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Marginal abatement cost curves of climate-smart agricultural practices to mitigate greenhouse gas emissions from smallholder dairy farms in Kenya

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ABSTRACT

While livestock play a vital role in supporting livelihoods of many people in Africa, they are also a major source of greenhouse gas (GHG) emissions. An increasing African population coupled with growing demand for livestock products means that there is an urgent need to implement cost-effective Climate Smart Agriculture (CSA) practices that reduce emissions from livestock systems. The objective of this research was to assess the effect of implementing CSA practices on milk yields and GHG emission intensities (EI) from three dairy production system types (no-graze, semi-intensive, and extensive) in Kenya. The research applied marginal abatement cost curves (MACC) as a novel methodology in the livestock sector in low and middle-income countries, to assess of the economic costs and trade-offs for the use of CSA practices in each of the dairy production systems. The research was conducted on 666 dairy farms in four counties in Kenya. Data from a farm survey and participatory workshops were used to categorise farms into production systems, estimate carbon emissions using the Agrecalc (Agricultural Resource Efficiency Calculator) tool, assess the effects of the use of CSA practices on milk yields and GHG EI, estimate the costs of implementing CSA practices, and develop the MACCs. Addressing the limited existing in situ experimental evidence available, especially related to livestock production, our results showed that common CSA practices enhance milk yields and reduce GHG EI in dairy production systems. Moreover, the novel nuanced insights indicated that these benefits were not equally experienced by all production systems, with only clear statistical effects observed in extensive production systems. In these systems, farms using five or more CSA practices saw a 44 % increase in milk production and a 25 % reduction in GHG EI compared to farms not using any CSA practices. The MACCs revealed that the costs associated with the implementation of the CSA practices were higher for extensive production systems, but increased milk production meant that the net increases in value production were higher for extensive production systems. This indicates that upfront investment costs are important barriers to the use of CSA practices. Our results provide strong evidence that rural development projects are likely to be more successful when targeting farm types and using a "toolbox" approach. Moreover, the results demonstrate the importance for the establishment of policy and financing mechanisms to facilitate financing and decreasing the perceived risks involved in investing in CSA practices.

1. Introduction

Livestock play a vital role in supporting the livelihoods of many people in Africa by providing income, food, nutrition, draft power, and manure for crop fertilization (Adesogan et al., 2020; Balehegn et al., 2021; Weiler et al., 2014). However, livestock are also a main source of greenhouse gas (GHG) emissions in most African countries, contributing on average between 23 and 33 % of anthropogenic GHG emissions (FAO Statistics Division, 2023; JRC European Commission, 2021). Enteric methane (CH_4), produced during digestion of feed by ruminant livestock

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accounts for between 46 and 60 % of total GHG emissions for livestock production, while CH_4 from manure management accounts for between 12 and 41 % of total CH_4 emissions in most countries (Chadwick et al., 2011; Ungerfeld et al., 2022). Nitrous oxide (N_2O) from livestock excreta deposited while grazing, applied as fertilizer, or from manure management accounts for the remaining GHG emissions from livestock (accounting for around 36 %) (JRC European Commission, 2021).

Demand for livestock products in Africa, particularly dairy, is expected to increase significantly over the coming decades due to population and income growth in African countries (Henchion et al., 2021). The continent-wide demand for meat and milk is expected to increase between 261 and 399 % by 2050 compared to 2010 levels (FAO, 2017a). As a country, Kenya is highly representative of these continental-wide trends. Its dairy herd is around 4 million head of dairy cattle (the third largest in East Africa) and has the highest *per capita* milk consumption in Africa. Similar to the continental trends, demand for milk in Kenya is expected to increase by 38 % by 2050 compared to production in 2019 (Enahoro et al., 2018). Meeting this increasing demand for dairy products in African dairy systems will result in increased animal GHG emissions, however, if demand can be met by increases in animal productivity rather than increases in herd sized, GHG EI should reduce and thus slow down the increase in absolute emissions due to increased production (Ericksen and Crane, 2018).

In response to these challenges, the Kenyan government has committed to ambitious targets both in terms of milk production and reducing GHG emissions from livestock as part of its National Livestock Policy (2019), Agriculture Sector Transformation and Growth Strategy 2019–2029, National Dairy Master Plan, and Nationally Determined Contributions (NDCs) to climate change mitigation under the 2015 Paris Agreement (Ministry of Agriculture, Livestock, Fisheries and Irrigation, 2010; Ministry of Agriculture, Livestock, Fisheries and Irrigation, 2019a; 2019b; Ministry of Environment and Forestry, 2020). Among the targets, the 2010 Dairy Master Plan stipulates an increase in total milk production by 150 % by 2030, while the Nationally Determined Contributions to the 2015 Paris Agreement requires a reduction in total GHG emissions by 32 % by 2030 compared to what would be expected without mitigation measures (business as usual - BAU). The National Climate Change Action Plan (NCCAP) 2018–2022 further specifies that the agriculture sector should reduce CO_2e by 7.1 % compared to BAU by 2030 (Ministry of Environment and Forestry, 2018). To meet these goals, Kenya has begun mainstreaming and encouraging relevant practices through programs such as the Kenya Climate Smart Agriculture Project (www.kcsap.go.ke).

As a result, there is an urgent need to implement cost-effective Climate Smart Agriculture (CSA) practices that can increase milk productivity and reduce GHG emissions from dairy systems in Africa. CSA practices aim to achieve the "triple wins" of minimizing GHG emissions, increasing livestock productivity, and adapting systems to future climate change (Anuga et al., 2020; FAO, 2017b). While absolute GHG emissions from dairy systems are expected to increase due to increased demand and production in Africa, such increases could be restricted through CSA practices that reduce the GHG emission intensity (EI) of milk production (Ndung'u et al., 2022). This approach can improve the efficiency of milk production, enhance profitability, and improve a farm's adaptation to climate change (Gerber et al., 2011).

While CSA practices have been widely promoted to reduce emissions from dairy and other livestock systems, little is known about their effect on animal productivity, GHG emissions and relative cost effectiveness at farm level (Anuga et al., 2020). Marginal abatement cost curves (MACCs) assess the trade-offs of mitigation measures (e.g., CSA practices) by examining their economic costs and GHG mitigation potential (e.g., Fellmann et al., 2021; Schmidt et al., 2021). However, as far as the authors are aware, only one MACC has been conducted for dairy production systems in low- and middle-income countries (LMICs) to assess the trade-offs involved in the use of CSA practices in Latin America (Duffy et al., 2021). Additionally, many of the existing MACC assessments are based on expert opinion and literature values (Jones et al., 2015), whereas only a few MACC studies have been based on in-situ, empirical data collection (Duffy et al., 2021). *In-situ* studies can provide a more accurate representation of the true costs and effectiveness of adopting CSA practices for mitigation by farmers.

The current research was undertaken under the auspices of the Kenya Climate Smart Agriculture Project (KCSAP) led by the Kenyan Ministry of Agriculture, Livestock, Fisheries and Cooperatives, and funded by the World Bank. The overall goal of the KCSAP project is, "to increase agricultural productivity and build resilience to climate change risks in the targeted smallholder farming and pastoral communities in Kenya, and in the event of an eligible crisis or emergency, to provide immediate and effective response". To help achieve this goal, the KCSAP project is upscaling CSA practices by supporting smallholder farmers to use various CSA practices. It also aims to better understand the effect of CSA use on GHG EIs (i.e. GHG emission per product).

In this regard, the objective of this research was to assess the effect of implementing CSA practices on milk yields and GHG EIs from three dairy production system types (no-graze, semi-intensive, and extensive) in Kenya. In addition, the research aimed to develop MACCs using data collected *in-situ* in order to assess of the economic costs and trade-offs for the use of CSA practices in these dairy production systems. We hypothesised that the use of CSA practices would both increase yields and decrease GHG EIs. Furthermore, we hypothesised that these effects would be different for the different production systems, with the extensive dairy production systems benefiting more compared to semi-intensive and no-graze systems from the use of CSA practices. We also hypothesised that the potential return on investment would be greater than the costs related to the implementation of CSA practices, leading to potential net increases in income.

2. Materials and methods

2.1. Study sites

The research was conducted on smallholder dairy farms in four counties in Kenya: Baringo, Bomet, Kericho, and Laikipia (Fig. 1). These counties have diverse agro-climatic conditions (Table 1) but are generally representative of mixed dairy farms in highland regions of Kenya (Bebe et al., 2003). Farms were selected from 4 to 6 wards in each county for conducting surveys, depending on logistical constraints. The counties and wards were selected because they were areas where farmers were supported by the KCSAP to use CSA practices.

Typically, smallholder dairy farms in Kenya are characterised by small farm sizes (<2 ha) and strong integration between crop and livestock components of the system where milk production may not be the primary production activity. Such integration of different farming activities can increase resilience to climate change. These farms are also usually low input and often receive minimal investment, leading to relatively low milk productivity (<4 L fat and protein corrected milk (FPCM) cow^{-1} day^{-1} or <1460 L FPCM cow^{-1} $year^{-1}$ in many cases) (Ndung'u et al., 2022). However, there is considerable heterogeneity within each site depending on altitude and microclimate, soils, and vegetation types (Staal et al., 2005; Thorpe et al., 2000; World Bank and CIAT, 2015). Generally, dairy farms can be categorised into three main production systems in Kenya: extensive, semi-intensive, and no-graze. The current study adopts the same definition of these production systems as outlined in the *Inventory of GHG emissions from dairy cattle in Kenya (1995)–2017* (Ministry of Agriculture, Livestock, Fisheries and Irrigation, 2020). Extensive production systems were characterised as farms where the dairy cows were fed for at least 70 % of the time through grazing practices throughout the year. No-graze production systems were characterised as farms where the dairy cows were fed for at least 70 % of the time through no-grazing practices throughout the year. All other farms were characterised as belonging to the semi-intensive production system.

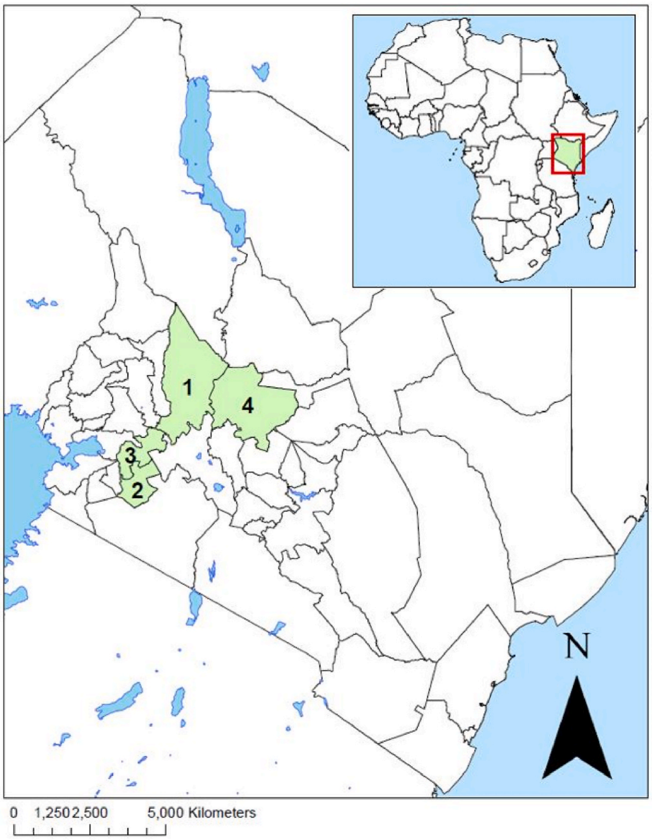

Fig. 1. Map of the counties where the research took place in Kenya. 1) Baringo, 2) Bomet, 3) Kericho, 4) Laikipia.

Table 1
Agro-climatic conditions of counties and sample numbers by district and production system.

Characteristics/ production system type[a]	Baringo	Bomet	Kericho	Laikipia
Climatic conditions	Semi-arid	Sub-humid	Sub-humid	Semi-arid
Annual precipitation (mm year^{-1})	Highland areas: 1000–1500 low land areas: 600	1000–1400	1400–2100	400–750
Temperature (°C)	10–35	16–24	10–29	16–26
Elevation (average masl)	1383	2016	2034	1861
Extensive production systems surveyed (number farms)	100	72	65	60
Semi-intensive production systems surveyed (number farms)	52	51	79	84
No-graze production systems surveyed (number farms)	28	16	19	40
Total farms surveyed (number farms)	180	139	163	184

[a] Figures sourced from County Government of Baringo (2018); County Government of Bomet (2018); County Government of Kericho (2018); County Government of Laikipia (2018). masl = metres above sea level.

The counties vary in terms of agro-climatic conditions, but rainfall distribution and seasonality were similar. All counties have a bimodal rainfall distribution, and seasonality typical of Kenyan highland regions, where the primary rainy season is from April to June, with a secondary rainy season between October and November. There is a warm dry season from December to March and a cool dry season that typically extends from June to September. Agro-climatic conditions by district are presented in Table 1 along with the number of farms surveyed in the research by production system.

2.2. Survey design

The surveys were conducted between October 24 and December 15, 2022, following a series of pilot field tests. Around 100 farms that benefited directly from support from the KCSAP project, and 100 farms that had not received direct support from the project were selected for survey in each county. It should be noted that even farms that did not receive direct support from KCSAP often reported using one or multiple CSA practices. The survey was adapted from Wilkes et al. (2019) - https://cgspace.cgiar.org/handle/10568/105737, see supplementary material). It consisted of a mixture of a recall survey questionnaire on livestock management practices (herd composition, milk production and milk sales, feeding, dairy management practices), and a limited number of direct physical measurements (i.e. heart girth of dairy cows, milk yields, feed and feeding management following ILRI's Manual 24 (Goopy and Gakige, 2019). The surveys also asked whether farmers used any CSA practices promoted by KCSAP. These CSA practices are listed in Table 2 and were grouped by theme. The surveys were conducted by trained enumerators on the farms and were recorded using the Open Data Kit (ODK), an online, open-source mobile data collection platform. Quality control was ensured by limiting the nature and magnitude of options for responses to survey questions, and survey results were checked periodically for major issues with the data collection process.

In addition to the survey, animal diets were recorded, and samples of the most common feeds were collected from a subsample of farms at each site. At the county scale, we obtained feed samples from at least six farms in each ward. This resulted in a total of 36 samples per county for the most representative feed types in Baringo, Bomet, and Kericho; and four wards were surveyed in Laikipia (24 samples per feed type). Subsequently, feed samples were transported to ILRI's Mazingira Centre for analysis of feed composition. Dry matter was determined by drying the samples at 105 °C in an oven (Genlab oven, model SDO/425/TDIG, UK) for 24 h while ash was determined by combustion in a muffle furnace (Nabertherm GmbH, Germany) at 550 °C for 6 h according to the methods of the Association of Official Analytical Chemists (Latimer, 2023). Fibre content (NDF and ADF) were analysed by the methods of Van Soest et al. (1991) using an Ankom 200 fibre analyser, model

Table 2
List of climate smart agricultural practices assessed with examples of the specific techniques used.

CSA practices	Examples of innovations
Improved cattle breeds use	Use of Improved cattle breeds, artificial insemination (AI) services; breeding improvements
Feed processing equipment	Chaff cutter; improved machinery for feed processing
Fodder improvement	Improved fodder; fodder establishment; fodder improvement
Feed preservation	Feeds preservation; hay; silage making
Feed supplements	Use of dairy concentrates; own farm feed formulations; other feed formulations
Vaccinations	East Coast Fever vaccination
Fertilizer use	Fertilizer use
Improved pasture	Improved pasture; legumes mixed with Kikuyu grass; improved pasture management; pasture establishment and management
Feeding of by-products	Use of stovers/crop residues
Water harvesting	Water harvesting (equipment and infrastructure)
Stall feeding and housing	Semi-zero grazing unit; Zero grazing unit; Improved housing; Improved dairy unit; Dairy unit improvement
Milk marketing	Milk marketing through cooperative membership

A2001, USA. Nitrogen content was determined with an organic elemental analyser (Vario Max, model vario SOLID Sampler, Germany), while gross energy (GE) was determined according to the methods by Harris (1970) using a bomb calorimeter (Parr 6200, model A1290DDEE, UK). These variables were used to calculate dry matter digestibility (DMD) according to the equation below (Oddy et al., 1983).

$$DMD\ g/100\ g\ DM = 83.58 - 0.824 * ADF\ g/100\ g\ DM + 2.626 * N\ g/100\ g\ DM$$

The proportional contribution of each feed item to the diet was calculated to create feed baskets for each livestock category per household per season. For cut and carry feedstuffs, the amount fed was recorded using the quantities reported by the farmer and converted to kilograms using conversion tables found in literature (Lukuyu et al., 2012). Fresh forages and concentrate samples were collected and analysed for DM content. For the contribution of pasture grazing to the diet, the area available per animal category per season was recorded to estimate pasture biomass production.

The dataset originally included 815 farms, but farms that did not report milk yield or did not provide detail on feed and feed management were removed, as well as any outliers. This resulted in a total of 666 farms across the four counties. All research and data collection activities were approved by the International Livestock Research Institute's Institutional Animal Care and Use Committee (IACUC) and Institutional Research Ethics Committee (IREC).

2.3. GHG emission estimations and the agrecalc tool

Survey data were used to calculate farm carbon footprints, namely total emission emissions and EIs, using Agrecalc (Agricultural Resource Efficiency Calculator). Agrecalc was developed by Scotland's Rural College and has been found to be amongst the best-performing carbon accounting tools based on its transparency, methodology and allocation (Sykes et al., 2017). The tool complies with LCA guidelines defined by ISO 14044 and PAS 2050standards. All livestock enteric CH_4 and N_2O emissions from excreta deposited on grazing land use IPCC (2019) Tier 2 country-specific calculations. IPCC (2019) Tier 2 methods which account for dietary characteristics and climate are employed for CH_4 and N_2O emissions from manure management. Direct N_2O emissions from organic and inorganic fertilisers also follow IPCC Tier 2 guidelines. It is important to note that Agrecalc employs UK Tier 2 country-specific emission factors, although the majority of these are comparable with Kenyan emission factors. Nitrous oxide emissions are likely the only notable difference between the UK and Kenyan GHG Inventories. However, due to their relatively small contribution to total emissions, this discrepancy is likely to have a minor impact overall. Moreover, this paper does not present absolute emissions but rather compares emissions between different production systems and the number of CSA practices they have adopted. Therefore, any differences in emission factors would not impact the results.

IPCC (2019) Tier 1 emission factors (EFs) are utilised for crop residues and indirect N_2O emissions related to volatilisation and leaching. Emission estimates for energy usage were calculated using EFs from DEFRA (2012). Emission factors from (Marinussen et al., 2012) were employed for embedded fertiliser emissions, and values from the Dutch Feedprint database (Vellinga et al., 2013) were utilised for purchased feed.

Agrecalc calculates standardised emission estimates in units of carbon dioxide equivalents (CO_2e) using global warming potential over 100 years (GWP_{100}) from the fourth assessment report (IPCC, 2019). Results are expressed as both total emissions per farm and GHG emissions per unit of product (kg CO_2e kg^{-1} of fat and protein corrected milk (FPCM)).

In cases where data were not collected from the survey or where any data were missing, recently published data or standardised estimates were used in their place. For example, milk yields were provided in litres per day, however, emissions are calculated on a yearly basis in Agrecalc in kg FPCM cow^{-1} day^{-1}. Therefore, a conventional 305-day lactation length was assumed to estimate annual milk yields (Kok et al., 2016; Kopec et al., 2020). Similarly, FPCM was standardised to 4 % fat and 3.3 % true protein in line with other recently published Kenyan studies (Ndung'u et al., 2022).

The Agrecalc tool estimates GHG emission for the dairy cattle systems using indirect methods as per the IPCC guidelines (IPCC, 2019). Indirect methods rely on proxy variables to estimate daily feed intake and enteric CH_4 emissions. The daily feed intake (GE, gross energy) is estimated by the summation of different energy requirements. Estimated daily feed intake is then multiplied by a CH_4 conversion factor (Ym) to calculate CH_4 emissions, as with direct emissions estimates.

The proxy variables used to determine energy requirements included in the survey were: liveweight, feed and feeding management and milk yield. As described in Section 2.2, liveweight measurements and certain data for feed and feeding management were recorded based on physical measurements taken at the farms, while the other proxy variables were estimated from farmer recall using survey questionnaires.

2.4. Statistical analyses

To assess the effect of the number of CSA practices on daily milk yield and GHG EIs, the number of CSA practices used per farm was transformed into a categorical variable in order to enhance sample numbers per group and generate a roughly even distribution of samples (Table S1). To achieve this, the number of CSA practices used by each farm was categorised into the following groups: 0, 1–2, 3–4, and ≥5 CSA practices. Multiple linear regression models were used to test for an association between the number of CSA practices and daily milk yield and GHG EIs. To account for the effects of socio-economic and agro-ecological factors on milk yield and GHG EIs, we included "county" in our regression models as a covariate. A post-hoc least significant difference test was applied to indicate which number of CSA practices categories differed from each other at the 5 % level of probability.

Multiple linear regression models were also used to test for an association between each individual CSA practice deemed as potentially beneficial by production system, daily milk yield, and GHG EI. Given high correlations in the use of some CSA practices, these CSA practices were grouped together and one CSA practice per group was included in the linear regression analyses as a proxy for all variables in the group. As such, *Feed preservation* and *Feed supplements* were removed with *Stall feeding and housing* acting as the proxy variable; and *Milk marketing* and *Water harvesting* were removed, with *Fertiliser use* being used as the proxy variable. *Vaccines* was removed due to the minimal use of this CSA practices among all production systems (Fig. S2). For extensive production systems, the individual CSA practices included in the multiple linear regression models were *Improved cattle breeds use*, *Fertiliser use*, *Improved pasture*, and *By-products-feeding.* For semi-intensive production systems, the CSA practices included in the multiple linear regression models were *Improved cattle breeds use*, *Fertiliser-use*, *Improved pasture*, *By-products feeding*, *Feed processing*, *Fodder improvement*, and *Stall feeding and housing.* For no-graze production systems the CSA practices included in the multiple linear regression models were *Improved cattle breeds use*, *Feed processing*, *Fodder improvement*, *Fertiliser use*, and *Stall feeding and housing.*

Due to skewness in data, both daily milk yield and GHG EIs were transformed using the log function. The estimated marginal means presented in the results have been back-transformed in order to provide results that are comparable to results from the scientific literature. All analyses were carried out within the RStudio environment version 2022.12.0 Build 353 for R (version 4.2.1) using the ade4 (Dray and Dufour, 2007), agricolae (Mendiburu and Yaseen, 2020), dplyr (Wickham et al., 2018), ggplot2 (Wickham, 2009), and emmeans (Searle et al., 2023) packages.

2.5. Costing and marginal abatement cost curves

To calculate the costs of implementation of the CSA practices, three workshops were held in three of the four counties surveyed, Baringo, Bomet, and Kericho in early February 2023. Around 30 farmers attended each workshop. At the workshops, farmers were asked to discuss and estimate the costs of implementation of each of the CSA practices including the use of labour, cost of the equipment and infrastructure, and the cost of applying the CSA practice (e.g., fuel use).

Using the average prices reported in the workshops, feed-related CSA practices were adjusted per production system based on the feed basket composition reported in the survey outlined in Section 2.2. Long-term infrastructure investments (e.g., stall infrastructure, water harvesting infrastructure) were annualised for a period of 15 years; land-use changes (e.g., improved fodder establishment, improved pasture establishment) were annualised for a period of 10 years; and the purchase or use of Improved cattle breeds were amortised over the average number of lactation periods of a dairy cow's life per production system according to the data reported in the survey outlined in Section 2.2. Cost estimates were then calculated per litre of milk production by dividing the annual cost estimates per dairy cow by the average annual milk production of a dairy cow in each production system for farms not using any CSA practices, as reported in the survey outlined in Section 2.2.

To estimate the cost of implementation of CSA practices per numeric category of CSA practices implemented (i.e., per use of 1–2 CSA practices, 3–4 CSA practices, and 5 or more CSA practices), the average number of CSA practices used per production system per numeric category of CSA practices was calculated. The proportion of use of each CSA practice used by farms in each of these groups was then calculated. These proportions were then used to calculate overall costs by multiplying the CSA implementation costs by the proportion of farms using that CSA practice, and then by the average number of CSA practices used by farms in that numeric category of CSA practices used for each production system.

Marginal abatement cost curves for each production system by the number of CSA practices used were developed both when accounting for the expected value production increases in milk yield and when these increases were not included to better present the required investment costs and the returns on investment. The value production increases in milk yield were calculated based on the statistical analyses outlined in Section 2.5 per numeric category of CSA practices implemented and per production system and the average milk sale prices reported in the farmer workshops.

3. Results

3.1. Dairy production systems and the use of CSA techniques

The composition of cattle herds differed by production system, as shown in Table 3. No-graze systems had a much lower percentage of male cattle (3 %) compared to extensive systems (14 %) and semi-intensive systems (11 %). On the other hand, lactating cows comprised a greater proportion of the herd in no-graze production systems (36 %) compared to extensive production systems (24 %) or semi-intensive production systems (29 %). Overall, no-graze production systems had fewer average heads of cattle (3.4 per farm) than extensive (4.0 per farm) or semi-intensive (3.92 per farm) production systems. Milk production also varied among production systems, with no-graze farms producing the highest average yield (6.25 L cow^{-1} day^{-1}), followed by semi-intensive farms (4.90 L cow^{-1} day^{-1}) and extensive farms (3.73 L cow^{-1} day^{-1}). This pattern was consistent across the four surveyed counties (Fig. S1).

Only a small proportion (6–7 %) of farms in each production system did not use any CSA practice (Table S1, Fig. S3). While, by definition, there were no KCSAP-supported farms that did not use any of the CSApractices promoted by the project, it was notable that many unsupported KCSAP farms reported using CSApractices across all production systems (Table S1). Overall, between 31 and 39 % of farms used 1–2 CSA practices, while 25–31 % of farms used 3–4 CSA practices, and 23–34 % of farms used five or more CSA techniques. The most used CSA practices used by farms across production systems were *Improved cattle breeds use* and *Fodder improvement* techniques, utilised by more than 50 % of farms (Fig. S2). *Feed preservation, Feed supplements*, and *Improved pasture* CSA techniques were also fairly commonly used (by around 20 % or more farms). More no-graze production systems used *Improved cattle breeds* (~70 %) compared to extensive production systems (~50 %). Similarly, *Feed supplements*, *Feed preservation*, *Feed processing*, and *Stall feeding and housing* were more commonly used by no-graze than extensive production systems. On the other hand, extensive production systems were more likely to adopt *Fodder improvement*, *Pasture improvement*, *Feeding of by-products* (i.e. crop residues), and *Water harvesting* compared to no-graze production systems.

Table 3
Cattle herd composition and average milk yield by production system. Mean number of heads is presented by cattle type followed by the proportion (%) of the herd for which that cattle type accounts in parentheses.

Descriptive variable	Production system		
	Extensive	Semi-intensive	No-graze
Adult males (heads)	0.19 (5)	0.12 (3)	0.00 (0)
Immature males (heads)	0.37 (9)	0.30 (8)	0.11 (3)
Cows (non-lactating - heads)	1.01 (25)	0.80 (21)	0.66 (20)
Lactating (heads)	0.96 (24)	1.13 (29)	1.20 (36)
Heifers (heads)	0.63 (16)	0.81 (21)	0.63 (19)
Calves (heads)	0.78 (20)	0.64 (16)	0.63 (19)
Pre-wean calves (heads)	0.06 (1)	0.11 (3)	0.13 (4)
Total cattle (heads)	4.00 (100)	3.92 (100)	3.38 (100)
Milk yield (litres cow^{-1} day^{-1})	3.7	4.9	6.3

3.2. The effect of the number of CSA practices on milk yields and GHG emission intensities

The multi-linear regression model for extensive dairy production systems showed a significant association between the number of CSA practices used by farms and milk yields at the 5 % level of probability ($p = 0.032$) (Table 4). Although the least significant difference test could not distinguish differences among farms with different numbers of CSA techniques at the 5 % level of probability, a visual inspection of the data coupled with the linear regression results suggests that there was a trend whereby the more CSA practices that are used by farms, the greater the milk yield for extensive dairy production systems (Fig. 2A).

A similar pattern was also observed for semi-intensive production systems. The linear regression model indicated a difference among farms using different numbers of CSA practices at the 10 % level of probability ($p = 0.068$) (Table 4). A visual inspection of the data suggests that farms that used five or more CSA techniques had higher milk production than farms using fewer or no CSA practices (Fig. 2B). The linear regression models for no-graze dairy production systems, however, indicated no significant relationships between the number of CSA techniques used and milk yields ($p = 0.751$).

Table 4
p-value of the multi-linear regression analyses assessing the effect of the number of Climate Smart Agriculture practices used on either milk yield or GHG emission intensities.

Production system	Milk yield (p-value)	GHG emission intensities (p-value)
Extensive	*0.032**	*0.065*.
Semi-intensive	*0.068*.	0.157
No-graze	0.751	0.829

* Significant at the 5 % level of probability.
Significant at the 10 % level of probability.

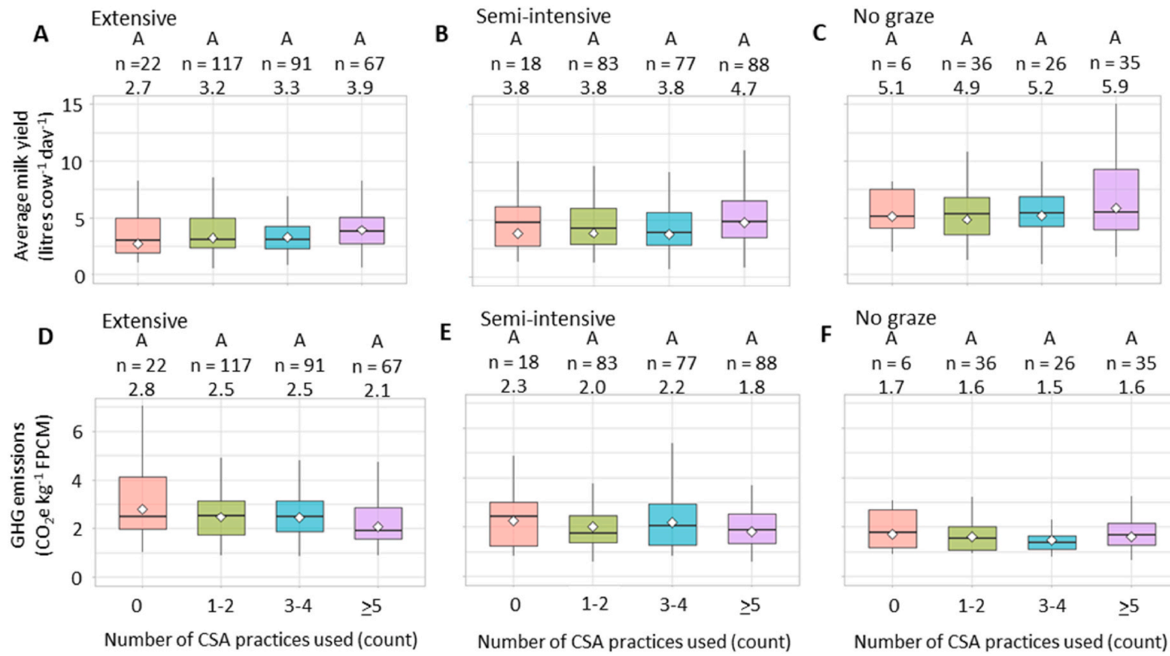

Fig. 2. Boxplots presenting daily milk yield by number of CSA practices used and production system across all counties (plots A = Extensive production system; B = Semi-intensive production system; C = No-graze production system); and average GHG emission intensities by number of CSA practices used and production system across all counties (plots D = Extensive production system; E = Semi-intensive production system; F = No-graze production system). Numbers at the top of each plot indicate means (also indicated as white square within boxplot), while n = the number of samples, and the letters indicate results of the post-hoc least significant difference test, with different letters indicating differences at the 5 % level of probability. Outliers outside the upper interquartile not shown, for boxplots with outliers see Fig. S4.

The linear regression results indicated that the number of CSA practices used by extensive production systems was associated with GHG EIs at the 10 % level of probability ($p = 0.065$) (Table 4). While the least significant difference test found no significant difference at the 5 % level of probability, visual inspection of the data suggested that the more CSA practices a farm used, the lower the GHG emission intensities (Fig. 2D). The linear regression results found no statistical association between the number of CSA techniques used by farms and GHG EI for semi-intensive or no-graze production systems ($p = 0.157$ and 0.829 respectively – Table 4, Fig. 2E and F). When assessing total farm GHG emissions by the number of CSA practices, no statistical pattern was observable at the 10 % level of probability ($p = 0.193$ for extensive systems; $p = 0.403$ for semi-intensive systems; and $p = 0.681$ for no graze systems).

The multiple linear regression models assessing the effects of individual CSA practices on milk yields and GHG EI revealed a significant effect for *Improved pasture* on milk yields at the 1 % level of probability ($p = 0.009$) and GHG EI at the 10 % level of probability ($p = 0.052$) for extensive production systems. As would be expected with the use of *Improved pasture*, milk yields were seen to increase, while GHG EI were seen to decrease (Tables S2 and S3).

For semi-intensive systems, *Improved cattle breeds use* and *Fertiliser use* displayed significant effects on milk yields at the 5 % ($p = 0.01$) and 10 % ($p = 0.07$) level of probability respectively. While the effect on milk yields from the use of Improved cattle breeds was positive, the effect from fertiliser use was negative (Table S4). *Fodder improvement* displayed a significant effect on GHG EI for semi-intensive systems at the 10 % level of probability ($p = 0.08$). As expected, the relationship was negative suggesting a decrease in GHG EI with the use of improved fodder (Table S5).

Fodder improvement also displayed a significant effect on milk yields in no-graze production systems at the 10 % level of probability ($p = 0.06$), however this relationship was negative, indicating a reduction in milk yields with the use of improved fodder (Table S6). *Improved cattle breeds use* was the only CSA practice in no graze systems that displayed a significant effect on GHG EI ($p = 0.002$). As expected, the use of this CSA practice had a negative association with GHG EI (Table S7).

3.3. Marginal abatement costs for the use CSA practices

The costs associated with implementing different CSA practices varied by production system, with the CSA practices generally being cheaper per litre of milk produced in no-graze production systems, followed by semi-intensive production systems. CSA practices were usually most expensive for extensive production systems, except for *Fodder improvement* because this accounted for a much smaller proportion of the feed basket in these systems (Table 5 – see Table S8 for an overview of the input costs and assumptions used to calculate costs of CSA practices

Table 5
Estimated annual cost of implementation of different CSA practices by production system per litre of milk produced.

CSA practice	Production system		
	Extensive (USD $ litre milk^{-1})	Semi-intensive (USD $ litre milk^{-1})	No-graze (USD $ litre milk^{-1})
Feed supplements	0.19	0.14	0.10
Stall infrastructure and housing	0.04	0.03	0.02
Water harvesting	0.03	0.02	0.01
Feed processing	0.08	0.10	0.07
Feeding of by-products	0.06	0.02	0.01
Milk marketing	0.00	0.00	0.00
Improved cattle breeds use	0.14	0.09	0.06
Fertiliser use	0.01	0.01	0.01
Improved pasture	0.04	0.02	0.02
Fodder improvement	0.02	0.03	0.05
Feed preservation	0.01	0.01	0.01

per litre of milk). Among the most expensive CSA techniques per litre of milk were *Feed supplements*, *Feed processing* and *Improved cattle breeds use*. However, despite their relatively higher costs, these practices were also among those most commonly used (Fig. S2).

When assessing the cost of the number of CSA techniques used and the GHG EIs abatement potential, it is evident that the cost of the implementation of CSA practices per litre of milk produced is much higher for extensive systems compared to semi-intensive or no-graze systems. However, the potential for GHG EI abatement is also much greater for extensive systems (Fig. 3A, B, and 3C).

When integrating the potential benefits of using CSA practices (milk yield value-production increases) in the cost calculations, the MACCs change dramatically (Fig. 3D, E, and 3F). Importantly, the net costs decrease most under the extensive production systems, with these farms generating more value through the implementation of CSA practices than it costs implementing them. According to these calculations, the use of five or more CSA techniques is most cost-effective, not only generating greater overall value, but also providing the greatest GHG EI reductions. In the semi-intensive and the no-graze production systems, net costs for the implementation of CSA practices meant farms could have to pay more to implement 1–4 CSA practices than they would generate in enhanced value production. However, when implementing five or more CSA techniques, then farms would generate more value through milk production than it costs to implement the CSA practices.

4. Discussion

4.1. CSA practices enhance milk yields and GHG emission intensities abatement potential

Our findings provide evidence that the use of CSA practices by dairy farms in Kenya can increase milk yields and reduce GHG EI (Table 4 and Fig. 2). Furthermore, while we found no evidence that overall farm-level GHG emissions decreased with the number of CSA practices used, which is more likely to be dependent on herd size, our results suggest that the more CSA practices used, the higher the milk yields and the greater the GHG EI abatement potential. This is an important novel finding as limited in situ experimental evidence exists assessing the potential of CSA practices to reduce GHG emissions, especially those related to livestock production such as improved livestock breeds and feed (Anuga et al., 2020). Notwithstanding the paucity of experimental evidence in this area, the results corroborate the few other studies that have found important gains in milk yield and GHG EI mitigation potential with the use of common CSA practices (Abhilash et al., 2021; Gerber et al., 2011; Paul et al., 2020; Thornton and Herrero, 2010).

The widespread use of some CSA practices across all the farms

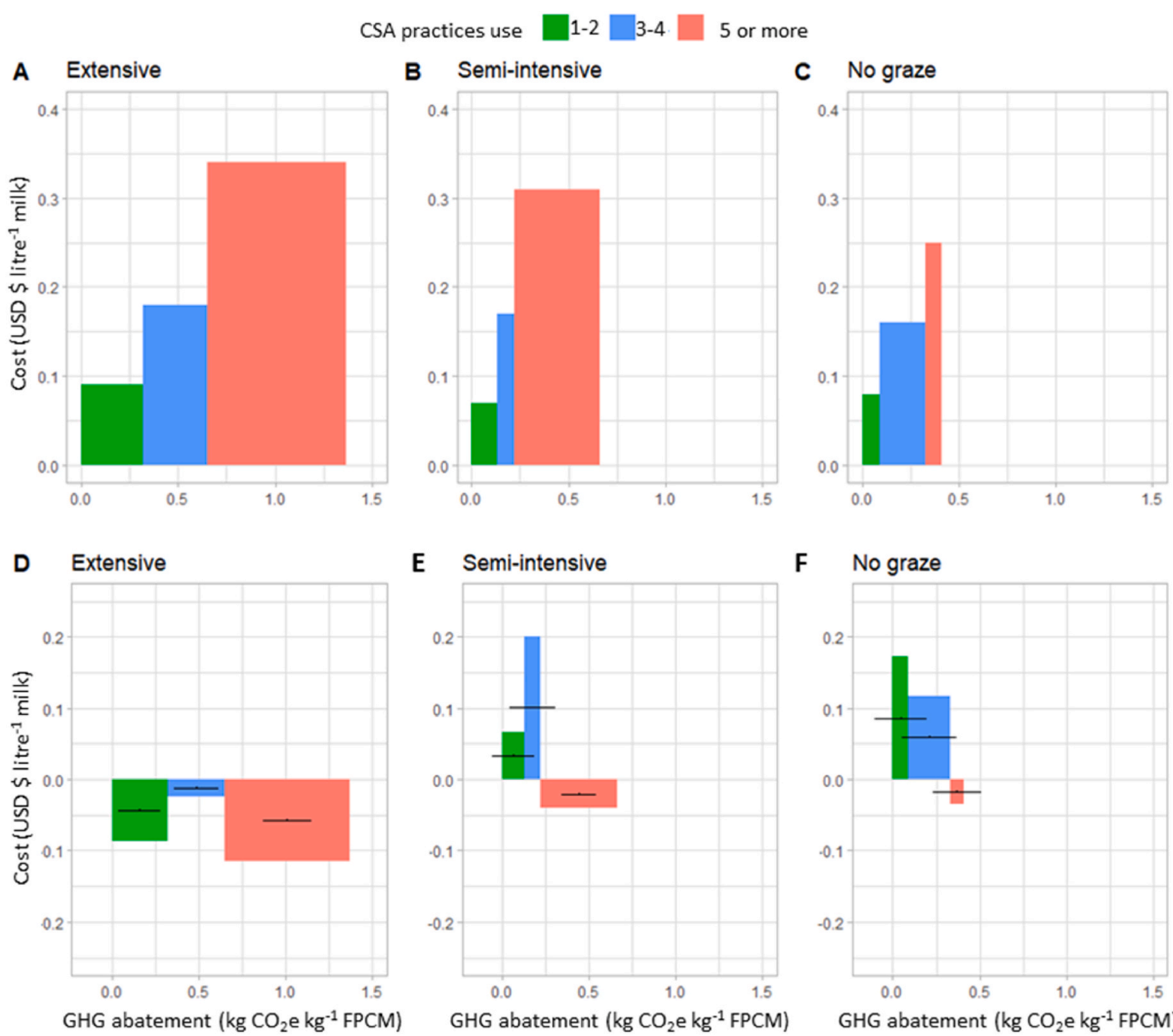

Fig. 3. Marginal abatement cost curves for the use of different numbers of CSA practices by production system across all counties. Plots A, B, and C present cost of implementation of CSA techniques when return on investment (additional milk production value) is not included. Plots D, E, and F present cost of implementation of CSA techniques when including additional milk production value derived from the use of CSA practices. Vertical (cost) and horizontal (GHG emissions intensities) bars on plots D, E, and F represent standard errors.

surveyed irrespective of direct participation in the project (Table S1) suggests that the use of these practices is relatively common in the study sites. It is not possible with the current data to assess whether this wider use of CSA practices in the broader community is a result of spill-over effects from the project, or whether the use of CSA practices was common before the project began. It is also important to note that while the results in the current research do not reveal a pattern in the proportional effect of using additional CSA practices, we would expect diminishing effects with increasing number of CSA practices used as it would be expected that by reducing yield gaps (through the use of CSA practices), proportional gains for each additional CSA practice would decrease. This pattern of diminishing effect was indeed found in a study assessing the effects of the use of CSA practices on crop yields in Pakistan where yields tended not to increase after farmers used at least four CSA practices (Sardar et al., 2021). The reason why the pattern of diminishing effect is not observed in our study is likely due to the inadequate number of samples (farms) in the different groups of CSA practices used, and especially the smaller number of farms that used higher numbers of CSA practices (Fig. S1).

Another important finding from the current research is that the positive effect of CSA practices on milk yields and GHG EI were not apparent in all dairy production systems. Specifically, the beneficial effects of the use of CSA practices appear to be most evident in extensive production systems, less evident in semi-intensive production systems, and imperceptible in no-graze systems (Fig. 2, Table 4). It is possible that this finding is an artefact of the smaller number of farms surveyed with no graze systems ($n = 103$), and especially using no CSA practices in no graze systems ($n = 6$, Table S1), making it more difficult to observe statistical patterns. Another reason could be that extensive systems had lower milk production overall. Therefore, the same increase in milk production (eg, 1 l) will have a bigger effect, as the percentage increase in milk yield and reduction in GHG emission intensity will be greater.

However, it could also be a result of the effect of diminishing returns, whereby proportional increases in milk yields and GHG EI abatement potential are more difficult to achieve the closer to the potential yields they become. Furthermore, no graze production systems may already be using a number of CSA farming practices not recorded by our farm survey which will likely decrease the effect of the use of additional CSA practices (as mentioned previously). As outlined in Gerber et al. (2011), GHG emissions per kg FPCM rarely decrease below 1.5–2.0 kg CO_2e per kg FPCM (similar to the levels observed in no-graze production systems in our research), irrespective of any increase in milk yields.

4.2. Upfront investment costs as potential barrier to lower GHG emission intensities and more profitable dairy production

Similar to the finding that the use of CSA practices were associated with greater GHG EI abatement potentials and increases in milk yields in extensive production systems compared to the other production systems, costs for the use of CSA practices in these production systems were also found to be higher (Table 5 and Fig. 3A, B and 3C). For example, while it cost farms around USD \$0.25 L^{-1} to use five or more CSA techniques in no-graze production systems, the cost of using five or more CSA techniques in extensive production systems was around 36 % more expensive at around USD \$0.34 L^{-1}. This is at least partly due to the fact that milk yields for extensive production systems are much lower than for semi-intensive or no-graze production systems (Fig. 2 and S1) thus heightening the proportional costs for the implementation of CSA practices. Notwithstanding these findings, it is also apparent that when net benefits are factored into the cost calculations, the use of CSA practices are comparatively much cheaper for extensive production systems than semi-intensive or no-graze production systems (Fig. 3D, E, and 3F). Indeed, the use of CSA practices provides net income increases for extensive production systems irrespective of how many CSA practices were used. This compares with semi-intensive and no-graze production systems where only the use of five or more CSA techniques resulted in enhanced value production.

This finding is important as it suggests that despite the net financial benefits for extensive farms, it is likely that the higher upfront costs constitute an important barrier to the greater use of CSA practices in extensive production systems (production systems that are also likely to be the least resource endowed), diminishing the likelihood for GHG emission mitigation in these farming systems. A number of studies have shown that not only are upfront investment costs important barriers to the use of CSA practices (Branca et al., 2021; Jones et al., 2013; Khatri-Chhetri et al., 2017), but the least resource-endowed farms are also more risk averse and less likely to experiment and begin using new CSA innovations (Kassa and Abdi, 2022; Ngoma et al., 2018). This reinforces the argument that despite the potential benefits of CSA practices, important structural barriers need to be resolved such as improved access to finance and markets for smallholders before such technologies will be more widely used (Bhattacharyya et al., 2020; Descheemaeker et al., 2016).

4.3. Marginal abatement cost curves in low and middle income countries

The use of MACCs to assess the trade-offs involved in the use of GHG mitigation measures such as CSA practices is a novel methodological approach in the livestock production sector in low- and middle-income countries. To the authors knowledge, only one other such study has been published in the scientific literature before (Duffy et al., 2021). Moreover, most MACC assessments undertaken in high income countries in the livestock sector rely on expert opinion and literature values (Jones et al., 2015). The current study has extended these studies by applying the MACCs both in a developing context in Kenya and by basing the analyses on data collected in situ. In doing so, the data and results presented in the current study are likely to more accurately represent the true costs and benefits for the use of CSA practices by smallholder farmers in Kenya.

This is an important development at a time that the government of Kenya is aiming to mainstream CSA practices in livestock production having committed to ambitious targets both in terms of milk production and GHG emissions reductions from livestock (Ministry of Agriculture, Livestock, Fisheries and Irrigation, 2010; Ministry of Agriculture, Livestock, Fisheries and Irrigation, 2019a; 2019b; Ministry of Environment and Forestry, 2020). In this regard MACC assessments are important tools to translate scientific information into information that is practicable by policy-makers, helping inform policies that facilitate farm-level mitigation strategies (Eory et al., 2018; Glenk et al., 2014; Jones et al., 2015).

While the results presented in this study pertain to a relatively small area in central-eastern Kenya, the farming systems types identified in the research are typical examples in the sub-humid and semi-arid regions of East Africa (Ministry of Agriculture, Livestock, Fisheries and Irrigation, 2020). As such it is likely that the results are generalisable to a larger geographical region within Kenya, East Africa and potentially more broadly. More importantly however, this case study provides a potential cost-effective template for the application of MACC to inform GHG mitigation policies at different scales and in different geographies. Such modelling approaches, as noted above can be extremely powerful tools for translating scientific data into practicable policy recommendations. Moreover, such analyses can fit into broader policy-making frameworks and processes that aim to upscale CSA practices (Selbonne et al., 2022).

4.4. Policy implications

Our results suggest that targeting extensive farm production systems may be one of the most effective and efficient ways of increasing milk production and reducing GHG EI in the locations studied. This does not mean changing extensive production systems into intensive production systems, but working with farmers to explore the use of appropriate technologies for their particular contexts and production systems. As articulated in Hammond et al. (2020) and Hyland et al. (2016), the targeting of farm types according to their specific opportunities and constraints enhances the likelihood of success for rural development projects.

The multiple linear regressions assessing the effects of individual CSA practices did not clearly show which CSA practices were more or less effective in increasing milk yields and decreasing GHG EI for which farm production types in the current study. Indeed, in some instances the results revealed unexpected findings that suggested that some CSA practices were associated with lower milk yields (i.e., the use of fertilisers in semi-intensive systems and improved fodder in the no graze systems) (Tables S2–S7). It is likely that this is a result of the experimental design where farms used multiple CSA practices at the same time, making it difficult to tease out precise impacts of individual CSA practices on milk yields and GHG EI. Nevertheless, the individual CSA practices that displayed significant positive associations with milk yields and negative associations with GHG EI such as the use of Improved cattle breeds and feeding practices (improved pasture and fodder), align with other studies in the region (Bateki et al., 2020; Ndung'u et al., 2022; Wilkes et al., 2020). Further research in this regard is recommended as currently there is a lack of deep understanding in terms of the costs and benefits, and synergies and trade-offs, of different CSA options in different types of farming systems (Thornton et al., 2018).

Notwithstanding these constraints in our data, it is still apparent that the CSA practices are used by different production systems to different degrees (Fig. S2). For example, no-graze production system farms were more likely to use practices such as improved feed preservation, feed supplements, and feed processing, while extensive production systems were more likely to use improved pasture and by-products feeding techniques. This is important as it confirms that different CSA practices will be suitable for different types of farms and production systems even within the same geographical contexts. We therefore concur with Notenbaert et al. (2017) that a "toolbox approach" may be one of the most effective ways to work with farms to explore the potential benefits of CSA practices as opposed to approaches where single technocratic solutions are promoted.

These results also shed light onto potential policy mechanisms for enhancing the likelihood that farmers begin to use more CSA practices. As found in this research and others, upfront investment costs present one of the largest barriers to the use of certain CSA practices (Bhattacharyya et al., 2020; Steenwerth et al., 2014). As such, policy mechanisms should specifically aim to facilitate financing for upfront investment costs and decrease the perceived risks involved in investing in CSA practices (Engel and Muller, 2016; Lipper et al., 2018; Volenzo Elijah et al., 2021).

Examples where such mechanisms have been successful in a number of contexts include conditional or unconditional microcredits related to the use of CSA practices, smallholder carbon market projects, smallholder livestock and crop insurance, and payment for ecosystem services schemes (Alix-Garcia et al., 2015; Engel and Muller, 2016; Gauvin et al., 2010; Lee, 2017; Meinzen-Dick et al., 2014; Ogunyiola et al., 2022). However, while there is growing interest in facilitating access to finance for smallholder farmers to support low-emission agricultural intensification, little is understood about how to deploy climate finance effectively and equitably in order to stimulate large scale use of CSA practices (Odhong' et al., 2019). Similar to VolenzoElijah et al. (2021), we therefore argue that further research on the characteristics of cashflows associated with costs of CSA practice use is undertaken, along with a detailed exploration of suitable financing mechanisms given smallholders' constraints to access finance.

5. Conclusion

Our results provide further empirical evidence that common CSA practices enhance milk yields and reduce GHG EI in dairy production systems in Kenya. However, these benefits were not equally experienced by the different production systems, with a clear statistical effect, where the use of more CSA practices were associated with greater milk yields and GHG EI savings, only apparent in the extensive production systems. It is likely that the limited impacts of CSA practices in the more intensive dairy production systems is a result of the fact that these systems are already producing milk yields closer to their maximum potential yields. Importantly, we found that the cost for employing the CSA practices was higher for extensive production systems, although when factoring in the benefits of using CSA techniques the net increases in value production were also highest for these systems. This suggests that upfront investment costs are important barriers to the use of CSA practices. We argue that our results provide strong evidence that the targeting of farms and the use of "toolbox" approaches to rural development projects are likely to be more successful than the promotion of a single technocratic solution. Furthermore, for CSA practices to be used more widely, our results suggest that policy and financing mechanisms need to be established to facilitate financing and to decrease the perceived risks involved in investing in CSA practices.

CRediT authorship contribution statement

Mark E. Caulfield: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation. **Michael Graham:** Writing – review & editing, Visualization, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **James Gibbons:** Writing – review & editing, Supervision, Software, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Louise McNicol:** Writing – review & editing, Methodology, Investigation, Formal analysis, Data curation. **Prysor Williams:** Writing – review & editing, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Dave Chadwick:** Writing – review & editing, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Jesse Gakige:** Writing – review & editing, Methodology, Investigation, Formal analysis, Data curation. **Andreas Wilkes:** Writing – review & editing, Validation, Methodology, Investigation, Formal analysis, Data curation. **Bernard Kimoro:** Writing – review & editing, Methodology, Investigation, Conceptualization. **Claudia Arndt:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2025.145281.

Data availability

Data will be made available on request.

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