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Article

Drivers of Sustainable Land Management in Eastern Africa

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Abstract: Land degradation is a serious impediment to improving rural livelihoods in Eastern Africa. This paper identifies major land degradation patterns and causes, and analyzes the determinants of sustainable land management (SLM) in three countries (Ethiopia, Malawi and Tanzania). The results show that land degradation hotspots cover about 51%, 41%, 23% and 23% of the terrestrial areas in Tanzania, Malawi and Ethiopia respectively. The analysis of nationally representative household surveys shows that the key drivers of SLM in these countries are biophysical, demographic, regional and socio-economic determinants. Secure land tenure, access to extension services and market access are some of the determinants incentivizing SLM adoption. The implications of this study are that policies and strategies that facilities secure land tenure and access to SLM information are likely to incentivize investments in SLM. Local institutions providing credit services, inputs such as seed and fertilizers, and extension services must also not be ignored in the development policies.

Keywords: adoption; land degradation; poisson regression; sustainable land management practices

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1. Introduction

Land degradation is an extensive and serious impediment to improving rural livelihoods and food security of millions of people in the eastern Africa. Recent estimates show that land degradation affected about 51%, 41%, 23% and 22% of the terrestrial areas in Tanzania, Malawi, Ethiopia and Kenya respectively [1 and Figure 1]. Addressing land degradation through the formulation of proper strategies and effective policies requires first the identification of both the proximate (direct) and underlying (indirect) causes [2,3,4]. In Tanzania, land degradation has been ranked as the top environmental problem for more than 60 years [5]. Soil erosion is considered to have occurred on 61% of the entire land area in this country [5]. Chemical land degradation, including soil pollution and salinization/alkalinisation, has led to 15% loss in the arable land in Malawi in the last decade alone [6]. The adoption and investment in sustainable land management is crucial in reversing and controlling land degradation, rehabilitating degraded lands and ensuring the optimal use of land resources for the benefit of present and future generations [7,8].

SLM, also referred to as 'ecosystem approach', ensures long-term conservation of the productive capacity of lands and the sustainable use of natural ecosystems. Sustainable land management is important for sustainable development because it facilitates land users to maximize the benefits from their land while maintaining the ecological support functions of the land resources [9]. The efforts directed at addressing the causes of land degradation or addressing the constraints to SLM adoption, however, have been largely insufficient. Recent reliable estimates show that the adoption of sustainable land management practices in sub-Saharan Africa is very low – about 3% of total cropland [10].

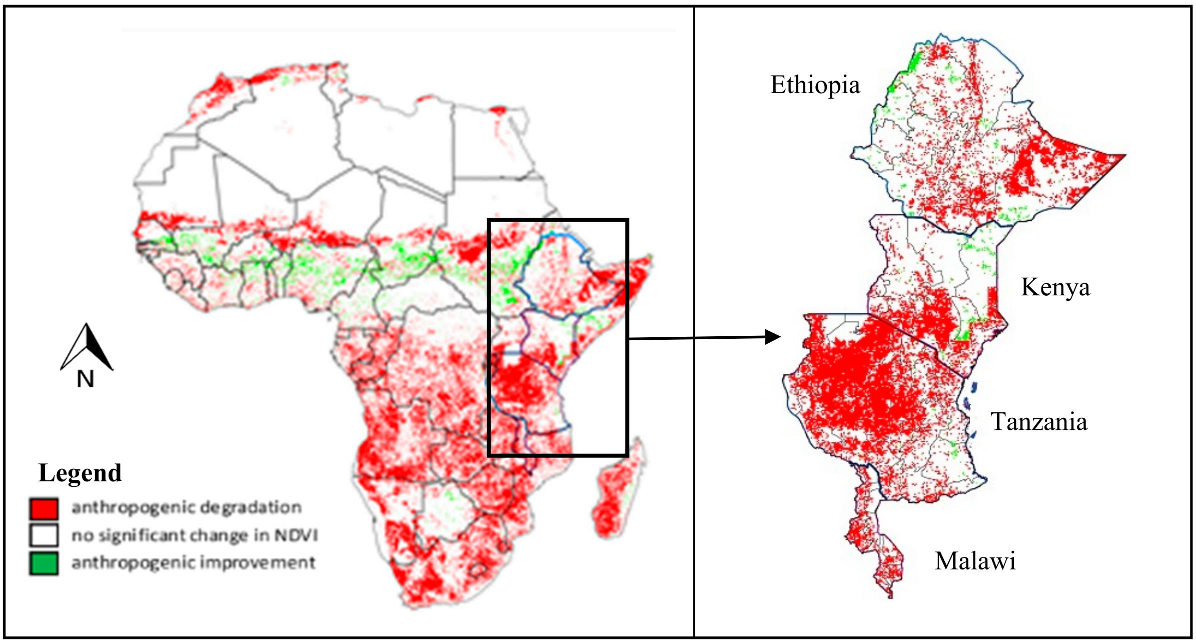

Figure 1: Biomass productivity decline in Eastern Africa over 1982-2006.
Source: Adapted from Le, Nkonya & Mirzabaev (1).

Several studies have been carried out to document significant determinants and constraints to adoption of SLM in eastern Africa, however, a number of limitations that should be fulfilled in next research are evident. These studies either focuses on some specific location(s) in the region (such as, [11] in Kenya, [12] in Malawi, [13,14,15] in Ethiopia) are considered subjective and lacking in scientific rigor and/or have weak explanatory power due to smaller sample size. The results from different studies are often contradictory regarding any given variable [16]. The current assessment is unique in that; it uses nationally representative data (at farm level) with diverse variables (both proximate and underlying) and that it includes socio-economic and behavioral factors. These include a mix of biophysical, demographic, socio-economic, and institutional variables.

Despite on-going land degradation and the urgent need for action to prevent and reverse land degradation, the problem has yet to be appropriately addressed, especially in the developing countries, including in Eastern Africa. Adequately strong policy action for SLM is lacking, and a coherent and evidence-based policy framework for action is missing [17]. Identifying the determinants of SLM adoption is a step towards addressing them [3]. The assessment of relevant drivers of land degradation by robust techniques at farm level is still lacking. There is an urgent need for evidence-based economic evaluations, using more data and robust economic tools, to identify the determinants of adoption as well as economic returns from SLM. The objectives of this paper are thus three-fold; i) to assess the determinants of SLM adoption in Eastern Africa, ii) to examine the determinants of number of SLM technologies adopted, and iii) to assess the determinants of simultaneous adoption of SLM technologies in Eastern Africa.

It is particularly important to study the diverse social–ecological context within a national or international scale. It further addresses and control for the diverse contexts such as regional and agro-ecological zonation to capture a wide spectrum of heterogeneous contexts in the three Eastern Africa countries. The approached used in the current study also account for the non-linear relationship between the drivers of land degradation and determinants of SLM. This approach could lead to innovative and comprehensive assessment of both causes of land degradation and SLM use and thus a better targeting of policy measures for combating land degradation and facilitating SLM uptake across different contexts.

The rest of this paper is organized as follows: section two provides a brief review of key studies on extent on the determinants of SLM adoption in Eastern Africa; section three presents the study methods and the empirical strategy; Section four outlines the data, study area and sampling procedure; section five discusses the findings of the study; section six concludes.

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2. Relevant Literature

Empirical review of literature on adoption of production related technologies dates back to Feder et al., [18] which summarizes that the adoption of new technology may be constrained by many factors such as lack of credit, inadequate and unstable supply of complementary inputs, uncertainty and risks. A comprehensive review of literature shows several factors determining investment in sustainable land management practices. These include; household and farm characteristics, technology attributes, perception of land degradation problem, profitability of the technology/practice, institutional factors, such as, land tenure, access to credit, information and markets and risks and uncertainty [19,20,21,22,23,24, 25,26,27,28,29,30]. Detailed empirical studies in developing countries include that of Pagiola [11] in Kenya in Malawi, Shiferaw and Holden [13], Gebremedhin and Swinton [14], and Bekele and Drake [15] in Ethiopia. All these studies highlighted the direction as well as the magnitude of factors hypothesized to condition the adoption of SLM.

Some of the significant factors facilitating the adoption of sustainable land management include; access to information (education and extension), access to both input and output markets, social, human and physical capital endowments, credit availability, profitability of the management technology, and property rights. The adoption of sustainable land management is also influenced by lack of local-level capacities, knowledge gaps on specific land degradation and SLM issues, inadequate monitoring and evaluation of land degradation and its impacts, inappropriate incentive structure (such as, inappropriate land tenure and user rights), inaccessible market and infrastructure constraints (such as, insecure prices of agricultural products, increasing input costs, inaccessible markets), and policy and institutional bottlenecks (such as, difficulty and costly enforcement of existing laws that favor SLM) and risks [31,32,7,8,33]. In summary, these factors are largely area specific and their importance is varied between and within agro-ecological zones and across countries. Thus, caution should be exercised in attempting to generalize such individual constraints across regions and countries.

Important contributions have been made by these previous studies on identifying the determinants of adoption of SLM practices, however, a number of limitations are evident. Despite the fact that a long list of explanatory variables is used, most of the statistical models developed by these studies have low levels of explanatory power [16]. The results from different studies are often contradictory regarding any given variable ([16]. Lindner [34] and Ghadim et al., [35] point out that the inconsistency results in most empirical studies could be explained by four shortcomings, namely; failure to account for the importance of the dynamic learning process in adoption, biases from omitted variables, poorly specified models and failure to relate hypotheses to sound conceptual framework.

Adoption studies using dichotomous adoption decisions models have inherent weakness [36]. The single stage decision making process characterized by a dichotomous adoption decision models is a direct consequence of the full information assumption entrenched in the definition of adoption, that is, individual adoption is defined as the degree of use of a new technology in the long run equilibrium when the farmer has full information about the new technology and its potential. This assumption of full information is usually violated and hence use of logit or probit models in modeling adoption decision may lead to model misspecification.

Recent studies have tried to overcome these limitations in different ways: model adoption sequentially [37], include farmers' personal perceptions, abilities and capabilities and risk preferences to capture the dynamic learning process [16], use of stochastic production function to capture importance of risk effects of factors inputs on production behavior [38], use a partial observability model to capture the varied access to information and levels of awareness of the new technology [36], use of a double hurdle model to capture the sequential decisions and multiple stages in investing in SLM [14] and determinants of adoption and intensity of adoption of SLM may be different, hence use a tobit model rather than probit or logit [39].

3. Empirical Strategy

3.1. Determinants of SLM Adoption: Logit Regression Model

The adoption of SLM technologies/practices in this study refers to use of one or more SLM technologies in a given plot. The adoption was of SLM technology/practice in a farm plot was measured as a binary dummy variable (1= adopted SLM in a farm plot, 0= otherwise).The two appropriate approaches to estimate such binary dummy dependent variable regression models are the logit and the probit regression models. The logit and probit models guarantee that the estimated probabilities lie between the logical limit of 0 and 1 [40]. Both probit and logit models are quite similar [41]. They generate predicted probabilities that are almost identical. The main difference between the two is in the nature of their distribution which is captured by Cumulative Distribution Function (CDF); probit has a normal distribution while logit has a logistic distribution. The choice of probit versus logit regression depends, therefore, largely on the distribution assumption one makes. Logit is however preferred because of its comparative mathematical simplicity. Sirak and Rice [49] argues that logistic regression is powerful, convenient and flexible and is often chosen if the predictor variables are a mix of continuous and categorical variables and/or if they are not normally distributed. Some of the predictor variables in this study objective categorical and therefore this study used logit model to examine the drivers of SLM adoption.

The reduced form of the logit model applied to nationally representative agricultural household survey data from Ethiopia, Tanzania and Malawi is presented as:

$$A= \boldsymbol{\beta_0} + \boldsymbol{\beta_1 x_1} + \boldsymbol{\beta_2 x_2} + \boldsymbol{\beta_3 x_3} + \boldsymbol{\beta_4 x_4} + \boldsymbol{\beta_5 z_i} + \boldsymbol{\varepsilon_i} \qquad \textbf{(1)}$$

where, A=Adoption of SLM technologies; x1 = a vector of biophysical factors (climate conditions, agro-ecological zones); x2= a vector of demographic characteristics factors (level of education, age, gender of the household head); x3 = a vector of farm-level variables (access to extension, market access, distance to market, distance to market); x4 = vector of socio-economic and institutional characteristics (access to extension, market access, land tenure, land tenure); zi= vector of country fixed effects; and $\boldsymbol{\varepsilon_i}$ is the error term.

Adoption studies using dichotomous adoption decisions models have inherent weakness [36]. The single stage decision making process characterized by a dichotomous adoption decision models is a direct consequence of the full information assumption entrenched in the definition of adoption, that is, individual adoption is defined as the degree of use of a new technology in the long run equilibrium when the farmer has full information about the new technology and its potential. This assumption of full information is usually violated and hence use of logit or probit models in modeling adoption decision may lead to model misspecification. Robust checks tare carried out to check these misspecifications. Further, assessment beyond adoption to intensity (number) of SLM adoption can also counter such inherent weakness. We explore this option in our study.

3.2. Determinants of Number of SLM Technologies Adopted: Poisson Regression Model

This models aims at analyzing the determinants of the number of SLM technologies adopted or applied in the same plot simultaneously. The number of SLM technologies is a count variable (ranging from 0 to 6 in this study). Thus the assessment of the determinants of intensity of adoption of SLM technologies requires models that accounts for count variables. Poisson regression model (PRM) is normally the first step for most count data analyses [43]. PRM assumes that the dependent variable y given vector of predictor variables x has a Poisson distribution. The probability density function of y given x is completely determined by the conditional mean;

$$\lambda(x) \equiv E(y|x) \qquad \textit{(2)}$$

$$f(y_i|x_i) = \frac{e^{-\lambda(x)}\lambda_i(x)^y}{\Gamma(1+y_i)} \qquad \textit{(3)}$$

where; $\lambda_{\mathrm{i}} = \exp(\alpha + \mathrm{X}'\beta) \quad \mathrm{y}_{\mathrm{i}} = 0,1,2,\ldots,i$

PRM specifies that each observation y_i is drawn from a Poisson distribution with parameter λ_i which is related to a ray of predictor variables X' [44]. The PRM is derived from the Poisson distribution by introducing parameters into the relationship between the mean parameter λ_i and predictor variables x. Wooldridge (2002) and Greene (2012) show that the expected number of events, y_i, (number of SLM technologies) is given as:

$$E(y_i|x_i) = \mathrm{var}[y_i|x_i] = \lambda_i = \exp(\alpha + \mathrm{X}'\beta) \qquad \text{for i = 1, 2… n.} \tag{4}$$

The log-linear conditional mean function $E(y_i|x_i) = \lambda_i$ and its equi-dispersion $Var(y_i|x_i) = \lambda_i$ assumptions are the main features of Poisson regression model [44].

Thus, the reduced form of the PRM applied to nationally representative agricultural household survey data from Ethiopia, Tanzania and Malawi is presented as:

$$\mathrm{NT} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1 x_1} + \boldsymbol{\beta_2 x_2} + \boldsymbol{\beta_3 x_3} + \boldsymbol{\beta_4 x_4} + \boldsymbol{\beta_5 z_i} + \boldsymbol{\varepsilon_i} \tag{5}$$

where, NT=Number of SLM technologies adopted – ranging from 0 to 6; x1 = a vector of biophysical factors (climate conditions, agro-ecological zones); x2= a vector of demographic characteristics factors (level of education, age, gender of the household head); x3 = a vector of farm-level variables (access to extension, market access, distance to market, distance to market); x4 = vector of socio-economic and institutional characteristics (access to extension, market access, land tenure, land tenure); zi= vector of country fixed effects; and $\boldsymbol{\varepsilon_i}$ is the error term.

PRM is preferred because it takes into account the non-negative and discrete nature of the data [45]. The assumption of equality of the variance and conditional mean in PRM also accounts for the inherent heteroscedasticity and skewed distribution of nonnegative data (ibid). PRM is further preferred because the log-linear model allows for treatment of zeros [45].

Some of the limitations of PRM in empirical work relates to the restrictions imposed by the model on the conditional mean and the variance of the dependent variable. This violation leads to under-dispersion or over-dispersion. Over-dispersion refers to excess variation when the systematic structure of the model is correct [46]. Over-dispersion means that to variance of the coefficient estimates are larger than anticipated mean – which results in inefficient, potentially biased parameter estimates and spuriously small standard errors [47]. Under-dispersion on the other hand refers to a situation in which the variance of the dependent is less than its conditional mean. In presence of under- or over-dispersion, though still consistent, the estimates of the PRM are inefficient and biased and may lead to misleading inference [48,44]. Our tests showed no evidence of under- or over-dispersion. Moreover, the conditional mean of the distribution of SLM technologies was similar to the conditional variance. Thus PRM was appropriately applied.

3. Data and Sampling Procedure

The data used for this study is based on household surveys in three countries; Ethiopia, Malawi and Tanzania conducted over different time periods. The surveys were supported by the Living Standards Measurement Study - Integrated Surveys on Agriculture (LSMS-ISA) project undertaken by the Development Research Group at the World Bank. The project aims to support governments in seven Sub-Saharan African countries to generate nationally representative, household panel data with a strong focus on agriculture and rural development. The surveys under the LSMS-ISA project are modeled on the multi-topic integrated household survey design of the LSMS; household, agriculture, and community questionnaires, are each an integral part of every survey effort. We describe the sampling procedure in each of the three countries below.

3.1. Ethiopia

The Ethiopia Rural Socioeconomic Survey (ERSS) data was collected during the period October 2011- March 2012 by the Central Statistical Agency (CSA). The ERSS sample is designed to be representative of rural and small town areas of Ethiopia. Based on population estimates from the 2007 Population Census, the CSA categorizes a town with a population of less than 10,000 as small. The ERSS rural sample is a sub-sample of the Annual Agricultural Sample Survey (AgSS) while the small town sample comes from the universe of small town Enumeration Areas (EAs).

The sample is a two-stage probability sample. The first stage of sampling entailed selecting primary sampling units – the CSA's enumeration areas (EAs). For the rural sample, 290 enumeration areas were selected from the AgSS enumeration areas based on probability proportional to size of the total enumeration areas in each region. For small town EAs, a total of 43 EAs were selected. The second stage involved random selection of households to be interviewed in each EAs. For rural EAs, a total of 12 households were sampled in each EA. Of these, 10 households were randomly selected from the sample of 30 AgSS households. The AgSS households are households which are involved in farming or livestock activities. Another 2 households were randomly selected from all other households in the rural EA (those not involved in agriculture or livestock). In some EAs, there is only one or no such households, in which case, less than two non-agricultural households were surveyed and more agricultural households were interviewed instead so that the total number of households per EA remains the same. Households were not selected using replacement. The sample covers a total of 3,969 households (and 24,954 farm plots).

3.2 Malawi

The Malawi 2010-2011 Integrated Household Survey (IHS) is a national-wide survey collected during the period March 2010- March 2011 by the national Statistics Office [49]. The sampling frame for the IHS is based on the listing information from the 2008 Malawi Population and Housing Census. The targeted universe for the IHS survey included individual households and persons living in those households within all the districts of Malawi except for Likoma and the people living in institutions such as hospitals, prisons and military barracks.

The IHS followed a stratified two-stage sample design. The first stage involved selection of the primary sampling units (PSUs) following proportionate to size sampling procedure. These include the census enumerations areas (EAs) defined for the 2008 Malawi Population and Housing Census. An enumerations area was the smallest operational area established for the census with well-defined boundaries and with an average of about 235 households. A total of 768 EAs (average of 24 EAs in each of the 31 districts) were selected across the country. In the second stage, 16 households were randomly selected for interviews in each EA. In total 12,271 households (18,329 farming plots) were interviewed.

3.2 Tanzania

The 2010-2011 Tanzania National Panel Survey (TNPS) data was collected during twelve-month period from September 2010 - September 2011 by the Tanzania National Bureau of Statistics [50]. In order to produce nationally representative statistics, the TNPS is based on a stratified multi-stage cluster sample design. The sampling frame the National Master Sample Frame (from the 2002 Population and Housing Census); which is a list of all populated enumeration areas in the country. In this first stage stratification was done along two dimensions: (i) eight administrative zones (seven on Mainland Tanzania plus Zanzibar as an eighth zone), and (ii) rural versus urban clusters within each administrative zone. The combination of these two dimensions yields 16 strata. Within each stratum, clusters were then randomly selected as the primary sampling units, with the probability of selection proportional to their population size. In rural areas a cluster was defined as an entire village while in urban areas a cluster was defined as a census enumeration area (from the 2002 Population and Housing Census). In the last stage, 8 households were randomly chosen in each cluster. Overall, 409 clusters and 3,924 households (6,038 farm plots) were selected.

Figure 2 presents the distribution of sampled households in the three countries.

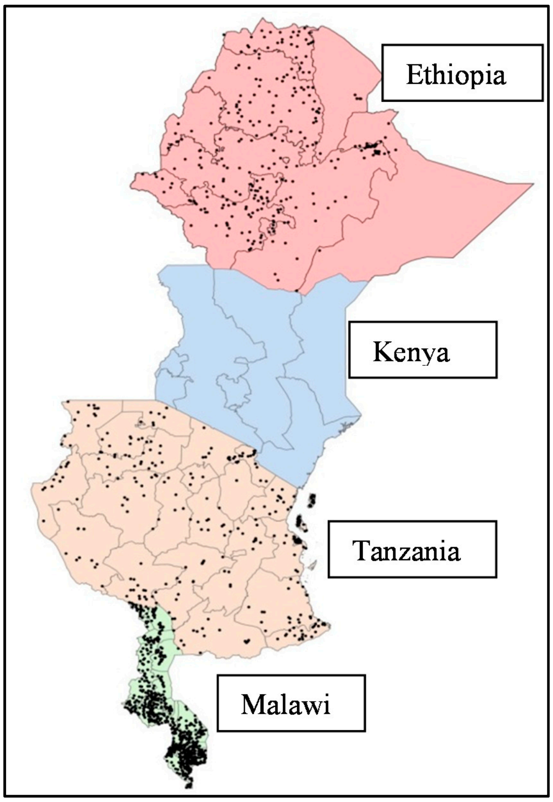

Figure 2: Distribution of sampled households
Source: Author's Compilation.

4. Results

The data used for this study is based on household surveys in three countries; Ethiopia, Malawi and Tanzania conducted over different time periods. The surveys were supported by the Living Standards Measurement Study - Integrated Surveys on Agriculture (LSMS-ISA) project undertaken by the

4.1 Descriptive Statistics of Variables Used in the Econometric Estimations

We discuss the results of the descriptive analysis on this section. Table 1 presents the results of the mean and standard deviation of all the independent variables used in the regression models. Results show substantial differences in the mean values of the biophysical, demographic, plot-level, and socioeconomic characteristics by country. Among the biophysical characteristics, notable differences can be noted in such variables as mean annual rainfall, topography (elevation) and agro-ecological classification.

For example, the mean annual rainfall ranged from as low as 1080 mm per annum in Ethiopia to as high as 1227 mm per annum in Tanzania; with the average for the region being about 1140 mm per annum. Regarding elevation, the average plot elevation for the region was 1280 meters above sea level. This varied substantially across countries. While the mean value of plot elevation in Malawi was 890 meters above sea level, the mean elevation in Ethiopia was 1916 meters above sea level. Similarly considerable differences is notable across countries with regards to agro-ecological classification; a larger proportion (46%) of Malawi is classified as warm arid/semiarid, while in Tanzania a bigger proportion (55%) is classified as warm humid/sub-humid and about 72% of Ethiopia is classified as cool humid/sub-humid environment.

Regarding demographic characteristics, no considerable change was reported with regard to such variables as average age of the household head (45 years) and average family size (4.2 adults). However, there seems to be a marginal difference in the education level of the household head; a low of about 1.7 years in Ethiopia, 2.7 years in Malawi and as high as 4.9 years in Tanzania. The gender

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of the household head was mainly dominated by men; 78% in Malawi, 79% in Tanzania and 82% in Ethiopia.

Table 1: Descriptive statistics of explanatory variables

Variable	Description	Malawi (N=18162)	Ethiopia (N=14170)	Tanzania (N=5614)	Total (N=37946)
Biophysical characteristics					
tempamt	Annual Mean Temperature (^0C*10)	216.811	189.622	225.374	207.925
rainfallan	Annual Mean Rainfall (mm)	1079.455	1227.814	1104.054	1138.495
terr_hlands	Terrain (1 = Highlands, 0 = Otherwise)	0.085	0.484	0.112	0.211
terr_plains	Terrain (1 = Plains, 0 = Otherwise)	0.463	0.077	0.438	0.315
terr_plateau	Terrain (1 = Plateaus, 0 = Otherwise)	0.452	0.540	0.450	0.484
elevation	Topography – meters above sea level (m)	890.515	1916.924	931.311	1279.838
aeztwa	AEZ (1 = warm arid/semiarid, 0 = Otherwise)	0.464	0.030	0.073	0.244
aeztwh	AEZ (1 = warm humid, 0=Otherwise)	0.327	0.021	0.550	0.246
aeztca	AEZ (1 = cool arid/semiarid, 0 = Otherwise)	0.123	0.225	0.029	0.147
aeztch	AEZ (1 = cool humid, 0 = Otherwise)	0.086	0.724	0.338	0.363
Demographic characteristics					
age	Age of household head (years)	43.295	45.724	49.298	45.090
sex	sex of household head (1=Male, 0=Other)	0.780	0.824	0.788	0.797
edu	Years of formal education of head (years)	2.704	1.725	4.995	2.677
adulteq	Size of household (adult equivalent)	4.166	4.076	4.863	4.235
Plot characteristics					
tittledeed	Possess title deed of plot (1=Yes, 0=Other)	0.786	0.332	0.105	0.516
sandy	Soil type (Sandy soils = Yes, 0 = Otherwise)	0.189	0.316	0.161	0.115
loam	Soil type (Loam soils = Yes, 0 = Otherwise)	0.625	0.265	0.508	0.375
clay	Soil type (Clay soils = Yes, 0 = Otherwise)	0.184	0.430	0.145	0.109
soilquality	Soil quality (1= Poor, 2= Fair, 3=Good)	0.890	1.301	0.768	1.026
plotdist1	Distance from plot to farmer's home (km)	0.766	3.930	5.442	2.639
plotdist2	Distance from plot from the market (km)	9.761	14.833	2.363	10.560
Socio-economic characteristics					
plotsize	Size of the plot (acres)	1.025	0.331	2.536	0.990
extension	Access to extension services (1=Yes, 0=No)	0.032	0.246	0.158	0.131
grpmember	Membership in farmer groups (1=Yes, 0=No)	0.118	0.243	0.213	0.179
creditacs	Access to credit (1=Yes, 0 = Otherwise)	0.143	0.266	0.086	0.180
creditamt	Amount of credit accessed (USD)	13.699	39.669	28.605	25.602
assetsval	Value of household assets (USD)	172.35	200.263	114.346	174.192
expmR	Annual household expenditure (USD)	1544.842	194.589	1810.742	1042.62
Country Dummy variables					
Malawi	(1 = Malawi, 0 = Otherwise) (n=18162)	0.478			
Ethiopia	(1 = Ethiopia, 0 = Otherwise) (n=14170)	0.373			
Tanzania	(1 = Tanzania, 0 = Otherwise) (n=5614)	0.148			

Source: Author's compilation.

Plot characteristics also differed by country. For instance, ownership of the plots (possession of a plot title-deed) was least in Tanzania (11%) followed by Ethiopia (33%) but higher in Malawi (79%). The distance from the plot to the farmer's house was considerable varied across countries. On average, plots were closer (0.8 km) in Malawi as compared to Ethiopia (3.9 km) and Tanzania (5.4 km). Similarly, the distance to the market from the plots varied substantially across countries; from 2.4 km in Tanzania to about 10 km in Malawi and 15 km in Ethiopia. Loam soils were predominant soil type in Malawi (63% of plots) and Tanzania (50% of the plots) while clay was predominant in Ethiopia (43% of plots).

The average size of the plots was 1 acre. These ranged from an average of 0.3 acres in Ethiopia to 2.5 acres in Tanzania. About 18% of the sampled farmers were involved in social capital formation as shown by participation in collective action groups (farmer groups and cooperatives and savings and credits cooperatives). This ranged from about 12% in Malawi to 25% in Ethiopia. The average proportion of sampled farmers with access to credit financial services was 18% (ranging from as low as 9% in Tanzania to 27% in Ethiopia). The average household assets were about 174 USD while the average annual household expenditure was 1040 USD. This varied substantially by country – 1545

USD in Malawi, 194 USD in Ethiopia and 1810 USD in Tanzania. The total number of plots considered in this assessment was about 18162 in Malawi, 14170 in Ethiopia and 5614 in Tanzania – representing about 48%, 37% and 15% respectively.

The adoption of the different SLM practices/technologies used in farm plots is presented in Figure 3. For example, the adoption of inorganic fertilizers ranged from 12% of farm plots in Tanzania to 39% in Ethiopia to 64% in Malawi. The adoption of improved seeds ranged from 13% in Ethiopia, 24% in Tanzania to 58% in Malawi. The use of organic manure is low; ranging from 9% in Tanzania, 11% in Malawi to 24% in Ethiopia. Cereal-legume intercropping was adopted in about 33% of plots in Tanzania, 35% in both Ethiopia and Malawi while crop rotation was done in just about 1% of farm plots in Malawi but applied in about 15% in Tanzania and 56% in Ethiopia. Lastly, soil erosion control (soil and water conservation) was adopted in 4% of farm plots in Ethiopia, 9% in Tanzania and 41% of in Malawi.

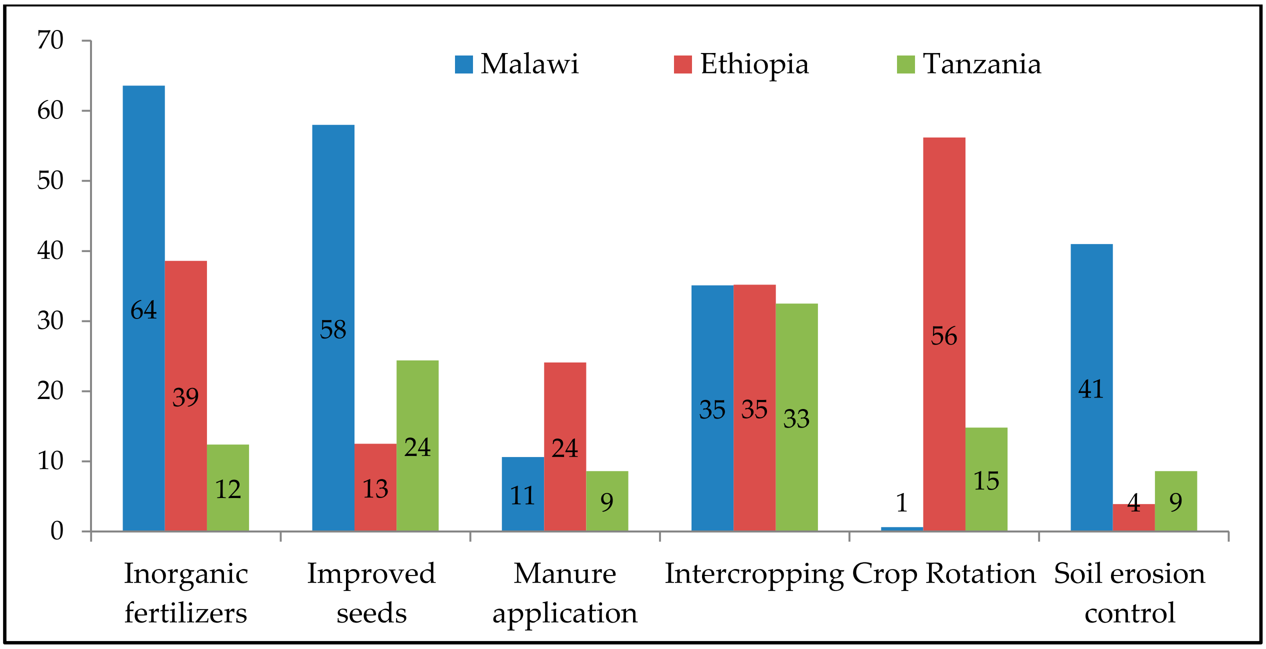

Figure 3: The distribution of different SLM technologies adopted in Eastern Africa Source: Author's compilation.

It is also important to assess the simultaneous use of different SLM practices. The total possible number of SLM used at any given time ranged from 0 to 6 (Figure 4). About 15% of the surveyed households did not apply any SLM technologies in their farm plots. At country-level, 15%, 11%, and 32% of the plots were not under any SLM technology in Ethiopia, Malawi and Tanzania respectively. Further, analysis shows that only one SLM technology was used in about 33% of the plots. At the country level, the proportion of plots with only on SLM technology was about 33%, 29% and 45%, in Ethiopia, Malawi and Tanzania respectively. Similarly, two SLM technologies were applied in about 27%, 21% and 16%, in Ethiopia, Malawi and Tanzania respectively. Fewer plots applied more than two SLM technologies simultaneously in one plot respectively.

Three SLM technologies were simultaneously used in about 17%, 21% and 5%, in Ethiopia, Malawi and Tanzania respectively while four SLM technologies were simultaneously applied in about 7%, 6% and 2% of the plots in Ethiopia, Malawi and Tanzania respectively. Figure 5 presents the plot of the mean number of SLM technologies applied by country. The average number SLM technologies applied per plot were 1.7. This was varied across the countries: 1.7, in Ethiopia 1.9 in Malawi and 1.0 in Tanzania (Figure 5).

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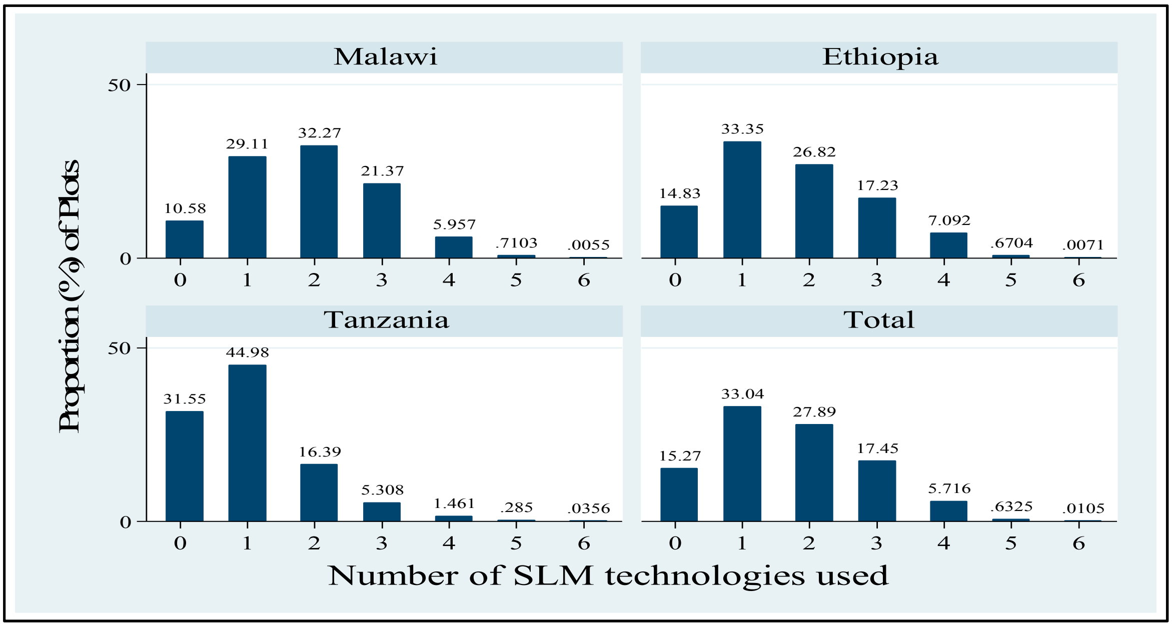

Figure 4: The distribution of number of SLM technologies adopted
Source: Author's compilation.

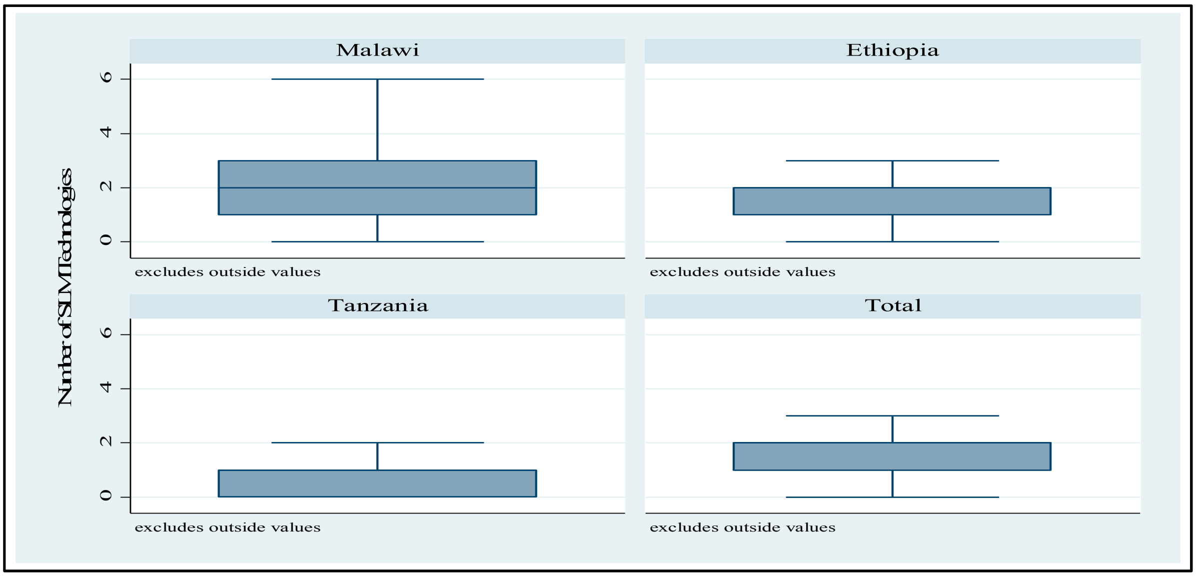

Figure 5: The mean number of SLM technologies adopted
Source: Author's compilation.

4.2 Determinants of SLM Adoption: Logit Regression Model Estimations

The results of the logit regression models on the determinants of adoption of SLM technologies are presented in Table 2. An adopter was defined as an individual using at least one SLM technology. The assessment was carried out using plot level data. The logit models fit the data well (Table 2). All the F-*test* showed that the models were statistically significant at the 1% level. The Wald tests of the hypothesis that all regression coefficients in are jointly equal to zero were rejected in all the equations at 1% [(Combined model: Chi^2 (30) = 2335, Pseudo R^2 = 0.0720, *p-value* = 0.000), (Ethiopia: Chi^2 (30) = 1649, Pseudo R^2 = 0.1387, *p-value* = 0.000); (Malawi: Chi^2 (30) = 1540, Pseudo R^2 = 0.1256, *p-value* = 0.000); (Tanzania: Chi^2 (30) = 394, Pseudo R^2 = 0.0563, *p-value* = 0.000)].

The results (marginal effects) suggest that biophysical, demographic, plot-level, and socioeconomic characteristics significantly influence SLM adoption. We discuss significant factors for each country model in the subsequent section. Results show that several biophysical, socioeconomic, demographic, institutional and regional characteristics dictate the adoption of SLM practices (Table 2). Among the proximate biophysical factors that significantly determine the probability of adopting

SLM technology include temperature, rainfall and agro-ecological zonal characteristics. Temperature positively influences the probability of using SLM technologies in Tanzania and in the combined model. For every 1% increase in mean annual temperature, the probability of SLM adoption increased by about 26% and 15% in Tanzania and in the combined model respectively, *ceteris paribus*. Rainfall on the other hand showed a negative effect on the probability of adopting SLM technologies in Tanzania and in the combined model. 1% increase in mean annual rainfall leads to 11% and 24% increase in probability of SLM adoption in Tanzania and in the combined model respectively, holding other factors constant. These findings is similar to Yu *et al*. [51], Belay and Bewket [52], and Kassie *et al*., [53] that increasing temperatures and erratic rainfall motivates the adoption of SLM practices such as conservation tillage, use of manure and intercropping for agricultural production to thrive.

Results further suggest that elevation and terrain are critical in determining SLM adoption in the case study countries. While taking lowlands as the base terrain, results show that SLM is more likely to occur in both the plateaus and the hilly terrains in both Malawi and in the combined model and also in the hilly terrains in Ethiopia. The probability of SLM adoption is 25% and 13% more for plots located in the plateaus of Malawi and in the combined model respectively, *ceteris paribus*. Similarly, SLM adoption is 70%, 39% and 33% more likely to be adopted in the hilly terrain of Malawi, Ethiopia and the combined model respectively, holding other factors constant. As expected, effect of agro-ecological zones on SLM adoption is mixed. For example, the adoption of SLM practices is 45% more likely to be adopted in warm humid/sub-humid environments of Malawi but 50% less likely to be adopted in similar environments in Ethiopia, *ceteris paribus*.

Significant plot level characteristics influencing the adoption of SLM technologies include the slope of the plot and soil type. While holding other factors constant, 1% increase in the slope of the plot increases SLM adoption by about 39%, 58% and 23% in Tanzania, Malawi and the combined model respectively. Further, the adoption of SLM is 15% and 26% more likely to occur in loam soils (as compared to clay soils) in Malawi and the combined model, *ceteris paribus*. The adoption of SLM technologies is also significantly influenced by such household-level variables as sex age and education level of the household head, and family size. Male-headed households are 11% less likely to adopt SLM technologies in Malawi but 20% more likely to adopt in Ethiopia compared to their female counterparts, holding other factors constant. This finding is similar to those of de Groote and Coulibaly [54] and Gebreselassie et al., [55] that the existing cultural and social setups that dictate access to and control over farm resources (especially land) and other external inputs (such as fertilizer and seeds) tend to discriminate against women.

Education and the abundance of labor supply through larger bigger family size positively influence the adoption of SLM technologies both in all case study countries and in the combined mode. For instance increase in education by 1 year of formal learning increases the probability of SLM adoption by about 6%, 4% and 2% in Ethiopia, Malawi and Tanzania respectively, *ceteris paribus*. This finding corroborate the previous studies that have shown that households with more education may have greater access to productivity enhancing inputs as a result of access to non-farm income ([56,57,58]. More education is also associated with greater ability to search, decode and apply new information and knowledge pertaining SLM [59,53]. Increased in family size by 1 adult increases the probability of SLM adoption by about 10%, 19% and 3% in the combined model, Ethiopia and Malawi respectively, *ceteris paribus*. This finding similar to that of Burger and Zaal [60], Belay and Bewket [52] and Kassie et al., [53] that larger household sizes may be associated with higher labor endowment, thus, in peak times such households are not limited with labor supply requirement and are more likely to adopt SLM practices.

Socio-economic variables including access to agricultural extension services, credit access, household assets and social capital (group membership) are also significant determinants of SLM technologies. Secure land tenure (ownership of title deed) positively influences the adoption of SLM technologies. Holding other factors constant, ownership of title deed increased the probability of SLM adoption by about 18%, 32% and 43% in Malawi, Tanzania and the combined model respectively. Security of land tenure has previously been associated with increased investment in long-term SLM practices such as manure application and conservation tillage practices [61,62]. Access to agricultural extension services increased the probability of SLM adoption by about 29%, 10% 21% and 10% in the

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combined model, Ethiopia, Malawi and Tanzania respectively, *ceteris paribus*. Previous studies indicate that agricultural extension services are important sources of information that is required in making farm decisions and in influencing technology adoption behavior [63].

Table 2: Drivers of adoption of SLM practices in Eastern Africa: Logit regression results

Variables	Combined (n=37946)		Ethiopia (n=14170)		Malawi (n=18162)		Tanzania (n=5614)	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
lntempamt	26.916***	3.242	8.111	6.444	5.836	20.789	14.503*	7.906
lntempamtsq	-0.210***	0.033	-0.076***	0.012	-0.006***	0.011	0.665	0.007
lnrainfallan	-23.501***	2.431	-0.612	4.769	-10.014	15.130	-10.883*	5.886
lnrainfallsq	0.040***	0.103	0.041**	0.670	0.022	0.120	0.061	0.004
lntempt#lnrainf	4.689***	0.455	0.582	0.890	2.010	2.829	1.932*	1.085
elevation	0.000***	0.000	0.000	0.000	0.002***	0.000	0.001**	0.000
terr_plateaus	0.133***	0.039	-0.109	0.114	0.246***	0.058	0.038	0.076
terr_hills	0.326***	0.054	0.388***	0.119	0.703***	0.150	-0.075	0.134
warm humid/sub-hum	0.514***	0.054	-0.504*	0.269	0.455***	0.105	0.119	0.160
cool arid/semi-arid	-0.014	0.071	-0.140***	0.213	0.309**	0.122	-0.035	0.231
cool humid/sub-hum	0.186**	0.076	-0.463*	0.252	-0.076	0.204	0.257	0.186
plotslope	0.228***	0.029	0.051	0.042	0.588***	0.056	0.388***	0.069
sandy	-0.031	0.053	0.509	0.072	0.032	0.069	0.035	0.098
loam	-0.263***	0.065	0.090	0.005	-0.150*	0.086	-0.026	0.118
age	0.001	0.006	0.036***	0.010	-0.008	0.010	-0.013	0.013
agesqrd	0.013	0.001	-0.007***	0.019	0.045	0.030	0.340	0.005
sex	0.002	0.041	0.203***	0.073	-0.106	0.068	-0.069	0.086
edu	0.101***	0.012	0.057**	0.023	0.042*	0.027	0.024**	0.023
edusq	-0.008***	0.001	-0.001	0.002	-0.004*	0.002	0.003	0.002
hhsize	0.103***	0.020	0.187***	0.052	0.026**	0.040	-0.028	0.025
lnplotdist1	-0.115***	0.023	-0.105**	0.043	-0.039	0.066	0.085**	0.036
lnplotdist2	-0.052***	0.014	-0.099***	0.025	-0.115***	0.025	-0.160***	0.046
irrigation	0.437***	0.121	0.906***	0.157	-0.861***	0.248	0.514*	0.270
plotsize	0.004	0.005	0.009	0.034	0.369***	0.051	0.003	0.004
tittledeed	0.431***	0.036	-0.029	0.061	0.177***	0.063	0.317***	0.113
extension	0.293***	0.054	0.103***	0.075	0.206***	0.303	0.097*	0.090
grpmember	0.206***	0.044	0.153**	0.071	0.122	0.085	0.080	0.083
creditacs	0.171***	0.043	0.177***	0.062	-0.005	0.075	-0.019	0.120
lncredit	0.345***	0.076	0.801***	0.193	0.025	0.137	0.135*	0.135
lnassests	0.197***	0.013	0.064**	0.032	0.156***	0.023	0.045*	0.024
constant	137.91***	17.257	-50.155	32.32	238.29**	115.61	87.59**	43.03
Ethiopia	0.356***	0.334	-	-	-	-	-	-
Tanzania	-0.421***	0.627	-	-	-	-	-	-
Model Characteristics	No. of obs. = 14170 LRChi²(36) =1649 Prob>chi² = 0.000 Pseudo R^2 = 0.2387		No. of obs. = 18162 LRChi²(34) =1540 Prob>chi² = 0.000 Pseudo R^2 = 0.2256		No. of obs. = 5614 LRChi²(34) =394 Prob>chi² = 0.000 Pseudo R^2 = 0.1563		No of obs. = 37946 LRChi²(34) =2335 Prob>chi² = 0.000 Pseudo R^2 = 0.1720	

***, **, and * denotes significance at 1%, 5% and 10% respectively. Numbers in parentheses are standard errors.
The dependent variable – adoption of SLM practices – is binary (1=adopted, 0=otherwise)
Source: Author's compilation.

Market accessed or proximity to markets (shown by distance to the market from the plot) has negative significant influence on the probability of SLM adoption in Malawi and Tanzania and in the joint models. 1% increase in distance to market reduced the probability of SLM adoption by 0.05%, 0.10%, 0.12% and 0.16% in the combined model, Ethiopia, Malawi and Tanzania respectively, holding other factors constant. The finding suggests that distance from the plot to market represents the transaction costs related to output and input markets, availability of information, financial and credit organizations, and technology accessibility (Pender et *al.*, 2006; von Braun et al., 2012). Social capital (membership in farmer organizations) increased probability of SLM adoption by 21% and 15% in the combined model and Ethiopia respectively, *ceteris paribus*. Our findings suggest that social capital is important in overcoming the transaction costs involved in accessing inputs and marketing of produce, and in accessing information [64,65,66]. Moreover, credit access increased probability SLM adoption by 17% and 18% in the combined model and Ethiopia respectively, *ceteris paribus*. Access to credit can ease cash constraints and facilitates the acquisition of farm implements, irrigation infrastructure, and purchase of inputs such as fertilizer and improved seed varieties [67].

Additionally, the amount of household assets positively influences SLM adoption. Findings show that 1% increase in assets value of the household increases the probability of SLM adoption by about 0.20%, 0.06% 0.16% and 0.05% in the combined model, Ethiopia, Malawi and Tanzania respectively, *ceteris paribus*. Wealthier households are deemed able to adopt SLM of practices because of their ability to finance farm inputs such as seeds and fertilizers [68]. Finally, results show that the adoption of SLM technologies was significantly higher (by about 36%) in Ethiopia but significantly lower (by about 42%) in Tanzania than in Malawi.

4.3 Determinants of Number of SLM Technologies Adopted: Poisson Regression Results

The results of the Poisson regression on the determinants of the number of SLM technologies used per plot are presented in Table 3. The assessment is done at plot level in each of the case study countries and a combined model is also estimated for all the three countries. The Poisson estimations fit the data well. All the models are statistically significant at 1% {(Ethiopia: LR $chi^2(30) = 1537$, Prob $> chi^2 = 0.000$ and Pseudo $R^2 = 0.035$; (Malawi: LR $chi^2(30) = 2139$, Prob $> chi^2 = 0.000$ and Pseudo $R^2 = 0.038$); Tanzania: LR $chi^2(30) = 401$, Prob $> chi^2 = 0.000$ and Pseudo $R^2 = 0.027$); (Combined model: LR $chi^2(32) = 3227$, Prob $> chi^2 = 0.000$, and Pseudo $R^2 = 0.029$)}. There was no evidence of dispersion (over-dispersion and under-dispersion). The corresponding negative binomial regressions were estimated, however, all the likelihood ratio tests (comparing the negative binomial model to the Poisson model) were not statistically significant – suggesting that the Poisson model was best fit for this study. The results (marginal effects) suggest that biophysical, demographic, plot-level, and socioeconomic characteristics significantly influence the number of SLM technologies adopted (**Table 3**).The relationships between these factors and the number of SLM technologies adopted are however mixed across the countries. Significant factors for each country and the combined model are discussed in the subsequent section.

Among the proximate biophysical factors that significantly determine the probability of adopting SLM technology include temperature, rainfall and agro-ecological zonal characteristics. While both temperature and rainfall showed negative significant effect on the number of SLM technologies adopted in Ethiopia and Malawi and in the combined model, elevation exhibited a positive relationship with the number of SLM technologies adopted. For every 1% increase in mean annual temperature, the number of SLM technologies adopted decreases by about 14%, 16% and 12% in the combined model, Ethiopia and in Malawi respectively, holding other factors constant. Similarly, for every 1% increase in annual mean rainfall, the number of SLM technologies adopted decreases by about 12%, 13% and 11% in the combined model, Ethiopia and in Malawi respectively, holding other factors constant. However, for every 1% increase in elevation, the number of SLM technologies adopted increase by about 0.1% in all countries and in the combined model *ceteris paribus*.

While taking lowlands as the base terrain, results show that the number of SLM technologies adopted is more likely to occur in both the plateaus and the hilly terrains. The number of SLM technologies adopted increases by about 8.5% and 10% in the plateaus of Malawi and in the combined model respectively, *ceteris paribus*. Similarly, the number of SLM technologies adopted is 13%, 7%, 10% and 11% more in the hilly terrain in the combined model, Ethiopia, Malawi and Tanzania respectively, *ceteris paribus*. As expected, the number of SLM technologies adopted differed across agro-ecological zones. For example, the number of SLM technologies adopted is 12%, 19% and 11% more in warm humid/sub-humid environments of the combined model, Ethiopia and Malawi respectively but 2%, 11% and 3% less in cool arid/ semi-arid environments in the combined model, Ethiopia and Malawi respectively. Similarly, the number of SLM technologies adopted is 10%, 39% and 4% more in the combined model, Ethiopia and Malawi respectively.

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Table 3: Determinants of number of SLM technologies adopted: Poisson regression results

	All (n=37946)		Ethiopia (n=14170)		Malawi (n=18162)		Tanzania (n=5614)	
Variables	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
lntempamt	-14.22***	0.672	-16.23***	0.957	-12.37***	2.327	-2.536	2.863
lntempamtsq	0.110	0.002	0.032	0.014	0.009	0.001	0.022	0.000
lnrainfallan	-11.69***	0.520	-13.14***	0.725	-11.24***	1.825	-2.204	2.214
lnrainfallsq	0.001	0.000	0.001	0.001	0.014	0.002	-0.001	0.001
lntempt#lnrainf	2.221***	0.097	2.491***	0.140	2.096***	0.337	0.391	0.413
elevation	0.001***	0.000	0.000***	0.000	0.001***	0.000	0.00***	0.000
terr_plateaus	0.100***	0.009	-0.003	0.024	0.085***	0.010	-0.005	0.029
terr_hills	0.132***	0.012	0.066***	0.025	0.098***	0.015	0.105**	0.048
warm humid/sub hum	0.119***	0.012	0.189***	0.071	0.104***	0.014	-0.063	0.062
cool arid/semi-arid	-0.024*	0.014	-0.105**	0.048	-0.033*	0.017	0.065	0.088
cool humid/sub-hum	0.099***	0.015	0.393***	0.052	0.038*	0.023	0.042	0.069
plotslope	0.062***	0.006	-0.017*	0.009	0.155***	0.008	-0.15***	0.025
sandy	-0.024**	0.011	0.012	0.056	-0.015	0.011	0.003	0.037
loam	-0.102***	0.014	0.020	0.009	-0.080***	0.014	0.006	0.046
age	0.001	0.001	0.004*	0.002	0.003*	0.002	0.004	0.004
agesqrd	0.022	0.010	0.029	0.004	0.045	0.003	0.011	0.003
sex	-0.015*	0.009	0.018	0.016	-0.019*	0.011	0.002	0.033
edu	0.017***	0.003	0.011**	0.005	0.017***	0.004	0.014*	0.008
edusq	-0.001***	0.000	-0.001	0.001	-0.001***	0.000	0.020**	0.001
hhsize	-0.042***	0.005	-0.063***	0.012	-0.020***	0.006	-0.014	0.010
lnplotdist1	-0.091***	0.007	-0.057***	0.013	-0.071***	0.012	0.001	0.013
lnplotdist2	-0.008***	0.003	-0.020***	0.005	-0.034***	0.004	-0.045**	0.018
irrigation	0.223***	0.026	0.349***	0.029	-0.219***	0.071	0.192**	0.088
plotsize	0.000	0.002	-0.014	0.009	0.025***	0.006	0.003**	0.001
tittledeed	0.145***	0.008	0.058***	0.012	0.086***	0.011	0.13***	0.038
extension	0.157***	0.010	0.182***	0.012	0.153***	0.019	0.069*	0.035
grpmember	0.057***	0.009	0.032**	0.013	0.048***	0.012	0.060**	0.030
creditacs	0.060***	0.009	0.023*	0.012	0.018	0.012	0.056	0.041
lncredit	0.171***	0.018	0.296***	0.046	0.062***	0.020	0.009	0.053
lnassests	0.048***	0.003	0.016**	0.007	0.026***	0.004	0.022**	0.009
constant	72.98***	3.600	80.29***	4.847	92.06***	13.54	13.040	15.43
Ethiopia	0.034***	0.018	-	-	-	-	-	-
Tanzania	-0.071***	0.029	-	-	-	-	-	-
Model Characteristics	No. of obs. = 14170 LRChi²(36) =1537 Prob>chi² = 0.000 Pseudo R^2 = 0.135		No. of obs. =18162 LRChi²(34) =2139 Prob>chi² = 0.000 Pseudo R^2 = 0.138		No. of obs. = 5614 LRChi²(34) =401 Prob>chi² = 0.000 Pseudo R^2 = 0.127		No of obs. = 37946 LRChi²(34) =3227 Prob>chi² = 0.000 Pseudo R^2 = 0.129	

***, **, and * denotes significance at 1%, 5% and 10% respectively. Numbers in parentheses are standard errors.
Source: Author's compilation.

Significant plot level characteristics influencing the number of SLM technologies adopted include the slope of the plot and soil type. The slope of the plot showed positive relationship with the number of SLM technologies adopted in Malawi and the combined model but negative relationship in Ethiopia and Tanzania. While holding other factors constant, 1% increase in the slope of the plot increases number of SLM technologies adopted by about 6% and 16% in the combined model and in Malawi respectively, but reduces the number of SLM technologies adopted by about 2% and 15% in Ethiopia and Tanzania respectively. The number of SLM technologies adopted in sandy soils (compared to clay soils) is 2.4% less in the combined model whereas the number of SLM technologies adopted is 8% and 10% less in loam soils (compared to clay soils) in the combined model and in Malawi respectively, *ceteris paribus*.

The number of SLM technologies adopted is also significantly influenced by household-level variables such as sex age and education level of the household head and family size. The number of SLM technologies adopted by male-headed households is 2% less compared to those adopted by their female counterparts both in Malawi and in the combined model. Whereas education level of the household head showed a positively and significantly effect on the number of SLM technologies adopted in all countries, family size showed inverse relationship. Increase in education level of the household head by 1 year of formal learning increases the number of SLM technologies adopted by about 1.1%, 1.9%, 1.4% and 1.7% in Ethiopia, Malawi, Tanzania and the combined model respectively, *ceteris paribus*.

Socio-economic variables including market access, access to agricultural extension services, access to credit services, household assets and social capital (group membership) are also significant determinants of the number of SLM technologies adopted. Proximity to markets (shown by distance to the market from the plot) has negative significant influence on the number of SLM technologies adopted in the three countries and the combined models. 1% increase in distance to market number of SLM technologies adopted by 0.01%, 0.02%, 0.03% and 0.105% in the combined model, Ethiopia, Malawi and Tanzania respectively, holding other factors constant.

Secure land tenure (ownership of title deed) positively influences the number of SLM technologies adopted. Ownership of title deed increased the number of SLM technologies adopted by about 6% 9%, 13% and 15% in Ethiopia, Malawi, Tanzania and the combined model respectively, *ceteris paribus*. Access to agricultural extension services increased the number of SLM technologies adopted by about 18%, 15% 7% and 16% in Ethiopia, Malawi, Tanzania and the combined model respectively, holding other factors constant.

Social capital (membership in farmer organizations) increased the number of SLM technologies adopted by 3% 5%, 6% and 6% in Ethiopia, Malawi, Tanzania and the combined model respectively, *ceteris paribus*. Moreover, credit access increased the number of SLM technologies adopted by 2% and 6% in Ethiopia and the combined model and respectively, *ceteris* paribus. Finally, results show that the adoption of SLM technologies was significantly higher (by about 3.4%) in Ethiopia but significantly lower (by about 7.1%) in Tanzania than in Malawi.

5. Conclusions and Policy Implications

Land degradation is increasingly becoming an important subject due to the increasing number of causes as well as its effects. This chapter utilizes nationally representative household surveys in three eastern Africa countries (Ethiopia, Malawi and Tanzania) to assess the determinants of adoption and extent of adoption SLM technologies.

The adoption of sustainable land management practices as well as the number of SLM technologies adopted is critical in addressing land degradation in Eastern Africa. To ensure rigor, three approaches are used to assess the determinants of SLM adoption. First, a logistic regression is used to assess the probability of adopting SLM technologies, a Poisson regression model to assess the number of SLM technologies adopted, and a multivariate probit model to assess the simultaneous adoption of different SLM technologies. Adoption and the number of SLM technologies adopted is determined by a series of factors; biophysical, socio-economic and demographic and plot characteristics. The key proximate biophysical factors influencing the adoption of SLM practices include rainfall, temperature, elevation and the agro-ecological characteristics. Among the relevant demographic and socio-economic factors include age and education level of the household head, family size, land size, membership in farmer cooperatives and savings and credit cooperatives, land tenure, access to credit and proximity to markets.

Securing land tenure and access to relevant agricultural information pertaining SLM will play an important role in enhancing the adoption and the number of SLM adopted. This implies that policies and strategies that facilities secure land tenure is likely incentivize investments in SLM in the long-run since benefits accrue over time. There is need to improve the capacity of land users through education and extension as well as improve access to financial and social capital to enhance SLM uptake. Local institutions providing credit services, inputs such as seed and fertilizers, and extension services must not be ignored in the development policies. The important role of rainfall and agro-ecological classification on adoption of and number of SLM technologies adopted suggests the need for proper geographical planning and targeting of the SLM practices by stakeholders. The assessment of simultaneous adoption of SLM technologies revealed that most of the SLM technologies are complementary to each other – such as the use of improved seeds and fertilizers, use of manure and use of fertilizers.

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