Invited paper presented at the 6th African Conference of Agricultural Economists, September 23-26, 2019, Abuja, Nigeria

An evaluation of the impact of soil carbon enhancing practices on farm output in Western Kenya

A paper submitted for presentation at the 6th International Conference for African Association of Agricultural Economists (AAAE), 23rd–26th September, 2019, Abuja, Nigeria.

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Abstract
Sustainable agricultural practices that enhance soil carbon simultaneously improve farm yields and income. Despite the expansive literature on adoption of soil carbon practices in Kenya, there is limited information on the impact of the elemental practices on farm output. This study attempts to fill this literature gap by evaluating the impact of soil carbon practices on farm output in Western Kenya. Results show that agroforestry, maize-legume intercropping, terracing and use of inorganic fertilizer are dominant soil carbon practices. Howbeit, the propensity score matching results reveal that maize-legume intercropping solely has observable impact on farm output. On average, farmers involved in the practice have an increase of 27% on maize output as opposed to those who don't, and as such adoption could improve their welfare. The findings suggests that interventions targeted on facilitating the uptake of maize-legume intercropping among resource-poor rural smallholder farmers should be pursued.

Key words: Impact, soil carbon, practices, output, Kenya

1. Introduction

For decades, soil erosion and nutrient depletion has been an inherent problem in many Sub-Saharan Africa (SSA) countries, resulting to unproductive agricultural lands (Kassie *et al.*, 2009). As a response to this, farmers have been impelled to invest in agricultural and sustainable land management practices (SLMP) such as application of farmyard manure, terracing, stone or soil buds and planting trees, that have the potential of improving land productivity (Liniger *et al.*, 2011). More significant are SLMP that enhance soil organic carbon (SOC) since they have the capability of mitigating effects of climate change, and increasing yields, thus boosting farmers' income and improving food security (Bekele & Drake 2003). Further, scientific evidence reveals that the most essential components of agricultural research and development are likely to occur when farmers adopt agricultural practices that enhance soil carbon (Powlson *et al.*, 2011; Koirala *et al.*, 2015). For example, the uptake of agricultural and SLMP such as minimum tillage and the use of organic fertilizer have been found to be cost-effective for resource poor farmers as they simultaneously sequester carbon and increase economic returns (Li-Y, Shibusawa & Kodaira 2013).

Even with the studied importance of SLMP that enhance soil carbon, adoption among farmers in East Africa is deficient (Bewket 2007; Adimassu *et al.*, 2014). However, the promotion of climate-smart, and sustainable intensification and agricultural practices within East Africa has notably accelerated the adoption of SLMP (Diwani *et al.*, 2013; Ng'ang'a *et al.*, 2016). In Kenya, the adoption of agricultural and SLMP has majorly been in the Western region, due to its potential in production of staple foods like maize and beans (Karugia & Wambugu 2009). For instance, the adoption rate by farmers in Western Kenya has been estimated at 16%, 48% and 58% for mulching, use of inorganic fertilizer and maize-legume intercropping respectively (Dallimer *et al.*, 2018). However, (Antle & Stoorvogel 2008) observed that adoption of these practices in Western Kenya is stunted, which could be attributed to various reasons. On a broader scope, adoption of soil carbon enhancing practices is influenced by various factors that can be categorized as socio-economic and farm specific (Shiferaw & Holden 2001), institutional (Akudugu, Guo & Dadzie 2012), and biophysical (Obayelu *et al.*, 2017).

Specifically, adoption of SLPM that enhance soil carbon in Kenya has been observed to be variedly affected by the hypothesized socio-economic, institutional, farm/plot level and biophysical factors (Mutoko, Hein & Shisanya 2014; Ogada, Mwabu & Muchai 2014; Mwangi *et al.*, 2015). Also, farmers' perceptions and knowledge concerning soil fertility enhancement practices are crucial for adoption (Odendo, Obare & Salasya 2010).Despite the extensive literature on the factors that influence adoption of SLMP in Kenya, there is unclear information on its impact on small-holder farmers' welfare. This study attempts to seal the scientific literature gap by evaluating the impact of the dominant soil carbon practices on farm output in Western Kenya. It is envisaged that interpreting the impact of SLMP that enhance carbon at the household level would be paramount in formulating targeted interventions, that would encourage more farmers adopt effective practices.

The rest of the paper is organized as follows. Section 2 provides a brief description of the study area, data collection procedure and the analytical framework. Section 3 presents the results followed by section 4 that concludes and gives policy recommendations.

2. Methodology

2.1 Study site

The survey was conducted in Western Kenya in Kakamega and Vihiga Counties (Fig. 1). The area experiences reliable rainfall from 1200-2000mm annually, high temperatures between 15 - 29 ^{0}C annually, with well drained fertile soils, rocky hills and forests (Okeyo *et al.*, 2014;

Savini *et al.*, 2016). The high population density of 982 and 550 persons per square kilometer for Vihiga and Kakamega respectively (KNBS 2009), has exerted pressure on land leading to poor agricultural land management practices.

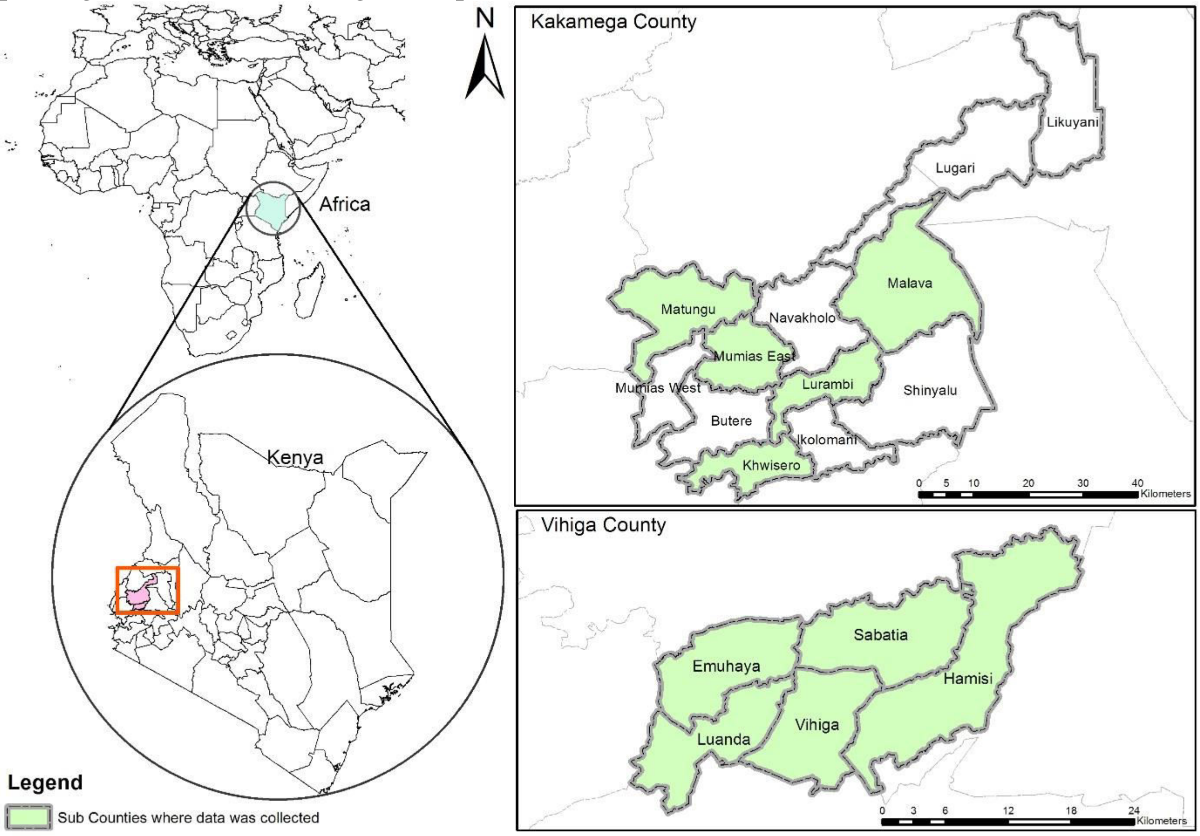

Fig. 1: Map of Western Kenya showing the counties and sub-counties studied

As a result, soil fertility degradation has replicated leading to production of yields below the agricultural potential (Odendo, Obare & Salasya 2010). Various projects have been implemented in the area (Kenya Agricultural Carbon Project (KACP) and yield gap) with the aim of promoting adoption of SLMP and establishing potential yields through the utilization of low cost soil fertility practices. This is a clear indication that there is need to prevent further soil deterioration and enhance productivity in the area.

2.2 Data collection and sampling procedure

Primary data was collected in August 2018 using semi structured questionnaires through face to face interviews with smallholder farmers, who implement various soil carbon practices in Kakamega and Vihiga. Prior to that, a focus group discussion (FGD) was carried out in the two study sites, with farmers and various stakeholders to obtain more insights on various SLMP in the area. A multi stage sampling technique was employed to derive a sample of 320 farmers distributed between the two Counties, following (Särndal, Swensson & Wretman 2003) in sample size determination. In the first stage, five administrative units (sub Counties) were selected from each County to ensure data variability and a lager sample representation. In the second stage, smaller administrative units (wards) were selected, two from each of sub County. Villages were then selected from each ward, totaling to 16 in each County. In the last stage, 10 farmers were randomly selected from each village. However, 334 farmers were interviewed to cover for any challenges that would arise from analysis.

2.3 Analytical framework

Both experimental and non-experimental methods have been used in evaluating impact of programs such as adoption of agricultural technologies. Experimental methods cater for missing data and selection bias but are limited to experimental studies, thus are very costly (Khandker, Koolwal & Samad 2010). Therefore, non-experimental methods have been widely used in empirical research, most prominently propensity score matching (PSM). PSM has been extensively employed on impact assessment studies because it compares observable characteristics between adopters and non-adopters of a technology by assigning them propensity scores (Ali & Abdulai 2010). The scores are the predicted probability of participating in an intervention based on the observable characteristics, enabling the reduction of selection bias (Asfaw 2010), thus its application in this study.

It was presumed by this study that farmers who adopt SLMP that enhance soil carbon have a higher probability of increasing their farm output, and that the surplus can be marketed for cash to generate income. Therefore, to evaluate the impact of adoption of a specific soil carbon practice on output, a dummy variable is included, which is equal to one for adopters and zero otherwise, as specified in Eq. 1;

$$Y_i = \alpha X_i + \beta D_i + \mu_i \qquad \text{(Eq. 1)}$$

Where; X_i = outcome of a target variable for the $i\ th$ household, D_i = dummy variable, and $D_{i=1}$ stands for adoption and $D_{i=0}$ non-adoption, and X_i = observable characteristics and μ_i = stochastic term reflecting unobserved variables that affect Y_i.

Since PSM is the probability of adopting a given soil carbon enhancing practice, outcomes between adopters and non-adopters are compared by matching propensity scores. The propensity score can therefore be computed as shown in Eq. 2;

$$P(X) = \Pr(D = 1 \mid X) = E(D \mid X) \qquad \text{(Eq. 2)}$$

Where; adoption (1) or non-adoption (0) is represented by $D = (1\ or\ 0)$, and X = a set of observable characteristics. The distribution of X, given the propensity score $P(X)$ is comparable between adopters and non-adopters.

Given that there could be a correlation between adoption of a certain soil carbon practice and the outcome (output), PSM acts as a correction model by providing unbiased estimates of treatment effects (Rosenbaum & Rubin 2006). The expected treatment effect (impact) of adopting a certain soil carbon enhancing practice or Average Treatment effect on Treatment (ATT) can therefore be specified in Eq. 3;

$$ATT = E(Y_{1i} - Y_{0i}/P_i = 1) \qquad \text{(Eq. 3)}$$

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

Baker (2000) highlights that a discrete choice model is the first step in estimating the impact of an outcome while using propensity scores. Thus, both the probit and logit model can be used for analysis since they yield almost similar results. The probit model was used in this study since it can be generalized to account for heteroscedasticity (Wooldridge 2009). The discrete model is however applied after establishing a suitable matching[1] estimator, which traces non-adopting farmers who have a propensity score that is very close to that of adopting farmers. The nearest neighbor matching (NNM), kernel based matching (KBM) and caliper matching are the most commonly used matching estimators in economic analysis (Caliendo & Kopeinig 2008). The independent variables in the discrete choice model are those that have been hypothesized to variedly influence the adoption behavior of SLMP by farmers in Western Kenya. Socio-economic characteristics (age, gender, education level, household size, labour, farming experience, household occupation and farm income), biophysical characteristics (slope and soil type), farm/plot specific characteristics (farm size and land tenure) and institutional characteristics (access to credit, market and extension services, and group membership) are variables that have been observed by various studies (Marenya & Barrett 2007; Ndiritu, Kassie & Shiferaw 2014; Kassie *et al.*, 2015).

[1] Matching is a method used to select non-adopters who are matched with adopters on based on variables that need to be controlled. (Caliendo and Kopeinig, 2008).

3. Results and Discussion

3.1 Farmer characteristics

The results of the t-test show insignificant differences in the means of independent variables, indicating a similarity in household characteristics between the two study sites (Kakamega and Vihiga Counties). Over two thirds of farmers are male, with an average of 50 years of age, and have over 20 years of farming experience. On average, a household has 6 members with a dependency ratio of less than 1. Education levels are low with almost half and a quarter of the farmers having attained primary and secondary education respectively. Consequently, poverty levels are high as more than 50% of the farmers are categorized as poor, based on accumulated wealth. The smaller farm sizes of less than 3 acres indicate that small-scale farming is dominant in the area. The farms are further sub-divided into plots averaging to less than an acre, where most of the SLMP are implemented. Farmers own one to three plots, where close to 70% of crop and livestock production is practiced. Most of the farmers have two to three total livestock units[2] (TLU) and grow two or three crop varieties. However, a combination of two crops (maize, 38% and beans, 31%) are common in the area, justifying the dominance of maize-legume intercropping as one of the second important SMLP. Other dominant SLMP in the area are inorganic fertilizer, agroforestry and terracing respectively. In most cases, the soils are loamy (over 80%), but a few farms have clay and sandy soils. The main source of labour for farm activities is a combination of both family and hired labour (over 60%) and family labour only (over 30%),though in a few cases only hired labour is employed. Almost two thirds of farmers have access to extension services, signifying that knowledge on SLMP might be well disseminated within the study area. However, access to credit is still a challenge as slightly more than one third of farmers can access credit for farming activities.

3.2 Impact of SMLP that enhance soil carbon on farm output

Among the four dominant practices in the area (i.e. the use of inorganic fertilizer, intercropping, agroforestry and terracing), only the analysis on intercropping yielded an insignificant chi-square value after matching observable variables. This made the variables comparable between adopters and non-adopters, thus PSM applied for intercropping only. The Kernel based matching (KBM) *bwidth 0.1* was the best matching estimator (Table 1), since it best fitted the selection criteria for the largest matching sample, lowest pseudo R^2 and lowest mean bias (Mulatu *et al.*, 2017).

[2] TLU was computed by adding up the total of shoats, cattle and poultry whereby 1 mature sheep or goat = 0.2 TLU, 1 mature chicken = 0.04 TLU and 1 mature cow = 1TLU (Njuki , Poole , Johnson, Baltenweck & Pali , 2011).

Table 2: Probit regression estimates used in estimating propensity scores for intercropping

Variable	Coefficient	Standard Error	*p* >z
Farming experience	0.004	0.007	0.601
Household size	0.086**	0.038	0.022
Distance to motorable road	0.012	0.013	0.357
Distance to local market	-0.002	0.002	0.495
Labour	0.226*	0.088	0.01
Group membership	0.132	0.188	0.483
Access to credit	-0.039	0.185	0.832
Access to extension services	-0.150	0.181	0.407
Gender of household head (*Male headed*)	-0.371*	0.206	0.071
Age of household head	0.011	0.008	0.156
Education of household head	0.035	0.098	0.721
Occupation of household head	-0.427**	0.202	0.034
Farm income	0.000	0.000	0.295
Land tenure	0.093	0.143	0.516
Farm size (*acres*)	-0.029*	0.016	0.065
Cons.	-0.493	0.600	0.411

NB: *, **, ***, stands for significance at *p<0.1, p<0.05* and *p<0.01* respectively. Prob > Chi2 = 0.002; Pseudo R2 = 0.0969

Table 1: 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)	0.010	292	4.3
Kernel bwidth (0.1)	*0.008*	292	*3.1*
Kernel bwidth (0.25)	0.015	292	3.5
Kernel bwidth (0.5)	0.030	292	6.0
Caliper (0.1)	0.044	292	10.3
Caliper (0.25)	0.044	292	10.3
Caliper (0.5)	0.044	292	10.3

Source: Authors survey (2018)

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The results of the initial step of PSM, the probit model in this scenario are summarized in Table 2. 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 labour availability positively and significantly influenced the adoption of intercropping as a soil carbon SLMP. This could imply that household members provide labour, given that maize legume intercropping is quite a labour intensive practice. This finding is consistent with (Ndiritu, Kassie & Shiferaw 2014; Kassie *et al.*, 2015) who observed that the size of a household can positively impact the adoption of agricultural practices that require a lot of labour , especially in cases where labour is costly for the households.

Being a male farmer reduced the likelihood of adopting intercropping. Mwangi *et al.* (2015) notes that male farmers adopt certain agricultural technologies based on their usefulness compared to their female counterparts whose adoption is guided by ease of use. Also, farm size had a negative impact on the adoption of intercropping, which could be because farmers opt to allocate resources that could be used to other off farm activities (Thuo *et al.*, 2014). Notably, the probability of practicing intercropping reduced for farmers whose occupation was farming. This could suggest that the households are involved in other farming activities that accrue more income so as to cater for their needs.

The above results are a clear indication that farmers who practice intercropping vary significantly from those who don't. Comparing the adopters verses the non-adopters would therefore give bias estimates, hence the use of PSM as a correction model for the biasness. The propensity scores were calculated for 252 farmers that had adopted intercropping, and 82 farmers who were non adopters (Table 3).

Table 3: Estimated propensity scores for maize-legume intercropping

Groups	Observations	Mean	Std. Deviation	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: Authors survey (2018)

The predicted propensity scores for adopters of intercropping 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. A further analysis of the propensity scores is exhibited by the density distribution of the scores in Fig. 2.The propensity score distribution for farmers who adopted (treated) maize-legume intercropping are represented by the top half, while the lower half shows of farmers who are non-adopters (control).

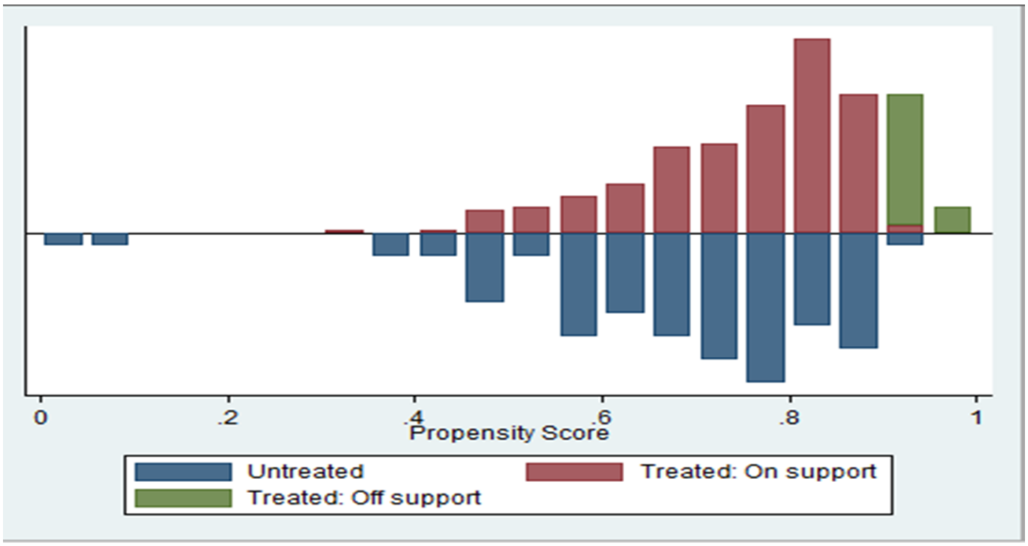

Fig. 2: Propensity score histogram
Source: Authors survey (2018)

Although some farmers in the treated group (farmers who practice intercropping) are off support, the propensity score distribution graph suggests that there is a high chance of attaining a large number of matched sample with good matches. This is an indication that a number of farmers who practice intercropping found a suitable match with those farmers who didn't. Nonetheless, matching should reduce the biasness that comes with observable farmer characteristics. Table 4 shows the results of the covariates balancing test, showing the differences in t test means and percentage bias before and after matching.

Table 4. Balancing tests for covariates

		Mean			**%reduction**	**t-test**	
Variable	Matching sample	Treated	Control	%bias	bias	t	p>t
Pscore	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
Household 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 to 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 to 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
Labour 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 to 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 to 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
Gender of household head	U	0.750	0.793	-10.1		-0.79	0.433
	M	0.767	0.757	2.4	76.7	0.24	0.812
Age of household head	U	54.560	51.573	20.9		1.66	**0.097**
	M	54.038	54.402	-2.5	87.8	-0.26	0.793
Education level of household head	U	1.671	1.537	13.4		1.04	0.301
	M	1.571	1.562	0.9	93.3	0.09	0.925
Occupation of household head	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	47733	20271	20.0		1.30	0.194
	M	23275	23901	-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 shows significant covariates before matching. U and M stands for unmatched and matched samples respectively.

Source: Authors survey (2018)

Table 5: Balancing covariates 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 stands for median and Likelihood ratio respectively

Source: Authors survey (2018)

Results reveal that, out of the 15 variables, the matched sample means for the variables are almost 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, labour, gender and occupation of the household head, and farm size) are insignificant after matching (as indicated in the *p>t* column). This suggests that the variables have been balanced, making them comparable, thus reducing selection bias. This is further ascertained by results in Table 5, whereby there is an observable reduction in Pseudo R^2, LR-Chi^2 and mean bias after matching. Consequently, the P > Chi^2 is insignificant after matching, supporting that the variables have been balanced between adopters and non-adopters.

The successful balance of variables between the two groups of farmers proved similarity 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 maize-legume intercropping on farm output is as summarized in Table 6. The results indicate that the adoption of intercropping has a positive and significant impact (at 5% significant level) on maize output, but an insignificant impact on beans output. This could be an implication 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, substantially increasing maize production. This is because where mono-cropping (maize is grown alone) is practiced weeds are common, resulting in a decline in output.

Table 6. Impact (treatment effect) of maize-legume intercropping on farm output

Outcome	Sample	Treated	Controls	Difference	S.E.	T stat
Maize output	Unmatched	1054	628.90	425.10	173.70	2.45
	ATT**	881.97	642.04	**239.93**	103.66	2.31
Beans 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 significant at $p<0.05$ and S.E is the standard error while ATT is the Average Treatment effect on Treatment

Source: Authors survey (2018)

The results further indicate that maize-legume intercropping increases maize output by an average of 240Kg (approximately 3 bags); therefore, it can be concluded that adoption of intercropping increases maize output by approximately 27%.This finding is consistent with (Ngwira, Aune & Mkwinda 2012) who observed that intercropping is a cost effective practice as it improves maize yields, and at the same time ensures attractive economic returns. This findings suggest that encouraging farmers to adopt intercropping can help in improving maize output thus improved incomes.

The results of the treatment effect assumes that all the applicable observable variables have been included in the treatment assigned. Thus it's important to carry out a sensitivity test to verify whether the estimated results from the PSM are prone to change if other unobserved variables were introduced. Else, the positive impact of maize-legume intercropping on maize output would be questionable. A sensitivity analysis test was therefore carried out, using the rosenbaum bounds (*rbounds*) test to check for hidden bias (Rosenbaum and Rubin, 2006). Since the impact on the outcome (farm output) was positive, the level of gamma reported was for the positive effect (sig+), at the point where 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 at least 60 percent before it would bias the estimated impact. Only then would the significance of the impact on value of output be questionable. Studies that have reported almost similar gamma values for the sensitivity analysis include (Ogutu, Okello & Otieno 2014; Miyinzi *et al.*, 2019), concluding that unobserved variables would negligibly alter the conclusion of a positive impact of adoption of maize-legume intercropping on maize output.

4. Conclusion and policy recommendations

The significance of sustainable land management practices cannot be overemphasized, more so those with the potential to enhance soil carbon. This study established the impact of SLMP that enhance soil carbon in Western Kenya on a sample of 334 farmers, using the propensity score matching method. The findings suggest that agroforestry, maize-legume intercropping, terracing and the use of inorganic fertilizer are dominant practices in the area respectively. However, the criteria for impact evaluation using PSM method revealed that maize-legume intercropping solely had a visible impact on farm output. This is an indication that interventions aimed at increasing adoption should be aimed specifically on an individual practice conditional on the determinant factors.

The size of a household and availability labour had a positive and significant influence on uptake, while gender and occupation of household head, and farm size had a negative and significant impact. The results of the impact evaluation, given by the average treatment effect on the treated shows that farmers who practiced maize-legume intercropping increased their maize output by approximately 240 kilograms (an average of 3 bags). This is an estimated 27% increase in maize output. Further, unobserved variables would not transform much the results of the evaluated effects. The study therefore concludes that adoption of maize-legume intercropping significantly improves maize output.

The findings from this study imply that maize-legume intercropping is an effective practice in boosting maize output, which represents a major component of Kenya's grain basket, and can help resource constrained rural farmers improve their farm income. Interventions that encourage uptake of the practice should therefore be pursued by relevant stakeholders. For instance, labour is a significant determinant in maize-legume intercropping adoption. Thus interventions that ease the burden of labour such as improved/modern, and cost-effective technologies should be established. Alternatively, it would be plausible to avail affordable inputs that enable implementation such as improved seed varieties and inorganic fertilizer.

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