ISSN 2306-7195
SMU

JAD 9 (2) 2019

Journal of Agriculture and Development

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Agriculture is the most important sector in the Ethiopian economy, contributing the lion's share of the GDP. Nearly 80% of the population live in the rural areas and derive their livelihoods directly or indirectly from agriculture. Given its importance, the performance of the sector is therefore reflected in the performance of the whole economy. With this background, the Journal of Agriculture and Development aims to stimulate research and thinking on agriculture and development studies in Ethiopia. The articles contained in the journal reflect the views of their authors and do not necessarily coincide with those of the Editorial Committee, Institute of Agriculture and Development Studies, JADS or of SMU.

Journal of Agriculture and Development

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Journal of Agriculture and Development

JAD 9 (2) 2019 December 2019

CONTENTS

Land Management Decisions in a Changing Climate: Empirical Evidence from North-West Ethiopia

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Abstract

The paper is aimed at determining the factors that influence farmers' decision to use two categories of sustainable land management (SLM) practices as climate change adaptation strategy in the Dabus sub-basin. It is based on analysis of data collected from 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 to be 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 SLM practices as adaptation strategy should take in to account agro-ecology specific factors that are relevant to the nature of the land management practices. Moreover, since scaling up of SLM practices 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.

Keywords: *climate change, adaptation, sustainable land management, structural/physical, non-structural*

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Introduction

The impact of climate change is detrimental in low-income Tropical African countries including Ethiopia that depend on agriculture as a main livelihood. The combination of the already fragile environment, dominance of the climate-sensitive sector in the economy, and low autonomous adaptive capacity in these regions aggravates the harmful effects of climate change and variability on agricultural production, food security, and ecosystems (IPCC 2007b). 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 (IPCC 2007b; Adger *et al*., 2005; Stern, 2007; World Bank 2010).

Ethiopia is heavily dependent on a 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 (Yirga, 2007). 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 (Abate, 2013; Tadege, 2007). 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 since 1988. During the two recent drought events, GDP declined by around 3-10 percent 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 (Nkonya. 2011; Tadege, 2007).

Following such recurrence of extreme events and the catastrophic effects, climate researchers believe Ethiopia as one of the victims of climate change (Philander 2008). 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 0.1^0C and 0.25^0C per decade, respectively (NMSA 2001). Historical trend also shows that mean temperature increased by 1.3^0C from 1996-2006 with more hot days and nights and fewer cold days and nights. The rainfall is highly variable from year to year, 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 percent each year (Nkonya, 2011; Camberlin, 2009).

With regard to the future, GCM (General Circulation Models) predictions show an increasing trend of temperature with moderate inter-model differences (Camberlin, 2009). Considering different emission scenarios, mean annual temperature will increase in the range of 0.9 and 1.1 ^{0}C by the year 2030 and in between 1.7 to 2.1 ^{0}C by the year 2050 from the average of 1961-1990 (IGAD-ICPAC 2007). Whereas, the corresponding result for annual precipitation show a change between 0.6 and 4.9 percent for 2030 and between 1.1 and 18.2 percent for 2050. Following this, the 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 percent by 2030 due to changes in the mean seasonal temperature and precipitation with more severe impacts towards the end of the century (IGAD-ICPAC, 2007).

Agriculture's heavy dependence on rainfall signifies that the main source of the economy is rooted on climate sensitive sector, and hence an episode of a single climate event could retard or even reverse whatever economic growth achieved in the past. In line with this, a study on consumption in rural Ethiopia (Dercon, 2004) shows that a rainfall shock in a single year has a lingering effect on household's welfare for many years to come. The same study showed that a 10 percent rainfall decrease in one year has an impact of 1 percent decrease on the growth rates of agricultural output for 4 to 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. Overall, climate impacts in Ethiopia are significant, but variable over regions and economic sectors. Thus, given the agro-ecological diversity of the country, understanding location specific climate pattern, its impacts on agricultural production and possible resilience options seems to be critical (Simane *et al*., 2016; Mertz *et al*., 2009).

Studies indicated that smallholder farmers perceive climate change and also adapt to reduce the negative impacts (Deressa *et al*., 2011; Mertz *et al*., 2009). In this regard, sustainable land management (SLM) practices have been shown to be effective for adaptation in moisture stress areas. Empirical evidence has also shown that synergistic relationships exist among different SLM practices (Nkonya, 2011). That is, holding all else constant, a household that uses more than one practice is likely to have better adaptation than a household using a single practice.

Soil and water conservation practices and agronomic practices that include improved crop varieties, soil fertility management practices, crop rotation, intercropping, conservation tillage, and agro-forestry practices enhance adaptation to climate change, reduce crop production risk and increases crop productivity (Nkonya, 2011; Lobell, 2008). However, previous studies in Ethiopia failed to explicitly address land management-based adaptation methods that farmers employ at local level given the diverse agro-ecological setting of the country. Existing studies are also highly aggregated and are of little help in addressing agro-ecology specific adaptations to climate change. They have paid little attention to the analysis of SLM practices as adaptation strategy and the factors influencing farmers' decision to use the practices. 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 is aimed at filling these knowledge gaps

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 (Pryanishnikov, 2003; Ervin and Ervin, 1982). On these premises, probit regression model is selected to analyze the determinants of using two sets of SLM practices (structural/physical and non-structural measures) as an adaptation strategy in the Dabus sub-basin. The structural/physical land management techniques refer to the use of physical soil and water conservation measures whereas the non-structural measures refer to agronomic practices such as the use of improved crop varieties, use of soil fertility management techniques, crop diversification, intercropping, crop rotation, conservation tillage, and changing planting date. The major focus of this paper is, therefore, to explore how physical, human, natural, and socio-economic factors influence farmer's decision to use these two sets of

SLM practices as adaptation strategy considering two major agro-ecologies in the Dabus sub-basin of the Blue Nile River.

Methodology

Data source and type

The paper is based on a cross-sectional household survey data of 734 mixed farmers enumerated during November and December 2016 from the Dabus sub-basin of the Blue Nile River in the North-west part of Ethiopia. The primary data majorly include demographic, socioeconomic, institutional, and biophysical attributes of the respondents. The data also include information on the types of SLM practices being implemented by smallholder farmers, factors affecting the practices and the constraints in implementing the practices. Survey questionnaires, FGD, and field observation were the data collection methods employed. Household-level data were collected through an open and close-ended survey questionnaire. FGD were also carried out to complement the responses acquired through the survey questionnaire. The primary data were substantiated by the data obtained from secondary sources.

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-climatic zones 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 the econometric method, the study employed the probit regression model to analyze the determinants of using the two sets of SLM practices as adaptation strategy to climate change.

Specification of the probit model

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 (Deressa et al. 2011). The models are based on farmers' utility or profit-maximizing behavior (Greene 2000) and the assumption here is that farmers adopt a technology/practice only when the perceived utility or 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 the determinants of farmers decision to use SLM practices as adaptation strategy.

It is assumed that subsistence 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 Y_j and Y_k represent a household's utility for the two choices, which are denoted by U_j and U_k , respectively. The linear random utility model could then be specified as:

$$U_j = \beta_j X_i + \varepsilon_j \quad \text{And} \quad U_k = \beta_k X_i + \varepsilon_k \quad \text{------------------------} \ (4.1)$$

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 (Green 2000) and Ervin (1982). 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 the other options (say *k*) depicted as:

$$U_{ij}\left(\beta_j X_i + \varepsilon_j\right) > U_{ik}\left(\beta_k X_i + \varepsilon_k\right), k \neq j \text{ -- (4.2)}$$

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

$$P\left(Y = 1 \middle| X\right) = P\left(U_{ij} > U_{ik}\right) \text{--- (4.3)}$$

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

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

$$P\left(X^* X_i + \varepsilon^* > 0 \middle| X = F\left(\beta^* X_i\right)\right.$$

where *P* is a probability function, *Uij, Uik,,* and *Xi* 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 (Green 2000).

As it is already mentioned, the purpose of this study is 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 zero or one depending on whether or not a farmer is applying any of the structural/physical or non-structural land management 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:

$$I_j^* = \beta X_j + \varepsilon_j \text{...}(4.4)$$

Where; β is vector of parameters of the model, Xj is vector of explanatory variables and *εj* is the error term assumed to have random normal distribution with mean zero and common variance δ^2 (Green 2000).

Ij= Unobservable households' actual decision to use a structural/physical and non-structural land management practice (which is also named to be a latent variable) 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

$$pro(adoption = 1) = \phi(\beta X_j) \text{...}(4.5)$$

$$pro(adoption = 0) = 1 - \phi(\beta X_j) \text{...}(4.6)$$

Definition of explanatory variables and working hypotheses

Dependent variable: The first dependent variable for the probit analysis (**adaptation1**) has a dichotomous nature measuring the decision of the farmer to use structural/physical SLM 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 (**Adaptation2**) has also a dichotomous nature measuring the decision of the farmer to use non-structural SLM 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.

The independent variables: It is hypothesized that the decision to make adaptive responses is influenced by a set of explanatory variables. Based on theories, the findings of past studies (Deressa *et al*., 2011, Nkonya, 2011;

Mertz *et al*., 2009; Deressa *et al*., 2009; Lobell, 2008; Asrat *et al*., 2004), and observation made in the study area, the variables presented in Table 4.1 are 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	+
Farmexperiance	Continuous	+/-
Activelabor	Continuous	+
Exposureadpt	Dummy	+
Cultivatedland	Continious	+
Slope	Categorical	+
Cropincome	Continuous	+
Noparcel	Integer	-
Exposurepercep	Categorical	+
Pronefarmland	Dummy	+
Farmdistance	Continuous	-
Agro-ecology	Dummy	+

Results and Discussion

Comparison of agro-climatic zones

Comparison of perception of climate change between the two agro-climatic zones indicated that 52 per cent of the respondents from the wet lowland and 62 per cent from the dry lowland had perceived change in climate (Table 4.2). This difference in perception between the two agro-climatic zones is statistically significant ($\chi 2 = 6.636$ with $P<0.01$). More perception in the dry lowland is attributed to the occurrence of a repeated drought and various environmental changes in recent years that caused crop failure. The majority of the respondents in the wet lowland (62 per cent) have exposure to adaptation measures to climate change as compared to 48 percent in the dry lowland showing existence of statistically verified difference between the two agro-climatic zones ($\chi2=14.659$ with $P<0.001$) in terms of exposure to adaptation measures.With respect to use of non-structural SLM practices, about 60 percent and 49 percent of the users are fond in the wet lowland and dry lowland, respectively (Table 4.2) and the difference in the use these practices between the two agro-climatic zones is statistically significant at 1 percent probability level ($\chi2=8.497$). However, the two agro-climatic zones are not statistically different in the use of physical SLM measures.

The average cultivated land per household in the wet lowland is 1.68 hectare compared to 1 hectare in the dry lowland and the mean difference is significant at 1 percent probability level (t =-9.6467). In terms of total land owned, the average is 6.6 hectares in the wet lowland as compared to 5.8 hectares in the dry lowland (t =-3.2930; P<0.001). With respect to farming experience, the average is 17.9 for the wet lowland as compared to 13 years for the dry lowland (Table 4.2).

Table 2 Comparison of agro-climatic zones in terms of socio-economic variables

Comparison variable		Agro-climatic zones						
		Wet lowland		Dry lowland		Total		χ^2 value
		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	191	52	206	56	397	54	0.714
	Users	176	48	161	44	337	46	
Adaptation through non-physical SLM	Non-users	147	40	187	51	334	46	8.497***
	Users	220	60	180	49	400	54	
		Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	***t* value**
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^{***}

*** Values are significantly different at $P < 0.01$

Determinants of SLM practices

Thirteen explanatory variables were included in the binary probit regression model as determinant factors affecting the use of SLM measures as adaptation strategy. Prior to running the probit model, the explanatory variables were checked for existence of multicollinearity problem using the 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 4.3). Hence, all the explanatory variables are included in the model. Finally, maximum likelihood estimation method was used to elicit the parameter estimates of the probit model.

Table 3 Variance Inflation Factor (VIF) for explanatory variables

Variable	**VIF**	**1/VIF**
Agroecology	1.5	0.665541
cultivated~d	1.34	0.748889
Slope	1.27	0.784632
pronefarml~d	1.26	0.794141
Exposureadpt	1.21	0.82679
Perception	1.21	0.828529
farmexperi~e	1.2	0.834582
exposurepe~p	1.17	0.853042
Cropincome	1.16	0.86443
Noparcel	1.15	0.871594
Educ	1.14	0.874496
Activelabor	1.08	0.921693
Farmdistance	1.08	0.922661
Mean VIF	**1.21**	

Tables 4 and 5 depict the mean values of the explanatory variables included in the model revealing statistically significant difference between users and non-users of the practices.

Table 4 Descriptive summary of explanatory variables (adaptation 1)

Dependent variable	Adaptation to climate change using structural/physical land management measures (adaptation 1)						
Independent variables	Famers who adapt (N=316)		Farmers who do not adapt (N=418)		Total		t value
	Mean	SD	Mean	SD	Mean	SD	
Slope	2.897196	0.649081	2.153846	0.877058	2.472	0.868749	-10.8913***
Cropincome	12131.523	1299.587	11199.157	924.9919	1598.21	1192.831	-8.9371***
Exposureadpt	0.696262	0.460949	0.332168	0.471816	0.488	0.500357	-8.6512***
Exposurepercep	2.084112	0.70706	1.475524	0.613671	1.736	0.720654	-10.0694***
Pronefarmland	0.691589	0.46292	0.479021	0.500435	0.57	0.495572	-4.9064***
Noparcel	1.82243	0.735589	2.164912	1.016153	2.018036	0.921451	4.3666***
Cultivatedland	1.611784	0.879643	1.141653	0.770244	1.342733	0.850461	-6.2192***
Farmdistance	1.761519	1.044059	2.243951	1.254578	2.03747	1.192203	4.6864***
Activelabor	2.485981	1.17377	2.122378	0.985361	2.278	1.084005	-3.6668***
Perception	0.78972	0.408463	0.398601	0.490469	0.566	0.496121	-9.7152***
Farmexperiance	17.00467	9.251569	14.26573	6.179708	15.438	7.757998	-3.7499***
Agroecology	0.61215	0.488403	0.416084	0.493772	0.5	0.500501	-4.4206***
Educ	1.280374	1.032745	0.451049	0.805278	0.806	0.997172	-9.7390***

*** Values are significantly different at $P < 0.01$.

Table 5 Descriptive summary of explanatory variables (Adaptation2)

Dependent variable	Adaptation to climate change using non-structural land management measures (Adaptation2)						
Independent variables	Famers who adapt (N=440)		Farmers who do not adapt (N=294)		Total (N=734)		t value
	Mean	SD	Mean	SD	Mean	SD	
Slope	2.67893	0.779729	2.164179	0.904384	2.472	0.868749	t = -6.5893***
Cropincome	11601.662	1173.684	11593.075	1223.696	1598.21	1192.831	t = -0.0782
Exposureadpt	0.6	0.4961073	0.4	0.4835091	0.5	0.5003566	t = -4.4966***
Exposurepercep	1.856187	0.70667	1.557214	0.705663	1.736	0.720654	t = -4.6423***
Pronefarmland	0.6856187	0.465047	0.39801	0.49071	0.57	0.495572	t = -6.5615***
Noparcel	1.97651	0.814092	2.079602	1.060015	2.018036	0.921451	t = 1.1662
Cultivatedland	1.439354	0.838267	1.199965	0.850312	1.342733	0.850461	t = -3.1000***
Farmdistance	1.967525	1.176693	2.141517	1.210374	2.03747	1.192203	t = 1.5937
Activelabor	2.294314	1.033175	2.253731	1.157713	2.278	1.084005	t = -0.4011
Perception	0.6889632	0.463694	0.3830846	0.487353	0.566	0.496121	t = -7.0159
Farmexperiance	15.57525	7.812625	15.23383	7.690907	15.438	7.757998	t = -0.4836
Agroecology	0.6287625	0.483946	0.3084577	0.46301	0.5	0.500501	t = -7.4472***
Educ	0.9331104	1.01443	0.6169154	0.942079	0.806	0.997172	t = -3.5672***

*** Values are significantly different at $P < 0.01$.

For structural/ physical SLM practices (adaptation 1), out of the thirteen explanatory variables hypothesized to explain farmers' decision of use of the practice, eleven were affirmed to be significant, while two were less powerful in explaining the variation in the dependent variable (Table 4.6). The chi-square test confirms the overall goodness of fit of the model at less than 1% probability level. Table 4.6 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. For use of non-structural SLM measures (adaptation 2) 8 explanatory variables and their marginal values are statistically significant in explaining farmers' decision to use the practices and are generally in the directions that would be expected (Table 4.7).

Slope category of cultivated land** (slope)**: For the structural measures (adaptation 1), this variable took the expected positive sign and its coefficient is significant at less than 1 percent probability level. 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 categories. Similarly, this variable positively and significantly influenced the adaptive responses through non-structural SLM (adaptation 2) practices ($P<1\%$). On the average, probability of adaptation increases by 9.4 percent as the slope category of a farm land changes from flat to steep and very steep. This finding is in line with the results of past studies that showed a positive relationship between slope category of a parcel and land management decisions (Simane et al. 2016; Deressa et al. 2011; Asrat et al. 2004; Gould 1989).

Table 6 Parameter estimates of the prbit regression model with marginal effects (adaptation 1)

adaptation1	**Coef.**	**Robust Std. Err.**	**Z**	**P>z**	**dy/dx**
slope: 2(gentle)	0.859651	0.535813	1.6	0.109	0.235232***
3 (steep)	2.388772***	0.517087	4.62	0.000	
4 (very steep)	2.759203***	0.709283	3.89	0.000	
Cropincome	0.000969***	0.000166	5.84	0.000	0 .0001937***
Exposureadpt	1.434466***	0.315493	4.55	0.000	0.2892063***
Exposurepercep					0 .2672321***
2 (medium exposure)	1.283574***	0.356038	3.61	0.000	
3 (high exposure)	2.394583***	0.44346	5.4	0.000	
Pronefarmland	0.523634	0.351561	1.49	0.136	0.1018843
Noparcel	-0.8361***	0.223834	-3.74	0.000	-0.1697717***
Cultivatedland	0.71687***	0.221225	3.24	0.001	0.1608822****
Farmdistance	-0.38728***	0.129279	-3	0.003	-0.0822392***
Activelabor	0.461275***	0.167923	2.75	0.006	0.0961324***
Perception	1.658744***	0.332317	4.99	0.000	0.3268772***
Farmexperiance	0.04125*	0.02502	1.65	0.099	0.0068929
Agro-climatic zone	1.38613***	0.379753	3.65	0.000	0.2573748***
Educ					0.2138982***
1(Basic education)	1.73804***	0.514294	3.38	0.001	
2 (primary education)	2.075244***	0.407237	5.1	0.000	
3 (secondary education)	2.723195***	0.571008	4.77	0.000	
_cons	-6.94869***	1.063771	-6.53	0.000	
Number of obs	734				
Wald chi2(18)	131.87				
Prob > chi2	0.0000				

*** Values are significantly different at $P < 0.01$.

Income from crop enterprise *(cropincome):* 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 SLM measures at 1 percent probability level. The calculated marginal effect shows that the probability of using structural SLM techniques increases by 0.02 percent as income from crop enterprise increases by one birr implying that more income may ease the constraint on the liquidity needed for the investment in SLM practices. Likewise, this variable is positively associated with using the non-structural SLM practices as adaptation measure (P<1%). The calculated marginal effect shows that the probability of adaptation through non-physical SLM techniques increases by 0.007 per cent as income from crop enterprise increases by birr 1.

Exposure to adaptation practices *(exposureadpt)***:** This variable had positive and significant effect on farmers' decision to use structural SLM measures (P<1%). The calculated marginal effect shows that the probability to adopt the techniques increases by 28.9 percent for farmers who have past knowledge of adaptation measures. This variable is also positively and significantly associated with using non-structural SLM practices (P<1%) with a calculated marginal effect of 10 percent. The finding is in line with previous studies (Simane et al. 2016; Asrat et al. 2004; Bekele and Holden 1998) that revealed the positive role of previous exposure on the current adaptive responses of the smallholder farmers.

Table 7 Parameter estimates of the probit regression model with marginal effects (Adaptation2)

Adaptation2	**Coef.**	**Robust Std. Err.**	**Z**	**P>z**	**dy/dx**
slope					.0941255***
2(gentle)	0.282189	0.207788	1.36	0.174	
3 (steep)	0.612079***	0.197267	3.1	0.002	
4 (very steep)	0.531583*	0.307448	1.73	0.084	
Cropincome	0.00019***	5.34E-05	-3.48	0.000	.0000697***
Exposureadpt	0.277658**	0.139614	1.99	0.047	.1007365*
Exposurepercep					.0655957*
2 (medium exposure)	0.450258***	0.144868	3.11	0.002	
3 (high exposure)	0.157895	0.197197	0.8	0.423	
Pronefarmland	0.318202*	0.137312	2.32	0.02	.1268056*
Noparcel	-0.06158	0.073625	-0.84	0.403	-.0240607
Cultivatedland	0.058839	0.085434	0.69	0.491	.0237616
Farmdistance	0.054931	0.054455	1.01	0.313	.0154823
Activelabor	-0.01193	0.055596	-0.21	0.83	.0006254
Perception	0.615679***	0.138079	4.46	0.000	.234494***
Farmexperiance	0.02128**	0.009264	-2.3	0.022	.0078245**
Agro-climatic zone	0.869699***	0.163101	5.33	0.000	.3014664***
Educ					.027255
1(Basic education)	0.244881	0.210366	1.16	0.244	
2 (primary education)	0.251007	0.15634	1.61	0.108	
3 (secondary education)	-0.08917	0.291392	-0.31	0.76	
_cons	-0.89408	0.335098	-2.67	0.008	
Number of obs	497				
Wald chi2(18)	117.88				
Prob > chi2	0.0000				

***, ** and * Indicate significance levels at $P < 0.01$ and $P < 0.05$, and $p<0.1$, respectively

Perceived risk level of farm land (Exposurepercep)*:* This variable is positively and significantly related to the dependent variable (adaptation 1) at 1 percent probability level. The probability of using structural land management techniques increases on average by 26.7 percent as the perceived risk level of farm land's exposure to land degradation changes 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 as adaptation strategy.

Number of parcels (noparcel): This variable negatively and significantly influenced farmers' adaptation decision through structural land management measures and the finding is consistent with previous studies (Deressa et al. 2009; Asrat et al. 2004; Bekele and Holden, 1998; Vieth et al*,* 2001). The marginal effect shows the probability of using the practices decreases by 17 percent as the number of parcels owned increase by one. This justifies that installing physical structures in small and fragmented plots creates difficulty on farming as it squeezes farm operations between the structures and also induces further stress on the scanty resources available at disposal of the smallholder farmers. However, this variable is less important in determining farmers' decision to use non-structural land management practices as adaptation strategy.

Size of cultivated land (cultivatedland): This variable is positively and significantly related to the use of structural land management practices ($P<1\%$) and the finding is in line with the prior hypothesis and past studies (Simane *et al*., 2016; Bekele and Holden, 1998; Vieth *et al*., 2001). The probability of using the practice increases by 16.1 percent as the size of cultivated land increases by one hectare justifying that structural land management measures are non-scale neutral and cannot be equally applied to all land sizes. However, these variables don't affect the use of non-structural measures as these practices are scale-neutral and can be equally applied both to small and large land sizes.

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

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

Farmer's perception of climate-change (*perception*)***:*** Consistent with a *priori* expectation and past research findings (Deressa et al. 2011; Bekele and Holden, 1998; Vieth et al. 2001), this variable is positively and strongly related with the use of structural land management measures (P<1%) 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 percent for farmers who perceived climate change as a risk. Likewise, perception of climate change positively and strongly induces the use of non-structural measures ($P<1\%$). The marginal effect indicates that the probability of using these techniques increases by 23.4% for those farmers who perceive climate change.

Cultivated land prone to land degradation *(pronefarmland):* This variable is significantly and positively associated with the use of non-structural land management practices ($P<5\%$). 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.

Farm experience (farmexperiance): This variable is positively associated with the 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, farm experience is not statistically significant in affecting the use of structural land management techniques.

Education level of the respondent *(educ)**:*** Education is positively and significantly related with using structural land management techniques at 1 percent probability level. The calculated marginal effect shows that the probability of practicing the techniques increases by 21.3 percent as the level of education increases. This finding is in agreement with past research

(Deressa et al. 2009; Tegene 1999; Pender 1996), which justified the role of education in inducing famers' decision to adopt agricultural technologies. Nevertheless, the role of education in affecting the use of non-structural land management practices is not statistically significant.

Agro-climatic zone *(agroecology)***:** Dwelling and farming in the wet lowland agro-climatic zone 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 percent for farmers in the wet lowland. Likewise, the probability of using non-physical land management measures increases by 30 percent for farmers in the wet lowland. This finding is alike with the prior expectation and past research findings (Deressa, 2011; Asrat et al.2004) showing that farmers living in the wet lowland are more experienced, better exposed to adaptation measures and have better access to climate specific extension advises compared to farmers in dry lowland.

Relative importance of significant explanatory variables

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. Besides, the strength of some of the significant explanatory variables varies between the two SLM categories as can be depicted from the respective significance levels (Table 4.8).

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 the use of structural land management techniques are turned out to be significant in determining farmers use of non-structural land management techniques. The comparison of the marginal effects from the probit regression decrees that any intervention that promotes the use of SLM practices as adaptation strategy should take in to account the specific factors that are relevant to the nature of the practices.

Table 4.8 Comparison of marginal effects after probit for the two sets of SLM practices

Explanatory variables	Adaptation 1(structural measures)		Adaptation2 (non-structural measures)	
	dy/dx	**P>z**	**dy/dx**	**P>z**
slope	0.235232***	0.000	.0941255***	0.003
Cropincome	0 .0001937***	0.000	.0000697***	0.000
Exposureadpt	0.2892063***	0.000	.1007365*	0.051
Exposurepercep	0 .2672321***	0.000	.0655957*	0.081
Pronefarmland	0.1018843	0.147	.1268056*	0.014
Noparcel	-0.1697717***	0.000	-.0240607	0.375
Cultivatedland	0.1608822****	0.000	.0237616	0.47
Farmdistance	-0.0822392***	0.002	.0154823	0.45
Activelabor	0.0961324***	0.004	.0006254	0.976
Perception	0.3268772***	0.000	.234494***	0.000
Farmexperiance	0.0068929	0.162	.0078245*	0.022
Agroecology	0.2573748***	0.000	.3014664***	0.000
Educ	0.2138982***	0.000	.027255	0.293

***, ** and * Indicate significance levels at $P < 0.01$ and $P < 0.05$, and $p<0.1$, respectively.

Conclusions and Recommendations

In this study, descriptive statistic is employed to compare the two agro-climatic zones and 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 SLM practices as adaptation strategy. The model result indicates that slope, exposure to adaptation, perceived level of land degradation, number of parcels, income from crop enterprise, size of cultivated land, farm-home distance, size of economically active family, perception of climate change, agro-ecology and education are important in determining farmers' decision to use SLM practices as adaptation strategy.

Four explanatory variables, which are strongly decisive in determining farmers' decision to use structural SLM measures, were found to be less important in determining the decision to use non-structural SLM practices. Moreover, two explanatory variables, which are not important in explaining farmer's decision to use structural SLM techniques, are turned out to be important in determining the decision to use non-structural SLM techniques. These findings of this study verbalize that any intervention that promotes the use of SLM practices as adaptation strategy should take in to account specific factors that are relevant to the nature of the practices. The results also revealed that agro-climatic differences determine adaptation decision and hence location specific intervention is required to enhance smallholder farmers' adaptation to climate change. Besides, SLM practices are knowledge and resource intensive and may not be easily implemented given the limited awareness and resource constraints of the 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 sustainability of land use systems in subsistence agriculture.

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