Animal 16 (2022) 100445

Contents lists available at ScienceDirect

Animal

The international journal of animal biosciences

Farm-level emission intensities of smallholder cattle (*Bos indicus*; *B. indicus–B. taurus* crosses) production systems in highlands and semi-arid regions

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ARTICLE INFO

Article history:
Received 30 June 2021
Revised 9 December 2021
Accepted 10 December 2021
Available online 10 January 2022

Keywords:
African livestock system
Carbon footprint
CP
Life cycle assessment
Primary data

ABSTRACT

Ruminants are central to the economic and nutritional life of much of sub-Saharan Africa, but cattle are now blamed for having a disproportionately large negative environmental impact through emissions of greenhouse gas (**GHG**). However, the mechanism underlying excessive emissions occurring only on some farms is imperfectly understood. Reliable estimates of emissions themselves are frequently lacking due to a paucity of reliable data. Employing individual animal records obtained at regular farm visits, this study quantified farm-level emission intensities (**EIs**) of greenhouse gases of smallholder farms in three counties in Western Kenya. CP was chosen as the functional unit to capture the outputs of both milk and meat. The results showed that milk is responsible for 80–85% of total CP output. Farm EI ranged widely from 20 to >1 000 kg CO_2-eq/kg CP. Median EIs were 60 (Nandi), 71 (Bomet), and 90 (Nyando) kg CO_2-eq/kg. Although median EIs referenced to milk alone (2.3 kg CO_2-eq/kg milk) were almost twice that reported for Europe, up to 50% of farms had EIs comparable to the mean Pan-European EIs. Enteric methane (CH_4) contributed >95% of emissions and manure ~4%, with negligible emissions attributed to inputs to the production system. Collecting data from individual animals on smallholder farms enabled the demonstration of extremely heterogeneous EI status among similar geographical spaces and provides clear indicators on how low EI status may be achieved in these environments. Contrary to common belief, our data show that industrial-style intensification is not required to achieve low EI. Enteric CH_4 production overwhelmingly drives farm emissions in these systems and as this is strongly collinear with nutrition and intake, an effort will be required to achieve an "efficient frontier" between feed intake, productivity, and GHG emissions.

Implications

Smallholder cattle production is an important activity in East Africa, but emissions of these farms are thought to be high but not well understood due to a lack of on-farm data. Enteric methane drives on-farm greenhouse gas emissions in smallholder cattle farms, which have great mitigation potential, without the need for industrial-style intensification. Identification and adoption of practices associated with low emission intensities will facilitate better resource use efficiency and lower greenhouse gas emissions at a regional level.

Introduction

Livestock plays a crucial role in the social and economic growth of Africa (Herrero et al., 2013). Driven by population increase, and improving the gross domestic product, and household incomes (Steinfeld et al., 2006), demand for livestock products is rapidly

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https://doi.org/10.1016/j.animal.2021.100445
1751-7311/

growing (Thornton, 2010). The consumption of beef and milk is forecast to increase by 261 and 399%, respectively, between 2010 and 2050 (FAO, 2017). Simultaneously, the supply of livestock products in Africa is constrained by competition with other sectors for scarce natural resources, suboptimal husbandry practices, and unreliability in supply and quality of feed (Thornton, 2010; Nkonya et al., 2016). These conditions are putatively responsible for the characteristically high proportion of regional anthropogenic greenhouse gas (**GHG**) emissions attributed to animal agriculture (25 compared to 14.5% globally) (Gerber et al., 2011; Gerber et al., 2013). The average carbon footprint of fat- and protein-corrected milk (**FPCM**) in Africa is estimated to be 7.5 kg CO_2-eq/kg FPCM (Poore & Nemecek, 2018), while the corresponding global mean is ~3.2 kg CO_2-eq/l, leading Opio et al. (2013) to conclude that Sub-Saharan Africa has the least efficient dairy production systems in the world when measure assessed by climate impacts. To date, the accuracy of these estimates has not been confirmed. Additionally, the mechanism behind what drives some farms to pollute more than others has not been elucidated. This is principal because most GHG inventories in Africa have been collated using the Intergovernmental Panel on Climate Change (**IPCC**) default (Tier I) emission factors (**EFs**), which results in an annual estimate of GHG emissions per capita by animal class, ignoring (among other factors) variability in production efficiency between individual animals and enterprise management. While this approach is generally necessitated by a lack of detailed field data, it results in a large degree of uncertainty in the presence of seasonality and variability in animal phenotype and feed baskets, conditions almost invariably present in the smallholder context (Herrero et al., 2013; Goopy et al., 2018). African countries where livestock are an important source of GHGs are now committed to quantifying their own EFs, at both national and finer spatial scales (Lee et al., 2017; Ndao et al., 2019), with the objective of providing improved reporting to the United Nations Framework Convention on Climate Change (UNFCCC) following the Paris Climate Agreement.

Several recently completed studies have begun to address the challenge for African countries namely, South Africa (du Toit et al., 2013a; 2013b), Benin (Kouazounde et al., 2015), Kenya (Pelster et al., 2016; Goopy et al., 2018; Zhu et al., 2018; Ndung'u et al., 2019; Goopy et al., 2021; Leitner et al., 2021; Ndung'u et al., 2021), and Senagal (Ndao et al., 2019; Ndao et al., 2020). Nonetheless, accurate estimation of EFs alone does not capture the entire variability in emission impacts across smallholder farms (Goopy et al., 2018; Ndung'u et al., 2019), because in situations where productivity also varies, a farm's overall GHG performance is better assessed by employing emission intensity (**EI**) (Moran & Wall, 2011) under the life cycle assessment (**LCA**) framework. This view is particularly pertinent to agricultural systems where the presence of unproductive livestock held for a variety of non-economic reasons has been suggested as a major cause of large on-farm emissions (Weiler et al., 2014). Paradoxically, it has been claimed that these systems are also the ones with the greatest potential to mitigate GHG emissions via increased productivity, and thus are among the most important to critically examine (Parry et al., 2007).

In LCA, environmental burdens such as GHG emissions are referenced to a functional unit (**FU**) that is the quantity of an output representing the purpose of the system. For livestock systems, the FU has commonly been set as FPCM (Opio et al., 2013; O'Brien et al., 2015; Garg et al., 2016; Rice et al., 2017) or energy-corrected milk (Rotz et al., 2010; Knapp et al., 2014; O'Brien et al., 2014; Ross et al., 2017; Rotz, 2018) in dairy enterprises, or as carcass weight (Rotz et al., 2019), live weight (Desjardins et al., 2012; Opio et al., 2013; Legesse et al., 2016) or live weight gain (McAuliffe et al., 2018a) in beef enterprises. However, the use of different FUs has been shown to have a profound effect on the EI of a given system (McAuliffe et al., 2018b and 2020), often resulting in multiple and mutually contradictory EIs and arguably, confusion (Weiler et al., 2014). Attempting to resolve this issue, Ross et al. (2017) assessed the suitability of different FUs in a dairy enterprise, finding that energy-corrected milk was generally the most robust measure. However, this conclusion was based on studies conducted in developed countries where comprehensive databases are available. In contrast, livestock systems in developing economies typically have multiple functions from a single enterprise and single animals (multi-purpose system).

In Kenya, farming enterprises at a small scale are common throughout the highlands areas of Central and Rift Valley (Thorpe et al., 2000; World.Bank & CIAT, 2015). They are characterised by: (i) crop and livestock interdependence, (ii) small and fragmented land holdings (often < 2 ha) with dependence on access to common land, (iii) keeping a wide variety of livestock phenotypes (indigenous > indeterminate cross-bred > exotic), and (iv) having low inputs and low investment (Thorpe et al., 2000). Commonalities notwithstanding, the resulting system displays a good deal of heterogeneity through differences between farms in resources, production focus (subsistence, >commercial), and technical ability. Individual farms have multiple outputs, of which livestock is only one facet and not well understood.

Using animal-level data collected across multiple seasons on 313 smallholder mixed farms in Western Kenya, this study elucidates the distribution of farm-level EIs as well as their determinants. Although dairy farming is the most developed agricultural sub-sector in Kenya, unintuitively, it is predominantly supported by smallholders in rural areas (Muriuki, 2003). In particular, Western Kenya's Central and Rift Valley highland regions produce 60% of the country's milk supply (Muriuki, 2003), and their systems are representative of wider East Africa where livestock are an integral part of mixed agriculture.

Thus, we hypothesised that:

(i) GHG EIs in smallholder livestock production systems in Western Kenya do not vary between (a) farms, (b) agro-ecological zones (**AEZs**) or (c) regions.
(ii) The contribution of meat production is unimportant to overall farm output as measured by CP production, and
(iii) EIs are similar to model-based estimates reported in the extant literature.

This work has been presented in a conference proceeding as Ndung'u et al. (2021).

Material and methods

Study sites

Data used in this study were collected from 313 smallholding farms located across three counties in Western Kenya: Nyando (56), Nandi (126), and Bomet (131). Collectively, the study region encompasses seven AEZs (refer to Table 1). Farms were selected randomly for each (county) study (see Supplementary Fig. S1), stratified by AEZ (for full detail refer to Goopy et al. (2018)). Data collection comprised five visits to each farm at an interval of 3 months between visits within 12 months at each site (i.e: 2014–2015 for Nyando, 2015–2016 for Nandi, and 2016–2017 for Bomet). This protocol also captured seasonal changes (local seasons: short rains in November to January; hot dry in February to April; long rains in May to July; and cold dry in August to October) in the feed basket and local pasture quality and abundance that was quantified through the use of harvesting from exclusion cages

Table 1
Description of Agro-ecological Zones where cattle in smallholder farms of Nandi, Bomet, and Nyando were sampled.

Agro-Ecological Zone	Study Region (s)	Description	Mean Annual Temperature (°C)	Elevation range (metres above sea level)
Lower Highland 1 (LH1)	Nandi and Bomet	Moderately cool and humid	15–18	1 800/1 900–2 200/2 400
Lower Highland 2 (LH2)	Nandi and Bomet	Moderately cool and sub-humid		
Lower Highland 3 (LH3)	Bomet	Moderately cool and semi-humid		
Upper Midlands (UM)	Nandi and Bomet	Temperate	18–21	1 300/1 500–1 800/1 900
Upper Midland 2 (UM2)	Nyando	Temperate and sub-humid		
Upper Midland 5 (UM5)	Nyando	Temperate and semi-arid		
Lower Midland 2 (LM2)	Nyando	Warm and sub-humid	21–24	800–1 500

and subsequent proximate analysis. Details for these procedures and their calculations have been previously published (Goopy et al., 2018; Ndung'u et al., 2019; Ndung'u et al., 2021). Live weight of all cattle were recorded at every visit, and daily milk production was measured for each lactating female. Farm management information, comprising material inputs and animal feeding strategies, was collected on a seasonal basis through farmer interviews during each visit. This approach facilitated the regular recording of animals entering and leaving herds as well as the commencement and completion of lactation, capturing irregular herd dynamics commonly observed among smallholders in the study region. Pasture formed the largest part of cattle diet across all counties, AEZs, and seasons, followed by maize stover and sugarcane tops (see Supplementary Table S1), both residues of crops grown for human consumption. A small amount of fodder crops dominantly Napier grass and Rhodes grass were also grown by some households. In all cases, the Napier grass and Rhodes grass were manually established for 1–20 years using cuttings. The nutritional quality of the resultant feed baskets was analysed using bulked representative samples by season and AEZ and is described elsewhere (Goopy et al., 2018; Ndung'u et al., 2019).

System boundary and functional unit

A cradle-to-farm gate approach was adopted to quantify herd-level EIs associated with cattle (Fig. 1). To eliminate the aggregation bias, or systematic underestimation of disproportionally large climate impacts caused by "weakest link" animals (McAuliffe et al., 2018a), these values were initially calculated on an animal-by-animal basis for each season and subsequently combined across seasons and then animals in that order (see below). Although cattle data were repeatedly recorded for a period of 12 months, which constitute the temporal boundary of this study, the herd structure of each farm was not always at a steady state due to the movement of animals in and out of the farms in the form of sales, purchases, and temporary relocation to other farms during feed shortages. Across the entire sample, however, this effect was assumed to be largely cancelled out due to the sufficient sample size.

The primary FU for the study was set as CP (kg), encompassing both meat and milk production from multi-purpose cattle. We assumed that all animals sold out of study farms were sold for meat (or sold for further rearing before being on-sold for meat). Commensurably, animals purchased onto study farms were accounted for as an offset to the gross output. Thus, the total CP yield from each animal during the study period was defined as the net growth measured by the embedded CP content (details below) plus the CP content of milk produced.

To estimate the CP content of meat, a dressing percentage of 52.1% of live weight (**LW**) was assumed based on the locally most relevant information (Muchenje et al., 2008). Meat yield was set at 85% of carcass weight (Department of Agriculture and Rural Development, 2016) with a CP content of 21% (Muchenje et al., 2008). Edible by-products (offal) were also included in the total meat CP yield to reflect the local culinary practice (Table 2). These included the heart, kidneys, liver, lungs, spleen, tripe, tongue, and pancreas. The average offal yield (5.3% LW) and its CP content (18.2%) were obtained from the literature (Nollet & Toldra, 2011).

In addition, FPCM (kg) (IDF, 2010) and bone-free carcass weight (kg) were adopted as auxiliary FUs to facilitate the comparison of results with single-commodity EI studies for milk and meat, respectively. The FPCM was standardised to 4% fat and 3.3% true protein. The bone-free carcass weight was estimated using the assumptions described above.

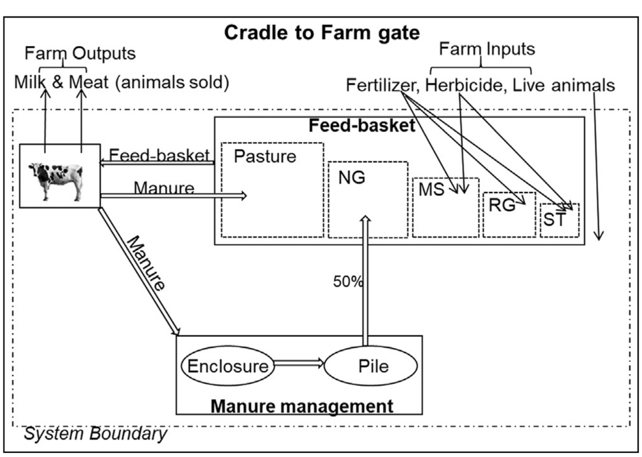

Fig. 1. System boundary for emission intensity assessment of cattle in smallholder farms. Squares show feedstuff in the feed basket where the sizes demonstrate the contribution of each feed to the overall feed basket (NG: Napier grass; MS: maize stover; RG: Rhodes grass; ST: sugarcane tops), ovals show the manure management systems. ⟹ shows the flow of raw materials and where the manure is deposited and → shows the farm inputs and output.

Inventory analysis

Enteric CH_4 emissions

Enteric CH_4 emissions were calculated according to the approach of Goopy et al. (2018). As discussed, a feed basket with various feedstuff contributing varied proportions to the total feed basket (see Supplementary Table S1) was determined at the AEZ level and per season to produce a representative estimate for seasonal digestibility (see Supplementary Table S2). Similarly, metabolisable energy requirement was determined on an individual animal basis as the sum of metabolisable energy requirement for maintenance, growth, locomotion, and lactation following CSIRO (2007) models per season. The two sets of information (i.e. total metabolisable energy requirements and feed digestibility) were then combined to produce estimates of DM intake for each animal; this value was used to estimate enteric CH_4 production using the conversion factor of Charmley et al. (2016).

Table 2
Edible by-products and their percentage yield, proportion, CP and CP yield from slaughtered cattle.

Offal	Average Yield (%live weight)	Proportion (%)	CP content(g/100 g)	CP (g/Offal Yield)
Heart	0.4	7.58	20.00	1.52
Liver	2.75	52.13	20.00	10.43
Kidney	0.155	2.94	16.40	0.48
Tripe	0.75	14.22	13.40	1.91
Spleen	0.185	3.51	21.17	0.74
Lungs	0.6	11.37	15.57	1.77
Tongue	0.375	7.11	16.83	1.20
Pancreas	0.06	1.14	18.00	0.20
Total	5.275	100.00		18.24

Manure CH_4 and nitrous oxide (N_2O) emissions

Animals were generally held in yards (bomas) near the farm dwelling overnight for security while grazing away from the homestead during the day for ~12 h/d. To capture the effect of the practice on manure emissions, we assumed that (i) 50% of the manure was excreted (and left) on pasture that the remainder was excreted in the enclosure and periodically heaped, resulting in equal proportions of (ii) piled (25%) and (iii) unpiled (25%) manure. Dong et al. (2006) states that storage conditions affect both the type and quantum of GHGs from manure and we used the assumed conditions to develop a composite EF for manure deposited in these situations (Table 3).

Dung excreted was estimated using DM intake and DM digestibility of the relevant feed basket. The carbon content of dung was based on an earlier study carried out under a similar condition (Zhu et al., 2018; Leitner et al., 2021). The nitrogen excreted was estimated by the difference between the nitrogen intake (derived from DM intake and the nitrogen (**N**) content of the relevant feed basket) and N embedded in carcasses and milk (see above). The mass ratios between protein and N were assumed to be 6.25 for meat and 6.38 for milk, respectively (Dong et al., 2006).

Half of the piled manure was assumed to be ultimately applied to Napier grass fields. The proportion of N retained beyond the storage period (Rufino et al., 2007) and the N_2O emission factor for that retained N at application (Dong et al., 2006) were obtained from existing studies. Based on interview results, the remaining 50% of piled manure was assumed to be exported for non-economic and non-functional activities outside the system boundary (e.g. home gardens) and therefore not considered at the calculation of post-storage emissions.

Carbon dioxide (CO_2) emissions from farm inputs

Farm management practices, such as agrochemical use and crop/crop by-product yields, were recorded as part of farmer interviews. Land use was quantified through physical surveys. No machinery was used in any of the study farms. Synthetic fertiliser and herbicides were used on some farms in Nandi (n = 31) and Bomet (n = 17), (but not Nyando) for the cultivation of RG, maize, and sugarcane. Fertiliser types varied between farms, although the application rates were relatively uniform (and low) due to standardised recommendations from agricultural extension officers (Mangale et al., 2016). These included: 28.5 kg N/ha as urea (46% N), 32.2 kg N/ha as calcium ammonium nitrate (26% N), 28.5 kg as nitrogen, phosphorus and potassium (NPK, 20% N), and 22.3 kg N/ha as di-ammonium phosphate (18% N and 46% P_2O_5). The background emissions attributable to agrochemical production were obtained from the ecoinvent database V3 (Wernet et al., 2016). Direct and indirect N_2O emissions associated with fertiliser application were calculated using IPCC emission factors (Dong et al., 2006). Nitrogen leaching was not considered due to the dry condition in the study region.

Depending on the AEZ and season, the contribution of crop residues to the feed basket ranged between 1 and 42% for maize stover and 9 and 34% for sugarcane tops, respectively (Goopy et al., 2018; Ndung'u et al., 2019). As outlined, these crops are grown for human consumption and the residues are fed to animals only opportunistically. Thus, GHG emissions from maize and sugarcane fields attributable to livestock production were quantified under the economic allocation method. A harvest index of 0.41 was assumed to estimate maize stover yield (Remison & Fajemisin, 1982), while sugarcane top yield was estimated as 4.89% of primary crop harvest (Kapur et al., 2013). Price data used for the final allocation are provided in Supplementary Table S3.

Table 3
Total yield factors for nitrous oxide (g N-N_2O/100 g N in manure) and methane (g C-CH_4/100 g C in manure) for cattle manure deposited/stored under different management conditions.

Management conditions	Weighting	Yield Factor (g CH_4-C/100 g C in manure (%) or g N_2O-N/100 g N in manure)	
		CH_4	N_2O
Pasture	0.50	0.031	0.004
Boma	0.25	0.01	0.079
Pile	0.25	0.43	0.45
Composite Value	1.00	0.126	0.134

Source: Leitner et al. (2021); N = Nitrogen, C = Carbon.

Impact assessment and interpretation

To make the results directly comparable with the largest pool of EIs in the literature (Poore & Nemecek, 2018), annual emissions attributable to individual animals were converted to global warming potential (**GWP**) under the 100-year Global Warming Potential (**GWP_{100}**) method, which assumes the characterisation factors of 28 and 265 for CH_4 and N_2O, respectively (Stocker et al., 2013) thereby reporting emissions using a measure of carbon dioxide equivalent (CO_2-eq). Individual values were aggregated for all animals on a single farm to estimate the farm-level GWP_{100}. Finally, the corresponding farm-level EI (CO_2-eq/kg CP) was derived as the ratio between GWP and the total (net) CP output.

Initial analysis of farm EIs (n = 313) identified a small number of farms across the three counties (n = 25) with nil or negative CP output, resulting in aberrant (infinitely large) EIs. Additionally, a small number of farms (n = 4) with positive but very low CP outputs (<3 kg CP per annum) returned extremely high EIs (>3 000 kg CO_2-eq/kg CP). With the upper bound for EIs in livestock systems posited to be ~1 000 kg CO_2-eq/kg CP (Gerber et al., 2011), the decision was made that EIs above this value would be truncated.

Similarly, the distribution of farm-level EIs was preliminarily studied under a variety of exploratory data analysis methods. As this revealed that the data were extremely right-skewed without a uniform variance, further investigations to explore the factors contributing to differences in EI were undertaken using quantile regression (Koenker & Hallock, 2001). The motivation for choosing quantile regression was threefold. Firstly, ordinary least square (**OLS**) regression makes the assumptions of normality and a constant variance (of residuals), neither of which was met in this instance. Secondly, as quantile regression is robust to outliers, the effect of individual farms with truncated EIs on estimators can be minimised. Thirdly, quantile regression provides an opportunity to estimate an individual model for each quantile so that the impact of explanatory variables on EIs can be separated elucidated for low-, intermediate-, and high-performing farms. The following quantiles were used for the present analysis: 0.85, 0.75, 0.5, 0.25, and 0.1 with a model created for each of these quantiles. A quantile of 0.85, for example, corresponds to farms with EIs larger than 85% of sample farms (for a given set of explanatory variables), (with identical characteristics of herd structure, location, AEZ, and protein output), thereby representing relatively low-performing farms. In contrast, $Q_{0.1}$ corresponds to farms with EIs which are lower than 90% of farms, and the model for this quantile represents high-performing farms. Median regression (with a quantile of 0.5), on the other hand, has a similar interpretation to OLS regression. Multicollinearity was investigated for each model, and variables with variance inflation factors >10 were sequentially removed to arrive at a suitable model for each quantile. The explanatory variables considered include herd size, parity, average age (of cattle), milk yield, meat yield, and total GHG emissions. Fixed effects associated with counties and AEZs were also included in the model.

Results

Table 4 describes the herd characteristic and animal performance of the sample population in Nandi, Bomet, and Nyando as well as the weather conditions of these sites. Of the three study sites, Nyando showed the lowest presence of productive females and production levels as compared to Nandi and Bomet. Similarly, the average live weights of the animals in all classes were lower in Nyando and highest in Nandi.

Distribution of farm emission intensities

Median farm EIs were estimated to be 60 (Nandi), 71 (Bomet) and 90 (Nyando) kg CO_2-eq/kg CP. However, the values of individual farms dramatically varied even within each county. There was also substantial variation in the frequency of occurrence of low, intermediate, and high EI farms between counties and AEZs, with Nyando having the greatest proportion of high EI farms (Fig. 2).

Enteric fermentation was by far the largest contributor to total farm emissions in all counties and AEZs, accounting for 96–97% of total GHG emissions. The second greatest contributor was manure emissions, with N_2O and CH_4 responsible for an average of 1.6 and 1.2%, respectively (Fig. 3). Emissions from the production and application of agrochemicals contributed <1% to total GHG emissions. This trend was uniform across all counties and AEZs, except that there was no use of agrochemicals in Nyando as mentioned above.

Milk production was consistently the more important element of CP production, responsible for >80% of the farm-level CP output across all counties and AEZs (Fig. 4). In two AEZs in Nyando (upper midland 5 and lower midland 2), low and negative animal growth rates combined with a slight increase in animal population during the study period (25 purchased vs. 15 sold) resulted in negative CP output.

Table 4
Comparison of climate, and demographic factors, productivity, and ownership of cattle of smallholder farms in Nandi, Bomet, and Nyando.

	Study sites		
Descriptive Factors	Nandi[a,e]	Bomet[b]	Nyando[c,d]
Climate Factors			
Rainfall (mm)	1 200–2 000	1 000–1 400	1 200–1 725
Soil Types	Nitisol, Acrisol	Nitisol, Cambisol	Nitisol, Regosol, Leptosol, Vertisol, Arenosol, Adosol, Planosol
Average land size (ha)	1.3[a]	1.5[b]	2.0[c]
Cattle Productivity			
Live weight			
Females > 2 years	306.9	280.6	216.3
Males > 2 years	265.9	259.6	216.0
Heifers 1–2 years	186.8	167.5	154.6
Young Males 1–2 years	156.9	136.5	143.5
Calves < 1 year	73.3	69.1	73.4
No. of Females/County (% of sample size)	487 (42.4)	505 (44.5)	176 (36.9)
No. of Males/county (% of sample size)	44 (3.83)	58 (5.12)	107 (22.43)
No. of Heifers/county (% of Sample size)	159 (13.84)	121 (10.69)	15 (3.14)
No. of Young males (% of sample size)	57 (4.96)	49 (4.33)	17 (2.94)
No. of Calves (% of sample size)	402 (34.99)	399 (35.25)	162 (33.96)
Average no. of lactating females/year	256	305	39
Percent females that calved down/year	40.3	31.9	15.6
Average milk yield (Litres/day)	4.1	3.9	2.2
Livestock ownership per household (numbers)	9.1	8.7	8.5
No. of cattle sold out	198	243	78
No. of cattle bought in	96	197	31

Source:
[a] GOK (2013).
[b] GOK (2018).
[c] Kirimi et al. (2010).
[d] Jaetzold and Schmidt (1983).
[e] Ndung'u et al. (2019).

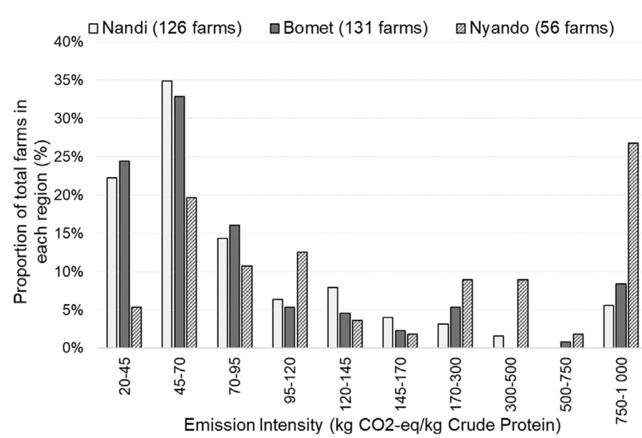

Fig. 2. Distributions of farm-level emission intensities for cattle in smallholder farms in Nandi, Bomet and Nyando.

Factors influencing farm-level emission intensities

Quantile regression revealed several management features that are highly influential to EI at the farm level, irrespective of the

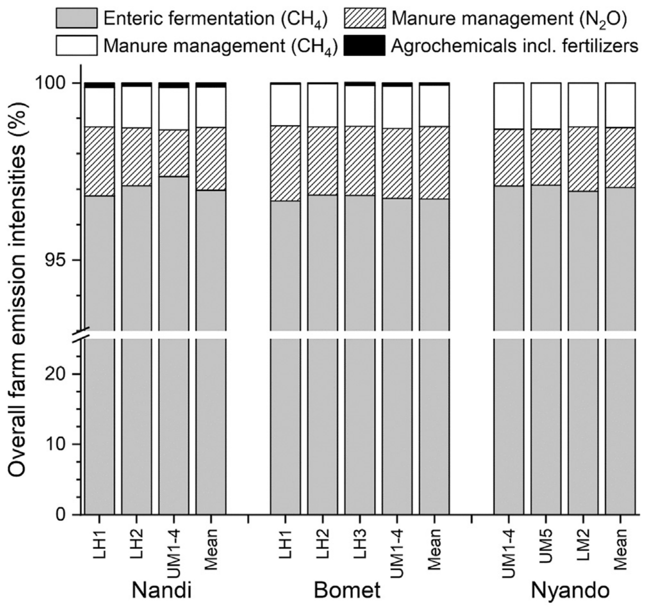

Fig. 3. Relative contribution of enteric CH_4, manure CH_4, and N_2O, and emissions from synthetic fertiliser production and application and agrochemical production to total greenhouse gas emissions related to cattle production by agro-ecological zones (Lower highland 1 (LH1), Lower highland 2 (LH2), Lower highland 3 (LH3), Upper midland 1 to 4 (UM1-4), Upper midland 5 (UM5), Lower midland 2 (LM2)) in Nandi, Bomet, and Nyando.

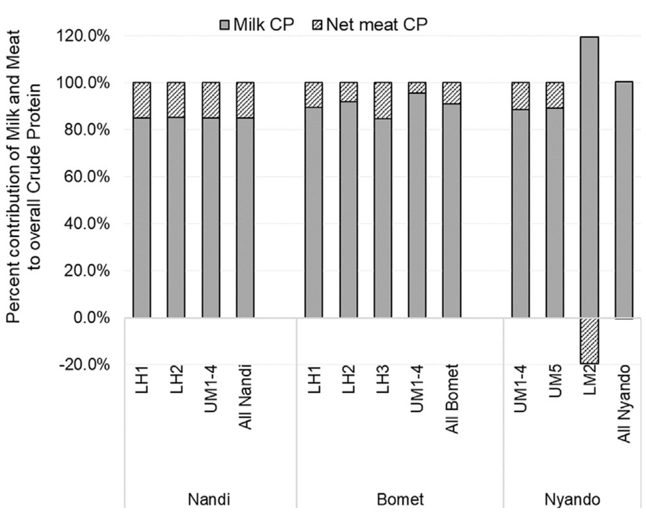

Fig. 4. Relative contribution of milk and meat to the total CP output by agro-ecological zones (Lower highland 1 (LH1), Lower highland 2 (LH2), Lower highland 3 (LH3), Upper midland 1–4 (UM1-4), Upper midland 5 (UM5), Lower midland 2 (LM2)) from cattle in Nando, Bomet, and Nyando.

county or AEZ (Table 5). Some factors were universally important, while others only at some EI quantiles. Despite the uneven contribution to total CP outputs, both meat and milk yields were significant drivers of EI across all quantiles investigated. Mean milk yield per cow, rather than milk production per farm, was found to be the most important driver of EI, with an increase in yield associated with a decrease in EI. An increase in herd size was found to increase EIs for low and medium EI (high and moderate performing) farms (Q_{10}: $\widehat{\beta_{HS}} = 1.35, p < 0.005$, Q_{50}: $\widehat{\beta_{HS}} = 1.86, p < 0.01$), whereas this tendency was not observed among high EI (low performing) farms. Although the average age of cattle was not important to EI, the proportion of females in a herd was negatively related to EI for most quantiles. The effect of calving percentage was only significant—and positive—for high EI farms ($P < 0.005$). Finally, there were no clear differences in EI between AEZs, likely because the intrinsic differences were captured by other variables in the models.

The coefficients for the average milk yield per cow and total farm meat yield across the five quantiles considered are illustrated in Figs. 5 and 6. A negative relationship was observed for both milk and meat, with a 1 kg increase in yield associated with a reduction in EI across all quantiles. The degree to which this occurs increased across quantiles, from $\widehat{\beta} = -1.18$ (SE = 0.05) for low EI farms (Q_{10}) to $\widehat{\beta} = -6.14$ (SE = 1.33) to high EI farms (Q_{85}) for milk, showing that EIs for low-performing, high EI farms are highly sensitive to changes in average milk (per cow). A similar pattern was also observed for the coefficients for meat yield, such that these models suggest that average milk yield and meat yield become increasingly important contributors to EIs across the quantiles. Thus, attempts to increase protein yield as a means of lowering EIs will be most effective at the upper quantiles, that is, for low-performing farms in terms of EIs. A similar pattern was observed for the coefficients for meat. Additional quantile results and plots are shown in the Supplementary Material S1.

Discussion

Median EIs of milk production for this study (2.3 kg CO_2-eq/kg milk) were less than half of the pan-African estimates of Opio et al. (2013) while perhaps unsurprisingly almost double that for European and North American systems. In some ways, however, nominal comparison of mean/median EIs between different dairy production systems obscures important findings from the present study. While EIs have been reported using total CP output as the primary FU, both milk CP and meat CP alone have been included to facilitate comparison with other studies (Table 6). Our data demonstrate that meat CP makes up 15–25% of farm CP output across systems, and thus to ignore this would result in a substantial overestimation of EI in smallholder farms (unless emissions attributable to the 'by-product' (meat) are appropriately allocated out of the system boundary). Next, although several other studies have applied an LCA framework to estimate EIs in African livestock systems (Opio et al., 2013; Weiler et al., 2014; MacLeod et al., 2018; Kiggundu et al., 2019), input data have been derived from a variety of secondary sources in every case, including posthoc farmer estimates, national census statistics, FAOSTAT databases, and modelling based on these secondary data. In contrast, the results reported here are based on measurements of individual animals' on-farm and actual feed baskets (see Supplementary Table S3). As such, this study provides a far clearer picture of, in particular, the variation of farm-level EI across, but also within, counties and AEZs. This approach, in turn, has led to the revelation that many farms in each of the counties (Nandi – 57%, Bomet – 58%, and Nyando – 20%) of the sampled farms had EIs comparable to European/North American intensified operations, doing so without employing high levels of inputs and mechanisation which are a hallmark of such operations. Exploration of the spectrum of EIs across farms provides insights into factors responsible for low EIs in smallholder farms, (something unachievable in studies relying on secondary data).

Prima facie, the differences between farms at the extremes of EI distribution were attributable to differences in CP output—very low EI enterprises had substantial outputs, whereas very high EI enterprises had little or in some cases no output at all in the course of the year. The absence of lactation females and growing animals resulted in a small number of farms exhibiting exceptionally large

Table 5
Estimated coefficients for each quantile regression model for estimating emission intensities for cattle, with associated *P*-values and pseudo R^2. NA is shown for variables that have been removed from the model based on high GVIF (multicollinearity).

Variable	q_{10}	p	q_{25}	p	q_{50}	p	q_{75}	p	q_{85}	p
Intercept	112.63	0.00*	150.58	0.00*	178.85	0.00*	366.23	0.04*	1197.50	0.00*
County = Nandi[a]	NA	NA	6.90	0.02*	9.13	0.15	9.14	0.75	NA	NA
County = Nyando[a]	NA	NA	−10.06	0.31	15.14	0.73	419.52	0.00*	NA	NA
AEZ = LH2[b]	1.82	0.57	1.20	0.75	NA	NA	NA	NA	NA	NA
AEZ = LH3[b]	4.93	0.83	7.69	0.32	NA	NA	NA	NA	NA	NA
AEZ = LM2[b]	−9.35	0.38	25.99	0.08	NA	NA	NA	NA	NA	NA
AEZ = UM[b]	−5.19	0.07	−2.82	0.39	NA	NA	NA	NA	NA	NA
Herd Size	1.35	0.00*	−0.52	0.49	1.86	0.01*	NA	NA	NA	NA
Average Parity[c]	−2.59	0.09	−3.33	0.08	NA	NA	−1.61	0.95	−17.33	0.61
Age females[d]	0.01	0.95	−0.19	0.20	−0.33	0.05	−1.68	0.43	−6.00	0.01*
Age all[e]	NA	NA	0.29	0.23	NA	NA	2.18	0.61	8.25	0.01*
Average milk yield	−1.18	0.00*	−1.33	0.00*	−1.52	0.00*	−2.28	0.03*	−6.14	0.00*
Meat yield	−0.53	0.00*	−0.62	0.00*	−0.88	0.00*	−1.80	0.01*	−4.62	0.00*
Calving[f]	5.01	0.21	−0.02	1.00	−6.73	0.52	−62.01	0.33	−275.17	0.00*
Females[g,f]	−47.13	0.00*	−79.91	0.00*	−79.22	0.00*	−252.18	0.31	−813.72	0.00
Total Emissions	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
Pseudo R^2	0.82		0.80		0.79		0.71		0.58	

GVIF = Generalised Variance Inflation Factor, q_{10} = 10th quantile, q_{25} = 25th quantile, q_{50} = 50th quantile, q_{75} = 75th quantile, q_{85} = 85th quantile, p = *P*-value at <0.05, AEZ = agro-ecological zone, LH1 = Lower highland 1, LH2 = Lower highland 2, LH3 = Lower highland 3, UM = Upper midland, LM2 = Lower midland 2, NA = data not available.
[*] Significant coefficients ($P < 0.05$).
[a] Baseline = Bomet
[b] Baseline = LH1
[c] Average parity was calculated for the adult females in the herd.
[d] Average age of adult females in the herd.
[e] Average of all animals in the herd.
[f] The number of females that calved during the one-year study period.
[g] The number of adult females in the herd.

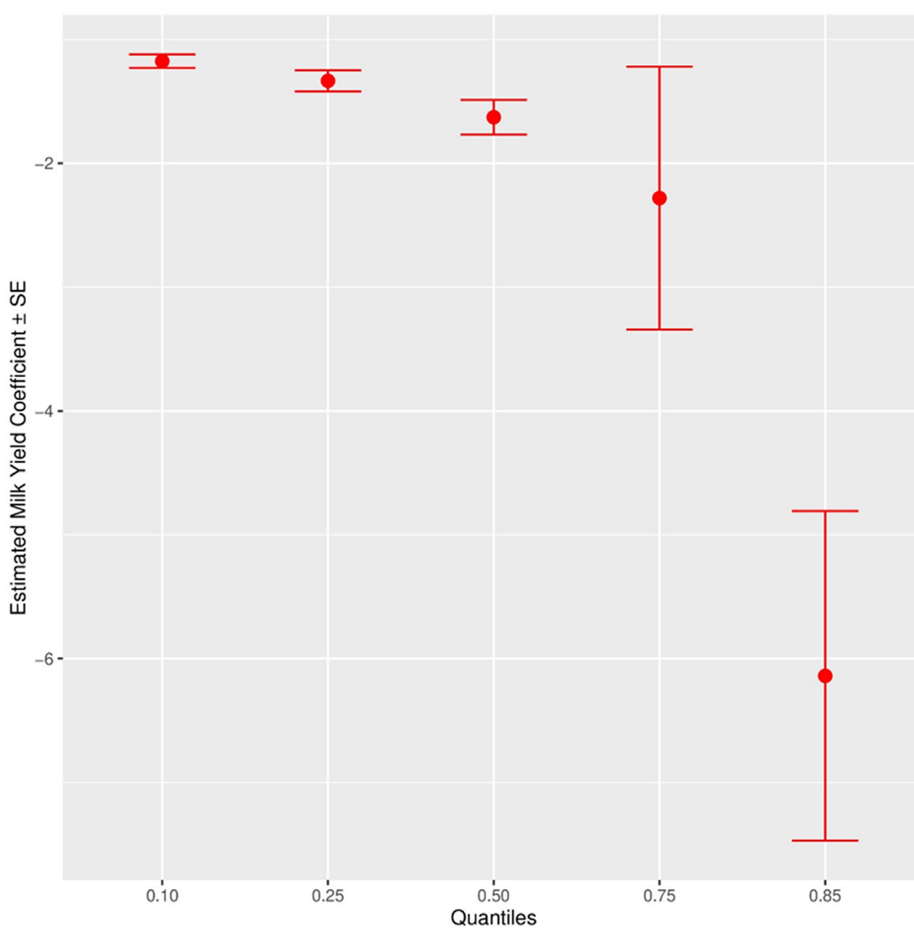

Fig. 5. Estimated coefficients for milk yield (±SE) from cattle across the 5-quantile regression models.

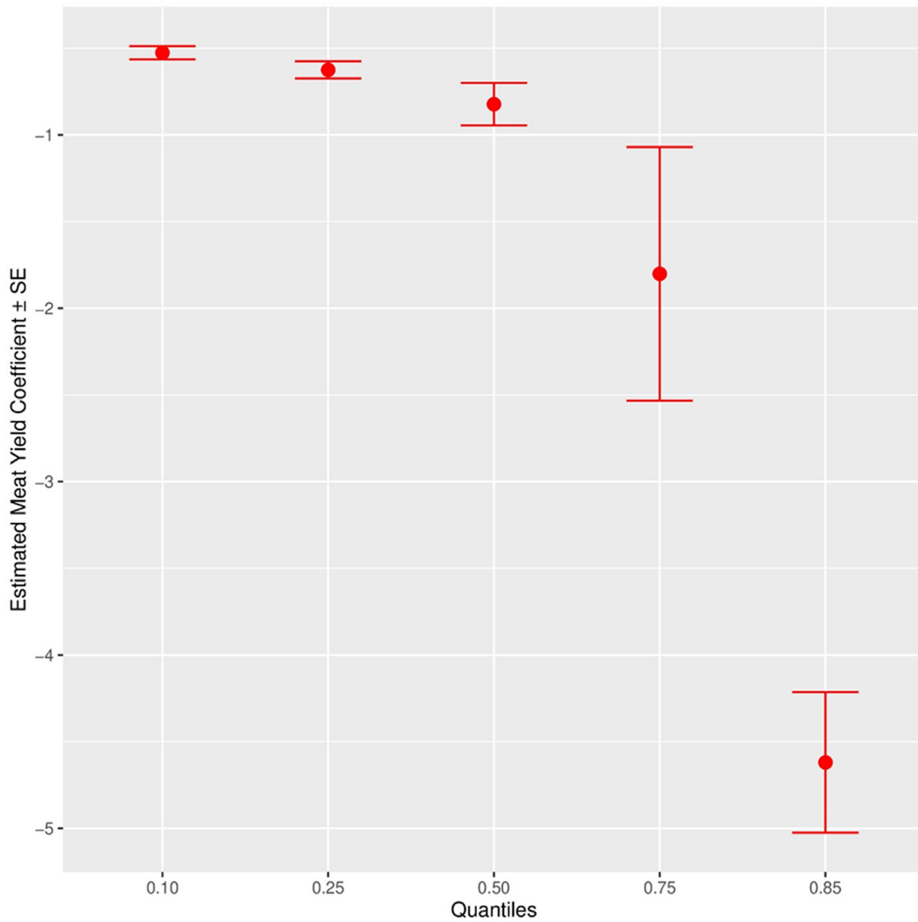

Fig. 6. Estimated coefficients for meat yield (±SE) from cattle across the 5-quantile regression models.

Table 6
Comparison of cattle emissions (kg CO_2-eq.) referenced to different functional units: a kilogram of fat- and protein-corrected milk (FPCM), milk, carcass weight, CP (milk and meat), protein (milk) and protein (meat) across multiple studies.

Region	FPCM	Milk	Carcass Weight	CP (milk & meat)	Protein (milk)	Protein (meat)	Study
Nandi	2.1	2.1	43	60	76	210	This study
Bomet	2.2	2.2	52	71	95	241	This study
Nyando	5.0	4.9	46	90	147	279	This study
Western Kenya	2.3	2.3	47	68	90	232	This study
Kaptumo, Kenya	–	0.9–4.3	–	–	–	–	Weiler et al. (2014)
Uganda	–	–	–	–	74.9	639.0	Kiggundu et al. (2019)
Africa	7.5	–	71.0	–	–	–	Opio et al. (2013)
India	1.9–2.3	–	–	–	–	–	Garg et al. (2016)
United States	–	–	21.3	–	–	–	Rotz et al. (2019)
Ireland	2.13	–	–	–	–	–	O'Brien et al. (2014)
Western Canada	–	–	22.0	–	–	–	Beauchemin et al. (2010)
Europe	–	1.3	22.6	–	–	–	Lesschen et al. (2011)
Global Estimates	2.8	–	46.2	–	–	–	Opio et al. (2013)

EIs. Although quantile regression mitigates statistical issues arising from the skewness, this observation brings to light a possible limitation of this study, in that we cannot be certain whether farms with very high EIs would continue to keep livestock for no return because their focus is not monetary (see below), or if this is a temporal anomaly caused by the structure of the study. However, to address this question would require longer-term data collection with commensurately greater resource needs and was thus well beyond the capacity of this study.

However, it is incorrect to conclude that EI is simply inverse correlated to livestock output across the EI farm spectrum – bigger is not necessarily better.

Between extremes of EI, the factors affecting farm-level EI seem more nuanced. A curious finding of this study was the presence of farms with very high and very low EI in close proximity to one another, even to the point of adjacent properties, militating against differences in EI being simply agro-ecological or even spatial in nature.

The production of methane from enteric fermentation overwhelmingly drive emissions on all farms in all regions. The importance of enteric CH_4 in the context of SHF is proportionally greater than other reports, especially those from Europe (O'Brien et al., 2014; 2015; Rotz et al., 2019), but also Uganda in the East African region (Kiggundu et al., 2019). There are two readily identifiable reasons for this. Firstly, the livestock systems in this study were low input in terms of fertilisers, purchased feeds, and mechanisation, which in intensive European farming systems account for 7–20% of total emissions (Opio et al., 2013; O'Brien et al., 2014; 2015). Secondly, emissions from manure management were low (as a result of a drier climate and lower N excretion), compared to those found in Europe under which manure may comprise 5–9% of total emissions (Opio et al., 2013; O'Brien et al., 2014; 2015). Thus, although it has been suggested elsewhere that improved manure management in smallholder farms could be a promising approach for reducing EIs (Weiske et al., 2006; Lesschen et al., 2011; Petersen et al., 2013), it seems unlikely that such a strategy would have a salutary effect on overall emissions (Rotz et al., 2019).

On the other hand, EI is strongly influenced by output or production (Gerber et al., 2011; Lesschen et al., 2011; MacLeod et al., 2018). While we determined that output as such was not inversely proportional to on-farm EI, we identified several production-related factors that were; the proportion of females in a herd, percentage of lactating females, calving percentage, and milk produced per lactating female, were all highly influential, suggesting that herd management is more important than scale in influencing EI at the farm level (Garnsworthy, 2004; Bell et al., 2011; Knapp et al., 2014; MacLeod et al., 2018).

Unfortunately, identifying the factors driving differential EIs at the farm level does not directly explain why these differences exist. Although strictly beyond the scope of this study, we posit that there are three broad elements that are likely causative factors, or important contributors to the observed differences in EI and that further, they are frequently interrelated: Knowledge, Opportunity, and Motivation. Many factors relating to herd management, including growth rate, female fecundity, and milk production, are strongly related to feeding in general and diet quality in particular (Huzzey et al., 2007; Robinson, 2007). Ayantunde et al. (2016) has shown the positive influence of extending grazing time on intake and in turn, animal performance, while Rodney et al. (2018) demonstrated the negative effects on lactation curves (Manzi et al., 2020) and fertility management due to poor nutrition. The positive impact on farm productivity by providing targeted, hands-on training to farmers has been demonstrated (Goopy & Gakige, 2016), while access to the technology and materials to produce good-quality feedstuff from on-farm by-product (Gakige et al., 2020) has the potential to lift production in an affordable manner. However, without access to reliable and trusted markets, many farmers may choose not to invest the required resources to make such improvements. Finally, many SHFs have interests in livestock that go beyond their monetised value and will not be motivated by the financial benefits that improving production can bring.

On-farm changes that increase livestock output also tend to increase total farm emissions because animals require increased energy intake to achieve the new production level. Thus, low EI operations will necessarily require a move towards an "efficient frontier", where increased output is achieved at a minimal increase to emissions per se. As such, milk yield per cow was found to be an important driver of EI in this study, probably because the increased intake of a lactating cow is channelled directly into increased production. Quantile regression has also demonstrated, however, that contrary to European/North American systems, an increase in operational scale does not necessarily lead to improved efficiency in East African smallholding farms. While this situation may not hold true across all of SSA, our findings suggest that climate-driven policy interventions should consider the creation of efficient herd structures (ie: a high proportion of productive females), and optimisation of the feeding of those individuals, rather than the expansion of the farm to ratchet up farm outputs.

Expressing the environmental impact of livestock production systems using an EI approach is important when comparing ostensibly similar farms in the same region (Browne et al., 2011) and is better able to demonstrate the potential of mitigation measures (Rotz et al., 2010) than comparisons based on GHG emissions per area or per animal alone. This approach is a considerably more data-demanding exercise, and thus resource requirements may limit an extensive use of EIs to inform GHG mitigation in developing countries in the immediate future.

Collecting data from smallholder farms facilitated the calculation of emissions attributable to individual animals and of enterprise-level EIs. Based on these data, we demonstrated a high level of variation in farm EI within and across regions, even within ostensibly similar operations. Contrary to existing evidence, certain low-input farms were found to generate notably lower emissions, with EIs comparable to those observed for enterprises in developed economies. Examining the characteristics of these low EI farms provides insight into effective strategies to move smallholder farms towards a low carbon future.

Although this study was limited in its geographic scope, this type of smallholder farming is ubiquitous throughout much of in Eastern Africa, thus the findings of this study have regional significance. Our results indicate that smallholder animal enterprises are not, as has been claimed, inefficient, uniformly high emitters and that exemplars for (relatively) low carbon farming are present in extant operations. Significant mitigation potential exists in improving productivity on a per animal basis and restructuring the herd in favour of productive females with high(er) milk outputs. This, in turn, relies on improved access to and quality of, animal feed. Increasing animal productivity, while retaining a low-input farm model, will not only contribute to reduced carbon footprint but will also likely have social and economic advantages such as increasing household incomes.

Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.animal.2021.100445.

Ethics approval

All animal data used in this study were collected as part of standard farming practices. As such, no part of this research was subject to the approval of an ethics committee.

Data and model availability statement

Data used for this study are publicly available (Goopy et al. 2018; Ndung'u et al. 2019).

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Author contributions

The authors confirm the contribution of the paper as follows:

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Melanie Robertson-Dean: Performed data analysis and interpretation – Statistical analysis

Cornelius Jacobus Lindeque Du Toit: Critical review of the paper.

Graham McAuliffe: Provided data analysis tools.

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John Goopy: Conceptualising and designing of the study, supervision of the study, data interpretation, drafting of the paper, critical review of the paper, final approval of the version to be published.

Declaration of interest

The authors declare no potential conflict of interest associated with this research.

Acknowledgments

The authors acknowledge the CGIAR Fund Council, Australia (ACIAR), Irish Aid, European Union, IFAD, the Netherlands, New Zealand, UK, USAID, and Thailand for funding the CGIAR Research Program on Livestock.

Financial support statement

This study was funded by the International Fund for Agricultural Development (IFAD) through the research projects "Greening Livestock: Incentive-Based Interventions for Reducing the Climate Impact of Livestock in East Africa" (Grant No. 2000000994) and further supported by the German Federal Ministry for Economic Cooperation and Development (BMZ issued through GIZ) Programme of Climate Smart Livestock (PCSL). The authors appreciate funding from the Biotechnology and Biological Sciences Research Council (BBS/E/C/000I0320) and the South African National Research Foundation, NRF Thuthuka Grant No. TTK180419322838.

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