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Original Article

Impact of Soil and Water Conservation Practice on Crop Productivity in Ethiopia

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Abstract - *The aim of this study was to evaluate the impact of soil and water conservation practices on rural farmers' crop productivity in Ethiopia.Both primary and secondary data were employedfor analysis in this study. About 190 sample respondents were selected for the primary data collection. Descriptive statistics with appropriate statistical tests and a non-parametric estimation method, propensity score matching,were used for analysis. The result of propensity score matching indicated that soiland water conservation practice has a positive and significant impact on crop productivity of6 quintal per hectare (3300 Ethiopian Birr)for maize crop and 3quintal per hectare (3600 Ethiopian Birr) for haricot bean crop because of the intervention. Thus, for agriculture-dependent countries like Ethiopia, soil and water conservation is vital in improving the livelihoods of the rural farm households through improving crop productivity. Yet, to realize the intended outcomes, more awareness creation, and continuous support areneeded fromthe government, especially the Ministry of Agriculture and non-governmental institutions working on agriculture to promote thesoil and water conservation practices by farmers.*

Keywords - *Soil and Water Conservation, Propensity Score Matching, Crop Productivity, Ethiopia.*

I. INTRODUCTION

The Ethiopian economy is primarily dependent on agriculture. Agricultural production makes up more than 40 percent of the annual Gross Domestic Product (GDP) of the country. Owing to this fact, the economic development of the country is extremely dependent on the performance of the agricultural sector. A large proportion of farmers earns their livelihoods from rain-fed agriculture and thereby depend directly on rainfall and agricultural productivity for their survival. However, the sector is among the most vulnerable in sub-Saharan Africa, which has suffered from recurrent droughts and extreme fluctuations of output. For instance, the sector's production has been growing by about2.3% during 1980-2000 while the population was growing on average at a rate of 2.9% per year, which led to a decline in per capita agricultural production by about 0.6% per year[1].

Ethiopia is one of the Sub-Saharan countries where soil erosion, sedimentation, depletion of nutrients, deforestation, and overgrazing cause basic problems,and this limits their ability to increase agricultural production and reduce poverty and food insecurity [2]. The immediate effect of soil erosion is reducing crop yield, followed by economic decline and related social problems. The low productivity of the sector is a function of backward implements and methods of production, low use of modern inputs, environmental degradation, and poor resource management. Environmental degradation has a significant socioeconomic and environmental consequence for society ([3, 4].

Soil erosion is among the major problems that human beings are facing. The most important causes of soil erosion include continuous cropping with short or no fallowing triggered by high population pressure, cultivation of highly inclined and marginal lands without appropriate erosion-controlling measures, insufficient drainage of irrigation water, deforestation, and overgrazing [5].Therefore, for economies like Ethiopia, by continuingto experience the worst land degradation in the world (1900 million tons of soil per year)[6] and high population growth, it could be impossible to achieve food sufficiency and sustainable economic growth. Jansky and Chandran [7] estimated that "land degradation reduces the annual agricultural GDP of Africa by 3%".

Soil erosion is the main form of land degradation, caused by the interacting effects of factors, such as biophysical and socio-economic aspects. Therefore, it is mandatory to apply farm technologies to mitigate the negative effects of soil erosion and nutrient depletion. It has been shownthat adopting andpracticing improved technology can increase agricultural production [4] and overcome the problem of soil erosion. Among these, soil and water conservation (SWC) practice is one thathas been implemented since the mid-1970s in Ethiopia [6]. Typical SWC practices used in Ethiopia include soil bunds, stone bunds, grass strips, waterways, trees planted at the edge of farm fields, [8].

Though land degradation is a major environmental and socio-economic problem, the government of Ethiopia has made very few soils and water conservation interventions thathave been carried out with limited success. Besides, soil erosion is a major contributor to the current food insecurity of Ethiopia. Even though SWC practicewas implemented in Ethiopia inthe 1970s [6, 9], evidence showsthe poor performance of the agricultural sector. The sector is growing by only 6%, whereas the overall growth is reported to be 10.9% [1].

The study area, Sodo district, is affected by soil erosion resulting in a reduction of soil moisture, land productivity, and plant nutrient loss. Rainfall in the area is uneven and erratic, which makesit worth recurrent drought and food shortage. To cope with this problem,few farmers in the study area have been applying different traditional and improved soil and water conservation practices to get high crop production and to conserve the soil and water[10]. Thus, this study aimed to evaluate the impact of Soil and Water Conservation (SWC) practice on rural farmers' crop productivity in the study area.

II. MATERIALS AND METHODS

A. Description of the Study Area

Gurage zone is located in the southwestern and northernmost part of the region of the Southern Nations, Nationalities, and Peoples Regional State (SNNPRS) (Figure 1). It is bounded by Siltie in the southeast, and Hadia zone and Yem special district in the south and southwest, respectively. The northern, western, and eastern parts sharea border with Oromia. According to the Central Statistical Agency (CSA) population projection [11], the total number of population of the zone is estimated at 1,724,323 in 2017 (48.5 % male and 51.5 % female). The overwhelming majority (84.9 %) live in the rural area depending on agriculture as means of livelihood. It falls into three agro-ecological zones, that is, *data, win dega,* and *kola.*

The study area, Sodo district (Figure 1), is one of the thirteen districts and two town administrations of the Gurage zone. The district is bordered in the south with Meskan district, in the west with Ezra Wolene district, in the northwest with Kokir Gedebano Gutazer district, in the southeast with Mareko district, and in the north with Oromia Regional State. Sodo district is located to the south of the Ethiopian capital, Addis Ababa, with a distance of 94 km and 200 km northwest of the regional capital, Hawassa. An average annual rainfall of 801–1200 mm characterizes the Sodo Gurage district, which is mono-modal. The mean annual temperature of the district ranges from 12.6–20 ^{0}c. The type of crops grown is predominantly wheat, *teff*, maize, haricot bean, barley, and sorghum[12]. The total cattle population of the district is about 348,295. Population projection revealed that the total population of the district for the year 2017 was 192,549 (49.9 % male and 50.1 % female), and about 88.6 % of the population reside in rural areas [11].

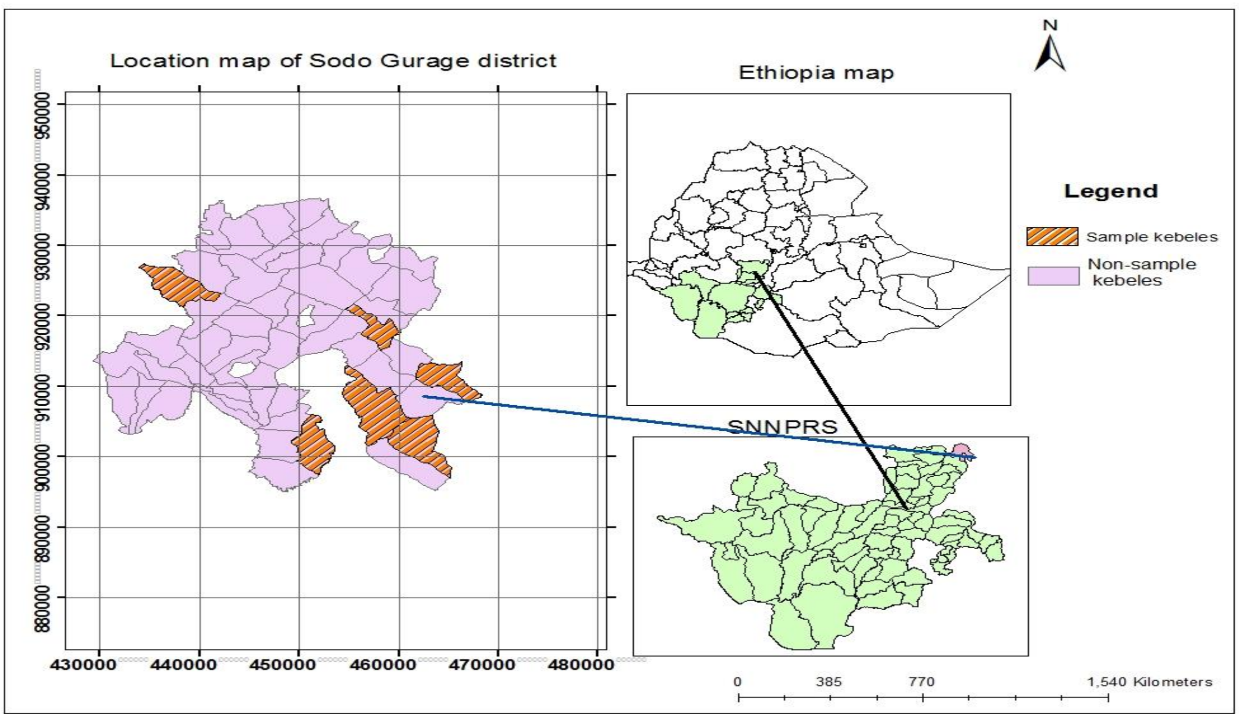

Fig. 1 Physical Map of The Study Area

B. Data sources and instruments for Collection

The study was a cross-sectional survey design that employed both primary and secondary data sources. The primary datawere collected from sample respondents using a semi-structured interview questionnaire. The questionnaire was first prepared in English, and then it was translated into the local language (Guragigna). The questionnaire was developed in the way itmeasures the study objectives and pretested for the collection of actual data. While, the supportive secondary data were collected from different published and unpublished sources, including books, journal articles, official reports and records, magazines, and the internet. They were used as background information to cross-validate statistical results, and support arguments.

C. Sampling technique and Sample Size Determination

Multi-stage sampling techniquewas employed to select in this study. In the first stage, Sodo Districtwas selected purposivelybecause of its engagement in soil and water conservation practice. In the second stage, three *kebeles* were selected randomly out oftwenty soil and water conservation practicing *kebeles*in the district. In the third stage, fromthree selected *kebeles*, households were stratified into two strata such as, participant and non-participantof soil and water conservation practice that would be considered as the target population for this study. The households included in the participant stratum are those who engaged in soil and water conservation practice, and in the non-participant stratum,those who haven't been involved at all.

To determine the sample size Yemane [13] formula was used with a 7 % precision level. Accordingly, with the total number of households 2650 in the three kebeles, the sample size is computed as:

$$\boldsymbol{n} = \frac{N}{1+N(e)^{\wedge}2} = \frac{2650}{1+2650(0.07)^{\wedge}2} = 189.488 \approx 190$$

Where n is the sample size, N is the total household population, and e is the level of precision. Thus, about 190 sample households (80 participants and 110 non-participants) were selected randomly from the two strata. To determine respective samples from four Kebeles for each stratum, sampling proportion to population was used. Finally, a representative sample for each stratum would be selected through systematic random sampling techniques.

Table 1. Distribution of Sample Households by Kebele

	Participant household		Non-participant household		Total Sample
Sample *Kebele*	Total	Sample	Total	Sample	
Dega Nurena	201	28	739	39	67
Firshi	150	21	770	41	62
Adele Borebore	215	31	575	30	61
Total	566	80	2084	110	190

Source: Own survey result (2017)

D. Method of Data Analysis

To meet the objective of the study, both descriptive and inferential statistics were used for analysis. In the descriptive statistics like, frequency and percentage distribution were used. In the inferential statistics, logistic regression to identify the determinants of SWC participation and Propensity Score Matching (PSM) model to evaluate the impact of SWC practice.

E. Specification of Econometric Model

Impact assessment requires a group affected by the program intervention, and a control group to compare the outcomes. For the purpose of this study, the intervention was soil and water conservation practices. However, the problem is to identify groups that look alike [14].To deal with this problem, the propensity score matching (PSM) technique was used, which, has gained popularity in recent years for its potential to remove a substantial amount of bias from non-experimental data. The main reason for employing this technique was that firstly, it helps to adjust for initial differences between a cross-section of the participant and non-participant groups by matching each participant unit to a non-participant unit based on "similar" observable characteristics. Secondly, it summarizes all the differences in a single dimension, the propensity score, which was then used to compute treatment effects [15].

According to Khandker*et al*. [14], the implementation of PSM involves six steps. These are an estimation of the propensity score, defining a region of common support, choosing a matching algorithm, testing matching quality, calculating average treatment effect on treated and sensitivity analysis. Accordingly, the application system for the purpose of this study is discussed as follows for each step.

Propensity score estimation

When estimating the propensity score, two choices have to be made. The First one concerns the model to be used for the estimation, and the second one the variables to be included in this model. Concerned about the model, since this study has binary treatment (participation and non-participation in soil and water conservation practices), the application of logic is appropriate. Regarding about the choice of variables that will be included in the model, according to Caliendo and Kopeinig[16], only variables that simultaneously influence the participation decision and the outcome variable should be included. In most cases, there will be no comprehensive list of clearly relevant variables that will assure that the matched comparison group will provide an unbiased impact estimate. For each evaluation, it is important to consider what factors make the nonparticipant units distinct from participant units. To the extent that these factors are associated with outcomes, controls for them are essential. One obvious set of factors to include in PSM estimation are explicit criteria used in determining participation in the intervention and also to consider factors associated with self-selections into the practices of soil and water conservation [17].

According to Gujarati [18], in estimating the logit model, the dependent variable is participation which takes a value of 1 if the household participated in soil and water conservation practices and 0 otherwise. The logit model is mathematically formulated as follows:

$$P_i=\frac{e^{zi}}{1+e^{zi}} \text{--}(1)$$

Where, Pi is the probability of participation in soil and water conservation:

$$Z_i=\beta_0+\sum \beta_i X_i + UI \text{---------------------------------------}(2)$$

Where B_0 = Intercept, β_i= regression coefficients to be estimated, X_i, = Variables and UI = a disturbance term.

The probability that a household belongs to the non-participant group is:

$$1\text{-}P_i=\frac{1}{1+e^{zi}} \text{--}(3)$$

Then odds ratio can be written as

$$\frac{\text{pi}}{1-\text{Pi}}=\frac{1+e^{zi}}{1+e^{-zi}}=e^{zi} \text{---}(4)$$

The left-hand side of equation (4), 1-P_i, is simply the odds ratio in favor of participating in SWC practice. It is the ratio of the probability that the household would participate in SWC to the probability that he/she would not participate in the SWC practice. Finally, by taking the natural log of equation (4), the log of odds ratio can be written as:

$$L_i=\text{Ln}\left(\frac{\text{pi}}{1-\text{Pi}}\right)=\text{Ln}\left(e^{\beta 0+}\textstyle\sum_{j=1}^{n} \beta_j x_{ij}\right)=Z_i=\beta_o+\textstyle\sum_{j=1}^{n} \beta jxij \text{--}(5)$$

Where, L_i is a log of the odds ratio in favor of participation in the SWC, which is not only X $_{Ji}$ linear in but also linear in the parameters.

As indicated above in the model, the logit model for this study can be identified as follows with variables of the study $Y_i=\alpha+\sum \beta_i X_i+\mathring{u}$, that is

$$Y_i=\alpha+\beta_1 Agehh+\beta_2 Sexhh+\beta_3 Educhh+\beta_4 Lvstown+\beta_5 Sizefam+\beta_6 DAcont+\beta_7 Farmsiz+\beta_8 Offpart+\mathring{u}_i \text{------------------------}(6)$$

Where: Y_i indicates SWC practice and takes value 1 for participant and 0; otherwise, α is intercepted, β_i is regression coefficients to be estimated, X_i is variables,and ů is the error term.

Agehh=Age of the household head, Sexhh=Sex of the household head, Educhh =education level of household head, Lvstown =Livestock Ownership, Sizefam =Family Size, DAcont = Frequency of contact with Development Agent, Farmsiz = Farm size, Offpart=Participation in off-farm economic activities

F. Defining region of common support

Defining common support is the second important step in PSM, where distributions of the propensity score for soil and water conservation (SWC) practice participant and nonparticipant groups overlap [14] because the average treatment effect on SWCpractice participants and on nonparticipants is only defined in the common support region. The common support region is the area within the minimum and maximum propensity scores of soil and water conservation practice participant and nonparticipant groups, respectively, and it is done by cutting off those observations whose propensity scores are smaller than the minimum and greater than the maximum of the participant of SWCpractice and nonparticipant groups, respectively [16].

G. Choosing matching algorisms

After identifying the probability of participation on SWC based on identified observable covariates through the use of the logit model, the second step of PSM is choosing matching algorism. Different matching criteria can be used to assign participants to non-participants on the basis of the propensity score. Doing so entails calculating a weight for each matched participant and non-participant set. There are four common matching algorisms in the PSM model. They are discussed below as follows.

Nearest neighbor matching: this is one of the most straightforward matching procedures. An individual from the non-participant of SWC is chosen as a match for a participant individual in terms of the closest propensity score (or the case most similar in terms of observed characteristics). Basically, this method involves two mechanisms of matching (matching with replacement and matching without replacement).In matching with replacement, nonparticipants can be used more than once as a match, whereas in without replacement is considered only once [17].

Nearest neighbor matching with replacement increases the average quality of matching and decreases the precision of estimation, while the reverse is true in the case of without replacement [16].

Caliper matching: applied to overcome the drawback of nearest neighbor matching that arises from the risk of bad matches, when the closest neighbor is far away. This can be avoided by imposing a tolerance level on the maximum propensity score distance (caliper). Bad matches are avoided, and hence the matching quality will rise [16, 17].

Radius matching: applied to overcome the shortcoming of caliper matching. The basic idea of this is to use not only the nearest neighbor within each caliper but all of the non-participants within the caliper. A benefit of this approach is that it uses only as many comparison units as are available within the caliper and therefore allows for usage of extra units when good matches are not available. Hence, it avoids the risk of bad matches [14, 16, 17].

Kernel matching: the matching algorithms discussed above have in common that only a few observations from the comparison group are used to construct the counterfactual outcome of SWC participants. Kernel matching and local linear matching are non-parametric matching estimators that use weighted averages of all non-participants in SWC to construct the counterfactual outcome. The major advantage of these approaches is the lower variance which is achieved because more information is used [14, 16].
Among all those matching algorism the one which will provide more number of matches will be employed to identify the impact of participation in SWC practice on food crop production.

H. Testing the matching quality

The fourth crucial step in the application of the PSM model is effect analysis. According to Caliendo and Kopeinig [16], matching quality has to be checked if the matching procedure is able to balance the distribution of the relevant variables in both the SWC practice participant and nonparticipant. Standard bias, t-test, joint significance, and pseudo-$R^{2,}$ and stratification test are the mechanism that different literatures suggested to test this situation. The basic idea of all approaches is to compare the situation before and after matching and check if there are any differences after conditioning on the propensity score. The primary purpose of the PSM is that it serves as a balancing method for covariates between the two groups since differences in covariates are expected before matching and should be avoided after matching. Consequently, the idea behind balancing tests is to check whether the propensity score is adequately balanced. In other words, a balancing test seeks to examine if, at each value of the propensity score, a given characteristic has the same distribution for the treatment and comparison groups. If there are differences, matching on the score is not completely successful, and remedial measures have to be done.

Based on this, matching is considered a good match when there is no statistically significant difference in the mean of covariates of both groups. The Pseudo-R^2shows how best the repressors explain the probability of participation, and it should be fairly low since there should not be a significant difference in the distribution of both groups after matching [14, 16, 17].

I. Calculating average treatment effect on treated

The average treatment effects (ATT) are defined as the average effect for sampled households with a given value of the explanatory variables. It is estimated by taking the difference between the treatment and control averages that are matched through the propensity scores, and finally,the average treatment effect on the treated group can be calculated by using the following equation developed by Becker and Ichino [19].
Finally, ATT can be computed as follows:

$$ATE = \epsilon(Y_{1i} - Y_{0i}) \quad \text{---------------------------------} \; (7)$$

Where ϵ (.) denotes the expected value and sample equivalent is given by:

$$ATE = \frac{1}{n}\sum_{i=1}^{n}(Y_{1i} - Y_{0i}) \quad \text{----------------------------} \; (8)$$

The average gain of adoption on household wellbeing compared to what would have been if these households had not adopter, specified as:

$$ATT = \epsilon(Y_{1i} - Y_{0i}/I_i = 1) = \epsilon(Y_{1i}/I_i = 1) - \epsilon(Y_{0i}/I_i = 1) \quad \text{---} \; (9)$$

Equation (6) is the average treatment effect on the treated (ATT), where the sample equivalent is written as:

$$ATT = \frac{1}{n}\sum_{i=1}^{n}(Y_{1i} - Y_{0i}/I_i = 1) = \frac{1}{n}\sum_{i=1}^{n}((Y_{1i}/I_i = 1) - (Y_{0i}/I_i = 1)) \quad \text{---------------------------------} \; (10)$$

J. Sensitivity Analysis

This is the final step in the application of the PSM model. Matching has become a popular method to estimate average treatment effects. It is based on the conditional independence or unconfoundeness assumption, which states that all variables simultaneously influencing the participation decision and outcome variables should be considered [20]. The estimation of treatment effects with matching estimators is based on the selection of observable characteristics. However, a hidden bias might arise if there are unobserved variables that affect assignment into treatment and the outcome variable simultaneously [21].

Since matching estimators are not robust against hidden biases, it is important to test the robustness of results to departures from the identifying assumption. However, it is impossible to estimate the magnitude of selection bias with non-experimental data. Therefore, this problem can be addressed by sensitivity analysis [16]. To check the sensitivity of the estimated Average Treatment Effect (ATT) with respect to deviation from the conditional independence assumption, this study has applied Rosenbaum bounding approach suggested by Rosenbaum [21].

K. Definitionand Hypothesis of variables

Dependent Variable: In this study, participation in the adoption of soil and water conservation practice was taken as the dependent variable, which was influenced by Independent variables. It is defined as a household that adopts SWC practice, and it was a dummy variable (1 for those who adopt and 0 otherwise).

Outcome Variables: The outcome variable for this particular study was crop productivity, especially on (Maize and haricot beans). They are major crops produced in that area, which was measured in quintal of crop productivity per hectare per year.

Explanatory Variables:

The explanatory variables (independent variables) were hypothesized to influence the application of soil and water conservation practice positively (+), negatively (-), and/or either positively or negatively (+/-). Based on literatures, the following relationships were hypothesized (Table 2).

Table 2. Explanatory Variables Determining Soil and Water Conservationpractice

Variable	Variable type	Measurement	Expected Sign
Age of the HH* head	Continuous	Age in years	+
Sex of the HH head	Dummy	0 for male,1 for Female	-/+
Educational level of the HH head	Discrete	The grade level of schooling of the sample HH	+
Farm size	Continuous	Area of the land owned by the HH in hectares (ha)	+
Family size	Discrete	The number of the household members	+
Frequency of Contact with Development Agent (DA)	Continuous	The number of contacts made with DAs	+
Livestock ownership	Continuous	Livestock owned by HH in TLU**	+
Participation in off-farm activities	Dummy	1 for participant, 0 otherwise	-/+

*Note: *HH stands for Household Head*

***TLU stands for Tropical Livestock Unit, where the values for the Livestock are Ox=1, Cow=1, Horse=1.1, Heifer=0.75, Calf=0.25, Donkey=0.7, Sheep=0.13, Goat=0.13,Mule=0.7 and Paultry=0.013 [22].*

Source: Survey Result (2017)

III. RESULTS AND DISCUSSION

A. Description of Sample Households' Characteristics

This section highlights the demographic and social characteristics of the sample households in the study area by using a mean comparison summary table for both continuous and discrete explanatory variables andusing descriptive statistics outputs such as mean, standard deviation, percentages, the frequency of the two groups of sample respondents were compared and contrasted with respect to socio-economic, institutional, demographic and communication characteristics so as to draw some important conclusion.

B. Age of household head

The mean age was identified to be 42.3 and 43.5for SWC participants and non-participant, respectively. The t-test result indicated that, there was no significant mean difference between the two groups in their age (Table 3).

C. Educational level

From SWC participant group respondents, 64 % of them have obtained formal education, whereas the rest,36 % of them have no formal education. Similarly, out of SWC non-participant group respondents, it was found that 55% /half/ of them have attained formal education. This indicated that SWC participant households had attained formal education more than non-participant households. The t-test result also indicates that there was a significant mean difference in educational level between the two groups at 1% of significance level (Table 3).

D. Family size

Themean family size of SWC participants was 6.1and that of non-participants was 5.7.The t-test result indicated that there was no significant mean difference between the two groups in their family size (Table 3).

E. Farm size

The mean land holding of SWC participants and non-participants was 1.8 and 1.6 hectares, respectively. In the study area, relatively SWC participants were found to be more landholders than non-participants. The t-test result indicated that, there was no significant mean difference between the two groups in their landholding.

F. Livestock ownership

Livestock it is one of the important assets in the livelihood of rural people. They are a source of income, power, organic fertilizer, and food for people. Besides, they are also considered as social security because people give more respect who own more number of livestock than the others.As indicated in Table 3,the mean tropical livestock unit of SWC participants was 3.4 while it was 2.6 for non-participants.The t-test result also indicated that there was a significant mean difference in educational level between the two groups at 1% of the significance level.

G. Frequency of contact with DA

It is obvious that farmers who contact more with Development Agent (DA) know more about new technologies for the better productivity and environmental protection than those who do not have contact. The average number of contacts of households made with DA in the last 12 months was 15, that is, 1.3 within a month. The average number of contacts made by SWC participants within the last 12 months was 18.9, while the average number of contacts made by non-participants was 5.8. The t-test result confirmed that there was a significant mean difference in contact with DA between the two groups at 1% of the significance level.

Table 3. Mean Comparison Test Among Hhs For Continuous Variable

Variable	SWC participation		SWC non-participant		
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**t-value**
Age of HH	42.3	7.852	43.5	5.671	1.026
Education level of HH	3.3	2.986	2.2	2.506	2.837**
Family size	6.2	1.813	5.7	1.940	1.024
Farm size	1.8	0.753	1.6	0.603	1.025
Livestock ownership	3.4	1.081	2.6	0.738	5.236***
Contact with DA	18.9	3.383	5.8	0.452	6.690***

*Note: ***, ** and * refer that Significant at 1%, at 5%, and * at 10% of level of significance, respectively*
Source: Survey Result (2017)

H. Sex of the respondent

As indicated in table 4, out of the total sample households,84.5% of them were male, and 15.5% of them were female. With regard to the participation in SWC by sex, it was found that 85% of SWC participants were male while 15 % of them were female, and from a non-participant, 84 % were male, and 16 % were female. This may indicate that the participation of females in SWC practice is less as compared with males. The Chi-square test analysis showed that there was no statistically significant difference in the sex of the respondent between SWC participants and non-participant households.

I. Participation in off-farm activities

About 41 % of respondents participated in nonfarm activities, while the rest didn't participate. Majority (55.5%) of Non-SWC participants responded that they participated in nonfarm activities, while the rest (44.5%) of them responded they did not. Similarly, out of SWC participant respondents, only 21.25% of them participated in nonfarm activities while the rest, 78.75% of them didn't.The Chi-square test result showed that at a 1% level of significance, there was a significant difference between SWC participants and non-participantin in terms of participation in Off-farm activities (Table 4).

Table 4. Mean Comparison Test For Discrete Variables

<table>
<tr><th colspan="2" rowspan="2">Variable</th><th colspan="2">SWC participation</th><th colspan="3">SWC non-participant</th></tr>
<tr><th>Frequency</th><th>Percent</th><th>Frequency</th><th>Percent</th><th>Chi-square (χ2)</th></tr>
<tr><td rowspan="3">Sex of HH</td><td>Male</td><td>68</td><td>85</td><td>92</td><td>84</td><td rowspan="3">0.188</td></tr>
<tr><td>Female</td><td>12</td><td>15</td><td>18</td><td>16</td></tr>
<tr><td>Total</td><td>80</td><td>100</td><td>110</td><td>100</td></tr>
<tr><td rowspan="3">Off-farmactivity participation</td><td>Yes</td><td>19</td><td>21.2</td><td>61</td><td>55.5</td><td rowspan="3">22.392***</td></tr>
<tr><td>No</td><td>61</td><td>78.8</td><td>49</td><td>44.5</td></tr>
<tr><td>Total</td><td>80</td><td>100</td><td>110</td><td>100</td></tr>
</table>

*Note: ***, ** and * refer that Significant at 1%, at 5%, and * at 10% of level of significance, respectively*
Source: Survey Result (2017)

J. Econometric Analysis

Estimation of propensity score

Impact of a certain program or policy can be conveniently be measured through the average difference between outcomes with the program and outcomes without the program, the latter representing the counterfactual. But in non-randomized program placement, like SWC practice, the counterfactual can be achieved through propensity score matching (PSM). In order to estimate the propensity score, household characteristics that would not be affected by program participation were considered. As specified earlier, the dependent variable in this model is binary, indicating whether the household was a participant in SWC practice which takes a value of 1 and 0 otherwise.

Before performing the econometric estimation itself, violations of different assumptions were tested using appropriate techniques. The presence of strong multicollinearity among continuous explanatory variables was tested using variance inflation factors (VIF), and contingency coefficient (CC) was used to check the existence of multicollinearity between discrete variables. There was no any continuous or discrete explanatory variable dropped from the estimated model since no serious problems of multicollinearity were detected from both the VIF and CC results. In addition, the presence of heteroscedasticity problem was tested using Breusch-Page (BP) test, and no heteroscedasticity problem was detected.

K. Logit regression result of factors affecting the probability of participation in SWC practice

The logistic regression model was employed to estimate propensity scores for matching treatment households with control households. The dependent variable in this model was a dummy variable indicating whether the household has been in the soil and water conservation practice which takes a value of 1 and 0, otherwise. The explanatory variables used are variables that explain soil and water conservation participation characteristics of the farm households. The logit estimate result appears to perform well for the intended matching exercise. The pseudo-R^2value 0.2735 shows that the competing households do not have many distinct characteristics overall, so that finding a good match between the treated and non-treated households becomes easier (Table 5).

Table 5. Logit results of household participation in soil and water conservation practice

Variable	Coefficient	Std. Err.	Z	p-value
Sex of HH	-0.3180773	.277093	-1.15	0.251
Age of HH	0.0281154	.0147731	1.90	0.057*
Education level	0.1132984	.0405189	2.80	0.005
Contact with DA	0.0825807	.0228547	3.61	0.000
Participation in Off-farm activities	-0.9737257	.2321258	-4.19	0.000
Family size	-0.2385827	.2227733	-1.07	0.284
Farm size	0.1493175	.1730876	0.86	0.388
Livestock ownership	0.577984	.1460026	3.96	0.000
_cons	-3.358532	.8319952	-4.04	0.000

Number of obs = 190 LR chi^2(8) = 70.73 Prob > chi^2 = 0.0000
Log likelihood = -93.95306 Pseudo R^2 = 0.2735
*Note: ***, ** and * refer that Significant at 1%, at 5%, and * at 10% of level of significance, respectively*
Source: Model Result (2017)

The logistic regression result above revealed that there were a number of variables that determine households' decision participation in SWC practice.The estimated coefficient results indicated that among eighthypothesizedvariables, only five variables, namely, Age of HH, Education level, contact with DA, Participation in off-farm activities, and livestock ownership,were found to havea significant influence on participation in SWC at 1% and 10% level of significances.

As shown in Table 5 above, the age of the household head influenced participation in SWC practice positively and significantly at a 10% level of significance. This indicated that older sample households are more likely to participate in the program compared to younger counterparts.The rest variables, such as, Education level of the household head, contact with DA, and livestock ownership in TLU, affects households' probability of participation in SWC practice positively and significantly at a 1% level of significance. The possible explanation for this relationship might be as the education level of the households increase. They are more interested, the probability of participating in SWC also increases, other factors being constant. Frequent contactwith the Development agent also increases the household's probability of participation in SWCpractice. Households' who own a large number of livestock are considered as a source of income, power, organic fertilizer, and food for people, so they are more interested to participate in SWC practice. Moreover, the logistic regression output also showed that participation in nonfarm activities household's probability of participation in SWC practices negatively at 1% significance level.

L. Matching Soil and water conservation (SWC) participants with non-participant households

Table6below shows the distribution of propensity scores for all households. As shown in the table, the propensity scores vary between 0.0421045-0.998538for sampleparticipants of SWC practice with a mean score of 0.61. At the same time, the score varies between 0.0059022-0.894567for non-participant households with a mean score of 0.28. The common support then lies between 0.0421045-0.894567. This means that households whose propensity score is less than the minimum (0.0421045) and larger than the maximum (0.894567) are not considered for matching purposes. Based on this procedure, 15 households (4 households from the SWC participant group and 11 households from the non-participant group were discarded from the study in impact assessment.

Table 6. Distribution of Estimated Propensity Score of Households

Group	Observation	Mean	STD	Min	Max
All household	190	0.3910525	0.263585	0.0056023	0.998538
SWC Participants	80	0.6413430	0.270316	0.0421045	0.998538
SWC non-participants	110	0.302659	0.258868	0.0059022	0.894567

Source: Model Result (2017)

The diagram below (Figure 3) shows the common support identified for the propensity score matching purpose. In other words, it implies that only observations in the same range that can be compared are identified as a common support to be matched.The bottom halves of the histogram show the propensity score distribution of SWC practice non-participant households, and the upper halves show the propensity score distribution of SWC practice participant households.

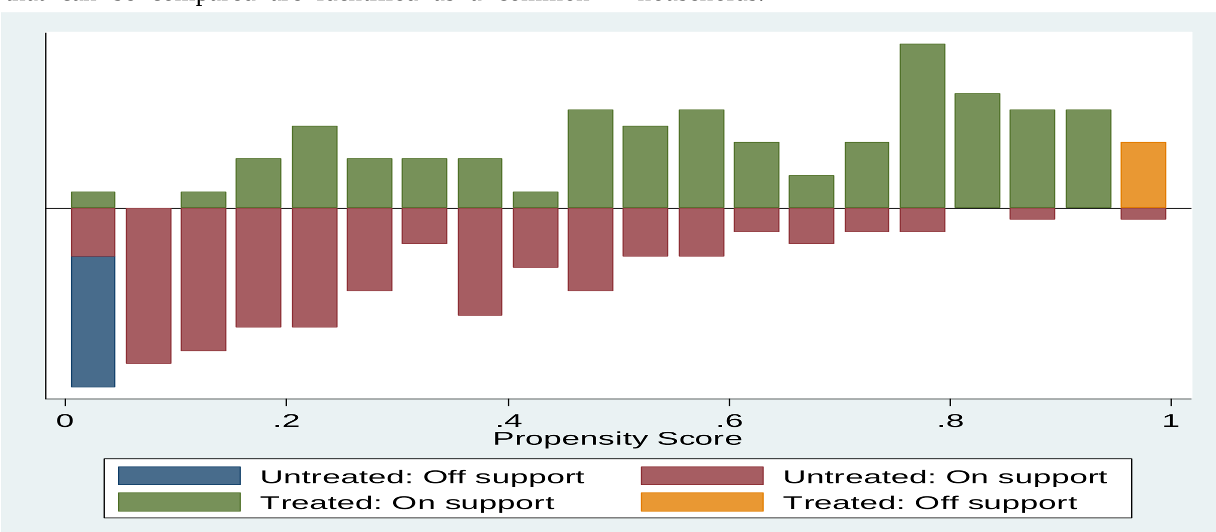

Fig. 2 Common Support Region For Estimated Propensity Score

The green-colored (treated on support) and the red-colored (untreated on support) indicated the observations in the SWC participant and non-participant group that have a suitable comparison, respectively. Whereas, the orange-colored (treated off support) and the blue-colored (untreated off support) indicate the observations in the SWC participant and non-participant group that does not have a suitable comparison, respectively.

M. Choice of matching algorithm

Different alternatives of matching estimators were conducted to match the treatment program and control households that fall in the common support region. The decision on the final choice of an appropriate matching estimator was based on three different criteria as suggested by Deheja and Wahba [23]. First, the equal means test (referred to as the balancing test), which suggests that a matching estimator which balances all explanatory variables (that is, results in insignificant mean differences between the two groups) after matching, is preferred. Second, looking into pseudo-R^2value, the smallest value is preferable. Third, a matching estimator that results in the largest number of matched sample sizes is preferred. To sum up, a matching estimator that balances all explanatory variables, with the lowest pseudo-R^2value and produces a large matched sample size is preferable.

Based on those criteria, the nearest neighbor of neighborhood 5 was found to be the best estimator for this study. Therefore, the impact analysis procedure was followed and discussed by using nearest neighbor 5.

Table 7. Performance Criteria of Matching Algorisms

Matching algorism	Performance criteria		
	Balancing test*	**Pseudo R^2**	**Matched sample size**
Nearest neighbor 1	5	0.094	175
Nearest neighbor 2	6	0.070	175
Nearest neighbor 3	5	0.070	175
Nearest neighbor 4	7	0.048	175
Nearest neighbor 5	8	0.021	175
Caliper 0.01	8	0.040	127
Caliper 0.1	5	0.094	175
Caliper 0.25	5	0.094	175
Caliper 0.5	5	0.094	175
Radius 0.01	4	0.222	175
Radius 0.1	4	0.222	175
Radius 0.25	4	0.222	175
Radius 0.5	4	0.222	175
Kernel 0.01	8	0.028	127
Kernel 0.1	7	0.044	175
Kernel 0.25	7	0.030	175
Kernel 0.5	7	0.066	175

Source: Own computation result (2017)

N. Testing the balance of propensity score and covariates

Once the best performing matching algorithm is chosen, the next task is to check the balancing of propensity score and covariate using different procedures by applying the selected matching algorithm (nearest neighbor 5 in this case), has created a covariate balance between SWC practice participant and non-participant households, which is important to conduct impact analysis. It should be clear that the main intention of estimating propensity scores is not to get a precise prediction of selection into treatment. Rather, to balance the distributions of relevant variables in both groups[24].

The following table 8 shows the balancing powers of the estimations are ensured by different testing methods. Reductions in the mean standardized bias between the matched and unmatched households, equality of means using two-test for joint significance of the variables were employed. The insignificance of variables after matching is because of the mean difference between the matched and unmatched variables, which means there is no difference. The fifth and sixth columns of Table 8 showthat the standardized bias before and after matching, and the total bias reduction obtained by the matching procedure, respectively. The standardized difference in covariates before matching is in the range of 0.9% and 74.8% in absolute value, whereas the remaining standardized difference of covariates for almost all covariates lies between 1.1% and 17.6% after matching. This is below the critical level of 20% suggested by Rosenbaum and Rubin [25]. Therefore, the process of matching creates a high degree of covariate balance between the treatment and control samples that are ready to use in the estimation procedure. Similarly, T-values also reveal that all covariates became insignificant after matching while four of them were significant before matching.

Table 8. Propensity Score and Covariates Balance Test

Variable	Sample	Mean		%bias	bias reduction	t-test	p-value
		Treated	**Control**				
P score	Unmatched	0.61134	0.28266	139.8		9.62	0.000
	Matched	0.59252	0.57345	8.1	94.2	0.50	0.618

Sex of household head	Unmatched	0.175	0.2	-6.4		-0.43	0.666
	Matched	0.18421	0.20789	-6.0	5.3	-0.37	0.715
Age of household head	Unmatched	43.55	42.718	11.3		0.77	0.444
	Matched	43.711	41.771	16.4	-133.2	1.65	0.102
Education level	Unmatched	3.2875	2.1545	41.1		2.84	0.005
	Matched	3.2237	3.2553	-1.1	97.2	-0.07	0.943
Contact with DA	Unmatched	4.85	2.3727	57.2		3.83	0.000
	Matched	4.6447	6.2711	-17.6	34.4	-1.63	0.106
Participation in Off-farm activities	Unmatched	0.2125	0.55455	-74.8		-5.01	0.000
	Matched	0.21053	0.25789	-10.4	86.2	-0.69	0.494
Family size	Unmatched	0.55	0.54545	0.9		0.06	0.951
	Matched	0.55263	0.57105	-3.7	-305.3	-0.23	0.820
Farm Size	Unmatched	1.525	1.4318	15.2		1.05	0.297
	Matched	1.5	1.3803	9.5	-28.5	1.21	0.227
Livestock ownership	Unmatched	3.2867	2.5954	74.7		5.24	0.000
	Matched	3.1526	3	16.5	77.9	1.45	0.150

Source: Own survey result (2017)

As indicated in Table 9 below, the low pseudo-R^2 and the insignificant likelihood ratio tests support that both groups have the same distribution in covariates after matching. These show that the matching procedure is capable to balance the characteristics in the participant and the matched non-participant groups. Therefore, the results can be used to evaluate the impact of Soil Water Conservation participation among households having similar observed characteristics.

Table 9. Chi-Square Test For The Joint Significance of Variables

Sample	Ps R^2	LR chi^2	p>chi^2
Unmatched	0.274	70.86	0.000
Matched	0.021	8.28	0.506

Source: Own survey result (2017)

All of the above tests suggest that the matching algorithm chosen was relatively best for the data of this study. Therefore, it was possible to proceed to estimate the average treatment effect on the treated (ATT) for the sample households.

O. Average treatment effect on the treated(ATT) to measure the impact

Since the balancing property is satisfied, what comes next is to match observations according to their propensity score in order to estimate the ATT, which measures the impact of the participation in SWC practice, given impact indicators. In this study, the productivity of nourishmentcrops (maize and haricot bean) was used to measure the impact of the practice.

P. ATT estimates with different matching methods

The analysis reveals that participating in SWC practice has a significant positive impact on the value of maize productivity. The Average Treatment Effect (ATT) calculated using the nearest neighbor of neighborhood 5 is presented in the Table 10 below. The ATT indicated in the table shows that SWC participants had increased maize productivity on average 6 quintals per hectare (3300 Ethiopian Birr-ETB) per year compared to non-participant households. This is in line with the objective of SWC participation which focuses on improving the productivity of crops and conservation of the environment of rural households. This indicates that (assuming there is no selection bias due to unobservable factors) maize productivity per hectare for participants of SWC practice is significantly greater than the non-participants. According to Khandker *et al.*[14] comparing different matching methods results is one approach to check the robustness of the average treatment effect. Since at least the findings of the already applied best one matching methods estimation results are quite similar, the researcher concluded that the consistency and robustness of PSM analysis. The information obtained from key informant interviews has also supported this finding.

In addition, participating in SWC practice has a significant positive impact on the value of Haricot Been productivity. The Average Treatment Effect on the treated (ATT) calculated using nearest neighbor of neighborhood 5 revealed that participation in SWC practice had increased the value of Haricot Been productivity by about 3 quintals per hectare (3600 ETB) on average as compared to the non-participation. It is the average difference between Haricot Bean's productivity of similar pairs of the households belonging to the non-participants. This indicates that (assuming there is no selection bias due to unobservable factors) Haricot Bean's productivity for plots that participated in SWC practice is significantly greater than the non-participants.

Table 10. ATT Estimation Result of SWC Practice on Maize And Haricot Bean Productivity

Outcome variable	Mean		ATT	S.E.	t-stat
	SWC participant	SWC non-participant			
Maize productivity (Quintal/ha)	76.743	69.742	6.003	1.806	3.48
Haricot bean productivity(Quintal/ha)	6.503	3.482	3.021	0.502	6.75

Source: Own estimation result (2017)

Q. Sensitivity Analysis

In order to check for unobservable biases, using the Rosenbaum Bounding approach, sensitivity analysis was performed on the computed outcome variables over which the causal inference of significant SWC effects must be questioned with respect to deviation from the conditional independence assumption. The basic question to be answered here is whether inference about treatment effects may be affected by unobserved factors (hidden bias).

Table 11 presents the critical level of $e^{\gamma}=1$ (first row), over which the causal inference of significant SWC practice outcomes must be questioned. The first column of the table shows those outcome variables which bear statistical differences between SWC participants and non-participant households in impact estimation. The rest of the values which correspond to each row of the significant outcome variables are p-critical values (or the upper bound of Wilcox on significance level -Sig+) at the different critical values of e^{γ}.

The results show that inference for the impact of soil and water conservation does not change, even though the participant and non-participant households were allowed to differ in their odds of being treated up to 200% ($e^{\gamma}=2$) in terms of unobserved covariates. That means for all outcome variables estimated, at various levels of the critical value of e^{γ}. The p- critical values are significant, which further indicates that the study has considered important covariates that affected both participation and outcome variables. Thus, it is possible to conclude that impact estimates (ATT) of this study for each outcome variables were insensitive to unobserved selection bias, being pure effects of conservation measures.

Table 11. Result of Sensitivity Analysis Using Rosenbaum Bounding Approach

Outcomes	$e^{\gamma}=1$	$e^{\gamma}=1.25$	$e^{\gamma}=1.5$	$e^{\gamma}=1.75$	$e^{\gamma}=2.0$
Value of maize productivity	6.1E-10	2.4E-11	4.2E 09	3.3E-08	4.9E-07
Value of Haricot Bean productivity	8.2E-16	7.9E-14	3.2E-11	4.8E-10	5.8E-09

Note: e^{γ} (Gamma) = log odds of differential due to unobserved factors where Wilcoxon significance level for each significant outcome variable is calculated.
Source: Own estimation result (2017)

IV. CONCLUSION

This study aimed to evaluate the impact of Soil and Water Conservation (SWC)practice on major crops produced in the study area, such as Maize and Haricot bean. Participation in the soil and water conservation practice was influenced by a combination of household demographic, biophysical, social-economic, institutional, and technicalfactors.Before proceeding to calculate the treatment effects on the treated (ATT), the result matches passed through different processes of matching quality tests such as t-tests, reduction in standardized bias, chi-square tests, and pseudo R^2. Obtaining a reliable estimate of a soil and water conservation practice needs to adequately control for such confounding factors. Next, a matched comparison was conducted on these households who share common characteristics in terms of identified independent variables except participating in soil and water conservation practice.

The matching result of ATT showed that SWC practice participant households had brought positive and significant impact on productivity by 6 quintals per hectare (3300 birrs) and 3 quintals per hectare (3600 birrs) from maize and haricot bean crop, respectively than non-participant households. So, it is clearly observable that participation in soil and water conservation practice hasa statistically significant and positive impact on household crop productivity and alsoincreases the rural households' income. These estimated performances of the program also show considerable variability by agro-ecological type of the sampled kebeles. It can be possible to conclude that in an agriculture-dependent country like Ethiopia, soil and water conservation practice is crucial in improving the livelihoods of the rural farm households. Thus, to realize the intended outcomes, future development strategies should consider on how to link such interventions with natural resource management-based income-generating activities that can provide farmers with short-term benefits. In addition, the agricultural sector has to be made more economically attractive so that farmers can invest more in conservation-based agriculture. This requires making the sector more productive by introducing improved technologies and providing the required infrastructure for the development of markets so that farmers can get the full benefit from their products.

The scope of this study was limited to the direct effects of the interventions on the value of crop productivity of households. Therefore, taking the other livelihood indicators into consideration is necessary to extend the research work to the other on-site and off-site effects of the SWC practice impact too. In realizing sustainable land management by providing farmers with short-term benefits and linked withnatural resources management based income generation at the household level. Moreover, determinants of such income diversification will haveimmense contribution to scaling up the intervention, and hence it is also one of thepotential areas for research and development.

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