Comparative analysis of on-farm greenhouse gas emissions from smallholder crop-livestock farming systems in Sub-Saharan Africa – A case study in Kenya

by

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I, Phyllis Wanjugu Ndung’u declare that the thesis, which I hereby submit for the degree

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At the University of Pretoria, is my own work and has not previously been submitted by me for a degree at this or any other tertiary institution.

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Preface

This thesis was written for my doctoral degree in Animal Science and the following is the list of publications that have been published or submitted in peer-reviewed journals from this work.

Peer-reviewed articles

1. **Ndung'u**, **P. W.,** T. Takahashi, C.J.L. du Toit, M. Robertson-Dean, K. Butterbach-Bahl, G. McAuliffe, L. Merbold, J. P. Goopy (2022). Farm-level emissions intensities of smallholder cattle (Bos Indicus; B. Indicus-B. Taurus crosses) production systems in Highlands and Semi-Arid regions. Animal, 16, 100445. https://doi.org/10.1016/j.animal.2021.100445
2. **Ndung'u, P.W.**, Kirui, P., Takahashi, T., du Toit, C. J. L., Merbold, L., & Goopy, J. P. (2021). Data describing cattle performance and feed characteristics to calculate enteric methane emissions in smallholder livestock systems in Bomet County, Kenya. Data in Brief, 39, 107673. https://doi.org/10.1016/j.dib.2021.107673
3. **Ndung'u, P. W.**, C.J.L. du Toit, T. Takahashi, M. Robertson-Dean, K. Butterbach-Bahl, L. Merbold, J. P. Goopy (Accepted). A simplified approach for producing Tier 2 enteric methane emission factors for ruminants. Animal Production Science.

Data repository

4. **Ndung'u, P. W.**, Goopy, J. P., & Kirui, P. (2021). Animal performance and feed characteristics data used to estimate the IPCC Tier 2 enteric methane emissions for smallholder livestock systems in Bomet, Kenya. Mendeley Data, V2. https://doi.org/10.17632/j5b9d7dd2b.2
5. **Ndung'u, P. W.,** & Goopy, J. P. (2022). Animal performance and feed characteristics data used to estimate the IPCC Tier 2 enteric methane emissions for smallholder livestock systems in Nandi, Kenya Mendeley Data, V1. https://doi.org/10.17632/3wsbwcmjbs.1

Peer-reviewed articles not included in this thesis

6. Goopy, J. P., **Ndung'u, P. W.,** Onyango, A., Kirui, P., & Butterbach-Bahl, K. (2021). Calculation of new enteric methane emission factors for small ruminants in western Kenya highlights the heterogeneity of smallholder production systems. Animal Production Science, 61(6), 602-612. https://doi.org/10.1071/AN19631

International conferences

1. **Ndung'u, P. W.,** Sonja Leitner, Lutz Merbold, Alice Onyango, Svenja Marquardt, John Goopy, Klaus Butterbach-Bahl, Michael Graha1, Claudia Arndt. (2022) Improved Emission Factors and Intensities for African Livestock Systems for GHG Accounting and Mitigation. Poster to be presented virtually at the 8th International Greenhouse Gas & Animal Agriculture Conference (GGAA). June 4th – 9th 2022, Orlando, Florida, USA.
2. **Ndung'u, P. W.** (2021). Environmental footprint of African livestock systems-case studies in Kenya Paper presented at the Tropentag 2021—Towards shifting paradigms in agriculture for a healthy and sustainable future. September 15-17, University of Hohenheim Germany
3. **Ndung'u, P.W.,** Takahashi, T., Du Toit, C. J. L., Robertson-Dean, M. R., Butterbach-Bahl, K. B., McAuliffe, G. A., Merbold, L. & Goopy, J. P. (2021). A partial life cycle assessment of smallholder livestock systems in Western Kenya. Paper presented at the Book of abstracts of the 72nd Annual Meeting of the European Federation of Animal Science. 30th August – 3rd September 2021, Davos, Switzerland. p. 232.
4. **Ndung'u, P.W.,** Takahashi, T., Du Toit, C. J. L., Robertson-Dean, M. R., Butterbach-Bahl, K. B., McAuliffe, G. A., Merbold, L., & Goopy, J. P. (2021). Quantifying on-farm greenhouse gas emissions in smallholder livestock systems in Western Kenya: cradle to farm gate partial life cycle assessment. Paper presented at the Joint XXIV International Grassland Congress and XI International Rangeland Congress. 25th – 29th October 2021, Nairobi, Kenya.
5. **Ndung'u, P. W.,** Takahashi, T., du Toit, C. J. L., Robertson-Dean, M., Merbold, L., Marquardt, S., & Goopy, J. P. (2020). Quantifying On-farm Greenhouse Gas Emissions in Smallholder Livestock Systems in Western Kenya: Life Cycle

Assessment. Paper presented at the Tropentag 2020 Virtual conference - Food and nutrition security and its resilience to global crises. September 9 - 11, Council for Tropical and Subtropical Agricultural Research, University of Hohenheim, Germany.

Lightning talk

1. **Ndung'u, P.W.** (2019). Why livestock greenhouse gas emissions matter. A lightning talk presented at the 8th CGIAR System Council. May 15 – 16. International Livestock Research Institute, Addis Ababa, Ethiopia.
2. **Ndung'u, P.W.** & Korir D. K. (2021) Opportunities of reducing the environmental footprint of African smallholder livestock systems. Presentation at the Euro Tier – International Trade Fair for Professional Animal Production. February 9 – 13 February. Hanover Fairground, Germany.

The subject of this thesis is related to greenhouse gas emissions from the livestock sector. This study is timely due to the increasing concern of climate change and the need for countries that are members of the United Nation Framework on Climate Change Convention (UNFCCC) to report their Nationally Determined Contributions to show efforts toward emissions reductions and GHG inventories. Efforts for emissions reduction can be well observed when accurate emissions are reported in the GHG inventories. This will not only help to show the trend in reductions but can also guide researchers on areas of prioritization in developing mitigation strategies.

The main objectives of this study were to develop region-specific enteric methane emission factors for cattle in a county in western Kenya using primary on-farm data collected for twelve months. Then using this data and data collected previously using the same data collection protocol, to conduct life cycle assessments (LCA) on the smallholder livestock system in Kenya. Lessons learned from the LCA study would then be used to guide a study to review the collection protocol previously developed for smallholder livestock systems to develop a much simpler, cost-effective protocol suitable for upscaling this study.

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Abstract

This thesis addresses the contribution of the smallholder mixed crop-livestock systems to greenhouse gas emissions. The first objective of the thesis was to quantify region-specific enteric methane emission factors for cattle in two counties (Bomet and Nandi) in Kenya. The calculated Tier 2 EFs were compared to the Intergovernmental Panel on Climate Change (IPCC) Tier 1 values for the Africa region and the emission factors were 25% to 45% lower than the IPCC default values for the county of Bomet in Kenya, a substantial difference. These differences were likely caused by the differences in feed digestibility values which were 13% higher than the IPCC values (62.2% vs 55%). Tier 2 emission factor values from a neighboring region in Western Kenya - Nandi County (published results) located close to Bomet county had similar agro-ecological zones and

the difference ranged between 4% lower to 4% higher than the emission factors from the Nandi region, a much smaller difference. The smaller difference was likely caused by the similar livestock keeping and climatic conditions in the two regions. In addition, Nandi Tier 2 emission factors were derived using the same approach as used for Bomet County region-specific activity data.

The second objective was to conduct a partial life cycle assessment (LCA) to quantify the carbon footprint of smallholder crop-livestock farming systems. The emissions intensities of the farms were highly variable and ranged from emissions intensities as found in developed countries to very high emissions intensities. This result was caused by the differences in farm outputs and herd structures. Farms in the highlands (Nandi and Bomet counties) showed lower emissions intensities while farms in semi-arid regions (Nyando county) showed much larger emissions intensities.

Conducting an LCA is data demanding while emissions reporting especially for the livestock sector in Africa requires locally specific data. As such simpler methodologies for acquiring such location-specific (and thus country-specific) data on the performance of the livestock systems and feed characteristics is needed. The third objective developed a simple, cost-effective protocol to derive locally specific data for quantifying enteric methane emission factors. Use of heart girth measurements, spot sampling of milk yield and use of default milk energy content showed the least bias compared with the actual measurements of either using specialized equipment or daily recording. However, the results were sensitive to feed quality values used by the model because the values from the literature may not be representative for specific regions and therefore if not actively collected may result in large bias and uncertainty.

GENERAL INTRODUCTION

General Introduction

Background

In Africa, approximately 70% of the rural population is either partly or fully dependent on agriculture for their livelihoods (Smith *et al.*, 2013). Among a range of factors, climate change (CC) poses the greatest threat to land and natural resources in the near future (Arias *et al.*, 2021). Various organizations (governmental & non-governmental) have invested in awareness raising of the threat of global CC and possible mitigation and adaptation pathways. The most prominent examples are the conference of the Parties (COP) meetings that assess the progress of combating global CC.

Short-lived greenhouse gases (GHG) such as methane (CH_4) (UNEP & CCAC 2021), have received attention during the last decades due to their impact on global warming (Nisbet et al., 2019). For example, CH_4 abundance is second after carbon dioxide (CO_2) in the atmosphere, has a short lifetime, and is more efficient in trapping radiation than CO_2. Because of its short lifespan and effect on global warming, lowering CH_4 emissions has been identified as one of the quickest ways to avert the 2.0ºC warming projected by the year 2050 (UNEP, 2021).

The livestock sector contributes 14.5% to the global anthropogenic GHG emissions (Gerber *et al.*, 2013) of which approximately 40% of those global emissions come from the enteric fermentation (Tubiello *et al.*, 2013). In most African countries, emissions from the agriculture sector particularly from the livestock sub-sector contributes more than half of the national GHG emissions (Tongwane & Moeletsi, 2018; Tubiello *et al.*, 2013). To reduce these emissions, accurate and reliable baseline information is essential (Tongwane & Moeletsi, 2018). Chapter three of this thesis embarks on using published methodology to produce region-specific estimates of enteric CH_4 emission factor (EF) for cattle in Bomet county in the western Kenya.

While accurate EF estimates provide useful insights into the contribution of the livestock sector to total GHG emissions, quantifying emissions against a product(s) (also known as emission intensity (EI)) enables the evaluation of the livestock systems against each other and is crucial in understanding their overall performance. The EI, which is calculated using a life cycle assessment methodology can show variability in production and emissions that may be caused by difference in animal husbandry, management practices, seasonality, and climate (e.g., agro-ecological zones) (Notarnicola *et al.*, 2017). In Africa, the amount of emissions per unit of animal product are reported to be high. For example, Opio *et al.* (2013) reported EI of milk in African livestock systems of almost thrice the global estimates (7.5kg CO_2-eq./kg fat protein corrected milk vs 2.8 kg CO_2-eq./kg fat protein corrected milk). The conclusion was based on secondary data and default models that generalize the livestock systems and may or may not represent the actual situation. In Chapter four of this thesis, an LCA study was conducted using primary datasets, two of which have been previously published and one additional dataset presented in chapter three of this thesis. The aim of the LCA approach is to evaluate the various aspects of environmental performance particularly this study, evaluated the GHG emission efficiency of heterogeneous smallholder mixed crop-livestock systems commonly practiced in Kenya.

Even with countries committing to emissions reduction, many have challenges in demonstrating their progress in emissions reduction without accurate and reliable baseline scenarios (Goopy *et al.*, 2018; Paul *et al.*, 2020). This is the case because of high capital and labor requirements. However, this situation is changing and the “high” emissions conclusion in Africa is being challenged using primary data for example in South Africa (du Toit, van Niekerk*, et al.*, 2013; du Toit, Meissner*, et al.*, 2013). Enabling creation of improved emission factors estimates in more countries by simplifying and streamlining data collection protocol has obvious advantages. In Chapter five, we assessed a simplification of data collection and calculations for accuracy and precision against standard protocols.

Objective of study

Objective 1: Quantify on-farm greenhouse gas emissions from smallholder crop-livestock farming systems.

The first objective of this thesis was to quantify enteric CH_4 emissions of cattle in smallholder livestock systems in Bomet County using the approach developed by Goopy *et al.* (2018). The outcome of this study contributes to building a solid database of region-specific EFs from the livestock sector which can be used in national greenhouse gas inventory compilation.

Objective 2: Partial life cycle assessment of CO_2-equivalent emissions intensities of smallholder mixed crop-livestock farming systems.

A partial LCA was conducted to quantify the emissions intensities of animal protein produced in smallholder livestock systems at the farm level. Data was collected in Bomet (chapter three of this thesis, and Nandi (Ndung’u *et al.*, 2019) and Nyando (Goopy 2018)). The drivers of variations between farms and across regions were identified and suggestions on how to improve farm productivity and subsequently lower GHG emissions intensities are highlighted.

Objective 3: Development of simplified methodologies

The third objective of this thesis was to investigate the effect using different measurement techniques and use of literature data to estimate on Tier 2 enteric CH_4 for livestock. The outcome would be simpler, faster, and cheaper approaches to obtaining activity data for estimating GHG emissions therefore promoting similar studies across African countries.

Outline of the thesis

Research activities for this thesis were carried out under the 'Greening Livestock: Incentive-based Interventions for Reducing the Climate Impact of Livestock in East Africa' project funded by the International Fund for Agricultural Development (Grant No. 2000000994). One of the project's aspects was to support the national governments in providing evidence-based information regarding the productivity of smallholder livestock systems in East Africa through detailed farm surveys. This would provide baseline information on the current situation in terms of productivity and emissions and a benchmark to test how much emissions reduction can be achieved when low emissions development strategies (LEDS) are developed and implemented.

This thesis consists of five chapters (**Figure 1**) where there is a general introduction of the thesis. In chapter one after the general introduction, a review of the literature was conducted. The first section describes the ruminant digestive system and the mechanism involved in methane production in the rumen. The second section reviews the existing approaches and methods of measuring enteric methane and lastly, emissions contribution and reporting of African livestock systems, identifying possible knowledge gaps towards better emissions accounting, reporting, and reduction tracking. Chapters two, three and four have the format of scientific publications. The second chapter reports the findings of the first objective of providing data that was used to derive Tier 2 CH_4 EFs. Using this data and previously published data in Western Kenya, an LCA was conducted to quantify EIs of smallholder livestock farms within a study site and across the sites presented in chapter three and hence addressing the second objective. Chapter four addressed the third objective and developed simpler and cost-effective data collection approaches that can be adopted in African region. Finally, chapter five integrates the results in a general discussion of the need to have region-specific animal-related data to inform GHG emissions inventories with data collection protocols adaptable to African countries and draw lessons for Africa’s smallholder livestock systems emissions efficiency.

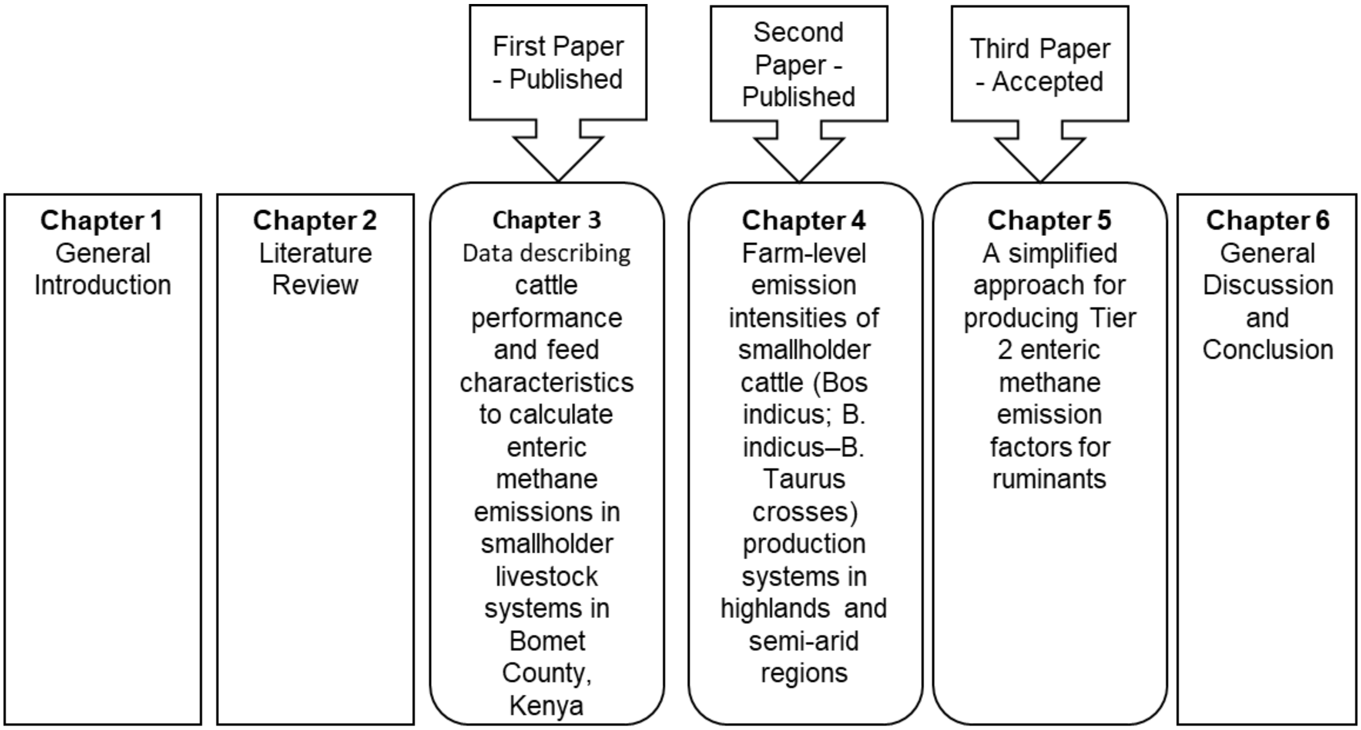

Figure 1: Diagram of thesis framework

CHAPTER ONE

1. Review of Literature

This chapter focuses on themes related to CH_4 formation in the rumen and its quantification. It explores how CH_4 is formed, factors affecting its formation, and ways of quantifying CH_4 from enteric fermentation. This is then related to how the production of CH_4 contributes to environmental issues from an African livestock farming system perspective.

1.1. Importance of methane gas

Methane forms a major component of natural gas; it is a hydrocarbon consisting of one carbon atom and four hydrogen atoms. CH_4 is odorless and flammable. Its production can be categorized through processes (i) biogenic: degradation of organic matter by microorganisms; (ii) thermogenic: breakdown of organic matter at high temperature and pressure; and (iii) pyrogenic: biofuel and coal mining (Saunois *et al.*, 2016) or sources i.e. natural or manmade (anthropogenic).

Methane is one of the top three GHG among carbon dioxide (CO_2) and nitrous oxide (N_2O) and is responsible for almost 20% of the earth's warming (Parry *et al.*, 2007). Secondly, it is more potent GHG than CO_2 as it can trap heat 28 times more than CO_2 (Alvarez *et al.*, 2012; Stocker *et al.*, 2013). Thirdly, it depletes the ozone layer in the stratosphere reducing its protective ability against harmful radiation heat. It has a 12-year lifespan in the atmosphere therefore short lived and hence for all these reasons, efforts to reduce CH_4 emissions have gained attention.

1.2. Methane sources

Methane has several natural (wetlands, termites, oceans, lakes) and anthropogenic sources (coal mining, landfills, wastewater treatment, and agriculture). Anthropogenic sources of CH_4 contribute ~50 – 65% of global CH_4 emissions (Stocker *et al.*, 2013) because of the increase in human activities (Saunois *et al.*, 2016; Saunois *et al.*, 2020) causing a $1^{O}C$ increase in global warming above the pre-industrial time (Fawzy *et al.*, 2020).

Agriculture is one of the key anthropogenic sources of CH_4 with emissions coming from livestock production (enteric fermentation and manure management), agricultural soils, and rice cultivation. It contributes approximately one-third of the total anthropogenic CH_4 emissions (Saunois *et al.*, 2016; Tubiello *et al.*, 2013). Globally, more than half of agriculture emissions are from livestock production where CH_4 is the dominant gas produced primarily from enteric fermentation hence a key category in GHG emissions (Saunois *et al.*, 2016; Tubiello *et al.*, 2013). Enteric fermentation is a digestive process in ruminants where plant materials inedible to humans are ultimately converted to high-quality edible products such as milk and meat. However, this digestive process is linked with CH_4 production.

1.3. Methane formation

1.3.1. Ruminant digestive system

The ruminant digestive system is characterized by the presence of four distinct organs, often referred to as “stomachs”: the rumen, reticulum, omasum, and abomasum. The animal harvests feed using the tongue and teeth, it is mixed with saliva and acted upon by salivary lipase and salivary amylase that break down fat and starch, respectively. Feed then passes through the esophagus to the reticulorumen (reticulum and rumen) where the liquid form is absorbed by the wall lining while the solid form is moved to the rumen where it is anaerobically degraded by microbes to produce substrates for energy production and ruminal gases such as CO_2 and CH_4. Fluids and nutrients from the ingesta are absorbed in the omasum through biphasic contractions while the ingesta then continues to the o abomasum (true stomach), a place of enzymatic break-down of food occurs.

The rumen is the largest of all the four compartments of a ruminant stomach. It is an important chamber of the stomach as this is where plant materials such as cellulose and hemicellulose, are broken down anaerobically with the help of microbes to produce glucose that can be used in the body. Depending on the species and age of the animal, rumen capacity ranges between 10 to 120 liters (Wolin *et al.*, 1997) and harbors bacteria, protozoa, fungi, and archaea whose function is to hydrolyze and ferment plant material and provide nutrients through VFA production and supply of microbial protein (Kamra, 2005). The optimal rumen environmental conditions to harbor microbes must have a pH of 6 to 7 and a temperature range of 38 to 42° C, factors mainly controlled by diet type (Castillo-González *et al.*, 2014).

The microbes perform specific functions in the rumen but also have a symbiotic relationship with one another and with the host (Wolin *et al.*, 1997). Bacteria are the most abundant microbes in the rumen with about $10^{10} – 10^{11}$ cells/ml, which are of many different species (Matthews *et al.*, 2019). The most common bacteria are the *Ruminococcus albus* and *Ruminococcus flavefaciens* (Koike & Kobayashi, 2009) as they are cellulose-degrading microbes. However, the existence and diversity of rumen bacteria depend mainly on diet type and the rumen environment (Wolin *et al.*, 1997) e.g. high grain diets often lower the rumen pH to <6 leading to the growth of gram-positive bacteria such as *Lactobacillus* whereas high fiber diets promote gram-negative bacteria such as Bacteroidetes (Matthews *et al.*, 2019; Oetzel, 2003). Once the cellulose is broken down into simple sugars (glucose), it is converted to volatile fatty acids (VFA) such as acetate, propionate, butyrate, and H_2.

The fungi consist of 8-12% of the rumen microbiome that also contribute to feed degradation (Matthews *et al.*, 2019). Fungi have been referred to as the best degraders despite their low population in the rumen, are affected by diet types too, and are important in the fermentation process as they initiate the feed degradation process and produce hydrogen (H_2) that is utilized by methanogenic archaea (Martinez-Fernandez *et al.*, 2016; Matthews *et al.*, 2019).

The archaea consist of ~3% of the rumen microbial population (Lin *et al.*, 1997), are strictly anaerobic, referred to as methanogens, the only rumen microbes known to produce methane, and utilize the end-products of the fermentation process as a source of energy (Hook *et al.*, 2010). Methanogens are of five genera in the rumen: *Methanobrevibacter, Methanosphaera, Methanomicrobium, Thermoplasma,* and *Methanobacterium* consisting of varying populations i.e., approximately 63%, 10%, 8%, 7%, and 2% respectively (Janssen & Kirs, 2008). Methanogen’s activity is very crucial to the fermentation process as they utilize H_2 produced during the feed degradation, which if left to accumulate would negatively affect the function of electron transfer for example the redox reaction of NADH in glycolysis (Whitman *et al.*, 2006; Wolin *et al.*, 1997), rendering fibre digestion inefficient.

The protozoa are mainly found in the liquid phase in the rumen and are responsible for the hydrolysis of lipids and like the fungi, can produce hydrogen during their degradation activity (Matthews *et al.*, 2019). However, protozoa do influence the bacteria's existence in the rumen and the concentration of VFA produced (protozoa promote the production of butyrate) (Alemu *et al.*, 2011).

Knowledge of the microbe's existence and activities is crucial for their survival during the interspecies interactions and well as for the survival of the host since the substrates of their activities and the end products provide energy either to the host animal or to other microbes. Hence, knowledge of rumen fermentation pathways is an important step toward understanding feed utilization and methane production in ruminant production.

1.3.2. Rumen fermentation pathways

Plant materials for ruminant animals that contain structural (cellulose and hemicellulose) and non-structural (starch and sugars) carbohydrates are the common feed resource for ruminants animals. The most abundant carbohydrates in forages are the structural carbohydrates that consist of large polymers such as cellulose. Cellulose contains many parts of glucose with β-1,4-glycosidic linkages and is packed closely into fibres and hence complex (Jayasekara & Ratnayake, 2019). Due to its complexity, its digestion requires microbial degradation to have access to the nutrients and utilize them. For example, the hydrolysis of cellulose is catalyzed by the cellulase enzyme that is produced by some microbes that are found in the rumen (Jayasekara & Ratnayake, 2019).

Once in the rumen, the feed stays for some time to be degraded, also known as the retention time. Retention time depends on the rumen condition that is influenced by diet (de Vega & Poppi, 1997). During this retention time, two activities, hydrolysis and fermentation of feed occur. These two activities are performed by different microbes categorized as hydrolytic or fermentative microbial organisms. The structural carbohydrates are broken down into soluble sugars through the hydrolysis process and by the hydrolytic microbes. The soluble sugars are then broken down through the fermentation process to intermediate compounds such as pyruvate, lactate, succinate, formate, and by-products such as H_2 and CO_2 in the glycolysis pathway. At this stage, the production of these intermediate compounds highly depends on the type of substrate present in the rumen that ultimately determines the type of microbes present and their population (Ungerfeld, 2020). At the pyruvate stage, different enzymes determine the type of VFAs produced. Propionate is produced through the acryloyl-CoA pathway and succinate pathways while acetate and butyrate are produced through the Acetyl-CoA pathways (Ungerfeld, 2020).

The type of VFA formed during the glycolysis process determines the amount of H_2 that will be available as a by-product in the rumen (Alemu *et al.*, 2011). The balance of H_2 in the rumen determines the Redox potential and hence feed degradation (Hegarty & Gerdes, 1999). Using Gibbs energy change (ΔG), H_2 concentrations can be determined and explained leading to conclusions on the VFA being produced (Ungerfeld, 2020). Acetate is the main VFA in the rumen as this is the most preferred pathway in an optimally performing fermentation process with optimum hydrogen partial pressure that promotes the role of NAD^+ to NADH (Ungerfeld, 2020; van Lingen *et al.*, 2016).

However, when there is high hydrogen partial pressure, the oxidation of NADH back to NAD^+ is inhibited and can lead to impairment of the fermentation process. The VFA formation pathway can also shift towards the formation of more propionate because propionate is an electron acceptor thereby accepting H_2. The VFAs formed are absorbed in the rumen wall and used by the host animal as a source of energy while their by-products are either utilized by other microbes or removed from the body as waste.

1.3.3. Methanogenesis process.

Methanogenesis is one of the H_2 sinks in the rumen besides propionate. Methanogenesis leads to the formation of CH_4 where methanogenic archaea utilized the hydrogen produced during feed break down by reducing CO_2 with H_2 to form CH_4 and this is the most common pathway. However, there is another pathway of reducing methanol with H_2 to produce CH_4, but it is only carried by one class of methanogens i.e., *Methanosphaera*. The production of CH_4 is promoted by the availability of H_2 caused by the pathways of the glycolysis process which are affected by factors such as diet type, retention, and animal species. The following subsection will explore factors promoting the availability of H_2 in detail.

1.3.4. Factors affecting the methanogenesis process.

Diet is the main factor that generally influence rumen fermentation pathways, rumen substrate, and end-products. This involves diet type, quality, and quantity. In diet type, feed on offer is either forage only or supplemented with concentrate. Forage differs in quality due to the form of carbohydrate present. Feed high in structural carbohydrates are of low quality and less digestible while feed with high non-structural carbohydrates is often referred to being better in quality and highly digestible. The quality of feed determines digestibility and is often affected by the stage of growth where overgrown forage has high fiber and vice versa (Haque, 2018; Robertson & Waghorn, 2002). Diet type and quality influence the quantity (feed intake) consumed where highly digestible feed promotes a high passage rate leading to higher intake (Beauchemin *et al.*, 2008) than less digestible feed. These diet factors are important in CH_4 production estimation as they have been identified as the primary determinant of CH_4 production (Blaxter & Clapperton, 1965; McCaughey *et al.*, 1997) However, the three diet factors are interdependent and can promote CH_4 production, for example, sheep research showed that CH_4 production reduces with the increased passage rate of the rumen digesta (Goopy, Donaldson*, et al.*, 2014).

Feeding on improved pasture quality through the incorporation of legumes in the diet has the potential to reduce CH_4 emissions. McCaughey *et al.* (1999) demonstrated a significant difference in CH_4 produced when cattle were fed on grass only and a mixture of grass and Alfalfa that led to an emissions reduction of up to 10%. Diets high in fibre promote the production of acetate and butyrate, H_2 and CO_2 that encourage CH_4 formation.

High fibre diets lead to high retention time in the rumen especially if the feed is highly lignified. This long retention time encourages high microbial activity that would cause the production of H_2 which leads to more CH_4 production as has been seen in sheep (Goopy, Donaldson*, et al.*, 2014). However, the retention time of highly fibrous feed can be reduced if the feed form is manipulated e.g., by reducing the particle size, and promoting faster microbial activity (Boadi, Wittenberg, *et al.*, 2004). Quantity of intake has shown to be influenced by the retention time of feed in the rumen (Müller *et al.*, 2013) through the high passage rate of feed that may lead to an increase in feed intake and since CH_4 production is strongly related to feed intake (Charmley *et al.*, 2016), can lead to high CH_4 production.

1.3.5. Factors limiting the methanogenesis process.

Limiting the methanogenesis process is necessary to benefit from livestock production through increased productivity and mitigate climate change through the reduction of enteric CH_4 emissions. Methane production represents a gross energy intake (GEI) loss (2-12% GEI) (Johnson & Johnson, 1995). Managing the H_2 produced in the rumen can contribute to a reduction in CH_4 formation. This can either be done through inhibiting pathways that encourage the production of H_2 or promoting pathways to which H_2 is utilized (alternative H_2 sink) to energy-generating pathways. These two choices can be achieved through either methanogenesis inhibitors, nutrition manipulation, or rumen microbial manipulation just to name a few. Use of methane inhibitors or chemical compounds that inhibit the activities of the rumen archaea has widely been researched.

1.3.5.1. Chemical compounds

An experiment conducted by Martinez-Fernandez *et al.* (2016) showed that dosing chloroform, a chemical compound does inhibit CH_4 production in steers fed both roughages: concentrates and roughage only caused by a rumen microbiota population shift involving a reduction in methanogen population, reduction in acetate formation, and redirection of H_2 to propionate formation rather than methanogenesis. However, feed intake was affected with dosing for the different diet presentations with a decrease in feed intake being observed for roughage: concentrate diet whereas an increase in the diet was observed in roughage diet only. Testing 3-nitrooxypropanol (3NOP), another methane inhibitor theoretically showed a decrease in methane formation by 30% while increasing the growth rate of dairy cows and no effect on feed intake (Hristov*, et al.*, 2015).

1.3.5.2. Nutritional manipulation

Nutritional manipulation aims to promote fermentation pathways that do not promote methanogenesis through the availability of CO_2 and H_2 substrates in the rumen which could reduce CH_4 production to approximately 40% (Benchaar *et al.*, 2001). This can either be done by improving the quality of the forage to increase digestibility or supplementing the base feed with concentrates, fats, or feed additives. Improving the quality of pasture-fed sheep in Australia was modeled to show the effect on CH_4 production when compared with unimproved pasture (Hegarty *et al.*, 2010). In that study, improving 24ha of pasture showed a similar profit margin as 100Ha of the unimproved pasture while CH_4 production was reduced by 44% yet only a quarter of the land was utilized. Improving 48Ha of pasture yielded the same amount of CH_4 as 100Ha of unimproved pasture but with double the profits. Therefore, improving pasture can reduce methane emissions.

Incorporating legumes into the diet leads to lower CH_4 yields. This has been observed mainly due to the low fibre content, and high digestibility of the legumes which leads to a higher passage rate (Beauchemin *et al.*, 2008). Legumes also have condensed tannins that have shown properties of inhibiting CH_4 formation (Beauchemin *et al.*, 2008) which inhibit the methanogenesis process. However, emissions per live weight gain were shown to be better reduced due to high growth rates in animals fed legumes than the reduction of absolute emissions which was smaller (Hegarty *et al.*, 2010). Grainger *et al.* (2009) showed that supplementing *Acacia mearnsii* that have condensed tannins reduced CH_4 production of lactating cows by 14% to 29% depending on the quantity offered but lowered the milk production and hence the need for further investigation before being recommended as a mitigation strategy.

Feeding concentrates influence CH_4 production through the shift of the rumen bacteria population to amylolytic bacteria and less cellulolytic bacteria that alter the intermediaries of VFA formation towards more propionate production and less CH_4 formation (Kamra, 2005). This not only reduces absolute emissions but also emissions intensities as the animal's productivity is increased. However, changes in the rumen microbial population can have detrimental effects leading to nutritional disorders such as acidosis.

Supplementing a diet with fats has traditionally been to increase the energy content of the feed to increase productivity but has an additional benefit of reducing CH_4 formation. Fats reduce CH_4 formation in the rumen by reducing the amount of organic matter for fermentation and inhibiting methanogenesis by reducing the amount of H_2 in the rumen (Johnson & Johnson, 1995). This happens because fats are not broken down in the rumen and therefore do not contribute to H_2. Hydrogenation of unsaturated fatty acids acts as an alternative H_2 sink and competes with methanogenesis leading to a reduction response (Boadi, Benchaar*, et al.*, 2004). The inclusion of unsaturated fatty acids showed to have affected the growth of methanogens in the rumen thereby causing a reduction in CH_4 production (Czerkawski *et al.*, 1966).

1.4. Methods of quantifying enteric CH_4

There is a strong relationship between the CH_4 production and quantity and quality of feed, and the age of animals (Blaxter & Clapperton, 1965; Johnson & Johnson, 1995). There is also near-linear relationship between livestock population and CH_4 emissions (IPCC, 2019). Due to the importance of CH_4 to global warming, reducing CH_4 emission is an important mitigation option for climate change. However, it is a challenge to reduce enteric CH_4, yet it is scantly known.

There exist methods of quantifying CH_4 from enteric fermentation that range from accurate measurements to estimated amounts. These measurements are achieved using either direct methods such as the use of respiration chambers, sulfur hexafluoride (SF_6) tracer technique, or indirect methods by use of prediction models. The use of these methods depends on the level of accuracy desired, the purpose of the study/experiment, sample size, and availability of resources. This section will discuss different approaches to quantifying methane emissions from livestock and the pros and cons of using these methods.

1.4.1. Respiration chambers

This is commonly referred to as a gold standard method of directly measuring CH_4 from rumen and hindgut. There are two types of respiratory chambers: open and closed circuits. The latter is more commonly used, and its principle of operation is collecting all the exhaled air that is removed by a pump and passes through a flow meter fitted with gas sensors and its concentration is measured using a gas analyzer whose sensitivity determines the accuracy of the measurements (Goopy J. P., 2005; Goopy, Robinson*, et al.*, 2014). This chamber also has a fan that helps facilitate the mixing of the air in the chamber as well as sensors that control both temperature and humidity. One animal is measured per day and hence is only ideal for a small sample size. It is best for testing interventions such as feed replacement/substitutions and their effects on methane production. The limitation of this method is that it requires a high capital investment therefore limited in producing large-scale measurements (Garnsworthy *et al.*, 2019). Data obtained from this method may not however be scaled up to grazing livestock systems due to the controlled environment in the chambers that may not necessarily depict the environmental conditions for the grazing animals (Pinares-Patiño *et al.*, 2008) but can be used to test the correlation with other measurement methods (Deighton *et al.*, 2014).

1.4.2. SF_6 tracer technique

The use of the SF_6 technique measures CH_4 directly under grazing conditions. It is less accurate when compared to the respiration chamber but requires relatively low capital investment. Its mode of operation includes the use of a trace gas that is inert, non-toxic, and can be measured accurately at low concentrations (Deighton *et al.*, 2014) with the same mixing properties in the rumen air as the CH_4 gas. Known amounts of the SF_6 are released in the rumen but before application, the rate of diffusion of the permeation tubes is first determined by placing them in a water bath at 39° C and the weight loss is recorded until it remains constant. Once stable, the tube is then placed in the rumen and measurements begin to be recorded. The techniques involve the use of a collection canister, a halter, and capillary tubing where the capillary tubing is placed at the nose of the animal and connected with the evacuated canister. A gas chromatograph is used to determine the concentration of both SF_6 and CH_4.

This technique can measure CH_4 emissions from grazing animals unlike the respiration chambers and when compared to respiration chambers, an agreement between results from the chambers and the SF_6 technique has been observed in a study conducted by Pinares-Patiño *et al.* (2008) though there are some differences due to some methodological shortcomings primarily from the rate of diffusion of permeation tubes (Pinares-Patino *et al.*, 2008) and only accounts for CH_4 produced from the rumen and doesn’t include hindgut fermentation (Storm *et al.*, 2012). Hence, I conclude that this is a reasonably good technique for measuring enteric CH_4 emissions.

1.4.3. Open-path laser Technique

This is a technique that uses laser to measure CH_4 emissions from grazing animals without too much interference of their grazing behavior. A laser is mounted at a corner of a grazing paddock with multiple laser paths determined by the direction of wind. These include multiple downward wind paths that are used to calculate the CH_4 emissions and one upward wind path for background CH_4. Data is then screened to filter wind statistics and laser light levels and those data points that do not meet the criteria are not used. The technique produces reliable emissions data during the day and highly variable data during the night due to low feed intake of cattle at night and the wind speeds therefore has an accuracy of up to 77% during the day. This technique is ideal to study emissions under grazing conditions, but the shortcoming is since the feed intake is unknown, it is not possible to determine CH_4 yield, cannot determine the individual measurements and it is technically demanding. It was noted that the emissions rate was sensitive to height of the source which in this case is mouth and nostril where most of the emissions are released. (McGinn *et al.*, 2011)

1.4.4. Greenfeed (GF) System

This is a short-term measurement technique that monitors CH_4 and CO_2 fluxes from the animal's breath. The device measures the CH_4 produced repeatedly for 3-6 minutes period every time the animal visits the unit to consume feed "bait", that has been established as 1kg (Hammond *et al.*, 2013; Hristov, Oh, Giallongo, Frederick, Weeks*, et al.*, 2015). CH_4 emissions are calculated by calculating CH_4 and CO_2 fluxes by multiplying the concentration of either of the two gases by the flow rate of the air exiting the device. The device is designed that it can be accessed by animals at any time hence can be used to measure CH_4 of grazing animals. Measurements from GF have shown to be comparable to respiratory chambers and SF_6 tracer technique. The technique has three shortcomings. Firstly, the use of "bait" feed (mostly supplements) may affect the feed intake due to the varying energy levels of the feed in the device when compared to the pasture being grazed on. This was reported to contribute to up to 5% of the dry matter intake. Secondly, the sampling points may not be representative of the day's emissions as there is a higher error term when compared to respiratory chamber and SF_6 tracer technique. Thirdly, the dry matter intake is unknown.

1.4.5. Use of extant values as a fixed parameter for predicting emissions

The use of predictive models to estimate CH_4 emissions is often preferred when the objective is to inform an inventory by calculating the emission of a population. In principle, CH_4 can be estimated using a known gross energy intake (GEI) (IPCC, 2019) or dry matter intake (DMI) (Charmley *et al.*, 2016; Niu *et al.*, 2021; Ramin & Huhtanen, 2013) value and either a CH_4 conversion factor (MCF, Y_m, % GEI that is converted into CH_4) or methane yield (MY, proportion of feed converted into CH_4, kg CH_4/kg DMI). Due to the limited information on feed intake under grazing management, GEI or DMI values can be derived using models that can estimate the intake based on animal performance and diet quality data that predicts the energy requirements for maintenance, growth, lactation, and activity.

The predicted GEI is then used together with Y_m values that have been derived from animal experiments. These values can differ based on the quality of the feed and hence continents and livestock production systems (IPCC, 2019; Johnson & Johnson, 1995). In a study conducted by Charmley *et al.* (2016), data were obtained from several published datasets in Australia whose feed basket is >70% forage and results showed a MY of 20.7 (±0.28) g/kg DMI (or 6.34% of GEI) that can be used in similar feeding systems and climate conditions to where the study was conducted. The IPCC recommends the use of 23.3 g/kg DMI (7.0% of GEI) in Africa for multi-purpose cattle (IPCC, 2019) whose feed basket is >75% forage which is 13% higher than reported by Charmley *et al.* (2016) despite similarities in the forage proportion. In other instances, MY can be developed for the country, for example, a MY of 23.1 g/kg DMI (r=0.84) was observed for dairy cows in the Netherlands (Dijkstra *et al.*, 2011), and in countries where concentrates contribute a substantial proportion in the feed basket, then the relationship between DMI/GEI and CH_4 production is no longer linear but curvilinear (Rotz *et al.*, 2012).

The predictive ability to use a simple linear model requiring only DMI to inform the CH_4 production has been compared with other models that require more than one variable such as neutral detergent fibre (NDF) content (Niu *et al.*, 2021; Storm *et al.*, 2012), fatty acids (FA) content (Niu *et al.*, 2018; Storlien *et al.*, 2014), and ether extracts (EE) content (Niu *et al.*, 2018; Niu *et al.*, 2021) where evidence showed better accuracy in CH_4 predictions is achieved when the above-named feed nutrient content are included compared to use of DMI only. However, the applicability of these models may be hindered by the lack of these specific data inputs, especially in developing countries where country-specific data availability is still a challenge (Ndung'u *et al.*, 2019).

1.5. Emission Intensities

Quantifying total emissions is important for national inventory reporting and emissions reduction tracking. However, there has been a growing need to demonstrate the carbon footprint of the products (Moran & Wall, 2011) in the need to reduce emissions from human-induced sources. According to the Center for Sustainable Systems (2021), the carbon footprint can be defined as the sum of GHG emissions produced directly and indirectly by a product's life cycle. It is calculated using a life cycle assessment (LCA) approach that enables calculations of emissions at every stage of the product thereby reporting the results as "emission intensity (EI)" i.e., emission per unit of product. Steinfeld, T. Wassenaar*, et al.* (2006) demonstrated that livestock contributes approximately 18% of the total anthropogenic emissions globally using the LCA approach.

In Africa, EI for milk was 7.5 kg CO_2-eq/kg fat-protein corrected milk, one of the highest globally (Opio *et al.*, 2013). To avoid negative outcomes as a result of increased emissions, calculating EI can demonstrate the major emissions hotspots in the product cycle and guide towards prioritization of emissions reductions from those sources (Ndung'u *et al.*, 2022) because different stages of production require different resources and have different emissions profiles (Opio *et al.*, 2013).

Life cycle assessment is an approach that quantifies the environmental impact of a product throughout the life cycle of a product (ISO:14040, 2006). It can demonstrate the production of emissions at different stages thereby informing points of concern (hotspots) and enabling modification of activities to reduce the production of emissions (Moran & Wall, 2011). One of the challenges in using LCA is the high demand for data needs. This element of LCA has made it difficult especially for African livestock systems assessment.

Results from LCA studies are difficult to compare mainly because of the system boundaries (i.e., cradle to farm-gate or cradle to grave), the functional unit (FU – a quantified description of a product e.g., kg of milk, carcass weight) described, and underlying assumptions defined. First, livestock production in developed countries is mostly specialized i.e., either dairy or beef production, and setting a FU is almost straightforward. However, for multi-purpose livestock production systems in developing countries, the functional unit may vary depending on the purpose of the activity and as Weiler *et al.* (2014) demonstrated, not including these benefits especially social benefits may result in higher EIs contrary to the actual situations (Garg *et al.*, 2016). Secondly, data used in most LCA studies are system-specific, primary data, therefore fewer errors while in most studies for developing countries, the level of uncertainty is great because of the use of secondary data that may not be well representative of livestock system as has been demonstrated by Garg *et al.* (2016).

In Kenya, livestock production is mainly dominated by smallholder livestock systems (SHLS) (Bebe *et al.*, 2002; Waithaka *et al.*, 2000). However, their contribution to climate change is still scarcely investigated especially in determining the carbon footprint of products from SHLS leading to the high uncertainties with EIs produced using default methodologies or global estimates (Opio *et al.*, 2013).

1.6. Smallholder livestock systems (SHLS)

Smallholder livestock systems are key players in providing food security at the local level in African countries. It is the most prevalent production system practiced in rural livelihoods and is the main producer of animal products in developing countries (Herrero *et al.*, 2013). Smallholder livestock systems have multiple objectives for keeping livestock that leads to a variation in herd size and composition and productivity levels across regions within a country and continent (Garg *et al.*, 2016; Weiler *et al.*, 2014). This is because livestock is not only a source of food but also a wide range of non-edible benefits such as manure that supports crop farming, a source of household income, creates employment, serves as a buffer towards risks through insurance, especially to the vulnerable communities, and have a cultural aesthetic value, especially to the pastoral communities (Herrero *et al.*, 2009; Weiler *et al.*, 2014).

Smallholder livestock systems have a high level of agricultural diversity; however, they commonly experience poor production levels due to resource scarcity such as capital. They practice rainfed farming but over the years there has been diversity in the existing and developing challenges. Most African countries are experiencing adverse effects due to climate variability and risks such as long drought periods, higher temperatures, and erratic rainfalls to an extent that by 2020 yields from rain-fed agriculture could be reduced by 50% (IPCC, 2007). These adverse effects are directly affecting livestock farming through poor quality and quantity of feed, water shortages, and high competition of natural resources such as land with human food crops hence it presents a challenge to sustainable livestock farming. Moreover, there is a high dependence on livestock for rural livelihood and the challenged survival of the livestock production presents food security and increased poverty threat since livestock has been identified as an important economic and social asset to achieve food and nutrition security due to its popularity among the rural livelihoods, the rich protein content in their products, and income generation from sales of surplus animals and animal products. On the other hand, due to the size of their enterprises, productivity at low inputs, and recycling nutrients, they can be able to quickly respond to the effects of these threats.

1.7. Conclusion

Livestock production contributes majorly to global emissions through enteric CH4 emissions. Mitigation options are therefore needed to reduce the emissions and has already been demonstrated in this review various approaches can be adapted to inhibit the activity of methanogens to produce methane. However, to track the reduction at a national level, accurate baseline estimates are needed, and therefore there is a need to develop country specific EFs. This not only serves as a baseline but also enables countries in Africa to move from the use of default EF for emissions reporting of their national inventories and use more accurate estimates from IPCC Tier 2 methodology.

The use of LCA has been limited in SHLS majorly due to the lack of data and the complexity of the approach. However, it can quantitatively show the diversity in emissions efficiency of SHLS to establish the possibility of having emission-efficient farms among the low-input livestock systems. But to conduct similar studies, data will continuously be needed and that can be expensive to obtain hence alternative data collection options that are cost-effective need to be investigated.

CHAPTER TWO

2. Data describing cattle performance and feed characteristics to calculate enteric methane emissions in smallholder livestock systems in Bomet County, Kenya

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Abstract

This dataset describes the performance of cattle in smallholder livestock systems of Bomet county in western Kenya. Information on live weight, milk production and quality, herd dynamics, and other production parameters were collected from field visits. Animals were weighed on scales; milk yield was recorded using a Mazzican ®milk collection and transport vessel provided to each farm and milk was analyzed for butterfat content (%). Pasture biomass yield was determined, feed samples were collected for each agro-ecological zone, and nutrient composition was determined for nitrogen (N) using the Kjeldahl method and gross energy (GE) using a bomb calorimeter. Distance covered while grazing was determined using GPS collars fitted to several animals for three consecutive days per area. Enteric CH_4 emissions factors (EF) were estimated for five animal classes to develop site-specific EFs as per the Intergovernmental panel on climate change (IPCC) protocol. This dataset has the potential to be used, amongst other purposes, for animal-scale life cycle assessment (LCA) to evaluate the efficacy of various greenhouse gas (GHG) mitigation options.

Specifications Table

Subject	Agricultural Sciences
Specific subject area	Livestock Science
Type of data	Tables Figure
How data were acquired	On-farms data collection for live weights, feed quantity and quality and animal productivity and modelling for emission factors
Data format	Primary (animal demographics, live weight, milk production, milk butterfat, feed N and GE), filtered (calving, weaning, mortality rate, distance covered during grazing), and analysed (enteric CH_4 EFs)
Parameters for data collection	131 smallholder farms selected through random stratification by location in Bomet County including 1,135 cattle in four agro-ecological zones (AEZs)
Description of data collection	9 farm visits over a 12-month period, 5 live weight measurements per animal, 4 pasture sample collections per locality, 4 milk quality assessments done (one per lactating female every three months), 2 farm surveys done after six months, daily grazing distance estimated once and daily milk production recording.
Data source location	Bomet (0°48'0.00" N 35°13'59.88" E) in Western Kenya
Data accessibility	Data is included in this article Repository name: Mendeley Data (https://data.mendeley.com/) Data identification number: 10.17632/j5b9d7dd2b.2 Direct URL to data: https://data.mendeley.com/datasets/j5b9d7dd2b/2

Related research article	Goopy, J. P., Ndung'u, P. W., Onyango, A., Kirui, P., & Butterbach-Bahl, K. (2021). Calculation of new enteric methane emission factors for small ruminants in western Kenya highlights the heterogeneity of smallholder production systems. Animal Production Science, 61(6), 602-612. doi: https://doi.org/10.1071/AN19631

2.1. Value of the Data

- Uniquely high-resolution dataset combining animal characteristics, animal performance, feed quality, and the enteric methane emission factor (EF). Among the first reliable source of primary data to investigate African livestock systems' contribution to climate change at the individual animal scale.
- The EFs from this dataset can be used to evaluate the environmental impacts of these systems and facilitate the identification of contributing factors.
- The datasets can also be used to estimate the carbon footprint (CF) of smallholder livestock systems using the life cycle assessment approach, thereby elucidating mitigation options across the supply chain.
- This dataset presents the differences between region-specific activity data and emission factors (known as Tier 2) factors and the Intergovernmental Panel on Climate Change (IPCC) default values (Tier 1), and activity data used to develop these default values.

2.2. Data Description

Data provided here describes the activity data of smallholder livestock systems. The climatic conditions of the agro-ecological zones (AEZ) in Bomet, Kenya are shown in **Table 2.1**.

Table 2.1: Description of Agro-ecological Zones (AEZ) in Bomet County

Agro-ecological Zone	Description	Mean Annual Temperature (^{O}C)	Annual Rainfall (mm)	Elevation range (meters above sea level)
Lower Highland 1 (LH1)	Moderately cool and humid	15.0 – 18.0	1,500 – 2,100	1,800/1,900 to 2,200 / 2,400
Lower Highland 2 (LH2)	Moderately cool and sub-humid	15.0 – 18.0	1,300 – 1,800	
Lower Highland 3 (LH3)	Moderately cool and semi-humid	15.7 – 18.0	1,280 – 1,650	
Upper Midlands 1-4 (UM1-4)	Temperate and humid/sub-humid/semi-humid/transitional	18.0 – 21.0	1,200 – 1,850	1,300/1,500 to 1,800 / 1,900

Source: (Jaetzold & Schmidt, 1983)

Table 2.2. shows herd dynamics, and the movement of animals in and out of farms through sales and purchases according to AEZs. **Table 2.3** presents the cattle herd production parameters. The seasonal average live weight (LW) (**Table 2.4**) and seasonal live weight changes (see **Figure 2.1**). There was a seasonal effect on weight change i.e., negative weight changes among the adult cattle and lower weight gains in the growing herd during the dry season due to feeding shortages while in subsequent wet seasons, there was a positive weight change.

Table 2.2: Population dynamics of cattle showing sales, purchases, deaths, and births of the animals in smallholder farms in Bomet county.

		Herd size and dynamics (numbers)									
AEZ	**Animal Class**	**S1**	**S2**	**S3**	**S4**	**Sale**	**Purchase**	**Death**	**Birth**	**Relocated**	**Calf to young adult**
LH1	Female adults (>2yrs)	144	136	125	120	25	13	4	na	3	na
	Male adults (>2yrs)	5	5	6	6	3	5	1	na	0	na
	Heifers (1-2yrs)	35	45	50	60	10	16	0	na	3	23
	Young males (1-2yrs)	5	5	9	14	9	5	0	na	1	11
	Calves (<1yr)	75	75	75	71	25	12	3	68	4	34
LH2	Female adults (>2yrs)	142	137	136	130	21	15	3	na	3	na
	Male adults (>2yrs)	18	15	11	10	11	2	3	na	0	na
	Heifers (1-2yrs)	30	45	54	53	11	16	0	na	9	24
	Young males (1-2yrs)	11	14	20	18	8	2	0	na	3	13
	Calves (<1yr)	70	75	60	61	12	16	10	45	6	37
LH3	Female adults (>2yrs)	74	66	65	65	16	12	6	na	1	na
	Male adults (>2yrs)	23	17	14	13	12	3	3	na	5	na
	Heifers (1-2yrs)	9	19	27	29	2	13	0	na	2	12
	Young males (1-2yrs)	12	11	12	13	4	3	0	na	3	5
	Calves (<1yr)	32	40	32	21	6	8	8	16	3	17
UM1-4	Female adults (>2yrs)	103	104	94	92	31	20	2	na	6	na
	Male adults (>2yrs)	5	5	4	3	2	4	0	na	3	na
	Heifers (1-2yrs)	9	15	18	25	7	13	1	na	2	11
	Young males (1-2yrs)	12	15	15	20	10	11	0	na	5	14
	Calves (<1yr)	60	67	61	46	18	8	6	39	5	25
Total Bomet	Female adults (>2yrs)	463	443	420	407	93	60	15	na	13	na
	Male adults (>2yrs)	51	42	35	32	28	14	7	na	8	na
	Heifers (1-2yrs)	83	124	149	167	30	58	1	na	16	70
	Young males (1-2yrs)	40	45	56	65	31	21	0	na	12	43
	Calves (<1yr)	237	257	228	199	61	44	27	168	18	113

na = not applicable to that animal class. S1 = season 1, S2 = season 2, S3 = season 3, S4, season 4.

Table 2.3: Summary of production performance parameters for Bomet cattle herd

Production Parameter		**Yield/Rate**
Milk production (liters/day)		4.44
Milk butterfat (%)		4.20
Average distance walked during grazing (km/day)		8.05
Birth rate (%)		33.3
Weaning rate (%)		28.3
Mortality rate (%)		
	Females (>2years)	3.0
	Males (>2years)	12.1
	Heifers (1-2years)	0.01
	Young males (1-2years)	0.0
	Calves (<1year)	6.8

Table 2.4: Live weights (kg, mean ± standard error of means) for females and males (>2 years), heifers and young males (1-2 years), and calves (<1 year) under four seasons and 4 agro-ecological zones in Bomet County

AEZ	**Animal Class**	**S1 (LW, kg)**	**n**	**S2 (LW, kg)**	**n**	**S3 (LW, kg)**	**n**	**S4 (LW, kg)**	**n**
LH1	Female adults (>2yrs)	310.4±6.16	144	313.3±6.21	136	321.8±6.40	125	320.1±6.77	120
	Male adults (>2yrs)	267.7±46.79	5	235.0±58.99	6	244.8±49.91	6	248.7±49.53	6
	Heifers (1-2yrs)	176.1±9.44	35	180.2±10.26	45	192.9±10.88	50	196.6±10.34	60
	Young males (1-2yrs)	169.3±18.71	5	162.9±22.49	5	158.4±21.55	9	161.1±14.60	14
	Calves (<1yr)	68.6±3.65	77	71.8±3.19	76	72.6±4.27	76	65.1±3.68	72
LH2	Female adults (>2yrs)	254.2±4.56	140	252.9±4.13	136	265.9±3.97	135	267.9±4.11	129
	Male adults (>2yrs)	239.3±14.45	18	248.0±17.58	15	299.2±19.95	11	314.6±23.29	10
	Heifers (1-2yrs)	143.0±8.46	30	147.8±6.46	45	155.8±6.13	54	170.1±5.79	53
	Young males (1-2yrs)	115.0±7.12	11	130.2±7.32	11	137.6±5.95	12	151.5±6.55	13
	Calves (<1yr)	67.2±3.56	69	68.7±3.37	74	70.5±4.30	65	77.4±4.86	60
LH3	Female adults (>2yrs)	266.4±8.02	74	266.0±8.51	65	270.6±9.33	64	266.8±9.21	65
	Male adults (>2yrs)	220.5±13.66	23	284.7±15.41	16	284.7±20.92	14	291.6±28.10	13
	Heifers (1-2yrs)	146.8±20.55	9	143.9±13.29	19	143.9±12.68	27	149.2±11.69	29
	Young males (1-2yrs)	120.9±8.91	12	125.4±9.76	11	125.4±10.81	12	133.0±10.85	13
	Calves (<1yr)	62.2±3.63	32	58.8±4.59	40	59.4±6.31	32	75.6±9.94	21
UM1-4	Female adults (>2yrs)	263.2±5.08	103	268.1±5.20	103	275.7±5.81	94	272.9±5.98	92
	Male adults (>2yrs)	183.1±12.97	5	206.4±19.37	5	253.9±35.22	4	224.0±82.97	3
	Heifers (1-2yrs)	148.5±18.14	10	171.5±15.43	16	196.9±12.28	19	186.7±12.85	26
	Young males (1-2yrs)	130.9±13.64	12	132.2±11.04	15	139.6±8.90	15	138.7±8.98	20
	Calves (<1yr)	65.3±3.72	60	71.5±4.08	67	69.4±5.02	61	73.6±5.88	46
Total Bomet	Female adults (>2yrs)	275.7±3.12	461	277.0±3.12	440	285.5±3.22	418	284.3±3.31	406
	Male adults (>2yrs)	228.1±9.43	51	246.8±11.32	42	278.9±13.83	35	284.4±17.83	32
	Heifers (1-2yrs)	157.9±5.97	84	162.4±5.32	125	171.1±5.32	150	178.5±5.14	168
	Young males (1-2yrs)	128.3±6.13	40	132.9±5.57	45	138.9±5.24	56	145.9±5.09	65
	Calves (<1yr)	66.5±1.88	238	68.8±1.88	257	69.4±2.41	235	71.9±2.63	199

n = sample size; S1= season 1, S2= season 2, S3= season 3, S4, season 4

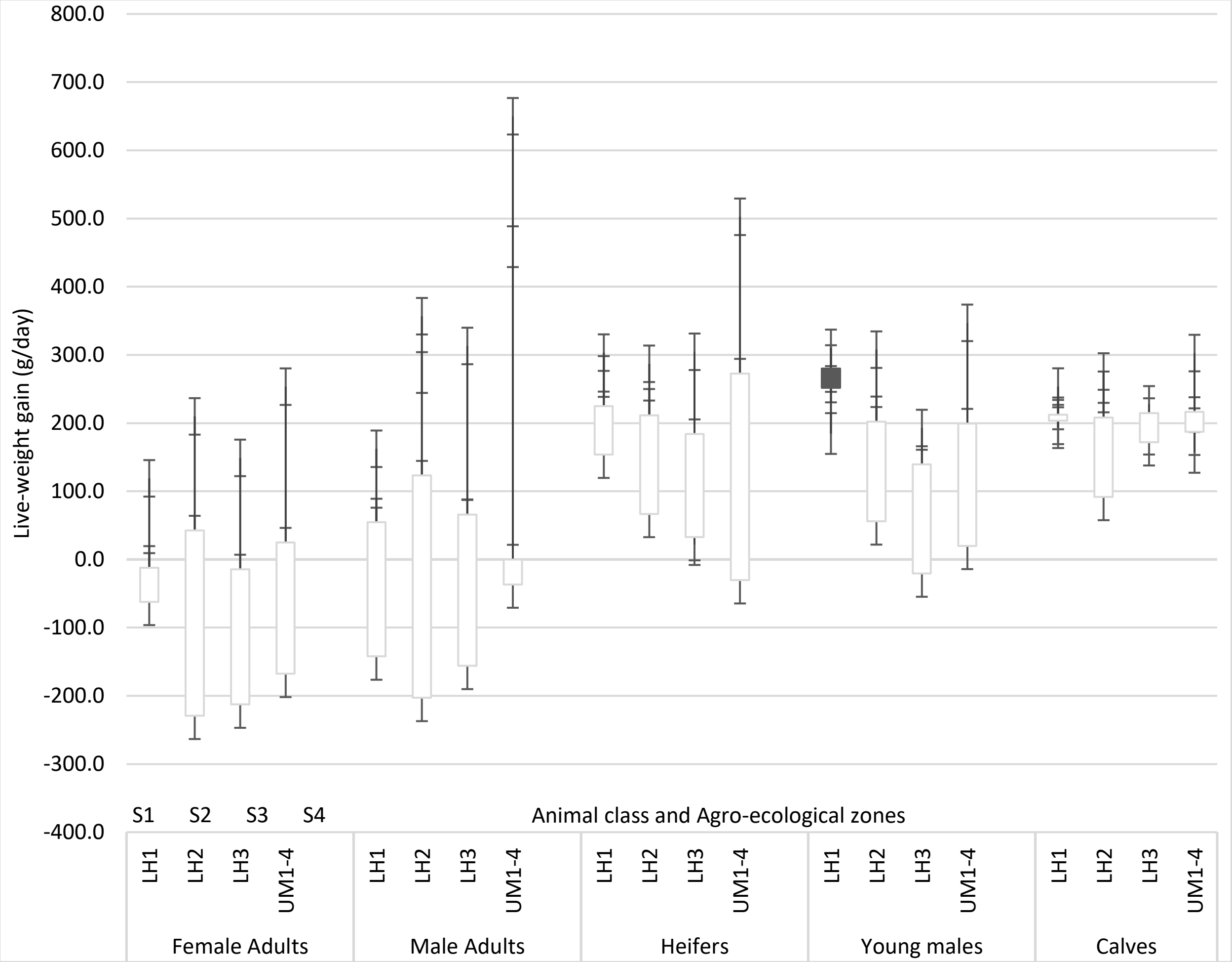

Figure 2.1: Mean live weight gains (g/day) for females and males (>2years), heifers and young males (1-2 years), and calves (<1 year) in seasons 1, 2, 3, and 4 and four agro-ecological zones in Bomet.

Table 2.5 shows the area of land allocated to the main animal feed resources and pasture biomass yield (**Table 2.6**) determined because it formed the highest proportion in the feed basket as shown together with the feed nitrogen content in **Table 2.7** and gross energy in **Table 2.8** of individual feedstuff and the whole feed baskets in each of the agro-ecological zones across four periods of the year (otherwise referred here as seasons).

Table 2.5: Average land size allocation for animal feed resources in Bomet

Feed type	Average land size (ha)
Pasture	0.94
Napier	0.21
Rhodes	0.27
Maize*	0.54
Banana Pseudostems	0.09
Sweet potatoes	0.17

* Maize is grown primarily for grain yield and animals benefit from the crop residue

Table 2.6: Pasture biomass yield (tonnes of dry matter (DM) per ha) ± standard error of means for the 4 agroecological zones in Bomet County across four seasons

Agro-ecological zones	Pasture Biomass Yield (Tonnes of DM/ha)			
	Season 1	Season 2	Season 3	Season 4
Lower Highland 1	2.20±0.225	4.43±0.548	3.91±0.682	3.83±0.362
Lower Highland 2	1.05±0.114	2.68±0.522	1.61±0.195	2.70±0.360
Lower Highland 3	1.49±0.154	3.39±0.555	2.74±0.656	3.05±0.545
Upper Midlands 1-4	1.94±0.402	3.38±0.749	2.47±0.536	3.92±0.367

Table 2.7: Feedstuff composing the feed basket with their individual and cumulative feed nitrogen (g/100g)

		Season 1			Season 2			Season 3			Season 4		
AEZ	Feedstuff	Proportion (%)	Feed N (g/100 g DM)	Feed N Ration (g/kg DM)	Proportion (%)	Feed N (g/100 g DM)	Feed N Ration (g/kg DM)	Proportion (%)	Feed N (g/100 g DM)	Feed N Ration (g/kg DM)	Proportion (%)	Feed N (g/100 g DM)	Feed N Ration (g/kg DM)
LH1	Pasture	39.7	2.44	9.68	56.9	2.27	12.92	64.7	2.42	15.66	64.7	2.49	16.12
	Napier	33.0	2.40	7.92	23.6	2.40	5.66	30.3	2.40	7.27	31.0	2.40	7.43
	Rhodes grass	3.3	0.96	0.32	2.4	0.96	0.23	3.0	0.96	0.29	3.1	0.96	0.30
	Maize Stover	22.8	1.19	2.71	16.3	1.19	1.94	na	-		na	-	
	Banana Pseudo stems	1.0	2.26	0.23	1.0	2.26	0.23	1.0	2.26	0.23	1.0	2.26	0.23
	Sweetpotato vines	1.0	3.52	0.35	1.0	3.52	0.35	1.0	3.52	0.35	1.0	3.52	0.35
	Total	**100.0**		**21.20**	**100.0**		**21.32**	**100.1**		**23.80**	**100.0**		**24.43**
LH2	Pasture	31.3	2.53	7.91	53.8	1.94	10.43	64.7	2.22	14.36	75.4	2.08	15.69
	Napier	21.0	2.12	4.46	14.2	2.12	3.00	28.4	2.12	6.01	19.7	2.12	4.18
	Rhodes grass	4.6	0.89	0.41	3.1	0.89	0.27	6.2	0.89	0.55	4.3	0.89	0.38
	Maize Stover	42.5	1.39	5.91	28.6	1.39	3.98	na	-		na	-	
	Banana Pseudo stems	0.6	2.79	0.17	0.4	2.79	0.11	0.8	2.79	0.23	0.6	2.79	0.16
	Total	**100.0**		**18.86**	**100.0**		**17.79**	**100.0**		**21.14**	**100.0**		**20.41**
LH3	Pasture	35.9	2.65	9.51	56.1	2.05	11.49	71.1	2.48	17.62	73.2	2.16	15.81
	Napier	16.8	2.24	3.77	11.5	2.24	2.58	19.4	2.24	4.34	18.0	2.24	4.02
	Rhodes grass	8.9	0.82	0.73	6.1	0.82	0.50	9.5	0.82	0.78	8.8	0.82	0.72
	Maize Stover	38.4	1.50	5.76	26.3	1.50	3.95	na	-		na	-	
	Total	**100.0**		**19.77**	**100.0**		**18.52**	**100.0**		**22.75**	**100.0**		**20.56**
UM1-4	Pasture	32.8	2.65	8.69	45.9	2.01	9.23	59.0	2.80	16.51	70.7	2.30	16.25
	Napier	23.8	1.80	4.28	19.1	1.80	3.44	33.6	1.80	6.05	23.7	1.80	4.27

Rhodes grass	4.8	0.85	0.41	3.8	0.85	0.33	6.7	0.85	0.57	5.1	0.85	0.43
Maize Stover	38.2	1.28	4.89	30.7	1.28	3.93	na	-		na	-	
Banana Pseudo stems	1.0	2.16	0.22	1.0	2.16	0.22	1.0	2.16	0.22	1.0	2.16	0.22
Total	**100.0**		**18.47**	**100.0**		**17.15**	**100.0**		**23.35**	**100.0**		**21.17**

na= not applicable

Table 2.8: Feedstuff composing the feed-basket with their individual and cumulative gross energy (MJ/kg DM)

		Season 1			Season 2			Season 3			Season 4		
AEZ	Feedstuff	Proportion (%)	GE (MJ/kg DM)	GE Ration (MJ/kg DM)	Proportion (%)	GE (MJ/kg DM)	GE Ration (MJ/kg DM)	Proportion (%)	GE (MJ/kg DM)	GE Ration (MJ/kg DM)	Proportion (%)	GE (MJ/kg DM)	GE Ration (MJ/kg DM)
LH1	Pasture	39.7	17.25	6.84	56.9	17.01	9.68	64.7	17.00	11.00	64.7	16.91	10.95
	Napier	33.0	16.08	5.31	23.6	16.08	3.79	30.3	16.08	4.87	31.0	16.08	4.98
	Rhodes grass	3.3	18.00	0.60	2.4	18.00	0.43	3.0	18.00	0.55	3.1	18.00	0.56
	Maize Stover	22.8	17.05	3.88	16.3	17.05	2.77	na	-	-	na	-	-
	Banana Pseudo stems	1.0	19.18	0.19	1.0	19.18	0.19	1.0	19.18	0.19	1.0	19.18	0.19
	Sweet potato vines	1.0	16.13	0.16	1.0	16.13	0.16	1.0	16.13	0.16	1.0	16.13	0.16
	Total	**100.0**		**16.98**	**100.0**		**17.02**	**100.1**		**16.78**	**100.0**		**16.84**
LH2	Pasture	31.3	16.80	5.25	53.8	17.08	9.19	64.7	17.23	11.15	75.4	17.16	12.94
	Napier	21.0	16.27	3.42	14.2	16.27	2.30	28.4	16.27	4.61	19.7	16.27	3.21
	Rhodes grass	4.6	17.57	0.80	3.1	17.57	0.54	6.2	17.57	1.08	4.3	17.57	0.75
	Maize Stover	42.5	17.40	7.40	28.6	17.40	4.98	na	-	-	na	-	-
	Banana Pseudo stems	0.6	17.91	0.11	0.4	17.91	0.07	0.8	17.91	0.14	0.6	17.91	0.10
	Total	**100.0**		**16.98**	**100.0**		**17.08**	**100.0**		**16.99**	**100.0**		**17.01**
LH3	Pasture	35.9	17.31	6.21	56.1	17.23	9.66	71.1	17.51	12.44	73.2	17.22	12.61
	Napier	16.8	16.41	2.76	11.5	16.41	1.89	19.4	16.41	3.18	18.0	16.41	2.95

	Rhodes grass	8.9	17.46	1.55	6.1	17.46	1.06	9.5	17.46	1.67	8.8	17.46	1.54
	Maize Stover	38.4	17.40	6.68	26.3	17.40	4.58	na	-	-	na	-	-
	Total	**100.0**		**17.21**	**100.0**		**17.19**	**100.0**		**17.29**	**100.0**		**17.10**
UM 1-4	Pasture	32.8	17.46	5.72	45.9	17.07	7.84	59.0	17.46	10.30	70.7	17.01	12.02
	Napier	23.8	16.30	3.88	19.1	16.30	3.12	33.6	16.30	5.47	23.7	16.30	3.86
	Rhodes grass	4.8	17.95	0.86	3.8	17.95	0.69	6.7	17.95	1.21	5.1	17.95	0.91
	Maize Stover	38.2	17.73	6.77	30.7	17.73	5.44	na	-	-	na	-	-
	Banana Pseudo stems	1.0	18.19	0.18	1.0	18.19	0.18	1.0	18.19	0.18	1.0	18.19	0.18
	Total	**100.0**		**17.40**	**100.0**		**17.27**	**100.0**		**17.16**	**100.0**		**16.98**

A comprehensive dataset of feed basket information containing the different feedstuff available in Bomet, the altitudes of the location of sampling, nutrient composition (i.e., nitrogen, acid detergent fibre, gross energy) of individual feedstuffs, and the dry matter digestibility of the feed-baskets grouped per AEZ are provided by Ndung'u, Goopy*, et al.* (2021). These activity datasets were then used in calculations of the energy expenditure estimates i.e., metabolizable energy requirements (MER, MJ/day) for maintenance, growth (weight gain or loss), lactation, and locomotion for individual animals per household. All MERs were then summed up to estimate dry matter intake (DMI, kg/day) that were then used to estimate daily methane production (DMP, g/day) and ultimately emissions factors (EF) as shown by Ndung'u, Goopy*, et al.* (2021). The estimated enteric methane EFs are presented in **Table 2.9.**

Table 2.10 presents a comparison between the estimated EFs with the IPCC default values for Africa (IPCC, 2019) and EFs from Nandi, Kenya (Ndung'u *et al.*, 2019), a region in close proximity to Bomet. The differences in EFs may be due to differences in live weights of all the animal classes, dry matter digestibility for Bomet as reported by Goopy *et al.* (2021), and methane conversion factor (Y_m). Nandi's study and the present study both used the same Y_m which was 10% higher than IPCC. The activity data was collected at 3 months intervals and the periods identified as seasons 1, 2, 3, and 4 and described below and the MERs, DMI, and DMP were also calculated per season.

- Season 1: 01/12/2016 to 28/02/2017 –Partly wet, warm, and dry
- Season 2: 01/03/2017 to 31/05/2017 –Cold and wet
- Season 3: 01/06/2017 to 31/08/2017 –Cold and dry
- Season 4: 01/09/2017 to 31/11/2017 –Warm, dry, and partly wet

Table 2.9: Live weight (mean ± standard error of means, LW kg) and emission factors (mean ± standard error of the mean, Kg CH4/head/year) for females and males (>2yrs), heifers and young males (1-2yrs) and calves (<1yr) in four agro-ecological zones in Bomet

	Females (>2yrs)		**Males (>2yrs)**		**Heifers (1-2yrs)**		**Young males (1-2yrs)**		**Calves (<1yr)**	
AEZ	**Mean LW (kg)**	**EF (kg CH_4/ head/yr.)**	**Mean LW (kg)**	**EF (kg CH_4/ head/yr.)**	**Mean LW (kg)**	**EF (kg CH_4/ head/yr.)**	**Mean LW (kg)**	**EF (kg CH_4/ head/yr.)**	**Mean LW (kg)**	**EF (kg CH_4/ head/yr.)**
LH1	316.4±0.14	58.8±2.10	249.3±1.23	34.2±5.43	186.5±0.30	31.8±1.82	162.9±1.77	30.0±2.72	69.9±0.23	18.7±0.86
LH2	260.2±0.11	44.3±1.25	275.3±1.87	38.4±2.99	154.2±0.60	26.6±1.23	133.6±0.31	27.2±1.71	71.0±0.35	18.7±1.03
LH3	267.4±0.31	42.8±2.11	264.7±3.25	36.9±3.52	146.7±2.03	24.0±2.64	125.8±0.47	23.4±1.82	64.0±1.39	17.2±1.44
UM 1-4	270.0±0.22	51.6±1.82	216.8±15.82	39.1±7.74	176.9±1.34	29.3±2.72	135.3±1.12	26.4±1.98	70.0±0.49	18.1±0.99
All Bomet	280.6±0.05	50.1±0.98	259.5±1.83	37.1±2.09	167.5±0.18	28.3±0.95	136.5±0.23	26.4±1.03	69.3±0.18	18.3±0.52

Table 2.10: Comparison between Intergovernmental Panel on Climate Change (IPCC) default values for grazing systems in Africa, estimated values from Nandi study and Bomet, Kenya for enteric methane emission factors (EF, kg CH_4/head/year) and average live weight (LW, kg) for females and males (> years), heifers and young males (1 – 2 years) and calves (<1 year)

Cattle category	**IPCC (2019) default values**		**Nandi Study (Ndung'u *et al.*, 2019)**		**The present study (Bomet)**	
	Average LW (kg)	**EF**	**Average LW (kg)**	**EF**	**Average LW (kg)**	**EF**
Females (>2 years)	275	67	307	47.8	280.6	50.1
Males (>2 years)	340	67	266	37.2	259.5	37.1
Heifers (1–2 years)	204	46	187	28.5	167.5	28.3
Young males (1–2 years)	204	46	157	27.2	136.5	26.4
Calves (<1 year)	82	31	73	25.8	69.3	18.3

2.3. Experimental Design, Materials, and Methods

Bomet (Latitude: 0°48'0.00" N, Longitude: 35°13'59.88" E) is located in the western part of Kenya (GOK, 2018) occupying an area of 2,037km^2. Smallholder farms were selected using a sampling protocol described by Ndung'u *et al.* (2019). Farms were visited 9 times in 12 months between December 2016 and January 2018 at an interval of 1.5 months. Animals were weighed at 0, 3, 6, 9, and 12th months using a cattle weight scale. Age of adult animals was determined using dentition while that of young cattle and parity was obtained from farmer recalled. Milk yield was recorded daily using uniform Mazzican (http://www.mazzican.com) provided to each farm and samples were collected at 1.5, 4.5, 7.5, and 9th month for butterfat analysis using the Gerber method, conducted in a local milk factory. Pasture biomass was determined by using exclusion cages set at grazing paddocks and grass was harvested at 3, 6, 9, and 12 months. Feed samples were collected during the first three months of the project, dried at 50°C, and analyzed for dry matter (DM), nitrogen (N) content using the Kjeldahl method (AOAC, 1990), and gross energy (GE) using a bomb calorimeter. Feed N and GE of the feed baskets were determined using an existing procedure to estimate the proportional contribution of different feedstuff to the overall feed basket Goopy *et al.* (2018).

The data were grouped into seasons (S1, S2, S3, and S4), AEZs (lower highland 1, 2, 3 (LH1, LH2, LH3) and upper midlands 1-4, (UM1-4)), and age groups of females and males >2years, heifers and young males 1-2years and calves <1year. This information was used to estimate MER for maintenance, growth, lactation, and travel based on equations from CSIRO (2007) and then summed up to obtain the total MER. Finally, using total MER, dry matter digestibility (DMD) (Goopy *et al.*, 2018), and GE of feed, DMI was estimated (see Equation 1) and used to estimate the DMP using Charmley *et al.* (2016) prediction equation (Equation 2);

$$\text{DMI (kg/day)} = \frac{\text{MER}_{\text{Total}}\text{(MJ/day)}/[\text{GE (MJ/kg DM)}*(\text{DMD}/100)]}{0.81}$$ **Equation 2.1**

$$\text{DMP (g/day)} = 20.7 * \text{DMI (kg/day)}$$ **Equation 2.2**

2.4. Acknowledgments

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CHAPTER THREE

3. 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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Abstract

Ruminants are central to the economic and nutritional life of much of SSA, but cattle are now blamed for having a disproportionately large negative environmental impact through emissions of 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 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 CO2-eq/kg CP. Median EIs were 60 (Nandi), 71 (Bomet), and 90 (Nyando) kg CO2-eq/kg. Although median EIs referenced to milk alone (2.3 kg CO2-eq/kg milk) was almost twice that reported for Europe, up to 50% of farms had EIs comparable to the mean Pan-European EIs. Enteric 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 of 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.

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

3.1. 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, Wassenaar*, et al.*, 2006), demand for livestock products is rapidly growing (Thornton, 2010). The consumption of beef and milk is forecasted 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 the supply and quality of feed (Nkonya *et al.*, 2016; Thornton, 2010). These conditions are putatively responsible for the characteristically high proportion of regional anthropogenic 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/kg FPCM, leading Opio *et al.* (2013) to conclude that Sub-Saharan Africa has the least efficient dairy production systems in the world when measured 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 IPCC default (Tier 1) emission factors, which results in an annual estimate of GHG emissions per capita by animal class, ignoring (amongst 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 (Goopy *et al.*, 2018; Herrero *et al.*, 2013). African countries where livestock is 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, van Niekerk*, et al.*, 2013; du Toit, Meissner*, et al.*, 2013), Benin (Kouazounde *et al.*, 2015), Kenya (Goopy *et al.*, 2021; Goopy *et al.*, 2018; Leitner *et al.*, 2021; Ndung'u, Kirui*, et al.*, 2021; Ndung'u *et al.*, 2019; Pelster *et al.*, 2016; Zhu *et al.*, 2018), and Senegal (Ndao *et al.*, 2020; Ndao *et al.*, 2019). Nonetheless, accurate estimation of EFs alone do not capture the entire variability in emissions 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 emissions intensity (EI) (Moran & Wall, 2011) under the life cycle assessment 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 (Garg *et al.*, 2016; O'Brien *et al.*, 2015; Opio *et al.*, 2013; Rice *et al.*, 2017) or energy corrected milk (Knapp *et al.*, 2014; O'Brien *et al.*, 2014; Ross *et al.*, 2017; Rotz, 2018; Rotz *et al.*, 2010) in dairy enterprises, or as carcass weight (Rotz *et al.*, 2019), live weight (Desjardins *et al.*, 2012; Legesse *et al.*, 2016; Opio *et al.*, 2013) or live weight gain (McAuliffe, Takahashi, Harris*, et al.*, 2018) 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, Takahashi, & Lee, 2018; McAuliffe *et al.*, 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 characterized 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) with a herd size of 2 - 4 commonly consisting of dairy cows, heifers and calves, 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 is 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 hypothesized that:

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

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

3.2. Material and methods

3.2.1. 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 3.1**). Farms were selected randomly for each (county) study (**See Supplementary Figure 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 and subsequent proximate analysis. Details for these procedures and their calculations have been previously published (Goopy *et al.*, 2018; Ndung'u, Kirui*, et al.*, 2021; Ndung’u *et al.*, 2019). Live weight of all cattle was 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 analyzed using bulked representative samples by season and AEZ and is described elsewhere (Goopy *et al.*, 2018; Ndung'u *et al.*, 2019).

A cradle-to-farm gate approach was adopted to quantify herd-level EIs associated with cattle (**Figure 3.1**). To eliminate the aggregation bias, or systematic underestimation of disproportionally large climate impacts caused by "weakest link" animals (McAuliffe, Takahashi, Harris*, et al.*, 2018), 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 constitutes the temporal boundary of this study, the herd structure of each farm was not always in 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 canceled out due to the sufficient sample size.

Table 3.1: 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 (^{O}C)	Elevation range (meters above sea level)
Lower Highland 1 (LH1)	Nandi and Bomet	Moderately cool and humid	15 – 18	1,800 / 1,900 to 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 to 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 to 1,500

3.2.2. System boundary and functional unit

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 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 4.2**). 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).

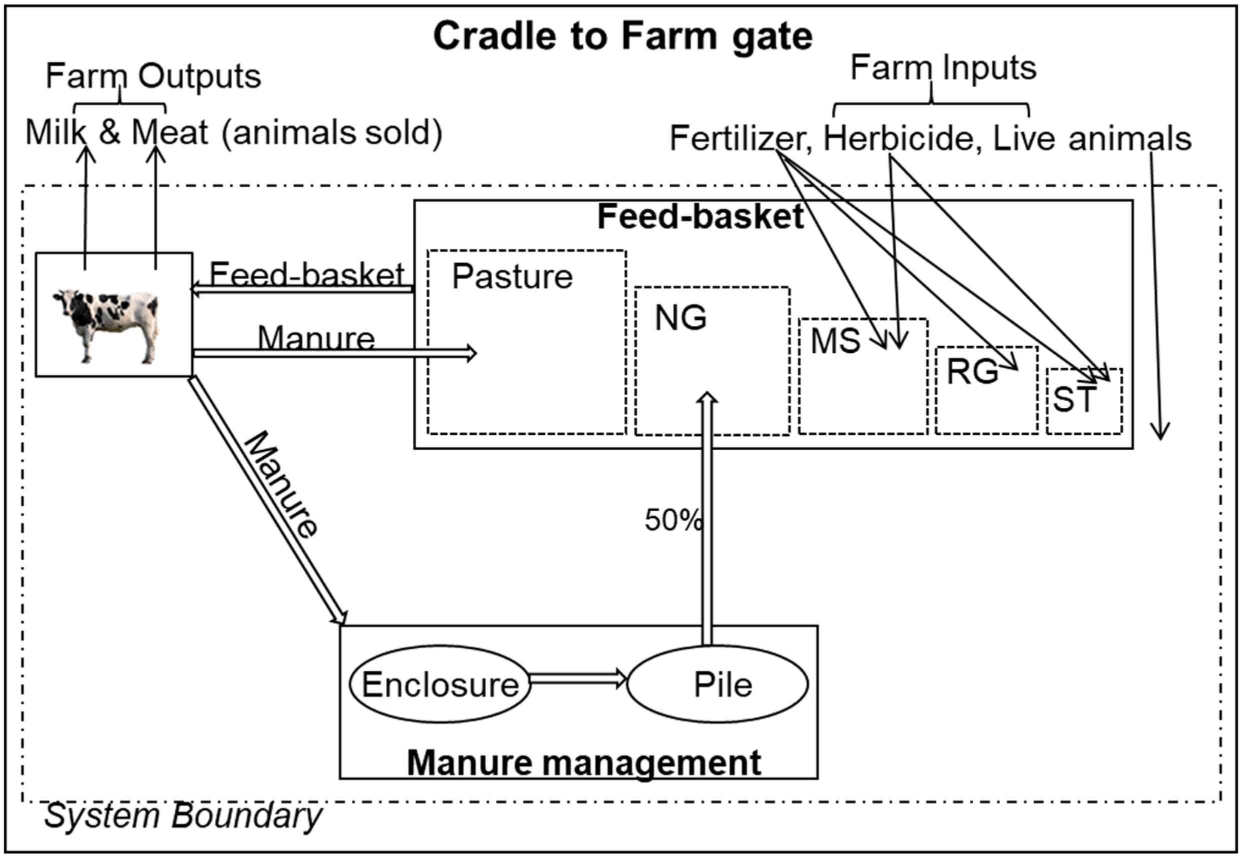

Figure 3.1: System boundary for emissions intensity assessment of cattle in smallholder farms. Squares show feedstuff in the feed basket where the sizes demonstrate the contribution of each feed to the overall feed basket (NG: Napier grass; MS: maize stover; RG: Rhodes grass; ST: sugarcane tops), ovals show the manure management systems. ⟹shows the flow of raw materials and where the manure is deposited and → shows the farm inputs and output.

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 standardized to 4% fat and 3.3% true protein. The bone-free carcass weight was estimated using the assumptions described above.

Table *3.2*: Edible by-products and their percentage yield, proportion, crude protein, and crude protein yield from slaughtered cattle

Offal	Average Yield (%live weight)	Proportion (%)	CP content (g/100g)	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**

3.2.3. Inventory Analysis

3.2.3.1. 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, metabolizable energy requirement was determined on an individual animal basis as the sum of metabolizable energy requirement for maintenance, growth, locomotion, and lactation following CSIRO (2007) models per season. The two sets of information (i.e. total metabolizable energy requirements and feed digestibility) were then combined to produce estimates of dry matter intake for each animal, this value was used to estimate enteric CH_4 production using the conversion factor of Charmley *et al.* (2016).

3.2.3.2. 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 ~12h/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. 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 4.3**).

Table 3.3: Total yield factors for nitrous oxide (g N-N_2O /100g N in manure) and methane (g C-CH_4/100g 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/100g 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

Dung excreted was estimated using dry matter intake and dry matter digestibility of the relevant feed basket. The carbon content of dung was based on an earlier study carried out under a similar condition (Leitner *et al.*, 2021; Zhu *et al.*, 2018). The nitrogen excreted was estimated by the difference between the nitrogen intake (derived from dry matter 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 in the calculation of post-storage emissions.

3.2.3.3. 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 fertilizer 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. Fertilizer types varied between farms, although the application rates were relatively uniform (and low) due to standardized 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 & 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 fertilizer 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 1-42% for maize stover and 9-34% 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 tops yield was estimated as 4.89% of primary crop harvest (Kapur *et al.*, 2013). Price data used for the final allocation is provided in **Supplementary Table S3**.

3.2.4. 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 characterization 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

(<3kg CP per annum) returned extremely high EIs (>3,000kg CO_2-eq/kg CP). With the upper bound for EIs in livestock systems posited to be ~1,000kg 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 squares (OLS) regression makes the assumptions of normality and 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 minimized. 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 and 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.

3.3. Results

Table 3.4 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.

3.3.1. 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 (**Figure 3.2)**.

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 (**Figure 3.3**). 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.

Table *3.4*: 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 >2years	306.9	280.6	216.3
Males >2years	265.9	259.6	216.0
Heifers 1-2years	186.8	167.5	154.6
Young Males 1-2years	156.9	136.5	143.5
Calves <1year	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: (GoK, 2013) ^{a}, (GOK, 2018) ^{b}, (Kirimi *et al.*, 2010) ^{c}, (Jaetzold & Schmidt, 1983) ^{d}, (Ndung'u *et al.*, 2019) ^{e}

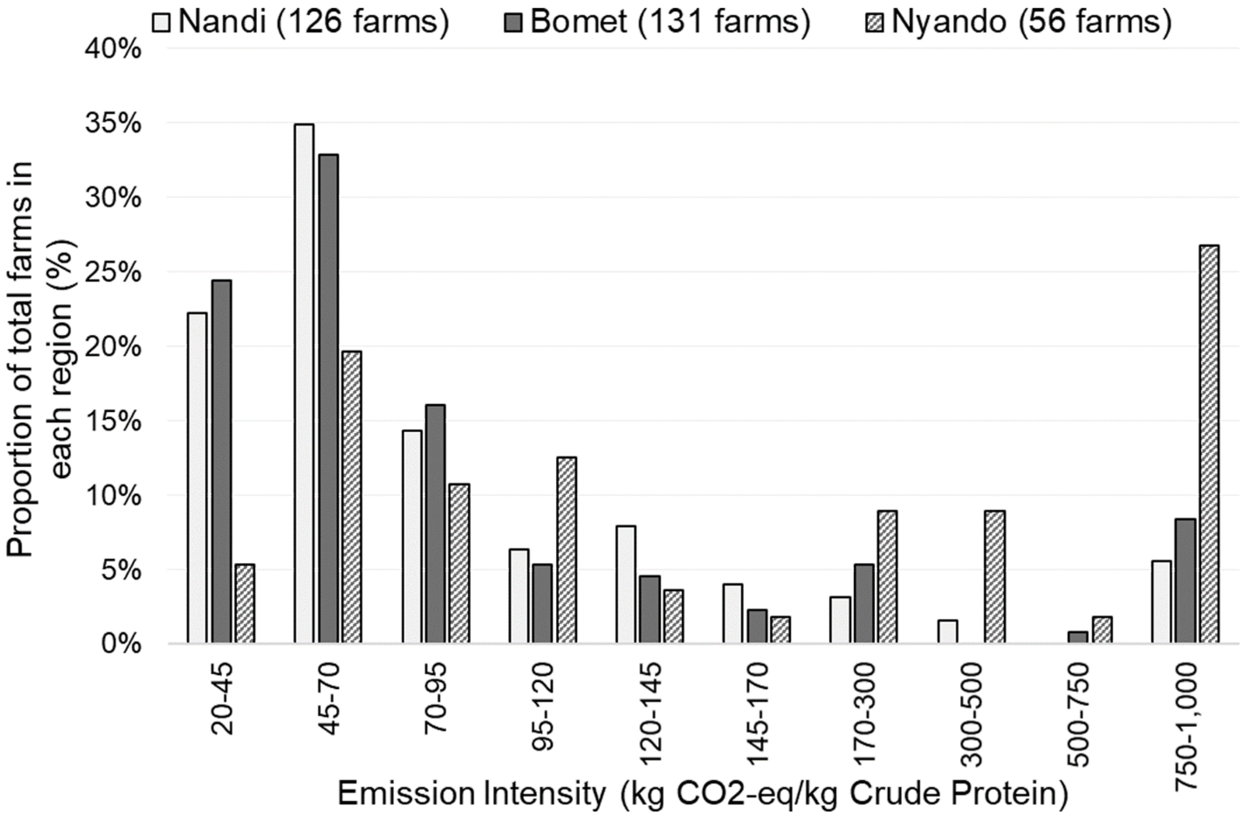

Figure 3.2: Distributions of farm-level emissions intensities for cattle in smallholder farms in Nandi, Bomet, and Nyando

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 (**Figure 3.4**). 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.

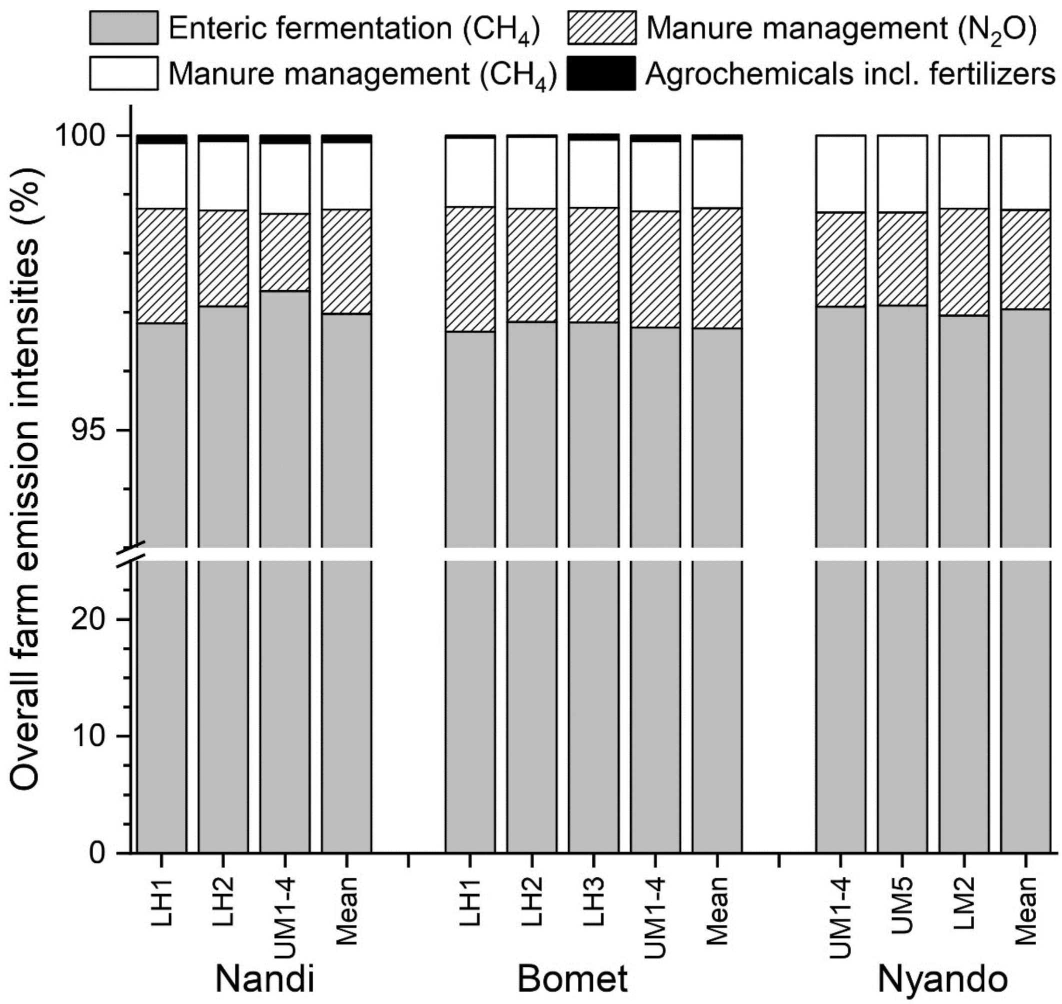

Figure 3.3: The relative contribution of enteric CH_4, manure CH_4, and N_2O, and emissions from synthetic fertilizer production and application and agrochemicals production to total greenhouse gas emissions related to cattle production by agro-ecological zones (Lower highland 1 (LH1), Lower highland 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

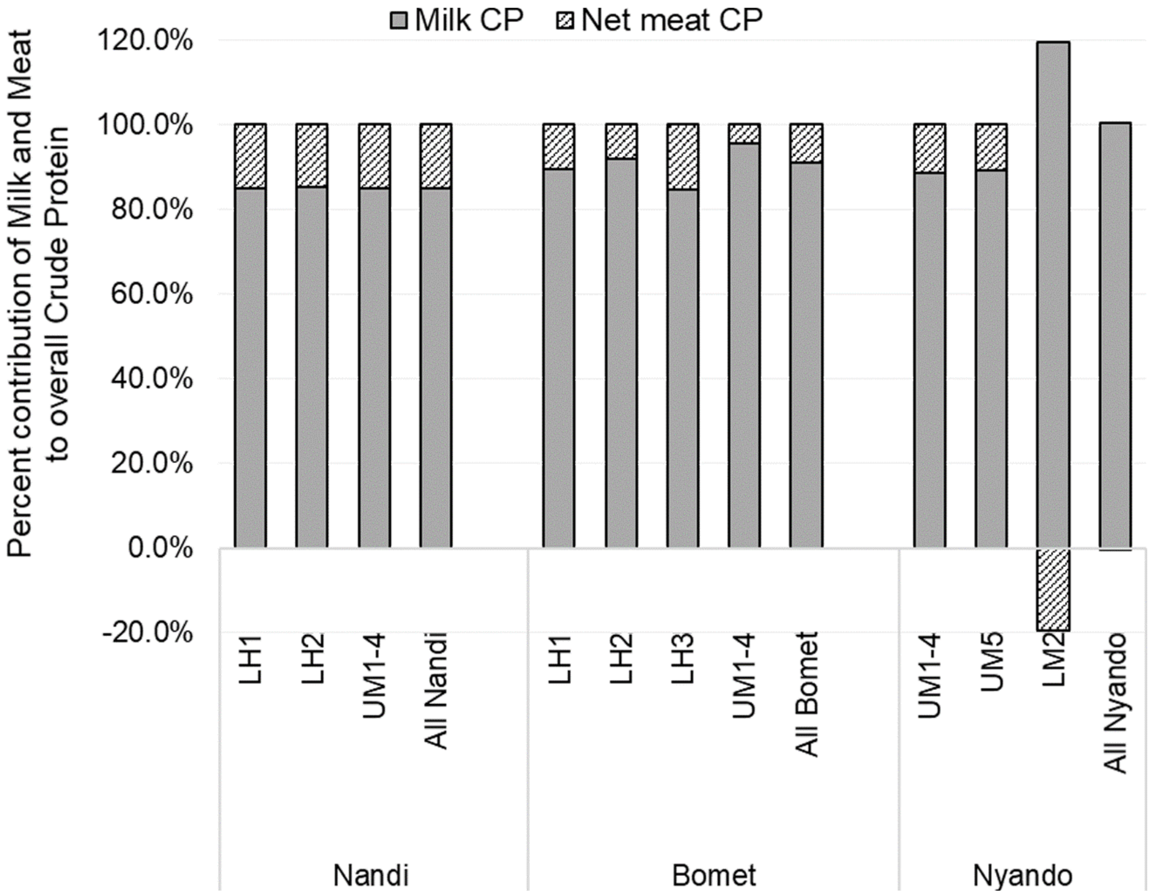

Figure 3.4: The relative contribution of milk and meat to the total crude protein output by agro-ecological zones (Lower highland 1 (LH1), Lower highland 2 (LH2), Lower highland 3 (LH3), Upper midland 1 to 4 (UM1-4), Upper midland 5 (UM5), Lower midland 2 (LM2)) from cattle in Nando, Bomet, and Nyando

3.3.2. 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 county or AEZ (**Table 3.5**). 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 (Q10: $\widehat{\beta_{HS}} = 1.35, p < 0.005$, Q50: $\widehat{\beta_{HS}} = 1.86, p < 0.01$,), 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 **Figure 3.5** and **Figure 3.6**. A negative relationship was observed for both milk and meat, with a 1kg 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 (Q10) to $\widehat{\beta}$ =-6.14 (SE=1.33) to high EI farms (Q85) 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 **Supplementary Material S1**.

Table 3.5: 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 [gf]	-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 = Generalized 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-ecologica 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.

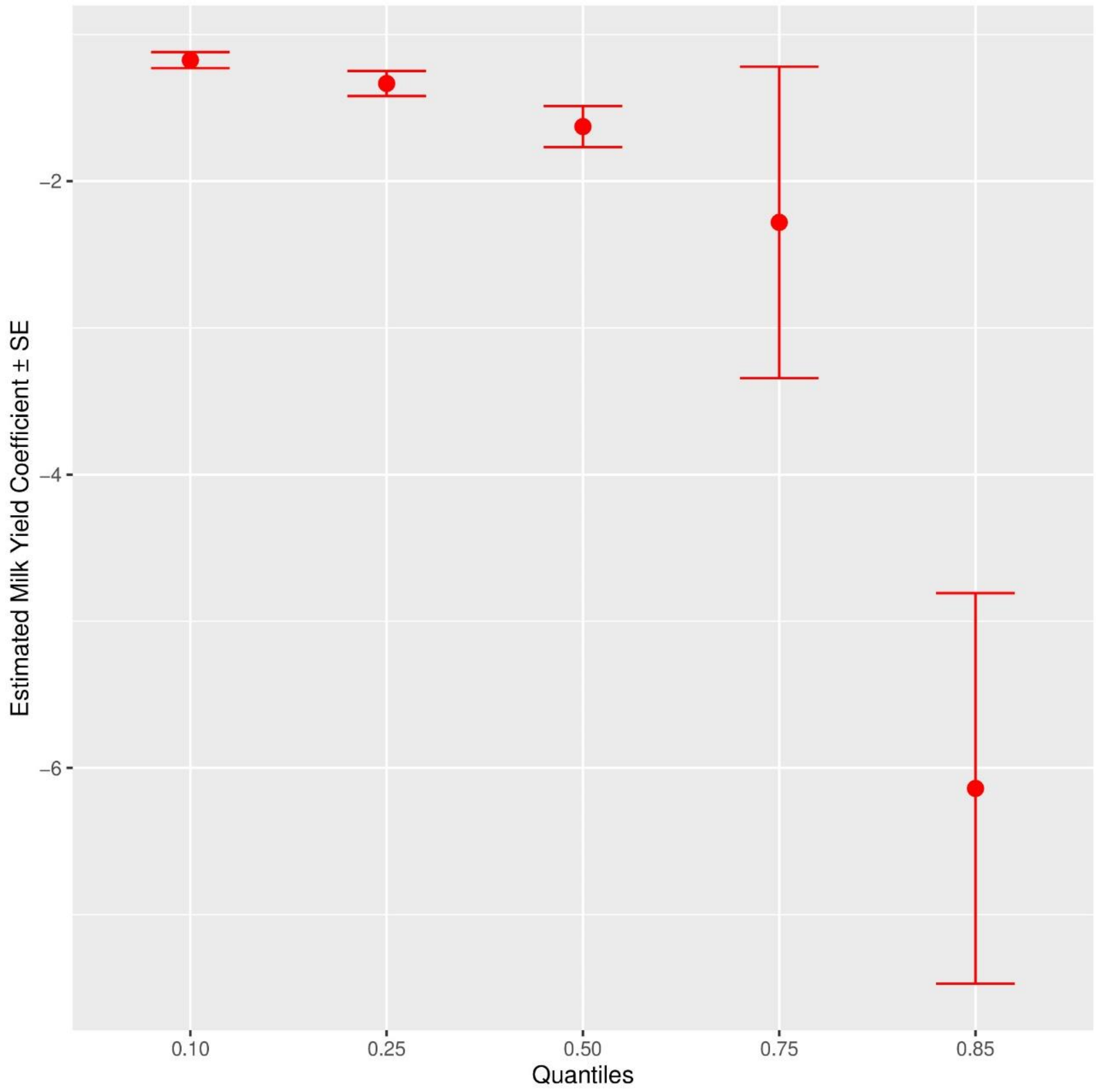

Figure 3.5: Estimated coefficients for milk yield (± SE) across the 5-quantile regression models

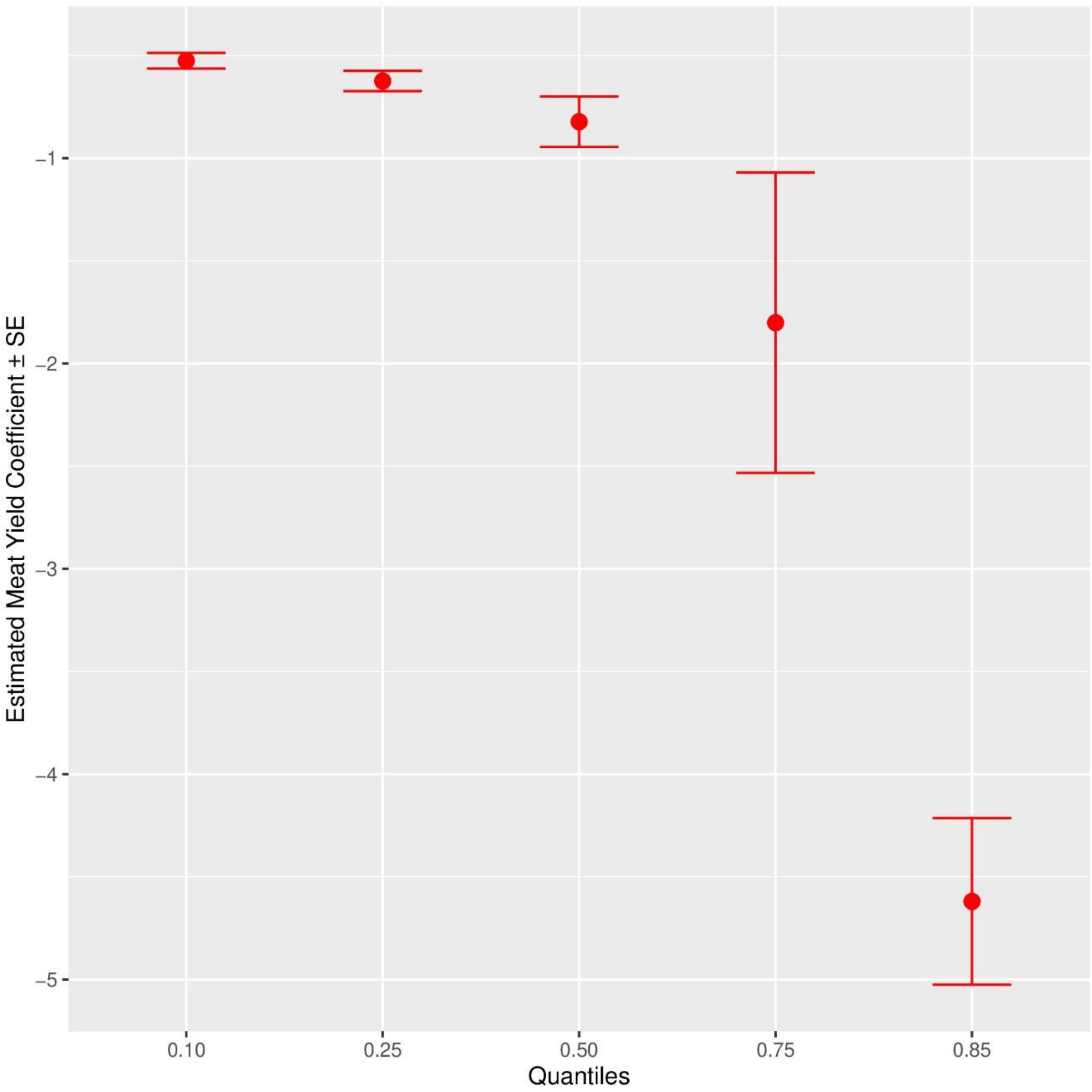

Figure 3.6: Estimated coefficients for meat yield (± SE) across the 5-quantile regression models

3.4. Discussion

Median EIs of milk production for this study (2.3kg 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, a 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 3.6**). 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 (Kiggundu *et al.*, 2019; MacLeod *et al.*, 2018; Opio *et al.*, 2013; Weiler *et al.*, 2014), input data have been derived from a variety of secondary sources in every case, including post hoc farmer estimates, national census statistics, FAOSTAT databases, and modeling 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 mechanization 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 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 scope of this study.

However, it is incorrect to conclude that EI is simply inversely correlated to livestock output (milk or meat) across the EI farm spectrum – bigger isn't necessarily better.

Table 3.6: Comparison of cattle emissions (kg CO_2-eq.) referenced to different functional units: a kilogram of fat- and -protein corrected milk, milk, carcass weight, crude protein (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)

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 drives 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; O'Brien *et al.*, 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 fertilizers, purchased feeds, and mechanization, which in intensive European farming systems account for 7 to 20% of total emissions (O'Brien *et al.*, 2014; O'Brien *et al.*, 2015; Opio *et al.*, 2013). 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 to 9% of total emissions (O'Brien *et al.*, 2014; O'Brien *et al.*, 2015; Opio *et al.*, 2013). Thus, although it has been suggested elsewhere that improved manure management in smallholder farms could be a promising approach for reducing EIs (Lesschen *et al.*, 2011; Petersen *et al.*, 2013; Weiske *et al.*, 2006), 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, which were all highly influential, suggesting that herd management is more important than scale in influencing EI at the farm level (Bell *et al.*, 2011; Garnsworthy, 2004; 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 byproducts (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 monetized 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 toward an “efficient frontier”, where increased output is achieved at a minimal increase in 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 channeled 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 SSA, our findings suggest that climate-driven policy interventions should consider the creation of efficient herd structures (i.e., a high proportion of productive females), and optimization 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 toward a low carbon future.

Although this study was limited in its geographic scope, this type of smallholder farming is ubiquitous throughout much of 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 favor of productive females with high(er) milk outputs. This, in turn, relies on improved access to quality animal feed. Increasing animal productivity, while retaining a low-input farm model, will not only contribute to a reduced carbon footprint but will also likely have social and economic advantages such as increasing household incomes.

3.5. Acknowledgments

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CHAPTER FOUR

4. A simplified approach for producing Tier 2 enteric methane emission factors based on East African smallholder farm data.

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Abstract

Accurate livestock greenhouse gas (GHG) emissions capturing is important in developing effective mitigation strategies and reporting level of gain achieved, but the cost and labor requirements associated with on-farm data collection often prevent this effort in low-and-middle-income countries. The aim of this study was to investigate the precision and accuracy of simplified activity data collection protocols in African smallholder livestock farms for estimation of country-specific enteric methane emission factors. Activity data such as live weight (LW), feed quality, milk yield, and milk composition were collected from 257 smallholder farms with a total herd of 1,035 heads of cattle in Nandi and Bomet counties in Western Kenya. The data collection protocol was then altered by substituting actual LW measurements with algorithm LW (ALG), feed quality (FQ) data sourced from the Feedipedia database, reducing the need for daily milk yield records to a single seasonal milk measurement (MiY), and using a default energy content of milk (MiE). Daily methane production (DMP) was calculated using these simplified protocols and the estimates under individual and combined protocols were compared with values derived from the published (PUBL) estimation protocol. Employing the algorithm LW showed good agreement in DMP with only a small negative bias (7%) and almost no change in variance. Calculating DMP based on Feedipedia FQ, by contrast, resulted in a 27% increase in variation and a 27% positive bias for DMP compared to PUBL. The substitutions of milk (MiY and MiE) showed a modest change in variance and almost no bias in DMP. It is feasible to use a simplified data collection protocol by using algorithm LW, default energy content of milk value, and seasonal single milk yield data (ALG + MiY + MiE), but full sampling and analysis of feed resources is crucial to produce reliable Tier 2 enteric methane emission factors. Reducing enteric methane emissions from livestock is a promising pathway to reduce the effects of climate change hence the need to produce accurate emissions estimates as benchmark to measure the effectiveness of mitigation options. However, it is expensive to produce accurate emission estimates especially in developing countries, hence important and feasible to simplify on-farm data collection.

Keywords: Cattle, heart girth, dry matter digestibility, milk yield, activity data, GHG inventory, mitigation, protocol

4.1. Introduction

In Sub-Saharan Africa (SSA) countries, the contribution of agriculture to the national anthropogenic methane (CH_4) emissions may be much higher than in developed countries and can reach up to 90%, with the majority of emissions being linked to livestock production (World Bank & CIAT, 2015).

Reducing enteric CH_4 emissions from ruminants is an important climate change mitigation option, especially for countries with low levels of industrialization (Steinfeld, T. Wassenaar*, et al.*, 2006). Yet, for developing countries reporting of CH_4 emissions from the livestock sector is highly uncertain due to a paucity of locally derived data on livestock production (Goopy *et al.*, 2018; Ndung'u *et al.*, 2018; Tongwane & Moeletsi, 2020).

As a basis for implementing effective strategies to mitigating CH_4 emissions from the livestock sector accurate knowledge of current emissions and a thorough understanding of underlying assumptions are essential (van Wijk *et al.*, 2020). To date, such information is largely missing for most livestock production systems in SSA countries, and many countries are facing challenges such as inadequate knowledge of key sources of GHG emissions and missing reliable accounting systems (Merbold *et al.*, 2021). This is specifically true for methane emissions from ruminants as the lack of accurate and reliable animal activity data for local agricultural systems (Goopy *et al.*, 2021; Goopy *et al.*, 2018) hampers the development of accurate national GHG inventories.

In order to close this knowledge gap, low-cost and simplified approaches to estimate GHG emissions from livestock production are key. Thus, the main aim of this study was to evaluate simplified data collection protocols for deriving enteric CH_4 emissions factors from cattle in East Africa.

The Intergovernmental Panel on Climate Change (IPCC) is the body tasked with providing guidance on GHG emissions calculations and reporting (IPCC, 2006). It provides three frameworks for emissions calculations, and these are based on the availability of data and the category of the emission source. The methodologies are in simple words split into Tier 1 (simple), Tier 2 (intermediate), and Tier 3 (complex) based on application and data requirements. While Tier 1 offers global approaches that were developed based on information mainly gathered in OECD countries (Goopy *et al.*, 2018), Tier 2 and 3 are better suited for reflecting GHG emissions from the livestock sector in specific countries, as in these calculations, site-specific or region-specific data are used.

However, Tier 1 is still the method most frequently used by developing countries as it requires only livestock census data or population estimates and a representative value of emission factor (EF) assigned to different continents and production environments (IPCC, 2019). On the other hand, Tier 2 and 3 require detailed characterization of livestock, their productivity, management, and feed quality to inform livestock feed intakes otherwise known as 'activity data' that are ultimately used to estimate enteric CH_4 production (Charmley *et al.*, 2016; IPCC, 2019). Yet, inventories created using the Tier 1 system have been demonstrated to be considerably less representative of the actual case than those using EFs generated through detailed investigations of enteric CH_4 emissions associated with livestock production in the Global South that take into account local conditions (e.g. seasonal fluctuations of quantity and quality of feeds, animal phenotype husbandry practices and management) (du Toit, Meissner*, et al.*, 2013; Goopy *et al.*, 2021; Goopy *et al.*, 2018).

Recently, several field studies have been undertaken in Western Kenya which collected detailed on-farm information on seasonal live weight change, milk production, and feed composition and quality, and used this information to create spatially explicit EFs for different production systems in the region (Goopy *et al.*, 2021; Goopy *et al.*, 2018; Ndung'u, Kirui*, et al.*, 2021; Ndung'u *et al.*, 2018). More studies using the same approach are underway by a team led by the International Livestock Research Institute for Tanzania, Uganda, and Ethiopia, so that more detailed information on CH_4 emissions from the livestock sector in East Africa will become available soon (Merbold *et al.*, 2021). While these studies meet an urgent demand for better GHG emissions estimates for ruminants in SSA, the data collection is resource-intensive, requires bulky and costly equipment, and is thus lengthy and expensive to undertake. This in turn makes the widespread adoption of the abovementioned approach difficult to achieve.

Consequently, simplified protocols particularly those that reduce the physical and labor requirements of the sampling protocol are urgently needed for a widespread uptake and subsequently the availability of spatially explicit enteric CH_4 emissions from livestock production in SSA. Thus in this study, we investigated (i) the feasibility of simplifying the data collection protocol developed by Goopy *et al.* (2018) of key activity data required in calculating Tier 2 enteric CH_4 EFs and (ii) how individual and combined modifications affect the accuracy and precision of CH_4 EF estimates. We hypothesized that when replaced by a simplified protocol, some activity data are more important for accurate CH_4 emissions estimates than others. Moreover, we hypothesized that the combination of estimates of the activity data leads to larger discrepancies in CH_4 estimates than replacing a single input variable only.

4.2. Materials and Methods

4.2.1. Methodological approach

The approach of the previously published method by Goopy *et al.* (2018) to calculate enteric CH_4 emissions from cattle in East Africa was to estimate individual animal feed intake (dry matter intake, DMI) inferred from energy expenditure, with total energy expenditure deemed to be the sum of metabolizable energy requirement (MER) for maintenance ($MER_{Maitenance}$), growth (MER_{Growth}), milk production ($MER_{Lactation}$), and locomotion/traction ($MER_{Locomotion}$). A CH_4 yield of 20.7g/kgDMI (Charmley *et al.*, 2016) is used to calculate daily methane production (DMP g CH_4/day). For details, we refer to Goopy *et al.* (2018).

Data used in this study were sourced from previously published studies conducted in Nandi and Bomet counties in Western Kenya (Ndung'u, Kirui*, et al.*, 2021; Ndung'u *et al.*, 2018). Thus, the current study investigated 257 smallholder farms (SHF) with a total herd of 2,270 cattle (992 females (> 2 years), 103 males (>2 years), 271 heifers (1-2 years), 104 young males (1-2 years) and 800 calves (<1 year)). However, due to the movement of animals through sales, purchases, and deaths, not all the animals were there for all four seasons and hence data used is as shown in **Table 4.1**.

Table 4.1: Composition of the study population by animal class and region

Class	**Nandi (126 HH)**	**Bomet (131 HH)**	**Total for each class**
Calves <1 year	47	13	60
Heifers 1 - 2 years	102	63	165
Males 1 - 2 years	20	21	41
Males > 2years	22	24	46
Females > 2 years	358	365	723
Total	549	486	1035

A set of activities including weighing cattle, heart girth (HG) measurement, recording milk yields, milk sampling for quality analysis, feed samples collection and farm sketches should be conducted seasonally. However, these activities are time-consuming and labour-intensive and hence these activities were split to be undertaken after one and half months in each season. Therefore, smallholder farms were visited nine times within 12 months at an interval of one and a half months. **Figure 5.1** shows the activities undertaken in each farm visit. Details of farm visits, data collection, and sample analysis have been extensively reported in Goopy *et al.* (2018) and Ndung'u *et al.* (2018). The following section briefly outlines the calculation of DMP and EF.

Activities	Season 1 – Short Rains			Season 2 – Hot Dry			Season 3 – Long Rains			Season 4 – Cold Dry			Season 1 – Short Rains
Animal weighing	▨	▨		▨	▨		▨	▨		▨	▨		▨
Setting cages/harvesting pasture	▨	▨		▨	▨		▨	▨		▨	▨		
Farm sketching/ survey		▨	▨					▨	▨				
Feedstuff sampling		▨	▨					▨	▨				
Milk sampling		▨	▨		▨	▨		▨	▨		▨	▨	
Milk records transfer		▨	▨		▨	▨		▨	▨		▨	▨	

Figure 4.1: Gantt chart Illustrating activity data collection schedules for calculating Tier 2 enteric methane emission factors in Goopy *et al.* (2018) and Ndung'u *et al.* (2019).

4.2.2. Calculation of daily methane production (DMP) and emission factor (EF) using full primary data

The DMP of cattle was determined as follows:

$$\text{DMP (CH}_4\text{ g/d)} = \text{DMI (kg)} * 20.7\text{g CH}_4\text{/kg DMI} \qquad \textbf{Equation 4.1}$$

DMI was estimated from the total MER of individual animals on a seasonal basis, calculated using algorithms derived from the CSIRO (2007). Live weight (LW) and LW change were used to calculate MER for maintenance, growth, and locomotion, while milk yield (MY) and the energy content of milk were used to calculate MER for lactation. Feed baskets (i.e., several feedstuffs available as feed for the cattle to form a feed basket) dry matter digestibility (DMD) was used to calculate all components of the MERs (except for locomotion) and DMI. The calculated DMP for each animal for each season was then multiplied by the number of days in each season and summed across seasons to produce an annual EF (kg CH_4/head/year).

Animal LW was measured with animal weighing scales, daily MY was measured using a graduated collection vessel and recorded by farmers. To determine feed DMD, feed samples such as pasture (collected from exclusion cages), grasses grown for fodder (purchased or grown e.g. Napier grass) crop residues that form the feed basket were analyzed for dry matter (DM), nitrogen (N), and acid detergent fiber (ADF) using the proximate analysis method and values of N and ADF used in equation 2 from Oddy *et al.* (1983). Locomotion data was determined by fitting GPS collars to animals for three consecutive days to determine the distance walked per day (km).

$$\text{DMD (\%)} = 83.58 - 0.824 * \text{ADF (\%)} + 2.626 * \text{N (\%)} \qquad \textbf{Equation 4.2}$$

4.2.3. Calculation of DMP using alternative data collection protocol options

In looking to simplify and reduce resource demands of the existing published method described above (hereafter referred to as PUBL), we first reviewed the operational requirements for data collection and analysis. From this deliberation, it was concluded that LW measurements, assessing milk production, and determination of the feed basket were activities that required high levels of resources.

4.2.3.1. Simplifying measurements of LW

Assessment of LW and LW change is a key measurement for determining energy requirements for maintenance, growth, and locomotion (CSIRO, 2007). The use of animal weighing scale requires a four-wheeled pick-up truck and field assistance to facilitate setting up the scales. Substituting HG measurements for scales would represent a) a large saving in time, b) reduce field staff requirement, and c) remove the necessity for heavy-duty vehicles. Measurements of HG were routinely undertaken during the original studies and were used to assess the accuracy and precision of LW estimates made using an algorithm (equation 3) developed for an independent population (Goopy *et al.*, 2017).

$LW (kg) = 73.599 - 2.291 * HG (cm) + 0.02362 * HG^2 (cm)$ Adj. $R^2 = 0.856$ **Equation 4.3**

4.2.3.2. The dry matter digestibility of the feed basket

Feed composition affects nutritive value, intake, and subsequently enteric methane production. The baseline (full primary data) assessement involved here was based on both, periodic collections of representative feed samples and their proximate analysis using wet chemistry to provide the most accurate assessment achievable of the DMD of feed baskets in different agro-ecological zones and seasons. Feed basket DMD was used repeatedly through re-calculation based on intake variation and thus highly relevant for DMP. The resources required to gather and record the information in the field is one cost, whereas chemical analysis of feed samples caused substantial costs, particularly in countries that do not have easy access to nutritional laboratories. We assessed the effect of substituting our field-measured values of DMD with the means of published values from the Feedipedia database (https://www.feedipedia.org/)

4.2.3.3. Milk quantity and quality

Energy for lactation may be the second greatest component of energy expenditure for the lactating animals (Dong *et al.*, 2006). As such, data on milk quality and quantity are considered crucial for the determination of energy expenditure. In theory, MY can be fairly simply obtained using basic measuring equipment and trained farmers. However, from field studies, this often turns out to be a challenge as smallholder farmers were not regularly used to record-keeping. Furthermore, in some livestock production systems that focus on meat not milk (e.g., extensive pastoral systems), milk is often only obtained upon household demand. Due to the uncommon tendency of record-keeping, MY records were often rather uncertain. Instead of using an average of daily MY records kept by farmers, we considered spot sampling where MY measurements were requested only on the day before the researcher's farm visit.

Determining the composition of milk requires the collection, careful handling, transport, and subsequent laboratory analysis of milk samples for butterfat (BF) and solid-non-fat (SNF) content hence needs a milk analysis equipment such as a lactoscan. This is a significant drain on project resources. We examined the effect of substituting a single published energy content of milk value (3.054MJ per kilogram of fat corrected milk) (CSIRO, 2007) on overall estimates of milk energy.

4.2.4. Summary of alternative measurement protocols

We assessed the effect of substituting individually four data inputs that would simplify measurements and significantly reduce resource requirements for the published method. In addition, we assessed the effects of each combination of these possible substitutions on the loss in accuracy and precision.

The following abbreviations are used to describe changes to the standard protocol:

ALG: Values for LW were derived from an algorithm (ALG) using HG measurements.

FQ: The indirectly measured DMD (derived from feed quality (FQ) values of nitrogen and acid detergent fibre) was based on values reported in the Feedipedia database, i.e., not using its measured values from the local laboratory.

MiY: This was done for female adult cows (>2 years) only. The average of daily milk yield (MiY) records kept by farmers was substituted with a single MY (sum of morning and evening milk) of the day before the 3-monthly farm visit for milk yield recording activity in the calculations of MER for lactation.

MiE: This was done for female adult cows (>2 years) only. The milk energy (MiE) derived from own measurements of milk BF and SNF was substituted with a default energy content of milk value from CSIRO (2007) in the calculations of MER for lactation.

Combinations between all the altered data collection protocols were also investigated.

4.2.5. Data analysis

To assess how simplifications of methods impact DMP and, thus, annual EF estimates, a sensitivity analysis was carried out. The recalculated DMP and EFs from alternative data inputs were assessed independently and in combination.

DMP was calculated for individual animals for four seasons and thereafter an average of all the seasons was calculated using R (R core team, 2021). There were 1,035 counts of DMP, one for each animal across all four seasons in the study (**Table 4.2**). A repeat of DMP calculations was done using the ALG, FQ, and ALG + FQ measurement protocols for all animals and thus also animal classes. The difference between the DMP derived from the altered measurement protocols and the PUBL DMP were calculated for each animal and the average and standard deviation (SD) of these were obtained to evaluate the loss of accuracy and precision in the new protocols. Twelve more calculations of DMP were run for females >2 years (n=723) to include milk quantity (MiY) and quality (MiE) adjusted measurement protocols and their two, three, and four-way combinations with ALG and FQ data collection protocols. Similarly, the differences between the DMP for each of the altered protocols and the PUBL DMP were found, and the accuracy and precision were obtained for these.

A linear mixed-effects model was fitted to the data to verify the statistical significance of the differences for each protocol in comparison to the PUBL DMP. Animal age and Region (Nandi, Bomet) were included as variables in this model.

Table 4.2: Composition of the study population by animal class and region

Class	Nandi (126 HH)	Bomet (131 HH)	Total for each class
Calves <1 year	47	13	60
Heifers 1 - 2 years	102	63	165
Males 1 - 2 years	20	21	41
Males > 2years	22	24	46
Females > 2 years	358	365	723
Total	549	486	1,035

4.3. Results

Our calculated DMP based on the simplified data collection approach showed a substantial deviation from DMP calculated on the existing standard data collection protocol (**Figure 4.2**). Yet the deviation was not uniform. Replacing LW measurements by LW estimated through HG measurements resulted in 4.88g/day lower DMP whereas substituting FQ results in considerably larger DMP (32.27g/day higher than published values). There was a substantial increase in variation on the use of algorithm LW (ALG) and Feedipedia FQ when compared to PUBL values i.e., SD= 10.22 and SD=6.55 respectively.

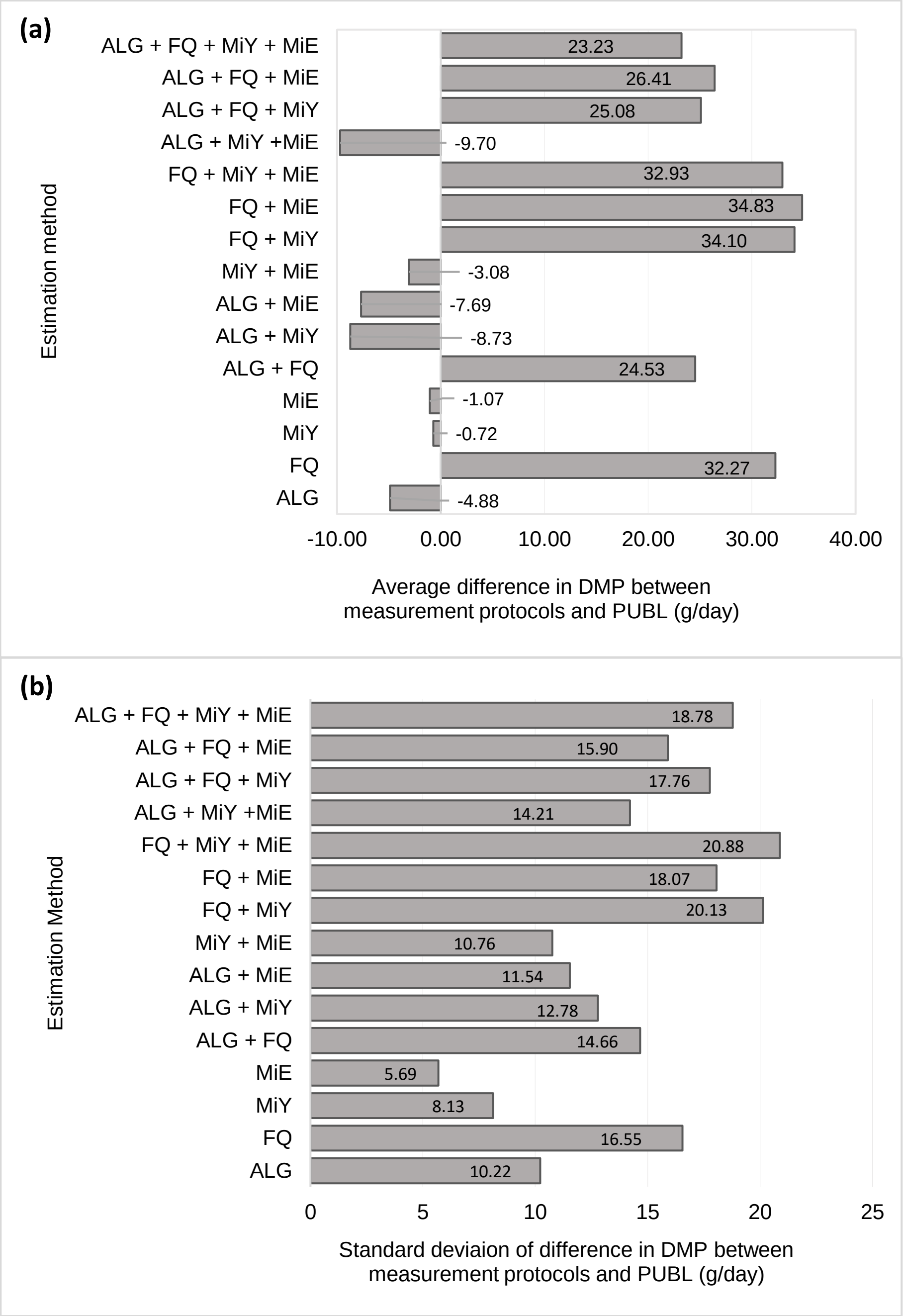

Figure *4*.2: (a) Average difference in daily methane production (g/day) for all cattle estimated in different estimation protocols of live weight (ALG) and feed quality (FQ) and their combination, and for all female cattle for protocols involving MiY and MiE. All protocols are compared to the reference protocol PUBL for each animal, which has an average DMP of 122g/day for all cattle and 139g/day for females (>2 years) only. **(b)** The standard deviation of the difference in daily methane production estimated under

ALG, FQ, MiY, and MiE and their combination when compared to the published (PUBL) protocol.

Combining two substitution measures tended to result in increased variance when compared to the measure that underestimates (ALG) and a slight reduction in variance when compared to the measure that overestimates (FQ).

Females (>2years) have an energy requirement for lactation that is part of the total energy requirement, and it is derived using milk yield and energy content of milk. The substitutions related to lactation (MiY and MiE) showed modest variation from the original measured values (SD = 8.18 and 5.69) and almost no bias (-1.07 and 0.72). Again, the substitution of DMD estimates from wet chemistry with mean values from the Feedipedia database in combination with both lactation substitutions showed large deviations and a substantial bias of 34.10 (FQ and MiY) and 34.83 (FQ and MiE) g/day. In general, three-way, and four-way combinations led to a slight improvement in precision. **Table 4.3** presents the comparison between the PUBL DMP and the simplified protocols. A linear mixed-effects model confirmed statistical significance for the differences for every measurement protocol compared to PUBL ($p<0.00005$) (see **Table 4.4**). However, there were no regional differences in the DMP calculated (p-value = 0.4530).

Table 4.3: A comparison of daily methane production (g/day) derived using the published protocol (PUBL) and simplified protocols of measurements of live weight (ALG), feed quality (FQ), milk yield (MiY) and energy content of milk (MiE) and their combinations.

Parameter/ Combinations	**Published Protocol (PUBL)**			**Simplified Protocols**		
	Average DMP (g/Day)	**S.E.M**	***n***	**Average DMP (g/Day)**	**S.E.M**	***n***
ALG	121.8	1.79	1,036	116.9	1.80	1,036
FQ	121.8	1.79	1,036	154.1	2.27	1,036
MiY	138.4	2.48	723	141.5	2.56	723
MiE	137.3	2.70	723	136.0	2.61	723
ALG & FQ	121.8	1.79	1,036	146.3	2.21	1,036
ALG & MiY	138.8	2.48	723	135.8	2.36	723
ALG & MiE	138.8	2.48	723	132.6	2.19	723
MiY & MiE	138.8	2.48	723	140.9	2.46	723
FQ & MiY	138.8	2.48	723	178.3	3.37	723
FQ & MiE	138.8	2.48	723	172.1	3.20	723
FQ & MiY & MiE	138.8	2.48	723	177.5	3.26	723
ALG & MiY & MiE	138.8	2.48	723	135.1	2.25	723
ALG & FQ & MiY	138.8	2.48	723	169.5	2.98	723
ALG & FQ & MiE	138.8	2.48	723	165.7	2.79	723
AlG & FQ & MiY & MiE	138.8	2.48	723	167.3	2.82	723

Simplified protocols are ALG – Algorithm weight, FQ – Feedipedia Feed quality values, MiY – Single milk yield measurement per season, MiE – default energy content of milk.

Table 4.4: The difference in daily methane production (DMP, g/day) between the published protocol and alternative data collection protocols and the significance levels (p-value) when compared to published values.

Variable	**Difference**	**p-value**
(intercept)	61.1	0.0000***
Protocol		
ALG	-4.9	0.0000***
FQ	32.3	0.0000***
MiY	-2.5	0.0000***
MiE	-2.8	0.0000***
ALG + FQ	24.5	0.000***
ALG + MiY	-10.5	0.000***
ALG + MiE	-9.4	0.000***
MiY + MiE	-4.8	0.000***
FQ + MiY	32.4	0.000***
FQ + MiE	33.1	0.000***
FQ + MiY + MiE	31.3	0.000***
ALG + MiY + MiE	-11.4	0.000***
ALG + FQ + MiY	23.3	0.000***
ALG + FQ + MiE	24.7	0.000***
AlG + FQ + MiY + MiE	21.5	0.000***
Region		
Nandi	1.9	0.4530^{NS}

Alternative protocols are ALG – Algorithm weight, FQ – Feedipedia Feed quality values, MiY – Single milk yield measurement per season, and MiE – default energy content of milk. The DMP derived by alternative protocols in the table is compared to the published DMP (PUBL). Nandi region is compared to Bomet region. *** = $p<0.01$; ^{NS} = Not significant

4.4. Discussions

The accuracy of estimating enteric methane emissions using models has been a key interest with numerous studies (du Toit, Meissner*, et al.*, 2013; Goopy *et al.*, 2021; Ndao, 2021; Ndung'u *et al.*, 2018). These studies largely agree on two conclusions, namely: i) appropriate assumptions need to be made that reflect the conditions of the livestock system under investigation, and ii) data inputs to be used by the model need to have sufficient accuracy to derive reliable estimates of the actual emission situation. The latter has been a challenge for developing countries due to the huge capital investments needed to achieve an up-to-date database on livestock parameters needed for such models.

The accurate estimation of DMP facilitates the creation of informed, region-specific EF for ruminant livestock, which is vitally important for the development of reliable GHG inventory and in turn, mitigation strategies for SSA countries. Although the data collection protocols for the recently completed studies (Goopy *et al.*, 2018; Ndung'u *et al.*, 2018), which formed our reference data in this work, are robust and sound, it was recognized that the resources such as an animal weighing scales, a utility vehicle, and several field assistants needed to undertake further studies may outstrip the capacity of some potential researchers. Thus, new approaches were sought to reduce the equipment and other resources while minimizing loss of veracity. Practical alternatives were found for the parameters which absorbed the greater amount of resources: LW, milk analysis and yield, and feed characteristics – and these were compared using estimates of DMP for the substitution, to our previously published estimates.

4.4.1. Heart girth algorithm to estimate liveweight.

Animals' LW and LW change are the most pervasive and arguably most influential measurements used in the calculation of DMP and thereby EFs. It is integral to the calculation of $MER_{Maitenance}$, MER_{Growth}, and of $MER_{Locomotion}$ and so the importance of the accurate measurement of LW is difficult to overstate. The results indicate that while ALG has a similar degree of precision to the use of animal scales, the measurement exhibits a degree of systematic bias, resulting in an underestimation of DMP by 7% (resulting in an EF reduction of ~2kg CH_4/head/year for an average-sized animal). This is not ideal, and a possible solution is to employ a better algorithm.

The algorithm used in this study was developed from cattle populations from West and East Africa, comprising 1,513 cattle. The original study (Goopy et al 2017) was found to have very good agreement with gravimetric measurement (Adj.R^2= 0.920) and similar prediction error with the aggregated dataset for African cattle that could be found in the literature (see **Table 4.5**). Though the weight of animals in this study significantly differed as compared to the dataset used for establishing the heart girth relationship, the prediction error remained similar to the original study. This suggests that the algorithm used is unlikely to be able to be further improved. If this is the case, the implications of the entrenched bias must be weighed against the tactical advantage of a simple HG measurement over cumbersome and costly scales.

It must also be emphasized that algorithms developed within a particular population, may be less accurate when employed outside of the population, especially if the algorithm is based on a simple linear regression model (Goopy *et al.*, 2017). Therefore, if a HG algorithm is to be used to assess LW in a different population, it is strongly recommended that the decision be informed by a preliminary assessment of the model's predictive capacity among the population where it is to be employed.

Table 4.5: Comparison of Prediction errors at 75th, 90th, and 95th percentiles for Quadratic model to estimate live weight using heart girth measurements between datasets from Goopy *et al.* (2017) study, and the present study

Study Sites	**Study**	**Prediction Error (Percentiles)**		
		75th	**90th**	**95th**
East Africa dataset	Goopy et al., 2017	±15%	±23%	±30%
West Africa dataset	Goopy et al., 2017	±14%	±21%	±27%
Aggregated dataset	Goopy et al., 2017	±15%	±22%	±29%
Validation dataset-Nyando	Goopy et al., 2017	±10%	±15%	±18%
Nandi dataset	Present study	±19%	±25%	±29%
Bomet dataset	Present study	±13%	±19%	±22%

4.4.2. Feed Quality – assessment of dry matter digestibility

Dry matter digestibility is an important input in the estimation of DMP, being a key determinant of intake (for a given energy requirement), and used in the calculation of $\text{MER}_{\text{Maintenance}}$, $\text{MER}_{\text{Lactation}}$, and DMI. Determination of DMD is an elaborate process involving several chemical assays, which is often difficult to carry out in research laboratories in SSA countries, so it was considered that substituting direct analysis for values freely available from reputable literature (i.e., Feedipedia) could confer significant advantages. The use of values from Feedipedia resulted in an overestimation of DMP of 24%. The causes underlying this are clear, while the magnitude of the error was not hypothesized. Studies such as those of Ndung'u *et al.* (2018), demonstrate the spatial and temporal variability in the composition of livestock feed, which our sampling during the establishment of the database used in this study was able to capture. By contrast, Feedipedia values do typically cover a range, we were simply limited to using a mid-range value in all calculations. Given the large reductions in both precision and accuracy, it is not recommended that this measurement change be adopted until region-specific or season-specific feed information is available in Feedipedia.

4.4.3. Lactation parameters

The substituted measures for MiE and MiY had the least impact on the DMP amongst the measures explored, with very little loss of accuracy (-0.1%) or precision (-0.02%). Concerning MiE, this was clearly because the value adopted from CSIRO (2007) was as well representative of the actual case in the populations studied. This was surprising given that the value was derived from European cattle, although, the work of Cheruiyot *et al.* (2018) suggests that variation in milk composition across commonly encountered African phenotypes is minimal because the milk samples were from a sample pool with dominant Holstein-Friesian origin which is commonly found in the European farms. However, the latter statement remains disputed as a study by Kebede (2018) brings this assertion into question due to the breed effect on milk fat. In view of this, it is suggested that adopting the given value for milk energy content, is likely a “no-regrets” option for further studies of this kind, but it is recommended that the milk from a small representative sub-sample be analyzed for comparison before committing to fieldwork.

Our data showed that a single day's milk collection (MiY) provided nearly identical estimates of seasonal milk production, as compared to the daily collection throughout the season, and that decreases in accuracy remained 0.03% lower and 0.01% higher in variation. This is likely the case for two important and inter-related reasons. Firstly, the lactation curves of smallholder cattle have been characterized as being of a slow, steady decline (Lobago *et al.*, 2007), meaning there is little variation in production from the beginning to the end of lactation. The second reason is that milk production itself is typically so low in these systems (<5L/day for mixed crop-livestock systems and <2L/day for pastoral and agropastoral systems) (Garnsworthy *et al.*, 2012; Ndung'u *et al.*, 2018), making the energy required for milk production less important to the overall calculation of DMP. While our results indicate that only single-day data is required to determine seasonal yield, there may be considerable risks associated with adopting such a practice. The dichotomous nature of high and low yield dairy systems in South Africa (Abin *et al.*, 2018), highlights the association between high production, good nutrition, and pronounced lactation curves in cattle (and vice versa for low production systems). This suggests that if a livestock production system is understood and production is known to be low, the "single sample" protocol may be adopted. Otherwise, repeated sampling is indicated, not least of all because, as production increases, the importance of $\text{MER}_{\text{Lactation}}$ to overall energy expenditure, also rises.

4.4.4. Operation costs

To compare the effect of simplifying the data collection protocols to the cost of operations, the relative contribution of transport logistics, expertise (staff), and equipment were computed based on Kenya's case studies projects costs incurred i.e., 30%, 28%, and 20% of the total budget respectively. Transport costs would be reduced significantly when the need for a heavy track was avoided as the fuel consumption would be reduced by half while the cost of hiring the heavy vehicle was reduced as well. Replacing daily milk measurements with spot sampling would completely remove the cost of providing measuring cans. Similarly, the cost of Lactoscan would be removed as well when the use of default milk energy value was adopted. The cost of nutrition laboratory services (22% of the total budget) was not altered as changing the source of the feed quality data showed a high loss of accuracy as discussed earlier in DMP estimates and hence not recommended. The combination of the use of algorithm LW (ALG), single MY measurement (MiY) and default milk energy (MiE) would cause an overall budget cost reduction of ~30% as shown in **Table 4.6**.

Table 4.6: Sources of expenditure and the comparison of their relative cost contribution to the overall budget for data collection for the published protocol (PUBL) with alternative data collection protocols that use algorithm live weight (ALG), single milk yield measurement (MiY), and default milk energy (MiE) and their combinations.

Protocol	**Relative cost contribution to overall budget (%)**				**Total Budget**
	Transport (Vehicle + Fuel + Driver)	**Expertise (Staff)**	**Equipment (Animal scale + Measuring cans + Lactoscan)**	**Laboratory (Feed analysis)**	
PUBL	30.0	28.0	20.0	22.0	100.0
ALG	20.0	27.0	13.0	22.0	82.0
MiY	30.0	28.0	9.0	22.0	89.0
MiE	30.0	28.0	17.0	22.0	97.0
ALG + MiY	20.0	27.0	2.5	22.0	71.5
ALG + MiE	20.0	27.0	10.8	22.0	79.8
ALG + MiY + MiE	20.0	27.0	0.2	22.0	69.2

4.5. Conclusion

This study has led us to the following key conclusions:

i) Actual measurements of LW data can be substituted with modeled live weight data using the heart girth algorithm. This still produces DMP estimates with a low bias and variation.

ii) Feed quality data cannot be substituted by averaged literature data as it causes a wide variation and highly biased results. Hence, diet quality information should not be compromised at any point and should be accurately determined to have better CH_4 estimates.

iii) Using the default energy content of milk representative of local dairy instead of actual measurements of milk quality contents only caused a bias of -1.07g/day and hence can be adopted.

iv) In the context of a low-producing dairy production system, a single milk yield recorded the day before a farm visit per season instead of a seasonal average for calculating energy requirements for lactation only caused a bias of 0.72g/day and hence can be adopted.

v) We can have a simplified protocol by using algorithm LW, default milk energy, and a single milk yield data and measured feed quality (ALG + MiY + MiE) that would produce DMP estimates with an error in DMP of ≤9.7g/day with reduced operation cost of ~30% of the total budget.

4.6. Acknowledgement

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CHAPTER FIVE

5. General Discussions and Conclusions

5.1. Summary of key findings

Kenya has committed to reducing emissions from the livestock sector in the nationally determined contribution (NDC) as it named livestock as one of the major sources of GHG emissions in the country (NCCAP, 2018; World Bank & CIAT, 2015). Emissions from the livestock sector have been increasing. For example from the dairy cattle sub-sector, a 28% increase in emissions was reported since the year 2010 and was mainly attributed to an increase in animal numbers (SDL, 2020). Trends in emissions reduction through the implementation of mitigation options can only be monitored and verified if there exist reliable country-specific baseline estimates. During the first Kenya NDC, the GHG inventories for the livestock sector were compiled using the Tier 1 default values due to a lack of data. This situation has since changed as researchers at the International Livestock Research Institute (ILRI) initiated the development of a new approach to produce Tier 2 emissions estimates from enteric fermentation (Goopy *et al.*, 2018). More studies followed that adopted that approach including the study in this thesis.

The results of animal performance and productivity and feed availability enable the understanding of emission efficiency of African smallholder livestock farms at the farm level. This chapter describes the key findings and the methodological approach of this study. Further, this chapter discusses the key findings against the objectives of this thesis in the following approaches: measures of GHG emissions, data needs, and alternative and simple approaches to collecting the data and lessons learned from the study.

5.2. Measures of GHG emissions

Emissions can either be reported as absolute (net) emission or emissions intensity (EI, emission per unit product).

5.2.1. Absolute emissions

The use of higher Tiers (Tier 2 and 3) to derive emissions estimates from enteric fermentation has been strongly encouraged to improve the accuracy of emissions reporting (IPCC, 2019). This is because the use of Tier 1 (default EFs) often generates high errors and uncertainties from failing to account for the variability of emissions due to animal productivity, feed quality, soils, and climatic conditions. Accurate estimates are important to develop and assess the GHG emissions reduction potential of mitigation strategies.

We conducted a study to derive region-specific (Tier 2) enteric methane emission factors (EF) for Bomet county (as described in Chapter 3) and compared the results with IPCC Tier 1 values for the African region. The calculations were based on the metabolizable energy requirements (MER) approach adopted from CSIRO (2007) and methane yield per dry matter intake derived by Charmley *et al.* (2016). The activity data used was from primary on-farm data of smallholder farms located in four agro-ecological zones (AEZ) (Lower Highland 1 (LH1), Lower Highland 2 (LH2), Lower Highland 3 (LH3), and Upper Midlands 1-4 (UM1-4) in Bomet.

In chapter two, the results showed that there were variations in EFs between the AEZs in all animal age classes driven by the differences observed in the activity data. These differences included average live weights, live weight gains, milk yield, and dry matter digestibility of the feed basket between the AEZs. A study by Lee *et al.* (2017) showed that differences in climatic conditions caused a variation in the nutritive value of grasses that also had an impact on animal performance and ultimately enteric methane emissions.

Our study showed similar results where animal performance differed across AEZs with higher animal performances being reported in the LH1 than in LH2, LH3, and Upper Midlands. This trend was also seen in the pasture biomass yield which could explain the reason for higher animal performance in the LH1 zone likely due to the availability of a higher pasture resource base that has a higher dry matter digestibility (Goopy *et al.*, 2021) and feed nitrogen content than the other AEZs. The enteric EFs were not any different from this trend where LH1 reported the highest values for all animal age classes except for males (>2 years) where UM1-4 reported the highest EF of all the AEZs.

The calculated Tier 2 EFs were compared to the IPCC Tier 1 values for the Africa region and Bomet EFs were 25% to 45% lower than the IPCC default values, a substantial difference. These differences were likely caused by the differences in feed digestibility values which were 13% higher than the IPCC values (62.2% vs 55%). When compared to Tier 2 EF values from a neighboring region in western Kenya (Nandi) (Ndung'u *et al.*, 2019) located close to Bomet and had similar AEZs and the difference ranged between 4% lower to 4% higher than the EFs from the Nandi region, a much smaller difference. The smaller difference was because the livestock keeping and climatic conditions in the two regions are similar but also because Nandi Tier 2 EFs were derived using region-specific activity data. The results suggest that there is a need to improve enteric methane emissions estimates using region-by-region activity data.

5.2.2. Emission intensity

Besides just understanding the extent of GHG emissions production during livestock farming, it is crucial to understand the activity's environmental performance in the context of food security. Emission intensity is a key parameter that enables understanding of the impacts of livestock production on climate change. In our study, we investigated the most common livestock production system, the smallholder livestock system, practiced by most livestock keepers in highland and semi-arid regions of Kenya.

Our LCA study shows that not all African farms are high emitters as often displayed. There is a wide variation in EIs between farms in the same locality and across regions with lower EIs being recorded in the highlands (Nand and Bomet) and higher emissions in the semi-arid regions (Nyando). This is linked to the strong relationship between productivity levels and emissions where high productivity levels showed low EIs and vice versa. There exist "high" productive farms that showed EIs like those of developed countries. However, there are also extreme cases of very low producers that drive the EIs very high because of high livestock numbers, with the majority being non-producing and very few productive animals coupled with low production.

More so, EIs are also driven by the sources of emissions. In our study, on-farm direct emissions which include CH_4 from enteric fermentation, CH_4 and N_2O from manure management, and CO_2 from feed production were considered in the analysis. Of these activities, CH_4 from enteric fermentation contributed the largest share (~95%) of the total on-farm emissions while manure emissions contributed approximately 3%. The contribution of enteric fermentation is considerably higher than high-input Western systems and precisely because this value is high, the results of Chapter 5 are relevant not only at the farm scale but also at the supply chain scale (because CH_4 is almost single-handedly driving the carbon footprint - otherwise an accurate CH_4 EF do not guarantee an accurate EI).

This study shows that there is potential to improve low productive farms to high productivity even at low input considering the existence of such farms already in the study. This will require management changes such as herd restructuring to have more productive animals in the herd and reduce emissions from enteric fermentation which contributes the highest proportion of total emissions by interventions such as improved feeding. Improved feeding gives double wins i.e., reduces enteric methane emissions and increases milk production for lactating females and higher growth rates for males and the growing herd that would eventually reach market weight much faster or reproduces. Livestock in these farms is not just for food, this study did not employ other benefits of the livestock that would be included as output. However, this has been shown to reduce the emissions intensities associated with the livestock in Kenya (Weiler *et al.*, 2014) and therefore should be considered in future research.

The EIs reported in this study are significantly lower than the literature for Africa (Opio *et al.*, 2013), therefore challenging the conclusion that African systems have low emissions efficiency. But to have a much better picture of how efficient our systems are, a study involving not just direct emissions but indirect emissions sinks, and removals need to be captured thereby presenting a clear picture for researchers and policymakers on actions to take in improving these systems to operate more sustainably.

5.3. Data needs, and alternative and simple approaches to collecting the data.

Obtaining primary data to conduct this study was expensive, tedious, and time-consuming even though it has enabled providing more accurate estimates of emissions. The first objective of this study has clearly shown the need for site-specific data and hence we sought to simplify the data collection methodology to produce a low-cost protocol. So, we investigated the changes in data collection of activity data that require a high cost to obtain activity data without loss of accuracy and precision because CH_4 is responsible for a large proportion of life cycle emissions in the studied system.

The use of a heart girth tape to determine the weight is common and the adoption of this method of weight determination only showed a bias of 7% compared to actual weight determination using an animal scale. Spot sampling of milk yields and use of literature values for milk energy showed a very small effect on the accuracy of the emissions estimates. However, there were large effects in using literature values for feed quality and therefore region-specific values are important to avoid over- or underestimation of emissions estimates. Overall, the data collection methodology can be simplified by using a simple heart girth tape, spot sampling of milk yield, and use of milk energy values from literature and region-specific feed quality values to develop Tier 2 enteric methane emissions estimates for African livestock systems. This will promote the availability of data that would improve the national inventories as well as conduct more LCA studies that can determine the carbon footprint of smallholder livestock systems.

5.4. Lessons learned.

There is a need to develop mitigation strategies to make livestock systems in East Africa more emission efficient that are informed by primary data. There are possible opportunities for developing scenarios of low emission development pathways for the livestock sector using the data provided by this study as a baseline scenario. This data should be used to inform areas that are like the agro-ecological zones assessed and climate conditions have an impact on vegetation that was observed to be critical in regard to enteric methane emissions calculations. Conducting an LCA to African livestock systems was challenging in accessing the global emissions data for agro-chemicals from the ecoinvent which needs to have a subscription and in comparing the studies across globe due to the assumptions made in each study which are very important to have in mind to avoid misinterpretation of results. Activity data is paramount in developing emission factors and improving GHG inventories and guidelines by the IPCC should be followed on data requirements.

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