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RESEARCH

Household- and plot-level impacts of sustainable land management practices in the face of climate variability and change: empirical evidence from Dabus Sub-basin, Blue Nile River, Ethiopia

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Abstract

Smallholder farmers can adapt to climate variability and change through sustainable land management (SLM) practices that help to offset the negative impacts at farm level. However, use of these practices as adaptation strategy remains low in Ethiopia in general and the study sites in particular. This study aimed at examining the factors that determine farmers' decision to use SLM measures and to quantify the impact of the practices on crop productivity at household and plot level. The study was based on household- and plot-level primary data and employed nearest-neighbor matching technique to quantify the impact of using the practices on value of production at household level and plot level. The results revealed that households that implemented SLM practices within the period (2004–2009) experienced a 24.1% higher value of production over non-users in 2016. Similarly, plots that received SLM measures within the period (2004–2009) experienced a 28.6% increase in value of production in 2016. The study also made further analysis at plot level using continuous treatment effects in order to take into account the number of years a plot has been under the practice. The result showed plots with SLM structure that are maintained for at least 6 years have a positive increase in value of production at the end of the 6th year, while those that received the practices recently or those that lacked continuous maintenance did not experience a statistically significant increase in value of production. The result also showed marginal benefit of sustaining the SLM practices increases over time at an increasing rate. The implication is that use of SLM measures and maintenance of the structures are crucial to reap significant benefits from the practices. Although value of production increases given the SLM practices, implementation is labor intensive and there is trade-off with other agricultural activities. Therefore, policy measures are required to incentivize implementation and maintenance of the SLM structures.

Keywords: Sustainable land management, Climate change, Adaptation, Matching, Treatment effect, Impact

Background

In primarily agricultural-based economies, the immediate trade-off between short-term welfare and long-term development represents major challenges. In this type of economies, land degradation poses major development challenge contributing to reduced output, lower economic growth and increased poverty [1, 2]. In recent years, this challenge is more aggravated in the face of changing climate and variability. More particularly, heavy dependence on rain-fed agriculture makes the sector most vulnerable to climatic change risks and led agricultural productivity to unsustainable level [3, 4].

Ethiopia's biophysical potential for sustainable agricultural development opportunities has been continuously challenged by land degradation and poverty [5, 6]. The

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problem is further aggravated by climate variability and change, population pressure, limited use of sustainable land management (SLM) practices, deforestation, rugged terrain characteristics, erratic rainfall, vulnerable soil and heavy dependence on rain-fed agriculture [7, 8]. The on-site cost due to erosion of top soil is estimated to be 2.0–6.75% of Ethiopia's agricultural GDP per annum [9, 10]. Ethiopia could also experience negative and positive off-site productivity effects on downstream plots in terms of eroded soil that is washed out [11, 12].

On-site and off-site costs of soil erosion are also critical challenges in the Dabus sub-basin of the Blue Nile River being intensified by the prevailing unsustainable land use system, watershed degradation, erratic rainfall and severe deforestation. Agricultural practice in the area is dominated by cereal crops cultivation, which necessitates frequent plowing that leads to little ground cover during the rainy season that in turn renders the soil to be more susceptible to erosion [13]. Therefore, there is an urgent need for efficient mechanisms that helps to reduce soil loss and improve agricultural output in the sub-basin.

Previous studies on productivity impacts of soil conservation measures revealed diverse results. A study by [14] in the Northern part of Ethiopia suggests that plots with stone terraces experience higher crop yields. A study by [2] also estimated that users of soil and water conservation measures achieved 17–24% higher value of production compared to non-users. Similarly, a soil and water conservation program evaluation study in Honduras by [15] revealed a positive effect on value of production. Conversely, [8], using matching methods and switching regression analysis on farm-level data from high rainfall areas in Northern Ethiopia revealed that plots with bunds resulted in lower yields compared to non-conserved plots.

A study by [16] indicated that only 31% of smallholder farmers in Ethiopia adopted soil and water management practices to address perceived changes in rainfall and only 4% adopted water harvesting technologies. Study results by [17, 18] also found similar results in South Africa and Kenya. However, there is inadequate evidence to what extent that smallholder farmers have used SLM practices for climate risk management in Sub-Saharan Africa in general and in Ethiopia in particular. The results of these previous studies are highly aggregated and are of little help in addressing local conditions in relation to adaptations to climate change. The studies have also paid little attention to the analysis of local factors that influence smallholder farmers' use of SLM practices as adaptation strategy. Moreover, the studies overlooked the likelihood crop productivity impact of SLM practices both at farm and plot level.

Since adaptation is a local response to climate stimuli, agro-ecology-specific factors that affect famers' decisions to use SLM practices and measuring the impact of the practices on rural livelihood is an important research gap that needs to be addressed. Hence, the present study aims to contribute to formulation of location specific climate change adaptation strategy through identifying household- and plot-level factors that determine use of SLM practices and productivity impact at both household and plot level. For this purpose, the study employed nearest-neighbor matching technique to measure household- and plot-level impacts of adopting SLM practices on value of agricultural production. The study also aims to understand the timing of benefits and then to calculate marginal benefits of each additional year of maintenance. For this purpose, it employed a continuous treatment effect estimation method and measured the length of time a plot of land must be maintained under SLM practices in order to experience a benefit.

Methods

Study area

The study was conducted in two major agro-ecologies of the Dabus sub-basin of the Blue Nile River in North-West Ethiopia (Fig. 1). The sub-basin is characterized by hot to warm moist and sub-humid lowlands. It has an area of 21,030 km^2, and the altitude ranges between 48 and 3150 masl. Annual rainfall is between 970 and 1985 mm, and maximum and minimum annual temperature varies between 20–35 and 8.5–20 °C, respectively. Considerable part of the sub-basin is cultivated and is typified by maize–sorghum and maize–sorghum–perennial complex.

Data and sampling procedure

A household survey conducted in November and December 2016 enumerated 734 farm households, which are spatially distributed in the wet lowland and dry lowland agro-ecologies of the Dabus sub-basin (Table 1). First 20 *Woredas* (districts) in the sub-basin were stratified into the two agro-ecologies. Two districts were randomly drawn from each agro-ecology (stratum) to represent different aspects of the agricultural activity in the sub-basin. Probability proportional to size (PPS) sampling procedure was employed to draw representative Kebeles (smallest administration units) from the selected districts. Accordingly, three Kebeles were drawn from each district making the total number of Kebeles in the sample 12. Finally, household heads were drawn from the selected Kebeles using PPS sampling procedure.

The household survey employed a structured questionnaire that addressed household characteristics, farmers' perceptions and use of SLM practices, factors that affect use of SLM practices, agricultural inputs and outputs, crop enterprise income and plot-level biophysical

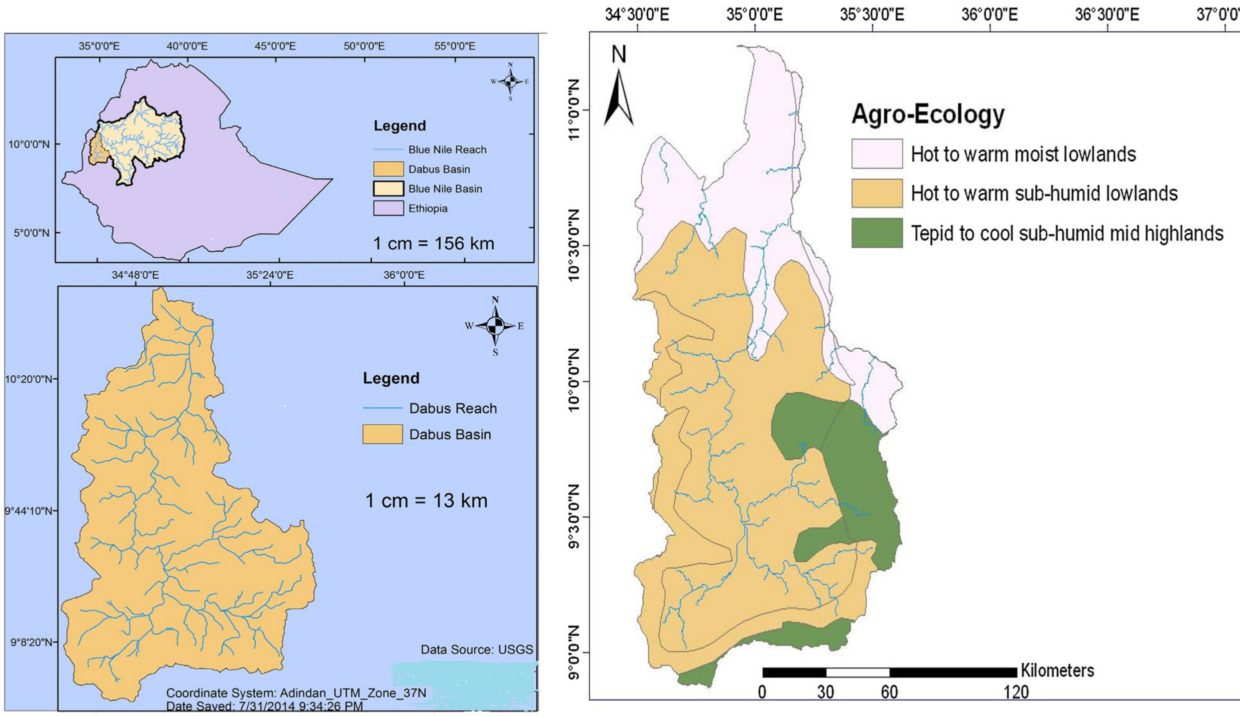

Fig. 1 Map of the study area and agro-ecological zones

Table 1 Distribution of respondents by agro-ecology and District

Wet lowland		Dry lowland	
District	**Number of respondents**	**District**	**Number of respondents**
Assosa	184	Mengie	189
Bambasi	183	Sherkole	178
Total	367	Total	367

characteristics. In addition, focus group discussions were conducted at village level to substantiate findings from household survey data. Data on grain prices for the years 2004–2016 are obtained from the Regional Office of the Ethiopian Central Statistical Agency.

Data analysis

The study used both descriptive and econometric methods to analyze the data. Descriptive method was employed to compare the two agro-ecologies of the study area and to describe users and non-users of SLM practices. Productivity was measured using gross value of output per hectare. Monetary value was used to measure output performances as households cultivate more than one crop and there needs to be some basis for aggregation.

The econometric models are used to address two primary questions. First, we calculated the impact that SLM measures have on value of production for users compared to non-users and at plot level, for plots that received the SLM practices versus those that did not. In doing so, we used a probit regression technique to have insight on which type of household or plot is more likely to use and maintain the SLM structures. Second, we estimated the marginal benefit of maintaining the SLM structure from year to year and how long farmers must maintain the structures in order to experience a benefit.

Specification of the probit model

Technology adoption models are based on farmers' utility or profit-maximizing behavior [19]. The assumption is that farmers adopt a technology/practice only when the perceived utility or profit from using new technology is greater than the traditional or the old technology. On this assumption, probit regression model is selected to analyze determinants of farmers' decision to use SLM practices as adaptation strategy. Suppose that Y_j and Y_k represent a household's utility for two choices, which are denoted by U_j and U_k, respectively. The linear random utility model could then be specified as:

$$U_j = \beta_j X_i + \varepsilon_j \text{ and } U_k = \beta_k X_i + \varepsilon_k \tag{1}$$

where U_j and U_k are perceived utilities of adaptation methods *j* and *k*, respectively, X_i is the vector of explanatory variables that influence the perceived desirability of the methods, B_j and B_k are parameters to be estimated, and ε_j and ε_k are error terms assumed to be independently and identically distributed [20]. Therefore, if a household decides to use option *j*, it follows that the perceived utility from option *j* is greater than the utility from other options (say *k*) depicted as:

$$U_{ij}\left(\beta_j X_i + \varepsilon_j\right) > U_{ik}(\beta_k X_i + \varepsilon_k), \quad k \neq j \tag{2}$$

The probability that a household will use method *j* among the set of SLM options could then be defined as:

$$\begin{aligned} &P(Y = 1|X) = P\left(U_{ij} > U_{ik}\right) \\ &P\left(\beta_j X_i + \varepsilon_j - \beta_k X_i - \varepsilon_k > 0|X\right) \\ &P\left(\beta_j X_i - \beta_k X_i + \varepsilon_j - \varepsilon_k > 0|X\right) \\ &P\left(X^* X_i + \varepsilon^* > 0\middle|X = F\left(\beta^* X_i\right)\right. \end{aligned} \tag{3}$$

where P is a probability function, U_{ij}, U_{ik} and X_i are as defined above, $\varepsilon^* = \varepsilon_j - \varepsilon_k$ is a random disturbance term, $\beta^* = (\beta_i - \beta_j)$ is a vector of unknown parameters that can be interpreted as a net influence of the vector of independent variables influencing the decision to use the SLM practices, and $F(\beta^* X_i)$ is a cumulative distribution function of ε^* evaluated at $\beta^* X_i$. The dependent variable is dummy (binary), which takes a value zero or one depending on whether or not a farmer is using any of the SLM practices as adaptive response to climate variability and change. Contrariwise, the explanatory variables are either continuous or binary/categorical. Then, the probit model is specified as:

$$I_j^* = \beta X_j + \varepsilon_j \tag{4}$$

where β is vector of parameters of the model, X_j is vector of explanatory variables, and ε_j is the error term assumed to have random normal distribution with mean zero and common variance δ^2 [2]. I_j = Unobservable (latent variable) households' actual decision to use SLM practice and what we observe is a dummy variable (use of land management measures) which is defined as: 1 if $I_j^* > 0$ and 0 otherwise

$$\text{pro(adoption} = 1) = \varphi\left(\beta X_j\right) \tag{5}$$

$$\text{pro(adoption} = 0) = 1 - \varphi\left(\beta X_j\right) \tag{6}$$

Nearest-neighbor matching

Given that a variety of differences exist between users and non-users of the SLM practices, it is important to control for these potential underlying effects in order to ensure reliable impact estimates. Thus, nearest-neighbor matching approach was used as it allows matching users to non-users at household and plot level. In addition, a continuous treatment effect estimation technique developed by [21] has been adopted to quantify differences in value of production.

In order to control for causal effect that arises due to self-selection bias or methodical assignment of treatment groups, we estimated the average treatment effect on the treated (ATT), using the nearest-neighbor matching method (NNM). This method matches users and non-users/control households based on observable characteristics and calculate the mean difference in outcomes between the two groups [22]. Thus, the control group is matched on the probability (propensity score) of adopting the SLM practices given a set of observable characteristics from the probit regression model. When matching users with non-users, we used the following definitions for user households: (1) the household implemented and continues to maintain stone terraces or soil bunds or grass strips on their cultivated land and (2) the household implemented the structures at least on 1/4 of the total cultivated land.

User households are paired with non-users when their respective observable characteristics are similar, as determined by a weighted average of the distance between values of the observed characteristics. Comparison households with propensity scores that are nearest to user households receive the highest weights and are matched accordingly. We trimmed 5% of the sample from the top and bottom of the non-participant distribution in terms of propensity scores to ensure comparisons over the same propensity score range. Then we compare average outcomes of user households with the matched non-user/comparison households. Once a balanced sample is realized, NNM technique was applied to estimate the average treatment effect of using SLM practices.

Each user household is matched to a non-user household with its closest propensity score allowing for five nearest neighbors in terms of absolute difference in propensity scores. Thus, for each household *i*, there are two potential outcomes: using SLM practice or not using. We denote users as $A_{i(1)}$ and non-users as $A_{i(0)}$, whereby the impact of using the practice is the difference in outcome between users and non-users ($\Delta = A_1 - A_0$). Thus, D is an indicator variable equal to 1 if the household uses the SLM practice and 0 otherwise. Then we find the average impact of the treatment on the treated (ATT) as follows when X is a vector of control variables:

$$\begin{aligned} \text{ATT} = E(\Delta|X, D = 1) &= E(A_1 - A_0|X, D = 1) \\ &= E(A_1|X, D = 1) - E(A_0|X, D = 1) \end{aligned} \tag{7}$$

There are two key results from this analysis. The first result is obtained from estimating the probit model which predicts the probability of each household using SLM practice. This result allows us to identify specific household-level determinants of using SLM practices, controlling for initial characteristics. The probit model is also integral to obtaining a balanced sample of user and non-user observations that help us to estimate impact. The second result estimates the average impact of SLM practices through measuring the difference in total value of production between users and non-users.

Continuous treatment effect estimates

We followed [21] to estimate the continuous treatment effect. For this purpose, farm plots were indexed by I where $i = 1, 2\ldots$ N and letting $t = T$ where t is the level of treatment defined as number of years a household has been implementing the selected SLM practices on a specific plot. Accordingly, there is a certain level of potential outcome, $Y_i(t)$ capturing a response to a level of treatment. A continuous treatment is considered where the treatment level lies in the interval $[t_0, t_1]$ and defines the potential outcome as value of production per hectare. For each plot, observation is made on the treatment level, vector of covariates X_i and potential outcome corresponding to the received level of treatment with interest of calculating average dose–response function defined as $\mu(t) = E[Y_i(t)]$.

Un-confoundedness for binary treatments given a set of covariates explaining adoption and non-adoption is generalized by [21]. Following this, in a continuous treatment case conditional on a set of covariate X_s, the extent of treatment is also random. Our assumption is that the number of years of maintaining the SLM structures is random conditional on a set of plot and household characteristics. Since the length of time for maintenance also depends on unobservable characteristics of farmers, we proxy the decision to invest labor/and or finance by including a binary variable that denotes manure and fertilizer application. Thus, we assume that farmers that decide to invest on agricultural inputs such as manure and fertilizer may have other non-observable traits that can be linked to investment decisions on agricultural technologies. Thus, we captured some of the non-observable characteristics by including these covariates.

We define the generalized propensity score (GPS) following [21]. Let $r(t, x) = f_{r/x}(t, x)$ be the conditional density of the treatment given the covariates, and then the GPS is $R = r(T, X)$. As in the case of binary propensity score, GPS has a balancing property that ensures within each given strata (where the conditional density holds the same value), the probability that $T = t$ does not depend on the covariates X. The estimation of the dose–response function requires that we first compute the conditional expectation of outcomes as a function of the treatment level t and the GPS score R. Then the dose–response at a particular t level of treatment is the conditional expectation over the GPS and given by:

$$\mu(t) = E[\beta(t, r(d, X))] = E[Y(t)] \text{ where } \beta(t, r) = E[Y/T = t, R = r] \quad (8)$$

In order to implement the above estimation, the first stage estimates the treatment level given the covariates: $T_i/X_i \sim N\left(\beta_0 + \beta_1' X_i \sigma^2\right)$. In the simple normal model β_0, β_1, σ can be estimated by maximum likelihood. The GPS is thus estimated as:

$$\hat{R}_i = \frac{1}{\sqrt{2\pi \hat{\sigma}^2}} \exp\left(-\frac{1}{2\sigma^2}\left(T_i - \widehat{\beta_0 - \hat{\beta_1} X_i}\right)^2\right) \quad (9)$$

In the second stage, the conditional expectation of Y_i given T_i and R_i is estimated using a quadratic approximation as suggested by [21].

$$E[Y_i, R_i] = \alpha_0 + \alpha_1 T_i^2 + \alpha_2 T_i^2 + \alpha_3 R_i + \alpha_4 R_i^2 + \alpha_5 T_i R_i \quad (10)$$

The parameters $(\alpha_0, \alpha_1 \ldots \alpha_5)$ are estimated using the calculated GPS R_i by ordinary least squares. Given the second-stage estimated parameters, the average potential outcome at treatment level t is estimated to obtain the entire dose–response function. We used bootstrap methods to calculate more robust estimates, standard errors and confidence intervals. The results and discussion section presents results for both binary treatment at household and plot level and the continuous treatment effects at plot level.

Results and discussions

Comparison of agro-ecologies on the use of SLM practices

Responses to climate shock through use of different land management measures are common in both agro-ecologies though intensity of use shows some degree of variation. Soil and water conservation measures and agronomic practices are common SLM measures among smallholder farmers in the study area. The relevance of these measures is reported to be increasing from time to time to adapt agricultural practices to the challenges of declining productivity attributed to climate factors [23].

The crux of this paper is to assess responses to climate variability and change through SLM practices including soil bunds, stone bunds, grass strips and to measure the impact of these practices at household and plot level. Accordingly, the two agro-ecologies were compared in terms of use of these practices. In the dry lowland agro-ecology, 25% of the respondents indicated use of soil/stone bunds while 12% stated use of grass strips indicating that about 37% the respondents have used these measures. In the wet lowland agro-ecology, use of the SLM measures is generally higher (52%) where 35% of the respondents used stone/soil bunds and 17% are users of grass strips (Table 2). The difference between the two agro-ecologies in the use of the practices is statistically significant ($\chi^2 = 18.82$; $P < 0.001$). This result implies that the role of SLM measures in coping with the adverse impacts of climate variability and change is well recognized by farmers though the intensity of use statistically varies between the two agro-ecologies.

Comparison of users and non-users of SLM practices

Unlike short-term land management technologies that reap increased yields within a season or year, benefits from long-term SLM measures may accrue over longer time horizons. Given this lag, the household survey for this study was designed to take into account previous land management intervention that farmers have implemented and the length of time that the practices have been maintained. Here, only three types of SLM practices, namely soil bund, stone bund and grass strip, were identified as the most common practices in the area. Accordingly, households that constructed and maintained any of these practices on at least 1/4 of their cultivated land since 2004 and onward and maintain the structures until the date of the survey in 2016 are considered users/adopters. With this criterion, 41% of the responds are found to be users of the practice.

Comparison is made between users and non-users of the SLM measures in terms of socioeconomic and environmental variables. The results revealed that households with farmland that is poor in fertility and steeper slope have adopted the SLM practices than those households with fertile plot and plain field. Moreover, significant percentage of the users have applied fertilizer and manure and received extension advice on soil conservation measures. The comparison also revealed significant differences between users and non-users in terms of frequency of challenges faced from extreme climate events, time spent in non-farm activities, cultivated land size, literacy level and other household characteristics (Table 3).

Following the comparison, the overall effect of the SLM practices is assessed through matching all user households with non-use households. In doing so first we made a probit model estimation to identify determinants of use of the practices and then evaluate if any impact exists due to the practice at household and plot level. To account for the hypothesized time lag for benefit realization, we split the user sample by reported date that the soil conservation measures were first built on plots. Then, we separately evaluate users that built the structure during the initial period (2004–2009) and in the recent period (2010–2016). The analysis started since 2004 because only 6% of the total users implemented the practices in any given year prior to 2004. Accordingly, for each of these periods separate NNM estimations were undertaken, maintaining the same variables for each analysis with a balanced sample.

Determinants of use of sustainable land management practices

Given that variety of differences exist between users and non-users of SLM practices, it is important to control for these potential underlying effects in order to ensure reliable impact estimates. Probit model is used to match user and non-user households and to provide information on household's probability of using the SLM practices on cultivated land. The probit regression results for household- and plot-level determinants of use of SLM practices are presented in Tables 4 and 5.

The results from the probit model estimation indicate that biophysical factors such as share of non-fertile lands and slope category of plots are significantly different between users and non-users, suggesting that plots on steep slopes; and plots with semi-fertile and non-fertile soil are correlated with land management decisions. On average, probability of using SLM practices increases by 21.1% as the proportion of plots with steep slope increases by 1%. This finding is in line with results of previous studies that showed a positive relationship between slope category of a plot and land management decisions [23, 24].

Moreover, respondents that have past experience of soil erosion problems are more responsive through SLM measures to combat similar future incidents. The probability of implementing SLM practices increases on

Table 2 Use of SLM measures for climate change adaptation

Use of stone/soil bunds and grass strips	Agro-ecology						χ^2 value	*P* value
	Wet lowland		Dry lowland		Total			
	N	%	*N*	%	*N*	%		
Non users	176	48	231	63	407	55	14.42	0.001
Users	191	52	136	37	327	45		
Total	367	100	367	100	734	100		

Table 3 Comparison of users and non-users of SLM practices

Variable	Non-users	Users	Mean difference (*P* value)
HH head age (years)	46.4	43.7	0.00
HH head sex (male = 1)	0.9	0.8	0.87
Education (literate = 1)	0.4	0.5	0.03
Household size (number)	0.59	0.58	0.61
Time spent on non-farm activity (months)	3.5	4.3	0.00
Land size in hectares	2.3	2.4	0.45
Household experienced erosion (yes = 1)	0.2	0.3	0.05
Household experienced drought (yes = 1)	0.4	0.6	0.03
Adult equivalent ratio	0.3	0.3	0.72
Steep slope (proportion)	0.1	0.2	0.00
Mixed slope (proportion)	0.05	0.1	0.21
Manure use (proportion of farmers)	0.4	0.6	0.04
Fertilizer use (proportion of farmers)	0.3	0.6	0.05
Received credit (yes = 1)	0.3	0.3	0.24
Semi-fertile plots (proportion)	0.3	0.4	0.13
Non-fertile plots (proportion)	0.2	0.4	0.00
Extension advice on SLM (yes = 1)	0.4	0.8	0.00
Distance from market (km)	5	4.6	0.22
Wet Kola agro-ecology (1 = yes)	0.3	0.4	0.00
Dry Kola agro-ecology (1 = yes)	0.2	0.1	0.00

average by 2.3% for households that have past experience of erosion risk on their cultivated land and at plot level, this probability increases to 3.4%. Users of the SLM practice have also past experience of crop failure due to terminal moisture stress and depletion of soil fertility as compared to non-users. In this regard, the probability of adopting SLM practices increases by 1.1% for households that have experience of crop failure due to drought. Likewise, probability of using SLM practices increases in the range of 3.9–7.1% as the proportion of infertile and semi-fertile plots increases by 1%. Similarly, the probability of implementing SLM practices increases by 42.1% as the proportion of non-fertile plots increases by 1%.

Distance from market revealed significant negative correlation with probability of using SLM practices. The probability of implementing SLM practices decreases by 3.1% as distance from market increases by 1 km. This finding may reveals that if farmers do not realize a market outlet for increased production, they may be less willing to implement the structures that could increase yields. Moreover, fertilizer/manure application is included as a matching binary variable as proxy to willingness to invest money/labor in technologies/innovations to increase output. The result shows that the decision to apply fertilizer/manure is positively related to SLM adoption decision verifying willingness of SLM users to invest in productivity enhancing technologies. The probability of practicing SLM increases by 5.3% for those households who are using fertilizer or manure on their cultivated land. The plot-level analysis revealed that the probability of implementing SLM practices increases by 14.3% for plots that received fertilizer or manure.

It is important that the probit model discussed above includes covariates that would not have changed after adopting land management practices. For example, we included total landholding size, biophysical characteristics of agricultural land, such as soil fertility and slope, and household head characteristics which are less likely to change over the study period. In order to control for endogeneity, we did not match user and non-user households based on assets which may have been affected by successful or unsuccessful investment in SLM practices (e.g., variables that proxy income such as changes in livestock holdings).

Impacts of SLM practices on value of production

Propensity scores are estimated both for the treated and control households (Fig. 2). Accordingly, the estimated propensity scores for the treated households vary between 0.069 and 0.964 with mean of 0.688. For the control households, the estimated propensity scores vary between 0.005 and 0.928 with mean of 0.401. Therefore, the common support region lies between 0.069 and 0.928. Flowing [10, 25] to evaluate the average treatment (ATT) effect on the treated, it is important to ensure that for each treated household a close non-treated is found.

Table 4 Probit results on household-level determinants of SLM practices (2004–2016)

Variable	*dy/dx*	SD
HH head age (years)	0.035	(0.021)
HH head sex (male = 1)	0.003	(0.021)
Land size in hectares	0.024**	(0.011)
Household experienced erosion (yes = 1)	0.023*	(0.041)
Household experienced drought (yes = 1)	0.011 **	(0.025)
Household size (number)	0.021	(0.003)
Adult equivalent ratio	0.013	(0.011)
Non-farm employment (months)	0.001	(0.011)
Steep slope plots (proportion)	0.211***	(0.032)
Mixed slope plots (proportion)	0.018	(0.028)
Manure/fertilizer use (yes = 1)	0.053***	(0.061)
Education of HH head (literate = 1)	0.031	(0.017)
Semi-fertile plots (proportion)	0.071**	(0.037)
Non-fertile plots (proportion)	0.039**	(0.062)
Extension advice on SLM (yes = 1)	0.053	(0.024)
Distance from market (km)	− 0.031**	(0.011)
Wet Kola agro-ecology (1 = yes)	0.241***	(0.028)
Dry Kola agro-ecology (1 = yes)	0.067**	(0.046)
Assosa Woreda	0.261***	(0.053)
Bambasi Woreda	0.217***	(0.101)
Sherkole Woreda	0.042*	(0.006)
Mengie Woreda	0.135*	(0.015)
Number of observations = 506		
Wald $\chi^2(20) = 218.21$		
Prob > $\chi^2 = 0$		
Pseudo $R^2 = 0.3232$		

*, **, and *** are significance level at 10, 5 and 1%

Dependent variable: household that used SLM practices (soil/stone bund, grass strips) on at least 1/4 of cultivated land (Yes = 1)

Table 5 Probit results on plot-level determinants of SLM practices (2004–2016)

Variable	*dy/dx*	SD
HH head age (years)	0.021	(0.018)
HH head sex (male = 1)	0.023	(0.001)
Household experienced erosion (yes = 1)	0.034*	(0.032)
Household experienced drought (yes = 1)	0.141**	(0.025)
Plots with steep slope (proportion)	0.301***	(0.022)
Plots with mixed slope (proportion)	0.015	(0.006)
Percentage of plots received manure/fertilizer	0.143***	(0.001)
Education of HH head (literate = 1)	0.044	(0.008)
Semi-fertile plots (proportion)	0.043**	(0.011)
Non-fertile plots (proportion)	0.421**	(0.004)
Extension advice on SLM (yes = 1)	0.048*	(0.001)
Plot size (hectare)	0.014*	(0.021)
Number of observations = 506		
Wald chi2(12) = 241.31		
Prob > chi2 = 0		
Pseudo $R^2 = 0.2412$		

*, ** and *** are significance level at 10, 5 and 1%

Dependent variable: plots that received SLM practices (soil/stone bund, grass strips) (Yes = 1)

To ensure this, households whose estimated propensity scores less than 0.005 and larger than 0.928 are not considered for the matching exercise and hence a total of ten observations have been dropped.

It is assumed that most SLM practices require a longer time horizon to experience significant benefits to user households. In this regard, the impact of the practices is analyzed in two ways. First the impact on the value of production is analyzed using the entire sample considering households that implemented the practice between 2004 and 2016. Then, in order to take into account the lag time in land management benefit, the sample is splinted between early users (2004–2009) and late users (2010–2016).

The result shows that households that implemented the practices in the first period (2004–2009) gained a 24.1 percept higher value of production (significant at $P < 0001$) in 2016 compared to matched households that did not implement the practice (Table 6). However, households that adopted the practices in later years (2010–2016) did not realize significant increases in value of production compared to matched households that did not implement the practice. This could be attributed to the fact that the time is not sufficient to allow the late users realize the effects of the practice in terms of replenishing soil nutrients that could help increase agricultural production. The result also pointed out the impact of using SLM measures is not significant when the entire sample (2004–2016) is used showing only 3% higher value of production over non-users (Table 6). This is attributed to the fact that the late users have yet to experience increase in production and hence miscomprehend the gains by early users.

A household-level aggregation is based on the thresholds that households that implemented the selected SLM structures on at least 1/4 of their cultivated land. This analysis depicted increase in value of production of early users of the SLM practices. However, plot-level disaggregated analysis allows a robustness check of the impact within households and across plots given differences in soil fertility, slope, soil degradation prevalence and application of external inputs such as manure and fertilizer.

The plot-level results are reflections of the household-level analysis. Accordingly, plots that received SLM measures in the first period (2004–2009) experienced a 28.6% increase in value of production (significant at $P < 0001$) compared to matched plots that did not receive

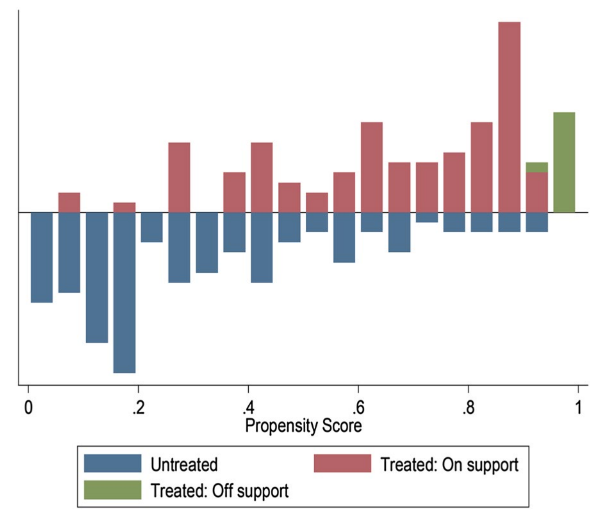

Fig. 2 Common support of the propensity scores

the measures (Table 6). On the other hand, plots that received the practice in recent period (2010–2016) had no significant increases in value of production compared to matched plots. The plot-level impact for the entire period (2004–2016) revealed only a 5% increase in value of production over matched plots, though the increase is not statistically significant.

Sensitivity analysis

Rosenbaum bound sensitivity test for possible hidden bias is presented in Table 7. As depicted in the table, the impact of SLM practices on value of production is inferred with the critical level of gamma (e^{γ}). The effect of practicing SLM (treatment effect) found to be significant at $P < 0001$ showing that the inference for the effect of practicing the land management measures is not changing when the odds of being treated for both users and non-users are changed twice ($e^{\gamma} = 3$) in terms of unobserved covariates. In other words, the outcome variable which is estimated at various level of critical value of e^{γ} is significant and this indicates that all important covariates that affected use of the SLM practice are well addressed in the impact analysis. Therefore, the estimated ATT is not rejected at all critical values even when we set e^{γ} at the largest value ($e^{\gamma} = 3$) compared to the value set in different literatures $e^{\gamma} = 2$ (100%). Therefore, the sensitivity analysis tends to show that the estimated impact (ATT) is mainly the effect of the SLM practices on value of production for both household- and plot-level cases. And hence, it is insensitive to an unobserved selection bias.

Table 7 Rosenbaum bound sensitivity analysis test for hidden bias

Gamma (e^{γ})	*P*-critical
$e^{\gamma} = 1$	0
$e^{\gamma} = 1.5$	0
$e^{\gamma} = 2$	0
$e^{\gamma} = 2.25$	2.80e−12
$e^{\gamma} = 2.5$	4.70e−18
$e^{\gamma} = 2.75$	5.80e−14
$e^{\gamma} = 3$	6.60e−16

Continuous treatment effect estimation results

Continuous treatment estimation procedure proposed by [21]) is customized to evaluate payoff period and marginal effects of the SLM measures on crop productivity expressed in terms of value production. Based on this approach, we estimate how plot-level value of production varies depending on number of years that the SLM measures are maintained. Impact is evaluated at plot level since households implement the SLM structures on diverse plots in different years. And the difference in impact is evaluated based on the length of time that the practices are maintained on a specific plot.

First, we estimate the conditional distribution of the number of years the SLM measure is maintained given a set of covariates. The treatment level (defined by number of years) is estimated in order to obtain a GPS using plot and household characteristics. Then treatment distribution is divided by treatment level whereby we define

Table 6 Average household-level and plot-level impacts of SLM practices

Impact	Outcome variable (value of production)	ATT	SE	Observations
Household level	2004–2009	0.241***	0.081	602
	2010–2016	0.013	0.044	614
	2004–2016	0.030	0.044	614
Plot level	2004–2009	0.286***	0.021	903
	2010–2016	0.015	0.041	915
	2004–2016	0.048	0.031	915

ATT Average Treatment Effect on the Treated

*** significant at ($P < 0.000$)

three time intervals in years: [1, 4, 5, 8, 9, 12] and for each interval a group of observations are identified. Accordingly, there are 330, 198 and 206 observations in each group, respectively.

For each of the covariates in the first regression, we test that the mean of one group is similar to the other two groups combined, and thus, we are able to satisfy the balancing property. Table 8 presents whether the GPS actually balances the set of variables in the different intervals of the treatment level. The first three columns presented the test whether the covariates have the same mean for observations within the same treatment intervals using the raw data. In this case, the raw data are unbalanced for most of the covariates as implied by significant mean differences. In contrast, the last three columns are mean differences after adjusting for the GPS to see whether the covariates are better balanced when we condition on the estimated GPS. When comparing the two sets of results, we can clearly see that the covariates are better balanced after the GPS adjustment as implied by non-significant mean differences.

The test result in Table 8 reveals that adjusting for the GPS improves the balance of the covariates across the treatment intervals, and the next step is estimating the second-stage model that generates OLS estimates on log of value of production. Based on [21], the parameters of the second-stage estimation do not have a direct meaning rather they are primarily used to test whether the covariates introduce any bias.

Following the bias test, we generate the derivative of the dose–response function, which reveals the marginal effect of an additional year of maintenance of the SLM structure. The result suggests that maintenance of the structures is crucial to reap significant benefits from resources invested on the practices. In this regard, users that maintain the practices for at least 6 years experienced a positive increase in value of production at the end of the 6th year (Table 9). However, users that have maintained the practices for less than 6 years do not experience a statistically significant impact on the value of production as implied by insignificant marginal effects during the initial 6 years of implementation. The negative marginal effect suggests that the SLM practices may require a longer time horizon to slow down soil loss and reach a point where nutrient replenishment and other biophysical improvements are realized to full potential.

Beyond the 6th year, maintaining the SLM structures results in positive marginal benefit that increases at an increasing rate. Thus, for each additional year one sustains the SLM practices, the higher the gains in value of production. As indicated in Table 9, if a household

Table 9 Estimated marginal effect per additional year of maintenance

Years	Marginal effects
1	− 0.1
2	− 0.08
3	− 0.05
4	− 0.03
5	− 0.01
6	0.04*
7	0.06*
8	0.08*
9	0.10*
10	0.12*
11	0.14*
12	0.16*

* Significant at 10% level

Table 8 Test for equality of means between treatment groups

Variable	Raw data treatment terciles			Data adjusted by GPS		
	[1, 4]	[5, 8]	[9, 12]	[1, 4]	[5, 8]	[9, 12]
HH head age (years)	− 0.32	0.88**	− 0.08	− 0.28	1.01	− 0.18
HH head sex (male = 1)	− 0.01	− 0.21	− 0.01	0.00	0.00	0.01
Household experienced erosion (yes = 1)	− 0.43*	− 0.10	0.26*	− 0.23	0.00	0.16
Household experienced drought (yes = 1)	− 0.32*	− 0.11	0.16	− 0.11	0.01	0.11
Steep plot (yes = 1)	0.01	− 0.21*	0.00	0.01	− 0.11	0.01
Manure/fertilizer (yes = 1)	− 0.12*	0.00	0.11*	− 0.02	0.00	0.01
Education of HH head (literate = 1)	0.00	0.01	0.01	0.01	0.01	0.00
Semi-fertile plot (yes = 1)	0.21**	0.01	0.23**	0.0	0.00	0.01
Non-fertile plot (yes = 1)	− 0.12**	0.01	0.09**	− 0.02	0.01	0.00
Plot size	− 0.22*	0.01	− 0.00	− 0.02	0.01	− 0.01

GPS generalized propensity score

* and ** are significance level at 10 and 5%

sustains the SLM structures for 8–9 years, the value of production would increase by about 10% and if a household continues to maintain the structures for 11–12 years the expected value of production increases by 16%. In this regard, maintenance should continue as far as the increase in marginal benefit becomes statistically insignificant. However, since the number of observations are minimal for households that sustained the SLM practices for more than 9 years, further enquiry is required to fully understand the impacts of long-term maintenance. Once the soil degradation problems are successfully controlled and the necessary soil components are replenished after long-term maintenance of the SLM structures, one would expect diminishing returns to such practices. Therefore, further research over a longer time period may provide an estimated envelope of benefits and marginal returns of the SLM structures in the study area.

Conclusions and policy recommendations

This study used primary data to determine smallholder farmers' response to climate variability and change through SLM practices and how these practices affected crop productivity. Accordingly, the study identified specific household-level and plot-level determinants of SLM decisions and measured household- and plot-level impact of the practice on value of production. Moreover, the study estimated the average impact among users given different lengths of time that the land management structures are maintained.

The result revealed that households that implemented any of stone bunds, soil bunds, grass strips during the period (2004–2009) experience a 24.1% higher value of production in 2016 compared to non-users. Conversely, households that implemented the practices in later years (2009–2016) have no significant increases in value of production. Analysis at the plot level suggests similar impact, whereby plots that received SLM measures in the first period have 28.6% higher value of production in 2016 compared to matched plots that did not receive the practices. The impact analysis also suggests long-term maintenance is crucial and users that maintain the structures for at least 6 years experienced a positive increase in value of production at the end of the 6th year.

The SLM practices are knowledge and resource intensive by their very nature and may not be implemented easily given the awareness level and resource endowments of smallholder farmers. Therefore, scaling up these adaptation benefits requires intervention of various stakeholders to provide technological support and training. The impact analysis shows longer maintenance of the SLM structures provides sustainable and greater payoffs overtime. Given the situation in the study area, significant benefits are experienced when maintaining the structures at least for 6 years. In line with this, further research could come up with policy options that encourage farmers to accept longer time horizons. Besides, further research is required to provide an estimated envelope of long-term benefit and marginal returns of the SLM practices. Creating market access may also motivate farmers to decide on SLM investment and long-term maintenance through boosting agricultural surplus, lowering transportation costs and improving input distribution mechanisms. Lastly, future research should address modeling of synergetic effects and complementarities among different SLM measures that can possibly enhance benefits for smallholder farmers.

Authors' contributions

PA generated the idea, designed the study, designed data collection instruments, carried out the data collection and analyzed the data, and wrote the manuscript. BS participated in the study design, shaped the data collection instruments, coordinated the entire data collection process, technically supported the data analysis process and revised the draft the manuscript. Both authors read and approved the final manuscript.

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Competing interests

The authors declare that they have no competing interests.

Availability of data and materials

Data sharing is not applicable to this article, for no datasets were generated or created during the current study

Consent for publication

Not applicable.

Ethics approval and consent to participate

Not applicable.

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References

1. Olarinde L, Oduol JB, Binam JN, Diagne A, Njuki J, Adekunle AA. Impact of the adoption of soil and water conservation practices on crop production: baseline evidence of the sub saharan africa challenge programme. Middle East J Sci Res. 2011;9(1):28–40.
2. Zeleke G, Hurni H. Implications of land use and land cover dynamics for mountain resource degradation in the Northwestern Ethiopian highlands. Mt Res Dev. 2001;21(2):184–91.

3. Barnichon R, Peiris S. Sources of Inflation in Sub-Saharan Africa. J Afr Econ. 2008;17(1):729–46.
4. Sonneveld BGJS. Land Under pressure: the impact of water erosion on food production in Ethiopia. PhD Thesis, Vrije Universiteit, Amsterdam, The Netherlands; 2002.
5. Shiferaw B, Holden TS. Farm-level benefits to investments for mitigating land degradation: empirical evidence for Ethiopia. Environ Dev Econ. 2001;6:336–59.
6. Tefera B, Ayele G, Atnafe Y, Jabbar MA, Dubale P. Nature and causes of land degradation in the Oromiya Region: a review. Socio-economics and Policy Research Working Paper 36. Nairobi, Kenya: International Livestock Research Institute (ILRI); 2002.
7. Okumu BN, Jabbar MA, Colman D, Russell N. A bio-economic model of integrated crop-livestock farming systems: the case of Ginchi watershed in Ethiopia. In: Barrett CB, Place FM, Aboud AA, editors. Natural resources management in african agriculture: understanding and improving current practices. Wallingford: CAB International; 2002.
8. Kassie M, Holden S, Köhlin S, Bluffstone R. Economics of soil conservation adoption in high-rainfall areas of the Ethiopian Highlands. Working Papers in Economics 400. Göteborg, Sweden: Environment for Development; 2008.
9. Yesuf M, Mekonnen A, Kassie M, Pender J. Cost of land degradation in Ethiopia: a critical review of past studies. Addis Ababa: EDRI/EEPFE; 2005.
10. Asrat Paulos, Belay Kassa, Desta Hamito. Determinants of farmers' willingness to pay for soil conservation practices in the Southeastern Highlands of Ethiopia. Land Degrad Dev. 2004;15:433–5.
11. Bojö J, Cassells D. Land degradation and rehabilitation in Ethiopia: a reassessment. AFTES Working Paper 17. Washington, DC: World Bank; 1995.
12. Hurni H. Degradation and conservation of the resources in the Ethiopian highlands. Mt Res Dev. 1988;8(2/3):123–30.
13. Asrat P, Simane B. Adaptation benefits of climate-smart agricultural practices in the Blue Nile Basin: empirical evidence from North–West Ethiopia. In: Leal Filho W, Munishi P, Ogugu N, Simane B, editors. Climate change adaptation in africa: fostering african resilence and capacity to adopt-Volume 1. Berlin: Springer; 2017.
14. Pender J, Gebremedhin B. Land management, crop production and householdincome in the highlands of Tigray, Northern Ethiopia: an econometric analysis. In: Pender J, Place F, Ehui S, editors. In strategies for sustainable land management in the East African Highlands. Washington, DC: International Food Policy Research Institute; 2006.
15. Bravo-Ureta BE, Almeida AN, Solis D, Inestroza A. The economic impact of marena's investments on sustainable agricultural systems in Honduras. J Agric Econ. 2010;62(2):429–48.
16. Yesuf M, Di Falco S, Deressa T, Ringler C, Kohlin G. The impact of climate change and adaptation on food production in low-income countries: evidence from the Nile Basin, Ethiopia. IFPRI Discussion Paper 828. Washington, DC: International Food Policy Research Institute (IFPRI); 2008.
17. Benhin J. Climate change and south african agriculture: impacts and adaptation options. CEEPA Discussion Paper No. 21. Pretoria, South Africa: Centre for Environmental Economics and Policy in Africa (CEEPA), University of Pretoria; 2006.
18. Kabubo-Mariara J, Karanja F. The economic impact of climate change on kenyan crop agriculture: a ricardian approach. CEEPA *Discussion Paper* No. 12. Pretoria, South Africa: Centre for Environmental Economics and Policy in Africa (CEEPA), University of Pretoria; 2006.
19. Pryanishnikov I, Zigova K. Multinomial logit models for Austrian Labor Market. Austrian J Stat. 2003;32:267–82.
20. Greene WH. Econometric analysis. 4th ed. New Jersey: Prentice Hall; 2000.
21. Hirano K, Imbens GW. The Propensity Score with Continuous Treatments. In: Gelman A, Meng X, editors. Applied bayesian modeling and causal inference from incomplete-data perspectives. New York: Wiley; 2004.
22. Quisumbing, A. R., B. Baulch, and N. Kumar. 2011. Evaluating the long-term impact of antipoverty interventions in Bangladesh: An overview. IFPRI Discussion Paper 1077. Washington, DC: International Food Policy Research Institute (IFPRI).
23. Asrat P, Simane B. Adapting smallholder agriculture to climate change through sustainable land management practices: empirical evidence from North–West Ethiopia. J Agric Sci Technol A. 2017;7(2017):289–301. https://doi.org/10.17265/2161-6256/2017.05.001.
24. Lobell DB, Burke MB, Tebaldi C, Mastrandrea MD, Falcon WP, Naylor RL. Prioritizing climate change adaptation needs for food security in 2030. Science. 2008;319(5863):607–10.
25. Caliendo M, Kopeinig S. Some Practical Guidance for the Implementation of Propensity Score Matching. J Econ Surv. 2008;22(1):31–72.