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Land Degradation, Tenure, and Poverty: A Geospatial Analysis of socio-ecological systems in western Kenya

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Valerie Graw, Melinda Smale, Gunter Menz[1]

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Tegemeo Institute of Agricultural Policy and Development

P.O Box 20498, 00200, Nairobi, Kenya

Tel: +254 20 2717818/76; Fax: +254 202717819

E-mail: egerton@tegemeo.org

1Valerie Graw is Research Associate at the Center for Remote Sensing of Land Surfaces (ZFL), University of Bonn, Germany; Melinda Smale is Professor, Department of Agricultural, Food and Resource Economics, Michigan State University, USA and Gunter Menz was Professor at the Department of Geography, University of Bonn, Germany

Tegemeo Institute

Tegemeo Institute of Agricultural Policy and Development is a Policy Research Institute under Egerton University with a mandate to undertake empirical research and analysis on contemporary economic and agricultural policy issues in Kenya. The institute is widely recognized as a centre of excellence in policy analysis on topical agricultural and food security issues of the day, and in its wide dissemination of findings to government and other key stakeholders with a view to influencing policy direction and the decision making processes. Tegemeo's empirically based analytical work, and its objective stance in reporting and dissemination of findings has over the past decade won the acceptance of government, the private sector, civil society, academia, and others interested in the performance of Kenya's agricultural sector.

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Tegemeo Institute of Agricultural Policy & Development

George Padmore Road, off Marcus Garvey Road

P.O. Box 20498, 00200, Nairobi, Kenya

Tel: +254 20 2717818/76; Fax: +254 20 2717819

E-mail: egerton@tegemeo.org

URL: http://www.tegemeo.org

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Abstract

Worldwide, most poor people live in rural areas and depend directly on agricultural land for most of their food, making them vulnerable to environmental changes such as land degradation. This study provides insights into land-population dynamics by focusing on the interlinkages between biophysical and socio-economic perspectives rather than either perspective taken alone. We analyze the interlinkages among socio-economic variables including land tenure and poverty, biophysical preconditions and trends in land productivity among 41 villages in western Kenya. We apply an interdisciplinary framework, combining and modeling panel survey data collected from households in western Kenya with biophysical data and vegetation trends based on remote sensing imagery. Data span the same time period and are linked in a Geographical Information System (GIS). We find that poverty, as well as trigger events such as the global food price crisis of 2008 and post-election crisis of 2007/8, are strongly related to land productivity. Linkages could not be validated between land productivity and land ownership as such, reflecting the fact that the change in ownership of land over the time period studied was not significant in the area of study. Yet links could be observed between productivity change and land fragmentation. Within a coupled human-environment system single indicators might have major impact but in combination with others could also trigger processes such as more intense land degradation. Therefore, using Ordinary Least Squares Regression (OLS) a set of indicators, including socio-economic and biophysical variables, could be defined which explained around 80% of the variation in significantly-decreasing productivity trends.

Key Words: GIS, poverty, land tenure, land degradation

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1. Introduction

Land degradation has been defined as a reduction or loss of biological and economic productivity (Sivakumar & Stefanski 2007, 106). The devastating droughts in the Sahel during the 1970s-80s created an initial awareness of the process of environmental degradation, pushing policy-makers and researchers to probe for greater insights into its causes (Thomas, 1997). Although drylands were the focus of early research about land degradation, the use of remote sensing imagery has since demonstrated that the problem affects all agro-ecologies worldwide (Bai et al., 2008; Nkonya et al., 2011). Bai et al. (2008) detected that 80% of total land degradation is located in humid areas, and nearly one-fifth (19%) of degrading land on a world scale is cropland.

People living in rural areas in particular depend on agricultural land, but often lack the capacity or information to improve the conditions of their land (von Braun & Gatzweiler 2013). Around 42% of 'very' poor[1] people live on degraded soils (Nachtergaele et al., 2010). In Kenya, for example, Bai and Dent (2006) found that around 40% of cropland is already affected by decreasing productivity trends. Compounding this problem, Muyanga & Jayne (2014) estimated that 40% of the rural population farms on 5% of the land, contributing in turn to the degradation problem by putting higher pressure on land resources.

Land degradation has many causes and consequences. Scientists attempt to chart these, and draw causal linkages, by measuring and interpreting a range of biophysical and socio-economic variables. Many studies limit measurement of biophysical aspects to soil and vegetation, such as vegetation trends or nutrient depletion in soil samples (Nicholson & Farrar, 1994; Bai et al., 2008; Dardel et al., 2014; Herrmann, Anyamba, & Tucker, 2005; de Jong et al., 2011). Even though ongoing research is beginning to consider the interplay among several biophysical and socio-economic variables, there is still an urgent need to develop an interdisciplinary framework which can be used to tackle the process of land degradation on global, regional and local scales (Vogt et al., 2011).

Here, we seek to address this gap in the literature about land-population dynamics. We offer an interdisciplinary analysis that combines socio-economic data collected from a panel of farm

[1] Poverty classifications are based on infant mortality rates (IMR) for the year 2000. See Nachtergaele et al. 2010 for further clarification.

households interviewed in four waves (2000, 2004, 2007, and 2010), data on biophysical preconditions based on remote sense imagery, and trends in land degradation in a Geographical Information System (GIS). Interlinkages refer to an approach to manage “sustainable development that seeks to promote greater connectivity between ecosystems and societal actions” (Malabed, 2001: 6; Graw, 2015). We explore the interlinkages of socio-economic factors, biophysical preconditions and land productivity by applying trend analysis and multivariate regression in a spatial environment. The time period covered by the two main data sources is the first decade of this century (2000-2010).

Our primary hypotheses explore the relationship between productivity trends of land referring to degrading land and 1) biophysical preconditions, 2) trigger events, 3) land tenure and 4) poverty. Although we cannot assert causality, where we find strong trend correlations between underlying biophysical factors and socio-economic factors, we can conclude that there is empirical evidence of a linkage, although it may be multi-directional. Besides pairwise correlation we assume that variables have a major impact on land productivity if they occur in combination with others. Testing of this hypothesis was conducted with 5) Ordinary Least Squares regression (OLS) by explaining variation of significant decreasing productivity trends with a set of socio-economic indicators.

While biophysical preconditions play a major role in land productivity, our second hypothesis reflects the notion that certain events can trigger conflict among different interest groups that place greater pressures on land. An example is Kajiado, a county in Southern Kenya, which experiences high rates of land degradation (Bai & Dent, 2006). Conflicts over use rights may reflect competition over land and water resources among populations with divergent objectives, such as herding, cultivation and wildlife/tourism (Campbell et al., 2000). A similar case can be found in Isiolo County, Kenya, where five different interest groups compete for land resources and ownership rights are clearly interpretable (Umar, 1997; Boye & Kaarhus, 2011). Decreasing productivity trends are in line with these conflicts in Isiolo as well as in Kajiado as productivity trend analysis show (Bai & Dent, 2006; Graw, 2015). In this study, we test for observable linkages between the global food price crisis in 2008 and the post-election crisis of 2007/8 and trends in land productivity.

The fact that insecure land tenure rights can lead to non-sustainable land management strategies and short-time exploitation of land resources has been widely documented (e.g., Barbier et al., 1997). In Kenya, Jayne & Muyanga (2012) report that 3% of the population controls 20% of arable land resources. They propose two explanations for this apparent paradox. One is that potentially arable land remains underutilized because of lack of public investment in the infrastructure needed for farmers to exploit it (thus, “land grabs”). A second explanation is the colonial settler history of countries like Kenya, where administrators differentiated “customary lands” from “state lands.” After independence, governments often allocated state lands to non-farming elites, to curry favor. They show that, over time, median farm sizes in Kenya have diminished for most famers, while large tracts of land remain unexploited. Elements of Kenya’s new constitution are intended to address this situation. Here, we test whether trends in land ownership, and in land fragmentation, are significantly linked to trends in land degradation.

So far, research has not demonstrated a clear link between poverty and land degradation (Lambin et al., 2001, Johnson, Mayrand, & Paquin, 2006). There is no question that poverty and land degradation interact, but their relationship seems to be more about the conditions of poverty, and how people cope with them, than income levels per se (Vosti & Reardon, 1997). Interlinkages between degrading lands and poverty also seem self-evident. However, in their case study of Uganda, Pender et al. (2004) recommend investigating the relationships among land degradation and variables such as household assets or income. Beyond poverty indices, we examine linkages of land degradation to additional socio-economic factors that underpin livelihoods in rural Kenya, such as fertilizer use on maize, farmland fragmentation, and household income sources.

Next, we describe the study area. Data and methods used are summarized in Section 3 and 4 while results are given in Section 5. Conclusions are drawn in the final section (6).

2. Study Area

The study area is western Kenya, and includes seven counties – Trans Nzoia, Bungoma, Uasin Gishu, Kakamega, Vihiga, Siaya and Kisumu (Figure 1). Lake Victoria is located in the South, and borders Kisumu, Vihiga and Siaya. Kenya is bordered on the west by Uganda. We chose this region for several reasons. First, western Kenya represents one of the grain baskets of the country (e.g., Kamau, Smale & Mutua. 2014). Maize production is highest especially in the northern counties of the area including Trans Nzoia and Bungoma. Second, according to the Intergovernmental Panel on Climate Change (IPCC) 2014, western Kenya is expected to be rather stable under certain climate change scenarios (Field et al., 2014, Figure 22-4), providing a study area for which current climate conditions are more likely to be representative.

Biophysical conditions in this area range from high to medium potential zones for maize production with a gradient from North to South which follows the topography.

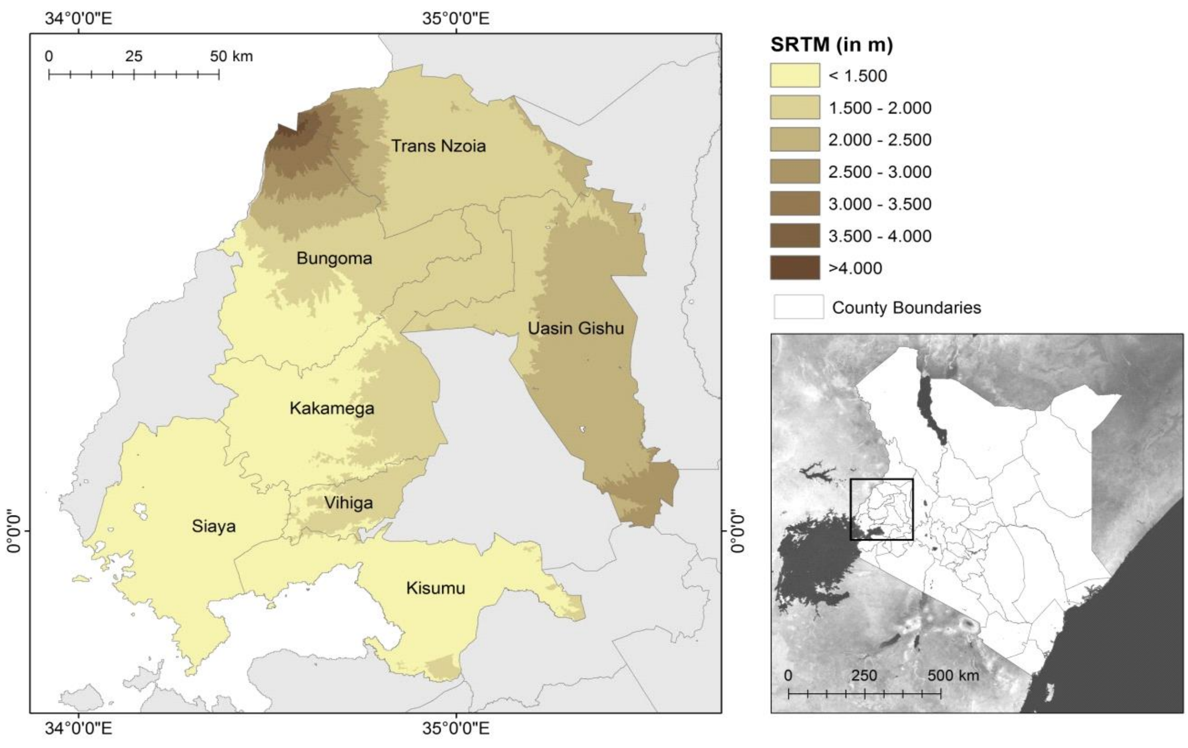


Figure 1: Study Area in western Kenya. The location within Kenya can be identified on the small overview map on the right.
Data source: Elevation data (SRTM) by CGIAR-CSI (http://srtm.csi.cgiar.org/), Cartography: Valerie Graw

The brown-shaded areas in Figure 1 are based on Shuttle Radar Topography Mission (SRTM)-data which gives information about surface elevation above sea level on 90-meter resolution. Altitudes from 900 to 1,500 m a.s.l. characterize the lowlands including the counties Kisumu, Siaya, western Kakamega and southern Bungoma. The high potential maize areas can be found in regions with higher than 2,000 m.a.s.l., including Trans Nzoia, Bungoma and Uasin Gishu (USAID & FEWS NET, 2011).

Maize constitutes the primary staple food in the study area and Kenya as a whole. Farmers depend on maize production for both consumption and cash, since maize is also sold on commercial markets and can be used to generate money to meet pressing needs such as school fees or health expenses. Agricultural production is undertaken throughout the year due to favorable climate conditions and continuous rainfall, especially in Trans Nzoia, Bungoma and Uasin Gishu. Income varies with regard to the agro-regional zones.

3. Data

The measurement of land productivity is based on earth observation information, particularly remote sensing data. Earth observation data are used to obtain information on land surfaces without being in situ. Especially data derived from satellites or aerial photography help to observe current and past conditions of the earth´s surface. Time series analysis moreover enables the observation of processes within a certain time span by analyzing images over the same area in different time frames. Depending on the sensor of the satellite a range of temporal and spatial resolutions to observe land surfaces including vegetation are available. Information on agricultural production can be derived from observation of vegetation development (Lewis, Rowland, & Nadeau, 1998; Grace, Husak & Bogle, 2014). Surfaces reflect and absorb light differently. This information is used to distinguish between different land cover types Analysis of trends in vegetation cover based on remote sensing methods is commonly used to assess increasing or decreasing productivity over time and draw conclusions regarding changes in soil conditions (e.g., Nkonya et al., 2011). Frequently, researchers conducting global and regional studies have employed indices to analyze vegetation trends (Nicholson, Tucker, & Ba, 1998; Tottrup & Rasmussen, 2004; Olsson, Eklundh, & Ardö, 2005; Hill et al., 2008).

The Normalized Difference Vegetation Index (NDVI) is the index most commonly used to assess land degradation, since it measures “greenness”, or the health and density of vegetation cover (Hurcom & Harrison, 1998; Tucker et al., 2005). Visible and near infrared light are used to calculate the NDVI by difference of near-infrared (NIR) and red (RED) light over their sum:

$$(1) \quad NDVI = \frac{NIR - RED}{NIR + RED}$$

[NIR= Near Infrared Light; RED= (Visible) Red light (Huete et al. 2002; Jiang et al. 2008)]

The values of the index originate in reflection and absorption of light by vegetation. Values range from -1 to 1. Considering equation 1, the greener and denser the vegetation, the higher the NDVI because more NIR can be reflected and more RED is absorbed by leaves of healthy vegetation. Unhealthy, brown and also very sparse vegetation is represented by a lower NDVI because more RED and less NIR is reflected.

The NDVI has several known drawbacks. First, spectral characteristics of the soil on which the respective vegetation is grown can influence NDVI values. Secondly, cloud cover in humid regions affect NDVI results due to interference of light flux. According to studies that were mostly conducted in tropical regions, the Enhanced Vegetation Index (EVI) performs better than the NDVI in areas with high biomass (Huete et al. 2002). Due to the incorporation of the blue band background information originating in the soil and also the effects of aerosols, such as occurs in cloudy areas are reduced in the EVI (Huete et al., 2002, Pettorelli et al., 2005). Since we expect cloud cover to be high in western Kenya due to high evaporation rates and biomass production, we chose the EVI for this analysis. The EVI is calculated according to:

$$(2)\ \ EVI = G * \frac{(NIR - RED)}{(NIR + C_1 * RED - C_2 * Blue + L)},$$

where C_1 and C_2 represent coefficients for aerosol resistance and *Blue* refers to the blue band in the satellite imagery. EVI includes a corrected aerosol impact in the RED. *L* represents the soil-adjustment factor and *G* a gain factor = 2.5 (Jiang et al. 2008).

Data on EVI was derived from MODIS Terra (MOD13A1), with a spatial resolution of 500 m and a biweekly temporal resolution with one image every 16 days. MODIS was launched in the year 2000, which limits longer time series analysis. Values range between -1 and +1 comparable with the NDVI. Very low and negative values refer to water, bare soil or ice while higher values refer to vegetation cover such as shrubland cover (0.2-0.3) or evergreen rainforest (0.6 to 0.8) (Weier & Herring, 2000). The higher the NDVI/EVI value the more dense and healthy the vegetation.

Biophysical data (Hypothesis 1) integrated for further analysis include: elevation data represented by Shuttle Radar Topography Mission (SRTM), data on potential evapotranspiration (PET); and an aridity index (AI). PET and AI data both refer to an annual average over the period 1950 to 2000 (Hijmans et al. 2005)[2]. Rainfall estimates (RFE) maintained by FEWS NET (Xie & Arkin, 1997) with 8 km resolution and decadal observations were furthermore included to assess biophysical preconditions or trends during the observed time span. It is noteworthy that RFE data and actual rainfall data collected in the study area and recorded in the Tegemeo database showed clear correlation. For the analysis also the total annual RFE (ΣRFE) was taken into account using the reference period 2001 to 2011 which is comparable with the ΣEVI data and again also covering the observation period of the household survey which we describe next.

[2] Data available via CGIAR-CSI (see: http://csi.cgiar.org/Aridity)

Information on trigger events (Hypothesis 2) was drawn from literature research and validated with socio-economic data of the panel-household survey mentioned in the following. To incorporate socio-economic factors into the analysis, including the calculation of the land tenure and land fragmentation (Hypothesis 3) and poverty indices (Hypothesis 4), we draw from panel data collected in personal interviews conducted by researchers at the Tegemeo Institute of Agricultural Development and Policy of Egerton University, in partnership with the Michigan State University. The sampling frame was originally prepared in consultation with the Kenya National Bureau of Statistics (KNBS) in 1997. KNBS used census data to identify all non-urban divisions in the country, and these were allocated to Agro-Ecological Zones (AEZ)[3]. Divisions were selected from each AEZ proportional to the size of population. The sample excluded large farms with over 50 acres and two pastoral areas, located in the north western and north eastern part of Kenya.

An initial survey was conducted in 1997, with a much more restricted survey instrument than those applied in later years. Later years include detailed modules about the changing demography of the household, agricultural production and marketing infrastructure, as well as complete information on farm and non-farm income sources and assets. The balanced panel collected in four waves (2000, 2004, 2007, 2010) consists of 1,200 maize-growing farm families living in 120 villages across 24 countries and 8 AEZ. For our analysis in western Kenya 41 villages with around 510 maize-growing families were taken into account. The 1997 data were not used because the survey instrument was not fully comparable for the parameters we analyze.

[3] Agro-Ecological Zones (AEZ) is a concept developed by FAO & IIASA classifying the globe into different zones depending on biophysical preconditions and length of growing period (see also: http://www.fao.org/nr/gaez/en/)

4. Methods

Productivity analysis was based on trend analysis of EVI data from MODIS with 500m resolution. The time period analyzed here covers the years 2001 to 2011, inclusive. The year 2000 was excluded from the trend analysis to avoid initiating a trend in a drought year. Moreover, the period from 2001 to 2011 encompasses the 10-year period of the panel survey data we utilize, matching the end-of-season time frame.

To operationalize the concept, among the 241 EVI datasets, the sum of annual EVI (ΣEVI) was calculated for each year from 2001 to 2011. Due to favorable climatic conditions, western Kenya is highly productive throughout the year with an up to 11-month cropping zone in the high-potential maize zones. The summation is preferred over the mean in such cases because it captures interannual variability (de Jong et al., 2011). The trend in the ΣEVI, which we refer to here as the "productivity trend," was calculated as the slope of a linear regression. By allocating each pixel to an individual point identifier, any additional information could be extracted and linked to the exact location of the pixel.

Household panel data are linked to village information in the dataset. As biophysical and socio-economic data are integrated in a GIS, the household information of the survey had to be linked to geospatial information. For each village, GPS-data was available so that households could be allocated to the respective village.

An important concept in this study refers to the "acting scope." This concept reflects the fact that the agricultural activities of household members typically extend beyond the confines represented by the GPS coordinates of the village. We defined an acting scope of a 10-km radius around each village, assuming that a farmer may walk this far to his or her fields in a day. Applying this procedure, out of 107 villages included in the household survey, 41 villages were integrated into the database of this study, all located in the seven counties of the study area in western Kenya. A total of 29,873 pixels were covered by all acting scopes of the villages. Water areas, including Lake Victoria, were masked in the analysis in order to avoid false alarms.

Significantly decreasing ΣEVI trends were observed between 2001 and 2011 ($p<0.05$). Pixel level data for productivity was scaled to match the acting scope of the village by calculating the share of area affected as the ratio of the number of pixels with significantly negative trend to the total number of pixels within each acting scope. The respective value represents the share of area (proportion) affected by significant negative trends. Figure 2 illustrates the calculation in abstract terms.

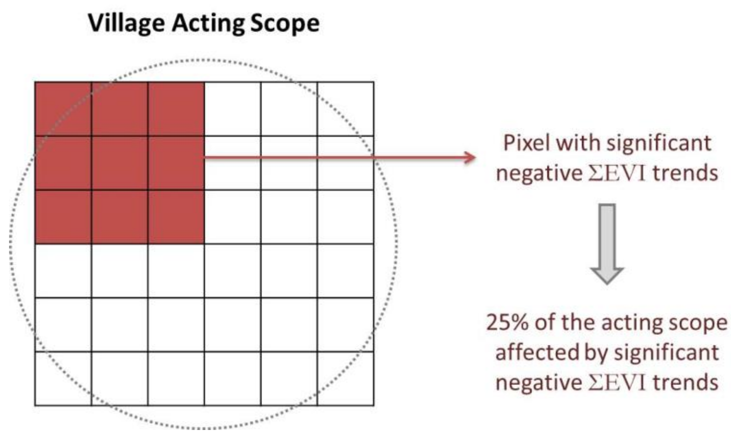


Figure 2: Visual representation of calculation of affected area within acting scopes

The same procedure was repeated for positive trends and "stable" conditions. "Stable" conditions refer to small changes between -0.05 and +0.05 ΣEVI between 2001 and 2011, assuming a natural variability of vegetation within the time period of the analysis. As the number of pixels with significantly positive trends (with $p<0.05$) was extremely small and did not vary much within the study area instead all positive trends with trend changes ΣEVI >0.05 were taken into account in the analysis. These included changes up to 0.7 ΣEVI value change between 2001 and 2011. For example, high positive trends can be found in the Mt. Elgon area located in the northwest of the study area.

Relevant socio-economic variables from the panel data were aggregated over households within villages and their respective acting scope.

Besides information on land tenure for every household we also looked into land fragmentation. Drawing from research on farm fragmentation (Blarel et al. 1992; Monchuk et al. 2010) we also test the Simpson index which is defined as

$$(3) \quad \text{Simpson Index} = 1\text{-} \left[\frac{\sum_f a_f^2}{(\sum_f a_f)^2}\right],$$

where a_f is the area per plot (fragment = f) The index ranges from 0 to 1 where zero means complete land consolidation and 1 high fragmentation . The Simpson Index is similar in construction to the Herfindahl index of industry concentration, which is measured in market shares, and has been used in the ecological literature to analyze the proportional abundance of species (Magurran 1998) and in analyses of crop or variety diversity on farms, where it is defined simply as unity minus the sum of squared area shares (Smale et al. 2006).

To test Hypothesis 4 regarding poverty, we began by constructing poverty indices based on the well-known Foster-Greer-Thorbecke (1984) index:

$$(4) \quad FGT_{\alpha} = (1/n)\sum_{i=1}^{h}\left(\frac{z-y_i}{z}\right)^{\alpha}$$

The parameter z is the poverty line, n is the number of people in the reference area (village, district, nation), h is the number of poor people (those with incomes at or below z), and y_i are individual incomes.

The FGT is parameterized by α. When α = 0, the formula is equal to h/n, which is the headcount ratio, or fraction of the population below the poverty line. When α = 1 it is interpreted as the poverty gap, or the amount of income it would take to raise people in poverty up to the poverty line. When α=2, the index is known as the severity of poverty. The poverty gap is more directly interpretable for policy purposes than is poverty severity. A simple headcount can also conceal important variation. Thus, we utilize all three versions of the index.

We followed the procedure employed by Mathenge, Smale and Olwande (2014) to calculate the index with the Tegemeo data. We estimated poverty lines for each survey year by adjusting the official rural poverty line for 2006 (established by the Government of Kenya at 1,562 Kenyan shillings (KES) per adult equivalent per month) with the Consumer Price Index. The resulting poverty lines, in nominal KES per capita per month, for the survey years were: 1,009 (2000), 1,336 (2004), 1,629 (2007), 2,144 (2010). Since these poverty lines are expressed in per adult equivalent terms per month, we also converted the annual household income into income per adult equivalents per month.

We drew additional variables from the panel data, including the total amount of fertilizer used on maize per ha and the number of fields per village to test hypotheses related to underlying determinants of poverty status. Since data points were linked to a certain village but fields of farmers could also be located in the acting scopes of the neighboring village, each acting scope was analyzed separately.

Finally, pairwise correlation among biophysical and socio-economic indicators was examined using STATA 13 and R. As it is rare for single indicators to have a major effect on land degradation when tested along, we also test for the possibility that certain livelihood structures (and multiple variables) lead to decreasing productivity. We conducted Multivariate Ordinary Least Squares (OLS) regression using Spatial Statistics in ArcGIS. In addition to the definition of the dependent variable and a set of explanatory variables the OLS-tool in ArcGIS provides the opportunity for specifying a minimum acceptable R^2 as a model requirement. Also, the variance inflation factor (VIF) can be decreased from a default setting of >7.5 to 5 to narrow down the likelihood of including redundant variables. Moreover, the minimum and maximum number of variables can be defined (Rosenshein, Scott, & Pratt, 2011).

The tool uses the following OLS regression equation (according to Rosenshein, Scott, & Pratt, 2011):

$$(5)\ y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \cdots \beta_n x_n + \varepsilon$$

Trends in productivity, represented by y, are explained by a number of explanatory variables $(x_1, \dots, x_n)$. The corresponding coefficients $(\beta_1, \dots., \beta_n)$ give information about the type of influence of the respective variable. The intercept is represented by β_0, the error by ε.

Summary statistics including the description of variables taken into account will be given in the results section.

5. Results and Discussion

Figure 3 gives a visual depiction of the study area showing ΣEVI trends from 2001 to 2011 and all 41 village acting scopes. The northern part of the study area is classified as the high-potential zone for maize production (yellow dots) while the middle and southern part of the study area—beginning in Kakamega and southern Bungoma—are described as areas with relatively less potential for maize production (orange squares). The household survey differentiates only these two classes of maize productivity.

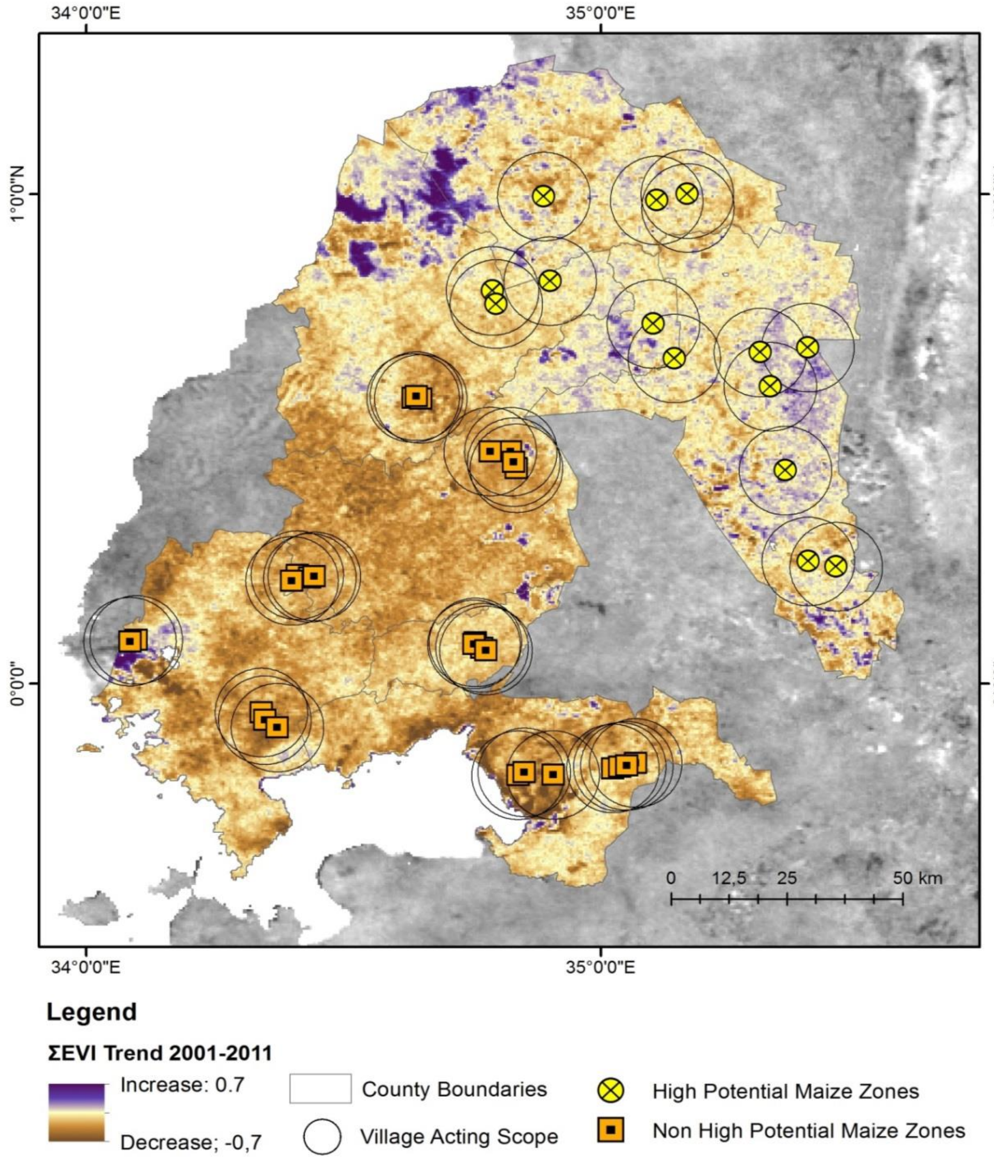


Figure 3: ΣEVI Trend from 2001 to 2011 with village GPS locations and acting scopes of the respective villages. The yellow dots show high potential maize areas the orange squares all other agro-regional zones. Cartography: Valerie Graw

i. Biophysical Preconditions

Initially, pixel-wise correlation within all 41 acting scopes was made among the biophysical variables to obtain insights about the preconditions of productivity in western Kenya. Negative correlations were found overall for SRTM and RFE (-0.66), which may express greater production potential for rainfed agriculture in lower-lying areas due to higher rainfall. A positive correlation of 0.47 was found for SRTM and ΣEVI trends from 2001-2011, suggesting that the highlands have higher productivity. Expected positive correlations were found between ΣEVI and AI and ΣEVI and ΣRFE. As rainfall represents the most limiting determinant for vegetation growth, a close relationship between vegetation and rainfall was expected (Nicholson, Tucker, & Ba, 1998; Davenport & Nicholson, 1993; Nicholson & Farrar, 1994). But a correlation between these two variables, ΣEVI and ΣRFE, computed on an annual basis of the village scale – by aggregating all pixel within the acting scopes per year – revealed an outlier in 2009. In 2009, correlations were not as homogenous as in each of the other years. Figure 4 shows a sharp decrease in ΣEVI during 2009, relative to other years in the time period covered by the data (2001 to 2011).

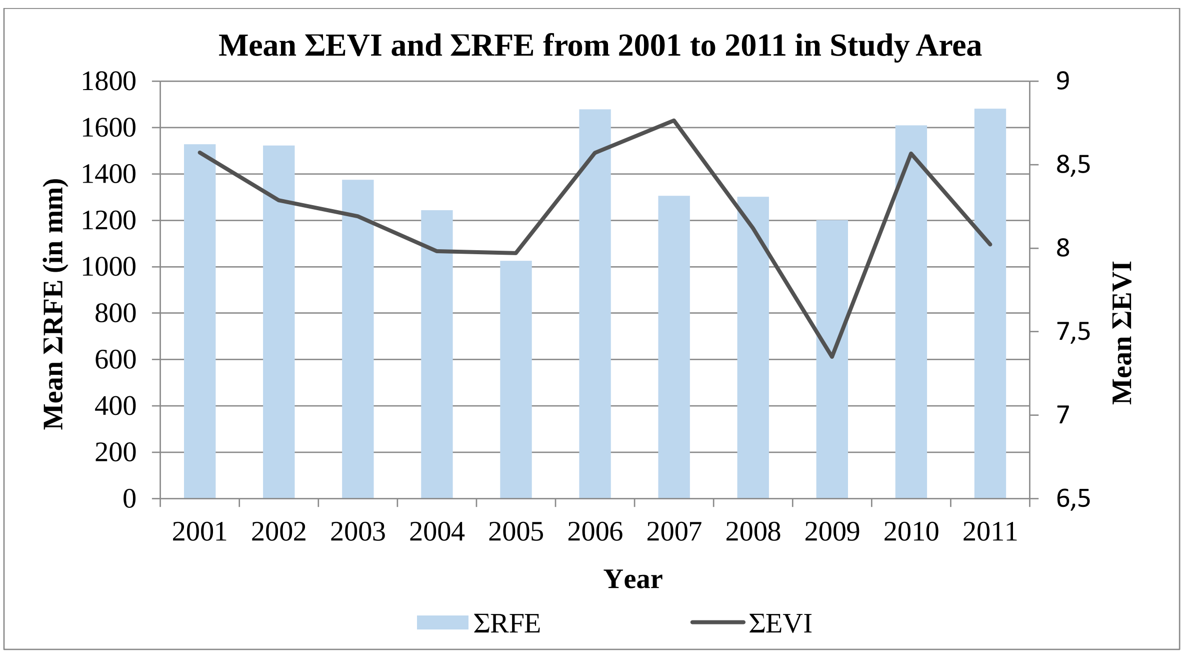


Figure 4: Mean ΣEVI and ΣRFE among all acting scopes between 2001 and 2011. RFEs are depicted as bars, EVI in lines. Data Sources: MODIS EVI 500m resolution, RFE by FEWS NET with 8km resolution

Decreasing rainfall trends are observed between 2006 and 2009. In general, these would also contribute to decreasing ΣEVI values. However, the sharp decrease in 2009 as seen in Figure 4 cannot be explained by rainfall trends alone. Insights into other factors are needed. Downward rainfall trends between 2003 and 2005 were also greater than the decreasing ΣRFE trends from 2006 to 2009, underscoring this result. Moreover, western Kenya is reported to be drought-prone and food secure (USAID & FEWS NET, 2011). The post-election crisis, combined with the global food price crisis, which took place in 2007/2008 and 2008, respectively, represent possible ‘trigger’ events for land degradation. Trigger events and other influential possible variables on productivity will be discussed in the following.

ii. Trigger Events: Post-election Violence and Global Food Price Crisis

The global food price crisis in 2008 and the post-election crisis experienced by Kenyans in 2007/2008 can be identified as trigger events that may have had a sudden, negative impact on productivity and economic development in western Kenya. Because fertilizer is energy-intensive, and energy prices contributed to the global food price crisis, fertilizer prices also rose sharply (Figure 5). Prices were negatively correlated with decreasing productivity, implying that the higher the prices, the greater the observed loss in productivity.

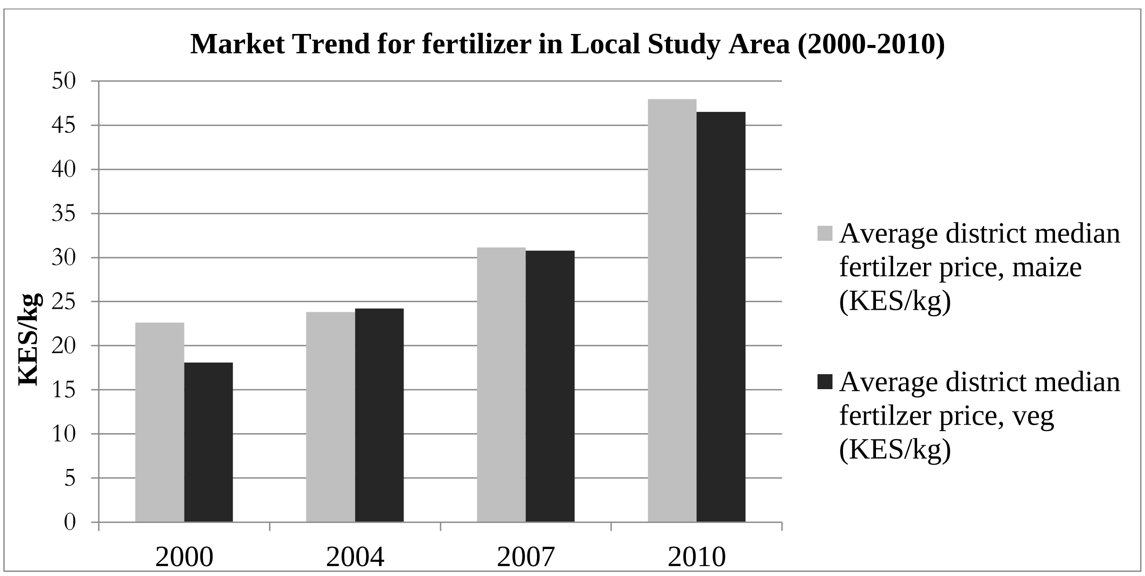
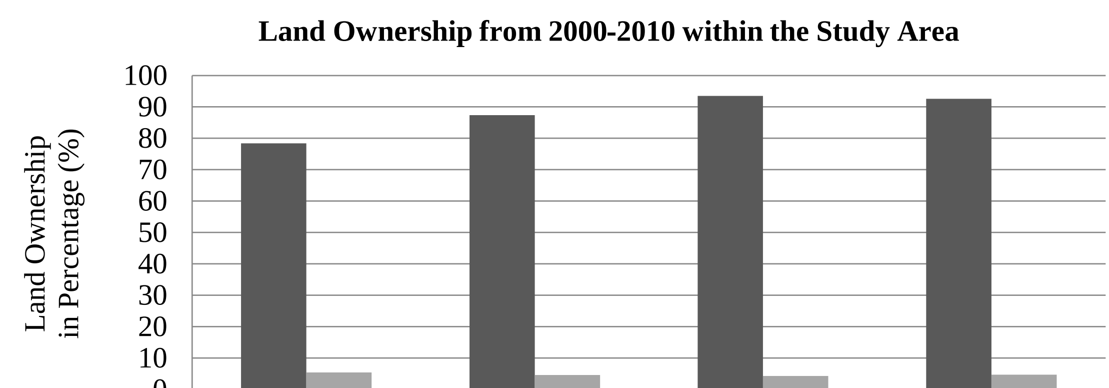


Figure 5: District fertilizer price of maize and vegetables based on the Tegemeo Survey data from 2000 to 2010.

Other researchers have reported that the post-election crisis, which began toward the end of 2007, had strong effects on productivity in maize-growing areas of central and western Kenya, and the area around Lake Victoria (Kriegler & Waki, 2012; Gibson & Long, 2009). Aside from deaths, an estimated 0.5 million people lost their homes (Gibson & Long, 2009). Blocked roads and violence disrupted transportation and access to markets (Dupas & Robinson, 2012). Political instability affects planting and input use decisions (Kriegler & Waki, 2009), crop management during the growing cycle, livelihood choices and stewardship of the environment (Raleigh & Urdal, 2007; Collier, 2008; Graw & Husmann, 2014).

iii. Land Tenure

Kamau, Smale, & Mutua (2014) found a positive and significant relationship between use of inorganic fertilizer and renting land when analyzing a different data set collected in several counties of western and central Kenya. Thus, we expected a positive correlation between trends in land ownership and decreasing productivity. We hypothesize that sustainable farming strategies are more likely to be found when land is owned while renting-in land usually focuses on maximizing production in a short time.



	2000	2004	2007	2010
Own	78,36	87,34	93,55	92,59
Rent	5,45	4,63	4,25	4,65

Figure 6: Percentage of households having own or rented land among all households within the study area.

Figure 6 shows the pattern in land ownership from 2000 to 2010. More households' farm on owned than rented fields. The trend in the percentages of fields owned is positive despite a slight decrease from 2007 to 2010, but is obviously statistically insignificant. Suggesting that owning land is a contributing factor to productivity, the lower the percentage of households owning land in the study area, the higher are the rates of decreasing productivity that could be observed.

With regard to ownership rates among the AEZ we observe an increase of 21.51% from 2000 to 2007 in the western highlands, while from 2007 to 2010, land ownership decreased in the western lowlands (-6.54%) as well as in the high potential maize-growing zones (-2.77%) by small magnitudes. As expected, land ownership, other assets, access to credit and income are positively interrelated. Typically, land ownership facilitates access to credit, transport and farm equipment. Although no credit has generally been provided specifically for maize production in Kenya (the Kilimo Biashara program is a notable counterexample), more land and assets qualify farmers for a range of other types of formal and informal credit, releasing cash constraints and enabling them to invest in farm productivity.

A prominent feature of farming in Kenya is that farm sizes shrink with growing populations as households subdivide their land for the next generation (Muyanga & Jayne, 2014). The mean population density in Kenya in 2010 was 411person/km². Correlations between the average number of fields, vegetation trends and stable conditions did not reveal clear results. But we observed a slightly positive correlation for the number of fields per village with decreasing productivity trends (0.42*), and a negative correlation of field numbers per village with increasing productivity (0.40*) and stable conditions (0.52*) between 2000 to 2010. There was no discernible difference in the results when comparing

As land ownership did not present significant results we tested for land fragmentation within the study area based on information on number and size of fields within the villages. Table 1 shows the correlation results of land fragmentation, represented by the Simpson and Shannon Index as defined in section 4, with productivity. For both indices the mean values – based on the total observation period – and trends – referring to the trend from 2000 to 2010 based on the household survey data were calculated.

Table 1: Correlation between land fragmentation (represented by Simpson Index) and productivity trends.

	Productivity Trends			
	Significant Negative ΣEVI Trend Pixel	Negative ΣEVI Trend Pixel with values <-0.05	Positive ΣEVI Trend Pixel with values>0.05	Stable ΣEVI Trend Values (-0.05 – 0.05)
Simpson Index Trend	-0,4556*	-0,5573*	0,5272*	0,6726*
Simpson Index Mean	-0,4415*	-0,6007*	0,5715*	0,7048*

*significant correlations with $p < 0.05$

By linking these to productivity trends we could observe overall significant correlations. According to the Simpson Index and its results when correlating it to productivity trends we can state that the lower the consolidation of land (the greater the fragmentation) the less negative productivity trends occur and the more stable trends can be observed.

iv. Poverty

There is no clear consensus about whether land degradation and poverty are causally related (Nkonya et al., 2013). While some studies assume a clear link between those two problems (Tiffen et al., 1994), others refute a close relationship (Lambin et al, 2001; Johnson, Mayrand, & Paquin, 2006). Wantchekon and Stanig (2015) found that in Africa the poorest regions mainly have better soil quality than wealthier regions. Moreover, infrastructure seems to be related stating that areas with worse road infrastructure have higher land fertility.

Correlating the mean poverty headcount ratio for the period 2000 to 2010 for each village with productivity trends showed a significant positive correlation (0.34*) with decreasing productivity trends and significant negative correlations with positive trends (-0.33*) and stable conditions (-0.41*). Poverty headcount trends from 2000 to 2010 showed a positive correlation with decreasing trends (0.29) and negative correlations for increasing trends (-0.29) and stable conditions (-0.24). For our study area in western Kenya, our analysis demonstrates an obvious relationship between productivity and poverty.

Table 2: Correlation between poverty indices and productivity trends.

	Productivity Trends			
	Significant Negative ΣEVI Trend Pixel	Negative ΣEVI Trend Pixel with values <-0.05	Positive ΣEVI Trend Pixel with values>0.05	Stable ΣEVI Trend Values (-0.05 – 0.05)
poverty headcount ratio	0.163	0.345*	-0.330*	-0.415*
poverty gap	0.113	0.286	-0.271	-0.361*
poverty severity	0.079	0.250	-0.237	-0.319*

*significant correlations with p < 0.05

Poverty gap and poverty severity also show a slightly positive correlation with decreasing productivity, while relating negatively to increasing and stable conditions. Correlation results are presented in Table 2. Separating the study area into high potential and other maize-growing regions, correlation coefficients were similar except for the poverty-productivity correlations, which were higher in the high potential maize-growing areas. To explore more fully the relationship between poverty and productivity, we took into account share of income and non/off-farm income to get deeper insights.

v. Income Shares and Off-farm Income

Rural households in Sub-Saharan Africa pursue complex livelihood strategies that include diversification of income sources, investing in a range of sources that do not covary with crop income (Bryceson, 2002; Djurfeldt & Djurfeldt, 2014). Literature has documented the growing share of nonfarm income in household earnings (Davis et al. 2009), and recent research has examined the relationship of nonfarm income source to maize intensification, including use of hybrid seed and fertilizer in Kenya (Mathenge et al., 2015a, b). Some literature has addressed the potential for nonfarm income to serve as a pathway out of poverty (Holden, Shiferaw & Pender, 2004), though it appears to be inconclusive.

Table 3: Correlation between Income Shares and Productivity

	Productivity Trends			
	Significant Negative ΣEVI Trend Pixel	Negative ΣEVI Trend Pixel with values <-0.05	Positive ΣEVI Trend Pixel with values>0.05	Stable ΣEVI Trend Values (-0.05 – 0.05)
Crop share trend	0.277	0.568*	-0.584*	-0.435*
Livestock share trend	-0.283	-0.535*	0.535*	0.497*
Business share trend	0.046	-0.203	0.218	0.110
Salary share trend	-0.282	-0.437*	0.453*	0.304
Agric. labor share trend	0.054	0.213	-0.213	-0.205

*significant correlations with $p < 0.05$

Table 3 shows correlations between trends in income shares by source and productivity. Income categories comprise crop income, livestock income, and off-farm income. Off-farm income sources include three subcategories: 1) salaries and remittances; 2) income from small-scale, informal business activities; and 3) income from agricultural labor on other farms.

Trends in crop income shares were positively correlated with decreasing trends in productivity (0.28), and negatively correlated with increasing trends and stable conditions (-0.58*; -0.44*).

These results are consistent with the notion that exploitation of ecological resources due to farming can result in more income from agriculture while simultaneously depressing productivity over the long run. By contrast, livestock income shares were significantly and negatively correlated with decreasing trends (-0.54*), exhibiting positive and significant correlations with rising productivity trends (0.53*) and stable conditions (0.49*). Clearly, livestock and crop income shares do not co-vary in the same direction in this agriculturally-based (as compared to range-based) production environment.

Similarly, there is a strong and significantly negative relationship between trends in income shares from salaries and remittances and declining vegetation. The magnitude of the coefficient is nearly as high as the coefficient on livestock income. However, the negative relationship between declining vegetation and business income shares is not statistically significant. In addition, the correlation between declining vegetation and wage income shares from working on other farms is positive, though statistically insignificant. This income share is small overall in the data, and this type of income is also relatively infrequent. When it occurs, we can hypothesize that there is a higher incidence of poverty and near-landlessness within at least a segment of the population, placing greater pressures on land resources.

vi. Accessibility

Accessibility is an important factor with regard to agricultural production especially when it comes to the need for seeds and fertilizer that can be obtained on the markets to assure a good harvest. A study on whole Kenya showed that among different socio-economic indicator groups of marginality – which represents lack of capabilities and possibilities that can lead to poverty (Gatzweiler & Baumüller, 2014) – access to information and infrastructure has the highest correlation with poverty rates (Graw, 2015). Besides accessibility other indicator groups were included such as health, education or economy.

To analyze accessibility in the study region a dataset created by Nelson (2000) on travel time to major cities was included in the analysis. Additional variables recorded in the Tegemeo survey data, such as distance to the next seller of fertilizer or certified maize, were also examined.

Considering the study area as a whole, we could not observe high correlations between trends in declining vegetation and variables measuring market access (by travel time to the next bigger city) or accessibility in general e.g. by having an own vehicle, having access to electricity or to information by having an own radio (see Table 4).

Table 4: Correlation between indicators of accessibility (to information and infrastructure) and productivity

	Productivity Trends			
	Significant Negative ΣEVI Trend Pixel	Negative ΣEVI Trend Pixel with values <-0.05	Positive ΣEVI Trend Pixel with values>0.05	Stable ΣEVI Trend Values (-0.05 – 0.05)
Distance Electricity Trend	-0.005	0.007	-0.021	0.050
Own Radio Trend	-0.173	-0.016	0.016	0.018
Own Vehicle Trend	-0.206	-0.445*	0.456*	0.343*
Travel time to city with 20,000 ppl.	0.059	0.266	-0.259	-0.303

*significant correlations with $p < 0.05$

When taking high potential and other maize-growing areas separately, correlations of land degradation with travel time to the next agglomeration of 20,000 inhabitants showed conflicting results. Thus, in the high potential zone, the greater the distance from a town of 20,000 inhabitants, the higher was the rate of productivity decline; in the lower potential area, the converse appeared to be true. We can deduce that accessibility seems to play a more important role in the high productive maize-growing areas where a surplus is produced. Fertilizer and seeds need to be planted in time to assure a good harvest, so that farmers using these inputs could also benefit by close proximity to the next market. These factors of accessibility might not play an as important role in the less productive areas where the primary objective of maize growers is to meet subsistence needs.

Other indicators of (market) accessibility, such as improved access to transportation over the ten year time period represented by the variable on vehicle ownership, distance to electricity, and ownership of radios, also generated differential outcomes by zone. While having a vehicle played a role in the high potential areas (a negative relationship with declining vegetation and a positive relationship for increasing trends and stable conditions), this factor had a negligible impact in other areas as correlation coefficients were not significantly different from zero.

In general, it might be the case that accessibility plays an unimportant role in the study area due to high population density and a dense road network. This conclusion can also be drawn from very low correlation coefficients for variables of accessibility except for those of owning a vehicle. The distance to the next market is never as great but differences between the two productivity zones are evident. These results are similar to those made by Okwi et al. (2007) who found no mentionable impact on production with regard to variables on accessibility in Nyanza Province which covers parts of the research area of this study, and to Chamberlin and Jayne (2009), for the major maize-growing areas of Kenya.

vii. Explaining Decreasing Productivity Trends with multiple variables

OLS regression analysis was included to test if there is a certain set of indicators which explains significant decreasing productivity trends. All variables used for the OLS regression are listed in Table 5.

Table 5: Summary Statistics of variables that were included in the OLS model.

Variable	Description	Mean	Min	Max	SD
	Dependent				
ΣEVI	Significant Negative Trends in ΣEVI (2001-2011)	15.42	0.00	45.72	14.58
	Explanatory				
Receive Credit	Households receiving credits	0.39	0.13	0.92	0.23
Own Radio	Households having an own radio (in %)	0.83	0.11	1.08	0.21
Own Vehicle	Households having an own vehicle (in %)	0.04	0.00	0.21	0.06
Mortality	Prime-Age mortality to an age range between 5-59 years	0.06	0.00	0.23	0.05
Elevation	Elevation in meters above sea level	1580.39	1146.02	2420.46	357.47
RainfallTrend	Rainfall Efficiency Trend (2001-2011)	12.66	2.42	28.09	6.39
FertilizerApplication	Amount of fertilizer applied in villages (kg/ha)	86.82	0.00	172.36	53.38

The model includes seven variables, all of which demonstrate significant coefficients and also robust probabilities which additionally highlight that all variables are statistically significant (Figure 7). Larger magnitudes of regression coefficients imply that the factor is more important in explaining variation in the negative trend.

Variables included in this model span multiple dimensions of livelihoods, including access to transport and information (the proportion of households in a village owing radios or vehicles), health status (the proportion of households in a village experiencing prime-age mortality[4] between survey periods), liquidity (rates of credit use per village), and use of productivity-enhancing inputs (total kgs of fertilizer applied to maize/total maize area per village).

The fitted regression shown in Figure 7 explains the variation of significantly negative productivity trends, based on trends of annual sum EVI as dependent variable.

Summary of OLS Results - Model Variables

Variable	Coefficient	StdErr	t	Probabil.	RobustSE	Robust_t	RobustPr	StdCoef	VIF
Receive Credit	-0.6459	0.1735	-3.7236	0.0007*	0.1392	-4.64005	0.00005*	-0.3269	1.3081
Own Radio	-0.7119	0.1767	-4.0286	0.0003*	0.1485	-4.79307	0.00003*	-0.3719	1.4467
Own Vehicle	-1.7438	0.7090	-2.4597	0.0193*	0.6147	-2.83679	0.00773*	-0.2138	1.2820
Mortality	0.8622	0.3579	2.4100	0.0217*	0.2699	3.19438	0.00308*	0.2166	1.3726
Elevation	-0.0364	0.0043	-8.3862	0*	0.0048	-7.53808	0*	-0.8842	1.8869
Rainfall Trend	1.4353	0.2224	6.4523	0*	0.1988	7.22123	0*	0.6285	1.6102
Total Fert.Maize	-0.2400	0.1590	-1.5096	0.1407*	0.0608	-3.94556	0.00039*	-0.1251	1.1651

OLS Diagnostics

Number of Observations	41	Akaike´s Information Criterion (AICc)	292,732,416
Multiple R-Squares	0.805555	Adjusted R-Squared	0.761309
Joint F-Statistic	19530523	Prob (>F), (7,33) degrees of freedom	0*
Joint Wald Statistic	191297225	Prob (>chi-squared), (7) degrees of freedom	0*
Koenker (BP) Statistic	5991222	Prob (>chi-squared), (7) degrees of freedom	0.540775
Jarque-Bera-Statistic	0.416191	Prob (>chi-squared), (2) degrees of freedom	0.812129

Figure 7: Report of the OLS model in ArcGIS 10.3[5]

[4] Prime-age mortality refers to an age range between 5 and 59 years (Chapoto, Kirimi, & Kadiyala, 2012)
[5] See also Rosenshein, Scott & Pratt (2011)

The signs of the coefficients on these variables are consistent with expectations. The lower the rate of credit access, the higher is the rate of productivity decline – liquidity enables households to diversify crops through special credit programs and also makes it easier for them to purchase inputs for maize. Similarly, the negative sign on the regression coefficient for fertilizer indicates that higher application rates to maize (on a village scale) over the 2000-2010 time period counteracted declining rates of productivity. Owning a radio provides access to range of information; vehicle ownership reduces the costs of reaching markets to either purchase inputs or sell products. Among these variables, those with the highest elasticity are, respectively: the proportion of households owning vehicles; the proportion of households owning radios; and the share of households having received credit. A 1% percentage point increase in total kgs of fertilizer applied per ha of maize in a village reduces the rate of productivity decline by 0.24% percentage points. In contrast to these, prime-age mortality relatives positively to land degradation, underscoring the crucial importance of health and labor constraints in combating productivity decline. When farm families lose adults in their prime, they lose knowledge and management experience in addition to labor and income-earning capacity, with long-term consequences.

With regard to the biophysical indicators, the results demonstrate clearly that the highlands are the more productive areas. The northern part of the study area, located in the highlands, is inhabited mostly by large scale farmers. In general analysis of rainfall trends need a longer time-series than only ten years to draw conclusions of extreme or long-term impact of rainfall (Easterling et al., 2000). Rainfall trends in this study were calculated by the mean sum over a ten year period. As vegetation quickly responds to precipitation a shorter period of rainfall data was nevertheless included even if showing a positive trend due to higher amounts of rainfall between 2006 and 2011 compared to the earlier years of the analysis. Therefore, although a negative sign on the rainfall elasticity was expected, the coefficient is positive and very large in magnitude.

Regarding model diagnostics, the mean VIF is 1.44 and since there is no VIF higher than 1.89, multicollinearity does not appear to influence results significantly. The OLS statistics suggest neither bias in model predictions due to non-stationarity nor inconsistency as a result of heteroskedasticity. Estimation of the same model in STATA 13 also generated the same results, supporting robustness of these findings.

The spatial autocorrelation for the fitted model and also many other models that were tested in the study area was significant, here with p=0.003, revealing a clustering of the villages based on the

OLS model. This validates the bisection of the area into high potential maize zones and other maize-growing zones.

Insights in the different possible OLS-models identified one model in the less potential areas that consists of only three variables, Elevation (SRTM (-)), aridity index (AI (+)) and Rainfall Trends (based on Rainfall Estimates from FEWSNET (+)), but explaining 83% of the variance of all significant decreasing trends in this area. Biophysical indicators may play a much more important role in the less productive areas where mostly small scale farmer cultivate maize while in the high potential maize regions rather indicators such as owning a vehicle, fertilizer use or accessibility in general (to information and infrastructure) have an impact on decreasing productivity trends and also contribute to stable conditions. In this part of the study area large scale farming is more common.

6. Conclusion

An interdisciplinary framework using remote sensing and GIS provides insights in the interlinkages of biophysical and socio-economic dynamics and their impact on land productivity change in western Kenya. While biophysical data was primarily based on remote sensing and GIS, socio-economic information was derived from a panel of household survey data collected by Tegemeo Institute of Agricultural Development and Policy and Michigan State University and embedded in a GIS. Both datasets covered a time period from 2001 to 2011, 2000 to 2010 respectively. In total 41 villages were included in the analysis. The purpose of the analysis was to identify which biophysical or socio-economic indicators are associated with land productivity trends in the study are. We tested hypotheses concerning single factors (biophysical preconditions, trigger events such as the global food price crisis or post-election violence, land tenure and fragmentation, and poverty), and a combination of factors in a multivariate regression. A common spatial scale had to be found in order to link the different data sources. Biophysical data was linked to the pixel-level while the households of the panel survey were spatially linked through village location based on GPS-coordinates. Therefore, acting scopes were created around each village with a radius of 10 km.

A pixel-wise analysis of rainfall and land productivity showed a sharp decrease in land productivity in 2009 which could not be explained by decreasing rainfall trends alone. Two trigger events could be identified that caused this drop in productivity: the global economic crisis in 2008 which lead to increasing prices (e.g., fertilizer prices), and the violence and insecurity that occurred during the election period in 2007/2008. These factors undoubtedly led to uncertainty in cropping decisions and impaired access to markets.

A close relationship was expected for land productivity and land ownership, but in western Kenya, a causal relationship could not be validated. This finding reflected the fact that the change in ownership of land over the time period of the study was not significant. A second indicator, the number of fields, was included to represent the pressure of rising populations on land as inheritance leads to fragmentation from one generation to the next. It could be underlined that with a higher number of fields and thereby higher pressure on the same area of land also decreasing productivity rates are occurring. The integration of the Simpson Index representing fragmentation of land additionally showed that the more land is fragmented the lower decreasing productivity trends could be observed.

The literature is ambivalent concerning the relationship of poverty and land degradation. Our analysis, which employed Foster-Greer-Thorbecke indices of poverty, demonstrates a correlation between declining trends in land productivity and higher rates of poverty as expressed by either headcounts or the severity of poverty per village in western Kenya.

Since we would rarely expect a single socio-economic variable to serve as a trigger for changes in rates of land degradation, we used OLS to examine correlations in a multivariate context. A best-fit model (explaining 80% of variation) included seven variables representing different dimensions of a livelihood, including mortality, credit receipt, radio ownership, vehicle ownership, and rates of fertilizer application to maize.

Using OLS to examine the role of key indicators in land productivity trends provides some policy insights concerning the weak components of a livelihood system in a certain area. For example, the strong positive relationship between prime-age mortality and decreasing land productivity underscores the fundamental link between health and family farm production. The contribution of fertilizer use in offsetting declining productivity is confirmed. Autocorrelation also shows a spatial clustering in western Kenya. While the northern part, which is classified as high potential for maize production, relies more on agricultural inputs such as seeds and fertilizer as well as access to markets and is dominated by large-scale farming, the southern part, mainly owned by small scale farmers, depends on favorable biophysical preconditions such as rainfall and topography.

Geospatial analysis of coupled human-natural systems helps to follow the interplay of biophysical and socio-economic indicators and thereby leads to a better understanding of spatial interlinkages while providing fruitful recommendation for further research. Studentized residuals as an output of the OLS regression tool which highlight possible missing indicators for the analysis can moreover provide information concerning areas in which further research is needed or which variables should be considered to improve a certain situation – in this case decreasing agricultural productivity.

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