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Does the adoption of soil carbon enhancing practices pay off? Evidence on maize yields from Western Kenya.

George Magambo Kanyenji*
Department of Agricultural Economics, University of Nairobi P.O. Box 29053-00625, Kangemi, Nairobi, Kenya. E-mail: geomagambo@gmail.com
Willis Oluoch-Kosura
Department of Agricultural Economics, University of Nairobi P.O. Box 29053-00625, Kangemi, Nairobi, Kenya. E-mail: willis.kosura@gmail.com
Cecilia Moraa Onyango
Department of Plant Science and Crop Protection, University of Nairobi P.O. Box 29053-00625, Kangemi, Nairobi, Kenya. E-mail: ceciliam.onyango@gmail.com
Stanley Karanja Ng'ang'a
International Center for Tropical Agriculture, P.O Box 823-00621 Nairobi, Kenya. E-mail: s.karanja@cgiar.org

Abstract

Soil carbon enhancing practices (SCEPs) have been proven to be low-cost solutions in enhancing agricultural productivity and alleviate the detrimental effects of climate change. These practices can be adopted as complementary or as substitute practices due to their associated ecological benefits and cost. In view of this, there is limited literature on the impact of adopting a combination of SCEPs since their effect may be lower or higher than individual technologies. A structured survey was utilized to collect data from 334 households in Western Kenya. The study utilized the multinomial endogenous treatment effect model to assess the determinants and impact of adopting on maize yield. The results reveal that adoption is influenced by plots specific characteristics (distance to the plot and tenure system), external support factors (access to credit and farmers participation in markets), tropical livestock units and literacy level. In addition, the results showed that adoption of farmyard manure, intercropping, and intercropping and farmyard manure combination has a significant and positive impact on maize yield. This implies that there is a need to promote SCEPs adoption among smallholder farmers given its positive impact and associated low cost of implementation

Keywords: Maize yields; low productivity; soil carbon enhancing practices; multinomial endogenous treatment effect; Western Kenya.

1. Introduction

By the year 2050, sub-Saharan Africa's (SSA) population is expected to double to nearly 2 billion people (FAO 2017). The projected population growth is a concern considering SSA's inability to feed its current population (FAO 2017). Agricultural production in SSA is currently characterized by sub-optimal use of inputs and low productivity (Lilyan et al. 2004;FAO 2017). The total production of most staple foods across SSA has been on the rise as a result of increased land under production as opposed to increased productivity (Jayne et al. 2016). Additionally, it is predicted that by 2020 income and yield from maize and wheat will have reduced by 50% among SSA countries (Mwungu et al. 2018) dues to reduction in productivity. The decline in productivity can be associated to poor land management practices (such as mono-cropping), soil degradation and low soil fertility (Odendo et al. 2010; Jaetzold et al. 2010; Cavanagh et al. 2010; Kihara et al. 2017). The situation has been complicated by the increased land pressure and reduction in land size holding among small-scale farmers who contribute to 75% and 70% of maize production and marketed output respectively (IPCC 2007; Olwande 2012); thus, constraining their ability to expand the area under production. This leaves enhancing productivity among the SSA countries the only viable solution to meet the constantly increasing demand of food. Within the last 3 decades, most SSA countries have shifted their focus to attaining food security through agricultural research and adoption of relevant technologies such as green revolution and climate-smart agriculture (Kotu et al. 2017).

Studies have highlighted the need to embrace the green revolution due to its success in enhancing productivity among Asian countries (Hazell 2009; Pretty et al. 2011; Jayne et al. 2014). The green revolution involves the adoption of irrigation, chemical fertilizer improved seeds and pesticides (Pretty et al. 2011). Despite green revolution success implementation in Asia, it has had some negative consequences namely increased soil acidity and reduction in crop biodiversity (Altieri & Nicholls 2005; Kotu et al. 2017). Currently, SSA food production systems are under threat due to the destruction of ecosystems services such as nitrogen fixation, biological control of weeds and pest, nutrient cycling and soil regeneration (Snapp et al. 2010; Pretty et al. 2011 Teklewold et al. 2013). Considering the negative impact of the green revolution and the deteriorating ecosystem, the importance of transition to more sustainable agricultural technologies has been emphasized (Pretty et al. 2011; Hinrichs 2014; Liverpool-Tasie et al 2015).

Adoption of technologies that can assist farmers in mitigating and adapting to climate change effects are of importance, as most farmers are vulnerable to changing weather patterns (Bryan et al. 2013). For instance, in Kenya maize yield has been decreasing at a rate of 0.07 ton/ha/decade with 50% and 68% variance in maize yield is accounted for by variation in seasonal climate indices and precipitation respectively (Mumo et al. 2018). The importance of maize in Kenya cannot be underestimated as its a significant crop in respect to food security as well as source of income at household level (Gitau & Meyer2019) Some of the sustainable technologies that have the potential to sequester soil carbon, regenerate ecosystems, provide low-cost solution to enhancing productivity, and acts as mitigation and adaption strategy among smallholder farmers are soil carbon enhancing practices (SCEPs) (Li et al. 2013; Lal 2013; Lal et al. 2015).

SCEPs include soil erosion management practices, mulch farming (crop residue and cover crop), tillage methods (conservation tillage), soil fertility management (organic fertilizer and chemical fertilizer), water management (drip irrigation, soil water storage and runoff farming) and farming systems management (agroforestry, intercropping, and crop rotation) (Lal 2013).

Therefore, SCEPs can be treated as climate-smart technologies that help farmers adapt to negative effects of climate change, improve agricultural productivity, mitigate greenhouse gasses emissions and enhance the sustainability of the ecosystem.

SCEPs help increase the amount of soil organic carbon content which has been universally proposed to be a measure of soil fertility and quality (Amundson et al. 2015). Moreover, SCEPs enhance the sustainability of soil functions that are critical for ensuring that ecosystems functions are maintained and hence enhancing crops and livestock production (Bekele & Drake 2003; Powlson et al. 2011). Sommers 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. However, the emphasis on the short-term effects on enhancing farmer's productivity cannot be overlooked as the practices enhance soil fertility and subsequently productivity. 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).

SCEPs technologies can be adopted as substitutes or in complementary (Teklewold et al. 2013; Gebremariam & Wunscher 2016; Muriithi et al. 2018) and if adopted in combination may offer higher impact. Extensive research has be conducted on adoption and the impact of adopting several single technologies on agricultural productivity such as minimum tillage (Jena 2019) on farmyard manure (Hassen 2018), and on intercropping with a legume (Ngwira et al. 2012, and Midefa et al. 2014). However, these studies failed to consider the complementarity and substitutability among practices and the combination of the practices under consideration. Several studies have been able to study the impact of individual and combination of technologies in Ethiopia (e.g. Teklewold et al. 2013), in Zambia (e.g. Manda et al. 2015), in Malawi (e.g. Kassie et al. 2014; Mutenje et al. 2016), and in Ghana (e.g. Gebremariam & Wunscher 2016; Kotu et al. 2017). However, different agro-ecological and sociocultural conditions, such as those found in Kenya (particular Western Kenya) limits the external validity of the existing findings.

In light of this, study sort to assess the adoption and impact of adopting SCEPs among maize smallholder farmers in Western Kenya. The study focused on Western Kenya because it is classified as a high potential area for maize production that is currently faced with decreasing land sizes due to high population growth. Moreover, the area is characterized by soil erosion, land degradation, and low soil fertility and land degradation which limits land productivity. The study considered two essential SCEPs that is farmyard manure (FYM) and intercropping maize with legumes. The two were chosen from a wide list of SCEPs because of their associated low costs of implementation, immediate impact on soil fertility for increase crop productivity and have been advocated for within the area by the Ministry of Agriculture, Livestock, Fisheries and Irrigation (formally known as the Ministry of Agriculture).

Focus group discussion in the area revealed that most farmers keep animals mostly for milk production and manure. Farmyard manure (FYM) has long term benefits as it releases nutrients to the soil slowly and helps increase organic matter (Place et al. 2003). Moreover, it can reduce infestation of *Striga hermonthica* a parasitic weed which results in 50-40% losses in maize yields since it increase soil organic matter contents which hinder growth of the weed (Waithaka et al. 2007; De Groote et al. 2008). Intercropping with leguminous plants has also been promoted in Western Kenya due to its potential to suppress weeds, fix nitrogen and reduce the incidence of pest and diseases (Ehui & Pender 2005; Waithaka et al. 2007).

The objective for the present the study was guided by seeking answers to two main research questions: what are the factors influencing the adopting of SCEPs and SCEPs' impact on maize yield? The study applies the use of maximum simulated likelihood estimation of multinomial endogenous treatment effect model that helps take into consideration the effect of observed and unobservable heterogeneity.

2. Econometric Framework

In agriculture, the decision to adopt a practice is not easy as it is anchored on several agricultural constraints such as drought, labor requirements, cash resources for the acquisition of inputs, weed, pest and disease control. Most agricultural technologies are often introduced to farmers as packages (Kassie et al. 2014; Teklewold et al. 2014).The study utilizes the expected utility framework to model the adoption of SCEPs. The expected utility theory suggests that a farmer will adopt a specific technology if it offers greater expected utility than the utility before adopting the practice. In this study, farmers have four alternatives to choose from (not adopting, intercropping only, FYM only and the combination of both). Therefore, a farmer will only adopt a combination of SCEPs that maximizes their utility (in this case maize yield) subject to land, input cost, labour and other constraints

When farmers are classified into adopters and non-adopters, endogeneity problems arise because the decision to adopt is influenced by unobservable characteristics that might be associated with the output variables. Adoption decision of a specific practice may have been informed by the unobservable factor such as farmer's technical and managerial ability to incorporating a technology to their farming system (Abdulai & Huffman 2014; Manda et al. 2015). Failure to consider endogeneity can under or overestimate the exact impact of adopting a technology. The multinomial endogenous treatment effect model was therefore, adopted to account for the unobserved and observed heterogeneity and control for self-selection. The analysis was done at plot level in order to cater for farmer's unobservable characteristics that are likely to influence the results (Manda et al. 2015; Gebremariam & Wunscher 2016).

2.1 Multinomial endogenous treatment effect model

The model as suggested by Deb & Trivedi (2006a) is a two-stage model. The first stage is a multinomial logit that models farmers' adoption decision. A farmer can adopt any of the four possible combinations (i.e. FYM, intercropping, FYM and intercropping or none of the practice) at their farm. The model assumes farmers are rational and will choose a practice that maximizes their indirect utility related to the practice adopted (Eq. 1)

$$V_{ji}^{*} = z_j'\alpha_i + \sum_{k=1}^{J} {}^{\delta}{}_{ik}\, l_{jik} + n_{ji} \quad (1)$$

Where V_{ji}^{*} is the indirect utility derived related to i ($i = 0,1,2,3$) practice and specific to household j , z_j is the vector of factors hypothesized to influence adoption of the SCEPs techniques, household characteristics, plot characteristics, and external support factors; α_i are the estimated parameters associated with hypothesized factors influencing adoption of each practice i ; n_{ji} are the independently and identically distributed the error terms and specific to practice i and household j ; l_{jk} is the latent factor that considers the unobserved characteristic specific to a household j adoption of SCEPs and maize yield. The unobserved characteristics include self-motivation, technical and management of farmers that may influence adoption of SCEPs (Abdulai & Huffman 2014)

A suggested by Deb & Trivedi (2006b), let *i=0* denote non-adopters of any of the two practices and $V_{ji}^* = 0$. While V_{ji}^* is not observed, it can be determined by the combination of SCEPs that a farmer has adopted, which can be represented as a set of dichotomous variables d_j and can be collected by a vector, $d_j = d_{j1}d_{j2}d_{j3} \ldots . d_{jJ}$. Also, let $l_j = l_{j1}l_{j2} \ldots . l_{jJ}$. Therefore the treatment probability equation can be written as Eq. 2

$$\Pr(d_j | z_j l_j) = g(z_j' \propto_1 + \sum_{k-1}^{J} {}^{\delta}{}_{1k} l_{jk} + z_j' \propto_2 + \sum_{k-1}^{J} {}^{\delta}{}_{2k} l_{jk} + \cdots + z_j' \propto_J + \sum_{k-1}^{J} {}^{\delta}{}_{Jk} l_{jk}) \quad (2)$$

Where g is an appropriate multinomial probability distribution. Therefore, a mixed multinomial logit (MMNL) structure can be defined as shown in Eq. 3.

$$\Pr\left(d_j | z_j l_j\right) = \frac{\exp(z_j' \propto_i + {}^{\delta}{}_i l_{ji})}{1 + \sum_{k=1}^{J} exp(z_j' \propto_i + {}^{\delta}{}_i l_{ji})} \quad (3)$$

The second stage of multinomial endogenous treatment effect model examines the impact of adopting SCEPs combination on the natural logarithm of maize yields. The outcome equation can be given by Eq. 4.

$$E\left(y_j | d_j x_j l_j\right) = x_j' \beta + \sum_{i-1}^{J} \gamma_i d_{ji} + \sum_{i-1}^{J} \lambda_j d_{ji} \quad (4)$$

Where y_j the maize yield outcome associated with each household $j . x_j$ represents exogenous covariates with parameter vectors β in relation to each household j . γ_i represents the treatment effects of adopting $(i = 1,2,3)$ compared to the non-adopters$(i = 0)$. If a farmer's decision to adopt SCEPS techniques is endogenous and assuming that parameter d_{ji} is exogenous it would yield inconsistent and biased estimates of γ_j. This creates the need to test for exogeneity in the outcome equation (4). The unobserved characteristics that may lead to self-selection are represented by the latent factor l_{ji} that is included in the model as a factor affecting the outcome in relation to each household (j) and practice under consideration(i). The factor-loading parameters are presented by λ_i. If the factor is positive (negative) it implies that the outcome and the treatment are correlated through unobservable characteristics; which presents evidence of positive (negative) selection. The model assumes a Gaussian (normal) distribution function since the outcome variable (maize yield) is a continuous variable. Equation (4) is then estimated through the maximum simulated likelihood (MSL) approach.

The independent variables in the outcome and adoption equation are identical in the model. However, Deb & Trivedi (2006a) guarantee a more robust identification if an instrumental variable is utilized in the model. Getting valid instrumental is a difficult task. However, a valid instrumental variable has to be an information related variable (Di Falco et al. 2011; Manda et al. 2015; Gebremariam & Wunscher 2016). The study utilized agricultural group membership as the instrumental variable. Kassie et al. (2013) indicate that agricultural groups are good sources of information regarding agricultural technologies' pro and cons, influencing farmer's adoption decision.

The instrumental variable was subjected to the simple falsification test to validate its usability as an instrumental variable. According to the test, a valid instrumental variable should influence the decision to adopt SCEPs, but should not influence the outcome variable among the non-adopters (Di Falco et al. 2011; Manda et al. 2015; Gebremariam & Wunscher 2016). Results from the first stage of the multinomial endogenous treatment effect model on adoption of SCEPs (as presented in Table 1) indicate that agricultural group membership influences the adoption of intercropping and manure, but it does not influence the outcome variable (maize yield) for the non-adopting sub-sample (Table A1 in the appendix), thus proving that membership to an agricultural group is a valid instrument.

Plot-level information was utilized to solve for farmers' unobserved effects that are likely to affect the model by constructing a panel data that can account for plot specific effects (Udry 1996; Manda et al. 2015). However, due to the difficulty of incorporating standard fixed effects in the multinomial endogenous treatment effect model, the study follows the Mundlak (1978) approach to account for the unobservable characteristic. The mean values of plot-level specific characteristics are included in the model.

3. Study Area, Data and Sampling Procedure

The study employed an inclusive household and plot level data collection in Vihiga and Kakamega Counties in Western Kenya in August 2018. The study sites were purposively selected since they represent a high potential area faced with low agricultural productivity, due to; 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 like the Agricultural Intensification in sub-Saharan Africa (AFRINT) project that has been in operation since 2002 have implemented in the areas to counter the effect of soil degradation promoting the technologies under consideration.

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 namely; 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 lie in a different agro-ecological zone 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. 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.

The next administrative structure the study considered after the sub-county, was the ward, and then the village. 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 was determined using Eq. 5 and Eq. 6 which resulted in 320 farmers (i.e. 160 farmers from each county). Additionally, in order 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.

$$n_0 = \frac{Z^2 pq}{e^2} \tag{5}$$

$$n_0 = \frac{1.96^2(0.5*0.5)}{0.055^2} = 317\ (\sim 320) \tag{6}$$

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

In the fourth stage, ten farmers from each village were interviewed by first picking a random farmer to start with then snowballing to get the other farmers. However, in order to cater for data problems, 14 additional respondents were interviewed leading to a final sample size of 334 farmers operating 710 plots. After controlling for plots that cultivated maize, the final sample size was 409 plots.

4. Results and Discussion

4.1 Descriptive Statistics

Table 1: Descriptive Statistics of variables included in the model

Variable	Description of Variable	Mean (SD/frequency)
Output Variable		
Maize yield	Maize yield in tones per acre	0.826 (0.56)
Practices adoption dummies (n= 409)		
Intercropping	% of plots that have adopted the intercropping only	40% (164)
FYM	% of plots that have adopted the farmyard manure only	15% (62)
Intercropping plus FYM	% of plots that have adopted the intercropping plus FYM.	34% (137)
Non-adopter	% of plots that have adopted none of the practices	11% (46)
Mean Plot- Level Variables		
Plot Size	Plot size in acres	0.75 (0.71)
Distance to Plot	Distance in walking minutes	6.63 (23.42)
Fertility Perception	% of plots that Household perceive to be Fertile	75%
Tenure system	% of plots that were owned with title deeds	49%
Socioeconomic variables (n = 334)		
Age of HHH	Age of HHH in years	53(14)
Gender of the HHH	% of male HHH	76%
HHH Participate in Farming	% of HHH that offer labour services to farming activities	91%
Literacy Level	Household literacy level	0.17 (0.13)
Tropical livestock unit	Tropical livestock unit (TLU)	3.22 (4.12)
Wealth	% of households classified as not poor	56%
Crop Market Participation	% of households that sold their produce	57%
Access Agricultural credit	% of households that had access to agricultural credit	22%
Access Extension	% of households that had access to extension	62%
Instrumental Variable		
Agricultural Group Membership	% of household that are members of an agricultural group	34%

HHH refers to Household Head

Table 1 presents summary statistics for the variables utilized in the analysis. Intercropping was adopted in 40% of the plots, FYM in 15%, a combination of both in 34% and non-adopters either of the practices in 11% of the plot. This signifies the low adoption rate among the practices in Western Kenya. On average FYM application was approximately 1.8 t ha^{-1} which is below the optimal 4.05t ha^{-1} as recommended by the Ministry of Agriculture, Livestock, Fisheries and Irrigation in Western Kenya (Salasya 2005). The average maize yield per acre was 0.83tons. About 57% of the farmers reported having sold at least one product from their farms in the last 12 months.

The average size of a plot was 0.75 acres and distance to the plot in walking minutes 7 minutes. However, the total farm size that at household worked on averaged at 0.91. The parcels of land are small due to high population density and uncontrolled subdivision of land. With land size been utilized as an indicator of wealth it confirms the results the poverty index that poverty rate within the area is high. On average 49% of the plots had secure tenure system as farmers owned title deeds to their plots. Majority (74%) of the farmers perceived their plots to be productive (fertile), but all agreed on the need to further enhance their fertility

On average the farmer's age was 53 years, with 76% of the respondents being male. This is an indication that majority of the farmers within the region were old farmers and with male farmers controlling the decision making process in regards to what practices to adopt and what crops to grow. The average household literacy level was 0.17, and 56% of the households would be classified as not-poor with an average Tropical Livestock Unit (TLU) of 3.22. The results indicate that there were significantly high poverty rate at 44% which is above the national average in rural areas at 39%. Additionally, 70% of the farmers provided their labour for farming activities an indication on time they devoted to farming activities. Besides, 34% of the farmers were members of an agricultural group while 22% had access to agricultural loan. This implies that majority of the farmers lacked access to agricultural credit to purchase inputs. Additionally, low membership in agricultural social groups signifies low information exchange among farmers. However, access to extension service was high at 62%, with most farmers receiving extension services mainly from Non-Governmental Agencies, and County extensional officer.

4.2 Determinants of Adoption of SCEPs Multinomial endogenous treatment effect model results

The first stage of the multinomial endogenous treatment effect model evaluates factors that affect the adoption of intercropping, FYM and combination of both as presented in Table 2. Literacy level significantly (at 5%) and negatively influenced the adoption of intercropping. An explanation to this could be that most households in Western Kenya have small pieces of land and have been practising intercropping for a long time; thus as people get educated they stop practising intercropping as they consider it as an old method of farming. The negative effect of literacy level on intercropping is consistent with the finding of Kassie et al. (2014) and Ndiritu et al. (2014) who stated that level of education negatively influenced the adoption of intercropping in Ethiopia and Kenya respectively.

TLU positively influenced the adoption of intercropping, manure and a combination of both. As the number of livestock kept in a household increases the feed requirements to sustain the animals also increases. Therefore, creating a need for farmers to intercrop to increase the amount of residue available to be fed to the animals. Additionally, having more animals increases the amount of manure available to be utilized on the farm.

Table 2: Mixed multinomial logit model estimates of Adoption of SCEPs in Western Kenya

Variables	Intercropping		Manure		Intercropping and Manure	
	Coef.		Coef.		Coef.	
Gender of HHH	-0.030	(0.51)	-0.242	(0.56)	-0.567	(0.49)
Age of HHH	-0.003	(0.01)	-0.018	(0.02)	-0.010	(0.02)
HHH Participates in Farming	-0.906	(0.76)	1.303	(1.10)	1.226	(0.91)
Tropical Livestock Unit (TLU)	0.433***	(0.12)	0.373***	(0.14)	0.397***	(0.13)
Literacy Level	-3.395**	(1.73)	1.624	(1.92)	0.796	(1.77)
Access Credit	-0.614	(0.41)	-1.240**	(0.51)	-1.081***	(0.42)
Access Extension	0.156	(0.46)	0.259	(0.53)	-0.435	(0.47)
Sell Crop Produce	-0.030	(0.46)	-1.273**	(0.54)	-0.817*	(0.46)
Wealth Category	0.063	(0.07)	-0.144*	(0.08)	-0.057	(0.08)
Mundlak fixed effect						
Plot Size	-0.384	(0.31)	-0.301	(0.42)	-0.572	(0.38)
Distance to Plot	-0.028**	(0.01)	0.011	(0.02)	-0.052**	(0.02)
Plot Fertility Perception	-0.067	(0.48)	1.039	(0.65)	-0.043	(0.50)
Plot Tenure	-0.760	(0.48)	1.730***	(0.50)	1.205***	(0.47)
Instrumental Variable						
Agricultural Group Membership	1.154**	(0.48)	-1.020*	(0.62)	0.551	(0.50)
_cons	1.724	(1.38)	-0.530	(1.81)	1.230	(1.48)

Robust Standard errors in parenthesis.
Log Pseudo likelihood = -539.5706 Wald Chi-Square (58) = 313.28 ***.
N=409 (from Sample Size of 324 Households). Statistical significance at *p<0.1, **p<0.05, ***p<0.01

Households classified as not being poor were less likely to apply FYM on their farm. A probable explanation could be that, as wealth increases households would tend to have enough capital outlay to invest in other capital-intensive practices such as irrigation and inorganic fertilizer. Cavanagh (2017) indicates that the wealth category of household determined the technologies they adopted with poorer household adopting fewer technologies that required more capital outlay in implementation. This is an indication of the role of resource endowment on adoption. Additionally, access to credit negatively influenced the adoption of manure and intercropping and manure combination. Farmers that had access to loans were able to adopt other practices that require a larger capital outlay such as irrigation and inorganic fertilizer.

Farmers that participated in markets through the sale of produce were less likely to implement manure and combination of intercropping and manure on their plots. A possible explanation is that most farmers in the region participating in markets were selling more of other crops such as bananas, African leafy vegetables and sugarcane (cash crop in Kakamega County) or tea (cash crop in Vihiga County) explaining why they were less likely to implement manure and intercropping and manure combination.

Households that owned title deed for their plots were more likely to adopt the use of manure and intercropping and combination of both. The results collaborate the finding of Kassie et al. (2013) and Manda et al. (2015) that secure land tenure encourages farmers to adopt agricultural technologies. This result reaffirms the importance of clearly defined property rights on adoption of agricultural practices.

Distance to the plot from the residence negatively influenced the adoption of intercropping and its combination with manure. This is an indication that plots nearer to the residence were more likely to have intercropping and its combination with manure implemented than plots further from the residence. Considering that manure application and spreading is a time-consuming process and bulky to carry it is thus preferred for plots nearer the residence.

Agricultural group membership positively influenced the adoption of intercropping and negatively the adoption of manure. Groups play a key role in information sharing between members of the group on the pro and con of the two practices and also on inputs and other innovation (Mutenje et al. 2016; Gebremariam & Wunscher 2016).

4.3 Impact of Adopting SCEPs

Table 3: Multinomial endogenous treatment effect model estimates of SCEPs impact on Maize yields

SCEPS	Net Crop yield per Acre		
Endogenous			% change
Intercropping	0.3543***	(0.069)	35%
Manure	0.1796*	(0.103)	18%
Manure and Intercropping	0.3270***	(0.088)	33%
Selection term			
Intercropping	-0.1716***	(0.037)	
Manure	-0.0136	(0.068)	
Manure and Intercropping	-0.2024***	(0.069)	
Lnsigma	-1.7403***	(0.306)	
Exogenous Factors			
Gender of HHH	-0.0219	(0.038)	
Age of HHH	-0.0018	(0.001)	
HHH Participates in Farming	-0.1589**	(0.058)	
Tropical Livestock Unit (TLU)	-0.0003	(0.007)	
Literacy Level	0.0747	(0.137)	
Access Credit	0.1100***	(0.033)	
Access Extension	0.0399	(0.034)	
Sell Crop Produce	0.1345***	(0.037)	
Wealth Category	0.0144**	(0.006)	
Plot Size	-0.1487***	(0.033)	
Distance to Plot	0.0028***	(0.001)	
Plot Fertility Perception	0.0185	(0.037)	
Plot Tenure	0.0080	(0.048)	

The baseline category are farm households that did not adopt any SCEPs. Sample size 409 plots and 334 households. 400 simulation draws were used

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

The study estimated the impact of adopting FYM and intercropping in isolation or as a combination in the second stage of the multinomial endogenous treatment effect model. After controlling for unobservable heterogeneity, the results indicate that the adoption of either manure, intercropping or combination of both significantly resulted into increase in maize yield. On average the adoption of intercropping increases maize yield by 35%, while manure by 18% and a combination of both by 33%. The increase of 35% in maize yield through intercropping is consistent with field trials in Kenya which indicated the potential of 40-20% increase in maize yield (Woomer 2007; Mucheru-Maina et al. 2010). Additionally, 18% increase in maize yield as a result of manure application is consistent with field trials that estimated that indicate the increase to ranges from 15-35% (Miriti et al. 2007; Woomer 2007). The low application rate of manure would be have resulted in the low impact of 18% on maize yield. This suggests that the application of manure at the recommended nutrition rate would result in higher impact. Additionally, the other exogenous factors (household characteristics, mean plot characteristics and support factors) also affect the maize yield per acre.

The loading factors (selection term) indicates that there was evidence of negative selection bias signifying that unobserved factors that enhance the probability of adopting SCEPs are related with maize yield than those expected under random assignment to be adopters of SCEPs. Additionally, the test of exogeneity of the treatment variable using the likelihood ratio was performed. The Likelihood ratio test value was [χ^2 (3) =8.1894, p=0.0423], which was significant, thus rejecting the null hypothesis of exogeneity and concluding that the treatment variable is endogenous. This justified the use of multinomial endogenous treatment effects model.

5. Conclusion and Implication

Soil carbon enhancing practices have the potential to alleviate the problem of low productivity faced by most SSA farmers at potentially low cost. These practices help in enhancing the soil carbon and thus enhancing the regeneration of the ecosystem. Previous studies tried to assess the impact of adoption without taking into account the complementarity and substitutability practices. This study acknowledges the complementary of the practices while assessing the adoption and impact of adoption on maize yield by utilizing multinomial endogenous treatment effect model.

The study reveals that adoption of SCEPS is affected by plot characteristics (distance to the plot from the residence and secure land tenure), literacy level, resource endowment (tropical livestock unit (TLU) and wealth category) and external support services (access to credit and participation in markets). Importantly, the study confirms trial experimental results by ascertaining that the adoption of the SCEPs has a significant and positive impact on maize yield. Adoption of intercropping had the highest impact on maize yield, followed by the combination of intercropping and manure. Despite manure contributing the lowest at 18% in terms of increasing maize yield, its application at the optimal nutrition rate would generate higher output yields while utilized in combination of intercropping. Future intervention programs that are aimed at enhancing productivity should advocate for the adoption of SCEPs in combination. Additionally, the optimum nutrition amount of manure application should be encouraged for maximum gains to be achieved.

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Appendices

Table A1: Test of validity of Instrumental Variable

	Ln Maize Yield Coef.	
Gender of HHH	0.1773	(0.187)
Age of HHH	0.0050	(0.007)
HHH Participates in Farming	-0.1224	(0.256)
Tropical Livestock Unit (TLU)	0.0624	(0.052)
Literacy Level	-0.2371	(0.469)
Access Credit	0.0534	(0.168)
Access Extension	0.1506	(0.169)
Sell Crop Produce	0.3211**	(0.150)
Plot Size	-0.2260*	(0.133)
Distance to Plot	0.0003	(0.004)
Plot Fertility Perception	-0.0452	(0.163)
Tenure	0.0082	(0.151)
Wealth Category	0.0187	(0.032)
Agricultural Group Membership	-0.0733	(0.216)
_cons	2.0153***	(0.693)

Robust Standard errors in parenthesis
Statistical significance at *p<0.1, **p<0.05, ***p<0.01
Sample size 46 R squared 32% Adjusted R squared 1.33%