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Research article

Prospects and constraints in smallholder farmers' adoption of multiple soil carbon enhancing practices in Western Kenya

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ABSTRACT

Most smallholder farmers in sub-Saharan Africa (SSA) are adversely affected by low soil fertility, land degradation and climate change-related shocks such as drought. These problems lead to low productivity and low household income. In addition, the adoption of soil carbon enhancing practices remains low in Western Kenya. This study analyses the factors that influence the probability and extent of adoption of soil carbon enhancing practices in Western Kenya utilizing plot-level information, socioeconomic characteristics and external supporting factors. Multivariate probit model and generalized ordered logit were utilized to assess the adoption of multiple soil carbon enhancing practices and the extent of adoption respectively. Results indicate that the adoption of soil carbon enhancing practices is correlated, suggesting interrelation in farmers' adoption decisions. Both the multivariate probit model and generalized ordered probit results indicate that the probability and extent of adoption of soil carbon enhancing practices are influenced by plot-level characteristics, literacy level, access to agricultural credit, agricultural group membership, participation in the market, and gender of the household.

1. Introduction

In most sub-Saharan Africa (SSA) countries', agricultural policies and areas of focus have targeted poverty reduction, the achievement of food security, and the mitigation of climate change effects. The three problems are evident among most African rural areas, where the main source of livelihood is agriculture. In Kenya, wheat and maize are considered the two most significant cereal crops (GOK 2009; Mati et al., 2011; Gitau et al., 2011). However, it has been predicted that by 2020, the income and yield from maize and wheat in SSA countries will have reduced by 50% and that by 2050 reduction in crop yield will be attributed to crop failure at 40% and 30%, respectively (Lobell et al., 2008; Thornton et al., 2011; Mwungu et al., 2018). Enhancing productivity, therefore, becomes vital, considering that increase in production level in Africa has largely been attributed to an increase in land under cultivation rather than enhanced productivity (Jayne et al., 2016). Additionally, increased land pressure and reduction in land size holding among small scale farmers who account for 75% of maize production (IPCC, 2007), has constrained the ability of smallholder farmers to expand the area under production. This phenomenon has made continuous cropping a common practice that subsequently leads to land degradation and low productivity.

Due to the reduction in land sizes, continuous cropping has become a common practice amongst smallholder farmers. Reduced fallowing, a practice that was common in earlier years, has led to land degradation which eventually results in low productivity. Achievement of food security in Kenya is still elusive due to land degradation, low productivity, and high poverty level among smallholder farmers, while variability in climate change exacerbates the situation. Recent studies have indicated that soil carbon enhancing practices (SCEPs) that help in carbon sequestration offer to be low-cost solutions to enhancing productivity (Li et al., 2013; Lal, 2015). SCEPs help increase the amount of soil organic carbon content, which has been universally proposed to be a measure of soil quality and soil fertility (Amundson et al., 2015). With the soil being one of the leading sources of atmospheric carbon, it becomes an important element to consider in reducing the atmospheric carbon level as both

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a mitigation and adaptation strategy among farmers (Lal, 2013; Lal et al., 2015).

Most soils in Kenya are characterized by soil nutrient deficiencies, soil degradation, and poor land management practices (Cavanagh et al., 2017; Kihara et al., 2017), adoption of SCEPs could be key in improving soil's structure and fertility. SCEPs also enhance the sustainability of soil functions that are critical for ensuring that ecosystem functioning is maintained and hence improving crops and livestock production (Bekele and Drake, 2003; Powlson et al., 2014). Sommer et al. (2016) indicate that the long term effects of adopting soil carbon sequestration practices may be lower in reducing atmospheric carbon as the soil acts as both a sink and source of carbon. Powlson et al. (2016) and Pezzuolo et al. (2017) highlighted the same and indicate that conservation practices have the ability to increases soil fertility through increased soil carbon accumulation and can act as a mitigating mechanism to climate change. However, the emphasis on the short term effects of enhancing farmer's productivity cannot be overlooked as the practices improve soil physical conditions (Powlson et al., 2016). Additionally, several field trials have shown the potential of adopting SCEPs in enhancing productivity and reducing land degradation (De Ponti et al., 2012; Otinga et al., 2013; Adamtey et al., 2016; Kafesu et al., 2018).

This study seeks to contribute to the limited literature on factors that influence the adoption of SCEPs utilizing plot-level information, household socioeconomic characteristics, and external support factors. The specific objective of the study was to assess factors that influence the adoption of SCEPs and the extent of adoption. In the present study, the extent of adoption was measured by the number of practices that a farmer has adopted. Previous studies have focused on some of the SCEPs practices but have separately analysed the components (e.g., intercropping and mulching) by using univariate models. This approach ignores the fact that the adoption of these technologies is path-dependent, where the decision to adopt a practice is partly dependent on earlier practices adopted. At the same time, these practices act as substitutes or complements. Therefore, the analysis of one practice independently without considering other practices can lead to biased results.

The SCEPs considered in this study include intercropping (maize-legume intercropping), mulching, farmyard manure (FYM), and inorganic fertilizer. The four practices were considered due to their immediate impact in improving soil condition and enhancing productivity compared to other practices such as agroforestry and use of grass strips whose benefit take longer to be realized in terms of enhancing soil fertility and crop productivity.

2. Analytical model

When analysing factors that may facilitate or inhibit the adoption of technology, univariate models such as logit and probit are utilized, which consider a single-equation for each SCEP technology. However, using a univariate model is disadvantageous in that it does not consider the interdependence in the adoption of multiple technologies (Teklewold et al., 2013; Muriithi et al., 2018; Mwungu et al., 2018). Moreover, univariate models fail to account for the fact that farmers are more willing to adopt an additional practice based on the experience and benefits derived from the previously adopted technologies. Univariate models, therefore, fail to acknowledge that farmers either adopt several technologies to substitute or complement a previous technology to solve an underlying problem. However, the multivariate probit model (MVP) takes into account the simultaneous adoption of multiple SCEPs technologies by considering the correlation among the disturbance terms that may arise from the relationship between the practices.

2.1. A multivariate probit model

For this study, MVP helped overcome the main disadvantages of univariate modes while considering multiple practices and accesses the influence of plot-level information, socioeconomic, and external supporting factors on the prospects of adopting SCEPs.

The multivariate model can be modelled from the random utility framework. A farmer i will adopt a SCEP in plot p if and only if U_b that represents the benefit of adopting a SCEP is greater than U_a (i.e., the benefit derived from traditional or existing practice). However, B_a denotes a farmer's decision to adopt mulching (1), intercropping (2), FYM (3), and inorganic fertilizer (4). Thus a farmer will adopt a practice on plot p if $Y^*_{ipa} = U^*_b - U_a > 0$. The net benefits that a farmer derives are influenced by the observed plot-level information, socioeconomic, and external supporting factors X'_{ip} and the error term ε_{ip} represented in Eq. (1).

$$Y^*_{ipa} = X'_{ip}B_a - \varepsilon_{ip} \; (a = 1,\ 2, 3, 4) \tag{1}$$

where Y^*_{ipa} a latent variable associated with the benefits of SCEP a and farmer i in plot p can be translated into a binary outcome equation for each choice of SCEP as shown in Eq. (2):

$$Y_{ipa} = 1 \;\; if \;\; Y^*_{ipa} > 0, \; and\; O\; otherwise \; (a = 1,\ 2, 3, 4) \tag{2}$$

The ε_{ip} is the error term that follows a multivariate normal distribution (MVN) each with zero conditional mean and variance-covariance matrix Ω, where Ω has values of 1 on the leading diagonal and correlation ρip = ρip as off-diagonal elements as shown in Eq. (3).

$$\Omega = \begin{bmatrix} 1 & \rho 12 & \rho 13 & \rho 14 \\ \rho 21 & 1 & \rho 23 & \rho 24 \\ \rho 31 & \rho 32 & 1 & \rho 34 \\ \rho 41 & \rho 42 & \rho 43 & 1 \end{bmatrix} \tag{3}$$

The off-diagonal elements in the variance-covariance matrix represent the unobserved correlation between the disturbance terms associated with the different types of SCEPs. The correlation matrix helps us in identifying if the practices are either substitutes or complements. The model was estimated based on the maximum likelihood estimation. Additionally, to guarantee the accuracy of the model, the number of random draws was increased to 30 which is approximately equal to the square root of the valid number of plot observations utilized in the estimation rather than the default five draws for MVP in Stata.

2.2. Generalized ordered logit

The MVP model, as defined above solely takes into consideration the probability of adopting the SCEPs. However, it does not take into account that farmers can adopt more than one practice, thus not taking into consideration the intensity of adoption. Following Wollni et al. (2010), Teklewold et al. (2013) and Muriithi et al. (2018) intensity of adoption can be measured by the total number of practices that a farmer has implemented in their plot. The generalized ordered logit model helps us assess the factors that might influence the extent of adoption.

A Poisson regression model would have been suitable for the analysis since the dependent variable – the extent of adoption – is count variable. Nevertheless, the model assumes that the probability of adopting any of the technologies is the same. In actual sense the likelihood of adopting the first technology may differ from the likelihood of adopting a second, and any subsequent technology as a farmer has been exposed to the advantages of the technologies and information regarding the technologies; and has thus increased probability to adopt more technologies compared to a farmer that has not adopted any technologies (Teklewold et al., 2013; Muriithi et al., 2018). Additionally, the ordered probit/logit model would have been suitable to analyse the data. However, the data violated the model's proportional odds assumption which states that the corresponding coefficients (expect the intercepts) ought to be identical across the different logistic regression (as defined by the number of practices adopted), other than differences resulting from sampling

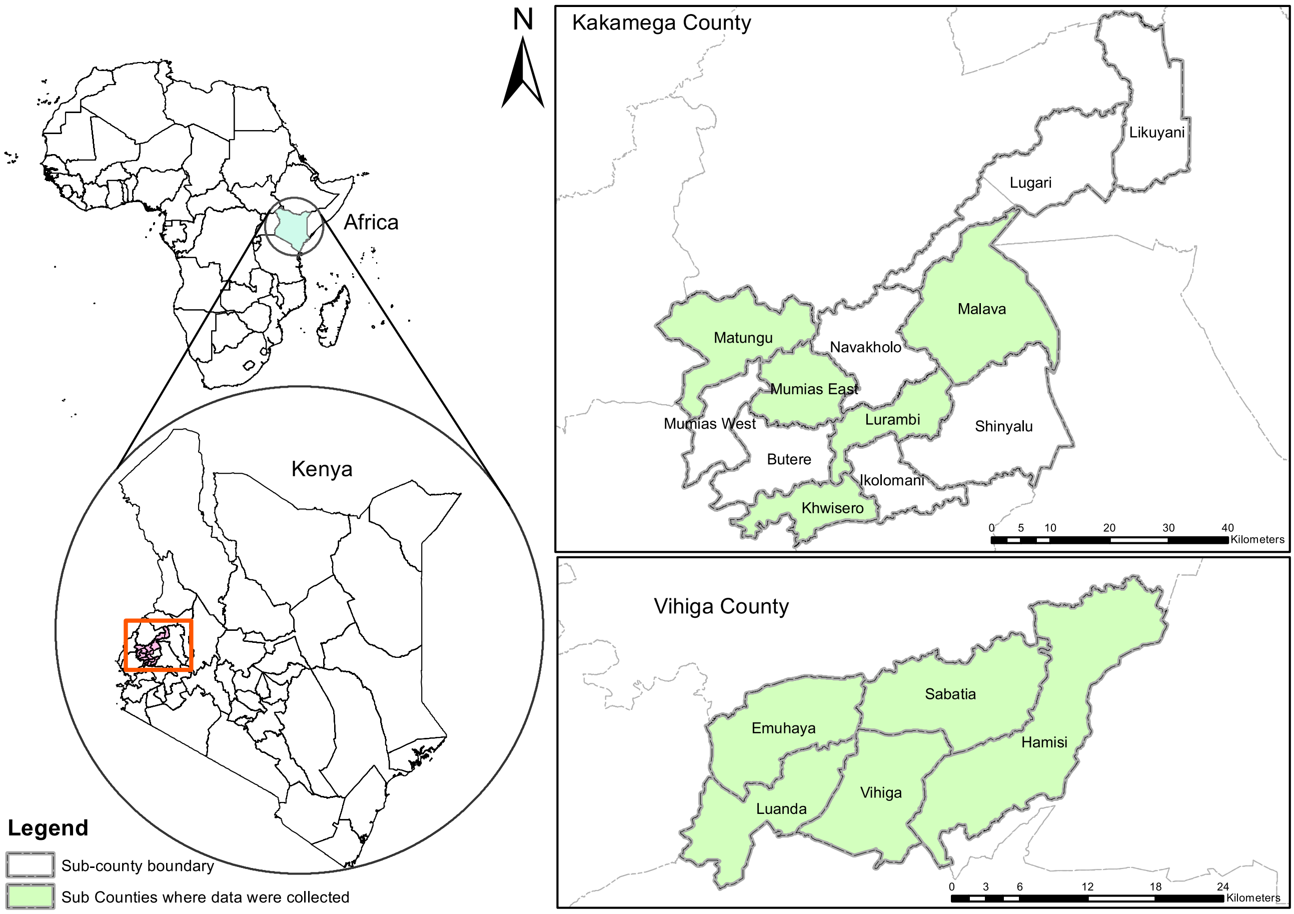

Figure 1. Map of the study area.

variability (Williams, 2016). Generalized ordered logit relaxes the assumption and is more powerful than ordered logit as it helps analyse factors that might influence a farmer adopting practices stepwise (Williams, 2016). It thus helps in determining what enhances or constrain a farmer from adopting the first practice compared to farmers that have adopted no practice, from the first practice to the second, from the second to the third practice and thereafter.

3. Study area, sampling data, and description of variables

3.1. Study area and sampling scheme

The study employed a comprehensive plot level and household data collection in Vihiga and Kakamega Counties in Western Kenya in August 2018. The questionnaire utilized in the data collection has been provided under supplementary content (Supplementary 1. Questionnaire). The study sites were purposively selected as they represent a high potential area faced with low agricultural productivity, caused by low soil fertility from prolonged farming, heavy leaching, soil erosion degradation, and poor farming techniques (Odendo et al., 2010; Jaetzold et al., 2010). Additionally, various projects such as Agricultural Intensification in sub-Saharan Africa (AFRINT) project and Kenya Agricultural Carbon Project (KACP) have been implemented in the area to counter the effect of soil degradation and promoted adoption of the soil carbon enhancing practices.

The survey incorporated a multistage sampling technique as follows. In the first stage, in order to increase the variability of data, five sub-counties were randomly selected in each county. Vihiga County has five sub-counties, thus all the sub-counties; that is, Vihiga, Emuhaya, Hamisi, Sabatia, and Luanda were selected. Kakamega has twelve sub-counties, but five were selected randomly. However, before randomly selecting the five sub-counties in Kakamega County, two sub-counties (i.e. Lugari and Likuyani) were eliminated since they receive more rainfall than the rest of the sub-counties and have one planting season while the rest of the sub-counties in Kakamega and Vihiga have two planting seasons per year. This was done to ensure uniformity of the agro-ecological zone from which data was collected. Additionally, the two sub-counties mainly have large scale maize producing farmers; thus their inclusion would have resulted in increased uncertainty in the data collected and results generated since the study's main target were smallholder farmers. The remaining ten sub-counties were assigned a random number, and five sub-counties namely Khwisero, Mumias East, Lurambi, Malava, and Matungu were randomly selected. Data were collected from the ten selected sub-counties as shown in Figure 1 below.

The next administrative structure the study took into consideration after the sub-county were the wards, and villages. In the second stage, due to time and money constraints, two wards were selected from each sub-county with the help of county extension officers. In the third stage, 16 villages from each county were selected distributed equally in the sub-counties and the wards. The target sample frame determined using Eq. 4 and Eq. 5 was 320 farmers (i.e., 160 farmers from each county), to ensure the variability of data, the number of farmers was limited to 10 farmers per village. In a general view, from each county the distribution of villages was as follows; in four sub-counties three villages were selected and in one sub-county four villages selected, to yield 16 villages. The villages were selected from the two wards already selected in each sub-county.

$$n_0 = \frac{Z^2 pq}{e^2} \tag{4}$$

$$n_0 = \frac{1.96^2(0.5*0.5)}{0.055^2} = 317(\tilde{}320) \quad (5)$$

where n_0 is the sample size, Z^2 is standard normal deviate at the selected confidence level (which is 1.96 for commonly used 95% confidence interval), p is the estimated proportion of an attribute that is present in the population, q is $1-p$ and e is the desired level of precision.

In the fourth stage, ten farmers from each village were interviewed by first randomly picking a farmer from the extension officer list of farmers within the village. The selected farmers would then direct the field enumerator to another farmer within the village. However, in order to cater to any data problem such as missing data and incompletely filled questionnaires, 14 additional respondents were interviewed leading to a final sample size of 334 farmers operating 710 plots.

3.2. Dependent variables

The dependent variables (SCEPs) considered were intercropping (maize-legume intercropping), mulching, FYM, and inorganic fertilizer. Maize-legume intercropping is one of the practices that helps in soil carbon sequestration (Lal, 2013, 2015) and improves soil fertility through nitrogen fixation and suppresses weeds and reduces the incidence of pests and diseases (Muriithi et al., 2018). The use of FYM denotes the application of dried livestock waste to farming plots. The use of manure is essential in supplying nitrogen (N), potassium (K), and phosphorus (P), which are important macro-nutrients to the soil (Otinga et al., 2013). Additionally, it enhances soil fertility, organic matter content and is a key component in integrated nutrient management (INM). The use of inorganic fertilizer is also important in improving productivity as it has an immediate impact on availing nitrogen (N), phosphorus (P), and potassium (K) to the plant (Otinga et al., 2013). Efforts to fight *Striga* infestation in Western Kenya showed that the use of inorganic fertilizer was useful in suppressing the weed by correcting phosphorus (P) deficiency and resulted to improvement in maize yield (Gacheru and Rao, 2001; Muriithi et al., 2018). Mulching is also useful in enhancing soil moisture, organic matter after the decay of crop residue and assists in decreasing surface soil erosion, preserving soil water content, sustaining agronomic yield, and recycling nutrients (Lal, 2013, 2015). The four practices taken together are important in improving soil fertility, restoring degraded farmland, controlling soil erosion, enhancing soil carbon and are also important measures in mitigating and adapting against climate change effects. Lal (2015) emphasis on the use of integrated nutrient management (INM), as it has the ability to enhance soil carbon sequestration. He notes that applying N and P fertilizers, use of manure, use of crop residue, cover crops, and crop rotation or intercropping helps create synergistic effects that help increase soil organic carbon sequestration and productivity when the practices are adopted in combination rather than in isolation.

3.3. Independent variables

3.3.1. Plot characteristics

Plot characteristics are important variables that influence the adoption of agricultural technologies as shown by Teklewold et al. (2013) and Manda et al. (2016). The plot characteristics considered in the study were plot size, distance to the plot in walking minutes, farmers' perception on the plot's fertility (assessed as either fertile or not), soil erosion (assessed as either affected by soil erosion or not), soil slope (assessed as either gentle, medium or steep), and soil type (assessed as either sandy, loam or clay). Plot size has been established to influence the adoption of certain practices, such as the use of inorganic fertilizer. For instance, smallholder farmers with slightly large farms have a lower probability of applying inorganic fertilizer as it is costly to apply on the entire farm, while at the same time it can be positive as the land size is utilized as a proxy to wealth (Ng'ang'a et al., 2016).

A plot's slope is a determinant of a farm's susceptibility towards soil erosion. It has been established that farmers owning farms with steep slopes invest more in practices that minimize erosion risk and enhance soil fertility. Ndiritu et al. (2014) indicate that farmers have a higher probability of applying fertilizer and manure on steep slopes compared to flat slopes. Kassie et al. (2013) and Manda et al. (2016) point out that a farmer's perception towards their plot fertility and susceptibility to soil erosion influences their likelihood to adopt inorganic fertilizer and manure. Kafesu et al. (2018) note that farmers' rating of plot fertility is consistent with results from lab-based soil analysis, justifying farmer's accuracy in understanding their farm characteristics. This study hypothesizes that farmers who perceived their plots to be of low soil fertility are likely to adopt SCEPs compared to farmers that perceive their plots to be fertile.

Distance from the homestead to the plot can be used as a proxy for the attention and monitoring efforts that a farmer gives to a plot (Teklewold et al., 2013). Plots further from the homestead are expected to receive less attention and monitoring. Additionally, an increase in distance from the homestead increases both transportation and transaction costs (Kassie et al. 2013); thus, reducing the probability of adopting practices that require bulky inputs for instance application of manure (Teklewold et al., 2013).

3.3.2. External support factors

Three factors considered were access to agricultural extension, credit and agricultural group membership. Contact with agricultural extension agents has been shown to influence the adoption of agricultural technologies (Teklewold et al., 2013; Ndiritu et al., 2014). However, the level of trust that farmers have in the agents determines the probability of farmers adopting the practices (Manda et al., 2016). To correct for this, the study assessed whether farmers utilized the information they obtained as a proxy of their trust level in the agricultural agents.

Agricultural groups are important sources of social capital through collective action. They also provide avenues for information dissemination and opportunity for farmers to learn from each other, thereby acting as extension agents. Lastly, the study considered access to agricultural loans. Lastly, access to credit was also considered with a specific interest in agricultural loans. To assess access to credit, the farmers were asked whether they accessed any loan/credit within the last 24 months and the purpose of the loan. This helped in determining whether the loan was an agricultural loan or not.

3.3.3. Location characteristics

Local markets act as both input and output markets. The distance to the local market is associated with transport and transaction cost of purchasing inputs and transporting their harvest to the market. Kassie et al. (2013) note that distance to the market can influence the availability of information and new technologies.

3.3.4. Household characteristics

Feder et al. (1986) noted that household characteristics influence the adoption of agricultural technologies. Some of the key household characteristics considered include age, gender, education level, experience in farming, and the main occupation of the household head, household size, literacy level, and human dependency ratio. A farmer's age can impact the adoption of agricultural technologies as older farmers are perceived to be more experienced than younger farmers (Kassie et al., 2009; Kassie et al., 2013). However, age can be a poor measure of a farmer's farming experience as it assumes that people start farming from a young age, therefore neglecting the fact that some farmers start farming after retirement from formal employment. To cater for this, farmer's years in farming experience was utilized.

Households that have educated household head are likely to be more aware and appreciative of new technologies (Ndiritu et al., 2014; Kamau et al., 2014). However, considering only the education of the household head ignores the influence of other household member's education levels. Therefore, a household literacy level, which is computed by taking into consideration the education level of all household members (Mwungu et al., 2018) was preferred to the household head education level.

Table 1. Wealth calculation table.

Indicator	Values						Points
How many people in the family are aged 0 to 17?	5 or more	3 or 4		1 or 2		zero	
	0	7		16		27	
Does the family own a gas stove or gas range?	No			Yes			
	0			13			
How many television sets does the family have	Zero		1		2 or more		
	0		9		18		
What are the house's outer walls made of?	Mud, bamboo, sticks			iron, aluminium, concrete, brick, stone, wood, asbestos			
	0			4			
How many radios does the family own?	Zero		1		2 or more		
	0		3		10		
Does the family own a sofa set?	No			Yes			
	0			9			
What is the house's roof made of?	Light (Salvaged, makeshift)			Strong (Galvanized iron, aluminium tile, concrete, brick, stone, or asbestos)			
	0			2			
What kind of toilet facility does the family have	None, open pit, closed pit, or other			Water sealed			
	0			3			
Do all children in the family of ages 6 to 11 go to school?	No		Yes		No children ages 6-11		
	0		4		6		
Do any family members have salaried employment?	No			Yes			
	0			6			

Table 2. Definition and summary statistics of variables in the analysis.

Variable	Description of Variable	Mean (SD)	Min	Max
Practices adoption (n = 640)				
Intercropping	% of households that have adopted the intercropping	48%	0	1
Farmyard Manure	% of households that have adopted the farmyard manure	42%	0	1
Inorganic Fertilizer	% of households that have adopted the inorganic fertilizer	74%	0	1
Mulching	% of households that have adopted the mulching	6%	0	1
Plot- Level Variables (n = 640)				
Plot Size	Plot size in acres	0.75 (0.71)	0.03	5
Distance to Plot	Distance in walking minutes	6.63 (23.42)	1	360
Fertility Perception	% of plots that Household perceive to be Fertile	74%	0	1
Soil Erosion Perception	% of plots that Household perceive to be affected by soil erosion	73%	0	1
	1 = Gentle	21%		
	2 = Medium	70%		
Slope	3 = Steep	9%		
	1 = Sand	10%		
	2 = Loam	83%		
Soil type	3 = Clay	7%		
Socioeconomic variables (n = 334)				
Age of HHH	Age of household head in years	53 (14)	22	90
Gender of the HHH	% of male HHH	76%	0	1
Occupation of HHH	% of HHH whose main occupation is farming	70%	0	1
Farming Experience of HHH	Household head farming experience in years	23 (15)	1	60
Dependency Ratio	The proportion of dependents in the household	0.87 (1.04)	0	7
HH Size	Number of people in a household	5 (2)	1	15
Literacy Level	Household literacy level	0.17 (0.13)	0	1
TLU	Tropical livestock unit	3.22 (4.12)	0	60.24
Wealth	% of households classified as not poor	56%	0	1
Distance to Local Market	Distance in walking minutes	30.40 (32.38)	1	180
External Support Factors				
Crop Market Participation	% of households that sold their crop produce	57%	0	1
Agricultural Group Membership	% of households that are members of an agricultural group	34%	0	1
Access Agricultural Credit	% of households that have access to agricultural credit	22%	0	1
Access Extension	% of households that have access to extension	62%	0	1

Note: HHH refers to Household Head, HH refers to Household, and SD refers to Standard Deviation.

Table 3. Complementarities and substitutability of SCEPs: Correlation coefficient of the error term matrix.

	Mulching	Intercropping	Farmyard Manure	Inorganic Fertilizer
Mulching	1			
Intercropping	0.18 (0.97)	1		
Farmyard Manure	-0.11 (0.11)	0.15 ** (0.06)	1	
Inorganic Fertilizer	0.09 (0.11)	0.60 *** (0.05)	0.28*** (0.07)	1

Notes: Robust Standard errors in parenthesis.
Likelihood ratio test of regression interdependence Chi-Square (6) = 96.90***.
n = 640. Statistical significance at *p < 0.1, **p < 0.05, ***p < 0.01.

Household size (the number of people in a household) is often utilized as a proxy for labour endowment (Kassie et al., 2009; Ndiritu et al., 2014; Manda et al., 2016). The larger the household size the higher the availability of labour in that particular household. However, because the ages of the household members may be skewed towards the younger members (1–14 years) or older members (above 65 years) as compared to the working-age members (15–65 years), a human dependence ratio was computed. The dependency ratio caters to the age differences in a household and was preferred to household size. Lastly, a farmer's main occupation influences their time allocation to farming activities. If the household head's main occupation is farming, that is an indication that they spend most of their time in farming activities and may be more inclined to adopt some practices (such as inorganic fertilizer and intercropping) that may be time-consuming to implement.

3.3.5. Resources constraints

The study utilized livestock ownership in the form of a tropical livestock unit (TLU) and the probability of a household being poor as measured by a wealth scorecard to measure a household resource constraint. The wealth scorecard was adopted from Schreiner (2009), where the farmers are asked a total of ten questions that help rate the poverty likelihood of the household (Table 1). The likelihood is then converted into a dummy variable where 1 denotes a household is most likely not poor and 0 a household is most likely poor.

3.4. Ethic consideration

Since the study was dealing with human subjects, the questionnaire utilized for data collection was reviewed and approved by the International Centre for Tropical Agriculture (CIAT) ethics committee before conducting the research. The committee comprises of Elise Talsma (Scientist at CIAT), Jennifer Twyman (Scientist at CIAT), Steve Prager (Principal Scientist and IRB CHAIR at CIAT), Ricardo Labarta (Senior Scientist at CIAT), Luis Augusto Becerra (Principal Scientist at CIAT), Maya Rajasekharan (Head, Program Coordination at CIAT), Maria Virginia Jaramillo (General Council at CIAT) and Enid Katungi (Scientist at CIAT). Additionally, before conducting an interview, the respondents (farmers) offered their consent to participate in the research study and the enumerators complied with all regulation.

4. Results and discussion

4.1. Descriptive statistics

Table 2 presents summary statistics for the variables utilized in the analysis of adoption and the extent of SCEPs. Inorganic fertilizer (74%) intercropping (48%) were the most adopted practices at the plot level. While FYM and mulching adoption rates were 42% and 6%, respectively. The average size of the plot and distance to the plot in walking minutes

Table 4. Adoption of SCEPs: Multivariate probit model (MVP) results.

	Mulching		Intercropping		Farmyard Manure		Inorganic Fertilizer	
	Coef.		Coef.		Coef.		Coef.	
Plot Size (in acres)	0.01	(0.11)	0.36***	(0.08)	-0.00	(0.08)	0.51***	(0.12)
Distance to Plot	-0.00	(0.01)	-0.00	(0.00)	-0.01***	(0.00)	0.03***	(0.01)
Fertility Perception	0.39*	(0.24)	-0.10	(0.12)	0.05	(0.12)	-0.04	(0.13)
Soil Erosion Perception	-0.52 ***	(0.18)	0.44***	(0.12)	-0.09	(0.12)	0.24*	(0.13)
Slope (Steep = Base Category)								
Plot Slope Moderate	-0.45	(0.28)	0.48***	(0.18)	0.07	(0.19)	0.53***	(0.20)
Plot Slope Flat	-0.06	(0.30)	0.80	(0.21)	-0.16	(0.21)	0.53**	(0.23)
HH Farming Experience	-0.01***	(0.01)	-0.00	(0.00)	-0.00	(0.00)	-0.01***	(0.00)
HH Main Occupation	-0.28	(0.18)	-0.09	(0.12)	0.40***	(0.12)	-0.00	(0.13)
TLU	0.04***	(0.01)	-0.01	(0.01)	-0.01	(0.01)	-0.01	(0.01)
Dependency Ratio	0.15**	(0.07)	-0.03	(0.06)	0.01	(0.06)	-0.07	(0.06)
Literacy Level	1.71**	(0.87)	-0.83*	(0.45)	0.96**	(0.49)	-0.06	(0.47)
Crop Market Participation	0.29	(0.18)	-0.32***	(0.11)	-0.33***	(0.11)	-0.10	(0.12)
Agricultural Group Membership	-0.17	(0.23)	0.37***	(0.12)	-0.16	(0.12)	0.14	(0.13)
Access Agricultural Loan	0.11	(0.23)	-0.06	(0.13)	-0.61***	(0.14)	-0.20	(0.15)
Access Extension	-0.14	(0.21)	-0.14	(0.12)	-0.01	(0.12)	0.11	(0.13)
Distance to Local Market	-0.01	(0.00)	0.00	(0.00)	-0.00	(0.00)	0.00	(0.00)
Wealth Category	-0.14	(0.24)	-0.10	(0.12)	0.05	(0.12)	-0.21	(0.13)

Note: Robust standard error in parenthesis, Statistical significance at *p < 0.1, **p < 0.05, ***p < 0.01.
N = 640 (from Sample Size of 334 Households).
Log Pseudo likelihood = -1207.79 Wald Chi-Square (68) = 250.44 ***.
Likelihood ratio test of regression interdependence Chi-Square (6) = 96.90***.
Coef stands for coefficient…. (this applies in all subsequent tables).

was 0.75 acres and 7 min respectively. On average, a farmer's age was 53 years, with 76% being male and with a farming experience of about 23 years. Additionally, 70% of the farmers were fulltime farmers.

The average household size was five people with a dependency ratio of 0.87, a literacy level of 0.17, and the nearest local market been 31 walking minutes away. 56% of the household would be classified as non-poor with an average tropical livestock unit (TLU) of 3.22. At least 34% of the farmer belonged to an agricultural group, and 22% had access to agricultural credit while 62% reported having accessed extension services. About 57% of the farmers reported having sold at least one product from their farms in the last 12 months.

4.2. Complementarity and trade-off among SCEPs

Table 3 presents the results on the substitutability and complementarities of SCEPs. The likelihood ratio test [Chi-Square (χ^2) = 96.90, ρ = 0.00] rejected the null hypothesis that there was zero association amongst the covariance of the error term in the equations. The results imply that there was a positive correlation coefficient between intercropping and FYM, intercropping and inorganic fertilizer, and between FYM and inorganic fertilizer; which indicates that the practices were adopted as are complements. The results point out that farmers use a combination of the practices to enhance agricultural productivity. The results are consistent with Muriithi et al. (2018) and Marenya and Barrett (2007) that manure and inorganic fertilizer are used in complementarities by small-scale farmers in Kenya.

4.3. Determinants of adoption: MVP model results

The Wald Chi-Square [Chi-Square (χ^2) = 250, ρ = 0.0000] statistics for the overall significance of the model was significant (Table 4), justifying the use of the MVP for the analysis. Additionally, the use of MVP was reaffirmed by the significance of the LR test [Chi-Square (χ^2) = 96.90, ρ = 0.00], thus rejecting the hypothesis that the agricultural practices under consideration (mulching, FYM, intercropping, and inorganic fertilizer) are independent. The two tests indicate that the adoption of these practices is interdependent and the use of univariate regression (logit and probit) would have yielded inefficient estimates.

Table 4 presents the MVP regression results showing how plot characteristics, farmer characteristics, household characteristics and resources, and external support factors influence the adoption of SCEPs. Plot size had a significant and positive effect on the implementation of intercropping and the use of inorganic fertilizer which is consistent with findings of Ndiritu et al. (2014), Manda et al. (2016) and Muriithi et al. (2018), who stated that an increase in plot size increases the likelihood of applying inorganic fertilizer and implementing intercropping with legumes to enhance soil fertility.

On the one hand, the distance from the homestead to the plot had a negative and significant influence on the adoption of FYM. On the other hand, it had a positive and significant influence on the adoption of inorganic fertilizer. This suggests that farmers utilized manure in plots nearer to the homestead due to its bulkiness and labour requirements associated with spreading the manure in the plot Waithaka et al. (2007); while inorganic fertilizer which is less bulky than manure was utilized in plots further from the residence. Castellanos-Navarrete et al. (2015) note that it requires two man-days to collected one kilogram (Kg) of N and 10 man-days to collect one kilogram of P.

Plots perceived to be more fertile had a higher likelihood of having mulching implemented since it is an effective practice in improving soil conditions by increasing soil organic matter, reducing soil water evaporation (Muriithi et al., 2018). However, interpretation of this result is approached with caution since enhanced soil fertility can be endogenous to mulching since the practice improves soil conditions and fertility. Therefore, without considering historical information of the plot, a causal inference of this result can be misleading.

Plots that were perceived to have been affected by soil erosion were more likely to have intercropping and inorganic fertilizer implemented on them, but mulching was less likely to be implemented. Applying inorganic fertilizer and intercropping can be explained by the need to improve soil fertility and legumes in fixing nitrogen respectively, in order to enhance the productivity of the plots (Teklewold et al., 2019). Plots that had gentle and moderate slopes had a higher likelihood of having intercropping and inorganic fertilizer implemented in them compared to plots with steep slopes. This finding is contrary to previous studies by Ndiritu et al. (2014) who noted that farmers with steep slopes were less likely to adopt the practices compared with farmers whose plots were slope was either gentle or moderate. This can be attributed to farmers being risk-averse.

Experienced farmers were less likely to adopt mulching and inorganic fertilizer. An indication that experienced farmers were less likely to adopt new technologies such as mulching and inorganic fertilizer as compared to farmers that just started farming (Manda et al., 2016). Households, where the household head's main occupation was farming, had an increased probability of adopting FYM since its application is labour intensive, and thus full-time farmers had more time on their disposal to transport and apply the manure on their plots.

Livestock wealth (in TLU) and human dependency ratio positively influenced the adoption of mulching. An increase in livestock kept in a household increases demand for animal feed requirement, which in turn, leads to increased utilization of crop residue as animal feed and subsequently increase in feed waste that can be utilized for mulching (Tey et al., 2014). On the one hand, the literacy ratio had a significant and positive influence on the adoption of mulching and FYM because households with a high literacy ratio were more likely to be searching for new information (Mwungu et al., 2018) and therefore had more knowledge on the benefit of adopting newer technologies (mulching and FYM) such as enhanced the formation of soil aggregated with the improvement of porosity, infiltration, and water-holding capacity (Gilley et al., 2002). On the other hand, it had a negative influence on the adoption of intercropping because most households in Western Kenya have had small parcels of land and have been practising intercropping for a long time; thus as people got educated they stop practising intercropping as they consider it as an old method of farming. Another plausible explanation is that most educated farmers had formal employments and higher disposable income and were, therefore, able to supplement the benefits of intercropping with the use of inorganic fertilizer, which is in agreement with the finding of Kassie et al. (2013) and Ndiritu et al. (2014).

Farmers that belonged to an agricultural group were more likely to adopt intercropping since group membership facilitates information sharing between members of a group on the benefits and cons of intercropping (Kassie et al., 2009). Additionally, farmers that had access to agricultural loans were less likely to adopt FYM because they were able to adopt other practices that require a larger capital outlay, such as irrigation.

Distance to the market can be utilized as a proxy to information and technology (Kassie et al., 2013) and in this case it negatively influenced the adoption of mulching, an indication that farmers nearer the market had access to information regarding mulching and its benefits compared to farmers farther from local markets (Tey et al., 2014). Farmers that participated in the market were less likely to adopt intercropping and use of FYM because most of the farmers in the region that participated in markets were selling more of other crops that cannot be intercropped such as bananas, African leafy vegetables, and sugarcane (cash crop in Kakamega County) or tea (cash crop in Vihiga County).

4.4. Determinants of the extent of adoption: generalized ordered logit results

The generalized ordered logit assumes that the effect of a variable may not be uniform across each level of the dependent variable. In this

Table 5. The extent of adoption of SCEPs: Generalized ordered logit results.

Variables	Level 1 (0–1 practice)		Level 2 (1–2 practices)		Level 3 (2–3 practices)	
	Coef.		Coef.		Coef.	
Number of Plots	-0.41***	(0.09)	-0.41***	(0.09)	-0.41***	(0.09)
Plot Size (in acres)	1.23***	(0.30)	0.54***	(0.16)	0.14	(0.15)
Distance to Plot	-0.00	(0.00)	-0.00	(0.00)	-0.00	(0.00)
Soil Erosion Perception	0.22	(0.25)	0.48**	(0.20)	-0.24	(0.23)
Slope (Steep = Base Category)						
Slope Moderate	0.57*	(0.29)	0.57*	(0.29)	0.57*	(0.29)
Slope Flat	0.61*	(0.34)	0.61*	(0.34)	0.61	(0.34)
Soil Type (Clay = Base Category)						
Soil Type Loam	0.36	(0.27)	0.36	(0.27)	0.36	(0.27)
Soil Type Sandy	0.41	(0.34)	0.41	(0.34)	0.41	(0.34)
TLU	0.01	(0.02)	0.01	(0.02)	0.01	(0.02)
Gender of HH	-0.52***	(0.19)	-0.522***	(0.18)	-0.52***	(0.18)
Age of HH	-0.01	(0.01)	-0.005	(0.01)	-0.01	(0.01)
Education level of HH	0.18	(0.18)	0.18	(0.18)	0.18	(0.18)
Household size	-0.00	(0.04)	-0.00	(0.04)	-0.00	(0.04)
HH Main Occupation	0.05	(0.18)	0.05	(0.18)	0.05	(0.18)
Crop Market Participation	-0.20	(0.16)	-0.20	(0.16)	-0.20	(0.16)
Access Agricultural Loan	-0.66***	(0.19)	-0.66***	(0.19)	-0.66***	(0.19)
Wealth Category	-0.03	(0.19)	-0.03	(0.19)	-0.03	(0.19)
Agricultural Group Membership	0.72***	(0.27)	0.37*	(0.20)	-0.06	(0.21)
Distance to Local Market	-0.00	(0.00)	-0.00	(0.00)	-0.00	(0.00)
_cons	1.85	(0.58)	0.88	(0.55)	-0.04	(0.56)

Note: Robust standard error in parenthesis, Statistical significance at *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.
n = 640 (from Sample Size of 334 Households).
Log Pseudo likelihood = -791.02 Wald Chi-Square (25) = 97.29 *** Pseudo R^2 = 7.04%.

case, the effect of an independent variable is not uniform across the number of practices adopted. Therefore, a variable may influence a farmer to adopt the first practice on their plot but may be ineffective in influencing them to adopt the second and the third practice.

There were four practices under consideration and thus five possible categories– zero practice, one practice, two practices, three practices, and four practices adopted. Among the five categories, 103 plots had zero practice, 137 plots had one practice, 252 had two practices, 147 plots had three practices, and one plot had all the four practices implemented. However, for the model to run effectively, one of the requirement is that all categories need to have at least 30 observations; thus the plot with all the four practices implemented was merged with the plots that had three practices, and the observations in that category increased to 148 plots (147 + 1 = 148). Therefore, the results contain three levels; level one moving from zero practice to one practice, level two moving from one practice to two practices, and level three moving from two practices to three practices. The results for the generalized logit model are presented in Table 5.

The number of plots a farmer owns had a significant and negative influence on the number of practices adopted. This could be an indication that farmers first adopted SCEPs on plots that they thought are of low soil fertility. Plot size positively influenced the extent of adoption to level two; the larger the plot a farmer had the higher the probability of them adopting the first and the second practices which is consistent with the finding of Barungi et al. (2013) and Ndiritu et al. (2014) as farmers adopted more agricultural practices to enhance the soil condition of the plot.

Farmers' perception of their plot being affected by soil erosion was not strong enough to motivate them to adopt the first practice but influenced them to adopt a second practice if they were already adopters. Mishra et al. (2018) indicate that farmers that are adopters of a given package of technologies have experienced the benefits of adopting and developed a positive attitude towards the practices and thus are more likely to adopt more practices than non-adopters. Farmers whose plot had gentle and moderate slopes had a higher probability of adopting more SCEPs. This contradicts the finding by Carlisle (2016) and Soule et al. (2000) who found that plots on a steep slope and highly erodible lands were more likely to have soil conservation practices implement. However, a plausible explanation is that farmers in Western Kenya are risk-averse.

The results show that access to agricultural loans had a significant and negative influence on the number of practices adopted because farmers that had access to agricultural loans had enough capital outlay to adopt other capital-intensive practices such as irrigation rather than SCEPs that are low-cost practices. Additionally, female-headed households had a higher probability of adopting more SCEPs compared to male-headed households.

Membership to an agricultural group positively influenced the number of SCEPs adopted indicating that members of an agricultural group were more likely to adopt the first and the second practice. However, it would not influence them to adopt a third practice since farmers that obtained information on SCEPs had experienced the benefits of adoption and thus were more likely to adopt the third practice due to the benefits of the practices rather than them having information about the practices. This points out to the initial significance of social capital in influencing the adoption of SCEPs.

4.5. The validity of the results

To better understand the factors that may facilitate or constrain the adoption of SCEPs, the study was conducted into two counties, Kakamega and Vihiga Counties. Data were collected from a total of 10 sub-counties within the two counties to increase the variability of the data which enabled the study to collect reliable information that can be utilized to generalize smallholder farmers found in high potential areas. The results

Table 6. Impact of adoption of SCEPs on maize yields: Multinomial endogenous treatment effect model.

	Coef.	Std. Error	Percent change	90kg Bag Equivalent
Endogenous Practices				
Intercropping	0.35***	(0.07)	35%	3.2
Manure	0.18*	(0.10)	18%	1.8
Manure and Intercropping	0.33***	(0.09)	33%	3.0
Selection term				
Intercropping	-0.17***	(0.04)		
Manure	-0.01	(0.07)		
Manure and Intercropping	-0.20***	(0.07)		
LnSigma	-1.74***	(0.31)		

Robust Standard errors in parenthesis Statistical significance at *p < 0.1, **p < 0.05, ***p < 0.01.

from this study can thus be used to give an overview of the prospect and constraints to adoption of SCEPs within the same agro-ecological zones in Kenya that are characterized as high agricultural potential areas but faced by high population density, soil erosion, low soil fertility, and low productivity.

4.6. Quantitative and economic linkage

The study is based on the assumption that enhanced adoption of SCEPs would enhance soil fertility, which can be measured through enhanced crop productivity. The assumption is key since it provides the study with the bases of coming up with policy implications that can be utilized to enhance the adoption of SCEPs. The second part of the study not documented in this paper was able to ascertain that the adoption of SCEPs does enhance maize yield. The study utilized a multinomial endogenous treatment effect model and showed that on average the adoption of intercropping increased maize yield by 35 percent (3.2 bags of 90Kgs per acre per season), while manure by 18 percent (1.8 bags of 90Kgs per acre per season), and a combination of both by 33 percent (3.0 bags of 90Kgs per acre per season) (Table 6).

5. Conclusion and policy implications

In Western Kenya, farmers are faced with low farm income as a result of low yields emanating from low soil fertility and land degradation. Empirical evidence has shown that the adoption of SCEPs can play a significant role in solving some of the aforementioned problems. The study, however, acknowledged that the adoption of practices can be complementary or a substitute. The study utilized MVP to analyse the adoption of multiple SCEPs and generalized ordered logit to access the extent of adoption as measured by the number of practices adopted.

The correlation results indicate a high complementarity between the SCEPs, reflecting the interdependence between agricultural practices adoption. This proves that the study eliminates the potential biases that would have resulted if each practice was studied separately. The study also revealed that the adoption of SCEPs is knowledge-intensive due to the influence of agricultural group membership and literacy level and farmer's knowledge and perception towards their plot characteristics. The influence of these factors shows the need for coming up with a better holistic policy that can be utilized in upscaling the adoption of SCEPs through a more innovative information dissemination method. This can be done by strengthening the existing farmers' group, increasing farmers' training frequencies, and on-farm demonstrations. While training farmers, it would be necessary to educate them on the different cost-effective practices that they can adopt and the need to have their soil scientifically tested to enhance of adoption of practices that tackle a specific problem in each plot the farmer has. This would provide a good platform for private soil testing companies to collaborate with farmers' group and market their services at competitive prices during training workshops or seminars.

Lastly, the study was able to highlight the role of gender in enhancing the adoption of SCEPs. This calls for the need to formulate policies that are gender-friendly and specific. For instance, farmers' training should be formulated in a manner that youth, women, and men are all able to participate and share knowledge freely. Additionally, to accommodate youth in agriculture, dissemination of information through the use of social media applications, short message services (SMS), and mobile phone-based applications would be encourage.

Declarations

Author contribution statement

George Magambo Kanyenji: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Willis Oluoch-Kosura, Cecilia Moraa Onyango, Stanley Karanja Ng'ang'a: Conceived and designed the experiments; Wrote the paper.

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Competing interest statement

The authors declare no conflict of interest.

Additional information

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