Interlinkages of Land Degradation, Marginality and Land Use Cover Change in Kenya

Development of an interdisciplinary framework using remote sensing and GIS

Dissertation

zur

Erlangung des Doktorgrades (Dr. rer. nat.)

der

Mathematisch-Naturwissenschaftlichen Fakultät

der

Rheinischen Friedrich-Wilhelms-Universität Bonn

vorgelegt von

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aus Siegen

Bonn 2015

Angefertigt mit Genehmigung der Mathematisch-Naturwissenschaftlichen Fakultät
der Rheinischen Friedrich-Wilhelms-Universität Bonn

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Tag der Promotion: 03.06.2015

Erscheinungsjahr: 2015

Acknowledgments

First, I would like to thank my supervisor Prof. Dr. Gunter Menz who accompanied the whole process of this research. I especially thank him for the freedom he gave me to develop my own research interests which he always highly supported. I enjoyed all discussions on my work and very much appreciate his questions which often lead to new ideas and solutions. Among all I am very thankful that Prof. Dr. Menz encouraged me to do this PhD research and saw the potential of my ideas.

I would also like to thank Prof Dr. Chinwe Ifejika Speranza as my second supervisor. Discussing my approaches and the paths I took for my research were very interesting particularly due to her own experiences in Kenya.

With his economic background, my tutor Dr. Franz Gatzweiler sometimes came up with deep-rooted questions which helped me to change my perspective many times and let me gain insights into different disciplines. I thank him for his great support during my whole research which also included several inspiring coffee breaks.

For infrastructural support I want to thank the Center for Development Research (ZEF), the Center for Remote Sensing of Land Surfaces (ZFL) and the Remote Sensing Research Group (RSRG) of the University of Bonn.

Field research activities and conference attendance were furthermore possible due to financial support of the Fiat Panis Foundation which I highly appreciate.

I also thank the Tegemeo Institute for providing a very interesting household panel dataset. Without these data a detailed analysis on the local scale would not have been possible. Special thanks go to Prof. Dr. Melinda Smale and Dr. Ephraim Nkonya for bringing light in economic perspectives and supporting me during my research activities with great discussions. Moreover I would like to thank the International Food Policy Research Institute (IFPRI) and HarvestChoice in Washington DC, USA, for fruitful research stays. It always feels like coming home when entering the IFPRI hall. I thank the whole team in DC for all knowledge exchange and great talks. Special thanks go to Dr. Ephraim Nkonya and Dr. Carlo Azzarri for support on all research levels.

With regard to my field research in Kenya I want to thank my assistant George Okwaro, as well as Emily Obonyo and the Kenya Forest Research Institute (KEFRI) for supporting me during my field research with transport but also with local insight and translation during my field visits. Thanks also go to the Kenyan Agricultural Research Institute (KARI) in Nairobi and Kitale as well as ESRI Eastern Africa and the IHub in Nairobi. Among that I would like to thank my Kenyan friends and colleagues, in Kenya and abroad, for great advice and especially a warm welcome to Kenya with a lot of good and joyful experiences.

Words of thanks also have to go to my colleagues and friends, Johann Müller, Andreas Rienow, Esther Amler and my two brothers for proof reading and comments on my final draft. I am also grateful to Frank Thonfeld and Johannes Schultz but also my research peers at ZFL, ZEF and RSRG for good discussions during the whole time of my studies. For all the kind words of support especially during the final stage of my PhD the whole RSRG team has to be mentioned. I am thankful to be part of such a great research team.

Not only with regard to my research but for the support on all levels during the time my PhD research was conducted I want to say "Thank you" to Julia Schmitz, Christina Bleffert, Johann Müller, Linell Edwards, Oliver Bauer, Heike Baumüller, Shahnila Islam, Anna Schwachula, Sarah Kober and all friends and colleagues from ZEF, ZFL and RSRG.

Last but not least I want to thank my family: My parents, who gave me the possibility to realize my personal and future interests, supported me wherever possible, followed my walk (and run) with love and interest and never doubted my decisions. My brothers – Jan Adriaan and Frederik – for every advice they gave their little sister whether with regard to research and doing a PhD but most of all to life in general. I am grateful you followed my first steps (and falls) and never stopped accompanying me.

Finally I dedicate this thesis to my grandpa, Rogier Mestdagh, who taught me to always choose the positive path even when life gets rough. Thank you up there for teaching me the golden way!

Zusammenfassung

Land Degradation (LD) ist ein globales Problem, welches das sozio-ökologische System auf der globalen Skala beeinflusst und durch dieses beeinflusst wird. Die vorliegende Arbeit untersucht basierend auf Methoden der Fernerkundung und der Nutzung von geographischen Informationssystemen (GIS) das Zusammenspiel von LD, Marginalität und Landnutzungswandel (land use cover change (LUCC)) in Kenia. Die Entwicklung eines interdiszplinären Forschungsrahmens basiert auf einer Analyse, die auf zwei verschiedenen Skalen stattfindet: Die nationale Skala wird durch Kenia repräsentiert, während auf der lokalen Skala ein detaillierteres Gebiet im Westen Kenias untersucht wird. LD ist durch den Verlust von Bodenfruchtbarkeit charakterisiert und somit direkt mit der Produktivität des Bodens verbunden. Durch die Kombination von biophysikalischen und sozio-ökonomischen Daten kann ein tieferes Verständnis von internen Dynamiken generiert und vermittelt werden, welches inbesondere im Hinblick auf gekoppelte Mensch-Umwelt-Systeme (Human-Environment-System (HES)) von Bedeutung ist. Zusätzlich werden q-squared Methoden angewandt. Sie beschreiben den simultanen Einsatz von quantitativen und qualitativen Methoden und geben damit Einblicke in verschiedene Disziplinen der Landsystemforschung.

Marginalität wird als Grundursache für Armut definiert und ist somit eng mit der Messung dieser verbunden. Jedoch geht das Verständnis von Marginalität über die einfache Perspektive eines monetären Wertes hinaus. Angelehnt an die Initiative des Global Land Programmes (GLP), das in den 1990er Jahren etabliert wurde, bezieht sich auch die Untersuchung von LUCC auf interdisziplinäre Konzepte. Die Landbedeckung (land cover) bezieht sich auf die biophysikalischen Aspekte und kann mit Methoden der Fernerkundung analysiert werden. Auf der anderen Seite beinhaltet Landnutzung (land use) eine aktive Komponente und wird definiert als die Inwertsetzung des Landes durch menschliche Aktivitäten. Die Frage, wie Land bspw. durch Landwirtschaft genutzt wird, kann durch Einblicke in sozio-ökonomische Strukturen, hier insbesondere Informationen über landwirtschaftliche Aktivitäten, beantwortet werden.

Die nationale Studie in Kenia untersucht alle 47 Counties des Landes. Unter Einbezug von Zensusdaten sowie Haushaltsinformationen kann die sozio-ökonomische Perspektive abgebildet werden. Die Untersuchung der biophysikalischen Parameter, welche LD und LUCC repräsentieren, wird mit Hilfe von Fernerkundungsdaten durchgeführt. Eine Zeitreihenanalyse mit MODIS Normalized Difference Vegetation Index (NDVI) Daten mit einer räumlichen Auflösung von 500m wurde genutzt, um Produktivitätstrends in den Jahren 2001 bis 2011 zu berechnen. Bei der Untersuchung der Trends von LD und Armut in Kenia konnte festgestellt werden, dass es keinen signifikanten Zusammenhang zwischen diesen beiden Prozessen gibt. Neben einem gleichzeitigen Anstieg von Armut und der Verminderung von Produktivität in West-Kenia konnte ein genau gegenläufiger Zusammenhang dieser Prozesse im Nordwesten sowie im Süden des Landes festgestellt werden. Basierend auf fünf Indikatorengruppen wurden verschiedene Dimensionen von Marginalität wie Gesundheit, Bildung, Zugang zu Infrastruktur

und Information sowie Ökonomie untersucht. Indikatorengruppen, die Zugang zu Infrastruktur oder Information repräsentierten, zeigten eine höhere Korrelation mit Armut als jede andere Indikatorengruppe. Durch Exploratory Regression und Ordinary Least Square Regression (OLS) konnte schließlich ein Set von acht Indikatoren ermittelt werden, welches Produktivitätstrends erklärt. Hierzu zählen: Armutsrate, Bevölkerungsdichte, Prozentanteil der Bevölkerung mit Grundbildung, Prozentanteil der Bevölkerung, die höhere Bildung in Anspruch nimmt, Local Autority Transfer Funds (LATF), Prozentanteil der Haushalte mit Zugang zu einer Fernleitung, sowie der Prozentanteil der Bevölkerung, der Düngemittel einsetzt. Die Untersuchung bezog alle 47 Counties mit ein. Die Analyse von LUCC wurde ebenfalls mit Fernerkundungsdaten von MODIS Land Cover Produkt (MCD12Q1) mit einer räumlichen Auflösung von 500m und jährlicher Bereitstellung durchgeführt. Mit diesen Daten konnten Anbauflächen identifiziert werden, welche zwischen 2001 und 2011 von LD betroffen waren. Auf diese Weise wurde ein Untersuchungsgebiet mit Bezug zur Thematik der Ernährungssicherung für die lokale Studie ausgewählt, welches sieben Counties im Westen Kenias umfasst: Trans Nzoia, Bungoma, Uasin Gishu, Kakamega, Siaya, Vihiga und Kisumu.

Der Westen Kenias ist durch eine hohe landwirtschaftliche Produktivität gekennzeichnet. Insbesondere Mais wird in dieser Region angebaut. Geostatistische Ansätze, wie sie auch in der nationalen Studie verwendet wurden, wurden auch in der lokalen Studie eingesetzt. Sozio-ökonomische Daten basieren hier auf Haushaltsinformationen und wurden vom Tegemeo Institut in vier Zeitabschnitten erhoben: 2000, 2004, 2007 und 2010. Durch die Verknüpfung der Haushaltsdaten mit den GPS-Lokationen der jeweiligen Dörfer konnten Haushaltsdynamiken in Aktionsradien von 10km um das jeweilige Dorf in Hinblick auf LD-Trends analyisert werden. Da in Gebieten mit hoher Biomasseproduktion NDVI Daten schlechtere Ergebnisse lieferten als der Enhanced Vegetation Index (EVI) wurde letzterer für die lokale Studie gewählt. Vegetationstrends wurden aus der jährlichen Summe des EVI berechnet. Begünstigt durch stabile Niederschläge und klimatische Grundvoraussetzungen wird Landwirtschaft das ganze Jahr hindurch in dieser Region betrieben. Insgesamt wurden 42 Dörfer in der lokalen Studie untersucht. Bei der Analyse von negativen Produktivitätstrends wurden ebenfalls qualitative Informationen hinzugezogen, um explizit stark negative Trends im Jahr 2009 genauer zu untersuchen. Die Unruhen in Kenia nach den Wahlen 2007 und 2008, sowie die Weltwirtschaftskrise im Jahr 2008 hatten einen signifikanten Einfluss auf die Nahrungsmittelproduktion in dieser Region, der nicht allein durch verringerte Niederschläge in diesem Zeitraum zu erklären ist. Darüber hinaus ließ sich durch räumliche Autokorrelation eine bipolare Raumstruktur in der lokalen Studie feststellen. Im nördlichen Teil liegen die hochproduktiven Maiszonen (HPMZ), während weiter südlich die weniger produktiven Maiszonen (nHPMZ) lokalisiert sind. Beide weisen unterschiedlich erklärende Variablen für sinkende Produktivität auf. Während die Produktivität in HPMZ eher durch Faktoren wie Zugang zu Transport und Information gesteuert wird, begründet sich diese in nHPMZ eher durch biophysikalische Voraussetzungen wie bspw. Niederschlag und Topographie.

Insgesamt haben sowohl die nationale als auch die lokale Studie gezeigt, dass Variablen, die sinkende und stabile Produktivitätstrends auf der jeweiligen Skala beeinflussen, in einer engen Beziehung zueinander stehen. Demgegenüber werden steigende Produktivitätstrends von anderen Variablen beeinflusst, die nicht notwendigerweise mit LD in Verbindung stehen. Mit Bezug auf das Konzept der LD Neutralität (land degradation neutrality) wird die Untersuchung von stabilen Trends für die zukünftige Forschung in den Fokus gesetzt. Die Identifizierung von beeinflussenden biophysikalischen und sozio-ökonomischen Variablen auf Produktivitätstrends trägt zu einem besseren Verständnis von gekoppelten HES bei und hilft Anknüpfungspunkte für politische Interventionen zu finden. Der interdisziplinäre Ansatz dieses Forschungsprojektes ist wegweisend für die Entwicklung von Strategien zur Ernährungssicherung auf politischer Ebene. Durch eine Validierung der Ergebnisse auf der jeweiligen räumlichen Ebene können Gebiete identifiziert werden, in welchen Handlungsbedarf erforderlich ist, um weitere Produktivitätsminderung zu verhindern und letztendlich Produktivität zu stabilisieren.

Abstract

Land degradation (LD) is a global problem affecting and being affected by socio-ecological systems. This thesis analyses the interlinkages of LD, marginality and land use cover change (LUCC) in Kenya based on remote sensing and geographic information systems (GIS). An interdisciplinary framework is developed using two different scales – a national scale looking at the country of Kenya and a local scale analyzing a specific area in western Kenya. LD stands for the decrease of soil fertility and, hence, land productivity. By combining biophysical and socio-economic data we obtain a deeper understanding of internal dynamics and their relationship to processes of decreasing productivity within a coupled Human-Environment System (HES). In addition q-squared methods are used which describe the simultaneous use of quantitative and qualitative methods and thereby support insights in different disciplines.

Marginality is defined as the root cause of poverty but goes beyond the solely economic perspective of poverty measurement. LUCC, based on the Global Land Programme (GLP) initiative started in the 1990s, represents another interdisciplinary concept. On the one hand land cover (LC) refers to the land surface and its biophysical determinants which can be detected with remote sensing. On the other hand land use (LU) includes an active component referring to activities on land by human impact. The question how land is e.g. used by agricultural production can be approached by gaining insight in socio-economic structures, especially via information on agricultural activities.

The national study on Kenya focuses on all 47 counties of the county. Insight in the socio-economic perspective was given with census data and household survey information while biophysical assessment on LD and LUCC was conducted via remote sensing imagery. Time series analysis of vegetation, using MODIS Normalized Difference Vegetation Index (NDVI) Terra (MOD13A1) with 500m resolution was included to analyze trends of land productivity from 2001 to 2011. Analyzing trends of LD and poverty in Kenya showed no significant relationship between both processes. While a simultaneous increase of poverty and decrease of productivity was observed in western Kenya, an exact reverse interplay was identified in northwestern and southern Kenya. Based on five indicator groups different dimensions of marginality such as health, education, access to infrastructure and information but also economy could be analyzed. Indicator groups that represent accessibility to infrastructure or information showed significant higher correlation with poverty than any other indicator groups. Finally a set of eight indicators could be detected that explains decreasing productivity trends with the use of exploratory regression and ordinary least square regression (OLS). This includes: poverty rates, population density, percent of population with basic literacy, percent of the population attending higher education, local authority transfer funds (LATF), households with access to a landline, and rates of any fertilizer use. The analysis included data from all 47 counties of Kenya. Analysis of LUCC was also based on remote sensing using MODIS Land Cover Product (MCD12Q1)

also with a spatial resolution of 500m. With this dataset croplands could be detected that were affected by LD. Based on these seven counties in western Kenya were identified also with regard to food security aspects: Trans Nzoia, Bungoma, Uasin Gishu, Kakamega, Siaya, Vihiga and Kisumu.

Western Kenya is characterized by high cropland productivity and represents the grain basket of the country. It is also the area where most of the maize production within the country takes place. The local analysis used the same geostatistical approach as for the national study but refined the methods using more accurate data. Socio-economic information was derived from a household panel survey collected in four waves (2000, 2004, 2007 and 2010) provided by the Tegemeo Institute. Besides demographic data also information on agricultural input is collected on the household level and can be linked to the GPS-location of the respective villages.

Additionally also LD analysis was refined. For the local study MODIS Enhanced Vegetation Index (EVI) with 500m resolution was chosen as this index is reported to perform better compared to the NDVI in areas with high biomass production. Due to favorable preconditions, such as stable rainfall, crop production here takes place throughout the whole year. In total, 42 villages were analyzed with regard to their acting scope which each covered an area of 10km around each village. Explaining decreasing productivity trends on the local level made obvious that also qualitative information is needed to validate and interpret results correctly. For example trigger events such as the post-election violence in 2007 and 2008, and the world economy crisis in 2008 had a significant impact on decreasing productivity trends in 2009 in the local study area. Therefore, the decrease of productivity could not solely be explained by decreasing rainfall within those years. Moreover, bisection within the study area was identified by spatial autocorrelation that classified the area in high-potential maize zones (HPMZ) in the northern part and non-high potential maize zones (nHPMZ) in the southern part. Using exploratory regression and OLS showed that decreasing productivity in the HPMZ is influenced by indicators such as accessibility to transport and information compared to the nHPMZ, where productivity trends rely more on biophysical preconditions such as rainfall and topography.

Taken together, the national and the local study both showed that variables explaining decreasing and stable productivity trends are in close relationship while increasing productivity is influenced by a different set of variables. Therefore, with regard to the concept of land degradation neutrality stable productivity trends need to be taken into account for future research. Identification of biophysical and socio-economic variables influencing productivity trends helps to get a better understanding of coupled HES. This supports the finding of starting points for political intervention. The interdisciplinary approach of this study is path leading for the development of food security strategies. Validation of the here presented results on the respective spatial scale can be used to identify areas where a need for action is required to stop ongoing productivity decrease and finally stabilize yields.

Content

Abbreviations

AEZ	Agro-Ecological Zones
AI	Aridity Index
ASAL	arid and semi-arid lands
AVHRR	Advanced Very High Resolution Radiometer
CBS	Central Bureau of Statistics
CGIAR	Consultative Group on International Agricultural Research
CGIAR CSI	CGIAR Consortium for Spatial Information
CIESIN	Center for International Earth Science Information Network
ESA	Europaen Space Agency
ESRI	Environmental System Research Institute
EVI	Enhanced Vegetation Index
FAO	Food And Agriculture Organization
FEWSNET	Famine Early Warning System
GIS	Geographic Information System
GLC	Global Land Cover
GLCF	Global Land Cover Facility
GoK	Government of Kenya
HES	Human-Environment System
GPS	Global Positioning System
HHID	Household ID
HPMZ	High Potential Maize Zone
IFAD	International Fund for Agricultural Development
IFPRI	International Food Policy Research Institute
ICSU	International Council for Science
IGBP	International Geosphere-Biosphere Programme
IHDP	International Human Dimensions Program on Environmental Change
IPCC	Intergovernmental Panel on Climate Change
KIHBS	Kenya Integrated Household Based Survey
KNBS	Kenya National Bureau of Statistics
LD	Land Degradation
LDN	Land Degradation Neutrality
LI	Land Improvement
LUCC	Land Use Cover Change
MEA	Millennium Ecosystem Assessment
MERIS	Medium Resolution Imaging Spectrometer
MoA	Ministry of Agriculture
MODIS	Moderate Resolution Imaging Spectoradiometer
MPI	Multidimensional poverty index
NDVI	Normalized Difference Vegetation Index
nHPMZ	non-High Potential Maize Zone
NIR	near-infrared light
NOAA	National Oceanic and Atmospheric Administration
NPP	Net Primary Production
OLS	Ordinary Least Square
PET	Potential Evapotranspiration

R	R Project for Statistical Computing/Software Language
RED	red light
RESTREND	Residual Trend of Sum NDVI
RFE	Rainfall Estimates
RUE	Rain use efficiency
SAE	Small Area Estimation
SAVI	Soil adjusted Vegetation Index
SD	Standard Deviation
SDG	Sustainable Development Goal
SEDAC	Socioeconomic Data and Applications Center
SLA	Sustainable Livelihood Approach
SLM	Sustainable Land Management
SRTM	Shuttle Radar Topography Mission
SSA	Sub-Saharan Africa
STATA	Data Analysis and Statistical Software
UMD	University of Maryland
UN	United Nations
UNCCD	United Nations Convention to Combat Desertification
UNEP	United National Environmental Programme
VIF	Variance Inflation Factor
WB	World Bank
WDR	World Development Report
WRI	World Resource Insitute

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I. Introduction

Land is used and shaped ever since by human activity. Until today, environmental change and thereby also the degradation of land shows an obvious link between natural processes and human activities. Coupled Human-Environmental Systems (HES) are influenced by multiple processes while none of them is only biophysical or solely socio-economic. In this thesis the interplay of environmental and socio-economic problems is addressed by an interdisciplinary framework leading to a substantial understanding of crucial processes such as land degradation (LD). Also livelihoods that directly depend on degrading lands and livelihood structures that can have an impact on environmental systems need to be addressed simultaneously.

Globally, it is questioned how we can feed the expected 9 billion people by 2050 (The Economist, 2011). With regard to ongoing LD processes this question becomes even more crucial. The answer to this relies on the understanding of internal dynamics that lead to LD but also of those factors that create respective feedback loops. This complex system – represented by the crucial triangle in this study – has to be targeted in ongoing and future research. In the 1990s the project Land Use Cover Change, abbreviated LUCC, was implemented by the International Human Dimensions Programme on Global Environmental Change (IHDP) and the International Geosphere-Biosphere Programme (IGBP) which set a milestone for a growing need of interdisciplinary research on land use and land cover aspects (Lambin et al. 2006). The Global Land Project (GLP) followed the LUCC-project and was established in 2006. Again an increasing need for research on socio-ecological systems was underlined by focusing on the effects of human activities on land and their feedback loops on the Earth System (GLP, 2005). Within the GLP also the aspect of vulnerability and fragile socio-ecological systems, is addressed which can be referred directly to LD processes (Turner, Lambin, & Reenberg, 2007). With regard to the 10-year international research initiative "Future Earth" coordinated by the International Council for Science (ICSU) (Griggs et al., 2013) this thesis evolves interdisciplinary methods and approaches to analyze coupled HES on different scales. Interlinkages represent a "strategic approach to managing sustainable development that seeks to promote greater connectivity between ecosystems and social actions" (Malabed, 2001: 6). This connectivity is addressed in the following analysis.

LD refers to the diminishing of soil productivity over time and affects biophysical and socio-economic systems in equal measure. The process of LD does not stick to administrative boundaries while taking place in all agro-climatic zones worldwide. Around 54% of the global population live in urban areas while the other half is located in rural areas and directly depend on agriculture (UN, 2014a, IFAD, 2010). Among the rural population, moreover 70% of the world´s very poor live on less than $1.25 a day. Also about 42% of the very poor live on degraded land which threatens their livelihoods (IFAD, 2010, Nachtergaele et al., 2010). An increasing population aggravates the problem by the need to produce more food in a shorter period of time.

While competition for land is becoming more intense agriculture has to put more focus on intensification rather than on extensification of land (Smith et al., 2010). Simultaneously socio-ecological systems undergo high pressure with regard to land use activities. Land cover and land use structures in the framework of LUCC therefore are analyzed in this thesis. But also analysis of livelihoods that depend on lands which are affected by decreasing productivity and their internal socio-economic dynamics is necessary to understand the full cycle.

Within this research the interplay of biophysical and socio-economic dynamics leading to LD and therewith decreasing agricultural productivity by accounting for feedback loops will be analyzed with the example of Kenya in a national study and western Kenya in a local study.

With the example of both studies – the national and the local study – the following research questions are addressed:

- Poverty and land degradation: is there a link in Kenya?
- If marginality is defined as being the root cause of poverty do variables that indicate marginality necessarily cause poverty and thereby land degradation?
- Which variables trigger degrading processes of land including decreasing productivity of vegetation?
    - Does a standard set of variables help to predict land degradation?
    - Do certain dimensions of marginality have more impact than others?
- How important is the spatial scale for modeling relationships of biophysical and socio-economic dynamics?

Five main parts structure this thesis. Besides introductory information, a theoretical framework will be followed by the national study on Kenya and a local study in western Kenya where major findings for biophysical and socio-economic data analysis with interdisciplinary research is conducted. Key research questions to address and focus areas of the studies are depicted in Figure I.1.

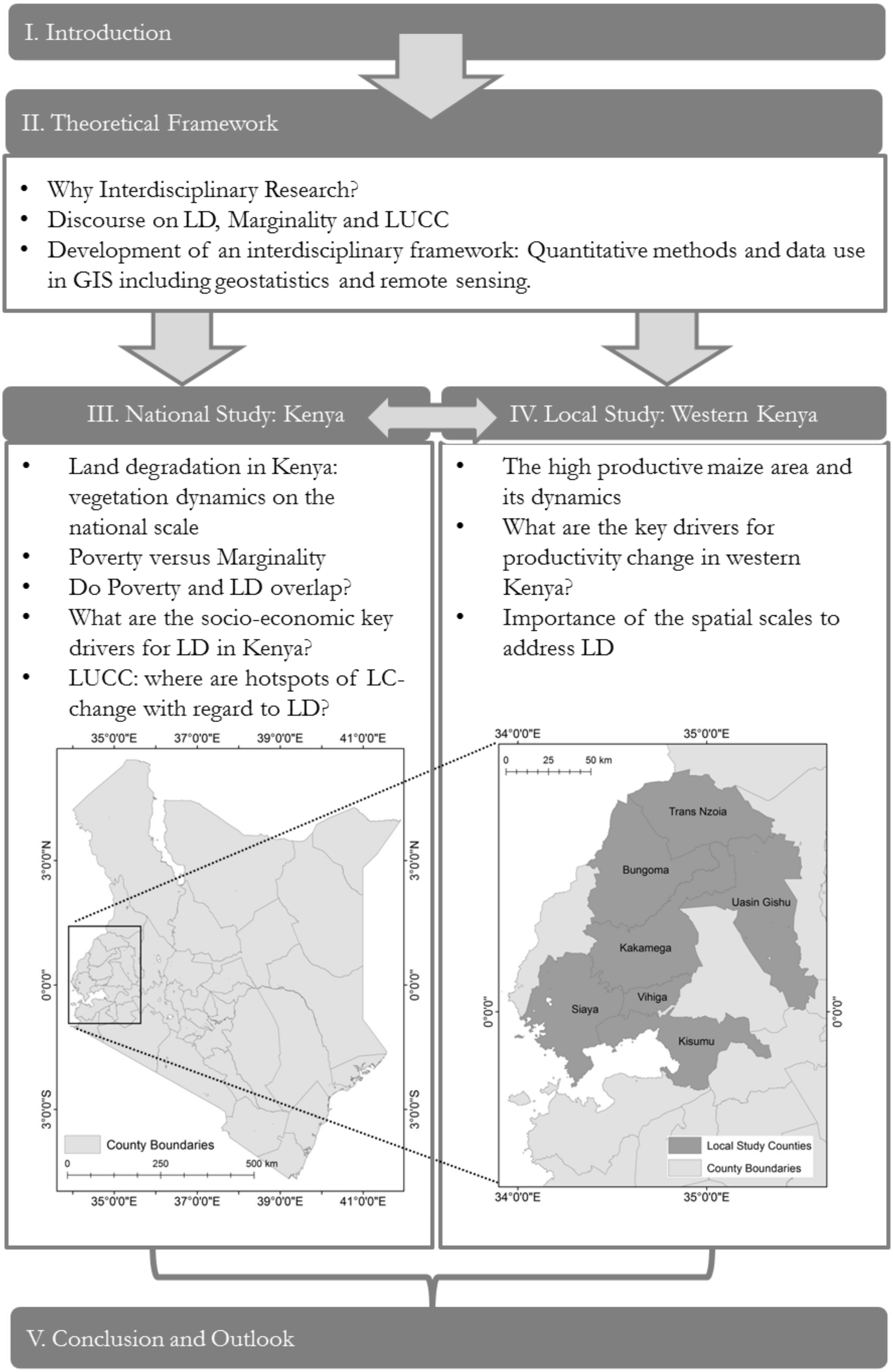


Figure I.1: Structure of the thesis.

Chapter II represents the interdisciplinary framework including a discourse on the main topics of this thesis and the development of an interdisciplinary framework in a Geographic Information System (GIS).

Interdisciplinary research is required for the understanding of environmental change. Knowing that the global system connects human activities and natural processes on different scales even strengthen the need for such approaches. People that act and depend on a single pixel of land must therefore become visible by linking socio-economic data, mainly based on administrative information, to the biophysical setting of an area, which can be analyzed on a pixel-level via remote sensing.

Remote sensing represents an outstanding tool to observe LUCC and therefore also environmental change. The ability to frequently monitor changes of the land surface due to a high temporal resolution of a sensor is one of its main advantages. Additionally, high spatial resolution with regard to the pixel size of an image is of further advantage compared to socio-economic data which are mostly depending on administrative units. A pixel refers to the addressed unit of remote sensing data which in this study mostly covers an area with a pixel-size of 500m x 500m. Socio-economic data, mainly obtained from national surveys such as the Census or household surveys cover usually bigger administrative areas such as districts or counties. This is also the case in Kenya. Moreover they are ordinarily limited to a certain point in time when data were collected.

Chapter II.1 deals with the "socializing of the pixel"[1] and the need for q-squared methods that refer to the combined use of quantitative and qualitative research. Chapter II.2 provides an overview about ongoing concepts and research of the three main topics LD, marginality - describing the root causes that may lead to poverty – and LUCC. Previous and current research developments will be discussed. The development of the interdisciplinary framework for the ongoing analysis will be introduced in chapter II.3. It provides insights in how biophysical and socio-economic aspects are addressed in the context of coupled socio-ecological systems with a focus on degrading lands. This also includes the use of different data types and formats in the analysis, such as remote sensing for biophysical assessment of LD (chapter II.3.1) and LUCC (chapter II.3.3), and socio-economic data collection from census and household surveys (chapter II.3.2).

The national study on Kenya (chapter III) deals with linkages of LD, marginality and LUCC in the interplay on the national level. In Kenya 40% of the total rural population farms on 5% of available land (Muyanga & Jayne, 2014). Thereby high pressure is put on existing land use systems, agricultural land in particular. LD analysis is based on time series analysis of the Normalized Difference Vegetation Index (NDVI) derived from remote sensing imagery. Besides trend analysis, also long-term dynamics are assessed such as the identification of variability

[1] The term "socializing the pixel" was based on the book chapter by Geoghegan et al. (1998).

hotspots (chapter III.2.1). The focus is on human-induced LD by correcting vegetation trends for rainfall. The analysis of the socio-economic component, represented by marginality, is based on the collection of census and household survey data (chapter III.2.2). Relationships of marginality and poverty are analyzed in addition to a national observation if poverty and land degradation in Kenya overlap. Interlinkages of biophysical and socio-economic variables to explain degrading trends on the administrative level of the county are analyzed with exploratory regression and ordinary least squares regression (OLS). In total, all 47 counties in Kenya are addressed in the national study. LUCC analysis (chapter III.2.3) is finally conducted to identify those areas where most changes take place. These links are further on linked to LD and land improvement (LI) based on the previous LD assessment. With regard to LUCC analysis a focus is on food security to identify the study area for the local level analysis. Hotspots of degrading croplands in particular will be identified which lead to western Kenya for further in-depth analysis.

The local study will be elaborated in chapter IV. Research is conducted in western Kenya, one of Kenya´s grain baskets. Here, a refined approach of LD assessment and socio-economic data analysis compared to the national study is applied. Research is conducted on the village level including 42 villages and their acting scopes around each village in seven counties of western Kenya (chapter IV.2). A panel household survey in four waves between 2000 and 2010 helps to deepen the analysis of socio-economic dynamics. One of the key aspects addressed in this chapter is qualitative data in addition to quantitative data which is here represented by remote sensing and household survey data. Trigger events in the region had enormous effects on productivity trends which cannot be answered with quantitative analysis exclusively (chapter IV.3.1). In order to explain decreasing productivity trends (chapter IV.3.2) the local study reveals bisection within the initial study area. This requires more in depth analysis even within the local scale highlighting different levels of productivity zones (chapter IV.3.3). Within this chapter analysis conducted on different spatial scales is an important aspect and needs to be addressed carefully.

This study goes beyond the scope of focusing on only single indicators of socio-economic data such as population densities or poverty rates to get into the internal dynamics of the process of human-induced LD. It is aimed at integrating diverse indicators that shape livelihoods such as health or education. The socio-economic setting of a livelihood plays a major role when it comes to LD or LI. There is a high need to understand the potential and gaps within livelihood structures and how a certain group of people act on land also from a qualitative data perspective. Moreover, these indicators can be influenced by addressing them in policy and research recommendation for identified areas. The interdisciplinary framework presented here will be path leading for future research on HES.

II. Theoretical Framework: Coupled Human-Environment Systems

"The status of land and the interactions of different factors can be understood only by carrying out multi-disciplinary land degradation assessment" (Nachtergaele & Licona-Manzur, 2008: 328)

Interdisciplinary research which addresses a problem from different perspectives by getting insights in different research approaches and methods is needed to get a full understanding of coupled HES (chapter II.1).

The discourse in chapter II.2 will give an overview on previous and ongoing concepts and research addressing each vertex of the so-called crucial triangle which will be expressed at the beginning of the chapter followed by a basic understanding of each of the vertices: LD, marginality and LUCC.

The interdisciplinary framework will be introduced in chapter II.3. All basic methodological and data-driven approaches on each of the determinants of the triangle that will be addressed throughout the thesis are given here.

1. What, Why, How? An Overview

One of the crucial processes affecting livelihoods globally is LD which describes the decrease of soil productivity and therewith also food production. How can we feed the expected 9 billion people by 2050? This question is steadily raised and a clear answer is not yet given (Tilman et al., 2001; UN, 2004; Godfray et al., 2010; The Economist, 2011). While describing a process that is caused by biophysical and socio-economic determinants feedback loops are crucial and strengthen the need for an interdisciplinary assessment. LD does not stick to borders and takes place in all agro-climatic zones worldwide (Bai et al., 2008; Nkonya, 2011; de Jong et al., 2011b). While research to identify regions affected by and at risk of LD (Grepperud 1996; Symeonakis & Drake, 2004) or analysis of temporal scales of LD (de Jong et al., 2011a; Ouedraogo et al., 2014) is still ongoing there is an increasing need to identify the impact of multiple indicators that trigger LD in a combined way (Vogt et al., 2011).

Several attempts have been made to include socio-economic indicators in LD analysis and modeling by including e.g. population growth (Grepperud, 1996; Ramankutty, Foley, & Olejniczak, 2002), poverty (Barbier et al., 1997; Duraiappah, 1998) or economy (Nkonya et al., 2011) as impact and outcome factors. Obviously a growing population will need more space and food. But this variable will not be changeable by simple policy recommendations. Poverty and economy – both are somehow interlinked depending on the definition of poverty[1] – are important and especially market situations and global economies play key roles and motivate for action. Global markets and environmental systems are therefore also closely interlinked. Nevertheless a focus merely on economy neglects other important impact factors.

[1] See also chapter II.2.2.

Most studies on LD include biophysical spatial assessment to first give a picture on where in the region LD takes place. Second mentioned then are socio-economic impacts that affect these processes in addition to either difficult biophysical preconditions or climate events such as heavy rainfall events or droughts. More insights are needed to understand the actual dynamics and the impact of livelihood structures on a system. It is aimed at finding the gaps and potential of socio-economic structures on different scales – from local to regional and global scales.

Even if interdisciplinary research is increasingly conducted most of it still neglects the complexity of many different indicators in the interplay.

1.1 Interdisciplinary Research

As stated by Addison, Hulme, and Kanbur (2010) – with regard to poverty measurements – but also by Vogt et al. (2011) – addressing LD assessment – research across different disciplines in general is required. Whether addressing LD, poverty, or marginality, they all force the need for interdisciplinary analysis by measuring those processes cross-disciplinary as well as with q-squared methods (Vogt et al., 2011, Addison, Hulme, & Kanbur, 2009). Q-squared methods refer to the integration of combining quantitative and qualitative methods, former mainly used by the term "mixed methods".

Interdisciplinary research helps to address different aspects such as (Klein, 1990, 11):

- to answer complex questions
- to address broad issues
- to explore disciplinary and professional relations
- to solve problems that are beyond the scope of any one discipline
- to achieve unity of knowledge, whether on a limited or grand scale

All objectives mentioned here apply for LD assessment, poverty/marginality and LUCC. LD is a complex process influenced by a wide range of impact factors including socio-economic livelihood structures. It is a contextual broad issue whether in spatial or temporal scales as degrading soils affect all climate zones and agro-ecological systems worldwide (Warren, 2002, Nkonya et al., 2011). LD and poverty affect multiple disciplines and vice versa. Beside biophysical effects and outcomes, social effects trigger economic effects. Insights in and from different disciplines are necessary to get a deeper understanding of processes and create new knowledge to maintain healthy soils in the future and reverse a self-catalytic spiral[2]. When addressing LD processes from different vertices it helps to get the full picture and to find the crucial determinants that impact environmental change on different scales.

When analyzing biophysical aspects or socio-economic behavior, quantitative data are predominantly needed. But qualitative data are also necessary to validate quantitative data and to

[2] The term of the "catalytic spiral" was used by Le Houérou (1996) to describe the process of LD as it includes a lot of different causes and consequences that impact each other.

finally identify the real impact of certain factors as some impact variables as e.g. on social behavior cannot be measured quantitatively. Combining the "strength of different disciplines and methods" helps to "produce deeper understandings" (Addison, Hulme, & Kanbur 2009: viii). Moreover does the use of mixed methods – remote sensing, GIS, census and household data as well as qualitative information by farmers during field visits, which are all used in this study – have potential scientific value to study population-environment interaction (Codjoe, 2007).

Nevertheless interdisciplinary research can have drawbacks. Addressing a problem from many disciplines at once means a lot of data handling simultaneously which includes different data types but also data referring to different spatial resolutions. Moreover in-depth knowledge about research in each discipline is highly recommended.

1.2 Operational Level: Socializing the Pixel

Research is depending on available and accurate data. Remote Sensing tends to be used mainly for biophysical purposes. Here, especially optical data which give "only" a reflection about what covers the earth surface on the pixel-level is taken into account. Using satellite imagery is also reported to enable detailed surface analysis over time due to frequent observations depending on the respective sensor while socio-economic data with regard to the conducted surveys only allow insights in a given situation – e.g. every decade as the case for census data (Mesev, 2008). But remote sensing itself is also broadly interdisciplinary (Fox et al., 2003) as it is not only used for biophysical analysis such as vegetation cover observation or land cover change (Lambin & Ehrlich, 1997; Wessels et al., 2004; Bai et al., 2008; de Jong, 2010), but also taken into account for a wide range of socio-economic studies such as urban sprawl or estimation of population (Miller & Small, 2003; Mesev, 2008; Rienow, Stenger, & Menz, 2014).

Difficulties arise when a common level, where biophysical and socio-economic variables can be linked, has to be found. Besides matching time frames pixel-data also have to be linked to a certain socio-economic level as those data are mostly based on administrative units whether a district, county, or village-level. The spatial resolution therefore also plays a key role. If studies talk about only a "few pixel" being affected in a certain area the spatial resolution and thereby the size of the pixel is much more important. Within and "on" a single pixel of land many people can be located who depend on this single pixel of land to make their living, especially in rural areas. By linking pixel-level information on biophysical impact to livelihood structures based on household survey information and census data will help to make socio-economic structures on a pixel more visible.

2. Interlinkages: Land Degradation, Marginality and Land Use Land Cover Change

Interlinkages refer to the strong link between "environment and development challenges" which are "interlinked across thematic, institutional and geographic boundaries through social and environmental processes" (Habiba, Chambers, & Baste, 2007:362).

LD can cause poverty and vice versa. But both processes are highly complex, hard to predict and to mitigate, and need to be viewed from different perspectives. Therefore an interdisciplinary framework for the understanding of LD processes by combining biophysical and socio-economic data is necessary. This study focuses especially on two of the biggest challenges of nowadays HES: Marginality/poverty and LD where land use and land cover change (LULC) is closely linked and cannot be neglected especially with regard to LD.

Assessment of LD and poverty is a well-known topic rising awareness world-wide. Working in development research and in developing countries forces the scientific community in this field to come up with a stable and multidimensional approach to find the most poor and deprived, and aiming at improving their situation. Nowadays it became obvious that the global population is part of a highly dynamic socio-ecological system where biophysical and socio-economic processes are linked and depend on each other. While interdisciplinary research is still one of the main targets in development research most studies focus on one discipline, e.g. soil science, remote sensing or social sciences This study tackles the problem of LD in an interdisciplinary framework. Figure II.1 shows the crucial triangle with each addressed topic at one vertex.

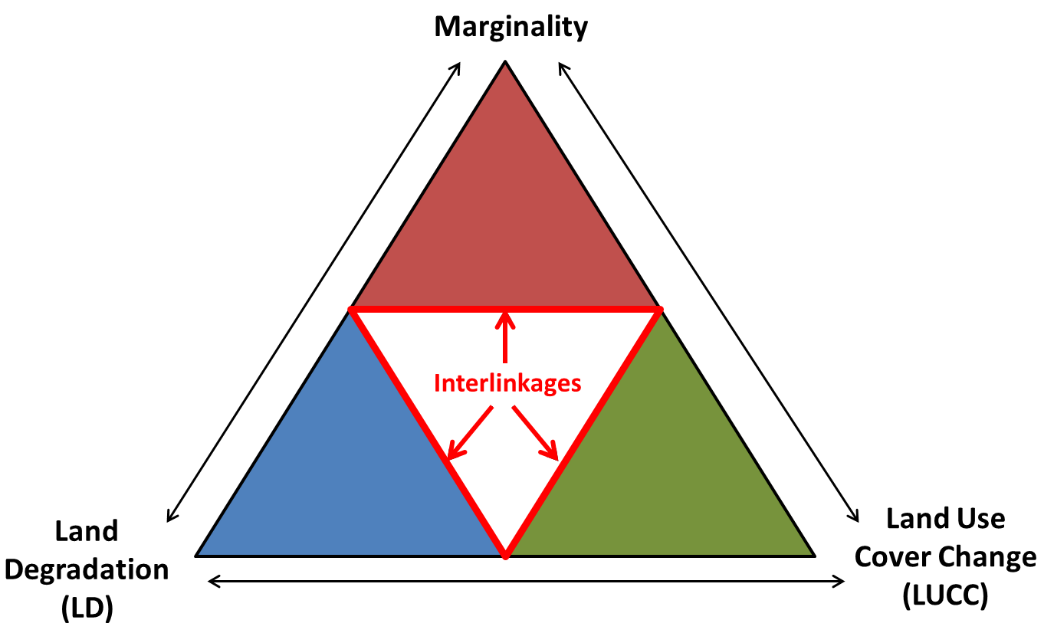


Figure II.1: The crucial triangle. Interlinkages of Marginality, Land Degradation and Land Use Cover Change.

Marginality, defined as the root cause of poverty (see also chapter II.2.2), represents the human and thereby socio-economic vertex while LD described the biophysical process of productivity decrease. LUCC is important for information on land used by livelihoods and is needed for further explanation and validation of LD processes. If land or soil conditions change, or if an area is cultivated differently might create false alarms when monitoring LD based on vegetation change.

As mentioned there is still an ongoing debate whether LD and poverty are interlinked. As marginality goes beyond the mere economic concept of poverty by including different characteristics of livelihoods addressing different potential capitals a link between LD and marginality is therefore expressed in more detail.

Human behavior, which is shaped by livelihood characteristics, influences how land is used and thereby how the surface of land is covered. Among several interest groups land is used differently referring to agriculture, livestock herding, pastoralism or even hunting. All these factors impact LUCC which then can also lead and indicate LD. But even within one single land use class land management strategies can have a different impact on the soil and trigger LD. This could be the case for the non-adequate use of agricultural innovations such as hybrid seeds and fertilizer. If those innovations are not adapted to the current soil conditions or used incorrect they might lead to decreasing instead of increasing yields. Among that marginality and poverty also impact those processes. Small scale farmers might have different strategies and especially possibilities to cultivate their land compared to large scale farmers. Large scale farming is often taking place on commercial farms with a focus on increasing yields and thereby income in the shortest time possible while having capital to afford agricultural input. Small scale farmer mainly farm subsistence-based and mostly have low income and possibilities to afford agricultural assets.

There is a requirement to get a better understanding of the relationship between human behavior and environmental change which includes LUCC and LD. This study does not put a focus on what comes first, whether LD intake or human impact. It is an obvious understanding that feedback loops are present. By establishing better conditions in one of both processes automatic improvement of the other process sets in (Duraiappah, 1998). If a disturbance in a system occurs a new equilibrium needs to be found whether better or worse. If we improve one of the variables we can aim at improving the system by creating better equilibriums (Behnke & Scoones, 1993).

Naturally occurring processes and risks such as droughts, rainfall variability or even natural degradation processes should further on not be neglected and will also be included in the study.

The following discourse on each of the three corners of the triangle will provide more insights into the basic concepts of this thesis. As research in each of the topics is manifold and steadily increasing it was aimed at providing an insight on the main concepts for the analysis of this study.

2.1. Land Degradation

LD is a global problem. Describing a crucial and dynamic process of soil productivity loss (Lal, Blum, Valentin, & Stewart, 1997; Reynolds et al., 2007; Bai et al., 2008) LD is affecting agro-ecological systems worldwide. According to Bai et al. (2008) 20% of cultivated areas, 30% of forests and 10% of grasslands are nowadays undergoing degradation on a global scale.

LD is addressed by different interest groups including – besides a wide field of researcher – especially policy makers trying to understand the process and its dynamics on different temporal and spatial scales to further control decreasing yields and secure food availability in the future. "Land degradation neutrality" (LDN), referring to a stabilization of the LD process, has become an emerging topic (Grainger, 2015). In the past, a focus was laid mainly on increasing food security and thereby "reverse" or avoid LD (MEA, 2005). Today, a more sustainable and realistic view is upcoming with a focus to stop the ongoing degrading processes, maintaining actual soil fertility and to not lose more productive land. In this regard LDN was established at the UN Conference on Sustainable Development (Rio+20) in 2012 and recently included in the "Sustainable Development Goals" (SDG). According to the Open Working Group final report on the sustainable development goals, Goal 15.3 aims at striving to achieve a land-degradation-neutral world by 2020 (UN, 2014b).

As LD is a very diverse process, which cannot be unified for all socio-ecological systems, approaches and assessment methods are steadily improving and the need for research is still present. Influenced by many different factors and with regard to the time frame since when LD was recognized a brief overview on the discussions of this crucial topic will be given here.

2.1.1 The jungle of definitions

A definition helps to tackle a problem. Especially for research, it is necessary to have a common understanding of a problem or process. With regard to LD definitions are steadily expanding to include as many impact variables and outcome factors as possible.

Besides the term "land degradation" other terms used are "desertification", "soil degradation", "vegetation degradation" "man-made desert", "desert encroachment" or "environmental degradation" (Barrow, 1991; Darkoh, 1998; Le Houérou, 1996; Reynolds et al., 2007; Verstraete, 1986). Definitions on LD are manifold and still changing according to new upcoming findings and impact factors. But all definitions comprise the embedding of human impact and human behavior as impact factors for degrading processes.

The term "desertification" was first mentioned by Aubreville in 1949 who defined it as the spreading of the deserts into arid and semi-arid regions (Verstraete, 1986; Dregne, 1986). The term is still used since then but was especially established and recognized during and after the drought periods of the Sahel in the 1970s and 80s. LD in "arid, semi-arid and dry sub-humid regions" that results from "various factors including climatic variations and human activities" is described via the term "desertification" as defined by UNCCD (1994: 4). But as mentioned LD itself occurs in all agro-climatic zones, a fact that is well-known due to cross-scaled research.

First seen as global-scale environmental problem LD, desertification respectively, was focused at the United National Conference on Desertification in Nairobi in 1977 (Meadows & Hoffman, 2002).

With regard to a recognized global problem according to the UNCCD LD is therefore now defined as:

> *"[…] reduction or loss of the biological and economic productivity and complexity of terrestrial ecosystems, including soils, vegetation, other biota, and the ecological, biogeochemical, and hydrological processes that operate therein"* (Sivakumar & Stefanski 2007: 106).

This broad definition already shows the multiple impacts and outcomes of LD. But even if the socio-economic component is added by "economic productivity" human behavior and consequences on social livelihoods are not directly addressed and go far beyond that.

LD as such is nowadays highlighted in the IPCC, the Kyoto protocol on global climate change, as central challenge to achieve the Millennium Development Goals (MDGs) and in National Action Plans (NAPs) of countries worldwide. According to the MDG 7 "principles of sustainable development into country policies and programmes and reverse the loss of environmental resources" should be integrated in current actions to sustain development (Lal, Safriel, & Boer, 2012, 12). Moreover LD is addressed in the latest discussion on the SDGs as mentioned.

Within this thesis a combined definition by UNCCD (1994) and Safriel and Adeel (2005)[3] is chosen defining LD as the *reduction or loss of biophysical and socio-economic productivity influenced by biophysical and socio-economic impact.*

2.1.2 Global (Mapping) Approaches on Land Degradation

Awareness to address LD and desertification rose during the droughts in the 1970s and 1980s in the Sahel. Research on soil degradation and LD as such had its first peak in the 1990s and is still increasing (de Jong, 2010). LD and soil degradation are often equally used terms (de Jong, 2010). New approaches are steadily coming up on how to measure and monitor LD. This includes identification of the main or minor causes that lead to decreasing soil fertility. Ideally, these new approaches identify measurements on how to improve the situation on the local, regional and even the global scale. Many attempts have already been made in the past to get a global picture of the situation on earth.

The United National Conference on Desertification in Nairobi in 1977 was the starting point for several global mapping approaches. As these were path leading for the mapping of LD the main

[3] Safriel and Adeel (2005: 636) defined LD as "reduction or loss of ecosystem services, notably the primary production service".

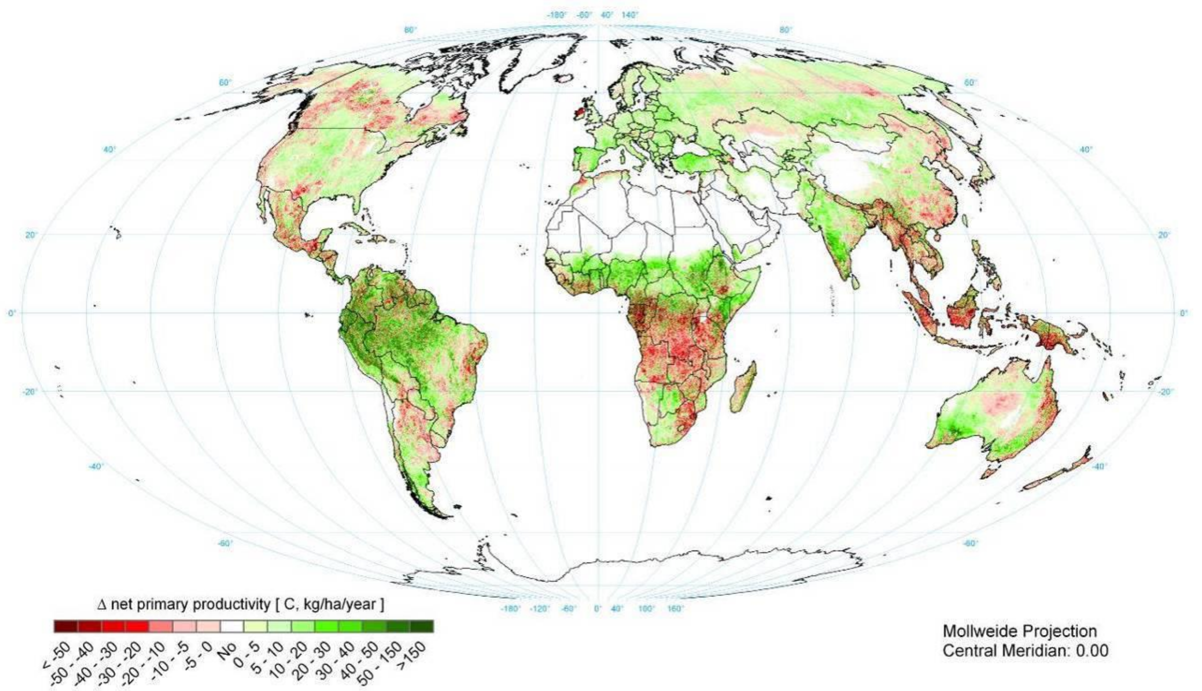
outputs and projects should be mentioned here. For the sake of completeness a table can be found in the annex (Annex 1) providing a good overview on global mapping approaches of LD which was conducted in a study by Nkonya et al. (2011).

The first mapping approach without taking geospatial data into account was conducted by the UN Food and Agriculture Organization (FAO) stating 35% of the earth´s surface being affected by desertification based on data from 1977 (Thomas & Middleton, 1994; Nkonya, 2011). The first global map based on geospatial techniques was the Global Assessment of Human-Induced Soil Degradation (GLASOD) which was published in 1990. Here, human impact in particular was addressed to be one of the main drivers of land and soil degradation. Major drawback was that data collection for this mapping approach was solely based on expert opinion and thereby represented qualitative measurements without any quantitative validation (Lal et al., 1997; Oldeman, 1991; Sonneveld & Dent, 2009). GLASOD included also different forms of soil degradation including water and wind erosion, nutrient depletion, salinity, contamination or physical LD (Nkonya, 2011). In general to raise awareness of the problem of LD, the GLASOD map was very useful and is still cited in research on LD mapping and assessment even if several new attempts to map LD globally were made since then. This includes the first World Atlas of Desertification (WAD) by UNEP published in 1992 giving a first impression about the extend and severity of LD (UNEP, 1992). The WAD reported 70% of agricultural land being affected by LD and 1/6 of the world´s population living and depending on those lands (Agnew & Warren, 1996). A second edition of this Atlas was published in 1997 (Middleton & Thomas, 1997).

Driven by innovative approaches, and especially the use of remote sensing and GIS, a new global mapping approach on LD was established in 2008 initiated by the FAO. It was named Land Degradation Assessment in Drylands (LADA) including six country studies[4] but also followed by a global approach, the Global Land Degradation Assessment in Drylands (GLADA) (Bai et al., 2008; Nachtergaele & Licona-Manzur, 2008). Using vegetation indices such as the Normalized Difference Vegetation Index (NDVI)[5] and analysis on Net Primary Productivity (NPP), based on sum NDVI, remote sensing came into focus for earth observation and especially LD assessment. For GLADA a time period covering 23 years from 1981 to 2003 was analyzed over which trends of e.g. NPP were observed. Map I.1 shows the change in NPP between 1982 and 2003 as depicted in Bai et al. (2008, 10). With regard to the national level study on Kenya decreasing NPP can bet identified especially in the southern part of the country.

[4] The six studies took place in: Argentina, Cuba, China, Senegal, South Africa and Tunisia.

[5] The Normalized Difference Vegetation Index (NDVI) measures the greenness of the vegetation and thereby density and health of land cover. More information on the NDVI will be given in part III chapter 2.1



Map II.1: Global Map on Change in Net Primary Productivity (NPP) based on data between 1981 and 2003. Source: Bai et al. 2008, 10.

A shift from a focus on arid, semi-arid and sub-humid areas, which define the areas where desertification is mainly mentioned, to a real global approach by reporting that about 80% of the degraded areas within 1981 to 2003 is found in humid areas was herewith made (Bai et al., 2008). Following GLADA the latest global mapping approach on LD was GLADIS, the Global Land Degradation Information System (Nkonya, 2011) which innovatively started to also integrate socio-economic variables in the assessment. GLADIS integrates six axes: four biophysical axes and two socio-economic axes including various indicators such as greenness trend or deforestation trend and water scarcity on the one hand and indicators including accessibility, agricultural value and tourism on the other hand that should represent the socio-economic axes (Nachtergaele et al., 2010). The project got public in 2010 with a beta version and a web-service[6]. The outcome was not gone as public as e.g. GLASOD or GLADA and also includes a warning to the user of this product nowadays to not use GLADIS information for national decision making. Nevertheless GLADIS has potential and marks a milestone to go to a more interdisciplinary analysis trying to use biophysical and socio-economic information in combination, even if there is still room for improvement.

[6] Via http://www.fao.org/nr/lada/index.php?option=com_content&view=article&id=161&Itemid=113&lang=en GLADIS and its different aspects such as Land Use Information, Database, Analysis and Degradation Index can be used (last accessed 08.02.2015).

2.1.3 Causes and Consequence: Indicators of and for land degradation assessment

Indicators and so-called causes and consequences to analyze and address LD are highly diverse. LD affects all components of land including soil, vegetation, nutrient balance or the ability to store water. This represents a wide range of possible biophysical indicators that can be measured. But the socio-economic indicators are as diverse including income, food security and health, capability and adaptation potential or even psychological aspects which can have tremendous effects for a household living in poverty (Kumar, 2014).

LD is also known as "syndrome" or "dryland syndrome" (Schellnhuber et al., 1997; Safriel, 2007). Observed processes of LD are mainly biophysical but often driven by human impact. Overgrazing e.g. refers to livestock keeping which is unsustainable if more livestock is kept than a certain area of land can feed. Soil compaction can also be a result of trampling of livestock or using machines on agricultural land not adapted to current conditions (Warren et al., 1986; Hamza & Anderson, 2005). Water logging and salinity both are also impacted by land use. In addition to a naturally occurring high salinity in soils fertilizer can add chemicals to the soil – including salts – that either invent this process or trigger it (Scherr, 1999). Water logging moreover can be provoked by biophysical preconditions and worsened by a wrong or non-existing drainage system in areas prone to water logging and in general (Barrow, 1991).

Among indicators that help to address LD different terms exist in research distinguishing between direct and indirect (Le Houérou, 1996), primary and secondary (Glantz & Orlovsky, 1983) or proximate and underlying causes (Lambin et al,. 2001; Verburg et al., 2002; Geist & Lambin, 2004) stating that some indicators have a larger impact on the process of LD than others. Moreover Reynolds et al. (2007) added the differentiation between slow and fast variables, referring to the time it takes until a variable becomes an indicator for LD. He defined slow variables that take a long time to react – such as decreasing soil fertility or a slowly increasing population in a certain area – as the crucial indicators that trigger LD processes the most (Reynolds et al., 2007).

Proximate causes according to Geist and Lambin (2004) are represented by agricultural activities, infrastructure, deforestation and related activities and increasing aridity (referring to climate change). Underlying driving forces list climatic and demographic factors, technology, economic factors, policy and institutional factors and cultural/sociopolitical impact (Geist & Lambin, 2004). Proximate causes seem to refer more to human impact and behavior except aspects of climate change (such as increasing aridity). Figure II.2 gives an overview on the proximate causes and underlying driving forces (of desertification) by Geist and Lambin (2004).

Human behavior and development is a huge impact factor for environmental change including LD. An increasing population is always seen as one of the main causes for degrading lands by increasing pressure on resources (Meyer & Turner, 1992). Obviously more food needs to be produced and therewith also periods of abandoned land are reduced which means less time for the soil to recover. This simple calculation was already made in 1798 by Malthus. In his "Essay on the Principle of Population" (Malthus, 1986) he explained that population growth will be exponential while food production will always be linear. Therewith at some point the carrying capacity will be crossed. But it needs to be mentioned that certain innovations including agricultural technologies such as hybrid seeds or chemical fertilizer were not included in the Malthusian theory (Rosegrant & Cline, 2003). Higher population densities mean less space and higher pressure on the "functionings" of the environment such as water, air and food (Imeson, 2012). As also urban areas are expanding pressure on already existing agricultural lands increases simultaneously (FAO & UNEP, 2000). A study by Drechsel et al. (2001) with data from 37 countries in Sub-Saharan Africa underlined a significant relationship between population pressure, reduced fallow periods and soil nutrient depletion which includes erosion. But there are also counterexamples showing that more people can also mean less erosion (Tiffen, Mortimore, & Gichuki, 1994) or where a clear link cannot be found between population density and LD and so population growth can create incentives but also disincentives (Scherr & Yadav, 1996, CGIAR, 1999). A study by Dubovyk, Menz, and Khamzina (2012) showed evidence that if we have abandoned lands we have more LD which thereby includes the human impact not only as a cause of LD but also as a factor to improve land conditions.

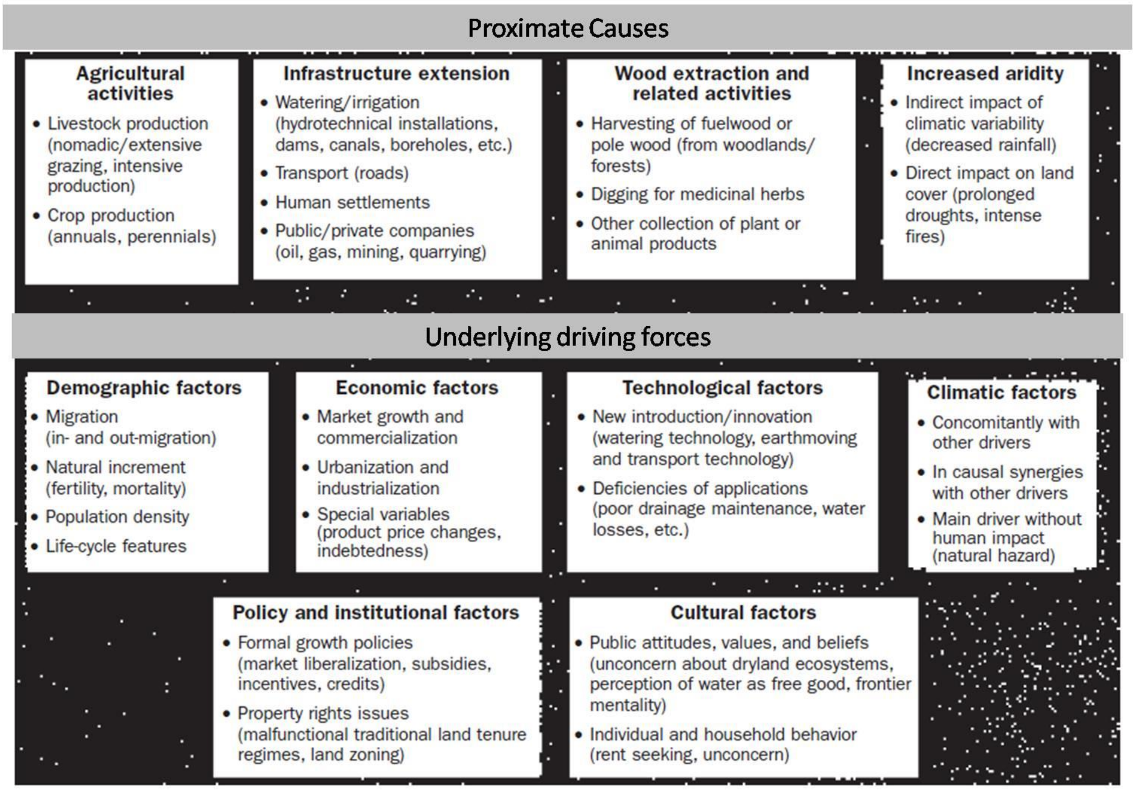


Figure II.2: Proximate and underlying causes for land degradation (desertification) according to (Geist & Lambin, 2004).

Besides all external aspects occurring natural degradation may not be neglected. Net degradation describes the result of natural degrading process and human interference subtracted by natural reproduction and restorative management referring to natural processes by environmental systems but still including human impact (Blaikie & Brookfield, 1987).

2.2. Marginality versus Poverty – similar terms but different impact?!

"Marginality is the position of people on the edges, preventing their access to resources and opportunities, freedom of choices, and the development of personal capabilities. Being excluded, not only from growth but also from other dimensions of developmental and societal progress, is an indication of the extremely poor being at the margins of society and in many cases marginality is a root cause of poverty" (von Braun & Gatzweiler 2014: 3).

Within coupled HES socio-economic impact needs to be measured to get a better understanding of internal processes which includes LD. One socio-economic aspect always mentioned in the course of degrading lands is poverty even if there is still not much evidence whether poverty is linked to LD or not (Imeson, 2012). According to (Scherr, 2000) poverty and economic marginalization lead to LD and LD leads to further poverty. But among that there are different characteristics of a livelihood system that have an impact on functionings of the environment and that are influenced by degrading land. This chapter will give some insights in marginality and poverty approaches which are not seen as completely opposite concepts but as two approaches that "overlap and are complementary" (von Braun & Gatzweiler, 2014: 4).

2.2.1 Who is poor? Who is marginal?

Poverty and marginality are two terms used in similar context. Poverty measurements often inform about peoples' welfare in monetary values. Well-known is the assessment and also definition of poverty by indicating a person living below "one dollar a day" as poor which was introduced in the World Development Report (WDR) on Poverty in 1990 by the World Bank (WB, 1990; Ravallion, Datt, & van de Walle, 1991). Here, absolute poverty is defined as the "inability to attain a minimal standard of living" (World Bank 1990; Bernstein, Crow, & Johnson 1992). In addition to that marginality is defined as

> *"an involuntary position and condition of an individual or group at the margins of social, political, economic, ecological and biophysical systems, preventing them from access to resources, assets, services, restraining freedom of choice, preventing the development of capabilities, and eventually causing extreme poverty"* (Gatzweiler & Baumüller, 2014: 30)

The concept on marginality thereby represents a much broader spectrum than only the one on the economic determinant also including social, political or even biophysical aspects.

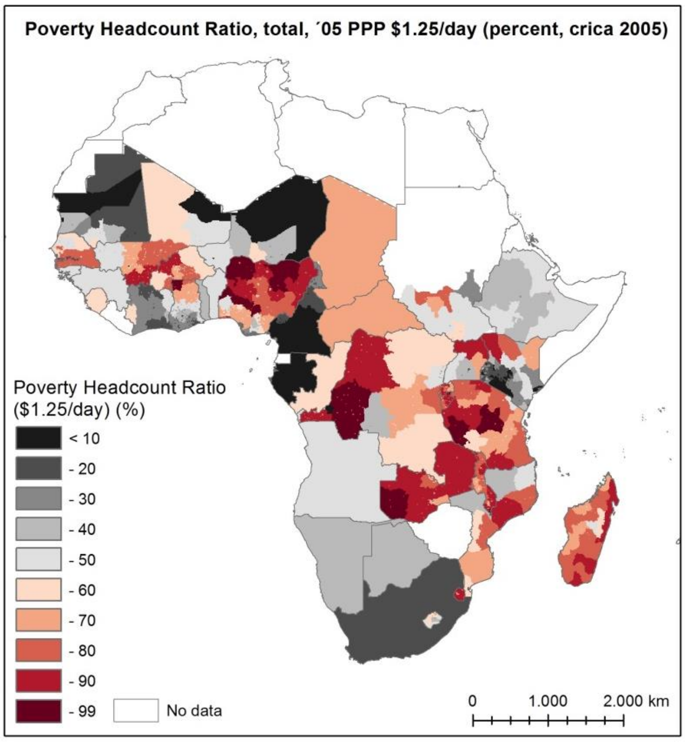
Ravallion et al. (2009) revisited the 1-dollar-a-day measure about 20 years later stating that an international comparison still needs to include country-specific information. Therefore national poverty lines were used to come up with an adjusted measurement of poverty. It included estimates of the head count index – standing for the percentage of people living below the poverty line compared to the total population – the poverty gap – measuring the magnitude or depth of poverty – and a severity of the poverty index which is the poverty headcount ratio multiplied by the squared difference between income of a poor person and the poverty line, aggregated over all poor people (Economic Commission for Africa, 2006: 93). Later the average poverty line was set at \$1.25 (Ravallion et al., 2009). Adjustments were also made among the poor: People living on \$0.75 to \$1 a day were defined as subjacent poor, those living on \$0.50 to \$0.75 a day as medial poor and people living below \$0.5 a day as ultra-poor (Ahmed et al., 2007). While early research on poverty was of descriptive character focusing on monetary values, poverty research started to shift to a more analytical approach during the last decades, realizing that the causes of poverty are important but "complex, multifaceted and difficult to isolate" (Haveman & Smeeding, 2007: 2). Especially in the 1990s more awareness was risen that poverty is a multidimensional concept that also includes social and psychological effects that can hinder people to use their full potential of possibilities to escape poverty (Jazairy & Stanier, 1993). But still to attain a minimal standard of living as quoted by FAO there should be more insight into the diversity of a livelihood than only looking into economic aspects. So this definition matches even more with the approach of the "Multidimensional Poverty Index" (MPI) (Alkire & Santos, 2011) which was established in collaboration with UNDP in 2010 at the University of Oxford. This approach aimed at not only focusing on economic variables but also including important aspects of human livelihoods such as education and standard of living (Alkire & Foster, 2011; Alkire & Santos, 2011). It also states that if only income is measured a lot of other important aspects will be neglected and crucial linkages will therefore be missed (Alkire & Santos, 2011). But as many indices also the multidimensional poverty index can be criticized by mentioning the unequal choice of indicators and inappropriate weighting. But according to Ravallion (2011) measurement of poverty should also rather look at different sets of indicators adapted to the region instead of focusing on a standard set.

Highlighted in a study by Adato and Meinzen-Dick (2002) besides income and expenditure many other factors are contributing to people´s vulnerability where LD is a huge contributing factor in rural areas. Five different case studies including soil fertility management practices in Kenya tackle the question why agricultural technologies are sometimes adapted but sometimes can not be examined (Adato & Meinzen-Dick, 2002). This was answered when looking into livelihood structures based on different capitals. Leaning on the sustainable livelihood approach five capitals are mentioned: *human capital* - representing e.g. knowledge and education -, *natural capital* -standing for natural available resources -, *financial capital* – income and expenditure or assets -, *physical capital* – representing aspects of health – and *social capital* – the most difficult capital to measure quantitatively as it includes being member of a group or social structures in a village where people can take advantage or disadvantage of (DFID, 1999).

Referring to poverty and especially multi-dimensional approaches a need to get a better picture of the most deprived people arises. Therefore the concept of marginality is mentioned here which fulfills the demanded need to get to a broader perspective regarding poverty reduction and development policies by also addressing ecological processes and vulnerabilities in addition to poverty (von Braun & Gatzweiler, 2014). The concept of marginality goes beyond that of poverty by looking from different angles which are represented by different spheres of life (Gatzweiler et al., 2011; Graw & Husmann, 2014). As more attention has to be paid to indicators which let people slide into poverty – e.g. lacking access to goods and services due to discrimination or remoteness but also to variables which can moreover help people to escape poverty by improving the conditions of these indicators the concept of marginality (Gatzweiler & Baumüller, 2014) – represents an inclusive and interdisciplinary research framework to analyze the causes of poverty.

2.2.2 Mapping Poverty and Marginality

Mapping approaches on poverty started in early 2000. Most of them followed the early definitions of poverty based on income measurements to depict the state of poverty worldwide but also within single countries (Bedi, Coudouel, & Simler, 2007). Mapping helps to identify hotspots and makes the poor and those living in inequality visible. Beyond efforts of finding the right poverty-lines several approaches on poverty mapping use small area estimation (SAE) for the analysis of poverty within a country which combines detailed household survey information with population census data (Simler & Nhate, 2005; Bedi, Coudouel & Simler 2007; Davis, 2003). These approaches rely on economic indicators and rarely include a wider range of other indicators.



Map II.2: Poverty Headcount Ratio of people living below $1.25/day in %. Data based on: HarvestChoice 2015 via http://harvestchoice.org/data/tpov_pt125 (last accessed 15.09.2015).

A still improving poverty mapping approach mapping sub-national poverty is conducted by Harvest Choice (Azzarri et al. 2012). The mapping so far focuses on Sub-Saharan Africa and is also based on national poverty lines while including household surveys for up to 29 countries. Map II.2 shows poverty mass in Sub-Saharan Africa. The focus here is on the poverty headcount ratio of people living below $1.25 per day in percentage.

Also to mention is the Atlas of Poverty published by the Center for International Earth Science Information Network (CIESIN) in 2006 (CIESIN, 2006). Besides poverty measurements global maps on e.g. infant mortality or hunger are included which from a logical understanding is closely linked to the concept of poverty and definitely to the concept of marginality. Hosted by CIESIN within the Socioeconomic Data and Applications Center (SEDAC) a lot of work and research on mapping of population densities on global scales was already established[7].

Mapping approaches on marginality are rare which is also due to the fact that the main focus is still on the terminology of poverty rather than on marginality. A marginalization index calculating the degree of marginality was developed for Mexico including variables on education, income and size of the city or village by Anzaldo and Prado (2005). Distance and accessibility played major roles in this approach while poverty mapping was based on SAE. Besides approaches focusing more on socio-economic viewpoint marginality can also be understood from a biophysical perspective with regard to marginal soils (Parr et al., 1990; Varvel et al., 2008). But here, the term marginal as such is not defined or discussed in detail. A study focusing on a solely biophysical marginality index was conducted by Cassel-Gintz et al. (1997) with data based on soil moisture and soil fertility as well as including climatic conditions that help to identify areas prone to erosion or other disturbances such as aridity. The study defines an index between 0.0 and 1, to highlight areas which favorable for agricultural production (0) and those which have a high marginality (1) and are therefore not suited for agricultural production. The map was produced on a global scale with a 50km-resolution (Cassel-Gintz et al., 1997).

The first global marginality hotspot mapping published in 2014 that included both, biophysical and socio-economic data, was path leading to set up a marginality mapping approach (Graw & Husmann, 2014). Here, different aspects of marginality are addressed by identifying proxies that each represents a so-called *sphere of life* by one indicator (Gatzweiler et al., 2011; Graw & Husmann, 2014) (Table II.1).

These marginality dimensions were used to give a picture on global marginality hotspots. By defining cut-off points for all marginality indicators and overlaying the different "marginal" dimensions helped to identify areas where several dimensions of marginality overlap. By this, regions can be identified in which in-depth research is necessary to validate the results and to get more detailed information on the regional and local level. By setting cut-off points we could state

[7] For more information please visit: http://sedac.ciesin.columbia.edu/ (last accessed: 08.02.2015)

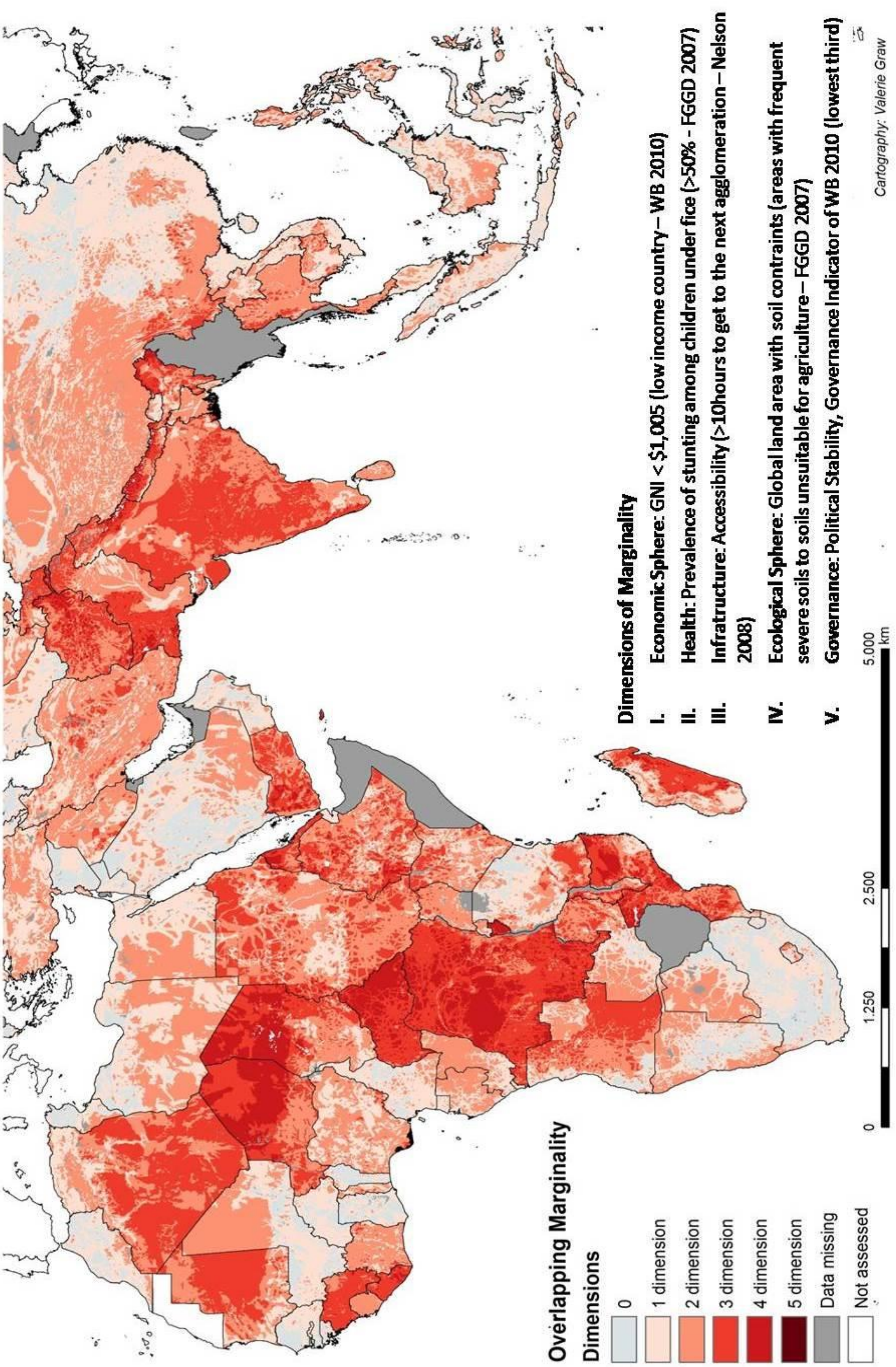
the areas which tend to be marginal according to the given dataset. Areas where more than three marginality dimensions overlap were stated as marginal (Map II.3).

However, also this approach focuses more on the socio-economic than on the biophysical aspects. Therefore an interdisciplinary approach tackling socio-economic and biophysical approaches equally should also be mentioned here. In addition, on a national scale further improvement and thereby more detailed information is highly needed as some indicators such as GNI – representing the economic sphere – or political stability – the proxy for governance – are only available on the national level by one data value for the whole country. Moreover it is necessary to look beyond a proxy indicator to represent a dimension such as health, education or accessibility and results have to be strengthened with statistical analysis.

Table II.1: Proxy Indicators for Global Marginality Hotspot Mapping. According to: Graw & Husman (2014)

Dimension	Proxy Indicator	Source
Economy	Gross National Income (GNI) PPP (current US$)	World Bank (compiled by data of the years 2008-2010)
Quality of Life	Prevalence of stunting among children under five	FAO 2007, FGGD
Landscape Design and Infrastructure	Travel time to major cities. Global Map of Accessibility	Nelson, A. (2000)
Ecosystems, natural resources and climate	Global land area with soil constraints	FGGD, IIASA 2000, GAEZ study
Public domain and institutions	Political Stability (representing a governance indicator)	World Bank 2009

Maps are a powerful tool and bear chances to get a spatial perspective of an emerging issue, such as poverty and marginality, but also give the opportunity to get insights in ecological vulnerabilities and environmental change. Geospatial analysis can help to visualize and observe the assets of the poor in their individual environment by combining social and economic data with biophysical data. Making the poor and marginalized visible and underpin their ecological environment is therefore one of the core issues within this study. Mapping marginality hotspots serves as an opportunity to get information on the spatial distribution of inequalities, but also highlights opportunities for future research by identifying areas where further research is needed and promising.



Map II.3: Global Marginality Hotspot Map for the year 2010 based on different data sources between 2007 and 2010). Source: Graw & Husmann, 2014.

2.3. Land Use and Land Cover (Change)

According to the FAO about 33% of the global land area is occupied by agriculture which represents the land use with the greatest impact on the environment (Ramankutty et al. 2006). The biggest change in land cover and land use occurred in the 20th century due to an increasing population and thereby an increasing demand for food that lead to expansion of crop areas and intensification of production (Meyer & Turner, 1992; Lambin et al., 2001).

Land cover land use (LCLU), or land use cover change, respectively LUCC, and LD are closely linked as LD represents and can causes changes in land cover and land use.

2.3.1 Land Use, Land Cover and Land Use Cover Change (LUCC)

The issue of LUCC includes a biophysical as well as a socio-economic perspective. *Land Cover* refers to the biophysical and biological cover of the land surface. This includes all attributes of the land surface such as vegetation, water, bare soil or other material that "covers" the land (Lambin & Geist, 2006). *Land Use* on the other hand already includes an active determinant by the added term "use" and is referring more to how humans impact the land (Meyer & Turner, 1994). This includes all land use activities such as irrigation or rainfed agriculture, pastoralism areas dominated by livestock or urban areas.

Research and awareness of LUCC and its change has its origins in the 1970s when land use change and its impact also on local to global scales was recognized (Turner, 1997; Lambin, Geist, & Rindfuss, 2006). The term "land use cover change" and especially its abbreviation LUCC was established in the 1990s in the research era of land use cover change studies the LUCC-project launched in 1994 in particular. Research was moreover strengthened by the big joint projects: The Geosphere Biosphere Programme (IGBP) and the International Dimensions Programme on Global Environmental Change (IHDP) which invented the LUCC project (Lambin & Geist, 2006). Objectives of the LUCC programme according to the IGBP were[8]:

- Development of a fundamental understanding of human and biophysical dynamics of land-use changes and their impacts on land cover
- Development of robust and regional sensitive global models of land-use/cover change with improved capacities to predict and project use/cover changes
- Development of an understanding of land-use/cover dynamics through systematic and integrated case studies
- Assistance in the development of a global land-use classification scheme

LULC both to environmental change and include biophysical as well as socio-economic points of view. Research on LUCC therefore represents a milestone for interdisciplinary research as approaches also incorporated insights from other disciplines such as social science or economics.

[8] According to:
http://www.igbp.net/researchprojects/pastprojects/landuseandcoverchange.4.1b8ae20512db692f2a680009062.html
(last accessed 08.02.2015)

2.3.2 Research and Monitoring of land cover and change

LUCC itself already includes the interplay of human behavior and ecological conditions and processes, and, thus, its research is multidisciplinary (Meyer & Turner, 1994; Geist, 2005). Mentioning proximate and underlying causes as already used for LD assessment, also erased in research on deforestation of tropical regions in relation to LUCC research (Geist & Lambin, 2002). The link to LD as part of LUCC is obvious. Moreover deforestation represents one process and trigger of LD (Blaikie & Brookfield, 1987). In general literature and research on land use and land cover change focused a lot on deforestation, in particular in the Amazon where extension of agricultural lands was a key driver for this process (Lambin, Geist, & Lepers, 2003; Morton et al., 2006, Gibbs et al., 2010). Change in cropland areas or agricultural expansion was not only in focus in the Amazon region but got a global interest also with regard to steady population growth (Ramankutty, Foley, & Olejniczak 2002). Human activities and especially their acting scopes are also getting more in focus by analyzing changes in urban areas and urban sprawl (Xiao et al., 2006; Rienow & Goetzke, 2015). Also detection of fire and its impact on e.g. forests (Nepstad et al., 1999; Langner, Miettinen, & Siegert, 2007) or moving of livestock to detect its impact on the environment (Kerr & Ostrovsky, 2003) is part of LUCC research.

For LUCC research remote sensing and its use in modeling approaches became a leading tool to observe changes on the land surfaces which goes in line with increasing technology in this field (Verburg et al., 2006; Giri, 2012). While land cover can be detected by remote sensing imagery, land use is more difficult to observe via this technology and needs more qualitative input, as e.g. from conducted surveys or interviews. Among that LUCC model settings can satisfy the impact of socio-economic structures to a certain extent by including them quantitative in the analysis. Land use and thereby land change is driven by management strategies and land reforms and thereby has a strong socio-economic link (Lambin & Meyfroidt, 2010). Analyzing human impact in LUCC science is therefore an emerging field (Hecheltjen, Thonfeld, & Menz, 2014).

Among others there is still the need for information on global and regional land cover for applied science to relate those to occurring processes and problems addressed by interdisciplinary research as it will also be the case in this thesis. In addition to global land cover mapping projects and approaches also more specified research was conducted where a focus on certain land cover types was present. Besides Croplands (Ramankutty & Foley, 1999) forest cover mapping and mapping of deforestation play major roles. A global mapping approach based on Landsat images and therewith a resolution of 30m was recently published by Hansen et al. (2013). The approach covers the time period 2000 to 2012 and represents a milestone for high-resolution global mapping of LC.

Global and regional mapping approaches that especially focus on identifying different land cover and land use classes are listed in Table II.2. The focus here is on land cover and use in general.

Table II.2: Global Land Cover Mapping Approaches.

Product	Data used	Source
Global Land Cover 2000 (GLC2000)	Data: SPOT VGT (S1) 1km resolution FAO Land Cover Classification System (LCCS), 22 classes	Global Land Cover 2000 database. European Commission, Joint Research Centre, 2003. http://bioval.jrc.ec.europa.eu/products/glc2000/glc2000.php (last accessed 08.02.2015)
ESA GlobCover (2005/2006 & 2009)	Data: MERIS 300m resolution FAO Land Cover Classification System (LCCS), 22 classes	Bicheron et al. 2011
AVHRR Global Land Cover Classification	Data: NOAA AVHRR 1km and 8km resolution product Classification by University of Maryland, 13 classes	Hansen et al. 1998
Global Land Cover SHARE (GLC-SHARE)	Based on GLC2009, Cropland Extent, MODSI VCF 2010, Africover, Corine LC data. 1km resolution FAO Land Cover Classification System (LCCS), 11 classes	Latham et al. 2014
MODIS Land Cover (MCD12Q1)	Data: MODIS 500m resolution, annually product from 2001 to 2012, two classification schemes available: IGBP (International Geosphere-Biosphere Programme) and UMD (University of Maryland).	Friedl et al., 2002

Individual mapping approaches also exist on regional and national scales. Here data input is usually derived from Landsat with 30m resolution with varying classification techniques.

2.4. Linking biophysical and socio-economic analysis

Research and literature is still emerging in each of the fields discussed in the previous chapters but especially at the crossing points of those fields. Each of the three topics – whether LD, marginality or LUCC – includes biophysical and socio-economic feedback loops. Especially research on LUCC goes straight towards a combination of several disciplines and includes these in diverse modeling approaches. The results are important for policy advice, especially climate change-policies (Veldkamp & Lambin, 2001; Pielke et al., 2002).

A growing population is seen as the major cause for the expansion of agricultural lands which triggers the need for intensification rather than extensification of agricultural lands. As also urban areas are included in research on LUCC, human behavior is always present and a key variable for identifying crucial environmental change processes (Lambin & Geist, 2006).

Connecting biophysical and socio-economic data is a growing field mostly assessed with the help of a Geographical Information System (GIS). Problems that occur address the spatial and temporal scale (Rindfuss et al., 2003). While biophysical data, land cover in particular, can be gathered annually or even biweekly with regard to vegetation index data, socio-economic data are collected in much longer time frames such as decades for census data or maybe every four years for household data[9] (Rindfuss et al., 2003). Change over a decade in socio-economic variables compared to changes that can be observed e.g. biweekly is difficult to combine and relate as a common scale has to be found.

Studies combining biophysical data and socio-economic data both based on quantitative assessment could be found for several regions, but mostly in sub-Saharan Africa especially with a focus on degrading lands and environmental change. An example for combination of poverty mapping with biophysical data is shown in the approach on poverty mapping in Uganda by Rogers, Emwanu, and Robinson (2006). Household survey data including indicators for health and well-being of Uganda´s population was linked to environmental variables such as temperature, elevation and agricultural production systems via discriminant analysis to explain variance in poverty data (Rogers, Emwanu, & Robinson, 2006). Fox (2003) published a compilation of multiple studies expressing possibilities and limitations of linking household information with remote sensing data. Different research areas are addressed including the linking of deforestation processes in the Amazon to household structures by (Moran, Siqueira, & Brondizio, 2004) and also the competition for land in the Kajiado district, Kenya where pastoralism of the Maasai is linked to land use changes (BurnSilver, Boone, & Galvin, 2004).

It is obvious that each of the topics mentioned in the discourse has a clear and strong link to many other disciplines. A clear distinction between LD, marginality and LUCC is difficult to

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[9] Referring to the Tegemeo Household Survey which is used in this thesis. More information is following especially in Chapter V where this data is used.

make but still each has its own field of research and terms are rarely mixed but rather extended by adding a biophysical or socio-economic component.

A complex and interdisciplinary framework that brings light into different socio-economic structures and how they are linked to degrading processes and environmental change is therefore missing. Nevertheless, there is an increasing need to identify interdisciplinary frameworks on the different topics. Research should rather refer to "coupled Human-Environment-Systems" which is already mentioned in multiple studies including also the field of vulnerability analysis (Turner et al., 2003; Reynolds et al., 2007).

3. Development of an Interdisciplinary Framework

This research study links biophysical and socio-economic data using different data types and formats. Each study – the national study on Kenya (chapter III) and the local study focusing on western Kenya (chapter IV) – takes advantage of slightly different approaches depending on available datasets and especially increasing opportunities. On the local level the approach could be refined due to more detailed data available, such as a four year household panel survey. Each study will include individual framework and workflow charts.

Figure II.3 shows a simplified general framework on how biophysical and socio-economic data are linked. The focus is on marginality assessment from a socio-economic perspective and LD representing the main biophysical part that will be explained with certain livelihood characteristics.

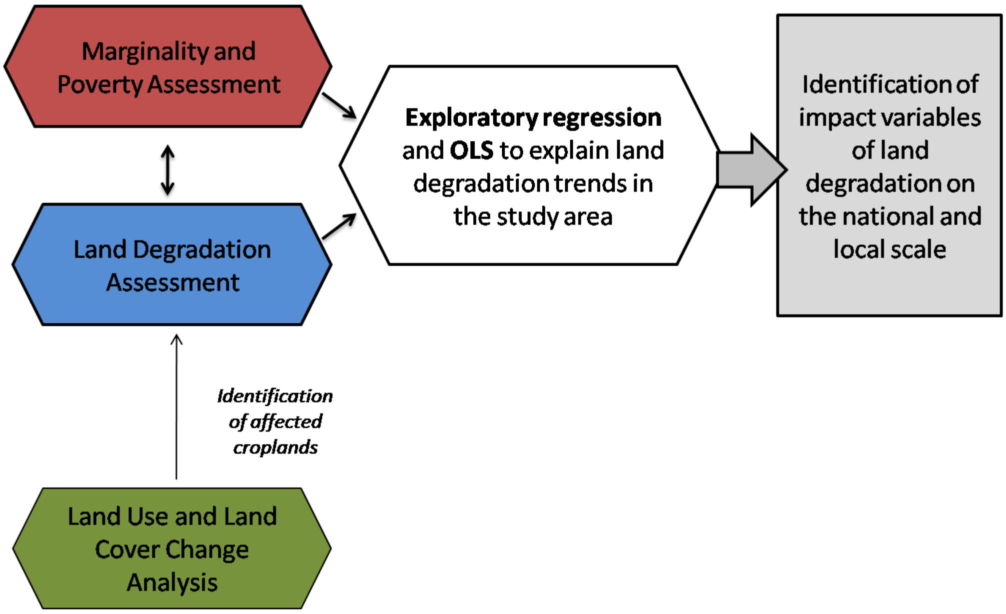

Figure II.3: Simplified general framework for the analysis of interlinkages of LD and marginality in Kenya (national study) and western Kenya (local study).

Main target in this thesis is environmental change, degrading lands and those lands where productivity on agricultural lands diminishes in particular. With regard to marginality this thesis refers to the concept of marginality as developed by von Braun and Gatzweiler (2014) which represents an inclusive and interdisciplinary framework to analyze the various patterns of poverty but focuses on the socio-economic aspects. LUCC analysis is included to explain changes in land productivity and identify agricultural areas at risk. Therefore, marginality will primarily represent the socio-economic sphere in this study while LD and LUCC assessment represent the biophysical dimension.

The interlinkages are made with statistical analysis mainly including exploratory regression and Ordinary Least Square Regression (OLS) which help to identify main causes and drivers of productivity change in terms of decreasing or increasing and even stable vegetation trends.

3.1 Land Degradation Assessment: Data and Methods

LD in this study is defined as the *reduction or loss of biophysical and socio-economic productivity influenced by biophysical and socio-economic impact*. The process of LD is therefore following the assessment of vegetation degradation addressing productivity reduction or loss. The following part will only focus on those data and methods that are path-leading for both, the national and the local study.

As the process of LD is not influenced by one single determinant there are multiple ways to assess changes of e.g. soil fertility, erosion or vegetation decrease and increase that are all related to LD processes.

3.1.1 Vegetation and Rainfall Analysis

The "pixel-level" is the addressed unit for the use of remote sensing data (Fisher, 1997). Depending on the spatial resolution of the image, also named raster data, derived from a sensor, information within the area a pixel is covering can be derived. Remote sensing became a leading method to get information about current situations and changing patterns on the land surface (Shoshany, Goldshleger, & Chudnovsky, 2013). Vegetation, i.e. vegetation indices, are mainly used as a proxy for the status of land and key indicator for desertification (Helldén & Tottrup, 2008; Nkonya et al., 2011; de Jong et al., 2012). Vegetation indices are derived from remote sensing imagery extracting the spectral information of two or more bands that thereby provide information on "terrestrial photosynthetic activity and canopy structural variations" (Huete et al., 2002: 195). Well known in LD assessment is the observation of the Normalized Difference Vegetation Index (NDVI) which gives information about density, amount and health of vegetation by using near infrared (NIR) and red light (RED)[10] to estimate green biomass. It is calculated by the difference of bands of NIR and RED over their sum (Tucker, 1979; Prince, 1991; Huete et al., 2002). Equation 1 shows the calculation of the NDVI according to (Huete et al., 2002; Jiang et al., 2008).

$$NDVI = \frac{NIR-RED}{NIR+RED} \qquad \text{[Equation 1]}$$

The NDVI reaches values between -1 and +1, where healthier and more dense vegetation expresses higher NDVI values compared to dry and sparse vegetation with much lower NDVI values. Therefore the NDVI is often mentioned in line with measurement of green vegetation, greenness (Bannari et al,. 1995; Ma, Morrison, & Dwyer, 1996) or greening and browning trends with regard to decreasing vegetation trends (de Jong et al., 2011a; de Jong et al., 2012). The greener and healthier vegetation the more flat its cell walls are. Thereby the more incident sunlight can be reflected and the more RED is absorbed which leads to a higher NDVI value. Vice versa the more sparse and "brown" vegetation cover appears, the less RED is absorbed and the less NIR is reflected. This calculation leads to different NDVI values around the globe where

[10] Also known as "visible light" (Tucker et al. 2005)

e.g. tropical regions with evergreen rainforest show higher NDVI values (0.6-0.8) than shrubland cover in Savanna regions in Sub-Saharan Africa (0.2-0.3) (Weier & Herring, 2000). Negative NDVI values refer to water, desert, snow-cover or even clouds and thereby non-vegetated areas.

Discussions about the reliability of the NDVI are still ongoing as the index does not distinguish between vegetation types and could create false alarms with regard to LD if a decreasing trend is e.g. only the result of land conversion. In some areas such as often in Namibia or South Africa an increasing NDVI could be based on bush encroachment which is actually a form of LD and not a sign for increasing productivity (Klerk, 2004; Helldén & Tottrup, 2008). Criticism of the NDVI is also linked to missing soil information which should be included as especially in arid areas vegetation is sparse and "greenness" is not measured in the same amount as in more humid regions. Dark soils might result in a higher NDVI than actually measured if solely vegetation would be taken into account (Huete, 1988). The soil-adjusted vegetation index (SAVI) therefore reduces soil and canopy background by correcting the NDVI with a soil brightness correction factor (Huete, 1988). Moreover, the enhanced vegetation index (EVI) is nowadays preferred when the study area is located in areas with high biomass (Huete et al., 2002; Geerken & Ilaiwi, 2004). As the NDVI saturates when vegetation cover reaches high levels the EVI is performing better in areas with high productivity (Huete et al., 2002; Pettorelli, 2013).

Equation 2 shows the calculation of the EVI with ρ as atmospherically corrected or partially atmospherically corrected surface reflectance. G is included as gain factor limiting the EVI value to a fixed range (Vacchiano et al., 2011). The canopy background adjustment is represented by L while C_1 and C_2 depict coefficients of aerosol resistance used by the blue band ($BLUE$) (Huete et al., 2002).

$$EVI = G \frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + C_1 \times \rho_{RED} - C_2 \times \rho_{BLUE} + L} \qquad \text{[Equation 2]}$$

In addition to the red and the near infrared band the blue band is added to remove residual atmosphere contamination such as smoke or thin clouds (Huete et al., 2002). Especially in tropical regions we have high cloud cover due to evaporation and evapotranspiration. Moreover the soil-adjusted vegetation index (SAVI), where the impact of soil type is included by an additional variable, and the EVI do highly correlate (Huete et al., 2002). Comparing NDVI and EVI values showed that NDVI values were always slightly higher than the EVI-values, especially in areas with high biomass production.

Nevertheless the NDVI is still the index most often used when identifying LD processes which is justified by its good spectral and temporal availability (Maselli, Gilabert, & Conese, 1998). According to Bai et al. (2008: 223) where LD is also defined as a "long-term decline in ecosystem function and productivity" the NDVI can be used to derive "deviation from the norm" and can therefore "serve as a proxy assessment of LD and improvement – if other factors" such as rainfall or slopes "that may be responsible are taken into account".

NDVI and EVI: Data Source

For the national study (chapter IV) two different NDVI time series analysis were taken into account based on two different datasets. For the long-term analysis from 1982 to 2006 data by the Global Inventory Modeling and Mapping Studies (GIMMS) derived from the National Oceanic and Atmospheric Administration (NOAA) Advanced Very High Resolution Radiometer (AVHRR) NDVI data with a spatial resolution of 8km was used. Imageries are biweekly maximum value composites for five continents[11]. Effects that could influence the observation of vegetation such as volcanic stratospheric aerosol caused by volcanic eruptions, calibration or view geometry are corrected in the GIMMS data (Tucker et al., 2005).

The second and main time series analysis covering the years 2001 to 2011 was based on Moderate Resolution Imaging Spectroradiometer (MODIS) Terra NDVI (Product: MOD13A1) with 500m resolution. MODIS was launched in 2000 and provides NDVI images with spatial resolution of 1km, 500m and 250m. The sensor has two different orbits – MODIS Terra and MODIS Aqua – which cross the equator at different points in time. MODIS Terra crosses it at approximately 10.30 am while MODIS Aqua crosses it at 1.30pm. As Kenya is located at the equator and facing high cloud cover starting from noon onwards in most regions MODIS Terra data were chosen for this analysis. Nevertheless, Terra and Aqua values are reported to be strongly correlated (R^2=0.97) (Gallo et al., 2005). The data are collected every 16 days, summing up to 22 datasets per year.

The local level, focusing on the high-productive regions in western Kenya takes advantage of the Enhanced Vegetation Index (EVI) and includes data by MODIS Terra (MOD13A1) with 500m resolution and a bimonthly temporal resolution.

Even if a higher resolution secured a more detailed analysis MODIS data with 500m resolution was selected matching with the spatial resolution of the MODIS land cover data. In doing so no resampling method was needed which could have modified the data and falsify results.

Rainfall Data

Vegetation growth is highly depending on precipitation which is validated by many studies showing high correlations and interplays (Malo & Nicholson, 1990; Davenport & Nicholson, 1993; Nicholson & Farrar, 1994; Herrmann, Anyamba, & Tucker, 2005). Therefore it is aimed at including rainfall data to especially highlight those areas where trend in vegetation could be referred to rainfall amounts and trends.

Rainfall Estimates 2.0 (RFE) (Xie & Arkin, 1997) data are available via the Famine Early Warning System Network (FEWSNET) portal[12] and provided on a daily and monthly temporal resolution.

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[11] Africa (AF), Australia and New Zealand (AZ), Eurasia (EA), North America (NA) as well as South America and Central America (SA).

[12] Data download via: http://earlywarning.usgs.gov/fews/downloads/index.php?regionID=af&productID=3&periodID=6 (last accessed: 08.02.2015).

Here, 10day decades are chosen which result in three datasets each month. The previous dataset RFE 1.0 based data collection on an interpolation method combining Meteosat and WMO Telecommunication System (GTS) data while additional including warm cloud information for daily precipitation estimates (Xie & Arkin, 1997). The RFE 2.0 data improved estimation of precipitation by also including stational rainfall data. Satellite infrared data by Meteosat 7, providing data in in 30-minute intervals, is included in the calculation of RFE 2.0. Moreover areas where clouds are depicted and which cross temperatures of less than 235K are included in the RFE 2.0 dataset (Xie & Arkin, 1997).

Stationary rainfall data was not possible to obtain. While common used rainfall data are available from the Climate Research Unit (CRU) with 0.5° resolution (50km) or the Tropical Rainfall Measuring Mission (TRMM) data with 0.25° resolution (28km), here RFE data was selected due to a spatial resolution of 8km by 8km per pixel which is higher than any other rainfall dataset based on remote sensing imagery.

Trend Analysis

Long time-series analysis is obviously preferred in research but especially when remote sensing data is taken into account. The use of long time series is limited by the respective sensor and the starting time of a campaign. AVHRR GIMMS NDVI data (Tucker, Pinzon, & Brown, 2004) was used for first insights of general vegetation development and behavior over a 25-year period from 1982 to 2006[13] for the national study on Kenya (chapter III) before looking into vegetation development between 2001 and 2011 which is the time period with main focus for the ongoing study – the national and the local study.

Trends were detected among mean annual values of NDVI using the slope of the linear regression (see Equation 4) according to Xie, Sha, & Yu (2008).

$$y = mx + b \qquad \text{[Equation 3]}$$

The parameter y is the predicted NDVI value with the slope m – the here used trend – within the observed time period. Information on the y-intercept is given with b.

The slope of the linear regression is used for all trend analysis in this thesis including vegetation trends, rainfall trends and later on trends of socio-economic data in the local study over a ten year penal survey in four waves between 2000 and 2010.

Significant trends are calculated with $p<0.05$ and used in both studies to correct vegetation trends for rainfall. This gives the opportunity to focus on human-induced changes on land by extracting the main limiting factor for vegetation growth.

[13] At the time the study was conducted NOAA AVHRR NDVI data by GIMMS was only available until 2006

3.1.2 Long Time-Series Analysis from 1982-2006 with GIMMS AVHRR NDVI 3g

In addition to the above mentioned methods advantage was taken out of provided long time series data based on GIMMS AVHRR NDVI covering the period from 1982 to 2006. The calculations here mentioned were used for the national study only to provide national temporal dynamics in vegetation cover.

NOAA AVHRR, on which GIMMS NDVI data are based on, was launched in July 1981. As the year 1981 is not fully covered, the starting point of the analysis was set at 1982. In total 600 images are used for the time series analysis from 1981 to 2006.

The ndvits[14] package implemented in R supports different analysis including local statistics and anomalies of maximum values. Expressing these calculations for Kenya helped to underline hotspots of vegetation dynamics and its distribution. Besides using the ndvits package for R vegetation variability was calculated. Observing variability in vegetation helps to relate major variability in vegetation to hotspots of LUCC. It is expected that those areas where the highest variability can be observed also represent those areas with the highest pressure on land resources. A longer time series from 1982 to 2006 was also chosen here to get long-term insights that can have effects on current trends.

Maximum Anomaly between 1982 and 2006

Maximum anomalies between 1982 and 2006 are calculated by the difference of the maximum of each year and the respective mean of maximum values over the whole observation period. The mean maximum anomaly is represented by the ratio between the Maximum NDVI between 1982 and 2006 and their mean.

$$Anomaly\ NDVI_{max} = \frac{NDVI_{max}}{\overline{NDVI_{max}}} \qquad \text{[Equation 4]}$$

The parameter $NDVI_{max}$ represents the maximum NDVI value for a year, while $\overline{NDVI_{max}}$ stands for the mean of maximum NDVI values over the observed time period. The general mean maximum anomaly therefore is represented by the mean of all observed maximum anomalies over the time period from 1982 to 2006.

Standard Deviation from Maximum Values between 1982 and 2006

The standard deviation of Maximum Anomalies gives insight in how much maximum values in NDVI scatter from the mean. This calculation can already give some insights in possible trends as it will be shown in chapter III.2.1.
The equation of the SD of Maximum Anomalies is as follows:

[14] Ndvits stands for ndvi time series analysis. A detailed description of the package is available via: http://www.icesi.edu.co/CRAN/web/packages/ndvits/ndvits.pdf (last accessed 04.02.2015).

$$SD = \frac{1}{n-1} + \left(\sum_{i=1}^{n} \frac{\mathrm{NDVI}_{\mathrm{max}}^{\mathrm{i}}}{\overline{\mathrm{NDVI}}} - \frac{1}{\mathrm{n}} \sum_{i=1}^{n} \frac{\mathrm{NDVI}_{\mathrm{max}}^{\mathrm{i}}}{\overline{\mathrm{NDVI}}} \right) \quad \text{[Equation 5]}$$

The parameter n describes the number of images taken into account which count 600 for the whole time period while $NDVI_{max}$ again represents the maximum NDVI value for a year and $\overline{NDVI}_{max}$ the mean of maximum NDVI values over the observed time period

Vegetation Variability (1982-2006)

NDVI variability between 1982 and 2006 was assessed to analyze temporal dynamics and to differentiate areas with high fluctuation of vegetation from more static areas. The variability was calculated among all 600 images by calculating the mean total variation of the time-series according to Franke et al. (2009):

$$\overline{\Delta_t} = \frac{1}{n} \sum_{i=2}^{n} |x_i - x_{i-1}| \qquad \text{[Equation 6]}$$

The mean total variation is calculated with n = 600, representing the number of images taken into account, x_i standing for the actual NDVI image used and by subtracting it with the values from the previous image (x_{i-1}). Main interest here was the total variation among all datasets. The map on variability (see chapter III.2) therefore represents inter-seasonal dynamics to identify those areas with ongoing and steady variability.

Since high variability in NDVI refers to higher land use cover dynamics it can be assumed that the more changes and external impact by e.g. human land use in terms of agriculture occur the higher the pressure on these areas which could lead to degrading lands.

3.2 Including Socio-Economic Data: Exploratory Regression and OLS

LD and marginality are often mentioned in unison – a crucial spiral influencing each other. According to Vosti and Reardon (1997) a link between LD and poverty is observed when referring to poverty in terms of the product of "asset components" including different livelihood capitals such as human resources or also social and political capital. This is exactly what the MPI and also the approach on marginality should tackle more by going deeper into livelihood structures that go beyond only economic indicators. The approach on marginality by looking into different dimensions relates to the sustainable livelihood framework where five so-called capitals of a livelihood are named. These capitals include the financial, physical, human, social and natural capital. Impact of different livelihood structures on land will be assessed by the use of different indicator groups of marginality similar to the different capitals.

Beside different indicator groups also single variables, which could e.g. represent one indicator group, were analyzed regarding their effect on LD. Therefore spatial statistics with ESRI ArcGIS, in particular the tools "Exploratory Regression" and "Ordinary Least Square (OLS)"[15], both implemented in ESRI ArcGIS 10.2, were used to get more information on the relevance and impact of different variables with regard to decreasing vegetation trends – decreasing productivity trends respectively – which represent LD in this study.

Main data and methods used in the study are listed in the following, in addition to more details given on e.g. respective surveys in each of the studies – the national study on Kenya and the local study in western Kenya.

Socio-economic Data

For the national study census data from the year 2009 and data derived from the Kenyan Integrated Household Budget Survey (KIHBS) covering the years 2005 and 2006 are included (KNBS, 2005/2006). The local study in western Kenya benefited from a panel household survey provided by Tegemeo[16] covering the time period 2000 to 2010 in four waves – 2000, 2004, 2007 and 2010 –. Poverty data were available from Census 1999 provided by the World Resources Institute (WRI) and for the year 2005/2006 derived from the KIHBS.

Methods

For the national study, indicator groups are built to later overlay the created marginality index map with available poverty data. As multiple indicators were collected from the mentioned surveys that could fit into one indicator group factor analysis was used to diminish the available variables. Factor analysis helps to reduce the number of variables to a fewer number of variables

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[15] Exploratory Regression and OLS are both tools of ESRI ArcGIS and part of the Spatial Statistics Tools.

[16] Detailed information on the household survey by Tegemeo will be given in the local study (chapter IV).

based on the correlation among them. It is aimed to explain relationships between several indicators by identifying so-called factors representing them (Bühl & Zöfel, 2004).
The factor analysis was made with STATA12 according to the following equation:

$$y_{ij} = z_{i1}b_{1j} + z_{i2}b_{2j} + \cdots + z_{iq}b_{qj} + e_{ij}$$ [Equation 7][17]

The parameter y_{ij} is described by a combination of unobserved factors (b_q). By the variable z the weight of the respective factor is represented that estimates how the unobserved factor accounts for the observed variable. The measurement error in y_{ij} is shown by the parameter e (Jackman, 2005).

In STATA, the mineigen, which represents the minimum eigenvalues to be retained, was set to 0.6 to exclude all variables lower than the indicated value to identify factors in each indicator group. In general the minimum amount of factors that should represent one indicator group was set at three.

Exploratory Regression and OLS

Regression analysis helps to better understand the importance of factors influencing a certain process or phenomena, to test hypothesis and to make better decisions in the future by predicting values (Scott & Pratt, 2009). OLS-regression is the best-known regression technique and can show if a certain set of variables represents a good model to explain a certain phenomenon (Rosenshein, Scott, & Pratt, 2011). With exploratory regression in ArcGIS and STATA different sets of indicators were analyzed. According to the regression formula used for OLS (Equation 8) the dependent variable (y) – in our case LD or improvement – can be explained by a certain set of explanatory variables (x) which are linked to a regression coefficient (β).

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \cdots \beta_n x_n + \varepsilon$$ [Equation 8][18]

The dependent variable y should be explainable by a set of indicators ($x_1, \dots, x_n$). The regression coefficient informs about the strength and type of a relationship, e.g. if it has positive or negative impact. The weaker an indicator the closer its coefficient is to 0. The regression intercept (β_0) shows the expected value of the dependent variable if all explanatory variables would be 0.

Within the ArcGIS tool "Ordinary Least Square" a feature dataset is used which includes all variables linked to the same ID which could be a point or a polygon. In this study the input feature dataset represents county boundaries as polygons including different information about the variables. The dependent variable can be defined in the model and in addition to that all possible explanatory variables can be chosen based on individual preference. The OLS analysis of ArcGIS gives a detailed report about the overall model performance but also of each single

[17] According to STATA Manuals13: http://www.stata.com/manuals13/mvfactor.pdf (last accessed 04.02.2015).
[18] Equation according to ArcGIS 10.2:
http://resources.arcgis.com/en/help/main/10.2/index.html#/Regression_analysis_basics/005p00000023000000/
(last accessed 04.02.2015)

indicator in relation to the dependent variable. But even if the OLS regression was successful by showing e.g. a high R^2 that should explain a big part of the phenomenon (the dependent variable), and stating that the chosen variables have significant impact on the dependent variable, at least six checks need to be made additionally to test the model performance and its variables as stated by the ArcGIS tool recommendation according to Rosenshein, Scott, & Pratt (2011). After running the OLS regression tool in ArcGIS one of the most important checks is the one for spatial autocorrelation (*Check 1*). According to Moran "the presence, absence, or characteristics of some spatial objects may sometimes have significant impacts on the presence, absence, or characteristics of the neighboring objects" (in Lo & Yeung, 2002: 117). Geographic features are often spatially auto correlated which means that possible clusters are only referring to the geographic location of the data and a dependency is shown which is only based on the spatial common variable. *Check 2* includes the importance of each variable. Each variable should have a significant impact or should at least be very close to high significance. According to ArcGIS by *Check 3* the expected relationship which can be seen in the sign of the coefficient (+/-) of each variable should be obvious. Via the VIF (Variance Inflation Factor) a testing for multicollinearity, is included identifying variables that are redundant (default setting VIF > 7.5) (*Check 4*). The VIF measures the effect of correlations with other variables in the model (Maindonald & Braun, 2010). The lower the VIF the more important a variable is for the model. Furthermore, using the Jarcque-Bera Test (*Check 5*) should show that the residuals are normally distributed and do not show different performances for high and low values. Finally the last check (*Check 6*) refers to the adjusted R^2-value which provides information on how much of our depending variable is explained by the chosen indicators.

Before running with the OLS model the "exploratory regression" tool of ArcGIS is used to get an idea of important variables and their interplay for the model and diminish the number of variables for model-testing since it calculates different possible OLS-combinations based on the settings given by the user. A maximum and minimum number of explanatory variables is set based on which a possible model for explaining and predicting the dependent variable is calculated. Thresholds can furthermore be set for R^2 and p-values. R^2 gives an overall rating of the model by calculating for how many percentages the set of variables explain the variance of the dependent variable. R^2 thereby tells how much the interplay of different socio-economic variables influences the process of LD and LI in this study. The p-values then give insights if certain variables do significantly influence the model and thereby have an important impact on LD processes.

But even if the exploratory regression helps to narrow down the number of indicators it is still an iterative process to finally find a good model shaped by the knowledge of the topic and underlined by a detailed literature review which is highly recommended and necessary to understand complex processes such as of LD. A comprehensive research on the impact of different indicators on LD and the environment supported the findings for a suitable model. So finally not only those indicators were used for the OLS model which seemed to have a big impact according to the exploratory regression but also indicators that went beyond that and were stressed in literature or by personal information with experts to maintain the choice.

The OLS-tool of ArcGIS generates an output report and furthermore an optional table of regression diagnostics. Table II.3 shows the output report with the respective indicators. The values are taken from the chosen model for the national study (chapter III) and were included to show the value range of each indicator.

Table II.3: Regression Diagnostics of the explaining model for land degradation among socio-economic indicators. Modified output generated by the ArcGIS Tool "Ordinary Least Square". The included values refer to the model chosen for the national analysis in chapter III.

Indicator	Value	Definition
AIC	314.4217	The Akaike's Information Criterion is a relative measure of performance used to compare different models. The smaller AIC indicates the superior model.
AICc	320.5328	Corrected AIC: second order correction for small sample sizes.
F-Stat	11.0587	Joint F-Statistic Value: Used to assess overall model significance.
F-Prob	0.0000000673	Joint F-Statistic Probability (p-value): The probability that none of the explanatory variables have an effect on the dependent variable.
Wald	676.4266	Wald Statistic: Used to assess overall robust model significance.
Wald-Prob	0.0000	Wald Statistic Probability (p-value): The computed probability, using robust standard errors, that none of the explanatory variables have an effect on the dependent variable.
K(BP)	13.5262	Koenker's studentized Breusch-Pagan Statistic: Used to test the reliability of standard error values when heteroskedasticity (non-constant variance) is present.
K(BP)-Prob	0.0950	Koenker (BP) Statistic Probability (p-value): The probability that heteroskedasticity (non-constant variance) has not made standard errors unreliable.
JB	3.0998	Jarque-Bera Statistic: Used to determine whether the residuals deviate from a normal distribution.
JB-Prob	0.2122	Jarque-Bera Probability (p-value): The probability that the residuals are normally distributed.
Sigma2	38.0529	Sigma-Squared: OLS estimate of the variance of the error term (residuals).

Finally the OLS tool of ArcGIS 10.2 creates an output feature class showing OLS residuals as calculated from the difference of observed and predicted values. Especially areas that show lower or higher residuals than predicted based on the set of indicators chosen are highlighted. Here, one or more variables are missing to more precisely predict the dependent variable.

Exploratory regression and OLS are both methods used within the national as well as in the local study. The individual dependent and explanatory variables will be discussed in each of the studies (chapter III and chapter IV). Moreover, the technique used to define the dependent variables is also to be found in the respective chapters.

3.3 Observing LUCC in Kenya

Insights in land use and land cover are needed if LD is assessed. As different data products on land use cover exist a special interest was also in land cover change over time. Therefore the land cover data of MODIS (Product MCD12Q1) providing land cover information for each year since 2000 is chosen for the national analysis. The spatial resolution of 500m per pixel matched with the MODIS NDVI data used for the vegetation time series analysis.

With regard to food security croplands were in focus for further analysis. Nevertheless the land use and land cover change analysis is conducted on the national level to also derive information in the most affected land cover classes and locate their hotspots of change.

Two different classifications are available: the International Geosphere-Biosphere Programme (IGBP)-classification and a second classification by the University of Maryland (UMD). Here, the IGBP-classification was chosen. The time period observed matched the MODIS NDVI analysis between 2001 and 2011.

Number of LCLU Changes (2001-2011)

For the analysis of LUCC we merged some of the classes in the given classification by IGBP to get fewer and unique land cover classes. The original dataset consists out of 16 land cover classes. Five forest types[19] were grouped to one single class called "forest". Also the two classes "cropland" and "mixed cropland" were grouped to one single class called "cropland" assuming that this land might be mainly used for crop cultivation also with regard to future outlook. In total nine classes were built for the ongoing analysis (see Table II.4). An individual number was given to each of the classes so that only one unique possibility for a certain land cover change exists for further calculations.

Table II.4: Reclassification of IGBP Classification of MODIS Land Cover Product MCD12Q1

Land Cover Type	Reclassification
Water	0
Cropland	1
Forest	10
Shrubland	100
Grassland	1000
Urban Area	10000
Bare Ground/Sparse Vegetation	100000
Snow/Ice	1000000
Wetland	10000000

[19] Evergreen needle leaf forest, evergreen broadleaf forest, deciduous needle leaf forest, deciduous broadleaf forest and mixed forest.

When all datasets for each year have been classified as described in Table II.4. the change from one year to the next year was calculated among the annual raster datasets to extract the information if a land cover change took place or not. Because of the reclassification described above every land cover change gets one unique number so that the information about the type of land cover change in each pixel can be backtraced. This means that the example of land cover change from Grassland to Shrubland has the unique ID= -900, from Grassland to Cropland (-999) or Forest to Cropland (-9).

The change in land cover from each time step to another therewith included no change (0) and change (all other numbers besides 0). To get the number of changes a second classification took place which just distinguished between two classes: change and no change. By adding up every single change the total number of changes in each pixel could be calculated

Interplay of LUCC and Land Degradation

Looking into the number of changes from 2001 to 2011 will help to identify areas with high variability in terms of LUCC. Overlaying furthermore the number of LUCC information with LD, which covers the same time frame, underlines dynamics of LUCC and LD.

LD data derived from trend analysis was reclassified for the overlay into decrease, increase and stable trends. Stable trends were those with a so-called tolerance between -0.005 and +0.005 NDVI values trend change. Decreasing trends are defined as those trends below -0.005 and increasing trends above +0.005 respectively. By overlaying this information with the number of LCLUC dynamics of change can be related to decreasing or increasing productivity within the mentioned period.

Of further interest are land cover classes that are affected the most by changes in productivity referring to vegetation dynamics and trends. An overlay of decreasing and increasing trends with land cover information will highlight areas affected by mainly decreasing or increasing vegetation trends.

As croplands are in focus for identifying the local study area later on cropland areas with productivity change were highlighted.

3.4 Interlinkages - Why and How to address them

> *"Household level studies can never cover large regions even with an exhaustive sampling. Therefore, the combination of different levels of information such as RS, maps and census data together with household level information can provide a detailed and complementary comprehension of land cover change and its determinants"(Soler and Verburg 2010, 372).*

LD needs to be addressed by an interdisciplinary framework (Vogt et al., 2011). Interdisciplinary research in general is needed in all fields of research. This becomes clear when getting insights in the three different areas of research for this study: LD, marginality/poverty and land use and land cover (change). All mentioned topics also address other disciplines. No definition of LD nowadays exists without mentioning the component of human behavior and thereby human impact on changing land productivity. When getting numbers on how many people live in poverty it is also directly mentioned that most of them live in rural areas and depend directly on natural resources. Here again the link is quite clear and it is questioned how the potential of the poor can be increased to farm more sustainable – if this is not already the case – and how to improve livelihood characteristics in general to escape the catalytic spiral. People cultivate land, people live on land, whether they are poor or not, but it gives them different possibilities in terms of capital to afford e.g. fertilizer or improved seed varieties which secure higher yields and thereby productivity. Changes in land use and land cover are therewith also directly linked to the already mentioned two topics: LD and marginality.

Referring to the research questions given in the introduction several links will be analyzed in their interplay. LD and poverty dynamics are analyzed via overlays in a GIS. As poverty as such in its definition is not satisfying, marginality, i.e., its different dimensions, will be addressed further to identify overlaps with poverty. The question if LD and LUCC are interlinked will be analyzed with remote sensing image processing and overlays. Due to the assessment of land cover and land use changes LD hotspots in croplands can be highlighted which then build the foundation for further analysis on the local scale. Main method and data used besides the described methods for each triangle is geospatial analysis to link the different angles and come up with an interdisciplinary approach on different scales. Each chapter will again provide processing charts in order to follow the methodological steps.

All three vertices already deal with impact variables that can be found in each of the other vertices. Putting each of the fringing concepts in a clear approach helps to get a more complete picture in the end. LD is addressed solely from a biophysical point of view by focusing on productivity trends based on vegetation analysis. Marginality on the other hand represents the socio-economic perspective only while LUCC will be addressed to get insights into changing land use and cover in the study area. Instead of using single approaches this study will therefore also insist on already unifying terms and approaches such as the usage of the term "coupled Human-Environment System" that comes closer to the highly dynamic processes taking place on every spatial scale whether global, regional or local.

III. The National Level: Interlinkages of LD, Marginality and LUCC in Kenya

"Poverty, income inequality, and natural resource degradation are severe problems in Kenya, especially in the rural areas" (Okwi et al., 2007: 16769). This strengthens the need for a deeper understanding of root causes of poverty and environmental change including LD and LUCC.

Kenya is a highly diverse country shaped by its biophysical preconditions and socio-economic dynamics. To get a better understanding of the countries characteristics chapter III.1 will give more information on these aspects.

Agricultural systems in Kenya are affected by LD that has a huge impact on Kenya´s rural population as 40% of the rural population live on 5% of Kenya´s rural land (Muyanga & Jayne, 2014). LD differs according to different biophysical settings and socio-economic impact and occurs in different forms, such as soil erosion, compaction or a decrease in soil fertility which leads to less productivity. LD analysis and distribution will be discussed in chapter III.2.1. Also LUCC is an interesting aspect in this country. Kenya is one of the leading countries in Sub-Saharan Africa with regard to the introduction of new technologies in agriculture. This aspect will play a key role in part III as well. According to different climatic regions different land cover is predominant and thereby shapes land use within the country. Chapter III.2.4 will give more insights on that.

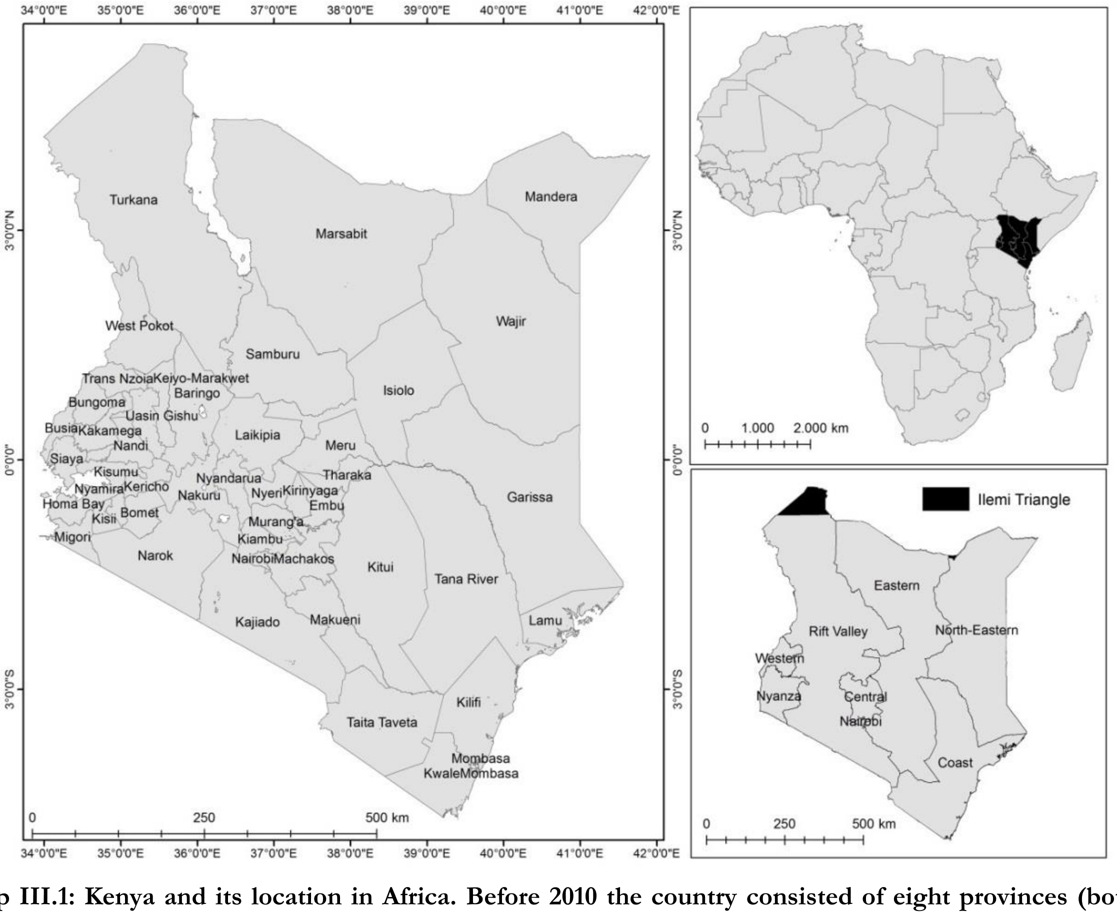
The national poverty prevalence is estimated at 45% while poverty rates in Kenya are listed among the highest in the developing world (KNBS, 2007; Okwi et al., 2007). Around 60% of the population living below the poverty line is found in rural areas (Mwangi, Mwabu, & Nyangito, 2006). Here agriculture or livestock keeping represents the main income and thereby makes the rural population depending on biophysical preconditions and external effects such as droughts, price volatility and also LD. Kenya is a very diverse country with regard to biophysical settings. But also with regard to socio-economic structures which are varying in different locations (chapter III.2.3). Chapter III.2 will give insights in LD, poverty and LUCC in Kenya and analyze relationships among them. Besides a detailed analysis of marginality structures (chapter III.2.3) and their comparison with poverty, a crucial aspect will be tackled by getting insights in poverty and LD dynamics to identify possible interlinkages (chapter III.3.2.1).

1. Study Area: Kenya in Eastern Africa

Kenya is located between 4°N and 4°S in Eastern Africa bordered by Ethiopia in the North, Somalia in the Northeast, Tanzania in the South and Uganda at the Eastern border. The total land area measures 582,646 km² with 11,230km² covered by water (1.9%) (Raleigh & Kniveton, 2012; Otolo, 2013). Around 84% of the country´s land surface belongs to the arid and semi-arid lands (ASAL) where 20% of the total population and 80% of livestock is located (Shisanya, Recha, & Anyamba, 2011). Administrative units have changed frequently during the last decades.

Since 2010 and in line with the 2010 Constitution of Kenya *counties* are the administrative unit of Kenya after the national level (GoK, 2010). In total 47 counties are listed which are again subdivided in constituencies. Before introducing the counties as main administrative unit the country consisted of eight provinces. Naming these is still common. Especially the provinces Rift Valley, Central and Western are still often used in the literature.

When searching for data on Kenya, especially geospatial data, there is still no clear agreement about the part located in the north-west, as part or non-part of Turkana County, the Ilemi-Triangle (Map III.1, bottom right). According to research on administrative boundaries of Kenya and latest information based on international representation by e.g. UNEP[20] or WB[21] the Ilemi-Triangle belongs to Kenya and is included in the analysis.



Map III.1: Kenya and its location in Africa. Before 2010 the country consisted of eight provinces (bottom right) while from 2010 onwards the actual administrative unit comprises out of 47 counties (big map on the left). Masking of water areas was made with a dataset provided by the Intergovernmental Authority on Development (IGAD)[22]. The province-level data was downloaded from GADM (http://www.gadm.org/)[23]. The county shapefile was derived from http://www.arcgis.com/features/ and validated with administrative maps provided by Kenya OpenData (available at: https://www.opendata.go.ke/facet/counties.) (last accessed 06.02.2015)

[20]See: http://data.worldbank.org/country/kenya (last accessed 06.02.2015)

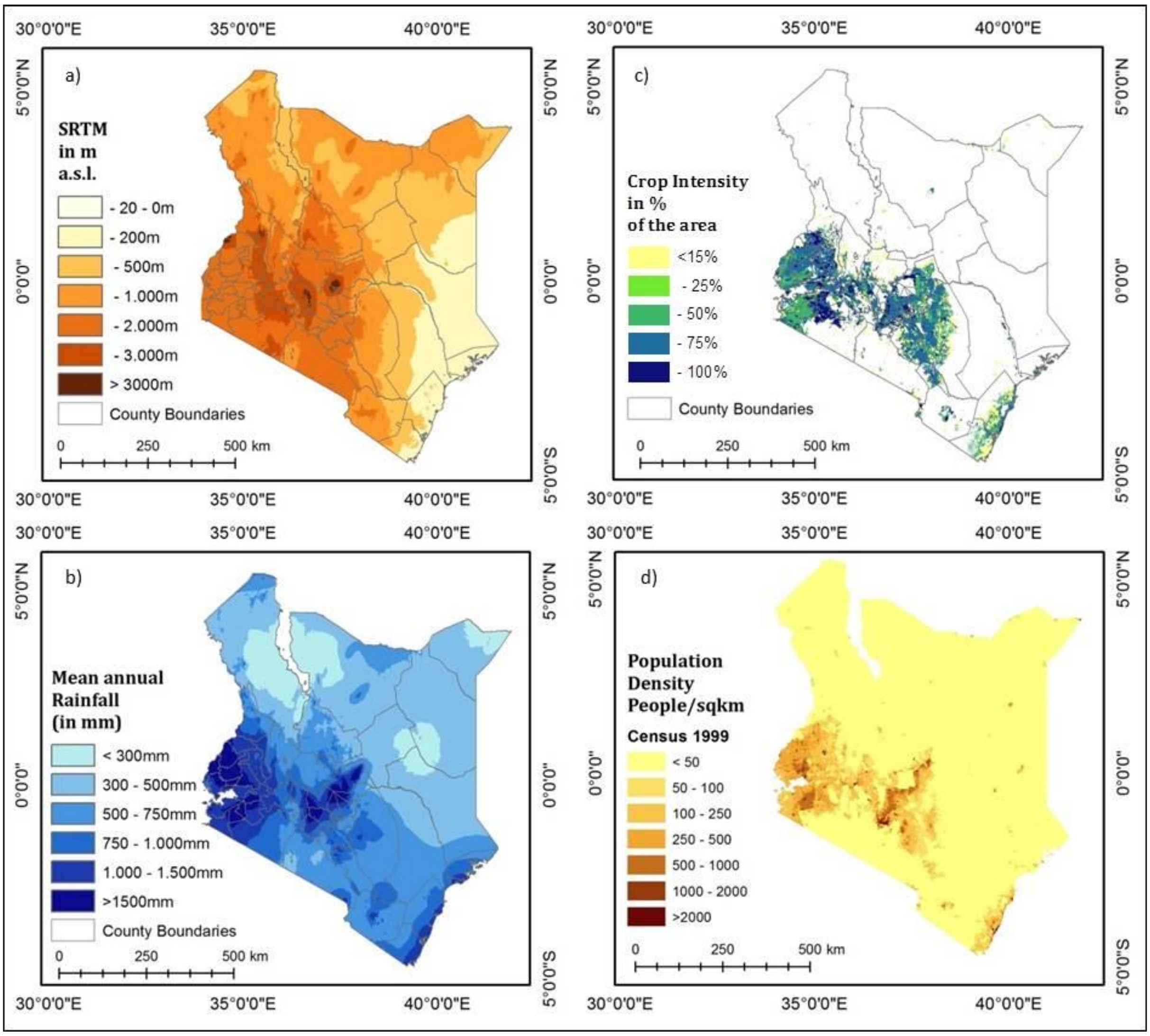
[21] See: http://www.unep.org/greeneconomy/AdvisoryServices/Kenya/tabid/56352/Default.aspx (last accessed 06.02.2015)

[22] Data was provided by the Meteorological Department in Nairobi.

[23]The province-level data by GADM does not include the Ilemi-Triangle as part of Kenya and is therefore not depicted here.

The economy of the country is growing showing an increasing Gross Domestic Product (GDP) from 3% in 2003 to 7% in 2007 (Radeny, van den Berg, & Schipper, 2012).

Kenya is bisected by the equator and very diverse in terms of climate, soils, ethnicities and land use activities. Map III.2 gives insights in some basic variables of the country including topography information (a) and annual rainfall (b) which both trigger crop production, seen by crop intensity (c) and thereby also population densities to a certain extend as seen in Map III.2d. The concentration of activities, whether agricultural or socio-economic can be identified in the southern part of the country, especially two bigger zones in western and central Kenya.



Map III.2: Basic Settings of the study area: Kenya: a) SRTM in m, Source: http://srtm.csi.cgiar.org/ (last accessed: 06.02.2015; b) Annual Rainfall, Source: WRI 2009; c) Crop Intensity, Source: WRI, 2009; d) Population density based on census 1999, Source: WRI 2009.

The following insights in biophysical and socio-economic settings are also based on information on a livelihood zone mapping approach by USAID & FEWSNET (2011). Livelihood zones represent areas where a population more or less share the same production system which is then depending on biophysical preconditions (Otolo, 2013). The map with the detailed zones according to USAID and FEWSNET (2011) can be found in Annex 2 for further clarification. Information in this chapter is related to these zones to take advantage of a classification by USAID and FEWSNET that is already based on analysis of coupled HES.

1.1 Biophysical Settings

Topography

Due to tectonic activity Kenya is shaped with coastal plains in the East to highlands in the Rift Valley area where also preconditions for agriculture are favorable. Tectonic activity is particularly known from the Rift Valley which runs from Northern Turkana down to the counties Narok and Kajiado. As mentioned this area is still known as Rift Valley province (see also Map III.1 for former administrative units of provinces). Kenya´s topography (Map III.2a) also reflects its rainfall patterns (Map III.2c) and thereby also agricultural activity. Three topographic zones are represented in Kenya known as high-, middle- and lowlands. Mount Kenya, located in Kenya´s center, represents the highest point with 5,199m a.s.l. while the highlands in general face altitudes between 1,980 and 2,700m a.s.l. (Otolo, 2013). Lowlands mark altitudes between 200 and 900m, the middle-land areas those between 900m and 1,900m a.s.l. then.

Climate

Rainfall distribution in Kenya and in whole Eastern Africa is very variable due to several major convergence zones that change complex climate patterns over short distances (Nicholson 1996).
Most areas in Kenya have a bimodal climate with two rainy seasons mostly from March to May (long rains) and October to November/December (short rains) which relies on the migration of the Intertropical Convergence Zone (ITCZ) from the southern to the northern hemisphere (Camberlin & Okoola, 2003). Annual rainfall ranges between 250mm to 1,000mm in the drylands and up to 2,500 mm in the highlands[24] (Nicholson, 1996).
The climate in Kenya varies throughout the country. Rainfall is the highest and continuous in the highlands in western Kenya while the lowest precipitation rates are reported in the arid lowlands in the northern and southern parts of the country (Amissah-Arthur, Jagtap, & Rosenzweig, 2002). According to Menz (1997) three main "precipitation corridors" can be identified with a width of each between 50-150km. While two of these corridors located in the northern part of the country run from east to west fed by wet conditions coming from the Indian Ocean, the third corridor has a diagonal south-west to north-east direction probably receiving moisturized air from the central-african region (Menz, 1997). The northwestern areas, including Turkana County, are prone to droughts while rainfall is unpredictable and highly variable and mostly occurs in form of heavy rainfall events that can also cause flooding (USAID & FEWSNET, 2011). With temperatures of around 24-29°C and annual rainfall of 300-400m evaporation rates are also high (Luseno et al., 2003). Also the northeastern area of the county is mainly arid and facing poor

[24] Rainfall amount and especially starting and ending of the short and long rainy season vary throughout the country. See also Figure III.1.

climate conditions with annual rainfall around 250-300m during long rains and 500-700mm during the short rains.
The southeastern area can also be divided in two zones: a small strip along the coast at the Indian ocean, around 16 to 24km long, which receives relatively heavy rainfall of up to 1,400mm during the year (Amissah-Arthur, Jagtap, & Rosenzweig, 2002). Southeast of this coastal strip a drier area follows with only around 200 to 900mm rainfall during the long rains (USAID & FEWSNET, 2011). Peaks in rainfall in southeast Kenya occur in April and November (Shisanya, Recha, & Anyamba, 2011).
Areas with unimodal climate can be found in western and central Kenya where also the highest amount of rainfall annually with up to 1,500mm. The highlands located in western Kenya benefit from high altitudes with about 1,900m to around 2,500m a.s.l. and receive continuous and stable rainfall mainly from February to September (see also Figure III.1).
Eastern Africa was affected by several droughts in the last decades followed by severe famines, crop failures and starving of livestock. Although droughts are naturally occurring in this area the last severe drought in eastern Africa also affecting Kenya occurred in 2011/2012. Western Kenya including the most agricultural productive zone was not affected. It represents a more food secure area not hit heavily by drought periods in the past. Areas such as northern Kenya and especially central and eastern Kenya are much more affected by droughts (Akong'a et al., 1988). Droughts as listed by the International Disaster Database EM-DAT[25] occurred in 1994, 1997, 1999, 2004, 2005, 2008, 2011 and 2014.

1.2 Socio-economic setting

Land use and Livelihood Characteristics

Shaped by climate and topography different so-called livelihood zones could be identified by USAID & FEWSNET (2011) giving more insights in the internal dynamics. As land use and livelihood characteristics are complementary to each other both aspects are combined in this section.

A general overview on planting, harvest and rain seasons can be derived from Figure III.1. The figure also shows the difference within the country as the seasonal calendar here is divided into Western and Rift Valley Area and Eastern and northern Kenya.

As already identified from Figure III.1 the eastern and northern parts have an additional part regarding livestock migration or livestock herding in general. Only around 20% of the national land surface is suitable for crop production keeping in mind that more than 80% of the total land area belongs to the ASAL (Amissah-Arthur, Jagtap, & Rosenzweig, 2002). While agricultural zones are located in western and central Kenya and focus on crop production the northern, north-eastern and southern parts of Kenya are mainly focusing on pastoralism and dryland

[25] Available via: http://www.emdat.be (last accessed: 06.02.2015)

farming. In the northern and north-western pastoral zone[26] almost the entire population relies on Nomadism and is gaining income from livestock. Markets here are inefficient including prices that are higher than the national average in addition to a poor infrastructural system in the area. Also dominated by pastoralism is the north-eastern area of Kenya where livestock represents 60 to 80% of the total household income. Only around 20% of the population living in this area is permanent settled while the others are also nomadic.

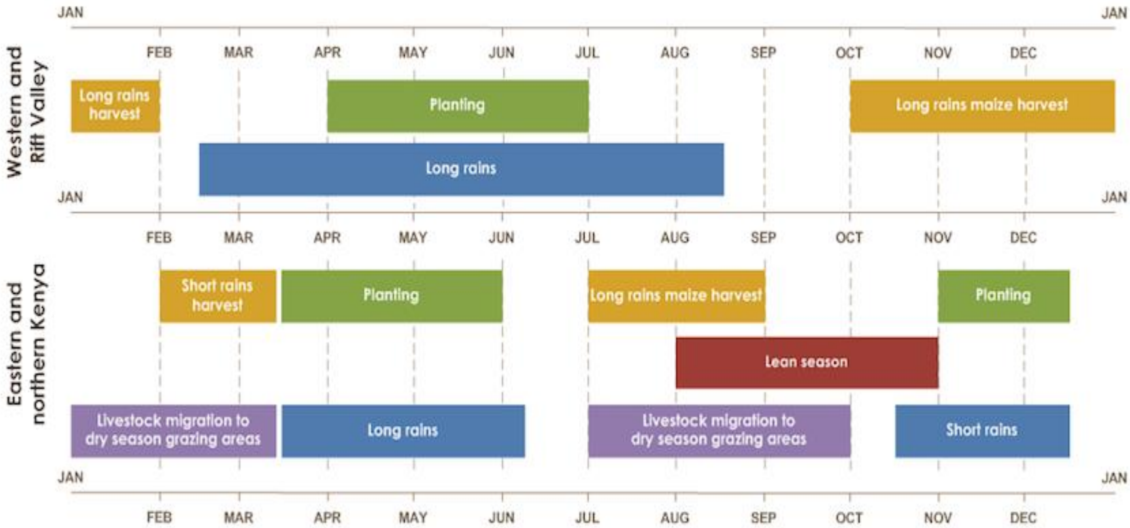


Figure III.1: Seasonal Calendar of a typical year (example from December 2013). Source: FEWSNET (available at: http://www.fews.net/east-africa/kenya) (last accessed: 06.02.2015).

The marginal mixed farming zone is following the small agricultural productive coastal zones where mixed farming and income from fishing, mangrove harvesting and tourism is gained (USAID & FEWSNET, 2011). Around 85% of the population is settled and derive their main income from livestock and crop production while smaller incomes come from small businesses activities and cash crop production (USAID & FEWSNET, 2011).

Another main pastoral zone is located in southern Kenya which is also dominated by arid and semi-arid areas and also belongs partly to the Maasai Mara reserve. The Maasai is the dominant ethnical group (95% of the population living here). Their source of income is mostly livestock as yields are usually very low (USAID & FEWSNET, 2011).

The productive areas in terms of agricultural production in Western and Central obviously gain most income from crop production and by selling the surplus. In addition to maize which is predominantly grown by almost 90% of the farmer, also sugarcane, coffee, tea and beans are produced on large and small scale farms (Wolgin, 1975, WRI 2007). Infrastructure and accessibility in general are constructed well compared to the rest of the country[27].

[26] Term according to the livestock zoning map of USAID and FEWSNET (2011), see also Annex 2.
[27] Based on data on accessibility in terms of travel time to the next agglomeration by Nelson (2008).

Population and Poverty

Population densities (Map IVI.2d) are highest in the productive areas in Kenya. Around 45.55 million people (2014)[28] live in Kenya, most of them – up to 75% – in the rural areas and about 25% in urban areas. Population densities are less in the ASAL, sometimes less than 50 persons per km^2, and the highest with more than 2,000 persons per km^2 in the western highlands (see also Map III.2d).

Nearly half of the population lives in poverty which is shown by a headcount ratio at national poverty lines of 46.1% (Radeny, van den Berg, & Schipper, 2012). Poverty rates vary throughout the country. Turkana County reports poverty rates of 94.3% while lowest poverty rates with 11.6% are shown in Kajiado (KNBS, 2005/2006). Measurements of poverty rates by the KIHBS are based on a calculation in percent of population and number poor below the poverty line which is defined as Ksh[29] 1,562 per month in rural areas and Ksh 2,913 in urban areas[30]. As mentioned the population living in Turkana County are mostly Nomads it is therefore difficult to measure their actual income. In general the county is faced by unfavorable agro-ecological preconditions but with regard to the criticism of measurement of poverty indices as elaborated in chapter II.2.2 awareness should be raised here that income as such alone is not a good measurement for poverty.

Kenya has about 70 ethnic groups. The biggest one with around 20% is Kikuyo, followed by Luo (13.91%), Luhya (13.28%), Kamba (10.95%) and Kalenjin (10.88)[31]. Ethnicity played a key role during the post-election violence which will be discussed in the local study (chapter IV) in particular.

Land Tenure

Due to Kenya´s colonial heritage two main types of farms are predominant in Kenya: large-scale farms mainly for commercial farming and small-scale farms which usually focus on subsistence farming (Wolgin, 1975, WRI, 2007).

Since Kenya´s independence land reforms were very unclear which contribute to individual land dynamics in Kenya (Duraiappah et al., 2000). As it would go beyond the scope of the study to discuss land tenure rights and conflicts among the national scale as they are highly diverse within certain counties, this topic will be raised in the respective sections.

[28] According to World Bank: http://www.worldbank.org/en/country/kenya (last accessed 08.02.2015)
[29] Kenyan Shilling (Ksh) is the Kenya´s currency Ksh 1 is equal to US$0.01 (based on www.oanda.com (last accessed 08.02.2015).
[30] According to: https://www.opendata.go.ke/Poverty/District-Poverty-Data-KIHBS-2005-6/pnvr-waq2 (last accessed 08.02.2015)
[31] according to the East Africa Living Encyclopedia by the African Studies Center of the University of Pennsylvania: http://www.africa.upenn.edu/NEH/kethnic.htm) (last accessed 08.02.2015)

2. Assessment on the National Level

The national study integrates multiple methods to observe interlinkages between biophysical and socio-economic variables to explain degrading trends in vegetation. LD analysis will be analyzed and based on vegetation time series analysis (chapter III.2.1) of long-term data from 1982 to 2006 (chapter III.2.1.1) and the baseline period 2001 to 2011 for the ongoing study.

Chapter III.2.2.1 will analyze a possible link between poverty and LD in Kenya. Assessment of marginality (chapter III.2.2) as the root cause of poverty[32] needs insights in internal household dynamics that go beyond simple economic measurements. Therefore chapter III.2.2.2 combines multiple so-called indicator groups which represent different dimensions of marginality in order to assess possible overlaps with poverty. Socio-economic data derived from Census 2009 and the Kenyan Integrated Household Based Survey (KIHBS) 2005/2006 (KNBS, 2005/2006) is further on applied to explain decreasing and increasing vegetation trends with exploratory regression and OLS regression in ArcGIS and Stata (chapter III.2.2.3).

As LD assessment should include information on land use and land cover chapter III.2.3 is analyzing LUCC in Kenya between 2001 and 2011.

Main methodological steps used for the national study are discussed in the Theoretical Framework (Part II).

2.1 Land Degradation Analysis

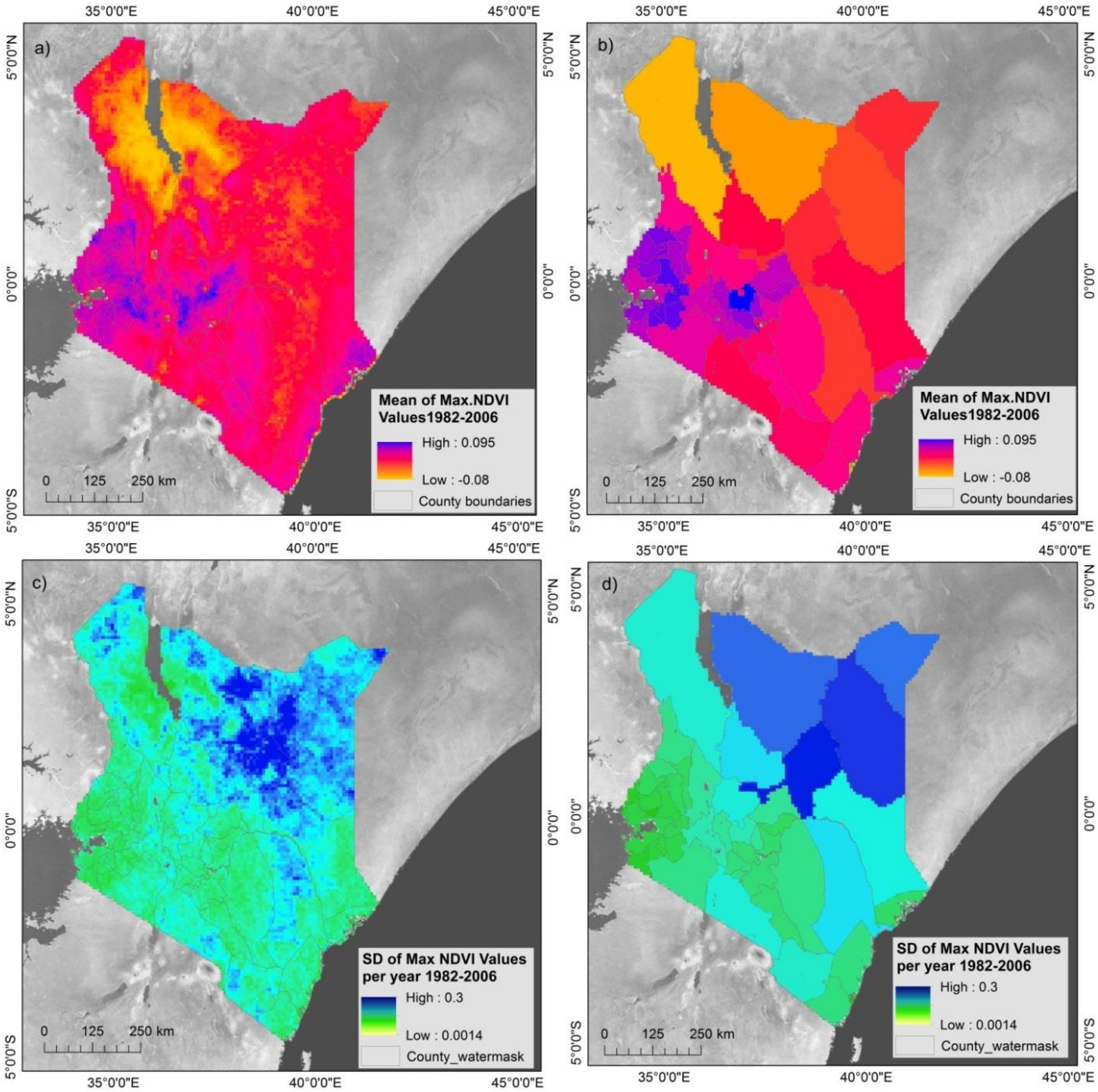
According to Bai and Dent (2006) around 40% of Kenya´s croplands are experiencing decreasing productivity trends based on an observed time period from 1981 to 2003 with vegetation data based on NOAA AVHRR. As described in chapter II a long-term NDVI analysis between 1982 and 2006 was conducted for first insights in distribution and dynamic of vegetation on the national scale before focusing on changes which occurred from 2001 to 2011 based on MODIS NDVI data.

2.1.1 Getting Insights: Long-Term Vegetation Time Series Analysis (1982-2006)

Time series analysis can have multiple faces. A common approach is the analysis of trends over mean annual values especially in areas which are highly variable in terms of climate and vegetation. This approach also includes effects of inter-annual variability (Forkel et al., 2013). Local analysis and observation of smaller areas – most likely within the same agro-ecological zone – rather benefit from seasonal trend analysis (Olsson, Eklundh, & Ardö, 2005; Verbesselt et al., 2010) focusing on growing period of e.g. crops (Dubovyk et al., 2013; Fuller, 1998). With regard to the high diversity in agro-ecological zones the mean annual NDVI in general was used here for the trend analysis on the national level.

[32] See chapter II.2.1 for further clarification.

Map III.3 shows anomalies of maximum NDVI values as well as the standard deviation of maximum values over the observed period of time (1982-2006). The two maps on the left side show the pixel-wise calculation while the corresponding opposite maps on the right show results made with zonal statistics on the county level.



Map III.3: Anomalies of Mean of Maximum NDVI values and standard deviation (SD) of Maximum NDVI values for the observation period 1982-2006. With zonal statistics of ArcGIS the county-perspective is given on the right.

Zonal statistics supported by ESRI ArcGIS[33] was consulted to get an additional view on the administrative level. Here the mean of all pixels within a county were calculated. Certainly, land cover changes do not stick to administrative boundaries. But policy advice and land management strategies mostly do which therefore supports the additional county-perspective throughout this analysis.

[33] Zonal Statistic is embedded in the Spatial Analyst Tools of ArcGIS 10.2.

Highest anomalies from the maximum NDVI values between 1982 and 2006 can be found in the agricultural regions with up to 0.095 NDVI change. This is expected due to growing and harvest periods and higher NDVI values in general compared to other land cover types. Lowest changes are found in the northern areas such as Turkana and Marsabit County but also in scattered parts of the north-eastern areas (with regard to the pixel-perspective) (Map III.3a). With regard to climate conditions and the fact that these areas are prone to droughts which occurred frequently during the observed time period also these results are as expected.

Map III.3 c and d show the Standard Deviation (SD) of maximum NDVI throughout the long-term period. Highest SDs can be identified in the north-eastern parts and some disperse areas in northern Turkana. In the agricultural areas as well as parts around Lake Turkana and the coastal areas lower SDs could be observed.

Vegetation dynamics refer to biophysical preconditions valid throughout the country. Time series analysis and anomalies in vegetation can be related to productivity which is especially focused in areas under agricultural production. But also those areas with stable conditions should be considered with regard to the ongoing discussions on Land Degradation Neutrality (LDN)[34].

Vegetation Variability (1982-2006)

Map III.4 shows the mean total variation as described in chapter II.3.1.2. High fluctuation in vegetation can be observed especially in the central highlands and the coastal lowlands. Both areas are in extensive agricultural use. With regard to crop production in the western areas variability was not as high as expected which can be explained by the fact that agricultural activities take place during the whole year due to unimodal climate conditions and continuous rainfall throughout the year. This also explains higher fluctuation in the central highlands where cropping periods are shorter than in western Kenya based on rainfall and climate conditions. Here e.g. maize varieties are grown that have a much shorter growing period (5-7 months) than in the western areas (up to 11 months)[35]. Arid and semi-arid areas where mainly pastoralism represents the main land use tend to be more stable in terms of variability. High temporal dynamics in vegetation can be related to higher stress on land and thereby could explain higher decreasing vegetation trends if looking from the angle of human impact causing LD.

Long-Term Productivity Trends (1982-2006)

Trends were detected among mean annual values of NDVI using the slope of the linear regression (see chapter II.3.1.1).

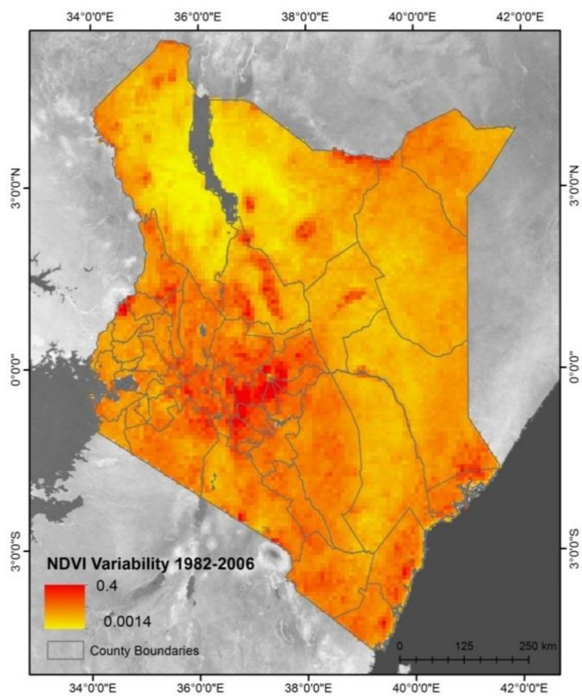
Every pixel gets a unique geolocation so that trends and all other statistical calculations can be linked to these. Map III.5 shows the NDVI trend from 1982 to 2006 based on the above

[34] Land Degradation Neutrality is discussed in Part II.

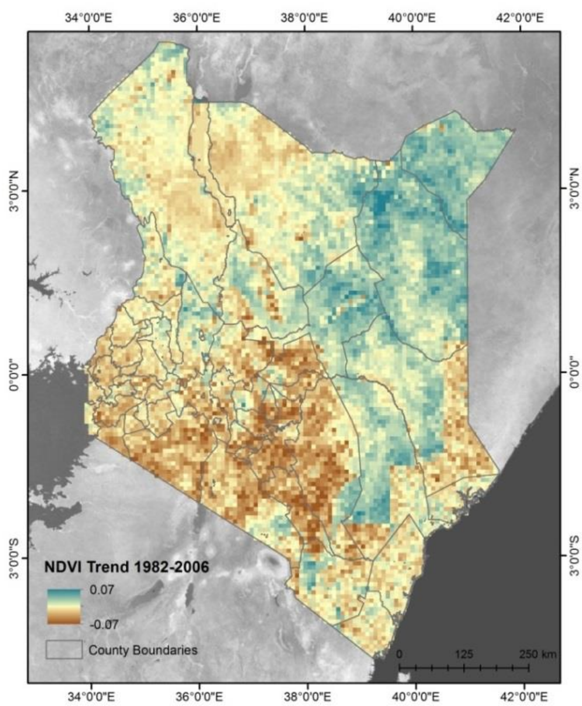
[35] Personal information by Kenya Seed in Kitale, Trans Nzoia County, examples of maize varieties of the central areas are given in the Annex (Annex 3).

mentioned approach. Degrading (browning) trends are detected in arid and semi-arid areas in southern and central Kenya. In northern Kenya as well as the coastal areas more stable conditions are depicted. Although northern Kenya, particularly Turkana County, is often mentioned to be one of the poorest and vulnerable regions/counties decreasing trends are not as high but rather stable conditions can be observed.

Increasing trends are to be found in Northeastern and Eastern Kenya. When calculating pixel with positive and negative trends, including a tolerance from -0.005 to +0.005 where we assume stable conditions, we could identify 54.22% of the area experiencing increasing trends while 25.24% show decreasing trends and 20.54.% stable conditions. NDVI variability and trends are correlated negatively (R^2= -0.2) which can also be stated by visual comparison of both maps (Map III.4 and Map III.5). The higher the variability the more rather negative trends occur.



Map III.4: Mean total variation of AVHRR NDVI values among 600 images from 1982-2006 with bi-monthly temporal resolution. High fluctuation in vegetation can be detected in the central highlands and the coastal lowlands.



Map III.5: NDVI Trend Analysis based on mean annual values from 1982 to 2006. The trend was calculated by the slope of the linear regression.

2.1.2 Changes between 2001 and 2011: the reference period for the ongoing study

MODIS Terra NDVI[17] data with 500m resolution (Product: MOD13A1) was chosen for the ongoing analysis as land cover information with the same resolution and time period, also by MODIS, is available and was integrated in this study (see chapter III.2.3) and socio-economic data could be matched to this observation period.

Figure III.2 gives an overview on how the LD analysis was undertaken. Input data is based on MODIS NDVI and RFE. Raw data is clipped to the respective areas – including marked water pixel. Mean annual NDVI values were built with ArcGIS cell statistics where the trend analysis represented by the slope of the linear regression is based on. Significant positive and negative rainfall pixel were masked to focus on human-induced LD.

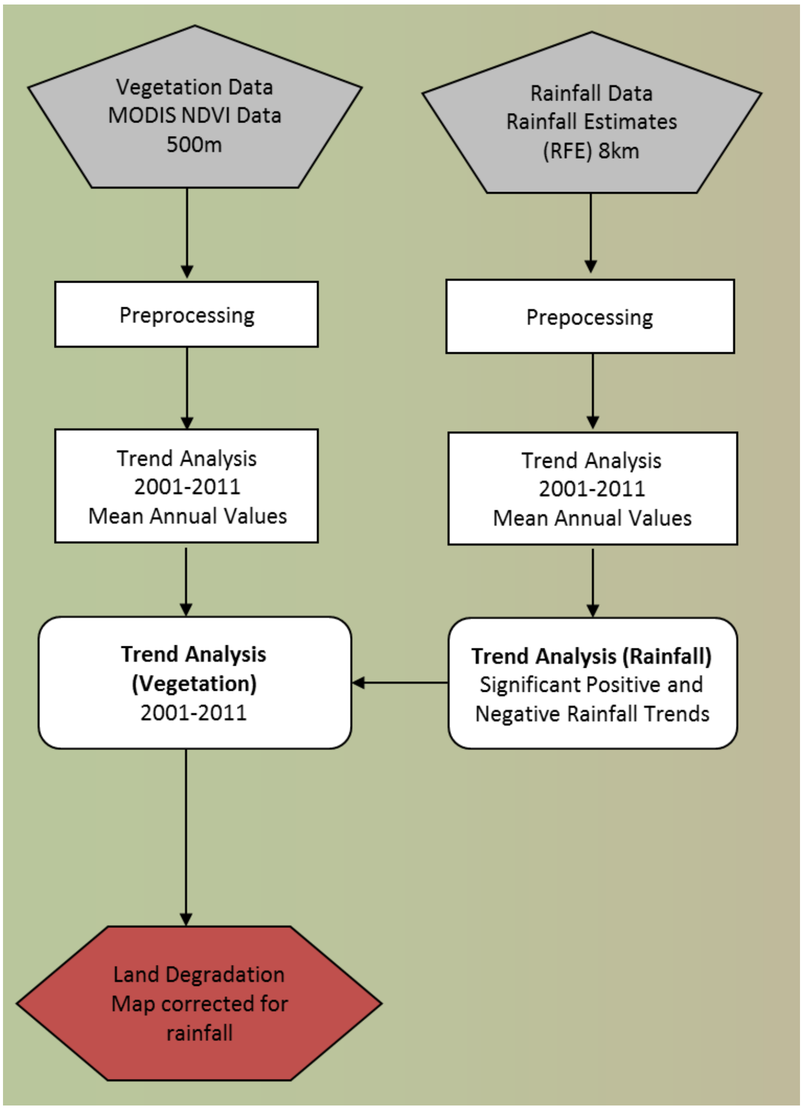


Figure III.2: Land Degradation Analysis; own draft

[17] For more information on the data please look at chapter II.3.1.1

In total, 241 images are used for the trend analysis with MODIS NDVI. Due to disturbances and missing pixel-values in one image of 2004[18] this dataset is excluded from the analysis. As the year 2000 was affected by a drought time series analysis here starts in 2001 to avoid starting time series analysis in a drought period as this could falsify results. The Sahel zone e.g. shows increasing vegetation trends since the mid-1980s (Herrmann, Anyamba, & Tucker, 2005). This development is also known as the "greening of the Sahel"[19]. But it needs to be taken into account that in 1983 and 1984 the Sahel zone was experiencing severe droughts which caused extreme famine. Studies showed that vegetation trends are significantly higher if the analysis started in 1983/1984 (Dardel et al., 2014). These results could be based on very low NDVI values at the starting point of the analysis and much higher values at the end point. As also end of 2011/ beginning of 2012 a drought occurred in Eastern Africa the end point of the analysis was chosen to be in 2011.

Human-induced land degradation: correcting vegetation trends for rainfall

In order to account for socio-economic factors the analysis is focusing on changes in productivity driven by land usage and human impact. Vegetation trends have to be corrected for impacts from natural sources such as precipitation. Vegetation growth is highly dependent on precipitation which is validated by many studies showing high correlations and interplays (Malo & Nicholson, 1990; Davenport & Nicholson, 1993; Nicholson & Farrar, 1994; Herrmann, Anyamba, & Tucker, 2005).

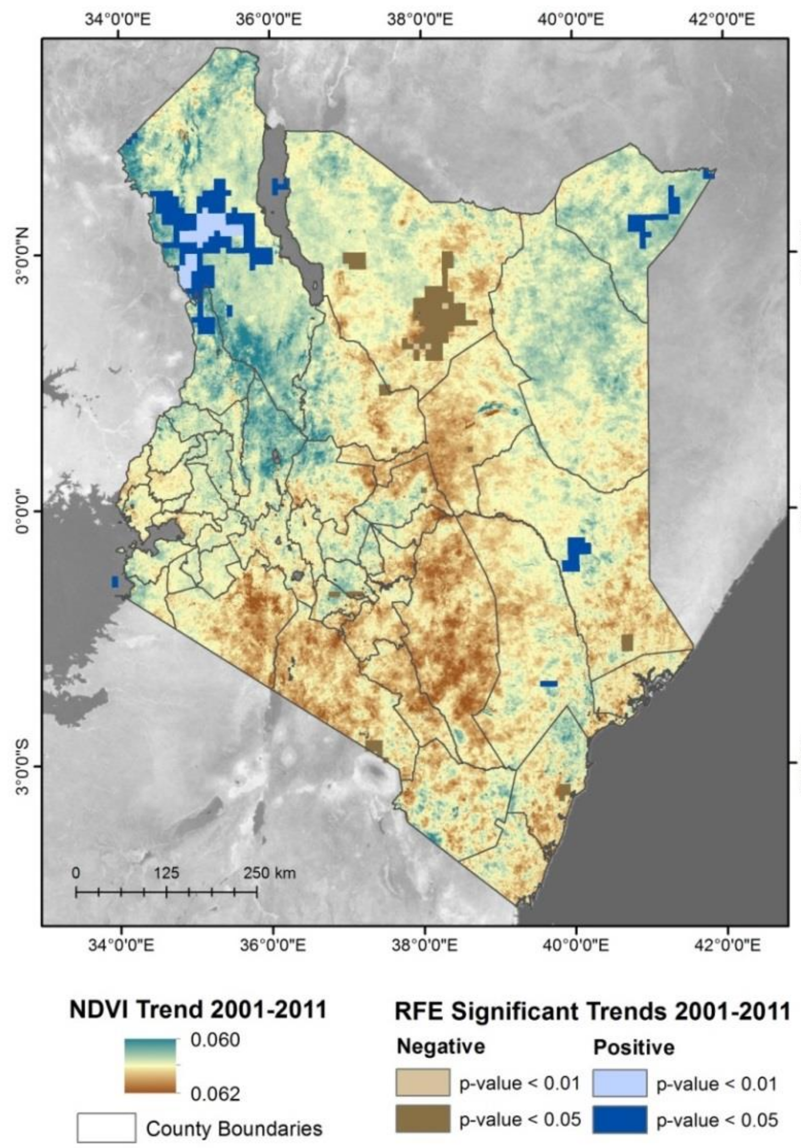
Trend analysis based on the slope of the linear regression of mean annual values of MODIS NDVI data follows the same approach as undertaken with GIMMS AVHRR NDVI data. A comparison of decreasing and increasing percentage areas shows 14.66% overlapping increasing and 59.91% overlapping decreasing pixel.

To delimit vegetation trends driven by precipitation that is appropriate in arid to semi-arid areas but also in sub-humid to humid areas those pixel being influenced by significant increasing and decreasing trends in precipitation have to be masked. RFE data (Xie and Arkin, 1997) were selected due to a spatial resolution of 8km by 8km per pixel which is higher than any other rainfall dataset based on remote sensing imagery. Mean annual values are used to calculate significant positive and negative trends per pixel with $p<0.05$ in R. The significant positive and negative trends represented by p-values are shown in Map III.76.

By masking those areas with significant rainfall trends in the NDVI time series analysis for the same time period we can assume to get insights in vegetation trends that are mainly influenced by human impact. Based on the different pixel sizes also those NDVI-pixels were masked that might not have been directly affected by significant rainfall trends.

[18] The image of Julian day 304 in 2004 – the 304th day of the year 2004 – showed high disturbances in the dataset and was therefore excluded.

[19] Time series analysis of vegetation in the Sahel showed increasing vegetation trends which consolidated the term "greening of the Sahel" due to the output maps, where increasing vegetation trends where shown as "greening trends".



Map III.6: Human-induced LD map for the time period 2001 – 2011.
MODIS NDVI Trends from 2001 to 2011 with masked significant rainfall trends (2001-2011) based on mean annual values of RFE data in the respective period. Trend analysis is based on mean annual values from 2001-2011; rainfall trends are masked for further analysis to focus on human induced LD.

Decreasing and increasing productivity in the respective livelihood zones

Based on the livelihood classification established by FEWSNET and USAID[20] those livelihoods were identified where most productivity changes due to decreasing or increasing trends from 2001 to 2011 occurred. Tolerance should still be included to abstain slight natural variability in vegetation trends. Therefore the cut-off point was set at below -0.005 and above +0.005 trend-NDVI values, respectively. The percentage of positive and negative trends within each livelihood zones is shown in Figure III.3. As already stated by visual interpretation marginal mixed farming zones and southern/south-eastern farming zones are affected the most with 40 to 70% of

[20] See also description of the study area (chapter IV.1)

decreasing pixel among the whole area. Positive trends could be observed in the river and fishing zones located around Lake Turkana and the Western Agro-Pastoral Zone which is also located in Turkana County.

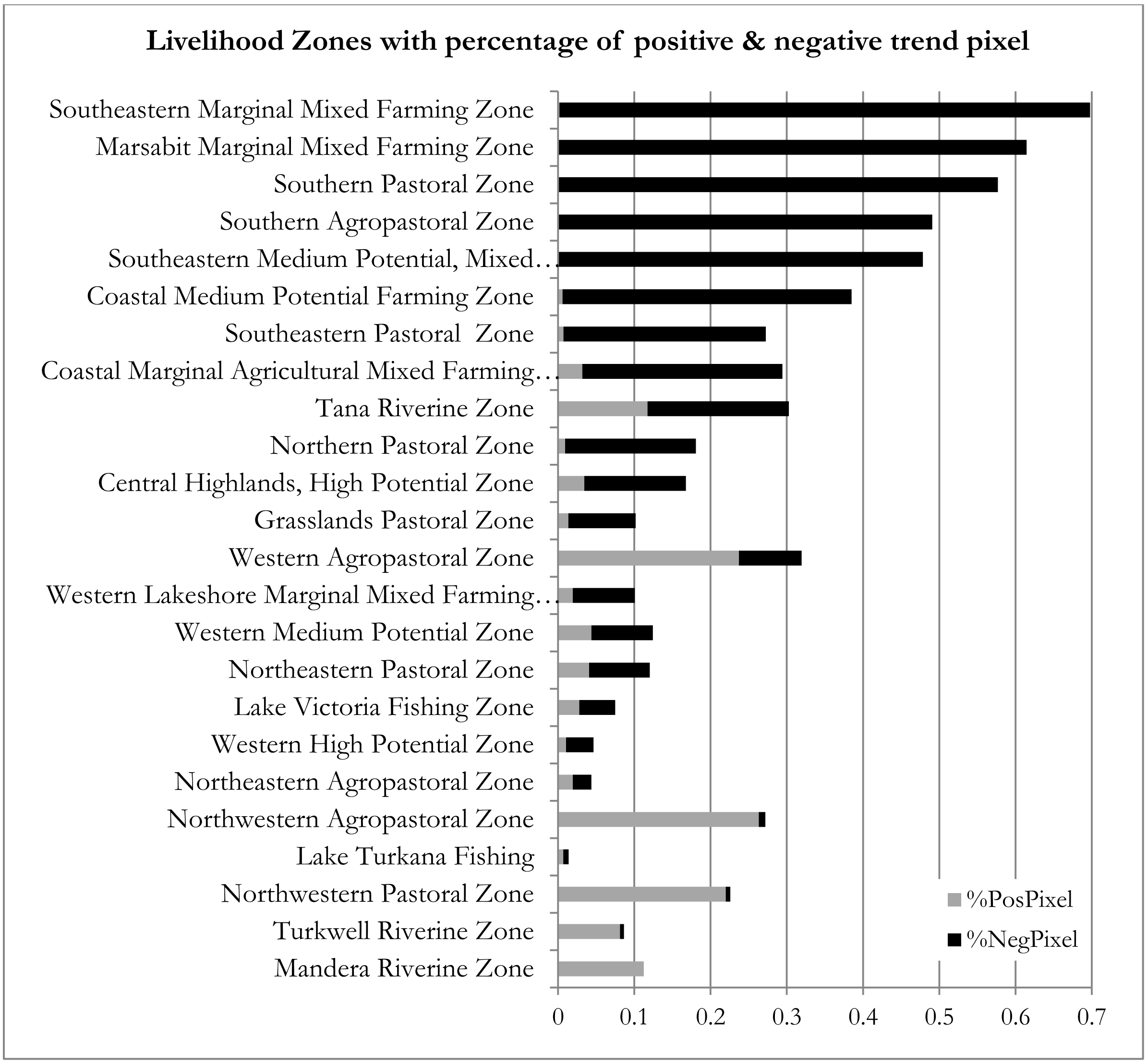


Figure III.3: Pixel (in %) with positive and negative trends (2001-2011) per livelihood zone according to the Livelihood Zone classification of FEWSNET and USAID (2011).

Trend pixels allocated to the 47 counties of Kenya are shown in Annex 4. Positive trends with around 20-35% of the county could only be found in West-Pokot (located in the high-potential areas) as well as in Turkana and Baringo located in the former Rift Valley Province. Highest decrease was calculated in Mombasa (Coastal area), Kitui, Makueni (Central semi-arid areas), Nairobi and in southern Kenya in the counties Narok and Kajiado with more than 50% decrease.

2.2 Marginality Mapping for Kenya

Marginality is defined as the main reason for poverty (Gatzweiler & Baumüller, 2014). Here, we address the link between marginality and LD or land improvement via different dimensions, called "indicator groups", of marginality. Poverty alone is seen as too narrowed by looking solely at economic determinants defined mainly by income but will still be included in the analysis

The national marginality analysis addresses four key questions:

- Do poverty and LD overlap and therewith represent causes of each other?
- Is it possible to derive enough information about socio-economic deprivation in Kenya by the poverty indicator as such?
- If Marginality is mentioned to be the root cause of poverty, should these indicators overlap?
- Can LD trends/productivity trends be explained by a certain socio-economic setting?

Figure III.4 shows the framework of the national approach to get insights in marginality, poverty and LD dynamics. The LD analysis (left/green side) was already described in chapter III.2.1. The right part (red and areas shifting from green to red) describes the socio-economic dynamics where analysis and mapping of marginality as well as poverty is performed. Data for the socio-economic analysis of the national study was merely based on Census data of the year 2009 and the KIHBS from 2005/2006. In addition, overlaps and interplays of poverty and marginality were approached. Finally, we aim to identify a set of socio-economic factors that are the main explanations for LD processes and help to tackle the right aspects within the respective administrative boundary. As LD trends were corrected for rainfall we can assume that primarily human induced productivity trends based on vegetation cover information are approached. The analysis takes advantage of several statistical operations such as correlation, exploratory regression and OLS-regression.

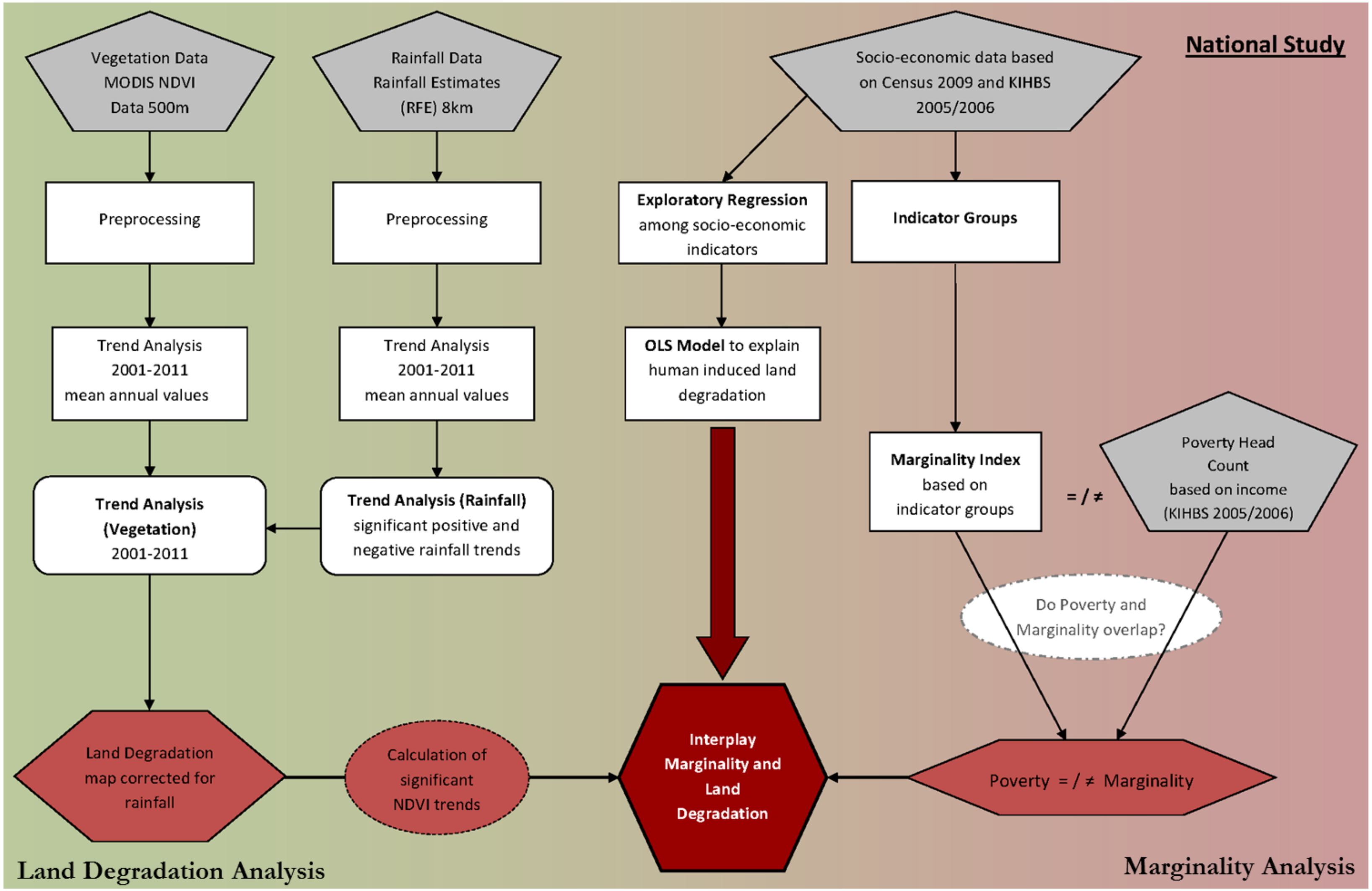


Figure III.4: Framework National Study: Interlinkages of Marginality/Poverty and Land Degradation

2.2.1 Poverty and Land Degradation– is there a link?

Poverty in Kenya has increased over the last two decades (Mwangi, Mwabu, & Nyangito, 2006). According to the KIHBS 2005/2006 46% of the Kenyan population is absolutely poor while about 60% of those poor live in rural areas and depend directly on agriculture and natural resources (Suri et al., 2008). A relationship between poverty and LD is expected which could be present due to a low capital to afford e.g. improved seeds and fertilizer to increase yields and add minerals back to the soil. Poverty can also be related to exclusion[21] as for example in South-Africa. During the apartheid less suitable areas were allocated to those of African descent which at that time – and still today – represent the majority of the poor population in South Africa (Gradín, 2013). These homelands[22] were located in northern parts of South Africa as well as in the hilly areas in the southwestern part close to the coast and experienced more degradation than other areas in the country (Hoffman & Todd, 2000; Wessels et al., 2004). Explaining these degradation processes with poverty from the socio-economic perspective is obvious but not fully satisfying. Homelands were mostly areas with lower soil fertility and higher slopes which made them thereby more prone to soil erosion (Hoffman & Todd, 2000). Land tenure thereby plays one of the key roles here as the homelands were part of the communal areas where people have only a few rights to own or sell land (Meadows & Hoffman, 2002). Having limited or no rights to own land in general offers less incentive to cultivate land sustainable. But with regard to biophysical preconditions these areas have always been less productive than the fertile areas – referring to the commercial land mainly inherited by white farmer that time (Hoffman & Todd, 2000). Results of the study by Hoffman and Todd (2000) showed that even if the situation has changed and South Africa became independent LD processes are still more severe in the former homelands where most of the rural poor live.

The link between poverty and LD is not always as obvious as it seems which is why several studies also confound a strong link (Lambin et al., 2001) or at least do not state a proved link (Johnson, Mayrand, & Paquin, 2006). But what happens when we shift from a narrow thinking about income measurements to a more diverse definition of poverty? Would a link be more obvious? An overlay was used to spot if LD and LI trends overlap with poverty state and poverty trends within nearly the same time frame.

Land Degradation and Poverty – State

Using the MODIS NDVI trend analysis from 2001 to 2011 and overlaying them with poverty head county information of KIHBS 2005/2006 offers the possibility to determine if poverty distribution is linked to LD or LI. NDVI trends were reclassified in decreasing (<-0.005) and

21 Being "excluded from" is also one of the indicators for marginality which can be the root cause of poverty (von Braun & Gatzweiler 2013).

22 Areas appropriated to the black population were called homelands during the apartheid.

increasing (>0.005) trends (see also Map III.7a). Poverty data by KIHBS 2005/2006[23] was classified in high poverty (>50%) and low poverty (<50%). On 14.94% of the area an overlap of high poverty and LD could be observed compared to 0.5% of low poverty and increasing trends. Low poverty and LD had an overlap of 6%, high poverty and LI 9.16%. Even if the highest rate is observed in degrading areas with high poverty the link is not as obvious as expected in addition to a bigger overlap of LI and high poverty than LI and low poverty.

Land Degradation and Poverty – Trends

The second observation includes trends of both variables applied to the time period 2001 to 2011. Poverty data for 1999 were derived from the Census 1999[24] available on the location level[25]. Data for the North-Eastern region were missing. Therefore this area is masked in the analysis. As no poverty data were available from the Census 2009 the next following dataset on poverty for change detection integrated the KIHBS covering the years 2005/2006. For the analysis of poverty trends we assume a linear trend based on the data of 1999 and 2005/2006. As KIHBS data were only available on county-level a common level had to be found. Therefore the analysis was conducted on location-level.

Map III.7a shows vegetation trends based on the NDVI trend analysis between 2001 and 2011. The Map focuses preferential on increasing and decreasing NDVI trends including a tolerance trend where just small changes in vegetation occurred (-0.005 to +0.005). Map III.7b shows the already mentioned poverty change from 1999 to 2005/2006. High percentages of people falling into poverty (dark red = more than 20%) and high percentages of people escaping poverty (dark green = less than -20%) were highlighted. Simple change detection shows increasing poverty rates in the north-eastern part of Kenya while the southern part is rather escaping poverty.

Two areas are highlighted where exact opposite trends can be detected: north-western Kenya, Turkana County in particular, and the southern counties Kajiado and Narok. In Turkana County vegetation increase is observed while at the same time poverty in this area is shown to be increasing. Increasing poverty rates can additionally be identified in Wajir and Mandera County east of Turkana County. In Kajiado and Narok County, located in southern Kenya, high vegetation decrease and simultaneously poverty decrease can be detected showing that people escape poverty while land is degrading. The poverty results shown would match with the second edition of the Kenya County Fact Sheets (CRA, 2013) where Kajiado County is rated as the "richest" and Turkana as the "poorest" county[26] even if the timeline is not matching exactly with

[23] According to KIHBS 2005/2006 poverty rates here are defined as the "percentage of population and number of poor below the poverty line of Kenya which is set at Ksh 1,562 per month in rural areas and 2,913 in urban areas per person per month, based on minimum provisions of food and non-food items" (KNBS 2005).

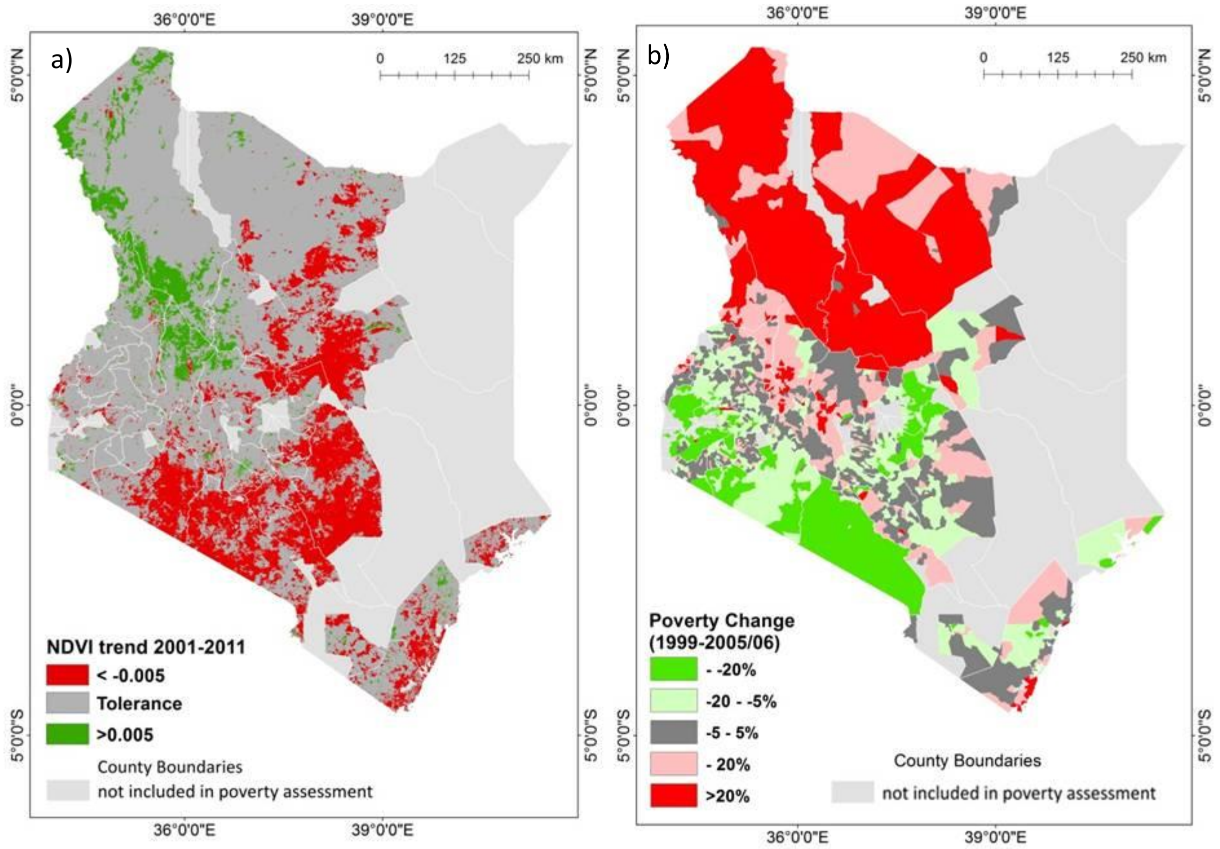
[24] Census 1999 poverty rates were based on expenditure per month which is Ksh 1,239 in rural areas and 2,648 in urban areas (WRI 2007).

[25] Locations represent the second administrative level (first administrative level since 2009 are counties).

[26] http://www.nation.co.ke/News/politics/Kajiado-richest-county-Turkana-poorest-/-/1064/1930892/-/ain94qz/-/index.html (last accessed: 08.02.2015)

the vegetation trend analysis. According to the daily nation[27] 2013 is the second year in a row that Kajiado is stated as the richest county and can be pulled out of poverty the easiest[28].

The increasing NDVI trend in Northwestern could be explained with migration rates. Unfortunately no data are available on migration rates especially on a small administrative level. Moreover this area is dominated by Nomads so pressure on single land parcels is not as high as in areas under continuous cultivation.



Map III.7: Processes of LD and poverty in the overlap (reference period: 2001-2022). a) NDVI Trend Change with Tolerance 2001-2011 based on MODIS NDVI 500m resolution, b) Poverty Change 1999-2005/2006 based on Census 1999 and KIHBS 2005/2006.

The counties Narok and Kajiado in southern Kenya and Turkana in the northwestern part of the country will also play a key role in the further analysis with regard to land cover change and LD in the interplay. These results, degrading trends in southern Kenya and increasing trends in northwestern Kenya are in line with problems of livestock pressure and land tenure which are most severe in Kajiado (Campbell et al., 2000) but also in Isiolo (Boye & Kaarhus, 2011) in central Kenya where also trends of decreasing poverty and increasing vegetation are identified. Kajiado county and surrounding areas are experiencing conflicts between herders, farmers and wildlife over more than 30 years which are mainly deriving from scarce water and land resources and thereby lead to a high competition between these three groups (Campbell et al., 2000). Also

[27] The Daily Nation is Kenya´s leading newspaper.

[28] See http://www.nation.co.ke/News/politics/Kajiado-richest-county-Turkana-poorest-/-/1064/1930892/-/ain94qz/-/index.html (last accessed 07.02.2015).

during the field visit in August 2013 personal information by local authorities in the Maasai Mara area made obvious that increasing livestock population is becoming a serious problem and leads to higher pressure on land due to competition on grassland resources but also diminishing grasslands is a severe issue here. In most parts of Kajiado and Narok the Maasai are resident but tolerate wildlife and farming which came up after the colonial period (Campbell et al., 2000). Having a high number of livestock often represents a status symbol in rural areas (Sawhney & Engel, 2004). It builds a kind of insurance as livestock can be sold in times with little to no harvest or other shortages. This is not only an example of Sub-Saharan Africa but valid for nearly all rural areas worldwide as also studies from South Asia and even northern Europe show (Sawhney & Engel, 2004; Pell, Stroebel, & Kristjanson, 2010; Johannesen & Skonhoft, 2011).

Overlapping trends of increasing poverty and decreasing productivity at the same time can be found in western Kenya and small areas along the coastline in the East.

Results of this chapter match with the analysis by Pender et al. (2004) where no evidence for a "poverty - land degradation trap" could be found expression that erosion was not linked to asset ownership (Pender et al., 2004: 24). But still the hypothesis that LD and poverty influence each other should not be neglected but rather analyzed regarding the type of poverty which leads to the following approach of marginality as the root cause of poverty.

2.2.2 Marginality Mapping: a socio-economic perspective

The Marginality Mapping for Kenya identifies good and bad performing areas with regard to different marginality dimensions such as e.g. health, education or accessibility.

The socio-economic data used within this study were collected from free available household surveys and census data. The Census 2009 and the KIHBS 2005/2006 was taken into account to depict the current situation and match the vegetation trend analysis later on. Most data refer to the administrative unit of the county. With help of literature research and factor analysis around 50 variables were analyzed for their possible link to poverty and environmental change. The indicator groups taken into account included variables on: Education, Health, Access to information, Access to Infrastructure and Employment/Economy. Governance indicators that e.g. represent political instability or violence per county or group activities and number of NGOs within a county were unfortunately not available or do not exist.

The indicators of accessibility were split stating that even if there is no physical access to close markets, access to information could be more important than having spatial access.

Indicators that were derived via factor analysis in STATA to represent five different marginality indicator groups are listed in Table III.1.

Table III.1: Indicator Groups with single indicators

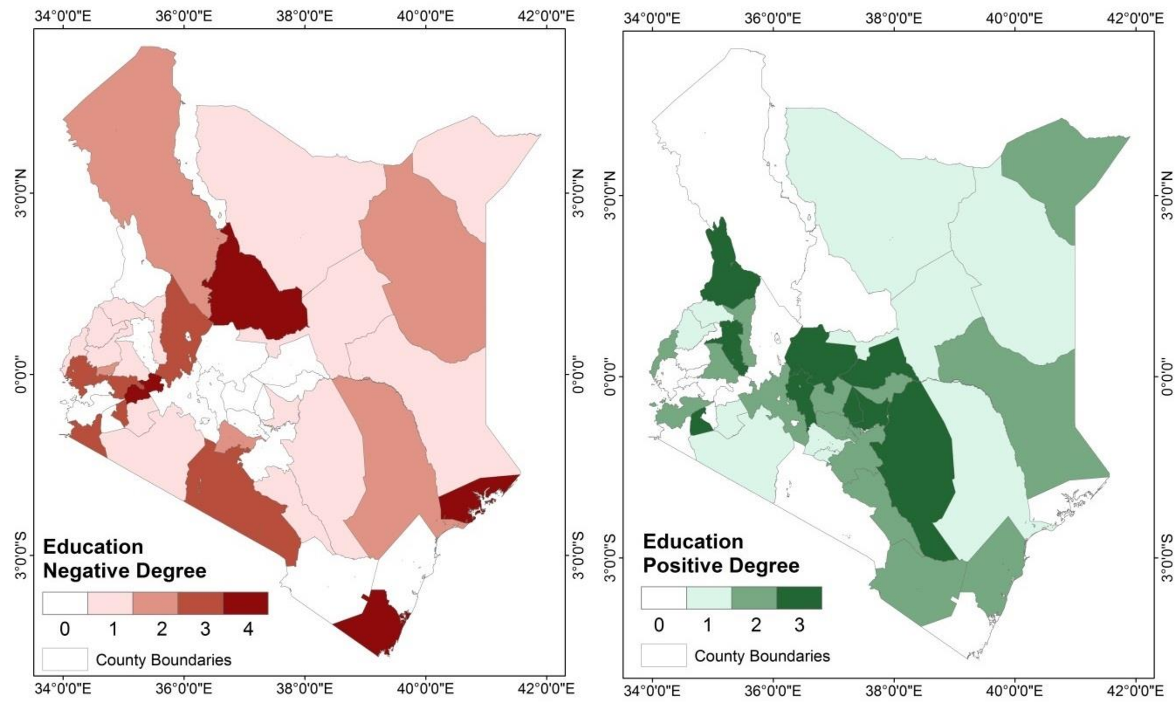
Indicator Group	Indicator
Education	Percentage of people never attended school
	Percentage of people with primary education
	Percentage of people with secondary education
	Percentage of people going university
	Percentage of people with basic literacy
Health	Underweight
	Stunted
	Malaria Cases
	Number of people living with HIV
	Tuberculosis incidence
	Nurses/doctors/clinical officers per 100,000ppl)
	Health facility (public, nongovernmental, private)
Access to Information	Households having a Radio
	Households having a TV
	Households having a Mobile
	Households having a Landline
	Households having a Computer
Access to Infrastructure	Paved Road
	Good/Fair Road
	Electricity
	Households having a bike
	Households having a motorbike
	Households having a tuktuk[29]
	Accessibility Nelson - travel time to next agglomeration with 50,000 people.
Employment/Economy	Employed
	Seeking Work

Each indicator was analyzed regarding its performance throughout the country. Best and worst performing areas were classified by standard deviation. The range of standard deviations between -0.5 to +0.5 were masked to focus on the areas that are either "good" (positive) or "bad" (negative) with regard to the performance of marginality indicators. By overlaying all positive areas and all negative areas the degree of marginality was identified by the number of the related overlapping areas. Equal weights were used for all indicators. Map III.8 shows the example for the indicator group of education. Five indicators were used within this group: Percentage of people that never attended school, percentage of people with primary education, percentage of people with secondary education, percentage of people going to university and percentage of people with basic literacy.

This analysis was done for each indicator group to afterwards create the Marginality Index. Each indicator group represents one possible root cause group for poverty. Hotspots of Marginality

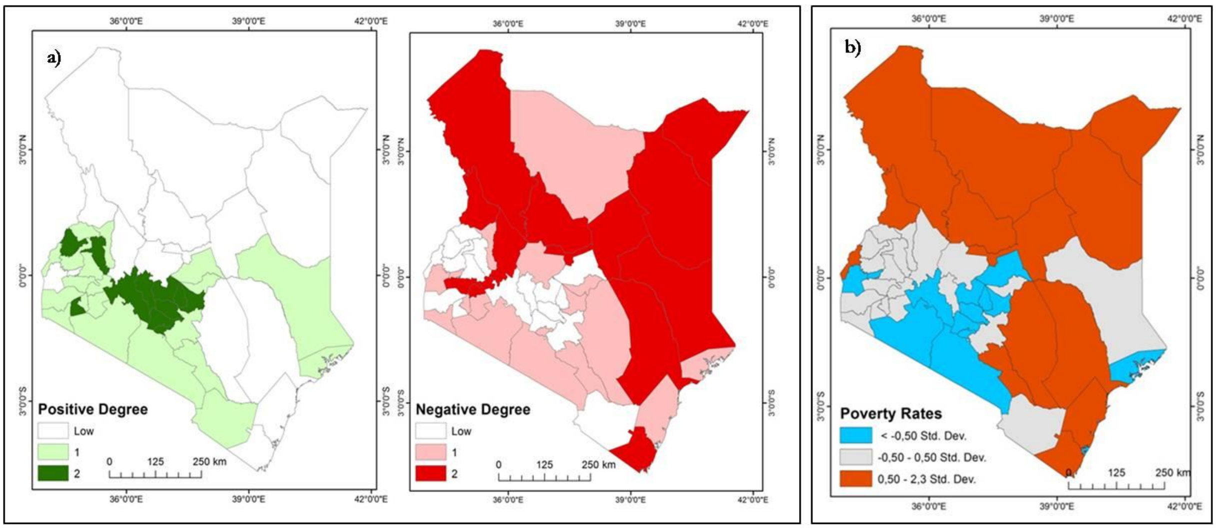
[29] A tuktuk is a very small vehicle.

but also of positive areas were highlighted by building two datasets: positive degree (green) and negative degree (red) of the indicator group (see example Map III.8). All negative and positive degrees of all indicator groups were combined and were each – the positive and the negative marginality index – divided into three groups based on quantiles.



Map III.8: Example for the Indicator Group Education.

Map III.9b shows the poverty rates based on the KIHBS 2005/2006 – the latest poverty information for Kenya at the time this study was set up. The poverty rates were also classified into three equal groups based on Standard Deviation to get an idea of poverty rate distribution among the country. Comparing Map III.9a and III.9b give an impression about the distribution of marginality and poverty. Overlaps but also differences are still obvious.



Map III.9: Marginality (a) as the root cause of poverty (b)? Marginality positive and negative degrees are found in Map III.9a. Poverty rates based on KIHBS 2005/2006 are shown in Map III.9b.

As poverty is not always a fixed combination of all dimensions of marginality but rather influenced by certain dimensions with different weights those indicators should be identified that are linked more to poverty than others and do have a higher impact on environmental change than others. Pair wise correlation between the degree of marginality of all indicator groups – positive and negative - with poverty rates was calculated in STATA (Table III.2).

Table III.2: Pair wise correlation between Marginality Degrees of the indicator groups (positive degree (+) and negative degree (-)) and Poverty Rates based on KIHBS 2005/2006 data.

	Econ (-)	Access Infra(-)	Access Infor(-)	Health (-)	Edu (-)	Access Infra (+)	Acces s Info (+)	Health (+)	Edu (+)	Econ (+)
Economy (-)	1									
Access Infra(-)	0.52	1								
Access Info(-)	0.36	0.77	1							
Health (-)	0.21	0.12	0.12	1						
Education (-)	0.22	-0.05	0.17	0.23	1					
Access Infra(+)	-0.08	-0.44	-0.44	-0.03	0.39	1				
Access Info(+)	-0.26	-0.53	-0.53	-0.23	-0.01	0.52	1			
Health(+)	-0.26	-0.20	-0.20	-0.17	-0.14	0.19	0.29	1		
Education (+)	-0.20	-0.02	-0.09	-0.06	-0.67	-0.35	0.10	0.05	1	
Economy (+)	-0.50	-0.14	-0.37	-0.24	-0.12	-0.07	0.20	0.32	0.18	1
Poverty Rates	0.49	**0.60**	**0.70**	0.19	-0.12	-0.29	-0.59	-0.17	0.10	-0.31

Accessibility – whether to information or infrastructure – is highly correlating with poverty (0.6 - 0.7). This indicator is also linked to economic structures showing a correlation of 0.5 for higher poverty rates with higher economic marginality which makes sense as capital is needed to afford access to information by having a phone or landline and use transport by e.g. having a car. But indicator groups such as accessibility or economy do not correlate with poverty in the same amount than e.g. health or education. It makes sense to identify single indicators that could give leading information on environmental change and thereby allow predictions when analyzing these indicators.

The correlation analysis among single indicators agreed to the previous results. Access to information – including electricity as basic requirement for electronic communication and information – was among the most important indicators related to poverty. Counties with a high rate of households having a radio or mobile had a negative correlation of -0.71 respectively -0.79 to poverty rates. Moreover access to improved sanitation, which can also be seen as health indicator as sanitation and transmission of diseases are closely related, was negatively correlating with poverty (-0.61). Single educational variables were shown to have a close relationship to poverty rates (correlation between -0.41 and -0.7). Obviously in those counties where more people have primary or secondary education or the more people never attended school have lower poverty rates than those where the education level is much lower.

2.2.3 A model to explain human-induced land degradation in Kenya

Two different data levels were used to find a model explaining LD in Kenya: the county-level and the pixel-level. To get representative information for vegetation trends on the county-level, the number of pixel within a county were addressed. The number of pixel with significant decreasing vegetation trends (with $p<0.05$) within the administrative unit between 2001 and 2011 were calculated in R. The ratio of the number of significant negative pixel to total amount of pixel in a county then gives insight in the percentage of the county area "affected" by either significant vegetation decrease or increase. This approach was also used to calculate general positive and negative trends with a sharp cut-off point at zero and positive and negative trends including a tolerance between -0.005 to +0.005. Pixel within the tolerance represent "stable" conditions. Water pixels were masked to eliminate misleading results.

Socio-economic data collection included other small surveys but Census 2009 and KIHBS 2005/2006 were rated as most reliable and best suited for this analysis. As LD is a very diverse process, driven and influenced by multiple variables having different impact, a wide set of possible indicators automatically arises by reflecting about the process itself. Among all indicators that were found in different surveys the selection of variables was driven by literature research as a baseline and shaped a deductive selection process. Still a set of about 100 different variables were identified by a first selection process which revealed a possible link to LD processes according to literature research. Variables also correlated among themselves especially when from the same indicator group. In general it was aimed at covering each dimension of marginality as discussed in the previous section: education, health, accessibility to information and infrastructure, demographic structures and economic variables.

As data originated from different sources similar indicators occurred in the dataset. Double entries were therefore checked such as e.g. the indicators "stunting" and "adequate height for age" which both have the same meaning even if named differently. As "stunting" is rated as an international indicator, also used in the MDGs (Klaver, 2010), it was preferred in the analysis.

Pair wise correlations among finally 47 variables were conducted for further selection. Those highly correlating with each other and with the dependent variable (vegetation trends) strengthening the explaining model were in the main focus.

Correlation results among socio-economic indicators and LD or LI based on vegetation trends were not as prominent. Only a few variables showed a correlation higher than 0.5 (positive and negative). Important variables that match this cut-off point (correlation >0.5 or <-0.5) are: population density, LATF and access to mobiles. The results highlight that there is not one single indicator influencing the process of LD but multiple indicators in combination.

2.2.3.1 Exploratory Regression among decreasing, increasing and stable trends

According to the *summary of variable significance*[30] similar variables were listed for negative and stable conditions of LD. For the explanation of positive trends different indicators although showed up that did not have an impact on negative and stable trends. The exploratory regression was run with a maximum of 10 variables and a minimal R^2 set at 0.6. Other model settings can be looked up in chapter II.3.2.

Among the first five variables that had significant impact on the models explaining **significant negative trends** are *fertilizer use* with 99.06% significance and 100% negative impact. The less percentage of the population is using fertilizer the higher the percentage area experiencing significant negative trends. This variable is followed by *population density* having a 100% positive impact on significant decreasing trends (significance in 97.25% of all models). Third listed is *Local Administrative Transfer Funds (LATF)* (80.26% significance, 99.99% positive impact), fourth is *stunting* (69.35% significance and 100% positive impact). *Household Expenditure* occurred to be the fifth variable with 32.87% significance in all models and 86.94% positive impact. But taking into account livelihood composition and income situations among livelihoods within the country household expenditure will not be a good explaining indicator. With regard to big areas as home of pastoralists including nomadic and semi-nomadic living income and expenditure are not simply possible to apply. Pastoralists might not use monetary value to sell or buy assets but use livestock and other products in exchange. This also weakens the indicator of poverty using monetary values as it does not represent the situation of the poor and marginalized appropriately. Variables with lower significant appearance explaining significant negative trends include *access to information*, other health indicators, *electricity* and *soughing of credit*.

When running the exploratory regression for **positive trends**[31] as dependent variable, the same indicator groups, especially health, education and access to information in terms of having a mobile phone and access to a landline, occurred but were not represented with similar impact and significance. Among the first five variables with high impact three do cover health indicators. But the significant impact was not as high as in the other models. First important variable was having *full immunization* with 79.88% being significant in all possible models and 100% negative impact on increasing trends. The lower the percentage of people being fully immunized the higher the positive trends. Similar significant impact showed the *GINI-coefficient* (78.03% significant) with 100% negative impact followed by the variables of *stunting* and *children being underweight*. Fertilizer *use* which was expected to have a high impact just occurred to be in 2.87% significant with only 71.35% positive impact.

Stable conditions were mainly explained by people with higher education (going to *youth polytech*) which appeared with 99.8% significance and 100% negative impact, *stunting* with 94.78% significant appearance and also 100% negative impact. Third mentioned variable is again *fertilizer*

[30] The summary of variable significance is shown in the output report when using the exploratory regression tool.
[31] Significant positive trends and those trends >0.005.

use (93.72% significance and 100% positive impact). Variables following include *access to electricity*, other health indicators such as *percentage of children being underweight* (an indicator very close to stunting) and *having access to information in terms of radio and landline*. In both, negative and stable conditions, the indicator groups on education, health, agricultural input and access to information were predominantly included. Population density played a bigger role for negative trends than for stable conditions.

Out of the exploratory regression we can state that negative and stable trends are most likely to be explained by the same set of indicators while positive trends seem to be influenced more by other indicators which also go beyond the scope of our set of socio-economic indicators. It is assumed that biophysical variables such as topography and aridity have a higher impact here.

2.2.3.2 OLS-regression model: A model to explain significant decreasing vegetation trends between 2001 and 2011

OLS was conducted including variables that were not recognized as being highly significant in the exploratory regression but could be of more impact in combination with other indicators. Different OLS-models were tested until only variables with significant impact were included and all other checks[32] resulted positively. It was aimed at covering all indicator groups representing the demographic, economic, accessibility, health, education and technological input dimension (here e.g. fertilizer use) as this is an important aspect in Kenya. One difficult sphere to include was the social sphere which is highly important but was not possible to include with quantifiable variables. The GINI-coefficient did not improve the model even if it is well known that inequality has a huge impact on livelihoods (Adger, 2000). At this point the hypothesis that social input is not relevant is strongly rejected but it has to be mentioned that the measuring of social variables which is more likely a qualitative variable is difficult to include in this quantitative assessment. Nevertheless it can be assumed that social impact is included in all chosen indicators to a certain extent as a motivation for e.g. education or the use of fertilizer. All actions are thereby also shaped by social input variables but variables as such have to be seen as a qualitative add to the assessment.

Finally a set of eight variables was chosen for the OLS model: *Population Density, Poverty Rates, Basic literacy Rates, Youth Polytechnic Attendance Rates, Stunting Rates, LATF, Households with access to a landline (in %) and Use of any Fertilizer (in %).*

As it would go beyond the scope of this study to describe every single indicator which was tested with its possible impact on LD the focus is on the eight mentioned indicators that were identified within the OLS-model with significant impact on LD within the county.

[32] Referring to the six important checks of OLS regression discussed in chapter II.3.2.

OLS-Model Output

The model explaining significant negative productivity trends among the 47 counties of Kenya has an R^2 of 0.7 (0.699533) and an adjusted R^2 of 0.64 (0.636277). Both, R^2 and adjusted R^2 give insights in the model performance. The multiple R^2 in general is slightly lower than the R^2 as it represents the complexity of the model. The chosen model explains around 70% of the variance of significant decreasing trends among all counties of Kenya.

Table III.3 lists the results of the OLS model. Coefficient signs (+/-) show the relationship of each explanatory variable to the dependent variable.

Table III.3: Results of OLS regression (based on the STATA output). (*)marks the significant indicators where p is <0.05. Testing for robust probability also showed significance in all indicators except stunting but this indicators crossed the significance-threshold just slightly (0.0782).

	Coefficient	Std.Error	t	p>|t|	[95% Confidence Interval]	
population density	0.0062	0.0019	3.2300	0.0030*	0.0023	0.0101
poverty rates	-0.1811	0.0678	-2.6700	0.0110*	-0.3183	-0.0438
youth polytech	10.8712	3.3670	3.2300	0.0030*	4.0550	17.6873
basic literacy	-0.3491	0.1408	-2.4800	0.0180*	-0.6342	-0.0640
stunting	0.3976	0.1826	2.1800	0.0360*	0.0278	0.7673
LATF	0.0395	0.0152	2.6000	0.0130*	0.0087	0.0703
hh with landline	-0.0415	0.0146	-2.8500	0.0070*	-0.0710	-0.0720
any fertilizer	-0.1480	0.0375	-3.9400	0.0000*	-0.2239	-0.0720
Intercept	8.6620	9.3531	0.9300	0.3600	-10.2723	27.5964

Number of observations	47
F (8, 38)	11.06
Probability > F	0
R-squared	0.6995
Adjusted R-squared	0.6363
Root MSE	6.1687

The explanatory indicators

Population Density was the persistent indicator among all possible models. As the assumption that more people equal to higher pressure result in more LD sounds obvious this indicator was already mentioned and highlighted in many other studies on LD often used to include a "socio-economic component" for LD assessment. Out of the OLS-regression moreover a positive coefficient was observed with a significant probability (p-value=0.003). When overlaying population density trends[33] with vegetation trends (including a tolerance of -0.005 to 0.005 NDVI trend change) based on the pixel level the highest percentage of pixels (21.17% of all pixels)

[33] Population data for trend calculation was taken from CIESIN (GPW, v3) for the years 2000 and 2010. Available via: http://sedac.ciesin.columbia.edu/data/collection/gpw-v3 (last accessed 11.02.2015).

could be identified where population increase and land improvement overlap. This number was followed by an overlay of about 10% for decreasing vegetation trends and population decrease in the same time. An expected high amount of population increase and LD could not be observed with merely 5.74% of all pixels. It is therefore rather about how people in a certain area manage their land, how they change it according to their needs – changing forest to cropland – and how and if they use sustainable land management practices to increase productivity again. If population density is used as the only explaining indicator for LD assessment and not in combination with other indicators, the analysis is not sufficient – at least not in Kenya. Population density can therefore be interpreted in two ways: the pressure on a certain area by an increasing population, or by referring to people to their abilities and possibilities in managing lands. We rather must link information about demography to the resulting impact. In this case we link population density to the de facto pressure on environmental resources.

Poverty rates (based on KIHBS 2005/2006) are included in the model to represent an economic indicator as it refers to income[34].

The *educatio*nal dimension of marginality in this model is represented by two educational indicators which influence the model differently. ***Basic literacy*** – referring to the percentage of people having a minimum of three years with basic education - describes basic knowledge that allows people to read, write and understand how to use and get information. The ***youth polytechnic*** attendance describes a higher education after primary education which focuses on professional and technical skills. It started in rural areas in the 1960s[35]. One Polytechnic in each province[36] was aimed to give children in rural areas that failed to enroll in secondary education a possibility to improve their skills. There is still ongoing discussion to increase the number of Polytechnics in the region (Dey, 1990).

Within the OLS-model a negative coefficient of *basic literacy* but a positive coefficient for *youth polytechnic attendance* was observed. That means the more people have basic education the less LD can be identified. But the more children go to the youth polytechnic the more LD is observed. According to Freeman and Omiti (2003) the education level of a rural population influences fertilizer use and the adoption of new technologies. A correlation between fertilizer use (any fertilizer) and primary education showed a coefficient of >0.6. The results of the OLS on education also match with findings by Pender et al. (2003) who used an econometric study in Uganda on strategies to increase agricultural production and reduce LD. Results showed that education on the one hand increases household incomes but at the same time also reduces crop production in lowlands. While in this study primary and secondary education both had a negative

[34] Poverty Dataset 2005/2006 from KIHBS refers to percentage of population and number of poor below the poverty line of Kenya which is set at Ksh 1,562 per month in rural areas and 2,913 in urban areas per person per month, based on minimum provisions of food and non-food items (according to (KNBS 2005/2006).
[35] Based on article from University World News: http://www.universityworldnews.com/article.php?story=20100716194758897 (last accessed: 08.02.2015)
[36] With regard to the Province-level which has been the administrative level before 2009.

coefficient stating that more education relates to lower degradation trends, a higher education such as youth polytechnic attendance had the opposite effect. This could lead to the assumption that a basic knowledge helps to e.g. adapt new technologies or fertilizer and use information. But if a higher education is attended this also means that people are leaving the rural areas to study in the cities or more central parts of the county. They can send money home or they are aiming at getting a good job position in the urban areas. And if farmers are no longer depending solely on their agricultural production it might not motivate them in the same amount and input will be lower than in other areas where there is a higher dependency on agricultural production to afford living. This was also evidenced in Uganda based on the study by Pender et al. (2003). Other than that it could also be assumed that more capital could enable a household to afford improved seeds and fertilizer or adopt other agricultural technologies.

Two variables were highlighted in the exploratory regression and then tested in the OLS-model representing the health dimension of marginality: morbidity and ***stunting***. Both variables had a positive coefficient on LD rates which derives the information of physical indicators triggering LD (and/or the other way around). If morbidity in a certain county is much higher than in others it is attributed to severe health problems. Besides that the single indicator on stunting is giving much more insights in the health situation of an area. Stunting is described as low height for a particular age (De Onis, Blössner, & Borghi, 2011) and was also used as a proxy representing the health dimension in the global marginality mapping approach (Graw & Husmann, 2014). If the height of a child is below the fifth percentile of the reference population at the same age they are defined as stunted (Lewit & Kerrebrock, 1997). Having a low height for age is therefore a very strong indicator for health conditions in terms of nutrition deficiency. By implication LD influences health as good soil conditions are important for agricultural production providing food and nutrition for livelihoods. A good health furthermore secures that the farmers are not lacking in strength to cultivate their fields.

Local Authority Transfer Funds (LATF) was established in Kenya in 1999[37] and represents government expenditures for the 175 local authorities within the country. The program was established to reduce debts of local authorities by improving financial management and service delivery (WB, 2013, KHRC & SPAN, 2010). Seven percent of the total fund is equally shared among the country while 60% is disbursed according to the relative population size of the local authorities (KHRC & SPAN, 2010). Reported by KHRC and SPAN (2010) there is not much awareness about the LATF. Within an undertaken survey around 36.3% stated that there is no real benefit from LATF. Moreover projects funded with this money are driven by the local authorities themselves without any involvement of the local population within those areas. The coefficient is positive showing that the more LATF is given to the local authorities, the more LD occurs. But it should be noted that the LATF is also based on the number of people living in an administrative unit – the more people the higher the funds are. But considering the integration of

[37] http://www.tisa.or.ke/about-devolved-funds/local-authority-transfer-fund/ (last accessed: 08.02.2015)

population density information in the model the VIF was taken into account. As it is not as high to state that the variable is redundant the integration of this indicator is confirmed.

Having access to a landline refers to access to electricity. Both indicators are highly correlating but for the OLS-model the combined information on having access to electricity including access to information by being able to communicate or gather information was showing higher impact.

Fertilizer Use showed the expected negative impact referring to more LD the less fertilizer is used. A variable on agricultural innovation and input was important in this study as Kenya is known for its increasing yields due to new technologies such as high yielding varieties and fertilizer use[38]. More detailed information will be given in part IV as this focuses on the high productive maize areas in western Kenya where this information is necessary for understanding the complexity in the area.

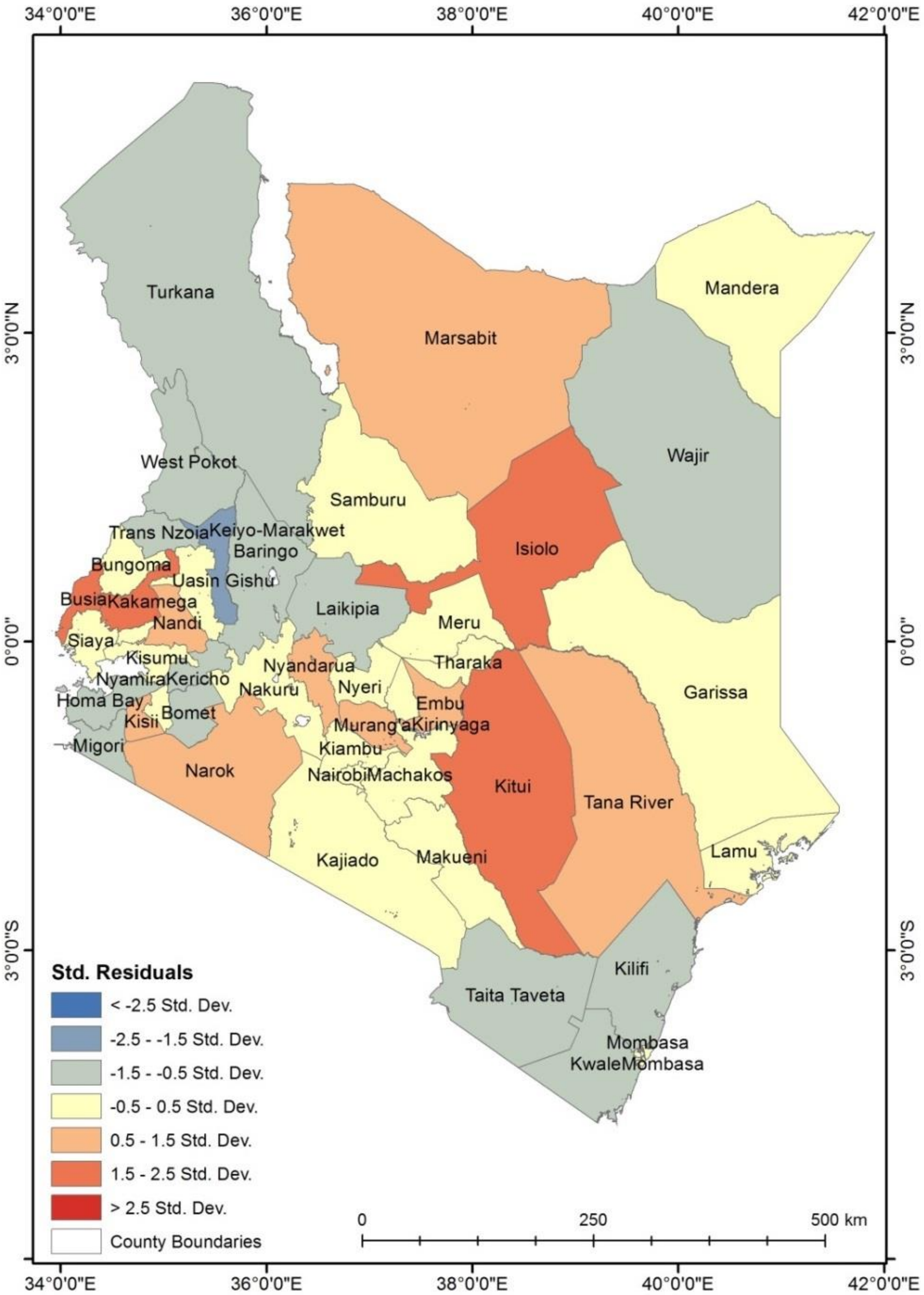
When testing different models it could be observed that including more variables increased the R^2 of the whole model. But this also meant that variables are included which are not significant and tended to be redundant shown by a high VIF. Therefore additional correlations were run among the variables of each possible model to exclude combining effects that strengthen a certain variable that is already included. This could e.g. be observed for the variable of *electricity* which increased the R^2 and adjusted R^2 of the model but did not appear to be significant. When looking into the final model it became obvious that one of the variables with significant impact for explaining LD is the variable *percentage of households having access to a landline*. For having access to a landline electricity in any form is needed. A high correlation (0.79) between electricity and having access to a landline moreover proved the logical outcome on the reasoning of a higher R^2 and a high VIF.

The model was also run for rainfall corrected and non-rainfall corrected trends. For the rainfall corrected approach we got stronger models, meaning a higher R^2, than for those with non-rainfall-corrected pixels including the same set of explanatory variables. As it can be assumed that those areas where degradation or improvement trends were observed and corrected for rainfall most likely show human-induced LD these model results warrant the use of solely socio-economic explanatory variables within the national approach. The significant negative trends corrected for rainfall are seen as the variable to be explained the best with socio-economic indicators. The results according to the R^2 are shown in Annex 5.

[38] More detailed information will be given in part V as this focus on the high productive maize areas in western Kenya where this information is necessary for understanding the complexity in the area.

Output: OLS residuals

An output feature class is generated in ArcGIS showing model over- and underperforming areas represented by residuals.



Map III.10: OLS output showing map with studentized residuals that represent residuals divided by an estimate of its standard deviation.

Looking at Map III.10 four counties that are underestimated can be identified: Kitui, Isiolo, Kakamega and Busia appearing in reddish coloring (Std. Dev. > 2.5). Here LD is higher than the model predicts according to the explanatory variables. Within these counties a variable is most likely missing that could explain degrading trends better if integrated in the model. One of the best examples here is Isiolo county which is affected by huge conflicts about land property rights as about five different ethnic groups claim for land (Boye & Kaarhus, 2011). In Kitui, located in the ASAL of Kenya and prone to droughts, pressure on land and soil quality is high and especially with regard to soil characteristics this area would need more information on this regard (Opere et al., 2004). Moreover biophysical aspects such as erratic and unreliable rainfall also have a severe impact on the environment in Kitui (Lasage et al., 2008). This area, and neighboring Machakos is vulnerable to soil erosion due to less fertile soils and heavy rainfall events at the beginning of the rainy season (Tiffen, Mortimore & Gichuki, 1994; Pagiola, 1996). It is also affected by droughts. Most farmers in these regions perform subsistent farming and crop failure thereby also has severe effects on livestock and livelihoods.

Over-prediction is reported in Keiyo-Marakwet (also known as Elgeyo-Marakwet). Here the actual significant decreasing trends are lower than predicted by the OLS model. Biophysical preconditions in this county are favorable for agriculture especially due to water resources coming from several water catchment areas (Adams & Watson, 2003). Due to irrigation practices therefore cultivation of land is not solely based on rainfall which is an advantage for this area.

Residuals were checked with the spatial autocorrelation tool based on Moran I[39]. As the p-value is non-significant (p-value= 0.61) the chosen model is not influenced by spatial autocorrelation and counties can be analyzed individually which could be a good starting point for individual policies and management recommendations.

The same approach with the exact same variables that explained significant decreasing vegetation trends in the OLS-analysis was used for significant positive trends. Even if expected the model should also work the other way around a very low R^2 (0.1943) was reported. Moreover we could not find significant impact of the variables that explained significant decreasing trends.

Going behind the process of LD and the concept of sustainability leads to the assumption that those variables which lead to LD or decreasing productivity not necessarily mean the opposite - increasing productivity – if those variables change to the other extreme. Sustainability refers to stable conditions by setting up and holding the equilibrium of an ecological system.

LD is first and foremost location-specific with few "win-win opportunities" (Pender et al., 2003). According to Pender et al. (2003) we also need a demand-driven approach that looks into the location-specific needs to combat LD. The local study (chapter IV) will therefore come up with more in-depth knowledge provided by a detailed household survey.

[39] The spatial autocorrelation tool is part of the spatial statistics tools in ArcGIS.

2.3 Land (Use) Cover Change and Land Degradation – National Study

Land cover changes in Kenya were observed for the same time period as vegetation trends (2001-2011). This chapter will give insights if the number of land cover changes is related to LD and LI. Moreover those land cover classes will be identified where most environmental changes in terms of decreasing productivity occur.

Figure III.5 shows the process chart for the land cover and land use analysis in Kenya. Basic steps were already discussed in Part II. Identifying the number of land cover changes leads to the analysis of stable land cover classes and eventually degrading or improving productivity trends occurring from 2001 to 2011.

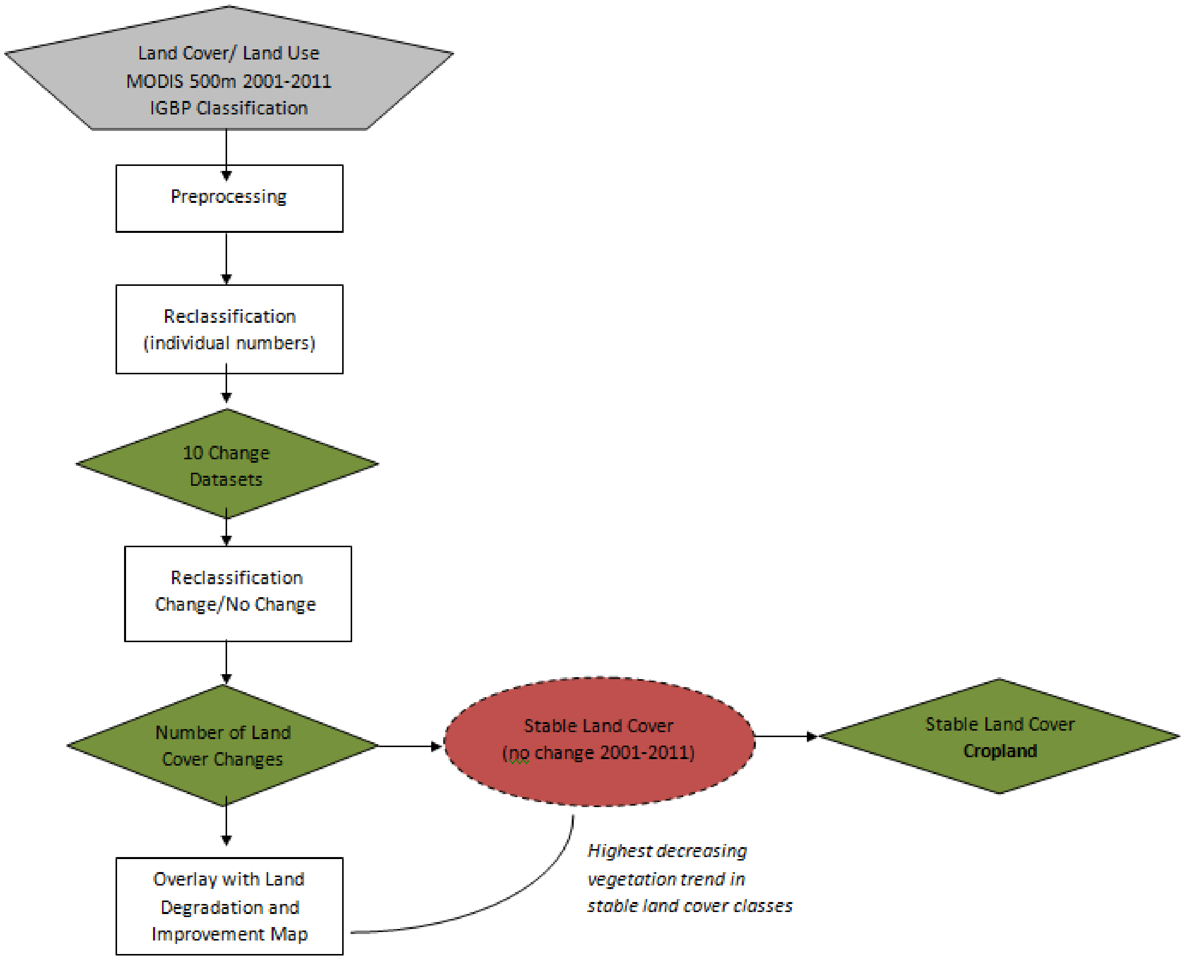
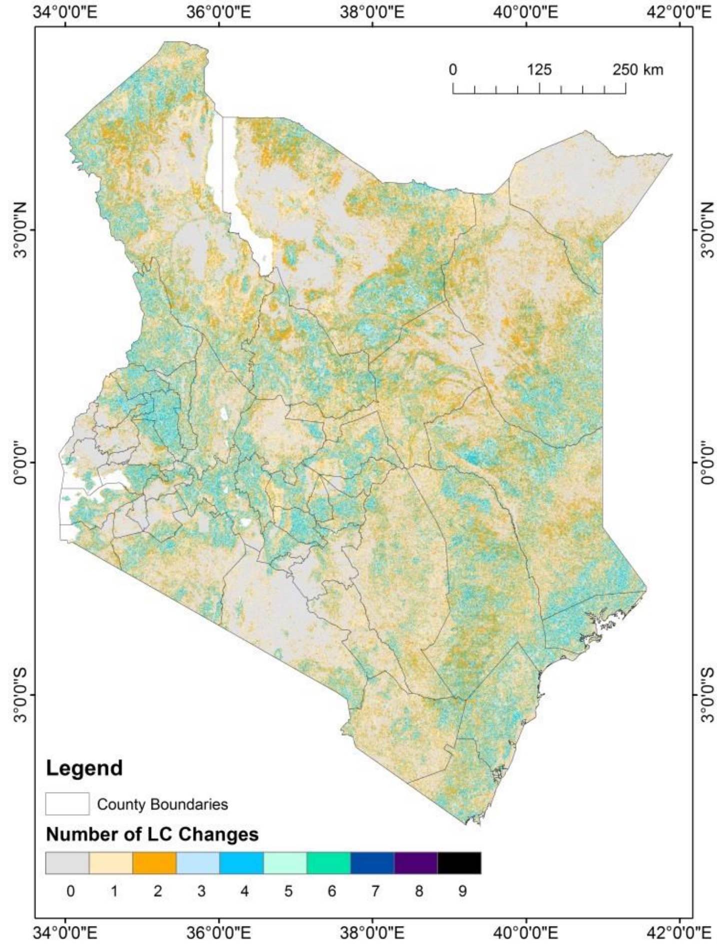


Figure III.5: Theoretical Framework for the Land Cover Change Analysis. See also chapter II.3.3.

2.3.1 Number of Land Cover Land Use Changes

MODIS provides the Land Cover Type Product MCD12Q1 (Friedl et al., 2002) with 500m grid resolution which represents the same pixel size also used for the MODIS NDVI time-series analysis. Annually data provision and a matching pixel size with the MODIS NDVI data used earlier in this study were key elements for choosing this dataset.

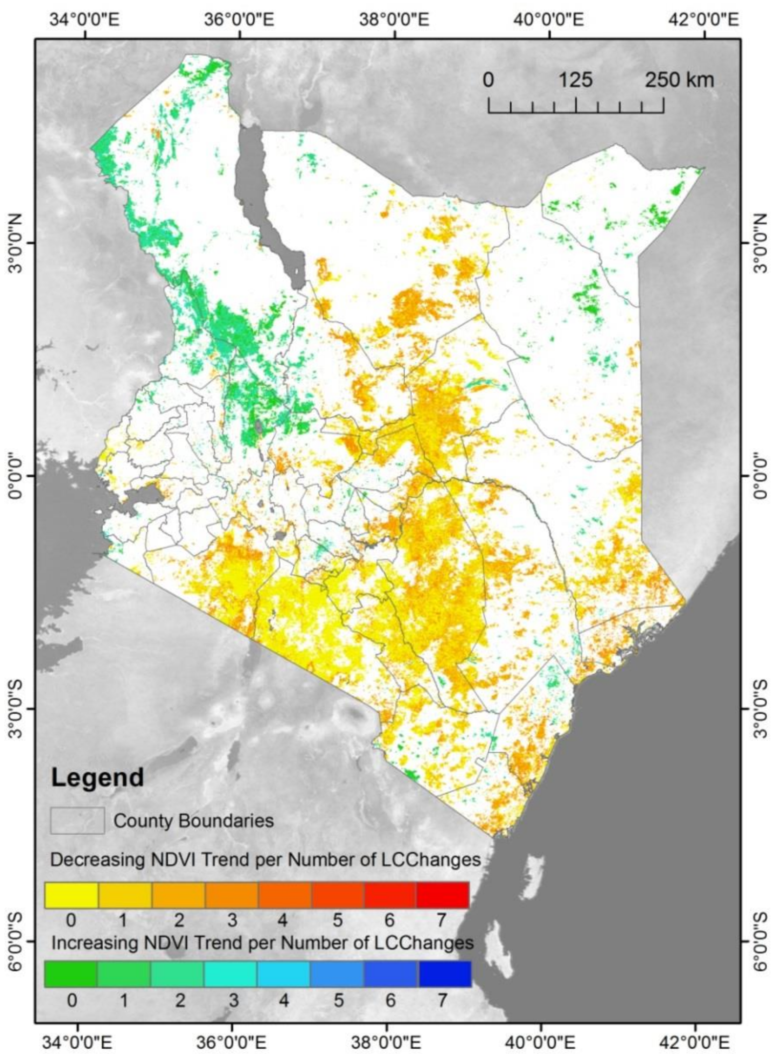


Map III.11: Number of Land Cover Changes from 2001-2011

Map III.11 shows the number of LULC changes as calculated based on the methods described in chapter II.3.3. Stable areas – where land cover changes are zero – can be identified in southern Kenya, Kajiado County in particular, but also in western Kenya north of Lake Victoria, around Lake Turkana, and in the northeastern part of Kenya bordering Ethiopia. Around 33.16% of the total land area experience zero changes from 2001-2011 while 16.11% changed once and 22.92% show two changes. Three (13.98%), four (9.53%) and five (3.42%) changes can still be observed in Map III.11 while areas experiencing more than five changes are occurring in less than 1% of the total land area.

2.3.2 Is there a link between the number of land cover changes and land degradation?

It is assumed that especially areas with intense cultivation meaning e.g. crop production throughout the year are facing higher degradation risk and vegetation decrease over time than areas where also intercropping takes place or the soil is not monotonous exploited. Even if not solely focused on croplands Map III.12 shows the overlay of the number of land cover changes - as seen in Map III.11 - with NDVI decrease and increase between 2001 and 2011 referring to NDVI trends. Three classes among the trends are built. Besides a "tolerance class" meaning NDVI trends between -0.005 and +0.005 the dataset was classified into "decreasing" (NDVI Trend <-0.005) and "increasing" (NDVI trend >0.005) vegetation trends. The overlay highlights the southern part of Kenya, especially the counties Narok and Kajiado where a stable land cover and decreasing trends overlap. Within this overlap are also Kitui and Isiolo – both counties that were also highlighted in the OLS-regression output as underpredicting –, parts of Marsabit and some small areas along the coastline. Also again the northwestern area, mainly Turkana Region but also West Pokot and Baringo are expressing increasing trends and seem to be linked to a more stable land cover.



Map III.12: Number of Land Cover Changes overlaid with vegetation decrease and increase over time (2001-2011).

Calculating the number of pixels with vegetation decrease and increase Figure III.6 presents the percentage of positive and negative pixel that can be found in the number of land cover class changes. The analysis focuses only on the actual number of land cover changes in general which means that intercropping – e.g. maize as the main crop with short cultivation of e.g. beans between two maize cropping periods – were not taken into account as this would go beyond the scope of this study.

Obviously the more often the land cover classes changed the less vegetation decrease could be observed also validated by a correlation coefficient of -0.92 between the number of land cover changes and the NDVI trends. With a correlation of -0.90 also increasing trends are reported to be lower the more often land cover changes. By comparing the same land cover changes with vegetation trends corrected for rainfall we could observe that this distinction only had minor effects. Even the correlation coefficients for NDVI trends corrected for rainfall and the number of land cover changes were exactly the same:

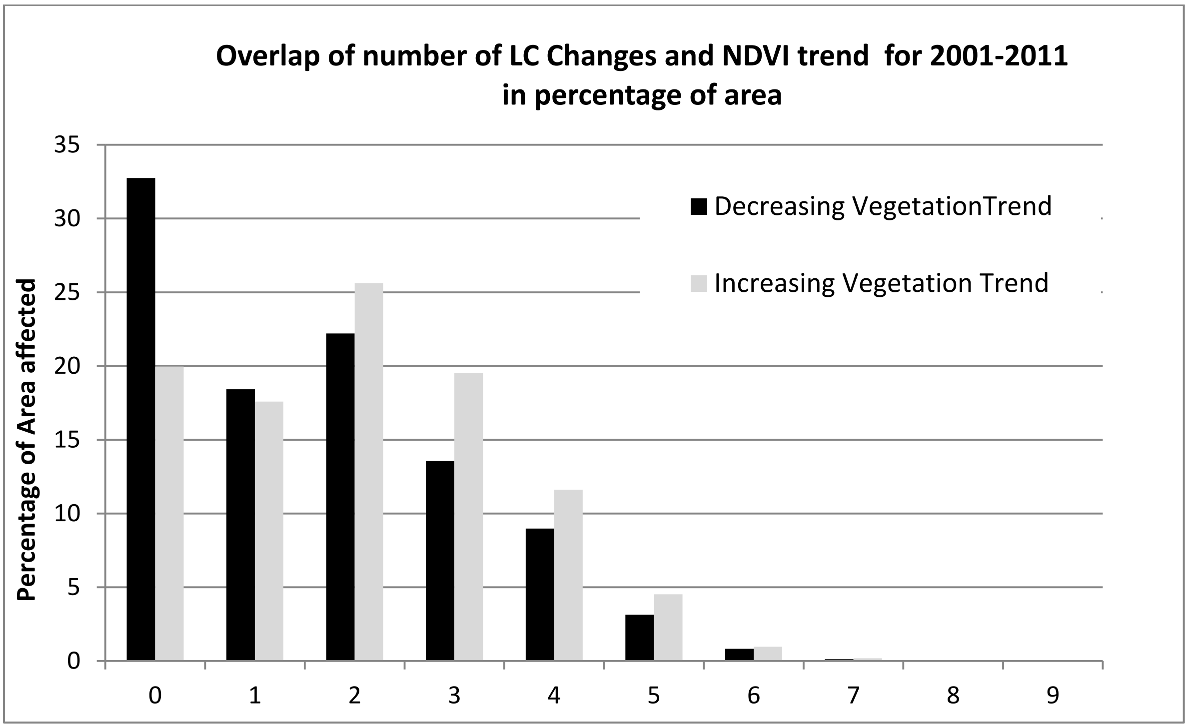


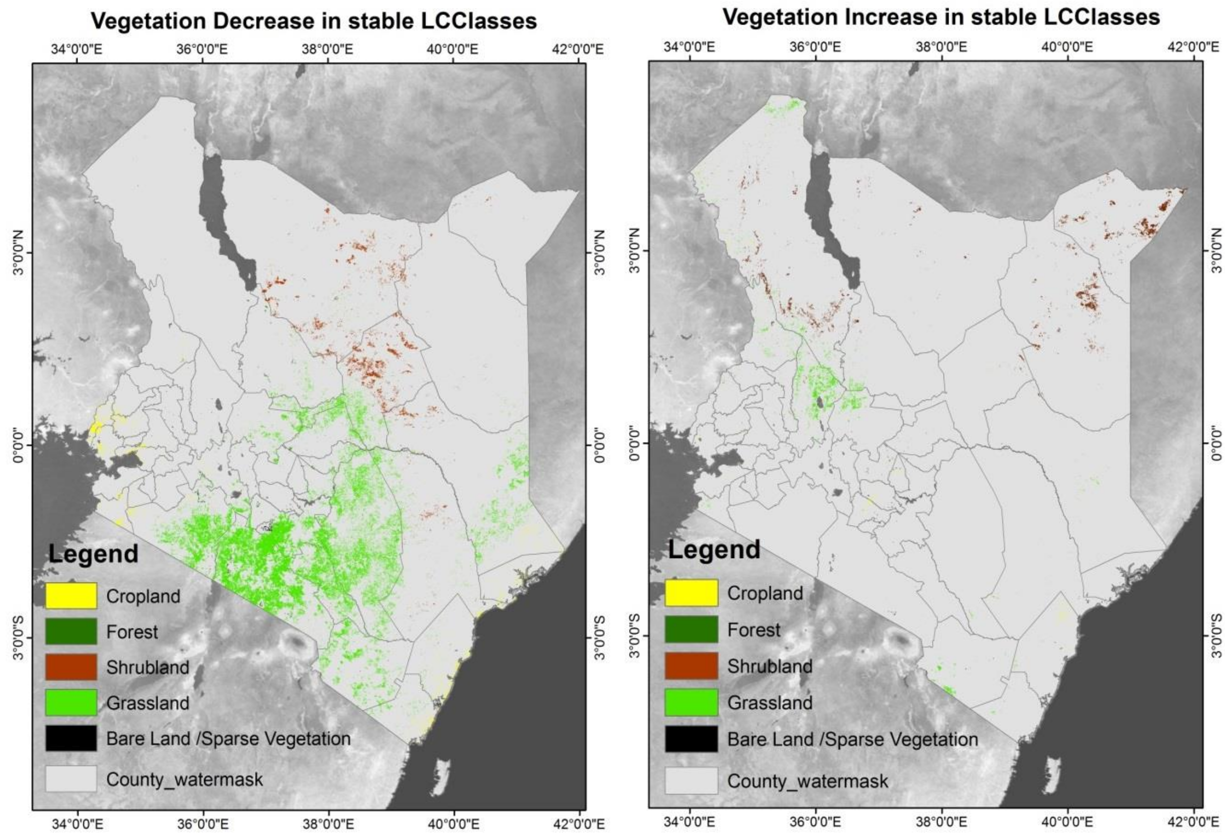
Figure III.6: Percentage of vegetation pixel with increasing and decreasing trends within a certain number of land cover changes (tolerance means "no trend" from -0.005 to +0.005 NDVI value trend)

As stable land cover over a long period of time shows higher vegetation degradation than multiple changes in land cover it is questioned which land cover classes create the highest LD rates. Interestingly, the relation of increasing and decreasing trends seems to go in line with a correlation coefficient of 0.9. The more land cover changes take place the more "stable" and thereby sustainable land management seems to be.

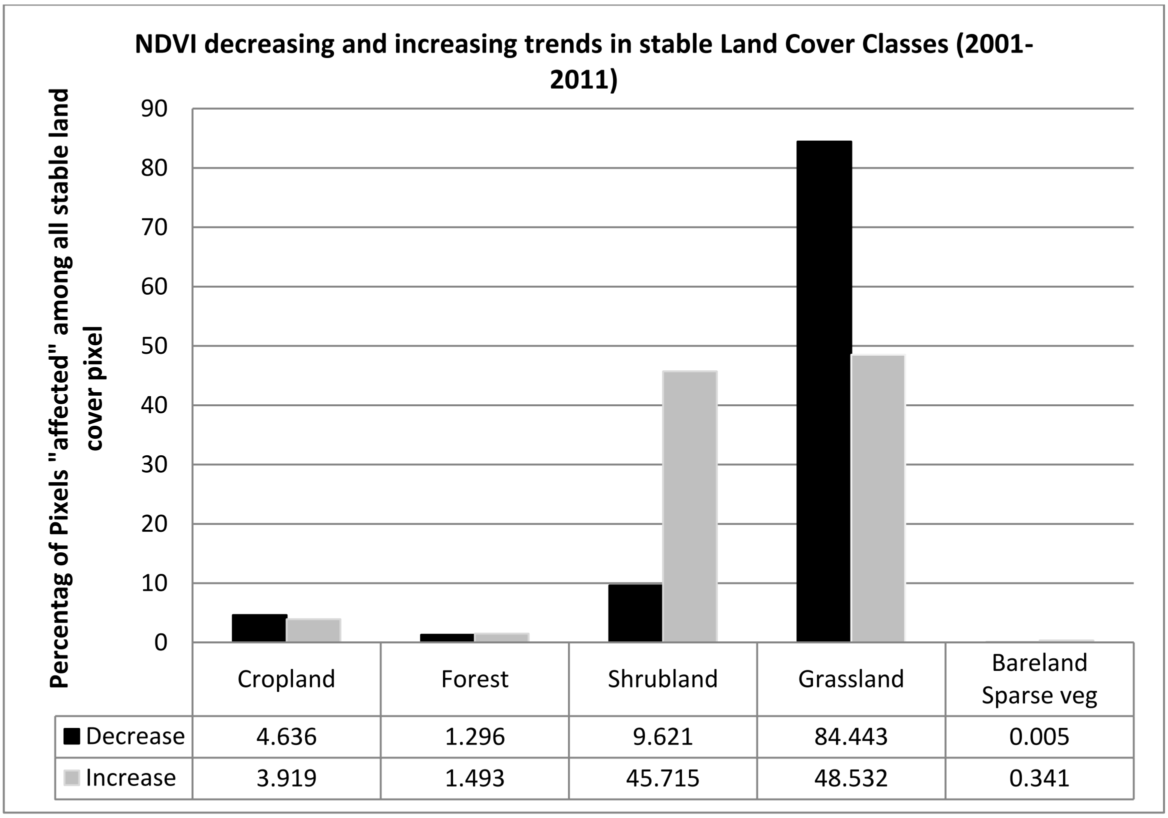
By extracting the land cover classes that have been stable from 2001 to 2011 and overlaying those with decreasing and increasing trends of NDVI within the same time period land cover classes could be identified that overlap with the areas with highest losses in terms of vegetation cover (Map III.13).

Map III.13 shows the overlap of stable land cover classes in areas with vegetation decrease (left) and stable land cover classes in areas with vegetation increase (right) referring to the time period 2001-2011. Again Southern Kenya and the counties Kajiado and Narok, are highlighted with regard to vegetation decrease as well as northern and central parts of Kenya such as Marsabit and Isiolo. Vegetation decrease in croplands is highest in western Kenya affecting the counties Trans Nzoia, Busia, Siaya, Kakamega, Kisumu, Vihiga, Kisumu and Migori.

With regard to Figure III.7 we can observe that mainly grasslands are affected by decreasing vegetation trends with 84.44% of the all stable land cover classes with decreasing trends. Vegetation increase in shrublands can be observed in the northern regions such as Turkana in northwest or Mandera and Wajir in northeastern Kenya bordering Ethiopia.



Map III.13: Stable Land Cover Classes in areas with vegetation decrease (left) and vegetation increase (right) from 2001-2011.



	Cropland	Forest	Shrubland	Grassland	Bareland Sparse veg
Decrease	4.636	1.296	9.621	84.443	0.005
Increase	3.919	1.493	45.715	48.532	0.341

Figure III.7: Vegetation decrease and increase in stable land cover classes between 2001 and 2011.

It would be of further interest what kind of changes took place in those areas where we had high numbers of land cover changes. As it goes beyond the scope of this study to analyze every single land cover change in detail we stick to the statement that shifting land cover which includes also crop rotation and inter-cropping in a certain amount is an advantage for sustainable land management. As the land cover classes used here refer to broader land cover type classes without distinguishing within the single classes especially for e.g. cropland we are not able to look at detailed changes for e.g. crop types. Nevertheless the classified land cover data by MODIS helped to get insights in land cover dynamics at least within greater land cover classes and analyze how vegetation dynamics occur within these classes.

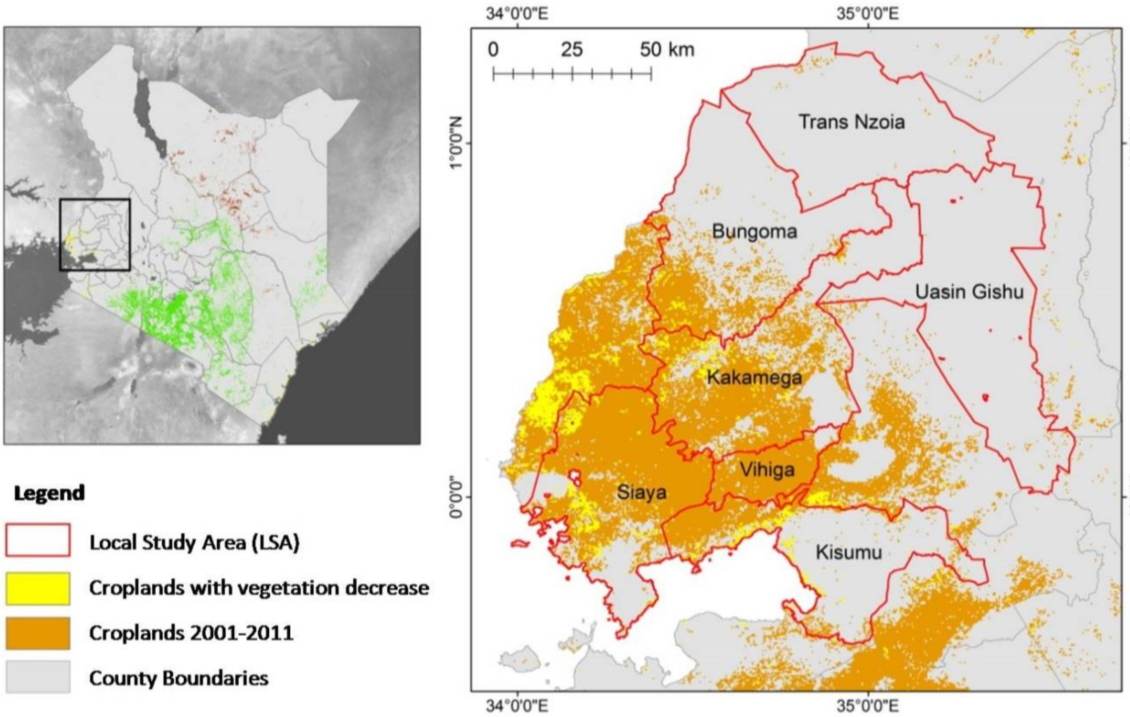
2.3.3 Croplands at risk

Between 1975 and 2000 agricultural land in Sub-Saharan Africa has increased by 57% (Brink & Eva, 2009). For further analysis croplands were of key interest as here degradation has high negative impacts with regard to food security in Kenya. As already mentioned western and central Kenya represent the country´s grain baskets where particularly maize is grown, the staple crop and consumed by every Kenyan. The western region is also an area being highlighted when analyzing vegetation decrease in croplands (see also Map III.13). This area is the most productive and important crop growing area – especially for maize – so this development is alarming if vegetation decrease is referred to decreasing productivity and could also refer to LD processes.

High poverty rates characterize the high productive areas in Kenya in general (KNBS, 2005/2006) while simultaneously food supply for Kenya´s population is depending on those regions. Nevertheless the used data on land cover provided by MODIS give insights on the national scale but should be used with caution when used for detailed analysis on the local scale.

A more in-depth analysis will be conducted in part IV focusing on cropland degradation and the linkages of LD and marginality in acting scopes using household survey panel data.

Map III.14 shows stable cropland cover over the time period 2001 to 2011 and those where simultaneously decreasing NDVI trends were observed. Land cover and land use data by MODIS were only integrated in the national study. With a glance on Map III.14 it can be seen that the land cover product is not as useful on the local scale. Especially Trans Nzoia, Uasin Gishu and Bungoma are mainly under crop production which is not obvious from the derived data. MODIS land cover data were therefore useful to identify those areas at risk but the choice of the local study area to include also the above mentioned high productive zones was also made with additional data input from literature and personal information.



Map III.14: Stable cropland cover between 2001 and 2011 (orange) and stable croplands experiencing NDVI decrease between 2001 and 2011 based on map III.13 with vegetation decrease (see also Map III.13 (left)).

3. Conclusion III: Hotspots on the National Level

Analysis on the national level gave insights from different perspectives into the dynamics of LD, marginality and poverty, and LUCC.

LD assessment using NDVI trend analysis covers the time period 2001 to 2011 and highlighted areas in Kenya with increasing and decreasing productivity trends that can be linked to LD processes. Southern Kenya, especially the counties Narok and Kajiado were highlighted with decreasing NDVI trends while the northwestern areas including mainly Turkana County showed increasing trends. Affected by decreasing NDVI trends were also counties in the central region such as Isiolo and Kitui. It can be stated that even if LD occurs in all agro-ecological zones especially Kenya´s arid and semi-arid lands (ASAL) do exhibit degrading vegetation trends.

An overlay of vegetation and poverty trends again highlighted two areas in Kenya: the northwestern areas with increasing vegetation trends and at the same time higher poverty rates and southern Kenya with decreasing vegetation trends and decreasing poverty rates. This is a controversial picture as poverty and LD area very often mentioned being concurrent. But poverty as such – measured only in monetary values – was rejected to indicate the status of a livelihood adequately. When relating indicator groups of marginality to poverty rates high correlations could be found between poverty and access to information and infrastructure while factors representing health or education had much lower correlation values. It is assumed that livelihood characteristics in the interplay give more information about the current status of a livelihood than only addressing one indicator as shown for poverty represented by e.g. income or expenditure. Therefore it is also assumed that socio-economic indicators in combination can give an explanation for human-induced LD.

Socio-economic impact factors triggering LD were identified via exploratory regression and OLS using a set of socio-economic indicators derived from Census 2009 data and the KIHBS 2005/2006. A model was found that could explain the variance of significant negative vegetation trends by around 70% on the county level. Further analysis revealed that positive trends are not necessarily triggered by the same variables that are linked to LD. Technical innovation and other agricultural input play key roles here. But if referring to stable conditions assuming that we need a consistent equilibrium to maintain stable land conditions – or so to say LD neutrality – that do not drop into LD a set of indicators representing our different dimensions of marginality such as health, education, economy, accessibility to infrastructure and information, demography and agricultural input is valid again.

Finding a model that represents all possible indicators and explains LD completely is a very difficult task if not impossible. As results of the OLS also showed residuals of the analysis highlighting areas where predictions are under- and overestimating it became obvious that analysis of LD with impacting variables help to narrow down the study area but local areas have their own dynamics. This was especially obvious for Isiolo County where different interest groups in combination with unclear land rights lead to conflicts that also have an impact on the environment. The analysis showed that a general model can be found to explain main drivers in a country but in depth knowledge and approaching different levels of analysis in addition is highly recommended.

Chapter III.2.3 assessed land cover changes within the time period 2001-2011 and overlaid them with LD trends based on the NDVI time-series analysis. It was shown that stable land cover conditions – where land cover has not changed or only changed one to three times within the observed time period – experienced higher degradation rates than those areas where land cover changed more than e.g. five times. As food security is one of the key interests with regard to LD analysis in this area, those regions where croplands are affected by decreasing vegetation trends were identified. Therefore western Kenya came into focus. As decreasing NDVI values do refer to decreasing productivity LD in western Kenya can have a severe negative effect on food production within the country. Western Kenya is representing one of the grain baskets of the country and is highly important for food security within the country. The local study following this part will improve the established approach by in-depth analysis supported with a panel household dataset on the village level.

IV. Convergence on the Local Level – Western Kenya

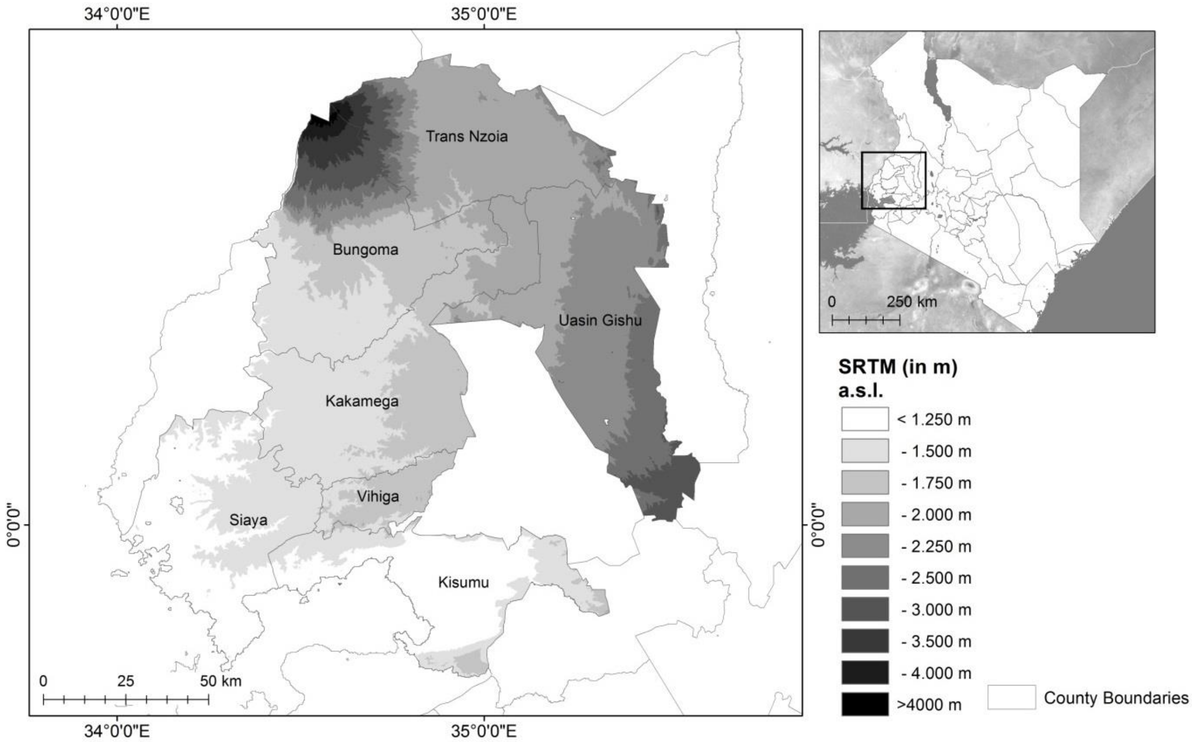
1. The Local Study Area: high potential and high dynamics

As chapter III was path leading on how the interplay of LD and marginality can be assessed, a local study on western Kenya with more detailed datasets will give the opportunity to validate findings from the national study and improve the previous approach. The local study area was selected based on land cover analysis and a key interest in croplands as the baseline for food security within the country. As mentioned western Kenya is the high productive agricultural area of the country and also the main maize producing region (Hassan & Karanja, 1997, Mathenge, Smale, & Olwande, 2012). As maize is the staple food crop in the country this area is very important when it comes to food security and therefore needs attention with regard to decreasing or increasing productivity (Hassan & Karanja, 1997; Smale, Byerlee, & Jayne, 2011; Smale & Olwande, 2014). With regard to the intensive use of agricultural innovations such as improved maize varieties and fertilizer use LD will be addressed in this study by focusing on decreasing productivity.

Agricultural innovations are used and practiced in the local region for about 50 years now – if we take the introduction of the first Hybrid in 1955 as starting point (Hassan & Karanja, 1997). This time span allows getting insights in the dynamics of a system where new technologies are introduced in simultaneously difficult environments when looking at climate variability and vulnerable livelihoods prone to stresses such as droughts, poverty, or national and global crisis.

The local study area is located in western Kenya and includes seven counties: Trans Nzoia, Bungoma, Kakamega, Uasin Gishu, Siaya, Vihiga and Kisumu (see Map IV.1) with an area of 17,632 km² located between 1°2'N and 0°25'S and between 33°E and 35°E. Shaped by topography Trans Nzoia, Uasin Gishu, Bungoma, Kakamega and Vihiga are receiving stable rainfall from March until September – in parts of Trans Nzoia also until November – with an unimodal climate including rainfall amounts between 1,200 to 2,200mm annually (USAID & FEWSNET, 2011). Altitudes range from 1,500 to 3,500m a.s.l. in these so-called highlands of Kenya up to >4,000m a.s.l. at Mount Elgon located at the border of Bungoma and Trans Nzoia County. Besides a small break in rainfall in July, the arid period occurs between December and February. The northern part of the study area, especially Trans Nzoia County, has the highest population density among the country, with more than 1,000persons/km² in some locations while the average population density in Kenya is around 56 persons/km² (CBS, 2006). Main income in these counties is earned from sale of crops as agricultural production takes place during the whole year. Besides maize also vegetables are harvested up to three times a year (USAID & FEWSNET, 2011).

Siaya and Kisumu County are both located at the equator and neighboring Lake Victoria. With elevations under 1,500m a.s.l. these areas are classified as lowlands. Compared to the highlands these areas are characterized by a bimodal climate with rainy seasons between February to May (long rains) and July to October (short rains) (Mugalavai et al., 2008). The rainfall amount with 500-1,000m annually is much lower here than in the northern part of the study area (USAID & FEWSNET, 2011). During the long rains most of agricultural activities take place to ensure income by food crop sale which makes up to 30% of the income of this region, followed by livestock sale and sale of cash crops (15%) (USAID & FEWSNET, 2011). The local study area is in general very food secure and is high resilient against stresses as also not heavily affected by droughts.



Map IV.1: Overview of the local study area including information on topography. Data source: SRTM 90m DEM by CGIAR-CSI with 90m resolution (available at: http://srtm.csi.cgiar.org/) (last accessed: 08.02.2015).

The long growing season in the northern counties, Bungoma and Trans Nzoia, can take up to 11 months of maize growing and harvesting activities. Maize varieties with a growing period of 11 months are especially chosen in the high productive maize growing areas as they assure a bigger harvest[40]. But there is also a shift towards cultivation of sugarcane throughout the region mainly by farmer owning fields of several hectares. For profitable yields sugarcane fields should be bigger than only 1ha which excludes most small scale farmers. The "sugar-belt" of the region is located in the southern part of the study area, former Nyanza Province, including the counties Kisumu and Siaya (Kennedy, 1989). But also Bungoma is nowadays known for its sugarcane production, which, depending on the variety, needs about 18 to 24 months from planting to harvest (Kennedy, 1989). This cultivation scheme occupies farmland which is not available for

[40] Personal Information from Kenya Seed where further information and knowledge on maize varieties and their distribution throughout the country was gathered.

other crop production for two crop cycles. It is ascertain that cultivating sugarcane is not profitable for small scale farmers as their farm sizes are rarely bigger than 1ha and agricultural land is also used for subsistence farming. In addition there would be no other "insurance" in terms of crop or vegetable production if a sugarcane harvest fails. In general growing sugarcane is a real investment as benefits out of sugarcane harvest take a long time and within the growing period incidental costs are ongoing. According to the Daily Nation, Kenya´s leading newspaper, the sugarcane industry is one of the "biggest scandals in the Agriculture sector" as services and inputs are only extended on credit and thereby put especially small scale farmers in dependency[41]. According to the article farmers in western Kenya pay excessive prices for services related to sugarcane production, harvest and selling. Mentioning the production of sugarcane also shows that the area is highly dynamic and still under transition with regard to a shift from maize to sugarcane production by many large scale farmers.

All seven counties were visited during a field research in August 2013. The aim was to get a general overview about cultivation habits and occurring problems from a farmer's perspective. Farmers in all seven counties were interviewed. General insights in a farmer´s struggles could be made. Furthermore it was experienced in what amount farmers are aware of environmental changes and what strategies they already adapt to cope with certain LD processes such as soil fertility decrease or erosion. All interviews were conducted for validation of ongoing assessment with remote sensing and available quantitative data from household surveys and census information. The interviews were solely qualitative and should only underline or refine assumptions and hypothesis made before, and guide further analysis.

Trans Nzoia, Uasin Gishu and northwestern Bungoma are located in the area of commercial maize production. Many seed companies, including Kenya Seed or Western Seed have breeding stations and distribution offices in Kitale – the capital of Trans Nzoia – also known as grain basket of Kenya (Namisiko & Aballo 2013). Also small-scale farms are found here while the area is dominated by large scale farming (WRI, 2007). South of the high potential maize zones the number of small scale farms increases. Kakamega County furthermore enters the area where two cropping seasons take place during the year (WRI, 2007). Within a normal year farmer mostly grow maize once and in between beans or vegetables.

1.1 The maize producing and consuming nation: "A farmer who does not grow maize is not a farmer".

For a better understanding of the agricultural dynamics in the croplands of the research area some insights in the development of the maize sector and the seed industry should be provided to highlight further interplays and dynamics within the region.

[41] Daily Nation, 22.06.2014; Available at: http://www.nation.co.ke/news/Why-the-poor-Kenyan-sugarcane-grower-slave/-/1056/2358254/-/7icxl8/-/index.html (last accessed 08.12.2014)

Discussions and interviews with farmers across the study area underlined the impression that growing maize defines being a farmer in Kenya. A women, met in Bungoma, who is a farmer herself and member of One Acre Fund[42] told *"A farmer who does not grow maize is not a farmer (…) if you don´t have maize, you have nothing to eat"*[43]. This statement highlights the importance of maize within the region.

The country is known for its maize "success story" among Sub-Saharan Africa including the intensive use of hybrid varieties during the 1960s and 1970s (Smale, Byerlee, & Jayne, 2011; Byerlee & Eicher 1997; Mathenge, Smale, & Olwande 2012). Today, maize is also the most widely-grown staple food of Sub-Saharan Africa (Smale, Byerlee, & Jayne, 2011). It is constituting 3% of Kenya´s GDP and 12% of the agricultural GDP (Wangia, Wangia, & Groote, 2002). Nearly every farmer in Kenya produces some maize as it is also grown under a wide range of ecological conditions (Hassan & Karanja, 1997). The main maize growing regions in Kenya are besides Rift Valley region especially located in western Kenya. To increase future maize production "Kenya will have to rely more on yield improvement than area expansion" (Ouma & De Groote, 2011, 530). Therefore, in this study the focus is on intensification rather than extensification[44].

Due to the implementation of a maize research program in 1955 which started in Kitale, the capital of Trans Nzoia, Kenya could make success in its maize farming sector (CIMMYT, 1986). But nevertheless this development is stagnating and also sustainable land management strategies need to be revised to avoid consequences as known from the Green Revolution in Asia in the 1960s and 1970s where non-adaptive use of fertilizer and imporved varieties triggered enormous LD processes (Hazell, 2009). This awareness is also addressed in the key message from the Executive Secretary of the UNNCCD as "the operationalization of a sustainable green revolution in Africa must address land degradation […]" (UNCCD, 2009). The right strategies for land improvement need to be analyzed to stop an ongoing spiral of yield decrease and livelihood vulnerability. Kenya has already faced these innovations but even if increasing yields depicted the benefit of hybrid maize varieties and fertilizer use, stagnation and even declining trends in yields are recognized. It is necessary to explore the factors that trigger these trends to find the right combination of structures and preconditions to keep a success story ongoing and manage land sustainable.

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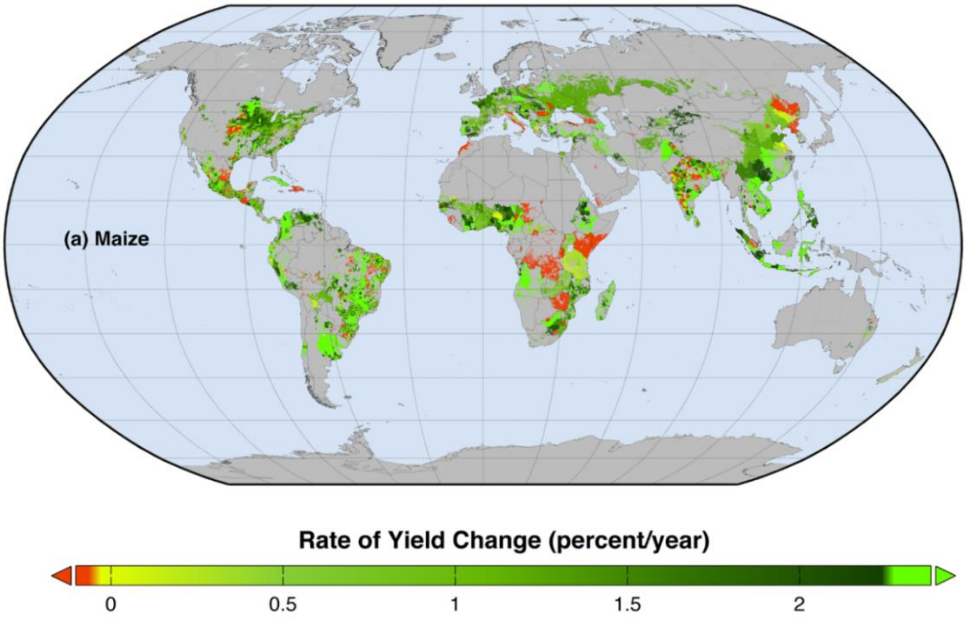
[42] One Acre Fund is a nonprofit organization supporting smallholder farmer in remote places in agriculture. A full set of services is provided to farmers in walking distance including the financing of farm inputs, distribution of seed and fertilizer, training on agricultural techniques and market facilitation to maximize profits from harvest sales. Headquarter of One Acre Fund in Kenya is located in Bungoma. See also: http://www.oneacrefund.org/(last accessed: 08.02.2015).

[43] Interview during field research in August 2013 in Bungoma. Here, a group of women was interviewed who participate in the program of the One Acre Fund.

[44] Intensification refers to producing higher yields per unit area by e.g. increasing agricultural production with agricultural technologies and innovation such as hybrid varieties or improved irrigation systems while extensification looks at expanding or altering land for cultivation (Smith et al., 2010).

In a study by Ray et al. (2013) future yields for the three main crops wheat, rice and maize were projected. It was stated that yields will not fulfill the food needs of a growing population in the future which therefore would need to be doubled. Map IV.2 shows the rate of yield change in maize on a global scale (Ray et al., 2013). Taking a closer look at SSA and especially Kenya, it is shown that yields will decrease which could be crucial for Kenya´s agriculture and development and thereby its population, especially the rural poor who depend on this income and food intake.



Map IV.2: Observed rates of percent maize yield changes per year. Source: Ray et al. 2013, 4

Around 70% of Kenya´s maize is produced by small-scale farmers (Hassan & Karanja, 1997). While in 1903 only 20% of Kenya´s food crop area was maize-cultivated this area has increased to 44% in 1960 (Hassan & Karanja, 1997). Cultivation and consumption of maize has increased since then and due to new technologies and know-how an increasing trend is still recognized. Especially in the 1950s maize research was improved. First hybrids were introduced to Kenya´s seed system in 1964 such as the H611, one of the first maize hybrids introduced in Kenya and still being used (Byerlee & Eicher, 1997). Systematic Maize Research focusing on varieties which are drought prone and resist nitrogen stresses took place (Bellon et al. 2002). But there is still a need for ongoing research to adapted varieties to the different AEZ as soil fertility is declining and also pest pressure increases the need for different varieties (Bellon et al., 2002). Maize production in Kenya is mainly rainfed and thereby highly depending on rainfall which is closely linked to the AEZ.

Kenya had two waves of maize cultivation. Between 1963 and 1974 large-scale farmers rapidly adopted new hybrids which were the major factor for growing maize yields within this period. In addition to that also the expansion of roads and seed distribution networks in the late 1960s, early

1970s enabled yield increase (Byerlee & Eicher, 1997). This slight increase can be identified in Figure IV.1.

The second phase (1963-1974) marked the adoption of improved seeds by small scale farmers. But the yield increase was smaller reasoned by partly improved seeds but no fertilizer use and an unfavorable policy environment. Additionally, severe droughts in 1979 and 1980 diminished maize production. Drastic cuts in funding for maize research resulted in reduced competitiveness and worsened the overall situation (Hassan & Karanja, 1997).

The liberalization of the maize market between 1986 and 1995 was responsible for a sharp increase in maize yield in the early 1980s compared to decreasing areas for growing maize. Before the liberalization, the Kenyan Government controlled all aspects of maize marketing including the distribution of other hybrid seeds outside the country. Since 1986 maize seeds from other companies abroad were allowed to be distributed to Kenyan farmers. The competitiveness within the seed market increased and costs for seeds slightly decreased. Expensive seeds, the non-availability due to big market distance, no access to markets, or a general lack of information lead to the non-adoption of hybrid seeds and/or fertilizer. In general we can observe high variability in the maize yields (Figure IV.1) which is also the case in whole SSA (Smale, Byerlee, & Jayne, 2011). Climatic factors, predominantly precipitation rates, are responsible for much of this variability as most cropping areas in developing countries are rainfed which makes them vulnerable to climate variability such as heavy rainfall events or droughts. Droughts can be easily identified as we can see sharp decreases which came along with drought periods[45].

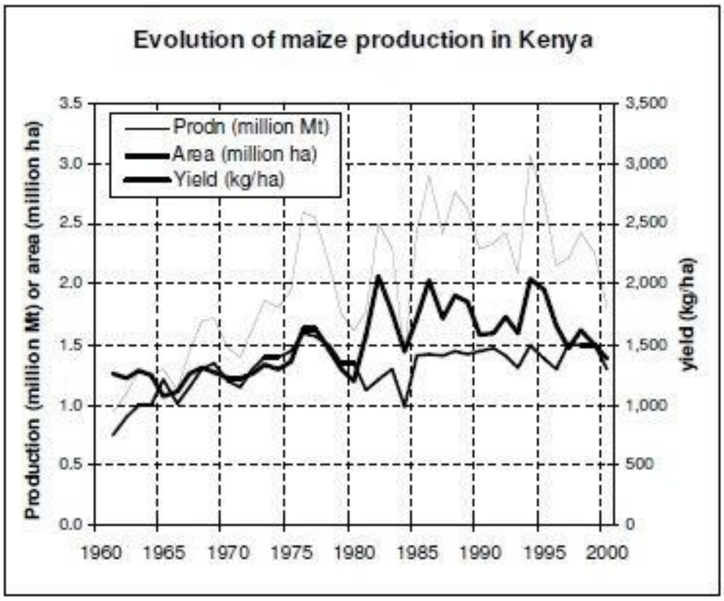


Figure IV.1 Maize Production in Kenya, Source: De Groote et al. (2005, 34)

[45] Droughts: 1979/1980, 1984, 1991, 1994, 1997, 1999, 2004, 2005, 2008, 2011, 2012 (based on: www.emdat.be) (last accessed: 08.02.2015).

But huge differences exist between small scale and large-scale farmers' adoption of improved seeds in high- and low-potential areas. In the areas with less potential for growing maize mostly small-scale farmers are located having limited access to credits which makes it more difficult to afford expensive HYV. With the extension of the railway and road network in the late 1960s to early 1970s the distribution and availability of new technologies, meaning HYV and fertilizer, was improved in genereal (de Groote et al., 2005). But this did not automatically imply easier access of small-scale farmers to seeds or fertilizer if they are not able to afford the high prices of seeds or fertilizer. Moreover, knowledge to apply the new technologies is needed to gain benefit from increasing yields and establish a better food security.

In the 1980s the Ministry of Agriculture (MoA) in collaboration with the German Agency for Technical Cooperation (GTZ)[46] aimed at increasing knowledge about biophysical and socio-economic preconditions in all areas of Kenya with the production of the "Farm Management Handbooks of Kenya (FMHB)". The series "Natural Conditions and Farm Management Information" was first produced in 1982/1983. A second edition has been produced in 2007. The later version is based on province level but is composed of parts for every county[47]. Information on soils and management strategies should be given to the farmers to improve their land productivity and secure sustainable land use. It includes additional information on the different AEZ within the country, possible crops and crop varieties that can be planted within these, the use and amount of fertilizer that should be used in combination with the varieties and also district information and statistics regarding socio-economic structures. But as written in the FMHB the "transfer of know-how is a major task and requires joint effort" (MoA 2007, 12). The handbooks are compulsory for all officers of the MoA. But the most important question arises when thinking about the actual use of this information: do the farmers – that depend on land, cultivate crop and could apply this knowledge – have access? During the field research in western Kenya every farmer was asked if he or she has heard about the FMHB. Out of 45 farmers not a single one was aware of these books even if they had education on agricultural farming in the area. But even if they would have had access to this information the MoA itself mentions that this information "cannot be blindly applied" (MoA 2007, 13) and "especially fertilizer recommendations will be replaced within the next ten or twenty years" (MoA, 13). Ten to twenty years is a long time-frame to assure sustainable farm management. Within this time span slow variables[48] are already triggering LD processes without being recognized in its dimension. Reliable information has to be tested and added in the very near time or the FMHB, which seemed to be the output of a very intense study, is useless. Among all, farming communities need to have access to this information or it should be provided in e.g. farming schools and training areas.

[46] Since 2011 GTZ is named GIZ = Gesellschaft für Internationale Zusammenarbeit (German Society of International Cooperation).

[47] The farm management handbooks are available for the following regions: Central Area, Coast Province Area, Eastern Area, Northern Rift Valley Area, Southern Rift Valley Area, Nyanza Area and Western Area

[48] According to the DDP (Reynolds et al., 2007) slow variables are more crucial than fast variables (chapter II.2.1.2.).

1.2 Data and Methods

The local study is a more detailed analysis of interlinkages of LD and Marginality compared to the national study. The study area was selected based on cropland performance and its importance for food security within the country. In addition, the selection was also data driven as an analysis of biophysical and socio-ecological determinants could benefit from a panel data set collected by the Tegemeo Institute in Nairobi, Kenya, which conducted household surveys in maize growing areas of Kenya from 2000 to 2010.

Biophysical Data

Aimed at using seasonal trend analysis insights in the cropping cycle of the region was helpful. By getting the mean values of each Julian day[49] based on MODIS NDVI over the whole time period from 2001 to 2011 a first assumption on growing periods and cropping cycles within the study area could be made. Analysis of length of growing periods (LGP) carried out by Kate Sebastian for HarvestChoice[50] (Thornton, 2014) was gaining more insights. Showing starting and ending times of a season highlighted partly long seasons in the northern areas and short but multiple cropping cycles in the southern part of the study area.

Adequate rainfall throughout the year and stable temperatures assure that only short periods with no or little vegetation exists in the local study area related to multiple cropping cycles within a year. Considering these results in addition to analysis of seasonality – based on Julian days between 2001 and 2011 – lead to the replacement of seasonal trend analysis by using the productivity of a full year represented by annual sum values of the EVI (ΣEVI). The use of the NDVI for a region with high biomass production was reconsidered and replaced by the Enhanced Vegetation Index (EVI) of MODIS, also with a spatial resolution of 500m and a temporal resolution of 16-days since 2000. The EVI is chosen as it has minimized effects of the atmosphere in high biomass areas (Huete et al, 2002; Masialeti, 2008; Wardlow & Egbert, 2010)[51].

Besides ΣEVI also ΣRFE was used to get insights in the dependencies of vegetation and rainfall. For the local approach the vegetation trend analysis was not directly corrected for rainfall as the biophysical components are also integrated in the regression analysis. In addition to that significant trends of rainfall, using the same approach as the national study, did not highlight any pixel in the local study area at all which might also not emerge due to the coarse resolution of the RFE data (8km) compared to the EVI data (500m). As information on precipitation is also integrated in the household surveys of Tegemeo (see chapter IV 3.2) they were additionally taken into account to verify the RFE-data.

In addition to EVI and RFE data other biophysical variables were included in the analysis (see also Table IV.1). Data on topography allows affiliating environmental processes closely

[49] Julian Days do simply count days within a year from 1 to 365 and do not distinguish between months.
[50] See also: http://harvestchoice.org/labs/measuring-growing-seasons (last accessed: 18.11.2014).
[51] For further details please on vegetation indices see chapter II.3.1.1.

correlating with climate variables such as precipitation and temperature. Digital elevation data (DEM[52]) by the NASA Shuttle Radar Topographic Mission (SRTM) was gathered via CGIAR-CSI, the CGIAR Consortium for Spatial Information. The dataset provides a resolution of 90m and is available on a global scale.

Within this study we focus on SRTM DEM data which represents data of surface elevation so that the classification of high- and lowlands is still part of the further developed model.

With regard to topography the aspects of slopes is shortly mentioned. Farmer in Kenya are aware of processes of nutrient loss. Several farmer in Bungoma, located within a hilly environment recognized that soil is more fertile at the "bottom of the hilly area"[53] (Figure IV.2). If slopes are high and in addition to that rainfed agriculture is dominating the nutrients can be transported along the slope and concentrate at the bottom of a hilly area as mentioned.

In addition to the SRTM 90m DEM data also data on accessibility are integrated in the study providing information about travel time to the next agglomeration and market access (Nelson 2000). A cost-distance algorithm was used to calculate the travel time between two locations while including many different data information on land surface characteristics, infrastructure or population density (Nelson, 2000). Information on accessibility helps to measure if a location is marginal or remote in terms of travel time and access to fulfill certain needs such as seeds, fertilizer or even a hospital.

Figure IV.2: Small scale farms in Bungoma County. Most farms in the region are characterized by high slopes as seen in the picture. A problem occurs when nutrients are washed out and are transported to the bottom of a field as the soil loses fertility. Source: by author

Additional biophysical information included Potential Evapotranspiration (PET) and an Aridity Index (AI). Both datasets are also available via CGIAR-CSI and are based on data from WorldClim Global Climate Data (Hijmans et al., 2005). Information on agro-ecological zones (AEZ), agro-"regional" zones respectively, as integrated in the Tegemeo Household Survey (see Chapter III 2.2. – following this chapter) is also used to get insights in the different biophysical dynamics. Table IV.1 gives a comprehensive overview of data variables and sources used to represent the biophysical perspective.

[52] DEM stands for "digital elevation model".
[53] Personal Information from a farmer in Bungoma County (August 2013), see also Figure IV.2.

Table IV.1: Data Sources for Biophysical Indicators

Variable	Data	Resolution	Source
Productivity	MODSI EVI	500m	Huete et al., 2002
Precipitation	Rainfall Estimates (RFE) (& Tegemeo HH Survey for validation)	8km (RFE) Per village (Tegemeo)	Xie & Arkin 1997
Slopes	SRTM	90m	CGIAR-CSI[54]
Accessibility	Travel time to next agglomeration with 50,000 ppl.	30arc seconds	Nelson, 2000
Aridity	Aridity Index	30arc seconds	CGIAR-CSI[16]
Potential Evapotranspiration	PET	30arc seconds	CGIAR-CSI[16]
Agro-Ecological Zones	AEZ by Tegemeo Survey	per village	Tegemeo based on FAO

Socio-economic data

Household level data collected by the Tegemeo Institute of Agricultural Policy and Development, Egerton University, Kenya, and Michigan State University, USA as panel for the years 2000, 2004, 2007 and 2010 provide detailed information about household structures and agricultural input. The survey was set up in 1997, at that time in collaboration with the Central Bureau of Statistics (CBS), now the Kenyan National Bureau of Statistics (KNBS). All non-urban divisions within Kenya where the survey was conducted were defined via Census data. Besides household characteristics different variables on agricultural land use and cultivation data on land tenure are included which play a key role in this study. The agricultural survey by Tegemeo focuses especially on maize growing areas and therefore covers the main croplands of the country. The survey was conducted in 1,578 households in 24 districts. Based on AEZ among whole Kenya the selection of two to three divisions within each AEZ was assured. All collected information in the surveys is linked to household IDs (HHID) which are again linked to the respective village. GPS information for each village is provided so that HHIDs belonging to a village can be analyzed and addressed in a geospatial environment.

[54] Available at http://www.cgiar-csi.org/(last accessed: 08.02.2015).

2. Analysis on the local level

Figure IV.3 shows the theoretical framework for the local study area. productivity assessment is again conducted based on vegetation analysis. The socio-economic input for the local study is derived from a household panel survey conducted by Tegemeo (see also chapter IV.1.2). Vegetation trends are not corrected for rainfall which is on the one hand due to a lack of detailed rainfall data and on the other hand biophysical data will be included later on in the OLS study to measure its impact. The local study benefits from more biophysical input such as information on topography, temperature or agricultural potential compared to the national study. Biophysical data are mainly based on remote sensing and provides information on a pixel- level. Spatial resolution differs among the dataset depending on the sensor (see also Table IV.1). Socio-economic information is based on the village level. How both data types are linked will be introduced in the following section. Again exploratory regression and OLS in addition to pairwise correlation will be used to identify interlinkages between productivity trends and the interplay of biophysical and socio-economic indicators.

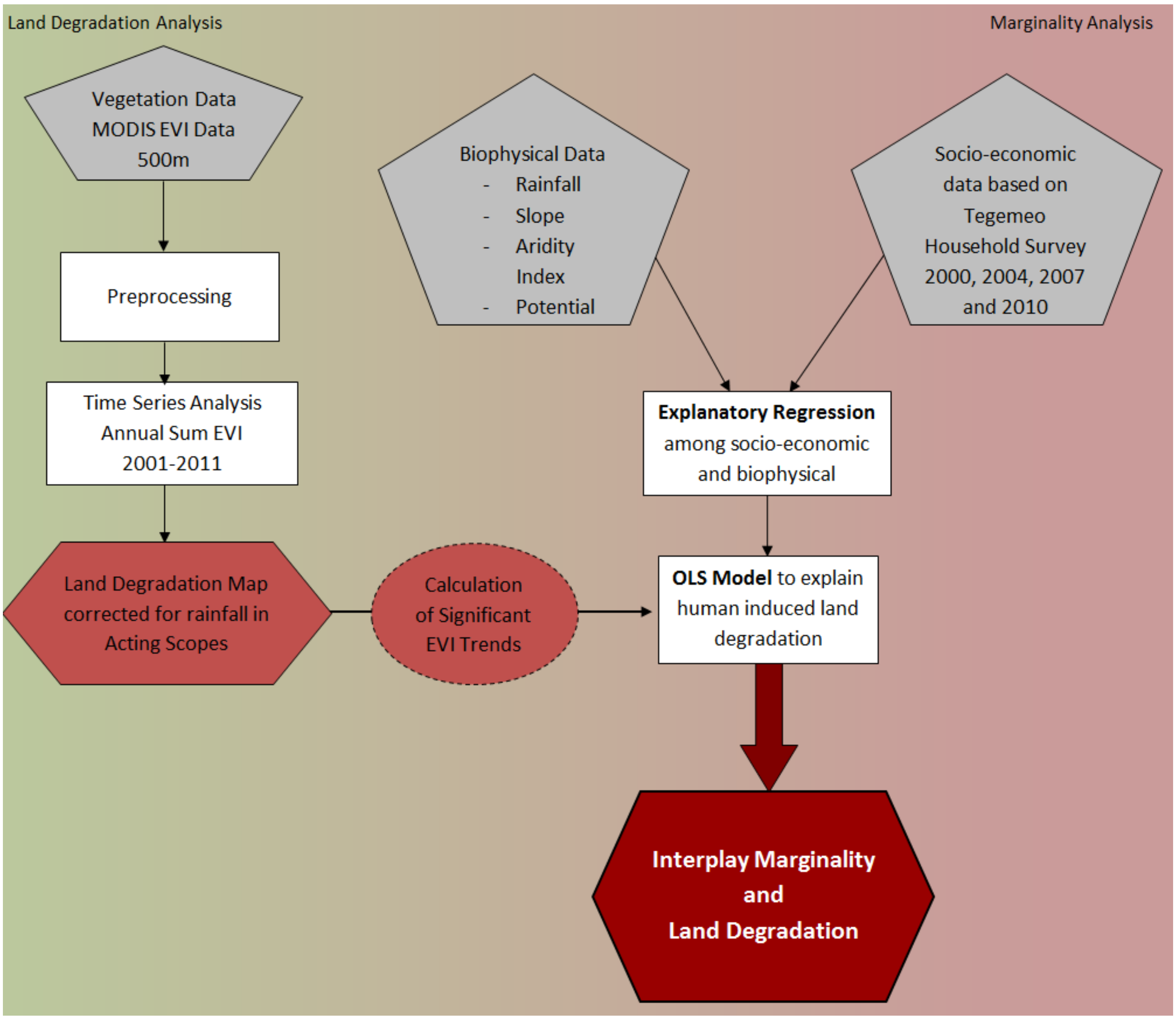


Figure IV.3: Theoretical Framework of the local study

2.1 Working with acting scopes

All information within the Tegemeo surveys (see also chapter III.2.2) is linked to HHIDs. In total 42 villages are taken into account for the local study. Geospatial location information is available for each village but not for the HHIDs. Therefore, only the location of the villages themselves and with them the HHIDs belonging to a certain village were mapped in a GIS. As people who belong to a certain village unlikely only act within the exact location of this village but also around this area – especially when they own or rent farms outside the village – acting scopes are used for further analysis. It is assumed that within a certain walking distance different agricultural activities – whether crop cultivation or livestock grazing – take place. A buffer zone of 10km around every village – which means a walking distance of two to three hours – is used to define these acting scopes (Figure IV.4). With regard to a definition of "far" already a global study on marginality struggled to find a reliable cut-off point that represents a lack of accessibility and thereby comes closer to a definition of distance or the answer to the question "how far is far?" (Graw & Husmann, 2014). Therefore a comfortable walking distance that can be easily reached within a day back and forth was realistically chosen to define the scopes.

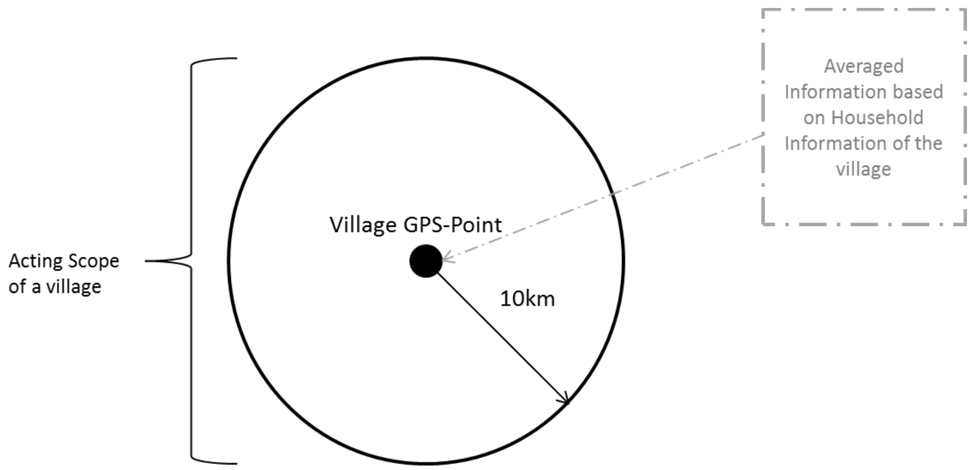


Figure IV.4: Working with Acting Scopes

Within a GIS all data are linked to its geolocation represented by either Pixel- or village-ID. OLS as well as pair wise correlation is used to analyze changes over time and find explanations among socio-economic and biophysical data and their interlinkages. For the biophysical data analysis, the smallest possible level is chosen which refers to the pixel level with a spatial resolution of 500m. As the socio-economic indicators based on the Tegemeo-survey are in some cases village-specific – such as information on size and number of fields per HHID or amount of fertilizer used on a field – the acting scopes had to be analyzed separately for each village. Even if certain acting scopes overlap and are therewith influenced by one or more villages these acting scopes had to be separated from each other. In total 42 villages are analyzed with each a number of around 1400 pixels. As water-pixels and urban areas are masked not all villages have the same number of pixels which is considered for further analysis, in particular for calculating the amount of pixel affected by increasing or decreasing trends within the village. In total 29,873 pixels are analyzed. By linking remote sensing data on productivity to socio-economic indicators derived from the Tegemeo panel dataset we aim at finding cause-action-relationships over and among the described period of analysis.

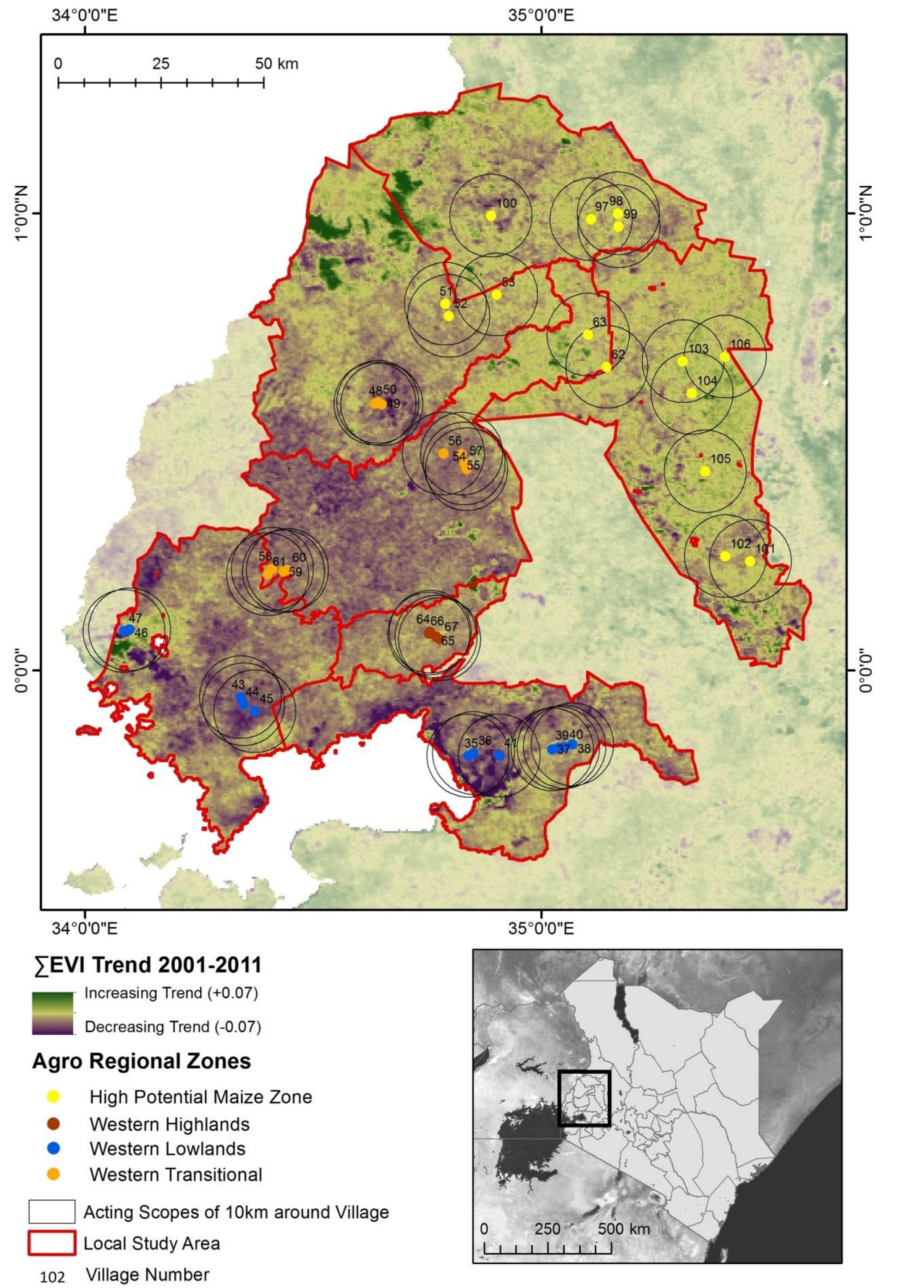
2.2 Land Degradation Analysis: Getting insights from the biophysical perspective

EVI trend analysis was used for LD assessment in the study area. Aiming at covering full cropping cycles the annual sum EVI (ΣEVI) was used here. As MODIS was launched in February 2000 images from January 2000 were missing to complete data for a full year. Based on information by the Kenya Food Security Outlook, a report generated from FEWSNET, USAID, MoA & WFP (2011) the drought period in 2011 affected the local study area minimally during that time. Due to the reasons mentioned above the reference period in the local study again covers the years 2001 to 2011.

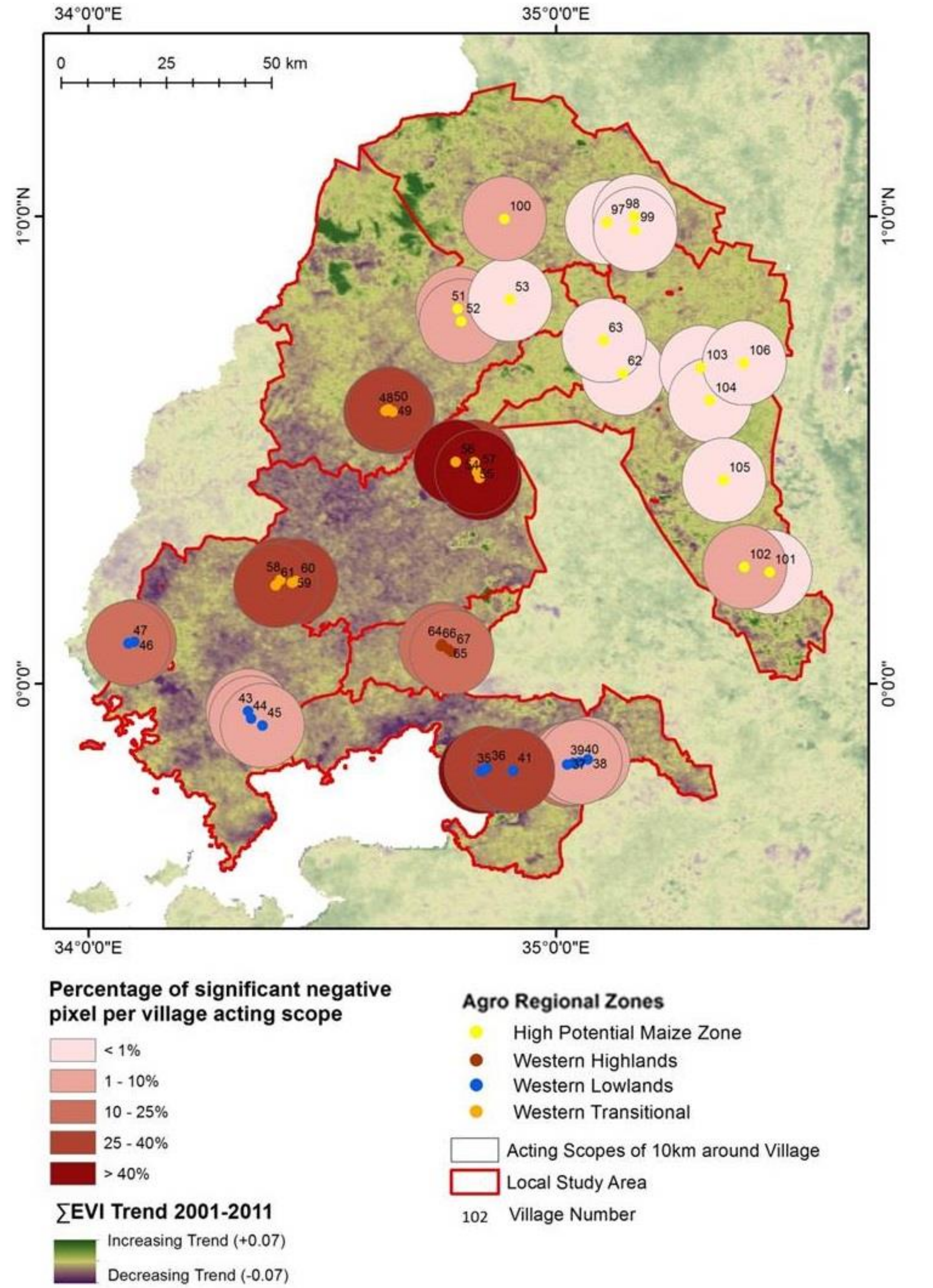
For the calculation of annual ΣEVI the replacement of the image of Julian Day 304 of the year 2004 was necessary to not falsify the results as it included 50% missing data values. The EVI values of the missing dataset were replaced by calculating the mean EVI out of the scenes from one time step before (Julian Day 289) and one time step after (Julian day 321) the missing image assuming a linear trend in vegetation cover during that period.

The trend analysis was made in R by calculating the slope of the linear regression among the 12 annual datasets for each pixel. Map IV.3 and Map IV.4 show the ΣEVI trends and acting scopes around the villages. Map IV.3 shows the study area including ΣEVI trends between 2001 and 2011 as well as the reference acting scopes for the ongoing analysis. Decreasing trends can be found in the southern part as in the counties Kisumu – close to Lake Victoria – as well as in Kakamega and Siaya. Increasing or stable trends are rather found in the northern areas including Bungoma, Trans Nzoia and especially the area around Mt. Elgon. Additionally information on agro-regional zones is included in the map which will also be of further interest in the ongoing study.

By calculating significant trends based on annual ΣEVI affected villages can be identified according to the percentage of pixels with significant negative trends in relation to the total amount of pixels in one acting scope. The more land of the acting scope (circles around each village dot) is affected with significant negative trends the darker the reddish color of the circles (see Map IV.4).



Map IV.3: Local Study Area in western Kenya with ΣEVI trends. The circles refer to the acting scope of every village. The villages are numbered. The dots which represent the GPS-point of a village are colored with regard to the agro-regional zone they are located in. ΣEVI trends show the decreasing and increasing vegetation/productivity trend from 2001 to 2011 based on the slope of the linear regression.



Map IV.4: Local Study Area in western Kenya with significant decreasing ΣEVI-trends in the village acting scopes (see also Map IV.3). The circles in red shades describe the acting scopes around each village with regard the amount of significant negative trend of ΣEVI pixels (in percentage) among the whole acting scope. Colored dots describe the agro-regional zones according to the Tegemeo survey in close relation to the AEZ-approach by FAO.

2.3 Interplays among biophysical and socio-economic variables

Biophysical Interplay

The presented LD analysis is based on vegetation trend analysis using the ΣEVI from 2001 to 2011. The same time frame and method is used for the RFE trend analysis. Biophysical data of AI and PET already refer to averages means as provided by CGIAR-CSI based on data from 1950 to 2000 provided by the WorldClim Database.

Vegetation is one of the fast variables[55] showing a quick response to changes while precipitation is known to be the dominant causative factor for vegetation growth and natural variability (Nicholson, Davenport, & Malo, 1990; Hermann, Anyamba, & Tucker, 2005). Pair wise correlation among all pixels within the study area based on the annual ΣEVI and ΣRFE showed an average correlation between RFE and EVI of 0.4944 among all 29,875 pixels over the observation period. But as RFE is based on 8km resolution data while EVI data have a resolution of 500m also an up-scaled correlation per acting scope was done to get an impression about vegetation and rainfall behavior within all acting scopes. The Mean of ΣEVI and ΣRFE was built for each year (2001-2011) and acting scope. Here, the average correlation was 0.6336 among all 42 village-observations. A strong relationship between rainfall and vegetation can therefore also be stated for the local study area. A comparison of ΣEVI and ΣRFE for all villages according to their acting scopes for each year identified outliers in some villages in 2009[56] which lead to further analysis in this regard.

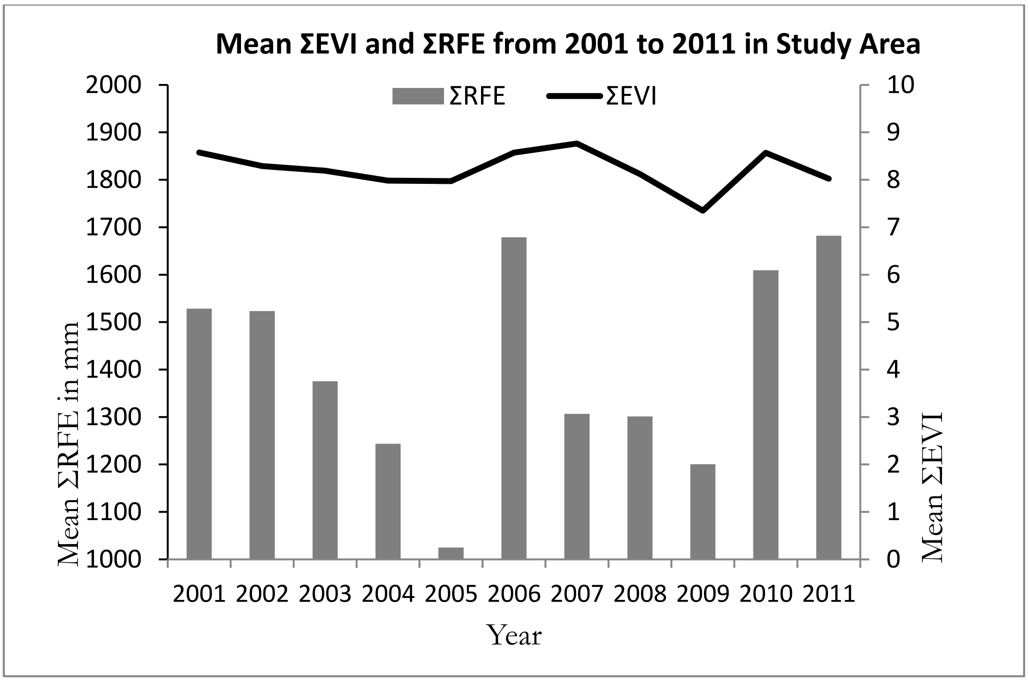


Figure IV.5: Mean ΣEVI and ΣRFE for all pixels in the study area.

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[55] According to Reynolds et al. 2007, chapter II.2.1.2.
[56] See also Annex 7.

Figure IV.5 shows ΣEVI and ΣRFE over time in the study area. Looking at the actual development of ΣEVI and ΣRFE the dependencies again become clear despite an obvious decreasing peak from 2007 to 2009. A drop in ΣEVI is observed in 2009 which is most likely not related to slightly decreasing rainfall trends only. Certain trigger events are identified in 2007 and 2008 which had an impact on productivity trends, especially decreasing trends: the post-election crisis in 2007 and the world economy crisis in 2008. As mentioned both will be addressed in the following analysis.

Especially in the High Potential Maize Zone a decrease in productivity could be observed[57]. The decreasing trend in 2011 again can be related to the maize disease, called Maize lethal necrosis (MLN), occurring in Eastern Africa[58].

Based on the pixel information all pixels with negative, positive or stable trends were calculated. Analyzing the interplay among other biophysical variables on the pixel-level furthermore showed a positive correlation of 0.5084 between AI and EVI and a negative correlation of -0.6632 between SRTM and RFE. According to the IPCC 2014 only low vulnerability of ecosystems to biome shifts are expected in the study area, western Kenya in particular (Field et al., 2014, Figure 22-4)[59]. Climate change is nevertheless mentioned to affect crop production worldwide. In Kenya, and Eastern Africa in general, climate change can improve also maize production by warmer climate conditions in locations of high elevation such as in the high potential maize zones in the study area referring to the A1F1 scenario (Field et al., 2014; Thornton, 2014). With regard to these prospects climate change was not highlighted in this study.

Impact of the three main biophysical variables – AI, PET and RFE – and their relationship to negative and positive trends are listed in Table IV.2.

Table IV.2: Correlations between biophysical variables – Aridity Index, Potential Evapotranspiration and Rainfall Estimates – and productivity trends on the village level.

	Neg_0.05	Signi Neg	Pos_0.05	Signi Pos	Stable
AI	0.68	0.56	-0.67	-0.29	-0.66
PET	0.54	0.28	-0.03	0.02	-0.02
RFE	-0.03	0.22	0.35	0.03	0.35

57 See also Annex 8.

58 Information during field research from several sources and stated by the international maize and wheat improvement Center (http://www.cimmyt.org/en/where-we-work/africa/item/maize-lethal-necrosis-mln-disease-in-kenya-and-tanzania-facts-and-actions) (last accessed: 08.02.2015).

59 The model to calculate vulnerability of ecosystems to biomes shifts is based on historical climate data (1901-2002) and projected vegetation (2071-2100) (Field et al. 2014, Figure 22-4: 1215)

Socio-economic interplay

The Tegemeo household panel survey provides different information that helped to get insights in social and economic activities within the households of the study area. Data are collected for agricultural inputs such as amount of fertilizer use, field size, land tenure or the cultivation system such as e.g. rainfed agriculture versus irrigation. All different dimensions of marginality are also fully represented in the local approach by extracting and including information on education, health, income, ownership of assets, access to the next agglomeration and market, infrastructure and information, and use of agricultural technologies.

Data merging and analysis was made with STATA12 and R. After extracting the information for all four years (2000, 2004, 2007 and 2010) trends were calculated for each village within the given time period of the survey (2000-2010). Several relationships could be observed by pair wise correlation among the different trends of the socio-economic indicators. Most of the relationships were already expected such as a positive correlation between *income* (whether from crop or livestock or in general) and *ownership of assets*. People having *own land* make *use of credits*, represented by a positive correlation of 0.4328 between these two variables. Farmers could either use the credit for buying own land or to afford seeds and fertilizer to guarantee further income. Around 90% of all farms in the research area are based on *rainfed agriculture* while only about 10% of farms are *irrigated* in 2007. In 2010 a slight decrease in *rainfed agriculture* among the villages in the study area of around 5% could be observed which has an exact increase in *irrigated agriculture* involving[60]. A relationship was found among having *rainfed* or *irrigated agriculture* in combination with *livestock income*. People that can afford irrigation on their fields are having more livestock or so to say those farmers who can also gather income from livestock are able to irrigate their fields[61]. *Accessibility* should play a key role when it comes to productivity even if it has to be kept in mind that the study area is already characterized by a good infrastructure. This is particularly valid for the northern area with commercial maize farming on large-scale farms (WRI, 2007). It could be observed that the longer it takes a farmer to get to the next agglomeration the less hybrid maize and fertilizer is used. Also the *crop diversification index* is higher, meaning a higher number of different crops planted, the closer a village was located to the next bigger agglomeration. This is again linked to the factor *having access* according to the definition of marginality. Accessibility seems to also have a relationship to *ownership of land* as the further away a village is located according to the definition of accessibility the fewer farmers do own their own land. Self-evident positive correlations between distance and price of seed or fertilizer are mentioned for the sake of completeness.

Seed prices go in line with *manure use* and show a positive correlation. The higher the price the more capital a farmer has to afford to make use of *improved varieties* which may lead to less available

[60] Average percentage based on Tegemeo survey data from 2007 and 2010. Data on irrigation and rainfed based agriculture were only available for the years 2007 and 2010.

[61] Positive correlation (0.5) between trend in irrigation and livestock income. Negative correlation (-0.52) between trend in rainfed agriculture and livestock income.

capital for other agricultural inputs such as fertilizer. A negative correlation was observed among trends of *land ownership* and *seed prices*. The higher the price trend the fewer farmers do own land but rather rent land. But both relationships are not showing high correlations, especially the one between renting land and seed prices.

Education and *Mortality* had the expected correlation by showing a decrease in education and an increase in decreasing productivity trends while also an increasing mortality showed higher amounts of decreasing productivity. Especially in high productive areas where innovations such as hybrid seeds or chemical fertilizer are used basic knowledge is necessary. The variable of education was represented by the *years the members of a household attended school*. *Mortality* again let reflect on health and was represented by the *number of households that experienced prime-age mortality since the previous survey*.

3. The Crucial Triangle: Interplay of Land Degradation, Land Use/Land Cover and Marginality on the Local Level

Western Kenya is known as one of Kenya´s grain baskets but there are internal dynamics that need to be pointed out to find drivers of decreasing and increasing as well as stable productivity. This chapter will identify indicators that play major and minor roles for productivity in the study area but also underline the importance of adding qualitative data to the analysis to get insights in dynamics on the local scale. Again exploratory regression, OLS and pair wise correlation were used for analysis.

Results of this part are also included in a paper by Graw et al. (2015)[62].

3.1 Adding Qualitative Information: Trigger Events and their Impact on Land and Productivity

According to approaches on vulnerability and especially the sustainable livelihood approach (SLA) events can have a big impact on a system – whether an ecological or social system – and can trigger processes such as LD (DFID, 1999). Events can refer to climate events such as droughts or heavy rainfall events but also socially and economically driven events such as conflicts among different groups or an economy crisis. Additionally given structures such as land rights and ownership or ethnicity play important roles in coupled HES. Mostly these are the indicators that are neglected in quantitative models as reliable data are missing and especially sensitive. In matter of completeness this chapter will give some insights in the most important structures and events that had an effect on productivity decrease with regard to land and agricultural production based on qualitative input linked to quantitative validation.

3.1.1 Post-Election Violence and World Economy Crisis as trigger for Productivity Decrease?!

Two major effects triggered the downward trend of production in 2009 as already pointed out in Figure IV.5. The post-election violence after the elections on 27th December of 2007 affected planting and harvest in the following year due to problems in transportation and rising insecurity in western Kenya (Kriegler & Waki, 2009). Secondly the world economy crisis in 2008 had impact on price development and price variability which affected food production in general. Insecurities and ethnic disturbances coming along with a lack of accessibility on the one hand and higher prices of seed and fertilizer[63] caused by the world economy crisis on the other hand affected farmers and their farms in the study area. A positive correlation was found for

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[62] Conference Paper *(submitted)*: will be presented at the World Bank conference on Land and Poverty taking place in Washington D.C., USA from 23rd until 27th of March 2015.
[63] According to Kenya Maize Development Program (KMDP): http://www.acdivoca.org/site/ID/kenyaKMDP (last accessed 07.02.2015).

decreasing vegetation trends and price increase for fertilizer and seeds showing that the higher the price trend was the bigger the area affected by decreasing vegetation trends. Consequently a reduction in planting and a decrease in fertilizer use was the outcome.

Figure IV.6 shows the development of prices of seed and fertilizer, particularly for maize and vegetables, based on the Tegemeo household survey. The increase of prices with regard to fertilizer and seeds can be clearly identified from 2007 to 2010. But there is also a general tendency for price increase. The seed price (red line) has a very sharp increase from 2007 to 2010 which most likely concludes to less cultivation or poor land management with regard to fewer or no fertilizer use.

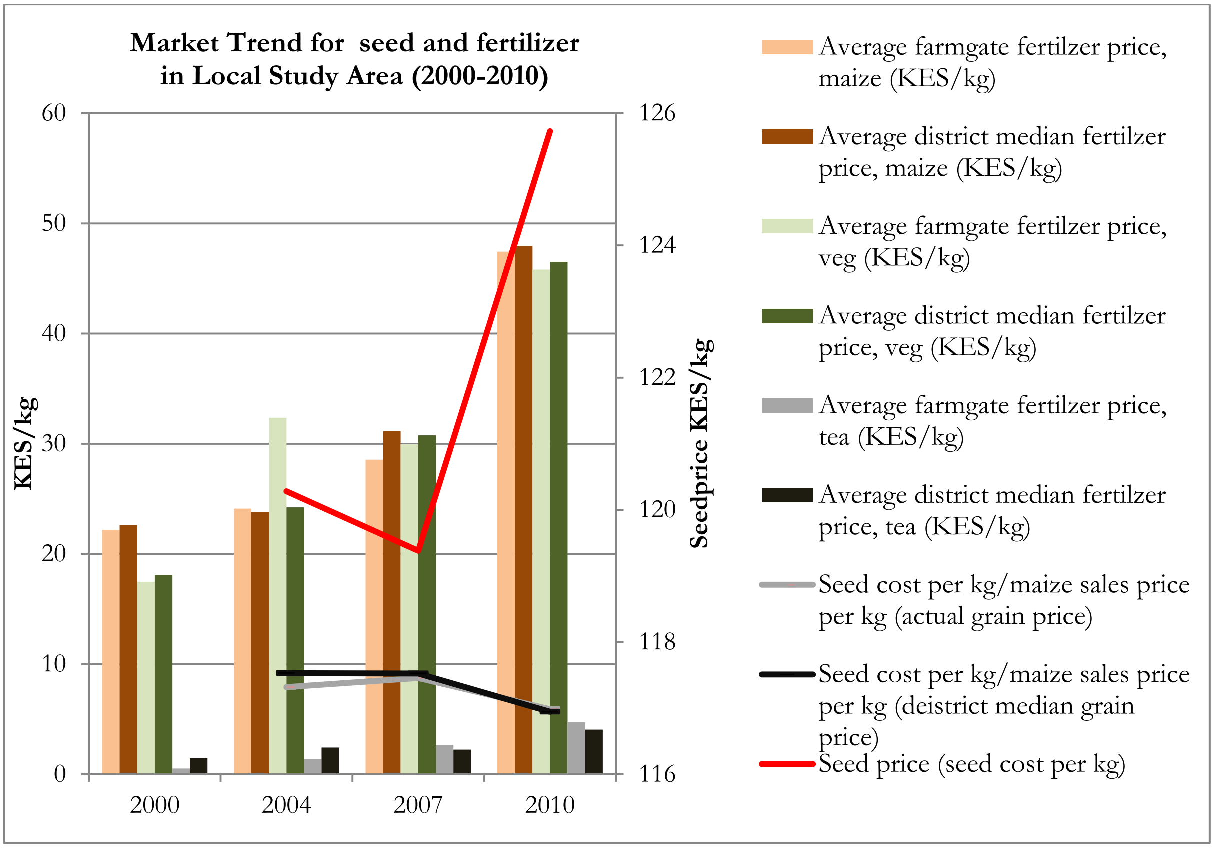
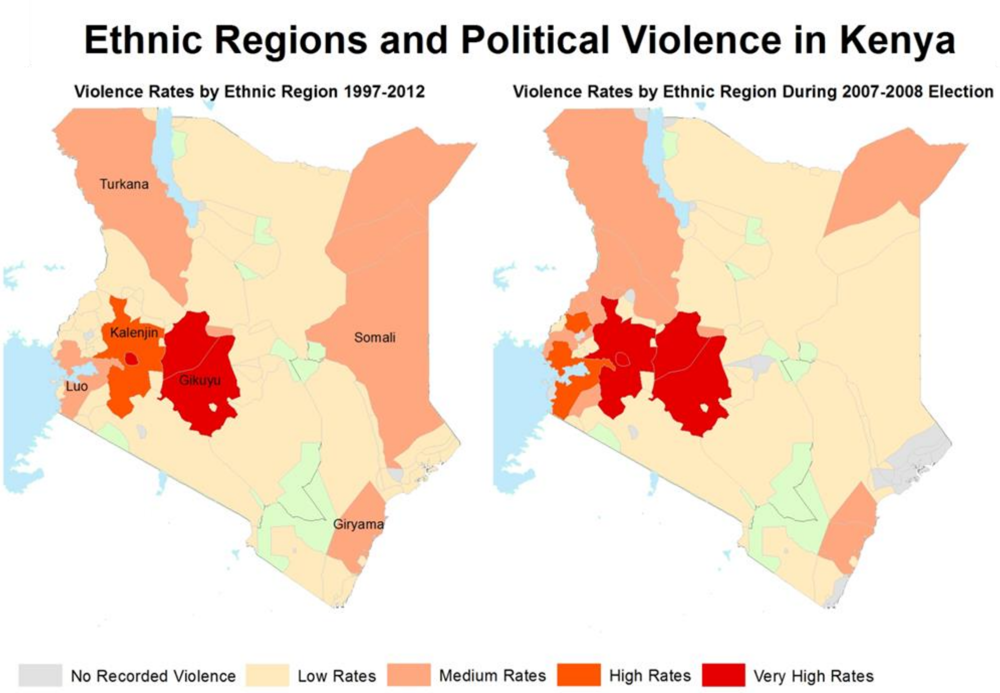


Figure IV.6: Development of Price Trends of seeds and fertilizer in the study area based on information derived from the Tegemeo Survey 2000-2010. The red line shows the seed price, the grey and black line seed costs.

The post-election crisis affected the western and Rift Valley area of Kenya the most. Among the 1,133 reported deaths due to the violence, 744 came from former Rift Valley and 134 from former Nyanza Province (Kriegler & Waki, 2009). Violence was concentrated here based on the ethnical group distribution within the country. Besides the mentioned deaths also around 500,000 people who had to leave their homes were reported after the post-election violence (Gibson & Long, 2009). Map IV.5 shows the areas that were affected during the election phase (right) and those which are generally affected by violence because of ethnic affiliation (left). High rates of violence can be found in central/southern Rift Valley including the counties Laikipia, Nyeri, Nyandarua, Muranga, Kirinyaga, Embu, Machakos, and Kiambu.



Map IV.5: Violence in Kenya; modified from the Armed Conflict Location and Event Data Project (ACLED). left: Violence Rates from 1997-2012; right) Violence Rates during the Election 2007-2008. Source: ACLED, 2013, 5

Due to interruptions also in the transport sector market centers had to close (Dupas & Robinson 2012). Mostly affected was transportation on the major roads including the Kisumu-Kakamega connection and areas located at the Uasin Gishu border and furter in Busia and Bungoma county (Kriegler & Waki, 2009). This includes nearly the entire local study area. But not only the prices of basic food items increased. Also prices for phone cards or soap rised in price for about 20-30% immediately after the elections and remained high in some cases much later (Dupas & Robinson 2012).

Political instability is a huge impact factor for several dimensions of a livelihood including environmental health (Schafer, 2002; Collier, 2008; Graw & Husmann, 2014) . This variable was already considered in the global approach on mapping marginality to represent the sphere of governance (Graw & Husmann, 2014). Unfortunately data on political instability is difficult to find and if it is mostly on a broad scale such as for a whole country. Moreover, data reflecting on governance is mostly very sensitive. Not all countries are willing to provide data that can represent some kind of instability without hesitation as they mirror the situation and thereby wealth of a country. In general, information on governance and political aspects are important to be included for complex analysis even though only by using qualitative information.

3.1.2 Land Tenure and Ownership: How Strong is the Expected Link to LD and Productivity?

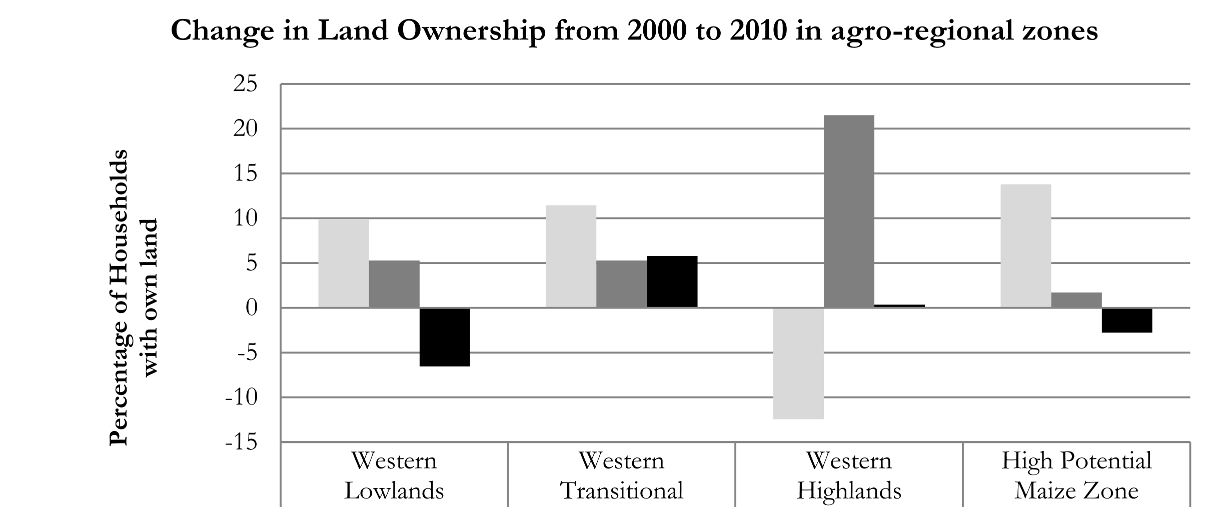
Considering literature research and the national analysis in this study where decreasing trends in southern Kenya, particularly in Narok and Kajiado, are most likely dominant due to land competition and difficulties in land tenure rights, this aspect was also looked at in western Kenya. Information if land is owned or rented is provided for all four years of the survey. Based on these the percentage of people owning or renting land per village as a mean value over the whole observation period and also the trend from 2000-2010 was calculated.

According to Barbier et al. (1997) farmers are more likely prone to exploit land and use unsustainable land management strategies to get short-term benefits if they do not own the land. A study conducted in seven counties – Bungoma, Kakamega and Homa Bay in Western as well as Nyeri, Tharaka, Kirinyaga and Muranga located in central Kenya resulted that a maximization of yields is in focus especially when farmer rent land (Kamau, Smale, & Mutua, 2014). Moreover they do more likely use inorganic fertilizer to increase yields as the use of inorganic fertilizer was significant positive related to renting land. In Namibia and Southern Africa links between LD and whether land is communal or commercial seem to be obvious (Klintenberg & Seely, 2004; Hoffman & Todd, 2000). Even if these land rights are triggered additionally by poverty, competition for land and biophysical preconditions linkages can be found between commercial and communal land use (Boonzaier et al., 1990; Ward et al., 1998; Hoffman & Todd, 2000). Insecurities are another reason to exploit current resources instead of cultivating an area sustainable. This might not only refer to rented lands but also to owned lands because of a lack in future perspectives. This could also be assumed during the post-election crisis and the world economy crisis where it was not absolutely clear how much value a land still has and moreover how long ownership lasts.

The example of Narok (chapter III) where poverty and LD were analyzed in their interplay showed that an obstructive situation of land rights and ownership lead to less productive areas and even LD due to various pressure coming from different interest groups. Even if the post-election violence made existing conflicts obvious, the roots are also to be found in relation to land ownership (Boye & Kaarhus, 2011). The complexity of socio-economic and biophysical factors within an area therefore increases the need for interdisciplinary analysis in a geospatial setting.

Pair wise correlation and exploratory regression showed that ownership of land has an impact on productivity trends. With regard to significant negative trends ownership of land occurred with >90% of negative impact on ownership trends. The more people own land the higher decreasing trends and the lower increasing trends could be observed. As it was expected to get opposite results correlations were also tested for negative and positive trends in general, including a tolerance, and for stable trends. Results state a positive link for an increasing number of household having own land with decreasing productivity trends as well as a negative correlation between increasing productivity trends and land ownership.

Making distinctions among the different agro-regional zones[64] with regard to land ownership gained insight in ownership and individual trends. Looking at changes between the different household surveys from 2000 to 2010 showed that especially in the western lowlands and the high potential zones a decrease of land ownership took place particularly from 2007 to 2010 (Figure IV.7).



	Western Lowlands	Western Transitional	Western Highlands	High Potential Maize Zone
change2000-2004	9.84	11.44	-12.45	13.78
change 2004-2007	5.28	5.29	21.51	1.70
change 2007-2010	-6.54	5.78	0.35	-2.77

Figure IV.7: Change in Land Ownership from 2000 to 2010 in agro-regional zones based on Tegemeo Data.

Especially in the lowlands this could be referred to decreasing rainfall trends but also to farmer who left the area after their property was destroyed in the course of the post-election violence (Kriegler & Waki 2009). In addition according to Kriegler and Waki (2009) around 350,000 people left their residence in the country with concentrations in Western, Nyanza, Rift Valley, Central, Nairobi and Coast Province in addition to about 1,916 Kenyans who flew to Uganda. In general a high number of people own their own land in the study area although there was an increase until 2010 as seen in Table IV.3. A slight decrease can be identified from 2007 to 2010 which might be related to the post-election crisis but still this decrease is very low (around 1%).

Table IV.3: Number of HH with own land among all HH in Study Area. Based on Tegemeo Survey 2000, 2004, 2007 and 2010.

Percentage of HH owning land between 2000 and 2004			
2000	2004	2007	2010
78.36	87.34	93.55	92.59

[64] The different locations of the zones see Map IV.3.

Population Density and Farm Size

Land tenure rights as such do not play a major role in western Kenya compared to other areas of Kenya e.g. in central or southern Kenya where land tenure rights are a more sensitive issue. During the field research it became obvious that the size of a farm is a much bigger issue in this region. Therefore data on the number of fields per village area was taken into account. In general a positive but low correlation could be observed for number of fields (mean) and decreasing productivity trends. Vice versa a negative correlation with stable and increasing productivity trends was reported. Looking at trends in the number of fields from 2000 to 2010 also gave positive correlation for significant decreasing (0.15) and decreasing (0.43) productivity and a negative correlation for stable and increasing trends (-0.4 to -0.5) (see also Table IV.4).

Table IV.4: Relationship of Number of fields and trends of number of fields between 2000 and 2010 to productivity trends.

	Significant Negative	Negative (<-0.05)	Positive (>0.05)	Stable (-0.05 - 0.05)
Field Number Mean	0.061	0.148	-0.151	-0.129
Field Number Trend	0.153	0.426	-0.404	-0.523

Especially in the productive regions of Kenya including the western highlands population is increasing. As fields are inherited and divided depending on the number of children a farmer has pressure on land resources increases intensely.

On smaller field sizes households still need to cultivate the same amount of food as before. If farmers own livestock less area for grazing will be available which also increases the pressure on land and thereby triggers LD processes even more. This relationship can also be found with regard to Table IV.5.

Table IV.5: Relationship of Population Density and Productivity

	Significant Negative	Negative (<-0.05)	Positive (>0.05)	Stable (-0.05 - 0.05)
Population Density	0.2874	0.4981	-0.4955	-0.4511
Population Density Trend	0.3519	0.5199	-0.5162	-0.4784

Nevertheless due to insecurities coming along with the post-election period and the world economy crisis farm management strategies might have been more unsustainable with regard to exploitation of land and leaving afterwards. But this is just a hypothesis which could not be assessed. A statistical analysis among different former provinces came to the result that in Nyanza province, including Siaya and Kisumu county, a relationship between poverty and distance to the nearest city with 20,000 inhabitants is significant and negative meaning that the further away people are located the less poor they are (Okwi et al., 2007).

3.2 Decreasing Productivity Trends

According to the summary of the variable significance of the exploratory regression biophysical variables, preconditions respectively, play key roles in all possible models. The first three variables having each 100% impact on significant decreasing trends are AI (+), SRTM (-) and PET (+). Results of a negative correlation with elevation (SRTM) highlight the term "productive highlands". AI and PET show a positive relationship to significant decreasing productivity trends while topography impacts negatively on them.

Socio-economic variables do not always describe unique dynamics of positive or negative impact on decreasing trends of productivity. Therefore bivariate analysis among the area between certain socio-economic indicators and productivity trends will be analyzed further on.

Considering the characteristics of the study some assumptions were set up. These included the importance of agricultural innovations and input such as hybrid seeds and fertilizer use but also access to transport and information. They also go in line with monetary aspects such as income or access to credits to afford the above mentioned. As it was aimed to rather identify the variables with the most important impact on agricultural productivity instead of finding a general model to explain trends – as in the national study – it was no longer aimed at covering all different dimensions of marginality as some specific variables might just not play an important role for decreasing productivity trends on the local scale.

Based on findings from the exploratory regression an **OLS-model** is built with trends of socio-economic data from 2000 to 2010 with the following variables:

- **(-) Getting credit** *(% of all households (hh) in the village)*
- **(-) Total fertilizer used per ha** *(kgs/ha)*
- **(-) Owning a radio** *(in % of all hh in the village)*
- **(-) Owning a vehicle** *(in % of all hh in the village)*
- **(+)Mortality** *(% of prime-age mortality per village)*
- **(-) SRTM** *(in m a.s.l.)*
- **(+)RFE-trend** *(based on the RFE trend analysis)*

As mentioned above several dimensions of marginality – including economic variables such as receiving credit or ownership of assets or health represented by mortality but also access to infrastructure and information (vehicle and radio) – showed the expected coefficients. Biophysical preconditions and impacts are represented by topography and rainfall in this model.

Rainfall is seen as the dominant natural variable influencing vegetation growth. Thereby a negative coefficient was expected with regard to decreasing productivity trends. But the RFE trend from 2001 to 2011 was solely positive due to a downward trend from 2001 to 2005 and a sharp upward trend in 2006 which lead to a general positive trend using the slope of the linear regression over the whole time period (see also Figure IV.5).

Credits can be used to afford seeds and fertilizer and thereby can represent agricultural input. Additionally, this variable can indicate where additional financial help is needed that comes along with decreasing productivity represented by a negative coefficient to explain significant decreasing trends. The relationship of *fertilizer use* was expected showing that the less fertilizer is used the more agricultural productivity is decreasing. The aspect of *transportation* will be discussed further but it can already be stated that with regard to the OLS-output a link to productivity is given.

The model performance with $R^2 = 0.76$ while all indicators being significant represents a good explanation so far. But when running the spatial autocorrelation a significant p-value of 0.004 stating a clustering of the observations was reported. With regard to the characteristics of the study area two parts can be identified: a high productive zone in the northern part of the study area and a second also still productive, but no longer classified as "High Productive Maize Zone" according to the agro-regional zoning based on the FAO classification used in the panel survey, part to the south.

3.3 High potential Maize Zones (HPMZ) and non-High Potential Maize Zones (nHPMZ) – How do they differ in the Study Area?

Based on the results of the OLS the study area was divided into two parts for further analysis: the high-potential maize zone (HPMZ) in the northern regions and the non-high potential maize zone (nHPMZ) south of it (Map IV.3)[65] as classified in the Tegemeo Survey[66].

Out of the exploratory regression variables such as *Distance to electricity*, *population density* and *accessibility* occurred in all models of the HPMZ, followed by *SRTM*, *owning land*, *PET* and *trend of fertilizer use* – mentioning the first seven variables with most impact and clear significance on positive and negative sides. For the nHPMZ *RFE Trends* and *growing vegetables* were followed by *accessibility*, *having an own radio, population density, PET and number of livestock*[67]. With slightly lower impact the variables *SRTM, AI* and *getting credit* came next. Variables such as *growing hybrid maize* or *fertilizer use* were listed much later while in the HPMZ variables such as *income* or *getting credit* played a minor role. An interesting OLS model explaining 83% of significant negative trends of ΣEVI in the nHPMZ was composed with only three biophysical variables: *SRTM* (-), *AI* (+) and *RFE* (+). It can be assumed that in an area where rainfed agriculture by small-scale and mostly subsistence farmer is taking place, biophysical variables play key roles. Education and access to livelihood needs are necessary but the less input in terms of fertilizer or hybrid seeds can be afforded, the more does production rely on biophysical (pre-)conditions. When taking a look at

[65] Map IV.3 shows the agricultural divisions. Yellow dots indicate the high-potential maize zones (here HPMZ), all other dots refer to the non-potential maize zones (nHPMZ).
[66] Villages within high potential zones were rated with 1 while all others were 0.
[67] Data on the number of livestock was collected for each year in each household. Mean values for each year were built to calculate the trend between 2000 and 2010 as well as the mean over the whole observation period.

the first results of the exploratory regression in the HPMZ biophysical variables still play key roles but are not as dominant as in the areas where farmer directly depend on rainfall and irrigation is not common. With *SRTM* (-) and *PET* (-) variables such as *growing hybrid maize* (+), *distance to electricity* (-) or trend of *seed prices* (-) lead to an explanation of around 81% of significant decreasing trends. Rainfall for example does not play a significant role in this model or at least does not lead to a high R^2 for the explanation of the variance of decreasing trends in the study area. This is explained by the different irrigation practices or better to say the difference in using more irrigation in the HMPZ compared to mainly/solely rainfed agriculture in the nHPMZ.

A main characteristic which relates to the measurement of poverty among the two areas can also be identified via income. While income in the HPMZ is around Ksh 197,685 per year it decreases more than half to 60,728 Ksh annually in the nHPMZ (Argwings-Khodhek et al., 1999).

Pair-wise correlation among the productivity trend variables with different socio-economic variables highlighted differences in the total area and in addition to the two mentioned zones. The following chapter focusses on indicators and indicator groups that represent also dimensions of marginality. They are analyzed with regard to their impacts on all productivity trends also including stable conditions[68] which were already highlighted as being important in the national study to maintain a socio-ecological equilibrium and also with regard to LD neutrality. Significant positive trends were not included as these had only marginal changes among the villages.

3.3.1 Basic livelihood characteristics

Education[69] could represent an important indicator in the area with regard to the use of agricultural innovative technologies which needs basic knowledge or training for effective outcome. Fertilizer use e.g. is positively influenced by the level of education of the household head (Freeman & Omiti, 2003). Education is represented as the *mean years of schooling of all household members* (Table IV.6). Expected negative correlations between decreasing productivity and education (-0.34) could be observed in addition to a positive correlation (0.44) between mean education among the study area and stable conditions of land.

The difference between HPMZ and nHPMZ is shown by a higher correlation between distribution of education and decreasing productivity trends. In general education trends were not as obvious as expected by e.g. also showing negative correlations between education trends and increasing productivity in the whole study area and the HPMZ while positive correlating in

[68] As not solely significant negative trends should be observed but also general trends several groups were analyzed. For each side – positive and negative – besides significant trends, general trends (where zero sets the sharp cut-off point) and trends including a tolerance ($x_{negative}$ < -0.05 & $x_{positive}$ > + 0.05). For further comparison and the hypothesis that a system rather needs to be stable than improve in terms of increasing productivity trends also a "stable" class was included that was represented by the tolerance in the last mentioned classification where the ∑EVI is between – 0.05 and +0.05.

[69] Education is measured in *years of school attendance* of all household members.

the nHPMZ. But within a household member can also get "education" by having access to information or by being trained and gaining knowledge through the household head or others. So even if the school attendance is low the knowledge is not necessary absent. In general there was no household where none of the members had any education.

Table IV.6: Correlations among basic livelihood characteristics (mean and trends from 2000 to 2010) with agricultural productivity trends based on the EVI-analysis.

all	Significant Negative	Negative (<-0.05)	Positive (>0.05)	Stable (-0.05-0.05)
Education Mean	-0.339	-0.279	0.247	0.444
Education Trend	-0.227	-0.050	0.034	0.133
Income Mean	-0.313	-0.528	0.504	0.604
Income Trend	-0.256	-0.347	0.329	0.401
Mortality Mean	0.118	0.386	-0.387	-0.344
Mortality Trend	-0.121	-0.337	0.348	0.248
Value of Assets Mean	-0.486	-0.707	0.698	0.691
Value of Assets Trend	-0.316	-0.452	0.448	0.421
HPMZ	**Significant Negative**	**Negative (<-0.05)**	**Positive (>0.05)**	**Stable (-0.05-0.05)**
Education Mean	-0.499	-0.155	0.121	0.348
Education Trend	0.197	0.478	-0.480	-0.317
Income Mean	-0.479	-0.308	0.261	0.475
Income Trend	-0.155	0.007	-0.030	0.107
Mortality Mean	0.370	0.257	-0.191	-0.631
Mortality Trend	-0.149	-0.272	0.321	-0.134
Value of Assets Mean	-0.608	-0.618	0.611	0.444
Value of Assets Trend	-0.332	-0.473	0.470	0.296
nHPMZ	**Significant Negative**	**Negative (<-0.05)**	**Positive (>0.05)**	**Stable (-0.05-0.05)**
Education Mean	-0.048	0.396	-0.463	0.114
Education Trend	-0.222	-0.132	0.099	0.263
Income Mean	0.352	0.349	-0.367	-0.140
Income Trend	0.127	-0.084	0.067	0.136
Mortality Mean	-0.253	0.141	-0.205	0.282
Mortality Trend	0.206	-0.011	0.015	-0.047
Value of Assets Mean	-0.027	0.195	-0.243	0.151
Value of Assets Trend	-0.144	0.144	-0.182	0.120

Mean *mortality* rates, represented by *households that experienced prime-age mortality* since the previous survey show positive correlation with decreasing productivity and vice versa for positive and stable conditions. While these correlations are higher in the HPMZ non-expected correlations are represented in the nHPMZ. Trends in mortality rates were negative for decreasing productivity and positive for increasing and stable trends in the whole study area and the HPMZ. Again nHPMZ showed different results. A general direction gets clear via the mean values over the whole observation period. Analyzing mortality trends can again be referred to the chicken-egg problem if related to degrading land. A decreasing productivity could in worst cases mean no food and therewith starving. As under-nutrition is a key factor for child mortality a link could be made but with regard to rather low trends a bigger sample size would be needed to verify these assumptions

Using income and value of assets as a replacement parameter for poverty observation clear positive relationships between increasing income to increasing and stable productivity could be found (0.5, 0.6) as well as negative relationship to significant negative (-0.26) and negative (0.35) trends. In addition the national study showed overlaps of increasing poverty rates and decreasing productivity for western Kenya (chapter III.2.2.1, Map III.7).

3.3.2 Coping Strategies and less need for agricultural exploitation: income shares

A farmer who is not solely depending on agricultural income is also encouraged to cultivate more sustainable and to not exploit ecological resources for income. Income diversification is besides that also mentioned as possibility to escape poverty and thereby also represents livelihood strategies to cope with stresses (Reardon, Crawford, & Kelly, 1994; Holden, Shiferaw, & Pender, 2004)(Table IV.7).

Table IV.7: Income diversification in correlation to productivity trends in the study area as well as in HPMZ and nHPMZ

all	Significant Negative	Negative (<-0.05)	Positive (>0.05)	Stable (-0.05-0.05)
Cropshare Mean	0.204	0.191	-0.174	-0.271
Cropshare Trend	0.277	0.568	-0.584	-0.435
Livestock Share Mean	-0.262	-0.470	0.454	0.523
Livestock Share Trend	-0.283	-0.535	0.535	0.497
Business Share Mean	0.272	0.326	-0.337	-0.239
Business Share Trend	0.046	-0.203	0.218	0.110
Salary Share Mean	-0.216	-0.050	0.051	0.042
Salary Share Trend	-0.282	-0.437	0.453	0.304
NonfarmInc Mean	-0.072	0.165	-0.168	-0.145
NonfarmInc Trend	-0.350	-0.567	0.571	0.497

Farmers might tend to have *non-farm income* and also benefit from it in difficult times such as the post-election crisis or the world economy crisis. An increasing trend in non-farm income was correlating positive with an increasing productivity trend in HPMZ but not in nHPMZ. Non-farm income in general might not be the case for poor small scale farmers who farm subsistent and need most of their time and energy to assure their livelihoods.

Livelihood shares also showed different impacts in the two zones. While means and trends in livestock share were correlating positive with significant negative and negative productivity trends in the HPMZ they correlated positive in the nHPMZ. This observation in opposite coefficients was also valid for increasing and stable production. While the HPMZ focuses more on the production of maize or crops only the nHPMZ also derives some income from livestock. As having animals also built a kind of insurance for the poor in rural regions worldwide it has impact on soil conditions at the same time. Increasing livestock also means increasing pressure on land by grazing and trampling. Keeping this in mind income share by salary or business might be more important. Positive trends in business share income had positive effects on increasing and stable productivity or the other way around.

3.3.3 Accessibility – to infrastructure and information

Having an *own vehicle* showed a negative correlation in the whole study area with regard to decreasing ΣEVI-trends. This was valid for the distribution (-0.41) within the study area where those villages where more people own a vehicle in general also had lower decreasing trends and for the trend analysis between 2000 and 2010 (-0.21). The correlation was also negative for decreasing productivity trends in the HPMZ and positive for all positive and stable trends (Table IV.8).

With regard to the nHPMZ there was nearly no relationship with regard to trends in ownership of a vehicle. Looking at the mean values nevertheless shows that in general having a vehicle is favorable for stable conditions in productivity and lower decreasing productivity trends. In general it is assumed that households in the HPMZ areas do more likely need transportation with access to markets to sell larger amounts of surplus maize compared to the households in nHPMZ where especially small scale and subsistence farming takes place. Accessibility with regard to travel time to the next bigger agglomeration of 50,000 people showed interesting and opposite results for the HPMZ and nHPMZ. While being more distant in terms of travel time is correlating positive with decreasing productivity in the HPMZ it is correlating negative in the nHPMZ stating that the more close villages in the nHPMZ the higher decreasing productivity trends and on the other hand the lower stable conditions or increasing productivity. Having close access to fertilizer and improved seeds is especially important for commercial farming in the HPMZ. Moreover markets should be reached in a short time to sell surplus and to avoid storage issues. In general the indicator of accessibility should be looked at carefully as accessibility in terms of remoteness is not as important in this area compared to other rural areas in Sub-Saharan Africa. As the study area in general shows close proximity to large towns the variable of accessibility or distance to the next market is not as powerful as in areas with lower population densities. This was also reported in the study on spatial determinants in rural Kenya by Okwi et al. (2007) for former Nyanza province.

If looking at accessibility in terms of access to electricity we somehow get a different picture. High correlations were found between the distance to electricity and decreasing productivity in the HPMZ but not in any other zone.

Table IV.8: Pairwise correlation among indicators of accessibility in the whole study area, the non-high productive maize zones (HPMZ) and the high productive maize zones (HPMZ).

all	Significant Negative	Negative (<-0.05)	Positive (>0.05)	Stable (-0.05-0.05)
Distance Electricity Mean	0.046	-0.083	0.089	0.035
Distance Electricity Trend	-0.005	0.007	-0.021	0.050
Own Radio Mean	-0.120	-0.289	0.278	0.341
Own Radio Trend	-0.173	-0.016	0.016	0.018
Own Vehicle Mean	-0.419	-0.499	0.481	0.553
Own Vehicle Trend	-0.206	-0.445	0.456	0.343
Accessibility	0.059	0.266	-0.259	-0.303
HPMZ	**Significant Negative**	**Negative (<-0.05)**	**Positive (>0.05)**	**Stable (-0.05-0.05)**
Distance Electricity Mean	0.633	0.716	-0.690	-0.661
Distance Electricity Trend	-0.804	-0.649	0.600	0.727
Own Radio Mean	-0.316	-0.150	0.146	0.148
Own Radio Trend	-0.060	-0.215	0.238	0.046
Own Vehicle Mean	-0.362	-0.138	0.122	0.182
Own Vehicle Trend	-0.435	-0.628	0.642	0.334
Accessibility	0.715	0.493	-0.469	-0.432
nHPMZ	**Significant Negative**	**Negative (<-0.05)**	**Positive (>0.05)**	**Stable (-0.05-0.05)**
Distance Electricity Mean	0.278	-0.254	0.292	-0.077
Distance Electricity Trend	-0.401	0.052	-0.129	0.407
Own Radio Mean	0.370	0.475	-0.471	-0.310
Own Radio Trend	-0.443	-0.235	0.182	0.434
Own Vehicle Mean	-0.084	0.012	-0.063	0.272
Own Vehicle Trend	0.043	0.053	-0.057	-0.025
Accessibility	-0.519	-0.907	0.873	0.706

3.3.4 Fertilizer and Manure Use

Improved varieties and fertilizer use are important in nowadays Sub-Saharan Africa to increase productivity. While Africa for a long time increased production by extensification – cultivating more land – intensification will be needed on the long run also with regard to an increasing population and diminishing space (AGRA, 2009).

Including the amount of maize planted in the area a negative correlation could be observed showing that the more maize in general is grown the more decreasing productivity trends can be observed Table IV.9. Positive correlations for positive and stable production are going in line with this by showing positive correlations of 0.5 and 0.6. With regard to trends in the amount of maize grown results were also as expected. The higher the amount of maize grown the more decreasing trends can be observed and the less the more increasing and stable the production.

Table IV.9: Correlations among fertilizer and agricultural input in the study area with agricultural productivity based on EVI analysis.

all	Significant Negative	Negative (<-0.05)	Positive (>0.05)	Stable (-0.05-0.05)
Hectar Maize Mean	-0.506	-0.585	0.553	0.691
Hectar Maize Trend	0.208	0.273	-0.245	-0.380
Hybrid Seed Mean	-0.089	-0.430	0.417	0.473
Hybrid Seed Trend	0.199	0.136	-0.123	-0.190
Mineral Fertl.Mz Mean	-0.228	-0.427	0.424	0.426
Mineral Fertl.Mz Trend	0.304	0.468	-0.452	-0.502
N Mean	-0.277	-0.581	0.576	0.568
N Trend	0.020	0.011	-0.017	0.016
Phosphor Mean	-0.269	-0.521	0.515	0.521
Phosphor Trend	0.069	0.055	-0.062	-0.016
Manure Mean	0.239	0.583	-0.575	-0.571
Manure Trend	-0.124	0.079	-0.088	-0.025

For variables such as fertilizer amount use and manure use opposite impacts can be detected. While these have negative impact on decreasing trends in the HPMZ a positive relationship can be found in the nHPMZ. As the high potential areas depend on fertilizer use with regard to the rate of hybrid seed adoption this indicator is of importance for the HPMZ. In the nHPMZ the positive trend can either refer to a reaction on decreasing trends or to the fact that in general more manure and fertilizer needs to be used in less productive areas. A very curious result was shown by the correlation between fertilizer/manure and decreasing vegetation trends. Usually using manure or fertilizer should increase productivity but here positive correlations were observed with decreasing productivity for fertilizer use. Use of chemical fertilizer can lead to decreasing soil fertility if wrong irrigation practices are used. It is furthermore assumed that more people in the southern part of the study area use manure instead of chemical fertilizer which is linked to the issue of affordability. Most poor will have to recourse on manure or organic fertilizer in times of low income or decreasing rainfall which already limits production and thereby again income. Chemical fertilizer might on the other hand push increasing yields more than organic fertilizer which increases the gap between the two areas. But in addition to that it is stated that the optimum level of fertilizer use has already surpassed (Kamau, Smale, and Mutua 2014) which means in turn that more fertilizer has to be used in general to increase production on the long run.

In Maseno, a town located in northern Kisumu bordering Kakamega County, so-called local farmer schools could be visited. Here, farmer from different income groups are trained how organic fertilizer can be produced and how they need to be applied. These farmer schools are a benefit for the region as knowledge is distributed among the area. Small scale farmer usually do not get as detailed training from seed companies as farmer from commercial fields in the north which make these farmer schools very important for the region.

Figure IV.8: Farmer School in Maseno in northern Kisumu. Here farmer are trained how they can generate natural fertilizer with different vegetation.

3.4 Conclusion IV: Where nearly all possible indicators come together – A Question of Scale

Western Kenya is a highly dynamic area not only because of intensive agriculture but also with regard to biophysical and socio-economic variables shaping this area. Rainfall is determining crop production especially on rainfed small scale farms mainly located in the south of the study area. The northern part, including Trans Nzoia, Uasin Gishu and northwestern parts of Bungoma county, represent the high potential maize zone, partly irrigated and characterized by large scale and also commercial farming of maize.

Internal dynamics among socio-economic variables in the interplay with biophysical preconditions within the study area were obvious. But still there has to be a high mindfulness in analyzing productivity trends in the interplay with socio-economic indicators without any qualitative assessment meaning e.g. personal information during field visits or literature research. Without q-squared methods, that allow the combination of qualitative and quantitative data, a detailed analysis will possibly fail. When taking the whole area under consideration without knowing about agricultural farming practices false alarms can easily be created by e.g. referring decreasing productivity trends simply to a decrease in rainfall even if this trend was not as correlative as expected. This also shows the importance of integrating land use and land cover information to LD assessment. Different land use and therewith land management strategies lead to different effects on the environment and therefore need to be addressed from different perspectives. This was the case when comparing the high potential maize zones (HPMZ) with the non-high potential maize zones (nHPMZ). Results for both areas in combination were somehow misleading and did not always match the assumptions and hypothesis made before. Moreover within OLS models including variables that are characteristic for the area spatial autocorrelation reported a clustering. By separating the areas based on their agricultural behavior into high productive (HPMZ) and less productive (nHPMZ) zones models could be strengthened and the different impact factors of both areas could be more precisely defined. While the northern area relies more on market access, seed price, fertilizer use or off-farm income to increase productivity and assure a living the southern part, where rainfed agriculture is prevalent and income is much lower, is highly dominated by biophysical preconditions and the access or ability to get credit. Vulnerability and poverty which is related to income is one of the key variables to be included. The more vulnerable a household is, the more it is prone to shocks. The higher the impact of a shock or trigger event is – as seen by the analysis of decreasing productivity trends after the post-election crisis in combination with the world economy crisis in 2007/2008 – the more likely it is, that LD and food insecurity by decreasing productivity trends will become an issue in this area. The observation period from 2000-2010 (respectively 2001-2011 for vegetation trend analysis) in general was not long enough to observe long-term effects but by combining biophysical variables and trends with socio-economic panel information the impact of different indicators could be observed and determined to find internal dynamics among these groups. Findings can be used by policy makers and for land management strategies to maintain a stable equilibrium. Positive and stable trends in this area are almost going in line. The more stable a system the more likely productivity can increase.

Pair wise correlation and also exploratory regression among the different zones made obvious that to create a real-world phenomenon and therewith a model that comes close to the actual situation is linked to a lot of circumstances and requires in-depth knowledge of internal dynamics that include qualitative information. Here, the resulted models were constructed based on the best of our knowledge. Nevertheless, the local study proved findings of the national study with regard to the used methods and explanation of trends. Negative trends, showing LD or decreasing productivity, are impacted by the same factors among groups of health or accessibility as also stable trends but with reversed impact. Those variables that appeared to have positive coefficients in one model to e.g. explain decreasing trends showed negative coefficients for explaining stable trends when testing with the same variables and the other way around. Positive trends on the other hand are influenced by a different set of indicators that more or less refer to economy and infrastructure. However biophysical indicators may not be neglected as they played key roles in decreasing and stable models in particular. Especially in nHPMZ an explaining OLS-model for decreasing vegetation trends could be found including only three biophysical variables (SRTM, AI and PET) explaining 83% of the variance of these trends.

This setting of biophysical and socio-economic variables in the interplay, which could be observed here, will arise in many other countries where agricultural technologies and innovations are used to increase productivity. Therefore similar approaches aligned to the respective setting of the study area – biophysical and socio-economic – should be taken into account for future research to also come up with adapted policy recommendations.

V. Conclusion and Outlook

Interlinkages within the crucial triangle – represented by the three vertices LD, marginality and LUCC – require an interdisciplinary framework to understand internal dynamics and feedback loops in coupled HES.

Around half of the global population lives in rural areas, 70% of them live in poverty and 42% of the extreme poor live on degrading lands (IFAD, 2010; Nachtergaele et al., 2010). Those livelihoods living on degraded lands need to be identified to get insight into characteristics of land management and improvement. The potential and the needs of those living on degraded lands and especially certain livelihood characteristics have to be understood to measure how human impact influences environmental change. There is no doubt that human behavior is a key factor to understand the maintenance of environmental health. Among all definitions of LD – as pointed out in the discourse a jungle of them exists – human behavior and therewith their impact on land is always present. A process which is mainly analyzed from a biophysical perspective with remote sensing or soil sampling assessment therefore becomes a strong socio-economic component. The same is valid for analyzing LUCC. Land cover can be easily observed by remote sensing as it addresses the cover of the earth surface and can be detected with optical data. Land use on the other hand has an active component which is not always easy to detect. Agricultural land, on which human impact is highly present, covers 33% of global land (Ramankutty et al., 2006). If we talk about human impact many different aspects can be addressed. But with regard to a growing global population – 9 billion people by 2050 – environmental change and LD in particular have a strong link to food security issues. Talking about food security puts the poor and marginalized livelihoods in focus, which directly depend on land that might be degrading. Most of them farm subsistence-based and might not have any other insurance strategies or income sources.

Poverty and LD are often mentioned in combination. A link sounds logical when thinking about low capital to afford improved seeds to increase yields or maintain soil fertility by adding fertilizer. A LD analysis in Kenya, located in Eastern Africa, was based on MODIS NDVI time series analysis with 500m resolution to get insights into hotspots of productivity change via vegetation trend analysis. Mainly decreasing productivity trends could be observed in central Kenya, including the counties Kitui and Meru but also in Isiolo County towards the northeast. Additionally, especially in southern Kenya, the two counties Kajiado and Narok were highlighted as degradation hotspots. Increasing trends were found in Turkana and Baringo County but also partly in northeastern Kenya. Both areas are dominated by pastoralists. Correcting the vegetation analysis for rainfall by masking pixel where significant positive and negative rainfall trends were observed lead towards an approach focusing on human-induced LD. Poverty rates for the years 1999 and 2005/2006 for Kenya were derived from census data of 1999 and the KIHBS 2005/2006 to calculate poverty trends and link them to LD. Both poverty measurements relied on assessment of income and expenditure which thereby only represent the economic dimension of a livelihood. When analyzing poverty and LD structures in their overlap contradictory results we reported. While some areas such as western Kenya presented the expected results – an overlap of increasing poverty rates and decreasing productivity based on vegetation analysis – two greater areas were highlighted that showed exact opposite trends. More people dropping into poverty by simultaneously increasing productivity trends were e.g. observed in Turkana County. On the other hand southern Kenya, the counties Kajiado and Narok in particular, showed more than 20% decreasing poverty rates while at the same time production decreased. Explanation for these trends could be made by looking into qualitative information derived from literature research and personal information during a field visit. Reasons could be found when looking into land tenure rights and the issue of competition for land. While in southern Kenya different interest groups claim for land and water and an increasing number of livestock triggers decreasing productivity at the same time also land rights are not as clear. Most of the area, especially the Maasai Mara reserve, is characterized by dynamic and unclear land rights which make incentive for sustainable land management more difficult with regard to responsibilities. Moreover, pressure due to an increasing number of livestock is becoming a severe problem. For the development of Turkana County no clear statement could be proved but it is known that this area is also characterized by a nomadic living and probably high migration rates. Considering this makes it also difficult to validate poverty rates given for this area. Although, a nomadic lifestyle might also be sustainable keeping in mind that pressure on land is not stationary taking place.

Poverty and LD do not necessarily overlap but in combination with livelihood structures they develop their own dynamics as seen in the national study.

Who is poor and who is marginalized? And is poverty equal to marginality? These questions were addressed in the national study. Marginality can be the root cause of poverty (von Braun & Gatzweiler, 2014). Poverty was for a long time solely defined by monetary values such as the "1-Dollar-a-day" or "people living below $1.25 a day" classification. There is a rising need to get more insight into the diversity and depth of poverty instead of only looking at income or expenditure. Moreover, poor farmers who farm subsistence based, rarely have regular income or can define themselves above or below a poverty line based on a monetary number such as the one-dollar-a-day definition resulted from the WDR in 1990 (WB, 1990). And what about those who live nomadic, have no income as such but exchange livestock for food or make their living by hunting? These are just two examples of how difficult it is to measure poverty also and especially among the poor themselves. Income alone does not define people as poor or non-poor. It is more about livelihood structures, about gaps in a certain livelihood potential and a lack of possibilities and/or accessibility. These findings go in line with the concept of marginality which looks into different dimensions of marginality or so-called spheres of life (von Braun & Gatzweiler, 2014; Graw & Husmann, 2014). By looking into these dimensions – which were in this thesis represented by indicator groups such as education, health, access to information and infrastructure and economy – helps to get more insight in the diversity and potential of a livelihood. The approach of marginality in this study was mostly based on quantitative data. On the national scale of Kenya, a highly diverse country in terms of biophysical and socio-economic settings, in depth analysis on links between marginality and poverty, were observed. The question was raised whether poverty and marginality do overlap, if they are the same, and if not, if there are certain indicators of marginality that do relate more to poverty than others? Based on the mentioned indicator groups regions with high and low marginality were identified and linked to poverty. Pair wise correlation showed that especially the indicator group of accessibility – whether to information or infrastructure – showed a high correlation to poverty rates. But unexpectedly all other indicators showed very low correlations based on information for all 47 counties of Kenya. This leads to the assumption that the combination of marginality indicators is much more important than focusing on single impact factors.

With the help of exploratory regression and OLS a model was identified that explained significant negative productivity trends on the national level addressing each of the 47 counties. All dimensions of marginality were included and represented by poverty, population density, basic literacy, higher education, access to a landline (and thereby to energy and information), funds addressed to local authorities and fertilizer use per county. An R^2 of 70% showed high performance of this model to explain significant decreasing trends. But looking into the model output which depicted residuals certain areas were highlighted in which the set of indicators was under- or over predicting the expected results and therefore claims for missing indicators to explain those decreasing trends more accurate. In Isiolo County for example, where the model was under-predicting, another important variable was missing in the model representing land rights and ethnicity. But this missing information represents rather qualitative information and is moreover difficult to measure quantitatively. Land rights in Isiolo are very unclear. Moreover five different ethnic groups compete for land in this county while additionally unfavorable biophysical preconditions such as high variability in rainfall, can further on trigger decreasing productivity.

Based on MODIS land cover data with 500m resolution croplands at risk could be selected by overlaying agricultural areas with decreasing productivity trends. The identified hotspots, located in western Kenya, lead to the selection of the local study area for further in-depth analysis.

The local study, observing interlinkages of productivity change and livelihood structures in western Kenya, benefitted from a refined interdisciplinary approach which was possible due to availability of more detailed datasets. Vegetation analysis was based on MODIS EVI. As this area is located in a region with high biomass production and characterized by multiple cropping circles within a year the annual sum EVI was used for the vegetation trend analysis. Socio-economic data could be derived from a household panel dataset provided by the Tegemeo institute which was collected in four waves: 2000, 2004, 2007 and 2010. This survey helped to get a comprehensive view on socio-economic dynamics on the village level. On the local scale and within the respective acting scopes of the villages individual dynamics came into play which again took place across disciplines as related to biophysical and socio-economic dynamics. The area is highly productive and one of the grain baskets of the country. Areas in the northern part of the study area are classified as high potential maize zones while others south of Bungoma were classified as non-high potential maize zones. This bisection also resulted in a clustering for a chosen OLS-model that integrated several marginality indicators. Therefore the area was divided into a high potential maize zone (HPMZ) and a non-high potential maize zone (nHPMZ). Both areas also differ largely in income structures. While in the HPMZ the annual average income is about Ksh 197,685 annually this rate is decreasing to Ksh 60,728 annually in the nHPMZ (Argwings-Kohdek et al., 1999). The northern part is dominated by large scale and commercial farming while the southern part, beginning in the area of Kakamega County is predominantly characterized by subsistence farming of small scale farmers. When analyzing internal dynamics different impact factors could be identified in each of the two areas. While the northern part is more relying on accessibility and innovative input for agriculture such as fertilizer and hybrid seeds the southern part is heavily depending on biophysical preconditions such as rainfall but also aridity and evapotranspiration.

The integration of qualitative data was an additional finding and advantage for the local study. Sharply decreasing productivity trends from 2007 to 2009 were first related to decreasing rainfall trends from 2006 to 2009. But two major trigger events occurred around that time, both not related to climatic impact: the post-election crisis in 2007/2008 and the world economy crisis in 2008. Both events lead to an increase of prices for seeds and fertilizer and thereby made it particularly difficult for small-scale farmers to maintain stable yields. Due to the post-election violence moreover insecurity arose throughout the country but especially in western Kenya. This possibly led to unsustainable land management strategies due to a lack in future perspectives.

With regard to an upcoming research topic on LD neutrality (LDN) both studies showed that the identified set of variables and impact factors for LD were also valid for models explaining stable productivity trends – and therewith LDN. But they did not explain increasing productivity. It is highlighted that stable conditions need to be targeted as appointed in the sustainable development goals (SDGs). Goal 15.3 requires to maintain global soil production and ensure that lands are not further degrading but stable conditions can be maintained to "achieve a land-degradation-neutral world" by 2020 (UN, 2014b: 21).

Both studies, the national study on Kenya and the local study in western Kenya, showed how dynamic biophysical and socio-economic variables are in their interplay. Interlinkages that refer to the "strategic approach of managing sustainable development that seeks to promote greater connectivity between ecosystems and societal actions" (Malabed, 2001) are in need to be addressed in all ongoing research activities. Scale and reference areas play a key role. The interdisciplinary framework which was set up to analyze the interlinkages for the crucial triangle helped to identify hotspots on different scales for more in depth analysis. The more defined the scale the more detailed data are needed for a complex understanding of internal dynamics among biophysical and socio-economic variables. But even if detailed quantitative data are available a validation including ground observation should not be neglected. A standard set of variables, represented by the different spheres of marginality, showed that LD is affected by a certain setting of livelihood structures. But this specific setting of variables cannot be standardized and applied elsewhere. Individual frameworks need to be developed adapted to the areas where hotspots of LD should be identified as in some regions some variables can play a major role while they have no impact in other areas at all. For a warrantable model that explains productivity trends also qualitative data is required that helps to shape a possible model. This has to be targeted with validation on the ground. Top down approaches that identify hotspots on a broader scale to then identify areas where more in depth analysis is needed is recommended for future research. The handling of heterogeneous data is one of the key elements to address here. The combination of q-squared methods and insights from different disciplines help to come closer to an understanding of coupled HES. As fertilizer and land management strategies – which are necessary for commercial farming – are used for yield increase these might superimpose any unfavorable livelihood settings that might have a negative impact on agricultural production here. If a chosen model is not influenced by spatial autocorrelation counties or villages can be analyzed individually which could be a good starting point for individual policies and management recommendations. A core issue with regard to the here presented interdisciplinary approach is the availability of data. The here conducted research was data dependent which means that other variables that could be of further interest are neglected if no data is available. Therefore the OLS analysis used in this study illustrates a good way to come closer to a set of explanatory variables to explain productivity change. If one set of indicators is able to explain trends in one area but is under- or over-predicting in another area those areas can be chosen for further in-depth analysis. Additional data gathering, whether quantitative or qualitative, can then empower and improve the chosen model.

If interdisciplinary research is conducted it therefore also demands extended knowledge and insight into each discipline. This aspect represented one of the main challenges in this thesis. Projects nowadays which are organized interdisciplinary and addressing one problem from different vertices have to be within the core of research on coupled HES. Livelihood systems are complex. But so are ecological systems. Finding an equilibrium for both that finally leads to the requested concept of LDN and lift people depending on degrading lands out of marginality and poverty is therefore one of the main targets for future research. Additionally, policy advice in developing countries has to be included in the development of an adequate framework with regard to possibilities and potentials for livelihoods on different administrative levels. It is questioned how research frameworks will be structured in the future and if a clear shift from narrowed concepts – such as also the definition of poverty which still relies on assessment of income – is possible. Even if there is still room for improvement in each discipline to understand the interlinkages targeted in this study in more detail, a baseline concept was developed that neglects the narrowed view of disciplinary concepts by approaching the local scale to understand a global problem.

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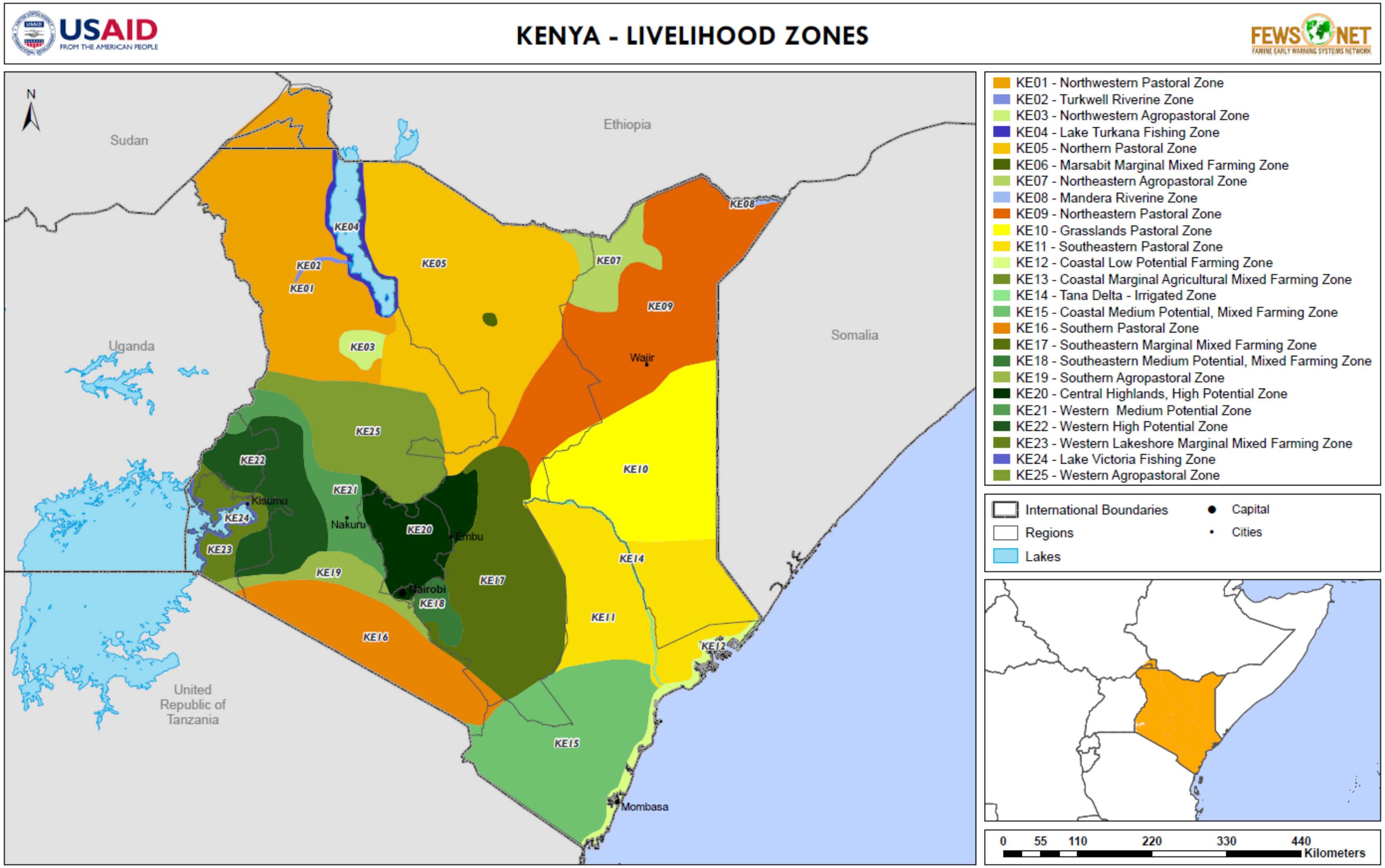
VII. Annex

Project and duration	What is monitored?	Techniques used and strength(s)	Extent/severity of land degradation	Scale/ resolution of maps	Limitations	End product
UNCOD (1977)	"Estimated" desertification; desertification hazard	Expert opinion: Limited number of consultants with experience in drylands	35%, or 3,970 million hectares of Earth´s surface is affected by desertification	Data not geo-referenced	Subjective due to expert opinion; no georeferenced data	Desertification hazard map
GLASOD (1987-1990)	Human-induced soil degradation; status of soil degradation, including the type, extent, degree, rate, and causes of degradation within physiographic units	Expert opinion (more than 250 individual experts): Data were later digitized to a GIS-database - four types (water erosion, wind erosion, wind erosion, chemical LD, physical LD) and four degrees of LD (light, moderate, severe, very severe). Global assessment taken into account, not only drylands	65% of the world´s land resources are degraded to some extent; 1,016-1,035 million hectares of drylands are experiencing LD	Produced at a scale of 1:10 million; 1:5 million FAO soil map was also integrated in the study (data for 1980-1990)	Subjective due to expert opinion; focus on soil degradation, does not include all types of LD; maps are too rough for national policy purposes	One map showing four main types of LD (water erosion, wind erosion, chemical degradation, physical degradation) and four degradation severities (light, moderate, strong, extreme)
ASSOD (1995)	Regional study of GLASOD: Assessment of Soil Degradation in South and Southeast Asia; data from 17 countries	Expert opinion (national institutions); Analysis due to the use of SOTER; data stored in database and GIS	> 350 million hectares of ASSOD area, or 52% of the total susceptible dryland area	1:5 million (data for 1970-1995)	Lack of available data; difficult to distinguish between human- and natural-induced degradation; subjective due to expert opinion	Variety of thematic maps with degree and extent of land degradation
SOVEUR (1998)	Regional Study of GLASOD: Soil Vulnerability Assessment in Central and Eastern Europe; data from 13 countries	Providing a database based on SOTER and the use of expert opinion, as in GLASOD; based on quantitative satellite data rather than expert opinion	About 186 million hectares or 33% of the area covered by the SOVEUR project is degraded to some extent.	1:2.5 million (data for 1973-1998)	Link to environmental and social pressure is missing	Provision of an environmental information system with a SOTER database for the 13 countries under consideration
UNEP (WAD) 1992, 1997	World Atlas of Desertification; 1st edition (1992): depiction of land degradation in drylands; 2nd edition (1997): assessment of several indicators such as vegetation, soil, climate, plus combating measurements and socio-economic variables, such as poverty and population data	Based on the GLASOD approach which used expert opinion	*see GLASOD*	Using GLASOD data with 1:10 million resolution	Focus on drylands; subjective due to expert opinion	World Atlas of Desertification, including maps on soil erosion by wind and water, chemical deterioration; case studies focus on Africa and Asia (due to ASSOD)
WOCAT (since 1992)	Soil and water conservation (SWC); conservation approaches and technologies to combat desertification should be mapped; network of SLM specialist	Expert opinion: Case studies in 23 countries on six continents with three questionnaires on mapping, technologies, and approaches; more objective due to the use of SOTER; SWC technologies, cost of SWC data can be used to assess cost of preventing or mitigating land degradation	Focus is put on SWC to guide investments to those areas where they are most needed and most effective (points show SWC method)	Small-scale world map (1:60 million), for showing current achievement of SWC	Good national case studies that cannot be extrapolated to global level. Mapping still in development; first draft exists	Detailed maps at (sub)country level; first draft of global overview of achievements in preventing and combating desertification exists (in collaboration with FAO and by request of the Biodiversity Indicators Partnership, Convention on Biological Diversity (COP10)

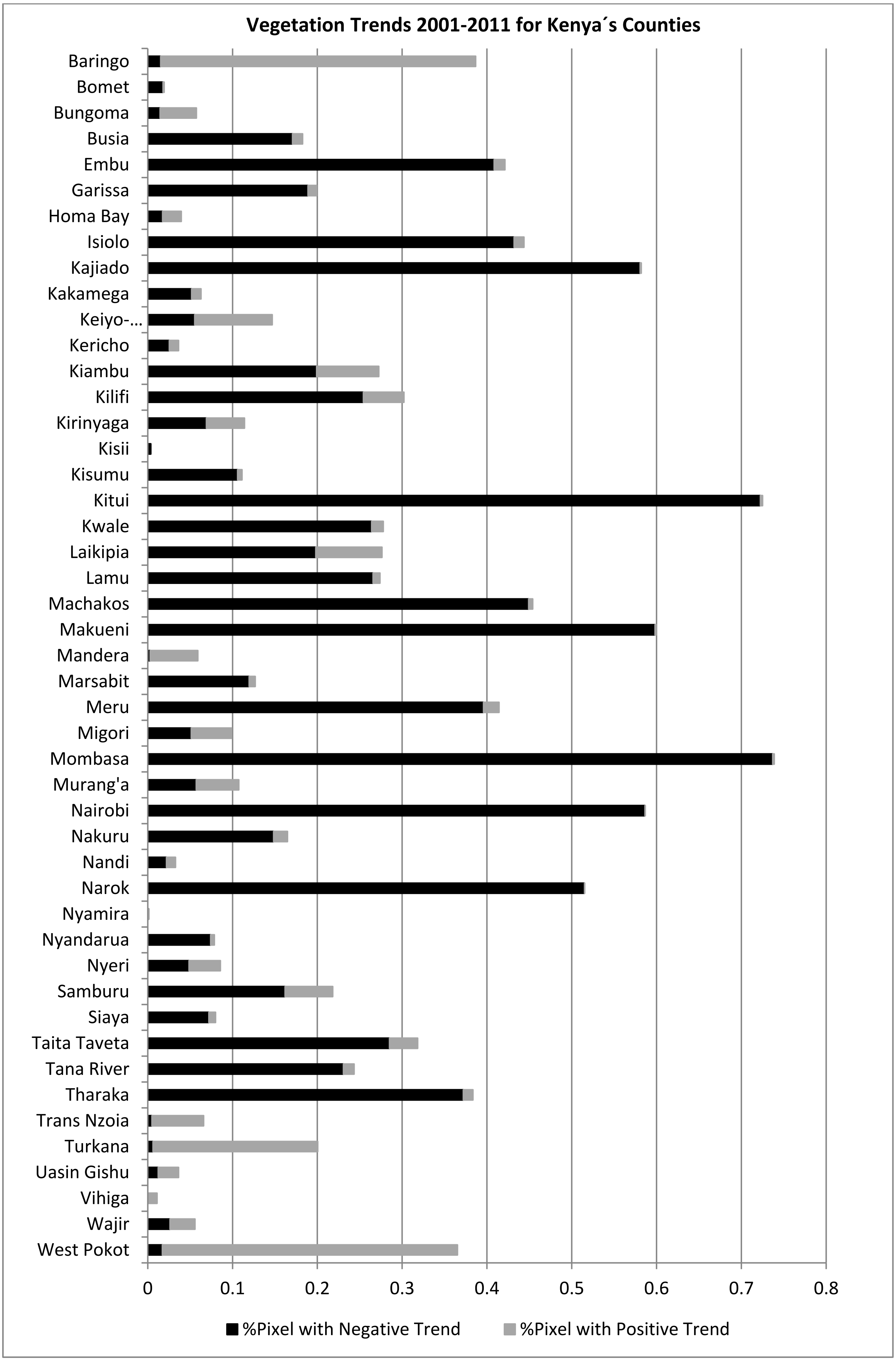
Project and duration	What is monitored?	Techniques used and strength(s)	Extent/severity of land degradation	Scale/ resolution of maps	Limitations	End product
USDA-NRCS (1998-2000)	Desertification vulnerability; vulnerability to wind and water erosion and "human-induced" wind and water erosion; analysis of soil moisture and temperature regimes, population density, serious conflicts with risk to desertification	GIS/modeling with FAO soil map, climate database; population data from CIESIN; depicting land quality classes with given datasets	34% of the land area is subject to desertification; 44% of the global population is affected by desertification	1:100 million; minimum scale 1:5 million; FAO soil map: 1:5 million	Socio-economic data takes into account only population densities - life is only classified as "human-induced". Positive: Categorizing land quality classes; seems as if NRCS distinguished between desertification and LD	Several maps on global soil climate map, land quality, desertification vulnerability, and human-induced desertification vulnerability; water and wind erosion and human-induced water and wind erosion
GLADA (2000-2008)	Soil degradation, vegetation degradation, national assessment (LADA), global assessment of degradation and improvement (GLADA); over a certain period (1981-2003, extended to 2006)	Remote Sensing (GIMMS dataset of 8-km-resolution NDVI data); input of SOTER in support of general NDVI methodology. Based on quantitative satellite data; not on expert opinion, correlation of land degradation with socio-economic data	24% of the land area was degraded between 1981 and 2003 (80% of the degraded area occurred in humid areas)	Grid cells of 32 km², Data for 1981-2003 (extended to 2006), LADA: 1:500,000-1:1 million	Primarily monitoring of land cover; analyzing trends - lack of information on the present state; degradation before 1981 and in areas where visible indicators could not be monitored yet were not included	Identifying hot spots of degrading and improving areas
MA (2005)	Drylands (62% of global drylands)	14 studies (global, regional, and sub-regional); based on remote sensing and other data sources, with georeferenced results computed into a map with grid cells of 10x10km²	60% of global ecosystem services degraded or used unsustainable	Grid cells of 100km² Data within the 1980-2000 period	Different studies used for MA with different definitions of LD and different time periods of assessment; no economic assessment of ecosystems	Global GIS database for 62% of all drylands and hyper arid areas of the world
GLADIS (2010)	Mapping of the status of LD and pressures applied to ecosystem goods and services by using six axes of biophysical and socio-economic determinants (biomass, soil, water, biodiversity, economics and social)	Remote Sensing and GIS (LADA database); Modeling; "Spider diagram approach", integration of more than population data for socio-economic determinants; broad analysis of the process of LD	Relationship: LD and poverty: 42% of the very poor live on degraded land, 32% of the moderately poor, and 15% of the non-poor	5 arc minute (corresponds to 9km x 9km)	Combining national and subnational data, taking into account different periods of the different inputs; lumping of many indicators loses focus and attribution	Global Land Degradation Information System; Provision of general data and analysis on LD due to a WebGIS

Annex 1: Global Mapping Approaches on LD Assessment. Based on: Nkonya, et al., 2011: 34-36



Annex 2: Livelihood Zones according to USAID and FEWSNET (2011). Agro-ecological zones are combined with livelihood characteristics and classified in livelihood zones.

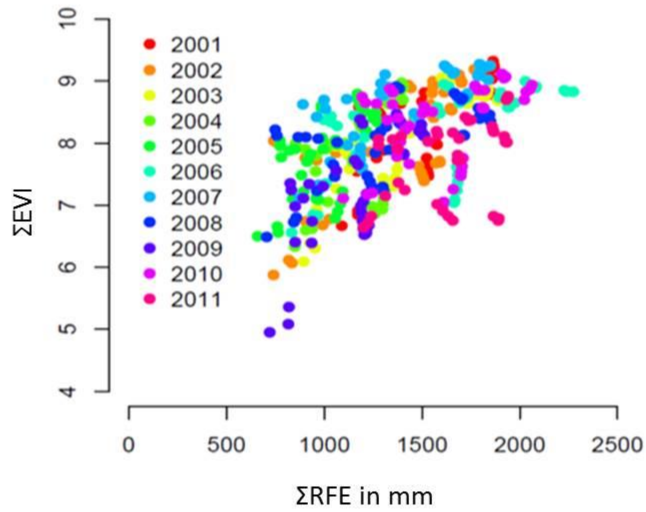
Annex 3: Different maize varieties for different regions. Visit at Kenya Seed in Kitale, Trans Nzoia County, August 2013.



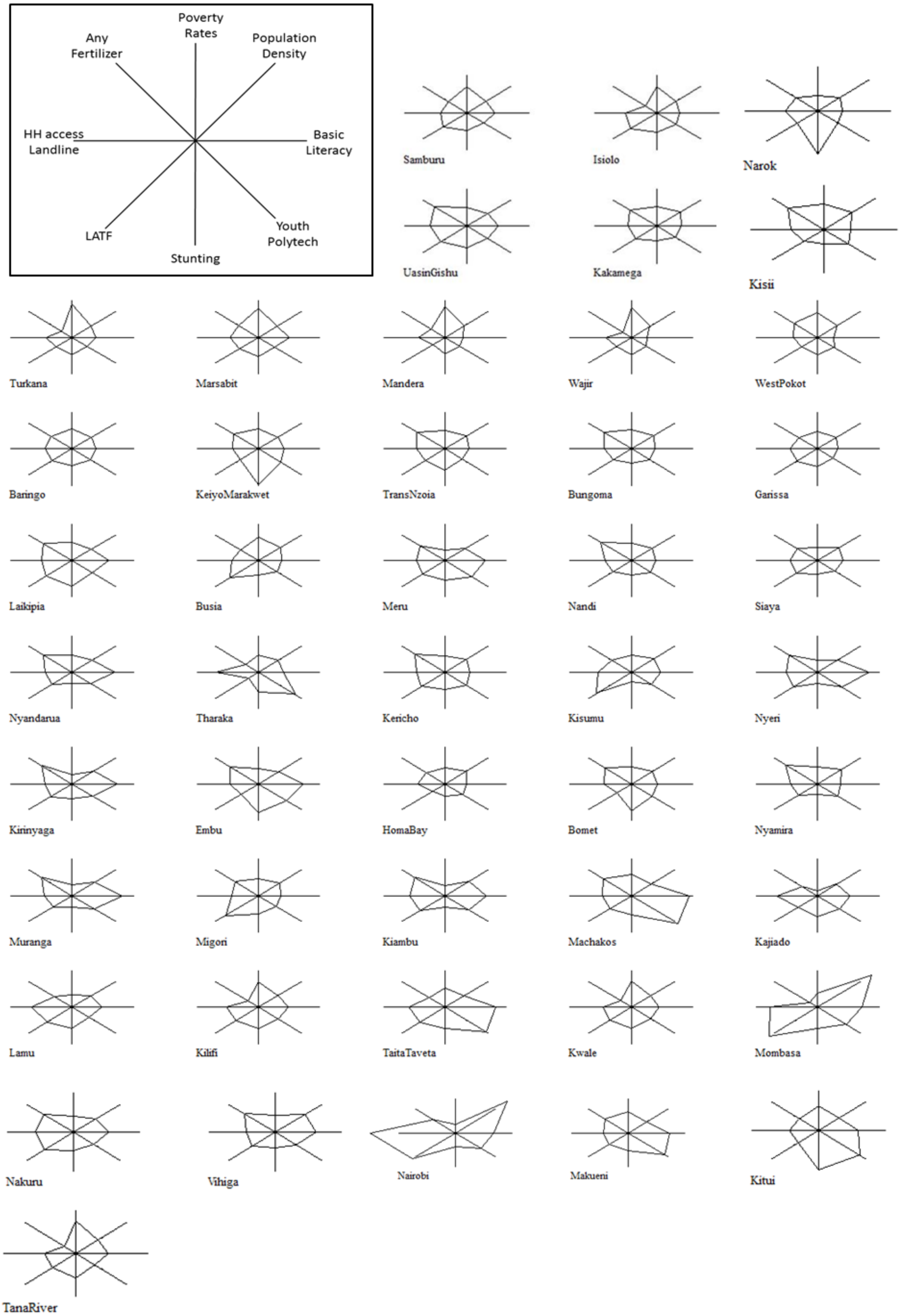
Annex 4: Pixel (in %) with positive and negative trend per county, (NDVI trend 2001-2011)

	Signi. Neg RFcorr	Signif. Neg. (non-RFcorr)	Neg. Trends (RF corr)	Neg. Trends (non-RF corr)	Signif. Pos. RFcorr	Signif. Pos. (non-RFcorr)	Pos. Trends (RFcorr)	Pos. Trends (non-RFcorr)
R^2	0.71	0.69	0.32	0.44	0.21	0.26	0.41	0.40

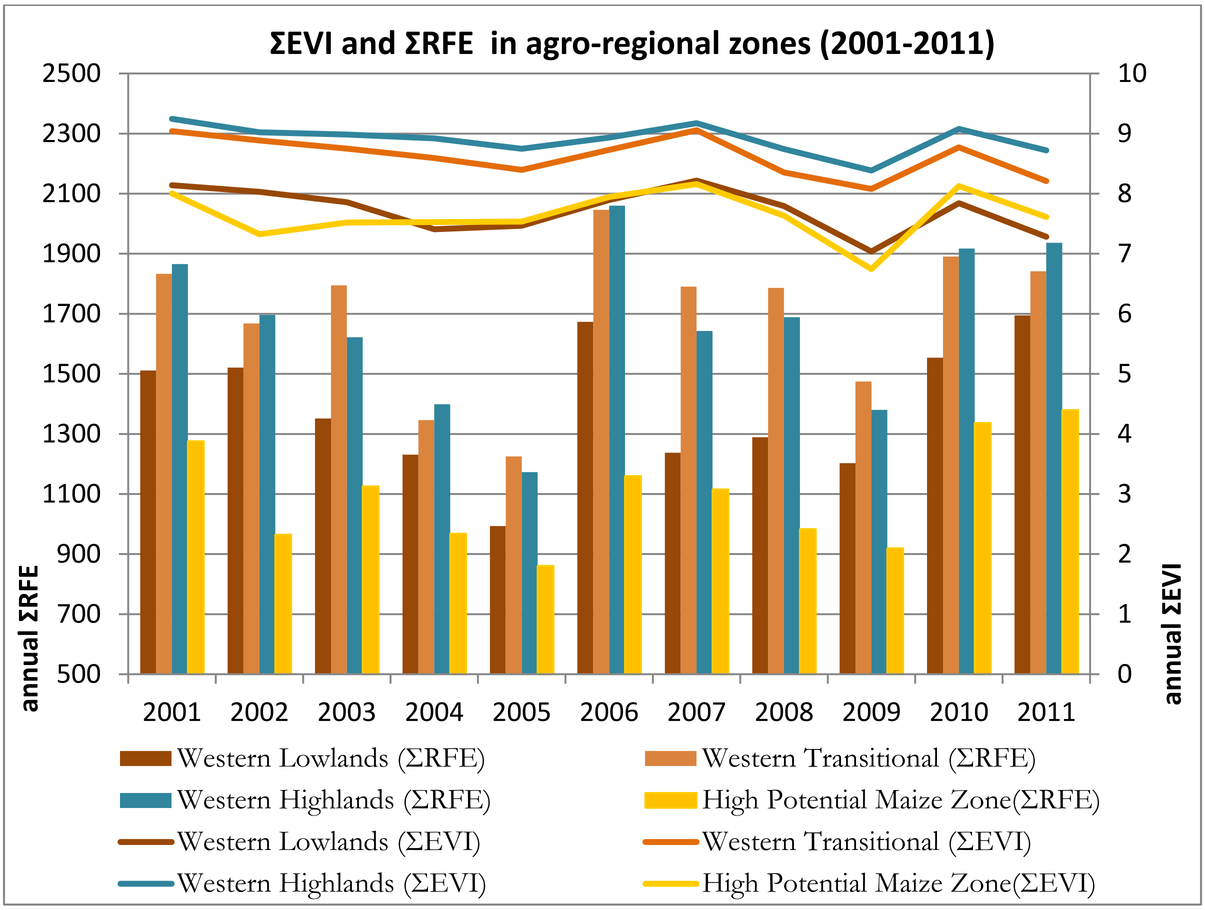
Annex 5: OLS-model results with the explaining variables of the final model for different depending variables that are represented by vegetation trends.



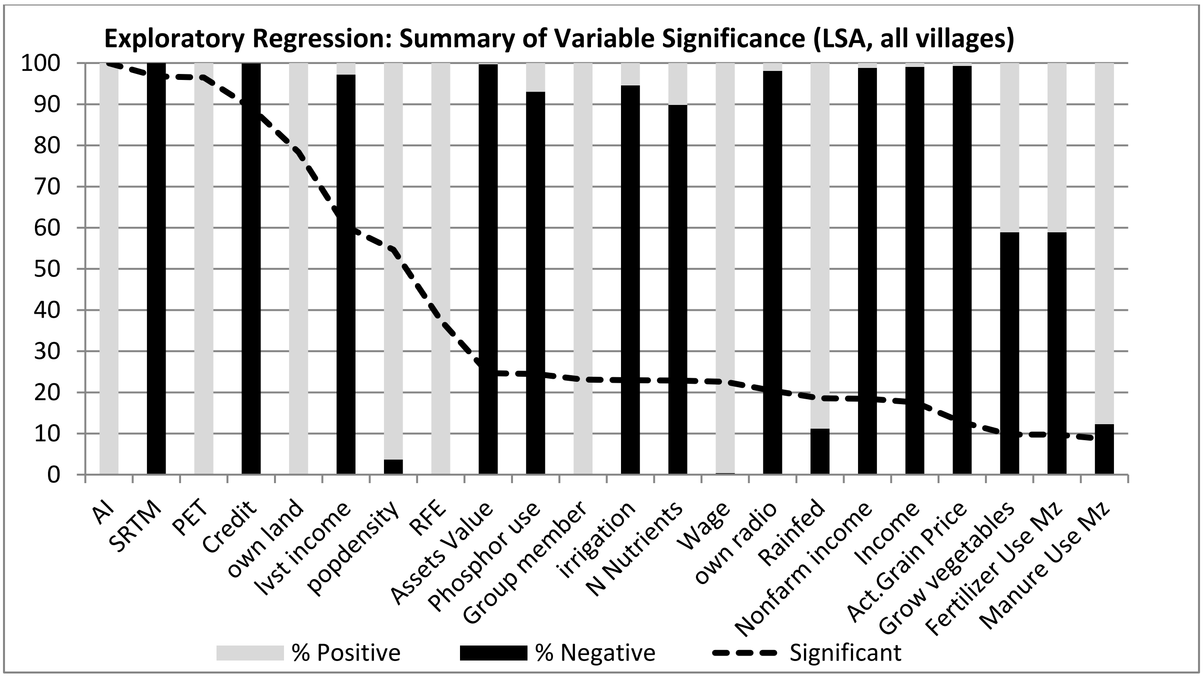
Annex 6: Distribution of Rainfall (ΣRFE) and Vegetation (ΣEVI) for the observation period.



Annex 7: Sunrays of the relating indicators for the OLS model in each county. The sunray at the up left depicts on which ray the indicators are located in the respective county. Source: own draft made with the software "sunray" by Guido Lüchters.



Annex 8: Mean values for ΣEVI and ΣRFE within the four different agro-regional zones based on the acting scopes of the villages. Lines show ΣEVI and bars show ΣRFE.



Annex 9: Summary of Variable Significance based on the output of the Exploratory Regression Tool of ArcGIS 10.2 for the study area including all village information, Significances below 5% were excluded in this graph.