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Acronyms and abbreviations

AFRINT	agricultural intensification in sub-Saharan Africa
ATT	average treatment effect on treatment
FGD	focus group discussion
HH	household
KACP	Kenya Agricultural Carbon Project
KBM	kernel-based matching
KI	key informants
KNBS	Kenya National Bureau of Statistics
LR	log likelihood
MVP	multivariate probit
NNM	nearest neighbor matching
PSM	propensity score matching
SE	standard error
SLMP	sustainable land management practices
TLU	total livestock units

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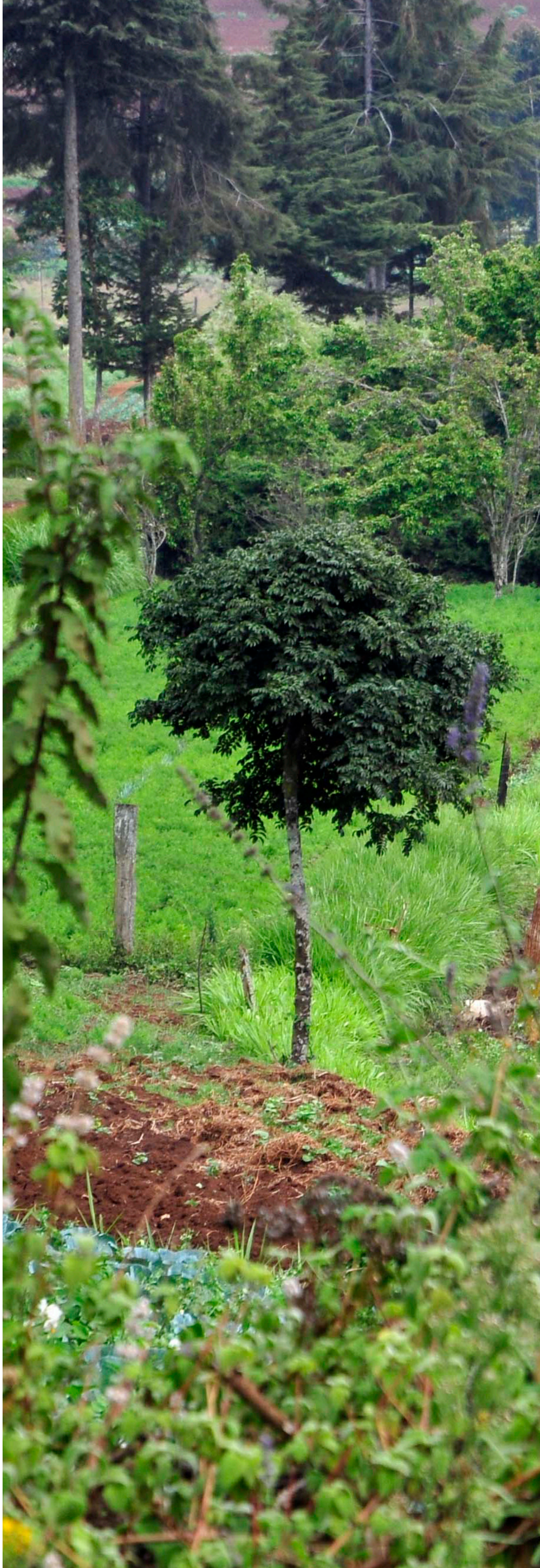
Abstract

Adoption of soil carbon practices has the capability of increasing yield, thus improving income and food availability. This paper assessed the adoption of agricultural practices that enhance soil carbon. Data from 334 households were collected in the rural areas of Western Kenya using a multistage sampling technique. The multivariate probit model and propensity score matching method were used to analyze the determinants of adoption of soil carbon practices and the impact on output, respectively. Results show that agroforestry, intercropping, terracing, and the use of inorganic fertilizer are the dominant soil carbon practices, which are discretely and diversely affected by socioeconomic, farm-level, institutional, and biophysical characteristics. However, the adoption of maize-bean intercropping alone has a great impact on maize production and increases output by approximately 240 kilograms. The findings from this study suggest that the adoption capacity of farming households can be accelerated by independently making interventions targeting individual practices rather than compounding the practices. Consequently, emphasis should target interventions that encourage the adoption of intercropping since its economic impact has been evidently underlined.

KEY WORDS

ADOPTION
SOIL CARBON
PRACTICES
IMPACT
OUTPUT
KENYA



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1. Introduction

Soil erosion and nutrient depletion cause land to become unproductive (Kassie et al., 2008). Consequently, farmers tend to invest in agricultural and sustainable land management practices (SLMP) – application of farmyard manure, terracing, stone or soil bunds, and planting trees –that have the potential to improve land productivity (Liniger et al,, 2011). The adoption of agricultural practices and SLMP that improve soil organic carbon has the potential to mitigate the effects of climate change, and increase yield, thus enhancing food security (Bekele and Drake, 2003). This is because soil organic carbon improves soil structure,[1] which, in turn, ensures the sustainability of nutrient release that is critical for crops and livestock production (Powlson et al., 2011). For example, in the Kenyan highlands, cattle manure is one SLMP with a high adoption potential due to its prospects in soil fertility enhancement and thus higher maize yield (Mugwe et al., 2009).

The promotion of agricultural practices and SLMP – minimum tillage and organic fertilizer – has been found to be cost-effective for resource-poor farmers because they both increase carbon sequestration and economic returns (Li et al., 2013). However, adoption of agricultural practices and SLMP that enhance soil carbon by farmers in East Africa is still limited (Adimassu et al., 2014; Bewket, 2007). In Kenya, for example, only about 5%, 7%, and 9% of the farmers engage in water and soil conservation practices, fertilizer application, and planting trees, respectively (Bryan et al., 2009).

The adoption of agricultural practices and SLMP has principally been in the western region of Kenya because of its high agricultural potential, especially in the production of staple foods such as maize and beans (Karugia and Wambugu, 2009). However, with continuous production over the years, soil fertility has continued to deteriorate (Djurfeldt et al., 2011). To counter this effect, various projects have been implemented in the area, such as Agricultural Intensification in sub-Saharan Africa (AFRINT), Kenya Agricultural Carbon Project (KACP), and the yield gap. These projects aim at intensifying production among smallholder farmers, promoting the adoption of SLMP, and establishing potential yield attainable through the use of low-cost soil fertility enhancing practices, respectively.

Also, despite the promotion of climate-smart and sustainable intensification and agricultural practices within East Africa (Diwani et al., 2013; Ng'ang'a et al., 2016), adoption of these practices is stunted in Western Kenya (Antle and Stoorvogel, 2008; Mutoko et al., 2014a). For instance, the average adoption rate by farmers in Western Kenya has been estimated at 16%, 48%, and 58% for mulching, inorganic fertilizer, and legume

[1] Soils are composed of minerals, organic matter, water, and air. The alignment of soil particles (soil structure) holds the minerals and organic matter and retains water. The air aids in biological processes that release nutrients into the soil, while the soil water moves nutrients to various parts of the plant.

intercropping, respectively (Dallimer et al., 2018). This is a clear indication that an urgent need exists to prevent further soil deterioration and enhance productivity in Western Kenya, hence the need to upscale the adoption of soil carbon practices.

The extensive literature has hypothesized that socioeconomic characteristics (age, gender, education level, income), institutional characteristics (access to credit, information, and markets), farm-level characteristics (farm size, output), and biophysical characteristics (slope) have varied effects, either positive or negative, on the adoption of SLMP in Kenya (Kassie et al., 2015; Kebebe et al., 2017; Mutoko et al., 2014a; Mwangi et al., 2015; Ndiritu et al., 2014; Wainaina et al., 2016). Farmers' perceptions and know-how regarding soil fertility enhancement practices are critical in their adoption (Odendo et al., 2010). Understanding farmer characteristics provides insights that aid in interventions that would enhance the adoption of soil carbon enhancing practices. Nonetheless, information is insufficient on the determinants of the adoption of such practices in Western Kenya, and their impact on farm output. Against this background, this study accordingly attempts to fill the literature gap by assessing the determinants of the adoption of soil carbon enhancing practices and their impact on farm output in Western Kenya.

Photo: Georgina Smith/CIAT

2. Methodology

2.1. Study area

The survey was administered in two counties in Western Kenya: Vihiga and Kakamega. This area has a rich and varied agro-ecological base (falling between the humid and subhumid agro-ecological zones), characterized by reliable rainfall (ranging from 1,200 to 2,000 mm annually), high temperatures (ranging from 15 to 29 °C annually), well-drained fertile soils, rocky hills, and forests (Okeyo et al., 2014; Savini et al., 2016). The area covers 8,309 square kilometers of land, and has a high population density and growth rate. For instance, according to the last population census, Vihiga and Kakamega counties have a population density of 982 and 550 persons per square kilometer, respectively, compared with the national average of 66 persons per square kilometer (KNBS, 2009).

The high population density in this area has exerted pressure on the land, thus affecting settlement and farming. This has led to poor agricultural management practices and continuous crop farming, and a reduction in the size of arable land to portions that are less than 2 ha (Kamau et al., 2014; Mutoko et al., 2014b; Ogada et al., 2014). This area faces soil fertility degradation, which has led to yields that are below the agricultural potential (Odendo et al., 2010).

2.2. Data collection and sampling procedure

Primary data were gathered via face-to-face interviews with smallholder farmers in Kakamega and Vihiga counties in Western Kenya using a semi-structured questionnaire. A focus group discussion (FGD) was carried out at the two study sites with farmers and various stakeholders[2] to obtain exploratory insights into the various SLMP applied by farmers. The participating farmers in the FGD were identified with the help of extension officers from the two counties, and men and women and youth from each of the sub-counties were equally represented. One extension agent and one soil expert who were conversant with the soil management practices in the study region were also identified; these were our key informants (KI). This was done to aid in the modification, development, and design of the questionnaire that was used for the study (Simon, 2006).

The study targeted smallholder farmers, both adopters and non-adopters of soil carbon enhancing practices. Following Israel (1992) and Särndal and Bengt (2003) when determining a sample in which the variability of the larger population adopting a certain practice is unknown, the formula in Eq. 1 was used to derive the sample size:

[2] An extension officer represented the Ministry of Agriculture from each county. A soil conservation expert represented the private sector, while two male and two female farmers each represented farmers who practice various SLM techniques on their farms from the five sub-counties in each county.

$$n = \frac{p\,(1-p)Z^2}{e^2}$$

Eq. 1

where n = sample size, ρ = share of population of interest, Z = confidence interval, and e = margin of error. However, p is presumed to have a value of 0.5 since the population is concealed, and would yield the maximum sample size, Z = 1.96 and e = 0.055. Therefore, the total sample size for the study was determined as shown in Eq. 2:

$$n = \frac{0.5\,(1-0.5)\,1.96^2}{0.0548^{\,2}} = 320$$

Eq. 2

The sample was drawn using a multistage sampling technique, equally distributed in Kakamega and Vihiga counties as they represent a high-potential area facing poor agricultural productivity, due to soil infertility. In the first stage, smaller administrative units (sub-counties) were selected from each county. To ensure data variability and greater sample representation, five sub-counties were considered from each county. Specifically, in Vihiga, all five sub-counties (Hamisi, Sabatia, Vihiga, Emuhaya, and Luanda) were selected. In Kakamega, 5 out of the 12 sub-counties were selected, based on the criteria of similar amount of annual rainfall received and existence of two planting seasons per year. This was done to ensure uniformity of the agro-ecological zone from which data were collected. The sub-counties selected were Khwisero, Matungu, Malava, Lurambi, and Mumias East.

In the second stage, with the help of agricultural extension officers, smaller administrative units (wards) where farmers employ various soil carbon enhancing practices on their farms were identified. Two wards were then selected from each sub-county due to time constraints. Each of the wards is composed of villages; therefore, three villages were selected from each of the four sub-counties and four villages from each sub-county in both Kakamega and Vihiga. This resulted in a total of 16 villages in each county.

In the third stage, ten farmers were selected from each village by randomly picking the first farmer and snowballing to obtain the remaining nine farmers. The targeted sample size as generated from Eq. 2 was 320 farmers, but a total of 334 farmers were interviewed to allow for any data challenges that could arise during the final data analysis. The interviews were conducted by five enumerators[3] especially trained for three days for familiarity with the questions in the data collection tool. The enumerators collected data on the socioeconomic attributes of the households: age, gender, education, farm income, household composition, farm characteristics, and access to credit, groups, information, and technical training. Data on production and marketing characteristics and soil management practices among the households were also collected. On average, one questionnaire took an hour to complete, and each enumerator completed about five questionnaires in a day.

2.3 Analytical framework

The decision to adopt a certain soil carbon enhancing practice is a discrete choice between adoption and non-adoption. Hence, the dependent variable Y_i takes the value of one if a household adopts a certain practice and zero otherwise. Therefore, several modeling approaches (probit and logit models) can be used to estimate Y_i. However, these models have a limitation of failing to incorporate simultaneous adoption behavior, which might overlook unobserved variations prompting adoption of multiple decisions (Lin et al., 2005). Thus, other modeling approaches exist (e.g., multinomial probit and logit) that permit the analysis of multi-categorical and simultaneous adoption decisions, and these are more applicable (Wooldridge, 2003). However, the multinomial logit and probit models restrict the relationship between regressors and the probabilities of the outcomes, as they assume independence across different outcomes (Dow and Endersby, 2004). Even in situations in which the outcomes are correlated, these models produce significant contrasting estimates relative to the true estimates, a shortfall that the multivariate probit (MVP) model is flexible enough to overcome (Young et al., 2009). This makes the MVP model a superior model compared with the multinomial logit and probit; hence, its application in the data analysis in this study.

The adoption decision operates under the assumption of the random utility framework whereby the utility (U_{ij}) a farmer derives from adopting a certain practice is greater than that of not adopting (U_{ik}), that is, $U_{ij} > U_{ik}$. The disparity between the utilities is therefore

[3] The enumerators were selected based on the criteria that they had an educational background in agriculture and experience in collecting data using electronic media, and they had collected data previously in Western Kenya.

a latent variable where $U_{ij} - U_{ik} > 0$, and can therefore be demonstrated as a function of a set of independent variables, X_{ij} (Ali and Abdulai, 2010), as shown in Eq. 3:

$$U_{ij} = \beta_i X_{ij} + \mu_{ij}$$

Eq. 3

where U_{ij} = utility gained by a farmer i who implements a given soil carbon enhancing practice j, β = coefficients to be estimated, X_{ij} = independent variables determining the adoption decision, and μ = the random term.

Supposing that dependent variable $Y_i = (y_i,...,y_i),(i=1,...,N)$ is the decision to adopt where Y_i takes the value of one if adopted and zero otherwise, the probability that a household will adopt a certain soil carbon practice conditional on X_{ij} could then be defined as

$$\Pr(Y_i=1) = X_{ij}\ \beta_i + \varepsilon_i$$

Eq. 4

where j = choice of a soil carbon enhancing practice and i = an individual household. The MVP model can therefore be specified as shown in Eq. 5 to Eq. 7 (Young et al., 2009):

$$I_1^0 = x'\beta_1 + \varepsilon_1 \quad \text{for} \quad I_1 = 1\,(I_1^0 > 0)$$

Eq. 5

$$I_2^0 = x'\beta_2 + \varepsilon_2 \quad \text{for} \quad I_2 = 1\,(I_2^0 > 0)$$

Eq. 6

$$I_j^0 = x'\beta_j + \varepsilon_j \quad \text{for} \quad I_j = 1\,(I_j^0 > 0)$$

Eq. 7

where I_1^0 = a given soil carbon enhancing practice, with the superscript zero depicting non-adoption and one depicting adoption; x is a set of independent variables that are uniform for all practices (the deterministic component) and are perceived to influence the adoption of soil carbon enhancing practices; β = the parameters to be estimated; and ε = the random term (stochastic component), consisting of unobservable factors explaining the marginal likelihood of choosing a given practice.

2.4. Variables in the model

The independent variables for the MVP model (Table 1) include variables considered in the adoption decision behavior of SLMP by farmers in Western Kenya. In this study, socioeconomic characteristics (gender, age, education, household size, livestock ownership, and income), biophysical characteristics (slope and soil type), farm-level characteristics (farm size, output, and land tenure), and institutional characteristics (access to information, extension services, credit, and group membership) are hypothesized to affect the adoption decision regarding soil carbon enhancing practices by smallholder farmers (Kassie et al., 2015; Marenya and Barrett, 2007; Ndiritu et al., 2014). According to the existing literature, the variables have varied effects on adoption; hence, in this study, the direction of effect of the hypothesized variables is subject to the model estimates.


Photo: Georgina Smith/CIAT

Socioeconomic characteristics

Adoption of SLMP may be variedly affected by gender of the household head, due to the perception of the practices in question and accessibility of resources compared to female counterparts. While García de Jalón et al. (2015) and Mwangi et al. (2015) found a negative impact on the adoption of cover crops, Marenya and Barrett (2007) found a positive impact on the adoption of fertilizer and manure. Older farmers are less likely to adopt new agricultural technologies such as improved crop varieties as they lack incentives to invest in farming activities for the coming years (Simtowe and Muange, 2013). Education positively influences the adoption of soil fertility management practices such as the use of fertilizer, as it gives farmers understanding of and insights into the importance of the practices on their farms (García de Jalón et al., 2015; Kamau et al., 2014). Similarly, the size of a household positively impacts the adoption of practices that require a lot of labor in cases in which labor is costly for the household (Kassie et al., 2015; Ndiritu et al., 2014). However, the effect can be negative when little or no labor is required (Freeman and Omiti, 2003).

Table 1 Description of variables for the model

VARIABLE	DESCRIPTION	EXPECTED OUTCOME
HH gender	Gender of household head (dummy variable 1 = male, 0 = otherwise)	+/–
HH age	Age of the household head in years	+/–
HH size	Number of household members	+/–
Farm size	Size of the farm in acres	+/–
Plot size	Size of the plot in acres	+/–
HH education level	Education level of the household	+
Wealth status	Probability of a household being poor based on the value of assets owned (dummy variable 1 = poor, 0 = otherwise)	+/–
Human dependency ratio	Ratio of dependents to that of breadwinners within the household	+/–
HH occupation	Occupation of the household head (dummy variable 1 = farming household, 0 = otherwise)	+/–
Farming experience	Number of years a household has been involved in farming activities	+/–
Number of crops	Number of crop varieties grown by a household	+/–
Total livestock units (TLU)	Total number of livestock owned by a household	+/–
Land tenure	Type of land ownership (1 = ownership with title, 2 = ownership without title, 3 = rented)	+/–
Plot management	Management of plots (1 = household head, 2 = spouse, 3 = joint)	+/–
Output	Total output from crops in kilograms	+/–
Farm income	Total income derived from crop and livestock farming in Kenyan shillings	+/–
Labor source	Source of labor used for farming activities (1 = family labor, 2 = hired labor, 3 = family & hired labor)	+/–
Access to market distance	Distance to the nearest road and market in walking minutes	+/–
Group membership	A dummy variable whereby a household head has been a member in a group for the last 12 months (1 = group member, 0 = otherwise)	+
Access to credit	A dummy variable whereby a household head has had access to credit to engage in farming activities for the last 12 months (1 = credit access, 0 = otherwise)	+/–

VARIABLE	DESCRIPTION	EXPECTED OUTCOME
Access to extension services	A dummy variable whereby a household head has been visited by private or government extension agents in the last 12 months (1 = extension services access, 0 = otherwise)	+
Slope	Ground inclination of the farm (1 = flat, 2 = slightly moderate, 3 = steep)	+/–
Soil type	Type of soil on the farm(1 = clay, 2 = loam, 3 = sandy)	+/–

NB: HH stands for household
Source: Survey Data (2018).

Farm income varies in its influence on the adoption of soil fertility practices. For instance, households with higher incomes have an incentive to adopt some practices as they have the capability of acquiring inputs (Kamau et al., 2014; Mwirigi et al., 2014). A contrasting finding is highlighted by a negative impact of income on the adoption of manure probably because farmers channel their resources for other prioritized activities (Waithaka et al., 2007). According to Wairore et al. (2016), livestock ownership significantly impacted the adoption of agricultural technologies since livestock products generate income that could increase capital for households. Consequently, the number of years a household has been involved in farming activities equips the household with the experience needed to implement various soil management practices (Freeman and Omiti, 2003; Nyaga et al., 2015), which concurs with the observation that farmers who have used fertilizer for a long duration were likely to continue with adoption since they have acquired the know-how and technical skills to use it.

Farm-level characteristics

Farm size has been found to hinder or encourage the adoption of agricultural technologies. Since households with larger farms are associated with wealth, they are more likely to adopt technologies that improve production and thus increase income (Kebebe et al., 2017; Pisanelli et al., 2008). However, in some observations (Thuo et al., 2014), farm size had a negative influence on adoption since farmers opted to allocate resources to off-farm activities. In most scenarios, farms are partitioned into plots, which independently influence adoption regardless of the farm size. Larger plots had a higher probability of adopting inorganic fertilizer, intercropping, and improved maize varieties (Ndiritu et al., 2014; Ogada et al., 2014).

Also, tenure security is an incentive to the adoption of SLMP. For instance, tenure security positively influenced investment in long-term land improvement practices such as agroforestry and terracing because of individual rights (Nyaga et al., 2015; Wainaina et al., 2016). Farmers aim to maximize output so as to enhance income; hence, the expectation of increased income encourages the adoption of practices such as fertilizer and improved seed varieties (Ogada et al., 2014). Various SLMP require labor for implementation and maintenance; hence, labor is a crucial factor. The availability of family labor increased the likelihood of adopting inorganic fertilizer and manure as well as other soil conservation practices, but manure use declined with the availability of hired labor (Kamau et al., 2014; Waithaka et al., 2007).

Institutional characteristics

As a proxy for market access, distance to accessible roads has a significant impact on the adoption of agricultural technologies. Longer distances inhibit market access and hence discourage the adoption of technologies such as the use of fertilizer and encourage the adoption of alternatives such as the use of manure (Kassie et al., 2015; Ogada et al., 2014). Positive outcomes have been observed where good infrastructure exists (Recha et al., 2015). Membership in groups enhances the adoption of technologies such as fertilizer as membership improves access to information and social capital benefits (Kassie et al., 2015). Extension agents are the most common information diffusers in the rural setup context. Access to extension services has been found to positively influence the adoption of SLMP such as terracing, use of fertilizer, intercropping, and conservation agriculture (Jaleta et al., 2013; Ndiritu et al., 2014). The availability of credit allows farmers to engage in costly adoptions since it enables them to acquire the inputs necessary for the implementation of SLMP such as minimum tillage, agroforestry, crop rotation, and the use of improved seed varieties (Ndiritu et al., 2014; Recha et al., 2015).

Biophysical characteristics

Biophysical characteristics also influence the type of soil fertility management practice adopted. For example, well-drained soils facilitate the adoption of fertilizer (Ogada et al., 2014). Similarly, soils with poor water retention capacity are susceptible to runoff and low organic matter and hence declining fertility, thus encouraging the adoption of fertilizer and ridges (Okeyo et al., 2014). Farms on steep slopes encourage the adoption of terracing and cover crops as anti-erosion and fertility measures (Wainaina et al., 2016).

In evaluating the impact of programs such as the adoption of a technology on the target group, various methods have been used, for example, experimental (randomized) and non-experimental methods. Experimental evaluations assume that there is no difference between the treatment group (adopters of a technology) and control group (non-adopters of a technology), only that the treatment group has access to the program/intervention. Non-experimental methods generate comparison groups similar to treatment groups using observed characteristics (Baker, 2000). Although experimental methods have the capability of addressing missing data and selection bias, they are limited to experimental studies and thus are quite costly (Khandker et al., 2010).

Non-experimental techniques have therefore been widely applied, with the most common in empirical research being the Heckman two-step method. This technique is capable of controlling for the variations in observed and unobserved attributes between treatment and control groups. However, the estimators are based on the assumption that the unobserved variables are normally distributed, thereby questioning the robustness of the results (Kiiza et al., 2013). Because of this setback, other non-experimental techniques have gained prominence in impact evaluation, with the most widely used being propensity score matching (PSM). This method matches control groups with treatment groups based on a set of observed characteristics by assigning them propensity scores. The score is therefore the estimated probability of participating in an intervention whose characteristics are observable (Ali and Abdulai, 2010). Moreover, PSM has been extensively employed by empirical studies on impact assessment because of its non-random selection of adopters and non-adopters, which may otherwise result in biased estimates (Asfaw, 2010), thus its application in this study.

This study posited that households that adopt soil carbon enhancing practices may increase output; thus, the surplus can be marketed for cash, which may translate into increased household income. Therefore, to evaluate the impact of the adoption of a specific soil carbon enhancing practice on output, a dummy variable is included, which is equal to one for adopters and zero otherwise, as specified in Eq. 8:

$$Y_i = \alpha X_i + \beta D_i + \mu_i$$

Eq. 8

where X_i = outcome of a target variable for the i^{th} household; D_i = dummy variable, whereby $D_{(i=1)}$ stands for adoption and $D_{i=0}$ for non-adoption; X_i = socioeconomic, farm-level, institutional, and biophysical characteristics; and μ_i = the stochastic term reflecting unobserved variables that affect Y_i.

In the context of this study, PSM is based on the probability of adopting a soil carbon enhancing practice, comparing outcomes between adopters and non-adopters with matching propensity scores. The propensity score is computed as shown in Eq. 9:

$$P(X) = \Pr(D = 1 \quad X) = E(D \mid X)$$

Eq. 9

where adoption (1) or non-adoption (0) is represented by $D=(1 \text{ or } 0)$ and X = socioeconomic, farm-level, institutional, and biophysical characteristics. The distribution of X, given the propensity score $P(X)$, is comparable between adopters and non-adopters.

However, in our estimation, the relationship between the adoption of soil carbon enhancing practices and the outcome (output) could be correlated. There is therefore a likelihood of selection bias given that the assignment of treatment is not random, and that the group of adopters is coherently different. PSM corrects

this by providing unbiased estimates of treatment; thus, it is used as a correction model to reduce self-selection bias (Rosenbaum and Rubin, 1983). Consequently, all observable characteristics have to be similar between adopters and non-adopters. The average treatment effect on treatment (ATT), the expected impact of adopting a given soil carbon enhancing practice, is the difference between the actual output and the output if no adoption occurred. This can be specified as Eq. 10:

$$ATT = E(Y_{1i} - Y_{0i}/P_i = 1)$$

Eq. 10

where Y_{1i} = output when the i^{th} farmer adopts a certain soil carbon enhancing practice, Y_{01} = output of the i^{th} farmer when he/she does not adopt, and P_i = adoption (1 = adopt and 0 = otherwise).

Photo: Georgina Smith/CIAT

3. Results and discussion

3.1. Descriptive statistics

A summary of the statistics of some of the variables, disaggregated by the two counties (i.e., Kakamega and Vihiga) is presented in Table 2. Results of the t-test revealed insignificant differences between the means of most variables, implying a similarity in household characteristics between the two counties. A majority of the farmers are older, with a mean of about 50 years of age, and have more than two decades of farming experience. On average, the households are composed of six members, with an estimated human dependency ratio[4] of less than 1. More than two-thirds of farming is male dominated, but the education levels are low. Almost a half and a quarter of the farmers have attained primary and secondary education, respectively (Table 2).

More than 50% of the farmers are categorized[5] as poor based on accumulated wealth. Nevertheless, farmers in Kakamega receive almost twice the annual farm income as farmers in Vihiga. However, the income from livestock surpasses that from crops in both counties, probably because the crops are mostly used for home consumption and sales are based on surplus production.

Table 2 Summary of descriptive statistics

	KAKAMEGA N = 172	VIHIGA N = 162
VARIABLE	MEAN	MEAN
HH age	51.94[a] (14.90)	55.83[a] (13.11)
HH size	5.30[a] (2.46)	5.41[a] (2.28)
Farming experience	20.50[a] (14.27)	25.28[a] (16.03)

4 The human dependency ratio was calculated by the sum of the percentage of people in the household who are below 14 years and the percentage of people who are above 64 years divided by the percentage of people between 15 and 64 years, commonly referred to as the working population. A dependency ratio of less than 1 implies that burdens are well distributed at the household level (KNBS, 2018).

5 The wealth category was measured by the probability of a household being poor, whereby households that were assigned a value of 1 were considered poor and 0 otherwise. A totality of wealth scores derived from ownership of assets such as television sets, radio sets, housing structures, toilet structures, and employment status was used in the computation. A total score of less than 35 was assigned a value of 1 and scores greater than 35 were assigned a value of 0 (Schreiner et al., 2009).

VARIABLE	MEAN	MEAN
Farm size	1.70[a] (1.72)	2.63[a] (10.98)
Plot size	0.87[a] (0.68)	0.97[a] (3.22)
Output* **	7,972.73[a] (24,410.00)	1,467.00[b] (1,829.02)
*Maize output****	1,242.50[a] (1,749.45)	638.70[b] (692.06)
*Bean output***	116.98[a] (300.23)	67.51[b] (148.65)
Farm income*	55,608.59[a] (224,347.70)	25,470.05[b] (57,171.64)
*Crop income***	39,769.71[a] (72,916.90)	19,767.74[b] (34,334.91)
Livestock income	56,341.11[a] (288,808.40)	
Human dependency ratio	0.70[a] (0.75)	1.04[a] (1.26)
Distance to road (walking minutes)		
Motorable road	4.90[a] (6.01)	4.76[a] (6.20)
Tarmac road	47.53[a] (49.36)	44.83[a] (42.81)
Distance to market (walking minutes)		
Local market	26.10[a] (32.28)	34.96[a] (31.96)
Livestock market	68.05[a] (47.95)	75.08[a] (43.12)
Urban market	116.48[a] (87.58)	106.85[a] (61.11)

NB: The value in parentheses is the standard deviation. The symbols *, **, and *** signify that the means were significantly different at P <0.1, 0.05, and 0.01, respectively; however, the means with the same superscript were not significant.
Source: Survey Data (2018).

The farm sizes indicate that small-scale farming is dominant in the area, whereby Kakamega and Vihiga have an average of 1.7 and 2.6 acres, respectively. The farms have further been subdivided into plots averaging almost an acre, where they practice farming, hence implementing most of the soil fertility[6] practices. On average, they own one to three plots in which almost 70% of the farmers practice farming (both crops and livestock).

Table 2 Summary of descriptive statistics (cont'd).

	KAKAMEGA N = 172	VIHIGA N = 162
VARIABLE	PERCENTAGE	PERCENTAGE
HH_gender		
Male headed	77.33	74.69

[6] Soil fertility has been used synonymously with soil carbon enhancing practices. It was used as a proxy since most farmers employ various practices to enhance soil fertility but they do not understand the complexity of the practices that increase carbon stocks in soil.

	KAKAMEGA N = 172	VIHIGA N = 162
Education level		
Primary	47.09	50.62
Secondary	25.00	28.40
Technical/vocational training	11.63	8.64
University	11.63	3.70
Wealth category		
Poor	52.91	50.00
Number of plots owned		
One plot	41.28	25.93
Two plots	32.56	28.40
Three plots	17.44	25.93
Household occupation		
Crop and livestock farming	68.60	70.37
Number of crop varieties grown		
Two crops	17.44	27.78
Three crops	81.98	70.37
Total livestock units (TLU) owned		
One TLU	18.02	11.11
Two TLU	51.74	62.96
Three TLU	23.26	22.84
Labor source		
Family & hired labor	65.12	61.11
Family labor only	31.98	37.04
Hired labor only	2.91	1.85
Group membership	68.02	54.32
Access to credit	38.95	35.19
Access to extension services	65.70	58.02
Soil type		
Loam soil	80.23	85.80
Clay soil	10.47	6.79
Sandy soil	9.30	7.41
Soil fertility practices		
Inorganic fertilizer	95.93	88.89
Intercropping	76.16	74.69
Terracing	61.05	78.40
Agroforestry	72.67	62.35

NB: The percentages need not add up to 100% as the highest frequencies were tabulated. **Source:** Survey Data (2018).


Photo: Georgina Smith/CIAT

In most cases, the soils are loamy (more than 80%), but a few farms have clay and sandy soils. Most of the farmers have from two to three total livestock units[7] (TLU) and grow two to three crop varieties. However, combinations of two dominant crops are grown in the area (maize 38% and beans 31%), justifying the dominance of intercropping as a soil fertility management practice. In addition, inorganic fertilizer, terracing, and agroforestry are common soil fertility practices in the area (Table 2). The main source of labor for farm activities is a combination of both family and hired labor (more than 60%) and family labor only (more than 30%), although in a few cases only hired labor is employed.

The motorable roads are more accessible to the farmers than tarmac roads, as depicted by the time taken (walking distance) to access these roads. However, the time taken to access local markets is less than that to access livestock and urban markets. More than half of the farmers belong to groups and social networks. However, access to credit is poor, whereby only 38% and 35% in Kakamega and Vihiga have access to credit facilities, respectively. Consequently, almost two-thirds of the farmers have access to extension services, signifying that knowledge on soil fertility practices might be well disseminated within the study area.

3.2. Determinants of adoption of soil carbon enhancing practices

Table 3 represents estimates of the variables used for the MVP model. The variables fit the model well with the Wald test = 817.15 and Prob > chi-square = 0.000, implying that the joint regression coefficients are significant in explaining the adoption of soil fertility practices. Results show that male-headed households are more likely to adopt agroforestry but are less likely to adopt intercropping and the application of inorganic fertilizer as a soil fertility enhancement practice. Female farmers are more likely to take up some practices than male farmers as in most cases they are responsible for much of the agricultural work, and thus have information on farming practices (García de Jalón et al., 2015). Moreover, women are influenced by perceptions on ease of use while men are influenced by the usefulness of a certain agricultural technology (Mwangi et al., 2015). Older farmers have a lower likelihood of using inorganic fertilizer. This is because older farmers are equated to have lost energy, being risk averse, and having short-term plans, which are key attributes in determining the choice of agricultural technologies (Ndiritu et al., 2014). Education had a positive and significant association with the adoption of terracing and use of inorganic fertilizer. This could be because education gives a better understanding of the usefulness of the practices on the farms for both soil and crop management (Kamau et al., 2014; Wainaina et al., 2016; Waithaka et al., 2007). The probability of being a poor farmer reduces the likelihood of employing intercropping as a soil fertility enhancement practice. The reason could be that, since intercropping involves at least two crops, several inputs are required, which poor farmers might lack resources to acquire. Households with a higher human dependency ratio and whose main occupation was farming were less likely to adopt intercropping. This could suggest that the households are involved in other farming activities that accrue more income other than intercropping so as to cater to the needs of the dependents.

[7] TLU was computed by adding up the total of shoats, cattle, and poultry whereby one mature sheep or goat = 0.2 TLU, one mature chicken = 0.04 TLU, and one mature cow = 1 TLU (Njuki et al., 2011).

Table 3 MVP model estimates for factors that influence the adoption of soil carbon enhancing practices in Western Kenya

	AGROFORESTRY		INTERCROPPING		TERRACES		INORGANIC FERTILIZER	
VARIABLE	Co-eff.	Robust SE	Co-eff.	Robust SE	Co-eff.	Robust SE	Co-eff.	Robust SE
HH gender	0.438**	0.201	-0.735***	0.229	0.159	0.208	-1.319***	0.398
HH age	0.013	0.008	0.006	0.009	0.010	0.008	-0.0613***	0.015
HH size	-0.041	0.041	0.068	0.049	0.032	0.042	0.0477	0.069
Farm size	0.016	0.053	-0.041	0.048	0.104	0.087	0.898***	0.231
Plot size	0.025	0.172	0.024	0.164	-0.106	0.179	-0.940**	0.371
HH education level								
Primary	-0.087	0.330	-0.145	0.422	0.700**	0.335	1.250**	0.510
Secondary	-0.287	0.381	0.094	0.456	1.016***	0.378	0.523	0.584
Tertiary/vocational training	-0.221	0.451	0.468	0.532	0.894**	0.454	0.829	0.715
University	-0.019	0.486	-0.199	0.570	1.172**	0.475	1.926*	1.001
Wealth poor	-0.020	0.200	-0.432**	0.205	0.119	0.193	0.107	0.358
Human dependency ratio	-0.012	0.075	-0.156*	0.083	0.0710	0.087	-0.0311	0.148
HH occupation	-0.070	0.211	-0.446*	0.228	0.206	0.197	-0.446	0.328
Farming experience	-0.011	0.007	0.007	0.008	0.001	0.007	0.0248*	0.013
Number of crops	-0.018	0.178	0.362*	0.191	0.250	0.196	1.784***	0.302
Total livestock units (TLU)	-0.281**	0.116	-0.027	0.127	0.194	0.119	0.480***	0.183
Land tenure								
Owned (without title)	-0.457**	0.187	0.112	0.188	0.008	0.183	0.347	0.376
Rented	-0.640	0.522	0.526	0.531	-0.421	0.543	-1.572**	0.794

	AGROFORESTRY		INTERCROPPING		TERRACES		INORGANIC FERTILIZER	
VARIABLE	Co-eff.	Robust SE	Co-eff.	Robust SE	Co-eff.	- Robust SE	Co-eff.	Robust SE
Plot management								
Spouse	-0.204	0.372	1.219**	0.512	-0.216	0.378	5.145***	1.139
Joint	0.118	0.216	0.905***	0.248	-0.171	0.212	0.548	0.389
Output	0.000	0.000	-0.000	0.000	-0.000	0.000	0.000	0.000
Farm income	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Labor source								
Hired labor only	0.067	0.639	0.331	0.603	-0.030	0.672	-3.064***	1.127
Family and hired labor	0.398**	0.188	0.356*	0.206	0.195	0.197	1.285***	0.415
Distance motorable road	-0.021	0.014	0.039**	0.016	-0.006	0.014	-0.0243	0.023
Distance tarmac road	0.003	0.002	-0.003	0.002	-0.002	0.002	-0.0127***	0.003
Distance local market	0.002	0.003	-0.004	0.003	-0.001	0.003	0.007*	0.004
Distance urban market	0.005***	0.001	0.002	0.001	0.001	0.001	0.009***	0.003
Group membership	0.261	0.194	0.040	0.201	0.050	0.193	0.330	0.339
Access credit	0.245	0.182	-0.111	0.199	0.014	0.184	-0.125	0.342
Access extension services	-0.122	0.188	-0.193	0.184	-0.335*	0.187	0.479	0.340
Slope								
Slightly moderate	0.086	0.201	-0.144	0.212	0.748***	0.196	0.669*	0.402
Very steep	0.248	0.325	-0.618*	0.340	2.036***	0.525	0.173	0.479
Soil type								
Loamy	-0.203	0.316	1.071***	0.291	0.478	0.296	1.078**	0.440
Sandy	-0.587	0.401	0.874**	0.406	0.464	0.407	6.285***	1.039
Constant	-0.212	0.871	-1.039	0.900	-3.459	0.953	-4.249	1.258

NB: SE stands for standard error; *, **, and *** represent significance at P < 0.1, P < 0.05, and P < 0.01, respectively.

The higher the number of years a household has on farming, the more likelihood of using inorganic fertilizer. This could be because the more years of experience farmers have, the more aware they are of the benefits of using soil fertility practices (Nyaga et al., 2015; Wairore et al., 2016). Consequently, the higher the number of crop varieties grown by a farmer, the more likely they are to practice intercropping and apply inorganic fertilizer. This finding is similar to that of Kamau et al. (2014), who found that the number of crops grown had a positive association with soil fertility practices. However, an increase in the number of livestock owned decreases the likelihood of practicing agroforestry but increases the likelihood of using fertilizer. According to Kassie et al. (2015), the probability of fertilizer use is likely to increase when it is complemented with other soil management practices such as the use of livestock manure.

Land tenure had a negative and significant effect on adoption, whereby land ownership without a title deed (security) and rented land reduced the likelihood of adopting agroforestry and the use of organic fertilizer, respectively. This resonates with Nyaga et al. (2015), who observed that secure land tenure gives farmers individualized rights on their farms, allowing them to make long-term investments such as growing trees. Similarly, insecurity of tenure inhibits the use of land improvement initiatives such as the use of fertilizer (Waswa et al., 2002). Households that have larger farm sizes are more likely to apply inorganic fertilizer but the likelihood of adoption decreases with the size of the plots. A similar observation (Mugwe et al., 2009; Mwirigi et al., 2014; Waithaka et al., 2007) of increased fertilizer use with increasing farm size suggests the need for farmers to improve fertility and thus improve yield. However, a decline in fertilizer use with plot size could mean that not all the plots are related to farming activities.

Plots that were managed by the spouse (female managed) relative to those managed by the household head (male managed) alone were more likely to adopt intercropping and the use of fertilizer. This could suggest that females have access to resources and the knowledge required to implement the practices. Also, plots that were jointly managed compared with those managed by the household head only were likely to practice intercropping. This finding is consistent with Ndiritu et al. (2014), who found that intercropping is a common practice among jointly managed plots relative to male-managed plots. Households that employed a combination of family and hired labor were more likely to adopt agroforestry, intercropping, and the use of fertilizer, but employing hired labor only reduced the likelihood of using fertilizer. This could mean that the practices are labor intensive, hence the combination of labor sources.

Households that had access to motorable roads were more likely to adopt intercropping, an implication that it is easier to acquire the inputs required to implement the practice. However, access to tarmac roads reduced the likelihood of using inorganic fertilizer since the farmers have to cover longer distances (Table 2). Access to local markets and urban markets encouraged adoption of the use of inorganic fertilizer, while practicing agroforestry was positively and significantly influenced by access to urban markets. According to Kassie et al. (2015) and Murage et al. (2015), market access is an incentive for farmers to adopt new technologies. Access to extension services had a negative and significant impact on the adoption of terracing. This finding contradicts Jaleta et al. (2013), Ndiritu et al. (2014), and Wainaina et al. (2016), who found a significant and positive impact on the adoption of soil conservation practices. These imply that extension agents might be lacking the skills and know-how for implementing some practices or have more inclination toward production practices.

Farms on slightly moderate slopes were likely to practice terracing and the use of fertilizer. However, where the slopes were very steep, farmers were more likely to practice terracing but less likely to practice intercropping. These findings concur with Wainaina et al. (2016) that farms on steep slopes require physical structures to prevent soil movement/erosion in order to contain nutrients. Both intercropping and the use of fertilizer were mostly practiced on farms with loamy and sandy soils. Intense cropping on soil causes degradation and hence the need to apply fertilizer. This observation is similar to that of Ogada et al. (2014).

3.3 Impact of adoption on output

In assessing the impact of soil carbon enhancing practices on output, PSM was used. According to Baker (2000), a discrete choice model is the first step in estimating the impact of an outcome while using propensity scores. This is, however, generated after finding a suitable matching[8] estimator (Table 4), which tries to find non-adopting farmers who have a propensity score that is very close to that of adopting farmers (Caliendo and Kopeinig, 2008).

[8] Matching is a method used to select non-adopters who are matched with adopters based on variables that need to be controlled. Three methods are common: nearest neighbor matching (NNM), kernel-based matching (KBM), and caliper matching (Caliendo and Kopeinig, 2008).

Table 4 Matching performance for different matching estimators

MATCHING ESTIMATOR	MATCHING CRITERIA PERFORMANCE		
	Pseudo-R^2	Matched sample	Mean bias
Nearest neighbor (1)	0.044	292	10.3
Nearest neighbor (2)	0.017	292	7.5
Nearest neighbor (3)	0.01	292	4.3
Kernel bwidth (0.10)	0.008	292	3.1
Kernel bwidth (0.25)	0.015	292	3.5
Kernel bwidth (0.50)	0.03	292	6.7
Caliper (0.10)	0.044	292	10.3
Caliper (0.25)	0.044	292	10.3
Caliper (0.50)	0.044	292	10.3

Source: Survey Data (2018).

Kernel-based matching (KBM) was used since it's the matching estimator that best fit the selection criteria for the largest matching sample, lowest pseudo R2, and lowest mean bias (Mulatu et al., 2017).

Table 5 represents the probit[9] model estimates for the variables that influence the adoption of intercropping[10]. The likelihood ratio test indicates the goodness of fit of the model with a P value of 0.002. Results show that household size and availability of labor positively and significantly influenced the adoption of intercropping. This could imply that household members provide labor that encourages adoption.

Table 5 Probit regression estimates used in estimating propensity scores for intercropping

VARIABLE	COEF.	SE	P > Z
Farming experience	0.004	0.007	0.601
HH size	0.086**	0.038	0.022
Distance motorable road	0.012	0.013	0.357
Distance local market	-0.002	0.002	0.495
Labor source	0.226*	0.088	0.010
Group membership	0.132	0.188	0.483
Access credit	-0.039	0.185	0.832
Access extension services	-0.150	0.181	0.407
HH gender	-0.371*	0.206	0.071
HH age	0.011	0.008	0.156

9 Both the probit and logit model can be used since they yield similar results; thus, either of the two can be applied in econometric analysis. However, this study used a probit model since it can be generalized to account for heteroscedasticity (Albright, 2015).

10 Of the four dominant practices (intercropping, agroforestry, terracing, and use of inorganic fertilizer), only intercropping best fit the criteria for an insignificant chi-square value after matching variables, making the variables comparable between adopters and non-adopters.

VARIABLE	COEF.	SE	P > Z
HH education level	0.035	0.098	0.721
HH occupation	-0.427**	0.202	0.034
Farm income	0.000	0.000	0.295
Land tenure	0.093	0.143	0.516
Farm size	-0.029*	0.016	0.065

NB: NB: *, **, and *** represent significance at P < 0.1, P < 0.05, and P < 0.01, respectively. Prob > chi2 = 0.002; pseudo R2 = 0.0969.
Source: Survey Data (2018).

However, the variables gender and occupation of the household head and farm size had a negative and significance influence on the adoption of intercropping. This could be explained by the fact that male farmers adopt practices that they deem important. Also, the effect of farm size could be because the households are involved in other farming activities to supplement income. These results are a clear indication that farmers who have adopted intercropping vary significantly from non-adopters. Thus, comparing the adopting versus non-adopting farmers would give bias estimates, hence the use of PSM to correct for the biases.

The propensity scores were calculated for 252 farmers that had adopted intercropping and 82 farmers who were non-adopters (Table 6). The predicted propensity score for adopters ranges from 0.325 to 1, with a mean of 0.781, while that for non-adopters ranges from 0.046 to 0.901, with a mean of 0.674. Therefore, the common support region would lie between 0.325 and 0.901.

Table 6 Estimated propensity scores

Groups	Observations	Mean	St. dev.	Min.	Max.
All farmers	334	0.755	0.143	0.046	1.000
Adopters	252	0.781	0.124	0.325	1.000
Non-adopters	82	0.674	0.168	0.046	0.901

Source: Survey Data (2018).

A further analysis of the propensity scores is exhibited by the density distribution of the scores (Figure 1). The bottom half shows the propensity score distribution of farmers who are non-adopters (control) while the upper half represents adopters (treated). Although some farmers in the treated group are off support, the propensity score distribution graph suggests that there is a high chance of attaining a large number of matched samples with good matches. This is an indication that several farmers who practice intercropping found a suitable match with those farmers who don't.


Photo: Georgina Smith/CIAT

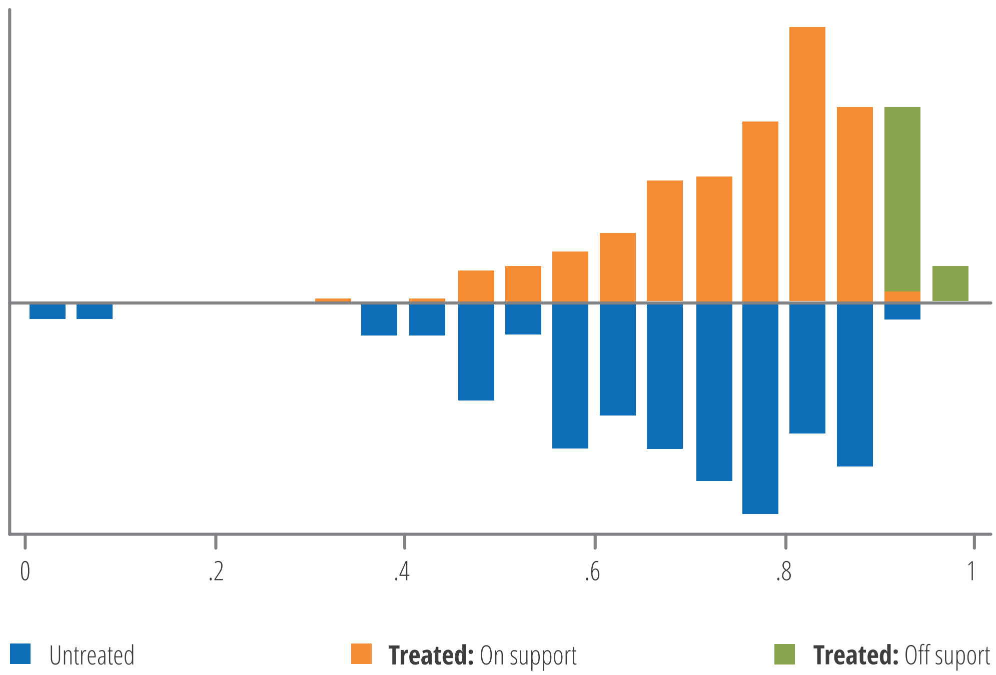

Figure 1 Propensity score histogram. Source: Survey Data (2018).

It is important to note that matching should have the capability of reducing the biases that comes with observable farmer characteristics. Table 7 shows the results of the covariate-balancing test, showing the differences in t-test means and percentage bias before and after matching.

Table 7 Balancing tests for covariates

VARIABLE	MEAN				% REDUCTION	T-TEST	
	Matching sample	Treated	Control	% bias	bias	t	P > t
P score	U	0.781	0.674	72.3		6.17	**0.000**
	M	0.751	0.748	2.3	96.8	0.31	0.756
Farming experience	U	23.591	20.415	20.5		1.64	0.103
	M	22.500	23.060	-3.6	82.4	-0.36	0.717
HH size	U	5.528	4.817	30.8		2.37	**0.018**
	M	5.029	5.180	-6.6	78.7	0.72	0.472
Distance motorable road	U	4.857	4.744	1.8		0.15	0.884
	M	5.157	4.857	4.9	-165.1	0.47	0.640
Distance local market	U	30.087	31.366	-3.8		-0.31	0.757
	M	30.262	31.459	-3.5	6.4	-0.38	0.703

VARIABLE	Matching sample	MEAN Treated	MEAN Control	MEAN % bias	% REDUCTION bias	T-TEST t	T-TEST P > t
Labor source	U	2.381	2.000	39.9		3.21	**0.001**
	M	2.300	2.232	7.1	82.1	0.73	0.465
Group membership	U	0.635	0.549	17.5		1.39	0.165
	M	0.605	0.603	0.4	97.8	0.04	0.968
Access credit	U	0.377	0.354	4.8		0.38	0.705
	M	0.367	0.368	-0.3	92.9	-0.03	0.972
Access extension services	U	0.623	0.610	2.7		0.21	0.831
	M	0.614	0.614	0.0	100.0	-0.00	1.000
HH gender	U	0.750	0.793	-10.1		-0.79	0.433
	M	0.767	0.757	2.4	76.7	0.24	0.812
HH age	U	54.560	51.573	20.9		1.66	**0.097**
	M	54.038	54.402	-2.5	87.8	-0.26	0.793
HH education level	U	1.671	1.537	13.4		1.04	0.301
	M	1.571	1.562	0.9	93.3	0.09	0.925
HH occupation	U	0.667	0.780	-25.6		-1.95	**0.052**
	M	0.724	0.763	-8.9	65.3	-0.93	0.355
Farm income	U	47,733	20,271	20.0		1.30	0.194
	M	23,275	23,901	-0.5	97.7	-0.13	0.895
Land tenure	U	1.536	1.561	-4.1		-0.31	0.757
	M	1.543	1.518	4.1	0.4	0.44	0.661
Farm size	U	1.642	3.720	-19.0		-2.12	**0.035**
	M	1.539	1.375	1.5	92.1	1.17	0.244

NB: The numbers in bold show significant covariates. U and M stand for unmatched and matched samples, respectively.
Source: Survey Data (2018).

The results reveal that the matched sample means for the variables are similar for adopters and non-adopters after matching, which was not the case before matching. In addition, the variables that were statistically significant before matching (household size, availability of labor, gender and occupation of the household head, and farm size) are no longer significant after matching (as indicated by the (P > t) column). This suggests that the variables have been balanced, making them comparable and hence reducing selection bias. This is further ascertained by the results in Table 8, whereby there is an observable reduction in pseudo R^2, LR-chi^2, and mean bias after matching.

Table 8 Balancing covariate indicators

SAMPLE	PSEUDO-R^2	LR-CHI^2	P > CHI^2	MEAN BIAS	MED. BIAS
Unmatched	0.097	36.06	0.002	15.7	17.5
Matched	0.008	4.56	0.995	3.1	2.5

NB: Med. and LR stand for median and likelihood ratio, respectively.
Source: Survey Data (2018).

Consequently, the P > chi^2 is insignificant after matching, supporting that the variables have been balanced between adopters and non-adopters. Having proven that the matching procedure has successfully balanced the variables between the two groups of farmers, a similarity is found in observable characteristics. Thus, the results were used to assess the impact of adopting intercropping on farm output, which was done by computing the ATT.

The impact of intercropping on output is summarized in Table 9. The results indicate that the adoption of intercropping has a positive and significant impact (at 5% significance level) on maize output, but an insignificant impact on bean output.

Table 9 Impact of intercropping on output

OUTCOME	SAMPLE	TREATED	CONTROLS	DIFFERENCE	S.E.	T STAT.
Maize output	Unmatched	1,054	628.90	425.10	173.70	2.45
	ATT**	881.97	642.04	**239.93**	103.66	2.31
Bean output	Unmatched	105.26	55.29	49.97	30.43	1.64
	ATT	94.07	60.35	33.72	30.18	1.12

NB: ** stands for significance at $P < 0.05$, S.E. is the standard error, and ATT is the average treatment effect on treatment.
Source: Survey Data (2018).

This could imply that beans are intercropped with maize as a complementary crop with the sole purpose of enhancing soil fertility. The finding is supported by Manda et al. (2016), who found that maize-legume production is among the sustainable land intensification practices that fix nitrogen in soils, thus substantially increasing maize production. This is because where monocropping (maize is grown alone) is practiced weeds are common, resulting in a decline in output. The results further indicate that intercropping increases maize output by an average of 240 kg (approximately three bags); therefore, it can be concluded that adoption of intercropping increases maize output by approximately 27%. This finding is consistent with Ngwira et al. (2012), who observed that intercropping is a cost-effective practice as it improves maize yield and at the same time ensures attractive economic returns. These findings suggest that encouraging farmers to adopt intercropping can help in improving maize output and thus increasing income.

The results of the treatment effect (adoption of intercropping) assume that all the relevant observable variables have been included in the treatment assigned. Thus, it is important to carry out a sensitivity test to verify whether the estimated results from the PSM are prone to other unobserved variables; otherwise, the positive impact of intercropping on maize output would be questionable. A sensitivity analysis was carried out using the Rosenbaum bounds (rbounds) test (Rosenbaum and Rubin, 2006) to check for hidden bias. Since the impact on the outcome (output) was positive, the level of gamma reported was for the positive effect (sig+), at the point where the 10% level of significance was exceeded. The values of gamma varied between 1.00 and 1.60, suggesting that any unobserved variable would have to increase the odds ratio by about 60% before it would bias the estimated impact. Only then would the significance of the impact on the value of output be questionable. Studies that have reported similar gamma values for the sensitivity analysis include Ogutu et al. (2014) and Miyinzi et al. (2019), concluding that unobserved variables would negligibly alter the conclusion of a positive impact of adoption of intercropping on maize output.

Photo: Georgina Smith/CIAT

Conclusions and recommendations

Soil infertility has inhibited smallholder farming capacity in sub-Saharan Africa, which has resulted in decreased farm yield and hence decreased household income. Preceding studies have revealed that SLMP –more so those that have the capability of enhancing soil carbon – are critical in enhancing fertility. However, the existing literature has delved into analyzing the determinants of the adoption of diverse SLMP without evaluating the impact they have on farming households' livelihood. This study therefore establishes the factors that influence the adoption of soil carbon practices in Kenya and their impact on output. The multivariate probit model and the propensity score matching method were used on survey data collected from 334 households in Western Kenya. Four dominant SMLP (agroforestry, intercropping, terracing, and inorganic fertilizer) that enhance soil carbon are dominant in the area. The findings reveal that adoption is determined by socioeconomic, farm-level, institutional, and biophysical factors that vary for each individual practice. Altogether, education level, availability of labor, and slope significantly increase the likelihood of adopting all four dominant practices. On the other hand, land tenure and gender have a negative and significant influence on the adoption of these dominant practices. These findings suggest that interventions aimed at increasing adoption should be aimed specifically at an individual practice conditional on the determinant factors.

An evaluation of the impact of adoption on output reveals that, of the four main practices, adoption of intercropping solely has a positive and significant impact on maize output. Comparatively, farmers who practice intercropping were found to have an increase of approximately 27% in maize output as opposed to those who don't. Further, unobserved variables would not transform much the results of the evaluated effects. The study therefore concludes that adoption of intercropping significantly increases maize output. The implication is that intercropping is an effective practice in boosting maize output, which constitutes a major component of Kenya's grain basket and can help resource-constrained rural farmers increase their farm income. Thus, policies that facilitate adoption of intercropping among smallholder farmers should be pursued. These include strategies such as being able to obtain affordable inputs required for the practice – improved seed varieties and inorganic fertilizer – since the results underline that being a poor farmer reduces the likelihood of adoption.

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