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Impact of Soil and Water Conservation Practice on Income in Chencha District, SNNP of Ethiopia

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Abstract
Land degradation, in the form of soil erosion and nutrient depletion, threatens food security and the sustainability of agricultural production in many developing countries. As part of intervention activities a number of soil and water conservation practices have been promoted to smallholder farmers living in highly degraded and drought prone areas of the country. This study was conducted to examine the impact of SWC intervention on the livelihood of smallholder farm households in terms household income. To meet this objective primary data was collected in 2019 from 146 SWC program participants and 130 non-participants that were randomly selected from 3 intervention area and 3 counterfactual peasant associations in Chencha district of SNNP respectively. Descriptive and inferential statistics and propensity score matching (PSM) models were used to address the stated objectives. Results of the descriptive statistics showed that before matching there was statistically significant difference between program participants and their counterfactual households in terms of farm size and participation in petty trade from continuous independent variables and from categorical variables sex of household, education of household head, biological and physical conservation method, intercropping as well as bench terrace were significant in favor of program participants. Results of the PSM model revealed that SWC intervention result in significant difference between program participant and nonparticipant households in terms of household income.
Keywords: Chencha, Income, land degradation, PSM model, Soil and water conservation
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1. Introduction

The rain-fed agriculture contributes 58 percent to world's food basket from 80 percent agricultural lands (Raju et al. 2008). As a consequence of global population increase, water for food production is becoming an increasingly scarce resource, and the situation is further aggravated by climate change (Molden, 2007).The rain-fed areas are the hotspots of poverty, malnutrition, food insecurity, prone to severe land degradation, water security and poor social and institutional infrastructure (Rockstorm et al. 2007; Wani et al. 2007). Soil conservation program is, therefore, considered as an effective tool for addressing many of these problems and recognized as potential engine for agriculture growth and development in fragile and marginal rain-fed areas (Joshi et al. 2005; Ahluwalia and Wani et al. 2006).

Agriculture is the main sector of the Ethiopian economy and contributes approximately 42% to the gross domestic product (GDP) and employs over 80% of the population (MoFED 2010; Diao 2010; ATA 2013). Despite its role, agricultural production is constrained by high climate variability where rainfall distribution is extremely uneven both spatially and temporally, and this has negative implications for the livelihoods of people (Georgis et al. 2010). Drought frequently results in crop failure, while high rainfall intensities result in low infiltration and high runoff causing enhanced soil erosion and land degradation. Land degradation in the form of soil erosion and declining land fertility is a serious challenge to agricultural productivity and economic growth (Lemenih 2004).

Ethiopia is a large country having 113 million hectares that is endowed with diverse climatic and physiographic condition, with a huge potential of water resource it accounts 122 BMC annual surface runoff and 2.9 BMC groundwater, though it is characterized by uneven spatial and temporal distributions. Between 80% - 90% of the country's surface water resources are found within four major river basins—Abay (Blue Nile), Tekeze, Baro Akobo and Omo Gibe and rainfall in the country ranges between 2250 mm per year in the south-western highlands and less than 200 mm in the North and South-East with a further decrease of less than 100 mm per year in the North. Temperatures are also very much modified by the varied altitude.

Soil erosion is one of the biggest global environmental problems resulting in both on-site and off-site effects. The economic implication of soil erosion is more serious in developing countries because of lack of capacity to cope with it and also to replace lost nutrients. These countries have also high population growth which leads to intensified use of already stressed resources and expansion of production to marginal and fragile lands. Such processes aggravate erosion and productivity declines, resulting in a population-poverty-land degradation cycle.

According to Lulseged T. and Paul L. G. Vlek (2008) Rapid population growth, cultivation on steep slopes, clearing of vegetation, and overgrazing are the main factors that accelerate soil erosion in Ethiopia. The annual rate of soil loss in the country is higher than the annual rate of soil formation rate. Annually, Ethiopia losses over 1.5 billion tons of topsoil from the highlands to erosion which could have added about 1.5 million tons of grain to the country's harvest. This indicates that soil erosion is a very serious threat to food security of people and requires urgent management intervention.

The country has a history of soil conservation and watershed management initiatives dating back to the 1970s. The basic approach has shifted from top-down infrastructure solutions to community-based approaches. There is now a supportive policy and legal framework in the form of policies that facilitate decentralized and participatory development, institutional arrangements that allow and encourage public agencies at all levels to work together, and an approach to natural resources that reacts local legislation and tenure practices.

The main environmental problems of the country include land degradation, soil erosion, and deforestation of natural resource, desertification and loss of biodiversity, and recurrent drought resulting in declining productivity and continuing in food shortage. Huge part of the country has fragile ecosystem which includes dry, humid, sub-humid, semi-arid, semi dry and arid conditions. This is frequently exposed to desertification and recurrent drought. The highlands constituting majority of land is currently under stress due to rising population pressure and their conservative socio economic practices. The extent of fertile land available for agriculture is decreasing due to increased soil erosion. Land degradation is caused by deforestation and faulty management practices (cultivating along the slope) of the natural resources, (soil, forest resource and water). It leads to both loss of agricultural production and increased risks of flooding, siltation and sedimentation.

In recent years, environment has become a key issue in Ethiopia. The main environmental problems of the country include land degradation, soil erosion, and deforestation of natural resource, desertification and loss of biodiversity, and recurrent drought resulting in declining productivity and continuing in food shortage. Huge part of the country has fragile ecosystem which includes dry, humid, sub-humid, semi-arid, semi dry and arid conditions. This is frequently exposed to desertification and recurrent drought. The highlands constituting majority of land is currently under stress due to rising population pressure and their conservative socio economic practices. The extent of fertile land available for agriculture is decreasing due to increased soil erosion. Land degradation is caused by deforestation and faulty management practices (cultivating along the slope) of the natural resources, (soil, forest resource and water). It leads to both loss of agricultural production and increased risks of flooding, siltation and sedimentation. The soil erosion and deforestation reduces the production potential of land and the overall utility of land resource, and thus making it unsustainable to produce sufficient to feed for the growing population. It also increases farmers' susceptible to food shortages and low income which threatens their survival.

1.2. Statement of the Problem

Soil erosion is a severe and continuous ecological problem in the north-western Highlands of SNNP Region, Bekele, et al (2015). Limited knowledge of farmers to practice soil and water conservation technologies is one of the major causes that have resulted in accelerated soil erosion.

Although efforts by most projects made on soil and water conservation measures, little was known about the contribution of the introduced soil and water conservation technologies on household income. This study will be therefore conducted to assess the impact of the soil and water conservation technologies on household income in Chencha district of SNNPR.

1.3. Objectives of the study

The general objective of the study is to analyze impact of soil and water conservation on farm income among farm households.

Specific objectives include

To assess socio-economic factors that affect use of soil and water conservation practices in the study area.
To analyze the impact of soil and water conservation practice on farm income in the study area.

2. RESEARCH METHODOLOGY

2.1. Description of the Study Area

2.1.1. Geographical Location

This study was conducted in chencha district in South Nations Nationalities and Peoples of Ethiopia. Chencha district is one of the 15 districts in Gamo Gofa zone of SNNP region of Ethiopia. Astronomical location of the district is between 37^0 29'57" to 37^0 39' 36" East Longitude and between 6^0 8'55" and $6^0$25'30" North Longitude. It is located about 521km south of Addis Ababa the capital city of Ethiopia and 36 km away from the zonal capital of Arba Minch. The district is subdivided in to 45 rural kebeles and 5 transition towns. The district is bordered by four districts; Aribaminch Zuria in the south and southeast; Mirab Abaya in the east; Kucha in the North and Northwest; and Dita in the West.

2.1.2. Population of the Study Area

According to district Finance and Economic office estimation, in 2016, the total population was estimated that 154,701 from this 69,842 are male and 84,859 are females implying, 54.9% of women. The household head number was male 17,621 and female 6,113 total 23,734. The district has high population number per square kilo meter which estimated 434 persons/km^2.

2.1.3. Land Use Systems and Coverage of the Study Area

According to the district's Agriculture and Natural Resource Office, the total area of the district is estimated to be 37,360 hectares. The average land holding per household is estimated to be 0.35 hectare. The major land uses patterns are private holding (farming), communal (grazing) and forest land. The current land use coverage's are cultivation of annual crop is 58%, Perennial crop is 12% and grazing lands is 6.6%. Among the total area, 9.4% of the land is currently unutilized and the remaining (15%) is covered by shrub/bush and natural and plantation forests. The farming practice in the district is mixed farming systems which are crop production and livestock keeping. The major means of livelihood in the area are subsistence rain fed agriculture, traditional weaving and involvement in off-farm activities (Agriculture Office 2017).

2.2. Sampling Technique and sample size

To determine the sample size of the study area, this study used Yamane's formula (1977) with 95 confidence levels. The reason for using this formula is because this kind of formula is valid for survey researchers which compose large population. Moreover, the population under investigation is homogenous in its socio-economic and geographic context and the formula enables to get manageable sample size.

$$n = \frac{N}{1 + N(e)^2} = \frac{900}{1 + 900(0.05)^2} = \frac{2700}{7.75} = 276$$

n= sample size N= total population of the sample
e= acceptable error in social science.

FGD was undertaken in each Kebele as well as discussions with experienced and knowledgeable key informants in the target areas. The number of participants in each group ranged from 9–11 farmers.

2.3. Method of Data Analysis

2.3.1. Descriptive and inferential statistics

Descriptive statistics such as mean, standard deviation, percentages, frequency, charts, and graphs, used to describe different categories of sample units with respect to the desired socioeconomic characteristics. Moreover, inferential statistics such as chi-square test (for categorical variables) and t-test (for continuous variables) were used to compare and contrast different categories of sample units with respect to the desired characters so as to draw some important conclusions.

2.3.2. Econometric analysis

Propensity score matching method

For more than two decades, advanced statistical methods known as propensity score (PS) techniques, have been available to aid in the evaluation of cause-effect hypotheses in observational studies. None the less, PS techniques have not yet been used widely in psychological research" (Harder, Stuart, & Anthony, 2010

In an observational study, covariates are usually not balanced between treatment groups. Rosenbaum and Rubin have demonstrated that observed covariates are balanced at each value of propensity score; it means that households in treated and control groups with equal propensity score have the same distributions of the observed covariates.

The propensity score can be understood as a proxy between cases and covariates influencing the exposure, so it can be used instead of additional analyses of the covariates to simplify the analysis. Therefore, the propensity score as a proxy variable aggregates multiple confounding factors into a single dimension.

This approach is, for example, widely applied when evaluating labor market policies (e.g., Bryson et al, 1997; Heckman et al, 1997; Dehejia and Wahba, 1999; Manski and Garfinkel, 2002; Sianesi, 2004). In the empirical labor economics literature, matching has been used to evaluate the returns from education (e.g., Blundell et al, 2005; Brand and Halaby, 2006) and the union membership wage premium (Eren, 2007). Empirical examples can be found in very diverse fields of observational studies whenever the researcher aims to evaluate the effect of a variable (often of some policy relevance) on another. In the demo-economic literature, researchers are often interested in the evaluation of the effects of demographic events, like childbearing or marital disruption, on economic variables, like wellbeing and labor force participation (e.g., Aassve et al, 2007; Aassve and Arpino, 2007). The approach is also applied in the educational literature to study the effect of educational programs and policies on students' performances (e.g., Hong and Raudenbush, 2006).

Specification of the PSM method

According to Caliendo and Kopeinig (2008), the estimation of the impact of household's adoption of SWC on a given farm income (Y) is specified as:

$$\tau_i = Y_i(D_i = 1) - Y_i(D_i = 0) \quad (5)$$

Where τi is treatment effect (effect due adoption of SWC), Yi is farm income of household *i*, Di is whether household *i* has got the treatment or not (i.e., whether a household is use or not).

However, one should notice that) *Yi* (*Di* = 1) and Yi (*Di* =0) cannot be observed for the same household at the same time. Depending on the position of the household in the treatment (use of SWC practices), either Yi (Di =1) or Yi (Di =0) is unobserved outcome (called counterfactual outcome). Due to this fact, estimating individual treatment effect τ_i is not possible and one has to shift to estimating the average treatment effects of the population than the individual one. Most commonly used average treatment effect estimation is the 'average treatment effect on the treated (τ_{ATT}), and specified as:

$$\tau_{ATT} = E(\tau/D = 1) = E[Y(1)/D = 1] - E[Y(0)/D = 1] \quad (6)$$

As the counterfactual mean for those being treated, E [Y (0)/ D = 1] is not observed, one has to choose a proper substitute for it in order to estimate ATT. One may think to use the mean outcome of the untreated individuals, $E[Y\ (0)/D = 0]$ as a substitute to the counterfactual mean for those being treated, E[Y (0)/D =1]. However, this is not a good idea especially in non-experimental studies, since it is likely that components which determine the treatment decision also determine the outcome variable of interest.

In this particular case, variables that determine household's decision to adopt SWC practices could also affect household's farm income. Therefore, the outcomes of individuals from treatment and comparison group would differ even in the absence of treatment leading to a self-selection bias.

By rearranging, and subtracting $E[Y\ (0)/D = 0]$ from both sides of equation (2), one can get the following specification for ATT.

$$E[Y(1)/D = 1] - E[Y(0)/D = 0] = 0 \quad (7)$$

Both terms in the left hand side are observables and ATT can be identified, if and only if E[Y (0)/D =1] − E[Y (0 /D = 0] = 0. i.e., when there is no self-selection bias. This condition can be ensured only in social experiments where treatments are assigned to units randomly (i.e., when there is no self-selection bias). In non-experimental studies one has to introduce some identifying assumptions to solve the selection problem. The two strong assumptions to solve the selection problem are Conditional Independence Assumption (CIA) and Common support region assumption.

Estimation of the propensity scores

Propensity score involves a series of empirical steps. First, logit model that predicts the probability of each household adopting SWC (propensity score) as a function of observed household and community characteristics was estimated, using a sample of participants and non-participants. In estimating the propensity score, the dependent variable used in the model was a binary variable a value of 1 for user of SWC and 0 otherwise.

The estimates of individual adoption using logit model are useful for two reasons. First, it gives some insight regarding the observable variable that should be included in the balancing function. Second, it provides a better understanding of adoption of SWC by the *kebeles* households.

According to Gujrat (2004), the logistic distribution function for the determining factors for WSM of the household can be specified as:-

$$\mathrm{p(i)} = \frac{1}{1+e^{-zi}} \quad (11)$$

Where p (i) is a probability of a household being diversified for ith household and Z(i) is a function of m explanatory variables (Xi) and expressed as:

$$Z(i) = \beta_o + \beta_1 X_1 + \beta_2 X_2 + \cdots \beta_m X_m \quad (12)$$

Where β_0 is the intercept and β_i is the slopes parameter in the intercept in the model which is estimated using maximum likelihood method.

The probability that a household belongs to not adopt is:

$$(1 - \mathrm{Pi}) = \frac{1}{1+\mathrm{e}^{\mathrm{z(i)}}} \quad (13)$$

Therefore,

$$\left(\frac{P_i}{1-p_i}\right) = \frac{1+e^{z(i)}}{1+e^{-z(i)}} = e^{z(i)} \quad (14)$$

And

$$\frac{P_{(i)}}{1-p_{(i)}} = \frac{1+e^{z(i)}}{1+e^{-z(i)}} = e^{\beta_o} + \sum_{i-1}^{m} \beta_i\, Y_i \quad (15)$$

Taking the natural logarithms of the odds ratio of equation (15) will result in what is known as the logit model as included below:

$$ln\left(\frac{P_{(i)}}{1-p_{(i)}}\right) = \ln\left[e^{\beta_o} + \sum_{i=1}^{m} \beta_i\, x_i\right] = Z_{(i)} \quad (16)$$

If the disturbance term U_i is taken in to account the logit model becomes:

$$Z_{I} = \beta_O + \sum \beta_i\, X_i + U_i \quad (17)$$

Choice of matching algorithm

After estimation of the propensity score, seeking an appropriate matching estimator is the major task of program evaluator. There are different matching estimators in theory. However the most commonly applied matching estimators are Nearest Neighbor matching (NN) Caliper matching, Kernel and local linear matching (Smith and Todd, 2005). The performance of different matching algorithms varies case-by-case and depends largely on the data sample (Caliendo and Kopeing, 2008).

Testing matching quality and overlap assumption

The "balancing properties" of the data was checked by testing that treatment and comparison observations had the same distribution (mean) of propensity scores and of control variables within grouping (roughly quintiles) of the propensity score.

3. RESULTS AND DISCUSSION

This chapter mainly presents the findings of the study with an appropriate level of discussion. It is divided in to two sub-headings that could give a brief account of the subjects that were being investigated by the study. The first sub-heading presents descriptive analysis of sample households. The second sub-heading is econometric model for impact of soil and water conservation on income by sample households.

3.1. Descriptive Analysis

In this section of analyses descriptive statistics such as mean, standard deviation, percentage, t-test and chi-square test were employed using SPSS version 20 and STATA 15 software programs. In this study, use of a technology refers to farmers who used SWC practices and those farmers who do not used on their farm land.

3.1.1. Descriptive statistics for socioeconomic variables in the study

A combination of different descriptive, the means and standard deviation and inferential, the t-test and X^2-test, statistics for explanatory variables of sample households were performed on the house hold level data to inform the subsequent empirical data analysis.

The descriptive and inferential results presented on Table 3 show from continuous independent variables, there was statistically significant difference between users and non-user household in terms of farm size and income from petty trade, in favor of the users of SWC practices.

Table 1. Descriptive statistics of continuous independent variables

Variables	Mean across adoption categories		t-test	P Value
	user	Non-user		
family size	2.000	2.000	0.50	0.61
Farm size	0.193	2.324	2.324**	0.02
Age of household head	44.00	45.00	0.70	0.46
Income from Petty trade	793.69	527.089	2.84***	0.004

Source: own survey, ***and ** indicates that at 1% & 5%significance level respectively

The descriptive and inferential statistics results presented in Table 4 show that 85.38% of users were male headed households. Regarding to education status of households 36.92 % were illiterate, 33.85 % was completed primary school, 26.15% of the household finalized secondary school. On the other hand, 97.69% and 98.46% user households participated on biological and Physical conservation methods respectively. Other remaining categorical variables, which have significant difference between users and non-user households, are described in table 2.

Table 2. Descriptive statistics for categorical variables

Variable	% of User	% of Non-User	X^2	P-value
Sex of House hold				
Male	85.38	69.18	10.14	0.001
Female	17.12	30.82		
Education				
Illiterate	36.92	49.32	12.5	0.006
Primary School	33.85	38.36		
Secondary School	26.15	10.96		
Above secondary school	3.08	1.37		
Biological soil conservation				
No	2.31	49.32	54.5	0.0001
Yes	97.69	50.68		
Physical conservation method				
No	1.54	36.3	52.08	0.0001
Yes	98.46	63.7		
Use of grass Strip				
Very Effective	20	6.85	52.08	0.0001
Moderately Effective	49.23	49.32		
Less Effective	30.77	43.84		
Intercropping				
Very Effective	6.92	10.27	7.99	0.099
Moderately Effective	53.85	36.99		

Less Effective	39.23	52.74		
Bench terrace				
Very Effective	30.77	24.66		
Moderately Effective	30	19.86	0.78	0.67
Less Effective	51.54	44.52		
Extension Service				
No	7.69	21.92	10.78	0.001
Yes	92.31	78.08		

Source: own survey (2016), ** and *** indicates 5% and 1% of significance probability level

3.2. Econometric Analysis

3.2.1. Propensity score matching (PSM)

This section presents the results of the logistic regression model which is used to estimate propensity scores for matching user households with non-user. As indicated earlier, the dependent variable in this model is binary variable indicating whether the household has used soil and water conservation or not and the outcome variable is the farm income. In the estimation, data from the two groups; namely, user and non- user households were pooled such that the dependent variable takes a value 1 if the household is user of SWC and 0 otherwise.

Table 3 shows the estimation results of the logit model. The estimated model appears to perform well for our intended matching exercise. The pseudo-R^2 value is 0.2376, which is fairly low. A low pseudo-R^2 value means that household used SWC practices, do not have many distinct characteristics overall and as such finding a good match between users of the practice and non-user and the pseudo-R^2 indicates how well independent variables explain the probability of using it.

Table 3. Propensity score matching estimation (logit model)

Use soil con	Coef.	Std.Err.	z	P>z	[95%Conf.	Interval]
age of HH head	0.018	0.014	1.290	0.198	-0.009	0.045
sex of HH head	1.226	0.381	3.220	0.001***	0.479	1.973
Education	0.053	0.184	0.280	0.776	-0.309	0.414
Family size	0.314	0.716	0.440	0.661	-1.089	1.716
Farm size	1.794	0.812	2.210	0.027**	0.203	3.385
Biological conservation	1.115	0.471	2.370	0.018**	0.193	2.038
Use of physical con.	2.027	0.964	2.100	0.035**	0.138	3.916
Use grass strip	-0.350	0.221	-1.580	0.114	-0.783	0.084
Use intercropping	0.209	0.235	0.890	0.375	-0.252	0.669
Bench terrace	0.237	0.182	1.300	0.193	-0.120	0.594
_cons	-10.222	2.655	-3.850	0.000	-15.425	-5.019

Note: *** & **, show significance at 1% and 5% level, respectively

Figure 4 portrays the distribution of the household with respect to the estimated propensity scores. In case of treatment households, most of them are found in partly the middle and partly in the right side of the distribution. On the other hand, most of the control households are partly found in the center and partly in the left side of the distribution.

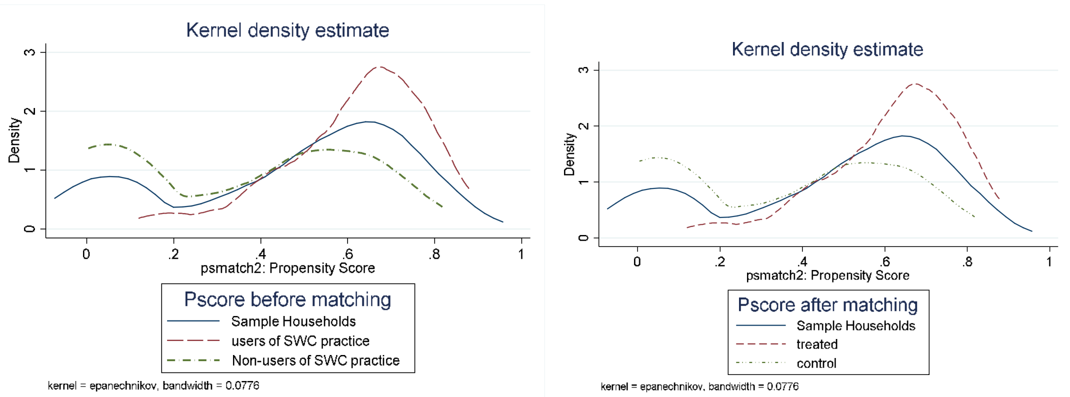

Figure 1.Figure 1. Kernel density of propensity score before and after matching
Source: own sketch (2020)

3.2.2. Matching adopters and non-adopter households

The estimated propensity scores vary between 0.1280 and 0.8756, with a mean of 0.6153 for treatment households and between 0.0036 and 0.8139 with a mean of 0.3424, for control households (Table 4). The common support region would then lies between 0.0036 and 0.8756 that is the minimum and the maximum value of treated and control households, respectively. This ensures that any combination of characteristics observed in the treatment group can also be observed among the control group. In other words, households whose estimated propensity scores are less than 0.0036 and larger than 0.8756 are not considered for matching exercise. This is because no matches can be made to estimate the average treatment effects on the ATT parameter when there is no overlap between the treatment and non-treatment group (Bryson *et al*., 2002). As a result of this restriction, 7 households from treated and 53 households from the control were discarded.

Table 4.Region of common support

Variable	Obs	Mean	Std. Dev	Min	Max
_pscore if usewsm=1	146	0.6153	0.1625	0.1280	0.8756
_pscore if usewsm=0	130	0.3424	0.2699	0.0036	0.8139
_pscore	276	0.4710	0.2635	0.0036	0.8756

Source: Own estimation (2019)

3.2.3. Choice of matching algorithm

Selecting matching estimator has its own criteria. The final choice of a matching estimator was guided by different criteria such as equal means test referred to as the balancing test, pseudo-R^2 and matched sample size (Deheia and Wahba, 2002). Balancing test is a test conducted to know whether there is statistically significant difference in mean value of per-treatment characteristics of the two groups of the respondent and preferred when there is no significant difference. Accordingly, matching estimators were evaluated by matching adopters and non-adopter households in common support region. Therefore, a matching estimator having balanced (insignificant mean difference in all explanatory variables) mean bears a low pseudo-R^2 value and also the one that results in large matched sample size is preferred.

Table 5. Performance of matching estimators

Matching Algorithm	Balancing test	Pseudo R2	Sample size
Kernel			
0.01	6	0.237	216
0.1	6	0.237	216
0.25	**6**	**0.237**	**216**
Caliper			
0.01	9	0.0496	222
0.1	9	0.0496	220
Radius caliper			
0.1	9	0.153	212
0.01	**8**	**0.124**	**220**

Source: Own estimation result, 2019

3.2.4. Testing the balance of propensity scores and covariates

Ensuring good balance between treated and control group is the most important step in using any propensity score method. The before and after matching covariate balancing tests presented on table 6 suggested that the proposed specification of the propensity score is fairly successful in balancing the distribution of covariates between the two groups as indicated by decreasing pseudo R2, decreasing mean standardized bias for all regions and the insignificant p-values of the likelihood ratio test.

Table 6. Propensity score and covariate balance

Sample	PsR2	LRchi2	P>chi2	Mean Bias	MedBias	B	R	%Var
Unmatched	0.264	100.76	0.000	39.7	37.5	125.1	0.14	38
Marched	0.069	25.00	0.123	15.7	11.2	63.8	1.22	15

Source: Own estimation result based on household responses, 2019

Different impact estimators were employed to get estimated treatment effect. Table 7 depicts the average impact of using soil conservation methods on farm income for the study area of interest following kernel matching, caliper and radius caliper matching techniques. Accordingly, there is at least some evidence to support the hypothesis soil conservation method has a positive and significant impact on income growth in the district.

3.2.5. Treatment effect on the treated (ATT)

This sub-section provides evidence as to whether or not the use of soil conservation practice has brought significant changes on farm income. The Kernel estimator with band width 0.25, the best matching estimator for the data at hand, was used to compute the average impact of soil conservation among adopter households.

Table 7.Average treatment effect on the treated (ATT)

Variable (*birr*)	ATT on Treated	ATT on Control	Diff.	SE	T-value
Farm Income KM(0.25)	2292.308	1874.231	418.07	183.97	2.270**
Farm Income KM(0.5)	2271.37	2089.47	181.89	158.89	1.15
Farm Income C(0.1)	2192.85	1915.71	277.14	211.50	1.31
Farm Income C(0.01)	2271.37	1928.62	342.74	208.12	1.65*

Note: SE = Bootstrapped standard errors with 100 replications;

4. Conclusion

Soil erosion is one of the biggest global environmental problems resulting in both on-site and off-site effects. The economic implication of soil erosion is more serious in developing countries because of lack of capacity to cope with it and also to replace lost nutrients. Soil erosion is a severe and continuous ecological problem in the north-western Highlands of SNNP Region specifically in the study area. Because of this problem, SWC practice was implemented by government, farmers and non-governmental organization in the three severely eroded kebeles four long period of time.

This study is targeted to analyze impact of SWC practices on income in Chencha district of SNNP. To analyze the data descriptive statistics and econometric statistics was used. The descriptive statistics like t-test and chi square test revealed that there was significant difference between two continuous variables which were, farm size and income from petty trade. From descriptive statistics, Sex of House hold, Education, Biological soil conservation, Physical conservation method, Use of grass Strip, Intercropping and Extension Service were significant at different significant level.

Regarding PSM model, after several PSM estimation steps we obtained significant difference between treated and control households. Means that, those treated households were higher income compared to control households. Therefore, SWC practice should be strengthened to increase household income and for better welfare for study area and other degraded areas of Ethiopia.

5. REFFERENCE

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