Does the adoption of soil carbon enhancing practices translate to increased farm yields? A case of maize yield from Western Kenya

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ABSTRACT
Improving agricultural productivity to improve food security and feed the future generation is needed. One of the ways to achieve this is by adopting low-cost solutions such as soil carbon enhancing practices (SCEPs). Given the complexity of adoption decisions, technologies are either adopted as substitutes or complements. A structured survey was utilized to collect data from 334 households in Western Kenya to estimate the impact of adopting SCEPs in combination and identify challenges hindering the adoption of the technologies. Two models, namely a multinomial endogenous treatment effect model and a multi-valued treatment effect model under conditional independence, were utilized to assess the impact of adoption on maize yield. Key variables established to influence adoption were literacy level, tenure security, and market participation. It was further revealed that adopting farmyard manure, intercropping, and a combination of intercropping and farmyard manure had a significant and positive impact on maize yield. This creates a need to promote the adoption of low-cost SCEPs to increase productivity and food security.

1. Introduction

Maize within Sub-Saharan Africa (SSA) is an important crop covering over 42 million (M) hectares and the primary source of calories among rural households (Prasanna et al., 2021). Production levels between 1961 and 2020 within SSA have increased by 476%, from 14M tons to the current value of 83M tons (FAO, 2021). However, this increment is attributed to the increased area under production rather than increased productivity. The area under production has increased from 14M hectares (ha) in 1961 to 42M ha in 2020. On the other hand, productivity has merely improved from 1 ton per ha to 2.5 tons per ha, compared to the world average of 5.7 tons per ha in 2020. To cater for the expanding population and meet the need of future generations, maize production must increase by 2.2% per year (Prasanna et al., 2021). Holding maize productivity constant, the area under production must increase by 184% within SSA to meet the future demand for the project population of 2 billion people. This creates a need to enhance production through other means rather than area expansion.

Maize production is a complex equation comprising several factors: climate, agronomy, genetics, policy, and political stability (Cairns et al., 2013). Smallholder farmers have no control over some factors. For instance, Powlson et al. (2014) predict that by 2050, due to climate change, crop yield will reduce by nearly 20%, with crop failure for maize and wheat at 40% and 30%, respectively. Therefore, smallholder farmers’ only option is to adopt agricultural technologies capable of withstanding such anticipated shocks.

Nevertheless, several other factors contribute to low maize productivity rather than climate change. Firstly, farmers use sub-optimal inputs such as improved seed varieties and fertilizers. For instance, fertilizer use within SSA is estimated at 8Kg per ha, falling below the world average of 137 kg per ha (Das et al., 2019). Secondly, farmers adopt poor land management practices, resulting in land degradation leading to low soil fertility and soil erosion, nutrient depletion, and loss of organic matter (Odendo et al., 2010; Cavanagh et al., 2017). Thirdly, increased land pressure within high agricultural areas due to the rise in urbanization and subdivision of land reduces smallholder farmers’ land size. These
enforcing factors create a need to find a solution that enhances soil fertility, thus improving productivity.

Several interventions and technologies within different countries have been proven to enhance productivity. For instance, the success of the green revolution is attributed to the use of improved seed varieties and chemical fertilizers. However, the contribution of other elements such as pesticides and irrigation cannot be overlooked. The green revolution has been promoted within SSA; however, the uptake is below optimal, as highlighted previously with the use of chemical fertilizer, limiting its success in SSA. Despite its overwhelming success in South Asia, the green revolution has also been attributed to reducing crop biodiversity and increased soil acidity (Kotu et al., 2017). Thus, destroying essential ecosystem services such as nitrogen fixation, nutrient cycling, and soil regeneration (Snapp et al., 2010; Teklewold et al., 2013). Due to this, emphasis has shifted to promoting more sustainable agricultural technologies.

A few sustainable agricultural technologies and interventions promoted within SSA include climate-smart agriculture, conservational agriculture, and soil carbon enhancing practices (SCEPs). Of particular interest to this paper are SCEPs due to their ability to sequester soil carbon while proving to be a low-cost solution to improving productivity (Lal, 2004a; Lal et al., 2014). In addition, SCEPs cover a wide range of technologies promoted within climate-smart agriculture and conservational agriculture. These technologies include mulch farming (crop residue and cover crop), soil erosion management practices, use of fertilizer (both organic and chemical), tillage methods (conservation tillage), water management (soil water storage, drip irrigation, and runoff farming), and farming systems management (intercropping, agroforestry, and crop rotation) (Lal, 2004b).

Before any technology is promoted to farmers, its benefits must be clearly outlined. In this regard, SCEPs assist in sequestrating carbon, directly resulting in an accumulation of soil organic carbon content and soil organic matter (Lal 2004b). This directly improves the quality of soil and fertility levels. Furthermore, apart from improved soil fertility, soil organic carbon and organic matter are instrumental in restoring soil and ecosystem functions disturbed due to soil degradation (Powlson et al., 2014). This has been ascertained by several field trials, such as Otinga et al. (2013) on the use of manure and Kafesu et al. (2018) on conserved tillage.

Evidence from published literature shows that farmers either adopt technologies as complements or substitutes (Gebremariam and Wunschler, 2016; Muriithi et al., 2018) and failure to account for this may lead to misplaced policy interventions. When households are faced with different shocks and overlapping constraints and objectives, they adopt several combinations of technologies that cater to their immediate goal (Gebremariam and Tesfaye, 2018). Several studies have recognized the substitutability and complementarity of technologies while investigating the impact of adoption, such as Gebremariam and Wunschler (2016), Kotu et al. (2017) in Ghana, Teklewold et al. (2013) in Ethiopia, Kassie et al. (2014) in Malawi, and Manda et al. (2015) in Zambia. However, the difference in agro-ecological and socio-cultural conditions, such as those found in Kenya (particularly Western Kenya), limit the existing findings' external validity.

Several interventions have been promoted in Kenya, particularly Western Kenya, such as the Kenya Agricultural Carbon Project (KACP) and Agricultural Intensification in SSA. For example, KACP rolled out in 2011, promoted climate-smart agriculture, and introduced certified and exchangeable carbon credit. All these programs directly advocated for adopting some of the SCEPs’ practices. This study was interested in low-cost practices such as intercropping maize with leguminous crops and farmyard manure (FYM), partly due to the high poverty rate and low access to credit within the regions (well-articulated in the descriptive statistics under the results section). But also due to their low cost of implementation and impact on enhancing productivity. Additionally, the area was considered since it’s classified as a high potential area, lying within the moist transitional maize production zones, but is characterized by high population, decreasing land sizes, land degradation resulting in low soil fertility and soil erosion (Ondobo et al., 2010; Jaetzold et al., 2010).

Despite the efforts to promote these technologies, the adoption rate for FYM and intercropping were still low are 56% and 53%, respectively (Waihaka et al., 2007; Dallimer et al., 2018). The study was thus designed to offer a better understanding of why the uptake of these technologies is low. The guiding questions for this study were, (a) which factors influence the adoption of SCEPs? and (b) what is the impact of SCEPs on maize yield? To answer these questions, a maximum simulated likelihood estimation was utilized through a multinomial endogenous treatment effect model that considers the effect of observed and unobservable heterogeneity with the incorporation of an instrumental variable (IV). Additionally, the results were validated using the multi-valued treatment effect model under conditional independence by using a semi-parametric approach to calculate the potential outcomes and control for selection bias. Given the complexity of finding good IV (Kubitszka and Krishna, 2020), the second model helped validate the results. Additionally, the model was suitable for this study since it generates doubly robust estimators.

2. Econometric framework

Considering the substitutability and complementarity of technologies, a farmer, in this case, is faced with four adoption decisions: adopting FYM only, intercropping only, the combination of FYM and intercropping, or not adopting any practice. However, their decision is a function of farming objectives and agricultural constraints such as production risk with a particular interest in climate change-related risks (i.e., drought, flood, etc.), labour requirements, marketing risk, and resources for the acquisition of inputs. This study adopted the expected utility framework to model this decision. The model suggests a farmer will only adopt a technology if and only if it offers superior expected utility than the utility derived before adopting the practice. Therefore, a farmer will only adopt a combination of SCEPs that maximize their utility (in our case, maize yield) subject to land, labour, input cost, and other constraints.

Whenever farmers are classified as adopters and non-adopters, the issue of endogeneity arises. Apart from the observable farmer characteristics, unobservable factors such as farmers’ technical and managerial ability to incorporate technology into their farming system might influence the adoption (i.e., adoption and maize yield) (Manda et al., 2015). Therefore, ignoring endogeneity results in overestimating or underestimating the true impact of adopting a practice. A multinomial endogenous treatment effect model was utilized to account for the unobserved and observed heterogeneity and control for self-selection. Additionally, the study was conducted at the plot level to control for farmers’ unobservable attributes likely to influence the results (Manda et al., 2015; Gebremariam and Wunschler, 2016).

2.1. Multinomial endogenous treatment effect model

The study applied the model proposed by Deb and Trivedi (2006a). In essence, the model is a two-step model where the first step is a multinomial logit model that examines farmers’ adoption decisions, while the second step is a multinomial endogenous treatment effect model (METEM) that examines the impact of adopting SCEPs combination on maize yield. Recall that a farmer has four adoption decisions to choose from i.e. adopting FYM, intercropping, a combination of FYM and intercropping or none of the practices at their farm. METEM assumes that farmers are rational and will choose a practice that maximizes their

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expected utility related to the practice adopted (Eq. 1). As early indicated, the study assumes the expected utility to be yield.

$$V_{yi}^j = \beta_i \alpha_i + \sum_{k=1}^{j} \delta_k \lambda_k + n_j$$

(1)

Where $V_{yi}^j$ is the expected utility derived related to $i (i = 0, 1, 2, 3)$ practice and specific to household $j$. While $\beta_i$ is the vector of factors hypothesized to impact the adoption of the SCEPs techniques such as plot characteristics, household characteristics, and external support factors. $\alpha_i$ are the estimated parameters associated with hypothesized factors affecting the adoption of each practice. $n_j$ are the independently and identically distributed error terms and specific to practice $i$ and household $j$. $\lambda_k$ is the latent factor that considers the unobserved characteristic specific to a household $j$ adoption of SCEPs and maize yield.

As suggested by Deb and Trivedi (2006b), $i = 0$ denote non-adopters of either of the two practices and $V_{yi}^j = 0$. While $V_{yi}^j$ 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, $d_j = d_j1, d_j2, d_j3, ... d_jJ$. Also, let $l_ji = l_j1l_j2 ... l_jJ$. The treatment probability equation can, therefore, be written as Eq. (2).

$$Pr(d_j | x_j) = \left( \frac{\exp(\beta_i \alpha_i + \delta_k \lambda_k + \sum_{k=1}^{j} \delta_k \lambda_k + ... + \delta_k \lambda_k + n_j)}{1 + \sum_{k=1}^{j} \exp(\beta_i \alpha_i + \delta_k \lambda_k)} \right)$$

(2)

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

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(3)

The second stage of the 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).

$$E(y_j | d_jx_j) = \lambda_j^y \beta + \sum_{i=1}^{j} \gamma_i d_i + \sum_{i=1}^{j} \lambda_i d_i$$

(4)

Where $y_j$ the maize yield outcome associated with each household $j$, $\lambda_j$ represents exogenous covariates with parameter vectors $\beta$ in relation to each household $j$ and $\gamma_i$ represents the treatment effects of adopting $(i = 1, 2, 3)$ compared to the non-adopters $(i = 0)$. If a farmer decision to adopt SCEPs techniques is endogenous and assuming that parameter $d_j$ is exogenous, it would yield inconsistent and biased estimates of $\beta$. This creates the need to test for exogeneity in the outcome of Eq. (4). The latent factor represents the unobserved characteristics that may lead to self-selection, $\lambda_j$ 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 $\lambda_i$. 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 continuous. Eq. (4) is then estimated through the maximum simulated likelihood (MSL) approach.

To ensure a more robust identification, Deb and Trivedi (2006a) recommend using an instrumental variable (IV) in the model. This is necessary since the independent variables in the outcome and adoption equation are identical. Obtaining a valid instrument is a challenging task; however, Gebremariam and Wunsch (2016) recommend the use of an information related variable as an IV. The study thus used agricultural group membership as IV. Kassie et al. (2013) indicate that agricultural groups are useful sources of information (i.e., pros and cons) regarding agricultural technologies and this does influence farmers’ adoption decisions.

A simple falsification test is one of the tests utilized to validate the usability of an IV. The test dictates that a valid IV should only influence the decision to adopt a practice(s) but should not influence the outcome variable among the non-adopters (Gebremariam and Wunsch, 2016). The IV (group membership) as utilized model was found to satisfy this condition as shown by adoption results, the first stage of METEM (Table 2) that agricultural group membership influences the adoption of intercropping and manure, but it does not impact the maize yield (outcome variable) for the non-adopting sub-sample (Table A1).

The use of plot-level information helps in the construction of panel data, which was critical to solve for farmers’ unobserved effects by accounting for plot-specific effects (Udry, 1996; Manda et al., 2015). Mean values of plot-level specific characteristics were included in the model, as suggested by Mundlak (1978) approach to account for the unobservable characteristic, given the difficulty of incorporating standard fixed effects in the METEM. Under the METEM, one has to conduct the test of exogeneity of the treatment variable to justify the model’s use. In these cases, the null and alternative hypotheses suggest the existence of exogeneity and endogeneity, respectively, in the treatment variable.

### 2.2 Multi-valued treatment effect model

This study also incorporated multi-valued treatment effect model to validate and enhance the robustness of the results generated by the METEM. Like METEM, the treatment variable in the multi-valued treatment effects model can take non-binary categories (categorical variable). The multi-valued treatment model is a more recent approach that borrows from Rosenbaum and Robin (1983) potential outcome approach for binary treatment variables.

This study used an advanced potential outcome approach for binary treatment, as Cattaneo et al. (2013) outlined, to estimate impact under conditional independence. The study indicates that each individual from a population can be assigned one of $I = 1$ possible treatment levels $(i = 0, 1, ....., I)$ (in this case, adoption of zero practice, FYM, intercropping, and the combination of FYM and intercropping). Therefore, since each individual can only receive one treatment level, only one of the $I = 1$ possible potential outcomes can be observed for each plot in the sample (considering the study was done at plot level rather than household level). Thus, there is a need to incorporate the ignorability assumption 1 in the model to estimate the parameter of potential-outcome distribution as we have a missing data problem based on our observed data.

The multi-valued treatment effect model proposed in this paper uses the efficient influence function (EIF) rather than the inverse probability weighting scheme (IPW) to construct the estimators. Efficient influence function (EIF) estimators are known to be consistent, asymptotically Gaussian, and semiparametric efficient under appropriate conditions. Additionally, the EIF estimator is recommended since it enjoys the double robust property where one needs to build two models and only correctly specify one model to obtain correct estimates of the treatment effect. The model yields the mean effect under each treatment; however, the contrast and margins command can be utilized to calculate the population-averaged treatment effects in relation to different levels of treatment. Lastly, incorporating the vector of covariates explains the treatment variable, which may overlap, helps yield estimators controlled for selection bias.

1 Ignorability assumption implies that selection to the treatment or control group is assigned randomly independent of observable characteristics and expected outcome.
Under the conditional independence assumption (CIA), covariates' selection is identified by including all variables that affect both participation and the outcome variable. However, conditional independence itself may not be directly tested as it depends on the underlying study assumption (Cattaneo et al., 2013). Farmers who adopted SCEPs practices had training within their farmers' groups or through extension services provided by country officers or private providers. The CIA requires that a farmer’s decision not to adopt any of the SCEPs be unrelated to their yield level as it would have been without adoption (as proven under METEM when testing for suitability of the IV). The study first calculated the correlation coefficients for household and plot attributes and each treatment variable and outcome variables. Variables identified to have a high correlation to both treatment and outcome variables were included as the covariates in the model. These variables included household size, household head experience in farming (in years), household literacy level, household head main occupation, access to credit, extension services, and membership to an agricultural group.

2.3. Study area and sampling design

The household data used in this study were collected in 2018 from Vihiga and Kakamega counties that are situated in the western part of Kenya (Figure 1). The two counties were selected because they represent a high agricultural potential area that practices subsistence farming and is characterized by a high population of smallholder farmers. Additionally, most farms within the counties are characterized by low soil fertility, sub-optimal use of inputs, and soil degradation is common (Odendo et al., 2010).

A total of 334 households operating 640 plots were selected following a multi-stage sampling procedure. Out of the 640 plots, 409 plots had maize grown in the last two seasons. The data was collected from five randomly selected sub-counties in each of the two counties. Furthermore, 16 villages were randomly selected from the five sub-counties selected in each County. This was then followed by a random selection of farmers from the sampling frame list provided by an extension officer within the region. The sampling frame comprised names of households from villages that had participated in agriculture and adopted SCEPs. Data was collected via a semi-structured questionnaire programmed in Survey CTO to enable the utilization of tablets during the data collection process. This ensured that only fully filled questionnaires were admissible. Trained field enumerators assisted in the collection of the data via face-to-face interviews with farmers. Before the data collection process, the semi-structured questionnaire was pretested, a focus group discussion was conducted, and revisions were made to better capture farmers characteristics and adoption of SCEPs. A detailed explanation of the sampling technique and how the sample size was arrived at is provided by Kanyenji et al. (2020).

2.4. Ethic consideration

Before conducting the research, International Centre for Tropical Agriculture (CIAT) internal review board approved the study’s questionnaire. This was necessary since the study was dealing with human subjects. Apart from the CIAT ethics committee, the questionnaire was also approved by the University of Nairobi ethics review board. Lastly, farmers were only eligible to participate in the survey once they offered their signed consent. The signed consent forms were collected daily in the evening for safe storage.

3. Results and discussion

3.1. Descriptive statistics

The use of FYM was adopted in 15% of the plots, intercropping in 40%, a combination of both in 34%, and non-adopters of neither of the
practices in 11% of the plots (Table 1). This signifies the low adoption of rate for these practices in Western Kenya. On average, the FYM application was approximately 1.8 t ha\(^{-1}\), which is below the optimal 7 t ha\(^{-1}\) recommended application rate (NAAIAP, 2014). Kanyenji et al. (2020) established that intercropping and FYM were adopted as complements rather than as substitutes within the regions. This was an indication that farmers utilized the practices in combination to improve soil fertility and productivity. The average maize yield per acre was 0.83 tonnes (i.e., nine bags of 90kg per acre per season\(^4\)). Over the last 12 months, nearly 57% of the farmers reported having sold at least one product from their farm. This signifies a higher dependence on on-farm income for most households within the region. The low level of literacy level indicates low level of education uptake within the households in the area. This is clearly articulated by the works of Mogaka et al. (2021) and Maina et al. (2020). The average household literacy level was 0.17, and a majority of the respondents (70%) provided labour for farming activities, highlighting the importance of agriculture in providing employment and a source of livelihood. The low level of literacy level indicates low level of education uptake within the households in the area. This is clearly articulated by the works of Mogaka et al. (2021) and Cavanagh et al. (2017), where most household members had attained primary level education. Literacy level rather than the education of the household head was utilized as it better explains education levels since the former ignores the influence of other household members' education level (Mwungu et al., 2018). Regarding institutional factors, only 22% had access to an agricultural loan, while 34% of the farmers belong to an agricultural group. Regarding institutional factors, only 22% had access to an agricultural loan, while 34% of the farmers belong to an agricultural group.

On average, each farmer operated a plot sized 0.75 acres, with the total household farm being 0.91 acres, while the plots were within 7 walking minutes from the homestead. The parcels of land are small due to the high population density (as illustrated by the average household size of 5 people) and continued subdivision of land and is within the acreage limits as established by previous studies (Cavanagh et al., 2017; Mignouna et al., 2010). The short walking distance from the homestead to the plots signifies farmers' close proxy to their plots and the inherent subdivision of land, forcing them to stay close to their farming plots. Poverty rate within the area is relatively higher at 44% compared to the national average in rural areas at 39%. Nearly half of the plots (49%) had a title deed issued, signifying a secure tenure. A majority (74%) of the farmers perceived their plots to be productive (fertile), but all agreed on the need to enhance soil fertility and increase production. On average, 76% of the respondents were male, while farmer's average age was 53 years. This signifies the dominance of old farmers, with minimal youth participating in farming. Additionally, it highlights male farmers dominance in controlling the decision-making process concerning what practices to adopt and what crops to grow, which is consistent with finding from Mogaka et al. (2021) and Maina et al. (2020). The average household literacy level was 0.17, and a majority of the respondents (70%) provided labour for farming activities, highlighting the importance of agriculture in providing employment and a source of livelihood. The low level of literacy level indicates low level of education uptake within the households in the area. This is clearly articulated by the works of Mogaka et al. (2021) and Cavanagh et al. (2017), where most household members had attained primary level education. Literacy level rather than the education of the household head was utilized as it better explains education levels since the former ignores the influence of other household members' education level (Mwungu et al., 2018). Regarding institutional factors, only 22% had access to an agricultural loan, while 34% of the farmers belong to an agricultural group. The low agricultural group membership signifies low information exchange among farmers. Previous studies such as Maina et al. (2020) and Mogaka et al. (2021) also articulate low access to agricultural loans. This creates the need to enhance the adoption of low-cost SCEPs, given the high level of poverty and poor credit access. However, 62% of the farmers accessed extension service mostly from non-Governmental agencies and County extensional officers.

### Table 1. Descriptive statistics of key variables.

| Variable                               | Description of Variable                                      | Mean  | SD/Frequency | Min | Max |
|----------------------------------------|--------------------------------------------------------------|-------|--------------|-----|-----|
| **Output Variable**                    |                                                               |       |              |     |     |
| Maize yield                            | Maize yield in tonnes per acre                               | 0.82  | 0.56         |     |     |
| **Practices Adoption Dummies (n = 409)**|                                                               |       |              |     |     |
| Non-adopter                            | % Plots that have adopted none of the practices               | 11%   | 46           | 0   | 1   |
| FYM                                    | % Plots that have adopted farmyard manure only                | 15%   | 62           | 0   | 1   |
| Intercropping                          | % Plots that have adopted intercropping only                  | 40%   | 164          | 0   | 1   |
| Intercropping plus FYM                 | % Plots that have adopted intercropping and FYM              | 34%   | 137          | 0   | 1   |
| **Mean Plot - Level Variables (n=409)**|                                                               |       |              |     |     |
| Plot Size                              | in acres                                                     | 0.75  | 0.71         | 0.03| 5   |
| Distance to Plot                       | in walking minutes from homestead to the plot                 | 6.63  | 23.42        | 1   | 360 |
| Fertility Perception                   | % Plots that household perceived to be fertile                | 75%   |              | 0   | 1   |
| Tenure system                          | % Plots that were owned with title deeds                     | 49%   |              | 0   | 1   |
| **Socioeconomic Variables (n = 334)**  |                                                               |       |              |     |     |
| Age of HHH                             | in years                                                     | 53    | 14           | 22  | 90  |
| Gender of the HHH                      | % Male HHH                                                   | 76%   |              | 0   | 1   |
| HH size                                | Number of people in a household                              | 5     | 2            | 1   | 15  |
| HHH Participate in Farming             | % HHH that offer labour services to farming activities        | 91%   |              | 0   | 1   |
| Literacy Level                         | Household literacy level                                     | 0.17  | 0.13         | 0   | 1   |
| TLU                                    | Tropical livestock unit (TLU)                                | 3.22  | 4.12         | 0   | 60.24 |
| Wealth                                 | % HH classified as not poor                                   | 56%   |              | 0   | 1   |
| Crop Market Participation              | % HH that sold their produce                                 | 57%   |              | 0   | 1   |
| Access Agricultural credit            | % HH that had access to agricultural credit                  | 22%   |              | 0   | 1   |
| Access Extension                       | % HH that had access to extension                            | 62%   |              | 0   | 1   |
| **Instrumental Variable (IV)**         |                                                               |       |              |     |     |
| Agricultural Group Membership          | % HH that are members of an agricultural group               | 34%   |              |     |     |

NB: HH refer to Household, HHH refers to Household Head.

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3 Adoption was defined as farmers that had implemented FYM and Intercropping on their plots for five years or more.

4 In Western Kenya, there are two rainy season per year.

5 A farmer could operate on more than one plot.
negatively influenced by literacy level has a negative; this is consistent with finding from Ndiritu et al. (2014) in Kenya and Kassie et al. (2014) in Ethiopia. A possible explanation for this could be that, in Western Kenya, farmers have small pieces of land where they have been practicing intercropping since the early 1970s, as explained during the focus group discussions. Therefore, as farmers got educated, they consider intercropping an “old” method of farming and opt for “new” farming methods such as inorganic fertilizer application. The finding also suggests that the more educated farmers become, the more likely they are to earn extra income, for instance from employment, and thus have enough disposable income to purchase fertilizers rather than adopt intercrop. Further evidence from descriptive statistics suggests that farmers with a higher level of literacy, the primary source of income were formal and informal employment - excluding casual laborers.

The number of livestock owned, as calculated by tropical livestock unit positively influenced the adoption of manure, intercropping, and a combination of both. This provides a good case for trade-off that influence farmers decisions. For a farmer to access cheap source of manure they need to keep livestock, however, due to reduced land size, which can be translated to reduced grazing land, farmers need to find alternative sources for feed. Therefore, farmers make the decision to adopt intercropping to increase the amount of crop residue utilized as feed. In turn, the livestock provide farmers with a cheap and constant source of manure.

A households wealth category influences the household decision in adopting FYM; households that would be classified as not being poor (wealthy household) were less likely to apply FYM on their farm. This could be explained by accessibility to capital outlay and its importance in purchasing necessary agricultural inputs such as inorganic fertilizer. This is better illustrated by the work of Cavanagh et al. (2017) that poorer household adopted fewer practices that required capital outlay to implemented compared to wealthy households. This signifies the role of resource endowments in the adoption of agricultural technologies. Additionally, access to credit negatively influenced the adoption of manure and a combination of intercropping and manure.

Market participation reduces farmers’ likelihood of implementing manure and the combination of intercropping and manure on their plots. While ownership of a plot with a title deed increased the likelihood of adopting the use of manure and intercropping and a combination of both. This is in line with Kassie et al. (2013) and Manda et al. (2015) findings that secure land tenure encourages farmers to adopt agricultural technologies. This result reaffirms the importance of clearly defined property rights on the adoption of agricultural practices.

### Table 2. Mixed multinomial logit model estimates of adoption of SCEPs.

| Variables                        | Coef.  | Coef.  | Coef.  |
|----------------------------------|--------|--------|--------|
| Gender of HHH                    | -0.03  | -0.24  | -0.56  |
| Age of HHH                       | -0.00  | -0.02  | -0.01  |
| HHH Participates in Farming      | -0.91  | 1.30   | 1.23   |
| Tropical Livestock Unit          | 0.43***| 0.37***| 0.40***|
| Literacy Level                   | -3.40**| 1.62   | 0.80   |
| Access Credit                    | -0.61  | -1.24**| -1.08***|
| Access Extension                 | 0.16   | 0.26   | -0.44  |
| Sell Crop Produce                | -0.03  | -1.27**| -0.82* |
| Wealth Category                  | 0.06   | -0.14* | -0.06  |

Mundlak fixed effect

| Plot Size                        | -0.38  | -0.30  | -0.57  |
| Distance to Plot                 | -0.03**| 0.01   | -0.05**|
| Plot Fertility Perception        | -0.07  | 1.04   | -0.04  |
| Plot Tenure                      | -0.76  | 1.73***| 1.21***|

Instrumental Variable (IV)

| Agricultural Group Membership    | 1.15** | -1.02* | 0.55   |
| c_cons                           | 1.72   | -0.53  | 1.23   |

NB: Robust Standard errors in parenthesis. Log Pseudo likelihood \( = -539.57 \) 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.

### Table 3. Multinomial endogenous treatment effect model estimates of SCEPs impact on maize yields.

| Endogenous Practice | Coef.  | % change (bags) |
|---------------------|--------|-----------------|
| FYM                 | 0.18*  | 18% (162kg)     |
| Intercropping       | 0.35***| 35% (288ks)     |
| FYM and Intercropping| 0.33***| 33% (270kg)     |

Selection Term

| FYM                  | -0.01  | (0.07)          |
| Intercropping        | -0.17***| (0.04)         |
| FYM and Intercropping| -0.20***| (0.07)         |
| Latigma              | -1.74***| (0.31)         |

Exogenous Factors

| Gender of HHH        | -0.02  | (0.04)          |
| Age of HHH           | -0.00  | (0.00)          |
| HHH Participates in Farming | -0.16** | (0.06) |
| Tropical Livestock Unit (TLU) | -0.00 | (0.01) |
| Literacy Level       | 0.07   | (0.14)          |
| Access Credit        | 0.11***| (0.03)          |
| Access Extension     | 0.04   | (0.03)          |
| Sell Crop Produce    | 0.13***| (0.04)          |
| Wealth Category      | 0.01** | (0.01)          |
| Plot Size            | -0.15***| (0.03)         |
| Distance to Plot     | 0.00***| (0.00)          |
| Plot Fertility Perception | 0.02   | (0.04)       |
| Plot Tenure          | 0.00   | (0.05)          |

NB: The baseline category is 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 distance between a plot and the homestead negatively affected the implementation of intercropping and its combination with manure. This signifies that the further a plot is from the homestead the less likely it is to have intercropping and its combination with manure implemented. Considering manure is a bulky commodity and its application is time-consuming explains why it’s preferred for plots nearer the homestead. Lastly, membership to agricultural groups and negatively the adoption of manure, but positively affected the implementation of intercropping. Groups play a crucial role in information (i.e., on pro and cons and required inputs) sharing for the two practices and other innovations (Gebremariam and Wunscher, 2016).

3.3. Impact of adopting soil carbon enhancing practices

Table 3 presents the effect of adopting intercropping and FYM in isolation and as a combination as obtained from the second step of METEM. The results indicate that the adoption of either FYM, intercropping, or a combination of both significantly increased maize yield. The adoption of FYM increased maize yield by 18% (162kg per acre per season), intercropping by 35% (288kg per acre per season), and a combination of both by 33% (260kg per acre per season). The multi-valued treatment effect model affirms the METEM results. However, there was slight variation as the adoption of intercropping improved production by 347kg, FYM by 155kg, and a combination of both by 281kg per acre per season (Table 4). The results in Table 4 are based on the contrast command, with the full model results presented in Table A2 in the appendix.

The increase of 18% and 35% and in maize yield through FYM and intercropping and respectively is consistent with field trials in Kenya, which indicated the potential of a 20–40% increase in maize yield following intercropping and 15–35% under FYM (Mucheru-Maina et al., 2010). However, the low impact of manure on maize productivity would be explained by the low application rate of manure within the area. This suggests that the application of FYM at the recommended rate would result in a higher impact. Lastly, the other exogenous factors (mean plot characteristics, household characteristics, and support factors) were found to influence the maize yield per acre. Considering the direct benefits that farmers observe via increased productivity, the two practices have other benefits, mainly environmental benefits. For instance, the adoption of intercropping has been established to be beneficial in nitrogen fixation, and the value of this has been estimated to be about US$ 81 ha⁻¹yr⁻¹ (Ng’ang’a et al., 2017). On the other hand, FYM is critical in controlling the levels of nitrogen and methane released into the atmosphere by animal waste. Good management of FYM can reduce global warming potential (GWP⁶) by 34% (Sefeedpari et al., 2019). The practices are thus beneficial to both farmers and the environment.

The selection terms (loading factors) indicate that there was presence of negative selection bias, suggesting that unobserved factors that enhance the probability of adopting SCEPs are related to 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 $\chi^2(3) = 8.19 \ p = 0.04$, which was significant, thus rejecting the null hypothesis of exogeneity and concluding that the treatment variable is endogenous. This justified the use of the multinomial endogenous treatment effects model.

4. Conclusion and implication

SCEPs are low-cost practices having the potential to alleviate the problem of low productivity inherent in most SSA smallholder farms by improving soil organic carbon. Several studies had attempted to ascertain the impact of adoption without taking into consideration the complementarity and substitutability of practices. The current study acknowledges the complementarity of practices while evaluating the adoption and impact of adoption on maize yield by utilizing METEM. Additionally, the study utilizes the multi-valued treatment effect model to affirm the METEM results. The second model is also superior as it overcomes the need to identify suitable IVs.

The adoption of SCEPS is affected by resource endowment (wealth category, and tropical livestock unit (TLU)) literacy level, external support services (participation in markets and access to credit), and plot characteristics (secure land tenure and distance to the plot from the residence). Additionally, the results ascertain the experimental results that the adoption of the SCEPs has a significant and positive impact on maize yield. The adoption of intercropping had the highest (35%) impact on maize yield, followed closely by the combination of intercropping and manure (33%), while manure had the lowest impact at 18%. Nevertheless, manure application at the optimal nutrition rate would result in greater maize yields.

This calls for a holistic measure in educating farmers on the direct (improved productivity) and indirect (improved soil biodiversity) advantages of SCEP. This can be achieved by targeting farmers through farmer groups and educating them on the cost-effective measures they can use, such as intercropping and FYM. Additionally, government agencies would be instrumental in a direct targeted approach that aims to enhance title deed insurance as this encourages farmers to invest in their farms for long-term benefits. Bearing in mind the complementary aspect in the adoption of SCEPs, all future intervention programs should advocate for the adoption of a SCEPS in combination. Additionally, adherence to recommended implementation of the practices should be encouraged. For instance, manure application in recommended amounts should be encouraged for maximum gains to be achieved.

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 Oluch-Kosura; Cecilia Moraa Onyango; Stanley Karanja Ng’ang’a: Conceived and designed the experiments; Wrote the paper.

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Data availability statement

Data associated with this study has been deposited at Harvard Dataverse.
Declarations of interests statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

Appendices.

Table A1. Test of validity for the instrumental variable (IV)

| Variables                        | Coef.     |
|----------------------------------|-----------|
| Ln Maize Yield                   |           |
| Gender of HHHI                   | 0.18      |
| Age of HHF                       | 0.00      |
| HHFI Participates in Farming     | –0.12     |
| Tropical Livestock Unit (TLU)    | 0.06      |
| Literacy Level                   | –0.24     |
| Access Credit                    | 0.05      |
| Access Extension                 | 0.15      |
| Sell Crop Produce                | 0.32      |
| Plot Size                        | –0.24     |
| Distance to Plot                 | 0.00      |
| Plot Fertility Perception        | –0.05     |
| Tenure                           | 0.01      |
| Wealth Category                  | 0.02      |
| Agricultural Group Membership    | –0.07     |
| _cons                            | 2.02      |

Note: Robust Standard errors in parenthesis; Statistical significance at *p < 0.1, **p < 0.05, ***p < 0.01; R squared 32% Adjusted R squared 1.33%.

Table A2. Multi-valued Treatment Effect Model Estimate of SCEPs impact on maize yields

| Practice                      | Coef.     |
|--------------------------------|-----------|
| Non-Adopter                   | 5.79      |
| Intercropping                 | 9.65      |
| Manure                        | 7.51      |
| Intercropping and Manure      | 8.91      |

Note: Sample size 409 plots and 334 households. 400 simulation draws were used; Robust Standard errors in parenthesis. Statistical significance at ***p < 0.01.

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