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Farming systems' typologies analysis to inform agricultural greenhouse gas emissions potential from smallholder rain-fed farms in Kenya

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ABSTRACT

Most sub-Saharan Africa smallholder farming systems are highly heterogeneous. Direct quantification of greenhouse gas emissions from these farming systems is hampered by diversity at farm-level. Each farm contributes differently to greenhouse gas (GHG) emissions and consequently GHG inventories. Typologies can be used as a mechanism of addressing farming systems' heterogeneity by grouping them into specific farm types. With the GHG quantification simplification initiatives in mind, we developed smallholder farm typologies based on soil fertility inputs. We assessed nitrogen application rate, soil fertility management technologies and the socio-economic factors diversity among the farm typologies in the central highlands of Kenya. We used data from a cross-sectional household survey with a sample size of 300 smallholder farmers. We characterized the farm types using principal component analysis (PCA). To develop farm typologies, we subjected the PCA-derived typologies related factors to cluster analysis (CA). The results showed six farm types: Type 1, comprising cash crop and hybrid cattle farmers; Type 2, comprising food crop farmers; Type 3, composed of coffee-maize farmers; Type 4, comprising millet-livestock farmers; Type 5, comprising highly diversified farmers, and Type 6, comprising tobacco farmers. Land size owned, total tropical livestock unit, the proportion of land and nitrogen applied to different cropping systems were significant in the construction of farm typologies. Univariate analysis showed the household head's level of education, hired labour, group membership, access to extension services, and proportion of income from cropping activities as critical factors influencing farm typologies in the study area. This study demonstrates the importance of smallholder farm typologies in identifying greenhouse gas emissions hotspots, designing quantification experiment and policy framing. We concluded that policies and intervention measures targeting climate-smart agriculture at smallholder farms

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should consider not only farm-level soil fertility management technologies but also socio-economic characteristics that influence their adoption.

Introduction

Smallholder farms play a substantial role in ensuring food security worldwide [30,55,73,83]. They support between 70 and 80% of the rural population [24] and therefore, vital in enhancing rural dietary supply and alleviating poverty [34,35]. In Kenya, for instance, smallholder farming systems contribute about 33% and 27% of gross domestic product (GDP) directly and indirectly, respectively [43]. However, climate variability remains a major threat to agricultural productivity and social development, especially in developing countries such as Kenya [16,71]. The increased effects of climate variability on most smallholders' farming systems call for the use of a robust methodology to enhance adoption of adaptation and mitigation measures that result in improved productivity and thus climate-smart agriculture (CSA). Studies have revealed that socio-economic, institutional and biophysical factors influencing adoption of CSA technologies differ across agroecological settings [45,85].

Smallholder farming systems in sub-Saharan Africa (SSA) produces a limited amount of greenhouse gas emissions (GHG) [79], and which can be an essential entry point in climate variability mitigation. However, only a few studies have documented GHG emissions from smallholder agricultural farming systems in SSA resulting to huge data gap [53,74,81]. This data gap has resulted to uncertainty in national and regional GHG inventories, adding further difficulties for the developing countries to accurately report their nationally determined contributions (NDCs) to the United Nations Framework Convention on Climate Change (UNFCCC) as per the Paris Agreement [78]. Further, smallholder farming systems are highly heterogeneous in terms of farm enterprises and are faced with a myriad of threats such as climate variability, land degradation, soil fertility decline, population pressure, land fragmentation and decrease in agronomic land [40,57,64]. These dynamics further constrain accurate reporting of smallholder farming systems GHG emissions and framing policies for mitigation.

Typologies provide bases for simplifying heterogeneous farming systems and analyses [21]. Typologies reduce heterogeneous farms to similar coherent groups that can be used to infer certain characteristics. For instance, Amadu et al. [5] used farm typologies to analyse the adoption of climate-smart agricultural technologies in Southern Malawi while Lopez-Ridaura et al. [50] assessed the impacts of CSA, improved animal husbandry, and climate shocks on food security in India. Given the applicability of farm typologies elsewhere, there is, therefore, a pressing need to construct smallholder farming systems typologies that can guide in designing of GHG emissions quantification experiments, hot spots identification and policy framing on climate adaptation and mitigation that aims at improving crop yields thus food security in SSA.

Smallholder farms in SSA exhibit diversity within and between agro-ecologies, and likewise within the same farm type [87]. The heterogeneity of these farms impedes implementation of governments' policies, interventions, mitigation, adaptation, and technological measures [22,29] including GHG emissions quantification, accounting and reporting. This is as a result of each smallholder farm being unique, and hence if interventions are to be most effective, site-specific measures are required. However, such an approach is somewhat impractical and expensive at large scale (countrywide and even regional). For climate-smart agriculture policies to be effective, they need to be grounded in civil societal and smallholder farmers' context [17], with thorough involvement of all relevant stakeholders [15]. One way of doing so is developing coherent farm types within the heterogeneous smallholder farming systems that serve as entry points in addressing the farms' diversity, designing direct quantification experiments, and formulating community-based climate action policies. For farm typologies to be adequately effective in informing agricultural GHG emissions hotspots and mitigation, they should be tailored around farm management practices that can result in the mitigation of GHG emissions.

To meet food demands for the ever-growing population, cope with declining soil fertility, and increased droughts' severity afflicting smallholder farming systems in SSA, there are concerted efforts towards diversification and intensification of agricultural production [68,92,94]. Diversification and intensification of farming systems complicate GHG emissions quantification and mitigation. For instance, despite the novel gains in the adoption of integrated soil fertility management (ISFM), an agricultural production intensification mechanism [59,65,93], existing analyses of its contribution to GHG remain scanty despite prior claims of its relevance [25]. Since most of the farmers in the central highlands of Kenya use inorganic fertilizer and animal manure sole or in combination [51,62], a key nitrogen source in smallholder farming systems that can contribute significantly to GHG emissions, there is need to develop farm typologies based on the soil fertilization to guide GHG quantification and climate mitigation.

Several studies have characterized farming systems in Kenya to enhance agricultural productivity and guide policy formulation [40,41,47,64,82,87,90]. Only a few studies have been conducted to generate farm typologies to aid GHG emissions quantification in the central highlands of Kenya [75]. Further, due to the dynamism of the smallholder farming systems, farm typologies become obsolete with time and need continuous updating [3]. The farming systems exhibit diversity even in socio-economic characteristics [87], which might profoundly influence resources available to adopt adaptation and mitigation measures. Further, the choice of variables involved in creating farm types is objectives-based. With the GHG quantification simplification initiatives in mind, we characterized smallholder farming systems in the central highlands of Kenya. We tested two hypotheses. First, we posit that the intensity of soil fertility management. (in terms of nitrogen application rates) is influenced by the farm typologies (e.g., [19,87,88]). Second, we conjecture that socioeconomic factors affecting the adoption CSA practices and the emissions of GHGs vary by farm typologies in Kenya as noted in prior studies elsewhere (e.g., [5,35,75]).

Our study contributes to the state-of-the-art literature on CSA adoption (e.g., [5,45,52]) and GHG mitigation (e.g., [25,36,53]). Specifically, we make three contributions. First, we derive farm typologies that can be used in identifying greenhouse gas emissions hotspots and designing direct quantification experiments. Second, we provide insights on GHG accounting, reporting, and mitigation from heterogeneous smallholder farming systems through farm typologies. Third, we provide a means to guide farmers' socio-economics tailored policy framing on GHG quantification and mitigation based on coherent farm types, hence enhancing adoption of mitigation and adaptation interventions, thus promoting sustainable agriculture.

Materials and methods

Study site description

The study was carried out in two sub-counties (Maara and Meru south) in Tharaka-Nithi County, Kenya, which covers an area of 732.9 km^2 excluding Mt. Kenya forest (Fig. 1). The study area lies between 37° 18′ 37″ & 37° 28′ 33″ East and 00° 07′ 23″ and 00° 26′19″ South on the eastern slopes of Mt. Kenya with an attitude of 600 m to 1830 m above sea level.

The site receives bi-modal rains; with long rains season starting from March to June and short rains season from October to December [67], annual rainfall range from 600 to 1800 mm [37]. Annual mean temperature ranges from 14 °C to 17 °C in the highlands and 22 °C to 27 °C in the lowlands with a long-term average temperature of 20 °C (Jaetzold et al., 2006). The study covered six agroecological zones (AEZ): Upper midland zone 1 (UM1), a coffee tea zone; Upper midland zone 2 (UM2), a marginal coffee zone; Upper midland zone 3 (UM3) a sunflower-maize zone; Lower midland zone 3 (LM3) a cotton zone; Lower midland zone 4 (LM4) a marginal cotton zone; and Lower midland zone 5 (LM5) a millet livestock zone (Jaetzold et al., 2006) (Fig. 1). The soil type is predominantly deep, well-drained, highly weathered *Humic Nitisols* with moderate to high inherent fertility.

The study area is principally maize growing zone with a mean farm size of 1.0 acre per household [62]. Predominant soil texture is clayey [66]. Majority of the smallholder farming systems are rain-fed with minimal use of fertilizers and typically non-mechanized [66]. The major socio-economic activities are agriculture and livestock rearing, especially tea, maize, coffee and dairy farming.

Farm typologies concept and application in climate action policy framing

Smallholder farming systems are socially dissimilar and spatially heterogeneous [87]. Several household variables such as assets, livelihood strategies, farm management socio-economics, biophysical resource, farm performance, farm inputs and dietary access have been used to construct farm typologies [40,41,77,82]. Variables involved in farm typologies construction are chosen based on research objective and differ among studies [3,4,86,87]. As shown in Fig. 2, the first step in creating farm typologies in selecting input variable to be used. Our study used nitrogen fertilizer application from different cropping systems to construct smallholder farming systems typologies.

Step by step comparison of farm functioning, expert knowledge, participatory ranking, and multivariate analysis are the four main methods used in categorizing smallholder farming systems [3]. Step by step comparison of farm functioning is a manual farming systems characterization method that emphases on tactical and strategic selection of the farmers and overall household objective [48]. This method is data extensive as it needs a lot of data to be collected using survey method from a stratified sample [48]. Consequently, this manual analysis of data and the creation of farm typologies has been superseded by statistical techniques [4]. The expert knowledge typologies construction techniques use farm clusters identified by farmers, local experts or key informants [77], thus can be implemented over a shorter time. The participatory ranking technique involves the classification of households based on observable assets by knowledge experts [44]. Finally, the multivariate analysis uses statistical data analysis such as principal component analysis (PCA) commonly referred as 'dimensional data reduction' and clustering analysis (CA) to group farming systems [4,40,96]. The multivariate technique is widely preferred over the three because of its reproducibility and integral statistical procedure [40,77]. Therefore, we used multivariate analysis in this study to create smallholder farming systems typologies.

Farming households' socio-economic factors influence farmers' acceptance of any intervention measure [39,69]. Hence, for intervention measures aimed at enhancing food security and GHG emissions mitigation to be accepted by society, they should match with societal socio-economic status [18]. Since most of the typologies are constructed using variables that have a direct influence on the research theme, for example, Tittonell et al. [87] were on soil fertility, Amadu et al. [5] and Makate et al. [52] were on climate-smart agriculture, and Aravindakshan et al. [6] were on agrarian change, there is need to integrate them with households' socio-economic context to enhance their acceptability. Our study used multinomial logistic regression

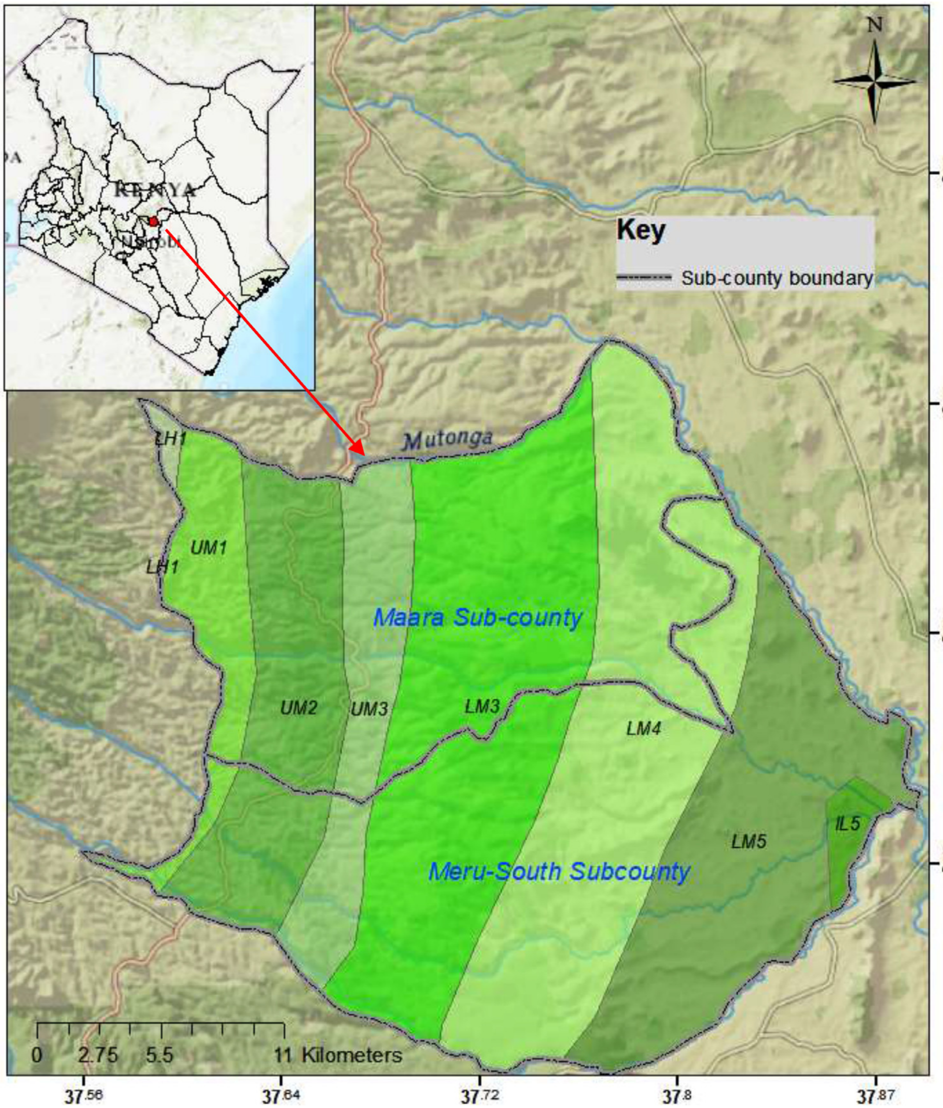


Fig. 1. Map showing the study area.

(MNLR) to analyse the farming households' socio-economic diversity among the farm typology, a primary determinant for outlining community-orientated policies and intervention measures (Fig. 2).

Farm typologies guide researchers, policymakers, and extensions officers on farmers' interwoven intervention mechanisms [22,50]. Our derived farm typologies can be instrumental in identifying environmental hotspots (GHG emissions hotspots), designing GHG quantification experiments, aligning the typologies with farming households' socio-economic characteristics, and promoting climate-smart agricultural technologies. Further, our farm typologies can be used in framing climate-smart action and sustainable agricultural diversification and intensification policies which are vital in promoting food security.

Sample size and sampling strategy

The sample size was calculated using the Cochran formula [8].

$$n = \frac{z^2 pq}{E^2} = \frac{1.96^2 \times 0.5(1-0.5)}{0.0565^2} = 300 \quad (1)$$

Where: n = Sample size, z = z value (e.g. 1.96 for 95% confidence level), p = percentage picking a choice, expressed as decimal (0.5), q = 1-p and E = 5.65% allowable error, expressed as decimal (0.0565).

The study design and implementation was a cross-sectional survey. The multi-stage sampling procedure was used to determine the interviewed households. First, Meru South and Maara sub-counties in Tharaka-Nithi County were purposely

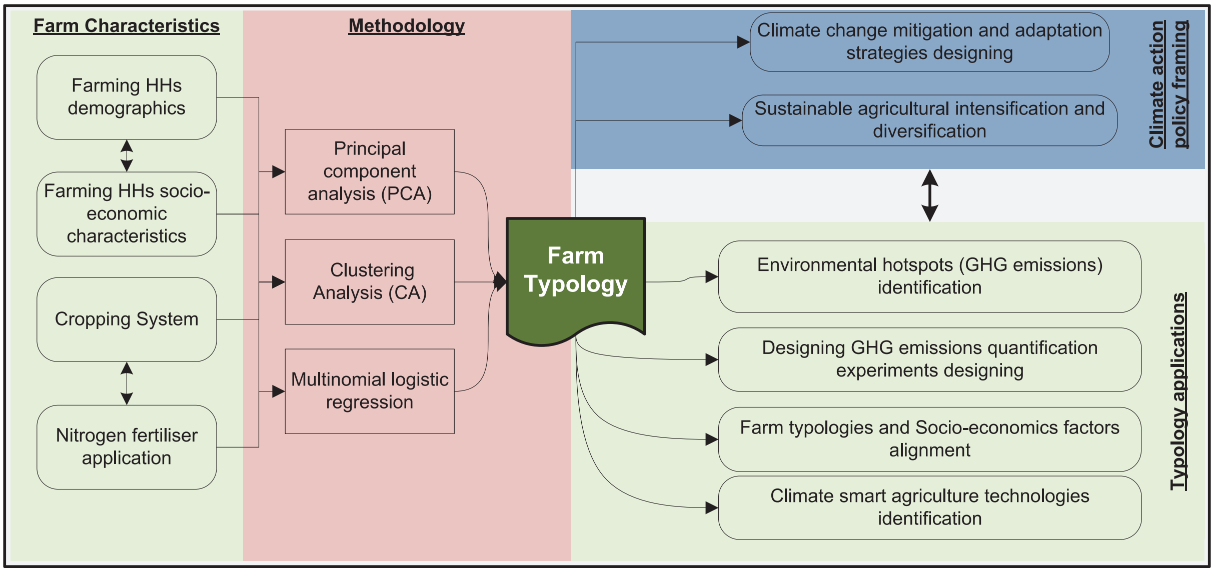


Fig. 2. Conceptual framework: farm typology derivation and applicability.

selected based on previous ISFM studies conducted in the area that could influence GHG emissions. Secondly, total sampling was used to select all ten wards in the selected sub-counties, where primary data were collected at the household level. Thirdly, probability proportionate to size sampling method was used to calculate the number of households (the sample size (n)) to be sampled in each ward using a sample frame obtained from respective agricultural offices at the ward level. The total number of farming households (N) in each ward was divided by the sample size to obtain the interval size (k). Finally, a simple systematic sampling procedure was used to collect data in each ward. The first household in each the ward was randomly selected; afterwards, each k^{th} farming household in the list was sampled.

Household data collection

Data collection was implemented using a semi-structured interview schedule, following pre-testing and appropriate modification. Household heads or most senior family member in their absence was interviewed. The study relied on farmers' farm records and remembrance of preceding six cropping seasons and alterations at the farm level. Three years were considered satisfactory to elucidate agricultural GHG emissions quantification. The interview schedule had questions on farm identity, socio-capital, cropping activities, soil management, land conversion history, organic resources management, farmer's perceptions on climate variability, livestock systems, demographics and wealth characteristics. The interview schedule was administered using Open Data Kit (ODK) mobile app using trained enumerators.

Data processing

Basic conversions were executed for various variables to obtain standard values. Nitrogenous (N) fertilizer application rate was calculated from nutrient concentration ratio. Nitrogen applied from manure was converted using 2.1% N for goat, 1.4% for cattle, and 3.1% for poultry [11,42]. Total tropical livestock unit (TLU) was calculated for each livestock where 1 TLU is equal to 1 mature cow of 250 kg [20]. The TLU for each livestock was determined following Jahnke [38] whereby a cattle, sheep, goat, pig, chicken, duck, rabbit has a TLU of 0.7, 0.1, 0.1, 0.2, 0.01, 0.03, and 0.02, respectively. Afterwards, the TLU was summed for each household. Household wealth asset index was determined using the Bill & Melinda Gate Foundation [13], 2010) guide, which assigns a weight to each household asset. Finally, households' income generated from crops, livestock and remittance was converted to percentage of the total estimated income.

Multivariate analysis

The study variables were checked for accuracy and consistency, after which one household was eliminated from the sample; hence, a total of 299 respondents were subjected to statistical analysis. Principal component analysis (PCA) and cluster analysis (CA) were consecutively used to construct farm typologies using statistical package for social sciences (SPSS version 23) software. The principal component analysis was used for data reduction, after which the resultant non-related principal components (PCs) were used as inputs in the CA. The multivariate analysis approach has been used in other studies to characterize farming systems (such as [12,40,47,50]).

Table 1.
Description of the variables used in creating farm typologies.

Variables description	Code	Unit
Total land size owned	Land size	ha
Total land size under cultivation	Cultivated land	ha
Proportion of land on maize	Proportion Maize	Percentage (%)
Nitrogen applied on maize	Nitrogen Maize	kg N ha^{-1}
Proportion of land on tea	Proportion Tea	Percentage (%)
Nitrogen applied on tea	Nitrogen Tea	kg N ha^{-1}
Proportion of land on coffee	Proportion Coffee	Percentage (%)
Nitrogen applied to coffee	Nitrogen Coffee	kg N ha^{-1}
Proportion of land on banana	Proportion Banana	Percentage (%)
Nitrogen applied on banana	Nitrogen Banana	kg N ha^{-1}
Proportion of land on Beans	Proportion Beans	Percentage (%)
Nitrogen applied on Beans	Nitrogen Beans	kg N ha^{-1}
Proportion of land on Napier	Proportion Napier	Percentage (%)
Proportion of land on Napier	Nitrogen Napier	kg N ha^{-1}
Proportion of land on tobacco	Proportion Tobacco	Percentage (%)
Nitrogen applied to tobacco	Nitrogen Tobacco	kg N ha^{-1}
Proportion of land on millet	Proportion Millet	Percentage (%)
Nitrogen applied on millet	Nitrogen Millet	kg N ha^{-1}
Tropical Livestock Unit	TLU	Numeric
Household Wealth Assets Index	WI	Numeric

Note; ha= hectares, kg N ha^{-}=kilogram Nitrogen per hectares.

The principal component analysis is highly sensitive to outliers [80], and therefore to ensure the robustness of PCA, the 20 variables used in the PCA were checked for outliers (Table 1). Box plots were used to detect outliers before PCA analysis [33]. Additionally, Kaiser Mayer-Olkin (KMO) and Bartlett's sphericity test was done to check data credibility for factoring, similar to Mugi-Ngenga et al. [61]. Orthogonal rotation (varimax method) was used to group study variables. All PCs exceeding an eigenvalue of 1 were initially retained. However, given that a Kaiser Normalization criterion is considered accurate for variables < 30 and sample size < 250 [26], which was not the case in our study. Therefore, we selected further analysis given that the explained cumulative variance was $\leq$60% [32]. We considered loading $\geq$ 0.50 only for interpretation [27].

All factors retained in PCA were used in CA to typify farming systems. We used a two-steps clustering procedure i) hierarchical agglomerative clustering algorithm using Ward's method to form the number of groups, and ii) partitioning algorithm to separate the groups to a given number of clusters. The numbers of clusters retained in hierarchical agglomerative clustering were used in partitioning. A dendrogram was used to select the number of clusters used as farm types. Tukey's Posthoc test was used to test the difference between the variables used in multivariate analysis (Table 1). Statistical differences ($P \leq 0.05$) were shown by superscripts letters.

Continuous data were subjected to one-way analysis of variance while cross-tabulation was used for categorical data to identify significant associations between socioeconomic factors and farm typologies [51,63], Table 2). A multinomial logistic regression model was used to evaluate socio-economic factors influencing farm typologies.

Note; Type 1, cash crop and hybrid cattle farmers; Type 2, food crop farmers; Type 3, coffee-maize farmers; Type 4, millet-livestock farmers; Type 5, highly diversified farmers, and Type 6, tobacco farmers.

Results and discussion

Principal components

The PCA analysis results revealed a KMO of 0.57 and Bartlett's sphericity test significance at $p < 0.001$. The KMO was greater than 0.50; hence PCA was considered appropriate [28]. The first PC had high positive loadings in the proportion of land on maize (0.922) and nitrogen applied on maize (0.924) which explained variance of 11.2%, and therefore, identified as maize cropping system (Table 3). The second PC had high positive loadings in the proportion of land on millet (0.863) and nitrogen applied on millet (0.730) explaining 9.4% of the variance, consequently, identified as millet cropping system (Table 3). The third PC had high positive loadings in the proportion of land under tobacco (0.892) and nitrogen applied on tobacco (0.889), explaining 8.7% of the variance and thus identified as tobacco cropping system (Table 3).

The fourth PC had high positive loading in the proportion of land on tea (0.818) and nitrogen applied on tea (0.850) which explained 8.5% of the variance, therefore, identified as tea cropping system (Table 3). The fifth PC had high positive loading in land size (0.831), and farm size (0.865) explaining 8.14% of the variance thus identified as land size characteristics (Table 3). The sixth PC had high positive loadings in the proportion of land on Napier (0.819) and nitrogen applied on Napier (0.734) which explained 7.74% of the variance, therefore, categorized as Napier cropping system (Table 3). Lastly, the seventh PC had high positive loading in TLU and WI, which explained 7.69% of the variance and therefore identified as livestock systems and household wealth assets index (Table 3).

Table 2.
Definition of independent variables used in the multinomial regression.

Variables	Definition
Dependant variable	
Farm typologies	1, 2, 3, 4, 5 & 6
Independent variables	
Household Head Gender	0 Female
	1 Male
Household Head Education	0 No formal Education
	1 Primary
	2 Secondary
	3 Tertiary
Hired Labour	0 No
	1 Yes
Group Member	0 No
	1 Yes
Credit Access	0 No
	1 Yes
Training Access	0 No
	1 Yes
Extension Access	0 No
	1 Yes
Household Head Age (years)	Continuous
Household Head Experience (years)	Continuous
Household size (number)	Continuous
Proportion of income from Crop (percentage)	Continuous
Proportion of income from Livestock (percentage)	Continuous
Proportion of income from Remittance (percentage)	Continuous

Smallholders farm typologies

The dendrogram from the cluster analysis illustrates how the nested clusters were cut to identify farm types (Annex 1). Farm Type 1 comprised of cash crop and hybrid cattle farmers ($N = 36$ (12%), Table 4). This farm type varied from the rest by the proportion of land and nitrogen applied on tea, coffee and napier. This farm type had the least proportion of land and nitrogen applied to maize. Further, farmers in this category neither grew tobacco nor grew millet and had the least proportion of land and nitrogen applied on beans. The farmers in this category also owned the least total land size. More so, they had moderate total TLU, the proportion of land and nitrogen applied on bananas.

Farm Type 2 was composed of food crop farmers ($N = 21$ (7%), Table 4). The key aspect that isolated this farm type from the others is that they primarily grew beans but did not grow either tea or tobacco. This farm type was also composed of farmers who had a low proportion of land and nitrogen applied on coffee, banana, napier and millet. Total TLU and land size owned were equally small (Table 4).

In farm Type 3, most of the households were coffee and maize farmers ($N = 102$ (34%), Table 4). These households had a moderate proportion of land and nitrogen applied to maize and coffee. These farmers had limited proportion of land and nitrogen applied on tea, banana, beans, tobacco and millet. Additionally, they had moderate total land size owned and nitrogen applied to napier but low proportion of land on napier and relatively low total TLU (Table 4).

Under farm Type 4, most of the households were millet-livestock farmers ($N = 19$ (6%), Table 4). These households were distinct from the rest by owning the largest tracks of land and highest TLU. They had the highest proportion of land and nitrogen applied to millet. These farmers were not tea, coffee or tobacco growers. They had a low proportion of land and nitrogen applied on maize, coffee and beans (Table 4).

Farm Type 5 comprised of highly diversified farmers ($N = 92$ (31%), Table 4). Farmers in this category had a high proportion of land and nitrogen applied to banana and coffee. They owned high to moderate land sizes and had moderate to low land and nitrogen applied on maize. Additionally, they had a moderate proportion of land and nitrogen applied to tea. These farmers had a low proportion of land and nitrogen applied to beans and millet. Further, they had a high proportion of land on napier, but moderate nitrogen applied to it and the lowest total TLU.

Farm Type 6 comprised of tobacco farmers ($N = 29$ (10%), Table 4). These farmers had the highest proportion of land and nitrogen applied to tobacco. They had a moderate proportion of land and nitrogen applied on maize, bananas, beans, napier, millet and coffee but low TLU (Table 4).

In reference to GHG emissions, Cash crop and hybrid cattle, highly diversified, *and* Tobacco farmers are expected to be the hotspots of GHG emissions because of their high nitrogen application rates. Food crop and coffee-maize farmers are probable to contribute to GHG emissions moderately. Though Millet-livestock is predicted to contribute least GHG emissions from cropping activities, high total TLU might contribute a significant amount of GHG emissions through manure production and enteric fermentation. The results showed that smallholder farms in Tharaka-Nithi County had a range of categories from cash crop-hybrid cattle, food crop, coffee-maize, millet livestock, highly diversified and tobacco farmers. Total land size owned, total tropical livestock unit, the proportion of land and nitrogen applied to different cropping systems were signifi-

Table 3.
Extracted principal components (PCs) from smallholder farmers in the study area.

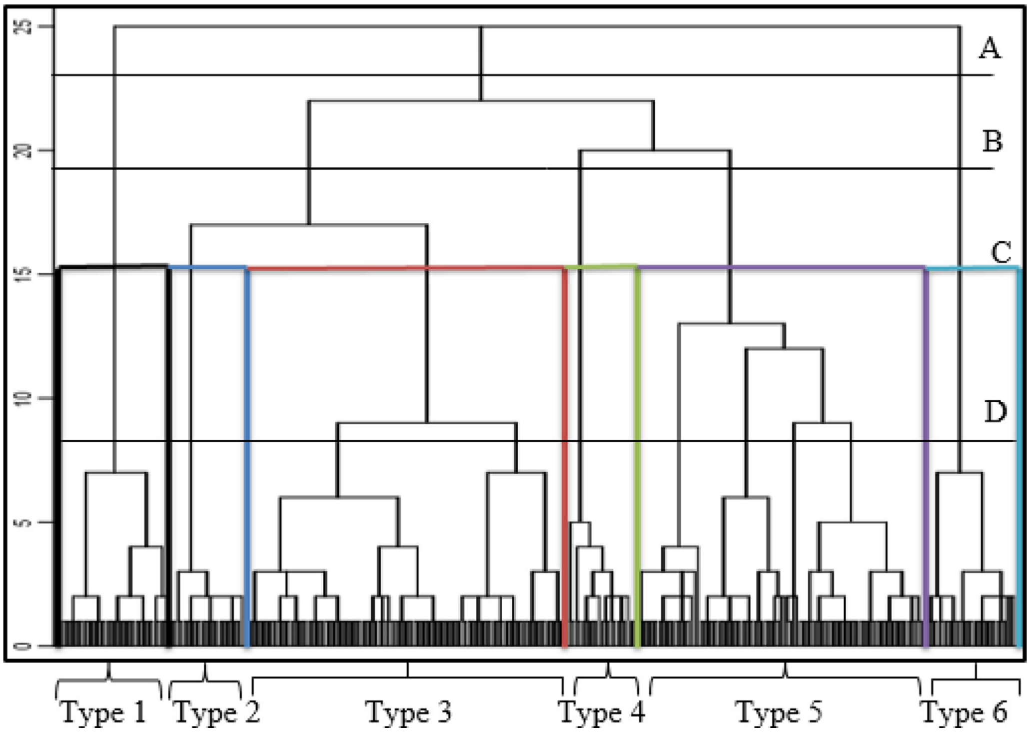
IndependentVariables	Principal Components						
	Maizecropping system	Milletcropping system	Tobacco croppingsystem	Teacropping system	Landsize characteristics	Napiercropping system	livestock systemsand household wealth assets index
Proportion Maize	**0.922**	−0.160	−0.009	−0.241	−0.106	−0.128	−0.022
Nitrogen Maize	**0.924**	−0.149	−0.005	−0.250	−0.096	−0.118	0.006
Proportion Millet	−0.115	**0.863**	−0.028	−0.080	0.111	−0.054	0.080
Nitrogen Millet	−0.095	**0.730**	−0.061	−0.103	−0.091	−0.103	−0.063
Proportion tobacco	0.002	−0.070	**0.892**	−0.075	−0.031	−0.069	−0.052
Nitrogen tobacco	0.023	0.008	**0.889**	−0.066	−0.026	−0.047	0.076
Proportion Tea	−0.286	−0.120	−0.096	**0.818**	−0.035	−0.058	0.002
Nitrogen Tea	−0.139	−0.056	−0.063	**0.850**	−0.109	0.134	0.075
Land size	−0.029	0.098	−0.034	−0.094	**0.831**	−0.062	0.162
Farm size	−0.093	−0.020	−0.020	−0.040	**0.865**	−0.046	−0.007
Proportion Napier	−0.210	−0.086	−0.070	−0.101	−0.042	**0.819**	−0.092
Nitrogen Napier	0.017	−0.028	−0.068	0.257	−0.082	**0.734**	0.271
TLU	−0.044	0.503	0.036	0.073	0.226	0.215	**0.535**
WI	0.008	−0.012	0.042	0.049	0.101	0.031	**0.838**
Proportion Coffee	−0.460	−0.364	−0.260	−0.112	−0.152	−0.169	0.413
Nitrogen Coffee	−0.314	−0.324	−0.211	−0.050	−0.141	0.158	0.302
Proportion Beans	0.197	−0.105	0.057	−0.183	0.019	0−0.110	−0.341
Nitrogen Beans	−0.050	−0.075	−0.023	−0.104	−0.061	−0.068	0.181
Proportion banana	−0.013	−0.110	−0.078	−0.008	−0.126	−0.090	0.037
Nitrogen banana	−0.086	−0.059	−0.024	−0.061	−0.046	0.367	−0.032
eigenvalue	2.242	1.888	1.740	1.696	1.628	1.549	1.535
% explained variance	11.2	9.4	8.7	8.5	8.1	7.7	7.7
% cumulative Variance	11.2	20.7	29.4	37.8	46.0	53.7	61.4

Bold number referred to loadings higher than 0.50. KMO (0.57, $p < 0.001$), TLU = tropical livestock unit, WI = household wealth asset index.

Table 4.
Smallholder farming systems' descriptive characteristics based on nitrogen application rates.

Independent Variable	Cash crop and hybrid cattle system *N* = *36*	Food crop system *N* = *21*	Coffee-maize system *N*= *102*	Millet-livestock system *N*= *19*	Highly diversified system *N*= *92*	Tobacco system *N*= *29*	P value
Land size	0.58^{b}	0.66^{b}	0.75^{ab}	**1.17**^{a}	**0.89**^{ab}	0.69^{b}	0.016
Cultivated land	0.51	0.54	0.65	0.93	0.83	0.59	NS
Proportion Maize	4.89^{d}	29.91^{b}	**43.12**^{a}	12.42^{cd}	20.61^{bc}	30.10^{b}	0.001
Nitrogen Maize	2.69^{d}	15.91^{b}	**22.42**^{a}	7.21^{cd}	10.80^{bc}	15.72^{b}	0.001
Proportion Tea	**2.69**^{a}	0.00^{b}	1.86^{b}	0.00^{b}	7.45^{b}	0.00^{b}	0.001
Nitrogen Tea	**146.04**^{a}	0.00^{b}	4.43^{b}	0.00^{b}	6.52^{b}	0.00^{b}	0.001
Proportion Coffee	**22.84**^{a}	7.17^{bcd}	**14.40**^{abc}	0.66^{d}	**17.13**^{ab}	2.71^{cd}	0.001
Nitrogen Coffee	**157.18**^{a}	26.53^{b}	**76.42**^{ab}	11.92^{b}	**77.42**^{ab}	13.51^{b}	0.001
Proportion Banana	4.19^{b}	1.95^{b}	2.59^{b}	0.00^{b}	**20.09**^{a}	4.03^{b}	0.001
Nitrogen Banana	29.67^{ab}	14.90^{ab}	13.96^{b}	0.00^{b}	**120.03**^{a}	23.45^{ab}	0.001
Proportion Beans	0.44^{c}	**34.38**^{a}	18.16^{b}	4.53^{c}	3.63^{c}	18.24^{b}	0.001
Nitrogen Beans	0.13^{c}	**97.57**^{a}	2.68^{bc}	0.47^{c}	1.59^{bc}	16.65^{b}	0.001
Proportion Napier	**13.74**^{a}	5.27^{ab}	6.09^{ab}	2.13^{b}	14.07^{a}	3.85^{ab}	0.001
Nitrogen Napier	**124.51**^{a}	21.00^{b}	40.42^{b}	27.30^{b}	39.57^{b}	14.71^{b}	0.001
Proportion Tobacco	0.00^{b}	0.00^{b}	1.06^{b}	0.00^{b}	0.00^{b}	**33.30**^{a}	0.001
Nitrogen Tobacco	0.00^{b}	0.00^{b}	2.04^{b}	0.00^{b}	0.00^{b}	**125.55**^{a}	0.001
Proportion Millet	0.00^{b}	1.19^{b}	0.17^{b}	**35.15**^{a}	0.66^{b}	1.24^{b}	0.001
Nitrogen Millet	0.00^{b}	0.09^{b}	0.00	**30.21**^{a}	0.17^{b}	0.89^{b}	0.001
TLU	2.36^{b}	1.91^{b}	1.73^{b}	**6.16**^{a}	1.51^{b}	1.70^{b}	0.001
Wealth Index	39.64	38.57	31.88	31.94	28.49	29.79	NS

The same superscript in the same row shows no significant difference between treatment means at p = 0.05, N = number of household heads in a farm type, NS = Not significant at P = 0.05, bold numbers indicate the most relevant explanatory variable(s) per farm type, land size and cultivated land = acres, the proportion of land allotted to different crops = percentage, nitrogen application on a crop = kg N ha^{-1}, TLU = tropical livestock unit.



Annex 1. Dendrogram with four cut tree points A, B, C and D. The dendrogram was cut at C and six farm typologies were identified. Type 1, cash crop and hybrid cattle system; Type 2, food crop system; Type 3, coffee-maize system; Type 4, millet-livestock system; Type 5, highly diversified system, and Type 6, tobacco system.

cant variables in constructing farm typologies. These classification variables were capable of differentiating farming systems. Dissimilar cropping systems and livestock intensities contribute differently to GHG inventories. Furthermore, nitrogen application rates might play a significant role in influencing these emissions.

The nitrogen application rates was a significant variable in typifying farming systems. Integrated soil fertility management (ISFM) technologies such as combined use of fertilizers and manure increase agricultural productivity [91,93]. However, nitrogen application has the potential to increase atmospheric GHG (CO_2, CH_4, N_2O) emissions [89]. Further, attempts directed towards agricultural GHG emissions measurements should consider farm-level nitrogen application rate. These farm typologies depicted different farming systems and their average nitrogen application rates. Therefore, nitrogen application in cropping systems can be an entry point for quantifying and simulating GHG emissions from individual cropping systems or whole farm emissions.

Total TLU was a significant variable in categorizing farming systems similar to [46,82]. Studies have demonstrated that livestock densities have been increasing in Africa and are sources of GHG emissions with significant amounts emanating from ruminants (e.g. [36]). The highest TLU was recorded in Type 4 that is concentrated in dry zones of the study are (LM5) mainly due to their large land sizes which are mainly used for livestock production. Livestock act as a GHG emission source and is projected to increase over time [70] through enteric fermentation and use of manure. Manure production increases with an increase in TLU, and its decomposition and management lead to GHG emissions [75].

Total and proportion of land allotted to each cropping system were important variables in capturing farms' diversity similar to [41,64]. The smallest land size was in Cash crop and hybrid cattle farming system while the largest in the millet-livestock farming system. Coffee and tea farmers owned small tracks of land as opposed to millet livestock farmers. The population density in coffee tea zones is high compared to the dry zone of millet-livestock hence, this can account for the small land size in Cash crop and hybrid cattle farming system.

Socio-economic factors influencing farm typologies

Univariate analysis of socio-economic factors influencing farm typologies

Results from the univariate analysis showed that household head level of education, hired labour, group membership, access to extension services and proportion of income from cropping activities were the significant socio-economic factors that influence farmers belonging to different farm typologies (Table 5).

Table 5.
Univariate analysis of socio-economic factors influencing farm types.

Independent variables	Definition	Cash crop and hybrid cattle system	Food crop system	Coffee-maize system	Millet-livestock system	Highly diversified system	Tobacco system	$\chi 2$ Value
HHH Gender	Female	7(13.5)	2(3.8)	21(40.4)	5(9.6)	15(28.8)	2(3.8)	NS
	Male	29(11.7)	19(7.7)	81(32.8)	14(5.7)	77(31.2	27(10.9)	
HHH Education	No education	3(18.8)	1(6.3)	4(25.0)	4(25.0)	4(25.0)	0(0.0)	0.032
	Primary	15(9.3)	7(4.3)	56(34.8)	13(8.1)	50(31.1)	20(12.4)	
	Secondary	11(14.5)	8(10.5)	30(39.5)	1(1.3)	21(27.6)	5(6.6)	
	Tertiary	7(15.2)	5(10.9)	12(26.1)	1(2.2)	17(37.0)	4(8.7)	
Hired Labour	No	7(7.6)	6(6.5)	26(28.3)	10(10.9)	36(39.1)	7(7.6)	0.043
	Yes	29(14.4)	15(7.2)	76(36.7)	9(4.3)	56(27.1)	22(10.6)	
Group Members	No	20(9.7)	13(6.3)	78(37.9)	17(8.3)	58(28.2)	20(9.7)	0.044
	Yes	16(17.2)	8(8.6)	24(25.8)	2(2.2)	34(36.6)	9(9.7)	
Credit Access	No	30(11.7)	18(7.0)	90(35.0)	18(7.0)	75(29.2)	26(10.1)	NS
	Yes	6(14.3)	3(7.1)	12(28.6)	1(2.4)	17(40.5)	3(7.1)	
Training access	No	20(10.9)	12(6.5)	63(34.2)	17(9.2)	57(31.0)	15(8.2)	NS
	Yes	16(13.9)	9(7.8)	39(33.9)	2(1.7)	35(30.4)	14(12.2)	
Extension Access	No	21(9.1)	18(7.8)	83(35.9)	16(6.9)	73(31.6)	20(8.7)	0.050
	Yes	15(22.1)	3(4.4)	19(27.9)	3(4.4)	19(27.9)	9(13.2)	
Mean								F value
HHH Age		55.18	49.48	53.04	54.16	55.49	49.38	NS
HHH Experience		28.39	21.57	23.92	28.11	25.43	22.21	NS
HH Size		3.94	4.55	4.34	4.60	4.18	4.06	NS
Proportion of income from Crops (%)		43.56	16.45	30.26	32.55	32.63	45.14	0.014
Proportion of income from Livestock (%)		23.70	19.83	19.59	32.82	21.12	16.87	NS
Proportion of income from Remittance (%)		3.50	4.92	4.52	1.05	3.67	1.47	NS

Association significant at $\alpha = 0.05$, HHH=Household head, HH = Household, χ^2 = chi square value.

Socio-economic factors influencing belonging to cash crop and hybrid cattle farming system

The multinomial logistic regression (MNLR) model identified six predictor variables: group membership, access to agricultural training, access to extension services, age of the household head, household head experience in agriculture and proportion of income from cropping activities, as significant factors influencing belonging to cash crop and hybrid cattle farming system (Table 6).

Group membership ($\beta = 1.713$, $P = 0.047$) positively predicted whether the farmer belonged to cash crop and hybrid cattle farming system (Table 6). This implied that farmers who belonged to agricultural groups were more likely to belong to cash crop and hybrid cattle farming system. Majority of these farmers grew coffee and tea as cash crops and reared cattle probably for dairy under high intensive management based on their small parcels of land (Table 6). These farmers marketed their coffee, tea and milk through farmers' cooperatives. Farmers in cooperatives are capable of improving their bargaining power hence gaining more from their agricultural products [51,62]. This could explain the positive prediction ($\beta = 0.010$, $p = 0.067$) by the proportion of income from cropping activities which was the highest in this farm typology (Table 6). Belonging to cooperatives also increase access to agricultural information, inputs and other agricultural services that boost their agricultural production [72].

It is worth noting that farmers who belonged to this farm type were among the oldest in the study area and had the highest farming experience (Table 6). Age of the household head (β=0.049, $P = 0.056$) and farming experience ($\beta = 0.065$, $P = 0.092$) positively influenced farmers belonging to this farm type. This implies that older and relatively more experienced farmers were more likely to belong to cash crop and hybrid cattle farming system than any other. Older and experienced farmers tend to trust traditional methods of technology transfer (i.e. extension officers) more than other types of agricultural training and could probably miss out new agricultural innovations. According to Macharia et al. [51], older farmers are more risk-averse and less likely to be flexible than younger farmers and thus have a lesser likelihood of information utilization on new technologies.

This could be the reason why access to agricultural extension ($\beta = 0.523$, $P = 0.088$) positively predicted whether a farmer belonged to this farm typology (Table 6). The higher the access to agricultural extension, the higher the likelihood of farmers belonging to cash crop and hybrid cattle farming system and which would result in higher incomes [14]. According to Mugi-Ngenga et al. [61], older farmers have less access to new information and trust the traditional extension officers. Further, this could also be explained by the negative prediction of access to agricultural training ($\beta = -1.439$, $P = 0.037$) on whether a farmer belonged to cash crop and hybrid cattle farming system (Table 6). It could be that the farmers in this farm typology either lacked access to formal training or were resistant to new knowledge and could be, they believed they knew based on their many years of experience.

Socio-economic factors influencing belonging to food crop farming system

MNLR indicated that access to agricultural training, access to extension services and proportion of income on cropping activities were significant variables in explaining whether a farmer belonging to food crop farming system (Table 6).

Access to agricultural training ($\beta = 0.046$, $p = 0.054$) positively predicted whether farmers belonged to food crop farming system (Table 6). These results imply that farmers with high access to agricultural training were more likely to belong to food crop farming system. Farmers in this group were younger with short farming experience (Table 6) implying that they had high access to modern technologies, more willing to learn, innovative and are lower risk-averse with longer planning horizons [54,63]. According to Macharia et al. [51], training is an important component of instilling knowledge and skills and hence builds the capacity of the target group. However, farmers in this farm typology did not have access to extension services as indicated by the negative prediction of access to extension services ($\beta = -1.328$, $p = 0.089$) towards whether farmer belonged to this farm type (Table 6). This implies that the farmers in this farm type had less contact with extension services a factor that could have highly contributed towards the low proportion of income from crops due to lack of information (Table 6). Access to extension services by farmers reduces externalities and increases profit [14] and improve production efficiency for all agricultural products [84]. The proportion of income from cropping activities ($\beta = -0.031$, $p = 0.010$) negatively predicted whether a farmer belonged to food crop farming system (Table 6). This implies that farmers with low crop income were more likely to belong to food crop farming system. The limited earning from cropping in this farm type could be attributed to the lower years of farming experience and age. According to Akinola & Adeyemo [1], high experienced farmers are more likely to increase agricultural productivity.

Socio-economic factors influencing belonging to coffee and maize farming system

The MNLR model showed that the gender of the household head, access to credit and access to the agricultural extension were important in explaining farmers who belonged to coffee and maize farming system (Table 6).

Household head gender ($\beta = -2.181$, $P = 0.076$) negatively predicted whether farmer belonged to coffee and maize farming system (Table 6). This implies that female-headed households were more likely to belong to this farm typology than households headed by their male counterparts. According to Mugwe et al. [62], majority of the land in the study area is owned by males and who also make most of the decisions including access to extension services thus more knowledgeable than their female counterparts [76].

Access to extension services ($\beta = 1.127$, $P = 0.080$) positively predicted whether farmers belonged to coffee and maize farming system. This implies that access to extension services had a high chance of predicting farmers belonging to coffee

Table 6.
Multinomial logistic regression analysis of socio-economic factors influencing farmers belonging to farm typologies: Base tobacco system.

Variables	Cash crop and hybrid cattle system	Food crop system	Coffee-maize system	Millet-livestock system	Highly diversified system
Constant	−2.811	−0.033	1.693	2.427	0.182
HHH Gender	−1.566	−0.706	−2.181*	−0.972	−0.978
HHH Education	0.357	0.603	0.444	−1.027*	0.526*
Hired labour	0.652	−0.800	−0.099	−0.978*	0.978*
Group Membership	1.713**	0.201	−0.530	−0.944	0.049
Credit Access	0.083	0.930	−0.730*	0.184	0.907
Training Access	−1.439**	0.046*	−0.793	−0.793	−0.439
Extension Access	0.523*	−1.328*	1.127*	−0.769	−0.769
HHH Age	0.049*	0.006	0.010	0.018	0.042**
HHH Experience	0.065*	−0.064	−0.014	0.038	−0.016
HH size	−0.027	0.292	0.153	0.381*	0.078
Proportion of income from Crops (%)	0.010*	−0.031**	−0.017	−0.019**	−0.012
Proportion of income from Livestock (%)	0.023	0.002	−0.007	0.020**	−0.014*
Proportion of income from Remittance (%)	0.065	0.039	0.083	−0.053	0.018

**, * significance at 5% and 10%, respectively, HHH=Household head, HH = Household, the presented values are model coefficients of each independent variable.

and maize farming system. However, there were more females not having access to extension services than their counterpart males (Table 6) which could be attributed to cultural norms and traditions [31] or lack of appropriate time schedules for the extension for females [2]. According to Mudege et al. [60], negative stereotypical views about women by extension officers and male counterparts limits their access to the extension services. Access to credit facilities negatively ($\beta = -0.730$, $P = 0.058$) predicted belonging to coffee and maize farming system (Table 6). This implies that coffee and maize farming system was composed of farmers with a low likelihood of accessing credit. With most of the land and property ownership belonging to males in the study area, including some of the properties belonging to female-headed households, the female-headed households with limited assets do not have access to credit mainly due to lack of collateral. This lowers the agricultural production and profitability Awotide et al. [7] partly by limiting access to agricultural inputs [23,95].

Socio-economic factors influencing belonging to the millet-livestock farming system

MNLR model revealed five predictor variables: Household head education level, hired labour, household size, the proportion of income from cropping activities and proportion of income from livestock activities were significant in explaining farmers who belonged to the millet-livestock farming system (Table 6).

Household head education level ($\beta = -1.027$, $P = 0085$) negatively predicted farmers who belonged to the millet-livestock farming system (Table 6). This implies that farmers who belonged to the millet-livestock farming system had low levels of education with the majority of the household heads having no formal education (Table 6). Low education depicted in this farm type can be attributed to either marginalization, or lack of parents will power to supports their children's' education [58]. Further, household size positively ($\beta = 0.381$, $p = 0.066$) influenced farmers who belonged to millet-livestock farming system (Table 6), implying that farmers with large household size were more likely to millet-livestock farming system. Additionally, hired labour ($\beta = -0.978$, $p = 0.091$) was a negative predictor in explaining whether farmers who belonged to millet-livestock farming system (Table 6). This implied that farmers who had no hired labour were more likely to belong to millet-livestock farming system since these households had adequate labour based on the large household sizes (Table 6). According to Odendo et al. [72], household sizes reflect the amount of labour available for agricultural activities. According to Bassey et al. [9], large households prefer using borrowed labour which is cheaper rather to hired one.

The proportion of income from cropping activities negatively ($\beta = -0.019$ $p = 0.049$) predicted farmer who belonged to millet-livestock farming system (Table 6). This signifies that farmers with a low proportion of income from agricultural activities were more likely to belong to this farm typology. Millet-livestock farming system farms are predominantly marginal areas with low agricultural potential where farmers grow drought-tolerant crops (e.g. millet) [37] which has low economic value hence the low proportion of income from cropping activities. The proportion of income from livestock activities ($\beta = 0.020$, $p = 0.040$) positively influenced farmers who belonged to this typology (Table 6). This farm type had the highest total TLU (Table 4); this could be the reason why this farm proportion from livestock positively predicted whether farmer belonged to this farm category. This agrees with Mganga et al. [56], who reported that livestock production is the main source income to arid-and semi-arid areas.

Socio-economic factors influencing belonging to highly diversified farming system

The multinomial logistic regression model showed four predictor variables: education level of the household head, hired labour, household head age and proportion of income from livestock activities were significant in explaining whether a farmer belonged to highly diversified farming system (Table 6).

Household-level of education positively ($\beta = 0.526$, $P = 0.099$) predicted whether a farmer belonged to highly diversified farming system (Table 6). This indicates that farmers belonging to this farm type had attained higher education. Secondly, the age of the household head positively ($\beta = 0.042$, $P = 0.016$) predicted farmers who belonged to highly diversified farming system (Table 6). This again implied that the older farmers were likely to belong to this farm type. Similarly, the farmers in this typology used hired labour, which positively ($\beta = 0.978$, $P = 0.058$) predicted belonging to highly diversified farming system (Table 6). This typology had the oldest farmers across the farm typologies (Table 5), and they used hired labour to manage their farms. Aged farmers are less energetic, and they need the support of hired labour to manage their farms. According to Bassey et al. [9], aged farmers use hired labour to enhance farming activities, which require more energy that they might not have. According to [10], young farmers are more energetic and economically active; therefore, with adequate access to farm inputs, they can boost agricultural productivity. More so, the proportion of income from livestock activities ($\beta = -0.014$, $p = 0.066$) negatively influenced farmers who belonged to farm this typology (Table 6). This implied that farmers with small herds of livestock were more likely to belong to highly diversified farming system. Farmers in this typology had moderate total TLU, which signifies the small number of livestock kept. This could explain why the proportion of income was negative predictors as low total TLU suggests that a small number of large ruminants [20]. Further, large ruminants are essential in agricultural systems and the economy as they raise more profits [49].

Conclusion

Smallholder farming systems can be essential entry points in greenhouse gas emissions mitigation. However, smallholder farms are both socially and spatially heterogeneous, which can hinder GHG emissions quantification, reporting and mitigation as each farm demand a specific approach. Individual farm-based GHG emissions quantification and mitigations intervention are quite impractical at a national or regional level, thus the need for developing farm typologies that can address the heterogeneity of the smallholder farming systems. Our study demonstrates the use of farming systems typology in identifying GHG emissions hotspots, designing quantification experiments, assessing the adoption of mitigation measures, and proposing climate action policy. We used multivariate analysis to construct six farm typologies among smallholder farming systems in the central highlands of Kenya. We hypothesized that the intensity of soil fertility management. (in terms of nitrogen application rates) is influenced by the farm typologies.

Our results support our hypothesis that nitrogen application rates significantly varied among the farm types, which might also be mirrored in quantities of GHG emissions. Given the high nitrogen application rates in cash crop and hybrid cattle, highly diversified, and tobacco farming systems, they were delineated as possible GHG emissions hotspots, farm type two were predicated to moderately emit GHG emissions, while millet livestock farming system was predicted to have the lowest contribution of GHG emissions, however, the high tropical livestock unit observed in it could contribute a significant amount of GHG through enteric fermentation and manure production. Based on soil fertilization rates, GHG quantification experiments can be set out to determine the contribution of farming systems towards national GHG budget. Since it is not economically possible to quantify greenhouse gas at each farm for national GHG inventories, these typologies provide plausible entry points in GHG emissions quantification experiments. We recommend the use of farm typology in implementation of direct quantification experiments in the study area and other agroecological settings to investigate the actual role of smallholder farming systems in GHG emissions and mitigation measures tailored with enhancing food security.

Given that socioeconomic determinants differed among farm typologies, climate action policies should consider typology specific determinants for them to be in line with the societal setting. Household head education level, gender, age, hired labour, household size and income from cropping or livestock rearing were significant farmer, farm and economic determinants of farmers belonging to a given farm typology. Therefore, policies and intervention measures targeting agricultural GHG emissions quantifications, and climate-smart agriculture should consider not only soil fertility management technologies but also total tropical livestock unit and other socio-economic variables that influence their adoption. It is worth noting that the institutional factors (agricultural training, extension access, credit access, and group membership) significantly determined farmers belong to a given farm typology and should also be put into considerations.

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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