Impact of land degradation on household poverty: evidence from a panel data simultaneous equation model

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Abstract

The debate on the land degradation – poverty linkages is inconclusive. 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. 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. While using a simultaneous equation model and controlling for unobserved heterogeneity, the findings suggest 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, land degradation significantly increases the probability of household poverty by 35% in Malawi and 48% in Tanzania. Poor households have 69% and 67% more likelihood to experience land degradation in Malawi and 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.

Keywords: Land degradation, poverty, panel data, simultaneous equation model, eastern Africa

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, 2011).

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.

2. Conceptual framework

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 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 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.

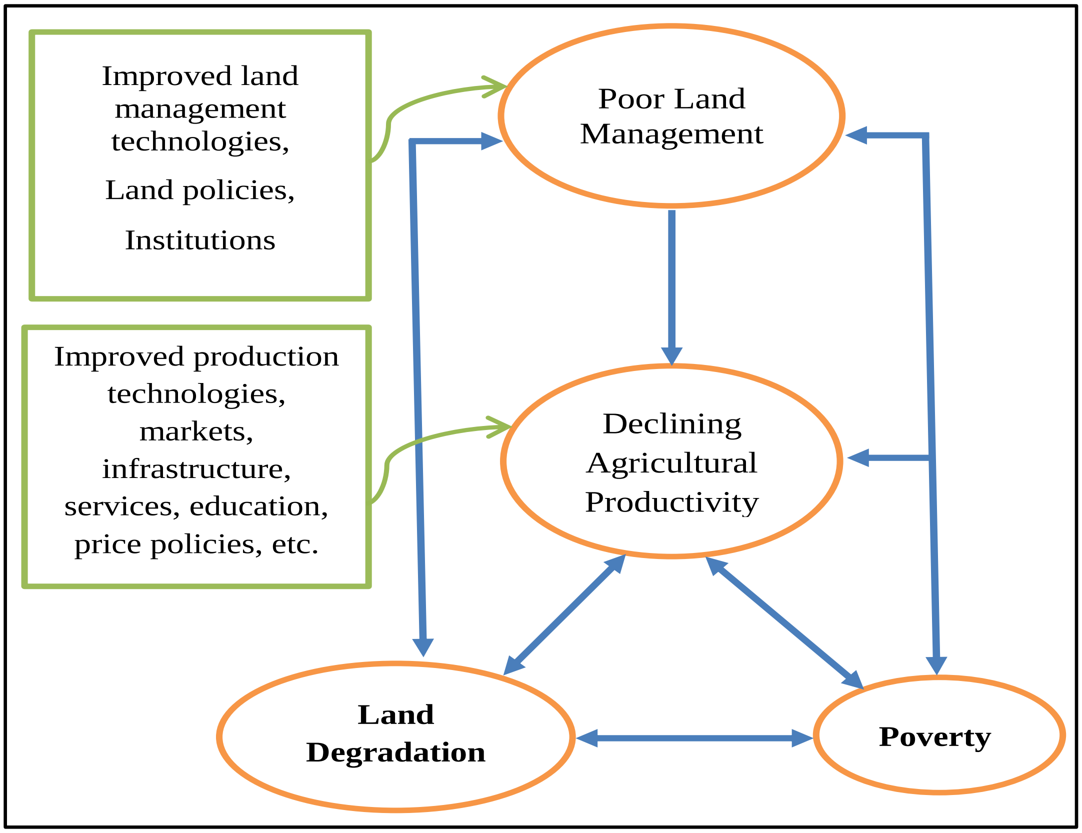

Figure 1: Conceptual framework land degradation and poverty relationships
Source: Author's compilation.

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.

3.1 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.

3.2 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.

4. Measuring Poverty and Land degradation

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.

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 1** shows the poverty lines used in this analysis in local currencies and USD equivalent.

Table 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).

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:

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

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).

Table 2 and **Figure 2** presents the descriptive analyses of poverty 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 2 and Figure 2**).

Table 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.

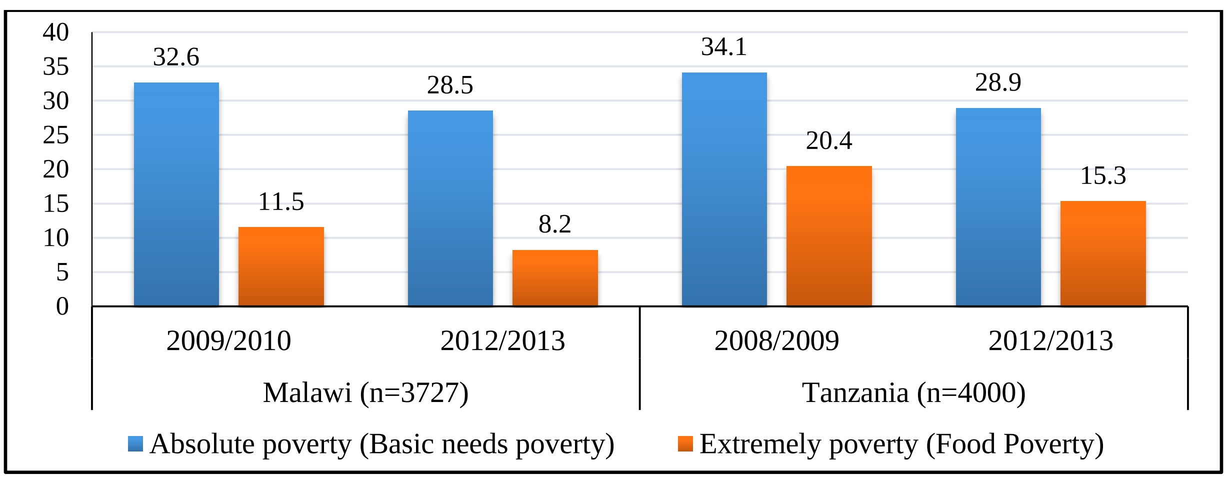

Figure 2: Trends of Poverty incidence in Malawi and Tanzania, 2008/09 – 2012/13

Source: Author's compilation.

Panel data provides the possibility of assessing poverty transitions within the sampled population across time. Results (**Table 3** and **Figure 3**) 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 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 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.

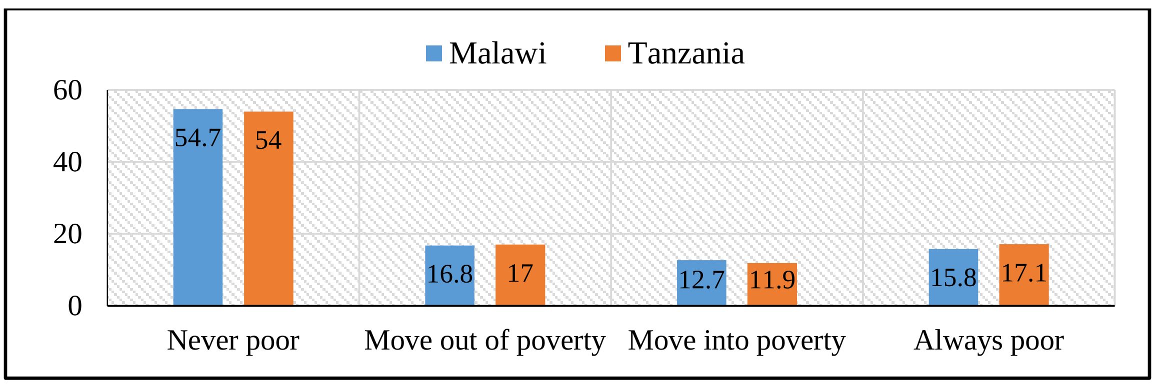

Figure 3: Absolute Poverty Transitions in Malawi and Tanzania, 2008/09 – 2012/13

Source: Author's compilation.

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.

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. 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:

$$\boldsymbol{EVI} = \boldsymbol{G}\,\frac{\boldsymbol{\rho_{NIR} - \rho_{red}}}{\boldsymbol{\rho_{NIR} + C_1 * \rho_{red} - C_2 * \rho_{blue} + L}} \qquad (\mathbf{2})$$

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 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.

$$\textbf{Degradation status} = EVI_{2013} - EVI_{2008} \quad (3)$$

The proportion of household with biomass (EVI) productivity decline (degraded) farms was 49% in Malawi 26% in Tanzania (**Table 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.

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.

Table 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.

Households Experiencing Soil 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**). 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: 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.

4.3 Relationship between land degradation 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 6**) 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 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.

The relationship between poverty and soil erosion is also describe in **Table 7**. 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.

Table 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.

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.

5. Empirical strategy for estimating causality between land degradation and poverty

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.

5.1 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:

$$\boldsymbol{P = f(L, X_{1i})} \qquad (\mathbf{4})$$
$$\boldsymbol{L = f(P, X_{2i})} \qquad (\mathbf{5})$$

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 (4) and (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.**

5.2 The two-stage probit least squares technique

The proper estimation of the SEM in (4) and (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:

$$\boldsymbol{L}^* = \begin{cases} \mathbf{1} & \boldsymbol{if} \ \ \boldsymbol{L} > \mathbf{0} \\ \mathbf{0} & \boldsymbol{otherwise} \end{cases} \qquad (\mathbf{6})$$

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

$$\boldsymbol{P} \ = \boldsymbol{\alpha_1}\boldsymbol{L}^* + \boldsymbol{\beta}_1' \, \mathbf{X_1} + \ \varepsilon_{\mathbf{1}} \qquad (\mathbf{7})$$

$$\boldsymbol{L}^* \ = \boldsymbol{\alpha_2}\boldsymbol{P} + \boldsymbol{\beta}_2' \, \boldsymbol{X_2} + \ \varepsilon_{\mathbf{2}} \qquad (\mathbf{8})$$

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 (7) and (8) respectively, $\boldsymbol{\varepsilon_1}$and $\boldsymbol{\varepsilon_2}$ are error terms in (7) and (8) respectively. Because L^* is not observed, the structural equations (7) and (8) are rewritten as:

$$\boldsymbol{P} = \boldsymbol{\alpha_1 \sigma_2 L^*} + \boldsymbol{\beta_1'}\, \mathbf{X_1} + \varepsilon_1 \qquad (\mathbf{7b})$$

$$\boldsymbol{L^*} = \frac{\boldsymbol{\alpha_2}}{\boldsymbol{\sigma_2}} \boldsymbol{P} + \frac{\boldsymbol{\beta_2'}}{\boldsymbol{\sigma_2}} \boldsymbol{X_2} + \frac{\varepsilon_2}{\boldsymbol{\sigma_2}} \qquad (\mathbf{8b})$$

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 (7b) and (8b) above),

$$\boldsymbol{P} = \mathbb{II}_1' \, \mathbf{X_1} + \boldsymbol{\upsilon_1} \qquad (\mathbf{9})$$

$$\boldsymbol{L^*} = \mathbb{II}_2' \, \mathbf{X_2} + \boldsymbol{\upsilon_2} \qquad (\mathbf{10})$$

where; $\mathrm{X_1}$ and $\mathrm{X_2}$is a vector of all the exogenous variables in (7) and (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 (9) is estimated using OLS while the reduced form of the binary choice variable (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:

$$\boldsymbol{\widehat{P}} = \widehat{\mathbb{II}}_{\mathbf{1}} \, \mathbf{X} \qquad (\mathbf{11})$$
$$\boldsymbol{\hat{L}^*} = \widehat{\mathbb{II}}_{\mathbf{2}} \, \mathbf{X} \qquad (\mathbf{12})$$

In the second stage, the original endogenous variables in (7) and (8) are replaced by their respective fitted values in (11) and (12). Thus, in the second stage, the following two models are fitted:

$$\boldsymbol{P} = \boldsymbol{\alpha_1 \hat{L}^*} + \boldsymbol{\beta_1}\, \mathbf{X_1} + \varepsilon_1 \qquad (\mathbf{13})$$

$$\boldsymbol{L^*} = \boldsymbol{\alpha_2 \widehat{P}} + \boldsymbol{\beta_2}\, \boldsymbol{X_2} + \varepsilon_2 \qquad (\mathbf{14})$$

Again, Equation 13 is estimated by OLS while Equation 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 (13) and (14) will be based on $\hat{L}^{*}$ and and $\hat{P}$ not on the appropriate L^{*} and P. Thus, the estimated standard errors in (13) and (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.

5.3 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:

$$\boldsymbol{P}^{*} = \begin{cases} \mathbf{1} & \boldsymbol{if\ \ P > 0} \\ \mathbf{0} & \boldsymbol{otherwise} \end{cases} \qquad (\mathbf{15})$$

$$\boldsymbol{L}^{*} = \begin{cases} \mathbf{1} & \boldsymbol{if\ \ L > 0} \\ \mathbf{0} & \boldsymbol{otherwise} \end{cases} \qquad (\mathbf{16})$$

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

$$\boldsymbol{P}^{*} = \boldsymbol{\alpha_1} \boldsymbol{L}^{*} + \boldsymbol{\beta}_1' \, \mathbf{X_1} + \varepsilon_{\mathbf{1}} \qquad (\mathbf{17})$$

$$\boldsymbol{L}^{*} = \boldsymbol{\alpha_2} \boldsymbol{P}^{*} + \boldsymbol{\beta}_2' \, \boldsymbol{X_2} + \varepsilon_{\mathbf{2}} \qquad (\mathbf{18})$$

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 (17) and (18) respectively, $\boldsymbol{\beta}_\mathbf{1}'$ and $\boldsymbol{\beta}_\mathbf{2}'$ are vectors of parameters in (17) and (18) respectively, $\boldsymbol{\alpha_1}$ and $\boldsymbol{\alpha_2}$ are the parameters of the endogenous variables in (17) and (18) respectively, $\varepsilon_{\mathbf{1}}$and $\varepsilon_{\mathbf{2}}$ are the error terms in (17) and (18)) respectively.

Because both P^{*} and L^{*} is not observed, the structural equations (17) and (18) are rewritten as:

$$\boldsymbol{P}^{*} = \frac{\boldsymbol{\alpha_1}}{\boldsymbol{\sigma_1}} \boldsymbol{L}^{*} + \frac{\boldsymbol{\beta}_1'}{\boldsymbol{\sigma_1}} \boldsymbol{X_1} + \frac{\varepsilon_{\mathbf{1}}}{\boldsymbol{\sigma_1}} \qquad (\mathbf{17})$$

$$\boldsymbol{L}^{*} = \frac{\boldsymbol{\alpha_2}}{\boldsymbol{\sigma_2}} \boldsymbol{P}^{*} + \frac{\boldsymbol{\beta}_2'}{\boldsymbol{\sigma_2}} \boldsymbol{X_2} + \frac{\varepsilon_{\mathbf{2}}}{\boldsymbol{\sigma_2}} \qquad (\mathbf{18})$$

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 (17) and (18)),

$$\boldsymbol{P}^{*} = \mathbb{II}_1' \, \mathbf{X_1} + \boldsymbol{\upsilon_1} \qquad (\mathbf{19})$$

$$\boldsymbol{L}^{*} = \mathbb{II}_2' \, \mathbf{X_2} + \boldsymbol{\upsilon_2} \qquad (\mathbf{20})$$

where; X_1 and $X_2$is a vector of all the exogenous variables in (17) and (18) respectively, $\amalg_1$and $\amalg_2$are vectors of parameters to be estimated, $\upsilon_1$and υ_2 are error terms.

The two reduced form equations (Equation 19 and 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:

$$\widehat{\boldsymbol{P}}^{*} = \widehat{\amalg}_{\mathbf{1}}\,\mathbf{X} \qquad (\mathbf{21})$$

$$\widehat{\boldsymbol{L}}^{*} = \widehat{\amalg}_{\mathbf{2}}\,\mathbf{X} \qquad (\mathbf{22})$$

In the second stage, the original endogenous variables in (17) and (18) are replaced by their respective fitted values in (21) and (22). Thus, in the second stage, the following two models are fitted:

$$\boldsymbol{P}^{*} = \boldsymbol{\alpha}_{\mathbf{1}}\widehat{\boldsymbol{L}}^{*} + \boldsymbol{\beta}_{\mathbf{1}}\,\mathbf{X}_{\mathbf{1}} + \varepsilon_{\mathbf{1}} \qquad (\mathbf{23})$$

$$\boldsymbol{L}^{*} = \boldsymbol{\alpha}_{\mathbf{2}}\widehat{\boldsymbol{P}}^{*} + \boldsymbol{\beta}_{\mathbf{2}}\,\boldsymbol{X}_{\mathbf{2}} + \varepsilon_{\mathbf{2}} \qquad (\mathbf{24})$$

Again, both Equation (23) and (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 (23) and (24) will be based on $\hat{L}^*$ and and $\hat{P}^*$ not on the appropriate L^* and P^*.

5.4 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)[1] 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.

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[1] 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

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%).

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**). 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.

6. Results

6.1 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 8** 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.

Results also show significant as well as insignificant differences in the independents variables used in the econometric estimation (**Table 8)**. 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.

Table 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.

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.

6.2 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 9**. 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 9** 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.

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.

Table 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.

6.3 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 10**. 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 10** 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 0.46% in Malawi (column 1) and 0.27% in Tanzania (column 5). Household per-capita expenditure also reduces the probability of soil erosion occurrence by 0.29% in Malawi and by 0.26% in Tanzania. Poverty assessments show that poor households have 0.69% and 0.67% 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 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.

7. 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 0.46% in Malawi and by 0.27% in Tanzania. Increase in household per-capita expenditure by 1% also reduces the probability of soil erosion occurrence by 0.29% in Malawi and by 0.26% in Tanzania. Poverty assessments show that poor households have 0.69% and 0.67% 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 0.38% 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.

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