Journal of Agricultural Science and Technology A 7 (2017) 289-302
doi: 10.17265/2161-6256/2017.05.001

Adapting Smallholder Agriculture to Climate Change through Sustainable Land Management Practices: Empirical Evidence from North-West Ethiopia

Paulos Asrat and Belay Simane

College of Development Studies, Center for Environment and Development Studies, Addis Ababa University, P.O. Box 56649, Addis Ababa, Ethiopia

Abstract: The objective of this paper was to determine the factors that influence farmers' decision to use two categories of sustainable land management (SLM) practices as adaptation strategy to climate change in the North-West Ethiopia. It was based on analysis of data collected from 734 farm household heads and employed probit regression model to analyze the determinants of adaptation to climate change through SLM measures. Based on the model result, factors, like perception of climate change, exposure to adaptation techniques, education, perception of land degradation, slope, land prone to degradation, number of parcels, crop enterprise income, land size, farm distance, economically active family size and agro-ecology are found important in determining farmers' decision to use structural land management practices. Likewise, perception of climate change, exposure to adaptation, farming experience, slope, crop enterprise income, land prone to degradation and agro-ecology are found important in affecting farmers' decision to use non-structural land management practices as adaptation measure. Therefore, in line with the findings of the analysis, any intervention that promotes use of land management practices as adaptation strategy should take into account agro-ecology specific factors that are relevant to the nature of the land management practices. Moreover, since scaling up of SLM practices as adaptation strategy is resource intensive, it requires both public and non-public investment for providing technological support and raising awareness. Failure to do so would adversely affect crop productivity and exacerbate food insecurity problems at farm household level.

Key words: Climate change, adaptation, sustainable land management, structural/physical and non-structural land management.

1. Introduction

The impact of climate change is detrimental in low income tropical African countries, including Ethiopia that depends on agriculture as a main livelihood. The combination of already fragile environment, dominance of climate-sensitive sector in economic activity and low autonomous adaptive capacity in these regions aggravates the harmful effects of climate change and variability on agricultural production, food security and ecosystems [1]. However, the effects of climate change vary across countries, and adaptation capabilities are influenced by geographical, economic, cultural and political factors, which require that adaptation programs must take into account country-specific circumstances [1-4].

Ethiopia is heavily dependent on rain-fed agriculture, and its geographical location and topography in combination with low adaptive capacity entail a high vulnerability to adverse impacts of climate change [5, 6]. The country has been suffering from such disasters, which manifest in the form of drought, flood, heavy rains, high temperature and frost with seemingly increasing trend from year to year [7, 8]. Although Ethiopia has a long history of drought in the past with recurrence of the event in an interval of a decade, recently the frequency and extent appear to be growing. For example, the country has experienced eight drought events since 1990 in less than two decades. Similarly, six serious flood attacks occurred

Corresponding author: Paulos Asrat, Ph.D. Research field: development research.

since 1988 [7, 8]. During the two recent drought events, GDP declines by around 3%-10% and flooding in turn causes significant damage to settlements and infrastructure, and undermines agriculture by delaying planting, reducing yields and compromising the quality of crops [8].

Following such recurrence of extreme events and the catastrophic effects, climate researchers believe Ethiopia as one of the victims of climate change [9]. Studies on the trend of climate in Ethiopia show that temperature has been increasing throughout the century with a mixed trend of precipitation. Average annual maximum temperature and average annual minimum temperature over the century have increased by 0.1 °C and 0.25 °C per decade, respectively [10]. On one hand, historical trend shows that mean temperature increased by 1.3 °C from 1996-2006 with more hot days and nights and fewer cold days and nights. On the other hand, rainfall is highly variable from year to year, from season to season and decade to decade with no regular trend. As a result, Ethiopia is experiencing the effects of climate change, and this can holdback economic progress in the range of 0.5%-2.5% each year [11].

With regard to the future, general circulation models (GCM) predictions show an increasing trend of temperature with moderate inter-model differences [11]. For example, mean annual temperature will increase in the range of 0.9-1.1 °C by the year 2030 and 1.7-2.1 °C by the year 2050 from the average of 1961-1990 [12]. Whereas, the corresponding results for annual precipitation show a change between 0.6% and 4.9% for 2030 and between 1.1% and 18.2% for 2050 [12]. Following this, crop simulation models, as well as econometric studies of climate change impacts, suggest a negative impact on crop productivity in Ethiopia on the order of 5% to 10% by 2030, due to changes in mean seasonal temperature and precipitation with more severe impacts towards the end of the century [12].

In line with this, a study on household consumption in rural Ethiopia [13] shows that rainfall shock in a single year has a lingering effect on household's welfare for many years to come. The same study shows that a 10% rainfall decrease in one year has an impact of 1% decrease on the growth rates of agricultural output for 4-5 years to come. These impacts of climate on agriculture are first-order effects that trigger direct and indirect economic impacts, which necessitate the need for an economy-wide framework to cope up with climate change shocks [13]. Overall, climate impacts in Ethiopia are significant, but variable over regions and crop type.

Studies indicated that smallholder farmers perceive climate change and also adapt to reduce the negative impacts [14, 15]. In this regard, sustainable land management (SLM) practices have been shown to be effective for adaptation in moisture stress areas. Sustainable land use practices, such as use of soil and water conservation measures, improved crop varieties and agronomic practices, enhance adaptation to climate change and increases crop productivity [16, 17].

However, most previous studies failed to explicitly address the types of land management based adaptation methods that farmers employ at local level. The studies are also highly aggregated and are of little help in addressing agro-ecology specific adaptations. Moreover, the studies have paid little attention to the analysis of SLM practices as adaptation strategy and the factors influencing farmers' decision to use the practices. Given the agro-ecological diversity of the country, understanding location specific climate pattern, its impacts and possible resilience options seems to be critical.

Since adaptation is a local response to climate stimuli, addressing agro-ecology specific adaptation decisions is an important research gap that needs to be addressed. Therefore, the present study aimed to use probit regression model to analyze the determinants of using two categories of SLM practices as adaptation strategy to climate change in the Dabus sub-basin of the Blue Nile River, North-West Ethiopia.

2. Methodology

2.1 Study Area

Dabus sub-basin of the Blue Nile River has an area of 21,030 km^2. The altitude in the sub-basin ranges between 485 m and 3,150 m above sea level. Annual rainfall ranges between 970 mm and 1,985 mm. The annual maximum and minimum temperature in the sub-basin varies between 20-35 °C and 8.5-20 °C, respectively. The sub-basin is characterized by hot to warm moist, sub humid and dry lowlands (Fig. 1). Its considerable part is cultivated and characterized by maize-sorghum and maize-sorghum-perennial complex.

2.2 Data Source

The paper is based on a cross-sectional household survey data of 734 mixed farmers during November and December 2016 from the Dabus sub-baisn of the Blue Nile River in the North-West of Ethiopia. The survey was conducted in four districts, spatially distributed throughout the sub-basin. The districts were purposefully drawn from two local agro-ecologies in the area, namely, wet kola (wet lowland) and dry Kola (dry lowland) to represent different aspects of the agricultural activity in the sub-basin. Following this, farm households were randomly drawn from each of the districts following probability proportional to size (PPS) sampling procedure.

2.3 Data Analysis

The study used descriptive and econometric methods to analyze the collected data. Descriptive method was employed to reveal differences and similarities between the two agro-ecologies of the study area, as well differences and similarities between users and non-users of SLM practices in terms of socio-economic and environmental variables. With regard to econometric method, the study employed the probit regression model to analyze the determinants of using different SLM practices as adaptation strategy to climate change.

2.3.1 Specification of the Probit Regression Model

Past studies showed that there are plausible methodological similarities among agricultural technology adoption and climate change adaptation methods, as both involve decisions on whether or not to adopt a given course of action [18]. The models are based on farmers' utility or profit-maximizing behavior [19], and the assumption here is that farmers adopt a technology/practice only when the perceived utility or

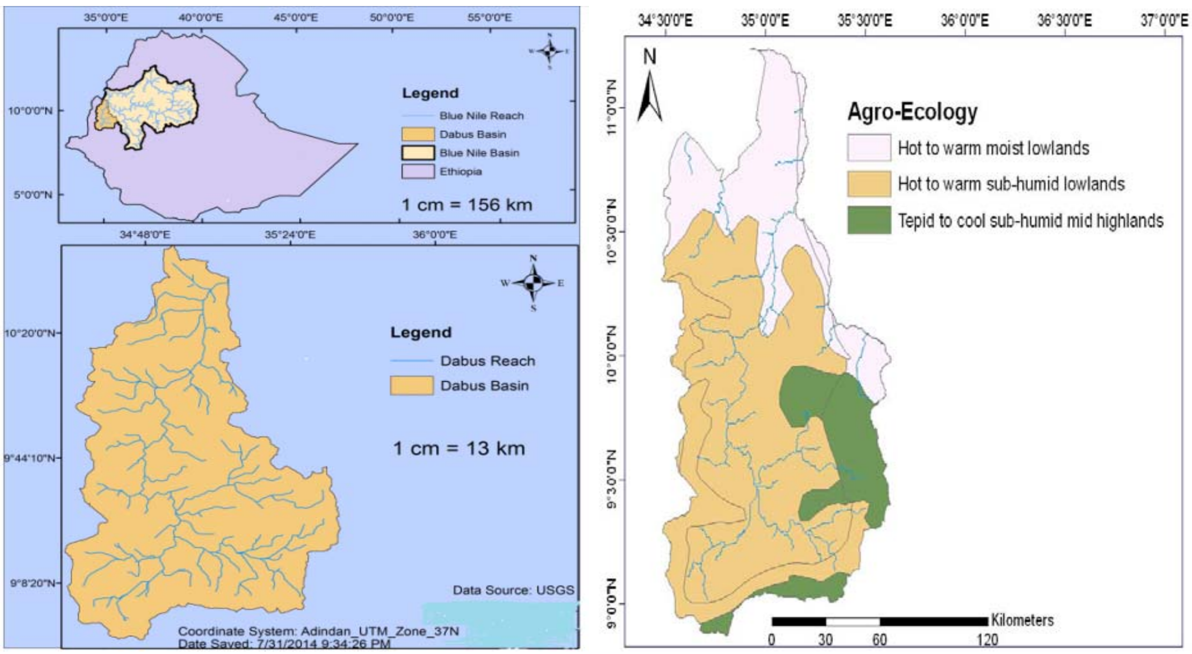

Fig. 1 Map of the research area and agro-ecological zones.

profit from using the new technology is greater than the traditional or the old technology. It is on these premises that probit regression model is selected for the analysis of determinates of farmers' decision to use SLM practices as adaptation strategy.

It is assumed that smallholder farmers use adaptation methods only when the perceived utility or net benefit from using such a method is significantly greater than the case without it. Although utility is not directly observed, the actions of economic agents are observed through the choices they make. Suppose that a household's utility for two choices is denoted by U_j and U_k, respectively, the linear random utility model could then be specified as Eq. (1):

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

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; ε_j and ε_k are error terms assumed to be independently and identically distributed [20]. In the case of climate change adaptation methods, if a household decides to use option j, it follows that the perceived utility or benefit from option j is greater than the utility from other options (say k) depicted as Eq. (2):

$$U_j\left(\beta_j X_i + \varepsilon_j\right) > U_k\left(\beta_k X_i + \varepsilon_k\right),\ k \neq j \quad (2)$$

The probability that a household will use method j among the set of climate change adaptation options could then be defined as Eq. (3):

$$P\left(Y=1 \mid X\right) = P\left(U_j > U_k\right)$$

$$= P\left(\beta_j X_i + \varepsilon_j - \beta_k X_i - \varepsilon_k > 0 \middle| X\right)$$

$$= P\{[X_i(\beta_j - \beta_k) + (\varepsilon_j - \varepsilon_k)] > 0 \mid X\}$$

$$= P[\left(X^* X_i + \varepsilon^*\right) > 0 \mid X] = F\left(\beta^* X_i\right) \quad (3)$$

where, P is a probability function, U_j, U_k 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 adaptation, and $F(\beta^* X_i)$ is a cumulative distribution function of ε^* evaluated at $\beta^* X_i$. The exact distribution of F depends on the distribution of the random disturbance term (ε^*), and depending on the assumed distribution that the random disturbance term follows, several qualitative choice models can be estimated [20].

As already mentioned, the purpose of this study was to analyze which of the hypothesized independent variables are related to the adaptive responses of farmers to climate-change induced land degradation problems. The dependent variables (adaptation 1 and adaptation 2) are dummy (binary), which take a value 0 or 1, depending on whether or not a farmer is applying any of the structural/physical or non-structural SLM practices as adaptive response to climate change induced land degradation. On the other hand, the explanatory variables are either continuous or binary/categorical. Based on this, the probit model is specified as Eq. (4):

$$I_j = \beta X_j + \varepsilon_j \quad (4)$$

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 0 and common variance δ^2 [20]. I_j is unobservable households' actual decision (which is also named to be a latent variable) to use a structural/physical and non-structural SLM practice, and the observed is a dummy variable which is defined as: 1 if $I_j > 0$ and 0 otherwise. Based on this, the probability of using SLM measures is specified as Eq. (5):

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

Similarly, the probability of not using SLM measures is defined by Eq. (6):

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

2.3.2 Definition of Explanatory Variables and Working Hypotheses

The first dependent variable for probit analysis (adaptation 1) has a dichotomous nature, measuring the decision of the farmer to use structural/physical land management practices as an adaptive response to climate change/variability. It is represented in the model by 1 for a user farmer and by 0 for a non-user farmer. Similarly, the second dependent variable (adaptation 2) has also a dichotomous nature, measuring the decision of the farmer to use non-structural land management practices as an adaptive response to climate change/variability. It is represented in the model by 1 for a user farmer and by 0 for a non-user farmer.

It is hypothesized that the decision to use the land management measures is influenced by a set of explanatory variables. Based on the findings of past studies, theories and observation made in the study area, Table 1 portrays the variables hypothesized to determine farmers' decision to use SLM practices as adaptation strategy to climate change/variability.

Table 1 Hypothesized explanatory variables and their direction of effect.

Explanatory variable	Type of variable	Hypothesized effect
Perception	Dummy	+
Education	Categorical	+
Farm experience	Continuous	+/-
Active labor	Continuous	+
Exposure adaptation	Dummy	+
Cultivated land	Continuous	+
Slope	Categorical	+
Crop income	Continuous	+
No parcel	Integer	-
Exposure perception	Categorical	+
Prone farmland	Dummy	+
Farm distance	Continuous	-
Agro-ecology	Dummy	+

Table 2 Comparison of agro-ecologies in terms of socio-economic variables.

Comparison variable		Agro-ecology						χ^2 value
		Wet lowland		Dry lowland		Total		
		No.	%	No.	%	No.	%	
Perception of climate change	Not perceived	177	47.7	139	38.3	316	43.1	6.636**
	Perceived	194	52.3	224	61.7	418	56.9	
Exposure to adaptation measures	No exposure	141	38.0	189	52.1	330	45.0	14.659***
	Have exposure	230	62.0	174	47.9	404	55.0	
Adaptation through physical SLM	Non-users	177	47.6	241	66.4	418	57.0	18.820***
	Users	194	52.4	122	33.6	316	43.0	
Adaptation through non-physical SLM	Non-users	92	24.8	202	55.6	294	40.2	49.330***
	Users	279	75.2	161	44.4	440	59.8	
		Mean	SD	Mean	SD	Mean	SD	*t* value
Income from crop enterprise (birr)		1,858.22	1,311.79	1,338.22	997.43	1,598.21	1,192.83	-4.9895***
Cultivated land (ha)		1.68	0.94	1.00	0.58	1.34	0.85	-9.6467***
Total land (ha)		6.60	2.98	5.81	2.17	6.21	2.63	3.2930****
Farm experience (years)		17.87	8.05	13.01	6.6.2	15.44	7.76	-7.3685***

* 1USD= 23 birr; *** Values are significantly different at P < 0.001.

3. Results and Discussion

3.1 Comparison of Agro-ecologies

Comparison of perception of climate change between the two agro-ecologies indicated that 52% of the respondents from the wet lowland and 62% from the dry lowland had perceived change in climate (Table 2). This difference in perception between the two agro-ecologies is statistically significant (χ^2 = 6.636; P < 0.01). More perception in the dry lowland agro-ecology is attributed to the occurrence of repeated drought and various environmental changes in recent years that caused crop failure. The majority of the respondents in the wet lowland agro-ecology (62%) had exposure to adaptation measures to climate change compared to 48% in the dry lowland, showing existence of statistically verified difference between the two agro-ecologies (χ^2 = 14.659; P < 0.001).

About 52% of the respondents from the wet lowland agro-ecology and 34% from the dry lowland were users of structural land management practices (Table 2). The difference in the use of the practice is statistically significant (χ^2 = 18.82; P < 0.001). Likewise, about 75% of the respondents in the wet lowland agro-ecology were users of non-structural land management techniques compared to 44% in the dry lowland. This difference is also statistically significant at less than 1% probability level (χ^2 = 49.33).

Respondents in the wet lowland agro-ecology on average earned more income from crop enterprise (1,858 birr) compared to 1,338 birr for the dry lowland (t = -4.9895; P < 0.001). The higher income in the wet lowland agro-ecology is associated with longer experience in crop farming and better use of agricultural technologies. The average cultivated land per household in the wet lowland agro-ecology was 1.68 ha, compared to 1 ha in the dry lowland, and the mean difference is significant at 1% probability level (t = -9.6467). In terms of total land owned, the average was 6.6 ha in the wet lowland agro-ecology compared to 5.8 ha in the dry lowland (t = -3.2930; P < 0.001). With respect to farming experience, the average was 17.9 for the wet lowland agro-ecology compared to 13 years for the dry lowland (Table 2).

3.2 Determinates of Using SLM Practices

Thirteen explanatory variables were included in the binary probit regression model as determinant factors affecting use of SLM measures as adaptation strategy. Tables 3 and 4 depict the mean values of the explanatory

Table 3 Descriptive summary of explanatory variables (adaptation 1).

Independent Variables \ Dependent variables	Adaptation to climate change using adaptation 1						t value
	Famers who adapt (n = 316)		Farmers who do not adapt (n = 418)		Total (N = 734)		
	Mean	SD	Mean	SD	Mean	SD	
Slope	2.897196	0.649081	2.153846	0.877058	2.472000	0.868749	-10.8913***
Crop income	2,131.523	1,299.587	1,199.157	924.9919	1,598.21	1,192.831	-8.9371***
Exposure adaptation	0.696262	0.460949	0.332168	0.471816	0.488000	0.500357	-8.6512***
Exposure perception	2.084112	0.707060	1.475524	0.613671	1.736000	0.720654	-10.0694***
Prone farmland	0.691589	0.462920	0.479021	0.500435	0.570000	0.495572	-4.9064***
No parcel	1.822430	0.735589	2.164912	1.016153	2.018036	0.921451	4.3666***
Cultivated land	1.611784	0.879643	1.141653	0.770244	1.342733	0.850461	-6.2192***
Farm distance	1.761519	1.044059	2.243951	1.254578	2.037470	1.192203	4.6864***
Active labor	2.485981	1.173770	2.122378	0.985361	2.278000	1.084005	-3.6668***
Perception	0.789720	0.408463	0.398601	0.490469	0.566000	0.496121	-9.7152***
Farm experience	17.00467	9.251569	14.26573	6.179708	15.43800	7.757998	-3.7499***
Agro-ecology	0.612150	0.488403	0.416084	0.493772	0.500000	0.500501	-4.4206***
Education	1.280374	1.032745	0.451049	0.805278	0.806000	0.997172	-9.7390***

*** Values are significantly different at P < 0.001.

Table 4 Descriptive summary of explanatory variables (adaptation 2).

Independent Variables \ Dependent variables	Adaptation to climate change using adaptation 2						t value
	Famers who adapt (n = 440)		Farmers who do not adapt (n = 294)		Total (n = 734)		
	Mean	SD	Mean	SD	Mean	SD	
Slope	2.678930	0.779729	2.164179	0.904384	2.472000	0.868749	-6.5893***
Crop income	1,601.662	1,173.684	1,593.075	1,223.696	1,598.210	1,192.831	-0.0782
Exposure adaption	0.600000	0.496107	0.400000	0.483509	0.500000	0.500357	-4.4966***
Exposure perception	1.856187	0.706670	1.557214	0.705663	1.736000	0.720654	-4.6423***
Prone farmland	0.685619	0.465047	0.398010	0.490710	0.570000	0.495572	-6.5615***
No parcel	1.976510	0.814092	2.079602	1.060015	2.018036	0.921451	1.1662
Cultivated land	1.439354	0.838267	1.199965	0.850312	1.342733	0.850461	-3.1000***
Farm distance	1.967525	1.176693	2.141517	1.210374	2.037470	1.192203	1.5937
Active labor	2.294314	1.033175	2.253731	1.157713	2.278000	1.084005	-0.4011
Perception	0.688963	0.463694	0.383085	0.487353	0.566000	0.496121	-7.0159
Farm experience	15.57525	7.812625	15.23383	7.690907	15.43800	7.757998	-0.4836
Agro-ecology	0.628763	0.483946	0.308458	0.463010	0.500000	0.500501	-7.4472***
Education	0.933110	1.014430	0.616915	0.942079	0.806000	0.997172	-3.5672***

*** Values are significantly different at $P < 0.001$.

variables included in the model, revealing statistically significant difference between users and non-users of the practices.

Prior to running the probit model, the explanatory variables were checked for existence of multicollinearity problem using variance inflation factor (VIF). Based on the VIF(X_i), the data has no problem of multicollinearity with a mean VIF value of 1.21, and for each explanatory variable, the value of VIF is less than 10 (Table 5). Hence, all explanatory variables are included in the model. Finally, maximum likelihood estimation method was used to elicit the parameter estimates of the probit model.

Accordingly, for structural/physical land management practice (adaptation 1), out of the 13 explanatory variables hypothesized to explain farmers' decision of use of the practice, 11 were affirmed to be statistically significant, while two were less powerful in explaining the variation in the dependent variable (Table 6). The chi-square test confirms the overall goodness of fit of the model at less than 1% probability level. Table 6 also portrays the calculated marginal effects after probit, which measure the expected changes in the probability of adaptation with respect to a unit change in an independent variable.

Similarly, for use of non-structural land management techniques (adaptation 2), eight explanatory variables and their marginal values are statistically significant in explaining farmers' decision to use the practice and are generally in the directions that would be expected (Table 7).

3.2.1 Slope Category of Cultivated Land

For structural measures (adaptation 1), this variable took the expected positive sign, and its coefficient is significant at less than 1% probability level. If all other things held constant, the probability of adaptation through structural land management techniques increases by an average of 23.5% as the slope category of the farm land changes from flat to higher slope category. Similarly, this variable positively and significantly influenced adaptive responses through non-structural land management (adaptation 2) practices ($P < 0.01$). On average, probability of adaptation increases by 9.4% as the slope category of farm land changes from flat to steep and very steep. This finding is in line with results of past studies that showed a positive relationship between slope category of a parcel and land management decisions [21-23].

3.2.2 Income from Crop Enterprise

The sign of this explanatory variable is consistent with the a priori expectation, and it is positively and significantly associated to farmers' decision to use structural land management measures at 1% probability level. The calculated marginal effect shows

Table 5 Variance inflation factor (VIF) for explanatory variables.

Variable	VIF	1/VIF
Agro-ecology	1.50	0.665541
Cultivated land	1.34	0.748889
Slope	1.27	0.784632
Prone farmland	1.26	0.794141
Exposure adaptation	1.21	0.826790
Perception	1.21	0.828529
Farm experience	1.20	0.834582
Exposure perception	1.17	0.853042
Crop income	1.16	0.864430
No parcel	1.15	0.871594
Education	1.14	0.874496
Active labor	1.08	0.921693
Farm distance	1.08	0.922661
Mean VIF	1.21	

Table 6 Parameter estimates of the prbit regression model with marginal effects for adaptation 1.

Adaptation 1	Coefficient	Robust standard error	*Z*	*P*-value	Marginal effect (dy/dx)
Slope:					
2 (gentle)	0.859651	0.535813	1.60	0.109	
3 (steep)	2.388772***	0.517087	4.62	0.000	0.235232***
4 (very steep)	2.759203***	0.709283	3.89	0.000	
Crop income	0.000969***	0.000166	5.84	0.000	0.0001937***
Exposure adaptation	1.434466***	0.315493	4.55	0.000	0.2892063***
Exposure perception:					
2 (medium exposure)	1.283574***	0.356038	3.61	0.000	0.2672321***
3 (high exposure)	2.394583***	0.443460	5.40	0.000	
Prone farmland	0.523634	0.351561	1.49	0.136	0.1018843
No parcel	-0.83610***	0.223834	-3.74	0.000	-0.1697717***
Cultivated land	0.71687***	0.221225	3.24	0.001	0.1608822****
Farm distance	-0.38728***	0.129279	-3.00	0.003	-0.0822392***
Active labor	0.461275***	0.167923	2.75	0.006	0.0961324***
Perception	1.658744***	0.332317	4.99	0.000	0.3268772***
Farm experience	0.04125*	0.025020	1.65	0.099	0.0068929
Agro-ecology	1.38613***	0.379753	3.65	0.000	0.2573748***
Education:					
1(basic education)	1.738040**	0.514294	3.38	0.001	
2 (primary education)	2.075244***	0.407237	5.10	0.000	0.2138982***
3 (secondary education)	2.723195***	0.571008	4.77	0.000	
Constant	-6.94869***	1.063771	-6.53	0.000	
Number of observation	734				
Wald chi2	131.87				
Prob > chi2	0.0000				

***, ** and * indicate significance levels at 1%, 5% and 10%, respectively.

Table 7 Parameter estimates of the probit regression model with marginal effects (adaptation 2).

Adaptation 2	Coefficient	Robust standard error	*Z*	P-value	Marginal effect (dy/dx)
Slope:					
2 (gentle)	0.282189	0.207788	1.36	0.174	
3 (steep)	0.612079***	0.197267	3.10	0.002	0.0941255***
4 (very steep)	0.531583*	0.307448	1.73	0.084	
Crop income	0.000190***	0.000053	-3.48	0.000	0.0000697***
Exposure adaptation	0.277658**	0.139614	1.99	0.047	0.1007365*
Exposure perception:					
2 (medium exposure)	0.450258***	0.144868	3.11	0.002	0.0655957*
3 (high exposure)	0.157895	0.197197	0.80	0.423	
Prone farmland	0.318202*	0.137312	2.32	0.020	0.1268056*
No parcel	-0.06158	0.073625	-0.84	0.403	-0.0240607
Cultivated land	0.058839	0.085434	0.69	0.491	0.0237616
Farm distance	0.054931	0.054455	1.01	0.313	0.0154823
Active labor	-0.01193	0.055596	-0.21	0.830	0.0006254
Perception	0.615679***	0.138079	4.46	0.000	0.2344940***
Farm experience	0.021280*	0.009264	-2.30	0.022	0.0078245*
Agro-ecology	0.869699***	0.163101	5.33	0.000	0.3014664***
Education:					
1 (basic education)	0.244881	0.210366	1.16	0.244	
2 (primary education)	0.251007	0.15634	1.61	0.108	0.027255
3 (secondary education)	-0.08917	0.291392	-0.31	0.760	
Constant	-0.89408	0.335098	-2.67	0.008	
Number of observation	734				
Wald chi2	117.88				
Prob > chi2	0.0000				

***, ** and * indicate significance levels at 1%, 5% and 10%, respectively.

that probability of using structural land management techniques as adaptation strategy increases by 0.02% as income from crop enterprise increases by 1 birr, implying that more income may ease the constraint on liquidity needed for investment on SLM practices. Likewise, this variable is positively associated with using non-structural land management practices ($P < 0.01$). The calculated marginal effect shows that the probability of adaptation through non-physical land management techniques increases by 0.007% as income from crop enterprise increases by 1 birr.

3.2.3 Exposure to Adaptation Practices

This variable had positive and significant effect on farmers' decision to practices structural land management measures ($P < 0.01$). The calculated marginal effect shows that the probability to adopt the techniques increases by 28.9% for farmers who have past knowledge of adaptation measures. This variable is also positively and significantly associated with using non-structural land management practices ($P < 0.01$) with a calculated marginal effect of 10%. The findings are in line with previous studies that reveal knowing available options makes smallholder farmers to be more receptive [23, 24].

3.2.4 Perceived Risk Level of Farmland

This variable is positively and significantly related to the dependent variable (adaptation 1) at 1% probability level. The probability of using structural land management techniques increases on average by 26.7% as the perceived risk of land degradation changes moves from low/no risk to medium and high risk level. However, this variable is not significant in affecting farmers' decision to use non-structural land management measures.

3.2.5 Number of Parcels

This variable negatively and significantly influenced farmers' adaptation decision through structural land management measures, and the finding is consistent with previous studies [23-25]. The marginal effect shows the probability of using the practices decreases by 17% as the number of parcels owned increase by 1. This justifies that installing physical structures in small and fragmented plots creates difficulty on farming, as it squeezes operations between the structures and also induces further stress on the scanty resources available at disposal of smallholder farmers. However, this variable is less important in determining farmers' decision to use non-structural land management practices.

3.2.6 Size of Cultivated Land

This variable is positively and significantly related to the use of structural land management practices ($P < 0.01$), and the finding is in line with prior hypothesis and past studies [24, 25]. The probability of using the practice increases by 16.1% as the size of cultivated land increases by 1 ha, justifying that structural land management measures are non-scale neutral and cannot be equally applied to all land sizes. However, this variables does not affect use of non-structural measures, as these practices are scale-neutral and can be equally applied both to small and large land sizes.

3.2.7 Farm-Home Distance

This variable influenced farmers' use of structural land management techniques negatively and significantly ($P < 0.01$). The probability of using the measures decreases by 8.2% as farm-home distance increases by 1 km. This implies that the further the location, the higher would be the opportunity cost of labor and other resources used for the practice, and hence farmers refrain from allocating resources. However, this variable is not important in affecting use of non-structural measures, since the practices are non-labor intensive as compared to structural measures.

3.2.8 Economically Active Household Size

Farmers' decision to use structural land management practices is positively and significantly associated with the size of economically active family ($P < 0.01$). The probability of using the practice increases by 9.6% as the number of economically active family members increases by 1, implying that more active members in a family provides the labor that might be required by the practices. However, this variable has no significant effect on the use non-structural land management measures as the practices are less labor intensive compared to the structural measures.

3.2.9 Farmer's Perception of Climate Change

Consistent with a priori expectation and past research findings [24, 25], this variable is positively and strongly related with use of structural land management measures ($P < 0.01$), showing that perceiving climate change as a risk induces adaptive response. The calculated marginal effect shows that the probability of the practice will increase by 32.7% for farmers who perceived climate change as a risk. Likewise, perception of climate change positively and strongly induces use of non-structural measures ($P < 0.01$). The marginal effect indicates that the probability of using these techniques increases by 23.4% for those farmers who perceive climate change.

3.2.10 Cultivated Land Prone to Land Degradation

This variable is significantly and positively associated with use of non-structural land management practices ($P < 0.05$). The calculated marginal effect shows that as the cultivated land's exposure risk increases, the probability of adaptation through non-structural land management measures increases by 12.7%. However, the role of this variable in affecting the use of structural land management measures is statistically insignificant.

3.2.11 Farm Experience

This variable is positively associated with use of non-structural land management practices at 5% significance level, implying that farmers with long farming experience are well aware of the risk of climate change and opt to adapt to the challenges. The marginal effect shows that the probability of using non-structural land management practices increases by 0.7% for each additional year of farming experience. However, the variable is not statistically significant in affecting use of structural land management techniques.

3.2.12 Education Level of the Respondent

Education is positively and significantly related with using structural land management techniques at 1% probability level. The calculated marginal effect shows that the probability of practicing the techniques increases by 21.3% as the level of education increases. This finding is in agreement with past research, which justified the role of education in inducing famers' decision to adopt agricultural technologies [26, 27]. Nevertheless, the role of education in affecting the use of non-structural land management practices is not statistically significant.

3.2.13 Agro-ecology

Dwelling and farming in the wet lowland agro-ecology is positively and significantly associated with farmers' use of structural land management measure, and the probability of using the practices will increase by 25.7% for farmers in this agro-ecology. Likewise, the probability of using non-physical land management measures increases by 30% for farmers in this agro-ecology. This finding is alike with the prior expectations and past research findings [26, 27], and shows that farmers living in the wet lowland agro-ecology are more experienced, better exposed to adaptation measures and have better access to climate specific extension advises compared to farmers in dry lowland agro-ecology.

3.3 Comparison of Probit Regression Results for Adaptation 1 and 2

Four explanatory variables (number of parcels, land size, farm-home distance and economically active family), which are strongly decisive in determining farmers' decision to practice structural land management techniques, were found to be less important in affecting the decision to use non-structural land management practices. This implies that these explanatory variables only affect the decision to use structural land management techniques (which are non-scale neutral in terms of land size, parcel size, labor and distance). However, the variables are less important in affecting the use of the non-structural land management techniques (which are scale neutral) that can be indiscriminately applied irrespective of physical

Table 8 Comparison of marginal effects after probit.

Explanatory variables	Adaptation 1 (structural measures)		Adaptation 2 (non-structural measures)	
	Marginal effect (dy/dx)	*P*-value	Marginal effect (dy/dx)	*P*-value
Slope	0.235232***	0.000	0.0941255***	0.003
Crop income	0.0001937***	0.000	0.0000697***	0.000
Exposure adaptation	0.2892063***	0.000	0.1007365*	0.051
Exposure perception	0.2672321***	0.000	0.0655957*	0.081
Prone farmland	0.1018843	0.147	0.1268056*	0.014
No parcel	-0.1697717***	0.000	-0.0240607	0.375
Cultivated land	0.1608822****	0.000	0.0237616	0.470
Farm distance	-0.0822392***	0.002	0.0154823	0.450
Active labor	0.0961324***	0.004	0.0006254	0.976
Perception	0.3268772***	0.000	0.2344940***	0.000
Farm experience	0.0068929	0.162	0.0078245*	0.022
Agro-ecology	0.2573748***	0.000	0.3014664***	0.000
Education	0.2138982***	0.000	0.027255	0.293

***, ** and * indicate significance at 1%, 5% and 10% levels, respectively.

size. Besides, the strength of some of the significant explanatory variables varies between the two land management categories, as can be depicted from the respective significance levels (Table 8).

Moreover, for all the significant explanatory variables, the calculated marginal effects after probit are higher for structural land management techniques compared to the non-structural measures. Apart from these, two explanatory variables (farm experience and farm land prone to land degradation), which are not important in explaining use of structural land management techniques, are turned out to be significant in determining farmers use of non-structural land management techniques (Table 8). Therefore, the comparison of the marginal effects from the probit regression decrees that any intervention that promotes use of land management techniques as adaptation strategy should take into account the specific factors relevant with the nature of the practices.

4. Conclusions and Recommendation

The present study employed descriptive statistic to characterize the two agro-ecologies of the study area and compare users and non-users of SLM practices as adaptive response to climate change. The study also employed binary probit regression model to analyze the determinants of using SLM practices as adaptation strategy. The model results indicate that slope, exposure to adaptation, perceived land degradation, number of parcels, income from crop enterprise, size of cultivated land, farm-home distance, size of active family, perception of climate change, agro-ecology and education are important in determining farmers' decision to use land management practices as adaptation strategy.

Four explanatory variables, which are strongly decisive in determining farmers' decision to use structural land management techniques, are found to be less important in determining the decision to use non-structural land management practices. Moreover, two explanatory variables, which are not important in explaining farmer's decision to use structural land management techniques, are turned out to be important in determining the decision to use non-structural land management techniques.

These findings verbalize that any policy or development intervention that promotes use of SLM practices as adaptation strategy should take into account specific factors that are relevant to the nature of the practices. The results from both descriptive statistics and probit regression model also reveal that agro-ecology differences determine perception and adaptation decision, and hence agro-ecology specific intervention is required to enhance smallholder farmers' adaptation to climate change. Besides, SLM practices are knowledge and resource intensive and may not be implemented easily, given the limited awareness level and resource constraints of smallholder farmers. Therefore, scaling up of the practices as adaptation strategy should be backed by both public and non-public investments to raise awareness and to provide technological support. Failure to do so would adversely affect crop productivity and food security at farm household level.

Acknowledgements

The authors wish to express profound gratitude to Addis Ababa University for financial and facility support in accomplishing this paper.

References

[1] Intergovernmental Panel on Climate Change (IPCC). 2007. "Climate Change 2007: Impacts, Adaptation and Vulnerability." In *Contribution of Working Group II to the Fourth Assessment Report.* Cambridge, UK: Cambridge University Press.

[2] Adger, W. N. 2003. "Social Capital, Collective Action and Adaptation to Climate Change." *Economic Geography* 79 (4): 387-404.

[3] Stern, N. 2007. *The Economics of Climate Change: The Stern Review.* Cambridge: Cambridge University Press.

[4] World Bank Group. 2010. "Economics of Adaptation to Climate Change." Ethiopian Country Study, Washington, Accessed August 6, 2010.

https://siteresources.worldbank.org/EXTCC/Resources/EACC_FinalSynthesisReport0803_2010.pdf.

[5] Asrat, P., and Belay, S. 2017. “Adaptation Benefits of Climate-Smart Agricultural Practices in the Blue Nile Basin: Empirical Evidence from North-West Ethiopia.” In *Climate Change Adaptation in Africa: Fostering African Resilience and Capacity to Adapt,* edited by Filho, W. L., Belay, S., Kalangu, J., Menas, W., Munishi, P., and Musiyiwa, K. Vol. 1. Cham, Switzerland: Springer International Publishing AG.

[6] Tizale, C. Y. 2007. “The Dynamics of Soil Degradation and Incentives for Optimal Management in Central Highlands of Ethiopia.” Ph.D. thesis, Department of Agricultural Economics, Extension and Rural Development, University of Pretoria, South Africa.

[7] Bizuneh, A. M. 2013. *Climate Variability and Change in the Rift Valley and Blue Nile Basin Ethiopia: Local Knowledge, Impacts and Adaptation.* Berlin: Logos Verl.

[8] Tadege, A. 2007. “Climate Change National Adaptation Program of Action (NAPA) of Ethiopia.” National Meteorological Agency, Ministry of Water Resources, Federal Democratic Republic of Ethiopia, Addis Ababa. Accessed June 2007. https://unfccc.int/resource/docs/napa/eth01.pdf.

[9] Philander, S. G. 2008. *Encyclopedia of Global Warming and Climate Change.* California: SAGE Publication, Inc.

[10] National Meteorological Services Agency (NMSA). 2001. “Initial National Communication of Ethiopia to the United Nations Framework Convention on Climate Change (UNFCCC).” NMSA, Ministry of Water Resources, Federal Democratic Republic of Ethiopia. Accessed July 2017. https://unfccc.int/resource/docs/natc/ethnc1.pdf.

[11] Camberlin, P. 2009. “Nile Basin Climates.” In *The Nile: Origin, Environments, Limnology and Human Use,* edited by Dumot, H. J. Vol. 89. Netherlands: Springer, 307-33.

[12] IGAD-ICPAC. 2007. “Climate Change and Human Development in Africa: Assessing the Risks and Vulnerability of Climate Change in Kenya, Malawi and Ethiopia.” Human Development Reports, UNDP. Accessed May, 2007. http://www.africa-adapt.net/media/resources/360/igad.pdf.

[13] Dercon, S. 2004. “Growth and Shocks: Evidence from Rural Ethiopia.” *Journal of Development Economics* 74 (2): 309-29.

[14] Deressa, T. T., Hassan, R. M., and Ringler, C. 2011. “Perception of and Adaptation to Climate Change by Farmers in the Nile basin of Ethiopia.” *Journal of Agricultural Science* 149 (1): 23-31.

[15] Mertz, O., Mbow, C., Reenberg, A., and Diouf, A. 2009. “Farmers’ Perceptions of Climate Change and Agricultural Adaptation Strategies in Rural Sahel.” *Environmental Management* 43 (5): 804-16.

[16] Nkonya., E., Place, F., Pender, J., Mwanjololo, M., Okhimamhe, A., Kato, E., Crespo, S., Ndjeunga, J., and Traore, S. 2011. “Climate Risk Management through Sustainable Land Management in Sub-Saharan Africa.” IFPRI Discussion Paper 01126, International Food Policy Research Institute (IFPRI). Accessed December 2011. http://ebrary.ifpri.org/cdm/ref/collection/p15738coll2/id/124952.

[17] Lobell, D. B., Burke, M. B., Tebaldi, C., Mastrandrea, M. D., Falcon, W. P., and Naylor, R. L. 2008. “Prioritizing Climate Change Adaptation Needs for Food Security in 2030.” *Science* 319 (5863): 607-10.

[18] Norris, P. E., and Batie, S. S. 1987. “Verginia Farmers’ Soil Conservation Decisions: An Application of Tobit Analysis.” *Southern Journal of Economics* 19: 79-90.

[19] Pryanishnikov, I., and Zigova, K. 2003. “Multinomial Logit Models for Austrian Labor Market.” *Austrian Journal of Statistics* 32 (4): 267-82.

[20] Greene, W. H. 2000. *Econometric Analysis,* 4th ed.. New Jersey: Prentice Hall.

[21] Ervin, C. A., and Ervin, E. D. 1982. “Factors Affecting the Use of Soil Conservation Practices: Hypothesis, Evidence and Policy Implications.” *Land Economics* 58 (3): 277-92.

[22] Gould, B. W., Saupe, W. E., and Klemme, R. M. 1989. “Conservation Tillage: The Role of Farm and Operator Characteristics and the Perception of Soil Erosion.” *Land Economics* 65 (2): 167-82.

[23] Asrat, P., Belay, K., and Desta, H. 2004. “Determinants of Farmers’ Willingness to Pay for Soil Conservation Practices in the Southeastern Highlands of Ethiopia.” *Land Degradation and Development* 15 (4): 433-8.

[24] Bekele, S., and Holden, S. T. 1998. “Resource Degradation and Adoption of Land Conservation Technologies in the Ethiopian Highlands: A case Study in Andit Tid, North Shewa.” *Agricultural Economists* 18 (3): 233-47.

[25] Vieth, G. R., Gunatilake, H., and Cox, L. J. 2001. “Economics of Soil Conservation: The Upper Mahaweli Watershed for Sirelanka.” *Journal of Agricultural Economics* 52 (1): 139-52.

[26] Pender, J. L., and Kerr, J. M. 1998. “Determinants of Farmers’ Indigenous Soil and Water Conservation Investments in India’s Semi-Arid Tropics.” *Agricultural Economics* 19: 113-25.

[27] Egziabher, T. G. 1999. “Willingness to Pay for Environmental Protection: An Application of Contingent Valuation Method (CVM) in Sekota District, Northern Ethiopia.” *Ethiopian Journal of Agricultural Economics* 3 (1): 123-30.