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Drivers of land degradation and adoption of multiple sustainable land management practices in Eastern Africa

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Abstract:

Land degradation is a serious impediment to improving rural livelihoods in Tanzania and Malawi. This paper identifies major land degradation patterns and causes, and analyzes the determinants of soil erosion and sustainable land management (SLM) in these two countries. 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. Some of the actions taken by communities to address loss of ecosystem services or enhance or maintain ecosystem services improvement include afforestation programs, enacting of bylaws to protect existing forests, area closures and controlled grazing, community sanctions for overgrazing, and integrated soil fertility management in croplands.

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1. Introduction

Land degradation is a major problem in Tanzania and Malawi. A recent assessment shows that land degradation hotspots cover about 51% and 41% of land area in Tanzania and Malawi, respectively (Le, Nkonya & Mirzabaev, 2014; Figure 1). Figure 1 shows a depiction of land degradation and improvement 'hotspots' in Africa. A country-specific hotspot map for Malawi and Tanzania is also presented alongside the African map. In Tanzania, land degradation has been ranked as the top environmental problem for more than 60 years (Assey *et al.,* 2007). Soil erosion is considered to have occurred on 61% of the entire land area in this country (ibid). 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 (Chabala *et al.,* 2012).

<<Figure 1 >>

Investments in sustainable land management (SLM) are an economically sensible way to address land degradation (MEA, 2005; Akhtar-Schuster et al., 2013; ELD Initiative, 2013). SLM, also referred to as 'ecosystem approach', ensures long-term conservation of the productive capacity of lands and the sustainable use of natural ecosystems. However, available estimates show that the adoption of SLM practices in sub-Saharan Africa, including Tanzania and Malawi, is low – just on about 3% of total cropland (WB, 2010). Several factors limit the adoption of SLM in the region, including: 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 (inappropriate land tenure and user rights), market and infrastructure constraints (increasing input costs, inaccessible markets), and policy and institutional bottlenecks (difficulty and costly enforcement of existing laws that favor SLM) (Thompson et al., 2009; Chasek et al., 2011; Akhtar-Schuster et al., 2011; Reed et al., 2011; ELD Initiative, 2013).

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 Tanzania and Malawi. Adequately strong policy action for SLM is lacking, and a coherent and evidence-based policy framework for action is missing (Nkonya et al., 2013). Identifying drivers of land degradation and the determinants of SLM adoption is a step towards addressing them (von Braun, et al., 2012).The assessment of relevant drivers of land degradation by robust techniques at farm level is still lacking in Tanzania and Malawi. 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 two-fold; i) to assess the determinants of SLM adoption in Malawi and Tanzania, and ii) to examine the costs and benefits of action verses costs of inaction against land degradation in Malawi and Tanzania.

The rest of this paper is organized as follows: section 2 provides a brief review of key studies on extent, drivers of land degradation and determinants of SLM adoption in Tanzania and Malawi; section 3 presents the study methods and the empirical strategy; Section 4 outlines the data, study area and sampling procedure; section 5 discusses the findings of the study; section 6 concludes.

2. Relevant Literature

Drivers of land degradation can be grouped into two categories, namely; proximate and underlying causes (Lambin & Geist, 2006; Lal & Stewart, 2013; Belay *et al.*, 2014; Pingali *et al.*, 2014). Proximate causes are those that have a direct effect on the terrestrial ecosystem. These include biophysical (natural) conditions related to climatic conditions and extreme weather events such as droughts and coastal surges.

Key **proximate drivers** include; climatic conditions, topography, unsuitable land uses and inappropriate land management practices (such as slash and burn agriculture, timber and charcoal extraction, deforestation, overgrazing) and uncontrolled fires (**Table 1**). The dry aid and semi-arid arid lands are prone to fires which may lead to serious soil erosion (Voortman *et al.,* 2000; D'Odorico, 2013). The erratic rainfall in these areas may also be thought to induce salinization of the soil (Safriel & Adeel, 2005; Wale & Dejenie, 2013). Similarly, practicing unsustainable agriculture such as land clearing, overstocking of herds, charcoal and wood extraction, cultivation on steep slopes, bush burning, pollution of land and water sources, and soil nutrient mining (Eswaran *et al.,* 2001; Lal, 2001; Dregne, 2002). Most deforestation exercises are associated with the continued demand for agricultural land, fuel-wood, charcoal, construction materials, large-scale and resettlement of people in forested areas. This often happens at the backdrop of ineffective institutional mechanisms to preserve forests. Grazing pressure and reduction of the tree cover continue to diminish rangelands productivity (Hein & de Ridder, 2005; Waters *et al.,* 2013).

<<Table 1 >>

Important **underlying drivers** of land degradation include land tenure, poverty, population density and weak policy and regulatory environment in the agricultural and environmental sectors (**Table 1**). Insecure land tenure may act as a disincentive to investment in sustainable agricultural practices and Technologies (Kabubo-Mariara, 2007). Similarly, a growing population without proper land management will exhaust the capacity of land to provide ecosystem services (Tiffen *et al.,* 1994). It is also argued that population pressure leads to expansion of agriculture into fragile areas and reduction of fallow periods in the cultivated plots. However, this is not always the case. Population pressure has been found to increase agricultural intensification and higher land productivity as well as technological and institutional innovation that reduce natural resource degradation (Tiffen *et al.,* 1994; Nkonya *et al.,* 2008).

Empirical review of literature on adoption of production – related technologies dates back to Feder *et al.*, (1985) 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 (Ervin, 1982; Norris & Batie, 1987; Pagioa, 1996; Shiferaw and Holden; 1998; Kazianga & Masters, 2001; Shively, 2001; Bamire *et al.*, 2002; Barrett *et al.*, 2002; Gabremedhin & Swinton, 2003; Habron, 2004 ; Kim *et al.*, 2005; Park & Lohr, 2005; Pender *et al.*, 2006; Gillespie *et al.*, 2007; Prokopy *et al.*, 2008).

Detailed empirical studies in developing countries include that of Pagiola (1996) in Kenya, Nakhumwa and Hassan (2001) in Malawi, Shiferaw and Holden (1998), Gabremedhin and Swinton (2003) and Bekele and Drake (2003) in Ethiopia. All these studies highlighted the direction as well as the magnitude of factors hypothesized to condition the adoption of SLM. 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 (Ghadim and Pannell, 1999). The results from different studies are often contradictory regarding any given variable (ibid). Lindner (1987) and Ghadim *et al.*(2005) 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.

3. Conceptual framework and Empirical strategy

The ELD conceptual framework is based on comparing the costs and benefits of action against land degradation versus the costs of inaction (**Fig. 2**). There are two broad categories of causes of land degradation; proximate and underlying. Proximate drivers are those that have a direct effect on the terrestrial ecosystem. These include both biophysical causes (natural) and unsustainable land management practices (anthropogenic). On the other hand, underlying drivers are those that indirectly affect the proximate causes of land degradation (such as institutional, socio-economic and policy factors). The level of land degradation determines its outcomes and/or effects – whether on-site or offsite; – on the provision of ecosystem services and the benefits humans derive from those services. Actors can then take action to control the causes of land degradation, its level, or its effects.

<<Figure 2 >>

The green rectangular box (**Fig. 2**) shows the economic analysis that is carried out while the green arrow shows the flow of information that is necessary to perform the different elements of the economic analysis. All indirect and off-site effects are accounted for in the economic analysis to ensure that the assessment is from society's point of view, and that it includes all existing externalities in addition to the private costs that are usually considered when individuals decide on land use. Similarly, actions against land degradation have direct benefits and costs - the costs of specific measures and economy-wide indirect effects – or the opportunity costs. In other words, resources devoted for these actions cannot be used elsewhere. Thus, mobilizing those resources to prevent or mitigate land degradation affects other sectors of the economy as well.

Institutional arrangements that determine whether actors choose to act against land degradation and whether the level or type of action undertaken will effectively reduce or halt land degradation, are represented as dotted lines encapsulating the different elements of the conceptual framework. It is essential to identify and understand these institutional arrangements in order to devise sustainable and efficient policies to combat land degradation. It is also crucial for the analysis to identify all the important actors of land degradation, such as land users, landowners, governmental authorities, and industries, as well as identify how institutions and policies influence those actors. Transaction costs and collective versus market and state actions are to be considered. In general, the institutional economics is particularly important in the assessment of land degradation when it comes to the definition and design of appropriate actions against land degradation, as well as of the inaction scenarios serving as a benchmark.

4. Empirical strategy

4.1 Drivers of land degradation

Different approaches are used to assess the drivers of land degradation in Ethiopia, Malawi and Tanzania; the logit regression model to assess the drivers of NDVI decline. The choice of this models is informed by the nature of the assessment and the kind of data available. Following Meyfroidt et al (2010) Lambin and Geist (2006) and Nkonya et al. (2011, 2013), the structural first difference model applied to nationally representative agricultural household survey data from Ethiopia, Tanzania and Malawi is presented as follows:

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

where, $\Delta\boldsymbol{NDVI}$= Net change in NDVI between 1982 and 2006 (1= decline, 0=otherwise); $\boldsymbol{x_1}$ = a vector of biophysical factors (climate conditions, agro-ecological zones); $\boldsymbol{x_2}$ = a vector of demographic characteristics factors (level of education, age, gender of the household head); $\boldsymbol{x_3}$ = a vector of farm-level variables (access to extension, market access, distance to market, distance to market); $\boldsymbol{x_4}$ = vector of socio-economic and institutional characteristics (access to extension, market access, land tenure); $\boldsymbol{z_i}$ = vector of country fixed effects; and $\boldsymbol{\varepsilon_i}$ is the error term.

4.2 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 (Wooldridge, 2002). Both probit and logit models are quite similar (Gujarati, 2004). 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 (1994) 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:

$$A = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 z_i + \varepsilon_i \qquad \textbf{(2)}$$

where, A=Adoption of SLM technologies; x_1 = a vector of biophysical factors (climate conditions, agro-ecological zones); x_2 = a vector of demographic characteristics factors (level of education, age, gender of the household head); x_3 = a vector of farm-level variables (access to extension, market access, distance to market, distance to market); x_4 = vector of socio-economic and institutional characteristics (access to extension, market access, land tenure, land tenure); z_i = vector of country fixed effects; and ε_i is the error term.

Adoption studies using dichotomous adoption decisions models have inherent weakness (Dimara and Skuras, 2003). 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.

4.3 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 and the corresponding proportion of plots in which these technologies were applied are as presented in **Table 2**. The number of SLM technologies is thus a count variable (ranging from 0 to 6 in our case). 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 (Areal et al., 2008). 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;

$$\lambda(x) \equiv E(y|x) \tag{7}$$

$$f(y_i|x_i) = \frac{e^{-\lambda(x)}\lambda_i(x)^y}{\Gamma(1+y_i)} \tag{8}$$

where; $\lambda_i = \exp(\alpha + X'\beta)$ $\quad y_i = 0,1,2,...,i$

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' (Greene, 2008). 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 (2008) show that the expected number of events, y_i , (number of SLM technologies) is given as:

$$E(y_i|x_i) = \mathrm{var}[y_i|x_i] = \lambda_i = \exp(\alpha + X'\beta) \quad \text{for } i = 1, 2 \ldots n. \tag{9}$$

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 (Greene, 2008).

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

$$\boldsymbol{NT}= \boldsymbol{\beta_0} + \boldsymbol{\beta_1 x_1} + \boldsymbol{\beta_2 x_2} + \boldsymbol{\beta_3 x_3} + \boldsymbol{\beta_4 x_4} + \boldsymbol{\beta_5 z_i} + \boldsymbol{\varepsilon_i} \quad \textbf{(10)}$$

where, ***NT***=Number of SLM technologies adopted – ranging from 0 to 6; $\boldsymbol{x_1}$ = a vector of biophysical factors (climate conditions, agro-ecological zones); $\boldsymbol{x_2}$ = a vector of demographic characteristics factors (level of education, age, gender of the household head); $\boldsymbol{x_3}$ = a vector of farm-level variables (access to extension, market access, distance to market, distance to market); $\boldsymbol{x_4}$ = vector of socio-economic and institutional characteristics (access to extension, market access, land tenure, land tenure); $\boldsymbol{z_i}$ = 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 (Winkelmann and Zimmermann, 1995). 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 (ibid).

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. Overdispersion refers to excess variation when the systematic structure of the model is correct (Berk and MacDonald, 2007). Overdispersion 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 (Xiang and Lee, 2005). Underdispersion 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 (Famoye et al., 2005; Greene, 2008). 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.

4.4 Determinants of simultaneous adoption SLM: Multivariate probit (MVP) model

Farmers are more likely to adopt a combination of SLM practices and technologies to deal with land degradation than adopting just a single practice or technology. SLM practices and technologies are alternatives that may be adopted simultaneously and/or sequentially as complements, substitutes, or supplements. However, previous studies on SLM adoption have ignored the possible interrelationships between the various SLM practices and technologies (Yu et al. 2008). These studies treat the adoption of alternative SLM practices and technologies as exogenous decisions. Such an approach may under- or over-estimate the influences of various factors on the adoption decisions (Wu et al. 1998). Recent empirical studies on technology adoption decisions assume that farmers consider a set of possible technologies and choose the particular technology bundle that maximizes expected utility (Marenya & Barrett 2007; Nhemachena & Hassan 2007; Yu et al. 2008; Kassie et al. 2009). The adoption decision is therefore multivariate and attempting a univariate modeling approach will exclude useful information contained in the interdependent and simultaneous adoption decisions.

In a single-equation statistical model, information on a farmer's adoption of one SLM does not alter the likelihood of his adopting another. However, the multivariate probit (MVP) technique simultaneously models the influence of a set of explanatory variables on each of the different SLM practices and technologies, while allowing the unobserved and/or unmeasured factors (error terms) to be freely correlated (Belderbos et al. 2004; Lin et al. 2005). The correlation of the error terms may arise from the fact that some SLM practices are complementarities (positive correlation) and substitutabilities (negative correlation) between different practices (Belderbos et al. 2004). Failure to capture unobserved factors and interrelationships among adoption decisions regarding different practices will lead to bias and inefficient estimates (Greene, 2008).

Following Greene (2008), we adopt the MVP econometric model to assess the determinants of adoption of alternative SLM practices and technologies in this study. The MVP model is characterized by a set of binary dependent variables (Y_{ipj}), such that:

$$Y^*_{ipj} = X'_{ipj}\beta_j + u_{ipj}, \; j = 1, \ldots, m \text{ and} \quad \textbf{(3)}$$

$$Y_{ipj} = \begin{cases} 1 \; if \; Y^*_{ipj} > 0 \\ 0 \; otherwise \end{cases}, \quad \textbf{(4)}$$

where; j = 1 ...m denotes the technology choices available (SLM in our case).

In equation (3), the assumption is that a rational i^{th} farmer has a latent variable, Y^*_{ipj}, which captures the unobserved preferences associated with the j^{th} choice of SLM. Y^*_{ipj} is assumed to be a linear combination of observed household, plot, institutional and socio-economic characteristics (X_{ipj}), that affect the adoption of j^{th} SLM, as well as unobserved characteristics captured by the stochastic error term u_{ipj}. The vector of parameters to be estimated is denoted β_j. Y^*_{ipj} is latent, hence the estimations are based on observable binary discrete variables Y_{ipj}, which indicate whether or not a farmer adopted a particular SLM on plot p. The reduced form of the MVP model applied to nationally representative agricultural household survey data from Ethiopia, Tanzania and Malawi is presented as:

$$A_{pj} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1 x_1} + \boldsymbol{\beta_2 x_2} + \boldsymbol{\beta_3 x_3} + \boldsymbol{\beta_4 x_4} + \boldsymbol{\beta_5 z_i} + \boldsymbol{\varepsilon_i} \qquad \textbf{(5)}$$

where; $\boldsymbol{A_{pj}}$ =Adoption of SLM technology j in plot p (1=adopted, 0=otherwise); $\boldsymbol{x_1}$ = a vector of biophysical factors (climate conditions, agro-ecological zones); $\boldsymbol{x_2}$ = a vector of demographic characteristics factors (level of education, age, gender of the household head); $\boldsymbol{x_3}$ = a vector of farm-level variables (access to extension, market access, distance to market, distance to market); $\boldsymbol{x_4}$ = vector of socio-economic and institutional characteristics (access to extension, market access, land tenure, land tenure); $\boldsymbol{z_i}$ = vector of country fixed effects; and $\boldsymbol{\varepsilon_i}$ is the error term.

In the MVP model, where the adoption of several SLM is possible, the error terms jointly follow a multivariate normal distribution (MVN) with zero conditional mean and variance normalized to unity (for identification of the parameters) where $u_{ipj} \sim MVN(0,\Omega)$ and the symmetric covariance matrix, Ω, is given by:

$$\Omega = \begin{bmatrix} 1 & \rho_{12} & \rho_{13} & \cdots & \rho_{1m} \\ \rho_{12} & 1 & \rho_{23} & \cdots & \rho_{2m} \\ \rho_{13} & \rho_{23} & 1 & \cdots & \rho_{3m} \\ \vdots & \vdots & \vdots & 1 & \vdots \\ \rho_{1m} & \rho_{2m} & \rho_{3m} & \cdots & 1 \end{bmatrix} \qquad (\boldsymbol{6})$$

Of particular interest in the covariance matrix (equation 3) are the off-diagonal elements which represent the unobserved correlation between the stochastic components of the different types of SLM. This assumption means that equation (3) gives a MVP model that jointly represents decisions to adopt a particular farming practice. This specification with non-zero off-diagonal elements allows for correlation across the error terms of several latent equations, which represent unobserved characteristics that affect choice of alternative SLM practices and technologies.

5. Data, sampling, choice of variables for econometric estimations

5.1 Data and sampling procedures

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.

5.1.1 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)

5.1.2 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 (NSO). 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.

5.1.3 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 (NBS). 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 3** presents the distribution of sampled households in the three countries.

<<Figure 3>>

5.2 Choice of variables for econometric estimations

5.2.1 Dependent variables

In the empirical estimation of the drivers of land degradation, biomass productivity decline (change in NDVI) for the period of 1982-2006 is used as the dependent variable. The net change is reported as either, decline, no change or improved. In this study thus, the depended was coded 1 = decline and 0 =otherwise. At country level, the plots showing a decline in NDVI were about 39% in Malawi, 49% in Ethiopia and 35% in Tanzania (see **Table 2)**.

<<Table 2>>

In the empirical estimation of the determinants of adoption of SLM practices, the dependent variable is the choice of SLM option(s) from the set of SLM practices applied in the farm plots as enumerated by the respondents. The list of the specific SLM practices is also presented in **Table 2**. They include six practices namely; soil and water conservation measures (especially those aimed at soil erosion control), manure application, modern crop seeds, inorganic fertilizers application, crop rotation (cereal-legume), and intercropping (cereal-legume).

Soil-water conservation practices include soil erosion conservation measures such as terraces, grass strips and gabions. They also include tillage practices that entail minimized soil disturbance (reduced tillage, zero tillage) and crop residue retention for better improved soil fertility and soil aeration (Delgado *et al.*, 2011, Page *et al.*, 2013; Teklewold *et al.*, 2013). Crop rotation and intercropping systems are considered as temporal diversifications aimed at maintaining farm productivity (Deressa et al., 2009, Kassie *et al.*, 2013). They also increase crop productivity through nitrogen (N) fixation (Triboi & Triboi-Blondel, 2014; Lin & Chen, 2014). The application of manure (farm yard and/or animal manure) on the farm plots aids the long-term maintenance of soil fertility and supply of nutrients in the soil (Diacono & Montemurro, 2010; Shakeel et al., 2014). The use of modern seed varieties and inorganic fertilizers (NPK) has the potential to spur productivity and hence improving the household food security situation and income (Jeffery *et al.*, 2011; Asfaw *et al.*, 2012, Folberth *et al.*, 2013).

Plots with at least one SLM technologies were about 89% in Malawi, 68% in Ethiopia and 85% in Tanzania. In organic fertilizers were applied in about 47% of the plots while improved seed varieties were used in about 36% of the plots. Manure use is low – average of 15% of the plots. Crop rotation and cereal-legume intercropping was practiced in about 24% and 35% of the plots respectively. Soil erosion control measure comprising of soil bunds, stone bunds terraces, plant barriers and check dams were used in about 22% of the plots. The variations in application of these practices by country are presented in **Table 2**.

5.2.2 Independent variables

The choice of relevant explanatory variables is based on economic theory, empirical review of previous literature, and data availability. Thus, we have utilized a total of 32 variables for the empirical estimations in this paper. These can be grouped as **biophysical**, **demographic**, **plot,** and **socio-economic** variables. Brief descriptions alongside the direction of the hypothesized effects of these variables on land degradation and on SLM adoption are presented in **Table 3** and discussed below.

<<Table 3>>

The relevant biophysical variables included are temperature, rainfall, soil properties (rooting condition) and agro-ecological zonal classification. Adequate and timely rainfall, optimal temperature and favorable soil conditions are some of the biophysical factors needed for agricultural production to thrive. Favorable rainfall, temperature and soil conditions are hypothesized to positively influence adoption of improved seed varieties and use of fertilizers (Belay & Bewket, 2013; Kassie *et al.*, 2013). On the contrary, inadequate rainfall, increasing temperatures are thus hypothesized to positively influence the adoption of such SLM practices as conservation tillage, use of manure and intercropping (Yu *et al.*, 2006). High rainfall is hypothesized to negatively influence adoption of such SLM as conservation tillage practices because it may encourage weed growth and also cause water logging (Jansen *et al.*, 2006).

Our analyses also include such standard household level variables as age, gender, and education level of the household head and household size (adult equivalent) and household size. Household demographic characteristics have been found to affect the adoption of SLM practices (Pender & Gebremedhin, 2008; Bluffstone & Köhlin, 2011; Belay & Bewket, 2013; Kassie *et al.,* 2013; Genius *et al.,* 2014). We hypothesize that higher level of education of the household decision maker/head is associated with adoption of SLM practices and technologies. Previous studies show a positive relationship between the education level of the household decision maker and the adoption of improved technologies and land management (Maddison, 2006; Marenya & Barrett, 2007; Kassie *et al.,* 2011; Arslan, 2013 and Teklewold *et al.,* 2013). Households with more education may have greater access to productivity enhancing inputs as a result of access to non-farm income (Kassie *et al.,* 2011). Such households may also be more aware of the benefits of SLM strategies due to their ability to search, decode and apply new information and knowledge pertaining SLM (Kassie *et al.,* 2011, Kirui and Njiraini, 2014).

The hypothesized effect of age on SLM adoption is thus indeterminate. Gender of the household decision maker plays a critical role in SLM adoption. Existing cultural and social setups that dictate access to and control over farm resources (especially land) and other external inputs (fertilizer and seeds) are deemed to discriminated against women (de Groote & Coulibaly, 1998, Gebreselassie *et al.,* 2013).We thus hypothesize that male-headed households are more likely to invest in land conservation measures than their counterparts. Household size may affect SLM adoption in two ways; 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 (Burger & Zaal, 2012; Belay & Bewket, 2013; Kassie *et al.,* 2013). On the other hand, higher consumption pressure occasioned by increased household size may lead to diversion of labor to off-farm activities (Yirga, 2007; Pender & Gebremedhin, 2008; Fentie *et al.,* 2013).

Relevant plot level characteristics identified from previous literature that determine SLM adoption include; plot tenure, plot size, and distance from the plot to the markets. 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. Previous studies do not find a consistent relationship between market access and land degradation. Good access to markets is associated with increased opportunity costs of labor as a result of benefits accrued from alternative opportunities; thus discouraging the adoption of labor-intensive SLM practices such as conservation farming (von Braun *et al.*, 2012). However, better market access may act as an incentive to land users to invest in SLM practices because of a reduction in transaction costs of access to inputs such as improved seed and fertilizers (Pender *et al.*, 2006) and improved access to output markets (von Braun *et al.*, 2012). We hypothesize that the further away the plot is from markets, the smaller the likelihood of adoption of new seed varieties and fertilizers. However, we hypothesize also that the further away the plot is from the markets the bigger the likelihood of adoption of alternative SLM practices such as conservation farming, crop rotation and manure application.

6. Results

6.1 Descriptive statistics of variables used in the econometric estimations

We discuss the results of the descriptive analysis on this section. **Table 4** 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.

<<Table 4>>

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

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.

6.2 Drivers of Land Degradation (NDVI decline): Logit regression results

The results obtained from the logit regression estimations on the drivers of NDVI decline are discussed in this subsection. Separate regressions were estimated with data for each of the three countries (Ethiopia, Malawi and Tanzania) and another 'combined' model was estimated with country dummies. All the regressions were estimated using maximum likelihood method with plot-level data. The logit estimations fit the data well (**Table 5**). 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 [(Ethiopia: Wald Chi^2 (33) = 419.1, *p-value* = 0.000, Malawi: Wald Chi^2 (33) = 3639.7, *p-value* = 0.000, Tanzania: Wald Chi^2 (33) = 1528.1, *p-value* = 0.000, combined model: Wald Chi^2 (34) = 4358.1, *p-value* = 0.000)].

The results (marginal effects) suggest that biophysical, demographic, plot-level, and socioeconomic characteristics significantly influence NDVI decline (land degradation). We discuss significant factors in the subsequent section. Robust checks show no evidence of multicollinearity, heteroskedasticity and omitted variables. The robust checks conducted include Ramsey reset test for omitted variables, the Breusch-Pagan /Cook-Weisberg test for Heteroskedasticity and the *VIF test* for multicollinearity. The standard errors reported are robust.

<<Table 5>>

The biophysical variables having significant effect on the probability of NDVI decline included rainfall, temperature, topography (elevation) and the agro-ecological characteristics. As expected, rainfall have positive while temperature have negative significant effect on NDVI decline in all countries and in the combined model. For example, 1% increase in annual mean temperature increases NDVI decline by 7%, 4%, 1.4% and 5% in the combined model, Ethiopia, Malawi and Tanzania respectively holding other factors constant. While 1% increase in annual mean rainfall reduces NDVI decline by 0.2% both in the combined model and in Ethiopia and 0.4% in Tanzania holding other factors constant. This finding is consistent with Safriel & Adeel (2005), Wale and Dejenie (2013) and Vu et al. (2014) that increasing temperatures together with erratic and declining rainfall accelerate land degradation.

As expect, the impact of terrain on the likelihood of NDVI decline is mixed. NDVI decline is less likely to occur in the plains as compared to the highlands in all countries. NDVI decline is also less likely to occur in the plateaus in Ethiopia but more likely to occur in both Tanzanian plateaus and in the combined model. Climatic conditions, soils, and land use vary across different agro-ecologies. Lowlands were selected as the base terrain. Results show that the probability of NDVI declining was about 26%, 28% and 22% more in plateaus of Ethiopia, Malawi and Tanzania than in the lowlands *ceteris paribus*. The probability of NDVI declining was about 32%, 35% and 36% in the hilly terrains of combined model, Ethiopia and Malawi respectively as compared to the lowlands holding other factors constant. As expected, elevation has a positively effect on the probability of NDVI decline in all countries. 1% increase in elevation leads to an increase in NDVI decline by 0.1% in Ethiopia and Tanzania holding other factors constant. This finding is similar to Waters et al. (2013) that farming on steep slope induces land degradation.

Among the demographic variables, the age and gender of the household head and household size had a significant relationship with the probability of NDVI decline. In Malawi and the combined model, male headed households are less likely to experienced NDVI decline by 2% and 5% respectively. This finding corroborates the earlier findings by de Groote and Coulibaly (1998) and Gebreselassie et al (2013) that the existing cultural and social setups that dictate access to and control over farm resources (especially land, fertilizer and seeds) are deemed to discriminate against women. While family size (in adult equivalents) has a negative significant effect on the probability of NDVI decline in Ethiopia, it has a positive effect in Malawi. 1% increase in household size leads to an increase in NDVI decline by 7% in Malawi but a 4% decrease in NDVI decline in Ethiopia, holding other factors constant. The negative relationship in Ethiopia may be explained by the increasing demand for food but with stagnant or declining agricultural productivity which has led to rapid expansion of agricultural land and reduced rehabilitation of soil fertility (Scherr and Yadav, 1996). However, the positive relationship in Malawi may be related to abundance of labor endowment, thus, increased capacity to manage land in a more sustainable way (Burger and Zaal, 2012).

Regarding plot-level variables, the slope of the plot, plot ownership status, soil type as well as distance of the plot to the market significantly influence the likelihood of NDVI decline. 1% increase in slope of the plot increases the probability of NDVI decline by 1%, 0.1%, 0.3% and

0.1% in the combined model, Ethiopia, Malawi and Tanzania respectively holding other factors constant. Secure land tenure (possession of a title deed) has a negative significant effect on probability of NDVI decline. Ownership of land title-deed reduces the probability of NDVI decline by 15%, 3%, 3% and 4% in the combined model, Ethiopia, Malawi and Tanzania respectively *ceteris paribus*. This finding is similar to Kabubo-Mariara (2007) that secure land tenure is an incentive to investment in sustainable agricultural practices and technologies. Further, membership in farmer cooperatives, access to and amount of credit significantly reduced the probability of NDVI declining in all countries. As expected these variables are linked to capacity of households to access productive inputs and technologies and thus manage their lands in a more sustainable manner. Regarding the regional characteristics as depicted in the combined model, taking Tanzania as the base country, the probability of NDVI decline is significantly higher in Malawi but significantly lower in Ethiopia.

6.3 Adoption of and number of SLM technologies adopted

6.3.1 Descriptive statistics

The adoption of the different SLM practices/technologies used in farm plots is presented in **Figure 4**. 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 4>>

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 5**). 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>>

Figure 6 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 6**).

<<Figure 6>>

6.3.2 Determinants of SLM adoption: logit regression model

The results of the logit regression models on the determinants of adoption of SLM technologies are presented in **Table 6**. 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 6). 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)].

<<Table 6>>

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 6**). 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, we expect 26%, and 15% increase in probability of SLM adoption holding other factors constant. 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. (2006), Belay and Bewket (2013) and Kassie et al. (2013) 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 (1998) and Gebreselassie et al. (2013) 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 (Kassie et al, 2011 Arslan, 2013 and Teklewold et al., 2013). More education is also associated with greater ability to search, decode and apply new information and knowledge pertaining SLM (Marenya & Barrett, 2007; Kassie et al, 2011). 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 (2012), Belay and Bewket (2013) and Kassie et al. (2013) 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 (Kabubo-Mariara, 2007; Deininger et al, 2009). Access to agricultural extension services increased the probability of SLM adoption by about 29%, 10% 21% and 10% in the 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 (Nhemachena & Hassan, 2007).

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 (Hogest, 2005; Wollni et al, 2011, Kirui and Njiraini, 2013). 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 (Pattanayak et al., 2003).

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 (McCarthy, 2011). 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.

6.3.3 Determinants of number of SLM technologies adopted: Poisson regression

The results of the Poisson regression on the determinants of the number of SLM technologies used per plot are presented in **Table 7**. 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 7**). 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.

<<Table 7>>

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.

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.

6.3.4 Determinants simultaneous adoption of SLM: multivariate probit (MVP) results

The results obtained from the multivariate probit (MVP) regression models to determine the determinants of simultaneous adoption of different SLM technologies are discussed in this subsection. Separate regressions were estimated for each country (Ethiopia, Malawi and Tanzania) and a combined model was estimated for all countries. All the MVP regression models were estimated using maximum likelihood method using plot-level observations. The MVP models fit the data well (**Table 8 and Table 9**). 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 each equation are jointly equal to zero are rejected in all the equations at 1% significance level.

The results (marginal effects) suggest that biophysical, demographic, plot-level, and socioeconomic characteristics significantly condition the households' decisions to simultaneously adopt various SLM technologies. The estimated MVP coefficients however, differ substantially across technology and country; thus indicating the appropriateness of differentiating among the SLM practices equations (**Table 8 and Table 9**).

<<Table 8>>

<<Table 9>>

The likelihood ratio tests for independence between the disturbances are also all rejected [(Ethiopia: Chi^2 (15) = 7887.24, *p-value* = 0.000), (Malawi: Chi^2 (15) = 1293.48, *p-value* = 0.000), (Tanzania: Chi^2 (15) = 587.29, *p-value* = 0.000), and (combined model: Chi^2 (15) = 7177.96, *p-value* = 0.000)]. These imply correlated binary responses between different SLM, and thus support the use of a MVP model. Detailed correlation matrixes are presented later in **Tables 10-13**. The correlations between the error terms of the six regressions for each country are presented in Tables 10-13. Some of the SLM practices are complementary (positive significant correlation coefficients), while others are substitutes/compete (negative significant correlation coefficients).

<<Tables 10 - Table 13 >>

Out of the 15 cases, the correlation coefficients are statistically different from zero in 14 cases in Ethiopia MVP model, 13 in Malawian model, 11 in Tanzanian model, and 14 in combined regression model case; confirming the appropriateness of the MVP model specification. All the Ethiopia inputs were complementary to each other except intercropping verses crop rotation and intercropping verses soil erosion control that showed a competing relationship. Similarly, in Malawi all inputs exhibited complementary relationship except only the use of improved seeds and soil erosion control that were substitutes. The relationships between SLM technologies both in Tanzania and the combined model were mixed. Intercropping was a substitute to crop rotation, improved seed and soil erosion control. The rests of the SLM technologies were complements.

7. 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 comprehensively assess the causes of land degradation and to ascertain the determinants of adoption and extent of adoption SLM technologies.

Significant proximate causes of NDVI decline in the selected case study countries include temperature, terrain, topography and agro-ecological zonal classification. Important underlying drivers of NDVI decline include factors such as land ownership and distance from the plot to the market. Further, relevant demographic and socio-economic drivers include age and gender of the household head, the size of the plot, access to and amount of credit, annual household expenditure and total household assets.

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. The next chapter demonstrates that investment into SLM is worthwhile both in the short and long run.

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List of Tables

Table 1: Empirical review of proximate and underlying causes of land degradation

Country	Proximate Drivers	Underlying drivers	References
Ethiopia	Topography, unsustainable agriculture, fuel wood consumption, conversion of forests, woodlands, shrub-lands to new agricultural land (deforestation)	Weak regulatory environment and institutions, demographic growth, unclear user rights, low empowerment of local communities, poverty, infrastructural development, population density	Pender *et al.*, 2001; Jagger & Pender, 2003; Holden *et al.*, 2004; Rudel *et al.*, 2009, Bai *et al.*, 2008; Belay *et al.*, 2014; Tesfa & Mekuria, 2014.
Kenya	Topography, deforestation and charcoal production, overgrazing, unsustainable agricultural practices	Poor/weak governance & institutional weakness in agric. sector, lack of defined property rights, poverty, population density	Pender *et al.*, 2004a; Bai & Dent, 2006; Waswa, 2012; Waswa *et al.*, 2013; Nesheim *et al.*, 2014.
Malawi	Charcoal and wood fuel (for domestic & commercial), timber production; unsustainable agric. methods (slash and burn with shorter rotations), mining	Past and current development processes in energy, forestry, agriculture & water sectors; poverty; lack of alternative energy sources; weak policy environment, lack of planning; insecure land tenure	Pender, 2004; Lambin & Meyfroidt, 2010; Rademaekers *et al.*, 2010; Thierfelder *et al.*, 2013; Kiage, 2013; Harris *et al.*, 2014.
Tanzania	Topography, climate change, settlement and agric. expansion, overgrazing, firewood, timber and charcoal extraction, uncontrolled fires	Market and institutional failures, rapid population growth, rural poverty, insecure tenure, and absence of land use planning, development of infrastructure	Pender *et al.*, 2004b; de Fries *et al.*, 2010; Fisher, 2010; Wasige *et al.*, 2013; Ligonja & Shrestha, 2013; Hackman, 2014.

Source: Kirui and Mirzabaev, 2014.

Table 2: Dependent variables

Variable	*Malawi (n=18,162)*	*Ethiopia (n=14,170)*	*Tanzania (n=5,614)*	*Total (n=37,946)*
NDVI decline in the plot (% of total plots)				
NDVI decline	38.5	48.7	34.7	47.6
Sustainable Land Management (SLM) practices (SLM) (% of plots)				
SLM adoption (at least 1 SLM)	88.6	84.9	68.4	85.2
Inorganic fertilizers use	63.6	38.6	12.4	46.7
Modern seeds varieties	58.0	12.5	24.4	36.0
Manure application	10.6	24.1	8.6	15.3
Intercropping	35.1	35.2	32.5	34.8
Crop rotation	0.6	56.2	14.8	23.5
Soil erosion control	41.0	3.9	8.6	22.4

Source: Authors' compilation

Table 3: Definitions of hypothesized explanatory variables

Variable	Definition	Hypothesized effect on land degradation	Hypothesized effect on SLM adoption
Temperature	Annual Mean Temperature (^{0}C)	+/−	+/−
Rainfall	Annual Mean Rainfall (mm)	+/−	+/−
Land cover	Land cover type	+/−	+/−
Soils	Soil rooting conditions, soil type	+/−	+/−
AEZ	Agro-ecological zone	+/−	+/−
Slope	Slope elevation (SRTM)	+/−	+/−
Age	Age of household head (years)	+/−	+/−
Gender	Gender of household head	−	+
Education	Years of formal education of HH head	−	+
Family size	Size of household (adult equivalent)	+/−	+/−
Plot slope	Slope of the plot (SRTM)	−	+
Tenure	Land tenure status of the plot	+	+
Soil type	Soil type of the plot	+/−	+/−
Extension	Access to agricultural extension	+/−	+/−
Home dist.	Distance to plot from the farmer's home	+	−
Market dist.	Distance from plot from the market	+	−
Assets value	Value of household assets	−	+
Plot size	Size of the plot	−	+
Credit access	Amount of credit accessed	−	+
Group membership	Membership in cooperatives/SACCOs	−	+
Irrigation	Access to irrigation water	+/−	+

Source: Authors' compilation.

Table 4: Descriptive statistics of explanatory variables (country and regional level)

		Malawi (N=18162)		**Ethiopia (N=14170)**		**Tanzania (N=5614)**		**Total (N=37946)**	
Variable	Description	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Biophysical characteristics									
tempamt	Annual Mean Temperature (^{0}C*10)	216.811	19.097	189.622	27.227	225.374	26.590	207.925	27.639
rainfallan	Annual Mean Rainfall (mm)	1079.455	253.774	1227.814	383.878	1104.054	320.785	1138.495	325.415
terr_hlands	Terrain (1 = Highlands, 0 = Otherwise)	0.085	0.345	0.484	0.442	0.112	0.232	0.211	0.321
terr_plains	Terrain (1 = Plains & lowlands, 0 = Otherwise)	0.463	0.499	0.077	0.267	0.438	0.496	0.315	0.465
terr_plateaus	Terrain (1 = Plateaus, 0 = Otherwise)	0.452	0.498	0.540	0.498	0.450	0.498	0.484	0.500
elevation	Topography – meters above sea level (m)	890.515	348.654	1916.924	450.688	931.311	556.612	1279.838	649.574
aeztwa	AEZ (1 = warm arid/semiarid, 0 = Otherwise)	0.464	0.499	0.030	0.172	0.073	0.261	0.244	0.430
aeztwh	AEZ (1 = warm humid/sub-humid, 0=Otherwise)	0.327	0.469	0.021	0.143	0.550	0.497	0.246	0.431
aeztca	AEZ (1 = cool arid/semiarid, 0 = Otherwise)	0.123	0.329	0.225	0.417	0.029	0.168	0.147	0.354
aeztch	AEZ (1 = cool humid/sub-humid, 0 = Otherwise)	0.086	0.213	0.724	0.776	0.338	0.311	0.363	0.298
Demographic characteristics									
age	Age of household head (years)	43.295	15.928	45.724	14.795	49.298	15.525	45.090	15.592
sex	sex of household head (1=Male, 0=Otherwise)	0.780	0.414	0.824	0.381	0.788	0.409	0.797	0.402
edu	Years of formal education of head (years)	2.704	4.865	1.725	2.876	4.995	3.921	2.677	4.222
adulteq	Size of household (adult equivalent)	4.166	1.876	4.076	1.602	4.863	2.779	4.235	1.963
Plot characteristics									
tittledeed	Possess title deed of plot (1=Yes, 0=Otherwise)	0.786	0.410	0.332	0.471	0.105	0.306	0.516	0.500
sandy	Soil type (Sandy soils = Yes, 0 = Otherwise)	0.189	0.392	0.316	0.238	0.161	0.368	0.115	0.318
loam	Soil type (Loam soils = Yes, 0 = Otherwise)	0.625	0.484	0.265	0.543	0.508	0.500	0.375	0.484
clay	Soil type (Clay soils = Yes, 0 = Otherwise)	0.184	0.387	0.430	0.343	0.145	0.352	0.109	0.312
soilquality	Soil quality (1= Poor, 2= Fair, 3=Good)	0.890	0.313	1.301	0.502	0.768	0.422	1.026	0.463
plotdist1	Distance from plot to farmer’s home (km)	0.766	1.174	3.930	110.51	5.442	23.723	2.639	68.173
plotdist2	Distance from plot from the market (km)	9.761	10.403	14.833	14.716	2.363	4.348	10.560	12.350
Socio-economic characteristics									
plotsize	Size of the plot (acres)	1.025	0.929	0.331	0.804	2.536	6.335	0.990	2.666
extension	Access to extension services (1=Yes, 0=No)	0.032	0.176	0.246	0.431	0.158	0.365	0.131	0.337
grpmember	Membership in farmer groups (1=Yes, 0=No)	0.118	0.323	0.243	0.429	0.213	0.410	0.179	0.383
creditacs	Access to credit (1=Yes, 0 = Otherwise)	0.143	0.350	0.266	0.442	0.086	0.280	0.180	0.385
creditamt	Amount of credit accessed (USD)	13.699	148.374	39.669	396.782	28.605	213.204	25.602	276.028
assetsval	Value of household assets (USD)	172.35	793.105	200.263	1401.883	114.346	370.743	174.192	1027.631
expmR	Annual household expenditure (USD)	1544.842	1590.911	194.589	396.546	1810.742	1460.523	1042.62	1459.205
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.

Table 5: Drivers of land degradation (NDVI decline) in Eastern Africa: Logit results

Variables	**Combined model (n=37946)**		**Ethiopia (n=14170)**		**Malawi (n=18162)**		**Tanzania (n=5614)**	
	Coef.	Std Err	Coef.	Std Err	Coef.	Std Err	Coef.	Std Err
tempamt	0.065***	0.006	0.036***	0.009	0.138***	0.029	0.053*	0.028
tempamtsq	-0.000***	0.000	-0.000***	0.000	-0.000***	0.000	-0.000**	0.000
rainfallan	-0.002***	0.000	-0.002**	0.001	-0.002	0.001	-0.004**	0.002
rainfallsq	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
tempt#c.rain	0.000***	0.000	0.000***	0.000	0.000**	0.000	0.000*	0.000
terr_plateaus	0.237***	0.030	0.260***	0.083	0.284***	0.042	0.218**	0.102
terr_hills	0.320***	0.042	0.346***	0.087	0.357***	0.074	-0.040	0.167
elevation	0.000	0.000	0.001***	0.000	0.000	0.000	0.000	0.000
aeztwh	0.343***	0.040	-0.490**	0.211	0.280***	0.064	0.112	0.234
aeztca	0.194***	0.049	-0.454***	0.162	0.124	0.087	0.278	0.353
aeztch	0.440***	0.053	-0.086	0.181	0.119	0.112	0.436*	0.252
lnage	-0.016	0.037	-0.004	0.064	-0.025	0.055	0.291**	0.148
sex	-0.054*	0.031	0.038	0.052	-0.022**	0.049	-0.105	0.113
edu	-0.024**	0.010	-0.003	0.017	0.022	0.017	0.017	0.030
edusq	0.002**	0.001	0.001	0.002	-0.002*	0.001	-0.002	0.002
adulteq	-0.004	0.007	-0.036**	0.014	0.070***	0.012	0.015	0.021
plotslope	0.977***	0.022	0.068**	0.029	2.304***	0.042	0.058***	0.085
tittledeed	-0.145***	0.028	-0.034**	0.042	-0.026**	0.047	-0.043*	0.143
sandy	-0.052	0.039	0.001	-0.002	-0.145***	0.050	0.221	0.138
loam	0.030	0.047	0.012	0.015	-0.108*	0.062	0.219	0.170
soilquality	-0.708***	0.043	-0.385***	0.134	-0.672***	0.062	-0.615***	0.139
lnplotdist1	-0.033	0.023	0.083**	0.035	-0.065	0.053	0.030	0.048
irrigation	-0.705***	0.098	-0.608***	0.102	-0.336	0.264	-0.307	0.411
lnplotdist2	-0.024**	0.011	-0.013	0.017	-0.002	0.018	0.006	0.059
extension	-0.290***	0.041	-0.543***	0.049	0.238**	0.106	-0.221*	0.127
plotsize	0.006	0.006	0.065***	0.023	0.026	0.027	0.008	0.008
grpmember	0.041	0.033	0.076	0.046	-0.141**	0.060	-0.150	0.108
creditacs	0.112***	0.031	-0.105**	0.042	0.191***	0.053	0.338**	0.132
lncredit	-0.030*	0.016	-0.078***	0.022	0.243***	0.037	0.060	0.087
lnassests	0.016	0.010	0.068***	0.024	-0.059***	0.016	-0.058*	0.032
_cons	5.720***	0.995	9.189***	3.451	129.18***	15.497	-2.328	4.380
Malawi	0.89***	0.060	-	-	-	-	-	-
Tanzania	-0.72***	0.105	-	-	-	-	-	-
Model Characteristics	N = 37946 Wald chi^2 (35)=4358 Prob > chi^2 = 0.0001 Pseudo R^2 = 0.35		N = 14170 Wald chi^2 (35)=419 Prob>chi^2=0.000 Pseudo R^2 = 0.22		N= 18162 Wald chi^2 (35)=3639 Prob > chi^2=0.000 Pseudo R^2 = 0.24		N = 5614 Wald chi^2 (35)=1528 Prob> chi^2=0.000 Pseudo R^2 = 0.35	

***, **, and * denotes significance at 1%, 5% and 10% respectively.
The dependent variable – NDVI decline – is binary (1=decline, 0=otherwise)
Source: Authors' compilation.

Table 6: 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 LR $Chi^2(36) = 1649$ Prob > $chi^2 = 0.000$ Pseudo $R^2 = 0.2387$		No. of obs. = 18162 LR $Chi^2(34) = 1540$ Prob > $chi^2 = 0.000$ Pseudo $R^2 = 0.2256$		No. of obs. = 5614 LR $Chi^2(34) = 394$ Prob > $chi^2 = 0.000$ Pseudo $R^2 = 0.1563$		No of obs. = 37946 LR $Chi^2(34) = 2335$ Prob > $chi^2 = 0.000$ 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.

Table 7: 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 LR $Chi^2(36)$ = 1537 Prob > chi^2 = 0.000 Pseudo R^2 = 0.135		No. of obs. =18162 LR $Chi^2(34)$ = 2139 Prob > chi^2 = 0.000 Pseudo R^2 = 0.138		No. of obs. = 5614 LR $Chi^2(34)$ = 401 Prob > chi^2 = 0.000 Pseudo R^2 = 0.127		No of obs. = 37946 LR $Chi^2(34)$ = 3227 Prob > chi^2 = 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.

Table 8: Drivers of simultaneous adoption of SLM in Eastern Africa: Multivariate Probit (MVP) results

	Fertilizer use				**Manure use**				**Intercropping**			
Variables	Combined n=37946	Ethiopia n=14170	Malawi n=18162	Tanzania n=5614	Combined n=37946	Ethiopia n=14170	Malawi n=18162	Tanzania n=5614	Combined n=37946	Ethiopia n=14170	Malawi n=18162	Tanzania n=5614
lntemp	7.924***	4.666***	28.693***	3.873***	4.827***	2.924***	11.00***	2.875*	6.715***	7.449***	15.911***	4.903***
lntempsq	-1.073***	-0.451***	-1.742***	-1.042***	-0.569***	-0.147***	-0.937***	-1.170***	0.408***	0.424***	0.108*	-0.702***
lnrainf	1.772***	1.734***	2.123***	0.974***	0.800***	1.224***	0.678*	-0.264	1.280***	2.248***	2.809***	0.211
lnrainsq	-0.084***	-0.088***	0.380***	-0.058	-0.138***	-0.140***	-0.234***	-0.100**	0.323***	0.022	0.683***	-0.285***
temp#rain	-0.120***	-0.216***	0.066***	-0.173***	-0.252***	-0.170***	-0.261***	-0.273***	0.343***	0.240***	0.835***	-0.286***
elevation	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	-0.001**	0.002***	0.000	-0.001***	0.002***	0.000
terr_plateau	0.042**	-0.070	0.017	0.113	0.022	-0.103***	0.006	0.082	0.175***	0.200***	0.183***	-0.033
terr_hills	0.000	-0.027	-0.103**	0.143	0.106***	-0.219***	-0.105*	0.169	0.243***	0.271***	0.224***	-0.082
aeztwa	0.267***	0.101	-0.109***	0.002	0.000	0.002	0.000	0.000	-0.175***	-0.135	-0.333***	0.105
aeztwh	0.387***	0.038	-0.168***	-0.702***	-0.128***	-0.394***	-0.126***	-0.235**	0.077**	-0.330***	0.131**	0.153*
aeztch	-0.089***	0.152	-0.307***	-0.592***	0.029	0.073	0.074	0.204	0.068**	-0.646***	0.836***	0.237**
plotslope	-0.051***	-0.074***	-0.008	-0.096**	-0.046***	-0.078***	-0.026	0.057	0.081***	0.033*	0.159***	0.064*
sandy	0.484***	0.367***	0.433***	0.382***	0.562***	-0.032	0.308**	0.492***	0.347***	0.072***	0.973***	0.997***
loam	0.442***	0.330***	0.528***	0.466***	0.322***	-0.112	0.307**	0.393***	0.867***	0.099***	0.944***	0.967***
age	-0.002	-0.001	-0.002	0.002	-0.110***	0.032	-0.070***	-0.064	-0.001	0.016***	0.004	0.005
agesqrd	0.000	0.000	0.000	0.000	0.000**	0.000	0.000**	0.000	0.000	-0.000***	0.000	0.000
sex	-0.028	-0.072**	-0.001	-0.017	-0.017	-0.090***	-0.013	0.068	-0.072***	0.069**	-0.125***	-0.039
edu	0.000	0.036***	-0.017*	0.012	0.011*	0.032***	0.029**	-0.003	0.019***	0.031***	-0.017	-0.009
edusq	0.001**	-0.001	0.002***	0.002	0.000	0.000	-0.003***	0.002*	-0.001**	-0.003***	-0.002**	0.000
adulteq	-0.025**	-0.052**	-0.055***	-0.023	-0.003	-0.085***	0.011	-0.048*	-0.018*	-0.058**	-0.050***	-0.021
lnplotdist1	-0.050***	-0.069***	-0.015	-0.091***	-0.093***	-0.110***	-0.115***	-0.083***	-0.081***	-0.067***	-0.089***	-0.031
lnplotdist2	-0.033***	-0.016	-0.082***	-0.138***	0.001	0.042***	-0.044***	-0.028	0.014**	0.043***	-0.060***	0.009
extension	0.343***	0.311***	0.694***	-0.001	-0.028	0.035	-0.028	-0.060	0.047**	-0.037	0.231***	-0.025
tittledeed	0.060***	0.024	0.037	0.136*	0.213***	0.210***	0.106***	0.221***	0.007	-0.120***	0.170***	0.048
plotsize	0.010***	0.073***	0.227***	-0.001	-0.091***	-0.071***	-0.090***	-0.032***	0.013***	-0.045***	0.076***	0.005*
grpmember	0.150***	0.119***	0.096***	0.153**	0.003	-0.095***	0.095**	-0.037	-0.054***	-0.062**	-0.103***	0.085*
creditacs	0.090***	0.139***	0.021	-0.151*	0.089***	0.106***	0.048	-0.166*	-0.012	0.014	-0.058*	-0.135*
lncredit	-0.104***	-0.383***	-0.128**	-0.068	-0.066	-0.492***	0.031	-0.192	-0.036	-0.194**	-0.158***	0.024
lnassests	0.051***	-0.022	0.053***	0.054***	0.030***	-0.070***	0.045***	0.066***	-0.012*	-0.045***	0.011	-0.014
constant	-56.59***	-39.067***	-166.69***	-33.13***	-33.56***	-26.53***	-57.87***	-23.23***	-47.06***	-51.04***	-118.97***	-26.43***
Malawi	-1.210***	-	-	-	0.456***	-	-	-	2.892***	-	-	-
Tanzania	-1.495***	-	-	-	0.255***	-	-	-	0.979***	-	-	-

***, **, and * denotes significance at 1%, 5% and 10% significance level respectively.
Source: Author's compilation.

Table 9: Drivers of simultaneous adoption of SLM in Eastern Africa: Multivariate Probit (MVP) results continued

	Crop rotation				Improved seed				Erosion control			
Variables	Combined n=37946	Ethiopia n=14170	Malawi n=18162	Tanzania n=5614	Combined n=37946	Ethiopia n=14170	Malawi n=18162	Tanzania n=5614	Combined n=37946	Ethiopia n=14170	Malawi n=18162	Tanzania n=5614
lntemp	0.267	2.582***	-3.216	-1.507	0.297	0.415	26.965***	-4.681***	-4.589***	-1.038**	-7.907***	5.045***
lntempsq	0.033	0.017	1.157***	-0.317**	0.096***	-0.613***	1.597***	0.743***	-0.100***	0.038	0.081	-0.219***
lnrainf	0.746***	0.369***	1.463	-0.612**	0.127	-0.640***	0.985***	-0.364	-0.996***	-0.205*	-0.238	0.665**
lnrainfallsq	0.296***	0.666***	0.159*	-0.237***	0.097***	-0.252***	0.973***	0.079**	-0.170***	-0.153***	0.030	-0.158***
lntempt#rain	-0.056***	0.120***	0.341***	-0.246***	0.158***	-0.178***	0.498***	0.069**	-0.156***	-0.215***	-0.013	-0.214***
elevation	0.000***	0.000***	0.002**	0.001***	0.000***	-0.000**	0.002***	-0.001***	-0.000***	0.000***	-0.001***	0.000**
terr_plateau	-0.040	0.028	0.185*	0.230***	0.016	-0.184***	0.186***	0.196**	0.081***	0.156***	0.055**	-0.109
terr_hills	0.202***	0.421***	0.562***	0.247***	-0.197***	-0.462***	0.373***	-0.185	0.070**	0.233***	0.091**	-0.101
aeztwa	0.320***	-0.297**	0.335***	0.254	-0.049	0.678***	-0.157***	0.185**	-0.147***	0.090	-0.412***	-0.143
aeztwh	0.378***	-0.190	-0.099	0.241**	0.395***	0.095	0.333***	0.124	0.241***	-0.081	-0.246***	-0.331**
aeztch	0.295***	0.433***	0.429*	0.028	0.850***	0.326*	0.476***	0.357***	-0.063*	0.059	-0.175***	-0.082
plotslope	-0.049***	-0.036*	-0.070	-0.024	0.059***	0.047**	0.008	0.172***	0.489***	0.042**	0.642***	0.399***
sandy	0.484***	0.367***	0.433***	0.382***	0.562***	-0.032	0.308**	0.492***	0.347***	0.072***	0.973***	0.997***
loam	0.442***	0.330***	0.528***	0.466***	0.322***	-0.112	0.307**	0.393***	0.867***	0.099***	0.944***	0.967***
age	0.009**	0.015***	0.027*	-0.006	0.005*	-0.003	0.013***	-0.015*	0.006	-0.008	0.006**	0.019
agesqrd	-0.000**	-0.000***	-0.000*	0.000	0.000	0.000	-0.000**	0.000	0.000	0.000*	0.000	0.000
sex	0.041	0.100***	-0.021	-0.010	-0.029	-0.017	-0.030	0.078	0.036	0.003	0.055**	-0.025
edu	-0.005	0.022**	0.053	-0.008	0.041***	0.047***	0.057***	0.042***	0.024***	-0.004	0.037***	0.032*
edusq	-0.002**	-0.005***	-0.004	0.000	-0.004***	-0.006***	-0.005***	0.004***	-0.002***	0.001	-0.003***	-0.001
adulteq	-0.034**	-0.108***	-0.045	0.020	-0.021**	0.047	-0.014	-0.012	-0.026**	-0.039	-0.030**	-0.074**
lnplotdist1	0.087***	-0.006	-0.253	0.069***	0.001	0.010	-0.129***	0.069***	-0.015	0.040*	-0.078***	0.001
lnplotdist2	-0.036***	-0.051***	0.009	0.049	-0.054***	-0.086***	-0.053***	-0.110***	-0.025***	-0.012	-0.009	-0.026
extension	0.573***	0.645***	0.227	-0.101	0.073***	0.240***	0.056	-0.045	0.138***	0.316***	0.128**	-0.091
tittledeed	0.046**	-0.020	0.103	0.080	0.040**	0.209***	0.073**	0.135**	0.148***	-0.005	0.143***	0.016
plotsize	0.006**	0.019	-0.025	0.003	-0.001	-0.015	0.055***	0.005	0.003	0.036***	0.026**	0.005
grpmember	0.107***	0.020	-0.170	0.043	0.087***	0.182***	0.068**	-0.063	0.118***	0.029	0.111***	0.028
creditacs	-0.001	-0.056**	0.202	0.047	0.042**	0.005	0.098***	0.361***	0.139***	-0.065**	0.069**	0.141
lncredit	-0.145**	-0.407***	-0.271	0.032	-0.122***	0.192	-0.168***	0.123	-0.071*	-0.109	-0.047	-0.399**
lnassests	0.030***	0.076***	-0.049	-0.012	0.063***	0.068***	0.089***	0.031*	-0.009	0.043***	-0.001	0.027
constant	-5.63***	-9.30***	-42.86	8.40	-6.55***	2.945	-158.86***	29.01***	29.54***	1.805	48.26***	-33.41***
Malawi	-0.884***	-	-	-	-5.469***	-	-	-	-1.661***	-	-	-
Tanzania	0.418***	-	-	-	-2.290***	-	-	-	-1.291***	-	-	-

***, **, and * denotes significance at 1%, 5% and 10% significance level respectively.

Source: Author's compilation.

Table 10: Correlation coefficients for MVP regression equations (Ethiopia n=14170)

	$\rho_{Fertilizer}$	ρ_{Manure}	$\rho_{Intercrop}$	$\rho_{Rotation}$	ρ_{Seed}
ρ_{Manure}	0.952 (0.003)***				
$\rho_{Intercrop}$	0.088 (0.013)***	0.106 (0.013)***			
$\rho_{Rotation}$	0.089 (0.013)***	0.081 (0.013)***	-0.103 (0.013)***		
ρ_{Seed}	0.166 (0.020)***	0.143 (0.021)***	-0.003 (0.021)	0.033 (0.021)*	
$\rho_{Econtrol}$	0.161 (0.026)***	0.134 (0.027)***	-0.076 (0.030)*	0.282 (0.027)***	0.032 (0.034)*

Likelihood ratio test of $\rho_{ManureFertilizer} = \rho_{IntercropFertilizer} = \rho_{RotationFertilizer} = \rho_{SeedFertilizer} = \rho_{EcontrolFertilizer} = \rho_{IntercropManure} = \rho_{RotationManure} = \rho_{SeedManure} = \rho_{EcontrolManure} = \rho_{RotationIntercrop} = \rho_{SeedIntercrop} = \rho_{EcontrolIntercrop} = \rho_{SeedRotation} = \rho_{EcontrolRotation} = \rho_{EcontrolSeed} = 0$: $chi^2(15) = 7887.24$ Prob > $chi^2 = 0.000$

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

Table 11: Correlation coefficients for MVP regression equations (Malawi n=18162)

	$\rho_{Fertilizer}$	ρ_{Manure}	$\rho_{Intercrop}$	$\rho_{Rotation}$	ρ_{Seed}
ρ_{Manure}	0.244 (0.015)***				
$\rho_{Intercrop}$	0.360 (0.012)***	0.106 (0.015)***			
$\rho_{Rotation}$	0.076 (0.046)*	0.068 (0.056)	0.069 (0.047)*		
ρ_{Seed}	0.207 (0.013)***	0.021 (0.016) *	0.071 (0.014)***	0.018 (0.025)*	
$\rho_{Econtrol}$	0.014 (0.012)	0.038 (0.014)***	0.001 (0.012)	0.001 (0.020)	-0.011 (0.013)*

Likelihood ratio test of $\rho_{ManureFertilizer} = \rho_{IntercropFertilizer} = \rho_{RotationFertilizer} = \rho_{SeedFertilizer} = \rho_{EcontrolFertilizer} = \rho_{IntercropManure} = \rho_{RotationManure} = \rho_{SeedManure} = \rho_{EcontrolManure} = \rho_{RotationIntercrop} = \rho_{SeedIntercrop} = \rho_{EcontrolIntercrop} = \rho_{SeedRotation} = \rho_{EcontrolRotation} = \rho_{EcontrolSeed} = 0$: $chi^2(15) = 1293.48$ Prob > $chi^2 = 0.000$

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

Table 12: Correlation coefficients for MVP regression equations (Tanzania n=5614)

	$\rho_{Fertilizer}$	ρ_{Manure}	$\rho_{Intercrop}$	$\rho_{Rotation}$	ρ_{Seed}
ρ_{Manure}	0.574 (0.024)***				
$\rho_{Intercrop}$	0.074 (0.026)***	0.112 (0.026)***			
$\rho_{Rotation}$	0.049 (0.030)*	-0.002 (0.031)***	-0.105 (0.026)***		
ρ_{Seed}	0.077 (0.030)*	0.070 (0.030)	-0.273 (0.024)***	-0.076(0.027)***	
$\rho_{Econtrol}$	0.171 (0.033)***	0.190 (0.036)**	-0.018 (0.032)	-0.016 (0.035)	0.065 (0.034)*

Likelihood ratio test of $\rho_{ManureFertilizer} = \rho_{IntercropFertilizer} = \rho_{RotationFertilizer} = \rho_{SeedFertilizer} = \rho_{EcontrolFertilizer} = \rho_{IntercropManure} = \rho_{RotationManure} = \rho_{SeedManure} = \rho_{EcontrolManure} = \rho_{RotationIntercrop} = \rho_{SeedIntercrop} = \rho_{EcontrolIntercrop} = \rho_{SeedRotation} = \rho_{EcontrolRotation} = \rho_{EcontrolSeed} = 0$: $chi^2(15) = 587.289$ Prob > $chi^2 = 0.000$

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

Table 13: Correlation coefficients for MVP regression equations (combined n=37946)

	$\rho_{Fertilizer}$	ρ_{Manure}	$\rho_{Intercrop}$	$\rho_{Rotation}$	ρ_{Seed}
ρ_{Manure}	0.783 (0.016)***				
$\rho_{Intercrop}$	0.162 (0.010)***	0.165 (0.010)***			
$\rho_{Rotation}$	0.079 (0.012)***	0.046 (0.012)***	-0.043 (0.011)***		
ρ_{Seed}	0.078 (0.014)***	0.090 (0.015)***	-0.322 (0.013)***	0.012(0.014)	
$\rho_{Econtrol}$	0.109 (0.014)***	0.096 (0.015)***	-0.024 (0.015)*	0.135(0.017)***	0.032(0.018)*

Likelihood ratio test of $\rho_{ManureFertilizer} = \rho_{IntercropFertilizer} = \rho_{RotationFertilizer} = \rho_{SeedFertilizer} = \rho_{EcontrolFertilizer} = \rho_{IntercropManure} = \rho_{RotationManure} = \rho_{SeedManure} = \rho_{EcontrolManure} = \rho_{RotationIntercrop} = \rho_{SeedIntercrop} = \rho_{EcontrolIntercrop} = \rho_{SeedRotation} = \rho_{EcontrolRotation} = \rho_{EcontrolSeed} = 0$: $chi^2(15) = 7177.96$ Prob > $chi^2 = 0.000$

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

List of figures

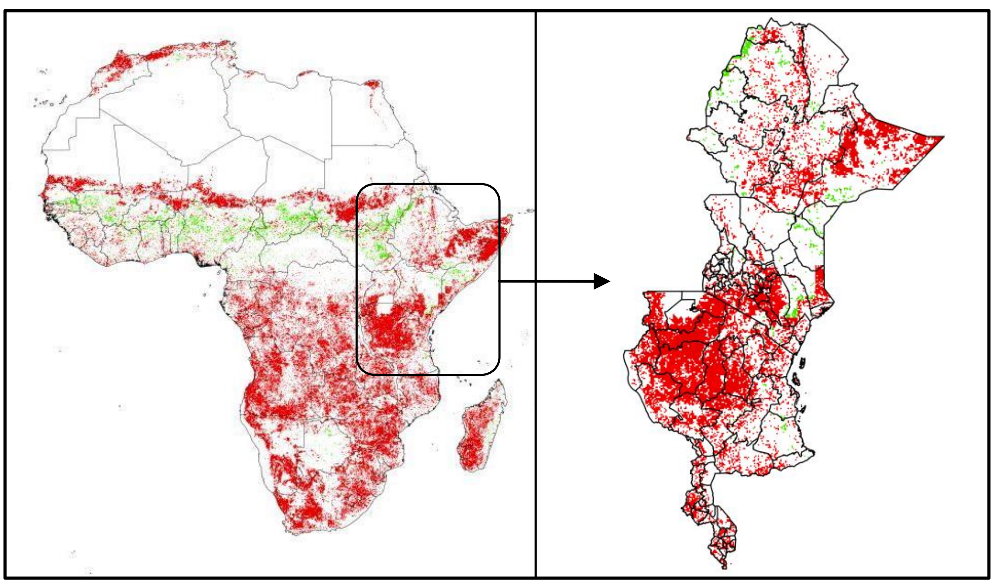

Figure 1: Biomass productivity decline in Eastern Africa over 1982-2006.
Source: Adapted from Le, Nkonya & Mirzabaev (2014).

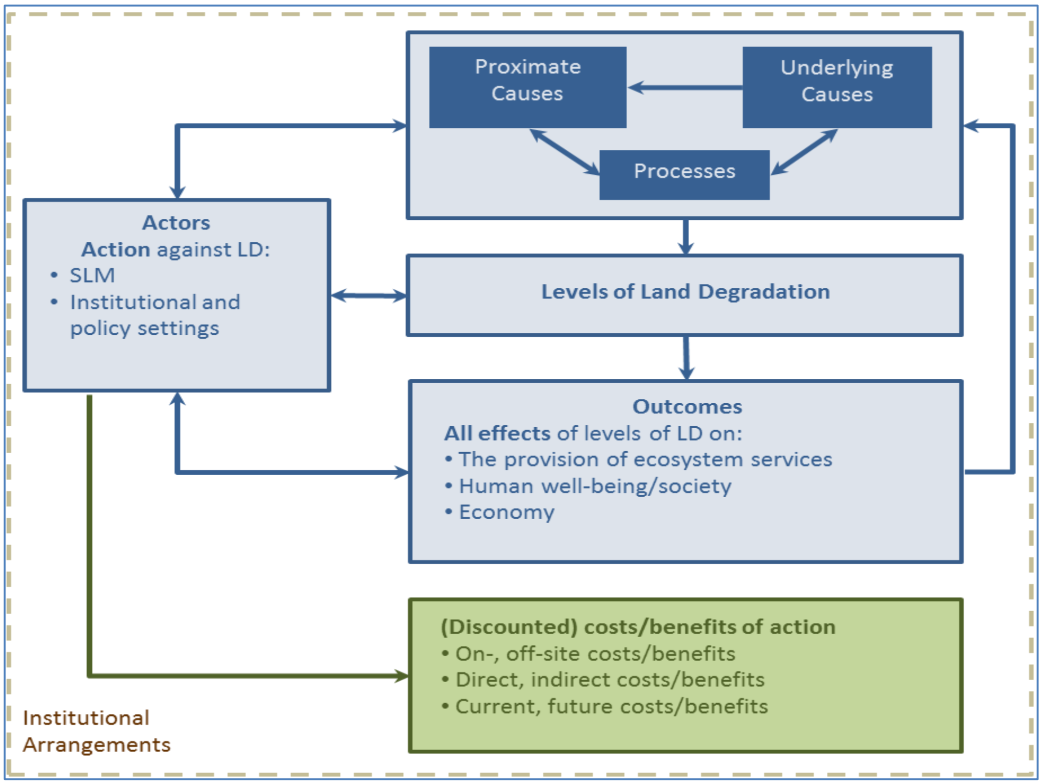

Figure 2: The Conceptual Framework of ELD Assessment

Source: Adapted from Nkonya et al. (2011).

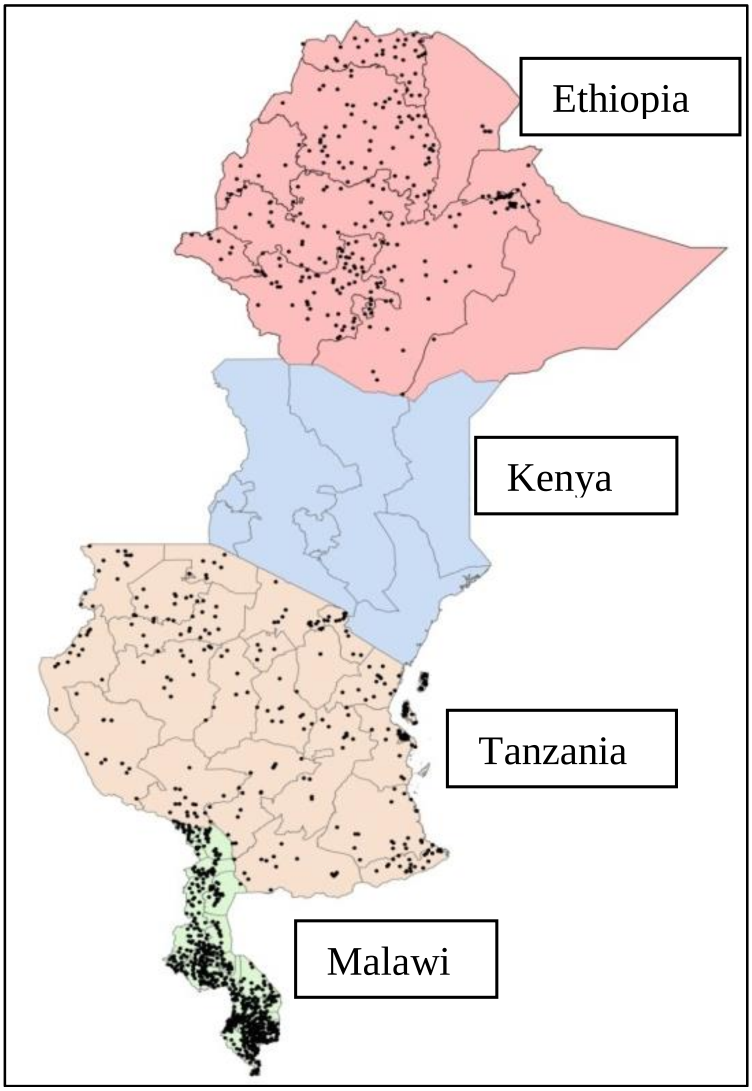

Figure 3: distribution of sampled households
Source: Authors' Compilation.

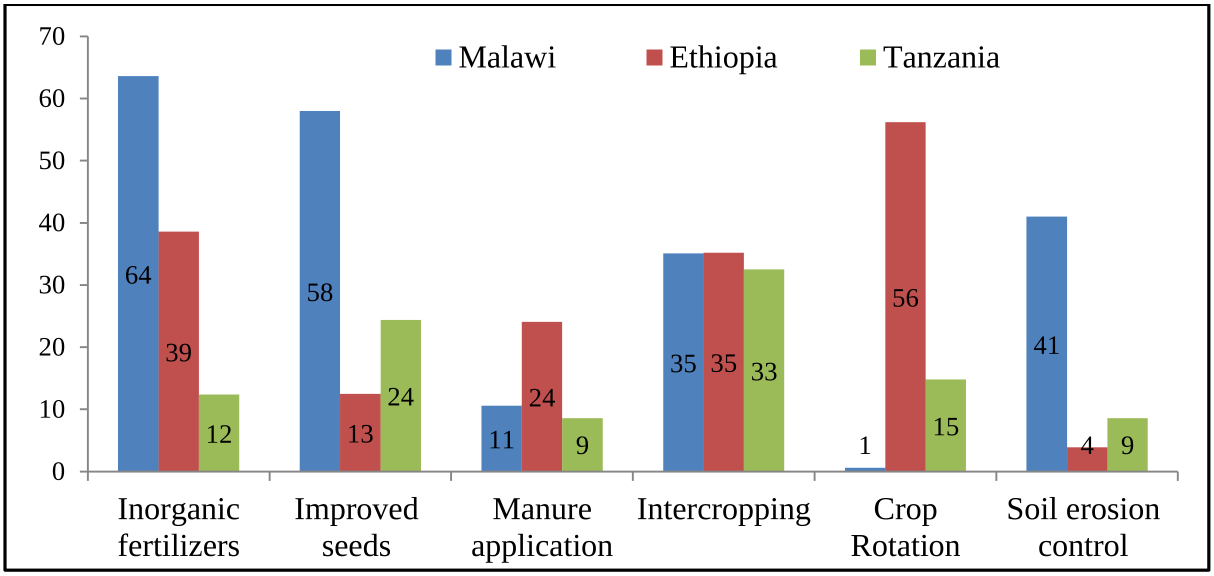

Figure 4: The distribution of different SLM technologies adopted in Eastern Africa
Source: Author's compilation.

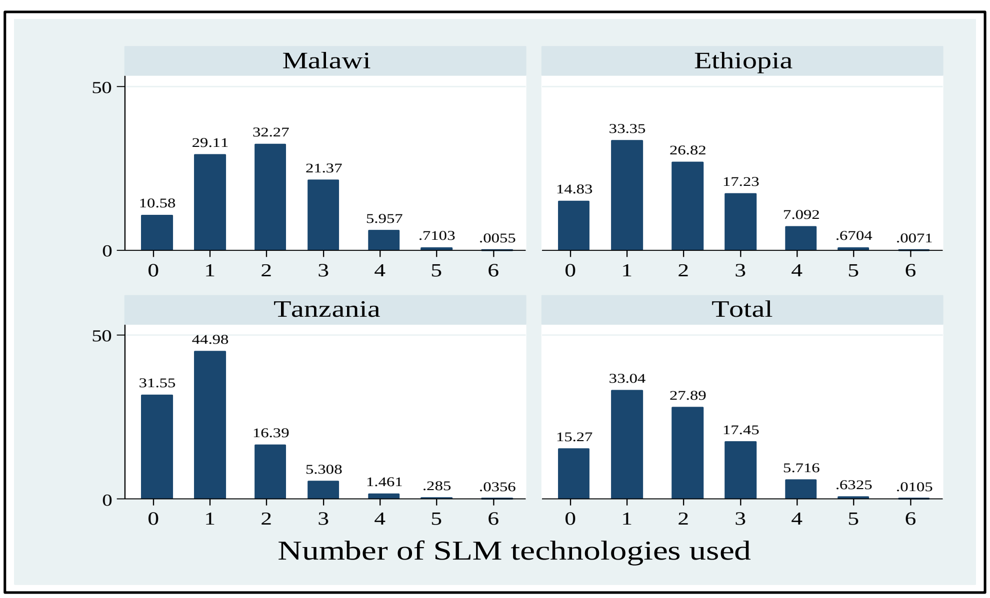

Figure 5: The distribution of number of SLM technologies adopted
Source: Author's compilation.

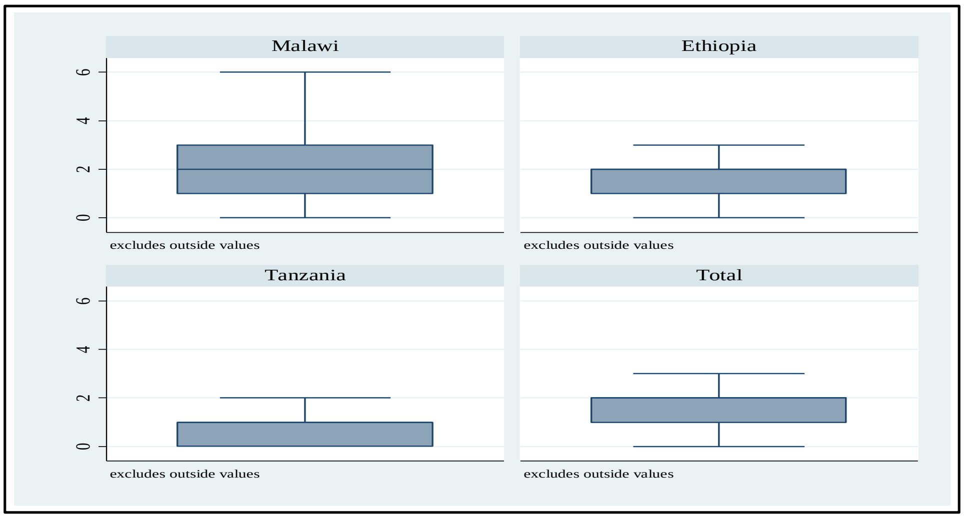

Figure 6: The mean number of SLM technologies adopted
Source: Author's compilation.