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Economics of Land Degradation, Sustainable Land Management and Poverty in Eastern Africa

The Extent, Drivers, Costs and Impacts

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Abstract

Land degradation – defined by the Economics of Land Degradation (ELD) initiative as a "reduction in the economic value of ecosystem services and goods derived from land" – is a serious impediment to improving rural livelihoods and food security of millions of people in the Eastern Africa region. The objectives of this study are fourfold: to identify the state, extent and patterns of land degradation in Eastern Africa (Ethiopia, Kenya, Malawi and Tanzania), to estimate and compare the costs and benefits of action versus inaction against land degradation; to assess simultaneously the proximate and underlying drivers of land degradation and the determinants of adoption of Sustainable Land Management (SLM); and to assess the causal effects of land degradation on the welfare of the households.

More recently, satellite–based imagery and remote sensing have been utilized to identify the magnitude and processes of land degradation at global, regional and national levels. This involves the use of Normalized Difference Vegetation Index (NDVI) derived from Advanced Very High-Resolution Radiometer (AVHRR) data and the use of high quality satellite data from Moderate Resolution Imaging Spectroradiometer (MODIS). Results based on NDVI measures show that land degradation occurred in about 51%, 41%, 23% and 22% of the terrestrial areas in Tanzania, Malawi, Ethiopia and Kenya, respectively between the 1982-2006 periods. Some of the key hotspots areas include west and southern regions Ethiopia, western part of Kenya, southern parts of Tanzania and eastern parts of Malawi. To ensure accuracy of the NDVI observations, ground-truthing was carried out in Tanzania and Ethiopia through focused group discussions (FGDs). The FGDs assessments indicate agreement in 7 sites out of 8 in Tanzania and 5 sites out of 6 in Ethiopia.

Following the Total Economic Value (TEV) framework, the cost of land degradation between 2001-2009 periods is about 2 billion USD in Malawi, 11 billion USD in Kenya, 18 billion USD in Tanzania and 35 billion USD in Ethiopia. These translate to annual costs of about 248 million USD in Malawi, 1.3 billion USD in Kenya, 2.3 billion USD in Tanzania, and 4.4 billion USD in Ethiopia – representing about 5%, 7%, 14% and 23%, of GDP in Kenya, Malawi, Tanzania and Ethiopia respectively. Taking action against land degradation is more favorable than inaction in both short-term (6 year) and a long-term (30 year) periods. During the 30-year period, for every dollar spent on taking action against land degradation users will expect a return of about $ 4.2 in Ethiopia, $ 4.1 in Kenya, $ 3.8 in Tanzania, and $ 3.7 in Malawi.

The study uses nationally representative household surveys and robust analytical techniques to capture a wide spectrum of heterogeneous contexts. A logistic regression model was used to evaluate the drivers of land degradation and to assess the determinants of probability of adoption of sustainable land management. Findings show that the key proximate drivers of land degradation include temperature, terrain, topography and agro-ecological zonal classification. Important underlying drivers of land degradation include factors such as land ownership, distance from the plot to the market, size of the plot, access to and amount of credit, and household assets. The adoption of sustainable land management practices is critical in addressing land degradation.

Secure land tenure, access to extension services and market access are significant determinants incentivizing SLM adoption. This implies that policies and strategies that facilitate 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.

Evidence from Simultaneous Equation Model with panel data shows significant causality between land degradation (EVI decline) and poverty. On one hand, land degradation significantly decreases household consumption per-capita and increases poverty. On the other hand, household poverty increases the likelihood of land degradation. Specifically, increase in household per-capita expenditure by 1% reduces the probability of EVI decline by 46% in Malawi and by 27% in Tanzania. Increase in household per-capita expenditure by 1% also reduces the probability of soil erosion occurrence by 29% in Malawi and by 26% in Tanzania. Poverty assessments show that poor households have 69% and 67% more likelihood to experience EVI decline in Malawi and Tanzania respectively. These findings are consistent with the hypothesis that poverty contributes to land degradation as a result of poor households' inability to invest in natural resource conservation and improvement. Land degradation in turn contributes to low and declining agricultural productivity, which in turn contributes to worsening poverty.

This study provides comprehensive assessments that highlight the drivers and the adverse economic consequences of land degradation and attempts to capture full valuation of losses incurred due to land degradation. It is hoped that this information expedites policy actions and investments into SLM to successfully address land degradation problems.

Zusammenfassung

Landdegradation – was die Initiative „Economics of Land Degradation“(ELD) als „reduction in the economic value of ecosystem services and goods derived from land” (ELD, 2013) definiert – ist ein ernstzunehmendes Hindernis bei der Verbesserung der ländlichen Lebensgrundlage und Nahrungsmittelsicherheit von Millionen von Menschen in Regionen Ostafrikas. Diese Studie verfolgt vier Ziele: Den Status, das Ausmaß und das Muster von Landdegradation in Ostafrika (Äthiopien, Kenia, Malawi und Tansania) zu identifizieren; die Kosten und den Nutzen von Bekämpfung und Nicht-Bekämpfung von Landdegradation zu schätzen und zu vergleichen; simultan die unmittelbaren und zugrundeliegenden Faktoren von Landverarmung und die Faktoren der Annahme von nachhaltigem Land Management (SLM) festzustellen; und die Kausaleffekte von Landdegradation auf den Haushaltswohlstand zu analysieren.

Seit jüngerer Zeit werden Satelliten- und Fernerkundungsbilder genutzt um das Ausmaß und den Prozess von Landdegradation auf globalem, regionalem und nationalem Level festzustellen. Das beinhaltet die Zugrundelegung des „Normalized Difference Vegetation Index“ (NDVI), welcher von „Advanced Very High Resolution Radiometer“ (AVHRR) Daten abgeleitet wird, sowie das Nutzen von Satellitendaten hoher Qualität generiert durch „Moderate Resolution Imaging Spectroradiometer“ (MODIS). Die Ergebnisse, basierend auf NDVI, zeigen, dass zwischen 1982 und 2006 ca. 51%, 41%, 23% und 22% der Bodenflächen in Tansania, Malawi, Äthiopien und Kenia von Landdegradation betroffen waren. Einige der wichtigsten Hotspotbereiche befinden sich in Süd- und West-Äthiopien, West-Kenia, Süd-Tansania und Ost-Malawi. Um die Richtigkeit der NDVI-Beobachtungen sicherzustellen, erfolgte eine Ground-Truth-Datenerhebung in Tansania und Äthiopien mittels gezielter Gruppendiskussionen (Focused Group Discussion = FGD). Die Analyse zeigt, dass 7 von 8 Standorten in Tansania und 5 von 6 Standorten in Äthiopien mit den zuvor ermittelten Werten übereinstimmen.

Basierend auf dem Konzept des ökonomischen Gesamtwertes (Total Economic Value, TEV) betragen die Kosten der Landdegradation im Zeitraum von 2001 bis 2009 etwa US$ 2 Milliarden in Malawi, US$ 11 Milliarden in Kenia, US$ 18 Milliarden in Tansania und US$ 35 Milliarden in Äthiopien. Dies ergibt Jahreskosten von ca. US$ 248 Millionen in Malawi, US$ 1,3 Milliarden in Kenia, US$ 2,3 Milliarden in Tansania und US$ 4,4 Milliarden in Äthiopien – was etwa 5%, 7%, 14% beziehungsweise 23% des jeweiligen Bruttoinlandproduktes (BIP) entspricht. Das Vorgehen gegen Landdegradation ist sowohl kurzfristig (6 Jahre), als auch langfristig (30 Jahre) gesehen günstiger als Untätigkeit. Im 30-Jahres-Zeitraum kann man für jeden investierten Dollar gegen Landdegradation einen Ertrag von ca. US$ 4,2 in Äthiopien, US$ 4,1 in Kenia, US$ 3,8 in Tansania und US$ 3,7 in Malawi erwarten.

Die Studie verwendet nationalrepräsentative Haushaltsumfragen und belastbare analytische Methoden, um ein breites Spektrum heterogener Inhalte zu erfassen. Ein logistisches Regressionsmodell wurde zur Evaluierung der Faktoren von Landdegradation und den Determinanten der Annahmewahrscheinlichkeit von nachhaltigem Landmanagement benutzt. Die

Ergebnisse zeigen, dass Temperatur, Gelände, Topographie und agrarökologische Zonenklassifizierung die wichtigsten unmittelbaren Determinanten von Landdegradation sind. Wesentliche zugrundeliegende Faktoren von Landdegradation sind u. A. Bodenbesitztum, Entfernung zwischen Grundstück und Markt, Größe des Grundstücks, Kreditzugang und –betrag sowie Haushaltsbesitztümer. Die Annahme von Verfahren zu nachhaltigem Landmanagement ist entscheidend bei der Bekämpfung von Landdegradation. Gesicherte Pachtverhältnisse, Zugang zu landwirtschaftlichen Beratungsdiensten und Märkten sind Entscheidungsfaktoren, die Anreize zur Annahme von SLM schaffen. Folglich schaffen Richtlinien und Strategien, die gesicherte Pachtverhältnisse und Zugriff auf SLM-Informationen erleichtern, häufiger Anreize zur Investition in SLM. Lokale Kreditinstitute, Vertreiber von Samen und Düngemitteln sowie landwirtschaftliche Beratungsdienste dürfen bei der Entwicklung von Richtlinien allerdings auch nicht vernachlässigt werden.

Ergebnisse des simultanen Gleichungsmodells (Simultaneous Equation Model) mit Paneldaten weisen auf einen signifikanten Kausalzusammenhang zwischen Landdegradation (EVI decline) und Armut hin. Einerseits verringert Landdegradation den pro-Kopf-Konsum signifikant und erhöht die Armut. Andererseits erhöht Haushaltsarmut die Wahrscheinlichkeit von Landdegradation. Im Einzelnen reduziert die Erhöhung der pro-Kopf-Ausgaben um 1% die Wahrscheinlichkeit von Landdegradation (EVI decline) um 46% in Malawi und um 27% in Tansania. Darüber hinaus reduziert dies auch die Wahrscheinlichkeit von Bodenerosion um 29% in Malawi und um 26% in Tansania. Armutsschätzungen zeigen, dass arme Haushalte eine um 69% beziehungsweise 67% erhöhte Wahrscheinlichkeit von Landdegradation (EVI decline) in Malawi und Tansania aufweisen. Diese Ergebnisse bekräftigen die Hypothese, dass Armut zu Landdegradation beiträgt – als Resultat des Unvermögens armer Haushalte in natürliche Ressourcenkonservierung und –verbesserung zu investieren. Landdegradation ihrerseits trägt zu niedriger und zurückgehender landwirtschaftlicher Produktivität bei, was wiederum zur Verschlimmerung der Armut führt.

Diese Studie bietet umfangreiche Analysen, welche die Treibfaktoren und nachteiligen ökonomischen Konsequenzen von Landdegradation herausstellen. Des Weiteren wird versucht, eine vollständige Bewertung der Verluste, die durch Landdegradation verursacht wurden, vorzunehmen. Diese Informationen werden hoffentlich genutzt um die Entwicklung von Richtlinien und Investitionen in SLM voranzutreiben und zur erfolgreichen Adressierung von Landdegradationsproblemen beizutragen.

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List of Abbreviations

AfDB	African Development Bank
AGDP	Agricultural Gross Domestic Product
AVHRR	Advanced Very High Resolution Radiometer
CSA	Central Statistical Agency
ELD	Economics of Land Degradation
FAO	United Nation’s Food and Agriculture Organization
FGDs	Focus Group Discussion
FTC	Farmer Training Centre
GDP	Gross Domestic Product
GIS	Geographic Information System
GLADA	Global Assessment of Land Degradation and Improvement
ibid	ibidem
IFPRI	International Food Policy Research Institute
LUCC	Land Use land Cover Change
MEA	Millennium Ecosystem Assessment
NDVI	Normalized Difference Vegetation Index
PES	Payment for Ecosystem Services
RUE	Rainfall Use Efficiency
SSA	Sub-Saharan Africa
SLM	Sustainable Land Management
TEEB	The Economics of Ecosystems and Biodiversity
TEV	Total Economic Value
UNCCD	United Nations Convention to Combat Desertification
UNECA	United Nation Economic Commission for Africa
USD	United States Dollars
ZEF	Center for Development Research, University of Bonn

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I dedicate this thesis to my loving parents.

Chapter 1

1. Introduction

1.1 Background Information and Study Context

Land degradation – defined by the Economics of Land Degradation (ELD) initiative as a "reduction in the economic value of ecosystem services and goods derived from land" (ELD, 2013) – is a global problem affecting 29% of land area in all agro–ecological zones around the world (Le *et al.*, 2014). Estimates show that about a 3.2 billion people – most of them in low income countries – reside on these degraded land (Le *et al.*, 2014). Recent statistics from UNCCD show that about 40 percent of global agricultural land has been degraded in the past 50 years by erosion, salinization, compaction, nutrient depletion, pollution and urbanization (UNCCD, 2007). About 1.9 billion hectares of land has been degraded worldwide (UN, 1997).

Recent data indicate that globally, an area of about 5–8 million hectares of productive land go out of production annually due to degradation (TerrAfrica, 2006). More agricultural land is rendered less productive in developing countries as depicted by considerable decline in crop yields (Vlek *et al*., 2010). There is no consensus on the exact extent, severity and impacts of land degradation in the Eastern Africa region or in sub-Saharan Africa (SSA) as a whole (Reich *et al.,* 2001; Stocking, 2006). However, recent assessments show that land degradation affected 51%, 41%, 23% and 22% of land area in Tanzania, Malawi, Ethiopia and Kenya respectively (Le *et al.*, 2014).

Resource loss due to land degradation in Eastern Africa is believed to be enormous (Maitima, 2009). To illustrate, about 1 billion tons of topsoil are lost annually in Ethiopia due to soil erosion (Brown, 2006), costing the country 3% of its Agricultural Gross Domestic Product (AGDP) (Yesuf *et al.,* 2008). 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 Tanzania (ibid). Chemical land degradation, including soil pollution and salinization/alkalinisation, has led to 15% loss in the arable land in Malawi and Zambia in the last decade alone (Chabala *et al.,* 2012).

Investment in sustainable land management (SLM) is a cost-effective and worthwhile way to address land degradation (MEA, 2005; Akhtar-Schuster *et al.,* 2011; 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, estimates show that the adoption of SLM practices is very low – just about 3% of total cropland in SSA (World Bank, 2010). Several factors limit the adoption of SLM, 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 (such as, inappropriate land tenure and user rights), market and infrastructure constraints (such as, volatile prices of agricultural products, increasing input costs, inaccessible markets), and policy and institutional bottlenecks (such as, difficulty and costly enforcement of existing laws that favor SLM) (Thompson *et al.,* 2009; Chasek *et al.,* 2011; Akhtar-Schuster *et al.,* 2011; Reed *et al.,* 2011; ELD Initiative, 2013).

Land degradation poses the greatest long–term threat to human survival and offers one of the greatest policy challenges in the foreseeable future in many low income countries (Scherr, 1999). The duo problem of land degradation and poverty is dire in rural areas of low income countries because the major economic activities hinge on agricultural–based livelihoods (Turner *et al*., 1994). This study posits that poverty and land degradation are interwoven and that the linkage between them is complex and mutually re–enforcing (poverty leads to land degradation while land degradation also contributes to poverty); a poverty–land degradation viscous cycle. Globally, an estimated 870 million people are poor – living on less than $1 USD a day; majority of whom reside in rural degrading areas of developing countries (FAO, 2012). Land degradation is therefore an important issue particularly on the welfare of the rural households in developing countries because it is closely linked to household poverty and food (in)security.

1.2 Problem Statement

Despite a backdrop of information on the natural resource loss, large economic losses due to land degradation and the urgent need for action to prevent and reverse land degradation, the problem has yet to be appropriately addressed, especially in the developing countries, including in Eastern Africa. Adequately strong policy action for SLM is lacking, and a coherent and evidence-based policy framework for action across all agro-ecological zones is missing (Nkonya *et al.*, 2013). Identifying drivers of land degradation is one step toward addressing them (von Braun, *et al.*, 2012).The assessment of relevant drivers of land degradation by robust techniques at farm and household levels is necessary. The adoption of sustainable land management practices is critical in addressing land degradation. There is, thus, an increasing need for evidence-based science to evaluate the determinants of adoption as well as economic returns from SLM. Reliable estimates on the exact impact of land degradation on the welfare (poverty) of farm households are not available.

1.3 Economics of Land Degradation (ELD) Initiative

This doctoral study is carried out under the auspices of a larger global research ‘‘The Economics of Land Degradation (ELD)’’ implemented by the International Food Policy Institute (IFPRI) and Center for Development Research (ZEF) which was commissioned in 2010-2011 by the United Nations Convention to Combat Desertification (UNCCD) in collaboration with the German Federal Ministry of Economic Cooperation and Development (BMZ). ELD was established to provide common methods and approaches to highlight the value of sustainable land management and the costs of land degradation. ELD research seeks to assess the state-of-the-knowledge on the economics of land degradation around the globe. The ELD research develops an analytical conceptual framework for a more comprehensive and integrated global assessment of land degradation by including the value of land ecosystem services. It also provides methods for assessment of the drivers of land degradation.

ELD methodology make use of satellite data to depict land degradation and improvement areas based on changes in biomass productivity as shown by the Normalized Differenced Vegetation Index (NDVI) (Le *et al*., 2014) and based on the losses or deterioration of ecosystem services as depicted by Land Use Cover Change (LUCC) (Nkonya *et al*. 2013). The total economic value (TEV) approach is used to analyze on-site and off-site direct and indirect societal costs and benefits of land degradation for both the present and the future periods (ibid). Through these assessments of the drivers and costs of land degradation and on the returns to investments for rehabilitating land or preventing land degradation, ELD aims at increasing the awareness and thus provide opportunities for mobilizing investments in sustainable management of land resources at nationally and globally.

The current study therefore demonstrates the application of these concepts and methods at the national and regional (district) in four Eastern African countries – Ethiopia, Kenya, Malawi and Tanzania which have been identified to be seriously affected by land degradation (Le *et al*., 2014). It also provide field and community-based information which form a "bottom-up" approach to assessment of land degradation in contrast to "top-down" satellite data analysis. Additionally (and unlike the global assessment), this thesis analyses the impact of land degradation on household welfare (poverty) using a combination of satellite and nationally representative agricultural household survey data.

1.4 Research Objectives and Questions

Based on the above background, context and research challenge, the aim of this study on the economics of land degradation, sustainable land management and household welfare is to identify the extent of land degradation, provide comprehensive assessments that highlight the extent, drivers and the adverse economic consequences of land degradation and to capture full valuation of losses incurred due to land degradation. Specifically, this study pursues its objectives as follows. First, it identifies the state, extent and patterns of land degradation in Eastern Africa (Ethiopia, Kenya, Malawi and Tanzania) using remotely sensed datasets. This involves the use of Normalized Difference Vegetation Index (NDVI) derived from Advanced Very High-Resolution Radiometer (AVHRR) data and the use of high quality satellite data from Moderate Resolution Imaging Spectroradiometer (MODIS). Second, it assesses simultaneously the proximate and underlying drivers of land degradation and the determinants of adoption of SLM in Eastern Africa using national representative agricultural household survey data.

Identifying drivers of land degradation is one step toward addressing them. Thus, the potential technological, institutional and policy measures to address land degradation are highlighted. Third, the study evaluates the costs and benefits of action verses inaction against land degradation in Eastern Africa using Total Economic Value (TEV) approach. TEV is a comprehensive approach that accounts for the losses of both market-priced provisional land ecosystems services and non-marketed supporting, regulating and cultural ecosystem services. Finally, this study estimates the causal relationship between land degradation on household poverty using panel data in Tanzania with robust analytical approach that accounts for endogeneity. In order to achieve these objectives and based on the preceding background and problem definition, the proposed study pursues answers to the following research questions:

1. What is the state of knowledge on extent of land degradation in Eastern Africa and how may remote and ground-level assessments complement each other?
2. What is the cost of land degradation in Eastern Africa and how the costs of action against land degradation compare with the costs of inaction?
3. What are the drivers (proximate and underlying) of land degradation and determinants of adoption of SLM practices?
4. What is the impact of land degradation on poverty?

Comprehensive assessments that highlight the drivers of land degradation, capture full valuation of losses incurred due to land degradation, and establish the adverse economic consequences of land degradation would expedite policy actions and investments into SLM to successfully address land degradation problems.

1.5 Contributions of the Study

A summary of some of the contributions from this study are presented in this subsection. Detailed contributions are highlighted throughout the study. The novelty of this study on the economics of land degradation, SLM and poverty in Eastern Africa is that it is the first to provide a comprehensive assessment that make the drivers and the adverse economic consequences of land degradation visible and capture a full valuation of losses incurred due to land degradation. It also reviews and ground-truth the land degradation 'hotspot map' proposed by Le *et al.* (2014).

There already exist a body of literature covering the extent and patterns of land degradation in Sub Saharan Africa (e.g. Bridges and Oldeman, 1999; Berry *et al*., 2003; Jones *et al*., 2003; Stringer and Reed, 2007; Bai *et al*. 2008; Stoosnijder, 2007; Nachtergaele *et al*. 2010; Lal & Stewart, 2013; Zucca *et al.*, 2014), albeit lacking in a number of ways. Most of these studies have not been successful in quantifying the extent and severity of land degradation in East Africa (Sonneveld, 2003; Berry *et al*., 2003; Stringer and Reed, 2007; Verchot, *et al.*, 2007). They also vary in the approaches used to estimate the extent and levels of land degradation. Most of the studies in Eastern Africa uses expert opinion methodologies (e.g. Oldeman *et al*., 1991; Bridges and

Oldeman, 1999; FAO, 2000; Jones *et al*., 2003; Sonneveld, 2003; Stringer and Reed, 2007; Verchot, *et al.*, 2007; Assey *et al.*, 2007). A number of deficiencies are associated with this approach: Information on expert opinions are perception-based and semi quantitative and therefore not built on objective measurements (Dejene, 1997; Jones *et al*., 2003; Kapalanga, 2008). Studies based on expert opinion methodologies are also said to have unknown magnitudes and directions of measurement errors (Kasprzyk, 2005; Le *et al*., 2014).

More recently, quantitative interpretation of satellite imagery (NDVI/NPP), and model-based approaches involving indicators and proxy variables measurable over large areas and over longer periods have been used (e.g. Bai *et al*., 2008; Vlek *et al*., 2010; Le *et al*., 2014). Some caveats associated with NDVI/NPP methodologies include: site-specific effects of vegetation/crop structure and site conditions autocorrelation, effect of atmospheric fertilization and intensive fertilizer use on NDVI, seasonal variations in vegetation phenology, and effect of soil moisture in sparse vegetative areas. Detailed steps on how these caveats were addressed are presented in Le *et al*. (2014). NDVI is preferred because it allows the assessment of land degradation over longer term period and on national and regional scales.

This study is also the first to complement remote sensing with ground level assessment in evaluating the state of knowledge on the extent of land degradation in Eastern Africa. Remotely-sensed dataset on biomass productivity decline is based on an updated methodology proposed by Le *et al*. (2014) while the remotely-sensed dataset on land use and land cover change (LUCC) is based on Total Economic Value framework proposed by Nkonya *et al*. (2015). To ensure accuracy of these remotely sensed estimations, ground-truthing was done through focused group discussions (FGDs) in Tanzania and Ethiopia. Besides, ground-truthing, the NDVI and LUCC assessments are also triangulated with both household and plot level data.

There is a fairly large body of existing literature on causes of land degradation and determinants of adoption of SLM, however, a number of limitations are evident. These studies either focuses on some specific location(s) in the region (de Bie, 2005; Stringer and Reed, 2007; Pender and Gebremedhin, 2006), are considered subjective and lacking in scientific rigor and/or have weak explanatory power due to smaller sample size (Olwande *et al*., 2009; Yesuf and Köhlin, 2009; Oostendorp and Zaal, 2011). Results from different studies are often contradictory regarding any given variable (Ghadim and Pannell, 1999; Nkonya *et al*., 2013). The contribution of this study stems from employing nationally representative agricultural household surveys and robust analytical techniques to capture a wide spectrum of heterogeneous contexts in the three Eastern Africa countries. This approach could lead to better targeting of policy measures for combating land degradation and facilitating SLM uptake across different contexts.

A review of existing literature showed that no study has comprehensively tackled the costs of land degradation and the value of benefits from land improvement either at the household, regional or national level in Eastern Africa. This study adopts a comprehensive approach (TEV) proposed by Nkonya *et al* (2015) that accounts for the losses of both market-priced provisional land ecosystems services and non-marketed supporting, regulating and cultural ecosystem services. Land degradation costs and benefits from land improvement are estimated for the 2001-2009 period at pixel level (and aggregated at district and national level) and simulated for a period of 30 years. The study is also the first to estimate the causal linkages between land degradation and poverty in the region. The study utilizes panel data from smallholder farm households which enables controlling for unobserved heterogeneity and account for endogeneity.

1.6 Organization of the Thesis

This thesis is organized into six chapters crafted to address the proposed research questions. Following this introduction (chapter 1) to the research context, problem, objectives and research questions, the first research question on the state of knowledge on the extent of land degradation in Eastern Africa is enumerated in chapter 2. Detailed description on how remote and ground-level assessments could complement each other is also described in this chapter. Chapter 3 answers the third research question on the cost of land degradation and how the costs of action against land degradation compare with the costs of inaction. Chapter 4 addresses the third research question on the drivers of land degradation and determinants of adoption of adoption of SLM practices. Chapter 5 tackles the fourth research question on the causal relationships between poverty and land degradation. This chapter assesses the impact of land degradation on poverty and vice versa using panel data. Chapter 6 concludes the thesis by summarizing the main research findings and providing the implications of the study for policy and practice.

Chapter 2

2. Assessment of Land Degradation ‘from Above and Below’

2.1 Overview of Methods of Assessing Land Degradation

Land degradation is defined as ‘‘the persistent reduction of the production capacity of a land, which may be manifest through any combination of a number of interrelated processes, such as: soil erosion, deterioration of soil nutrients, loss of biodiversity, deforestation or declining vegetative health’’ (Le *et al.*, 2012). Assessments of land degradation vary in methodology and outcome (Stoosnijder, 2007; Lal & Stewart, 2013; Zucca *et al.*, 2014). There are two broad approaches to evaluate land degradation: ground-based measurements and remote sensing.

Ground-based measurements, also referred to as survey-based (direct) field observations, include approaches such as experts’ opinions, land users’ opinion, field monitoring and measurements, productivity changes, farm-level studies, and modeling. These approaches are important in evaluating land degradation process at the national and local levels (Van Lynden and Kuhlmann 2002). On the other hand, above-ground measurements involves the use of remotely sensed satellite imagery, Radio Detection and Ranging (RADAR), and GIS data. An extensive review of these methods including their appropriateness, strengths, and limitations is provided in Nkonya *et al*. (2011) and Kapalanga (2008).

Ground-based measurements have been utilized to evaluate the severity, degree and extent of land and soil degradation at global, regional national and local levels. For example, the Global Assessment of Human-induced Soil Degradation (GLASOD) which is based on expert opinion, provides information on the global distribution, intensity and the causes of erosional, chemical, and physical degradation (Bridges and Oldeman, 1999; Jones *et al*., 2003). The World Overview of Conservation Approaches and Technologies (WOCAT) provides information on soil and water conservation (SWC), conservation approaches, and technologies to combat desertification in 23 countries spread across six continents (Bai *et al*. 2008; Nachtergaele *et al*. 2010). Other studies that use expert opinions conducted at national and local levels include Sonneveld (2003) in Ethiopia, and Berry *et al*. (2003) in Chile.

Direct field observations using soil erosion indicators such as eroded clods, flow surfaces, pre-rills and rills have been used to effectively monitor the effects of erosion from tillage and harvesting in Kenya (de Bie, 2005). Further examples includes the participatory degradation appraisal carried out in Botswana (Reed and Dougill, 2002). This approach combines three approaches; the land user opinion, the farm-level field observations and assessment of productivity changes. Stringer and Reed (2007) also uses a participatory approach that integrates the expert opinions and the experiences of the local knowledge (key informant interviews, focus group discussions and questionnaires) to enhance accuracy, coverage and relevance of land degradation assessment in Botswana and Swaziland.

Soil erosion and its related risks has been studied using various models such as Universal Soil Loss Equation (USLE), Wind Erosion Equation (WEE) (Arnalds *et al*., 2001; EUSOILS, 2008), Revised Universal Soil Loss Equation (RUSLE) (EUSOILS, 2008), Coordination of Information on the Environment (CORINE) (Dengiz and Akgul, 2004), and Pan-European Soil Erosion Risk Assessment (PESERA) (Kirkby *et al*., 2004).

Remote sensing approach is vital in measuring land degradation especially over a larger scale – regional, national to global scales in a consistent manner. This approach is considered a cost-effective and time-efficient because one image can be used to assess land degradation over a big area (Lu *et al.,* 2007; Gao and Liu, 2010). Land degradation can be identified in various ways using remote sensing techniques, including;

(i) Manual visual approach; such as image differencing of two images – Rasmussen *et al*. (2001) in Burkina Faso; Collado *et al*. (2002) in Argentina; Borak *et al*. (2000) in sub Saharan Africa,

(ii) Interpretation of aerial photography and satellite imagery; such as Gupta *et al*. (2002) in China; Ries and Marzolf (2003) in Spain;

(iii) Spectral index ("Land degradation Index") such as Chikhaoui *et al*. (2005) in Morocco;

(iv) Land-cover mapping and "Steppe Degradation Index" Spatial and temporal metrics of land cover change: Borak *et al*. (2000) in sub Saharan Africa.

Recent empirical evaluations of land degradation, however, show a shift from manual visual approaches, interpretation of aerial photography and satellite imagery to a more model-based approach involving indicators and proxy variables, measurable over large areas and over longer periods. These approaches have been criticized for exaggerating the result on the levels of land degradation, and that they are perception-based and semi quantitative, and therefore not built on objective measurements. Land-cover exercises map degradation using image brightness values on a snapshot satellite image, thus cannot represent persistent land degradation.

(v) Model-based approach – involving indicators and proxy variables: The most widely used index for assessment is the vegetation indices such as the Normalized Difference Vegetation Index (NDVI).

NDVI is an index of plant "greenness" or photosynthetic activity. Vegetation indices have been used for a long time in a wide range of fields, such as vegetation monitoring; climate modelling; agricultural activities; drought studies and public health issues (Running *et al*., 1994). Vegetation indices are radiometric measures that combine information from the red and near infra-red (NIR) portions of the spectrum to enhance the 'vegetation signal'. NDVI allows reliable spatial and temporal inter-comparisons of terrestrial photosynthetic activity and canopy structural variations. NDVI is generally computed for all pixels in time and space, regardless of biome type, land cover condition and soil type, and thus represent true surface measurements. There are varied NDVI datasets available including; the Moderate Resolution Imaging Spectroradiometer (MODIS), Advanced Very High Resolution Radiometer (AVHRR), and Landsat satellite sensors (Brown *et al*., 2006; Fensholt and Proud, 2012; Beck *et al*., 2011).

Some studies utilizing this approach include: Diouf and Lambin (2001) in Senegal; Prince *et al*., (1998) Nicholson *et al*. (1998), Herrmann *et al*., (2005) in the Sahel; Prince (1998, 2002) in Zimbabwe and Mozambique, Vlek *et al*. (2010) in SSA, Bai *et al*. (2008) and Le *et al*. (2014) at the global level. de Pinto *et al*. (2013) extents NDVI estimation to predict/detect future land degradation and its economic effects globally with inclusion of climate change effects.

However, remote sensing datasets may have structural errors. These structural errors may be conceptualized as falling into one of three related categories: errors arising from the type of sensor used, errors arising from the spatial and temporal resolution of the analysis, and errors arising from the derived data used (i.e. indices, land cover/land use classifications, etc.). A step by step procedure to address these shortcomings relating to measurement of biomass productivity (NDVI) changes is presented in Le *et al.,* (2014).

The nobility of this study stems from combining remote sensed land degradation dataset and ground-based surveys (ground-truthing) to evaluate the extent of land degradation. Remotely-sensed dataset on biomass productivity (NDVI) decline is based on an updated methodology proposed by Le *et al*. (2014) while the remotely-sensed dataset on land use and land cover change (LUCC) is based on Total economic Value framework proposed by Nkonya *et al*. (2015). Survey-based datasets collected through Focused Group Discussions (FGDs) are used to complement the remote-sensing observations. The survey based observations are important because they provide ground-based estimates of land degradation from the perspectives of the communities involved. The next sections, describes the datasets used, methods of analysis, and the results. A brief discussion of the implications of these results is presented in the conclusion.

2.2 The Extent of Land Degradation in Eastern Africa

The total population of Sub-Saharan Africa (SSA) is currently estimated at 750 million people (UNDP, 2005), but this is projected to grow past the one billion mark by 2020 (UNDP, 2005, Haub, 2009). The region is the poorest in the world, with an estimated one in every three people living below the poverty line. The demand for food is putting greater pressures on the natural resource base. Assessments of land degradation in the region vary in methodology and outcome (Stoosnijder, 2007; Lal & Stewart, 2013; Zucca *et al.*, 2014). The GLASOD survey, based on expert opinion, concluded that in the early 1980s about 16.7% of SSA experienced serious human-induced land degradation (Middleton & Thomas, 1992; Yalew, 2014). Using standardized criteria and expert judgment, Oldeman (1994) revealed that about 20% of SSA was affected by slight to extreme land degradation in 1990. These assessments were done based on 'experts' opinion and for varying time period.

The data from the FAO TERRASTAT maps 67% (16.1 million km^2) of the total land area of SSA as degraded (FAO, 2000), with country-to-country variations. These variations are quite large: Ethiopia is the most seriously affected (25% of territory degraded) while Kenya and Tanzania records 15% and 13%, respectively. Malawi is the least affected (9%). The figure for Tanzania (13%) is quite low compared to a later study (Assey *et al.*, 2007) based on expert opinion that showed about 61% of the territory affected by land degradation. The TERRASTAT datas*et al*lows the further classification of the degraded lands by the relative degree of severity of degradation.

Thus out of the 67% degraded land in SSA, the four sub-categories exist, namely; light (24%), moderate (18%), severe (15%), and very severe (10%). In contrast, the GLASOD data shows that about 25%, 14% and 13% of land area is degraded in Ethiopia, Kenya and Tanzania respectively. However, the main weakness of these studies is that it is based on subjective expert judgment and must be approached with caution.

GLASOD global survey (Nachtergaele, 2006) and FAO`s global forest resource assessment (2005) identified six main types of land degradation predominant across SSA countries (**Table 2.1**). Among them, water and wind erosion are the most widespread type of land degradation (46% and 38% respectively), followed by chemical and physical deterioration of soils (16%). The other types of land degradation include salinization and water logging, decline in soil fertility, and loss of habitat (especially forest and woodland). Previous studies have not been successful in quantifying the extent and severity of these types of land degradation in East Africa. However, it is notable that water erosion, declining soil fertility and nutrient depletion are important in all the four countries. While salinization (irrigated land) is severe in Kenya (30%) and Tanzania (27%), loss of forest and woodland in these countries is estimated at 0.7% per annum.

Table 2.1: Land degradation types and extent in Sub Saharan Africa

Type of land degradation	Affected land (% of total)	Affected population (% of total)	Countries affected	Main cause(s)
Water Erosion	46	97	All countries in eastern Africa (Kenya, Tanzania, Ethiopia, Malawi, Zambia)	Deforestation, overgrazing, agric. Practices
Wind Erosion	38	18	Botswana, Chad, Djibouti, Eritrea, Mali, Niger, South Africa and Sudan	Overgrazing, deforestation
Salinization			Severe in Kenya (30%), Tanzania (27%)	Water management
Soil fertility and nutrient depletion	Approx. 100	Approx. 100	All countries	Agric. practices, overgrazing, deforestation,
Loss of Habitat (Deforestation)	0.7% of annual change of Forest & Woodland area in East & Southern Africa		Hotspots: Burundi (-5.2%), Comoros (-7%), Nigeria (-3.3%), Togo (-4.5%), Uganda (-2.2%), Zimbabwe (-1.7%)	Deforestation, overgrazing, agricultural practices

Source: Adopted from Global Forest Resource Assessment (FAO, 2005) & Nachtergaele, (2006).

More recently, satellite–based imagery (remote sensing) have been utilized to identify the magnitude and processes of land degradation at global, regional and national levels. This involves the use of Normalized Difference Vegetation Index (NDVI) derived from Advanced Very High-

Resolution Radiometer (AVHRR) data. Several studies have applied this technique, including; Evans & Geerken, 2004; Bai *et al.*, 2008; Hellden & Tottrup, 2008; Vlek *et al.*, 2010. While using rain-use efficiency (RUE) adjusted NDVI, Bai *et al.* (2008) map the global land degradation trends. Their assessment shows that land degradation has affected about 26% of SSA. The areas affected are also different from those reported by GLASOD and TERRASTAT surveys and by Oldeman (1994).

Unlike this GLASOD and TERRASTAT assessment, Bai *et al.,* (2008) estimated that about 24% of the global land area has been degrading (significant decline in NDVI) in 25 years. Much of the areas they identify do not overlap with those indicated in the GLASSOD survey. However, Sub Saharan Africa region remains the most affected. Country estimates (**Table 2.2**) show that Tanzania was the most affected country; 41% of its land territory degraded. Ethiopia and Malawi both had 26% of their territories degraded while about 18% of Kenya land area was degraded in the same period. In terms of populations affected; about 40% and 36% of people in Tanzania and Kenya were living in these degraded areas. Similarly, about 30% and 20% of the Ethiopian and Malawian population was affected by land degradation over the same period. It is however notable that these estimates do not take into account the effect of atmospheric fertilization, the rainfall factor and the effect of soil moisture in sparse vegetative areas.

Table 2.2: Statistics of degraded areas by country for Eastern Africa (1981–2003)

Country	Degrading area (km^2)	% Territory	% Total population	Affected People	% Territory (GLASOD)
Ethiopia	296,812	26	29	20 million	25
Kenya	104,994	18	36	11 million	15
Malawi	30,869	26	20	2 million	9
Tanzania	386,256	41	40	15 million	13

Source: Bai *et al.*, 2008 and FAO, 2000.

Similarly, the work of Vlek *et al.* (2008) estimated that 10% of SSA was significantly affected by land degradation. Vlek *et al.* (2010) also map the geographic extent of areas in SSA affected by land degradation processes over the period of 1982–2003 (**Figure 2.1**). While utilizing long-term NDVI, they show that about 27% of the land is subject to degradation processes including, soil degradation, overgrazing, or deforestation. Following Vlek *et al.,* (2010), the land degradation 'hotspots' map shows that Ethiopia, Kenya, Tanzania and Malawi are the most affected in the

Eastern Africa region, thus they were selected as case studies countries for this assessments. Some of the key hotspots areas include west and southern regions Ethiopia, western part of Kenya, southern parts of Tanzania and eastern parts of Malawi (**Figure 2.1**).

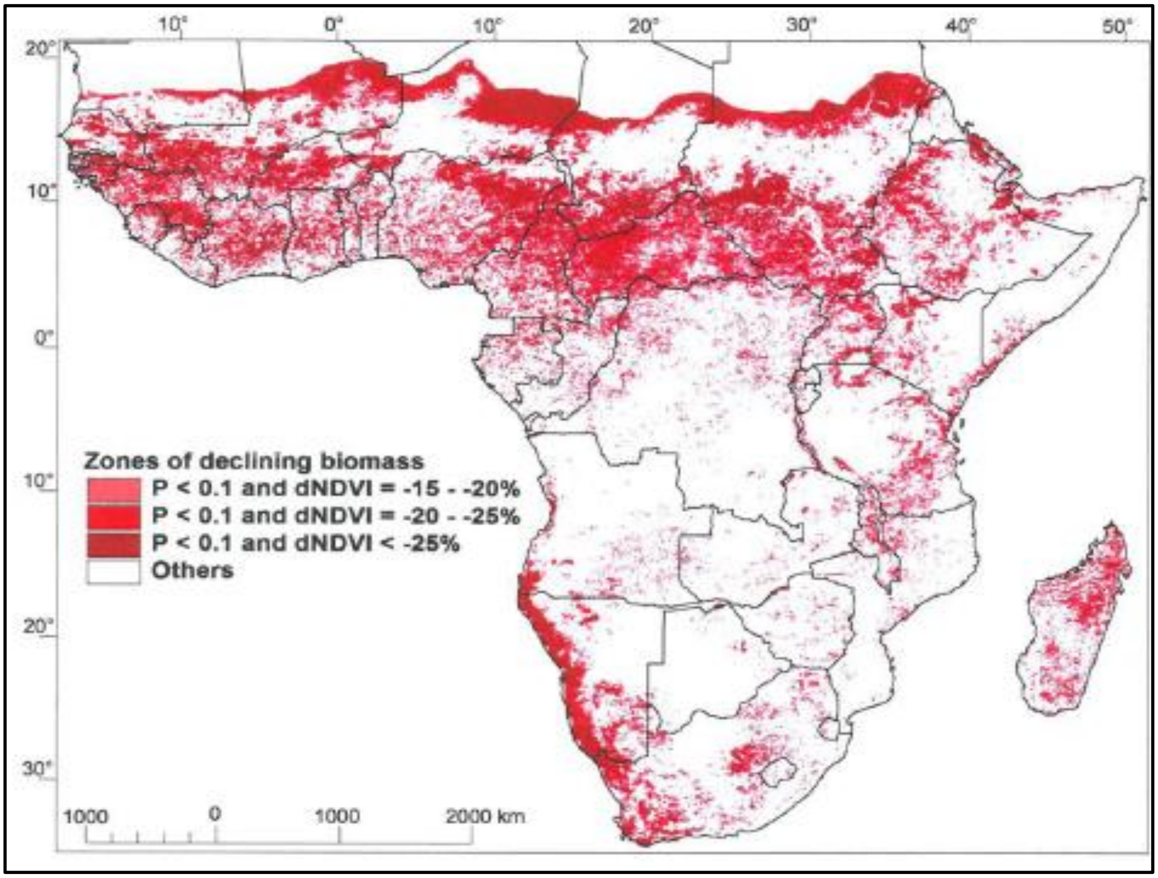

Figure 2.1: Geographic overview of land degradation in SSA[1]
Source: Vlek *et al.*, 2010.

The hotspot areas in Ethiopia are characterized by high population pressure (on land and forests), farming activities on steep slopes and frequent famines occasioned by unreliable rainfall. The hotspots in Kenya are characterized by intensive crop farming that increases pressure on soils. The arid and semi-arid conditions of the southern parts of Tanzania and eastern parts of Malawi may also be a contributing factor to the high degradation levels. Detailed studies have been carried out in these Eastern Africa countries as presented in the next chapters.

[1] *Note: The geographic spread of the area subject to human-induced degradation processes among the different climatic zones of SSA. The red spots show the pixels with significantly declining dNDVIhuman/dt.*

2.3 Assessment of land degradation from ‘above’

Two approaches are used to evaluate the extent of land degradation in this study: biomass productivity (NDVI) decline and Land Use land Cove Change (LUCC).

2.3.1 Data sources

This study uses the Le *et al*. (2014) land degradation dataset which builds upon the GLADIS methodology and recommendations to estimate biomass productivity decline. Le *et al*. (2014) dataset is useful in identifying “global geographic degradation hotspots or improvement hotspots”. Le *et al*. (2014) calculates statistically significant long-term trends in NDVI from 1982 – 2006 using data obtained from Global Inventory Modeling and Mapping Studies (GIMMS) which is derived AVHRR. Le *et al*. (2014) dataset is preferred because it corrects for the effects of rainfall factor and atmospheric fertilization (Harris *et al*., 2014). The datas*et al*so addresses some of the structural challenges associated with NDVI assessments by masking out pixels with unreliable NDVI trends.

The MODIS data is used to evaluate land cover land use change (LUCC) between 2001-2009 period following Nkonya *et al*. (2015). MODIS is a valuable source of both NDVI and LUCC information globally, though it is only available from 2001. For this analysis, the land cover information was chosen for the period 2001–2013 as a measure of recent degradation trends. This study used collection 5 of the MODIS land cover type dataset (MCD12Q1), which provides annually land cover information at a 500 metres spatial resolution (Friedl *et al*., 2010). Input datasets used in the classification procedure include information from MODIS bands 1-7, the enhanced vegetation index, land surface temperature, and nadir BRDF-adjusted reflectance data.

2.3.2 Extent of Land Degradation due to NDVI decline

More recently, Le, Nkonya and Mirzabaev (2014) analyzed global land degradation using decline in NDVI over 1982-2006 period by main land cover/use types counted globally for each country in the Global ELD project. Unlike Bai *et al.*, (2008) they carry out a number of adjustments to the data such as correction of RF (rainfall factor) and AF (atmospheric fertilization), and account for seasonal variations in vegetation phenology. The land degradation hotspots in Eastern Africa are presented in **Figure 2.2 and Figure 2.3**.

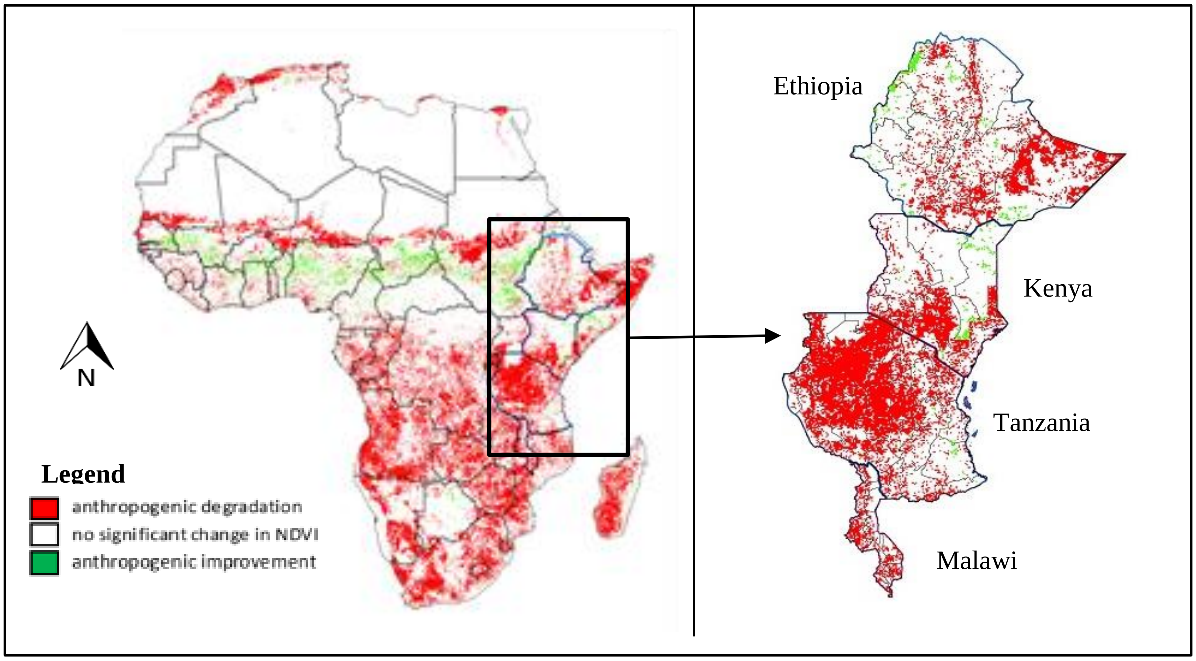

Figure 2.2: Biomass productivity decline in Eastern Africa over 1982-2006.
Source: Adopted from Le, Nkonya & Mirzabaev (2014). Cartography: Oliver K. Kirui

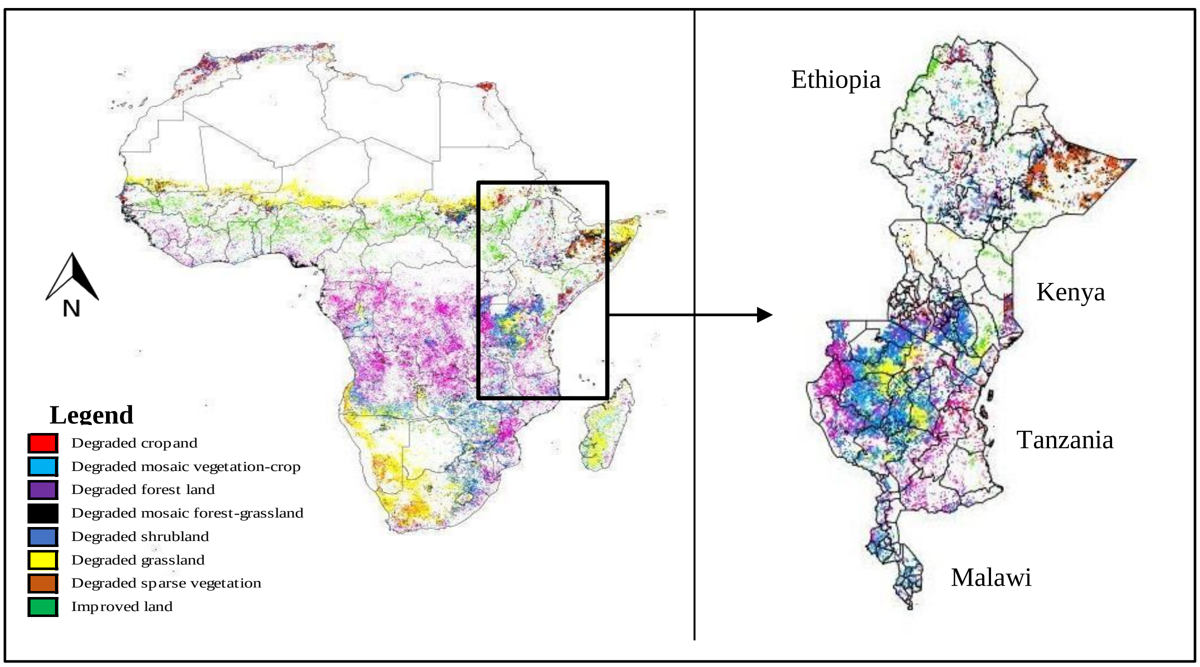

Figure 2.3: Biomass productivity decline by biome in Eastern Africa over 1982-2006.
Source: Adopted from Le, Nkonya & Mirzabaev (2014). Cartography: Oliver K. Kirui

The results (**Table 2.3**) show that a total of about 453,888 km^2 (51%) and 38,912 km^2 (41%) of Tanzania's and Malawi's land area was degraded respectively. In Ethiopia, land degradation was reported in about 228,160 km^2 (23%) and just about 127,424 km^2 (22%) in Kenya. These areas varied across the main land cover-land use type by country. For example, in Ethiopia much of degradation (32%) was experienced in areas with sparse vegetation, in Kenya the highest proportion of degradation was experienced in forested areas (46%) while shrub-land and mosaic vegetation and crop each had 42%. In Malawi highest proportion of degradation was experienced in mosaic forest- shrub/grass (57%) and grasslands (56%) while in Tanzania 76% of degradation reported in degradation was experienced in mosaic forest- shrub/grass and in grasslands.

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Table 2.3: Area (km^2 and percentage) of long-term (1982-2006) NDVI decline

	Area (km^2) of NDVI decline and in percentages for the corresponding land use							
Country	Cropland	Mosaic vegetation-crop	Forested land	Mosaic forest-shrub/grass	Shrub land	Grassland	Sparse vegetation	*Total*
Ethiopia	35904 (18%)	30976 (19%)	9984 (16%)	59776 (27%)	37824 (20%)	7808 (14%)	45888 (32%)	228160 (23%)
Kenya	15808 (31%)	40512 (42%)	21568 (46%)	9664 (10%)	21952 (42%)	15232 (18%)	2688 (4%)	127424 (22%)
Malawi	576 (50%)	6720 (31%)	11072 (34%)	1088 (57%)	17984 (51%)	1472 (56%)	N/A	38912 (41%)
Tanzania	12608 (32%)	112768 (62%)	139968 (36%)	18688 (66%)	93504 (70%)	75712 (76%)	640 (30%)	453888 (51%)

Source: Adopted from Le, Nkonya & Mirzabaev (2014).

In summary, various methods have been used to estimate the extent/levels of land degradation in the Eastern Africa region all resulting in different results. They include expert opinions and, more recently, use of NDVI measures. A number of deficiencies are associated with these approaches. For instance expert opinion methodologies: (i) have unknown magnitudes and directions of measurement errors, and related point, (ii) they are perception-based and semi quantitative and therefore not built on objective measurements. However, recent empirical research shows a shift from expert opinion approach to the quantitative data based interpretation of aerial photography and satellite imagery (NDVI and NPP) and further to a more model-based approach involving indicators and proxy variables measurable over large areas and over longer periods (Le, Nkonya and Mirzabaev (2014)).

Some caveats associated with NDVI/NPP methodologies include: site-specific effects of vegetation/crop structure and site conditions autocorrelation, effect of atmospheric fertilization and intensive fertilizer use on NDVI, seasonal variations in vegetation phenology and time-series, large errors('noises') in the NDVI data, and the effect of soil moisture in sparse vegetative areas (Huete *et al*., 2002; Le at al., 2014). Detailed steps to address these caveats are presented in Le *et al.,* (2014). They include accounting for both rainfall factor (RF), and atmospheric fertilization (AF) in the final degradation and improvement 'hotspot maps'. Further, to ensure accuracy of observations they need to be ground-truthed and triangulated with household/plot level data analysis. Furthermore, NDVI cannot distinguish between categories of land degradation nor can it provide information on some types of land degradation, such as loss of biodiversity or soil erosion. For example, an increase in NDVI from invasive species is often mistaken a land improvement. It is difficult to isolate the natural or anthropogenic causes of land degradation while using NDVI approach alone. The use of ground-based measurements will complement these measurements.

2.3.3 Extent of Land Degradation due to LUCC

Based on high quality satellite data from Moderate Resolution Imaging Spectroradiometer (MODIS), the changes in land use and cover for Ethiopia, Kenya, Malawi and Tanzania during the 2001 and 2009 period are discussed in this subsection. LUCC for SSA is also presented for comparison purposes. **Figure 2.4** shows the size of different land use categories in thousand hectares in 2001 and in 2009. For the 2001 period, the biggest land use categories in Ethiopia were shrub-land, grassland and woodland – 41.8, 28.5 and 22.4 million ha respectively. For the period 2009, assessment show that the biggest land use categories in Ethiopia were shrub-land (45 million ha), grassland (29 million ha) and woodland (22 million ha).

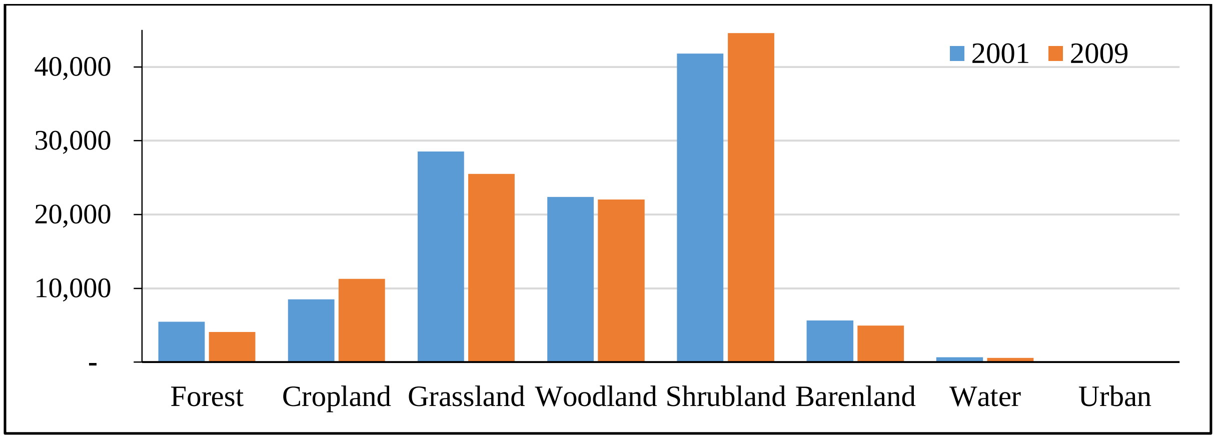

Figure 2.4: Land area of terrestrial biomes in 2001 and 2009[2] in Ethiopia ('000 hactares)
Source: Author's compilation based on MODIS data.

Similarly, in Kenya, the largest land use categories in 2001 were shrub-land, grassland and woodland – 25.2, 21.9 and 3.8 million ha respectively (**Figure 2.5**). For the period 2009, assessment show that the largest land use categories were grassland (29 million ha), shrub-land (19 million ha) and woodland (4 million ha).

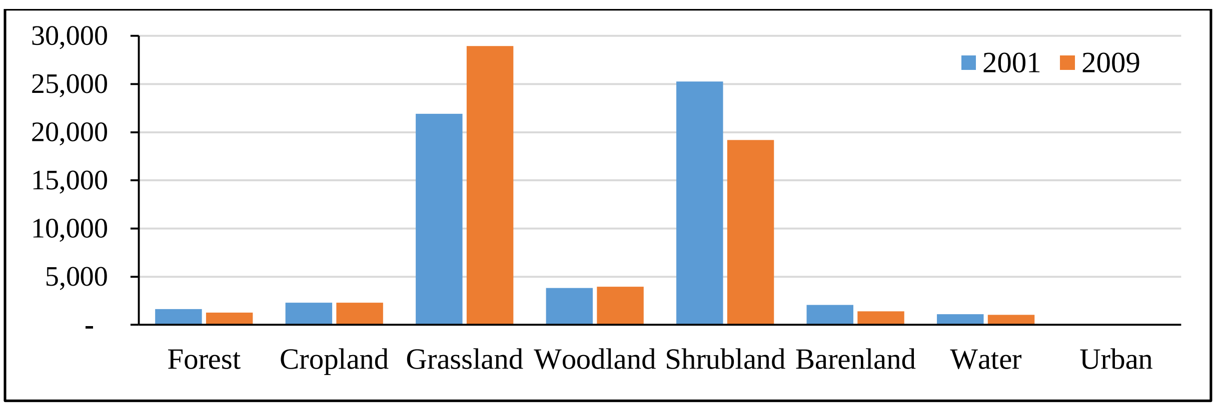

Figure 2.5: Land area of terrestrial biomes in 2001 and 2009 in Kenya ('000 hactares)
Source: Author's compilation based on MODIS data.

[2] Tabulation of these land use in 2001 and in 2009 are Appendix Table 8.1 and Table 8.2 respectively.

In Malawi, the largest land use areas in 2001 were grasslands (5.7 million ha), woodland (3 million ha) and water (2.4 million ha) (**Figure 2.6)**. For the period 2009, assessment show that the largest land use categories were grasslands (7 million ha), water (2 million ha) and woodland (2 million ha). However, in Tanzania (**Figure 2.7)** the largest land use categories in 2001 were grasslands (51 million ha), woodland (29 million ha) and water (6 million ha) and the largest land use categories in 2009 were grasslands (57 million ha), and woodlands (26 million ha).

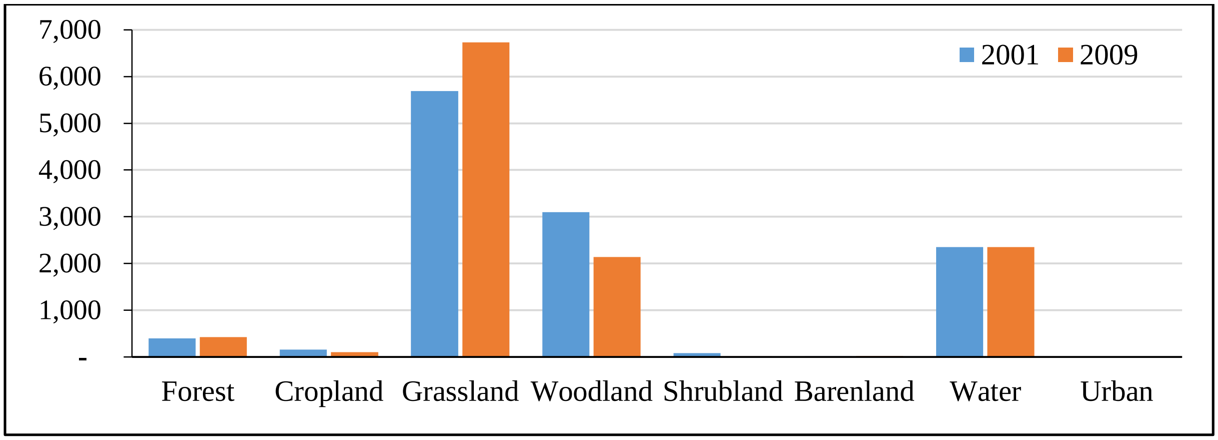

Figure 2.6: Land area of terrestrial biomes in 2001 and 2009 in Malawi ('000 hactares)
Source: Author's compilation based on MODIS data.

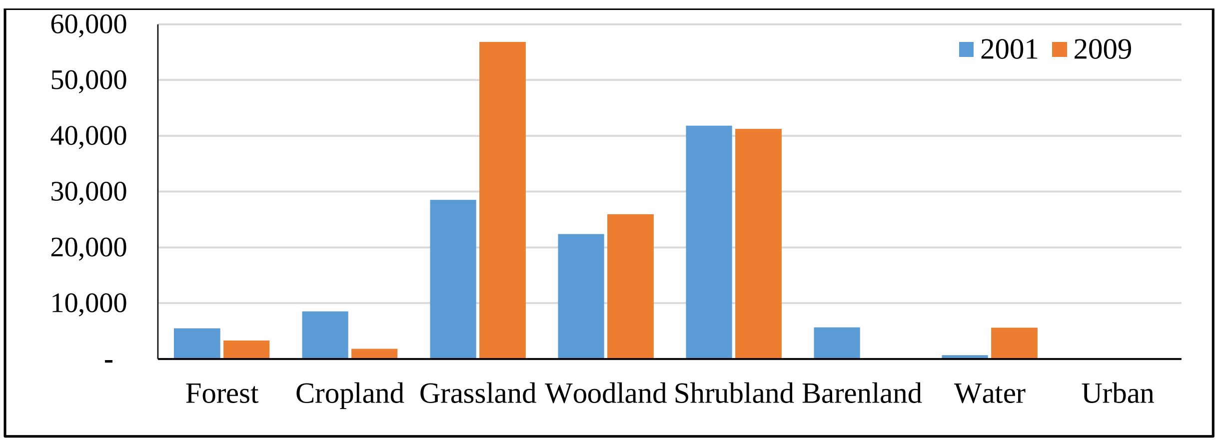

Figure 2.7: Land area of terrestrial biomes in 2001 and 2009 in Tanzania ('000 hactares)
Source: Author's compilation based on MODIS data.

Besides showing the state of land use in 2001 and 2009, the land use changes between the two periods (2001 and 2009) are also depicted in **Figure 2.8**. The land use changes depicted here includes the total area gained, total area lost and the net change. The net change refers to the total gained area minus the total lost area. The summary Tables presenting the area gained between 2001 and 2009 is presented in **Appendix (Table 8.3)**. Large land areas increase reported in Ethiopia were grassland (10.1 million ha), woodland (8.1 million ha), shrub-land (7.7 million ha) and cropland (7.5 million ha). The biggest land area gainers in Kenya were grassland (12 million ha), shrub-land (3.2 million ha), woodland (2.6 million ha), and cropland (1.7 million ha). However, the biggest land area gainers in Malawi were grassland (2.1 million ha), woodland (1.1 million ha), and forests (0.21 million ha). Finally, the largest land area increases in Tanzania included grassland (14.3 million ha), woodland (9 million ha), cropland (1.4 million ha), and forest (1.3 million ha). Generally, the trend in these countries follows that of SSA – in which the largest gainers included grassland (169 million ha), woodland (135 million ha), cropland (84 million ha), shrub-land (75 million ha) and forests (46 million ha).

Large land areas lost reported in Ethiopia were grasslands (13.8 million ha), woodland (8.3 million ha), shrub-land (4.9 million ha) and cropland (4.7 million ha) **(Appendix Table 8.4)**. The biggest land area losers in Kenya were shrub-land (9.2 million ha), grasslands (5 million ha), woodland (2.5 million ha), and cropland (1.7 million ha). However, the biggest land area losers in Malawi were woodland (2.1 million ha), grasslands (1.1 million ha), and forests (0.18 million ha). While in Tanzania the largest land area increases included woodland (11.9 million ha), grasslands (8.7 million ha), cropland (2.7 million ha), and forest (2 million ha). Similar to the trend in increase land area, the trend in land area loses follows that of SSA–in which the largest losers were grassland (181.8 million ha), woodland (140.4 million ha), shrubland (64.1 million ha) and forests (53.6 million ha).

The net change in the different LUCC categories is presented in **Figure 2.8**. The changes as absolute numbers (gained area-lost area) as well as percentage changes relative to the land areas in the baseline (2001) are both presented. As depicted in **Figure 2.8**, the biggest net areas that increased in Ethiopia in absolute values were cropland (2.8 million ha) and shrub-land (2.6 million ha) while the net losers were grasslands (3 million ha) and forests (1.4 million ha). The net gainers in Kenya were grasslands (7 million ha) and woodlands (0.13 million ha) while the net losers were grasslands (6.1 million ha) and bare-land (0.67 million ha).

The net gainers in Malawi were grasslands (1 million ha) and forests (0.03 million ha) while the net losers were woodland (1 million ha) and bare-land (0.07 million ha). The net gainers in Tanzania were grasslands (5.6 million ha) and bare-land (0.02 million ha) while the net losers were woodlands (2.9 million ha) and cropland (1.3 million ha). In the SSA region, net gainers were cropland (38 million ha) and shrub-land (11 million ha) while net losers were bare-land (21 million ha), grasslands (12 million ha) and cropland (8 million ha).

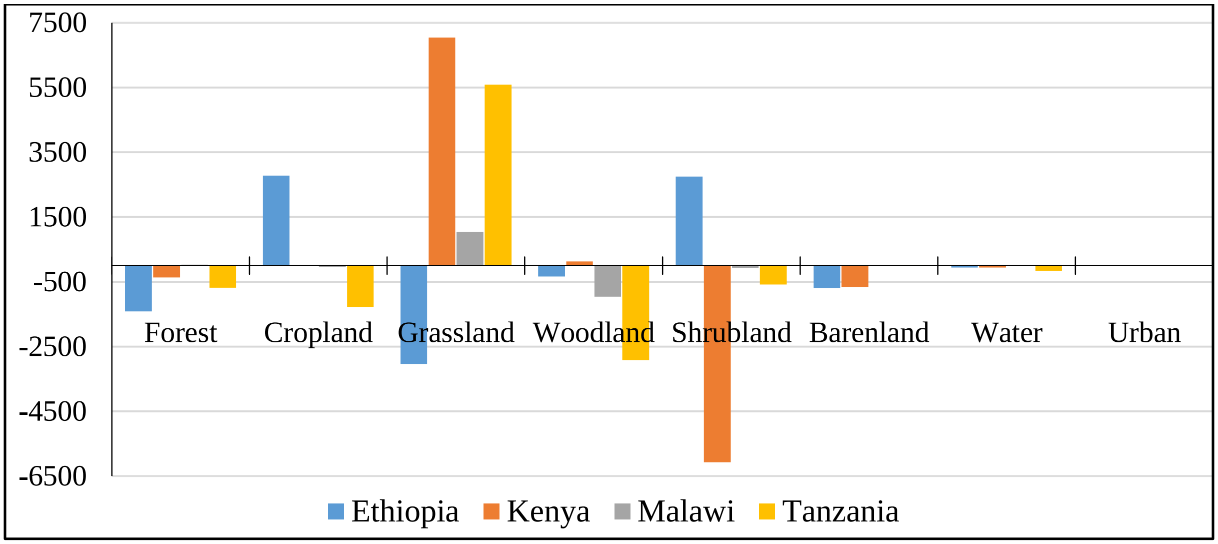

Figure 2.8: Net change[3] in land area of terrestrial biomes between 2001- 2009 (ha)
Source: Author's compilation based on MODIS data.

To provide a more succinct picture, these changes relative to the baseline (2001) land areas are presented. On this account, the net gainers in Ethiopia were cropland (33%) and shrub-land (7%) while net losers were forests (26%), bare-land (12%) and grasslands (11%). The net gainers in Kenya were grasslands (32 %) and woodlands (3 %) while the net losers were bare-land (32 %), shrub-land (24%), and forests (23 %). The net gainers in Malawi were bare-land (57 %) and grasslands (18 %) while the net losers were shrub-land (81 %), cropland (34%), and woodland (31 %). The net gainers in Tanzania were bare-land (29 %) and grasslands (11 %) while the net losers were shrub-land (59 %), cropland (41%), and forests (17%).

[3] Tabulations of the net change in Land use for each of the terrestrial biomes between 2001- 2009 is presented in Appendix Table 8.5

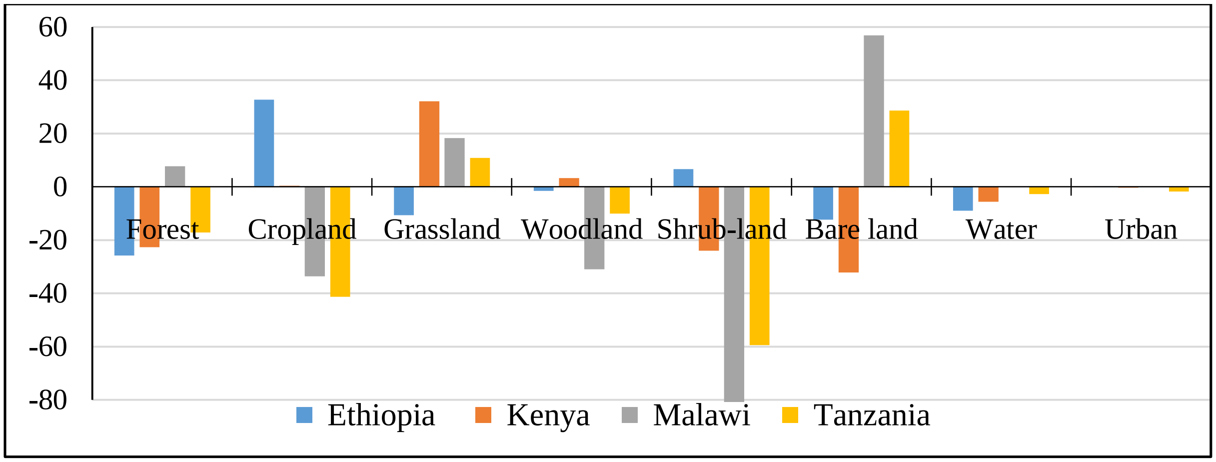

Table 2.4: Net change in land area of terrestrial biomes between 2001- 2009 (%)
Source: Author's compilation based on MODIS data.

Detailed land use changes within the country are presented in **Appendix (Table 8. 5 to Table 8.9).** In **Ethiopia,** for example, (**Appendix, Table 8.6**) while vast increases are reported for cropped area in Harari (750%), Gambela (101%), Addis Ababa (55%), Amhara (54%) and Tigray (48%); significant decreases were reported in Benshangul (65%), Afar (36%) and Somali (29%) regions. These changes may be associated to the conversion of forests and grasslands to cropland. Forests decreased in all the regions (shift to cropland and shrub-lands) ranging from (16-100%) except only in Afar and Gambela where it increased by 4% and 32% respectively. Similarly, grasslands decreased in all regions by about 9% to 70% except only in Amhara region where it increased by about 7%.

The detailed land use land cover changes by province in Kenya are presented in **Appendix Table 8.7.** The changes can be summarized into four major categories at the national level:

i) Deforestation, especially in the Rift valley (32%), Nyanza (32%), Nairobi (57%) and North eastern (59%);
ii) Massive shift from shrub lands (Nyanza and Coast), bare lands North Eastern, Coast and Rift Valley), and in some areas, from croplands (Eastern, Western and Nairobi) to grasslands. Human movement and settlement in arid ASAL areas (low lands) as population pressure mounts in the high potential (highlands);
iii) Considerable reductions in the cropped area in Nyanza, Rift Valley, Western and Eastern provinces and big increases in the copped area in Coastal (new settlements), North-Eastern and Central provinces; and

iv) Reductions in the extent of water bodies in Western and Coast provinces (frequent droughts in recent past, but with increased rains the reservoirs are recharging).

Malawi on the other hand showed (**Appendix Table 8.8**) vast increases for cropped land in Chiradzulu (85%) and Mulanje (73%) districts but big reduction were reported in Ntcheu (80%), Nsanje (78%) and Chitipa (74%) districts. Forests increased in Nsanje (190%), Chikwawa (115%) and Chitipa (48%) districts. However, forests decreased in Dowa (100%), Kasungu (77%) and Blantyre (70%) districts. It is notable also that the grasslands increased in all districts with greatest increase reported in Lilongwe (36%), Nkhata Bay (36%) and Mchinji (35%). Wet lands and water bodies shrank in Balaka (90%), Mulanje (90%) and Lilongwe (89%). No notable change was reported in shrub-lands and urban areas.

In **Tanzania** (**Appendix Table 8.9**), forests decreased in Zanzibar West (76%), Unguja North (75%) and Tabora (70%). However, forests increased in only two districts; Iringa (15%) and Mbeya (14%) districts and large reductions reported in Zanzibar West (76%), Unguja North (74%) and Tabora (69%). Large cropped land increases were reported in Pemba North (82%), Pemba South (39%) and Mtwara (38%) regions but big reductions were reported in Tabora (76%), Ruvuma (72%) and Iringa (70%) regions. The land use changes in Tanzania are further summarized as follows; increased grasslands in Zanzibar West (65%) and Zanzibar South (37%) and woodlands in Zanzibar South (102%) and Pemba North (88%). However, reduction in grasslands were exhibited in Kigoma (39%) and Pemba North (26%) and woodlands reductions exhibited in Mtwara (79%), Mara (73%) and Dodoma (66%).

2.4 Assessment of Land Degradation from 'Below' and Ground-truthing of Remote Sensing Land Degradation Maps

2.4.1 Alternative ways for Ground-truthing

Ground-truthing refers to a process in which a pixel on a satellite image is compared to what is there in reality. Ground-truthing data is useful in the interpretation, analysis and validation of the remotely sensed data. Ground-truthing is usually done on site and it involves performing surface observations or measurements of various properties of the features of the ground resolution 'cells' that are being studied on the remotely sensed dataset. ''It also involves taking geographic coordinates of the ground resolution ‘cell’ with GPS technology and comparing those with the coordinates of the pixel being studied provided by the remote sensing software’’ (Wikipidia). Other alternative ways to carry out ground-truthing include field measurements and surface observations, interviews and personal experiences with local communities and key informants.

Ground-truthing is expensive and time consuming exercise. It requires visiting as many sites as possible so as to have sufficiently large reference dataset. The logistical challenges of accessing remote locations, communication problems, equipment failure, physical stress, unstable political environments are some of the challenges associated with ground-truthing exercises. Recent advances in affordable GPS receivers and digital data field recorders, however, allow the researcher greater flexibility in the carrying out this exercise easily. Due to budget and time limitations, ground-truthing work (field observations and interviews with local communities) described this study was carried out in seven locations in Ethiopia and eight Tanzania as discussed in the next section.

In this study, the FGDs surveys are used as a complement to the remote-sensing based observations and to evaluate the accuracy and determining reliability of the land degradation ‘hotspots’ map developed by Le *et al*. (2014). The surveys provide ground-based estimates of land degradation from the perspectives of the land users or the communities involved.

2.4.2 Site Selection

The sites used to evaluate the accuracy of the land degradation ‘hotspots’ map were selected following a three step procedure for two case study countries – Ethiopia and Tanzania. Firstly, the sites selection considered different land use categories (forests, croplands, grasslands, shrub-lands). Secondly, for each of the land use category, both degraded (red) and improved (green) site were selected following Le *et al*. (2014). Thirdly, the site chosen consisted of communities (or groups of communities) that spans at least 8 km^2 which is the size of a single pixel in the Le *et al*. (2014) dataset. Other dynamics such as accessibility, cost, and security were also considered in making the final choices. Eight different locations were purposely selected in Tanzania while seven were selected in Ethiopia with the help local collaborating partners. Thus, the sites represent a range of agro-ecological zones, different land use categories and include both areas indicated as degraded and improved (**Figure 2.9**).

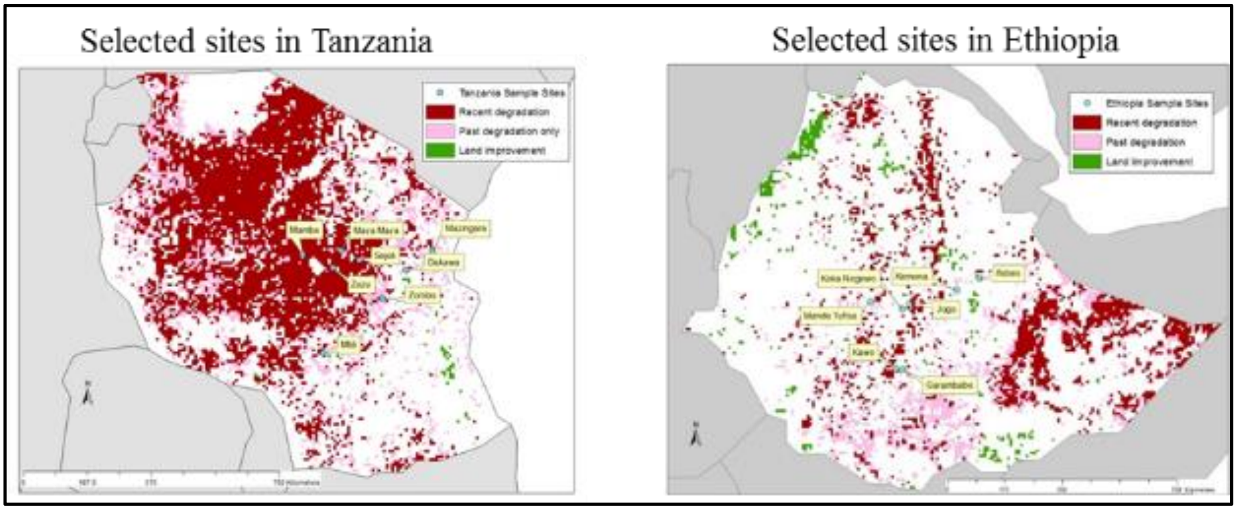

Figure 2.9: Selected ground truthing sites[4] in Ethiopia and Tanzania
Source: Author's compilation.

2.4.3 Sampling Procedure of the Focus Group Discussions' Participants

The processes of land degradation or improvement were identified using FGDs conducted with local communities in each of the selected sites using semi-structured questionnaires. To ensure rich discussions on ecosystem values the selection criteria ensured that a broad variety of land users would be present, especially those knowledgeable of the land use developments from 1982 to 2013. On average, each FGD comprised about 10 voluntary participants. Therefore participants in the FGDs were diverse and were chosen based on the following criteria:

- The opinion leaders and village elders with knowledge about land use changes over the last decades and also aware of the size and boundaries of their communities,
- Participants also included other community, women, youth, customary/cultural leaders,
- A balance between males and females in the group was considered,
- Both the old and relatively younger participants were selected because they could provide informed perception on land use change over the 30 year reference period,
- People with various occupational backgrounds that typically represented the community – such as local leaders, crop producers, livestock producers, those who earn their livelihoods from forest and non-agricultural terrestrial biomes (teachers, artisans, and traders) were selected.

[4] *Note: Dark red indicates pixels that demonstrate both long-term degradation (1982-2006) as well as degradation in recent (2000-2006) years, green pixels indicate sites with improved land*.

Table 2.5 summarizes the main information about the participants of the FGDs per village in the two countries. A total of 58 and 96 people contributed to the FGDs in Ethiopia and Tanzania respectively. About 34% and 37% of participants were female in Ethiopia and Tanzania respectively. The average age of the discussants was 46 years and 50 years in Ethiopia and Tanzania respectively. At least 80% of the participants in Ethiopia and 50% Tanzania had been involved in discussions about environmental changes/issues during the previous year with extension agents, forest experts, local and national NGOs etc.

Table 2.5: Characteristics of Focus Group Discussants in Ethiopia and Tanzania

District	Village	Total participants	Female participants (%)	Average age (years)	Average years of education (years)	Discussed environmental changes/issues Previously (%)
Ethiopia						
1. Guba Goricha	Kemona	8	50%	45	2	75%
2. Tulo	Ifabas	11	36%	45	5	100%
3. Becho	Mande Tufisa	13	23%	51	4	77%
4. Lume	Jogo	6	17%	51	6	33%
5. Nonsebo	Garambabo	9	44%	36	5	100%
6. Kokosa	Kawo	12	52%	51	4	86%
7. Lume	Koka Negewo	11	36%	47	3	100%
Total		**58**	**34%**	**46**	**4**	**81%**
Tanzania						
8. Kilosa	Zombo	11	45%	46	8	81%
9. Morogoro	Dakawa	9	56%	44	7	22%
10. Mufindi	Mtili	15	40%	57	8	46%
11. Kongwa	Sejeli	13	31%	42	6	92%
12. Dodoma	Zuzu	11	36%	55	7	18%
13. Bahi	Maya	11	18%	60	5	100%
14. Manyoni	Mamba	15	33%	51	7	13%
15. Handeni	Mazingira	11	37%	45	7	55%
Total		**96**	**37%**	**50**	**7**	**53%**

Source: Author's compilation.

2.4.4 Conducting Focused Group Discussions

The FGDs were conducted in the local language with the help of a translator at the farmer training centers at the village or in a similar available community meeting room over a period of about 4-5 hours. The FGDs were organized into three parts: (i) identification of current and previous land use, forest changes and cropping patterns and intensity, (ii) identification and valuation of the ecosystem services provided by land, and (iii) actions taken to address land degradation and to enhance ecosystem services provided by land.

In the first part, the FGDs began with sketching of the community map and identification of different land use types on a flipchart. Some communities had detailed sketches of community maps showing the community boundaries and the different allocations of land use categories. Thus, discussions were carried out around these existing maps to gain a common understanding on the share of different land use types (forest, shrub-land, grassland, bare soil, water, cropland, and residential area) of the total community land area. All this information was elicited for 1982, 2000, 2006 and 2013. Information on the main source of livelihoods including crop farming, livestock farming, mixed farming, forest harvesting, fisheries, or non-agricultural activities etc. Further information included the trend on deforestation and its drivers. The discussion also identified the main crops grown in the community, their yields, and the changes in crop farming practices such as single (mono-cropping), double or triple cropping, and inter- cropping and mixed cropping methods, for the years 2000, 2006, and 2013. Various techniques, including relative questions (such as, were yields this year higher or lower than five years ago? How was the rate of deforestation in 2006 compared to 2000?), and collaborative sketching of community land use maps were used elicit the information and guide the discussions. As observed during the FGDs, intense discussions occurred before an agreed response for each of the questions was recorded.

In the second part, the concept of valuation of ecosystem services (defined by the Millennium Ecosystem Assessment (MA, 2005)) was introduced. The FGDs participants were asked to identify the provisioning (direct) ecosystem services including crops, wild foods, livestock, livestock feed, fuel (fuelwood, dung), genetic resources, fresh water, ornamental resources, and medicinal plants they derived from land. They were also asked to identify the regulating and supporting (indirect) ecosystem services such as regulation of air quality, water purification, regulation of diseases and pests, pollination and seed dispersal, erosion regulation, waste treatment, natural hazard regulation, climate stabilization, nutrient cycling, noise buffering and soil formation. The cultural ecosystem services such as spiritual values, aesthetics, recreation, ecotourism, cultural heritage and education were also identified. After identifying the important ecosystem services, the participants were asked to rate the importance of these services in contributing to their livelihoods, and to identify the value each of these services in 1982 and 2013.

For ease of discussion, the tangible provisioning services were discussed first, followed be the support and regulatory services, and the cultural services. All these ecosystem services were identified for each of the major land use category existing in the community. FGDs participants were encouraged to provide their responses and where there were variations in these responses, they were encouraged to build consensus through discussions. There were intense discussions on these topics and the values reported are the average values as agreed upon by the FGDs participants. In cases where services were not market-based, the FGDs participants provided their Willingness to Pay (WTP) for these services. A consensus was also sought for these (WTP) values. In estimating the value of regulating and supporting and the cultural ecosystem services (non-marketed services), the participants were asked to estimate the total value of these regulating and supporting and cultural ecosystem services as a proportion of the already elicited provisioning ecosystem services. It is notable that all these services were identified and valued both on-site and off-side. Finally, in the third part, the actions taken to address land degradation and to enhance/maintain ecosystem services provided by land for each of the major land use type were identified. The analysis of this data is reported in the next subsections.

2.4.5 Comparison between remote sensing and ground-truthing assessments

The processes of land degradation (or improvement) identified were analyzed at each site using this FGDs data. The assessment of the information from these randomly selected sites is compared how they agree or disagree with remote sensing datasets – long term trends in biomass (by Le *et al.*, 2014) and the land use/cover change analysis based on MODIS dataset. As described earlier, a decrease in NDVI is considered degradation while an increase is considered improvement (Le *et al.*, 2014). On the other hand, a qualitative ordinal ranking of Total Economic Value was used as a guideline to assess whether observed land-cover changes constituted degradation or improvement.

A total of 15 sites (8 in Tanzania and 7 in Ethiopia) were analyzed to compare remote sensing analyses with survey results for selected sites. The FGDs participants expressed land degradation or improvement of the major biomes which have occurred in the community over three decades (1982-2013). Each community was chosen to represent a particular biome as described earlier. The first section of the FGDs (changes in land use and land cover changes, cropping intensity and yields, and deforestation) was designed to elicit, either directly or indirectly, the presence or absence of land degradation and the associated impacts. It was primarily designed to allow direct comparison to available remote sensing estimates in this analysis. This direct comparison isolates reliability of remote sensing estimates of land degrading processes.

The comparison between remote sensing data reported by Le *et al*. (2014), the MODIS land use/cover change analysis and the responses of the perception about trend of land degradation from the FGDs conducted at each site are presented in **Table 2.6**. The FGDs assessment showed a relatively high degree of agreement with the remote sensing data. There was agreement between Le *et al*. (2014) and the FGDs in 7 sites out of 8 in Tanzania and 6 sites out of 7 in Ethiopia. This presents an accuracy of about 88% and 86% respectively. The disagreement between the Le *et al*. (2014) and the FGDs in Tanzania were reported in Mamba village. While remote sensing data showed improvement, the FGDs perceptions showed degradation. Similarly, remote sensing data showed improvement in Kemona village in Ethiopia but the community response was mixed.

On the other hand, the comparison between MODIS land cover change assessments and the FGDs were mixed. There was agreement between MODIS land cover change and the FGDs in 6 sites out of 8 in Tanzania and in only 3 sites out of 7 in Ethiopia – representing an accuracy rate of 75% in Tanzania and 43% in Ethiopia. Overall, there was complete agreement (3/3, or 100%) in five sites in Tanzania (Dakawa, Sejeli, Zuzu, Maya Maya and Mazingira) and two sites in Ethiopia (Garambabo and Kawo). The other three sites in Tanzania (Zombo, Mtili and Mamba) and the other six sites in Ethiopia (Kemona, Ifabas, Mande Tufisa, Jogo and Koka Negewo) each had an agreement of 2/3, or 67%.

Table 2.6: Comparison between the Le *et al*. (2014) land degradation map, the Focus Group Discussions (FGDs), and the MODIS Land Cover Change analyses

District	Village	Biomass productivity decline (Le *et al*., 2014)	Focused Group Discussion (FGDs) Assessment	MODIS Land-Cover Change	Agreement
Tanzania					
1. Kilosa	Zombo	Degraded	Degraded	**Mixed**	2/3
2. Morogoro	Dakawa	Degraded	Degraded	Degraded	3/3
3. Mufindi	Mtili	Improved	Improved	**Mixed**	2/3
4. Kongwa	Sejeli	Degraded	Degraded	Degraded	3/3
5. Dodoma	Zuzu	Degraded	Degraded	Degraded	3/3
6. Bahi	Maya Maya	Degraded	Degraded	Degraded	3/3
7. Manyoni	Mamba	**Improved**	**Degraded**	**Degraded**	2/3
8. Handeni	Mazingira	Improved	Improved	Improved	3/3
Ethiopia					
9. Guba Goricha	Kemona	**Improved**	**Degraded**	Improved	2/3
10. Tulo	Ifabas	Degraded	Degraded	**Mixed**	2/3
11. Becho	Mande Tufisa	Degraded	Degraded	**Mixed**	2/3
12. Lume	Jogo	Degraded	Degraded	**Improved**	2/3
13. Nonsebo	Garambabo	Degraded	Degraded	Degraded	3/3
14. Kokosa	Kawo	Improved	Improved	Improved	3/3
15. Lume	Koka Negewo	**Degraded**	**Mixed**	**Mixed**	2/3

Source: Author's compilation.

FGDs also provide information that may not be observable using satellite imagery such as soil erosion, nutrient depletion, or change in crop yields. The field surveys also provide clarity on the ambiguous surface processes such as invasive species that tend to increase vegetative cover which would lead to erroneous conclusions with remote sensing analysis. However, some of the information elicited through FGDs – such as land cover, cropping patterns, crop yields – date back to 30 years, thus, this kind of information rely on the ability of the FGDs to recall these values.

2.4.6 Perception of the importance of ecosystems services in 1982 and 2013

The FGDs participants were asked to indicate their perception of the importance of ecosystem services to their livelihoods in 1982 and in 2013. The ecosystem services can be grouped into three categories; provisioning, regulating and support services, and cultural services. **Figure 2.10** summarizes the perception of the importance of these services to livelihoods of the local communities in 1982 and 2013 in Ethiopia. Almost all provisioning ecosystem services (crops, fuelwood, freshwater, and livestock and livestock feed) were rated very important in both 1982 and 2013. Only wild foods (vegetables and fruits) were no longer important in 2013.

The importance of regulating and support services seems to increase from just important in 1982 to very important in 2013. Part of the reason for the change is the rise in awareness by the government and non-governmental organizations on the importance of maintaining the ecosystems for sustained development. Assessment further shows a decline in importance for cultural ecosystem services. Some of the drivers of this change include; change in belief systems, entry of different religions and destruction of traditional places of worships such as forests.

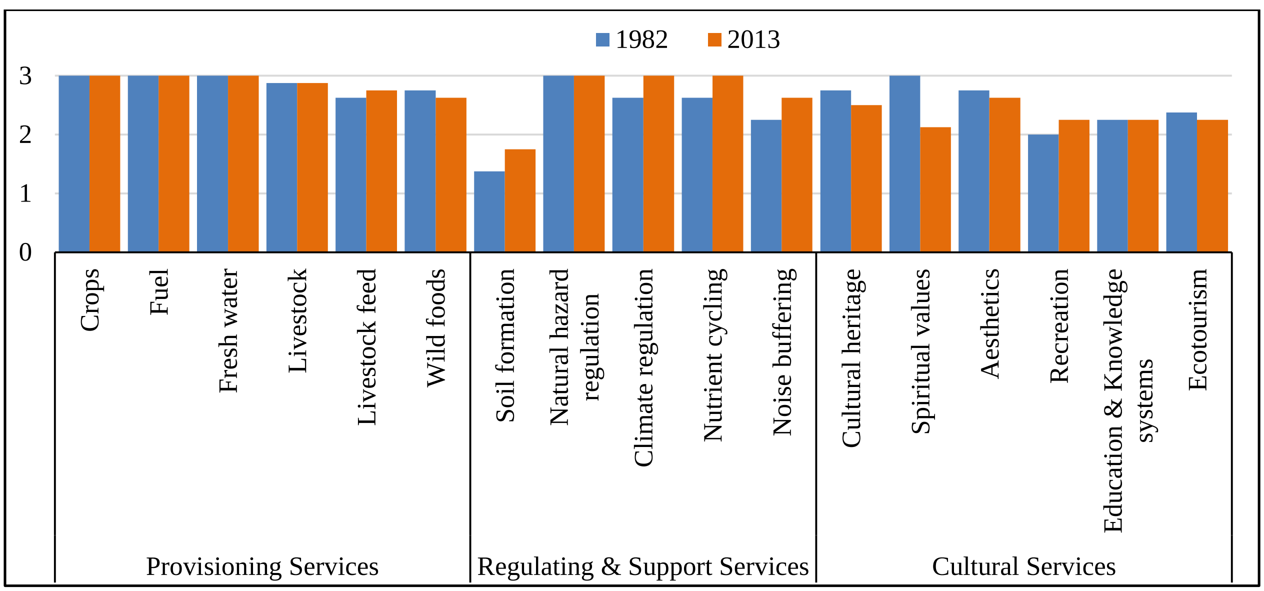

Figure 2.10: Ecosystems services and perception of their importance in Ethiopia (1982 & 2013)
Note: Ecosystem importance index: 0 = Not aware; 1 = Not important; 2 = Important; 3 = Very important

Figure 2.11 summarizes the trend of importance of these services for both 1982 and 2013 in Tanzania. Both the provisioning and the supporting and regulating ecosystem services (except soil formation) remain very important in both 1982 and 2013. Similarly, the cultural ecosystem services are important both in the baseline period and in 2013.

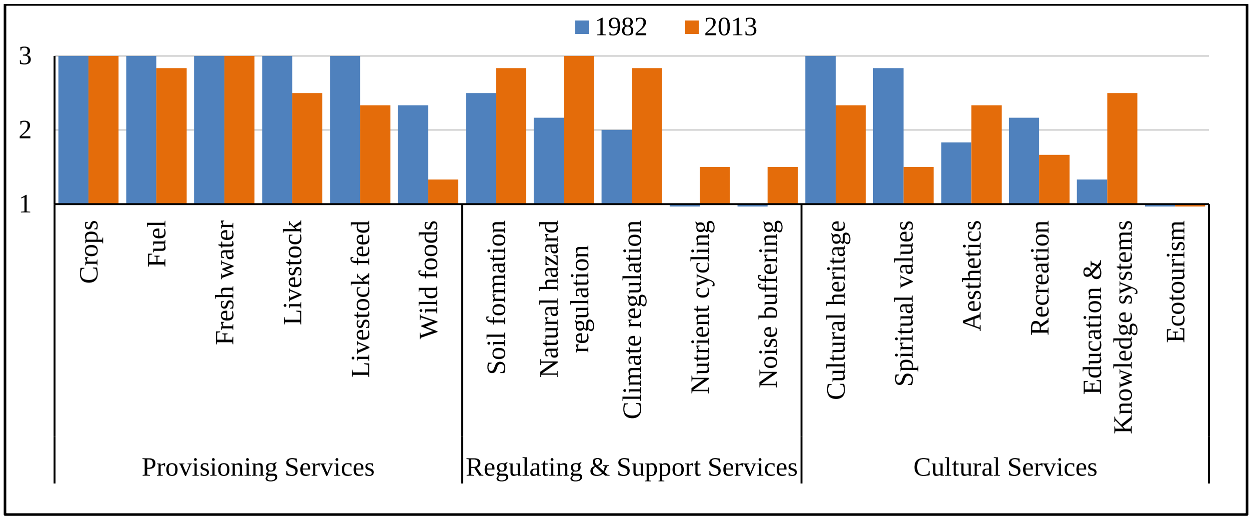

Figure 2.11: Ecosystems services and perception of their importance in Tanzania (1982 & 2013)
Note: Ecosystem importance index: 0 = Not aware; 1 = Not important; 2 = Important; 3 = Very important

The results of the assessment of the perception of trend in value of ecosystem services for major land use types for seven local communities in Ethiopia and eight communities in Tanzania are presented in **Table 2.7**. From the community perspective in Tanzania, results show that the ecosystem services value of cropland is decreasing in all districts except one (Mufindi). Similarly, the value of forest ecosystem services is all decreasing in all cases except in Mufindi district. On the other hand the trend in value of grassland is mixed. Two districts reported an increase (Sejeli and Zuzu communities), while two districts reported a decline (Dakawa and Mazingira).

In Ethiopia results show that the ecosystem services value of cropland is mixed; the ecosystem services value is improving in three communities (Ifabas, Jogo and Kawo) but declining in four other communities (Kemona, Mande Tufisa and Garambombo and Koka Negewo). The value of forest ecosystem services is all declining in all cases except in Garambombo where it is improving. The trend in value of grassland is also declining in all communities except in Kawo community where it is reported to remain constant. The trend in shrubland ecosystem services value is mixed; declining in Ifabas and Tufisa, improvement in Kemona and constant in Jogo.

Table 2.7: Perceptions of Trend in Value Ecosystem Services of major Biomes[5]

District	Village	Trend of ES value of Cropland	Trend of ES value of Forest	Trend of ES value of Grassland	Trend of ES value of Shrubland
Tanzania					
1. Kilosa	Zombo	Declining	Declining	N/A	N/A
2. Morogoro	Dakawa	Declining	Declining	Declining	N/A
3. Mufindi	Mtili	Improving	Improving	N/A	N/A
4. Kongwa	Sejeli	Declining	Constant	Improving	Improving
5. Dodoma	Zuzu	Declining	N/A	Improving	N/A
6. Bahi	Maya	Declining	Declining	N/A	Declining
7. Manyoni	Mamba	Declining	N/A	Constant	Declining
8. Handeni	Mazingira	Declining	Declining	Declining	N/A
Ethiopia					
9. Guba Goricha	Kemona	Declining	Declining	Declining	Improving
10. Tulo	Ifabas	Improving	Declining	Declining	Declining
11. Becho	Mande Tufisa	Declining	Declining	Declining	Declining
12. Lume	Jogo	Improving	Declining	Declining	Constant
13. Nonsebo	Garambabo	Declining	Improving	Declining	N/A
14. Kokosa	Kawo	Improving	Declining	Constant	N/A
15. Lume	Koka Negewo	Declining	Declining	Declining	N/A

Source: Author's compilation.

2.4.7 Economic Valuation of Ecosystem Services

After eliciting information on the importance of ecosystem services from the FGDs participants, these various ecosystem services were valued for both 1982 and 2013. The tangible direct provisioning services were valued first. This was particularly easier to estimate because most of these products (crops, animals, animal products, timber, fuelwood, fodder etc.) are tradeable in the market. Regulatory and support ecosystem services and cultural services are not tradable and thus Contingent Valuation approach was used to reveal the value of these Ecosystem Services. Contingent Valuation is a stated-preference method that allows the consideration of non-use values that can only be elicited by directly asking land users.

[5] Note: N/A implies that the biome (land use type) is negligible in the community.

The total values of the indirect ecosystem services and the cultural services were thus estimated as a proportion of the direct ecosystem services. Communities that valued these services stated a high proportion while the communities that deemed that these services were not that important provided a lower proportion (**Table 2.8**).

Results show that the annual TEV of direct provisioning services in forest biome amounted to about $ 18,330 per hectare in Ethiopia and $ 21,640 per hectare in Tanzania in 1982. These declined to about $ 14,485 in Ethiopia and $ 12,503 in Tanzania in 2013. In 1982, the value of indirect (regulatory and support services) represented about 71% and 66% of the value direct provisioning services in Ethiopia and Tanzania respectively. This declined marginally in 2013 to about 64% in Ethiopia and 57% in Tanzania. On the other hand, the value of cultural services obtained from forest biome in 1982 represented about 45% and 62% of the value of direct provisioning services in Ethiopia and Tanzania respectively. This too declined to about 29% in Ethiopia and 38% and Tanzania in 2013.

The annual TEV of direct provisioning services in cropland biome amounted to about $ 5,035 per hectare in Ethiopia and $ 2,173 per hectare in Tanzania in 1982. These declined to about $ 3,666 in Ethiopia and $ 1,257 in Tanzania in 2013. In 1982, the value of regulatory and support services as a proportion of direct ecosystem services represented about 41% in Ethiopia and 63% in Tanzania. This increased marginally to about 44% in Ethiopia in 2013 but declined to about 54% in Tanzania. Further, the value of cultural services obtained from forest biome in 1982 represented about 37% and 16% of the value of provisioning services in Ethiopia and Tanzania respectively-declining to about 19% in Ethiopia but increasing to about 20% and Tanzania in 2013.

The annual TEV of direct provisioning services in forest biome amounted to about $ 2,281 per hectare in Ethiopia and $ 5,096 per hectare in Tanzania in 1982. These declined slightly too to about $ 2,095 in Ethiopia but increased substantially to about $ 8,803 in Tanzania in 2013. The value of indirect (regulatory and support services) represented about 58% and 41% of the value direct provisioning services in Ethiopia and Tanzania respectively. The value of cultural services obtained from grassland biome in 1982 represented about 26% and 34% of the value of direct provisioning services in Ethiopia and Tanzania respectively but declined to about 14% in Ethiopia and 10% and Tanzania in 2013.

Table 2.8: Total Economic Values of forest, grassland and cropland (USD/ha/year)

Biome	Country	Value of Direct Ecosystem (Provisioning) services		Value of Indirect Ecosystem (Support & Regulatory) services		Value of Cultural Ecosystem services	
		1982	2013	1982	2013	1982	2013
Forest	Ethiopia	18,330	14,485	71%	64%	45%	29%
	Tanzania	21,639	12,503	66%	57%	62%	38%
Cropland	Ethiopia	5,035	3,666	41%	44%	37%	19%
	Tanzania	2,173	1,257	63%	54%	16%	20%
Grassland	Ethiopia	2,281	2,095	58%	58%	26%	14%
	Tanzania	5,096	8,803	41%	31%	34%	10%

Source: Author's compilation.

The overall results of the total values of ecosystem services are presented for the three main land use categories, namely; forest, crop land, and grasslands (**Table 2.9**). The values presented are on per hectare basis, converted to USD and corrected for inflation (all values are presented in 2003 real USD) to allow meaningful comparisons. Forest biome is the leading biome in terms of its annual TEV values - about $ 27,956/ha in 2013 and $ 39,593/ha in 1982 in Ethiopia and about $ 24,382/ha in 2013 and $ 49,336/ha in 1982 in Tanzania. Cropland on the other hand has a total TEV of about $ 5,976/ha in 2013 and $ 8,962/ha in 1982 in Ethiopia and about $ 2,187/ha in 2013 and $ 3,890/ha in 1982 in Tanzania. Finally, grasslands biome has a total TEV of about $ 3,603/ha in 2013 and $ 4,197/ha in 1982 in Ethiopia and about $ 12,412/ha in 2013 and $ 8,918/ha in 1982 in Tanzania. All these biomes record significant reduction in TEV between 1982 and 2013.

Table 2.9: Total Economic Values of forest, grassland and cropland (USD/ha/year)

Biome	Country	Value of Direct Ecosystem (Provisioning) services		Value of Indirect Ecosystem (Support and Regulatory) services		Value of Cultural Ecosystem services		Total Economic value of Ecosystem services	
		1982	2013	1982	2013	1982	2013	1982	2013
Forest	Ethiopia	18,330	14,485	13,014	9,270	8,249	4,201	39,593	27,956
	Tanzania	21,639	12,503	14,281	7,127	13,416	4,751	49,336	24,382
Cropland	Ethiopia	5,035	3,666	2,064	1,613	1,863	697	8,962	5,976
	Tanzania	2,173	1,257	1,369	679	348	251	3,890	2,187
Grassland	Ethiopia	2,281	2,095	1,323	1,215	593	293	4,197	3,603
	Tanzania	5,096	8,803	2,089	2,729	1,733	880	8,918	12,412

Source: Author's compilation.

2.5 Actions taken to address Ecosystem Services Loss and to enhance or Maintain Ecosystem Services Improvement

The actions that the communities take to address loss of ecosystem services or enhance or maintain ecosystem services improvement are presented in **Table 2.10**. For example, afforestation is one key action taken to address loss of forests' ecosystem services and to enhance ecosystem services improvement within forest ecosystems in Tanzania (Zombo and Maya communities) and Ethiopia (Kemona, Ifabas, Jogo and Garambabo communities). To further curtail deforestation, area closures and stricter enforcement of existing byelaws and enacting new ones were some of the approaches taken by local communities both Tanzania (Zombo, Dakawa, Mtili, Maya and Handeni communities) and Ethiopia (Kemona, Ifabas and Koka Negewo communities). The byelaws constitute community sanctions and fines and imprisonment with the help of government law enforcement agencies.

A number of actions were applied to maintain or address the deterioration in the quality of cropland. The most common approach in the two countries was soil fertility management (use of fertilizer and organic manure). Other SLM practices such as crop rotation and use of soil and water conservation measures such as crop and fallow rotations, soil and stone bunds, and terracing.

Likewise, area closure controlled grazing and community sanctions for overgrazing were the most common approaches used to maintain the quality and address decline in grassland ecosystem service values. Area closures (zoning) were particularly successful way to address degraded community grasslands in Ethiopia. This zoning was particularly successful when followed by strong community byelaws to sanction and punish offenders.

Table 2.10: Actions to maintain ecosystem services or address loss of ecosystem services

District	Village	Actions for cropland	Actions for forest	Actions for grassland
Tanzania				
1. Kilosa	Zombo	Use tractors to break land, crop and fallow rotations, fertilizer use	Afforestation, bylaw for protection of the existing forest	-
2. Morogoro	Dakawa	Use of inorganic fertilizer, promotion of SLM	Strongly enforced bylaws; fines for illegal logging	Area closure for rehabilitation; controlled grazing
3. Mufindi	Mtili	Use of inorganic fertilizers	Bylaw for protection of the existing forest - protected areas	-
4. Kongwa	Sejeli	Leave land fallow, mulching, crop rotation	-	Protected areas; Bylaws and community fines and sanctions
5. Dodoma	Zuzu	Organic manure application	-	Burn dry grasses so that green grass can re-grow
6. Bahi	Maya	Apply organic manure	Protected forest Bylaw and punishment (fine imprisonment)	Bylaws, punishment - fine and imprisonment
7. Manyoni	Mamba	Apply organic manure SLM practices	-	Protected areas; bylaws; fines and punishment
8. Handeni	Mazingira	Use new seed varieties	Development of bylaws	-
Ethiopia				
9. Guba Goricha	Kemona	Fertilizer, composting, soil and stone bands	Afforestation, protection of the existing forest	Area closures Soil and stone bunds, check-dam, planting of trees
10. Tulo	Ifabas	Fertilizer , composting, soil and stone bands, terracing	Area closure, afforestation, watershed management	None
11. Becho	Mande Tufisa	Fertilizer, composting	None	Terracing, stone & soil bunds
12. Lume	Jogo	Fertilizer, soil and stone bunds	Afforestation	Area closures
13. Nonsebo	Garambabo	-	Afforestation, watershed management	Water and soil conservation
14. Lume	Koka Negewo	Fertilizer, composting, crop rotation	Protected forests	None

Source: Author's compilation.

2.6 Conclusions

Land degradation is a serious impediment to improving rural livelihoods and food security of millions of people in the Eastern Africa region. Proper identification of areas experiencing land degradation is important in creating policies and practices aimed at restoring the land and in developing policies to improving livelihoods. Evaluating and monitoring land degradation is a complex process. Various methods have been used to estimate the patterns, extent and level of land degradation all resulting in different results. More recently, satellite–based imagery and remote sensing have been utilized to identify the magnitude and processes of land degradation at global, regional and national levels. This involves the use of Normalized Difference Vegetation Index (NDVI) derived from Advanced Very High-Resolution Radiometer (AVHRR) data and the use of high quality satellite data from Moderate Resolution Imaging Spectroradiometer (MODIS). Ground-truthing is undertaken to ensure accuracy and to determine the reliability of this satellite and remote sensing data.

This chapter identified land degradation patterns in Ethiopia, Kenya, Malawi and Tanzania 'from above' (i.e. based on remote sense datasets) and 'from below' (ground-truthing of remotely sensed data). Assessment of land degradation 'from above' was based on two measures: (i) biomass productivity decline based NDVI data, and (ii) Land Use Cover Change using MODIS data. It also presented the results of the ground-truthing of NDVI hotspots in Ethiopia and Tanzania and actions taken to address the deterioration of ecosystem services values. Results from the biomass productivity decline show that land degradation hotspots cover about 51%, 41%, 23% and 22% of the terrestrial areas in Tanzania, Malawi, Ethiopia and Kenya respectively. Some of the key 'hotspot' areas include west and southern regions Ethiopia, western part of Kenya, southern, eastern and central parts of Tanzania and eastern parts of Malawi. The MODIS LUCC data (for the period 2001-2009) showed an increase in cropland area in Ethiopia by 33%. However, cropland area reduced in cropland in Malawi by 34% and in Tanzania by 41%. Forests reduced in Kenya by 23%, Ethiopia by 26% and Tanzania by 17% but forested areas surged in Malawi by 7%. On the other hand grassland reported increases in Kenya (32 %), Malawi (18%) and Tanzania ((11%) but reduced in Ethiopia (11%).

To ensure accuracy of the NDVI observations, ground-truthing was carried out in Tanzania and Ethiopia through focused group discussions (FGDs). The FGDs participants were diverse and were chosen based on robust criteria to represent the communities. The aim of the FGDs was to compare the remote sensing data reported by Le *et al*. (2014) and the MODIS land cover change and the responses from the FGDs participants' perception on land degradation at each of the selected site. The FGDs assessment showed moderately high degree of agreement with the remote sensing data. There was agreement between Le *et al*. (2014) and the FGDs in 7 sites out of 8 in Tanzania and 6 sites out of 7 in Ethiopia – representing an accuracy of about 88% and 86% respectively. There was also agreement between MODIS land cover change and the FGDs in 6 sites out of 8 in Tanzania and 3 sites out of 7 in Ethiopia – representing an accuracy of about 75% and 43% respectively.

Some of the local level initiatives taken by local communities address loss of ecosystem services or enhance/maintain ecosystem services improvement in forest biome included afforestation programs, area closures and stricter enforcement and enacting of bylaws to protect existing forests. Some actions applied in grassland included area closures, and controlled grazing and community sanctions for overgrazing. In croplands, actions involved soil fertility management (use of fertilizer and organic manure) and SLM practices such as crop rotation and use of soil and water conservation measures such as crop and fallow rotations, soil and stone bunds, and terracing. Successful actions in managing forest and grassland biomes were largely through collective/participatory community management at community level. This underscores the importance of participatory involvement in policy formulation and enforcement for effective resource management at community level. On the other hand, actions on cropland were undertaken at household level. Successful actions on cropland biome therefore requires easing the constraints faced by the resource–scare farmers such as access to and cost of fertilizer, and also improving their capacity, through training, on the importance of tillage practices such as crop rotations and mulching.

Chapter 3

3. Cost of Land Degradation and Improvement

3.1 Introduction

Land degradation in the Eastern Africa region has substantial environmental, social and economic costs. Land degradation not only reduces the productive capacity of agricultural land, rangelands and forest resources but also significantly impacts on the biodiversity (Davidson & Stroud, 2006). The costs and consequences of land degradation can be direct or indirect. Direct costs may include costs such as; costs of nutrients lost by soil erosion, lost production due to nutrient and soil loss, and loss of livestock carrying capacity. On the other hand, indirect costs may include costs such as; loss of environmental services, silting of dams and river beds, reduced groundwater capacity, social and community losses due to malnutrition and poverty. Estimating these costs and the consequences of land degradation continues to be a daunting task (Bojo & Cassells, 1995; Morris, 2007; Croitoru and Sarraf, 2010 Hoffmann *et al*., 2014).

Sustainable land management is increasingly becoming an important topic in the post-2015 sustainable development agenda because land degradation poses a great challenge for sustainable development. The economic consequences of land degradation are severe among the poor and marginalized populations who usually occupying degraded land and heavily depend on natural resources. Thus, addressing land degradation is important to eradicating poverty and achieving food security for the poor agricultural-based communities. Despite the increasing need for addressing land degradation, investments in sustainable land management are low; especially in low income countries.

To date, few studies have comprehensively tackled the costs and consequences of land degradation either at the global, regional or national level using different parameters and approaches such as expert opinion, measurement of top soil losses as a result of erosion, rate of deforestation, soil fertility (nutrient balance) and vegetation index (as observed through GIS and remote sensing techniques). Land degradation has adverse effect on productive capacity of land, and thus, on food security of the farm households (Beinroth *et al.*, 1994; Nkonya *et al.*, 2011; von Braun *et al.*, 2012).

Soil fertility degradation is indeed considered the most important food security constraint in SSA (Verchot, *et al.*, 2007).

Information on the exact effect of land degradation on agricultural productivity for the Eastern African region (at national, regional and plot/field level) is very scanty. Previous studies have no consensus on the exact amount of productivity losses in crop and livestock production due to land degradation in Eastern Africa. Few available country data on the economic costs land degradation show that the direct cost of loss of soil and nutrients in the case study countries are enormous. For example, an earlier study by Lal, (1995) showed up to 50% decline in productivity of some crop lands in SSA due to land degradation processes. Other studies showed yield reduction ranging from 2% to 40% – a mean of 8.2% (Eswaran, 2001). Lal (1995) estimated that past erosion in SSA had caused yield reduction of 2–40% (mean of 6.2 %), and that if present trend continued, the yield reduction would increase to 16.5% by 2020.

It is estimated that about 1 billion tons of topsoil is lost annually in Ethiopia due to soil erosion (Brown, 2006). The loss of soil by water erosion in Kenya is estimated at 72 tons per hectare per year (de Graff, 1993) and even higher in Tanzania; 105 tons/ha/year in 1960's and 224 tons/ha/year, 1980's-90's). Further, salinization happened in another 30% of the irrigated land of irrigated land in Kenya and in 27 percent of irrigated land in Tanzania. An earlier study by Dregne (1990) reported permanent reduction (irreversible) soil productivity losses from water erosion in about 20% of Ethiopia and Kenya. This study is however based only on expert opinion on a few areas and extrapolated nationwide; thus they are not representative. Odelmann (1998) estimated that about 25% of cropland and 8-14% of both cropland and pasture were degraded by soil degradation. The study is also older and largely based on expert opinion and smaller areas.

In Ethiopia the annual costs of land degradation relates to soil erosion and nutrients loss from agricultural and grazing lands is estimated at about $106 million (about 3% of agricultural GDP) from a combination of soil and nutrient loss (Bojo & Cossells, 1995; Yesuf *et al*., 2008). It is further estimated that other annual losses included $23 million forest losses via deforestation and $10 million loss of livestock carrying capacity (Yesuf *et al*., 2008). All these translated to an annually total loss of about $139 million (about 4% of GDP). In Malawi, the losses may be even higher; 9.5–11% of GDP in (FAO, 2007). In Kenya, it is reported that irreversible land productivity losses due to soil erosion occurred in about 20% over the last century (Dregne 1990). Further, a high percentage 30% and 27% of high value irrigated land may have been lost due to salinization over the last century in Kenya and Tanzania respectively (Tiffen *et al*., 1994).

This chapter contributes to the existing literature on cost of land degradation by using the Total Economic Value (TEV) approach following the comprehensive definition of land degradation proposed by Millennium Ecosystem Assessment (MEA, 2005). The rest of this chapter is organized as follows; the next section describes the conceptual framework and discusses previous studies on the costs of land degradation. This is followed by a description of analytical methods and the data used in the assessment. This is followed by the discussion of the results while the last section concludes and proposes some policy implications.

3.2 Conceptual Framework

This study utilizes the Total Economic Value (TEV) approach – that captures the comprehensive definition of land degradation as proposed by ELD initiative (2013). TEV is broadly sub-divided into two categories; use and non-use values (**Figure 3.1**). The use value comprises of direct and indirect use. The direct use includes marketed outputs involving priced consumption (such as crop production, fisheries, tourism) as well as un-priced benefits (such as local culture and recreation value). The indirect use value consists of un-priced ecosystem functions such as water purification, carbon sequestration among others. The non–use value is divided into three categories namely; bequest, altruistic and existence values. All these three benefits are un-priced. In between these two major categories, there is the option value, which includes both marketable outputs and ecosystem services for future direct or indirect use.

Following Remoundou *et al*., 2009, Noel and Soussan, 2010, Nkonya *et al*., 2011 and ELD Initiative, 2013, the TEV framework is represented as follows: Land and its ecosystem services are naturally occurring and therefore tend to be undervalued; this is especially because ecosystem services are intangible and lack a ready market like in the case of other tangible market goods. In an ideal scenario, the ecosystem services should be regarded as capital assets or natural capital failure to which leads to higher rates of land degradation due to their omission (Daily *et al*. 2011, Barbier 2011a). Therefore, in order to foster comprehensive decision making, the economic values of ecosystem services have to be determined and included. Several methods of evaluating ecosystem services exist but attaching economic values to ecosystem services has remained a challenge due to prevalent unknowns and actual measurement limitations (Barbier *et al*. 2010, 2011a, 2011b, Nkonya *et al*. 2011).

Consequently, Daily *et al*. (2000) suggests that the assessment of natural capital should follow three steps: (i) examining of alternative options such as degrading soil ecosystem services verses their sustainable management, ii) identifying and measuring the costs and benefits of each alternate option, and iii) comparing the costs and benefits of each of the options while considering their long-term effects. However, compiling individual preferences and their attached values to ecosystem services for each alternative option is not an easy task (Daily *et al*. 2000; Barbier 2011b.) Additionally, economic values are associated to the number of (human) beneficiaries and their socioeconomic context. Therefore, these services are contingent to local or regional conditions which contribute to the variability of the values (TEEB 2010).

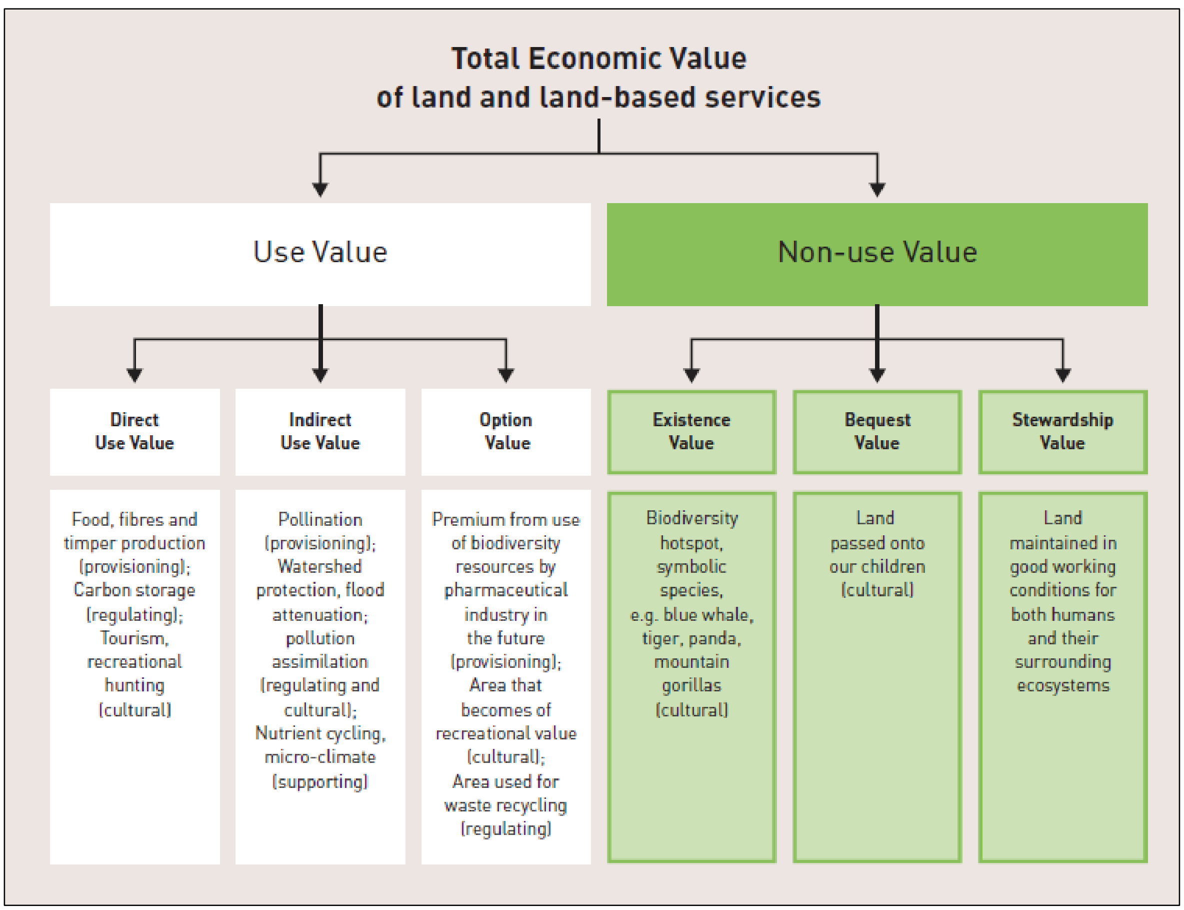

Figure 3.1: Total Economic Value
Source: ELD Initiative, 2013.

TEV approach is not without limitations[6]. Non-use and indirect-use values are complex and mostly non-tradable thus posing a challenge in their measurement and in assigning monetary values (Balmford *et al.*, 2008). Barbier *et al* (2010) and Balmford *et al* (2008) further criticize TEV in that it has the potential of double-counting of benefits from ecosystems services – this arise from the complex nature of ecosystem services themselves.

Dasgupta (2011) reiterates that the social worth of natural resources can be decomposed into three parts: their use value, their option value, and their non-use value. These components appear in different proportions, depending on the resource. It is noteworthy that estimating the value of environmental (accounting prices) is not just to value the entire environment; rather, it is to evaluate the benefits and costs associated with changes made to the environment due to human activities. Earlier, Dasgupta (2000) contends that the links between rural poverty and the state of the local natural–resource base in poor countries can offer a possible pathway along which poverty and resource degradation is synergistic over time. This implies that the erosion of the local natural resource base can make certain categories of people deprived even while the country's economy (GNP) increases (ibid).

Some costs and consequences of land degradation documented in literature for the Eastern Africa region are presented in **Table 3.1**. For example, in Ethiopia the annual costs of land degradation relate to soil erosion and nutrients loss from agricultural and grazing lands is estimated at about \$106 million (about 3% of agricultural GDP) from a combination of soil and nutrient loss (Bojo & Cossells, 1995; Yesuf *et al.,* 2008). Other annual losses included \$23 million forest losses via deforestation and \$10 million loss of livestock capacity (Yesuf *et al.,* 2008). All these translated to an annually total loss of about \$139 million (about 4% of GDP). In Malawi, the losses are even higher; 9.5–11% of GDP (FAO, 2007). Further, high percentage – 30% and 27% – of high value irrigated land was lost due to salinization over the last century in Kenya and Tanzania respectively (Tiffen *et al.,* 1994).

World Bank (1992) estimated the annual yield losses for specific crops to be 4–11% in Malawi. Sonneveld (2002) modeled the impact of water erosion on food production in Ethiopia in which he concludes that the potential reduction in production would range from 10% –30% by 2030. However, other non-quantified losses in all these studies include human capital costs of drought

[6] See a comprehensive review by Nijkamp *et al*., 2008 and Seppelt *et al*., 2011.

and malnutrition, rural poverty and environmental services costs due to the impact of sedimentation of streams and rivers. The other core effect of land degradation is on food supply. Davidson and Stroud (2006) show that there is continuously decreasing cereal availability per capita in the Eastern Africa region (from 136 kg/year in the 1980s to 118 kg/year in 2000s) due to land degradation. This translates to annual economic loss from soil erosion in SSA of about USD 1.6 to 5 billion (ibid).

Table 3.1: Cost and consequences of land degradation in Eastern Africa

Consequence	Nature and extent of the effect
Soil nutrient loss and loss of productive land resources	- Average annual soil nutrient losses of 23 kg/ha from 1980s-1990s increased to 48 kg/ha in 2000 (FAO, 2006). - Loss of soil by water erosion estimated at 72 tons/ha/year in Kenya; and 224 tons/ha/year in 1980-2000 in Tanzania (de Graff, 1993).
Salinization	- 30% of irrigated lands lost in Kenya due to salinization; Loss of irrigated lands due to salinization in Tanzania (27% of irrigated land) (Liniger *et al.,* 2011).
Loss of Land Productivity	- The productivity loss in Africa from soil degradation estimated at 25% for cropland and 8-14 percent for both cropland and pasture (Odelmann, 1998). - Irreversible soil productivity losses of at least 20% due to erosion reported to have occurred over the last century in large parts of Ethiopia and Kenya (Dregne, 1990).
Crop Yield Losses	- Under continuous cropping without nutrient inputs; cereal grain yields declined from 2-4 tons/ha to under 1 ton/ha in SSA (Sanchez *et al.,* 1997). - Crop yield losses due to erosion ranged from 2-40% (mean of 6%) for SSA (Lal, 1995). While annual yield losses for specific crops varied from 4-11% in Malawi (World Bank, 1992).
Loss of forest resources	- Forest loss over the period 1990 – 2005 was 12.7% in Malawi. Annual forest losses of 1.1% in Ethiopia, Malawi and Tanzania; and 0.3% in Kenya , chief source of energy (at least 70%) is fuel wood and charcoal in all Eastern Africa countries (UN-Habitat, 2011).
Increased food insecurity	- In 1990-2000 cereal availability per capita in SSA decreased from 136 to 118 kg/year. - The cereal yields have stagnated over the last 60 years (Morris, 2007).
Increased poverty	- 45% of SSA's population lived below the poverty line of less than 1 USD per day; the number of rural people living below the poverty line were more than twice that of those in urban settings (Ravallion *et al.*, 2007). - 73 percent of the rural poor currently residing on marginal and degraded lands (Scherr, 2001).

Source: Kirui and Mirzabaev, 2014.

The decrease in agricultural productivity represents an on-site cost. Other socioeconomic on-site effects include the increase of production costs due to the need for more inputs to address the negative physical impacts of land degradation. The indirect effects which are more difficult to quantify include; conflicts between different land users (such as farmer and herders) as a result of forced expansion of the agricultural frontier and the migration of households and communities towards pastoral land and economic losses arising from land degradation which constrain the development of services in rural areas.

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3.3 Analytical Approach

This study utilizes the Total Economic Value (TEV) approach proposed by Nkonya *et al*. (2015) which assigns value to both tradable and non-tradable ecosystem services to estimate the costs of land degradation. As described in the previous chapter (chapter 2) land degradation happens in two ways, and the cost of land degradation is computed for each of them as follows:

(i) Land degradation as a result of Land Use and land Cover Change (LUCC): the loss of ecosystem services could be due to LUCC that leads to replacement of biomes with higher ecosystem value by those with lower value (i.e. LUCC that leads to loss in the total value of ecosystem services). There are five major land use types under focus in this study namely; cropland, grassland, forest, woodland, shrub-lands and barren land.

(ii) Using land degrading management practices on a static land use (i.e. no change in land use from the baseline to end-line period). Due to data availability and time constraint, this analysis focusses on the cropland biome (maize, rice and wheat) in this study[7]. The analysis is simulated for a 40-year period.

3.3.1 Cost of degradation due to Land Use and land Cover Change (LUCC)

The cost of land degradation due to LUCC (e.g. from forest to crop) is given by:

$$\boldsymbol{C_{LUCC}} = \sum_{\boldsymbol{i}}^{\boldsymbol{K}}(\Delta \boldsymbol{a_1} * \boldsymbol{p_1} - \Delta \boldsymbol{a_1} * \boldsymbol{p_2}) \quad for\ i = 1,2, \dots k \qquad (\mathbf{3.1})$$

where; C_{LUCC} = cost of land degradation due to LUCC; a_1 = land area of biome 1 being replaced by biome 2; P_1 and P_2 are TEV per unit of area for biome 1 & 2 respectively, and i = biome.

By definition of land degradation, $P_1 > P_2$; this means, LUCC that does not lead to lower TEV is not regarded as land degradation but rather as land improvement or restoration. To obtain the net loss of ecosystem value, the second term in the equation nets out the value of the biome 1 replacing the high value.

[7] The focus is on anthropogenic land, but due to the lack of relevant TEV data, this study used Value Transfer approach which assigns ES values from existing studies to ES valuation in other areas with comparable ES (Desvousges *et al*., 1998; Troy & Wilson, 2006).

3.3.2 Cost of land degradation due to use of land degrading management practices

The estimation of cost of land degradation due to use of land degrading management practices follows the methodology proposed by Nkonya *et al*. (2015). The provisioning services of crops are well known and they have direct influence on the rural households. The ecosystem services provided by cropland are, however, less known. Carbon sequestration services are easily measured and in this are done in this study by analyzing the carbon sequestration due to sustainable land management (SLM) and compare this with land degrading practices.

This study uses the Decision Support System for Agro-technology Transfer (DSSAT) crop simulation model to determine the impact of SLM practices on crop yield and soil carbon (Gijsman *et al*., 2002). DSSAT is one of the most popular crop modeling software packages in the world. It mathematically describes the growth of crops and its interaction with soils, climate, and management practices. DSSAT combines crop, soil, and weather databases for access by a suite of crop models enclosed under one system. The models integrate the effects of crop systems components and management options to simulate the states of all the components of the cropping system and their interaction. When calibrated to local environmental conditions, crop models can help understand the current status of farming systems and test what-if scenarios.

The DSSAT model was modified by incorporating a soil organic matter and residue from the CENTURY model. Thus, the DSSAT-CENTURY model used in this study was designed to be more suitable for simulating low-input cropping systems and conducting long-term sustainability analyses and has been has been calibrated using many experiments around the world.

Two crop simulation scenarios are used as follows:

(i) SLM practices are the combination of organic inputs and inorganic fertilizer. Integrated soil fertility management (ISFM) – combined use of organic inputs, recommended amount of chemical fertilizer and improved seeds (Vanlauwe and Giller 2006) is considered as an SLM practice.

(ii) Business as usual (BAU). The BAU scenario reflects the current management practices practiced by majority of farmers. These could be land degrading management practices:

$$\mathbf{CLD} = \left(\boldsymbol{y^c - y^d}\right)\boldsymbol{P} * (\boldsymbol{A - A^c}) + (\boldsymbol{y_1^c - y_2^c}) * \boldsymbol{A^c})\boldsymbol{P} - \boldsymbol{\tau}\Delta \boldsymbol{CO_2} \qquad (\mathbf{3.2})$$

where; CLD =cost of land degradation on cropland, y^c = yield with ISFM, y^d = yield with BAU, A=total area that remained under cropland in baseline and end-line periods, A^c = cropland area under BAU. P = price of crop i; y_1^c, y_2^c are yield under ISFM in period 1 and 2 respectively; ΔCO_2=change in the amount of carbon sequestered under SLM and BAU and τ = price of CO_2 in the global carbon market. The net carbon sequestration was compute after considering the amount of carbon dioxide emission from nitrogen fertilization and from manure application.

The study focuses on three major crops: maize, rice and wheat, which cover about 42% of cropland in the world (FAOSTAT, 2013) and 35% of cropland in Eastern Africa (Appendix A1). DSSAT simulated maize, rice and wheat yields at a half degree resolution (about 60 km). To capture the long-term impacts of land management practices, the model was run for 40 years. The DSSAT, like other process-based models, have a number of disadvantages as reported by Lobell and Burke (2010) and Lobell *et al*. (2011). Process-based crop models give point estimates and do not include all relevant biological processes. For example, DSSAT cannot simulate the effect of salinity, soil erosion, phosphorus, potassium, intercropping and other processes that could affect yield.

3.3.3 Total cost of land degradation

The total cost of land degradation was obtained by summing the costs due to LUCC and costs on static land use, as follows:

$$\boldsymbol{TCLD = \sum(C_{LUCC} + CLD)} \qquad (\mathbf{3.3})$$

where; TCLD = total cost of land degradation, C_{LUCC} is cost of land degradation due to LUCC, CLD = cost of land degrading due to use of land degrading practices on a static biome.

The annual cost of land degradation is obtained by dividing the total costs of land degradation by the total number of years (eight in this case) – assuming that the rate of land degradation follows a linear trend:

$$\boldsymbol{TCLD_a = \frac{TCLD}{T}} \qquad (\mathbf{3.4})$$

where; $TCLD_a$ = annual cost of land degradation; T = time from baseline to end-line period. T is also required to reflect a long-term nature of land degradation.

3.3.4 Cost of taking action against land degradation

The methodology for establishing the cost of action for degradation due to LUCC has to put into consideration the cost of regenerating the high value biome lost and the opportunity cost of foregone benefits derived from the lower value biome being replaced (Torres *et al*., 2010). For example, if a forest was swapped with cropland, the cost of planting trees or allowing natural regeneration (if still feasible) and the cost of maintenance of the new plantation until it reaches maturity has to be put into consideration; so should be the case for the opportunity cost of the crops being foregone to replant trees or allow natural regeneration. This means the cost of taking action against land degradation due to LUCC is given by:

$$\boldsymbol{CTA_{ia} = A_{ia}\frac{1}{\rho^t}\left\{z_i + \sum_{t=1}^{T}(x_i + p_j x_j)\right\}} \qquad (\mathbf{3.5})$$

where; CTA_i = cost of restoring high value biome i in agro-ecological zone a; ρ^t = discount factor of land user; A_i= area of high value biome i that was replaced by low biome value biome j; z_i = cost of establishing high value biome i; x_i = maintenance cost of high value biome i until it reaches maturity; x_j = productivity of low value biome j per hectare; p_j = price of low value biome j per unit; t = time in years and T = planning horizon of taking action against land degradation. The term $p_j x_j$ represents the opportunity cost of foregoing production of the low value biome j being replaced.

The benefits of restoring degraded land goes beyond the maturity period of biome; thus this study used the land user's planning horizon to fully capture the entailing costs and benefits. Poor farmers tend to have shorter planning horizon while better off farmers tend to have longer planning horizon (Pannell *et al* 2014). The planning horizon also depends on the type of investment. For example, tree planting requires longer planning horizon than annual cropland. For brevity however, this study assumes a 30 year planning horizon for all the biomes considered (Nkonya *et al*., 2015). This assumption implies that during this time, farmers will not change their baseline production strategies dramatically. It is important to consider the biome establishment period since it has important implications on decision making. Poor land users are less likely to invest in restoration of high value biomes that take long time to mature. Trees take about 4-6 years to reach maturity (Wheelwright and Logan 2004). Given this a six year maturity for trees was assumed. A three year maturity age for natural regeneration or planting for grasslands was assumed. Replanting is necessary if the LUCC involved excessive weeding of grass. Natural regeneration may take longer than three years but for simplicity a three natural regeneration period was assumed.

The importance of agro-ecological zones is also taken into consideration. The cost of land degradation is therefore computed for the different agro-ecological zones. For example, establishing a biome in a semi-arid area is more difficult than would be the case in humid and sub humid regions. Pender *et al*. (2009) illustrate this using the survival rate of planted trees in the Niger, which was only 50%. Other challenges also face farmers in arid and semi-arid areas (with annual average rainfall below 700 mm) when compared to land users in humid and sub humid areas (with annual precipitation above 700 mm) (IISD 1996). Hence for any given region, the cost of establishing any biome in arid and semi-arid areas was assumed to be twice the corresponding cost in the humid and sub humid regions.

3.3.5 Cost of inaction against land degradation

The cost of inaction will be the sum of annual losses due to land degradation, given by:

$$\boldsymbol{CI_{ia} = \sum_{t=1}^{T} C_{LUCC}} \qquad (\mathbf{3.6})$$

where CI_i = cost of not taking action against degradation of biome i in agro-ecological zone a. Land users will take action against land degradation if $CTA_i < CI_{ia}$ (Nkonya et al., 2013).

3.4 Data

a. **Land use land cover change (LUCC):** The land use land cover change data used in this study is sourced from the Moderate Resolution Imaging Spectroradiometer (MODIS) for the period 2001 and 2009. The extent of each biome (forest, grassland, cropland, woodland, shrub-land, and bare land) in 2001 and the corresponding change in 2009 is reported earlier in chapter two (**Figure 2.8**).

b. **Total Economic Value (TEV):** The **total economic value data** is derived from The Economics of Ecosystems and Biodiversity (TEEB) database, which is based on more than 300 case studies – reporting more than 1350 Ecosystem Services values (De Groot *et al* 2012). The spatial distribution of the terrestrial biome studies is shown in **Figure 3.2**. Due to a large variation of the data source and methods used, data were standardized[8] to ensure that the reported values are comparable. The data were converted to 2007 US$ to allow value comparison across time. Nkonya *et al*. (2015) describes in detail the criteria used for including studies in the database; and the weakness of the ecosystem service values included in the database.

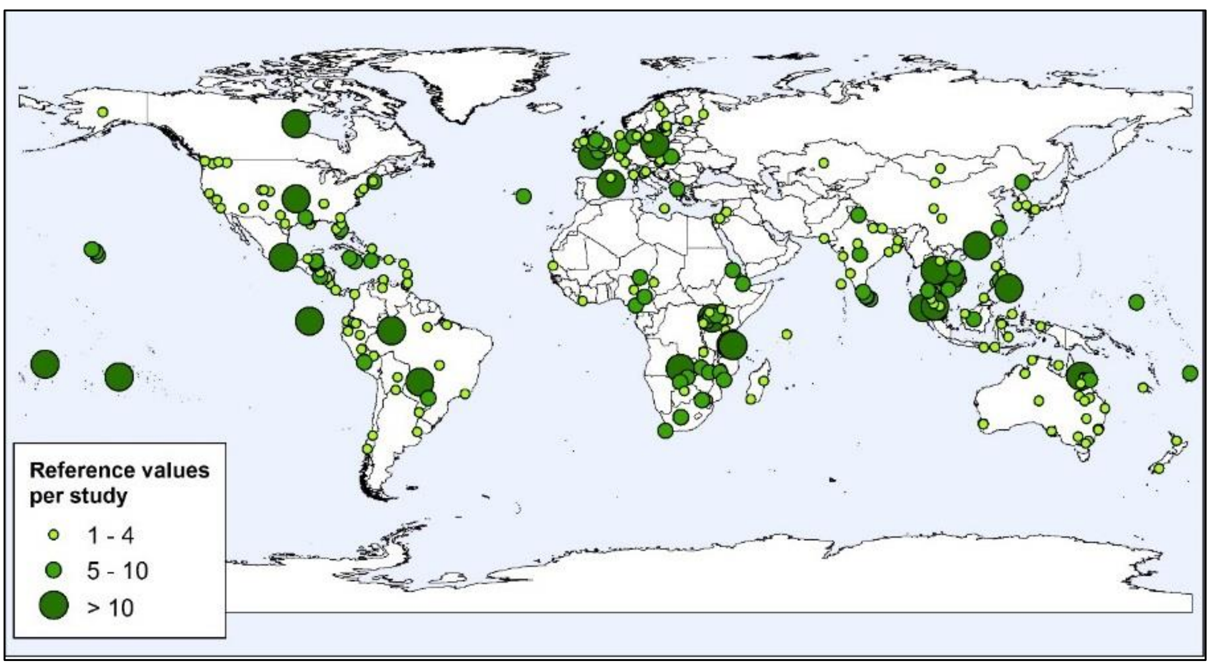

Figure 3.2: Location of TEEB database of terrestrial ecosystem service valuation studies
Source: Nkonya *et al*. (2015).

[8] For details of standardization methods used, see de Groot *et al* (2010).

c. **The Gross Domestic Product (GDP):** The Gross Domestic Product was obtained from the World Bank database.

d. **Crop yields:** The Crop yields for the ten-year baseline period (2001-2010) were sourced from the Food and Agriculture Organization Corporate Statistical (FAOSTAT) database

e. **Crop simulation – Decision Support System for Agrotechnology Transfer (DSSAT):** Crop yields simulation is done for two management scenarios: the integrated soil fertility management (ISFM) which is the land improvement scenario, and the business-as-usual (BAU) which is the land degrading management scenario. Secondary data from household surveys and literature review is used to determine adoption rate of ISFM. Corroborating data on conservation agriculture was obtained from AQUASTAT website. The DSSAT simulations are then estimated at each pixel (half degree resolution) to determine the yield under ISFM and BAU scenarios. The yield differences are then used to estimate the costs of land degradation on a 'static cropland biome'.

f. **Cost of Action and Cost of Inaction:** The data used to estimate the cost of action and the cost of inaction is sourced from Nkonya *et al*. (2015). Cost of action data includes data on cost of establishing high value biome, cost of maintenance of the high value biome and the opportunity cost of foregoing production of the low value biome (being replaced by high value biome).

3.5 Cost of Land Degradation due to Land Use Cover Change

As noted in the methodology section, the analysis of the costs of land degradation follows the comprehensive TEV framework. Description of the results therefore begin with the presentation of the total **terrestrial ecosystem value** for each of the countries followed by the costs of land degradation – loss of ecosystems values due to LUCC. The GDP, TEV, and costs of land degradation due to LUCC are all reported in **Table 3.2**. These values have been converted to 2007 USD to allow for fair comparisons. The total TEV includes the value of provisioning, regulating, habitat and cultural ecosystem services. Results show that annual TEV ranged from $ 24.98 billion in Malawi, $ 127.7 billion in Kenya, $ 206.4 billion in Ethiopia, to $ 223.1 billion in Tanzania. The GDP values for 2007 ranged from $ 3.6 billion in Malawi, $16.8 billion in Tanzania, $19.3 billion in Ethiopia, to $ 27.2 billion in Kenya.

The cost of land degradation due to LUCC in the four countries (**Table 3.2** and **Figure 3.3**) ranged from US$ 1.98 billion in Malawi, $10.65 billion in Kenya, $18.47 billion in Tanzania, to US$

34.82 billion in Ethiopia. The average annual costs of land degradation in the four countries are also presented. This is the average of the costs of land degradation per year assuming a linear trend. These costs ranged from $ 0.25 billion in Malawi, $1.33 billion in Kenya, $2.31 billion in Tanzania, to $4.35 billion in Ethiopia. The results of costs of land degradation due to LUCC are further presented in per hectare basis. They range from $38 in Ethiopia and $25 in Tanzania to $23 in Kenya and $21 in Malawi.

To provide a better visibility, the average annual costs of land degradation and further present these annual costs as a percentage of both GDP and TEV present in **Table 3.2**. The cost the cost of land degradation as a percentage of GDP was the highest in Ethiopia (23%) and Tanzania (14%). Kenya and Malawi experienced the smallest loss of ecosystem services values as a percentage of GDP (5% and 7% respectively). The costs of land degradation as percentage of TEV is the lowest Malawi (0.9%), followed by Kenya and Tanzania (both reported at 1%) but highest in Ethiopia (2.1%). These costs at regional/district level are presented in the subsequent subsection.

Table 3.2: Terrestrial ecosystem value and cost of land degradation due to LUCC

Country	GDP	TEV	Costs of land degradation due to LUCC (2001-2009)	Annual costs of land degradation due to LUCC	Cost of LD as % of 2007 GDP	Cost of LD as % of TEV	Annual costs of land degradation due to LUCC (per ha)
	US$ billion				%	%	US$/ha
Ethiopia	19.346	206.41	34.825	4.353	22.5%	2.11%	38.49
Kenya	27.236	127.74	10.645	1.331	4.9%	1.04%	22.88
Malawi	3.647	24.98	1.980	0.248	6.8%	0.94%	21.01
Tanzania	16.825	223.10	18.474	2.309	13.7%	1.03%	24.53

Source: TEV and Land Degradation –Author’s compilation; GDP – World Bank data

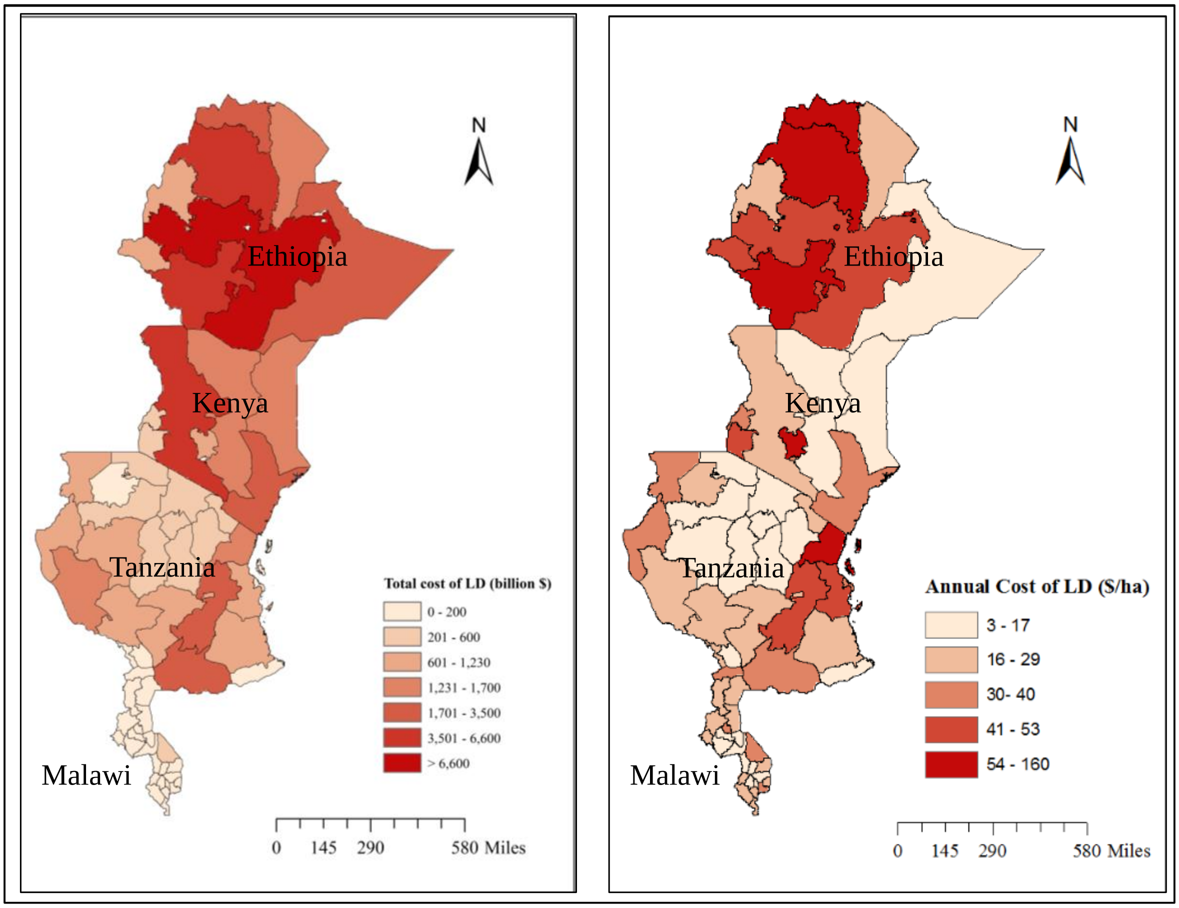

Figure 3.3: Cost of land degradation due to LUCC for the period 2001-09.
Source: Author's compilation.

The cost of land degradation due to LUCC can be presented in terms of loss of provisional ecosystem services or loss of other ecosystem services (regulating, habitat and cultural services). Provisioning ecosystem services are services with direct impact on land users while regulating, habitat and cultural services are indirect local and/or global benefits. Loss of the regulating, habitat and cultural services is regarded as costs of land degradation borne by the international community – outside the district or region of analysis.

Figure 3.4 shows that loss of provisioning services account for about 65% and 60% of the cost of land degradation in Malawi and Tanzania respectively while the loss of regulating, habitat and cultural services in these two countries accounted only for 35% and 40% of the total costs respectively. The losses in provisioning services were reported at 57% and 52% in Kenya and Ethiopia respectively. This results suggests that the costs of and degradation borne 'outside' community is substantially high.

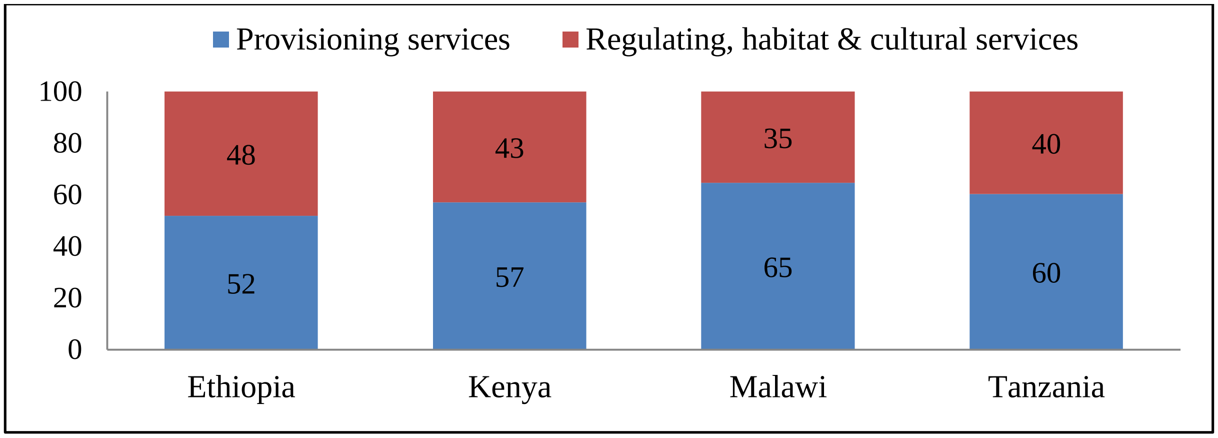

Figure 3.4: Provisioning verses other components of cost of land degradation
Source: Author's compilation.

3.6 Cost of land degradation due to use of land degrading practices on cropland

As described in the methods section, three crops (maize, wheat and rice) that constitute the bulk of production were considered for analysis. Data availability also contributed to the choice of these crops. The simulated results of the yields of rain-fed maize and wheat and irrigated rice yields under BAU and ISFM scenarios for a period of forty years are presented in **Table 3.3**. The results are structured in to two time periods; base-line and end-line. The base-line period refers to the first 10 years while the end-line refers to the last 10 years of the simulation period.

The base-line maize yields in the BAU scenario is 2.4 tons/ha in both Ethiopia and Malawi, 2.1 tons/ha in Tanzania and 1.6 tons/ha in Kenya. In the end-line period, maize yields declined to 1.8 tons/ha in Ethiopia, 1.6 tons/ha in both Malawi and Tanzania and 1.4 tons/ha in Kenya. This implies a decline of 34% in Malawi, 27% in Tanzania, 25% in Ethiopia and 17% in Kenya compared to yield in the past 30 years. Results further show that average maize yields are higher under ISFM scenario as compared to the BAU scenario. During the base-line period, the yield of ISFM maize yield ranged from 2.8 tons/ha in Ethiopia, 2.5 tons/ha in Malawi, 2.3 tons/ha in Tanzania to 1.8 tons/ha in Kenya. However, the yield declines to 2.4 tons/ha in Ethiopia, 1.9 tons/ha in both Malawi and Tanzania and 1.8 tons/ha in Kenya in the end-line period. These represent declines of about 23% in Malawi, 16% in Tanzania 12% in Ethiopia and 3% in Kenya.

The net effect of use of land degrading management practices on maize yields is presented in the last column of **Table 3.3**. This is obtained by comparing the simulated end-line yields for both the

ISFM and BAU scenarios. Results show that the yield decline due to land degradation is high in Ethiopia (36%) and Kenya (32%) followed by Malawi (22%) and Tanzania (22%). The inverse of the yield decline may also be interpreted as benefits of using ISFM. Thus the use of ISFM leads to increase in maize yields by about 36% in Ethiopia, 32% in Kenya, 22% in Malawi and Tanzania.

The base-line rice yields in the BAU scenario is 6.1 tons/ha in Malawi, 5.9 tons/ha in Tanzania and 3.6 tons/ha in Kenya. In the end-line period of the BAU, rice yields declined to 4.2 tons/ha in Tanzania, 4.0 tons/ha in Malawi and 3.2 tons/ha in Kenya. This implies a decline of 33% in Malawi, 29% in Tanzania, and 9% in Kenya compared to yield in the past 30 years. Results further show that average rice yields are higher under ISFM scenario as compared to the BAU scenario. During the base-line period, the yield of rice under ISFM ranged from 6.6 tons/ha in Malawi, 6.2 tons/ha in Tanzania to 4.4 tons/ha in Kenya. However, in the end-line period of the ISFM scenario, the yield declines to 4.7 tons/ha in Malawi, 4.5 tons/ha in Tanzania, and 4.2 tons/ha in Kenya. These represent declines of about 32% in Kenya, 16% in Malawi, and 8% in Tanzania as a result of use of land degrading management practices on irrigated rice.

Table 3.3: Change in maize, rice and wheat yields under BAU and ISFM scenarios

	BAU		ISFM		Yield Change (%)		Change due to land degradation
	Baseline (y_1^d)	End-line (y_2^d)	Baseline (y_1^c)	End-line (y_2^c)	BAU	ISFM	Percent
Country	Yield (tons/ha)		Yield (tons/ha)		$\%\Delta y = \frac{y_2 - y_1}{y_1} * 100$		$\%D = \frac{y_2^c - y_2^d}{y_2^d} * 100$
				Maize			
Ethiopia	2.39	1.79	2.79	2.44	-25.1	-12.6	36.0
Kenya	1.63	1.35	1.84	1.79	-17.1	-2.5	32.4
Malawi	2.37	1.57	2.51	1.92	-33.5	-23.3	22.0
Tanzania	2.14	1.57	2.29	1.92	-26.6	-16.0	22.3
				Rice			
Kenya	3.55	3.21	4.36	4.23	-9.4	-3.0	31.6
Malawi	6.06	4.04	6.61	4.68	-33.3	-29.2	15.9
Tanzania	5.88	4.17	6.16	4.51	-29.0	-26.8	8.0
				Wheat			
Ethiopia	1.67	1.33	1.80	1.66	-20.4	-7.9	24.7
Kenya	2.77	2.34	3.09	3.08	-15.6	-0.3	32.0
Malawi	0.55	0.52	0.53	0.52	-6.4	-2.1	0.2
Tanzania	0.66	0.64	0.67	0.68	-3.5	0.6	5.9

Note: y_1 = Baseline yield (average first 10 years); y_2 = Yield end-line period (average last 10 years).

Source: Author's compilation.

The base-line wheat yields in the BAU scenario is 2.8 tons/ha in Kenya, 1.7 tons/ha in Ethiopia, 0.7 tons/ha in Tanzania, and 0.6 tons/ha in Malawi. In the end-line period of the BAU scenario, wheat yields declined to 2.3 tons/ha in Kenya, 1.3 tons/ha in Ethiopia, 0.6 tons/ha in Tanzania, and 0.5 tons/ha in Malawi. This implies a decline of 20% in Ethiopia, 17% in Kenya, 6% in Malawi, and 4% in Tanzania compared to yield in the past 30 years. Results further show that average wheat yields are higher under ISFM scenario as compared to the BAU scenario. During the base-line period, the yield of wheat under ISFM ranged from 3.1 tons/ha in Kenya and 1.8 tons/ha in Ethiopia to 0.7 tons/ha in Tanzania and 0.5 tons/ha in Malawi. The end-line period, the yield remain largely unchanged in Kenya, Malawi and Tanzania but declines to 1.7 tons/ha in Ethiopia. These wheat yield declines in the ISFM scenario are marginal – ranging from about 0.3 % in Kenya and 0.6% in Tanzania, to 2 % in Malawi and 8% in Ethiopia. Consequently, the analysis show that yield decline on rain-fed wheat as a result of the use of land degrading management practices are high in Kenya (32%) and Ethiopia (25%) but lower in Tanzania (6%) and least in Malawi (0.2%).

Ensuing the simulation of the yields for the forty years period, is the estimation of the costs of land degradation on the static cropland for the three crops. Results (**Table 3.4**) show that the total annual costs of land degradation associated with use of land degradation practices were about US$ 305 million in Ethiopia, US$ 270 million in Kenya, US$ 162 million in Tanzania, and US$ 114 million in Malawi. When these losses are expressed as percent of GDP, Malawi is the most severely affected by cropland degradation – loses about 3% of its GDP annually. Similarly, Ethiopia loses about 2%, while Tanzania and Kenya each lose about 1% of GDP. Statistics show that the three crops (maize, rice and wheat) account for about 42% of the cropland globally. Assuming that the overall levels of degradation in all cropland is comparable to that occurring on the three major crops, then these costs range from 2.3% in Tanzania, 2.4% in Kenya, 3.8% in Ethiopia to 7.5% in Malawi. The annual costs on static maize, wheat, and rice biomes are also presented as a percentage of the total cropland area to enhance comparison across countries. The annual costs per hectare ranged from as high as US$ 194 in Malawi and US$ 117 in Kenya to as low as US$ 90 in Tanzania and just US$ 27 in Ethiopia.

It is noteworthy that the costs of land degradation due soil fertility mining as reported in **Table 3.4** are conservative. Other aspects of land degradation on a static cropland biome including soil erosion and salinity, and offside costs of pesticide use are not considered because of lack of data.

Table 3.4: Annual Cost of land degradation on static cropland – DSSAT results

Country	Annual cost of maize, wheat, rice degradation	Annual cost of maize, wheat, rice degradation	Annual cost of total cropland degradation	Annual cost of land degradation (per ha)
	2007 US$ million	(% GDP)	(% GDP)	US$/ha
Ethiopia	304.96	1.58	3.75	27.02
Kenya	269.77	0.99	2.36	116.70
Malawi	114.09	3.13	7.45	194.18
Tanzania	161.94	0.96	2.29	89.63

Source: Author's compilation

3.7 Total Cost of land degradation

Table 3.5 presents the total annual costs of land degradation – sum of costs due to LUCC and costs due to use of land degrading practices on a static cropland biome. These costs are also presented as a percent of GDP. The total annual cost of land degradation ranged from US$ 361 million in Malawi and US$ 1600 million in Kenya to US$ 2471 million in Tanzania and US$ 4658 million in Ethiopia. When expressed as a percent of GDP, total costs of land degradation are the highest in Ethiopia (24%) and Tanzania (15%) followed by Malawi (10%) and the least in Kenya (6%). For a better comparison between countries, the total annual costs of land degradation are converted to per hectare basis. Results show that annually, the total costs of land degradation are highest in Ethiopia ($ 41) and Malawi ($ 31) followed by Kenya ($ 28) but least in Tanzania ($ 26).

Table 3.5: Annual total cost of land degradation (costs on static cropland and LUCC costs)

Country	Cost of land degradation on static biome (cropland)	Annual Cost of land degradation due to LUCC	Total Annual Cost of land degradation	Total cost of land degradation as % of GDP	Total Annual Cost of land degradation
	2007 US$ million			%	US$/ha
Ethiopia	305.0	4353.1	4658.1	24.1	41.2
Kenya	269.8	1330.6	1600.4	5.9	27.5
Malawi	114.1	247.5	361.6	9.9	30.7
Tanzania	161.9	2309.3	2471.2	14.7	26.2

Source: Author's compilation.

3.8 Costs of action versus inaction against land degradation

This section presents the results of the assessment of the costs of action against land degradation which help in determining whether the action against land degradation could be justified economically. Nkonya *et al* (2013) notes that land users will take action against land degradation if the cost of inaction is greater than the cost of action. To completely rehabilitate degraded land due to LUCC in a period of six years, a total of about \$ 54 billion in Ethiopia, \$ 37 billion in Tanzania, \$ 18 billion in Kenya, and \$ 4 billion in Malawi (**Table 3.6 and Figure 3.5**). But if no action is taken to rehabilitate degraded lands over the same period, it would lead to a loss of about \$ 169 billion in Ethiopia, \$ 103 billion in Tanzania, \$ 55 billion in Kenya, and \$ 12 billion in Malawi. The cost of action as a percent of cost of inaction in a 6-year time period represents just about 32% in Ethiopia, 33% in Kenya, 37% in Malawi and 36% in Tanzania. Consequently, during the first six years, for every dollar spent on taking action against land degradation users will expect a return of about \$ 3.1 in both Ethiopia and Kenya, \$ 2.7 in Malawi and \$ 2.8 in Tanzania.

Table 3.6: Cost of action & inaction against LUCC-related land degradation (US\$ billion)

Country	Cost of Action	Cost of Inaction	Cost of Action as % cost of Inaction	Returns from action	Cost of Action	Cost of Inaction	Cost of Action as % cost of Inaction	Returns from action
	First 6 years				30–years horizon			
Ethiopia	54.05	168.67	32.0	3.1	54.17	228.32	23.7	4.2
Kenya	18.03	55.33	32.6	3.1	18.07	74.89	24.1	4.1
Malawi	4.24	11.52	36.8	2.7	4.25	15.60	27.3	3.7
Tanzania	36.56	102.56	35.6	2.8	36.63	138.83	26.4	3.8

[a] The inverse of the corresponding percent is the returns to investment

Source: Author's compilation based on MODIS data.

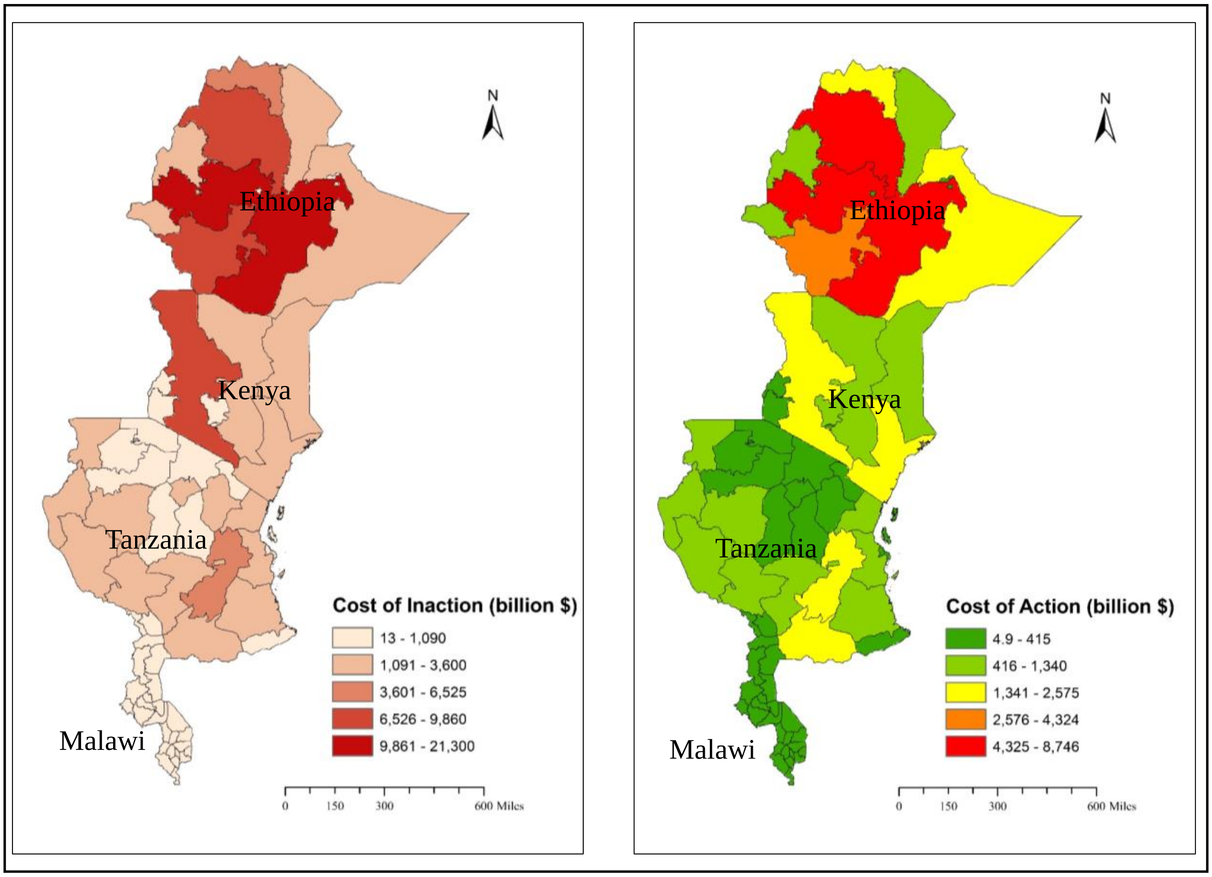

Figure 3.5: Cost of action & inaction against LUCC-related land degradation
Source: Author's compilation.

During the entire 30-year planning horizon, the cost of action is about $ 54.2 billion in Ethiopia, $ 36.6 billion in Tanzania, $ 18.1 billion in Kenya, and $ 4.3 billion in Malawi. However, if no action is taken to address land degradation over the 30-year period, it would lead to a loss of about $ 228 billion in Ethiopia, $ 139 billion in Tanzania, $ 75 billion in Kenya, and $ 16 billion in Malawi. These imply that the cost of action as a percent of cost of inaction represented about 24% in Ethiopia and Kenya, 26% in Malawi and Tanzania. Consequently, during the 30-year period, for every dollar spent on taking action against land degradation users will expect a return of about $ 4.2 in Ethiopia, $ 4.1 in Kenya, $ 3.8 in Tanzania, and $ 3.7 in Malawi.

The costs of action and costs of inaction against land degradation were also computed with considerations of different ranges of uncertainty due to data and assumptions. Specifically, the uncertainty in this study was captured by the variation in the discounting rate. Following Nkonya *et al* (2015), the discounting rate for developing countries was estimated at 25%. To estimate the uncertainty in estimation of ''future'' costs of action and costs of inaction, this study estimated these costs with lower discounting rate (scenarios 1 and 2) and higher discount rates (scenario 3 and 4) for the 30-year period as shown in **Figure 3.6** and **Figure 3.7**. Results show that with lower discounting rates, the costs of action and costs of inaction are both higher while the costs of action and costs of inaction are both lower when using a higher discount rate. Results for 6 year-period are provided in Appendix **Figure 8.2** and **Figure 8.3.**

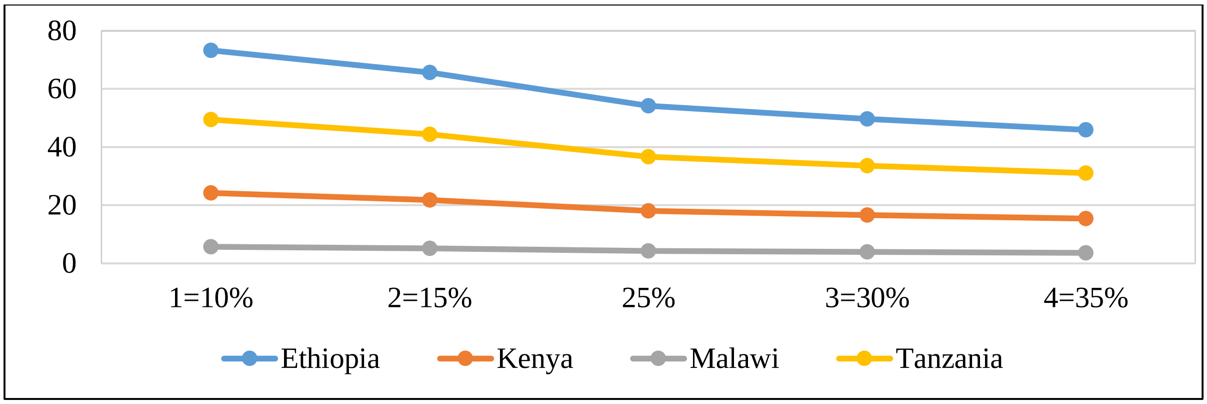

Figure 3.6: Cost of action (billion USD) against LUCC land degradation in 30 years in different scenarios

Source: Author's compilation based on MODIS data.

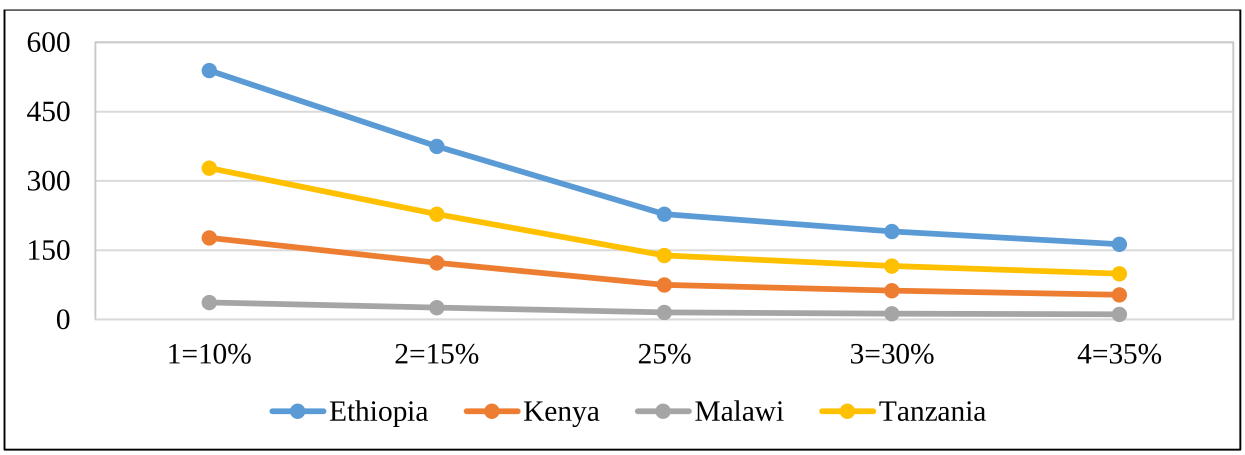

Figure 3.7: Cost of Inaction (billion USD) against LUCC land degradation in 30 years in different scenarios

Source: Author's compilation based on MODIS data.

The costs of action and inaction against LUCC land degradation for the six-year and thirty-year periods are also computed on per ha basis as presented in **Table 3.7**. Analysis show that during the six-year period the costs of action per ha ranged from as high as $ 477 in Ethiopia and $ 384 in Tanzania to as low as $ 343 in Malawi and $ 310 in Kenya. However, the costs of inaction over the same period is about $ 1491 in Ethiopia, $ 1090 in Tanzania, $ 978 in Malawi and $ 951 in Kenya. During a 30-year period the costs of action per ha is about $ 478 in Ethiopia, $ 385 in Tanzania, $ 344 in Malawi and $ 311 in Kenya. However the costs of inaction increase to about $ 2019 in Ethiopia, $ 1475 in Tanzania, $ 1323 in Malawi, and $ 1287 in Kenya.

Table 3.7: Cost of action & inaction against LUCC-related land degradation per hectare

Country	Cost of Action	Cost of Inaction	Cost of Action	Cost of Inaction
	(6 years)		(30 years)	
Ethiopia	476.6	1491.4	477.7	2018.7
Kenya	309.9	951.1	310.6	1287.4
Malawi	343.0	977.7	343.7	1323.4
Tanzania	384.3	1089.5	385.1	1474.7

Source: Author's compilation based on MODIS data.

The results at district/regional levels for the four countries are varied. In Ethiopia, results show that the annual cost of land degradation is about $4.1 billion (**Table 3.8**). Only about $1.7 billion (42%) of this cost of land degradation represent the loss of provisional ecosystem services. The other 58% represents the loss of supporting and regulatory and cultural ecosystem services. The annual costs of land degradation were higher in Southern Nations ($1.6 billion), Dire Dawa ($822 million) and Afar ($654 million) regions but least in Somali ($4 million), Addis Ababa ($4 million) and Harari ($8 million) regions.

The results further show the costs of action were about $54.1 million in a six-year period and about $54.2 million over a 30-year horizon whereas the costs of inaction in six-year period were about $169 million and about $228 million in a 30-year period. This implies that the costs of action against land degradation are lower than the costs of inaction by about 4.2 times over the 30 year horizon; i.e. the ratio of action to cost of inaction is 24.8%. This implies that each dollar spent on addressing land degradation is likely to have about 4.1 dollars of returns. The ratio of costs of action to cost of inaction in the 30-year period was high in Oromia (27.2%), Harari (26.7%), Gambela (26.7%), and Amhara (25.2%) regions. The returns from action were the highest in Tigray ($5.8), Somali ($4.4), and Dire Dawa ($ 4.4) regions and lowest in Oromia ($ 3.7), Harari ($3.8) and Gambela ($3.8) regions.

Table 3.8: Cost of action and inaction against land degradation in Ethiopia (million USD)

Region	Annual costs of Land Degradation	Annual costs of land degradation in terms of provisional ES only	Cost of Action (6 years)	Cost of Inaction (6 years)	Cost of Action (30 years)	Cost of Inaction (30 years)	Ratio of Cost of action: cost of Inaction (30 years)	Returns from action (30 years)
	Million USD						%	$
Addis Ababa	3.564	0.396	0.045	0.135	0.045	0.182	24.8%	4.04
Afar	654.287	270.585	8.578	26.331	8.595	35.641	24.1%	4.15
Amhara	296.628	140.036	4.504	13.234	4.514	17.913	25.2%	3.97
Benshangul	197.078	106.565	2.685	8.588	2.693	11.625	23.2%	4.32
Dire Dawa	822.324	176.375	9.836	31.973	9.863	43.278	22.8%	4.39
Gambela	107.765	76.750	1.870	5.189	1.873	7.024	26.7%	3.75
Harari	8.268	6.218	0.151	0.419	0.151	0.567	26.7%	3.75
Oromia	128.042	96.575	2.381	6.489	2.385	8.783	27.2%	3.68
Somali	4.200	1.552	0.051	0.168	0.052	0.227	22.7%	4.41
Southern	1569.461	686.605	21.256	64.619	21.301	87.468	24.4%	4.11
Tigray	303.782	138.263	2.691	11.532	2.702	15.609	17.3%	5.78
Total	**4095.40**	**1699.92**	**54.05**	**168.67**	**54.17**	**228.32**	**24.8%**	**4.21**

Source: Author's compilation based on MODIS data.

In **Kenya**, results show that the annual cost of land degradation is about $ 1.3 billion (**Table 3.9**). About 51% of this cost (or $ 666 million) represent the loss of provisional ecosystem services. The other half represents the loss of supporting and regulatory and cultural ecosystem services. The annual costs of land degradation were higher in Rift valley ($445 million), Coast ($283 million) and Eastern ($209 million) provinces but least in Nairobi ($2 million), Western ($30 million) and Nyanza ($70 million) provinces. The results further show the costs of action were about $18 million in a six-year period and about $18.1 million over a 30-year horizon whereas the costs of inaction in six-year period were about $55 million and about $75 million in a 30-year period.

This implies that the costs of action against land degradation are lower than the costs of inaction by about 4.1 times over the 30 year horizon; i.e. the ratio of action to cost of inaction is 24%. This implies that each dollar spent on addressing land degradation is likely to have about 4.1 dollars of returns. The ratio of costs of action to cost of inaction in the 30-year period was high in Nairobi (28%), Rif Valley (26%), North Eastern (25%), and Central (25%) provinces. The returns from action were the highest in Coast ($4.6), Nyanza ($4.5), and Western ($ 4.1) provinces and lowest in Nairobi ($ 3.6) and Rift Valley ($3.9) provinces.

Table 3.9: Cost of action and inaction against land degradation in Kenya (million USD)

Region	Annual costs of Land Degradation	Annual costs of land degradation in terms of provisional ES only	Cost of Action (6 years)	Cost of Inaction (6 years)	Cost of Action (30 years)	Cost of Inaction (30 years)	Ratio of Cost of action: cost of Inaction (30 years)	Returns from action (30 years)
	Million USD						%	$
Central	79.634	35.691	1.085	3.239	1.087	4.384	24.8%	4.034
Coast	282.672	128.895	3.337	11.283	3.346	15.272	21.9%	4.565
Eastern	208.807	125.718	2.993	9.353	3.001	12.660	23.7%	4.219
Nairobi	2.289	1.050	0.036	0.097	0.036	0.131	27.8%	3.602
North Eastern	185.088	110.820	2.815	8.369	2.821	11.328	24.9%	4.016
Nyanza	70.324	30.206	0.818	2.753	0.820	3.727	22.0%	4.544
Rift Valley	444.969	219.726	6.533	18.959	6.546	25.663	25.5%	3.920
Western	30.251	14.043	0.417	1.273	0.418	1.724	24.2%	4.127
Total	**1304.03**	**666.15**	**18.03**	**55.33**	**18.07**	**74.89**	**24.1%**	**4.14**

Source: Author's compilation based on MODIS data.

In **Malawi**, results show that the annual cost of land degradation is about $244 million (**Table 3.10**). Only about $153 million (62%) of this cost of land degradation represent the loss of provisional ecosystem services. The other (about 38%) represents the loss of supporting and regulatory and cultural ecosystem services. The annual costs of land degradation were higher in Mangochi ($27 million), Nkhata Bay ($24 million), Nkhotakota ($20 million), and Rumphi ($20 million) districts but least in Balaka ($0.8 million), Chiradzulu ($0.9 million) and Blantyre ($2 million) districts.

The results also show that the costs of action were about $4 million in a six-year period and about $4.3 million over a 30-year horizon whereas the costs of inaction in six-year period were about $12 million and about $17 million in a 30-year period. This implies that the costs of action against land degradation are lower than the costs of inaction by about 3.7 times over the 30 year horizon; i.e. the ratio of action to cost of inaction is 27.3%. This implies that each dollar spent on addressing land degradation is likely to have about 3.7 dollars of returns. The ratio of costs of action to cost of inaction in the 30-year period was high in Nkhata Bay (29.8%), Mzimba (28.3%), Ntcheu (28.3%), and Nsanje (28.1%) districts. The returns from action were the highest in Salima ($4.1), Mangochi ($3.9), Balaka ($ 3.8) and Karonga ($ 3.8) districts. The lowest returns from action were reported in Nkhata Bay ($ 3.4), Ntcheu ($3.5) and Mzimba ($3.5) districts.

Table 3.10: Cost of action and inaction against land degradation in Malawi (million USD)

Region	Annual costs of Land Degradation	Annual costs of land degradation in terms of provisional ES only	Cost of Action (6 years)	Cost of Inaction (6 years)	Cost of Action (30 years)	Cost of Inaction (30 years)	Ratio of Cost of action: cost of Inaction (30 years)	Returns from action (30 years)
	Million USD						%	$
Balaka	0.750	0.501	0.013	0.036	0.013	0.049	26.0%	3.84
Lilongwe	9.972	7.022	0.176	0.485	0.176	0.657	26.8%	3.73
Machinga	11.027	7.081	0.197	0.525	0.197	0.710	27.7%	3.61
Mangochi	27.302	14.968	0.403	1.169	0.403	1.583	25.5%	3.92
Mchinji	5.594	4.297	0.104	0.284	0.104	0.384	27.2%	3.68
Mulanje	6.605	4.021	0.112	0.308	0.112	0.416	26.9%	3.72
Mwanza	6.245	4.267	0.111	0.301	0.111	0.408	27.3%	3.66
Mzimba	19.635	13.027	0.367	0.961	0.368	1.301	28.3%	3.54
Nkhata Bay	24.379	9.222	0.415	1.031	0.416	1.395	29.8%	3.36
Nkhotakota	19.988	11.710	0.337	0.916	0.338	1.240	27.2%	3.67
Nsanje	4.219	2.865	0.079	0.210	0.080	0.284	28.1%	3.57
Blantyre	1.934	1.276	0.035	0.095	0.035	0.128	27.3%	3.66
Ntcheu	4.381	3.128	0.086	0.224	0.086	0.303	28.3%	3.53
Ntchisi	5.559	4.002	0.102	0.275	0.103	0.373	27.5%	3.63
Phalombe	3.948	2.739	0.072	0.195	0.072	0.264	27.3%	3.67
Rumphi	19.568	12.281	0.331	0.908	0.331	1.229	26.9%	3.71
Salima	5.023	2.826	0.076	0.227	0.076	0.307	24.7%	4.05
Thyolo	4.655	3.054	0.081	0.226	0.081	0.306	26.6%	3.76
Zomba	4.668	2.744	0.083	0.222	0.083	0.301	27.7%	3.61
Chikwawa	8.780	6.034	0.155	0.428	0.155	0.580	26.7%	3.74
Chiradzulu	0.874	0.587	0.016	0.043	0.016	0.058	26.8%	3.73
Chitipa	9.246	6.722	0.173	0.469	0.174	0.634	27.4%	3.65
Dedza	7.436	5.233	0.135	0.369	0.135	0.499	27.0%	3.70
Dowa	4.889	3.393	0.086	0.242	0.086	0.328	26.4%	3.79
Karonga	12.394	7.899	0.205	0.579	0.206	0.784	26.3%	3.81
Kasungu	15.321	12.205	0.295	0.797	0.296	1.079	27.4%	3.65
Total	**244.39**	**153.11**	**4.24**	**11.52**	**4.25**	**15.60**	**27.3**	**3.67**

Source: Author's compilation based on MODIS data.

In **Tanzania**, results show that the annual cost of land degradation is about $2.3 billion (**Table 3.11**). Only about $1.3 billion (57%) of this cost of land degradation represent the loss of provisional ecosystem services. The other (about 43%) represents the supporting and regulatory and cultural ecosystem services. The annual costs of land degradation were higher in Morogoro ($297 million), Ruvuma ($214 million), and Rukwa ($193 million) districts but least in Zanzibar West ($3 million), Dar-Es-Salaam ($6 million) and Unguja North ($7 million) districts.

Moreover, results show that the costs of action were about $36.5 million in a six-year period and about $36.6 million over a 30-year horizon. However, the costs of inaction in six-year period were about $103 million and about $139 million in a 30-year period. This implies that the costs of action against land degradation are lower than the costs of inaction by about 3.8 times over the 30 year horizon; i.e. the ratio of action to cost of inaction is 26.4%. This implies that each dollar spent on addressing land degradation is likely to have about 3.8 dollars of returns. The ratio of costs of action to cost of inaction in the 30-year period were high in Singida (29.5%), Lindi (29.4%), and Morogoro (28.2%) regions but lowest in Pemba South (15.3%), Mwanza (17.1%) and Pemba North (17.4%) regions. The returns from action were the highest in Pemba South ($6.5), Mwanza ($ 5.9) and Pemba North ($ 5.8) regions. The lowest returns from action were reported in Singida ($ 3.4), and Lindi ($3.4) districts.

Table 3.11: Cost of action and inaction against land degradation in Tanzania (million USD)

Region	Annual costs of Land Degradation	Annual costs of land degradation in terms of provisional ES only	Cost of Action (6 years)	Cost of Inaction (6 years)	Cost of Action (30 years)	Cost of Inaction (30 years)	Ratio of Cost of action: cost of Inaction (30 years)	Returns from action (30 years)
	Million USD						%	$
Arusha	56.032	30.290	0.880	2.479	0.882	3.356	26.3%	3.81
Pemba South	7.337	2.032	0.046	0.223	0.046	0.302	15.3%	6.53
Lindi	122.851	69.604	2.360	5.935	2.364	8.033	29.4%	3.40
Manyara	60.588	41.192	1.108	2.987	1.111	4.044	27.5%	3.64
Mara	42.107	14.759	0.417	1.523	0.418	2.061	20.3%	4.93
Mbeya	160.688	116.777	2.918	8.003	2.924	10.833	27.0%	3.70
Morogoro	297.369	171.086	5.195	13.621	5.204	18.438	28.2%	3.54
Mtwara	15.219	6.292	0.181	0.596	0.182	0.807	22.5%	4.45
Mwanza	70.762	23.992	0.551	2.387	0.552	3.231	17.1%	5.85
Pwani	129.504	62.931	2.139	5.711	2.142	7.731	27.7%	3.61
Rukwa	192.746	122.226	3.083	8.790	3.089	11.898	26.0%	3.85
Dar-Es-Salaam	6.371	2.661	0.070	0.246	0.070	0.333	21.0%	4.76
Ruvuma	214.386	144.504	3.592	10.002	3.599	13.539	26.6%	3.76
Shinyanga	44.896	20.818	0.504	1.737	0.506	2.352	21.5%	4.65
Singida,	55.587	29.423	1.055	2.644	1.056	3.578	29.5%	3.39
Tabora	100.566	73.526	1.839	5.037	1.842	6.817	27.0%	3.70
Tanga	161.926	88.442	2.541	7.113	2.545	9.628	26.4%	3.78
Zanzibar South	9.159	3.047	0.124	0.347	0.124	0.470	26.3%	3.80
Zanzibar West	3.225	0.903	0.038	0.116	0.038	0.157	24.2%	4.14
Dodoma	32.033	18.172	0.475	1.419	0.476	1.920	24.8%	4.03
Iringa	144.596	85.781	2.452	6.631	2.456	8.976	27.4%	3.65
Kagera	157.460	85.285	2.251	6.736	2.256	9.117	24.7%	4.04
Pemba North	8.569	2.397	0.064	0.273	0.064	0.369	17.4%	5.75
Unguja North	6.737	2.120	0.068	0.233	0.068	0.316	21.5%	4.65
Kigoma	157.616	79.468	2.014	6.140	2.017	8.311	24.3%	4.12
Kilimanjaro	36.721	20.272	0.598	1.634	0.599	2.212	27.1%	3.70
Total	**2295.05**	**1318.00**	**36.56**	**102.56**	**36.63**	**138.83**	**26.4%**	**3.79**

Source: Author's compilation based on MODIS data.

3.9 Conclusions

This chapter demonstrates that the consequences and losses due to land degradation are enormous. Based on TEV framework, the costs of land degradation due to LUCC between 2001-2009 periods were \$1.98 billion in Malawi, \$10.65 billion in Kenya, \$18.47 billion in Tanzania, to US\$ 34.82 billion in Ethiopia. This represents about 5%, 7%, 14% and 23% of GDP in Kenya, Malawi, Tanzania and Ethiopia respectively. When these costs are converted to per hectare basis, they range from \$38 in Ethiopia, \$25 in Tanzania, \$23 in Kenya and \$21 in Malawi annually. The total annual costs of land degradation associated with use of land degradation practices in maize, wheat and rice croplands were about \$305 million in Ethiopia, \$270 million in Kenya, \$162 million in Tanzania, and \$114 million in Malawi. These costs on static cropland degradation are, however, conservative. Only three crops were considered, other aspects of land degradation common on a static biome (cropland) including soil erosion and salinity, and offside costs of pesticide use are not considered because of lack of data.

It is worthwhile to take action against land degradation. As expected, the TEV computation shows that the costs of action are lower as compared to costs of inaction against land degradation in all the countries both in a 6-year and a 30-year cycle. During the entire 30-year planning horizon, the cost of action is about \$ 54.2 billion in Ethiopia, \$ 36.6 billion in Tanzania, \$ 18.1 billion in Kenya, and \$ 4.3 billion in Malawi. However, if no action is taken to address land degradation over the 30-year period, it would lead to a loss of about \$ 228 billion in Ethiopia, \$ 139 billion in Tanzania, \$ 75 billion in Kenya, and \$ 16 billion in Malawi. These imply that the cost of action as a percent of cost of inaction represented about 24% in Ethiopia and Kenya, 26% in Malawi and Tanzania. Consequently, during the 30-year period, returns to investment in action against land degradation are at least four folds. Specifically, for every dollar spent on taking action against land degradation land users will expect a return of about \$4.2 in Ethiopia, \$4.1 in Kenya, \$3.8 in Tanzania, and \$3.7 in Malawi.

Policies and strategies that incentivize better sustainable land management and discourage deforestations ought to be emboldened so as to achieve UNCCD’s target of zero net land degradation by year 2030. The costs of land degradation due to LUCC constitute the biggest proportion of the total costs of land degradation. Therefore, strategies and mechanisms must be developed to address LUCC such as payment for ecosystem services (PES) and participatory management of community resources such as forests and grazing lands.

As demonstrated in the previous chapter, local level initiatives have also proven successful in ensuring sustainable management of land and land resources. Some of the key activities currently practiced by local communities include; area closures and stricter enforcement and enacting of bylaws to protect forests, controlled grazing and community sanctions for overgrazing. Thus, participatory involvement of the local communities is important for successful and effective policy formulation and enforcement at community level. The next chapter highlights the cause of land degradation and the determinants of SLM adoption.

Chapter 4

4. Drivers of Land Degradation and Adoption of Multiple Sustainable Land Management Practices

4.1 Introduction

Land degradation is an extensive and serious impediment to improving rural livelihoods and food security of millions of people in the eastern Africa. Recent estimates show that land degradation affected about 51%, 41%, 23% and 22% of the terrestrial areas in Tanzania, Malawi, Ethiopia and Kenya respectively (Le, Nkonya and Mirzabaev, 2014). Addressing land degradation through the formulation of proper strategies and effective policies requires first the identification of both the proximate (direct) and underlying (indirect) causes (Vlek *et al*., 2010; von Braun *et al*., 2012; Pingali *et al*., 2014).

A review of literature show that there exist numerous and complex proximate and underlying causes of land degradation in the region (Kirui and Mirzabaev, 2014). Relevant proximate causes include topography and climatic conditions (such as wind, temperature and rainfall). Other significant human activities identified as the direct drivers of land degradation include unsustainable and inappropriate land management practices such as land clearing, deforestation, wood and charcoal extraction, overgrazing/overstocking of herds, cultivation on steep slopes, bush burning, soil nutrient mining and uncontrolled fires (Eswaran *et al*., 2001; Lal, 2001; Dregne, 2002; Barac, 2003; Gareng, 2015).

Significant root causes underlying the fore mentioned direct causes of land degradation in the region include insecure land tenure, poverty, population density, access to information and markets, and weak policy and regulatory environment in the agricultural and environmental sectors (Kabubo-Mariara, 2007; Tiffen *et al*., 1994; Nkonya *et al*., 2008). Tackling the direct human causes of land degradation requires an understanding and addressing of these root causes through appropriate mitigative and remedial strategies.

Different methods have been used to deduce the causes of land degradation. They include the use of expert opinions (Oldeman *et al*., 1991), quantitative analyses (Bai *et al*., 2008; Vlek *et al*., 2008; 2010), use of inferential statistics (Barbier, 1997; Nkonya *et al*., 2011), and the use of satellite imagery and remote sensing techniques (Hoffman *et al*., 1999; FAO, 2003; Archer, 2004; Yang *et al*., 2005; Le *et al*., 2012; 2014). The advantages and inherent weaknesses of each of these approaches are discussed in detail in the next section.

The adoption and investment in sustainable land management is crucial in reversing and controlling land degradation, rehabilitating degraded lands and ensuring the optimal use of land resources for the benefit of present and future generations (Akhtar-Schuster *et al.,* 2011; ELD Initiative, 2013). Sustainable land management is important for sustainable development because it facilitates land users to maximize the benefits from their land while maintaining the ecological support functions of the land resources (TerrAfrica, 2006). The efforts directed at addressing the causes of land degradation or addressing the constraints to SLM adoption, however, have not been largely insufficient. Recent reliable estimates show that the adoption of sustainable land management practices in sub-Saharan Africa is very low – about 3% of total cropland (World Bank, 2010).

Several studies have been carried out to document significant determinants and constraints to sustainable land management using different approaches. These studies highlighted the direction and the magnitude of factors hypothesized to determine the adoption of SLM technologies. Some examples of these detailed empirical studies in developing countries include that of Pagiola (1996) in Kenya, Nakhumwa and Hassan (2012) in Malawi, Shiferaw and Holden (1998), Gabremedhin and Swinton (2003) and Bekele and Drake (2003) in Ethiopia.

Some of the significant factors facilitating the adoption of sustainable land management include; access to information (education and extension), access to both input and output markets, social, human and physical capital endowments, credit availability, profitability of the management technology, and property rights. The adoption of sustainable land management is also influenced by lack of local-level capacities, knowledge gaps on specific land degradation and SLM issues, inadequate monitoring and evaluation of land degradation and its impacts, inappropriate incentive structure (such as, inappropriate land tenure and user rights), inaccessible market and infrastructure constraints (such as, insecure prices of agricultural products, increasing input costs, inaccessible markets), and policy and institutional bottlenecks (such as, difficulty and costly enforcement of existing laws that favor SLM) and risks (Thompson *et al*., 2009; Chasek *et al*., 2011; Akhtar-Schuster *et al*., 2011 Reed *et al*., 2011; ELD Initiative, 2013).

There is thus a fairly large body of existing literature on causes of land degradation and determinants of adoption of SLM in eastern Africa, however, a number of limitations that should be fulfilled in next research are evident. These studies either focuses on some specific location(s) in the region, are considered subjective and lacking in scientific rigor and/or have weak explanatory power due to smaller sample size. The results from different studies are often contradictory regarding any given variable (Ghadim and Pannell, 1999). The current assessment is unique in that; it uses nationally representative data (at farm level) with diverse variables (both proximate and underlying) and that it includes socio-economic and behavioral factors. These include a mix of biophysical, demographic, socio-economic, and institutional variables.

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

4.2 Relevant Literature

4.2.1 Drivers of land degradation

Drivers of land degradation can be grouped into two categories, namely; proximate and underlying causes (Lambin & Geist, 2006; Lal & Stewart, 2010; 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. Proximate causes are also related to unsustainable land management practices (anthropogenic) such as over-cultivation, overgrazing and excessive forest conversion. On the other hand, the underlying causes are those factors that indirectly affect proximate causes. Lack of institutions, poverty, and insecure land tenure may underlie land degradation by hampering incentives to invest in sustainable land management practices (Kabubo-Mariara, 2007; FAO, 2011a). Geist & Lambin (2004) and Nkonya *et al.,* (2013) present a review of these proximate and underlying drivers of land degradation. A summary of some of the empirical studies undertaken to identify and assess proximate and underlying causes of land degradation in selected countries in Eastern Africa region are presented in **Table 4.1**.

Key **proximate drivers** in Eastern Africa 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. 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; Lal *et al*., 2012). Most deforestation exercises are associated with the continued demand for agricultural land, fuel-wood, charcoal, construction materials, large-scale timber logging 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 continues to diminish the productivity of rangelands (Hein & de Ridder, 2005; Waters *et al.,* 2013).

Arid and semi-arid climatic conditions with high evaporation rates; together with poor management of irrigation water (in the 4.5% irrigated cropland of SSA) is a major cause of salinization. Additionally, fragmentation, overexploitation of the forest resources and conversion of forest lands to agriculture increases deforestation rates in the region. Overstocking is identified to primarily drive degradation of rangelands, decline of vegetation productivity (and eventually livestock productivity), and loss of resilience of the rangeland for droughts (WRI, UNEP, and UNDP, 1994). Indeed, overgrazing was estimated to cause about 50% of all soil degradation in semi-arid and arid regions of Africa (ibid). The increasing demand for food brought about by an increasing population but with stagnant or declining agricultural productivity has led to rapid expansion of agricultural land and reduced rehabilitation of soil fertility through shortening of the fallow periods in extensive land use systems (Scherr & Yadav, 1996).

Important **underlying drivers** of land degradation in the region include land tenure, poverty, population density and weak policy and regulatory environment in the agricultural and environmental sectors (**Table 4.1**). 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).

Table 4.1: 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.

Various methods have been utilized to infer the drivers of land degradation. Firstly, the use of expert opinions (Oldeman *et al.*, 1991) – expert opinions has been utilized especially for the global level assessments like in the Global Assessment of Human-Induced Soil Degradation (GLASOD). However, this method is criticized for being subjective and lacking in scientific rigor. Secondly, the quantitative analyses of drivers of land degradation (Bai *et al*., 2008; Vlek *et al*., 2008; 2010).

These assessments however, do not provide causation but rather correlation between indicators of land degradation (such as NDVI) and the hypothesized variables; (iii) thirdly, the use of inferential statistics (Barbier, 1997; Nkonya *et al*., 2011) – like the quantitative assessment method, the estimates from the inferential statistics limit the interpretation of the causal relationships because of the weak explanatory power (due to smaller sample size). The sample is also highly aggregated to present regional and/or national aggregates that make interpretation unreasonable for the in-country diverse settings. Lastly, the other method involves the use of remote sensing techniques (Hoffman *et al*., 1999; FAO, 2003; Archer, 2004; Yang *et al*., 2005; Le *et al.*, 2012; 2014). These techniques are varied and they include: image differencing of two images (Rasmussen *et al*., 2001; Borak *et al*., 2000), visual interpretation of images (Gupta *et al*., 2002; Ries & Marzolf, 2003), spectral index (Chikhaoui *et al*., 2005), vegetation indices and ratios of signals (Budde *et al*., 2004; Khan *et al*., 2005), land-cover mapping and "Steppe Degradation Index" with ancillary data, spatial and temporal metrics of land cover change (Borak *et al*., 2000), and soil adjusted vegetation index (Mackay & Zietsman, 1996). These approaches have been criticized for the following weakness: they exaggerate the result on the levels of land degradation, they are perception-based and semi quantitative, and therefore not built on objective measurements, and that the land-cover exercises maps degradation using image brightness values on a snapshot satellite image, thus cannot represent a persistent land degradation.

Recent empirical expeditions, however, show a shift from manual visual approach to the interpretation of aerial photography and satellite imagery and to further to a more model-based approach involving indicators and proxy variables, measurable over large areas and over longer periods. The most widely used index for assessment is the vegetation indices is the NDVI (Prince *et al*., 1998; Diouf & Lambin, 2001; Herrmann *et al*., 2005; Le *et al.*, 2012; de Pinto *et al*., 2013. Some advantages of using NDVI are that it uses a single index with readily available dataset, it can be used for global coverage, and the temporal and spatial extensions are possible with this method. However, this method is not without limitations. The accuracy of observations is sometime questioned; hence need for ground-truthing; it is difficult to differentiate land cover and land use and other human interventions; and the resolution is coarse especially for small coverage.

Land degradation and its accompanying effect of low productivity are not simply a technical issue but rather more complex including socio-economic and behavioral factors and require a change in approach. This study therefore include household level variables; missing in the previous studies.

This assessment is also unique in that the study uses nationally representative data (at farm level) with diverse variables (both proximate and underlying). These include a mix of biophysical, demographic, socio-economic, and institutional variables. This study also address and control for the diverse contexts such as regional and agro-ecological zone classification (AEZ).

4.2.2 Determinants of SLM Adoption

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).

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; Ghadim *et al*., 2005). The results from different studies are often contradictory regarding any given variable (ibid). Linder (1997) points 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.

Use of binomial or multinomial qualitative choice models in assessing adoption of technologies is well established in adoption literature (Feder *et al*., 1985). Greene (2000) argues that qualitative choice models seek to determine the probability that an individual with a given set of attributes will make one choice rather than an alternative. The two most popular functional forms used for adoption models are the probit and logit models. Several studies have utilized these two techniques in modeling determinants of decision to invest in SLM practices in developing countries. Some of the studies that use probit includes; Feather and Amacher (1994), Khanna (2001), Rahelizatavo (2002), Zhong (2003), Lichtenberg (2001) and Kim *et al*. (2005). Some of the studies that use logit include; Dorfman (1996) Fuglie (1999), Caswell *et al*. (2001), Hindsley (2002), Daberkow & McBride (2003), Friedrichsen (2003) Habron (2004), Wu *et al*. (2004), Moreno & Sunding (2005) and Prokopy *et al*., (2008). Others studies use multiple regressions to assess the number of SLM practices a farmer has invested in; these studies include; Alonge & Martin (1995), Napier *et al*. (2000), Rahelizatavo & Gillespie (2004) and Park & Lohr (2005).

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.

Recent studies have tried to overcome these limitations in different ways: model adoption sequentially (Leathers and Smale, 1991), include farmers' personal perceptions, abilities and capabilities and risk preferences to capture the dynamic learning process (Ghadim and Pannell, 1999), use of stochastic production function to capture importance of risk effects of factors inputs on production behavior (Fufa and Hassan, 2003), use a partial observability model to capture the varied access to information and levels of awareness of the new technology (Dimara and Skuras, 2003), use of a double hurdle model to capture the sequential decisions and multiple stages in investing in SLM (Gabremedhin and Swinton, 2003) and determinants of adoption and intensity of adoption of SLM may be different, hence use a tobit model rather than probit or logit (Nakhumwa and Hassan, 2003). To overcome these challenges and concerns, this study adopted a multivariate probit model (MVP) that accounts for simultaneity of choices and interdependent (potential correlations) among the adoption decisions (Greene, 2003). The results concerning any particular variable, however, were not any different from the MVP and Poisson regressions. For prudence therefore, the MVP and Poisson regression results are not presented in the discussions because they only serve to confirm the logit results.

4.3 Conceptual framework

The ELD conceptual framework is based on comparing the costs and benefits of action against land degradation versus the costs of inaction (**Figure 4.1**). 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.

The green rectangular box (**Figure 4.1**) depicts the economic analysis conducted while the green arrow shows information flow that is essential to conduct the different levels of the economic analysis. All the indirect and off-site effects are incorporated in the economic analysis to ensure a comprehensive assessment from the society's point of view; the analysis takes account of all prevailing externalities in addition to the private land use costs incurred by individuals subsequent to land use decisions. Similarly, actions against land degradation have direct benefits and costs - the costs of specific measures and economy-wide indirect effects – or the opportunity costs. This implies that the resources set aside for these actions cannot be put into use elsewhere and thus, mobilizing these resources to avert or alleviate land degradation affects other sectors of the economy as well.

The dotted lines represent institutional arrangements that guide actors' choice of action against land degradation and whether their action choices actually and effectively lessen or stop land degradation. It is important to identify and comprehend these institutional arrangements in order to come up with sustainable and effective policies of combating land degradation. It is also of prime importance that the analyses recognizes all the key actors of land degradation such as land users, land owners, governmental authorities, and industries, as well as identify how institutions and policies impact those actors. Transaction costs and collective versus market and state actions are to be considered. In general, the institutional economics aspect should not be left out in the assessment of land degradation especially when defining and designing the appropriate actions against land degradation, and the inaction scenarios which serve as a benchmark.

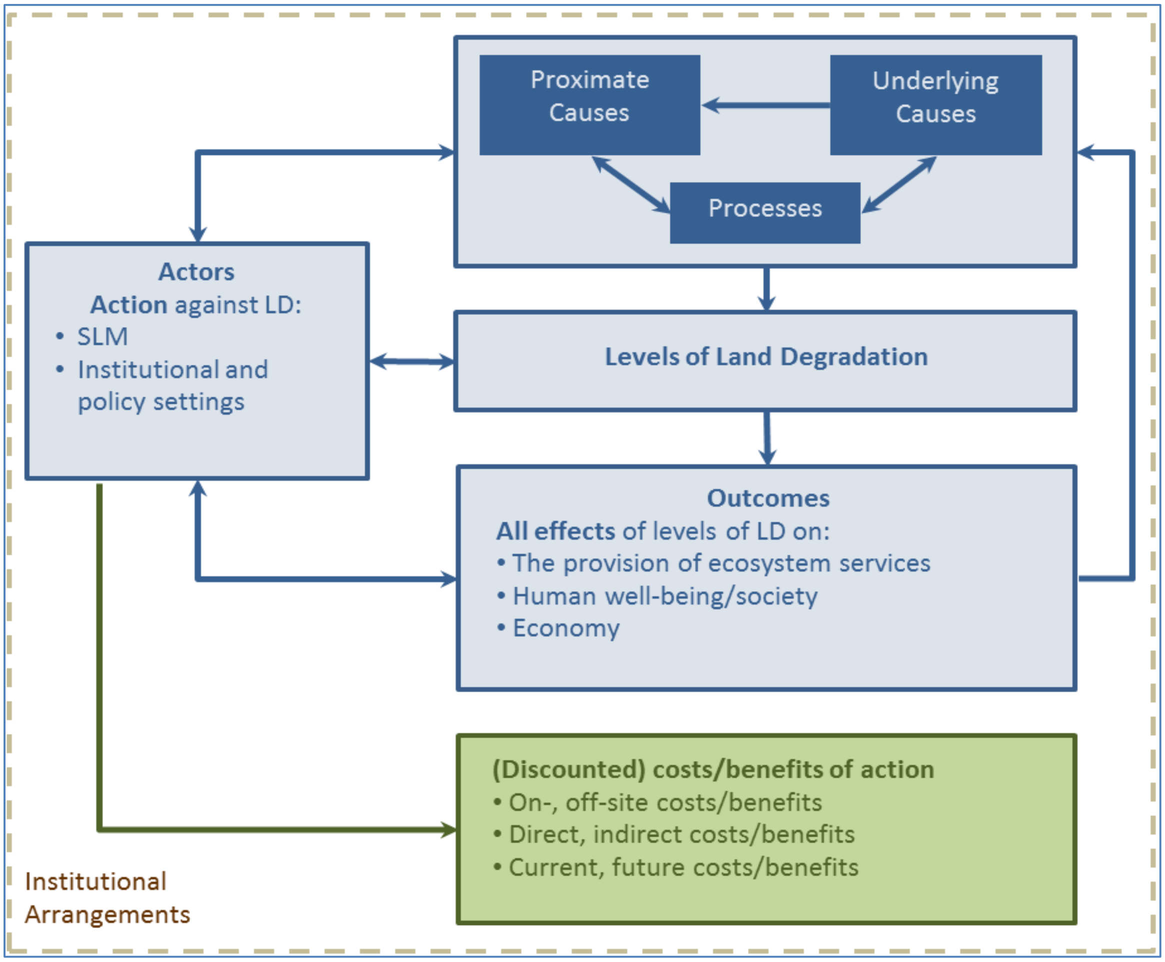

Figure 4.1: The Conceptual Framework of ELD Assessment

Source: Nkonya *et al.* (2011).

4.4 Data, sampling, choice of variables for econometric estimations

4.4.1 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'' (NSO, 2014). The sampling procedure in each of the three countries is described below.

a. 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).

b. 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.

c. 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 4.2** presents the distribution of sampled households in the three countries.

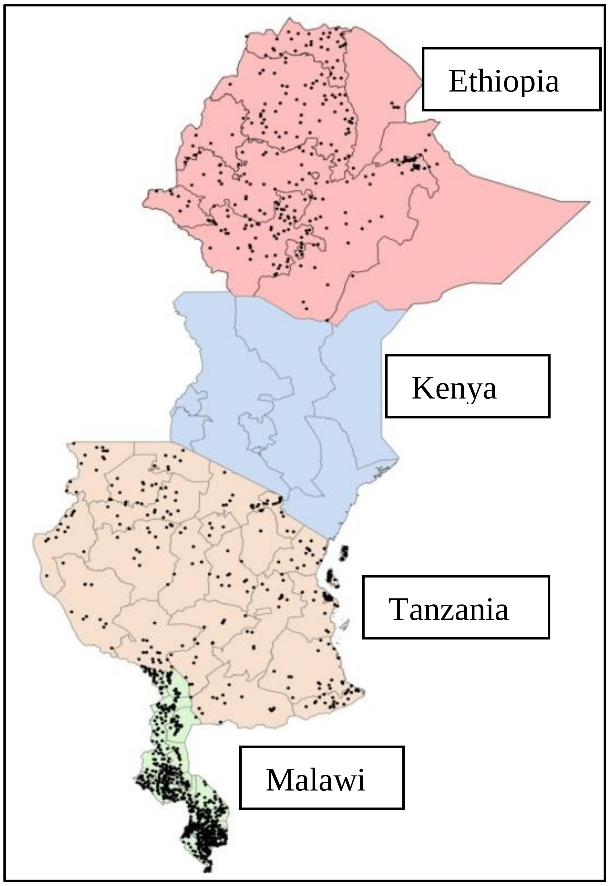

Figure 4.2: Distribution of sampled households
*Source:*Authors' Compilation.

4.4.2 Variables used in the econometric estimations

a. Dependent variables

Two approaches are used to assess the drivers of land degradation. The first approach is the use of biomass productivity decline (change in NDVI) for the period of 1982-2006. 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 (**Table 4.2)**.

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 4.2**. 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; Teklewold *et al.*, 2013).

Table 4.2: Dependent variables used in econometric analysis

Variable	**Malawi (n=18,162)**	**Ethiopia (n=14,170)**	**Tanzania (n=5,614)**	**Total (weighted) (n=37,946)**
NDVI decline in the plot (% of total plots)				
NDVI decline	38.5	48.7	34.7	41.7
Sustainable Land Management (SLM) practices (SLM) (% of plots)				
Inorganic fertilizers use	63.6	38.6	12.4	46.7
Modern seeds varieties	58.0	12.5	24.4	36.1
Manure application	10.6	24.1	8.6	15.3
Intercropping	35.1	35.2	32.5	34.7
Crop rotation	0.6	56.2	14.8	23.3
Soil erosion control	41.0	3.9	8.6	22.4

Source: Authors' compilation

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 (Asfaw *et al.*, 2012, Folberth *et al.*, 2013). 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 23% and 36% 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.

b. Independent variables

The choice of relevant explanatory variables is based on economic theory, empirical review of previous literature, and data availability. Thus, a total of 34 variables have been utilized for the empirical estimations in this chapter (34 in the drivers of land degradation regression model and 33 in the SLM adoption model). 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 4.3** and discussed below.

Biophysical variables

The biophysical variables included in the drivers of land degradation regression model include such proximate biophysical factors as temperature, rainfall and topography, land cover type, and soil properties (soil type). The choice of these variables was guided by numerous previous studies; Barrow, 1991; Voortman *et al.,* 2000; Safriel & Adeel, 2005; Lu *et al.,* 2007; Gao & Liu 2010; Bonilla & Johnson 2012; Wasige *et al.,* 2013; Thierfelder *et al.,* 2013; Belay *et al.,* 2014; and Tesfa & Mekuria, 2014[9]. Unlike the previous studies that considered some of these variables either at regional (aggregate) scale (Vlek *et al*., 2008; 2010, Le *et al.,* 2014) or at global scale (Bai *et al*., 2008; Le *et al.,* 2012), these variables are explored at household (farm) level using national representative data in three different countries (Ethiopia, Malawi and Tanzania). It is hypothesized that farming on steep slope induces land degradation (Waters *et al.,* 2013).

The slope of the farm plot is critical in determining land degradation (especially water run-off/soil erosion) (Lieu et *al.,* 1994; Sonneveld *et al.,* 2011). Similarly, increasing temperatures (evaporation rates) together with erratic and declining rainfall are expected to accelerate land degradation (Safriel & Adeel, 2005; Wale & Dejenie, 2013). Climatic conditions, soils, and land use vary across different agro-ecologies; thus the analyses include controls for variations in agro-ecological zones across farm households. Soil properties (soil type) influence choice of farming activities and hence degradation process (Fischer *et al.,* 2000). Deep fertile loam soils with good rooting conditions are rich in carbon stocks (Padmanabhan *et al.,* 2013) and thus hypothesized to be less degraded.

[9] See Nkonya *et al.,* (2013) and Kirui & Mirzabaev (2014) for empirical review of drivers of land degradation

In the SLM adoption regression model, the relevant biophysical variables included are temperature, rainfall, soil properties 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*., 2008). 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). Deplorable soil conditions are not favorable to plant growth (Padmanabhan *et al.,* 2013). Deep fertile soils are hypothesized to positively be related to adoption of improved seeds but negatively related to adoption of manure and inorganic fertilizer. On the other hand, poor shallow soils are positively related to manure application, conservation tillage, and inorganic fertilizer use.

Demographic characteristics

The 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). Higher level of education of the household decision maker/head is hypothesized to have a positive association 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).

Age of the head of household can be used to capture farming experience especially when the primary occupation is farming. Previous studies provide a mixed relationship between age (years of farming experience) and adoption of SLM (Shiferaw and Holden, 1998; Maddison, 2006; Nhemachena & Hassan, 2007: Kassie *et al.*, 2011). More experienced farmers may have greater accumulation of physical, financial and social capital hence more likely to adopt SLM practices (Quisumbing, 1995, Kassie *et al.*, 2013). Age can however be associated with risk-averse behavior (Hill *et al.,* 2008; Genius *et al*., 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 discriminate against women (de Groote & Coulibaly, 1998, Gebreselassie *et al.,* 2013). Thus male-headed households are hypothesized to invest more 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 non-farm/off-farm activities (Yirga, 2007; Pender & Gebremedhin, 2008; Fentie *et al.,* 2013).

Plot characteristics

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). Thus this study hypothesizes that the further away the plot is from markets, the smaller the likelihood of adoption of new seed varieties and fertilizers.

However, the study hypothesizes 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.

Proximity to basic services (proxied by distance to the locational headquarters) is an important determinant of SLM adoption (Maddison, 2006). This study posits a negative relationship between adoption of SLM and the distance to the locational headquarters. Agricultural extension services are important sources of information that is required to make farm decisions. There exists a positive relationship between contacts with extension agents and farmers' technology adoption behavior (Nhemachena & Hassan, 2007). The study posits a positive relationship between access to extension services and adoption of SLM practices. Security of land tenure/ownership has been associated with increased investment in long-term SLM practices such as manure application and conservation tillage practices (Deininger *et al.*, 2009).

Insecure land tenure may act as a disincentive to investment in sustainable agricultural practices and technologies (Kabubo-Mariara, 2007). It is also argued that insecure land tenure (such as short term rented plots) is associated with short-term market-based inputs such as improved seeds and fertilizers (Kassie & Holden, 2007). This study hypothesizes that ownership of a title deed or official registration document has a positive relationship with adoption of long-term SLM practices (conservation farming, and manure application). The relationship between land tenure and intercropping and crop rotations practices is indeterminate. This study also includes country dummies as proxies for diverse institutional setups will capture regional and spatial differences.

Socio-economic characteristics

The adoption of agricultural technologies is often linked to sufficient financial and asset endowment. Farm and nonfarm income, farm size and assets ownership denote wealth status of the household. Farm income has previously been associated with a positive relationship with technology adoption at the farm (Matuschke & Qaim, 2008; Collier, & Dercon, 2013). Similarly, alternative (non-farm) income sources are associated with better technology adoption because of their financial capacity to leverage these technologies and practices (Holden & Shiferaw, 2004, Shiferaw *et al.*, 2009).

Table 4.3: Definitions of hypothesized explanatory variables

Variable	Definition	Hypothesized effect on land degradation	Hypothesized effect on SLM adoption
Biophysical characteristics			
Latitude	Latitude coordinates	+/−	+/−
Longitude	Longitude coordinates	+/−	+/−
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)	+/−	+/−
Demographic characteristics			
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 characteristics			
Plot slope	Slope of the plot (SRTM)	−	+
Soil rooting	Soil rooting conditions of the soil	+/−	−
Tenure	Land tenure status of the plot	+	+
Soil type	Soil type of the plot	+/−	+/−
Home dist.	Distance to plot from the farmer's home	+	−
Market dist.	Distance of plot from the market	+	−
Services dist.	Distance to basic services	+	−
Extension	Access to agricultural extension	+/−	+/−
Socio-economic characteristics			
Farm income	Farm income	−	+
Nonfarm income	Non-farm income	+/−	+
Assets value	Value of household assets	−	+
Plot size	Size of the plot	−	+
Credit	Amount of credit accessed	−	+
Group	Membership in cooperatives/SACCOs	−	+
Expenditure	Total household expenditure (per capita)	+/−	+/−

Source: Authors' compilation.

4.4.3 Descriptive statistics of the independent variables

The results of the descriptive analysis are discussed in this section. **Table 4.4** 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.

The average plot elevation for the region was 1280 meters above sea level. This varied substantially across countries. While the mean value of plot elevation in Malawi was 890 meters above sea level, the mean elevation in Ethiopia was 1916 meters above sea level. Similarly considerable differences is notable across countries with regards to agro-ecological classification; a larger proportion (46%) of Malawi is classified as warm arid/semiarid, while in Tanzania a bigger proportion (55%) is classified as warm humid/sub-humid and about 72% of Ethiopia is classified as cool humid/sub-humid environment.

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

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). 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. 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.

Table 4.4: Descriptive statistics of explanatory variables (country and regional level)

Variable	Description	Malawi (N=18162)		Ethiopia (N=14170)		Tanzania (N=5614)		Total (N=37946)	
		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
topography	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									
plotslope	Slope of the plot (SRTM)	1.459	0.556	1.524	0.665	1.552	0.566	1.497	0.602
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: Authors' compilation.

4.5 Drivers of Land Degradation

A logistic regression model is used to assess the drivers of NDVI decline (land degradation) in Ethiopia, Malawi and Tanzania. The choice of logit model 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:

$$\Delta \boldsymbol{NDVI} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1 x_1} + \boldsymbol{\beta_2 x_2} + \boldsymbol{\beta_3 x_3} + \boldsymbol{\beta_4 x_4} + \boldsymbol{\beta_5 z_i} + \boldsymbol{\varepsilon_i} \qquad \textbf{(4.1)}$$

where, $\Delta \boldsymbol{NDVI}$*= Net change in NDVI between 1982 and 2006 (1= decline, 0=otherwise) in the corresponding pixel which the plot is located;* $\boldsymbol{x_1}$ *= 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 error term.*

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 (marginal effects) fit the data well (**Table 4.5**). 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) = 419.09, *p-value* = 0.000, Malawi: Wald Chi^2 (33) = 3639.69, *p-value* = 0.000, Tanzania: Wald Chi^2 (33) = 1528.13, *p-value* = 0.000, combined model: Wald Chi^2 (34) = 4358.08, *p-value* = 0.000)].

The results (marginal effects) suggest that biophysical, demographic, plot-level, and socioeconomic characteristics significantly influence NDVI decline (land degradation). Significant factors are discussed 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 4.5: 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.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Temperature	0.065***	0.006	0.036***	0.009	0.138***	0.029	0.053*	0.028
Temperature_sq	-0.000***	0.000	-0.000***	0.000	-0.000***	0.000	-0.000**	0.000
Rainfall	-0.002***	0.000	-0.002**	0.001	-0.002	0.001	-0.004**	0.002
Rainfall_sq	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Temp#Rain	0.000***	0.000	0.000***	0.000	0.000**	0.000	0.000*	0.000
Terrain_plateaus	0.237***	0.030	0.260***	0.083	0.284***	0.042	0.218**	0.102
Terrain_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
Warm humid	0.343***	0.040	-0.490**	0.211	0.280***	0.064	0.112	0.234
Cool arid	0.194***	0.049	-0.454***	0.162	0.124	0.087	0.278	0.353
Cool humid	0.440***	0.053	-0.086	0.181	0.119	0.112	0.436*	0.252
Log_age	-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
Education	-0.024**	0.010	-0.003	0.017	0.022	0.017	0.017	0.030
Education_sq	0.002**	0.001	0.001	0.002	-0.002*	0.001	-0.002	0.002
Family_size	-0.004	0.007	-0.036**	0.014	0.070***	0.012	0.015	0.021
Plot_slope	0.977***	0.022	0.068**	0.029	2.304***	0.042	0.058***	0.085
Tittle_deed	-0.145***	0.028	-0.034**	0.042	-0.026**	0.047	-0.043*	0.143
Sandy_soil	-0.052	0.039	0.001	-0.002	-0.145***	0.050	0.221	0.138
Loam_soil	0.030	0.047	0.012	0.015	-0.108*	0.062	0.219	0.170
Soil_quality	-0.708***	0.043	-0.385***	0.134	-0.672***	0.062	-0.615***	0.139
Lnplotdist_home	-0.033	0.023	0.083**	0.035	-0.065	0.053	0.030	0.048
Irrigateion	-0.705***	0.098	-0.608***	0.102	-0.336	0.264	-0.307	0.411
Lnmarket	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
Plot_size	0.006	0.006	0.065***	0.023	0.026	0.027	0.008	0.008
Group_member	0.041	0.033	0.076	0.046	-0.141**	0.060	-0.150	0.108
Credit_access	0.112***	0.031	-0.105**	0.042	0.191***	0.053	0.338**	0.132
Log_credit	-0.030*	0.016	-0.078***	0.022	0.243***	0.037	0.060	0.087
Log_assests	0.016	0.010	0.068***	0.024	-0.059***	0.016	-0.058*	0.032
Constant	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 = 0.000l 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.

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.

4.6 Determinants of SLM Adoption

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:

$$\boldsymbol{A} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1 x_1} + \boldsymbol{\beta_2 x_2} + \boldsymbol{\beta_3 x_3} + \boldsymbol{\beta_4 x_4} + \boldsymbol{\beta_5 z_i} + \boldsymbol{\varepsilon_i} \qquad \textbf{(4.4)}$$

where, $\boldsymbol{A}$*=Adoption of SLM technologies;* $\boldsymbol{x_1}$ *= 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.*

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.

The adoption of the different SLM practices/technologies used in farm plots is presented in **Figure 4.3**. For example, the adoption of inorganic fertilizers ranged from 12% of farm plots in Tanzania to 39% in Ethiopia to 64% in Malawi. The adoption of improved seeds ranged from 13% in Ethiopia, 24% in Tanzania to 58% in Malawi. The use of organic manure is low; ranging from 9% in Tanzania, 11% in Malawi to 24% in Ethiopia. Cereal-legume intercropping was adopted in about 33% of plots in Tanzania, 35% in both Ethiopia and Malawi while crop rotation was done in just about 1% of farm plots in Malawi but applied in about 15% in Tanzania and 56% in Ethiopia. Lastly, soil erosion control (soil and water conservation) was adopted in 4% of farm plots in Ethiopia, 9% in Tanzania and 41% of in Malawi.

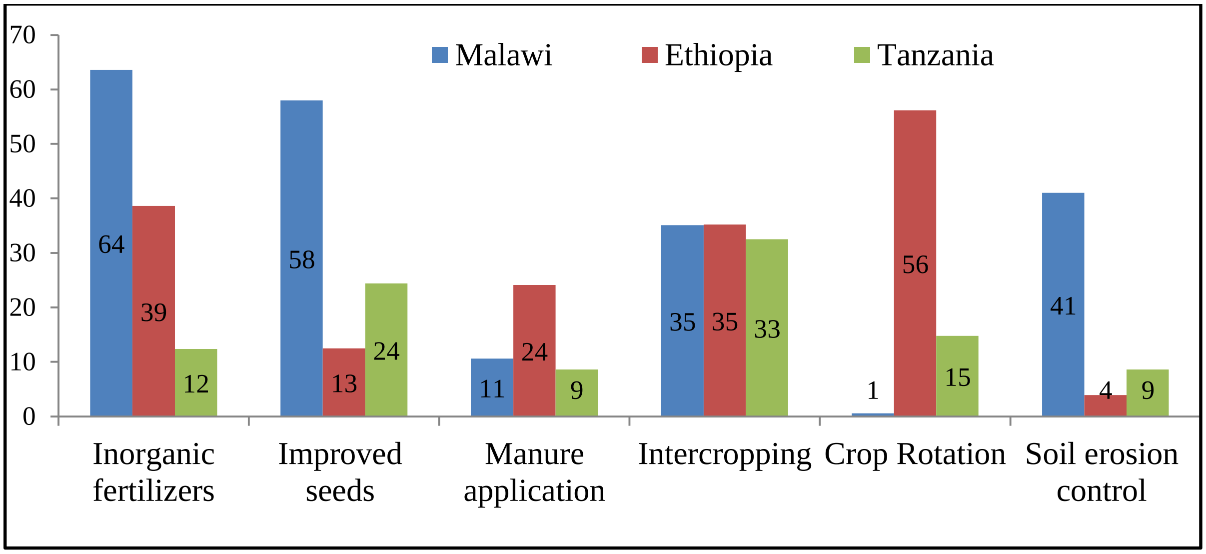

Figure 4.3: The distribution of different SLM technologies adopted in Eastern Africa
Source: Author's compilation.

It is also important to assess the simultaneous use of different SLM practices. The total possible number of SLM used at any given time ranged from 0 to 6 (**Figure 4.4**). About 15% of the surveyed households did not apply any SLM technologies in their farm plots. At country-level, 15%, 11%, and 32% of the plots were not under any SLM technology in Ethiopia, Malawi and Tanzania respectively.

Further, analysis shows that only one SLM technology was used in about 33% of the plots. At the country level, the proportion of plots with only on SLM technology was about 33%, 29% and 45%, in Ethiopia, Malawi and Tanzania respectively. Similarly, two SLM technologies were applied in about 27%, 21% and 16%, in Ethiopia, Malawi and Tanzania respectively. Fewer plots applied more than two SLM technologies simultaneously in one plot respectively. Three SLM technologies were simultaneously used in about 17%, 21% and 5%, in Ethiopia, Malawi and

Tanzania respectively while four SLM technologies were simultaneously applied in about 7%, 6% and 2% of the plots in Ethiopia, Malawi and Tanzania respectively.

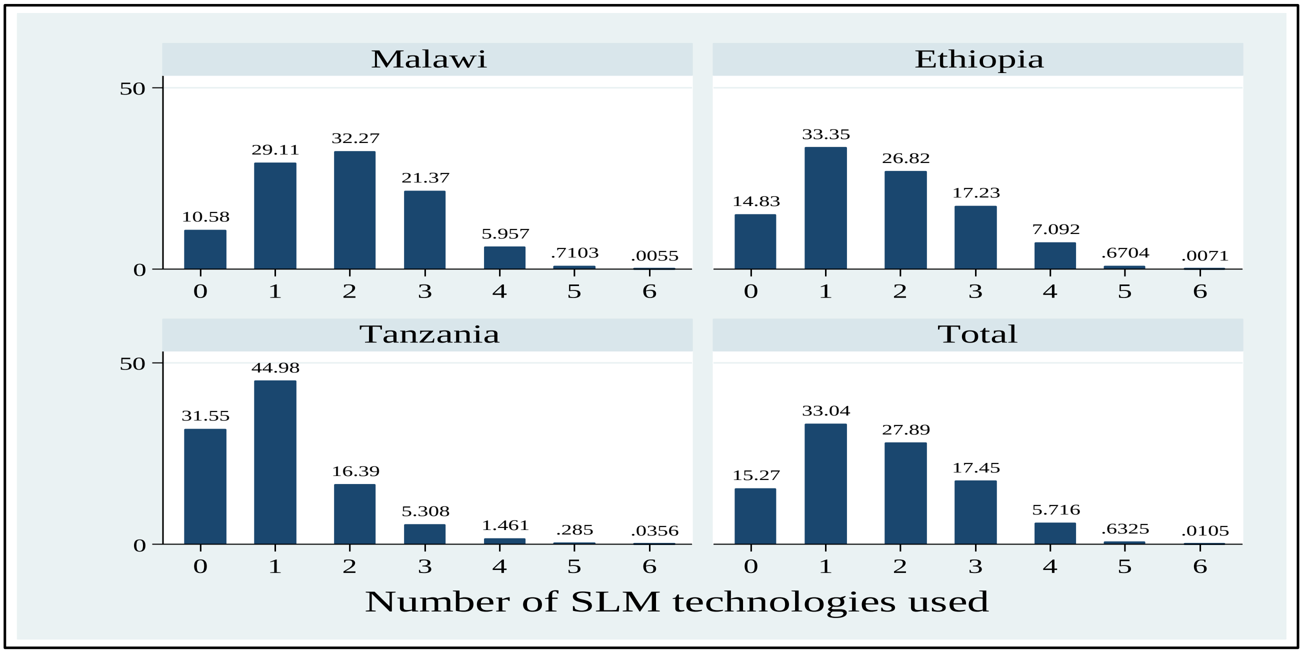

Figure 4.4: The distribution of number of SLM technologies adopted in Eastern Africa
Source: Author's compilation.

The results of the logit regression models on the determinants of adoption of SLM technologies are presented in **Table 4.6**. 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 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 at 1% [(Combined model: Chi^2 (30) = 2335, Pseudo R^2 = 0.0720, *p-value* = 0.000), (Ethiopia: Chi^2 (30) = 1649, Pseudo R^2 = 0.1387, *p-value* = 0.000); (Malawi: Chi^2 (30) = 1540, Pseudo R^2 = 0.1256, *p-value* = 0.000); (Tanzania: Chi^2 (30) = 394, Pseudo R^2 = 0.0563, *p-value* = 0.000)]. The results (marginal effects) suggest that biophysical, demographic, plot-level, and socioeconomic characteristics significantly influence SLM adoption. Significant factors are discussed 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 4.6**). 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, the probability of SLM adoption increased by about 26% and 15% in Tanzania and in the combined model respectively, *ceteris paribus*. Rainfall on the other hand showed a negative effect on the probability of adopting SLM technologies in Tanzania and in the combined model. 1% increase in mean annual rainfall leads to 11% and 24% increase in probability of SLM adoption in Tanzania and in the combined model respectively, holding other factors constant. These findings is similar to Yu *et al*. (2008), 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.

Table 4.6: 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.
Log_temperature	26.916***	3.242	8.111	6.444	5.836	20.789	14.503*	7.906
Log_tempamtsq	-0.210***	0.033	-0.076***	0.012	-0.006***	0.011	0.665	0.007
Log_rainfall	-23.501***	2.431	-0.612	4.769	-10.014	15.130	-10.883*	5.886
Log_rainfallsq	0.040***	0.103	0.041**	0.670	0.022	0.120	0.061	0.004
Log_tempt#l Log_rain	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
terrain_plateaus	0.133***	0.039	-0.109	0.114	0.246***	0.058	0.038	0.076
terrai_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
Plot_slope	0.228***	0.029	0.051	0.042	0.588***	0.056	0.388***	0.069
Sandy_soil	-0.031	0.053	0.509	0.072	0.032	0.069	0.035	0.098
Loam_soil	-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
Age_sq	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
Education	0.101***	0.012	0.057**	0.023	0.042*	0.027	0.024**	0.023
Educationsq	-0.008***	0.001	-0.001	0.002	-0.004*	0.002	0.003	0.002
Famiy_size	0.103***	0.020	0.187***	0.052	0.026**	0.040	-0.028	0.025
Log_plotdist_home	-0.115***	0.023	-0.105**	0.043	-0.039	0.066	0.085**	0.036
Log_plotdist_market	-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
Plot_size	0.004	0.005	0.009	0.034	0.369***	0.051	0.003	0.004
Tittle_deed	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
Group_member	0.206***	0.044	0.153**	0.071	0.122	0.085	0.080	0.083
Credit_access	0.171***	0.043	0.177***	0.062	-0.005	0.075	-0.019	0.120
Log_credit	0.345***	0.076	0.801***	0.193	0.025	0.137	0.135*	0.135
Log_assests	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. The dependent variable – adoption of SLM practices – is binary (1=adopted, 0=otherwise).
Source: Author's compilation.

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. Ownership of title deed increased the probability of SLM adoption by about 18%, 32% and 43% in Malawi, Tanzania and the combined model respectively, *ceteris paribus*. 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 to make farm decisions and in influencing farmers' 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*. 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.,* 2010, 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.

4.7 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 (biomass productivity (NDVI) decline) and to ascertain the determinants of adoption SLM technologies.

From the assessment of drivers of land degradation, the 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 is critical in addressing land degradation in Eastern Africa. This chapter highlights that the adoption of SLM technologies 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 of SLM technologies. 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 SLM technologies suggests the need for proper geographical planning and targeting of the SLM practices by stakeholders.

Chapter 5

5. The Impact of Land Degradation on Household Poverty: Evidence from a Panel Data Simultaneous Equation Model

5.1 Introduction

The debate on the land degradation – poverty linkages is inconclusive (Nkonya *et al.*, 2013; Gerber *et al.*, 2014). However, the inter-linkages between land degradation and poverty are thought to be strong in the rural areas of low income countries where livelihoods predominantly depend on agriculture (Turner *et al.*, 1994). Earlier studies pointed to a bidirectional link between poverty and land degradation: while poverty leads to land degradation, land degradation also contributes to poverty (Barbier, 2000; Lambin *et al*., 2001; Eswaran *et al*., 2001). There exist a poverty-land degradation vicious cycle; that is, though poverty can be argued as an outcome of degrading land, it is also seen as a cause of land degradation (Reardon and Vosti 1995).

Land degradation contributes to low and declining agricultural productivity, and this in turn contributes to worsening poverty. Poverty in turn is posited to contribute to land degradation as a result of poor households' inability to invest in natural resource conservation and improvement (ibid). On the other hand, however, it is also argued that the poor depend heavily on land; therefore, they have a strong incentive to invest their resources into preventing or mitigating land degradation in efficiently working market conditions (de Janvry *et al.*, 1991; Nkonya *et al.*, 2008; 2011). With increasing population pressures, absence of proper technologies, lack of appropriate institutional and economic conditions and poverty situation, there are no incentives for SLM among the rural farming communities. What is experienced is rather resource mining (FAO, 2011b).

Poverty coupled with population growth may lead to resource degradation and thus exacerbates poverty (Dasgupta, 1995; Scherr, 2000). Poor farmers are unable to use productivity enhancing inputs such as fertilizers thus contribute to natural resource degradation. Lack of such complementary capital as financial, human and physical limits the capacity of farmers to invest in land management and hence increase poverty among the rural poor. Insecure land tenure rights is also a considered a disincentive to investment in land management practices among the rural poor – which further leads to deeper poverty (Gabremedhin & Swinton, 2003; Kabubo-Mariara, 2007).

Institutional arrangements that govern access to and use of resources may also undermine resource management leading to heightening of poverty (Leach *et al.*, 1997).

Despite the inter-linkage between poverty and land degradation, earlier studies have either focused on land degradation and SLM adoption (see Kirui and Mirzabaev, 2014 for an extensive review) or on poverty (Bigsten and Shimeles, 2003; Geda *et al.*, 2001). Designing appropriate policies to address the dual problem of poverty and land degradation requires proper understanding on the linkages between them. Therefore, this study seeks to contribute to the existing literature by establishing the causal relationships between poverty and land degradation and examines its magnitude using nationally representative panel data in Malawi and Tanzania.

5.2 Relevant literature

Research on poverty and its linkages to land degradation has grown immensely in the past few decades. Yet, there are still major gaps in studying the impact of poverty on land degradation or vice versa. This is partially due to the complexity and context specificity of the linkages as well as a lack of systematic approaches adequately dealing with the effects of confounding factors. Extensive analyses of the complex linkages of these two key variables – poverty and land degradation – are important, especially in developing countries where the objective of meeting food security is still not fully achieved.

A summary of the critical review of the vast literature relating to poverty, land degradation and agricultural productivity is shown in **Figure 5.1**. This figure is very schematic; the relationships are not linear and they do not comprehensively cover the entire issues but only the topics and causal relationships under the focus in the current study. Some of the identified "poverty – land degradation linkages" are as follows: land degradation is seen to contribute to declining agricultural productivity, and this in turn increases poverty (Barbier, 2000, Reardon and Vosti, 1995). On the other hand, poverty also leads to land degradation though declining land productivity (Reardon & Vosti, 1995; Lambin *et al.*, 2001). Land degradation can contribute directly to poverty, not necessarily through its impact on agricultural productivity (Buys, 2007). Other studies, however, do not find these relationships tenable. For example, Reardon & Vosti (1995) Scherr & Yadav (1996), Scherr (2000) and Nkonya *et al.*, (2008) do not find the above correlation between poverty and land degradation to be consistent. Some places with higher poverty rates report less land degradation (Nkonya *et al.,* 2008).

Poor land management practices are seen to catalyze these dynamics and may thus exhaust the capacity of land to continue providing ecosystem services. It may drive a region faster to the point where human activities have harmful consequences on the resource base (Dasgupta 2000). An increasing population increases demand for fuel, building materials, land for crops and livestock; forcing people onto new land. The original vegetation cover of the new land is removed as less fertile (marginal) land is brought into agricultural production. Marginal land is less suitable for production and more prone to degradation due to its shallow soil, poor soil properties and unfavorable topographic conditions. However, there is some evidence that increasing population pressure and land scarcity may act as a stimulus to improved resource management especially when the population-supporting capacity of the land is not exceeded (Cleaver & Schreiber 1994; Dasgupta 2000, Nkonya *et al*., 2008). Similarly, earlier studies postulated that poverty contributes to rapid population growth (ibid).

Poverty may lead to poor land management, which causes a decline in agricultural productivity and land degradation. This in turn can cause further impoverishment, i.e. a vicious cycle (Deininger, 2003). The declines in agricultural productivity and poverty are shown to be a bi-directional relationship; poverty may reduce agricultural productivity through farmers' inability to use productivity enhancing inputs (Deininger and Feder, 2001). This is further exacerbated by a host of other factors such as poor policies, missing institutions, and unaffordable technologies (ibid).

The two green boxes to the left of **Figure 5.1** show some of important aspects that can reverse the poverty-land degradation situation. For instance, there is a broad consensus that SLM practices are critical in reversing the current land degradation trends and in ensuring adequate and sustainable food supply for the future. Improving agricultural productivity can be achieved by providing incentives for the development and dissemination of SLM technologies as well as innovative institutions and land use policies. Some of the good and recommended practices include better production technologies such as improved seed varieties and cultivars, irrigation, and adaptive farming systems (Huang *et al.,* 2002; Stoop *et al.,* 2002; Wale & Yalew, 2007). An improved macroeconomic environment, better access to markets and to public services, better infrastructure, and extension services to farmers may increase the adoption of sustainable land use and management practices.

Awareness raising, promotion, training and financial or material support for best SLM practices is also important (Barrett *et al.*, 2001). This may also serve as an indirect means to reducing poverty by improving agricultural productivity (Barrett *et al.*, 2001; Pretty *et al.*, 2003). Directly targeting the poor with specific poverty reduction strategies is helpful.

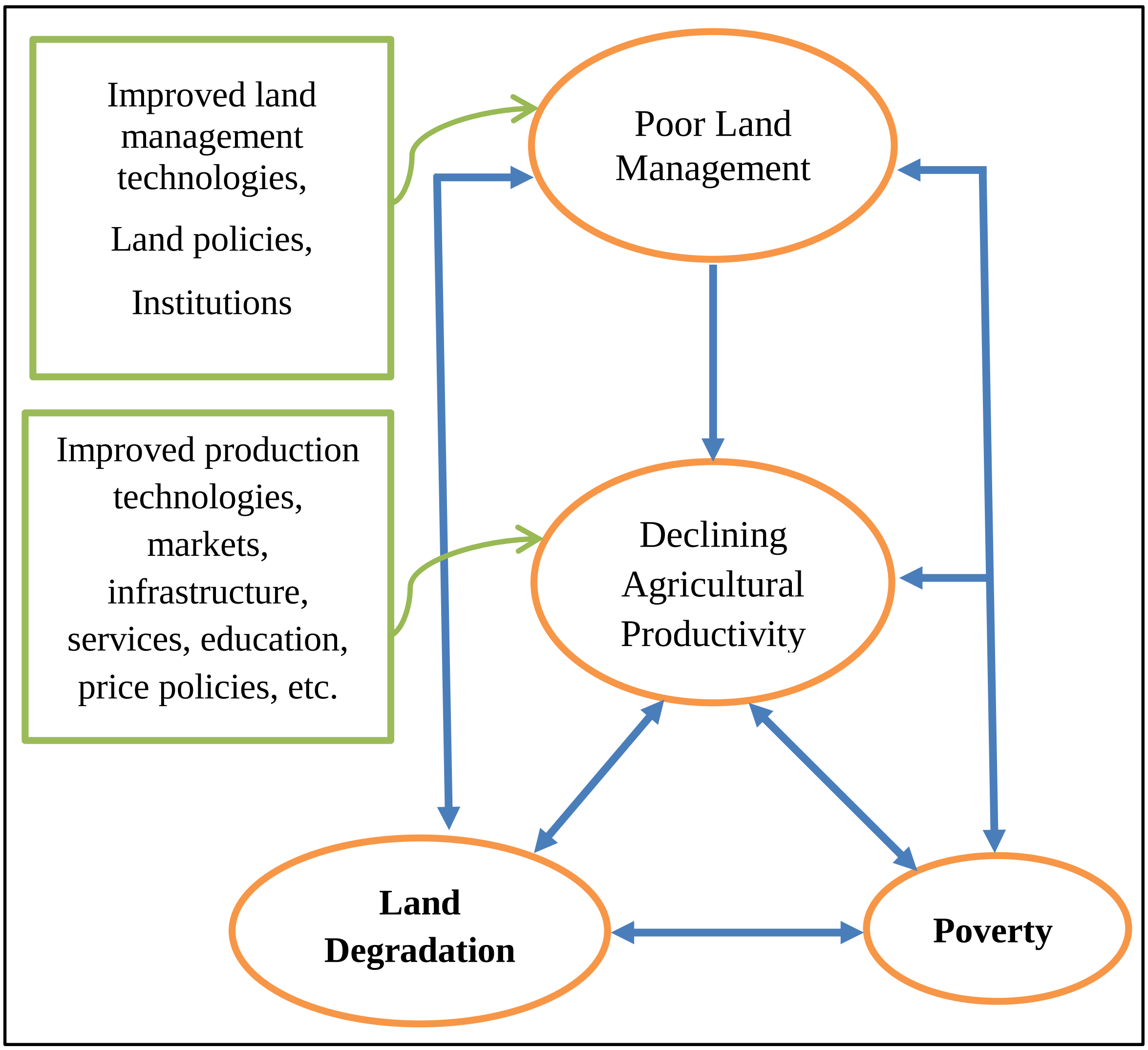

Figure 5.1: Conceptual framework land degradation and poverty relationships[10]

Source: Author's compilation.

[10] *Note: This assessment excludes the opportunity cost of productive soil mining, where returns from soil mining are invested in non-agricultural productivity.*

5.3 Data sources

The data used for this chapter is based on two waves of the Tanzania National Panel Survey (TNPS) and the Malawi Integrated Household Survey (IHPS). Both TNPS and IHPS 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 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’’ (NSO, 2014, NBS, 2014).

I. Malawi

The Malawi Integrated Household Panel Survey (IHPS) is a multi-topic panel survey with a strong focus on agriculture that is implemented by the National Statistical Office (NSO) of Malawi. ‘‘The first round of the panel comprises 3,246 households interviewed from March to November 2010 as part of the larger 2010/11 Integrated Household Survey (IHS3). The second round has a sample of 4,000 households interviewed between April and December 2013. The sample design for the second round of the NPS revisits all the households interviewed in the first round of the panel, as well as tracking adult split-off household members. The IHPS data are representative at the national, urban/rural and regional levels.

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 IPHS 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. The panel data allow for comparable measures of household food and non-food consumption, caloric intake, dietary diversity, and objective and subjective measures of food security at the household-level in 2010 and 2013'' (NSO, 2014).

II. Tanzania

The 2008-2009 National Panel Survey (NPS) was based on a stratified, multi-stage cluster sample design. ''The principle strata were Mainland versus Zanzibar, and within these, rural versus urban areas, with a special stratum set aside for Dar es Salaam. Within each stratum, clusters were chosen at random, with the probability of selection proportional to their population size. In urban areas a 'cluster' was defined as a census enumeration area (from the 2002 Population and Housing Census), while in rural areas an entire village was taken as a cluster. This primary motivation for using an entire village in rural areas was for consistency with the HBS 2007 sample which did likewise.

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 3,280 households were selected.

The sample design for the second round of the NPS revisits all the households interviewed in the first round of the panel, as well as tracking adult split-off household members. The original sample size of 3,265 households was designed to representative at the national, urban/rural, and major agro-ecological zones. The total sample size was 3,265 households in 409 Enumeration Areas (2,063 households in rural areas and 1,202 urban areas).

Since the TZNPS is a panel survey, the second round of the fieldwork revisits all households originally interviewed during round one. If a household has moved from its original location, the members were interviewed in their new location. If a member of the original household had split from their original location to form or join a new household, information was recorded on the current whereabouts of this member. All adult former household members (those over the age of 15) were tracked to their new location. The total sample size for the second round of the NPS has a total sample size of 3924 households. This represents 3168 round-one households, a re-interview rate of over 97 percent'' (NBS, 2014).

5.4 Measuring Poverty and Land degradation

5.4.1 Measuring Poverty

Poverty analysis requires three main elements, namely welfare indicator, poverty line, and a set of measures that combine individual welfare indicators into an aggregate poverty figure (Ravallion, 1998; Deaton & Zaidi, 2002; Haughton & Khandker, 2009). Welfare indicator is important in ranking all the population from the person with the lowest welfare to the person with the highest welfare. On the other hand, poverty line is used to compare the chosen indicator in order to classify individuals into poor and non-poor (Ravallion, 1998; Haughton & Khandker, 2009).

Accompanying the Tanzania national Panel survey (TNPS) and the Malawi Integrated Household Panel Survey (IHPS) is detailed documentation on the construction of the consumption aggregate, the derivation of the poverty line and the estimation of the poverty measures (National Bureau of Statistics (NBS) of Tanzania (2014) and National Statistics Office (NSO) of Malawi (2014). The two panel surveys used a similar approach to arrive at the poverty measures. The next section summarizes the three components of poverty analysis as presented in the National Bureau of Statistics (NBS) Tanzania, 2014)

5.4.1.1 The welfare indicator

There is consensus on the use of economic measures of living standards to analyze poverty. Specifically, consumption is preferred because it is likely to be a more accurate and useful measure of welfare than income (Ravallion, 1998). The consumption aggregate is guided by theoretical and practical considerations and is comprised of four components: food, non-food, durable goods and housing. The panel two waves of panel data for both Malawi and Tanzania collected relevant data on each of these four components and has been compiled and computed for each of the sampled household – thus available in its aggregated version from the World Bank database and the National Bureau of Statistics of Tanzania and Malawi.

Food Component was computed by including all possible sources of consumption such as food produced by the household, purchases in the market, meals eaten away from home, food received as a gift. The aggregate food consumption was computed to capture only actual consumptions and not mere total food produced at home or total food purchased. The non-purchased food (home produced and food received as gifts) were valued by comparing with the similar products purchased from the markets.

Non-food Component contains a relatively large number of items such as: water, kerosene, electricity, health, transportation, communications, recreation, education, furnishings, personal care, etc. data is only collected for the purchases of these non-food items. It is assumed that the consumption of these items from own-production or as gifts is negligible. Other items such as financial transactions (payment of mortgages or debts), losses (theft) and sporadic consumptions (marriages, dowries, births and funerals) are excluded from the consumption aggregate.

Durable Goods Component is measured from the stream of services derived from all durable goods possessed by the household over a reference period. The utility flow from a particular good though not observable, can be assumed to be proportional to the value of the good. This component is possible to compute when information on the number of durable goods owned, their age, and their value is available. Unfortunately, the data for the two countries provides data only on the number of durable goods owned by the household and thus the calculation of this consumption was not possible du to missing information on age, current or original value and the expected lifespan of the durable goods. Thus this component was excluded to avoid providing imprecise estimates.

The Housing conditions Component is used to compute the flow of services received by the household from occupying its dwelling. The limited or non-existent rental markets in Malawi and Tanzania – like in many other developing countries limits the estimation and inclusion of this component in the consumption aggregate. Some ways to elicit data on this component would be to ask the household the state the hypothetical rents they would be willing to pay for dwelling in their houses or to impute rents. However, the hypothetical self-reported rents that the households would pay for renting their dwelling are not always usable, particularly in rural areas where very few households rent. Imputed rents were not estimated in the data. Thus, for the sake of consistency, this component is excluded from the consumption aggregate. Further detailed discussions on how each component was calculated are outlined in (National Bureau of Statistics of Tanzania (2014) and National Statistics Office of Malawi (2014).

5.4.1.2 Poverty line

Ravallion (1996; 1998) defines poverty line as the monetary cost to a given person, at a given place and time, of a reference level of welfare. This implies that two persons with the same welfare level will be treated the same way regardless of the location where they live. Any person that does not attain that minimum level of standard of living is thus considered poor.

Every country estimates their national poverty line. Thus, the poverty line used for the analysis in Malawi was derived by the National Statistics Office of Malawi (NSO, 2014) while in Tanzania the poverty lines were derived by National Bureau of Statistics (NBS) Tanzania, (NBS, 2014. The real consumption aggregate at prices of each wave of survey was adjusted with a Fisher food price index to capture the changes in cost of living differences across waves. This allows for assessment of poverty dynamics between across waves.

It is also noteworthy that total poverty line comprises food and non-food components. The food poverty line represents the cost of a food bundle that provides the necessary energy requirements per person per day while the non-food poverty line represents an allowance for basic non-food needs. The total poverty line is the sum of the food and non-food poverty lines. The poverty lines for the first wave are updated to the prices of the second wave using the same price index to adjust for cost-of-living differences across waves. **Table 5.1** shows the poverty lines used in this analysis in local currencies.

Table 5.1: Poverty lines per adult equivalent per annum

Item	**Malawi**		**Tanzania**	
	Kwacha	USD	Shillings	USD
Food	53,262	202.4	244,183	239.3
Non-food	32,589	123.8	68,028	66.7
Total	85,852	326.2	312,197	306.0

Source: Adopted from (NBS) Tanzania (2014) and NSO (Malawi) (2014).

5.4.1.3 Poverty measures

The literature on poverty measurement is extensive, however, following Foster, Greer and Thorbecke (FGT) (Ravallion, 1998); poverty measures can be summarized by the following equation:

$$\boldsymbol{P_{\alpha} = \frac{1}{n}\sum_{i=1}^{q}\left(\frac{z-y_1}{z}\right)^{\alpha}} \qquad (\mathbf{5.1})$$

where α is some non-negative parameter, z is the poverty line, y denotes consumption, i represents individuals, n is the total number of individuals in the population, and q is the number of individuals with consumption below the poverty line.

‘‘The headcount index $(\alpha = 0)$gives the share of the poor in the total population, i.e., it measures the percentage of population whose consumption is below the poverty line. This is the most widely used poverty measure mainly because it is very simple to understand and easy to interpret. However, it has some limitations, in that it takes into account neither the gap of the consumption of the poor with respect to the poverty line, nor the consumption distribution among the poor. The poverty gap $(\alpha = 1)$ is the average consumption shortfall of the population relative to the poverty line. Since the greater the shortfall, the higher the gap, this measure overcomes the first limitation of the headcount. Finally, the severity of poverty $(\alpha = 2)$ is sensitive to the distribution of consumption among the poor: a transfer from a poor person to somebody less poor may leave the headcount or the poverty gap unaffected but will increase this measure. The larger the poverty gap is, the higher the weight it carries’’ (Ravallion, 1998).

5.4.1.4 Poverty results

The results presented in **Table 5.2**, **Figure 5.1** and **Figure 5.2** is for panel households over time for both Malawi and Tanzania. Stricter comparisons and analyses of the poverty dynamics over time, requires the use of panel sample of individuals interviewed during the first wave and tracked and re-interviewed during the subsequent wave(s). Results show that the incidence of absolute poverty declined from 33% of the population in 2009/10 to 29% in 2012/13 in Malawi and also declined from 34% of the population in 2008/09 to 29% in 2012/13 in Tanzania. Extreme poverty also declined, but by a lower degree. The proportion of the population with consumption below the food poverty line declined from 12% in 2009/10 to 8% in 2012/13 in Malawi and from 20% in 2008/09 to 15% in 2012/13 in Tanzania (**Table 5.2 and Figure 5.2**).

The depth and severity of poverty also declined in the two countries (**Table 5.2** and **Figure 5.3**). The depth of poverty (or poverty gap) measures the average consumption expenditure shortfall of the poor as a share of the basic needs poverty line, while the severity of poverty (or squared poverty gap) additionally takes into account the distribution of consumption among the poor (i.e. reflects inequality among the poor).

The poverty gap, which is the average consumption shortfall of the population relative to the poverty line, declined from 10% to 8% in Malawi and slightly declined from 10% to 9% in Tanzania (**Fig. 5.3**).

Table 5.2: Poverty results

Variables	**Malawi (n=3727)**		**Tanzania (n=4000)**	
	2009/2010	2012/2013	2008/2009	2012/2013
	Mean (S.E)		Mean (S.E)	
Poverty Incidence (absolute poverty)	32.6 (0.74)	28.5 (0.71)	34.1 (0.78)	28.9 (0.74)
Poverty Incidence (extremely poor)	11.5 (0.50)	8.2 (0.43)	20.4 (0.66)	15.3 (0.59)
Poverty Gap (%)	10.2 (0.8)	7.9 (0.5)	9.9 (0.6)	8.6 (0.3)
Poverty Gap squared (%)	4.4 (0.5)	3.2 (0.3)	4.0 (0.4)	3.7 (0.7)

Source: Author's compilation.

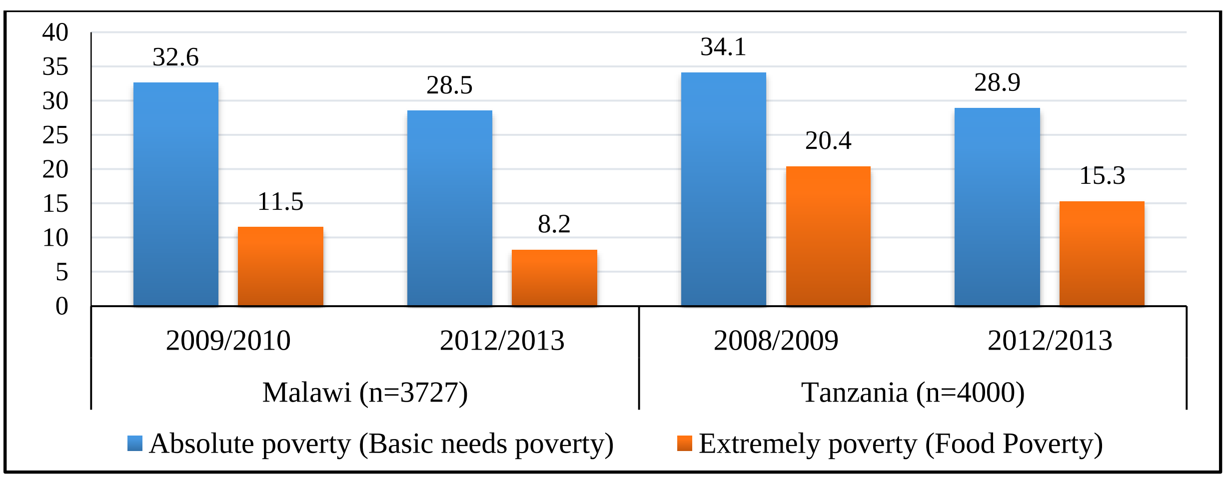

Figure 5.2: Trends of Poverty incidence in Malawi and Tanzania, 2008/09 – 2012/13
Source: Author's compilation.

The results of the estimated poverty gap for 2012/13 implies that the average consumption level of the poor about 92% of the national poverty line in Malawi and about 91% of the of the national poverty line in Tanzania. This suggests that majority of the poor are living close to the poverty line; thus small income transfers would significantly lead to decline in poverty. Similarly, the severity of poverty is low (3.2% in Malawi and 3.7% in Tanzania) indicating low levels of inequalities among the poor (**Fig. 5.3)**.

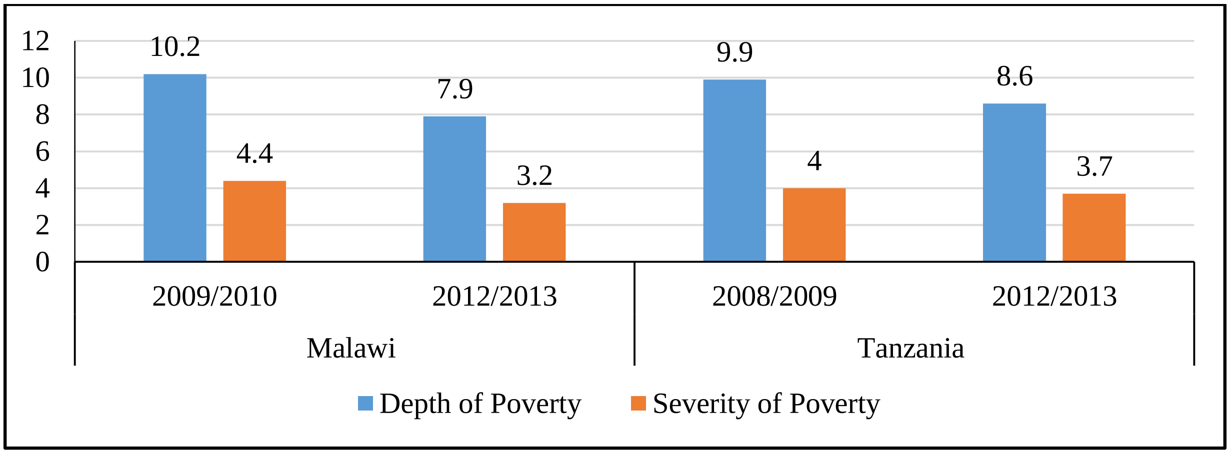

Figure 5.3: Trends of depth and severity of Poverty in Malawi and Tanzania, 2008– 2013
Source: Author's compilation.

5.4.1.5 Poverty Transition between waves

Panel data provides the possibility of assessing poverty transitions within the sampled population across time. Results (**Table 5.3** and **Fig. 5.4**) show that about 70% of the people remain in their respective absolute poverty status in Malawi: 55% stayed out of absolute poverty and 16% stayed absolutely poor. Out of the remaining 30% of the population, 17% escaped absolute poverty and the remaining 13% moved into absolute poverty between 2008/9 and 2012/2013. In Tanzania, the situation is almost similar; 71% of the people remain in their respective absolute poverty status – 54% stayed out of absolute poverty and 17% stayed in absolutely poverty while 17% escaped absolute poverty and 13% moved into absolute poverty.

Table 5.3 also presents the analysis of poverty transitions with respect to extreme poverty situation. Results for Malawi indicate that 83% of the population stayed out of extreme poverty and 2.5% stayed in extreme poverty while 9% escaped extreme poverty and 6% moved into extreme poverty. In Tanzania, 71% of the population stayed out of extreme poverty, 14% escaped extreme poverty, 9% moved into extreme poverty while 7% stayed in extreme poverty.

Table 5.3: Poverty Transitions in Malawi and Tanzania, 2008/09 – 2012/13

Poverty measure	Country	Never poor	Move out of poverty	Move into poverty	Always poor	Total
Absolute poverty	Malawi	54.7	16.8	12.7	15.8	100
	Tanzania	54.0	17.0	11.9	17.1	100
Extreme poverty	Malawi	82.8	9.0	5.8	2.5	100
	Tanzania	71.1	13.6	8.5	6.8	100

Source: Author's compilation.

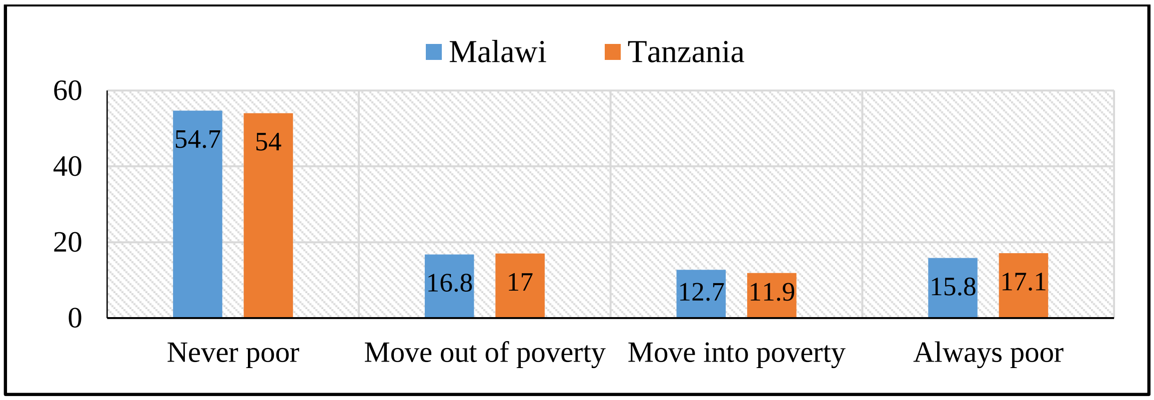

Figure 5.4: Absolute Poverty Transitions in Malawi and Tanzania, 2008/09 – 2012/13
Source: Author's compilation.

5.4.2 Measuring Land degradation

This study hypothesizes that increased land degradation leads to a reduction in the earnings among the rural predominant agricultural populations and thus reduces per-capita consumption expenditure. Different measurements and proxies have been used to impute land degradation in literature as described in chapter 1 of this thesis. In this chapter however, estimations are limit to two land degradation proxies, namely; biomass productivity decline and soil erosion occurrence in the farm plots.

5.4.2.1 Biomass productivity (EVI) decline

Vegetation indices have been used for a long time in a wide range of fields, such as vegetation monitoring; climate modelling; agricultural activities; drought studies and public health issues (Running *et al.*, 1994). ''Vegetation indices are radiometric measures that combine information from the red and near infra-red (NIR) portions of the spectrum to enhance the 'vegetation signal'.

Such indices allow reliable spatial and temporal inter-comparisons of terrestrial photosynthetic activity and canopy structural variations. They are generally computed for all pixels in time and space, regardless of biome type, land cover condition and soil type, and thus represent true surface measurements. Due to their simplicity, ease of application, vegetation indices have a wide range of usage'' (Running *et al*., 1994). An important uniqueness of the geo-referenced TNPS and IHPS datasets is that it includes these vegetation measures for both the baseline and end-line periods. On such measure is the Enhanced Vegetation Index (EVI). EVI, developed by the MODIS Science Team, take full advantages of the sensor capabilities. In order to increase the sensitivity to the vegetation signal, EVI uses the measurements in the red and near infrared bands (like NDVI), and also in the visible blue band, which allows for an extra correction of aerosol scattering. EVI is measured at pixel level of 1x1 km^2 spatial resolution and 16-day frequency. EVI also performs better than NDVI over high biomass areas, since it does not saturate as easily. The measurement of EVI can be presented as:

$$\boldsymbol{EVI = G\,\frac{\rho_{NIR} - \rho_{red}}{\rho_{NIR} + C_1 * \rho_{red} - C_2 * \rho_{blue} + L}} \qquad (\mathbf{5.2})$$

where; ρ are atmospherically corrected (Rayleigh and ozone absorption) reflectance, L is the canopy background adjustment, C_1 and C_2 are coefficients related to aerosol correction and G is a gain factor. The blue band is used to remove residual atmosphere contamination caused by smoke and sub-pixel thin clouds.

There are different growing seasons across the country in both Malawi and Tanzania. Thus to obtain a better measure, the total change in greenness (integral of daily EVI values) was estimated by adding these values for both 2008/09 and 2009/10 for the baseline period and the 2011/12 and 2012/2013 growing seasons for the end line period for both Malawi and Tanzania. To estimate degraded (and non-degraded) lands, the total EVI for the baseline growing period (2008/09) was subtracted from the total EVI for the end line growing period (2012/13) as shown in **Equation 5.3.** If the change in EVI is less than zero, then the land is degraded, and if the change is greater or equal to zero then the land is non-degraded.

$$\textbf{Degradation status} = \boldsymbol{EVI_{2013} - EVI_{2008}} \qquad (\mathbf{5.3})$$

The proportion of household with biomass (EVI) productivity decline (degraded) farms was 49% in Malawi 26% in Tanzania (**Table 5.4**). It is noteworthy that the proportion of households that reported a change in the crop planted in the plots in the baseline period and the end-line period was negligible – just 1.6% thus the change in EVI may not be directly attributed to the change in crop planted.

Table 5.4: Proportion of Households Experiencing biomass productivity (EVI) decline

Land degradation measure	**Malawi**		**Tanzania**	
	2008/09	2012/13	2008/09	2012/13
Change in greenness (integral of daily EVI)	114.4	113.9	119.6	135.9
Proportion of households with decline EVI	50.6		25.9	

Source: Author's compilation.

EVI is preferred because it performs well under high aerosol loads and biomass burning conditions (Huete *et al*., 2002). Use of EVI is also desirable because it entails uniformity in measurement within the country and across countries and that it ensures accuracy in the assessment.

5.4.2.2 Households Experiencing Erosion

Soil erosion is a predominant impediment to the agricultural production in Malawi and Tanzania (Jones, 2002; Matata *et al.*, 2008). To complement and augment EVI measurements, it is important to include land users' reported measures such as the occurrence of soil erosion. About 39% and 37% of households in Malawi experienced soil erosion in at least one of their plots in 2008/09 and 2012/2013 respectively (**Table 5.5**). Similarly, about 23% and 19% households experienced soil erosion in at least one of their farm plots in 2008/09 and 2012/2013 respectively in Tanzania. The predominant source of erosion in Tanzania is erosion from rain/water, accounting for more than 90% of all the soil erosion causes. In Malawi, the two important causes of erosion are water erosion and terrain, each accounting for about 50% of soil erosion.

Table 5.5: Proportion of Households Experiencing Erosion in Malawi and Tanzania

Land degradation measure	**Malawi**		**Tanzania**	
	2008/09	2012/13	2008/09	2012/13
Proportion of households with at least one plot subject to erosion	39.3	37.1	22.5	18.9
Cause of erosion				
Rain/water/flooding	95.7	96.1	93.8	97.3
Wind	1.1	1.3	2.2	1.5
Animals	2.1	1.2	2.8	0.5

Source: Author's compilation.

5.4.2.3 Relationship between land degradation, soil erosion and poverty

The simple relationship between poverty and land degradation is described in this section before an in-depth assessment of cause-effect relationship is estimated in the next section. Results (**Table 5.6** and **Fig. 5.5**) show that about 10% of the households in Malawi and 19% in Tanzania are both poor and living in degraded lands. On the other hand 22% of the households in Malawi and 15% in Tanzania are poor but their lands are not degraded. Similarly the non-poor households living in degraded lands are 16% in Malawi and 31% in Tanzania. Finally, 52% of the households in Malawi and 34% in Tanzania are both not-poor and living in non-degraded lands. The trend and relationship between land degradation and poverty is not clear to establish with such a simple descriptive analysis.

Table 5.6: Relationship between land degradation and poverty in Malawi and Tanzania

Country	Poor and Degraded	poor and Not-degraded	Not-poor and degraded	Not-poor and Not degraded	Total
Malawi	10.3	22.3	15.6	51.8	100
Tanzania	19.2	14.9	31.5	34.4	100

Source: Author's compilation.

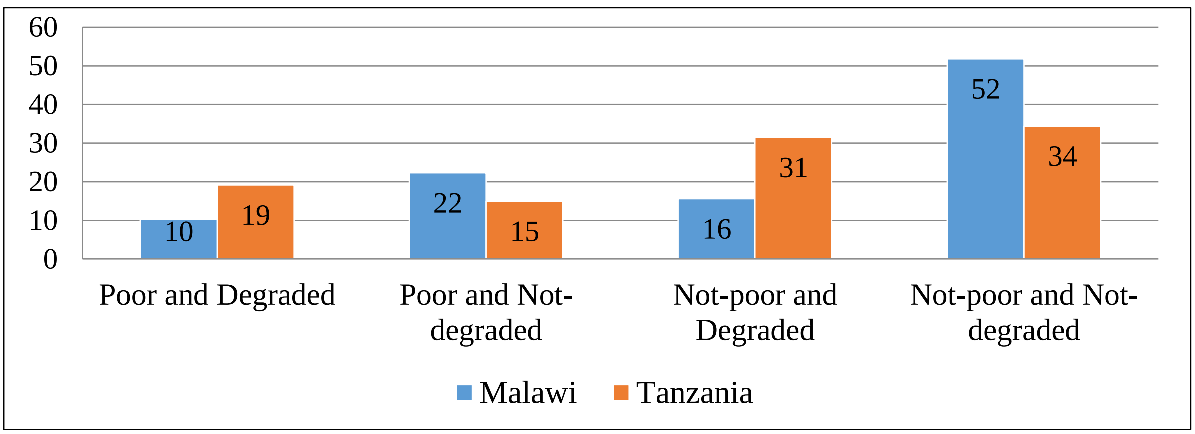

Figure 5.5: Relationship between land degradation and poverty in Malawi and Tanzania
Source: Author's compilation.

The relationship between poverty and soil erosion is also describe in **Table 5.7** and **Fig. 5.6**. Results show that about 13% of the households in Malawi and 11% in Tanzania are both poor and living in eroded lands in 2008/09 period. This reduced to 11% in Malawi and 4% in Tanzania in 2012/13 period. On the other hand 20% of the households in Malawi and 28% in Tanzania are poor but their lands are not eroded during the baseline period. This also declined to 17% and 25% in Malawi and Tanzania during the end-line period (20012/13). Similarly the non-poor households living in eroded lands are 26% in Malawi and 9% in Tanzania at the baseline period but decline marginally to 25.7% in Malawi and 7% in Tanzania during the end-line period.

Finally, majority of households – 41% of the households in Malawi and 56% in Tanzania are both not-poor and living in non-eroded lands during the baseline period. This increased to 46% in Malawi and 64% in Tanzania during the end-line period (2012/13). This assessment also indicates that is not easy to establish a clear trend and relationship between soil erosion and poverty with a simple descriptive analysis.

Table 5.7: Relationship between soil erosion and poverty in Malawi and Tanzania

Country	Year	Poor and Eroded	Poor but Not-eroded	Not poor but Eroded	Not poor and Not-eroded	Total
Malawi	2008/09	12.8	19.9	26.3	41.1	100
	2012/13	11.4	17.1	25.7	45.9	100
Tanzania	2008/09	6.5	27.6	9.3	56.6	100
	2012/13	4.1	24.9	6.8	64.2	100

Source: Author's compilation.

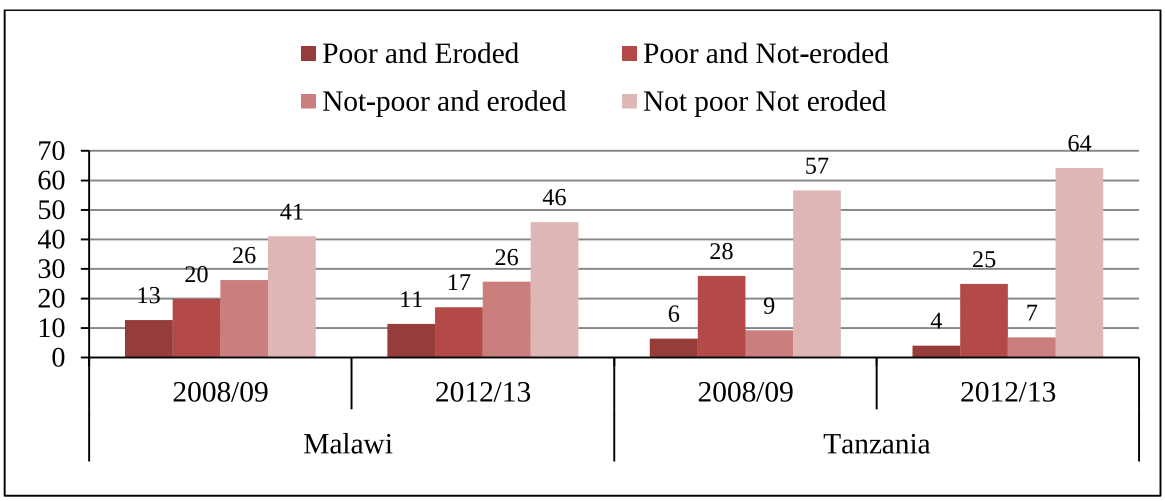

Figure 5.6: Relationship between soil erosion and poverty in Malawi and Tanzania
Source: Author's compilation.

5.5 Empirical strategy

The empirical strategy adopted to assess the causality between poverty and land degradation is presented in this section. First, the problem of endogeneity encountered in studying the causal relationship between poverty and land degradation is outlined. This is followed by description of **two-stage probit least squares (2SPLS)** and **recursive biprobit** approaches used to address this problem.

5.5.1 The problem of endogeneity

The objective of the study and the nature of the problem being estimated dictate the selection of a proper econometric estimation strategy. The focus of the study is to examine the causal linkages between poverty and land degradation. To ensure robustness and to validate these assessments, two different proxies have been applied for each of these two variables as described in the preceding section. Land degradation proxies are biomass productivity (EVI) decline and occurrence of soil erosion while poverty proxies are annual per capita consumption expenditure and poverty status of the household (based on the national poverty line).

This study envisages that there exists a bidirectional link between poverty and land degradation as described in the conceptual framework section. Poverty and land degradation are jointly determined as follows:

$$\boldsymbol{P = f(L, X_{1i})} \qquad (\mathbf{5.4})$$

$$\boldsymbol{L = f(P, X_{2i})} \qquad (\mathbf{5.5})$$

where; P = is poverty (measured as a continuous variable (annual household consumption per capita) or a binary variable (poor=1, 0=otherwise)), L = is land degradation (binary variable; defined as 1=degraded, 0=otherwise or 1=eroded, 0=otherwise), X_{1i} *and* X_{2i} *= vector of other exogenous variables in (5.4) and (5.5);* X_{1i} *and* X_{2i} *have some variables in common.*

Ordinary Least Squares (OLS) estimations are not appropriate because the endogenous variables are correlated with the error terms. This implies that the application OLS estimation of an equation that contains an endogenous explanatory variable generally produces biased and inconsistent estimators. One of the widely used approaches to address the problem of endogeneity and simultaneity is the use of simultaneous equations models with instrumental variables (Greene 2012; Wooldridge, 2010). The simplest and the most common estimation method for the simultaneous equations model with instrumental variables is the two-stage-least-squares (2SLS) method, developed independently by Theil (1953) and Basmann (1957). It is an equation-by-equation technique, where the endogenous regressors on the right-hand side of each equation are being instrumented with the regressors from all other equation. 2SLS can be used to estimate any identified equation in a system. Simultaneous equations model applications with panel data allow to control for unobserved heterogeneity while dealing with simultaneity.

Thus following Maddala (1983), Keshk (2003) and Wooldridge (2010) the recommended econometric approach to deal with the problem of endogeneity and simultaneity between **household consumption per capita** and **land degradation** (or soil erosion) is a **two-stage probit least squares (2SPLS)** specification. This involves a **simultaneous equation** model in which one of the endogenous variables is **continuous** and the other is **binary**. On the other hand, the recommended econometric approach to deal with the problem of endogeneity and simultaneity between **poverty** and **land degradation** (or soil erosion) is a **recursive biprobit** model. This involves a **simultaneous equation** model in which both endogenous variables are **binary.**

5.5.2 The two-stage probit least squares technique

The proper estimation of the SEM in (5.4) and (5.5) depends on the nature of P and L and how they are observed. P is observable but L is a latent variable (which takes the value of 1 for households experiencing land degradation (or soil erosion) and zero otherwise). This can be represented as:

$$\boldsymbol{L^* = \begin{cases} 1 & if\ L > 0 \\ 0 & otherwise \end{cases}} \qquad (\mathbf{5.6})$$

Therefore, including the parameters, the relationship between poverty and land degradation is expressed as follows:

$$\boldsymbol{P = \alpha_1 L^* + \beta_1' \mathrm{X}_1 + \varepsilon_1} \qquad (\mathbf{5.7})$$

$$\boldsymbol{L^* = \alpha_2 P + \beta_2' X_2 + \varepsilon_2} \qquad (\mathbf{5.8})$$

where; $\boldsymbol{P}$ is a continuous endogenous variable – household consumption per capita, $\boldsymbol{L}^*$ is a dichotomous endogenous variable – land degradation (or soil erosion) (observed as 1 if $L^* > 0$, 0 otherwise), $\mathbf{X}_1$ and $\mathbf{X}_2$ are matrices of exogenous variables in (4) and (5) respectively, $\boldsymbol{\beta}'_1$ and $\boldsymbol{\beta}'_2$ are vectors of parameters in (4) and (5) respectively, $\boldsymbol{\alpha_1}$ and $\boldsymbol{\alpha_2}$ are the parameters of the endogenous variables in (5.7) and (5.8) respectively, $\varepsilon_{\mathbf{1}}$and $\varepsilon_{\mathbf{2}}$ are error terms in (5.7) and (5.8) respectively. Because L^* is not observed, the structural equations (5.7) and (5.8) are rewritten as:

$$\boldsymbol{P} = \boldsymbol{\alpha_1 \sigma_2 L^*} + \boldsymbol{\beta}'_1 \mathbf{X_1} + \varepsilon_{\mathbf{1}} \qquad (\mathbf{5.7})$$

$$\boldsymbol{L}^* = \frac{\boldsymbol{\alpha_2}}{\boldsymbol{\sigma_2}}\boldsymbol{P} + \frac{\boldsymbol{\beta}'_2}{\boldsymbol{\sigma_2}}\boldsymbol{X_2} + \frac{\varepsilon_2}{\boldsymbol{\sigma_2}} \qquad (\mathbf{5.8})$$

Estimation then follows the typical two-stage estimation process. In the first stage, the following two models are fitted using all of the exogenous variables (i.e., exogenous variables in both (5.7) and (5.8)),

$$\boldsymbol{P} = \mathbb{II}'_{\mathbf{1}} \mathbf{X_1} + \boldsymbol{\upsilon_1} \qquad (\mathbf{5.9})$$

$$\boldsymbol{L}^* = \mathbb{II}'_{\mathbf{2}} \mathbf{X_2} + \boldsymbol{\upsilon_2} \qquad (\mathbf{5.10})$$

where; X_1 and $\mathrm{X}_2$is a vector of all the exogenous variables in (5.7) and (5.8) respectively, $\mathbb{II}_1$and $\mathbb{II}_2$are vectors of parameters to be estimated, $\upsilon_1$and υ_2 are error terms.

The reduced form equation for the continuous variable (5.9) is estimated using OLS while the reduced form of the binary choice variable (5.10) is estimated using a probit model. The parameters from these reduced-form equations are then used to generate the predicted values for each of the endogenous variable and the predicted values are then substituted for each endogenous variable as they appear on the right hand side of the respective equations in the second stage, as follows:

$$\widehat{\boldsymbol{P}} = \widehat{\mathbb{II}}_{\mathbf{1}} \mathbf{X} \qquad (\mathbf{5.11})$$

$$\widehat{\boldsymbol{L}}^* = \widehat{\mathbb{II}}_{\mathbf{2}} \mathbf{X} \qquad (\mathbf{5.12})$$

In the second stage, the original endogenous variables in (5.7) and (5.8) are replaced by their respective fitted values in (5.11) and (5.12). Thus, in the second stage, the following two models are fitted:

$$\boldsymbol{P} = \boldsymbol{\alpha_1}\widehat{\boldsymbol{L}}^* + \boldsymbol{\beta_1}\,\mathbf{X_1} + \varepsilon_1 \qquad (\mathbf{5.13})$$

$$\boldsymbol{L}^* = \boldsymbol{\alpha_2}\widehat{\boldsymbol{P}} + \boldsymbol{\beta_2}\,\boldsymbol{X_2} + \varepsilon_2 \qquad (\mathbf{5.14})$$

Again, Equation 5.13 is estimated by OLS while Equation 5.14 is estimated by probit.

The final step in the procedure involves the correction of the standard errors by bootstrapping. This is necessary because the outputted standard errors for each model in the second stage in (5.13) and (5.14) will be based on $\hat{L}^*$ and and $\hat{P}$ not on the appropriate L^* and P. Thus, the estimated standard errors in (5.13) and (5.14) will be incorrect. The required correction of standard errors was accomplished by bootstrapping following Timpone (2003) and Mooney (1996) techniques. This study takes advantage of panel data to better control for unobserved heterogeneity and to obtain more efficient estimation results than using cross-sectional data.

5.5.3 The recursive biprobit technique

Recursive biprobit technique when both *P* and *L* are latent variables. (*P* takes the value of 1 for poor and zero otherwise while *L* takes the value of 1 for households experiencing land degradation (or soil erosion) and zero otherwise). This can be represented as:

$$\boldsymbol{P}^* = \begin{cases} \mathbf{1} & \boldsymbol{if}\ \boldsymbol{P} > \mathbf{0} \\ \mathbf{0} & \boldsymbol{otherwise} \end{cases} \qquad (\mathbf{5.15})$$

$$\boldsymbol{L}^* = \begin{cases} \mathbf{1} & \boldsymbol{if}\ \boldsymbol{L} > \mathbf{0} \\ \mathbf{0} & \boldsymbol{otherwise} \end{cases} \qquad (\mathbf{5.16})$$

Therefore, including the parameters, the relationship between poverty and land degradation is expressed as follows:

$$\boldsymbol{P}^* = \boldsymbol{\alpha_1}\boldsymbol{L}^* + \boldsymbol{\beta}'_{\mathbf{1}}\,\mathbf{X_1} + \varepsilon_1 \qquad (\mathbf{5.17})$$

$$\boldsymbol{L}^* = \boldsymbol{\alpha_2}\boldsymbol{P}^* + \boldsymbol{\beta}'_{\mathbf{2}}\,\boldsymbol{X_2} + \varepsilon_2 \qquad (\mathbf{5.18})$$

where; $\boldsymbol{P}^*$ is a dichotomous endogenous variable – household poverty (observed as 1 if $\boldsymbol{P}^* > 0$, 0 otherwise), $\boldsymbol{L}^*$ is a dichotomous endogenous variable – land degradation (or soil erosion) (observed as 1 if $L^* > 0$, 0 otherwise), $\mathbf{X}_1$ and $\mathbf{X}_2$ are matrices of exogenous variables in (5.17) and (5.18) respectively, $\boldsymbol{\beta}'_{\mathbf{1}}$ and $\boldsymbol{\beta}'_{\mathbf{2}}$ are vectors of parameters in (5.17) and (5.18) respectively, $\boldsymbol{\alpha_1}$ and $\boldsymbol{\alpha_2}$ are the parameters of the endogenous variables in (5.17) and (5.18) respectively, $\varepsilon_1$and ε_2 are the error terms in (5.17) and (5.18)) respectively.

Because both P^* and L^* is not observed, the structural equations (5.17) and (5.18) are rewritten as:

$$\boldsymbol{P}^* = \frac{\boldsymbol{\alpha_1}}{\boldsymbol{\sigma_1}}\boldsymbol{L}^* + \frac{\boldsymbol{\beta}_1'}{\boldsymbol{\sigma_1}}\boldsymbol{X_1} + \frac{\varepsilon_1}{\boldsymbol{\sigma_1}} \qquad (\mathbf{5.17})$$

$$\boldsymbol{L}^* = \frac{\boldsymbol{\alpha_2}}{\boldsymbol{\sigma_2}}\boldsymbol{P}^* + \frac{\boldsymbol{\beta}_2'}{\boldsymbol{\sigma_2}}\boldsymbol{X_2} + \frac{\varepsilon_2}{\boldsymbol{\sigma_2}} \qquad (\mathbf{5.18})$$

Estimation then follows the typical two-stage estimation process. In the first stage, the following two models are fitted using all of the exogenous variables (i.e., the exogenous variables in both (5.17) and (5.18)),

$$\boldsymbol{P}^* = \mathbb{III}_1' \, \mathbf{X_1} + \boldsymbol{v_1} \qquad (\mathbf{5.19})$$
$$\boldsymbol{L}^* = \mathbb{III}_2' \, \mathbf{X_2} + \boldsymbol{v_2} \qquad (\mathbf{5.20})$$

where; X_1 and X_2 is a vector of all the exogenous variables in (5.17) and (5.18) respectively, $\mathbb{III}_1$ and $\mathbb{III}_2$ are vectors of parameters to be estimated, v_1 and v_2 are error terms.

The two reduced form equations (Equation 5.19 and 5.20) are estimated using probit models. The parameters from these reduced-form equations are then used to generate the predicted values for each of the endogenous variable and the predicted values are then substituted for each endogenous variable as they appear on the right hand side of the respective equations in the second stage, as follows:

$$\widehat{\boldsymbol{P}}^* = \widehat{\mathbb{III}}_1 \, \mathbf{X} \qquad (\mathbf{5.21})$$
$$\widehat{\boldsymbol{L}}^* = \widehat{\mathbb{III}}_2 \, \mathbf{X} \qquad (\mathbf{5.22})$$

In the second stage, the original endogenous variables in (5.17) and (5.18) are replaced by their respective fitted values in (5.21) and (5.22). Thus, in the second stage, the following two models are fitted:

$$\boldsymbol{P}^* = \boldsymbol{\alpha_1}\widehat{\boldsymbol{L}}^* + \boldsymbol{\beta_1}\,\mathbf{X_1} + \varepsilon_1 \qquad (\mathbf{5.23})$$
$$\boldsymbol{L}^* = \boldsymbol{\alpha_2}\widehat{\boldsymbol{P}}^* + \boldsymbol{\beta_2}\,\boldsymbol{X_2} + \varepsilon_2 \qquad (\mathbf{5.24})$$

Again, both Equation (5.23) and (5.24) are estimated by probit. The final step in the procedure involves the correction of the standard errors by bootstrapping. This is necessary because the outputted standard errors for each model in the second stage in (5.23) and (5.24) will be based on $\widehat{L}^*$ and and $\widehat{P}^*$ not on the appropriate L^* and P^*.

5.6 The instruments

This study uses a fixed effects and instrumental variable IV (IV-FE) estimation model to account for possible endogeneity of poverty (and per capita household consumption) on land degradation. This approach requires an instrument that is correlated with poverty but uncorrelated with the outcome variable (land degradation). Previous studies (Noor *et al*., 2008; Elvidge *et al*., 2009; Weng *et al*., 2012; World Bank, 2013) have used nighttime light intensity (NTLI)[11] to proxy poverty at the grid, sub-national, and national levels. The intensity of night lights provides information on outdoor and some indoor use of lights (Henderson, 2012).

The justification for using the NTLI as an IV is that; as income increases, light usage per person both for consumption investment activities also increases (Henderson, 2012; Mveyange, 2015). This study proposes distance from the household to the nearest NTLI as a novel instrument, and argues that it is both relevant to the endogenous explanatory variable (poverty and per capita household consumption), and uncorrelated with the error term.

On the other hand, the instrument used to control for possible endogeneity of land degradation on poverty and per capita household consumption are mean annual temperature and mean annual rainfall. Several previous studies (such as; de Leeuw and Nyambaka, 1988; Rivas-Arancibia *et al*., 2006; Padilla and Pugnaire, 2007; Miranda *et al*., 2009; Mathias and Chesson, 2012; Kang *et al*., 2013; Liu *et al*., 2014; Yan *et al.*, 2014) have used rainfall/precipitation and/or temperature to predict biomass productivity. These studies have shown that precipitation and temperature have an influence on above ground biomass by affecting seed germination, seedling growth, plant phenology.

This study postulates that the less the rainfall (or the higher the temperature), the less the biomass productivity (increased degradation). This study, therefore, argues that rainfall can only influence poverty through biomass productivity (crop yields). Extreme rainfall events such as flooding that lead to destruction of property and cause poverty in other direct ways are unforeseen in this study. Changes in the inter-annual biomass productivity as a result of change in the type of crop planted are considered negligible – the number of households that reported a change in crop type in the baseline and end-line periods was minimal (1.6%).

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[11] Nighttime Lights Time Series is collected by US Air Force Weather Agency is obtained at NOAA's National Geophysical Data Center. Available at: http://www.ngdc.noaa.gov/dmsp/downloadV4composites.html

Literature has also documented the use of monthly precipitation data to estimate the probability of soil erosion occurrence under different frameworks such as Revised Universal Soil Loss Equation (RUSLE) (Weesies *et al*., 1997; Renard and Freimund, 1994; Yu, 1998; Millward and Mersey, 1999; Angulo-Martínez and Beguería, 2009; Hernando and Romana, 2015) and in the GIS-based Universal Soil Loss model (Angima *et al*., 2003; Fu *et al*., 2005; Lufafa *et al*., 2013). These studies show that rainfall intensity and duration are the most important factors affecting soil erosion. Ziadat *et al*., (2013) further shows that soil erosion could occur at a relatively small intensity on wet soils as a result of subsequent rainfall events. Data used in this study showed that water was the leading cause (more than 95%) of erosion in both Malawi and Tanzania (**Table 5.5**). Therefore, the instrument used to control for possible endogeneity of soil erosion on poverty and per capita household consumption is mean annual rainfall.

Controlling for unobserved heterogeneity across districts and regions is crucial. Therefore, a wide range of district, regional and village-level characteristics are included in the fixed effect estimations described above.

5.7 Results

5.7.1 Descriptive statistics: Test of means differences between baseline and end-line periods

The results of the test of difference in means between the baseline and the end-line period for the explanatory variables are discussed in this sub-section. **Table 5.9** presents the results of the mean values of both the dependent and the independent variables used in the regression models for the baseline year 2008/09, the end-line year 2012/13 and the test of significant difference in means of these variables.

Among the dependent variables, the proportion of poor households significantly declined from 33% in 2008 to 28% in 2013 in Malawi and from 34% in 2008 to 29% in 2013 in Tanzania. The difference in the proportion of poor households was highly statistically significant at 1% level. Further, the mean annual household per capita expenditure increased, though insignificantly, from about MK. 181,540 to MK. 188, 328 in Malawi and significantly increased form Tsh. 565,895 to Tsh. 946,521. The total biomass productivity (EVI) increased significantly from about 120 in 2008 to 136 in 2013 in Malawi but declined from 114.4 to 113.9 in 2013, albeit insignificantly.

Meanwhile, the proportion of households experiencing soil erosion significantly (marginally) declined from 39% in 2008/09 to 37% in 2012/13 in Malawi and from 16% to 11% in Tanzania over the same period.

Table 5.8: Descriptive statistics of the selected variables for the 2008/2009 and 2012/2013

	Malawi			Tanzania		
Variable	**2012/13**	**2008/09**	**Diff.**	**2012/13**	**2008/09**	**Diff.**
Poor	28.45	32.63	-4.18***	28.98	34.10	-5.12***
Expenditure	784243	810211	-25968	3977795	2882156	1095640***
Expenditure_pc	188328	181539	6789	946521	565895	380627***
EVI_total	135.99	119.58	16.41***	113.86	114.42	-0.56
Erosion	37.06	39.05	-2.01*	10.87	15.72	-4.86***
Temperature	21.28	21.25	0.03	23.33	23.32	0.04
Rainfall	1068.9	1071.2	-2.25	1108.1	1111.3	-3.19
Pot_wetness_index	13.44	13.41	0.03	13.67	13.75	-0.08
Elevation	935.90	938.90	-3.00	755.80	759.10	-3.27
Terrain_plains	42.50	41.43	1.07	63.59	63.41	0.14
Terrain_plateaus	49.88	50.08	-0.20	28.28	28.01	0.27
Terrain_hills	7.63	8.50	-0.87	6.92	7.27	-0.35
Warm_arid aez	45.25	45.03	0.22	6.36	6.65	-0.29
Warm_humid aez	33.28	33.33	-0.05	63.13	63.64	-0.51
Cool_arid aez	9.48	8.80	0.68	3.81	3.73	0.08
Cool_humid aez	12.00	12.85	-0.85	25.03	24.28	0.75
Age	42.42	43.07	-0.65*	46.05	47.54	-1.49***
Sex	76.90	77.60	-0.70**	75.42	75.50	-0.08
No_school	64.15	66.38	-2.23**	23.67	24.98	-1.31
Pri_school	11.03	10.65	0.38	0.05	0.83	-0.78***
Sec_school	10.53	8.88	1.65**	57.31	58.25	-0.94
High_school	8.98	9.35	-0.37	1.56	1.45	0.11
Tech_school	2.95	2.48	0.47	14.49	12.02	2.47***
College_school	1.68	1.65	0.03	1.66	1.34	0.32
Uni_school	0.70	0.63	0.07	1.26	1.13	0.13
Familz_size	4.88	5.11	-0.23***	5.14	5.83	-0.69***
Market_distance	7.75	7.78	-0.03	32.97	41.48	-8.51***
Farm_size	1.70	1.82	-0.12***	4.28	5.10	-0.82***
Extension_info	36.38	21.10	15.28***	37.63	35.70	1.63***
Electricity	14.60	13.05	1.55**	25.57	18.43	7.14***
Radio	0.59	0.63	-0.04	0.79	0.86	-0.07
TV	0.22	0.18	0.04***	0.24	0.19	0.05***
Cellphones	0.95	0.88	0.07**	1.38	0.81	0.57***
Fridge	0.11	0.08	0.03***	0.12	0.12	0.00
Bike	0.52	0.49	0.03	0.54	0.58	-0.04**
Mbike	0.01	0.01	0.00	0.06	0.04	0.02***
Goats	0.89	1.05	-0.16	2.92	2.80	0.12
Cattle	0.24	0.30	-0.06	1.79	1.91	-0.12
Improved_wall	56.78	50.63	6.15***	49.50	42.45	7.05***
Improved_roof	46.08	42.18	3.9***	71.10	63.03	8.07***
Improved_floor	35.48	33.75	1.73	45.21	40.22	4.99***
Improved_water	85.05	83.03	2.02**	52.76	49.85	3.91
Improved_toilet	8.18	11.38	-3.20***	21.17	13.20	7.97***

Source: Author's compilation.

Results also show significant as well as insignificant differences in the independents variables used in the econometric estimation (**Table 5.9)**. For example, the differences in the biophysical variables were largely insignificant in both Malawi and Tanzania. The mean annual rainfall the mean annual temperature was 21 degrees Celsius for both 2008 and 2013 in Malawi and 23 degrees Celsius for both 2008 and 2013 in Tanzania. The annual mean rainfall was about 1070 mm per annum in Malawi for both 2008 and 2013 and about 1110 mm per annum in both 2008 and 2013 in Tanzania. Elevation remained unchanged at about 936 metres above sea level in Malawi and about 756 metres above sea level in Tanzania. The proportions of households interviewed in different agro-ecological zones and terrains remained unchanged. This is expected because of the panel nature of the observations.

Regarding demographic characteristics, marginal changes were reported with regard to variables such as average age, and proportion of male-headed households. The average age of the head of the household was 43 years in Malawi and 47 years in Tanzania in 2008 but decreased to 42 years in Malawi and 46 years in Tanzania in 2013. Male headed households were about 77% in Malawi and about 75% in Tanzania in both 2008 and 2013 periods. The average family size in 2008 was 4.9 in Malawi and 5.1 individuals in Tanzania. This increased in 2013 to an average of 5.1 and 5.8 individuals in Malawi and Tanzania respectively. These increases were significantly different at 1% level of significance.

There seems to be a substantial decline in the distance to the nearest major market in Tanzania – about 41 km in 2008 to 33 km in 2013. However, this was marginally significant at 10% level of significance. The distance to the nearest major market in Malawi remained unchanged at about 8 km. the proportions with access to agricultural extension services increased by 15% (from initial 21% in 2008 to 36% in 2013) in Malawi and by 2% in Tanzania (from initial 36% in 2008 to 38% in 2013). Similarly households connected to the electricity grid increased significantly from 13% to 15% in Malawi and from 19% to 26% in Tanzania. The average number of TVs, working cellphones, fridges and motorcycles owned per households increased significantly in both Malawi and Tanzania. However, the average number of bicycles owned declined in Tanzania.

The proportion of households with better living conditions as depicted by improved wall, roof, and floor also significantly increased in both countries. The proportion of households with access to improved drinking water sources increased from 83% to 85% in Malawi – this was statistically significantly at 5% level of significance. Moreover, the proportion of households with access to improved toilet facilities in Tanzania increased from 13% to 21%. This was highly statistically significant at 1% level.

5.7.2 Impact of land degradation on household poverty and household per capita expenditure

The estimates of the second stage equations for poverty with bootstrapped standard errors are presented in **Table 5.10**. As described in the empirical strategy section, different estimation strategies were applied based on the nature of the variables under assessment as well as for robust checks. The Wald test suggests that the null hypothesis that land degradation (EVI decline and soil erosion) is exogenous in the household per capita expenditure equation (column 2 and 4 in Malawi and column 7 and 8 for Tanzania) is rejected at 1% level of significance; thus justifies the use of the 2SPLS. Similarly, the Wald test suggests that the null hypothesis that land degradation (EVI decline and soil erosion) is exogenous in the poverty equation is rejected at 1% level of significance; thus justifies the use of the recursive biprobit approach. All the presented results in **Table 5.10** are marginal effects.

Results show that land degradation, measured by EVI decline and soil erosion and instrumented by mean annual rainfall, significantly decreases the household per-capita expenditure and thus increases poverty in both Malawi and Tanzania.Household reporting EVI decline experienced reduction in the log of per-capita expenditure by about 1.1% in Malawi (column 1) and 0.38% in Tanzania (column 5). EVI decline significantly increases the probability of household poverty by 35% in Malawi (column 2) and 48% in Tanzania (column 6). Similarly, soil erosion significantly decreases the household per-capita expenditure in Tanzania. Households experiencing soil erosion reported about 2.9% reduction in the log of per-capita expenditure in Tanzania (column 7). Households experiencing soil erosion are 38% more likely to be poor in Malawi (Column 4) and 26% more likely to be poor in Tanzania (column 8). This study therefore concludes that land degradation (EVI decline and soil erosion) exacerbates poverty situation among farm households. This finding corroborates those of Barbier (2000) and Buys (2007). This finding suggests the importance of including land degradation perspective in poverty analysis among the rural households in Malawi and Tanzania. The pathways through which land degradation influence poverty should be explored so as to improving household welfare.

Table 5.9: Second stage results of impact of land degradation (soil erosion and EVI decline) on poverty and consumption expenditure

	Malawi (N=8000)				Tanzania (N=7454)			
	Log_expm	Poverty	Log_expm	Poverty	Log_expm	Poverty	Log_expm	Poverty
	2SPLS	Biprobit	2SPLS	Biprobit	2SPLS	Biprobit	2SPLS	Biprobit
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
degraded	**-1.072****	**0.347****			**-0.381*****	**0.479****		
eroded			**-0.035**	**0.384***			**-2.913****	**0.259***
age	-0.015***	0.006	-0.013***	0.008	0.012***	-0.009	0.032**	-0.005
agesq	0.000**	0.000	0.000*	0.000	-0.000**	0.000	-0.000**	0.000
sex	-0.048*	0.013	-0.049*	-0.004	-0.099***	0.028	-0.202***	0.012
no_school	-0.148*	0.796**	-0.200***	0.781**	0.146	0.343***	0.083	0.341***
pri_school	-0.139*	0.670**	-0.175**	0.651**	0.228*	0.163**	0.220	0.165**
sec_school	-0.053	0.642**	-0.098	0.637*	0.340**	-0.514**	0.689**	-0.470
high_school	-0.012	0.492	-0.047	0.458	0.244*	-0.123	0.184	0.006
tech_school	0.071	0.186	-0.002	0.076	0.223	0.034	0.072	0.741
uni_school	0.142	0.000	0.181	0.000	0.357**	0.715***	0.277	0.703**
hhsize	-0.117***	0.251***	-0.121***	0.258***	0.077***	0.178***	0.091***	0.179***
lnmrktdist	-0.021	-0.011	-0.01	0.002	0.111***	-0.008	0.070***	0.003
lndisdist	0.042***	-0.020	0.027***	-0.041**	0.014	0.068	0.080***	-0.011
extinfo	0.013	-0.115***	0.021	-0.158***	-0.003	0.167***	-0.021	0.140
farmsize	0.030***	-0.052***	0.021***	-0.065***	0.001*	-0.012***	0.002	-0.012**
goats	0.011***	-0.022***	0.012***	-0.025***	0.003**	-0.015***	0.007**	-0.015**
cattle	0.001	-0.013	-0.001	-0.012	-0.004	-0.023***	-0.007	-0.024***
radio	0.059***	-0.221***	0.057***	-0.240***	0.003***	-0.289***	0.010***	-0.284***
tv	0.100***	-0.520***	0.121***	-0.514***	0.085***	-0.460***	0.036	-0.462***
fridge	0.125***	-0.263	0.104***	-0.286	0.179***	-0.303**	0.208***	-0.298*
bike	0.078***	-0.086**	0.072***	-0.127***	0.048***	-0.050*	0.036	-0.043
mbike	0.199***	-0.757**	0.202***	-0.850**	0.077**	-0.119	0.057	-0.130
rooms	0.031***	-0.126***	0.035***	-0.138***	0.016***	0.002	0.026**	0.003
terr_plateau	-0.011	-0.073	0.002	0.025	0.243	-0.229	-0.733	-0.108
terr_plains	0.033	0.048	0.048	0.157**	0.347*	-0.368**	-0.578	-0.266
_cons	-0.255**	-0.265	0.423**	-1.387***	0.131***	-0.126***	0.048***	-0.050*
region (district)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Source: Author's compilation.

Most of the other variables in the presented models are consistent with expectations. For example, positive determinants of household per capita expenditure included rainfall, age, education, access to extension and ownership of cattle and small ruminants. On the other hand, household per capita expenditure is negatively and significantly associated with age squared, interaction of rainfall and temperature, male headed households and distance to the nearest major market. Improved living standards as depicted by the conditions of the dwelling's room, floor, toilet and drinking water are positively correlated with household expenditure and negatively associated with poverty.

5.7.3 Impact of household poverty and household per capita expenditure on land degradation

The estimates of the second stage equations for EVI decline and soil erosion with bootstrapped standard errors are presented in **Table 5.11**. The Wald test suggests that the null hypothesis that land degradation (EVI decline and soil erosion) is exogenous in the household per capita expenditure equation (column 1 and 2 in Malawi and column 5 and 6 for Tanzania) is rejected at 1% level of significance; thus justifies the use of the 2SPLS. Similarly, the Wald test suggests that the null hypothesis that land degradation (EVI decline and soil erosion) is exogenous in the poverty equation is rejected at 1% level of significance; thus justifies the use of the recursive biprobit approach. All the presented results in **Table 5.11** are marginal effects.

Results show that poverty, measured by household per-capita expenditure, and instrumented by distance to the nearest nighttime light intensity point, increases the probability of land degradation (measured by NDVI decline and occurrence of soil erosion). Specifically, 1% increase in household per-capita expenditure reduces the probability of EVI decline by 46% in Malawi (column 1) and 27% in Tanzania (column 5). Household per-capita expenditure also reduces the probability of soil erosion occurrence by 29% in Malawi and by 26% in Tanzania. Poverty assessments show that poor households have 69% and 67% more likelihood to experience EVI decline in Malawi and Tanzania respectively. However, the impact of poverty on soil erosion, though positive, was statistically insignificant.

The finding that poverty aggravates biomass productivity decline (land degradation) is consistent to Dasgupta and (1995) and Scherr (2000) who argue that poverty coupled with population growth may lead to resource degradation but contrary to de Janvry *et al.* (1991) but Nkonya *et al.*, (2008 and 2011) who argue that the poor depend heavily on land; therefore, they have a strong incentive to invest their resources into preventing or mitigating land degradation in efficiently working market conditions. Poor farmers are unable to use productivity enhancing inputs such as fertilizers thus contribute to natural resource degradation. Lack of such complementary capital as financial, human and physical limits the capacity of farmers to invest in land management and hence increase poverty among the rural poor.

The other variables used in the estimations are consistent with theoretical expectations and consistent with the findings described in chapter three of this thesis (using cross-sectional plot-level data). For example, positive determinants of EVI decline included the interaction between rainfall and temperature, elevation household size and distance to the market. Negative significant determinants of EVI decline included rainfall and access to extension.

Overall, this finding is consistent with the hypothesis that poverty contributes to land degradation as a result of poor households' inability to invest in natural resource conservation and improvement. Land degradation in turn contributes to low and declining agricultural productivity, which in turn contributes to worsening poverty. It is important to note that the environment at which smallholder farmers operate is complex and the challenges they face are compound. Investment in SLM is not a determined by poverty alone. Other aspects such as the absence of proper technologies, lack of appropriate institutional and economic conditions and are disincentives for SLM among the rural farming communities (FAO, 2011a).

Table 5.10: Second stage results of impact of poverty and consumption expenditure on land degradation (soil erosion and NDVI decline)

	Malawi (N=8000)				Tanzania (N=7454)			
	EVI decline	EVI decline	Erosion	Erosion	EVI decline	EVI decline	Erosion	Erosion
	2SPLS	Biprobit	2SPLS	Biprobit	2SPLS	Biprobit	2SPLS	Biprobit
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
lnexpmr	**-0.463*** **		**-0.294*** **		**-0.266** **		**-0.263** **	
poor		**0.693*** **		**-0.005**		**0.667*** **		**-0.121**
pwi	-0.043	-0.016	-0.014	-0.011	-0.019***	-0.024***	-0.007	-0.008
lntemp	-8.295***	-8.430***	2.770***	2.817***	-2.437***	-2.189***	-0.145	-0.006
lnrain	0.604***	0.646***	0.232**	0.247**	-1.685***	-1.606***	-0.490***	-0.486***
lnelevation	-1.543***	-1.595***	-0.189***	-0.237***	0.288***	0.303***	-0.004	0.012
farmsize	0.154***	0.138***	0.028**	0.010	0.005*	0.004*	0.004**	0.002
terr_plains	-0.245***	-0.239***	-0.443***	-0.453***	-0.730***	-0.736***	0.204	0.123
terr_plateaus	0.098	0.066	-0.304***	-0.318***	-0.640***	-0.646***	0.337*	0.276
terr_hills	0.004	0.000	0.000	0.000	-0.957***	-0.953***	0.564***	0.504**
warm_arid	-0.775***	-0.779***	-0.631***	-0.647***	1.937***	1.807***	-0.998***	-0.942***
warm_humid	-0.795***	-0.830***	-0.213***	-0.270***	-0.293	-0.332	-0.580***	-0.529**
cool_arid	-0.646***	-0.655***	-0.219***	-0.205**	-1.195***	-1.173***	-0.691***	-0.659***
age	-0.010	-0.010	0.006	0.005	-0.006	-0.009	0.032***	0.029***
agesq	0.000	0.000	0.000	0.000	0.000	0.000	-0.000***	-0.000***
sex	-0.018	0.005	0.028	0.025	0.006	0.001	0.140***	0.121**
no_school	0.989**	1.504***	0.131	0.458**	1.023**	1.143***	0.580	0.797*
pri_school	0.841*	1.356***	0.189	0.478**	1.260**	1.326**	0.276	0.568
sec_school	0.876*	1.374***	0.058	0.327	1.157***	1.287***	0.638	0.829*
high_school	0.705	1.142**	-0.030	0.184	1.100**	1.231***	1.052**	1.168***
tech_school	0.736	1.048**	-0.062	0.073	1.200***	1.309***	0.528	0.662
college_school	0.801	1.033*	0.092	0.179	1.321***	1.411***	0.304	0.386
hhsize	-0.063***	-0.043***	-0.014	0.029***	0.006	-0.029***	0.054***	0.040***
lnmrktdist	0.222***	0.227***	0.073***	0.084***	-0.159***	-0.160***	0.022	0.020
lndisdist	0.041*	0.042*	0.016	0.010	0.200***	0.175***	0.030	0.019
extension	0.116***	0.139***	0.301***	0.304***	-0.094	-0.129*	-0.121**	-0.098
cellphones	0.028	-0.036	0.042*	-0.034**	0.036	0.006	-0.008	-0.077***
cattle	0.006	0.005	-0.006	-0.008**	0.002	0.001	-0.009***	-0.010***
goats	0.016**	0.012*	0.021***	0.016***	-0.001	-0.001	0.004*	0.003
region	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
_cons	56.372***	51.013***	-12.038***	-15.861***	26.579***	21.007***	6.015*	1.479
Chi^2	1980.5	700.1	2086.5	2076.6	2141.9	2040.7	537.2	551.8
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Source: Author's compilation.

5.8 Conclusions

The debate on the land degradation – poverty linkages is inconclusive. Land degradation contributes to low and declining agricultural productivity, and this in turn contributes to worsening poverty. Poverty in turn is posited to contribute to land degradation as a result of poor households' inability to invest in natural resource conservation and improvement. On the other hand, however, it is also argued that the poor depend heavily on land; therefore, they have a strong incentive to invest their resources into preventing or mitigating land degradation in efficiently working market conditions. This chapter contributes to the debate by empirically estimating the causality between poverty and land degradation using two waves of nationally representative panel data collected in Tanzania in 2008 and 2011. The study adopts two-stage probit least squares (2SPLS) specification (simultaneous equation approach) to deal with the problem of endogeneity and simultaneity between poverty and land degradation.

The analysis also take advantage of panel data to better control for unobserved heterogeneity and to obtain more efficient estimation results. The findings are consistent with hypothesis that poverty contributes to land degradation as a result of poor households' inability to invest in natural resource conservation and improvement. Land degradation in turn contributes to low and declining agricultural productivity, which in turn contributes to worsening poverty.

Specifically, increase in household per-capita expenditure by 1% reduces the probability of EVI decline by 46% in Malawi and by 27% in Tanzania. Increase in household per-capita expenditure by 1% also reduces the probability of soil erosion occurrence by 29% in Malawi and by 26% in Tanzania. Poverty assessments show that poor households have 69% and 67% more likelihood to experience EVI decline in Malawi and Tanzania respectively. Household experiencing EVI decline showed a reduction in the log of per-capita expenditure by about 1.1% in Malawi and 38% in Tanzania. EVI decline significantly increases the probability of household poverty by 35% in Malawi and 48% in Tanzania. Households experiencing soil erosion are 38% and 26% more likely to be poor in Malawi and in Tanzania respectively. These findings suggest the importance of including land degradation perspective in poverty analysis among the rural households who heavily depend on land resources for their livelihoods. The pathways through which land degradation influence poverty should be explored so as to improving household welfare.

Chapter 6

6. General conclusions

Land degradation – defined by the Economics of Land Degradation (ELD) initiative as a "reduction in the economic value of ecosystem services and goods derived from land"– is a serious impediment to improving rural livelihoods and food security of millions of people in the Eastern Africa region. Proper identification of areas experiencing land degradation is important in creating policies and practices aimed at restoring the land and in developing policies to improving livelihoods. Evaluating and monitoring land degradation is a complex process. Various methods have been used to estimate the patterns, extent and level of land degradation all resulting in different results.

More recently, satellite–based imagery and remote sensing have been utilized to identify the magnitude and processes of land degradation at global, regional and national levels. This involves the use of Normalized Difference Vegetation Index (NDVI) derived from Advanced Very High-Resolution Radiometer (AVHRR) data and the use of high quality satellite data from Moderate Resolution Imaging Spectroradiometer (MODIS).

This study identified land degradation patterns in Ethiopia, Kenya, Malawi and Tanzania 'from above' (i.e. based on remote sense datasets) and 'from below' (ground-truthing of remotely sensed data). Assessment of land degradation 'from above' was based on review and application of two approaches: (i) biomass productivity decline based NDVI data (proposed by Le *et al*., 2014) and (ii) Land Use Cover Change using MODIS data (proposed by Nkonya *et al*., 2015). It also presented the results of the ground-truthing to check the accuracy and to determine the reliability of the satellite and remote sensing data in Ethiopia and Tanzania and actions taken to address the deterioration of ecosystem services values.

Results from the biomass productivity decline show that land degradation hotspots cover about 51%, 41%, 23% and 22% of the terrestrial areas in Tanzania, Malawi, Ethiopia and Kenya respectively. Some of the key 'hotspot' areas include west and southern regions Ethiopia, western part of Kenya, southern, eastern and central parts of Tanzania and eastern parts of Malawi. The MODIS LUCC data (for the period 2001-2009) showed an increase in cropland area in

Ethiopia by 33%. However, cropland area reduced in cropland in Malawi by 34% and in Tanzania by 41%. Forests reduced in Kenya by 23%, Ethiopia by 26% and Tanzania by 17% but forested areas surged in Malawi by 7%. On the other hand grassland reported increases in Kenya (32 %), Malawi (18%) and Tanzania ((11%) but reduced in Ethiopia (11%).

To accuracy of the NDVI observations was assessed using ground-truthing exercise carried out in Tanzania and Ethiopia through focused group discussions (FGDs). The FGDs participants were diverse and were chosen based on a criteria that allowed wide representation of the communities. The information elicited from the FGDs participants' perception on land degradation at each of the selected site was used to compare the remote sensing data reported by Le *et al*. (2014) and the MODIS land cover change. The FGDs assessment showed moderately high degree of agreement with the remote sensing data. There was agreement between Le *et al*. (2014) and the FGDs in 7 sites out of 8 in Tanzania and 6 sites out of 7 in Ethiopia – representing an accuracy of about 88% and 86% respectively. There was also agreement between MODIS land cover change and the FGDs in 6 sites out of 8 in Tanzania and 3 sites out of 7 in Ethiopia – representing an accuracy of about 75% and 43% respectively.

This study also demonstrates that losses due to land degradation are enormous. Based on TEV framework, the costs of land degradation due to LUCC between 2001-2009 periods were about 2 billion USD in Malawi, 11 billion USD in Kenya, 18 billion USD in Tanzania and 35 billion USD in Ethiopia. Assuming a linear trend, this translate to annual costs of about 248 million USD in Malawi, 1.3 billion USD in Kenya, 2.3 billion USD in Tanzania, and 4.4 billion USD in Ethiopia – representing about 5%, 7%, 14% and 23%, of GDP in Kenya, Malawi, Tanzania and Ethiopia respectively. When these costs are converted to per hectare basis, they range from $38 in Ethiopia, $25 in Tanzania, $23 in Kenya and $21 in Malawi annually.

The total annual costs of land degradation associated with use of land degradation practices in maize, wheat and rice croplands were about 305 million USD in Ethiopia, 270 million USD in Kenya, 162 USD million in Tanzania, and 114 USD million in Malawi. These costs on static cropland degradation are, however, conservative. Only three crops were considered, other aspects of land degradation common on a static biome (cropland) including soil erosion and salinity, and offside costs of pesticide use are not considered because of lack of data.

It is worthwhile to take action against land degradation. As expected, the TEV computation shows that the costs of action are lower as compared to costs of inaction against land degradation in all the countries both in a 6-year and a 30-year cycle. During the entire 30-year planning horizon, the cost of action is about 54 billion USD in Ethiopia, 37 billion USD in Tanzania, 18 billion USD in Kenya, and 4.3 billion USD in Malawi. However, if no action is taken to address land degradation over the 30-year period, it would lead to a loss of about 228 billion USD in Ethiopia, 139 billion USD in Tanzania, 75 billion USD in Kenya, and 16 billion USD in Malawi. Consequently, during the 30-year period, returns to investment in action against land degradation are at least four folds. Specifically, for every dollar spent on taking action against land degradation land users will expect a return of about 4.2 USD in Ethiopia, 4.1 USD in Kenya, 3.8 USD in Tanzania, and 3.7 USD in Malawi.

Policies and strategies that incentivize better sustainable land management and discourage deforestations ought to be emboldened so as to achieve UNCCD’s target of zero net land degradation by year 2030. The costs of land degradation due to LUCC constitute the biggest proportion of the total costs of land degradation. Therefore, strategies and mechanisms must be developed to address LUCC such as payment for ecosystem services (PES) and participatory management of community resources such as forests and grazing lands.

Some of the local level initiatives taken by local communities address loss of ecosystem services or enhance/maintain ecosystem services improvement in forest biome included afforestation programs, area closures and stricter enforcement and enacting of bylaws to protect existing forests. Some actions applied in grassland included area closures, and controlled grazing and community sanctions for overgrazing. In croplands for example, actions such as soil fertility management (use of fertilizer and organic manure) and SLM practices such as crop rotation and use of soil and water conservation measures such as crop and fallow rotations, soil and stone bunds, and terracing proved effective.

Successful actions in managing forest and grassland biomes were largely through collective/participatory community management at community level. This underscores the importance of participatory involvement in policy formulation and enforcement for effective resource management at community level. On the other hand, actions on cropland were undertaken at household level. Successful actions on cropland biome therefore requires easing the constraints faced by the resource–scare farmers such as access to and cost of fertilizer, and also improving their capacity, through training, on the importance of tillage practices such as crop rotations and mulching.

This study further used nationally representative household surveys in three eastern Africa countries (Ethiopia, Malawi and Tanzania) to comprehensively assess the causes of land degradation (NDVI decline) and to ascertain the determinants of adoption SLM technologies. A logit regression model was specified to assess the drivers of NDVI decline. From this assessment, the significant proximate causes of NDVI decline in the selected case study countries included variables such temperature, terrain, topography and agro-ecological zonal classification. Important underlying drivers of NDVI decline included factors such as land ownership, distance from the plot to the market, and socio-economic variables such as the size of the plot, access to and amount of credit, and total household assets.

The adoption of sustainable land management practices is critical in addressing land degradation in Eastern Africa. Logit model was also used to estimate the significant determinants influencing the decision to adopt SLM technologies. Results highlighted that the adoption of SLM technologies is determined by a series of factors such as 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. The relevant demographic and socio-economic factors included 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 of SLM technologies. 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 SLM technologies suggests the need for proper geographical planning and targeting of the SLM practices by stakeholders.

The debate on the land degradation – poverty linkages is inconclusive. Land degradation contributes to low and declining agricultural productivity, and this in turn contributes to worsening poverty. Poverty in turn is posited to contribute to land degradation as a result of poor households' inability to invest in natural resource conservation and improvement. On the other hand, however, it is also argued that the poor depend heavily on land; therefore, they have a strong incentive to invest their resources into preventing or mitigating land degradation in efficiently working market conditions. This study contributes to the debate by empirically estimating the causality between poverty and land degradation using two waves of nationally representative panel data collected in Tanzania in 2008 and 2011. The study adopts two-stage probit least squares (2SPLS) specification (simultaneous equation approach) to deal with the problem of endogeneity and simultaneity between poverty and land degradation. The assessment also utilized panel data to better control for unobserved heterogeneity and to obtain more efficient estimation results. The findings are consistent with hypothesis that poverty contributes to land degradation and that land degradation in turn contributes to worsening poverty.

Specifically, increase in household per-capita expenditure by 1% reduces the probability of EVI decline by 46% in Malawi and by 27% in Tanzania. Increase in household per-capita expenditure by 1% also reduces the probability of soil erosion occurrence by 29% in Malawi and by 26% in Tanzania. Poverty assessments show that poor households have 69% and 67% more likelihood to experience EVI decline in Malawi and Tanzania respectively. Household experiencing EVI decline showed a reduction in the log of per-capita expenditure by about 1.1% in Malawi and 38% in Tanzania.

EVI decline significantly increases the probability of household poverty by 35% in Malawi and 48% in Tanzania. Households experiencing soil erosion are 38% and 26% more likely to be poor in Malawi and in Tanzania respectively. These findings suggest the importance of including land degradation perspective in poverty analysis among the rural households who heavily depend of land resources for their livelihoods. The pathways through which land degradation influence poverty should be explored so as to improving household welfare.

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8. Appendix

Table 8.1: Land area of terrestrial biomes in Eastern Africa 2001 ('000 hactares)

Country	Forest	Cropland	Grassland	Woodland	Shrub-land	Bare land	Water	Urban
Ethiopia	5485	8505	28534	22379	41826	5653	644	73
Kenya	1632	2303	21921	3821	25257	2070	1119	45
Malawi	396	157	5689	3096	80	11	2351	8
Tanzania	4015	3080	51262	28881	981	84	5759	81
SSA	305041	79736	726706	484846	252659	473895	24514	3458

Source: Author's compilation based on MODIS data.

Table 8.2: Land area of terrestrial biomes in Eastern Africa 2009 ('000 hactares)

Country	Forest	Cropland	Grassland	Woodland	Shrub-land	Bare land	Water	Urban
Ethiopia	4072	11288	25498	22045	44580	4957	586	73
Kenya	1261	2312	28958	3946	19188	1403	1056	45
Malawi	427	104	6731	2137	15	17	2349	8
Tanzania	3330	1807	56853	25964	398	108	5602	80
SSA	297021	118070	714001	479810	263701	452629	22538	3086

Source: Author's compilation based on MODIS data.

Table 8.3: Gained land area of terrestrial biomes between 2001- 2009 ('000 hactares)

Country	Forest	Cropland	Grassland	Woodland	Shrub-land	Bare land	Water	Urban
Ethiopia	858.2	7506.8	10679.8	8064.9	7679.7	1211.3	11.5	0.1
Kenya	349.4	1672.9	12046.9	2628.0	3156.9	298.4	11.4	0.0
Malawi	214.9	90.9	2117.3	1107.7	8.8	14.7	19.5	0.0
Tanzania	1280.4	1448.1	14329.5	8978.3	276.9	84.6	73.3	0.0
SSA	45578.2	83501.1	169083.9	135381.8	75174.8	14086.5	1782.3	1.8

Source: Author's compilation based on MODIS data.

Table 8.4: Lost land area of terrestrial biomes between 2001- 2009 ('000 hactares)

Country	Forest	Cropland	Grassland	Woodland	Shrub-land	Bare land	Water	Urban
Ethiopia	2271.1	4723.4	13715.6	8398.8	4926.1	1907.6	69.5	0.0
Kenya	720.8	1663.8	5010.6	2502.9	9226.4	965.4	73.9	0.1
Malawi	184.3	143.7	1075.3	2067.1	73.8	8.3	21.4	0.0
Tanzania	1964.9	2721.6	8737.7	11895.0	859.3	60.7	230.4	1.4
SSA	53597.8	45167.8	181789.1	140417.9	64132.9	35352.1	3758.9	374.2

Source: Author's compilation based on MODIS data.

Table 8.5: Net change in land area of terrestrial biomes between 2001- 2009 (ha and %)

Country	Forest	Cropland	Grassland	Woodland	Shrub-land	Bare land	Water	Urban
Ethiopia	-1412899 (-25.8%)	2783381 (32.7%)	-3035811 (-10.6%)	-333918 (-1.5%)	2753523 (6.6%)	-696317 -12.3%)	-58038 (-9.0%)	82 (0.1%)
Kenya	-371322 (-22.7%)	9074 (0.4%)	7036319 (32.1%)	125040 (3.3%)	-6069477 (-24.0%)	-667004 (-32.2%)	-62506 (-5.6%)	-93 (-0.3%)
Malawi	30597 (7.7%)	-52749 (-33.6%)	1042056 (18.3%)	-959338 (-31.0%)	-65021 (-81.4%)	6341 (56.9%)	-1886 (-0.1%)	0 (0.0%)
Tanzania	-684551 (-17.1%)	-1273497 (-41.3%)	5591728 (10.9%)	-2916689 (-10.1%)	-582400 (-59.4%)	23928 (28.6%)	-157100 (-2.7%)	-1121 (-1.8%)
SSA	**-8019576** **(-2.6%)**	**38333300** **(48.1%)**	**-12705200** **(-1.7%)**	**-5036101** **(-1.0%)**	**11041960** **(4.4%)**	**-21265470** **(-4.5%)**	**-1976578** **(-8.1%)**	**-372429** **(-7.8%)**

Source: Author's compilation based on MODIS data.

Table 8.6: Land area of terrestrial biomes in Ethiopia in 2009 and change (%) between 2001-2009

Region	Forest	Cropland	Grassland	Woodland	Shrub-land	Bare-land	Water	Urban
Addis Ababa	547 (-83%)	21346 (55%)	7639 (-14%)	4168 (-60%)	4359 (135%)	0 (0%)	0 (0%)	16986 (0%)
Southern Nations	1601977 (-16%)	1572582 (32%)	2966063 (-8%)	4399802 (6%)	592581 (1%)	25514 (-60%)	75899 (-14%)	5029 (0%)
Tigray	2678 (-96%)	883125 (48%)	2015347 (-25%)	206842 (-56%)	1825997 (62%)	5986 (-25%)	615 (-38%)	2337 (0%)
Afar	9347 (4%)	306724 (-36%)	1105000 (-24%)	50180 (-78%)	5152517 (45%)	3047947 (-23%)	44618 (-30%)	1394 (0%)
Amhara	53050 (-73%)	4718757 (54%)	7741655 (7%)	2154996 (-47%)	590340 (-7%)	8705 (-8%)	291419 (-2%)	7871 1%)
Benshangul	6109 (-89%)	15551 (-65%)	1942578 (-1%)	2999229 (4%)	1244 (658%)	0 (0%)	0 (0%)	1011 (0%)
Dire Dawa	0 (-100%)	3799 (8%)	18394 (-70%)	1599 (-2%)	79561 (114%)	0 (0%)	0 (0%)	1927 (0%)
Gambela	303322 (32%)	27181 (101%)	367905 (-60%)	1851237 (34%)	2118 (1622%)	96 (-53%)	847 (27%)	301 (0%)
Harari	178 (-89%)	11616 (750%)	15100 (-43%)	287 (-57 %)	9580 (49%)	0 (0%)	0 (0%)	328 (0%)
Oromia	2093924 (-31%)	3691870 (21%)	8730579 (-11%)	10300000 (14%)	7299026 (2%)	100415 (-2%)	172965 (-10%)	32141 (0%)
Somali	697 (-90%)	35394 (-29%)	587443 (-46%)	69080 (-16%)	29000000 (1%)	1768027 (15%)	0 (0%)	3676 (0%)
Total	**4,071,828** **(-25.8%)**	**11,287,940** **(32.7%)**	**25,497,700** **(-10.6%)**	**22,045,380** **(-1.5%)**	**44,579,890** **(6.6%)**	**4,956,689** **(-12.3%)**	**586,363** **(-9.0%)**	**73,002** **(0.1%)**

Source: Author's compilation based on MODIS data.

Table 8.7: Land area of terrestrial biomes in Kenya in 2009 and change (%) for 2001-2009

Region	Forest	Cropland	Grassland	Woodland	Shrub-land	Bare land	Water	Urban
Central	278491 (-4%)	111675 (73%)	566330 (-9%)	328781 (0%)	42322 (89%)	0 (0%)	205 (200%)	2583 (0%)
Coast	102629 (-22%)	696549 (83%)	5848000 (25%)	588823 (26%)	1118269 (-58%)	2774 (-44%)	11971 (-38%)	5521 (-2%)
Eastern	148682 (7%)	142464 (-32%)	7662832 (33%)	336351 (-46%)	6700583 (-18%)	363423 (-7%)	376009 (-5%)	3471 (0%)
Nairobi	1995 (-57%)	1626 (-52%)	44331 (-1%)	7735 (157%)	246 (64%)	55 (100%)	0 (0%)	17820 (0%)
North Eastern	24830 (-59%)	223651 (264%)	5055477 (76%)	249834 (18%)	7057993 (-25%)	2569 (-83%)	0 (-100%)	5371 (0%)
Nyanza	34998 (-32%)	351766 (-26%)	524171 (3%)	345138 (77%)	11684 (-58%)	12518 (13%)	335463 (-4%)	1804 (0%)
Rift Valley	606930 (-32%)	587047 (-20%)	9160266 (26%)	1629349 (-7%)	4243482 (-14%)	1020752 (-38%)	320882 (-6%)	8459 (0%)
Western	62342 (-1%)	196921 (-47%)	96274 (-27%)	460162 (92%)	13433 (-32%)	779 (200%)	11780 (-13%)	342 (0%)
Total	**1,260,897 (-23%)**	**2,311,699 (0%)**	**28,957,680 (32%)**	**3,946,173 (3%)**	**19,188,010 (-24%)**	**1,402,869 (-32%)**	**1,056,309 (-6%)**	**45,370 (0%)**

Source: Author's compilation based on MODIS data.

Table 8.8: Land area of terrestrial biomes in Malawi in 2009 and change (%) between 2001-2009

Region	Forest	Cropland	Grassland	Woodland	Shrub land	Bare land	Water	Urban
Balaka	164 (-14%)	547 (-39%)	207908 (3%)	4209 (-59%)	82 (-77%)	14 (0%)	0 (-100%)	246 (0%)
Lilongwe	6778 (25%)	2432 (27%)	498002 (36%)	117169 (-51%)	123 (-99%)	27 (0%)	0 (-100%)	779 (0%)
Machinga	27850 (25%)	1763 (-59%)	212172 (10%)	99650 (-15%)	697 (-72%)	711 (-29%)	40546 (-6%)	164 (0%)
Mangochi	26498 (-33%)	16645 (-2%)	345330 (11%)	258198 (-7%)	3799 (-37%)	4715 (117%)	247730 (-1%)	1886 (0%)
Mchinji	1667 (-4%)	287 (-43%)	249534 (35%)	62506 (-50%)	0 (-100%)	0 (0%)	0 (0%)	55 (0%)
Mulanje	13830 (1%)	3826 (73%)	127418 (6%)	49483 (-12%)	4742 (-27%)	0 (0%)	0 (-100%)	0 (0%)
Mwanza	1927 (-63%)	738 (-64%)	166133 (5%)	46982 (-6%)	14 (-50%)	0 (0%)	0 (0%)	96 (0%)
Mzimba	28342 (15%)	2842 (-56%)	827534 (19%)	176027 (-42%)	451 (-90%)	0 (0%)	0 (0%)	355 (0%)
Nkhata Bay	166597 (2%)	15483 (-6%)	158521 (36%)	85424 (-31%)	1052 (-87%)	1927 (55%)	710297 (0%)	0 (0%)
Nkhotakota	36214 (19%)	9962 (-8%)	193491 (8%)	193300 (-8%)	1052 (-75%)	3006 (5%)	347120 (0%)	0 (0%)
Nsanje	11821 (190%)	1667 (-77%)	134292 (29%)	42965 (-43%)	164 (50%)	0 (0%)	1011 (-10%)	1011 (0%)
Blantyre	301 (-70%)	1121 (-1%)	185606 (9%)	13119 (-51%)	0 (-100%)	0 (0%)	0 (0%)	2446 (0%)
Ntcheu	1695 (-31%)	806 (-80%)	291296 (6%)	31062 (-30%)	0 (-100%)	0 (0%)	0 (0%)	0 (0%)
Ntchisi	3143 (-26%)	260 (-44%)	117142 (6%)	51328 (-10%)	27 (-86%)	0 (0%)	0 (0%)	0 (0%)
Phalombe	4141 (16%)	1394 (-44%)	92092 (21%)	32784 (-33%)	150 (-58%)	396 (21%)	13215 (3%)	219 (0%)
Rumphi	45397 (32%)	7543 -71%)	264703 (5%)	156690 (2%)	301 (-97%)	533 (457%)	193409 (0%)	55 (0%)
Salima	2801 (0%)	6682 (5%)	168429 (18%)	36350 (-42%)	205 (-88%)	2050 (159%)	94607 (0%)	164 (0%)
Thyolo	1572 (-5%)	3990 (-2%)	132201 (1%)	28903 (-3%)	0 (-100%)	0 (0%)	0 (0%)	0 (0%)
Zomba	8691 (10%)	3758 (-15%)	197454 (12%)	27304 (-46%)	656 (-49%)	383 (-73%)	68437 (5%)	137 (0%)
Chikwawa	8268 (115%)	4277 (-14%)	403053 (27%)	87446 (-51%)	424 (158%)	0 (0%)	232 (0%)	492 (0%)
Chiradzulu	137 (-52%)	683 (85%)	70077 (3%)	5002 (-31%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)
Chitipa	5494 (48%)	3703 (-74%)	300807 (29%)	98119 (-36%)	232 (-96%)	0 (0%)	0 (0%)	0 (0%)
Dedza	3184 (-2%)	2911 (-13%)	282222 (21%)	80490 (-37%)	96 (-97%)	465 (580%)	141822 (0%)	0 (0%)
Dowa	0 (-100%)	4004 (28%)	261532 (26%)	40587 (-56%)	219 (-94%)	0 (0%)	0 (0%)	109 (0%)
Karonga	19747 (42%)	6546 (-42%)	218035 (25%)	135904 (-23%)	369 (-92%)	3266 (185%)	490349 (0%)	0 (0%)
Kasungu	410 (-77%)	478 (-67%)	625939 (26%)	175794 (-41%)	41 (-99%)	0 (0%)	0 (0%)	0 (0%)
Total	**426,667 (8%)**	**104,351 (-34%)**	**6,730,920 (18%)**	**2,136,793 (-31%)**	**14,896 (-81%)**	**17,492 (57%)**	**2,348,774 (0%)**	**8,213 (0%)**

Source: Author's compilation based on MODIS data.

Table 8.9: Land area of terrestrial biomes in Tanzania in 2009 and change (%) between 2001-2009

Region	Forest	Cropland	Grassland	Woodland	Shrub land	Bare land	Water	Urban
Arusha	165449 (-1%)	56466 (-63%)	3212453 (7%)	210245 (-20%)	86039 (-32%)	15934 (-12%)	192302 (-6%)	1380 (0%)
Pemba South	8473 (-46%)	25063 (39%)	8418 (-10%)	3676 (122%)	232 (-53%)	123 (-25%)	3608 (-12%)	109 (-11%)
Lindi	105143 (-41%)	69804 (-47%)	5835414 (20%)	629150 (-57%)	4933 (-63%)	3430 (192%)	8828 (-30%)	5084 (0%)
Manyara	62383 (-12%)	29764 (-63%)	4027333 (5%)	334069 (-18%)	36146 (-57%)	4236 (-20%)	6915 (-13%)	328 (0%)
Mara	18558 (-40%)	136560 (-15%)	1875726 (12%)	51834 (-73%)	11424 (-44%)	10973 (112%)	802731 (-2%)	1968 (0
Mbeya	107521 (18%)	58366 (-11%)	3436255 (6%)	2070228 (-8%)	3826 (-91%)	1913 (-43%)	145976 (-5%)	957 (0%)
Morogoro	876812 (-11%)	70624 (-60%)	3462985 (17%)	2322864 (-10%)	4879 (-78%)	0 (-100%)	0 (-100%)	2665 (0%)
Mtwara	8350 (-31%)	34861 (38%)	1652539 (9%)	33317 (-79%)	5589 (-60%)	410 (-12%)	3293 (-27%)	28780 (0%)
Mwanza	84125 (-8%)	246158 (24%)	1530150 (0%)	79834 (-21%)	26019 (-3%)	33699 (110%)	1493171 (-2%)	2528 (-1%)
Pwani	135508 (-40%)	132310 (-48%)	2248742 (21%)	620432 (-21%)	7311 (-45%)	1271 (-47%)	20047 (-28%)	123 (0%)
Rukwa	160543 (-10%)	106086 (20%)	1903330 (3%)	4392368 (0%)	7420 (-55%)	5070 (11%)	927566 (-3%)	4059 (0%)
Dar-Es-Salaam	1640 (-36%)	24174 (-43%)	97613 (23%)	23628 (10%)	1421 (-5%)	314 (130%)	847 (-30%)	12053 (-6%)
Ruvuma	237535 (-16%)	19760 (-72%)	1310872 (-15%)	4816835 (8%)	2091 (-90%)	1175 (72%)	13625 (-14%)	2214 (0%)
Shinyanga	9170 (-64%)	90835 (-47%)	4159151 (15%)	749927 (-31%)	27208 (-78%)	123 (350%)	191 (-75%)	1080 (0%)
Singida,	52872 (-44%)	39876 (-33%)	4533192 (11%)	199326 (-63%)	28247 (-62%)	2651 (-13%)	36911 (-18%)	437 (0%)
Tabora	7981 (-69%)	38605 (-77%)	5686472 (19%)	1903166 (-27%)	7926 (-82%)	1708 (-46%)	19487 (29%)	3635 (0%)
Tanga	177202 (-33%)	125847 (-28%)	1424023 (4%)	1077368 (10%)	14950 (-46%)	929 (39%)	3635 (-44%)	1462 (0%)
Zanzibar South	28165 (-16%)	12586 (-43%)	29641 (37%)	16836 (102%)	260 (-5%)	68 (-58%)	2378 (-35%)	0 (0%)
Zanzibar West	1613 (-76%)	7325 (25%)	9019 (65%)	3198 (34%)	424 (-9%)	41 (-40%)	1722 (-5%)	793 (-38%)
Dodoma	13310 (-28%)	42814 (-69%)	3951297 (13%)	165053 (-66%)	15059 (-49%)	3908 (79%)	36788 (-34%)	1189 (0%)
Iringa	564280 (15%)	62233 (-70%)	4224391 (19%)	1320944 (-27%)	7844 (-94%)	2911 (70%)	21865 (-4%)	2487 (0%)
Kagera	111730 (-41%)	249575 (-49%)	1114867 (-4%)	1447091 (35%)	6068 (-56%)	9935 (35%)	1044147 (-1%)	970 (0%)
Pemba North	10249 (-47%)	25117 (82%)	10386 (-26%)	4332 (88%)	506 (6%)	260 (12%)	3047 (-16%)	82 (-40%)
Unguja North	3362 (-74%)	15210 (15%)	17396 (14%)	8391 (249%)	232 (-60%)	41 (-57%)	2077 (-8%)	0 (-10%)
Kigoma	203289 (-39%)	64406 (-43%)	208797 (-39%)	3327121 (11%)	5261 (-45%)	3649 (28%)	804412 (-1%)	3225 (0%)
Kilimanjaro	174838 (5%)	22248 (-49%)	882852 (8%)	152590 (-5%)	86845 (-31%)	2938 (-38%)	6655 (45%)	2023 (0%)
Total	**3,330,100** (**-17**%)	**1,806,674** (**-41**%)	**56,853,310** (**11**%)	**25,963,820** (**-10**%)	**398,161** (**-59**%)	**107,712** (**29**%)	**5,602,224** (**-3**%)	**7,9629** (-2%)

Source: Author's compilation based on MODIS data.

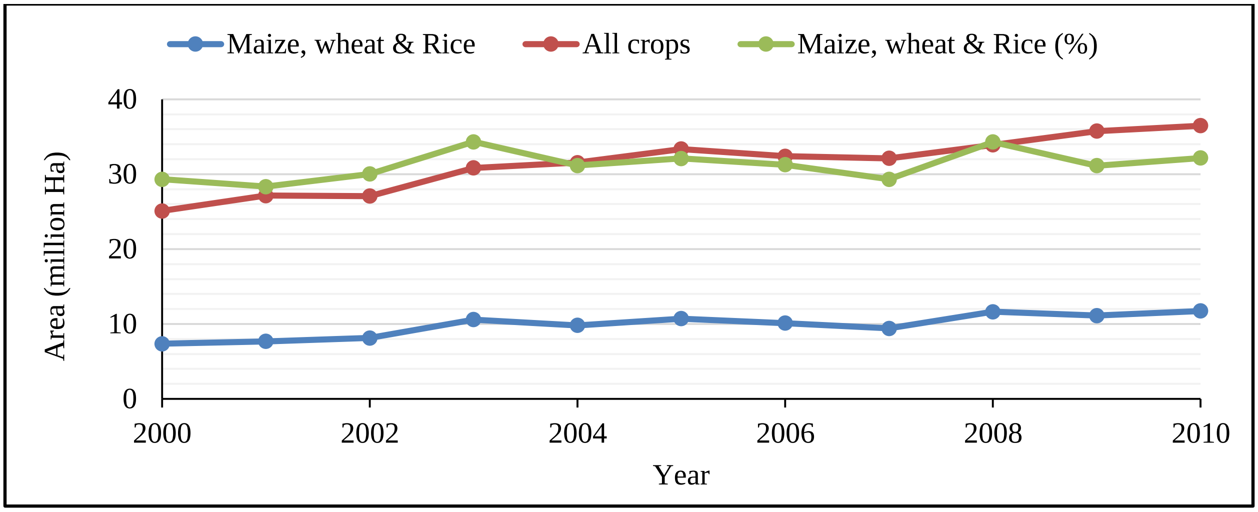

Figure 8.1: Maize, Wheat and Rice Area in Ethiopia, Kenya, Malawi and Tanzania in 2000-2014.
Source: Author's compilation based on FAOSTAT data.

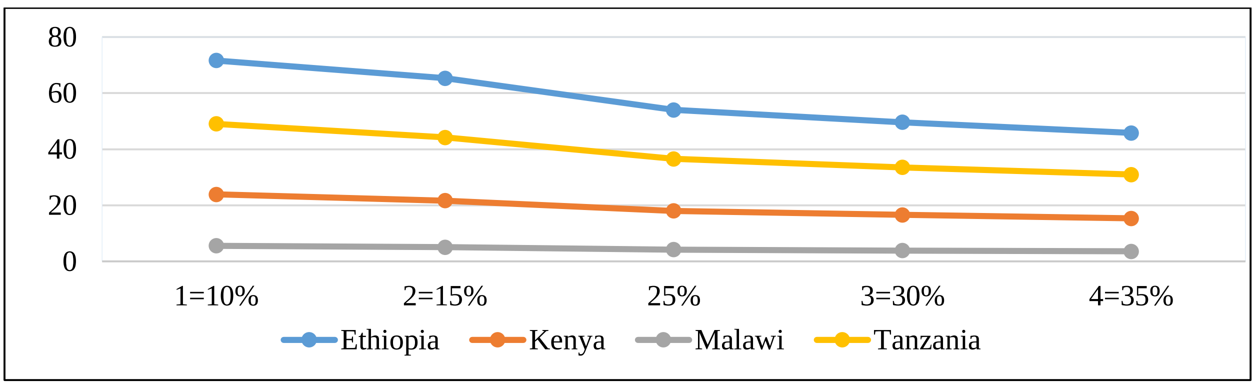

Figure 8.2: Cost of action against LUCC land degradation in 6 years in different scenarios
Source: Author's compilation based on MODIS data.

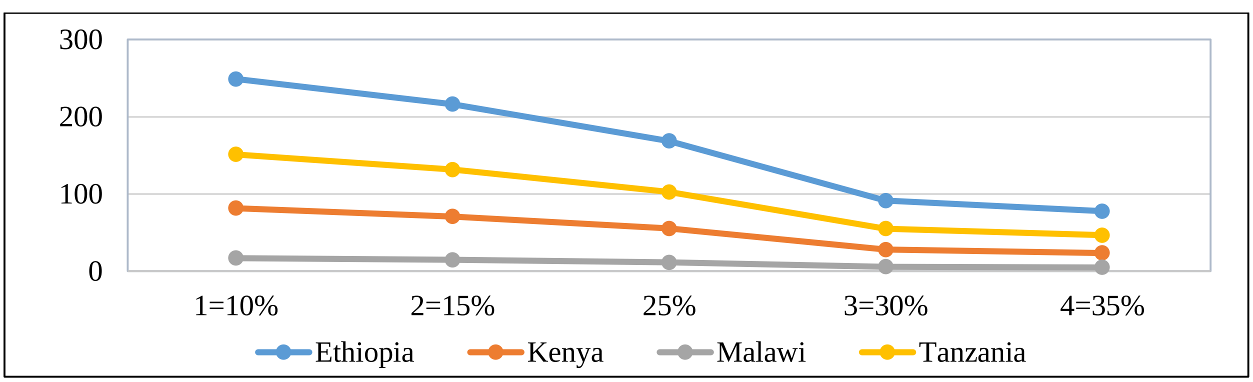

Figure 8.3: Cost of inaction against LUCC land degradation in 6 years in different scenarios
Source: Author's compilation based on MODIS data.