (2009) reported GHG overestimations during typical stable nighttime
274 conditions and underestimations during unstable conditions. They suggested that this bias might
275 be caused by a deficiency in the bLS model of Flesch et al. (2004). Furthermore, the authors
276 suggested that it might be caused by an error in the parameterization of the turbulent kinetic
277 energy dissipation rate, which is the rate at which turbulence energy is absorbed by breaking

278 turbulent air fluxes down into smaller and smaller fluxes until it is converted into heat by
279 viscous forces. Flesch et al. (2014) suspected that the bias might be caused by problems with
280 the laser temperature sensitivity of the instruments. They based their suspicion on the work
281 from Laubach et al. (2013) who found out that at least for their instruments the temperature
282 sensitivity was greater than the value given by Boreal Laser Inc. and also reported sensitivity
283 differences between their lasers.

284 4.2 Data filtering

285 The bLS technique worked generally well for our site during nighttime in most of the dry nights
286 until around 0300 - 0500 EAT and until 0100 - 0300 EAT in the rainy nights until the friction
287 velocity decreased or condensation occurred on the retroreflector (**Fig. 5**). The latter can also
288 be seen in the smaller number of measurements remaining after data filtering (Table 2). We
289 chose the relatively restrictive filter that only allowed for data with deviations of 22.5° from
290 the mean wind direction since the wind was coming from the same direction all the time.
291 Interestingly, using the Obhukov length as filter criterion showed no results since it was always
292 inside the proposed range of Gao et al. (2009). The same applies for a filter using integral
293 turbulence characterists (Foken and Wichura 1996) and for one using a threshold of the standard
294 deviation reported by WindTrax (Gao et al. 2009). Only the friction velocity filter criterion
295 resulted in some rejected data points mainly at the end of the night when the turbulence intensity
296 declined (**Fig. 5**). This shows that it is important to adapt the filtering methods to the
297 measurement location in order to retain as much high quality data as possible. Due to the very
298 homogenous wind conditions, 67.7 % of the data passed the filtering criteria. In comparison,
299 Gao et al. (2009) retained 40 % and Flesch et al. (2014) 63 % of the nighttime data after
300 applying their filters, indicating that the conditions at the site were beneficial for the bLS
301 approach in general and specifically for a setup that cannot be adjusted to changes in the main
302 wind direction.

303 4.3 Diurnal variations

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

309 As expected, the CH₄ production in animals decreases over the course of the night due to the
310 absence of feed inside the bomas and the resulting decrease in the rumination process. This
311 decrease leads to the conclusion that our results might underestimate the total annual emissions
312 since the animals are free-grazing during the day, indicating that the actual methane emissions
313 are in the range of the values of the first hours of the night. Our measurements took place at the
314 end of the dry season and went on into the beginning of the rainy season. Feed availability
315 increases in the rainy season due to plant growth which is leading to increases in beef (milk)
316 production and, therefore, also methane production. As a consequence, highest productivity of
317 animals is usually observed towards the end of the rainy season (Demarchi et al. 2016). The
318 animals experience a clear seasonal effect of feed restriction through LW losses in productive
319 females and reduced gains in other cattle classes mainly during the dry season and/or droughts.
320 This results in a lower daily methane production since they have to meet their energy
321 requirements by mobilization of their endogenous tissue rather than through consumption and
322 fermentation of feed (Goopy et al. 2020). Considering these factors we are still confident that
323 our observations show the correct order of magnitude for methane emissions per head and year.
324 Yet, we suggest undertaking additional investigations during the whole day to verify or correct
325 our calculated mean methane emission values in the future. Places such as Kapiti Research
326 Station could provide a well-suited platform to carry out such measurements. In addition, more
327 repetitions of similar measurements as ours could potentially reduce the uncertainty of the mean

328 EF estimates since we only observed a total of 14 nights. Our measurements took place during
329 a period of one month, which restricts the usability of the calculated emission estimates on an
330 annual scale because we observed the animals during a period of relatively low emissions
331 leading to a potential underestimation of the actual EFs.

332 4.4 Comparison with other studies

333 The predicted methane emission factors of the IPCC are based on measurements from the
334 Organization for Economic Cooperation and Development (OECD) countries and thus may not
335 be representative of the African livestock systems, breeds, soil and climate conditions (i.e.
336 Goopy et al. 2020; Pelster et al. 2016). The Tier 1 EFs for cattle in Africa were largely adjusted
337 by expert knowledge depending on countries' national inventories. Due to a scarcity of data on
338 GHG sources and sinks, most developing countries currently quantify agricultural GHG
339 emissions and reductions using IPCC Tier 1 emission factors with few exceptions such as
340 Kenya for its dairy sector. However, conducting in-situ measurements leads to more accurate
341 measurements and can be used to validate the IPCC values at the same time (Dong et al. 2006)
342 while simultaneously providing an opportunity to track GHG mitigation actions. At the
343 moment, the lack of reliable information on agricultural GHG emissions for developing
344 economies limits the possibility for low-carbon agricultural development and also the
345 opportunities for livestock keepers to benefit from carbon markets and the negotiating position
346 of developing countries in the global climate policy discussions (Rosenstock et al. 2013).

347 Our calculated mean value of $75.4 \pm 5.69 \text{ kg yr}^{-1} \text{ head}^{-1}$ is considerably higher than the IPCC
348 Tier 1 value. As shown in Table 4, six other studies also calculated their own methane EFs for
349 enteric fermentation of cattle in SSA countries. However, the observed breeds and the
350 corresponding different LWs differ widely and limit the comparability. The observed LWs
351 range from 162.3 kg in the IPCC values (Dong et al. 2006) to up to 440 kg in the study from
352 Tongwane and Moeletsi (2020). Du Toit et al. (2013) observed Holstein and Jersey cattle in

353 South Africa, Kouazounde et al. (2015) observed Borgou, Somba and Lagune breeds in Benin,
 354 Goopy et al. (2018), and Ndung'u et al. (2019) collected their data from East African shorthorn
 355 Zebus and Zebu - Bos Taurus crossbreeds from smallholder livestock systems. Goopy et al.
 356 (2020) observed Boran yearling steers, whereas, Tongwane and Moeletsi (2020) looked at the
 357 total number of South African cattle including multiple breeds with Bonsmara being the
 358 dominant beef cattle breed. In addition, this study observed mature female Zebu - Bos Taurus
 359 crossbreeds.

360 *Table 4 Comparison of the calculated methane emission factors for mature female cattle with other publications located in*
 361 *Africa*

Author	Cattle Type	Mean LW (kg)	CH₄ EF (kg yr⁻¹ head⁻¹)	Location
Dong et al. (2006)	Beef	200.0	41.0	IPCC Tier 1 (SSA)
Goopy et al. (2018)	Dairy	216.3	28.3	Kenya
Goopy et al. (2020)	Beef steers	162.3	37.2	Kenya
Ndung'u et al. (2019)	Dairy	306.9	47.8	Kenya
Du Toit et al. (2013)	Beef	360.0	73.1	South Africa
Tongwane and Moeletsi (2020)	Beef	440.0	96.6	South Africa
Kouazounde et al. (2015)	Multi-purpose	187.8	63.3	Benin
Present study	Beef	420.0	75.4	Kenya

362

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

370 country. Tongwane and Moeletsi (2020) obtained and used data from the South African
371 Department of Environmental Affairs and the Department of Agriculture, Forestry and
372 Fisheries to calculate their EFs.

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

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

388 The other study cited here, Goopy et al. (2020), tested the relationship between feed intake and
389 enteric CH₄ production to simulate the influence of the dry seasons by feeding different
390 maintenance energy requirement levels. Their mean EF is higher than the one from Goopy et
391 al. (2018) despite lower LW. However, it has to be noted that Goopy et al. (2020) did not
392 observe female nor mature animals and the experiment aimed at simulating extreme conditions
393 in terms of feed scarcity.

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

407 Methane EFs from African cattle are generally lower than those from cattle in developed
408 countries. Ominski et al. (2007) reported EFs of $90 \text{ kg CH}_4 \text{ yr}^{-1} \text{ head}^{-1}$ and
409 $94 \text{ kg CH}_4 \text{ yr}^{-1} \text{ head}^{-1}$ for beef cows and bulls in Canada, Castelán-Ortega et al. (2014) reported
410 $82.5 \text{ kg CH}_4 \text{ yr}^{-1} \text{ head}^{-1}$ for the tropical regions and $70.5 \text{ kg CH}_4 \text{ yr}^{-1} \text{ head}^{-1}$ for the temperate
411 regions in Mexico as mean values for calves, heifers, steers and bulls, and Basarab et al. (2005)
412 reported $102.5 \text{ kg CH}_4 \text{ yr}^{-1} \text{ head}^{-1}$ for beef cows in Alberta, Canada. All of the available studies
413 no matter from which continent urge for country and/or even region-specific EFs for the
414 different cattle breeds since one or few EFs cannot reliably predict the methane emissions for
415 cattle breeds in all of the 51 SSA countries.

416 5 Conclusions

417 In this study, we determined the CH₄ emissions from free-grazing mature female African beef
418 cattle using an IPCC Tier 2 approach for Kenya. The measurements were conducted for a herd
419 of 300 to 400 animals during 14 nights in 10-min intervals resulting in a mean EF of
420 $75.4 \pm 5.69 \text{ kg yr}^{-1} \text{ head}^{-1}$. These estimates might differ from the actual methane emissions due
421 to a systematic bias of the bLS technique reported by Flesch et al. (2014) leading to
422 overestimations of around 10 % for nighttime conditions or to underestimations due to the fact
423 that the animals could not be observed during daytime or during a period of high CH₄
424 production such as at the end of the rainy season. Our results, together with the six other
425 publications carried out in Africa, express the need for the continued development of country-
426 specific or ideally region-specific EFs since the estimates differ depending on the region, animal
427 breed, and livestock systems.

428 In the course of most nights, methane emissions showed a decreasing trend due to the lack of
429 feed in the bomas and, therefore, reduced rumination. Improved EF estimates could be obtained,
430 if measurements based on the bLS technique were carried out together with a modeling
431 approach that quantifies EFs from field measurements of LW, milk production, locomotion,
432 etc., similar to the study by Ndung'u et al. (2019). Differences in the methodologies could be
433 investigated, which would help to improve the accuracy of a range of methods. Additionally,
434 observing a herd for an entire diurnal cycle would help to detect and characterize regular CH₄-
435 emission patterns. Furthermore, measurements distributed over the whole year, especially at
436 the end of the rainy season, could help to verify or improve the calculated EFs.

437 **Declarations**

438 **Funding statement**

439 LM and SL acknowledge financial support of the CGIAR Fund Council, Australia (ACIAR),
440 Irish Aid, European Union, International Fund for Agricultural Development (IFAD), the
441 Netherlands, New Zealand, UK, USAID, and Thailand for funding to the CGIAR Research
442 Program on Livestock. We acknowledge the support provided by the Programme for Climate-
443 Smart Livestock (PCSL) implemented by GIZ and commissioned by the Federal Ministry for
444 Economic Cooperation and Development (BMZ), Germany.

445 **Conflicts of interest/Competing interests**

446 The authors have no relevant financial or non-financial interests to disclose.

447 **Availability of data and material**

448 Not applicable.

449 **Code availability**

450 Not applicable.

451 **Authors' contributions**

452 All authors contributed to the study conception and design. Material preparation, data collection
453 and analysis were performed by Kevin Wolz, Sonja Leitner, Lutz Merbold, Benjamin Wolf and
454 Matthias Mauder. The first draft of the manuscript was written by Kevin Wolz and all authors
455 commented on previous versions of the manuscript. All authors read and approved the final
456 manuscript.

457 Ethics approval

458 Not applicable.

459 Consent to participate

460 Not applicable.

461 Consent for publication

462 Not applicable.

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