Universidade de Évora - Instituto de Investigação e Formação Avançada
Universidade do Algarve - Faculdade de Ciências e Tecnologia

Programa de Doutoramento em Ciências Agrárias e Ambientais

Tese de Doutoramento

A spatially explicit methodology for assessing and monitoring land degradation neutrality at a national scale

Helene Wanjiru Gichenje

Orientador(es) | Sérgio Rui Borreicho Coelho Godinho
Teresa Pinto Correia

Évora 2020

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ABSTRACT

Land degradation is occurring in all parts of the terrestrial world, and is negatively impacting the well-being of billions of people. In recognition of the need for sustained global action on land degradation, the Sustainable Development Goals, adopted by the global community in 2015, include a specific goal aimed at halting the decline of land resources and achieving land degradation-neutrality (LDN) by 2030. The primary objective of this doctoral research was to operationalise the LDN target at the national level, using Kenya as the case study. The main research questions addressed in this dissertation have been positioned within a social-ecological systems framework in which ecosystems are integrated with human society. The first task of this research focused on determining the extent of land degradation and regeneration, and in establishing the LDN national baseline using the three LDN indicators (land cover, land productivity, and carbon stocks). This was then followed by identifying the key drivers that affect land degradation (browning) and land regeneration (greening) trends within the 4 main land cover types (agriculture, forest, grassland and shrubland), and within an area characterised by land cover change. The third task involved an assessment of the effectiveness of the current land-use policy framework, and associated institutions, to facilitate the implementation of LDN. Finally, in the last part of this dissertation, a climate-smart landscape approach at the water catchment level was proposed as a possible mechanism through which LDN can be operationalised at the sub-national level.

Keywords: land degradation-neutrality; NDVI; land-use policy framework; water catchment area; Kenya

Metodologia espacialmente explicita para a avaliação e monitorização da neutralidade da degradação do solo à escala nacional

RESUMO

A degradação do solo é um fenómeno que está a acontecer em todas as partes do mundo terrestre, com impactos negativos no bem estar de milhares de milhões de pessoas. Reconhecendo a necessidade de uma ação global contra a degradação do solo, os Objetivos de Desenvolvimento Sustentável, adotados pela comunidade global em 2015, incluem um objetivo específico para travar o declínio de recursos terrestres e atingir a neutralidade de degradação do solo (NDS) até 2030. A presente tese de doutoramento teve como grande objetivo a operacionalização da NDS a nível nacional, usando o Quénia como caso de estudo. As principais perguntas de investigação consideradas nesta dissertação foram colocadas num enquadramento socio-ecológico, em que ecossistemas estão integrados com a sociedade. A primeira tarefa desta investigação consistiu em determinar valores de degradação e de regeneração do solo para estabelecer a base de referência de NDS nacional usando três indicadores de NDS (cobertura de solo, produtividade do solo e reservas de carbono). Seguidamente foram identificados os principais fatores que influenciam a degradação do solo (browning) e a regeneração do solo (greening) nas 4 principais coberturas de solo (agricultura, floresta, pastos e matos), bem como numa área marcada por alterações da cobertura de solo. Para a terceira tarefa foi avaliada a eficácia do atual quadro político sobre o uso de solo, bem como das instituições associadas, na viabilização da implementação da NDS. Na última parte da dissertação é adotada uma escala a nível da bacia hidrográfica, como uma abordagem "climate smart" adequada para a operacionalização da NDS a um nível sub-nacional.

Palavras-chave: neutralidade de degradação de solo; NDVI; políticas públicas de uso do solo; bacia hidrográfica; Quénia

Chapter

1

INTRODUCTION

1.1 Background

Land degradation is one of the most pressing global problems affecting terrestrial ecosystems. Land degradation is occurring in all parts of the terrestrial world, and is negatively impacting the well-being of at least 3.2 billion people, and costing more than 10% of the annual global gross product in loss of biodiversity and ecosystem services (IPBES, 2018). Hence halting and reversing current trends of land degradation is an urgent priority to ensure the sustainability of life across the planet. Land degradation has been defined in many and various ways (Yengoh et al., 2014). For the purpose of this thesis, the following definition by the United Nations Convention to Combat Desertification (UNCCD) is adopted: the “loss, in arid, semi-arid and dry sub-humid areas, of the biological or economic productivity and complexity of rainfed cropland, irrigated cropland, or range, pasture, forest and woodlands resulting from land uses or from a process or combination of processes, including processes arising from human activities and habitation patterns” (UNCCD, 1994). This definition implies an impact on above-ground vegetation production, as well as the explicit reference to degradation caused by human factors.

According to the Millennium Ecosystem Assessment (MEA), the causes of land degradation include indirect factors like population pressure, socioeconomic and policy factors, and globalization phenomena like distortions to international food markets and direct factors like land use patterns and practices and climate-related processes (MEA, 2005). Land degradation occurs through the interaction of natural environmental change and variability and human causes, whereby these complex interactions involve patterns and processes over a range of spatial and temporal scales (Zika & Erb, 2009). Further, the effects of demographic pressure and unsustainable land management practices on land degradation are being exacerbated worldwide due to the effects of climate change, which include (but not limited to) changing rainfall patterns, increased frequency and intensity of drought and floods, rising temperatures, and profound ecological shifts (UNCCD, 2015a). These interactions involve multiple processes and feedbacks, and are highly complex, and carry implications for sustainable livelihoods over the next several decades (Sivakumar, 2007). As a result of land degradation, a landscape loses its ability to provide ecosystem goods and services (D’Odorico et al., 2013), resulting in both direct and indirect impacts on overall human welfare (Nkonya et al., 2016).

1.2 Assessing land degradation with remote sensing-based vegetation index data

The productivity of vegetation can be quantified as the amount of dry organic matter accumulated by vegetation per unit area and per unit time through the process of photosynthesis (g of C m−2 yr−1), and is termed as Net Primary Production (NPP) (Yengoh et al., 2014). Given the temporal and spatial nature of land degradation, direct field measurements of above-ground vegetation production are rarely possible at a national or global scale (Higginbottom & Symeonakis, 2014). The most frequently utilized method employing Earth Observation (EO) datasets for the measurement of the extent of degradation is trend analysis of vegetation index data, most commonly the Normalised Difference Vegetation Index (NDVI), as a proxy for NPP (Higginbottom & Symeonakis, 2014). NDVI is expressed as:

$$NDVI = (NIR - RED) / (NIR + RED)$$

where NIR and RED are reflectance values in the near-infrared and red wavebands, respectively. NDVI values range between −1 and 1, with NDVI < 0 indicating cloud or water, and values > 0.7 dense canopy coverage. The NDVI is most commonly credited to C.J. Tucker who in the late 70's compared satellite data with sampled aboveground biomass data from the Sahel zone of northern Senegal, and found a strong correlation between the satellite data and the end-of-season aboveground dry biomass (Higginbottom & Symeonakis, 2014). Since then the relationship between the NDVI and vegetation productivity is well established theoretically and empirically (Pettorelli et al., 2005), and a considerable number of studies have reported on a close coupling between NDVI and in-situ NPP measurements (Wessels et al., 2006; Prince & Tucker, 1986; Tucker et al., 1986).

Several datasets provide NDVI products at various spatial and temporal resolutions from a suite of sensor systems. The longest continuous record of NDVI data comes from the Advanced Very High Resolution Radiometer (AVHRR) instrument onboard the National Oceanic and Atmospheric Administration (NOAA) satellite series 7, 9, 11, 14, 16, and 17, starting in July 1981, which forms the basis of generating long-term

NDVI products (Pettorelli et al., 2005). The most appropriate choice for NDVI trend analysis using long-term AVHRR based datasets is the third generation data set from the Global Inventory Modeling and Mapping Studies (GIMMS 3g), which is found to have the highest temporal consistency (Tian et al., 2015). This long-term NDVI time series (8km pixel size, available twice monthly) spans the period July 1981 to December 2015.

The most commonly used time series techniques to examine trends in NDVI are described by Higginbottom & Symeonakis (2014) as follows. Linear trend analysis (parametric) applies a linear regression model to quantify change in the dependent variable, y (i.e., NDVI) against an independent variable, x (i.e., time). The direction and magnitude of change from this model thus explains the change in NDVI over the period analysed. The Theil-Sen trend (non-parametric) is functionally similar to linear least squares regression. Trends are estimated using the median values and are therefore less susceptible to noise and outliers. The Mann-Kendall test (non-parametric) measures the photosynthetic intensity of the growing season. Values of +1 indicate a continually increasing and −1 a continually decreasing trend. Jamali et al. (2012) compared parametric and non-parametric techniques for analysing trends in annual NDVI derived from the AVHRR sensor. To generate annual data, the mean NDVI of a four-month long green season was computed for fifteen sites (located in Africa, Spain, Italy, Sweden, and Iraq) from the GIMMS product for the periods 1982-2006. Trends in these time series were then estimated by linear regression (parametric) and the combined Mann-Kendall test with Theil-Sen slope estimator (non-parametric), and compared using slope value and statistical significance measures. Results indicate that slopes and their statistical significances obtained from the two approaches compare favourably with one another.

Vegetation productivity depends on several factors including climate (rainfall, length of growing season); land use; the global increase in nitrate deposition and atmospheric carbon dioxide; large scale ecosystem disturbances such as fires; intensive use of chemical fertilizers in intensified croplands (Le et al., 2016; Bai et al., 2008). NDVI time series, when combined with other time series data (environmental and socioeconomic) enables the spatially explicit interpretation of the causes and processes of changes in vegetation greenness (Vu et al., 2014). A number of correlation studies between NDVI and climate factors (rainfall, soil moisture, temperature) have been used to isolate changes in vegetation productivity due to climate factors from those caused by both anthropogenic and natural factors (Huang & Kong, 2016; Ibrahim et al., 2015; Vu et al., 2014; Vlek et al., 2010). In semi-arid areas, vegetation, and therefore NDVI, is highly correlated to rainfall (Wessels et al., 2012). For any long-term permanent degradation to be detected, a number of methods have been proposed to remove the precipitation influence from the NDVI trend. The Rain Use Efficiency (RUE) measure, refers to the ratio of aboveground NPP to annual precipitation (Yengoh et al., 2014). The application of RUE as an indicator of land degradation has been widely questioned due to several limitations as highlighted as follows by Higginbottom & Symeonakis (2014). At high precipitation amounts, factors other than rainfall become limitations to NPP, and increases in precipitation do not induce further productivity; while at very low precipitation there may be no vegetation present resulting in RUE values approaching infinity. Further, at low biomass levels the vegetation is unable to prevent runoff and infiltration from occurring, thus subsequently low RUE will be observed. Moreover, recent studies have demonstrated how soil moisture models reveal degraded areas more clearly than the rainfall models given that soil moisture is the water that is directly available to the plants. Ibrahim et al. (2015) and Chen et al. (2014) investigated the impact of soil moisture on vegetation at large spatial (Sahel and Australia, respectively) and long-term temporal (1982-2012 and 1991-2009, respectively) scales, using satellite-derived soil moisture products. Their results showed a strong positive relationship between soil moisture and NDVI. Alternative methods to isolate changes in vegetation productivity due to climate factors include: i) the Residual Trend method (Wessels et al., 2012), in which significant trends in the NDVI residuals express land improvements or degradations that are independent of the climate variable; and ii) the Trend-correlation approach (Vu et al., 2014; Le et al., 2012; Vlek et al., 2010), whereby a pixel is considered to have a strong correlation between its inter-annual NDVI and climate factors if its determination coefficient (R2) is significant and greater than 0.5, together with a positive and significant Pearson’s correlation coefficient (R) (Vu et al., 2014).

The use of NDVI as a proxy for land degradation is not without its shortcomings. As summarised by Le et al. (2016), Table 1.1 presents the various image processing techniques that can be used to address the factors confounding the relationship between NDVI and land-based biomass productivity. Further, while NDVI can serve as an indicator of NPP to measure temporal changes in vegetation and as a proxy for land degradation, it is important to note that it does not tell us anything about the kind of degradation or regeneration processes (Bai et al., 2008). However, as it is rarely possible to obtain direct field measurements at comparable spatial and temporal scales, the validation of NDVI trend analysis remains an issue of major concern (Higginbottom & Symeonakis, 2014). Although simulation approaches, e.g. as proposed by Wessels et al. (2012) for testing the sensitivity of NDVI trend analysis for the detection of land degradation, cannot replace field validation, they offer consistent and repeatable methodologies to better understand NDVI trend detection methods.

Table 1.1: Limitations to the use of NDVI and mitigating measures (adapted Le et al., 2016).

Limiting factors	Affected relationship or process	Mitigating/correcting measure
1. Effect of cloud-cover or cloud-shade	NDVI versus NPP weakened	Mask ineligible pixels
2. NDVI is not a suitable indicator of NPP in bare, or very sparse vegetation	NDVI versus NPP weakened	Mask ineligible pixels (Eliminate pixel with NDVI < 0.05, occurring in sparse vegetation areas)
3. Seasonal variations in vegetation phenology and time-series autocorrelation	Inter-annual NDVI (NPP) trend confounded	Use annually average NDVIs instead of bi-weekly or monthly NDVIs
4. Site-specific effects of vegetation structure and site conditions	NDVI versus NPP weakened	Land-use/cover-specific interpretation Note that for areas with dense vegetation, NDVI less sensitive to actual biomass change
5. Larger errors in the NDVI data compared to the small NDVI trend itself	Not reliable Inter-annual NDVI trend	Do not consider pixels with no statistical significance or very small magnitude of NDVI trend
6. Effect of inter-annual rainfall variation on NDVI (NPP)	Mixture between climate-driven and human-induced NPP trend	Correct rainfall effect by considering NDVI-rainfall correlation
7. Effect of atmospheric fertilization (AF) on vegetation greenness and growth	Mixture between climate-driven and human-induced NPP trend	Correct partly AF effect by consider NPP growth in pristine areas
8. Effect of intensive use of fertilizer in croplands on NDVI (NPP)	Mixture between fertilizer-driven NPP and soil-based NPP	Mask areas with high fertilizer use
9. Irrelevance of considering NPP in urbanized areas	NPP is not relevant indicator	Mask ineligible pixels (Mask pixels from bare surface, urban and industrial areas)

1.3 Conceptual framework

Commitments by the world's governments to address land degradation date back to the Plan of Action to Combat Desertification in 1977, followed, almost two decades later, by the establishment of the UNCCD in 1994 (Grainger, 2015). In recognition of the need to re-galvanise international action on land degradation, the Sustainable Development Goals (SDGs) (adopted by the global community in 2015), include a goal related to land degradation and the accompanying target to achieve a land degradation-neutral world by 2030. Specifically, target 15.3 of the SDGs states "By 2030, combat desertification, restore degraded land and soil, including land affected by desertification, drought and floods, and strive to achieve a land degradation-neutral world" (UN, 2017). The UNCCD defines land degradation-neutrality (LDN) as a "state whereby the amount and quality of land resources necessary to support ecosystem functions and services and enhance food security remain stable or increase within specified temporal and spatial scales and ecosystems" (UNCCD, 2015). The land degradation-neutrality (LDN) concept expresses the desire to prevent further land degradation, and involves the pursuit of two linked goals: reducing the rate of degradation of non-degraded land; and increasing the rate of restoration of degraded land (Kust et al., 2017; Grainger, 2015).

As underscored in the MEA report, it is important to improve our knowledge of the interactions between socioeconomic factors and ecosystem conditions, to further understand the impacts of land degradation on human well-being (MEA, 2005). Systems consisting of ecological and social processes and components, in which components interact within a dynamic structure that facilitates interdependencies and feedbacks influenced by direct and indirect drivers at different temporal and spatial scales are referred to as social-ecological systems (SES) (Virapongse et al., 2016). The SES framework (Ostrom, 2009) emphasises the "humans-in-nature" perspective in which ecosystems are integrated with human society. A number of studies have contextualised land degradation within a SES framework. For example, Turner et al. (2016) in representing land degradation around the concept of a SES, found that there was a strong tendency to favour measurements of ecological data (such as the supply, health, and resilience of the ecological system) over socio-economic and cultural data, resulting in a lack of information about how the human factors change within the context they appear in. The authors also pointed out the issue of scale, and the need to address the connectedness from the field or farm scale to national and global scale economies.

Cowie et al. (2018), in an article that summarises the key features of the scientific conceptual framework for LDN (as developed by the Science-Policy Interface of the UNCCD), position LDN in a cause and effect framework that is embedded within a SES. In this causal framework, the complex interrelationships between the state of the land-based natural capital and the drivers and pressures, the consequent impacts, and human responses, is demonstrated. The major factors leading to land degradation are land use changes (such as conversion from forest to agriculture, or agriculture to urban areas) and unsustainable land management practices, which are driven by both socio-economic (e.g., market forces) and biophysical (e.g., drought) factors (Orr et al., 2017). This LDN conceptual framework also points to the mechanism for neutrality to be achieved through a pro-active focus on planning to balance anticipated negative changes, with actions planned to deliver positive changes (Cowie et al., 2018).

Okpara et al. (2018) conceptualise LDN as operating in a system of non-linear pathways and interacting feedbacks. As illustrated in Figure 1.1, the main research questions (RQs) for this dissertation have been positioned within the SES-based LDN framework as framed by Okpara et al. (2018). Using Kenya as the study area, the primary objective of this doctoral research was to operationalise the LDN concept at the national level. To achieve LDN, Okpara et al. (2018) elaborate on the following key concepts, which help to frame the main RQs that were investigated for this dissertation:

- the role of baselines which represent the reference point against which neutrality can be assessed across temporal and spatial dimensions (RQ 1);
- the integrated perspective of land as a system whose use, distribution and management occurs within complex human and ecology systems (RQ 2);
- the opportunities and limitations of interactions between institutions, governance systems, and cross-scale multi-stakeholder networks (RQ 3);
- multi-scale dynamics, interactions and processes imply that it is essential to re-orient LDN planning towards integrated approaches that achieve and maintain both systems resilience and neutrality outcomes (RQ 4).

The RQs investigated for this dissertation are discussed in detail in section 1.5 below.

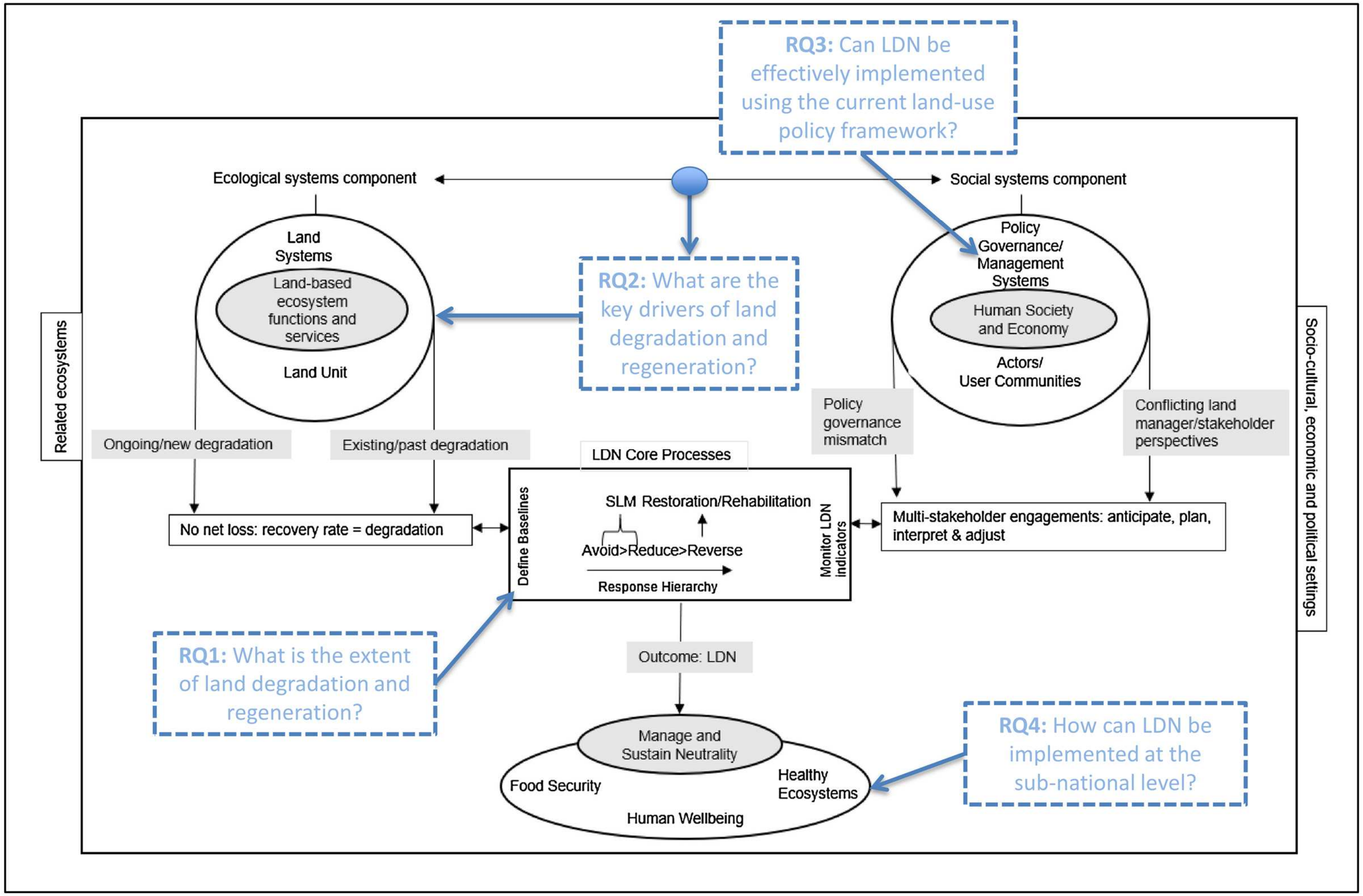

Figure 1.1: The thesis research questions positioned within a SES-based LDN framework (adapted Okpara et al., 2018).

1.4 Country context

1.4.1 Geographic setting

Kenya is located on the eastern coast of the African continent and extends from 33°9′E to 41°9′E and from 4°63′N to 4°68′S, with the Equator bisecting the country into almost two equal parts. The country has a total area of 582,646 km^2, and is endowed with diverse physical features, including a highly variable terrain and land cover. The low plains along the coast gradually change to low plateaus that extend to the eastern and northern parts of the country. From the low plateaus, the terrain rises to an elevated plateau and mountain region in the southwest forming the Kenyan highlands. The Rift Valley separates the Kenyan highlands into east and west. The two elevation extremes in the country are the Indian Ocean at sea level, and the highest point is Mount Kenya in the highlands at an altitude of 5,199 m. The predominant land cover classes are agriculture, forest, shrubland and grassland, and account for approximately 90% of the land cover area in Kenya (Gichenje & Godinho, 2018).

1.4.2 Climatic setting

Most of the country lies within the eastern end of the Sahelian belt, a region that has been severely affected by recurrent droughts over the past decades (Leroux et al., 2017). The climate of the country varies considerably across time and space, and is influenced by proximity to the equator, topography, the Indian Ocean, and the seasonal northward and southward movement of the Inter-Tropical Convergence Zone (ITCZ) (GoK, 2015). Temperatures in the country vary by region, with the highlands experiencing considerably cooler temperatures than the coastal and lowland regions. For the period 1982-2015, the spatial distribution of the mean daily temperature is presented in Figure 1.2a. The country experiences bimodal rainy seasons, and typically the long rains are from March to May, while the short rains are from October to December (Gichangi et al., 2015). Kenya's average annual precipitation is typically 680mm, ranging from less than 250mm in the northern part of the country, to about 2,000 mm in the western part of the country (GoK, 2015). Figure 1.2b presents the spatial distribution of annual mean sum of the rainfall for the period 1982-2015. The temperature and rainfall data were obtained from the Climate Research Unit (CRU) of the University of East Anglia time series at 0.5° resolution (TS v. 3.24.01) (Harris et al., 2014).

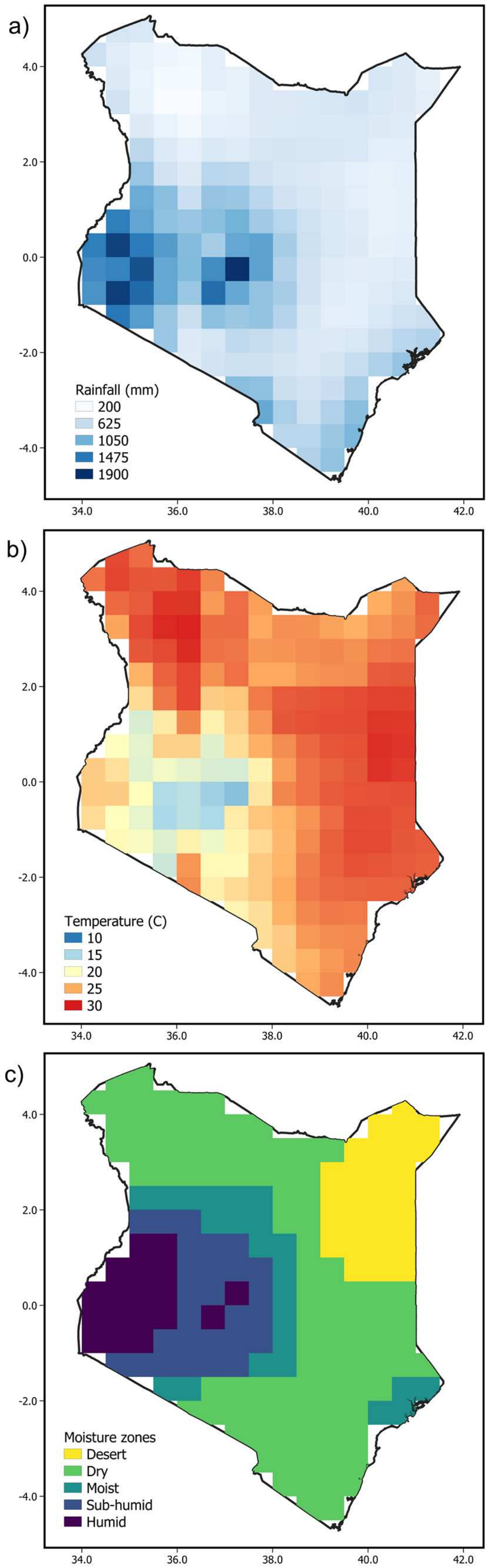

Figure 1.2: Main climate characteristics of Kenya: a) rainfall (annual mean sum (mm) over the period 1982-2015; b) temperature (mean daily temperature (°C) over the period 1982-2015; c) moisture zones.

The United Nations (UN) Food and Agriculture Organization (FAO), has developed a moisture regime classification for Africa based on climate, soils and terrain data that in turn indicates the length of crop growing period (FAO, 2018a). The FAO moisture regimes are for the 30-year reference period from 1991 to 2020, and at a spatial resolution of 10km. Based on the FAO moisture regimes, Kenya can be classified into the following 5 distinct moisture zones: desert, dry, moist, sub-humid, and humid (Figure 1.2c). The desert and dry regions are commonly referred to as the arid and semi-arid lands (ASALs).

1.4.3 Socio-economic setting

According to the last population and housing census in Kenya, the population of the country was 38.6 million in 2009 (GoK, 2018). The current population estimates indicate a population of 47 million in 2017 (GoK, 2018). Given the population estimates for 2017, the average population density for the country is 81 persons/km2, which ranges from as high as 5,000 persons/km2 in the predominantly urban Nairobi and Mombasa counties, to as low as below 10 persons/km2 in Tana River, Marsabit, and Isiolo counties.

The agricultural sector is the backbone of the Kenyan economy. It contributes about 33% of total Gross Domestic Product (GDP), and an additional 27% to GDP through linkages to other sectors such as manufacturing, distribution and services (GoK, 2019). The sector employs more than 40% of the total population and about 70% of the rural population. The main crops by market value are tea, cut flowers, sugar cane, vegetables, coffee and maize, which contribute approximately 90% of Kenyan crop market value. Livestock contributes less than 20% to agriculture GDP. However, the livestock sector plays an important economic and socio-cultural role among many Kenyan communities, particularly the northern ASALs that have more than 60% of the country's beef cattle population. The other key sectors in the Kenyan economy are services, and industry, which contribute approximately 47% and 20% respectively to GDP (GoK, 2019).

Administratively, the country is made up of two formal levels of government: the national government and 47 semi-autonomous county governments, which were created by the new Constitution of Kenya (GoK, 2010), as the new devolved units of governance. Each county has its own government with local representation in the form of elected governors and members of county assemblies. The Constitution (GoK, 2010) and the devolution laws provide a comprehensive legal and regulatory framework governing the operations of the county governments. For example: Schedule 4 of the Constitution delineates responsibilities between the national and county government; and the County Governments Act (GoK, 2012) mandates that each county is to carry out critical planning functions, including the responsibility to prepare a county spatial plan, with the aim (inter alia), to protect and develop natural resources in a manner that aligns with national and county policies.

1.5 Research objectives and thesis outline

Kenya ratified the UNCCD in 1997 (GoK, 2002). As a tool for implementing the provisions of the convention, Kenya has prepared two National Action Programmes (NAPs), the first in 1999 and the next one in 2002. The 2002 NAP (GoK, 2002) highlighted that the following factors have contributed to accelerating the pace of land degradation in Kenya: drought; population pressure; encroachment of rangelands; deforestation and soil erosion. Other studies have also suggested multiple mechanisms influencing vegetation dynamics in Kenya, for example: deforestation has been attributed to intense human activity due to population growth leading to the encroachment of forests for agriculture, pastures, woodfuel, and timber, with illegal settlements and excisions occurring in some protected forests; the conversion of marginal lands to agricultural land; and the sub-division of land resulting in the fragmentation of the rural landscape (Mulinge et al., 2016; FAO, 2014; Were et al., 2013; UNEP, 2009).

Bai & Dent (2006), using GIMMS NDVI data for the period 1981-2003, estimated severe land degradation in 17% of the land area in Kenya. Severe land degradation in the Bai & Dent (2006) study was defined as those areas with both declining net primary productivity and declining rain-use efficiency. More recently, Le et al. (2016) mapped global degradation hotspots using GIMMS NDVI data that was corrected for the effects of inter-annual rainfall variation, atmospheric fertilization and intensive use of chemical fertilizers. The Le et al. (2016) study estimated that a total of 22% of the land area in Kenya has degraded between 1982 and 2006 (Mulinge et al., 2016). Through an analysis of land use and land cover change over the period 2001 and 2009, Mulinge et al. (2016) estimated that about 30% of the Kenya's landmass was subject to severe land degradation. Further, Mulinge et al. (2016) calculated that i) the economic costs emanating from land degradation at the national scale amount to about 1.3 billion USD annually, or about a 4.9% equivalent of the Kenyan GDP in 2007; and ii) the returns to investment in action against land degradation are about four times the costs of inaction in the first six years. On the basis of these results, Mulinge et al. (2016) recommended that actions on land rehabilitation and reclamation are justified to reverse the trends in land degradation in Kenya. In this regard, there is a compelling case for Kenya to take action to achieve LDN.

Using Kenya as the case study, the overarching objective of this thesis was to operationalise the LDN concept at the national level. Guided by the conceptual frameworks discussed above, the thesis will address the following four research questions and specific objectives:

1. What is the extent of land degradation and regeneration?
    a. Distinguish NDVI trends driven by climate factors from those driven by human (including natural) factors;
    b. Identify areas of significant monotonic NDVI trends and provide quantitative classes of human-induced greening and browning trends;
    c. Analyse the distribution of human-induced greening and browning trends in relation to land cover changes; and
    d. Establish the baseline LDN state in 2015 for the three indicators (land cover, land productivity, and carbon stocks).
2. What are the key drivers of land degradation and regeneration?
    a. Identify and characterise the drivers that affect greening and browning NDVI trends within the 4 main land cover types (agriculture, forest, shrubland and grassland), and within an area characterised by land cover change;
    b. Conceptualise the relationship between the LDN goal and the other SDGs; and
    c. Discuss the findings in relation to the implications for elaborating national policies to address LDN actions that aim at reducing and preventing land degradation, and incentivizing land restoration.
3. Can LDN be effectively implemented under the current land-use policy framework?

a. Identify the main policy instruments (as contained in laws, regulations, policies and plans) and associated institutions, which directly or indirectly aim at regulating and influencing land-use in a rural context.
b. Examine if the main policy instruments include specific measures to implement LDN, and evaluate the roles and responsibilities of key institutions.
c. Discuss what policy and institutional improvements are required to overcome gaps and make the best use of opportunities to advance the pursuit of LDN.

4. How can LDN be implemented at the sub-national level? For a selected water catchment area:

a. Compute the LDN baseline; identify and describe the drivers that affect greening and browning trends within the main land cover types; characterise the area using key climate change variables; and identify appropriate SLM interventions for the main land cover areas.
b. Conceptualise a climate-smart landscape and reflect on the possible benefits, challenges, and policy implications of LDN implementation therein.

This dissertation consists of five chapters. **Chapter 1** presents the background for this research including a description of the use of NDVI for assessing land degradation, the LDN conceptual framework, an overview of the country context, and an outline of the research objectives. In **Chapter 2** the LDN national baseline for Kenya is established using the three LDN indicators (land cover, land productivity, and carbon stocks). **Chapter 3** identifies the key drivers that affect land degradation (browning) and land regeneration (greening) trends within the 4 main land cover types (agriculture, forest, grassland and shrubland) and within an area characterised by land cover change. The methodological approach used is the random forest classification algorithm, whereby the dependent variable is represented as 4 classes of NDVI greening and browning trends (strong browning, moderate browning, moderate greening, and strong greening). The explanatory variables are broadly grouped into 2 categories, natural and anthropogenic, and include a number of variables as proxies for broad socio-economic development. **Chapter 4** presents an assessment of the effectiveness of existing legal, policy and planning instruments, as well as associated institutions, to facilitate the implementation of LDN. This qualitative assessment is framed around a portfolio of place-based measures that are appropriate to the Kenyan context and address the LDN response hierarchy to avoid, reduce and restore land degradation, as well as the enabling conditions that support the implementation of LDN. In **Chapter 5** an analysis and contextualisation of LDN at the sub-national level for a selected water catchment area is presented by describing the spatial and temporal characteristics for key land degradation and climate change variables. A climate-smart landscape approach for the water catchment is then proposed as a possible mechanism through which LDN can be operationalised. To conclude, **Chapter 6** synthesises the key findings across the preceding four chapters, highlights the main research limitations, and provides suggestions for future research to support the implementation of LDN.

Chapter

2

ESTABLISHING A LAND DEGRADATION NEUTRALITY NATIONAL BASELINE THROUGH TREND ANALYSIS OF GIMMS NDVI TIME SERIES

Based on the published manuscript:

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Abstract

The land degradation-neutrality (LDN) national baseline for Kenya in 2015 was established in terms of the three LDN indicators (land cover, land productivity, and carbon stocks), and using trends in GIMMS NDVI and land cover datasets over the 24-year period from 1992 to 2015. Human-induced land degradation was separated from degradation driven by climate factors using soil moisture data and the residual trend method. On the basis of Kendall's tau of the NDVI residuals computed using annual mean data of the NDVI and soil moisture relationship, the country has experienced persistent negative trends (browning) over 21.6% of the country, and persistent positive trends (greening) in 8.9% of the country. The land cover change map for the period 1992–2015 showed that in 5.6% of the area there was a change from one land cover class to another. Pronounced changes in terms of land area were the increase in grasslands by 12,171 km^2, the decrease of bare land by 9,877 km^2, and the decrease in forests by 7,182 km^2. Browning and greening trends account for 13% and 12%, respectively, of the land cover change areas. By establishing the LDN national baseline, the LDN concept is now operational. As a first step, targeted field level assessments, alongside the collection of data for the computation of soil organic carbon stocks, should be undertaken in selected browning, greening, and land cover change sites. These field studies will provide decision makers with key information on how to plan for the implementation and monitoring of LDN interventions.

***Keywords**: GIMMS NDVI; Kenya; land cover change; land degradation-neutrality; RESTREND*

2.1 Introduction

Land degradation is a key global environment and development problem that is recognized as a priority by the international development community. The Sustainable Development Goals (SDGs) were adopted by the global community in 2015, and include a goal related to land degradation and the accompanying target to achieve a land degradation-neutral world by 2030. Specifically, goal 15.3 of the SDGs states "By 2030, combat desertification, restore degraded land and soil, including land affected by desertification, drought and floods, and strive to achieve a land degradation-neutral world" (UN, 2017).

The United Nations Convention to Combat Desertification (UNCCD) defines land degradation-neutrality (LDN) as a "state whereby the amount and quality of land resources necessary to support ecosystem functions and services and enhance food security remain stable or increase within specified temporal and spatial scales and ecosystems" (UNCCD, 2015). The land degradation-neutrality (LDN) concept expresses the desire to prevent further land degradation, and implies maintaining the balance between "not yet degraded" and "already degraded" land (Kust et al., 2017). The pursuit of LDN has two linked goals: reducing the rate of degradation of non-degraded land; and increasing the rate of restoration of degraded land (Kust et al., 2017; Grainger, 2015). A key operational and technical challenge relevant to the implementation of LDN is the need to define the LDN baseline to monitor the direction of any change (Akhtar-Schuster et al., 2017; Kust et al., 2017; Grainger, 2015). In consideration of this challenge, Grainger (2015) stresses that for each country participating in a LDN scheme the first priority must be to establish a robust national baseline for the current extent of degraded land and its rate of change.

The UNCCD has identified the following 3 biophysical indicators (and associated metrics) to measure LDN: land cover (land cover change); land productivity (net primary productivity, NPP); and carbon stocks (soil organic carbon) (UNCCD, 2016a). In the absence or to complement national data the UNCCD has proposed the following global data sources and approaches for the assessment of the LDN baseline at the country level (UNCCD, 2016b). The proposed data source for land cover data is the European Space Agency Climate Change Initiative (ESA-CCI) land cover dataset (v 1.6.1) for the years 2000, 2005 and 2010. Land cover data (300m resolution) for the years 2000 and 2010 are to be used to provide estimates of land cover change. For land productivity data, the Joint Research Centre Land Productivity Dynamics (LPD) Normalised Difference Vegetation Index (NDVI) time series dataset (1 km pixel size, 1999 to 2013) is proposed. The LPD NDVI dataset includes the following 5 qualitative classes of land productivity trends: declining productivity, early signs of decline, stable but stressed, stable but not stressed, and increasing productivity. To measure soil organic carbon (SOC) stock at the standard depth of 0-30cm, data can be derived from SoilGrids250m database, which provides global predictions for organic carbon as well as other standard soil properties at a resolution of 250m. Further, the UNCCD proposes that changes in the value of the LDN indicators over a 10 to15 year assessment period can provide an indication of land degradation trends. With Kenya as the study area, the overarching objective of the current study was to use a methodology for establishing a LDN national baseline that capitalises on the availability of long-term NDVI and land cover datasets over the 24-year period from 1992-2015. This alternative methodology to the UNCCD LDN approach described above, was developed to assess the practicalities of the technique and to evaluate the spatial output across land cover classes, with the view of identifying areas to prioritise actions in the pursuit of LDN at the national level.

Land degradation has been defined in many and various ways. In the current study, we interpret land degradation in terms of the UNCCD's definition as the "loss, in arid, semi-arid and dry sub-humid areas, of the biological or economic productivity and complexity of rainfed cropland, irrigated cropland, or range, pasture, forest and woodlands resulting from land uses or from a process or combination of processes, including processes arising from human activities and habitation patterns" (UNCCD, 1994). This definition implies an impact on above-ground vegetation production, as well as the explicit reference to human-induced land degradation. The LDN indicator on land productivity is intended to measure the above-ground vegetation production by use of NPP. The most widely used remote sensing method for the assessment of land degradation is trend analysis of NDVI data, as a proxy for NPP (Higginbottom & Symeonakis, 2014). A number of studies (Wessels et al., 2006; Prince & Tucker, 1986; Tucker et al., 1986) have reported a close coupling between NDVI and in-situ-NPP measurements. Bai & Dent (2006) investigated the correlation between Global Inventory Monitoring and Modeling System (GIMMS) NDVI data and field-measured NPP in a grassland area in Kenya over the period 1984-1994. Over this 11-year period, the correlation coefficient for annual above-ground total NPP was 0.765. As NDVI is strongly correlated with NPP (Huang & Kong, 2016; Vlek et al., 2010), it represents a useful tool with which to couple climate and vegetation performance at large spatial and temporal scales (Pettorelli et al., 2005). While NDVI can serve as an indicator of NPP to measure temporal changes in vegetation and as a proxy for land degradation, it is important to note that it does not tell us anything about the kind of degradation or regeneration processes (Bai et al., 2008).

The longest continuous record of NDVI data comes from the Advanced Very High Resolution Radiometer (AVHRR) instrument onboard the NOAA satellite series 7, 9, 11, 14, 16, and 17, starting in July 1981 (Pettorelli et al., 2005). Recent studies in diverse regions of the world in which the GIMMS NDVI time series data from the AVHRR instrument has been used to detect changes in photosynthetically active vegetation reveal diverse patterns of decline and increase in vegetation productivity (Huang & Kong, 2016; Erasmi et al., 2014; Ibrahim et al., 2015; Vu et al., 2014). In these studies, various methods were used to aggregate the NDVI data, including annual mean NDVI (Ibrahim et al., 2015; Vu et al., 2014), annual sum of NDVI (Erasmi et al., 2014), and seasonal sums of NDVI (Huang & Kong, 2016). de Jong et al. (2011) compared trend estimates using GIMMS NDVI values aggregated using various methods, and noted that aggregating data to yearly mean values does not severely influence NDVI trend analysis due to similar trend slopes found between the linear models of NDVI anomalies and yearly mean values.

A number of studies between NDVI and climate factors (rainfall, soil moisture, temperature) have been used to isolate changes in vegetation productivity due to climate factors from those caused by both anthropogenic and natural factors (Huang & Kong, 2016; Ibrahim et al., 2015; Vu et al., 2014; Le et al., 2012; Vlek et al., 2010). The Residual Trend (RESTREND) method was used in the current study to remove the climate influence from the NDVI trend. RESTREND consists of 3 steps (Wessels et al., 2012). First a linear regression between NDVI and the climate factor is calculated per pixel. Then the difference between the observed NDVI values and NDVI estimated from the climate relationship, referred to as the NDVI residuals, is calculated. Lastly, a trend analysis is then performed on the NDVI residuals, with the resulting significant trends in vegetation production being independent of the climate variable.

For NDVI trend analysis, parametric (Ibrahim et al., 2015; Vu et al., 2014) and non-parametric (Huang & Kong, 2016; Erasmi et al., 2014) methods can be used. In parametric methods, a linear regression model is used to quantify change in the dependent variable, y (i.e., NDVI) against an independent variable, x (i.e., time) (Higginbottom & Symeonakis, 2014). The direction and magnitude of change from this model thus explains the change in NDVI over the period analysed. The non-parametric approach for estimating trends in time series data allows for the quantification of the rate of change in vegetation greenness for every single pixel, and uses the median slope to characterize a trend in the data (Erasmi et al., 2014). The Mann-Kendall significance test (non-parametric), also known as Kendall's tau (τ), ranges from −1 to +1. Values of Kendall's tau greater than 0 indicate a continually increasing (monotonic greening) trend, and those less than 0 indicate a continually decreasing (monotonic browning) trend (de Jong et al., 2011). While the Mann-Kendall significance test is a widely accepted method in environmental sciences used to verify the existence of significant long-term trends in time series, the weakness of the method is its sensitivity to autocorrelation in the time series (Erasmi et al., 2014). As autocorrelation will increase the probability that the Mann-Kendall test detects a significant trend, it can be removed from the time series by applying a technique known as pre-whitening (Yue et al., 2002).

Two studies have recently investigated the link between NDVI trends and land cover changes. Leroux et al. (2017) analysed Moderate Resolution Imagery Spectroradiometer (MODIS) NDVI trends in relation to land cover changes using Landsat images between 2001 and 2013 in south-western Niger. They observed a strong decrease (25% and greater) in biomass production for plateaus, degraded hillslopes, natural vegetation and cropland loss land cover types. For the other types of land cover classes, no clear trend patterns were observed. In the study by Gouveia et al. (2016) in the Iberian Peninsula, Corine land cover maps for the years 1990, 2000 and 2006 were compared with GIMMS NDVI trends. Less than 20% of the area with decreasing NDVI trends was associated with land cover changes, and the most affected land cover types were transitional woodland-shrub, permanent and annual crops; while the most affected land cover types associated with increasing NDVI trends were transitional woodland-shrub, annual crops and forest (Gouveia et al., 2016).

On the basis of the above discussion, the long-term GIMMS NDVI and the ESA-CCI land cover datasets for the period 1992-2015 were used to establish a LDN national baseline for Kenya. The specific objectives of this study were to:

i. apply the RESTREND method to distinguish NDVI trends driven by climate factors from those driven by human (including natural) factors;
ii. identify areas of significant monotonic NDVI trends using non-parametric methods (Mann-Kendall significance test) and provide quantitative classes of human-induced greening and browning trends;
iii. analyse the distribution of human-induced greening and browning trends in relation to land cover changes; and
iv. establish the baseline LDN state in 2015 for the 3 indicators (land cover, land productivity, and carbon stocks).

2.2 Data and methods

2.2.1 Study area

Kenya is located on the eastern coast of the African continent and extends from 33°9′E to 41°9′E and from 4°63′N to 4°68′S, with the Equator bisecting the country into almost two equal parts (Figure 2.1). Most of the country lies within the eastern end of the Sahelian belt, a region that has been severely affected by recurrent droughts over the past decades (Leroux et al., 2017). Kenya has a total area of 582,646 km^2, which is characterized by a highly variable terrain. The climate of the country varies considerably across time and space. It is hot and humid along the coast, temperate inland, and very dry in the north and northeast parts of the country (GoK, 2015). The country experiences bimodal rainy seasons, and typically the long rains are from March to May, while the short rains are from October to December (Gichangi et al., 2015). Kenya's average annual precipitation is typically 680mm, ranging from less than 250mm in the northern part of the country, to about 2,000 mm in the western part of the country (GoK, 2015).

Figure 2.1: Study area.

2.2.2 Data

The processing and analysis of the raster data described below was based on a number of statistical techniques implemented in the statistical programme R (R Core Team, 2017). Specific scripts were developed in R to process and analyse the data.

GIMMS NDVI data

The latest version (3g.v1) of the GIMMS NDVI dataset was used in this study (https://ecocast.arc.nasa.gov/data/pub/gimms/3g.v1/). This long-term NDVI time series (8km pixel size, available twice monthly) spans the period July 1981 to December 2015. Using the gimms R package (Detsch, 2016), the GIMMS NDVI 3g.v1 data was processed as follows. NDVI data for the period the January 1992 to December 2015 in nc4 format (Network Common Data Form, version 4) were downloaded from the ECOCAST site. Associated with each semi-monthly NDVI 3g.v1 record are 3 flag values indicating the data reliability on a pixel basis. NDVI data with a flag value of 0 (i.e. from data) were converted to tif image format, cropped to the extent of the study area, and projected to the WGS84 coordination system. The semi-monthly NDVI data were aggregated to monthly data by retaining the highest value per pixel. This technique is known as the monthly maximum value composite (MVC) and has been shown to minimize the degree of influence of clouds, sun angle, water vapour, aerosols and directional surface reflectance on the NDVI image (Holben, 1986). Finally, the monthly NDVI data were further aggregated to an annual mean time series.

MODIS NPP data

Given the availability of moderate resolution MODIS annual NPP data (1km) from 2000, this dataset was proposed for monitoring progress on the land productivity indicator from 2015 going forward. The MODIS primary production products (MOD17) provide data of vegetation primary production on vegetated land at 1km resolution at an 8-day interval (Zhao et al., 2005). The latest MODIS annual NPP global dataset (MOD17A3, version 055) is produced and is available from the Numerical Terradynamic Simulation Group (NTSG)/University of Montana (UMT) (http://files.ntsg.umt.edu/data/NTSG_Products/MOD17/GeoTIFF/MOD17A3/GeoTIFF_30arcsec/). The latest version corrects the problem of the original dataset (version 4 of the MOD17 NPP and Gross Primary Productivity (GPP) products) resulting from the cloud-contaminated MODIS in fraction of absorbed photosynthetically active radiation (FAPAR) and leaf area index (LAI) inputs to the MOD17 algorithm (Running & Zhao, 2011). We downloaded the global annual NPP dataset for the period 2000 to 2015, representing the total NPP for the year in gC/m2. The global layers were cropped to the extent of Kenya, and then resampled to match the 8km GIMMS NDVI data using the nearest-neighbour algorithm. The annual NPP layer for 2015 was also resampled to match the 300m land cover data using the nearest-neighbour algorithm.

<u>Soil moisture data</u>

In order to assess the relationships between NDVI and climatic conditions soil moisture data was obtained from the combined active–passive microwave data set of the European Space Agency Climate Change Initiative (ESA-CCI) (http://www.esa-soilmoisture-cci.org/node/145). The combined soil moisture product at 0.25° spatial resolution and daily temporal resolution, covers the period from November 1978 to December 2014. The combined soil moisture product is produced by rescaling and merging volumetric soil water data (m3m-3) from the passive satellite, and degree of saturation (%) data from the active satellite, against a reference land surface model data set using a cumulative distribution function matching approach (Liu et al., 2012; Liu et al., 2011; Wagner et al., 2012). The soil moisture data for the combined soil moisture product is provided in volumetric units, m3m-3.

Soil moisture data was chosen as opposed to rainfall data for three reasons. First, the soil moisture data was available at a finer spatial resolution than the rainfall data. In the absence of a dense network of weather stations in the study area with long term rainfall data records, the best alternative is satellite based data from the Climate Research Unit (CRU) of the University of East Anglia (Harris et al., 2014). The CRU time series monthly rainfall data set consists of observations at 0.5° resolution for the period 1901-2016. Second, the ESA-CCI soil moisture product has been explicitly evaluated over Kenya. McNally et al. (2016) evaluated the quality of time series data of the combined soil moisture product from the ESA-CCI over East Africa. The authors noted substantial spatial and temporal gaps in the early part of the ESA-CCI soil moisture record. However, adequate data coverage was provided beginning in 1992. From this point forward, there was improved pixel-wise correlation analysis and qualitative comparisons with Noah 3.3 (a water and energy balance land surface model) and VIC 4.1.2 (a variable infiltration capacity semi-distributed macro-scale hydrologic model), particular over Kenya. Third, recent studies have demonstrated how soil moisture models reveal degraded areas more clearly than the rainfall models given that soil moisture is the water that is directly available to the plants. Ibrahim et al. (2015) and Chen et al. (2014) investigated the impact of soil moisture on vegetation at large spatial (Sahel and Australia, respectively) and long-term temporal (1982-2012 and 1991-2009, respectively) scales, using satellite-derived soil moisture products. Their results showed a strong positive relationship between soil moisture and NDVI.

The combined ESA-CCI soil moisture data for the period January 1992 to December 2014 was used in this study. The data comes with the different quality flags, and only flag 0 (no data inconsistency detected) pixels were used in this study. The global daily data were cropped to the extent of the study area and aggregated to annual mean values. To match the 24-year NDVI data, the mean of the annual mean soil moisture for the 23 years (1992-2014) was used as data for the year 2015. The data were then resampled and projected to match the 8-km NDVI data using the nearest-neighbour algorithm.

Land cover data

The land cover product used in this study was the time series of annual global land cover maps at 300 m spanning the period from 1992 to 2015 released by the ESA-CCI on 10 April 2017 (https://www.esa-landcover-cci.org/?q=node/175). The ESA-CCI land cover maps (v 2.0.7) were produced with the reprocessing and the interpretation of a number of different satellite missions, including: the ENVISAT-MERIS Full and Reduced resolution reflectance recorded from 2003 to 2012 at 300 m resolution; the NOAA-AVHRR HRPT dataset recorded at 1 km covering the period from 1992 to 1999; the SPOT-Vegetation time series spanning from 1998 to 2012; and the PROBA-V from 2013 to 2015 (ESA, 2017). The ESA-CCI land cover maps use the Land Cover Classification System (LCCS) developed by the United Nations (UN) Food and Agriculture Organization (FAO), which consists of 22 land cover classes.

Global land cover maps for the period 1992-2015 were downloaded and cropped to the extent of Kenya. The 22 land cover classes were aggregated into 9 land cover classes (Table 2.1) in line with land categories used by the Intergovernmental Panel on Climate Change (IPCC) for change detection (ESA, 2017).

Table 2.1: Original Land Cover Classification System (LCCS) classes and new aggregated classes.

Original LCCS classes	Aggregated classes
Rainfed cropland Irrigated cropland Mosaic cropland (>50%) / natural vegetation (tree, shrub, herbaceous cover) (<50%) Mosaic natural vegetation (tree, shrub, herbaceous cover) (>50%) / cropland (< 50%)	Agriculture
Tree cover, broadleaved, evergreen, closed to open (>15%) Tree cover, broadleaved, deciduous, closed to open (> 15%) Tree cover, needleleaved, evergreen, closed to open (> 15%) Tree cover, needleleaved, deciduous, closed to open (> 15%) Tree cover, mixed leaf type (broadleaved and needleleaved) Mosaic tree and shrub (>50%) / herbaceous cover (< 50%) Tree cover, flooded, fresh or brakish water Tree cover, flooded, saline water	Forest
Mosaic herbaceous cover (>50%) / tree and shrub (<50%) Grassland	Grassland
Shrubland	Shrubland
Lichens and mosses Sparse vegetation (tree, shrub, herbaceous cover)	Sparse vegetation
Shrub or herbaceous cover, flooded, fresh-saline or brakish water	Wetland
Urban	Settlement
Bare areas	Bare areas
Water	Water

Data to compute soil organic carbon stock

Data to compute the soil organic carbon stock was obtained from SoilGrids250m (ftp://ftp.soilgrids.org/data/recent/). SoilGrids250m is a collection of updateable soil property and class maps of the world produced using automated soil mapping based on machine learning algorithms (Hengl et al., 2017). This soil database has approximately 150,000 soil profiles, obtained from numerous soil profile datasets, including the Africa Soil Profiles Database (AfSP). The AfSP contains 591 soil profiles for Kenya, which have been collected from 1972 to 2011 (Leenaars et al., 2014). The UNCCD recommends that in the absence of a national soil organic carbon (SOC) database, SoilGrids250m can be used to compute the SOC stocks as representing data for the year 2000 (UNCCD, 2016b).

The total SOC stock in tonnes per hectare at the standard fixed depth interval of 0–30 cm, was computed using the GSIF package in R (Hengl, 2017) as a per the following equation (Hengl et al., 2018):

SOC stock [ton/ha]= SOC/1000*BLD*(1-CRF/100)*HOT/100*10

Where:

SOC = soil organic carbon content (%: g/kg)

BLD = bulk density of fine earth (kg/m3);

CRF = coarse fragments (volumetric %: cm3/cm3)

HOT = horizon thickness or depth interval (0-30cm)

These 3 data sets (soil organic carbon content, bulk density of fine earth, and coarse fragments volumetric) at 4 depths (0, 5, 15, and 30 cm) were downloaded from SoilGrids250m, and cropped to the extent of the study area. The computed SOC stock layer was resampled to match the 300m land cover data using the nearest neighbour algorithm.

2.2.3 Methods of analysis

The Residual Trend (RESTREND) method

As NDVI trends are not always monotonic but can change (Forkel et al., 2013), we tested for changes (called breakpoints) in the GIMMS NDVI trend before applying the RESTREND method. Using the greenbrown R package (Forkel et al., 2015; Forkel et al., 2013), we checked for significant (at a confidence level of 95%) structural changes in the annual aggregated NDVI time series data.

The RESTREND method was then applied as follows. First, on a per-pixel basis, a linear regression was applied to the GIMMS NDVI and soil moisture annual mean data for the period 1992-2015. NDVI was defined as the dependent variable and soil moisture as the independent variable. The statistical significance between the annual NDVI and soil moisture data was tested using Pearson's correlation coefficient at a confidence level of 95%. Second, the difference between the observed NDVI values and NDVI estimated from the soil moisture relationship, referred to as the NDVI residuals, was calculated. Lastly, we applied the Mann-Kendall significance test at 95% confidence level to the NDVI residuals both with and without the pre-whitening technique. The pre-whitening procedure applied, as described by Yue et al. (2002), involves the removal of the trend component from the time series prior to pre-whitening. The Mann-Kendall significance test, also known as Kendall's tau (τ), ranges from −1 to +1.

Assessment of land cover change

We computed the land use change from 1992 to 2015 as follows. The land cover classes for the 1992 land cover layer were assigned values from 1 to 9, while the land cover classes for the 2015 layer were assigned values from 10 to 90. These two layers were then summed to create a land cover change layer, enabling each pixel to be identified as having undergone change or having remained the same over the 24-year period. We also examined the change from year to year over the 24-year period (increase or decrease in km^2) within each land cover class. With the aim of relating land cover changes with the NDVI trends, the 8km Kendall's tau of the NDVI residuals layer was resampled to match the 300m land cover data using the nearest-neighbour algorithm. We then investigated the association between NDVI residual trends and the land cover change map for the period 1992-2015.

Establishing the baseline LDN state in 2015

The LDN national baseline is an integral component of the recently defined LDN conceptual framework (Cowie et al., 2018) as it defines the reference state of the LDN indicators at time zero (i.e. the year 2015 when the SDGs were adopted) against which the LDN target will be assessed in 2030 (the target date for the SDGs). As noted by Grainger (2015), a LDN baseline would provide information on the historical rate of degradation, as well as on the current extent of degradation at the start of the monitoring period. Hence, in this study we described the baseline LDN state for each of the 3 LDN indicators (land cover, land productivity, and carbon stocks) across the main land cover classes in the following two dimensions: i) as trends over a specific time period (for the current study we used the 24-year period from 1992-2015); and ii) the state of each of the 3 LDN indicators in 2015. Trends of the LDN indicators using time series data was intended to highlight the trajectories of change and identify areas to prioritise LDN actions. The start of the monitoring period used in this study was 2015, and provides the basis for periodic monitoring of progress towards meeting the LDN goal by 2030. The MODIS annual NPP dataset was proposed for monitoring progress on the land productivity indicator from 2015 going forward. Using Pearson's correlation coefficient at a confidence level of 95%, we tested the strength of the linear association on a per-pixel basis between the GIMMS NDVI and MODIS NPP annual data for the period 2000-2015.

Of note for the case of Kenya was that: i) there were no time series national estimates for SOC stocks; and ii) the soil data has been collected over several decades (1972-2011), hence the computed SOC stocks was denoted to represent the year 2000, as recommended by the UNCCD (UNCCD, 2016b). Hence, across the main land cover classes, the baseline LDN state for Kenya in 2015 was established as follows: i) the trends over the period 1992-2015 in land cover change, and the greening and browning of the NDVI residuals; ii) the state of each of the 3 LDN indicators: the area of each land cover class for the land cover map for 2015; the annual MODIS NPP in 2015; and the mean SOC stock in 2000.

2.3 Results

2.3.1 Human induced land degradation from 1992 to 2015

As the methodology used in the current study was based on detecting monotonic greening and browning trends, we tested for breakpoints in the GIMMS NDVI trend before applying the RESTREND method. No breakpoints were detected in the annual aggregated NDVI time series data. The spatial distribution of the correlation between the annual NDVI and soil moisture data (using Pearson's correlation coefficient at a confidence level of 95%) revealed that 63% of the pixels were positively and significantly correlated. This result indicates that for most of the area in Kenya, soil moisture has a positive impact on NDVI.

Figure 2.2 illustrates the results of the Mann-Kendall significance test at 95% confidence level applied to the NDVI residuals, (a) without pre-whitening, (b) with pre-whitening; and (c) the difference between (a) and (b). Most of the pixels (66.4% and 69.5%, without pre-whitening and with pre-whitening, respectively) were characterised by no significant trend. The negative trends occur in the area formerly known as the Eastern province of Kenya. The positive trends occur primarily along the north-western border of the country. After pre-whitening for the removal of autocorrelation, the area affected by significant greening is reduced from 12.8% to 8.9%, while the browning trend remains about the same (20.8% and 21.6%, without pre-whitening and with pre-whitening, respectively). On the basis of Kendall's tau on the pre-whitened NDVI residuals computed from the NDVI-soil moisture relationship over the 24-year period from 1992-2015, the area of country that has experienced persistent browning was 21.6%, while persistent greening has occurred in 8.9% of the country. The following 5 quantitative classes were used to describe the degree or intensity of the human-induced greening and browning trends: strong browning (-0.4 to -0.8); moderate browning (<0 to -0.4); moderate greening (>0 to 0.4); strong greening (0.4 to 0.8); and no significant trend. Strong browning has occurred in 11.8% of the country, with moderate browning occurring in 9.8% of the country. Strong greening has occurred in 5% of the country, with moderate greening occurring in 3.9% of the country.

Using the land cover map for 2015 (Figure 2.3), the browning and greening trends across all land cover classes was examined (Table 2.2). The highest percentage of strong browning trends were observed in settlement and agricultural areas. Trends in the other land cover classes were generally in line with the overall national browning and greening trends. The distribution of the browning and greening trends within the main land cover classes (agriculture, forest, grassland, and shrubland) was shown in Figure 2.4. These four land cover classes account for approximately 90% of the land cover area during the period from 1992 to 2015.

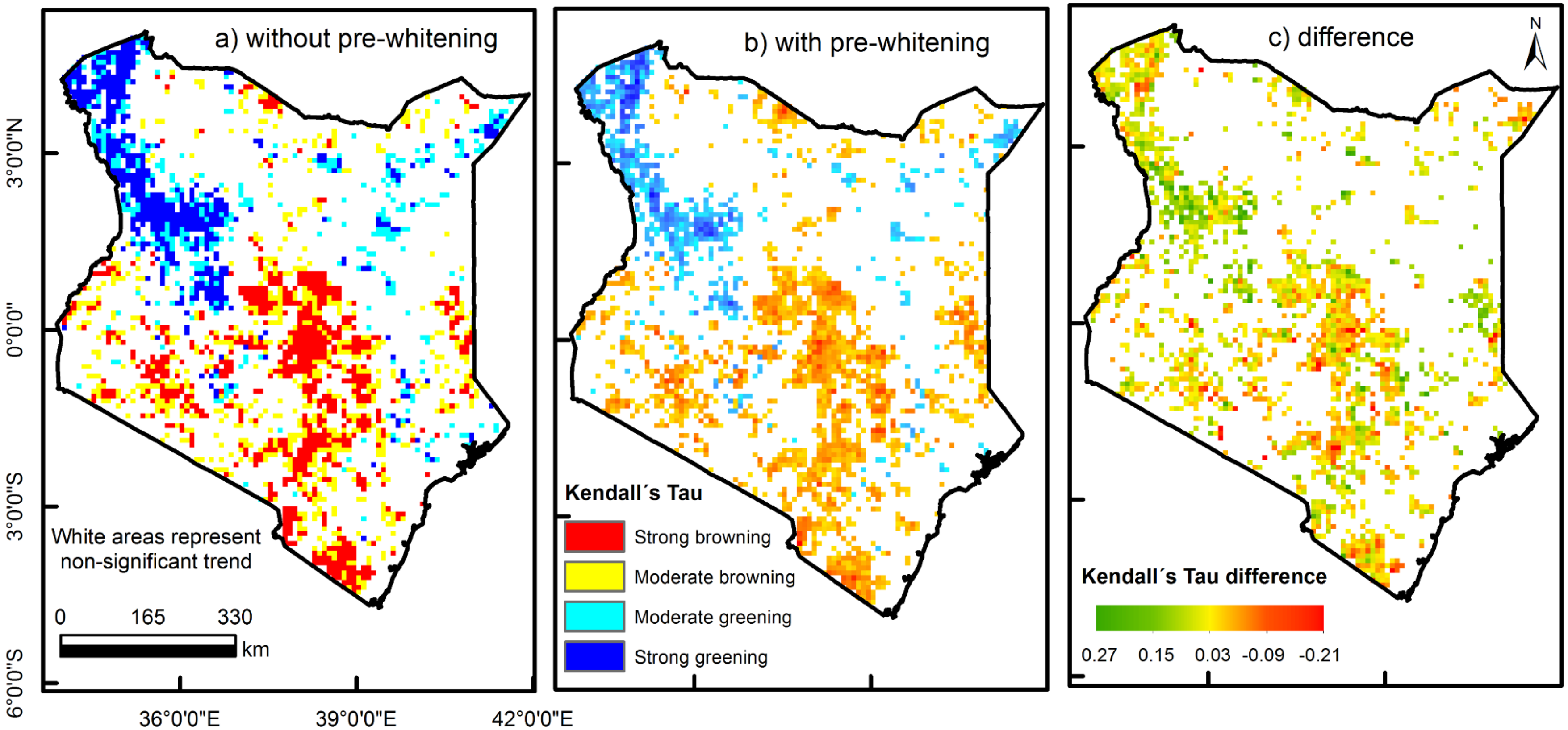

Figure 2.2: Spatial pattern of Kendall's tau of the NDVI residuals computed from the NDVI-soil moisture relationship (a) without prewhitening, (b) prewhitened, and (c) the difference between (a) and (b).

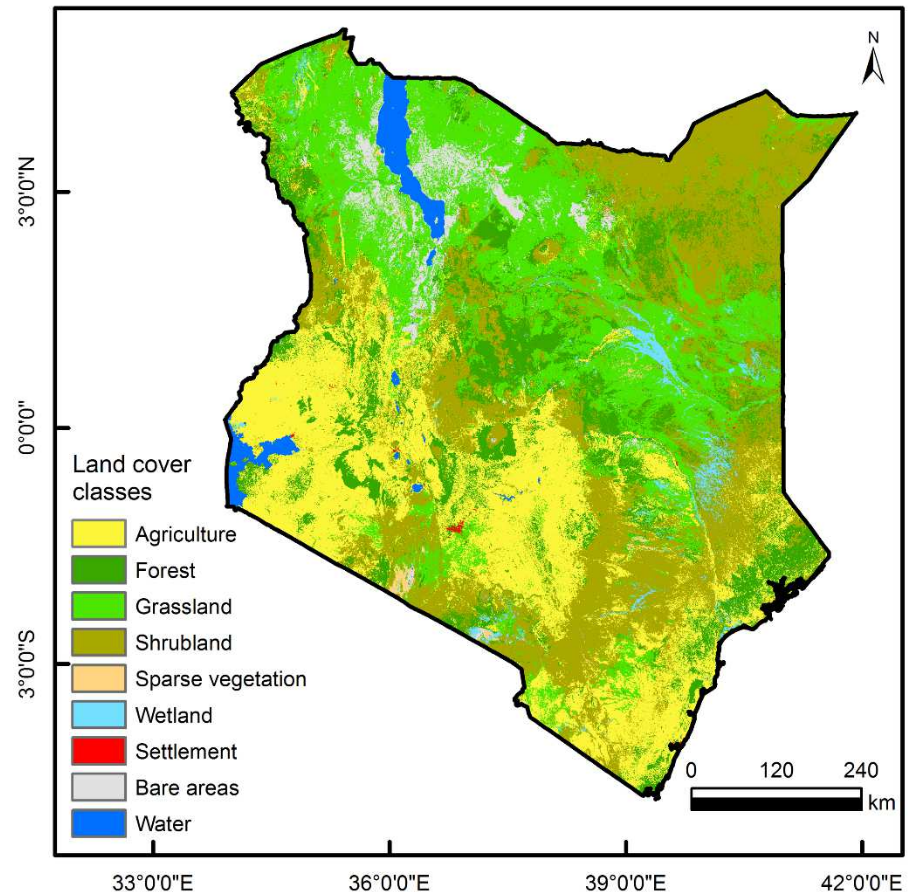

Figure 2.3: Land cover map for 2015 using the aggregated land cover classes (from Table 2.1).

Table 2.2: Browning and greening trends computed from the NDVI-soil moisture relationship over the 24-year period from 1992 to 2015.

Land cover classes	Kendall's tau (1992-2015) (% area in each category)				
	Moderate browning	**Strong browning**	**Moderate greening**	**Strong greening**	**No trend**
Agriculture	12	17	3	3	65
Forest	9	13	4	5	69
Grassland	7	7	5	7	74
Shrubland	11	11	4	4	70
Sparse	10	11	1	1	77
Wetland	6	6	7	7	74
Settlement	7	34	3		56
Bare	4	3	6	6	81
Water	-	-	-	-	-

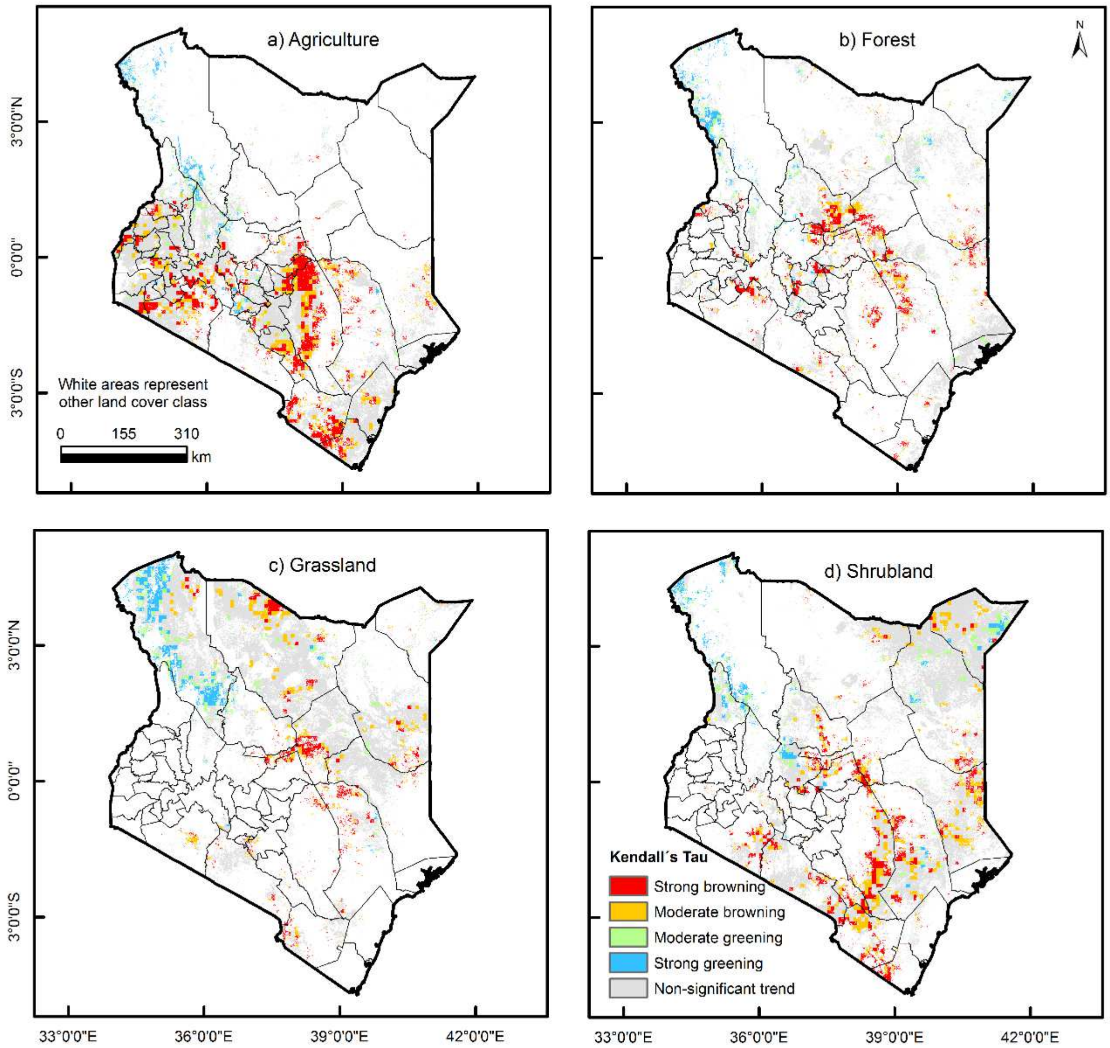

Figure 2.4: Distribution of human-induced greening and browning trends within (a) agriculture, (b) forest, (c) grassland, and (d) shrubland land cover areas.

2.3.2 Land cover change

The land cover change map for the period 1992 to 2015 showed that for 94.4% of the area of Kenya there was no change in land cover class, and in only 5.6% of the area was there a change from one land cover class to another. Pronounced changes during the period from 1992 to 2015 in terms of land area were: the increase in grasslands by 12,171 km^2, the decrease of bare land by 9,877 km^2, and the decrease in forests by 7,182 km^2 (Table 2.3). We examined the conversion between land cover class. For example, Table 2.3 shows that over the 24-year period, the reduction in forest land was predominantly due to the conversion to agricultural (24%), grassland (38%) and shrubland (31%) areas.

The annual change in area (increase or decrease in km^2) within each land cover class was examined and showed that the magnitude of change across land cover classes was more pronounced during the first half of the 24-year period (Figure 2.5).

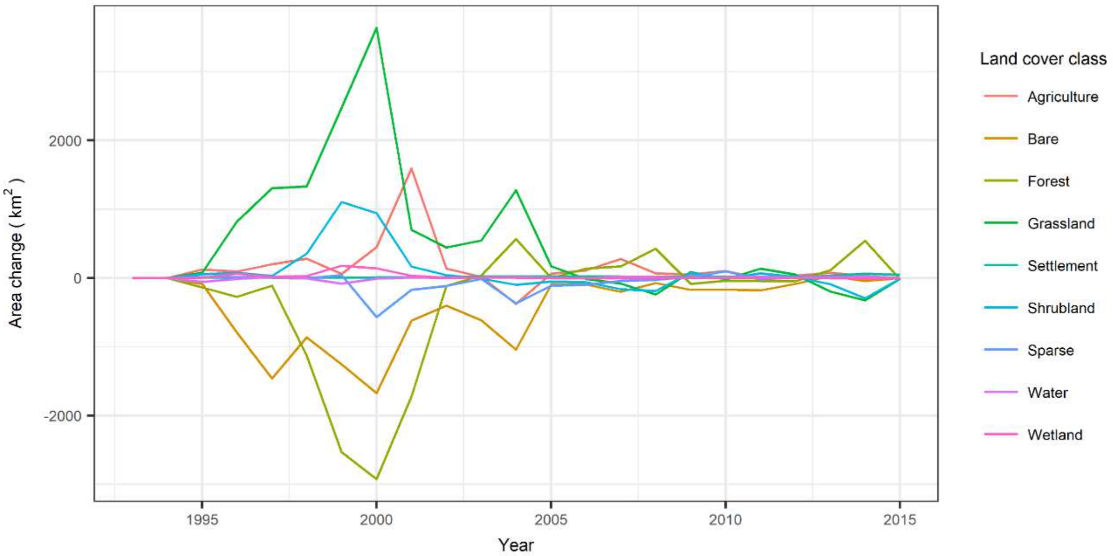

Figure 2.5: Annual change in area (km^2) within each land cover class from 1992 to 2015.

We also investigated the association between areas of greening and browning trends and the land cover change map for the period 1992-2015 (Table 2.3). Land cover change areas with browning trends account for 13% of the area, while greening trends account for 12% of the area. Of the areas with simultaneous land cover change and browning trends, 55% were forest areas. While of the areas with simultaneous land cover change and greening trends, bare and grassland areas account for 57% and 23%, respectively.

Table 2.3: Land cover change from 1992 to 2015 and associated browning and greening trends**.**

Land cover class in 1992	**Change 1992-2015**		**Land cover class in 2015 (% area that changes from land cover class in 1992 to land cover class in 2015)**									**LC change share (%) of NDVI trends**	
	area (km^2)	**%**	**Agriculture**	**Forest**	**Grassland**	**Shrubland**	**Sparse**	**Wetland**	**Settlement**	**Bare**	**Water**	**Browning**	**Greening**
Agriculture	3,378	2.4	-	75	11	5	-	-	5	-	3	13	5
Forest	-7,182	-7.7	24	-	38	31	1	4	1	1	-	55	9
Grassland	12,171	9.5	60	25	-	0	6	-	2	6	-	11	23
Shrubland	1,958	1.2	5	92	0	-	-	-	3		-	9	4
Sparse	-1,299	-31.7	1	2	96	-	-	-	-	1	-	1	2
Wetland	471	5.3	0	84	0	4	-	-	5		6	-	-
Settlement	394	593.5	-	-	-	-	-	-	-	-	-	-	-
Bare	-9,877	-34.7	1	0	95	0	3	-	-	-	1	11	57
Water	-15	-0.1	20	8	22	2	3	3	4	38	-	-	-

2.3.3 The LDN baseline for 2015

The statistical analysis (using Pearson's correlation coefficient at a confidence level of 95%) indicated that MODIS NPP and GIMMS NDVI were significantly correlated with a correlation coefficient of 0.85. Due to the strong positive relationship between the GIMMS NDVI and the MODIS NPP annual datasets for the period 2000-2015, we used the MODIS NPP annual data for the start of the monitoring period in 2015.

The baseline LDN for Kenya in 2015 was presented in three tables. Table 2.2 and Table 2.3 (described above) provide information, across the land cover classes and over the period 1992-2015, on land cover change, and the trends in greening and browning for the NDVI residuals. Table 2.4 shows the state of each of the 3 LDN indicators in 2015 (2000 for SOC stock) across the land cover classes. The mean MODIS NPP and the mean SOC stock computed for each land cover class, showed that agricultural and forest land have high values for both NPP and SOC. Given the central role of SOC in a range of soil functions and its known benefits to improved soil fertility and productivity (Stockmann et al., 2015), areas with high SOC denote soils of high quality and with high amounts of carbon, resulting in a high value of NPP. However, given the high amount of strong browning trends observed in settlement areas (Table 2.2), an unusual result is the high SOC and NPP values for settlement areas. Due to the limited number of soil profile data for Kenya, it is proposed that data for estimating SOC stocks should be collected at sites where specific LDN interventions are designed at the subnational level.

Table 2.4: Status of 3 LDN indicators in the baseline year (2015).

Land cover classes	Land cover area (km^2)	MODIS NPP g C/m^2	Soil organic carbon[1] (0-30cm) (ton/ha)
Agriculture	144,324	699	65.23
Forest	86,577	497	59.81
Grassland	140,446	178	33.58
Shrubland	167,942	330	45.51
Sparse	2,796	235	30.77
Wetland	9,427	405	35.88
Settlement	461	569	67.62
Bare	18,561	131	39.51
Water	12,113	-	-

Note: 1. The mean SOC stock is for the year 2000.

2.4 Discussion

The key contribution of this research was the use of long-term NDVI and land cover datasets over the 24-year period from 1992-2015 for establishing a LDN national baseline. Further, this study demonstrated that the Mann-Kendall significance test (Kendall's tau) could be used to describe quantitative classes of human-induced greening and browning NDVI trends. The following 5 quantitative classes were used to describe the degree or intensity of the human-induced greening and browning trends: strong browning (-0.4 to -0.8); moderate browning (<0 to -0.4); moderate greening (>0 to 0.4); strong greening (0.4 to 0.8); and no significant trend. By using the long term GIMMS NDVI data corresponding to the 24-year period land cover data that has recently become available, we captured significant human-induced greening and browning trends and the trajectory of land cover change, as well as the long-term association between them.

Validating the results of the current study through field studies would be challenging given the spatial and temporal extent of the analysis, and that there is no country-wide programme for the monitoring of biomass resources in Kenya. Hence we compared the results obtained in the current study with previous studies. Bai & Dent (2006), using GIMMS NDVI data for the period 1981-2003, estimated severe land degradation in 17% of the country. Severe land degradation in the Bai & Dent (2006) study was defined as those areas with both declining net primary productivity and declining rain-use efficiency. More recently, Le et al. (2016) mapped global degradation hotspots using GIMMS

NDVI data that was corrected for the effects of inter-annual rainfall variation, atmospheric fertilization and intensive use of chemical fertilizers. The Le et al. (2016) study estimated that a total of 22% of the land area in Kenya has degraded between 1982 and 2006 (Mulinge et al., 2016). The results obtained in the current study on the extent of land degradation in Kenya compare reasonably well with these two studies. In the current study, the estimation of browning trends was 21.6% for the period 1992-2015 (Figure 2.2)

In the Bai & Dent (2006) study, two areas with the sharpest decline in the combined land degradation index were the drylands around Lake Turkana and marginal croplands in the area formerly known as the Eastern Province of Kenya. For the period 1982-2011, Musau et al. (2016) investigated the spatial and temporal variations of vegetation dynamics in East Africa. Using GIMMS leaf area index time series data, strong negative trends were mainly clustered in the areas east of Lake Turkana, with weaker negative trends occurring throughout the Eastern Province. These two locations correspond to the clustering of browning trends in the current study as illustrated in Figure 2.2.

Land cover change studies in Kenya have mainly been at the sub-national scale. The FAO 2015 Global Forest Resources Assessment for Kenya (FAO, 2014) is based on land cover data derived from LANDSAT Thematic Mapper images. Between 1990 to 2000 there was a decline of forest land; however the trend reversed from 2000 to 2010 with an increase in forest area. Were et al. (2013) in their analysis of land cover dynamics over four decades (1973 to 2011) using Landsat images, revealed that the forests-shrublands land cover class decreased by 428 km^2 at the annual average rates of 1% in the Eastern Mau Forest. Mulinge et al. (2016) analysed land use and land cover change in Kenya at the national level over the period 2001 and 2009 using MODIS data. In the Mulinge et al. (2016) study, two land cover classes were used to categorise land under trees, forests and woodlands. The cumulative change under these two categories showed a decrease in tree cover. These observations were consistent with the results obtained in the current study, whereby the loss of forest land during the period 1995-2002 was followed thereafter by an increasing trend (Figure 2.5). For the period 2001 and 2009, there was a cumulative loss in forest land due to the large loss in forest land in 2001 (Figure 2.5). The Mau Forest was also identified as an area with strong browning trends in Figure 2.4.

The FAO report also provides data that shows that the area under cropland has consistently been increasing over the period 1990 to 2010 (FAO, 2014). This is in line with the results obtained in the current study where there has been a cumulative increase in agricultural land from 1992-2010 (Figure 2.5). However, in the FAO report the data provided shows that the area under grassland increased during the period 1990-2000 but has gradually been decreasing from 2000 to 2010. In the current study, there was a cumulative increase in grasslands over the periods 1992-2000 and 2000-2010 (Figure 2.5). While the land cover class categories used in the Mulinge et al. (2016) study differ from those used in the current study, the following common changes were noted when compared to land cover changes for the period 2001-2009 in the current study: the increase in croplands; the increase in grasslands; and the reduction in shrublands.

As the methodology used in the current study was based on detecting monotonic greening and browning trends, the approach used is not appropriate when there are NDVI trend changes. Abrupt NDVI negative trend changes may occur, for example, due to wildfires or diseases, while gradual changes, such as a persistent climate change due to a decrease in yearly rainfall, occur over longer periods (de Jong et al., 2013). The strengths of the Mann-Kendall (MK) non-parametric trend test are that it does not require the data to be normally distributed (de Jong et al., 2011), and that it can tolerate outliers in the data (Fensholt et al., 2012). As noted previously, the weakness of the method is that trend detection can be affected by autocorrelation in the time series (Erasmi et al., 2014). However, this limitation can be addressed by a technique known as pre-whitening (Yue et al., 2002). A further limitation on the application of the methodology used in this study pertains to the broader data challenges in relation to monitoring of the 232 indicators of the 17 SDGs (UN, 2017). Chattopadhyay (2016) describes some of these data challenges as: the paucity of data; infrequent and uneven coverage of data; lack of uniformity in rules and procedures for gathering data; and the dearth of publicly available data resources. With respect to data for calculating SOC stocks for Kenya, the specific data gaps were a lack of uniform national coverage due to the limited number of soil profiles, and the lack of trend data.

Notwithstanding the limitations discussed above, the approach used in the current study is suggested as a quantitative methodology for setting a LDN national baseline that uses long-term NDVI and land cover data. By establishing the LDN baseline for Kenya in 2015 (Table 2.2, 2.3 and 2.4), this study presents the first step to putting the LDN concept into practice. As such, the LDN concept is now operational as it provides decision makers with information on the trends in land cover change, the spatial distribution of the different degrees of human-induced browning and greening trends across land cover classes (shown for the 4 main land cover classes in Figure 2.4), as well as the association between browning and greening trends and land cover change. It is now possible for decision makers in Kenya to identify areas for priority action. Specifically, based on the results obtained, we recommend the following priority actions. First, areas with strong browning trends should be the focus of targeted actions aimed at halting the browning trends and restoring the degraded land. For example, in forested land (Figure 2.4b), strong browning trends occur in the southern part of the Mau Forest, the southern part of Mount Kenya National Park, and in parts of Mount Elgon National park. These areas are known as “water towers” as they provide most of Kenya’s renewable water resources (GoK, 2015). The rehabilitation of Kenya’s water towers is a current priority for the national government, and has been identified as one of the flagship projects under Kenya’s long-term development plan, Vision 2030. By the end of 2014, the government reported that 266 km^2 of forest land within the water towers had been reclaimed and rehabilitated (GoK, 2014). Action also needs to be taken in other strong browning areas, particularly agricultural areas and grasslands, given their importance for food and livestock production. In the strong browning areas, policy makers and affected stakeholders could assess the suitability of introducing a phased LDN scheme, focused on restoring degraded lands, improving national land use planning systems, and establishing national monitoring capacities (Grainger, 2015). An alternative (or complementary) approach would be establishing pilot projects to test the feasibility of LDN at the local community or landscape scales (Chasek et al., 2015).

Second, further investigation is needed on the areas of land cover change, and in particular, those with simultaneous browning trends. Over the 1992-2015 period, 5.6% of the land area in Kenya underwent land cover change, of which browning trends accounted for 13% of the change area. Field studies of these areas, which occur predominantly in forest land (55%), would provide information on the processes and factors driving vegetation cover changes and dynamics, to inform policy development on land management broadly, and specifically for the planning of LDN interventions. Third, as LDN implies a balance between not yet degraded and already degraded land (Kust et al., 2017), field assessments are also recommended in areas with greening trends. These targeted field level assessments (in selected browning, greening, and land cover change sites) will provide decision makers with key information on how to plan for the implementation and monitoring of LDN interventions. It is important that the field assessments in the priority sites be carried out using standardised methodologies and protocols, to enable the comparison of results across sites, and also to allow for the reliable interpretation of results, which ultimately inform planning and decision-making processes.

Fourth, investment is needed in the collection of data for the computation of SOC stocks, ensuring wide national coverage and the collection of trend data. The collection of SOC stock data would not just be for the purpose of monitoring the LDN goal of the SDGs. Keesstra et al. (2016) note the pivotal role soils play in relation to ecosystem services, and demonstrate the linkage of soil functions to several of the SDGs resulting from the important contribution that soils make to food security, human health, biodiversity preservation, water security, climate change, and land management. In this regard, Keesstra et al. (2016) advocate for the cheap and reliable monitoring of soil organic matter, as it is a key attribute of soils that positively affects most soil functions.

In the context of pursuing LDN, the identification of the important drivers of greening and browning trends, is crucial for planning appropriate sustainable land management measures aimed at reducing and preventing land degradation, and incentivizing land restoration. According to the MEA (2005), the drivers of land degradation change over time and vary by location. Previous studies suggest that multiple mechanisms have changed vegetation dynamics in Kenya. The main drivers attributed to deforestation have been intense human activity due to population growth and the resulting economic expansion, which has led to encroachment of forests for agriculture, pastures, woodfuel, and timber, with illegal settlements and excisions occurring in some protected forests (Mulinge et al., 2016; FAO, 2014; Were et al., 2013; UNEP, 2009). Marginal lands have also likely been converted to agricultural land (Mulinge et al., 2016; UNEP, 2009). Fragmentation of the rural landscape has also occurred due to the sub-division of land (Were et al., 2013; UNEP, 2009). These findings point to the complex series of driving factors influencing vegetation dynamics in Kenya. For this reason, our next research steps will focus on understanding the drivers associated with the human-induced greening and browning trends and land cover change dynamics across land cover types.

The coarse spatial resolution GIMMS NDVI data used in the current study was determined by the availability of NDVI data with the same temporal scale as the time series of the land cover maps from 1992 to 2015. While deriving significant trends from NDVI time series requires a long temporal resolution, the coarse spatial resolution the GIMMS NDVI data limits its usefulness for detailed studies (Pettorelli et al., 2005). In this regard, future studies of the complex processes underlying vegetation dynamics would benefit from moderate and moderately high resolutions of satellites such as MODIS (250m, February 2000 - to date) and LANDSAT 5/7/8 (30m, January 1984 - to date), respectively.

2.5 Conclusion

This study sought to establish a LDN national baseline based on long-term trends in GIMMS NDVI and land cover data. The LDN national baseline for Kenya over the 24-year period from 1992-2015 was characterised as follows:

- Significant (95%) trends of the NDVI residuals computed from the NDVI-soil moisture relationship over the 24-year period and corrected for autocorrelation, indicate persistent negative trends (browning) over 21.6% of the country, and persistent positive trends (greening) in 8.9% of the country. Strong browning has occurred in 11.8% of the country, with moderate browning occurring in 9.8% of the country. Strong greening has occurred in 5% of the country, with moderate greening occurring in 3.9% of the country.

- The land cover change map over the period 1992-2015 showed that for 94.4% of the area of Kenya there was no change in land cover class. In 5.6% of the area (32,400 km^2) there was a change from one land cover class to another. Pronounced changes in terms of land area were: the increase in grasslands by 12,171 km^2, the decrease of bare land by 9,877 km^2, and the decrease in forests by 7,182 km^2.
- Browning and greening trends account for 13% and 12%, respectively, of the land cover change areas.
- The mean SOC stock and the mean MODIS NPP computed for each land cover class, show that agricultural and forest land have high values for both NPP and SOC.

By establishing the LDN national baseline, the LDN concept is now operational. As a first step, targeted field level assessments, alongside the collection of data for the computation of SOC stocks, should be undertaken in selected browning, greening and land cover change sites. These field studies will provide decision makers with key information on the processes and factors driving vegetation cover changes and dynamics, to inform policy development on land management broadly, and specifically on how to plan for the implementation and monitoring of LDN interventions.

Chapter

3

AN ANALYSIS OF THE DRIVERS THAT AFFECT GREENING AND BROWNING TRENDS IN THE CONTEXT OF PURSUING LAND DEGRADATION-NEUTRALITY

Based on the published manuscript:

Gichenje H, Pinto-Correia T, Godinho S. 2019. An analysis of the drivers that affect greening and browning trends in the context of pursuing land degradation-neutrality. *Remote Sensing Applications: Society and Environment* **15**. DOI: 10.1016/j.rsase.2019.100251

Abstract

Understanding the drivers of land degradation and regeneration is crucial for planning appropriate responses within both degraded and non-degraded land. In this paper, using Kenya as the study area, we sought to identify the key drivers that affect greening and browning trends within the 4 main land cover types (agriculture, forest, grassland and shrubland) and within an area characterised by land cover change. The methodological approach used was the random forest classification algorithm, whereby the dependent variable was represented as 4 classes of NDVI greening and browning trends (strong browning, moderate browning, moderate greening, and strong greening). The explanatory variables (n = 28) were broadly grouped into 2 categories, natural and anthropogenic, and included a number of variables as proxies for broad socio-economic development. All models showed strong performance, and the mean values for accuracy and Kappa were 0.96 and 0.95, respectively. Variables that repeatedly featured as the 5 most important variables across the datasets were: travel time to an urban area, distance to towns, distance to roads, distance to rivers, slope and vulnerability to climate change impacts. When the variables were grouped by SDGs, the results obtained showed that the variables grouped under the SDGs 15 (life on land), 8 (economic growth) and 13 (climate action) cumulatively accounted for approximately 80% of the prediction of the greening and browning trends. Our results raise the following considerations to enrich on-going and future policy and planning discussions aimed at addressing land degradation-neutrality *(LDN): the implementation of LDN should be anchored on tried and tested SLM interventions; further analysis of the drivers of greening and browning trends should be undertaken at the sub-national level; integrated approaches that lead to greater alignment across multiple development priorities, including climate change, should be promoted; and targeted enforcement of environmental legislation is needed to deter processes and activities that are likely to lead to the degradation of land.*

Keywords*: drivers; land degradation-neutrality; NDVI; random forest; Kenya,*

3.1 Introduction

Land degradation is recognised as a key global and developmental priority. In 2015 the Sustainable Development Goals (SDGs) were adopted by the global community, and include a goal related to land degradation and the accompanying target to achieve a land degradation-neutral world by 2030. Specifically, target 15.3 of the SDGs states "By 2030, combat desertification, restore degraded land and soil, including land affected by desertification, drought and floods, and strive to achieve a land degradation-neutral world" (UN, 2017). One of the issues highlighted in the current discourse on the implementation of land degradation-neutrality (LDN) is the need to identify and address the key drivers of land degradation (Akhtar-Schuster et al., 2017; Chasek et al., 2015; Solomun et al., 2018). According to the Millennium Ecosystem Assessment (MEA) (2005) land degradation is caused by a combination of indirect factors (such as population pressure, socioeconomic and policy factors), as well as direct factors (such as land use patterns and practices, and climate-related processes) that change over time and vary by location. A recent review of the drivers of land degradation and the theoretical foundations behind their cause-and-effect mechanisms was undertaken by Mirzabaev et al. (2016). Thus the intent in this introduction section was not to provide and exhaustive review of the drivers, but rather to highlight, based on a review of recent literature, the context-specific nature of the drivers of land degradation.

Cowie et al. (2018), in an article that summarises the key features of the scientific conceptual framework for LDN (as developed by the Science-Policy Interface of the United Nations Convention to Combat Desertification (UNCCD)), classify the drivers of land degradation in two broad categories: natural and anthropogenic. Pulido & Bocco (2014) note that in the literature, the emphasis has been on understanding the natural drivers (such as climate, topography, and soil characteristics) and on the measurements of degradation patterns through remotely sensed data. A number of studies in arid and semi-arid regions of the world have analysed the relationship between vegetation productivity (as measured by Normalised Difference Vegetation Index (NDVI)) and climate factors (rainfall, soil moisture, temperature) (Chen et al., 2014; Eckert et al., 2015; Erasmi et al., 2014; Huang & Kong, 2016; Ibrahim et al., 2015; Vlek et al., 2010).

Climatic factors have a direct impact on biomass productivity because they determine the type and the development of natural and cropped vegetation (Leroux et al., 2017). These studies demonstrated positive relationships between NDVI and rainfall and soil moisture, with a stronger influence of soil moisture on NDVI than rainfall (Ibrahim et al., 2015), as well as a stronger influence of rainfall on NDVI than temperature (Huang & Kong, 2016).

The influence of anthropogenic factors such as population density, market access, land tenure, and poverty, on land degradation is less definitive, and depending on the context, could lead to both land improvement and land degradation (Mirzabaev et al., 2016; von Braun et al., 2013). Divergent findings have been reported in the following recent studies in which land degradation has been represented by trend analysis of NDVI data: a global study by Mirzabaev et al. (2016), a national study in Vietnam by Vu et al. (2014), and a subnational study in south-western Niger by Leroux et al. (2017). In the Leroux et al. (2017) study, the areas with increased biomass production generally occurred around villages, and close to rivers and markets. However in the Mirzabaev et al. (2016) study, the results showed that longer distance to markets positively influenced land improvement. Likewise, population density was shown to have different impacts on land degradation. In the Mirzabaev et al. (2016) study, higher population density was positively associated with land degradation in the global model, however this relationship was not statistically significant in the regional models for Sub-Saharan Africa, North America, and Europe. The results of the binary logistic regression model in the Vu et al. (2014) study also showed that population dynamics were an important factor affecting land degradation as follows: an increase in change in population density and annual growth rate of the rural population led to a reduction in the intensity of land degradation in agricultural areas; while an increase in the annual growth rate of the urban population led to a reduction in the intensity of land degradation in severely degraded areas. In the Leroux et al. (2017) study, demographic variables were not among the top 5 most important variables. Similarly confounding results were obtained for economic variables. The Mirzabaev et al. (2016) study showed that more intense night-time lights (a proxy for higher socio-economic development) was positively associated with land degradation. Further, using infant mortality rates as a proxy for poverty, an increase in this variable was positively and significantly associated with land improvement in the global, as well as in the regional model for Asia (Mirzabaev et al., 2016). In the Vu et al. (2014) study, the variable poverty was not statistically significant, while areas with increased growth of agricultural production led to less intensity of land degradation. No economic variables were used in the Leroux et al. (2017) study.

While the different methodologies and datasets used in various studies in part explain the divergent findings, it becomes evident from these findings that the drivers of land degradation are shaped by various socio-economic, institutional and technological particularities of the location (Mirzabaev et al., 2016). As highlighted above, the influence of the drivers of land degradation can vary within and between regions and countries, which underscores that land degradation is a very contextual phenomenon that cannot "be judged independently of its spatial, temporal, economic, environmental and cultural context" (Warren, 2002).

In the context of the prevailing SDG development agenda, we argue that it is important to model the SDGs as an integrated system, as these goals were envisioned as an "integrated and indivisible" balance of the three dimensions of sustainable development (i.e. environmental, economic and social) (UN, 2015). Since the SDGs were adopted, a number of studies have attempted to conceptualise the linkages between and within the SDGs. Akhtar-Schuster et al. (2017) highlight the linkages between land and biodiversity, and land and climate change, including the opportunity for advancing LDN action through adaptation approaches across the three Rio Conventions (the UNCCD, the UN Framework Convention on Climate Change (UNFCCC) and the Convention on Biological Diversity (CBD)). Further, Akhtar-Schuster et al. (2017) demonstrate that the goals related to poverty, hunger, water and sanitation, energy, and sustainable consumption and production are relevant to the sustainable management of land systems. In addition, noting that soil science is a land-related discipline, Keesstra et al. (2016) demonstrated the linkages between soil functions to several of the SDGs. Through the functions of soils and the ecosystem services that are linked to those functions, Keesstra et al. (2016) discuss the contribution that soils make to food security, human health, biodiversity preservation, water security, climate change, and land management. Recently, in the seminal assessment report on land degradation and restoration by the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES, 2018) (i.e. the intergovernmental body for biodiversity that corresponds to the IPCC (Intergovernmental Panel on Climate Change) for climate change), a number of lead experts believed that not only was addressing land degradation essential for reaching the majority of the SDGs, but that it would also deliver co-benefits for nearly all of the SDGs. Hence, our analysis included a number of variables as proxies for broad socio-economic development that represent some of the SDGs.

Using Kenya as the study area, the aim of the current paper was to identify the key drivers associated with greening and browning trends in Kenya. Kenya is a party to the UNCCD. As a tool for implementing the provisions of the convention, Kenya has prepared two National Action Programme (NAPs), in 1999 and in 2002. The most recent NAP (GoK, 2002a) identifies that the following factors have contributed to accelerating the pace of land degradation in Kenya: drought; population pressure; encroachment of rangelands; deforestation and soil erosion. Other studies have also suggested multiple mechanisms influencing vegetation dynamics in Kenya, for example: deforestation has been attributed to intense human activity due to population growth leading to the encroachment of forests for agriculture, pastures, woodfuel, and timber, with illegal settlements and excisions occurring in some protected forests (Mulinge et al., 2016; FAO, 2014; Were et al., 2013; UNEP, 2009); the conversion of marginal lands to agricultural land (Mulinge et al., 2016; UNEP, 2009); and the sub-division of land resulting in the fragmentation of the rural landscape (Were et al., 2013; UNEP, 2009).

The current study was based on the results obtained by Gichenje & Godinho (2018), in which a LDN national baseline for Kenya for the 1992-2015 period was established. The baseline LDN state was described as: the state in 2015 of each of the 3 LDN indicators (land cover change, net primary productivity, and soil organic carbon (SOC) stocks) across the main land cover classes; and the trends in GIMMS NDVI and land cover data for the 1992-2015 period. The trend analysis did not include the SOC stocks as there are no time series national estimates for this indicator in Kenya. In this regard, the specific objectives of this study were to:

i. identify and describe the drivers that affect greening and browning NDVI trends within the 4 main land cover types (agriculture, forest, grassland and shrubland), and within an area characterised by land cover change area;
ii. conceptualise the relationship between the LDN goal and the other SDGs; and
iii. discuss these findings in relation to the implications for elaborating national policies to address LDN actions in Kenya that aim at reducing and preventing land degradation, and incentivizing land restoration.

3.2 Materials and methods

3.2.1 Study area

Kenya is located on the eastern coast of the African continent and extends from 33°9′E to 41°9′E and from 4°63′N to 4°68′S and has a total area of 582,646 km^2. The results obtained by Gichenje & Godinho (2018) indicate that over the 24-year period from 1992-2015: most of the land area (69.5%) was characterised by no significant NDVI trends; persistent negative NDVI trends (browning) occurred in 21.6% of the country (with strong browning in 11.8%, and moderate browning in 9.8% of the country); and persistent positive NDVI trends (greening) occurred in 8.9% of the country (with strong greening in 5%, and moderate greening in 3.9% of the country) (Figure 3.1).

3.2.2 Data sets

The processing and analysis of the data described below were implemented in the statistical programme R (R Core Team, 2018).

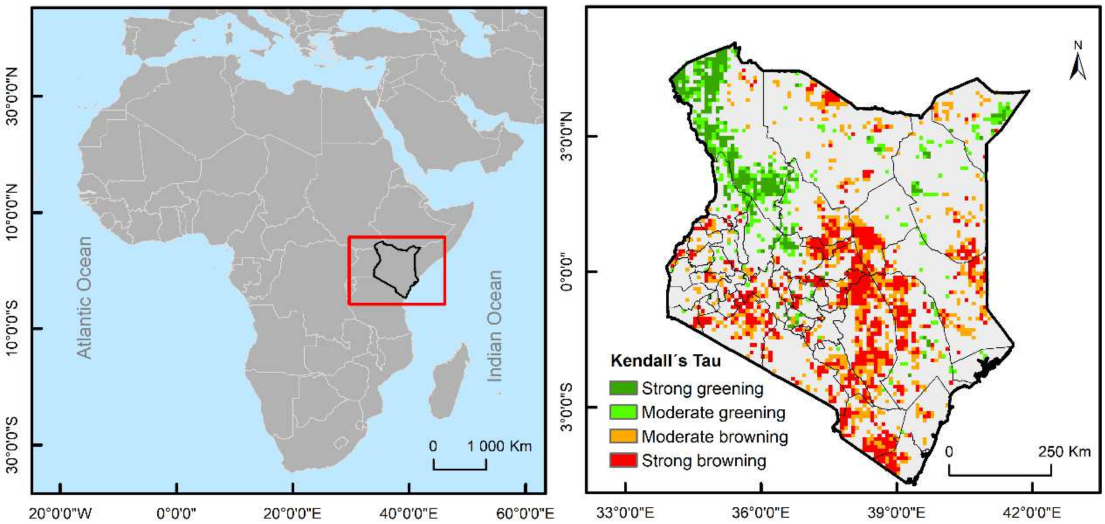

Figure 3.1: Study area with spatial pattern of greening and browning trends (Gichenje & Godinho, 2018).

<u>*Dependent variable*</u>

We used the spatial data of Kendall's tau on the Sen slope of the annual mean GIMMS NDVI time series from 1992-2015 (Gichenje & Godinho, 2018) to derive the dependent variable. The following 5 datasets at 300m resolution with greening and browning trends were used as dependent variables: agriculture, forest, grassland, shrubland, and the land cover change (LCC) area. Over the period from 1992 to 2015 agriculture, forest, grassland and shrubland accounted for approximately 90% of the land cover area in Kenya. The spatial distribution of the browning and greening trends within these four land cover classes was shown in Figure 3.2 a-d. Between the years 1992 and 2015, in 94.4% of the area of Kenya there was no change in land cover class, and in only 5.6% of the area was there a change from one land cover class to another. The spatial distribution of the browning and greening trends within the land cover change area was shown in Figure 3.2 e.

The dependent variable was represented as the following 4 classes to represent the degree or intensity of the human-induced greening and browning trends: strong browning (SB); moderate browning (MB); moderate greening (MG); and strong greening (SG). Numerically these 4 classes are represented by the following values of Kendall's tau: SB: -0.4 to -0.8; MB: <0 to >-0.4; MG >0 to <0.4; SG: 0.4 to 0.8. Of note on the use of the term human-induced was because the greening and browning trends used in this study were separated from degradation driven by climate factors using soil moisture data (Gichenje & Godinho, 2018). The share of greening and browning trends within the 5 datasets, as well as the number of observations, were presented in Table 3.1.

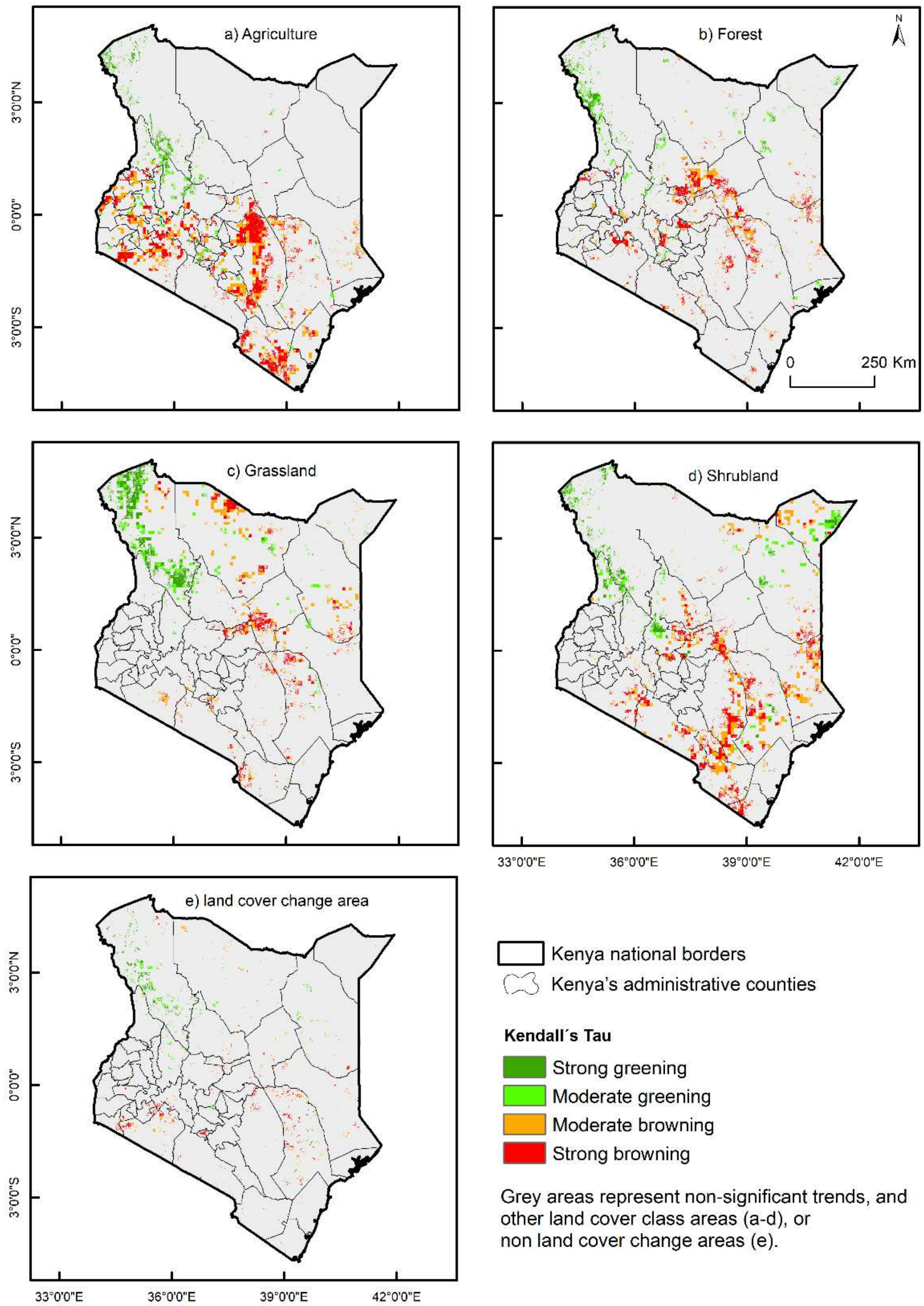

Figure 3.2: Spatial pattern of greening and browning trends within the 5 dataset areas (Gichenje and Godinho, 2018).

Table 3.1: Share of greening and browning trends within the different datasets.

NDVI trend	Agriculture	Forest	Grassland	Shrubland	LCC area
	300m resolution				
Moderate greening (MG)	8.4%	14.3%	20.1%	15.2%	22.7%
Strong greening (SG)	8.1%	12.2%	28.1%	13.0%	24.3%
Moderate browning (MB)	36.4%	29.5%	29.3%	37.8%	23.4%
Strong browning (SB)	47.1%	44.0%	22.6%	34.0%	29.7%
Total observations	494,439	256,662	338,938	441,095	80,522

Explanatory variables

Based on a review of the literature regarding the main drivers of land degradation, the selection of variables as proxies for broad socio-economic development, and the availability of data at the national scale, 28 explanatory variables were used in the analysis (Table 3.2). The explanatory variables were broadly grouped into 2 categories: natural and anthropogenic. Of particular note when selecting the explanatory variables was the issue of reverse causality between the dependent and explanatory variables raised by Mirzabaev et al. (2016), whereby, for example, poverty may lead to land degradation, but at the same time, land degradation may lead to poverty. To ensure that we assessed causal relationships, we endeavoured to use explanatory variables from as close to the start of the NDVI trend analysis (i.e. 1992).

Natural factors: Two climate-related spatial datasets, the moisture regime and the vulnerability index, were downloaded from the Food and Agriculture Organization of the United Nations (FAO) GeoNetwork site, which is an open-source portal to spatial data and information (http://www.fao.org/geonetwork/srv/en/main.home) (FAO, 2018a). These datasets have been produced under the Climate change predictions in Sub-Saharan Africa: impacts and adaptations (ClimAfrica) project, which aimed to provide a better understanding of climate change, assess its impact on African ecosystems and population, and develop the correct adaptation strategies. The moisture regime dataset was derived from a combination of soil and climatic data to indicate the agro-climatic conditions that determine the moisture regimes. The moisture regime for Kenya for the 30-year reference period from 1991 to 2020 at a spatial resolution of 10km was used in this study. The country is classified into 5 distinct moisture zones (desert, dry, moist, sub-humid, and humid). The second spatial dataset, the vulnerability index (30 arc/sec spatial resolution), indicates the level of vulnerability to climate change impacts in 2010, computed from indexes representing exposure, sensitivity and adaptive capacity to climate change.

Slope was computed from elevation data that was obtained from Google Earth Engine (GEE), which is a cloud-computing platform for processing satellite images and other Earth observation data. The Shuttle Radar Topography Mission (SRTM) digital elevation data for 2000, with a resolution of 90m at the equator (Jarvis et al., 2008), was cropped to the extent of the study area, and downloaded from GEE. The elevation layer (in meters) was then used to compute the slope layer (in degrees). Landform vector data for Kenya, computed using LANDSAT TM images acquired mainly in 1997, was downloaded from the FAO GeoNetwork site. Soil type (based on the World Reference Base soil classification system) and soil depth (depth to bedrock up to 200cm) spatial data at 250m resolution were obtained from SoilGrids250m (ftp://ftp.soilgrids.org/data/recent/) (Hengl et al., 2017). The global layers were cropped to the extent of the study area.

Anthropogenic factors: The agriculture sector is a major contributor to the Kenyan economy. In 2015, the agriculture sector grew by 5.6% and accounted for about 30% of GDP (KIPPRA, 2016). Maize is the most important food crop in Kenya (GoK, 2015a). To represent the economic driver of land degradation (and regeneration) we used the following variables related to the agricultural sector. Based on a study conducted by the FAO, vector data for maize yields (production per area cultivated) over the period 1986-1990 was downloaded from the Intergovernmental Authority on Development (IGAD) Climate Prediction and Applications Centre (ICPAC) GeoPortal (http://geoportal.icpac.net/layers/geonode%3Aken_maize_production) (ICPAC, 2018). The proportion of low potential agricultural land (annual rainfall of 612.5 mm or less) in 1994 was obtained as tabular data from a statistical report published by the Kenya National Bureau of Statistics (https://www.knbs.or.ke/) (GoK, 1994a). Tabular data for the proportion of parcels using fertilizer in 2006 was obtained from the Kenya Data Portal (http://kenya.opendataforafrica.org) (GoK, 2018). The Kenya Data Portal provides public datasets for free in easy reusable formats. The cattle density in 2009 was computed from the 2009 cattle population census tabular data obtained from the FAO CountrySTAT site for Kenya (https://countrystat.org/home.aspx?c=KEN&tr=134) (FAO, 2018b).

Vector data on the rivers, roads, and towns in Kenya were downloaded from the FAO GeoNetwork site. The rivers and roads data were derived using LANDSAT TM images (Bands 4,3,2) acquired mainly in the year 1995. The towns data included a total of 143 towns (29 major towns and 114 other towns). The nearest distance (in km) from each cell in the study area to the rivers, roads and towns was computed. In addition, spatial data of the travel time (spatial resolution of 1km) in hours by vehicle to an urban area with a population density of more than 2,500 people per km^2, computed using the accessibility surface of Kenya, was downloaded from the International Livestock Research Institute GIS services site (http://192.156.137.110/gis/search.asp?id=380) (ILRI, 2007). To represent a form of land zoning (Geist & Lambin, 2004), we used the variable on protected areas in Kenya in 2006, which was downloaded as vector data from the World Conservation Union site (http://www.wri.org/resources/data-sets/kenya-gis-data) (IUCN et al., 2006). As protected areas are designated areas in which particular legal restrictions and other requirements apply to regulate land use, this variable was used to capture the impact of policy and institutional conditions.

A number of variables were used as proxies for broad socio-economic development. Remotely sensed night-time lights for 1992 and 2013 at a resolution of 30 arc second grids was downloaded from the National Oceanic and Atmospheric Administration (NOAA) Defense Meteorological Program (https://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html) (NOAA, 2018). These layers were used to create the night-time lights for 1992 and the night-time lights difference between 1992 and 2013. The two spatial layers were cropped to the extent of the study area. Tabular data for the following variables were obtained from various statistical reports published by the Kenya National Bureau of Statistics: population density in 1989; population density growth between 1989 and 2015; primary school enrolment in 1992; primary school enrolment growth between 1992 and 2015; under-five mortality rate in 1993; access by households to piped water, electricity and the main sewer in 1999 (GoK, 2017; GoK, 2016a;

GoK, 2002b; GoK, 1994a; GoK, 1994b;). Additional tabular data for the following variables were obtained from the first United Nations Development Programme (UNDP) national human development report for Kenya (http://hdr.undp.org/sites/default/files/kenya_1999_en.pdf): annual per capita income in 1994; under weight children in 1994; and the gender development index in 1999 (UNDP, 1999).

The tabular and vector data were rasterized using a raster of Kenya's administrative counties. All the layers were projected to the WGS84 coordination system and were resampled using the nearest neighbour algorithm to 300m. A description of all the variables used in the analysis was provided in Table 3.2. The last column of Table 3.2 denotes the SDG the variable most closely represents. As noted above, given the importance of the agricultural sector to the economy in Kenya, we categorised the variables maize yields, fertilizer use and cattle density under SDG 8 on economic growth. In addition, the variables distance to roads, distance to towns, and travel time were also categorised under SDG 8 as they represent accessibility to markets both for the inputs and outputs of agricultural production. The two population variables (population density and population density growth) were assigned NA as they do not characterise any particular SDG goal. The variables used in this analysis represent 10 of the 16 substantive SDGs.

Table 3.2: Description of variables.

Variable name	Description	Source of data	Resolution	SDG
A. Dependent variable: *human-induced land degradation over the 24-year period from 1992-2015 for:*				
i) 5 datasets: agriculture, forest, grassland, shrubland and the LCC area	A categorical variable with 4 classes to represent the degree of land degradation: strong browning; moderate browning; moderate greening; and strong greening.	Gichenje & Godinho (2018)	300m	15
B. Explanatory variables[1]				
Natural				
1. Zone (1991 to 2020)	A categorical variable with 5 categories of moisture zones: desert, dry, moist, sub-humid, and humid.	FAO GeoNetwork	10km	13
2. Vulnerability (2010)	Represents the level of vulnerability to climate change impacts.		30 arc/sec	13
3. Slope (2000)	Slope computed in degrees.	Google Earth Engine	90m	15
4. LandForm (1997)	A categorical variable with 15 categories: mountains; hills and mountain footridges; plateaux; escarpments; volcanic shield and volcanic craters; plain; footslope; valley; complex landform; depression; alluvial plain; fan; delta plain and/or coastal plain; badland; and water body.	FAO GeoNetwork	vector	15
5. SoilType (1972-2011)	Type of soil based on World Reference Base (WRB) international standard for soil classification system.	SoilGrids250m[2]	250m	15
6. SoilDepth (1972-2011)	Depth of soil profile from the top to parent material or bedrock.	SoilGrids250m	250m	15
Anthropogenic				
7. MaizeYield (1986-1990)	Maize yields (kg/ha) as a ratio of total production in kg and hectares cultivated.	ICPAC GeoPortal	vector	8

[1] The explanatory variables are abbreviated according to the variable names used in the variable importance plots (Figure 3.4, 3.6, 3.8, 3.10, 3.12).
[2] SoilGrids250m includes soil data obtained from numerous soil profile datasets, including the Africa Soil Profiles Database (AfSP). The AfSP contains 591 soil profiles for Kenya, which have been collected from 1972 to 2011 (Leenaars et al., 2014).

Variable name	Description	Source of data	Resolution	SDG
8. LowAgric (1994)	Proportion (%) of low potential agricultural land per land area.	Statistical Abstract 1994 (GoK, 1994a);	tabular	2
9. Fertilizer (2006)	Proportion (%) of land units in which fertiliser is used.	Kenya Data Portal	tabular	8
10. CattleDen (2009)	Cattle density (cattle per km^2) based on the cattle population census of 2009.	FAO CountrySTAT	tabular	8
11. DistRiver (1995)	The nearest distance to a river (km).	FAO GeoNetwork	vector	15
12. DistRoad (1995)	The nearest distance to a road (km).		vector	8
13. DistTown(2002)	The nearest distance to a town (km).		vector	8
14. Travel (2007)	The time in hours to an urban area with a population density of more than 2,500 people per km^2.	ILRI GIS services	1km	8
15. Protected (2006)	A categorical variable with 2 categories: protected, and not protected.	IUCN	vector	15
16. NightLight (1992)	Average visible, stable, cloud free night-time lights in 1992.	NOAA	30 arc/sec	7
17. NightLightDiff (1992-2013)	Difference in the night-time lights between 1992 and 2013.		30 arc/sec	7
18. PopDen (1989)	Population density (persons per km^2) based on the population census of 1989.	Statistical Abstract 1994 (GoK, 1994a); Statistical Abstract 2016 (GoK, 2016a)	tabular	NA
19. PopDenGrow (1989-2015)	Growth in population density between 1989 and 2015.		tabular	NA
20. Income (1994)	Annual per capita income (1,000's of Kenya shillings).	Kenya National Human Development Report 1999 (UNDP, 1999)	tabular	1
21. Gender (1999)	The gender disparity index measures gender disparities based on three components: longevity, educational attainment and standard of living.		tabular	5
22. UnderWt (1994)	Proportion (%) of underweight children 6 to 60 months of age who are below 2 standard deviations from the median weight-for-age of the reference population.		tabular	2
23. Mortality (1993)	Probability (%) of a child dying between birth and the fifth birthday, per 1,000 live births.	Kenya Demographic and Health Survey 1993 (GoK, 1994b)	tabular	3

Variable name	Description	Source of data	Resolution	SDG
24. PrimEduc (1992)	Total number of children (1,000's) of primary school age enrolled in primary school.	Statistical Abstract 1994; Statistical Abstract 2017 (GoK, 2017)	tabular	4
25. PrimEducGrow (1992-2015)	Growth in primary school enrolments between 1992 and 2015.		tabular	4
26. Electricity (1999)	Proportion (%) of households in which the main type of lighting is electricity.	Kenya 1999 Population and Housing Census (GoK, 2002b)	tabular	7
27. PipedWater (1999)	Proportion (%) of households with access to piped water.		tabular	6
28. Sewer (1999)	Proportion (%) of households in which the main type of human waste disposal is the main sewer.		tabular	6

3.2.3 Methods

As the relationship between land degradation and its drivers can be non-linear (Reynolds et al., 2011), the methodological approach used in the current study was based on machine learning. Machine learning consists of the ability of computers to learn without being explicitly programmed. The efficiency of machine learning modelling methods has resulted in their extensive application in earth sciences (land, ocean and atmosphere) (Lary et al., 2016). Machine learning is a system of techniques and algorithms used for the analysis of classification (for a categorical dependent variable) and regression (for a quantitative dependent variable) problems. The methodological approach used in this study was the random forest (RF) algorithm implemented using the randomForest package in R (Liaw & Wiener, 2002). The RF approach, proposed by Breiman (2001), involves the use of a large number of decision trees, i.e. a "forest." The "random" component of the RF approach is whereby the algorithm does not give each tree all the data; rather a random set of variables and random samples of observations are used with replacement (known as bootstrapping). Data not included are described as out-of-bag (OOB) data (Breiman, 2001). The trees are then aggregated and the final prediction is the average prediction over all of the trees. RF was chosen for this study to solve a classification problem, because of the strengths of the RF classifier in handling multisource data and multicollinearity, requiring very few parameters to be set, robustness to overfitting (as it builds a large collection of de-correlated trees), and in the processing speed (Belgiu & Drăguţ, 2016).

To study the relationship between the drivers that affect greening and browning NDVI trends, a statistical approach based on two main steps was used. The flowchart of the methodology used in the analysis was illustrated in Figure 3.3. Given the large number of explanatory variables (and in particular the proxies for socio-economic development, variables 16-28 in Table 3.2), the first step consisted of selecting the most important variables. For this step, we used the Boruta package in R that is built around the RF algorithm (Kursa & Rudnicki, 2010). Using the datasets for each of the 4 main land cover types and the LCC area (i.e. 300m resolution, 4 classes of greening and browning trends, 28 explanatory variables), we specified for the Boruta analysis the number of trees (ntree = 1000) and the number of iterations (maxRuns = 1000). In the subsequent step, only the explanatory variables confirmed as important from the Boruta procedure were used in the analysis.

The second step consisted of running the RF analysis using each of the 5 datasets. To avoid relying on the ranking of the important variables from a single RF classification, we replicated the classifications 100 times so as to improve the classification diagnostics and performance (Millard & Richardson, 2015). We split the dataset into a training set (80%), and a test set (20%). The largest split was used for training the model, while the test set was used to score the model. The two key parameters to be tuned in the RF model were specified as follows: the number of trees (ntree = 1000); and the default value for a classification problem for the number of variables randomly sampled (i.e. mtry = √(number of variables)) was retained. Other parameters to run the RF model were: the retained explanatory variables, x; the dependent variable, y; and the training data, train. For the 4 land cover datasets, browning trends account for a much larger share of the greening and browning trends (Table 3.1). For consistency in the methodology, for each of the 5 datasets, we randomly created 10 balanced datasets which were run 10 times (i.e. 100 classifications) using different randomly generated train and test data.

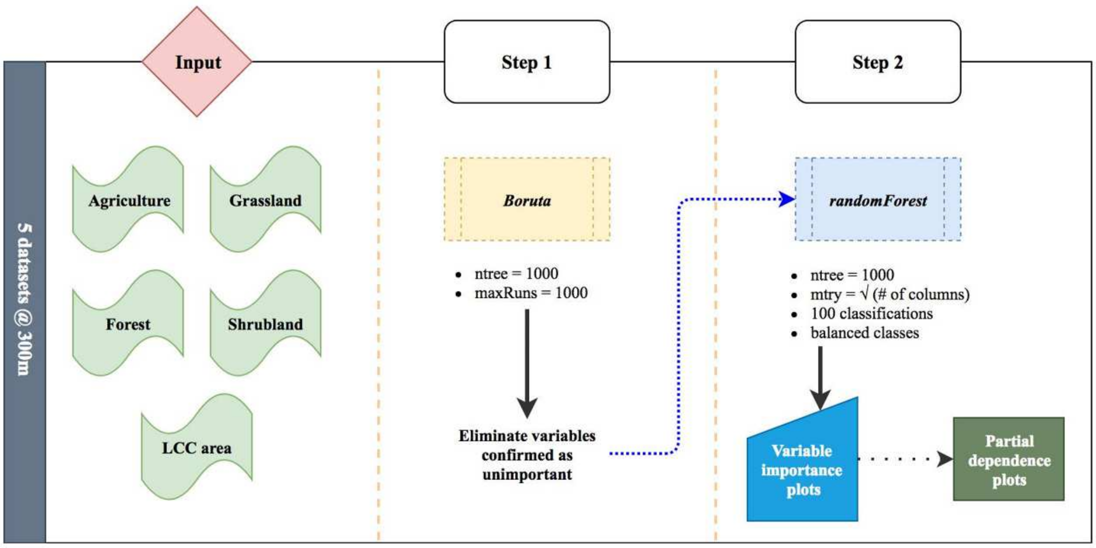

Figure 3.3: Flowchart of the methodology.

A key output from the second step of the analysis was the variable importance measure. In this study, we used the mean decrease in accuracy (MDA), which is computed using the OOB portion of the data, and is the normalised difference of the classification accuracies obtained when the values of the variable are randomly permuted (or excluded) compared to the original observations (Liaw & Wiener, 2002). The variable importance plots were derived from the mean of the 100 classifications. High MDA values indicate that the variables are important for the classification of the data. To conceptualise the linkages between the LDN goal and the other SDG goals, we computed the relative importance of each explanatory variable by calculating the weight of each explanatory variable against the sum of the MDA for all variables. We then summed the relative importance for each variable by SDG group and plotted the relative importance by SDGs across the 5 datasets. We also grouped the explanatory variables into the 2 categories described in Table 3.2 (natural, and anthropogenic), as well as by environmental vs. socio-economic factors, and derived the relative importance per group. For the latter grouping of variables, all variables under SDGs 15 (life on land), 13 (climate action) and 6 (water and sanitation) were grouped under environment, and the remaining under socio-economic.

We produced partial dependence plots (PDP) (Friedman, 2001) for the most important variables from the RF models. The PDP plots were produced from the best performing model (highest accuracy) of the 100 classifications, and using the *pdp* package in R (Greenwell, 2017). These plots illustrate the marginal effect between a specific individual variable and the different degrees of greening and browning trends, while accounting for the averaged effects of the other variables. The following two performance metrics from step 2 were computed using the prediction of the test data and the confusion matrix from the caret package in R (Kuhn, 2017): accuracy, which is the ratio of the total number of correctly classified cases to the total number of cases; and Kappa, which can be interpreted as the amount of accuracy generated by chance. A value of 1 for these performance metrics indicates a perfect classification. The accuracy and Kappa metrics were derived from the mean of the 100 classifications.

3.3 Results

3.3.1 Variable selection

None of the 28 explanatory variables were rejected from the Boruta procedure. Hence all 28 variables were used in the RF analysis.

3.3.2 Drivers that affect greening and browning trends

All RF models showed strong performance, and the mean values for accuracy and Kappa were provided in Table 3.3. The VI plots for the 5 datasets were derived from the mean of the 100 classifications. As depicted across the VI plots (Figure 3.4, 3.6, 3.8, 3.10, 3.12), there were a number of variables that repeatedly featured as the 5 most important variables across the different datasets. These were distance to rivers, distance to towns, distance to roads, travel time to an urban area, slope and vulnerability. The other key feature across the VI plots was that there were two tiers of variables. The first tier were those variables with a MDA greater than the mean MDA (illustrated in Figure 3.4, 3.6, 3.8, 3.10, 3.12 as the vertical red dashed line), and the second tier were those variables with a MDA less than the mean MDA. The first tier of variables were made up of all the natural variables (as categorised in Table 3.2) (except for soil depth in the VI plots for agriculture, forest, shrubland and the LCC areas), as well as the variables distance to roads, towns, and rivers, travel time, and protected areas.

Table 3.3: Mean performance metrics from 100 RF iterations for the different datasets.

Metric	Agriculture	Forest	Grassland	Shrubland	LCC area
Accuracy	0.9546	0.9640	0.9592	0.9498	0.9730
Kappa	0.9395	0.9520	0.9456	0.9330	0.9640

Using the best model from the 100 iterations for each dataset, we first produced partial dependence plots (PDPs) for the 3 most important variables from the overall VI plot to graphically characterise the relationship between each variable and the different greening and browning trends (MG, SG, MB, and SB). For the most part, these PDPs showed highly variable patterns, and were limited in explaining the relationship between the main explanatory variables and the different greening and browning trends (Appendix A includes the PDPs for the top variable across the 5 datasets for the 4 classes of trends). In light of this limitation, we produced the PDPs by merging MG and SG into one class greening, and MB and SB were merged into the class browning.

To provide an interpretation of the PDPs it is important to note the following. First, it is the trend or shape of the PDPs, rather than the actual values, that describe the relationship between the explanatory and dependent variables (Sankaran et al., 2008). Further, horizontal lines in the PDPs indicate areas where the explanatory variable has no effect on the prediction of the greening or browning trends. Second, to avoid drawing conclusions from the PDPs in regions with almost no data, it is important to show a rug (display of the distribution (as well as the minimum and maximum values) for the explanatory variable on the horizontal axis). Third, the vertical axis of each plot was provided on the same scale (i.e., the default logit scale which shows the log of the predicted probabilities, and is expressed as ŷ). Fourth, as the PDPs are centered on zero, when there are two classes, one PDP will be the mirror image of the other, (Berk, 2008). Hence, only one of the two plots is required for interpretation. Below a description is provided of the PDP of the greening trend.

In agriculture areas, from the VI plot (Figure 3.4), the 3 most important variables were distance to rivers, distance to towns, and slope. Greening trends increased with increases in the distance to rivers until ~25 km, with no dependence above ~25 km (Figure 3.5a). There was a general positive relationship between distance to towns and greening trends (Figure 3.5c). When distance to towns was greater than ~125 km there was no dependence with greening trends. At very low slopes the relationship with greening trends was as negative (Figure 3.5e). As slope increased, there was a marked increase in greening trends, followed by variable patterns at higher and more infrequent slopes.

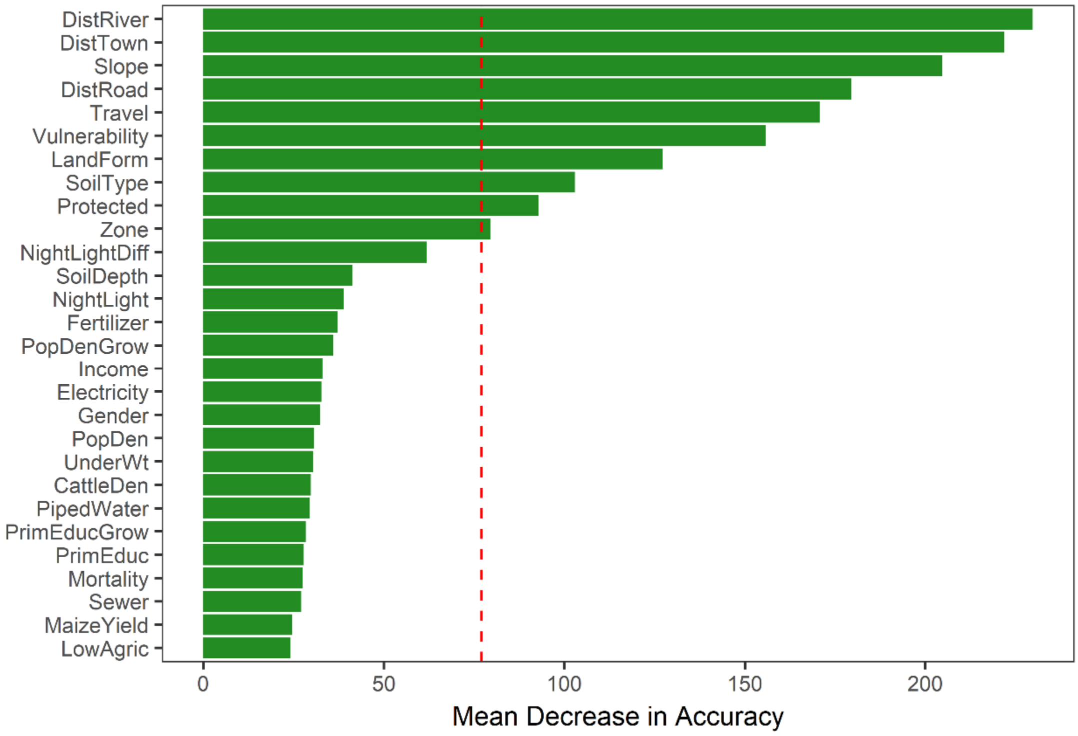

Figure 3.4: Variable importance (VI) plot for agriculture areas (the mean MDA is represented by the vertical red dashed line).

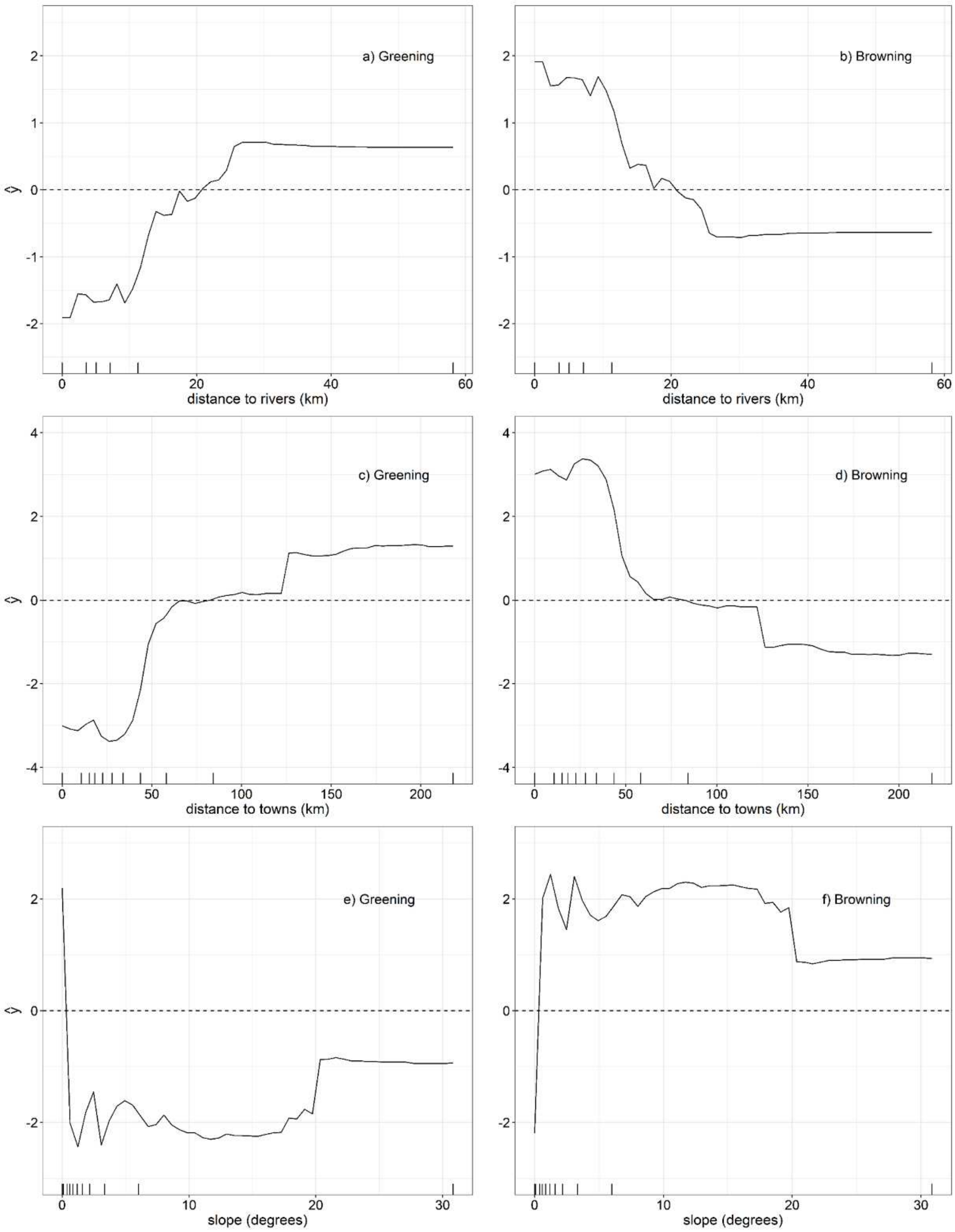

Figure 3.5: Partial dependence plots (PDPs) for agriculture areas.

In forest areas, the 3 most important variables were travel time, distance to towns, and slope (Figure 3.6). At low travel times (less than ~3 hours) and at short distance to towns (less than ~40 km) there was a negative relationship with greening trends (Figure 3.7a, c). As travel time increased, there was a marked increase in greening trends, followed by variable patterns at longer travel times (above ~8 hours) (Figure 3.7a). As distance to towns increased (above ~40 km) there was a general positive relationship with greening trends, (Figure 3.7c). At very low slopes the relationship with greening trends was as negative (Figure 3.7e). As slope increased, there was a general positive relationship with greening trends.

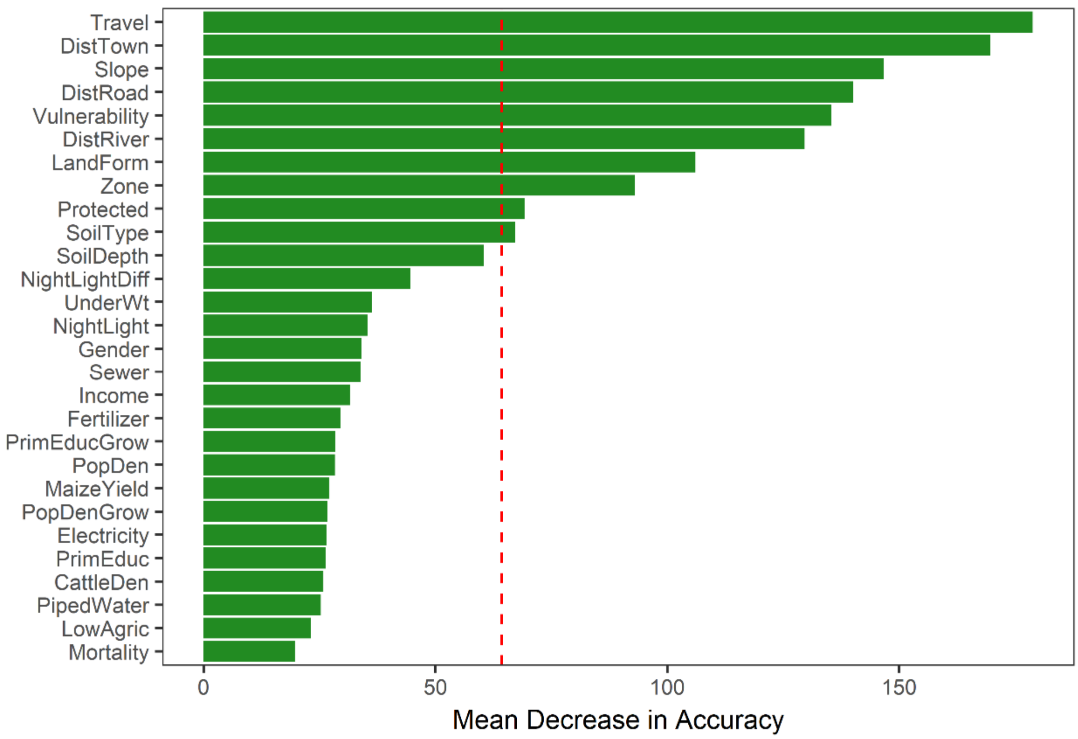

Figure 3.6: VI plot for forest areas (the mean MDA is represented by the vertical red dashed line).

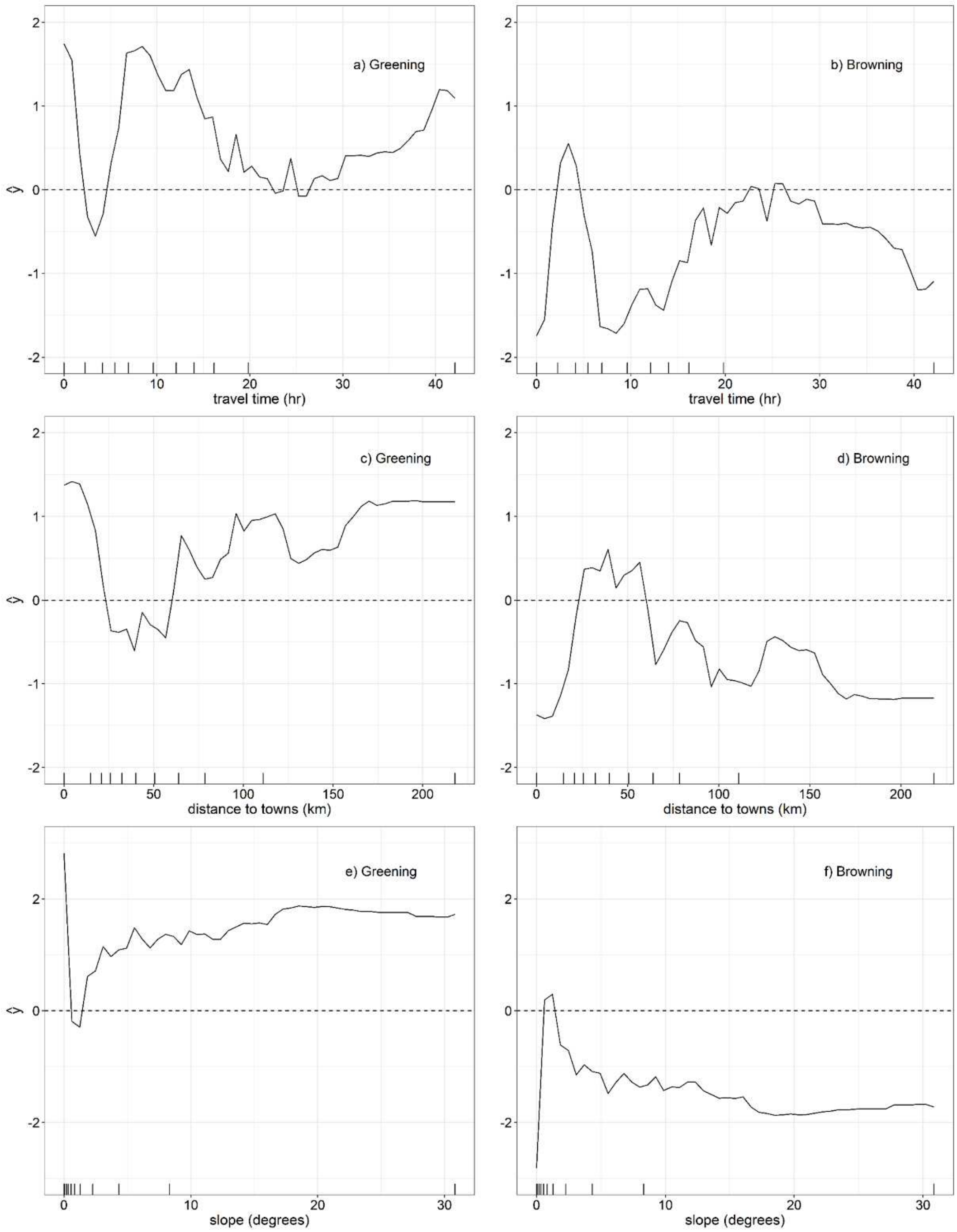

Figure 3.7: PDPs for forest areas.

In grasslands the 3 most important variables were distance to towns, distance to roads, and travel time (Figure 3.8). At various thresholds, distance to towns (Figure 3.9a), and travel time (Figure 3.9e) had both positive and negative influences on greening trends. At short distance to towns (less than ~20 km) and at low travel times (less than ~2 hours), there was a negative relationship with greening trends. While at long distance to towns (above ~80 km) and at long travel times (above ~15 hours), there was a general positive relationship with greening trends. When the distance to roads was less than ~60 km, there was a positive association with greening trends (Figure 3.9c). When distance to roads was more than ~60 km, greening trends decreased.

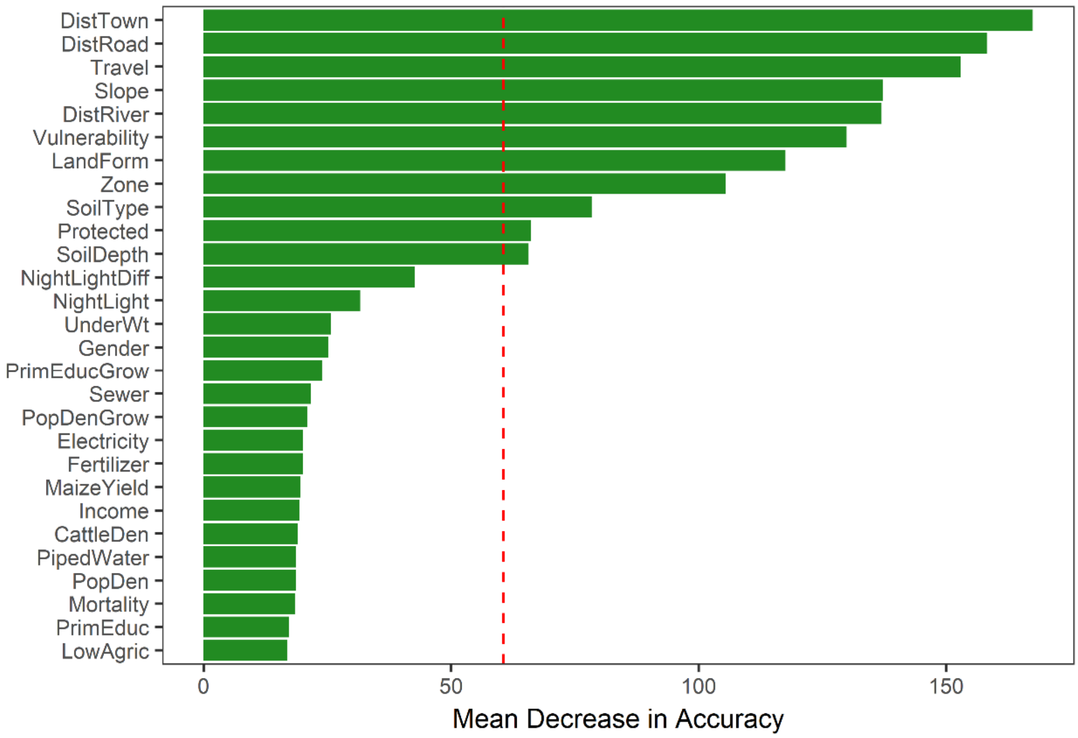

Figure 3.8: VI plot for grasslands (the mean MDA is represented by the vertical red dashed line).

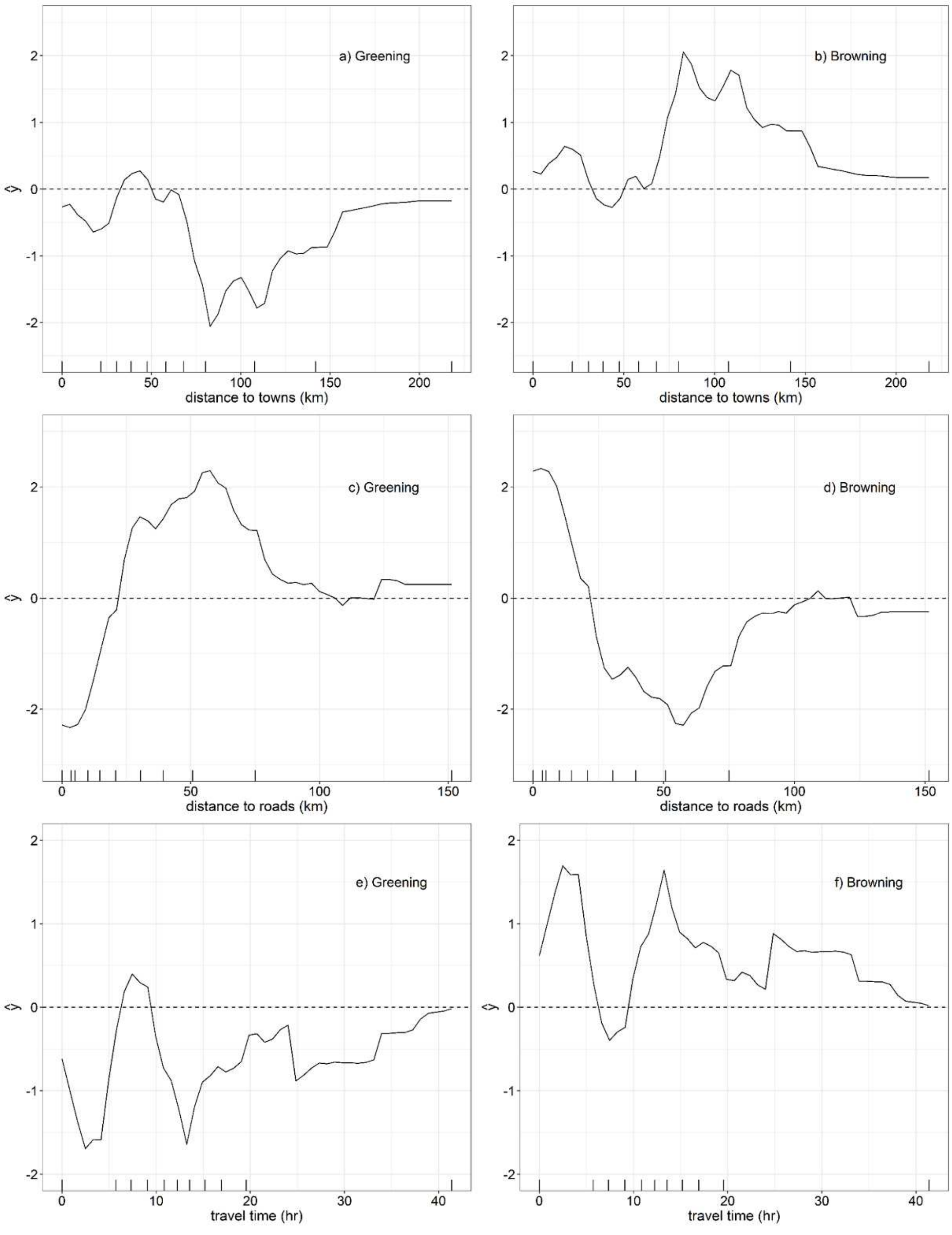

Figure 3.9: PDPs for grasslands.

The 3 most important variables for shrublands were distance to roads, distance to towns, and slope (Figure 3.10). When the distance to roads was less than ~50 km, there was a positive association with greening trends (Figure 3.11a). When distance to roads was more than ~50 km, there was little to no dependence with greening trends. At various thresholds, distance to towns had both positive and negative influences on greening trends (Figure 3.11c). At short distance to towns (less than ~10 km), there was a negative relationship with greening trends. When distance to towns were between ~10 - 75 km, greening trends sharply increased, then decreased. While at long distance to towns (above ~75 km), there was a general positive relationship with greening trends. At very low slopes the relationship with greening trends was as negative (Figure 3.11e). As slope increased, there was a general positive relationship with greening trends.

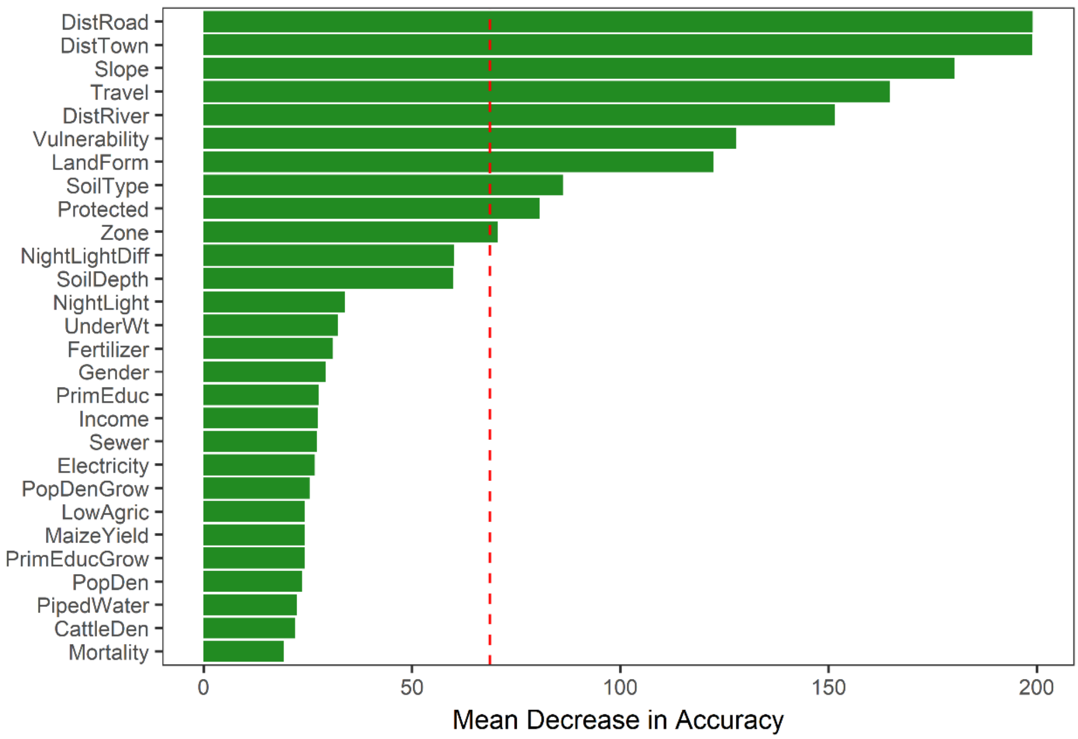

Figure 3.10: VI plot for shrublands (the mean MDA is represented by the vertical red dashed line).

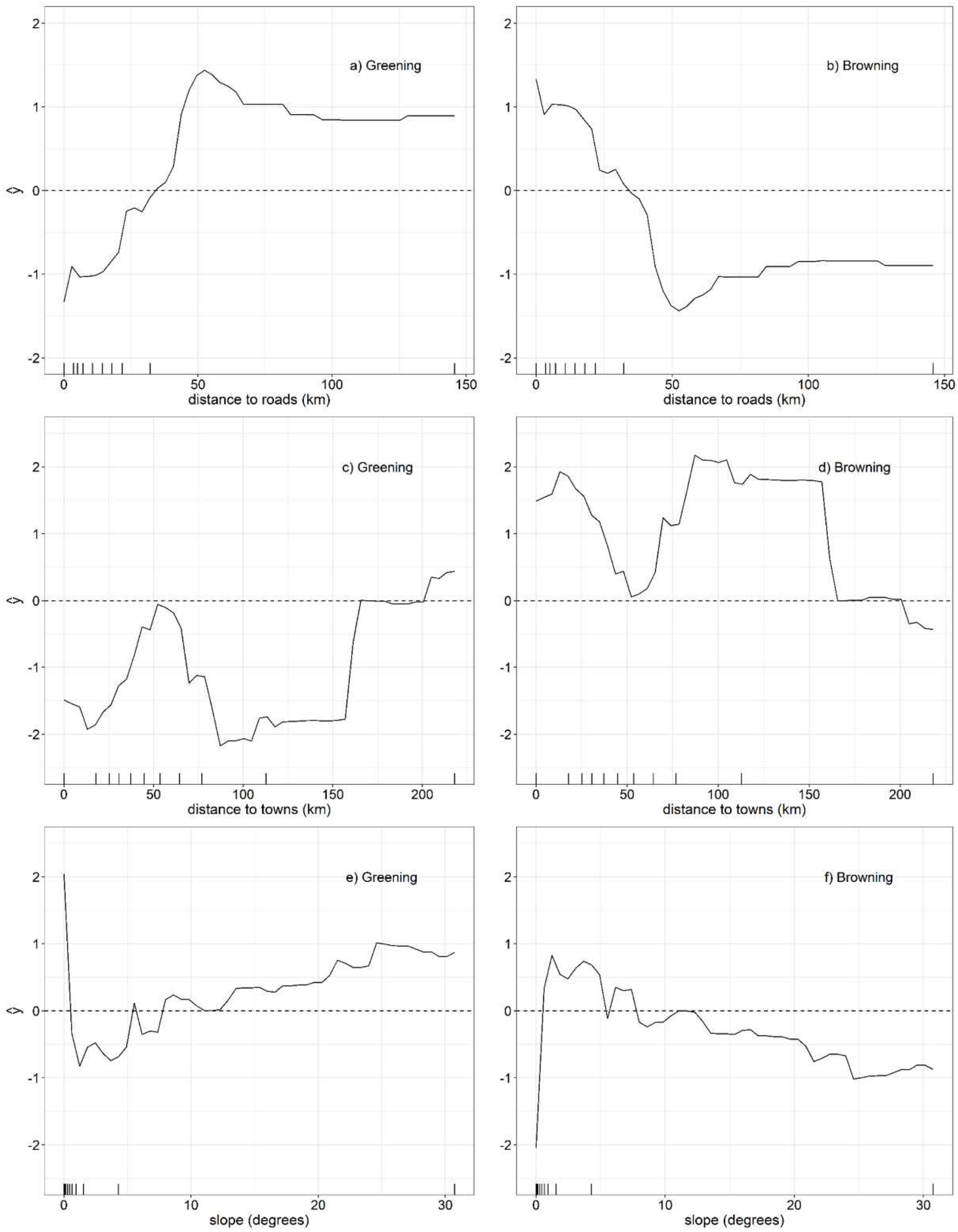

Figure 3.11: PDPs for shrublands.

The VI plot for the land cover change area (Figure 3.12) showed that the 3 most important variables were distance to towns, distance to rivers, and travel time. At short distance to towns (less than ~25 km), there was a negative relationship with greening trends (Figure 3.13 a). Greening trends generally increased with increases in the distance to towns between ~25 - 50 km, and thereafter decreased. When the distance to rivers was less than ~20 km, there was a positive association with greening trends (Figure 3.13c). When distance to rivers was more than ~20 km, there was little to no dependence with greening trends. At low travel times (less than ~3 hours), there was a negative relationship with greening trends (Figure 3.13 a). When travel times were between ~3 - 14 hours, greening trends sharply increased, then decreased.

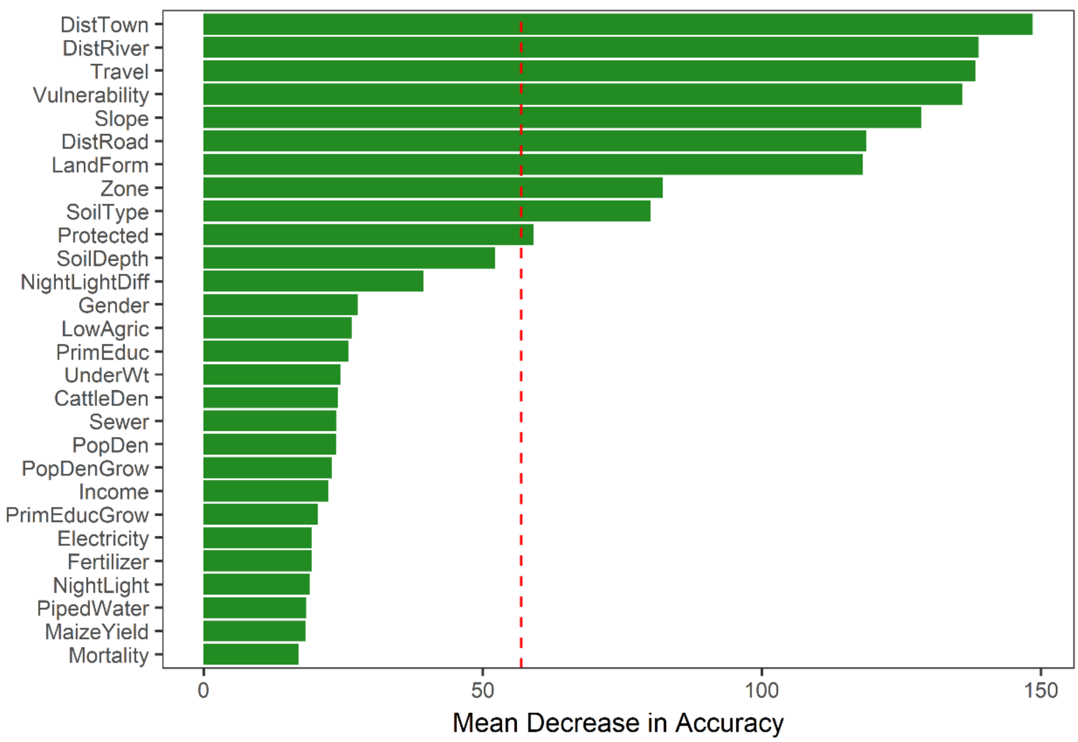

Figure 3.12: VI plot for the land cover change area (the mean MDA is represented by the vertical red dashed line).

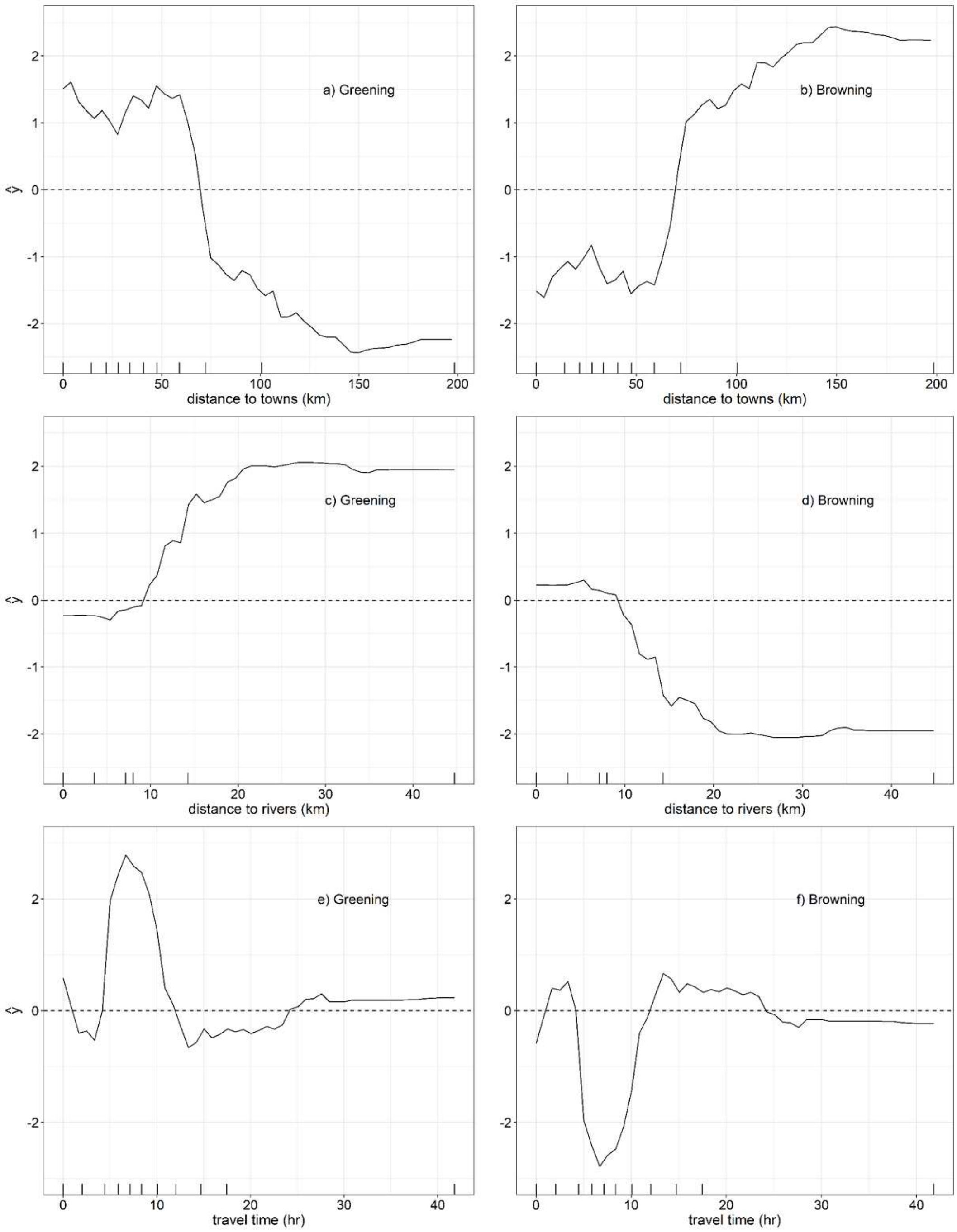

Figure 3.13: PDPs for the land cover change area.

3.3.3 Grouping of variables

When the variables were grouped by SDGs, the results obtained across the datasets showed that the variables grouped under the SDGs 15 (life on land), 8 (economic growth) and 13 (climate action) cumulatively accounted for approximately 80% of the prediction of the greening and browning trends (Figure 3.14). When the variables were grouped by natural vs. anthropogenic factors, the results obtained across the datasets showed that natural factors accounted for approximately a third of the prediction of the greening and browning trends. When the variables were grouped by environmental vs. socio-economic factors, each of the groups accounted for approximately 50% of the prediction of the greening and browning trends.

3.4 Discussion

3.4.1 Drivers that affect greening and browning trends

The results obtained in this study provided us with an understanding of the drivers of greening and browning trends across the 4 main land cover areas (agriculture, forest, grassland and shrubland) and within the area characterised by land cover change. Across the 5 datasets used in the analysis, the variables that repeatedly featured as the 5 most important variables were: travel time to an urban area, distance to towns, distance to roads, distance to rivers, slope and vulnerability to climate change impacts. These variables represent the specific conditions with respect to access to markets and the environment, and coincide with the most important variables identified in the RF analysis in the Leroux et al. (2017) study. While previous studies undertaken in Kenya (see Introduction section) attest to anthropogenic drivers of vegetation changes and specifically refer to the influence of population pressure, in the current study the two population variables used did not feature amongst the most important drivers.

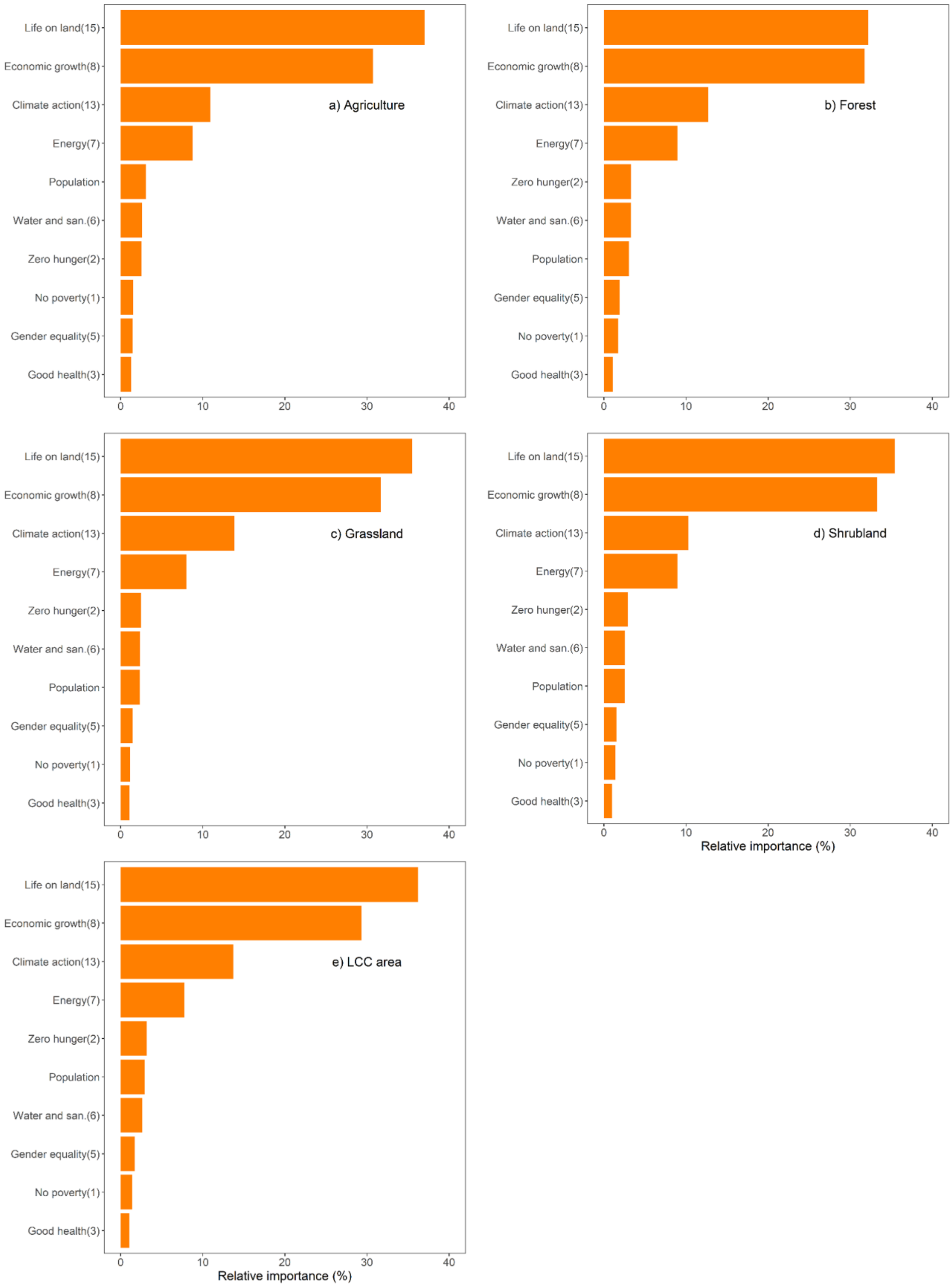

Figure 3.14: Relative importance by SDGs across the 5 datasets.

A key output of the analysis was the graphical representation using the PDPs of the relationship between the explanatory variables and the greening and browning trends. When the PDPs were illustrated with the different classes of greening and browning trends (MG, SG, MB, and SB), the PDPs showed highly variable patterns (Appendix A). To improve on the interpretability, the PDPs were then generated as a binary case, i.e. by modeling land degradation (browning) and restoration (greening) as a binomial phenomenon as manifested in nature. As illustrated (Figure 3.5, 3.7, 3.9, 3.11, 3.13) for each explanatory variable, the greening PDP was the mirror image of the browning PDP. While the PDPs were used to illustrate the influence of one variable on the greening and browning trends (while accounting for the averaged effects of the other variables), in reality land degradation and restoration are complex phenomena influenced by multiple interacting processes (IPBES, 2018; MEA, 2005; Mirzabaev et al., 2016). Hence it is important to keep in mind that PDPs are based on the assumption that the explanatory variable for which the PDP is computed is not correlated with other explanatory variables (Molnar, 2019), and that in the presence of substantial interactions PDPs can be misleading (Goldstein et al., 2015). Notwithstanding, these graphical illustrations can be a powerful and simple tool that can be used to facilitate greater knowledge exchange between and within a diverse group of stakeholders (researchers, policy makers, community leaders, farmers, etc.), hence enriching the debate that informs decision-making and policy for addressing LDN (Stringer & Dougill, 2013).

The most important anthropogenic variables identified in the current study, i.e. distance to roads, distance to towns, and travel time, not only represent accessibility to markets both for the inputs and outputs of agricultural production, but also access to alternative income opportunities for households to pursue. These variables express the remoteness or proximity of households to markets. Mirzabaev et al. (2016) in their review of the causality associated with drivers representing market access, indicate that this variable could have diverging consequences on land degradation in different contexts: e.g. in some cases land users with good market access have more incentives to invest in sustainable land management; while in other cases the high market access raises opportunity cost of labour, making households less likely to adopt labour-intensive sustainable land management practices. A few generalised interpretations from the PDPs can be provided as follows. In agriculture areas, the PDPs indicate that with increasing distances to towns, regeneration was more likely (Figure 3.5a). In Kenya, farming is predominantly (75%) carried out on small scale holdings (GoK, 2017). The relationship portrayed in the agriculture PDPs for the variable distance to towns (Figure 3.5c, d) implies that smallholders closer to towns are not sufficiently investing in land management practices that enhance the regeneration of land and/or mitigate against land degradation. In grasslands and shrublands, the PDPs indicate that with increasing distances to roads, regeneration was more likely (Figure 3.9c; and Figure 3.11a), implying that grasslands and shrublands are exploited less sustainably when they are more accessible by road.

With respect to the second group of important variables identified in the current study, i.e. the drivers related to the natural ecosystem, the results from the PDPs indicated the following. In general, the influence of slope (apart from at very low slopes) in forests and shrublands was similar, in that the relationship with greening trends was positive, and negative with browning trends (Figure 3.7e, f; and Figure 3.11e, f). In agricultural areas, the influence of slope was much more variable (Figure 3.5e, f). As noted by Vu et al. (2014), in agricultural land, crop productivity may be constrained by slope, which acts as an important driver for soil erosion and/or landslides, while in forests, steep slopes may act as a deterrent to the exploitation of forest resources, as well as to the conversion of forests to agricultural land. Our results indicate that in Kenya slope generally acts as a deterrent to the exploitation of land resources.

In two datasets, i.e. agricultural and the LCC areas, the PDPs for the variable distance to rivers indicated that with increasing distances to rivers, regeneration was more likely (Figure 3.5a; and Figure 3.13c). This result implies that the exploitation of water resources from rivers is leading to land degradation. Noting that the agriculture sector in Kenya is dominated by rain-fed and small-scale farms, which produce approximately 70% of the gross marketed agricultural output (GoK, 2015b), addressing food security will require the provision of environmentally sound irrigation infrastructure. In particular, expanding smallholder irrigation schemes (e.g. rainfall harvested and retained in ponds and small dams on small farm holdings) has the potential to transform and increase the productivity of the agricultural sector in Kenya. As land degradation is exacerbated by climate change (changing precipitation patterns, increased incidence of severe weather events) (Akhtar-Schuster et al., 2017), a shift away from rain-fed agricultural production will also buffer smallholders against the anticipated negative repercussions of climate change. Over the decades, Kenya has experienced periods of droughts and floods. Future climate projections for Kenya based on Global Climate Modelling data, as highlighted in the country's National Adaptation Plan for the period 2015-2030 (GoK, 2016b) submitted to the UNFCCC, include: an increase in mean annual temperature between 0.8 and 1.5°C by the 2030s, and 1.6°C to 2.7°C by the 2060s; a possible increase in average rainfall by the 2060s especially from October to December; an increase in the proportion of annual rainfall that occurs in heavy events. A priority for Kenya in the face of these climate projections is to implement a range of measures aimed at building climate resilience.

Despite the additional complexity associated within the area characterised by land cover change (i.e. it represents areas where there have been changes from one land cover class to another, as well as includes several land cover classes), the results obtained indicate that there is a core set of important variables influencing greening and browning trends across the 5 datasets used in the study. As illustrated across all the VI plots (Figure 3.4, 3.6, 3.8, 3.10, 3.12), the variables with high MDA values (i.e. greater than 50, indicating their importance for the prediction of greening and browning trends), were made up of primarily all the natural variables (as categorised in Table 3.2), as well as the variables travel time, distance to roads, towns, and rivers, and protected areas. As the variables travel time and vulnerability were obtained closer to the end date of the trend analysis, the relationship between these two variables with the greening and browning trends was interpreted as associative. The results from the current study have reinforced the well-established view in the published literature that land degradation and regeneration are products of complex interactions between both the biophysical environment and human actions.

3.4.2 Conceptualising the relationship between the LDN goal and the other SDGs

By computing the relative importance of grouped variables, we provided an alternative way of broadly understanding the factors that influence greening and browning trends in Kenya. Specifically, we illustrated the relative importance of variables grouped by SDGs (Figure 3.14). The most important variables by SDG group were: life on land (SDG 15), economic growth (SDG 8), and climate action (SDG 13). Variables grouped as natural vs. anthropogenic factors accounted for approximately a third and two-thirds, respectively, of the prediction of the greening and browning trends. Variables grouped as environmental vs. socio-economic factors, each accounted for approximately 50% of the prediction of the greening and browning trends. We suggest that the grouping of variables is of relevance to policy makers, as it provides a framework for understanding the interdependence between the social, environmental and economic factors in addressing LDN. Cognisant that the LDN goal depends on the other SDGs, policy makers can promote policy coherence and integrated approaches that can take advantage of mutually reinforcing actions across multiple development priorities.

3.4.3 Model evaluation and limitations

Despite the relevance of the novel results obtained, there are limitations to this study that should be noted. First and foremost, though every attempt was made to obtain data corresponding to the start of the trend analysis i.e. 1992, this was not possible for some variables. Hence the relationship between variables dated closer to the end date of the trend analysis (e.g. travel time was computed in 2007; vulnerability to climate change impacts was computed in 2010) and the greening and browning trends can only be interpreted as associative. Secondly, while the SDGs capture the qualitative aspects of economic development, environmental sustainability, and social inclusion, limited by data availability, the selection of variables used in this analysis fall short of this aspiration. For example, while SDG 8 is aimed at promoting "sustained, inclusive and sustainable economic growth, full and productive employment and decent work for all," the variables categorised under SDG 8 (i.e. maize yields, fertilizer use, cattle density, distance to roads, distance to towns, and travel time) represent the importance of the agricultural sector to the economy and the accessibility to markets. Thirdly, the analysis was based on variables with different spatial and temporal resolutions. Most of the variables representing agricultural activities and the proxies for broad socio-economic development were obtained from national statistical reports, and were at the county level. As noted in the Methods section, the RF algorithm was chosen for the analysis in the current study due to its strength in handling multi-source data. Further, by using the Boruta procedure (Kursa & Rudnicki, 2010) as the first step in the methodological process, we ensured that only the most relevant variables were retained in the analysis. The high performance metrics obtained across the different datasets (Table 3.3) suggests no loss in classification performance from the inclusion of the coarse resolution data. Fourth, while the RF model performed strongly in predicting the 4 classes of trends (MG, SG, MB, and SB), the interpretability of the PDPs for these 4 classes was limited. Capitalising on the strengths of the RF model, we computed PDPs for two classes of trends i.e. greening (MG and SG) and browning (MB and SB) and improved on the interpretability of the PDPs.

Machine learning approaches (such as the RF methodology used in this study, and its strengths as discussed in the Methods section) present an opportunity to radically reduce the complexity related to the processing of large and diverse datasets. A key constraint for many countries in addressing the SDGs is the data challenges in relation to the 232 indicators of the 17 SDGs (UN, 2017). These challenges include: the paucity of data; infrequent and uneven coverage of data; lack of uniformity in rules and procedures for gathering data; and the dearth of publicly available data resources (Chattopadhyay, 2016). Big data, and in particular earth observation data for earth sciences applications, can improve national statistics for greater accuracy, by ensuring that the data are spatially-explicit and directly contribute to calculate the agreed SDG targets (Anderson et al., 2017). Hence machine learning approaches, in combination with big datasets, provide researchers with unique opportunities to not only investigate problems related to land degradation (as demonstrated in the current study), but more broadly to monitor, measure, and report on progress towards achieving the SDGs.

3.4.4 Policy implications for addressing land degradation neutrality

One of the key messages emerging from the seminal assessment report on land degradation and restoration (IPBES, 2018), is that “eliminating perverse incentives that promote degradation and devising positive incentives that reward the adoption of sustainable land management (SLM) practices are required to avoid, reduce and reverse land degradation.” SLM, as broadly defined by FAO/TerrAfrica in Liniger et al. (2011) as “the adoption of land use systems that, through appropriate management practices, enables land users to maximise the economic and social benefits from the land whilst maintaining or enhancing the ecological support functions of the land resources” offers a viable technical response for addressing LDN across the productive landscapes of Kenya. A range of SLM practices are being implemented in Kenya, with varying results. In western Kenya, low cost and simple SLM practices of manuring and intercropping have been shown to accrue yield and financial benefits to smallholder farmers; however terracing and agroforestry required substantial upfront time and resource investments from individual farmers, with a long time lag (5-10 years) between implementation and accrual of the benefits (Dallimer et al., 2018). Mganga et al. (2015) documented that agro-pastoral communities in semi-arid areas in south-eastern Kenya are practicing simple SLM practices, notably grass reseeding, rainwater harvesting and soil conservation, and dryland agroforestry using multi-purpose tree species, which have resulted in enhanced environmental resilience but also improved livelihoods of the agro-pastoralists. However, Mulinge et al. (2016) in a study exploring the causes, extent and impacts of land degradation in Kenya, noted that in a national survey of households in 2013, only 40% were adopting SLM practices such as: cut-off drains and drainage trenches, terraces planted with fodder species, contour ploughing, tree planting, use of manure, inorganic fertilizer and compost. To address the low adoption of SLM practices, rather than focusing only on the biophysical aspects of land degradation, more emphasis needs to be given to understanding how livelihoods will be affected by SLM interventions, as well as on how livelihood strategies may limit SLM adoption (Cordingley et al, 2015). The choice by rural households of income strategies and land management practices are context-dependent and a product of many and complex factors, that vary in influence for different types of households (Emerton & Snyder, 2018; Pender et al., 2006). Accordingly, addressing LDN across the productive landscapes in Kenya will require a keen understanding of the interactions between the proposed SLM interventions and livelihood options, particularly those associated with the access to markets variables used in this study (i.e. travel time, distance to roads and towns).

To disentangle the complexity associated with the patterns portrayed in the PDPs, and in particular to provide a keener understanding of the influence of the different thresholds on the greening and browning trends, further analysis is required at the sub-national level to provide insights into the dynamics of the human-environment interactions associated with land degradation and regeneration. Hence, as this study was undertaken at the national level, we propose a localised diagnostic of the drivers of greening and browning trends in Kenya. A key governance change in Kenya since 2013 has been the transfer of the majority of the national government functions to the 47 county governments, as stipulated under the 2010 constitution of Kenya (GoK, 2010). The decentralization of functions to the county level presents an enormous opportunity to address LDN in a tangible way that takes into account the specific biophysical and socio-economic contexts at the local level. One of the key guiding principles of the National Environment Policy (GoK, 2013) is the principle of subsidiarity that provides decentralised and devolved authority and responsibility for management of the environment and natural resources to the lowest level possible. This principle is highly relevant to addressing LDN as it expresses that the obligation to take action on land degradation will be at the most immediate (or local level). From a practical standpoint, counties operate closest to the people and can better target interventions that are effective given the local context of both man made and natural drivers of land degradation. In this regard, county governments will be better able to select appropriate policies and strategies, as well as undertake targeted research to better inform policy and implementation gaps, such as the interactions between proposed SLM interventions and livelihood strategies, as discussed above.

In the context of the prevailing SDG development agenda, the analysis undertaken in this study included not only well-established drivers of land degradation, but also a number of variables as proxies for broad socio-economic development. The results obtained indicated that while there are some variables that are more important than others, no variable was considered unimportant from the analysis (application of the Boruta procedure), and the inclusion of 28 variables representing 10 of the 16 substantive SDG resulted in models with high performance metrics. Further, by computing the relative importance of grouped variables, we demonstrated the interdependence between the social, environmental and economic factors in influencing the greening and browning trends. Our results indicate that addressing LDN requires an “integrated and indivisible” balance of the environmental, social and economic dimensions of sustainable development. Thus LDN implementation in Kenya will require integrated approaches through greater alignment and closer coordination across multiple development priorities (e.g. food, energy, water, climate change, health, etc.) (IPBES, 2018). The coordination and collaborative involvement between relevant government agencies, county governments, private sector, civil society and communities will be an essential component of the integrated approach. As such, the outcomes of this study can be used not only as information to engage diverse stakeholders, but also as a tool for the co-construction of solutions to address LDN.

In the current study, the NDVI trends used in the analysis were independent of the climate influence (Gichenje & Godinho, 2018). Notwithstanding the use of human-induced greening and browning trends, the two climatic variables (zones and vulnerability to climate change impacts), were variables with high MDA values and accounted for on average 12% of the prediction of the greening and browning trends. For this reason we propose that the integrated approach to addressing LDN encompass actions to address climate change. The IPBES has emphasised that the adoption of SLM practices can contribute substantially to the adaptation and mitigation of climate change (IPBES, 2018). This message echoes the findings by Akhtar-Schuster et al. (2017), who noted that climate change will impact biodiversity, ecosystems and land productivity, and argued that LDN should be operationalised by addressing synergies across the 3 Rio Conventions.

Across the 5 datasets, environmental variables were responsible for 50% of the influence on greening and browning trends. Alongside the implementation of "tried and tested" SLM practices (Stringer & Dougill, 2013), targeted enforcement of environmental legislation is required to deter processes and activities that are likely to lead to the degradation of land. This needs to occur especially in ecologically vulnerable areas (e.g. on hill sides, along rivers, lakes, seas and wet lands, in protected areas, etc.). The Environmental Management and Co-ordination Act (EMCA) (GoK, 1999) is the overarching law on environmental matters in the country. The EMCA is a framework law for environmental management, in which various aspects of the environment are governed through subsidiary regulations and standards (e.g. environmental impact assessment and audit; water quality; waste management; wetlands, river banks, lake shores and sea shore; public complaints committee). Various other legal and policy instruments (e.g. the Land Act, Land Use Policy, Climate Change Act, Agriculture and Food Authority Act, Forest Act, Forest Policy, and the Water Act) are also available for the government to meet its constitutional obligations of ensuring the sustainable use, management and conservation of the environment and natural resources (GoK, 2010). Local authorities need to use existing legal, policy and planning instruments more appropriately and proactively, particularly to avoid land degradation and confer resilience in land that is not degrading (Cowie et al., 2018).

3.5 Conclusion

The key contribution of this study was to identify and demonstrate the influence of the key human-environment drivers of land degradation and regeneration, using a large set of explanatory variables, including proxies for broad socio-economic development that represent the SDGs. The methodological approach used was the random forest classification algorithm, whereby the dependent variable was represented as 4 classes of NDVI greening and browning trends (strong browning, moderate browning, moderate greening, and strong greening). The explanatory variables (n = 28) were broadly grouped into 2 categories, natural and anthropogenic. Across the 4 main land cover areas (agriculture, forest, grassland and shrubland) and within an area characterised by land cover change, variables that repeatedly featured as the 5 most important variables were: travel time to an urban area, distance to towns, distance to roads, distance to rivers, slope and vulnerability to climate change impacts. The most important variables by SDG group were: life on land (SDG 15), economic growth (SDG 8), and climate action (SDG 13). Variables grouped as natural vs. anthropogenic factors accounted for approximately a third and two-thirds, respectively, of the prediction of the greening and browning trends. Variables grouped as environmental vs. socio-economic factors, each accounted for approximately 50% of the prediction of the greening and browning trends.

To enrich on-going and future policy and planning discussions aimed at addressing LDN in Kenya, we propose the following: the implementation of LDN should be anchored on tried and tested SLM interventions that are proven to improve livelihoods, rehabilitate degraded landscapes, and enhance the provisioning of critical ecosystem services; further analysis of the drivers of greening and browning trends should be undertaken at the sub-national level to provide a better understanding of the dynamics of the human-environment interactions associated with land degradation and regeneration; integrated approaches should be adopted across multiple development priorities, including climate change, that balance the three dimensions of sustainable development; and targeted enforcement of environmental legislation is needed, particularly in areas that are not degrading to avoid land degradation and to confer resilience to the land.

3.6 Appendices

3.6.1 Appendix 3.A: Partial dependence plots for the 4 classes of greening and browning NDVI trends (strong browning; moderate browning; moderate greening; and strong greening).

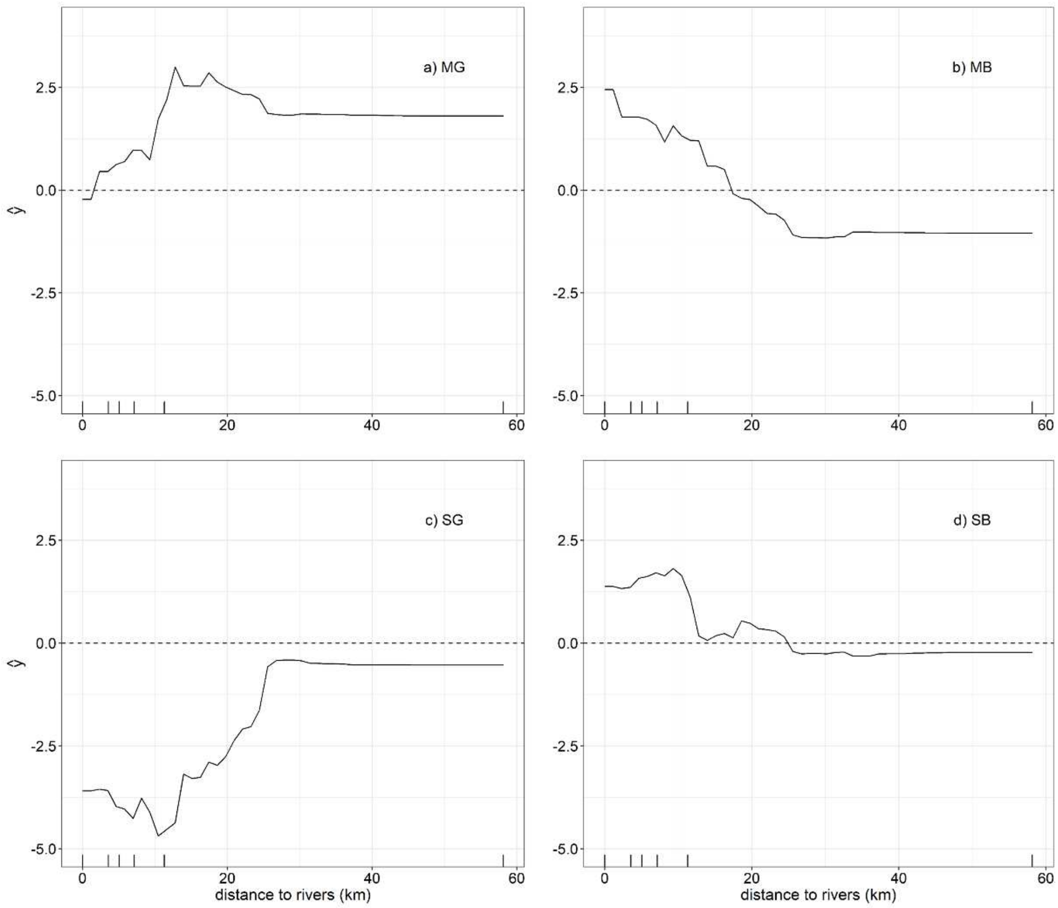

Figure 3.A1: Partial dependence plot (PDP) for the variable distance to rivers in agriculture areas.

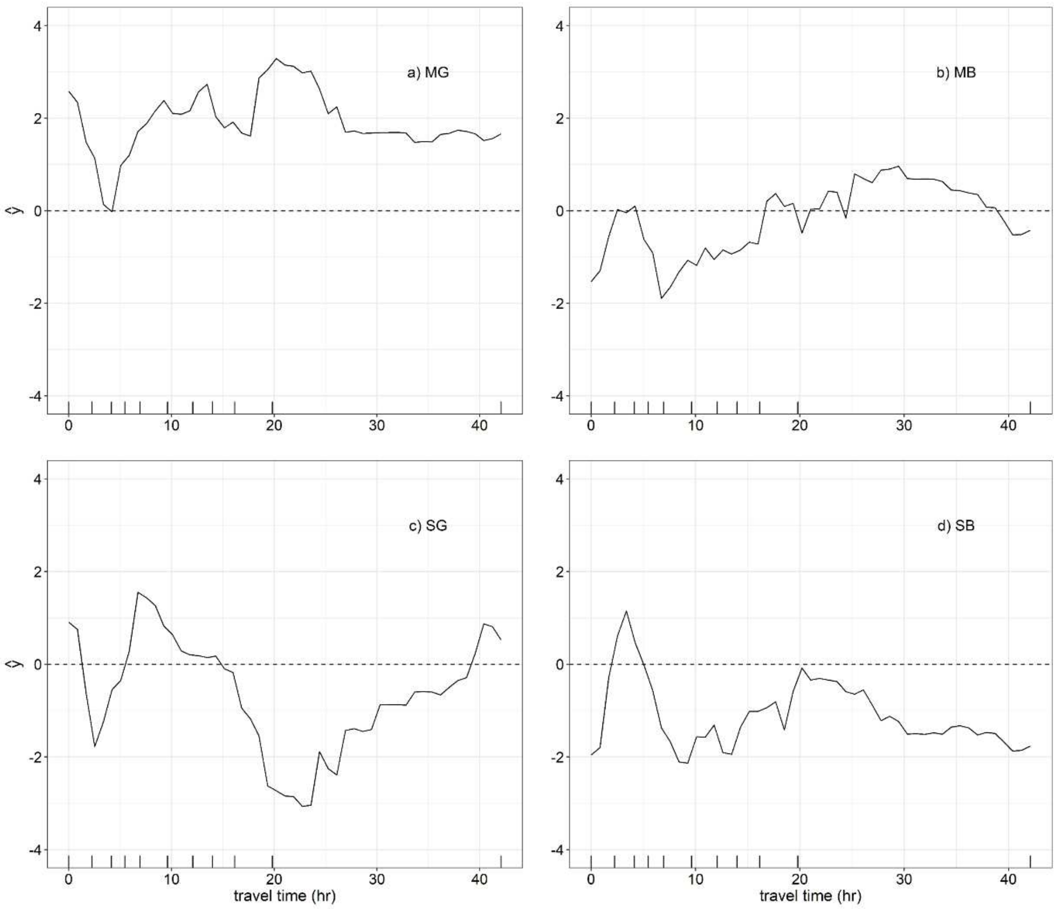

Figure 3.A2: PDP for the variable travel time in forest areas.

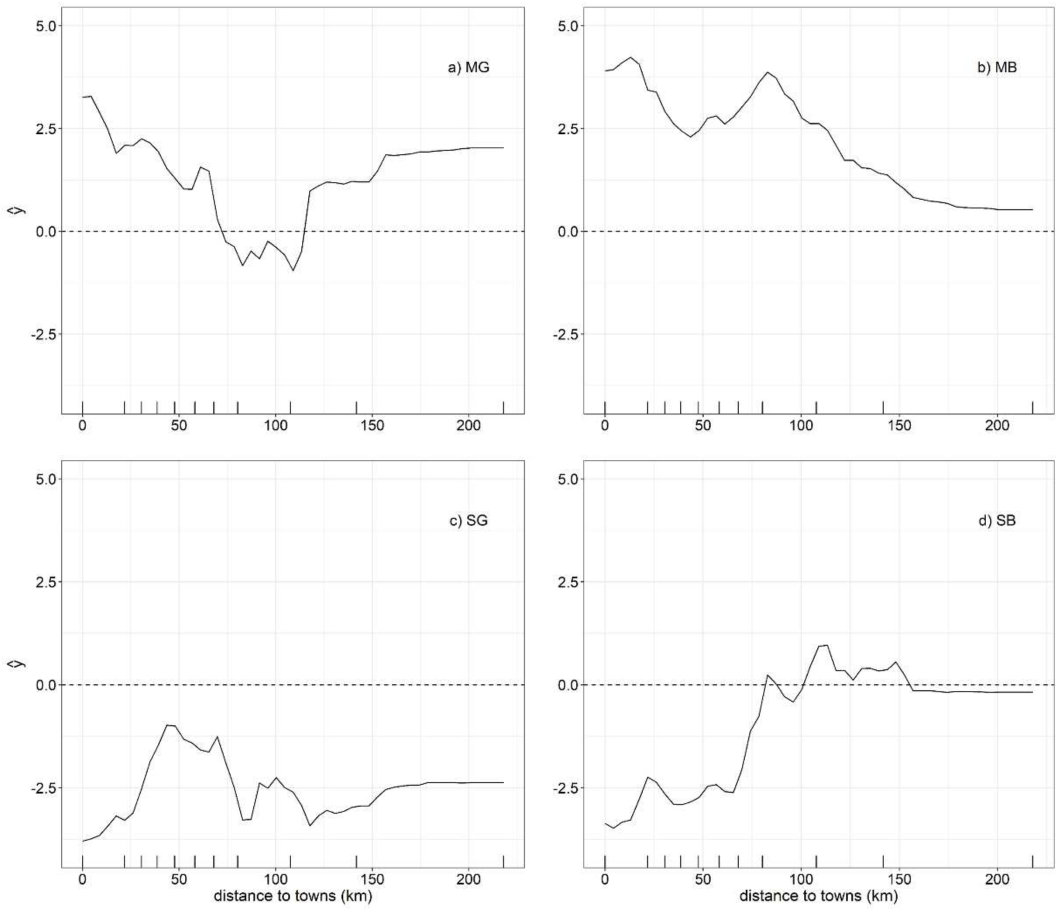

Figure 3.A3: PDP for the variable distance to towns in grasslands.

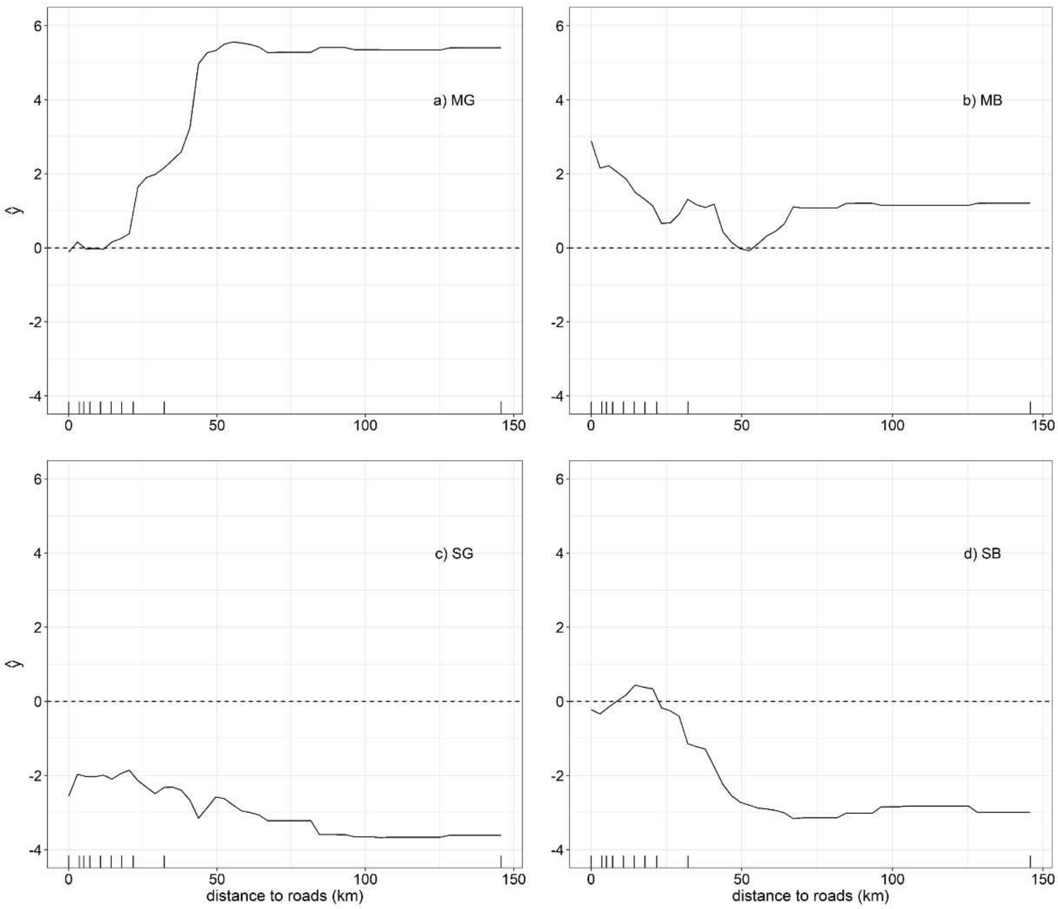

Figure 3.A4: PDP for the variable distance to roads in shrublands.

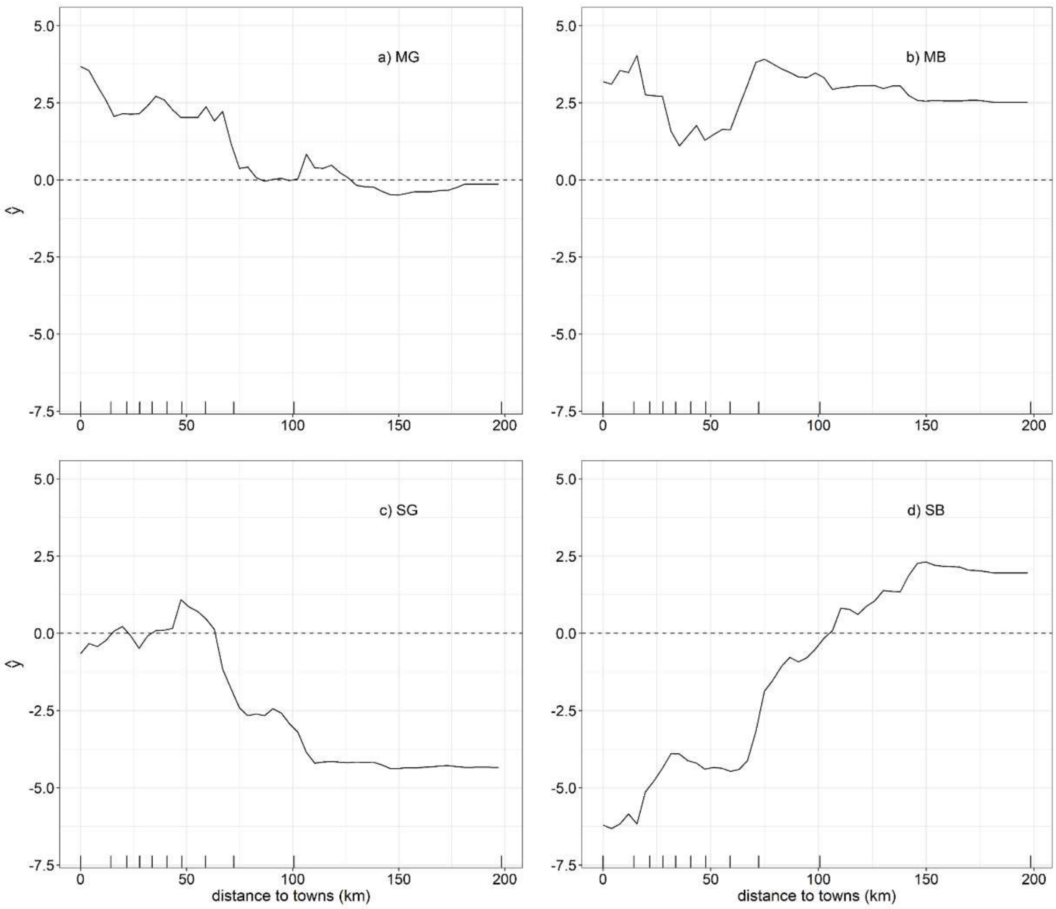

Figure 3.A5: PDP for the variable distance to towns in the land cover change area.

Chapter

4

OPPORTUNITIES AND LIMITATIONS FOR ACHIEVING LAND DEGRADATION-NEUTRALITY THROUGH THE CURRENT LAND-USE POLICY FRAMEWORK IN KENYA

Based on the published manuscript:

Gichenje H, Muñoz-Rojas J, Pinto-Correia T. 2019. Opportunities and limitations for achieving land degradation-neutrality through the current land-use policy framework in Kenya. *Land* **8** (8), 115. DOI: 10.3390/land8080115

Abstract

The United Nations Convention to Combat Desertification (UNCCD) land degradation-neutrality (LDN) scientific conceptual framework underscores that LDN planning and implementation should be integrated into existing planning processes and supported by an enabling policy environment. Land-use planning, which requires the integration of different policy goals across various sectors concerned with land-use, can be an effective mechanism through which decisions with respect to LDN can be coordinated. Using Kenya as a case study, we examined current policy instruments that directly or indirectly impact on the use of land in a rural context, to assess their potential to implement LDN objectives. The qualitative content analysis of these instruments indicated that they are rich with specific legal provisions and measures to address LDN, and that there are a number of relevant institutions and structures across governance levels. However, the main shortcoming is the disjointed approach that is scattered across policy areas. Key policy improvements needed to support effective implementation of LDN include: a national soil policy on the management and protection of soil and land; a systematic and coordinated data collection strategy on soils; mobilisation of adequate and sustained financial resources; streamlined responsibilities and governance structures across national, regional and county levels.

***Keywords**: land degradation neutrality; land-use; spatial plans; Kenya*

4.1 Introduction

Land degradation is a serious global environmental and development challenge. According to the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES), land degradation is occurring in all parts of the terrestrial world, and is negatively impacting the well-being of at least 3.2 billion people, costing more than 10% of the annual global gross product in loss of biodiversity and ecosystem services (IPBES, 2018). In recognition of the need for continued action on land degradation across impacted countries, regions and landscapes, the Sustainable Development Goals (SDGs), adopted by the global community in 2015, include the following specific target (15.3): “By 2030, combat desertification, restore degraded land and soil, including land affected by desertification, drought and floods, and strive to achieve a land degradation-neutral world” (UN, 2017). The United Nations Convention to Combat Desertification (UNCCD) defines land degradation-neutrality (LDN) as a “state whereby the amount and quality of land resources necessary to support ecosystem functions and services and enhance food security remain stable or increase within specified temporal and spatial scales and ecosystems” (UNCCD, 2015). The LDN concept expresses the desire to maintain the balance between “not yet degraded” and “already degraded” land (Kust et al., 2017).

The LDN scientific conceptual framework, as developed by the Science-Policy Interface of the United Nations Convention to Combat Desertification (UNCCD) (Cowie et al., 2018), proposes that the implementation of LDN should be “integrated into existing land use planning processes, and implemented by existing institutions.” According to Cowie et al. (2018) and Chasek et al. (2015) the implementation of specific measures to achieve LDN can be differentiated across the following three states of land: i) in land that is not degrading, avoiding land degradation involves the use of proactive measures such as appropriate regulation and planning; ii) in land that is degrading, measures to reduce land degradation can be achieved by incorporating sustainable land management practices; and iii) in land that is already degraded, interventions are required to reverse degradation through restoration or rehabilitation, which actively assist in the recovery of ecosystem functions. Recognising that “prevention is better than cure,” avoiding degradation is the priority, followed by reducing on-going degradation, then by the restoration and rehabilitation of already degraded land. This sequencing of actions is known as the LDN response hierarchy (Cowie et al., 2018). Rather than being an additional process, the planning of the appropriate response to address LDN can be made operationally feasible using existing land-use planning processes (Orr et al., 2017). Land-use planning, which broadly, aims to allocate land to different uses across a landscape in a way that balances economic, social and environmental values, is a process whereby relevant actors make decisions about how the land and its resources should be used and managed (FAO, 1993). It requires the coordination of different policy goals across various sectors concerned with land-use and land resources. For the purpose of this study, we define the land-use policy framework to include the policy instruments and associated institutions, which directly or indirectly aim at regulating and influencing land-use in a rural context. Policy instruments (as contained in laws, regulations, policies and plans) are the means through which the government uses “to get people to do things they otherwise would not have done, or it enables them to do things they might not have done otherwise” (Schneider & Ingram, 1990).

To date, a few studies have assessed whether existing laws and policies at the national level are adequate to implement LDN. Bodle (2017) assessed how the various legal provisions in Germany address actions required along the LDN response hierarchy discussed above, as well as require or allow that degradation is offset by restoration (e.g. permission for a project that would degrade a habitat is granted only if the applicant restores or upgrades land to a functionally equivalent extent). Speranza et al. (2019), for the case of Nigeria, not only examined the extent to which the existing laws and policies engaged with the LDN response hierarchy, but also how the current institutional arrangements and the extent to which various LDN indicators were captured in the policy documents. Both studies noted that the existing laws and policies were not conducive to facilitating implementation of the LDN target, in large part due to the fact that mechanisms to address LDN were scattered across several instruments without much coordination.

Kenya ratified the UNCCD in 1997 (GoK, 2002). As a tool for implementing the provisions of the convention, Kenya has prepared two National Action

Programmes (NAPs), the first in 1999 and the next one in 2002. The 2002 NAP (GoK, 2002)was designed to address the following challenges: inadequate policies and regulatory frameworks; sectoral approaches to programming; uncoordinated and frequent shifts of mandate of dryland issues from one institution to another; low and uncoordinated funding; inadequate involvement of local communities in programming and decision making; and inadequate capacity for implementation, monitoring and evaluation. However, the implementation of the NAP was hampered by weak coordination between the various implementing institutions, and the absence of an overarching monitoring and evaluation framework to guide the scaling-up of activities (World Bank, 2010).

Kenya, along with over 120 countries, is part of the UNCCD LDN Target-Setting Programme (TSP) (UNCCD, 2019). The TSP provides technical and financial support to countries focused on three key areas: accessing the best available data for target setting; conducting multi-stakeholder consultation processes to mainstream LDN into national SDG agendas; and identifying investment opportunities for LDN implementation (UNCCD, 2019). Nonetheless, it remains to be fully explained whether LDN can be effectively implemented under the current land-use policy framework. In this regard, we examined whether the current land-use policy instruments and institutions in Kenya, across governance levels, have the potential to implement LDN objectives. Overall, this study was intended to answer the following two broad research questions:

i) Does the current land-use policy framework have the potential to contribute to achieving LDN?
ii) What policy and institutional improvements are required to overcome gaps and make the best use of opportunities to advance the pursuit of LDN?

Following this introduction, the next section describes the study area, criteria and methods applied in this study. The third section examines the potential of the current land-use policy framework to address LDN, framed around the LDN responses and a set of enabling conditions. In section 4 we critically discuss the implications of policy and institutional opportunities and inefficiencies, and provide some key recommendations. The final section presents a synthesis of our main findings and some concluding remarks.

4.2 Materials and methods

4.2.1 Study area

Kenya is an equatorial country located on the eastern coast of Africa (Figure 4.1) that extends from 33°9′E to 41°9′E and from 4°63′N to 4°68′S, and has a total area of 582,646 km^2. Most of the country lies within the eastern end of the Sahelian belt, a region that has been severely affected by recurrent droughts over the past decades (Leroux et al., 2017). At the sub-national level, two counties, Lamu and Makueni, were selected for this study because as of 31 April 2019, both counties had finalised their own county spatial plans. Lamu county is located in the north-eastern end of the Indian Ocean coastline of Kenya, and has a land surface area of 6,474 km^2 that includes the mainland and over 50 islands (GoL, 2017). Makueni county has a land surface area of 8,035 km^2, and is located in the south-eastern region of Kenya, in a predominantly arid and semi-arid region (GoM, 2019).

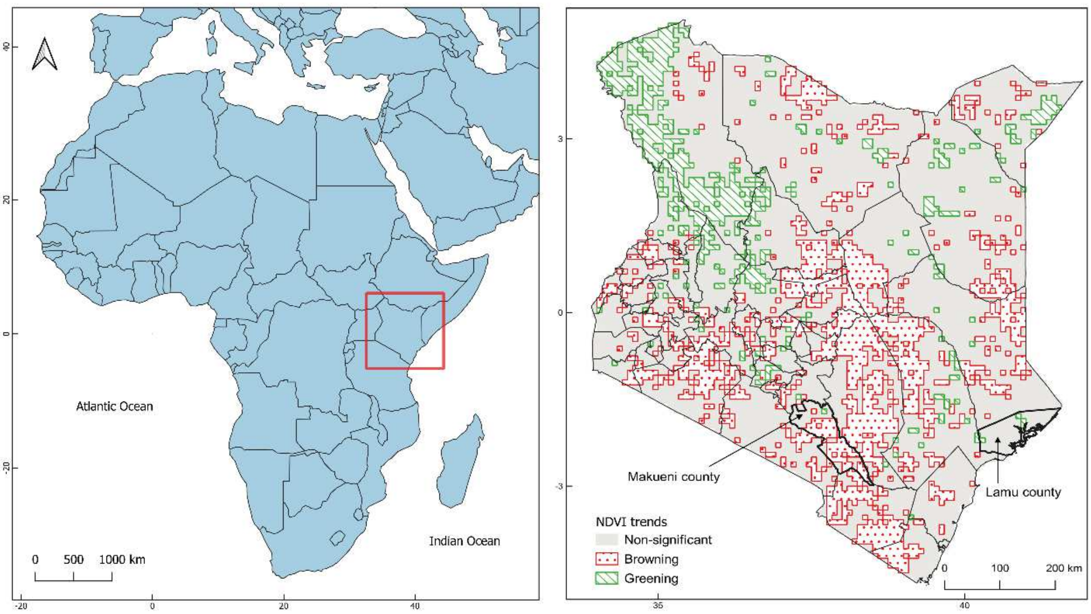

Figure 4.1: Study area.

The LDN national baseline for Kenya was established by Gichenje & Godinho (2018). The LDN baseline is the reference state that provides information on where land has degraded or improved, against which neutrality will be assessed.

On the basis of the results in the aforementioned paper (Gichenje & Godinho, 2018), which used trends in the Normalised Difference Vegetation Index (NDVI) as a proxy for trends in land productivity or the functioning of the land, most of the land area (69.5%) was characterised by non-significant trends (Figure 4.1). Persistent negative NDVI trends (an indication of land degradation and termed as a browning trend) occurred in 21.6% of the country, while persistent positive NDVI trends (an indication of land regeneration and termed as a greening trend) occurred in 8.9% of the country. Lamu county is primarily characterised by non-significant NDVI trends (95%), while Makueni county has predominantly browning trends (52%). Of note is that the trends illustrated in Figure 4.1 refer to human-induced trends, as the climate influence was removed from the NDVI trends (Gichenje & Godinho, 2018).

4.2.2 Methods

The methodology adopted in this study primarily involved a content review of official government legal, policy and planning documents. Through this review we also identified the main institutions responsible for the mandate outlined in each of the instruments, and the administrative level at which they operate. We reviewed laws, policies and plans explicitly aimed at regulating land and land-use, and those indirectly influencing the use of land in a rural context. This review was guided as follows. First, in contrast to LDN, which is a relatively new concept, land degradation is not a new environmental challenge for Kenya. Land degradation is a complex multidimensional process that has been defined in many and various ways (Yengoh et al., 2014). For the purpose of this study, the following definition by the UNCCD is adopted: the “loss, in arid, semi-arid and dry sub-humid areas, of the biological or economic productivity and complexity of rainfed cropland, irrigated cropland, or range, pasture, forest and woodlands resulting from land uses or from a process or combination of processes, including processes arising from human activities and habitation patterns” (UNCCD, 1994). In its broadest sense, land degradation is the decline in the bio-physical properties of both above and below ground functions and resources. In this regard, we focused on assessing the potential of the current land-use policy framework to address land degradation from this broad perspective related to the management and protection of soil and land. Second, the objective of this study was to assess the potential to address LDN through the intentions expressed in the various instruments examined. The focus was to provide information on intentionality and not on the effectiveness resulting from the implementation of the instruments. Policy instruments are implemented when they are in use and when they have an effect on decisions made by households or farmers (Primdahl & Brandt, 1997). Thus, an assessment of policy effectiveness would require an analysis of management results at the scale at which actions to address land degradation are taken, i.e. landscape, farm or plot, which is outside the scope of our study. Following is an elaboration of the main steps of the methodology.

Criteria for content analysis of legal, policy and planning instruments

The first step comprised of a systematic analysis of official government documents (legislation, policies, strategies, spatial and action plans). Government websites, as well as other online sources were searched to assemble the documents. All documents considered in this analysis were obtained from online sources by the cut-off date of 31 April 2019. Guided by Le Gouais & Wach (2013) on the identification of themes or criteria in undertaking a qualitative analysis of policy documents, we framed the analysis around a portfolio of options for advancing LDN, as outlined below.

According to Akhtar-Schuster et al. (2013), LDN can only be achieved through a portfolio of place-based measures that are appropriate to context. Furthermore, one of the key messages emerging from the seminal assessment report on land degradation and restoration (IPBES, 2018), is that "eliminating perverse incentives that promote degradation and devising positive incentives that reward the adoption of sustainable land management (SLM) practices are required to avoid, reduce and reverse land degradation." SLM, as broadly defined by FAO/TerrAfrica in Liniger et al. (2011), is "the adoption of land use systems that, through appropriate management practices, enables land users to maximise the economic and social benefits from the land whilst maintaining or enhancing the ecological support functions of the land resources." In line with the LDN response hierarchy proposed by Cowie et al. (2018) and the need to offset land degradation as proposed by Bodle (2017), the current instruments would need to propose responses that avoid, reduce, reverse and offset land degradation. Through a review of recent studies and initiatives that document SLM practices in Kenya, we identified some examples of measures that can be implemented across the country's main productive landscapes. Over the period from 1992 to 2015 agriculture, forest, grassland and shrubland land cover classes accounted for approximately 90% of the area in Kenya (Gichenje & Godinho, 2018). In addition, we identified a number of enabling conditions to support the implementation of LDN. We grouped the enabling conditions into the following 6 broad "means of implementation" (Stafford-Smith et al., 2017), identified under SDG 17 that aim to strengthen SDG implementation: finance; technology; capacity building; policy and institutional coherence; multi-stakeholder partnerships; and data, monitoring and accountability. Examples of the means of implementation to support the implementation of LDN were selected based on a number of priority gaps identified in the IPBES report (IPBES, 2018).

The LDN responses and the means of implementation were jointly considered as the portfolio of options to address LDN, and as the criteria for undertaking the content analysis of the selected documents (Table 4.1). Given the predominance of greening and non-significant NDVI trends at the national level (Figure 4.1), and the precautionary principle underlying the LDN response hierarchy (Cowie et al., 2018), achieving LDN in Kenya at the national level would first require approaches to avoid land degradation, followed by actions to restore and reverse degraded lands. As such, Table 4.1 represents a LDN operational approach for Kenya, and frames the actions that will need to be implemented using existing laws, policies, plans and related institutions across different land cover types and states of land degradation. Table 4.1 was populated with examples to guide the review of the various laws, policies and plans.

Table 4.1: Portfolio of options for addressing LDN.

LDN responses	**Measures**		
Avoid	*Aim: confer resilience through appropriate regulation, planning and management practices*[1,2]		
(Greening, Non-sig.)	Agriculture	Forest	Grasslands and Shrubland
	Prepare integrated wetland resource, forest resource, and mountain ecosystems management plans for environmentally sensitive areas[3] Management activities, such as forest patrols and environmental education projects[4]		
Reduce **Reverse**	*Aim: mitigate land degradation through SLM*[1,2] *Aim: actively recover the productive potential and ecological services through SLM*[1,2]		
(Browning)	Agriculture	Forest	Grassland and Shrubland
	Manuring[5,6] Inter-cropping[5] Grass strips[6] Agroforestry[5,6] Terracing[5,6]	Improve species richness[4] Buffer zone for extractive use[4,6] Afforestation[6] Gully rehabilitation[6]	Rain water harvesting[6,7] Terracing[6] Dryland agroforestry(Grass reseeding[7] Removal of undesirable species[8] Grazing enclosures[8]
Offset	*Aim: for a project that would degrade a habitat, permission is granted only if the applicant will restore or upgrade land to a functionally equivalent state* Similar SLM practices as outlined for reduce / reverse		
Means of implementation[9]			
Finance: Eliminate perverse incentives that promote degradation and devise positive incentives that reward the adoption of SLM practices Examples of market-based approaches: credit lines, insurance policies, payments for ecosystem services and conservation tenders.			
Technology: Strengthen institutional competencies: technical capacities, technologies Support landscape scale approaches that integrate the development of agricultural, forest, energy, water and infrastructure agendas			
Capacity building: Enhance capacities for planning and adaptive management Education and training to promote farmer and public awareness			
Policy and institutional coherence: Harness synergies in actions across the 3 Rio Conventions (UNCCD, UNFCCC, and CBD) Coordinate policy agendas across key sectoral priorities, e.g. food, energy, water, climate, health, rural, urban and industrial development Secure land tenure, property and land-use rights, vested in individuals and/or communities, in accordance with national legislation at the appropriate level			
Multi-stakeholder partnerships: Promote participatory approaches to management of natural resources: e.g. community-based forest management			
Data, monitoring and accountability: Improve information systems for monitoring, verification and reporting to enhance evidence-based decision-making			

Note: 1. Cowie et al., 2018; 2. Chasek et al., 2015; 3. GoK, 2016a; 4. Glenday, 2006; 5. Dallimer et al., 2018; 6. GoK, 2016b; 7. Mganga et al., 2015; 8. Verdoodt et al., 2010; 9. IPBES, 2018.

Much of the literature and the practice indicate that similar SLM practices can be implemented where land is and is not degrading (Chasek et al., 2015). Hence it should be noted that the SLM practices proposed under the reduce/reverse approach can be used to offset land degradation, and should also be used proactively alongside planning, regulatory and management measures to avoid degradation. As grassland and shrubland land cover areas are found primarily in what is commonly referred to as the arid and semi-arid lands (ASALs) of Kenya, we compiled examples for these two land cover types together given the similarity of bio-physical conditions.

Following Le Gouais & Wach (2013) the content analysis of the selected documents was done by examining the meaning of the text, rather than relying on the presence and frequency of any specific key words. We examined legislation to assess only if they contained requirements that address the LDN responses (i.e. avoid, reduce/reverse and offset), while policies and plans were examined to identify if they included specific measures to address the LDN responses as well as the means of implementation. The analysis was qualitative, resulting in a "yes" or "no" score to indicate the presence or absence of specific examples to address each of the elements of the portfolio of options to address LDN.

Institutional mapping

Land degradation is a complex process that involves a multiplicity of interconnected environmental, economic and social issues, which cut across the responsibilities of different government agencies (Chasek et al., 2015). Hence, effectively addressing LDN will require cooperation, collaboration and coordination across actors, sectors, institutions and policy domains (Briassoulis, 2019). The key institutions established and responsible for the mandate of the various instruments examined, were identified and mapped to evaluate their individual roles and responsibilities. By undertaking the institutional mapping we sought to highlight the roles of the most relevant institutions with respect to addressing LDN.

4.3 Potential of the current land-use policy framework to address LDN

In Kenya, at the national and county levels, there are a number of legal, policy and planning instruments that have the potential for addressing LDN. These instruments fall into 3 main tiers. In the first tier, there are the laws, and include the constitution that is the supreme law of the country, and the various laws (or acts) made by parliament (or county assembly's), and which must be consistent with the constitution. Secondly, there are the policies, strategies and action plans that are elaborated in relation to specific legislation, and convey what the government intends to achieve. Thirdly, there are the spatial plans, which are the main land-use planning tools that are elaborated at the national and county levels and are intended to provide a framework for the coordinated, integrated and balanced spatial development of the country's territorial space (GoK, 2016a). The following 32 documents were examined in this study: the national constitution, 14 acts (10 national, 1 regional, and 3 county), 14 policies, including strategies and action plans, (10 national, 2 regional, 3 county), and 3 spatial plans (1 national, and 2 county). The results of the content analysis are summarised in Figure 4.2. To support the review and verification of the analysis undertaken, summaries of specific provisions and measures included in each document are provided in Appendix 4.A (laws), and 4.B (policies, strategies and plans). These tables do not purport to cover all the possible provisions and measures contained in the documents, but are intended to highlight the breadth and scope of interventions with respect to addressing LDN. Next is an analysis of how the key components of the portfolio of options for addressing LDN (Table 4.1) are dealt with across the different instruments, followed by a description of the institutional context for addressing LDN.

	Legal instruments	Avoid	Reduce & Reverse	Offset	Policies and plans	Avoid	Reduce, Reverse & Offset	means of implementation: Finance	Technology	Capacity building	Policy and institutional coherence	Multi-stakeholder partnerships	Data, monitoring and accountability
NATIONAL													
horizontal	Physical Planning Act (1996)[1]	☑	☒	☑	Kenya Vision 2030 (2007)[16]	☑	☑	☑	☑	☑	☑	☑	☑
horizontal	Environmental Management and Co-ordination Act (1999)[2]	☑	☑	☑	National Environment Policy (2013)[17]	☑	☑	☑	☑	☑	☑	☑	☑
horizontal	Constitution of Kenya (2010)[3]	☑	☑	☒	National Spatial Plan: 2015-2045 (2016)[18]	☑	☑	☑	☑	☑	☑	☑	☑
horizontal	Land Act (2012)[4]	☑	☑	☑	National Land Use Policy (2017)[19]	☑	☑	☑	☑	☑	☑	☑	☑
horizontal	Climate Change Act (2016)[5]	☑	☒	☒	National Climate Change Action Plan: 2018-2022 (2018, draft)[20]	☑	☑	☑	☑	☑	☑	☑	☑
sector / area based	Wildlife Conservation and Management Act (2013)[6]	☑	☑	☑	National Policy for the Sustainable Development of Northern Kenya and other Arid Lands (2012)[21]	☑	☑	☑	☑	☑	☑	☑	☒
sector / area based	Agriculture and Food Authority Act (2013)[7]	☑	☑	☒	Forest Policy (2014)[22]	☑	☑	☑	☑	☑	☑	☑	☑
sector / area based	Community Land Act (2016)[8]	☑	☑	☒	Mining and Minerals Policy (2016)[23]	☑	☑	☑	☑	☑	☑	☑	☒
sector / area based	Mining Act (2016)[9]	☑	☑	☑	Climate Smart Agriculture Strategy: 2017-2026 (2017)[24]	☑	☑	☑	☑	☑	☑	☑	☑
sector / area based	Forest Conservation and Management Act (2016)[10]	☑	☑	☑	National Wildlife Conservation and Management Policy (2017)[25]	☑	☑	☑	☑	☑	☑	☑	☑
sector / area based	Water Act (2016)[11]	☑	☑	☑									
REGIONAL													
	6 Regional Development Authority (RDAs) Acts (1974-1990)[12]	☑	☑	☒	Kerio Valley Development Authority Strategic Plan: 2014-2018 (2014)[26]	☑	☑	☑	☑	☑	☑	☑	☑
					Ewaso Ng'iro South Dev. Authority Strategic Plan: 2017-2022 (2017)[27]	☑	☑	☑	☑	☑	☑	☑	☑
COUNTY													
	County Governments Act (2012)[13]	☑	☑	☒	Makueni County Vision 2025 (2016)[28]	☑	☑	☑	☑	☑	☑	☑	☑
	Makueni County Sand Conservation and Utilisation Act (2015)[14]	☑	☑	☒	Lamu County Spatial Plan: 2016-2026 (2017)[29]	☑	☑	☑	☑	☑	☑	☑	☑
	Makueni Climate Change Fund Regulations (2015)[15]	☒	☒	☒	Lamu County Integrated Development Plan: 2018-2022 (2018)[30]	☑	☑	☑	☑	☑	☑	☑	☑
☑	presence of provision/measure				Makueni County Integrated Development Plan: 2018-2022 (2018)[31]	☑	☑	☑	☑	☑	☑	☑	☑
☒	absence of provision/measure				Makueni County Spatial Plan: 2019-2029 (2019)[32]	☑	☑	☑	☑	☑	☑	☑	☑

Note: 1. GoK, 1996; 2. GoK, 1999; 3. GoK, 2010; 4. GoK, 2012a; 5. GoK, 2016c; 6. GoK, 2013a; 7. GoK, 2013b; 8. GoK, 2016d; 9. GoK, 2016e; 10. GoK, 2016f; 11. GoK, 2016g; 12. GoK, 1974-1990; 13. GoK, 2012b; 14. GoM, 2015a; 15. GoM, 2015b; 16. GoK, 2007; 17. GoK, 2013c; 18. GoK, 2016a; 19. GoK, 2017a; 20. GoK, 2018a; 21. GoK, 2012c; 22. GoK, 2014a; 23. GoK, 2016h; 24. GoK, 2017b; 25. GoK, 2017c; 26. GoK, 2014b; 27. GoK, 2017d; 28. GoM, 2016; 29. GoL, 2017; 30. GoL, 2018; 31. GoM, 2018; 32. GoM, 2019.

Figure 4.2: Policy documents analysed and synthesis of the content analysis.

4.3.1 Avoid

The avoidance of land degradation has a strong legal basis in the Constitution of Kenya (the Constitution) (GoK, 2010). The bill of rights as enshrined in the Constitution (GoK, 2010) provides citizens with the right to a clean and healthy environment, which includes the right "to have the environment protected for the benefit of present and future generations." Constitutional provisions of key relevance to LDN are primarily contained within Chapter 5 on Land and Environment, in which it is stated that government is required to ensure the sustainable use, management and conservation of the environment and natural resources. The Constitution (GoK, 2010) also contains enforcement provisions with respect to the environment in which the state is required to establish systems of environmental impact assessment, and environmental auditing and monitoring, that will enable the state to meet its obligations with respect to, inter alia, eliminating "processes and activities that are likely to endanger the environment" and ensuring "sound conservation and protection of ecologically sensitive areas."

The key legislation that gives full effect to the environment provisions contained in the Constitution is the Environmental Management and Co-ordination Act (EMCA) (GoK, 1999) which contains significant provisions (Part V) for the protection and conservation of the environment. The EMCA is a framework law for environmental management, in which various aspects of the environment are governed through subsidiary legislation (e.g. environmental impact assessment; environmental audit and monitoring; international treaties; environmental restoration; public complaints committee). Further, the EMCA is the overarching law on environmental matters in the country, as Article 148 of the act states that in situations where the provisions of national and county government laws relating to the management of the environment conflict with the act, the provisions of the EMCA shall prevail (GoK, 1999).

The most direct provisions on the protection of soil and land are contained within the following laws, whereby the relevant authorities are given the mandate to undertake the following: EMCA (GoK, 1999): issue guidelines and prescribe measures for the management and protection of any area declared to be a protected natural environment area; Agriculture and Food Authority Act (GoK, 2013b): prescribe land preservation national guidelines for the purposes of the conservation of the soil, or the prevention of the adverse effects of soil erosion on any land; and Community Land Act (GoK, 2016d): allow registered communities to make rules or by-laws for the conservation and management of the land. From Figure 4.2 we note that all the laws examined (except the Makueni Climate Change Fund Regulations (GoM, 2015b)) include provisions that contain planning, management and/or regulatory practices to ensure that LDN can be avoided.

Of particular relevance within the various policies and plans are the following measures to avoid degradation. The National Environment Policy (GoK, 2013c) states that a National Soil Conservation Policy will be developed (there is no evidence that this has been initiated). To protect natural resources and prevent environmental degradation, the National Land Use Policy (GoK, 2017a) advocates for the strengthening of the capacity of regulatory and enforcement agencies, and prohibits settlement and other activities within sensitive ecological zones. The National Spatial Plan (NSP) (GoK, 2016a) includes policy statements on: the preparation of integrated management plans for environmentally sensitive areas in wetland, forest, and mountain ecosystems; the development of an integrated land-use master plan for the ASALs; and the need to strictly regulate the subdivision of land in high potential agricultural areas.

4.3.2 Reduce and reverse

The majority of laws examined prescribe measures to reduce degradation and/or reverse degraded land (Figure 4.2). For example: the Constitution (GoK, 2010) includes the target to achieve and maintain a tree cover of at least 10% of the land area; the EMCA (GoK, 1999) prescribes re-forestation and afforestation for the management of hill tops, hill slopes and mountainous areas; the Agriculture and Food Authority Act (GoK, 2013b) calls for the provision of guidelines to address the drainage of land, including the construction, maintenance or repair of drains, gullies, contour banks, terraces and diversion ditches; and the Makueni County Sand Conservation and Utilisation Act (GoM, 2015a) includes provisions to promote the sustainable use of sand resources through planting of trees, and building of gabions and dams.

The content analysis of the policies and plans indicates that they all include specific measures to reduce/reverse degradation (Figure 4.2). Examples of measures proposed are: rehabilitation of degraded water catchments; good soil management practices to avert landslides, mudslides, and floods; forest cover through afforestation, reafforestation and agroforestry; species diversification through planting of indigenous and exotic species; restoration of degraded soils and conservation of soil biodiversity through integrated soil fertility management; and preventing encroachment by providing a buffer zone of at least 100 meters along the edges of the mangrove ring (Appendix 4.B). Of particular note are the targeted interventions identified in the National Climate Change Action Plan (NCCAP) (GoK, 2018a), which while aimed at mainstreaming climate change adaption and mitigation actions into sector functions, also comprehensively support the implementation of LDN. Not only are the measures across legal and policy instruments well-aligned with the SLM practices identified in Table 4.1, there are specific instruments to operationalize LDN actions within the four main land cover classes (e.g. for agriculture areas, the Agriculture and Food Authority Act (GoK, 2013b) and the Climate Smart Agriculture Strategy (CSAS) (GoK, 2017b); for forests, the Forest Conservation and Management Act (GoK, 2016f), and the Forest Policy (GoK, 2014a); and for ASALs, the Community Land Act (GoK, 2016d) and the National Policy for the Sustainable Development of Northern Kenya and other Arid Lands (GoK, 2012c)).

4.3.3 Offset

A number of laws at the national level include clauses with the obligation to offset by restoration any damage or harm done to the environment (Figure 4.2). The Environmental Restoration Orders contained in the EMCA (GoK, 1999) are the main legal provisions to remedy any environmental or ecological damage resulting from a violation of the EMCA and other laws. These orders place the burden on the wrongdoer to take affirmative steps that will, to the extent feasible, undo the effects of any environmental harm caused. The environmental restoration orders also specify the action that must be taken to remedy the harm to the environment, and the time frame within which the action must be taken. In the case of the Forest Conservation and Management Act (GoK, 2016f) and the

Wildlife Conservation and Management Act (GoK, 2013a), the requirement to offset degradation is contained in restoration clauses with respect to mining and quarrying, which are permitted activities in forests and national parks, under certain conditions.

4.3.4 Means of implementation

The majority of the policies and plans contain provisions on the means of implementation of the portfolio of options for addressing LDN (Figure 4.2), as discussed below.

Finance

A number of dedicated public funds (e.g. the Land Reclamation and Restoration Fund, the Desertification Trust Fund, the National Drought and Disaster Contingency Fund, the Climate Change Fund, the Forest Management and Conservation Trust Fund) are mentioned across the policy and planning documents (Appendix 4.B). In addition, the Makueni County Climate Change Fund Regulations (GoM, 2015b) establishes the Makueni County Climate Change Fund. Going forward, it will be important to take stock of the experience and effectiveness of these dedicated funds, to draw out lessons on what works and what doesn't, so as to provide information on the most suitable mechanism for achieving sustainable environmental finance. The policies and plans also included innovative finance mechanisms such as payment for environmental services schemes, carbon markets, green bonds, and insurance schemes (Appendix 4.B). Further, at the operational level, the regional and county level documents identify investment marketing and promotion bills, resource mobilization frameworks, and revenue resource mapping as modalities to bridge financial gaps (Appendix 4.B).

Technology and capacity building

Vision 2030 (GoK, 2007), the country's long-term development plan, identifies the strengthening of technical capabilities in science, technology and innovation as one of the key foundations for the socio-economic transformation of the country. This goal has filtered down into the policies and plans which include statements related to promoting scientific research and technical capabilities, e.g.: conduct research on natural resource and environment conservation technologies (National Land Use Policy (GoK, 2007)); capacity development of at least 50 Water Resources Users Associations (NCCAP (GoK, 2018a)); strengthen research and extension systems relevant to rain-fed crop production, including soil and water conservation, organic farming and agroforestry (National Policy for the Sustainable Development of Northern Kenya and other Arid Lands (GoK, 2012c)); key decisions on forest management and conservation shall be informed by forestry science founded on appropriate knowledge derived from research (Forest Policy (GoK, 2014a)); and enhance human capacity in weather data collection, and analysis of government staff, traditional weather forecasters, and communities (CSAS (GoK, 2017b)).

Policy and institutional coherence

While the policy and planning documents examined contain different statements on the means to attain coherence (e.g. mainstreaming of climate change, securing rights in land, and harmonising policy agendas with other relevant policy areas and instruments) (Appendix 4.B), in this section we focus on spatial planning, which as previously stated is Kenya's main land-use planning tool. Spatial planning aims at balancing the different demands for land-use in order to ensure that competing policy goals are reconciled, and can be an effective tool to achieve land management coordination horizontally (across different land-use decision makers) and coherence vertically (across governance levels) (FAO, 2015). Kenya's first spatial plan, the National Spatial Plan (NSP), is intended to guide the long-term spatial development of the country for a period of 30 years (2015-2045) (GoK, 2016a). The main spatial organisation of the NSP is the National Spatial Structure (NSS), which was developed not only in consideration of the geography, physiography and natural resource endowments of the country, but also on an analysis of the trends in economic performance, population and demographic dynamics, land use patterns, and human settlements. The NSS provides a spatial illustration of national projects and other socio-economic development policies. For example, there are 3 terrestrial-based spatial areas defined for the agricultural sector in the NSS: ASALs, high agriculture potential areas, and medium agriculture potential areas. The NSP proposes that the ASALs should be developed for large-scale commercial production of livestock. In high agriculture potential areas, the proposed strategy is intensification to increase productivity. While medium agriculture potential areas are to be optimised by promoting investment in irrigation agriculture for high value crops. At the national level, agriculture land cover areas have the highest browning trends (Gichenje & Godinho, 2018)), indicating that this land cover type should be the priority for the implementation of reduce/reverse response measures. Thus, the proposed strategies indicated above for agricultural areas, should only be considered once measures have been taken to mitigate land degradation in agricultural areas with browning trends.

The Lamu and Makueni county spatial plans [17,18], in contrast with the strategic nature of the NSP, are operational documents as they are planned for a 10-year time frame. Both county spatial plans contain sections devoted to situating the county planning within the national policy and planning contexts (e.g. the Constitution, the NSP). The spatial organisation concepts in the county spatial plans related to rural land-use, designate areas for their agricultural productive potential and for environmental protection, two strategies that are aligned with the NSP. Different LDN response strategies are required in the two counties. In Makueni county, across the 4 main land cover types, browning trends are approximately 50% of the share of the trends, which calls for more focused implementation of reduce/reverse response measures (such as afforestation, rehabilitation of water catchment areas, promotion of soil conservation, as indicated in Appendix 4.B across the Makueni policy and planning documents). In Lamu county, non-significant trends are predominant across the main land cover types, indicating that the priority is to avoid land degradation through appropriate regulation, planning and management practices. In this regard, the Lamu County Integrated Development Plan (GoL, 2018) advocates for the formulation of laws, policies, strategies and regulations on the use of land (Appendix 4.B).

In addition to the global development agenda (i.e. the SDGs), Kenya also adopted the African Union's long-term vision, Agenda 2063 (AUC, 2015). Existing planning processes are intended to support the integration of global and regional development agendas at the national and sub-national levels. Specifically, Kenya's long-term development plan, Vision 2030 (GoK, 2007) is implemented through a series of 5-year medium-term plans (MTPs) at the national level. The Third MTP for the period 2018-2022 (GoK, 2018b) articulates that it aims to implement policies, programmes and projects to facilitate the attainment of the SDGs, as well as the priorities of the first ten-year implementation plan of Agenda 2063. At the county level, the CIDPs are intended to be aligned to the national MTP, and by extension are vehicles for the implementation of internationally agreed development goals.

Multi-stakeholder partnerships

Enshrined within the Constitution (GoK, 2010) are legal provisions that provide for public participation in the management, protection and conservation of the environment, as well as for the protection of indigenous knowledge. As a result, the policies and plans contain strong statements on the need for participatory approaches. Examples of this are provided in the guiding principle of the National Environment Policy (GoK, 2013c) and the Forest Policy (GoK, 2014a), whereby coordinated and participatory approaches are advocated for the protection and management of environmental and forest resources. Ultimately, participatory mechanisms aim to ensure that state and non-state actors interact in planning, implementation and decision-making processes. Among the key non-state actors in Kenya are the multilateral agencies and bilateral donors that provide financial, technical and capacity development support. Other non-state actors (both international and local) include civil society and private sector organisations that are involved in a range of roles including advocacy, community empowerment, policy analysis, and technical support. The formal multi-stakeholder forums created under the different instruments are discussed below in the institutional context section.

Data, monitoring, and accountability

Several policy and planning instruments contain requirements specifically related to soil and land data, and some more generally on reporting on the status of environment resources. For example: the National Environment Policy (GoK, 2013c) proposes that a national data and information management policy on environmental and biological resources be developed, and requires that there is periodic reporting on county and national status of the environment; the National Land Use Policy (GoK, 2017a) states that the assessments of land resources needs to be carried out, including basic soil surveys, farming systems, soil degradation surveys as well as production potentials of the soils in the country, and requires that the Ministry of Lands prepare a status report on land-use in Kenya once every 10 years for rural areas; the EMCA (GoK, 1999) requires that the NEMA prepare an annual report on the state of the environment in Kenya; the Forest Policy (GoK, 2014a) states that reports on the status and resource assessments of forests will be published on a regular basis; the NSP (GoK, 2016a) requires that status reports on the implementation of the NSP be prepared by the national government periodically, and by the county government annually. At the operational level, the regional and county level policies and plans included different mechanisms for measuring the outcome and impact of activities, e.g. systematic data collection of planned activities, outputs and outcomes for tracking progress and informing decision-making; and requirements on indicator identification, frequency of data collection, responsibility for data collection, data analysis and use (Appendix 4.B).

4.3.5 Institutional context

The responsibility for addressing LDN is spread across 9 national ministries, 6 regional development authorities (RDAs), 47 county governments and legislative assemblies, as well as the 3 branches of the national government (the Executive; Parliament; and Judiciary) (Figure 4.3). Administratively, the country is made up of two formal levels of government: the national government and 47 semi-autonomous county governments, which were created by the Constitution (GoK, 2010) as the new devolved units of governance. Each county has its own government with local representation in the form of elected governors and members of county assemblies. In the context of LDN, Schedule 4 of the Constitution (GoK, 2010) delineates responsibilities between the national and county government as follows. The national government is responsible for: general principles of land-use planning and the co-ordination of planning by the counties; protection of the environment and natural resources, in particular: fishing, hunting and gathering; protection of animals and wildlife; disaster management; and agricultural policy. The responsibilities of the county government include the implementation of specific national government policies on natural resources and environmental conservation, including soil and water conservation, and forestry. In addition, through the County Governments Act (GoK, 2012b), each county is mandated to carry out critical planning functions, including the responsibility to prepare a county spatial plan, with the aim (inter alia), to protect and develop natural resources in a manner that aligns with national and county policies. Clustered along a number of key roles, Appendix 4.C illustrates the institutions, agencies, committees, associations and forums that, across administrative levels, play various roles with respect to the implementation of government functions (including policy, regulatory, research and training, service provision, etc.), and also support the coordination within and between the national government, the county governments, and relevant stakeholders.

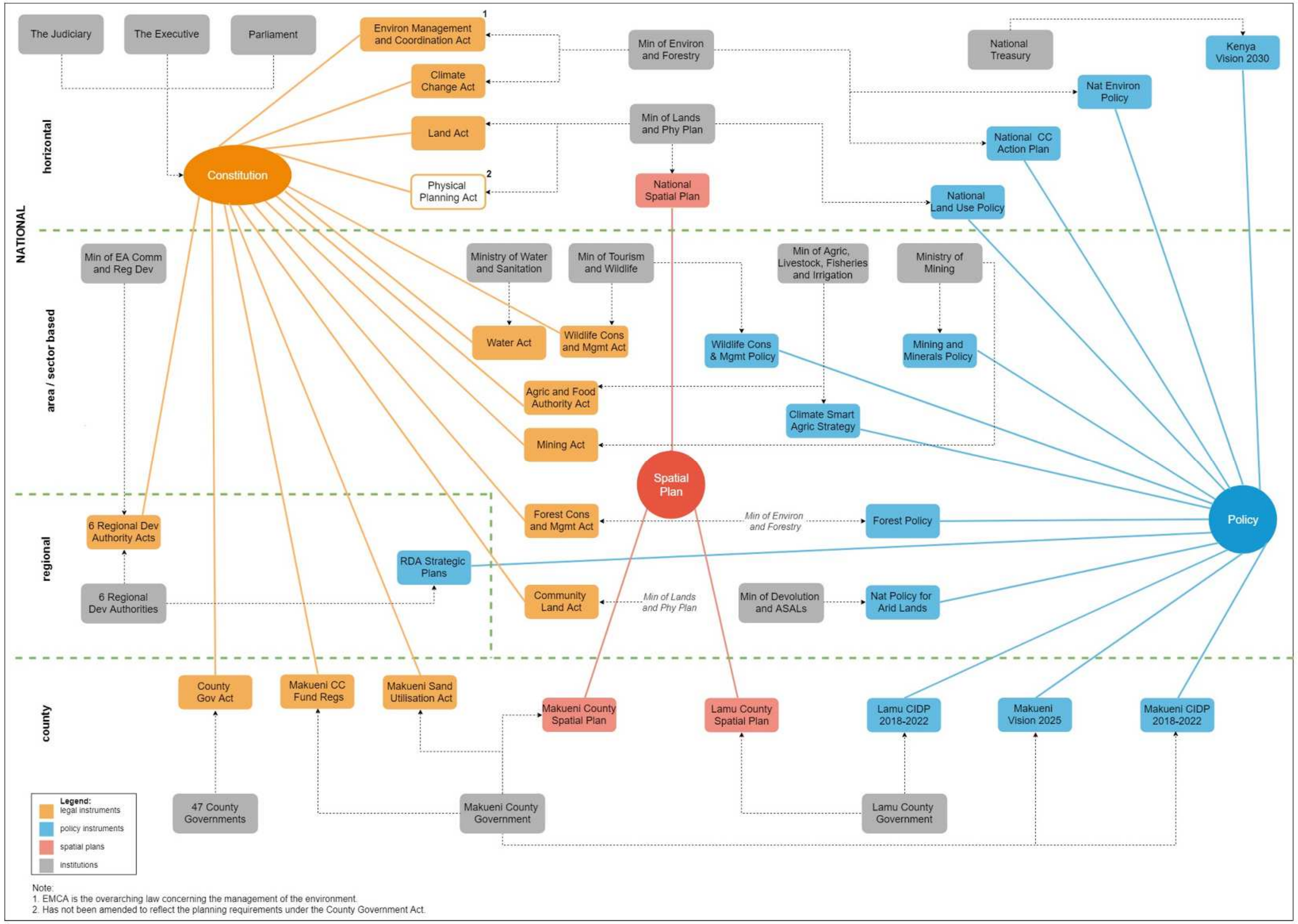

Figure 4.3: The current land-use policy framework.

Under the Ministry of Environment and Forestry, the National Environment Management Authority (NEMA) is the principal institution with the responsibility for the coordination and implementation over all matters and policies relating to the environment, including environmental international conventions, and the development and enforcement of environmental standards and regulations. Two other national environmental oversight bodies are the Environment and Land Court (with duties that include hearing and ruling on matters related to the environment, and on the use and occupation of, and title to, land), and the National Environmental Tribunal (with the mandate to hear disputes arising from NEMA decisions, as well as appeals made in relation to other acts). As the National Environment Policy (GoK, 2013c) is anchored on the principle of subsidiarity that provides decentralised and devolved authority and responsibility for management of the environment and natural resources to the lowest level possible, the obligation to take action on land degradation rests at the county level. At the county level, an example of a multi-stakeholder forum is the County Environment Committee. Established under the EMCA (GoK, 1999), it is to be represented by the following: county government; national government (including an officer of the NEMA); every Regional Development Authority whose area of jurisdiction falls wholly or partially within the county; and non-governmental actors from within the county (farmers or pastoralists, business community, environmental management organisations).

The agriculture sector is a cornerstone of Kenya's economy, and plays a key role in shaping the rural productive landscapes. It directly contributes approximately 33% of the total Gross Domestic Product (GDP), and about 70% of the rural population is engaged in this sector (GoK, 2019). To facilitate horizontal coordination across the national government on agriculture, the CSAS (GoK, 2017b) identifies the roles that various ministries (e.g. energy, land, environment) are expected to play in support of the implementation of the strategy. In accordance with the Intergovernmental Relations Act (GoK, 2012d) that provides the legal framework for the consultation and cooperation between the national and county governments and amongst county governments, the following three mechanisms facilitate the coordination of the agriculture sector (GoK, 2018c): the Intergovernmental Forum on Agriculture, co-chaired by the

Cabinet Secretary of the ministry responsible for agriculture and by the Chair of the Council of Governors, provides a platform for stakeholder consultations and cooperation, and also approves and makes recommendations on programmes, strategies, plans and performance monitoring instruments; the Joint Agriculture Sector Steering Committee (JASSCOM) provides technical direction for sector transformation initiatives agreed between the two levels of government; and the Joint Agriculture Sector Technical Working Groups are the platforms for intergovernmental technical consultations organized along a number of working groups (e.g. crops, livestock, fisheries, irrigation), and responsible for preparing and submitting reports to the JASSCOM.

To further the coordination and coherence in the implementation of the NSP (GoK, 2016a), the following three institutional arrangements are proposed. The National Physical Planning Council, to be chaired by the President of Kenya, is to be responsible, among others, for providing policy guidance for the implementation of strategic spatial projects of national importance, and is to be composed of: Cabinet Secretaries of relevant ministries (e.g. Economic Planning, Devolution, Agriculture, Tourism, Environment, Transport and Infrastructure); Governors from all the counties; and representatives of state agencies. The National Technical Committee, composed of the National Director of Physical Planning (Ministry of Lands), Directors from the various relevant national departments, as well as County Directors of Physical Planning, is responsible for providing technical leadership and ensuring that physical planning is coordinated within the national government. The County Physical Planning Committee is responsible for ensuring that the aspirations of the NSP (GoK, 2016a) are articulated in the preparation of county plans, and is chaired by the Governor of the county, and composed of the Deputy Governor, County Executive Committee members from various sectors, and directors from various relevant County departments (e.g. Lands and Physical Planning, Economic Planning, Agriculture, Tourism, Environment).

Sandwiched between the national government and county governments are the 6 RDAs whose main mandate, as spelt out in the 6 individual RDA Acts (GoK, 1974-1990), is to plan and co-ordinate the implementation of development projects within river basins. Examples of other structures that exist at the regional level are the Basin Water Resource Committees (a multi-stakeholder forum established under the Water Act (GoK, 2016g) and responsible for the management of the water resources within a respective basin area) and the Forest Conservation Committee (a multi-stakeholder forum established under the Forest Conservation and Management Act (GoK, 2016f) to make recommendations to the relevant national and county government organisations in relation to the conservation and utilisation of forests).

4.4 Discussion

The content analysis undertaken in this study has served to demonstrate that the policy instruments (the national constitution, 14 laws, 14 policies (includes strategies and action plans) and 3 spatial plans) were rich with specific legal provisions and measures that broadly address the portfolio of options to address LDN (i.e. the placed-based measures that are appropriate to the Kenyan context, as presented in Table 4.1). We can affirmatively respond to our first broad research question that the current land-use policy framework has the potential to contribute to achieving LDN, as demonstrated by the pertinent measures contained across policy instruments, and the presence of relevant institutions and structures across governance levels. However, the main shortcoming in the current land-use policy framework is the disjointed approach on the management and protection of soil and land, that is scattered across various policy areas. For example, the following laws each individually prescribe for the development of guidelines or regulations for the management of and protection of soil and land: the EMCA (GoK, 1999), the Agriculture and Food Authority Act (GoK, 2013b), and the Community Land Act (GoK, 2016d). Notwithstanding the lack of a systematic approach to addressing LDN, the following opportunities were evident.

First, Kenya has a strong legal foundation to address LDN that is anchored in the Constitution (GoK, 2010). Entrenched within the Constitution are the environmental rights of citizens, the obligations of the state for sustainable environmental management, as well as guiding norms and principles with respect to public participation and safeguarding of indigenous knowledge. The strategic and principle-orientated vision on the environment articulated in the Constitution (GoK, 2010) pervades to other lower legal, policy and planning instruments, and provides for a powerful and potentially transformative step towards attaining environmental sustainability (Boyd, 2012), and more specifically for addressing LDN. Legal requirements to address the LDN responses, i.e. avoid, reduce/reverse and offset, are contained in a number of laws (Figure 4.2). However, the EMCA (GoK, 1999), (which has undergone a number of amendments over time to give full effect to the provisions of the constitution) with its subsidiary legislation and regulatory institutions, is the legislation for environmental management that takes precedence and has the potential to coordinate other horizontal and sectoral laws and policies with mandates relevant to the management and protection of soil and land. As noted by Bodle (2017), in the absence of an overarching holistic concept for land and soil protection, the key priority for governments is to effectively use existing laws, and in the case of Kenya, particularly the EMCA (GoK, 1999), for the purpose of achieving LDN. A key starting point would be the strengthening of the capacity of regulatory, enforcement and coordination agencies (e.g. NEMA, the Kenya Forest Services, the Kenya Wildlife Services (Appendix 4.C)), as advocated in the National Land Use Policy (GoK, 2017a). The enhanced capacity of these agencies would help deter processes and activities that are likely to lead to the degradation of land.

Second, while specific measures to address the portfolio of options to address LDN are scattered in a number of laws, policies and plans (Figure 4.2), the implementation of various initiatives contained within the following instruments would give teeth to addressing LDN. As proposed in the National Environment Policy (GoK, 2013c), the development of a National Soil Conservation Policy could provide an overarching policy framework on land and soil protection to overcome the existing fragmentation. The assessments of land resources (including basic soil surveys, farming systems, soil degradation surveys) as suggested in the National Land Use Policy (GoK, 2017a), would provide data and information on where land has degraded or regenerated and a sound basis for decision-making to address LDN. In addition, given the comprehensive nature of the targeted land based climate change adaptation and mitigation interventions articulated in the NCCAP (GoK, 2018a), this action plan could be used as a first step towards implementing LDN, and as a tool for addressing synergies between climate change and land degradation.

Third, the strategic orientated, long-term (30 year planning horizon) NSP (GoK, 2016a) is well placed to play a critical role in the integration and coordination of policy agendas across key development, socio-economic and environmental sectors, institutions, and actors, at the national, regional and county levels. Among the mechanisms suggested by Briassoulis (2019) to overcome the challenges related to the integration of LDN into existing land-use planning processes are: a proactive, forward-thinking and precautionary decision culture; strategic decision making, which is long-term, encompasses all spatial/organisational levels, and is supported by suitable instruments; and participatory modes of governance and decentralised planning. Notwithstanding the reporting requirements and the institutional structures of the NSP, there is an absence of information on how the requirements set out in the NSP will be complied with and enforced. This presents an opportunity for the development of a robust monitoring and evaluation framework for the NSP, with strong compliance and enforcement components, as well as on mechanisms to ensure effective feedback on the performance of the spatial plan across sectors and governance levels.

Relying on the current land-use policy framework to address LDN will likely result in some gaps and anomalies. Reports from the pilot countries participating in the LDN TSP indicate that every country has its own cocktail of challenges, including so called “failures of the past” (Chasek et al., 2019). In light of the challenges the 2002 NAP (GoK, 2002) was designed to address, the assessment carried out in the current study has indicated a number of failures of the past. Specifically, the current land-use policy framework was weak on coherently addressing: data on the existing soil and land conditions; secure funding for implementation of LDN initiatives; and clear delineation of responsibilities across various levels of government. Following is a discussion on the key policy and institutional improvements required to advance the pursuit of LDN in Kenya.

As land degradation is not a static state, but rather, a continuum, monitoring of the rates, causes, and effects of land degradation will need to be done continuously, with sequential updates (Stavi & Lal, 2015). While a number of laws, policies and plans contain requirements specifically related to soil and land data, an important gap, and perhaps the most important barrier to achieving the LDN objective in Kenya, is the lack of systematic and coordinated data collection strategy on soils and the impacts of land degradation. One of the 3 biophysical metrics proposed by the UNCCD to measure LDN is soil organic carbon (SOC) (UNCCD, 2016). However, in Kenya, there is no uniform national coverage of SOC data due to the limited number of soil profiles, nor any SOC trend data (Gichenje & Godinho, 2018). SOC is arguably one of the most important soil indicators because of its central role in a range of soil functions, including its known benefits for improved soil fertility and productivity, and its contribution to food security (Stockmann et al., 2015). Keesstra et al. (2016) demonstrate the linkage of soil functions across several of the SDGs (e.g. food security, human health, biodiversity preservation, water security, and climate change), and advocate for the cheap and reliable monitoring of SOC. This implies that investment by countries in the collection of SOC stock data would not just be for the purpose of monitoring the LDN goal, but would also provide information more broadly to support implementation of a number of SDGs. However, field measurement of SOC, and other soil properties, is a resource-intensive exercise in terms of labour, time and money (BIO, 2014). In consideration of these barriers, machine learning prediction and remote sensing approaches offer cost-effective techniques for mapping a number of soil properties including SOC (Nijbroek et al., 2018; Vågen et al., 2016), and are areas that would benefit from government support for scientific and technical research. Further, as land degradation cannot "be judged independently of its spatial, temporal, economic, environmental and cultural context" (Warren, 2002), concerted data collection on socio-economic and cultural factors, and their interactions over time and space, will be required to provide information into the planning processes that address LDN.

While the implementation of some SLM measures (Table 4.1) are likely to be within reach of many land users (Chasek et al., 2015), significant investments will be required to coherently implement transformative LDN programmes and projects, that include sustainable interventions at scale, while featuring innovation in terms of locally adapted technologies, inclusive governance arrangements, and financial mechanisms (UNCCD, 2018). Given that funding for LDN initiatives from the national budgets may not be sufficient, and that the UNCCD's financial mechanisms (the Global Mechanism and the Global Environment Facility) have not mobilised enough resources to implement the Convention (Chasek et al., 2019), countries will need to pursue strategies to attract innovative sources of funding. One such source is the independent LDN Fund that pools capital from public and private sources to support LDN initiatives (UNCCD and Mirova, 2017). Operational since the end of 2018, the LDN Fund has made its first investment in Latin America in a programme focused on restoring degraded land and promoting SLM (Mirova, 2019).

Other innovative sources of funding include market-based approaches, such as financial and economic instruments, payments for ecosystem services, farm subsidies, conservation tenders and biodiversity offsets (IPBES, 2018). The legal, policy and planning instruments included a number of these innovative finance mechanisms as well as dedicated funds (Appendix 4.B). Further, at the operational level, the regional and county level documents contained statements on the need to bridge financial gaps and attract additional investments for projects by engaging external partners, particularly the private sector. To ensure that sufficient funding is available for LDN implementation over an extended period, Kenya will need to harness a mixture of financial sources and mechanisms, but more importantly, create a coherent and enabling environment for LDN investments (Chasek et al., 2019).

Furthermore, to effectively address LDN, greater governmental collaboration and cooperation is necessary across the responsibilities of different government agencies in order to: bring together the fragmented knowledge base on e.g. agriculture, rangeland management, meteorology, hydrology, soil science, indigenous and local knowledge; incorporate the input of all relevant stakeholders; bridge the science-policy divide; and implement coordinated activities at the national level that will also interact with the community and international levels (Chasek et al., 2015). With respect to environment functions, the Constitution (GoK, 2010) delineates specific roles and tasks to the national and county governments (Section 3.5). While no role for the RDAs is provided in the Constitution of Kenya, the responsibility for the 6 RDAs is subsumed under the Ministry of East African Community and Regional Development (Appendix 4.C). In this context, there is need to clearly delineate responsibilities at the national, regional and county levels so as to avoid the duplication of roles, as well as to streamline the implementation of interventions to address LDN.

The national government needs to play the following key functions: policy coherence and coordination on the management of soils and land, first and foremost through the elaboration of the National Soil Conservation Policy; designating at the national level the main agency that will be responsible for LDN implementation; enhancing the capacity for the effective enforcement of environmental legislation through the NEMA and other national enforcement and coordination agencies (Appendix 4.C); developing a national soil reporting framework with standardised rules and protocols and designating the national agency to lead on this activity; creating a coherent and enabling environment for LDN investments to attract, in particular, innovative sources of LDN funding; strengthening the compliance and enforcement mechanisms related to spatial planning; targeted research to further enable evidence-based decisions regarding land degradation and restoration (IPBES, 2018), through the specialised agencies (e.g. Kenya Agricultural and Livestock Research Organization, Kenya Forestry Research Institute) (Appendix 4.C); meeting the reporting requirements as stipulated in various instruments; and streamlining governance structures to enable effective interactions among the numerous actors across national, regional and county levels and across policy domains.

At the sub-national level, the UNCCD TSP proposes the analysis and contextualisation of LDN at the watershed scale to provide decision support for the formulation of policies and programmes towards transformative LDN interventions (UNCCD, 2017). The RDAs, established based on river basins and large water bodies, offer an entry point for the implementation of landscape-scale approaches that integrate the development of agricultural, forest, energy, water and infrastructure agendas (IPBES, 2018). Another feasible entry point for implementing LDN at the landscape-scale would be within areas with community land tenure. The new Community Land Act (GoK, 2016d) provides a broad framework for the management and administration of community land, and promises land security for approximately 6 to 10 million people primarily in ASAL areas (Wily, 2018). Land tenure insecurity can prevent farmers from adopting SLM practices (Dallimer et al., 2018). With greater security of access to and use of natural resources by communities, proven SLM practices could be brought to scale on community lands.

The 47 counties represent the lowest devolved units of government in Kenya. As most land management decisions take place at individual farm scale (Dallimer et al., 2018), the decentralization of a number of national government functions to the county level presents an enormous opportunity to address LDN in a tangible way. The local-scale and biophysical and socioeconomic contexts within which land degradation occurs (Stavi & Lal, 2015), implies that counties, which operate closest to the people, can better target SLM interventions. To improve on policy design and implementation a better understanding is required of the relationship between farmers' decisions, land-use change and public policies (Primdahl et al., 2004). Further, since the choice of land management practices adopted by rural households is context dependent and a product of many factors (Emerton & Snyder, 2018; Pender et al., 2006), county governments need to better target a range of services, particularly extension and research, and to strengthen research-extension-farmer linkages to better select appropriate response options and inform LDN policy and implementation gaps.

4.5 Conclusions

The current land-use policy framework in Kenya forms a strong platform for addressing LDN. However, an overarching approach on the management and protection of soil and land is required to ensure that Kenya can effectively achieve the LDN target by 2030. The qualitative content analysis of the national constitution, 14 laws, 14 policies (includes strategies and action plans) and 3 spatial plans, across institutional and governance levels, highlighted that: there is a strong legal foundation to address LDN that can be anchored in the guiding principles and entrenched environmental rights provided in the national constitution; the targeted land-based climate change adaptation and mitigation interventions articulated in the NCCAP (GoK, 2018a) could be used as a vehicle to support effective synergies between climate change and land degradation;

and, the integrative potential of the strategically orientated NSP (GoK, 2016a) can be realised through mechanisms that ensure compliance and enforcement across policy domains and governance levels.

Relying on the current land-use policy framework to address LDN will likely result in some gaps and anomalies. Key policy and institutional improvements needed to support effective implementation of LDN include putting in place: a national soil conservation policy to provide an overarching policy framework on land and soil protection; a systematic and coordinated data collection strategy on soils and the impacts of land degradation; mechanisms for the mobilisation of adequate and sustained financial resources; streamlined responsibilities and governance structures across national, regional and county levels. While the focus of this analysis has been on public policies, processes and agencies, numerous and diverse non-governmental actors also play a crucial role in the protection and management of soil and land in Kenya. Hence, across all levels of government, platforms, pathways and incentives need to be strengthened and/or created to effectively facilitate the role of diverse stakeholders.

The participation by Kenya in the UNCCD TSP programme presents an opportune time to integrate the reforms discussed above in the formulation of a new NAP to outline how LDN will be achieved by 2030. Specifically, the new NAP should be action-orientated and fully financed, and focused on steering Kenya towards the implementation of better land management practices. In a country like Kenya, where soil and land fundamentally underpin livelihoods and economic activity, the sense of urgency and priority given to creating an enabling policy environment for improving the condition of degraded ecosystems and to promoting sustainable land management, cannot be overstated.

4.6 Appendices

4.6.1 Appendix 4.A: Provisions and measures included in the main laws relevant for addressing LDN

	Legal instruments	LDN response hierarchy		
		Avoid	**Reduce & Reverse**	**Offset**
NATIONAL				
horizontal	**Physical Planning Act (1996)**	• Preparation of different types of plans: regional physical development plan, local physical development plan (para. 16,24) • Powers of local authorities: to control or prohibit the subdivision of land or existing plots into smaller areas (para. 29)	N/A	• The local authority concerned shall require the developer to restore the land on which such development has taken place to its original condition within a period of not more than ninety days (para. 30.4.a)
	Environmental Management and Co-ordination Act (1999)	• Formulate the National Environmental Action Plan every six years (para. 37) • Prepare a County Environment Action Plan every five years (para. 40)	• Protection and conservation of the environment (Part V): re-forestation and afforestation, and other measures for management of hill tops, hill slopes and mountainous areas; measures to curb soil erosion; prescribe measures for the management and protection of any area declared to be a protected natural environment area	• Environmental restoration orders (Part IX: para 108): require the person on whom it is served to restore the environment as near as it may be to the state in which it was before the taking of the action which is the subject of the order
	Constitution of Kenya (2010)	• Chapter 5 on Land and Environment: sound conservation and protection of ecologically sensitive areas; ensure sustainable exploitation, utilisation, management and conservation of the environment and natural resources	• Achieve and maintain a tree cover of at least 10% of the land area of Kenya	N/A

	Legal instruments	LDN response hierarchy		
		Avoid	**Reduce & Reverse**	**Offset**
	Land Act (2012)	• Conservation of ecologically sensitive public land (para. 11): identify ecologically sensitive areas that are within public lands and demarcate or take any other justified action on those areas and act to prevent environmental degradation and climate change	• Conservation of land based natural resources (para. 19): may contain measures to protect critical ecosystems and habitats	• The lesee it to restore the land to the same conditions they were at the beginning of the lease (para. 66.1.c) • Entry orders/rights of way: the restoration of the land to its former state at the conclusion of the work (para. 139.5.e)
	Climate Change Act (2016)	• Formulate programmes and plans to enhance the resilience and adaptive capacity of human and ecological systems	N/A	N/A
sector / area based	**Wildlife Conservation and Management Act (2013)**	• Every national park, marine protected area, wildlife conservancy and sanctuary shall be managed in accordance with a management plan that complies with the requirements prescribed (para. 44)	• Protection of endangered and threatened ecosystems: measures to be taken to restore and maintain the ecological integrity for enhanced wildlife conservation (para. 46)	• Mining and quarrying in a national park: the miner has undertaken through execution of a bond the value to rehabilitate the site upon completion of operations to a level prescribed by the Service and the Mining Act (para. 45)
	Agriculture and Food Authority Act (2013)	• Land preservation guidelines for the purposes of the conservation of the soil, or the prevention of the adverse effects of soil erosion on, any land, include (para. 23): prohibiting, regulating or controlling the undertaking of any agricultural activity for the protection of land against degradation, the protection of water catchment areas or otherwise, for the preservation of the soil and its fertility	• Land preservation guidelines (para. 23): reforestation or re-afforestation of land; the drainage of land, including the construction, maintenance or repair of drains, gullies, contour banks, terraces and diversion ditches	N/A

Legal instruments	LDN response hierarchy		
	Avoid	**Reduce & Reverse**	**Offset**
Community Land Act (2016)	• Land use and development planning (para. 19) shall consider any conservation, environmental or heritage issues relevant to the development, management or use of the land; consider any environmental impact plan pursuant to existing laws on environment	• Environmental and natural resource management: rules and by-laws may provide for the conservation and rehabilitation of the land (para. 37)	N/A
Mining Act (2016)	• A mining licence shall not be granted to a person under this Act unless the person has obtained an environmental impact assessment licence, social heritage assessment and the environmental management plan has been approved (para 176)	• The Cabinet Secretary may prescribe regulations on the measures to be observed to protect and rehabilitate the environment (para. 223)	• Upon completion of prospecting or mining, the land in question shall be restored to its original status or to an acceptable and reasonable condition as close as possible to its original state (para 179)
Forest Conservation and Management Act (2016)	• Management plans: every public forest, nature reserve and provisional forest shall be managed in accordance with a management plan; every county government shall be responsible for the preparation of a management plan with respect to forests in the county; a community that owns a community forest may prepare a management plan for that community forest (para. 47)	• Formulate a public forest strategy for the protection, conservation and management of forests and forest resources, which will include measures for the protection, conservation, and management of forests and forest resources (para. 6)	• Consent for quarrying operations in a forest area (para. 46): licensee to undertake compulsory restoration and re-vegetation immediately upon the completion of the activity (para. 46.4)
Water Act (2016)	• Formulate of a basin area water resources management strategy (para. 28)	• Agreements as to protection of sources of water: e.g. protecting the catchment areas, drainage of land, carrying out soil conservation measures, control of vegetation (para. 104)	• Damage caused by works of a permit holder: the Authority may by order require the permit holder to construct such additional works as are necessary (Schedule 3, para. 4)

Legal instruments	LDN response hierarchy		
	Avoid	**Reduce & Reverse**	**Offset**
REGIONAL			
6 Regional Development Authority (RDAs) Acts (1974-1990)	• Functions of the RDAs (para10): to initiate such studies, and to carry out such surveys; to assess alternative demands within the Area on the resources thereof, including agriculture (both irrigated and rainfed), forestry, wildlife and tourism industries	• Functions of the RDAs (para10): to cause the construction of any works necessary for the protection and utilization of the water and soils of the Area	N/A
COUNTY			
County Governments Act (2012)	• Principles of county planning (para. 102): protect and develop natural resources in a manner that aligns national and county governments policies	• Maintain a viable system of green and open spaces for a functioning eco-systems	N/A
Makueni Sand Utilisation Act (2015)	• Designate and gazette in the County Gazette sand utilization and conservation sites (para. 27)	• Riverbed sand utilisation (para. 29): sand utilization from any riverbed shall be undertaken in a manner that allows for an adequate reserve of the sand to be retained to ensure water retention	N/A
Makueni Climate Change Fund Regulations (2015)	N/A	N/A	N/A

4.6.2 Appendix 4.B: Provisions and measures included in the main policies and plans relevant for addressing LDN

	Policies, strategies, and plans	LDN response hierarchy Avoid (+) Reduce & Reverse (++)	Means of implementation (*) (financial measures: $)
NATIONAL			
horizontal	**Kenya Vision 2030 (2007)**	+ Preparation of the First National Spatial Plan for Kenya to guide physical development activities (p. 14) + A national land use policy to be completed as a matter of urgency to guide the transformation expected under Vision 2030 (p. 21) ++ Rehabilitation of degraded water catchments areas while promoting on-farm forestry (p. 129)	* Strengthening technical capabilities: The capacities of science, technology and innovation institutions will be enhanced through advanced training of personnel, improved infrastructure, equipment, and through strengthening linkages with actors in the productive sectors (p. 20) * Establish a Geographical Information System (GIS)-based Land Information System will be necessary to facilitate the management of geo-spatial information relating to land (p. 22) $ Use of market-based environmental instruments: Design and implement selective incentives/disincentives that will reward good practices in environmental management and penalise those that harm the environment (p. 131)
	National Environment Policy (2013)	+ Develop and implement a National Soil Conservation Policy (para. 4.7.2) ++ Promote integrated watershed management and alternative livelihood opportunities to enhance community participation and empowerment in the conservation and management of mountain ecosystems (para. 4.4.2) ++ Promote good soil management practices to avert landslides, mudslides, floods and other disasters that are preventable (para. 4.7.2)	* Develop and implement awareness raising strategies and capacity development on the opportunities for adaptation and mitigation measures as per the climate change action plan (para. 5.1) * Promote technologies for efficient and safe water use, especially in respect to wastewater use and recycling (para. 6.2) * Develop a national data and information management policy on environmental and biological resources (para. 7.1) $ Revitalise the Desertification Trust Fund (para. 4.5.3); promote and institutionalise payment for environmental services schemes to support catchment protection and conservation (para 4.2.2)
	National Spatial Plan: 2015-2045 (2016)	+ Prepare integrated wetland resource, marine resource, forest resource, and mountain ecosystems management plans for environmentally sensitive areas	* Mainstream climate change, water management, green energy generation and agriculture into the national and county planning processes * Develop and maintain an inventory of all vital habitats in the country, and create a biodiversity information data base of all plant and animal species, indicating their potential use

Policies, strategies, and plans	**LDN response hierarchy** **Avoid (+)** **Reduce & Reverse (++)**	**Means of implementation (*)** (financial measures: $)
	+ Develop and implement an Integrated Land Use Master (Development) Plan for the ASALs ++ Protect and increase forest cover, riverine vegetation and critical water catchment areas in the ASALs ++ Intense forest cover through afforestation, reafforestation and agroforestry in the highlands	$ Revitalize the Desertification Trust Fund and National Drought and Disaster Contingency Fund
National Land Use Policy (2017)	+ Enhance the capacity of regulatory and enforcement agencies (para. 3.13) + Prohibit settlement and other activities within sensitive ecological zones (para. 3.13) ++ The conservation and enhancement of the quality of land and land-based resources (para. 3.5) ++ The improvement of the condition and productivity of degraded lands in rural and urban areas (para. 3.5)	* **Carry out an assessment of land resources including basic soil surveys, farming systems, soil degradation surveys as well as production potentials of the soils in the country (para. 3.5)** * Provide incentives for community participation in conservation of natural resource and environment (para. 3.14) * Conduct research on natural resource and environment conservation technologies (para. 3.14) * Mainstream climate change adaptation and mitigation in rangeland management (para. 3.11) $ Establishment of a Land Reclamation and Restoration Fund (para. 4.6.8); Set up a special fund for management and reclamation of wetlands (para. 3.18)
National Climate Change Action Plan (2018*, draft)*	++ Food and nutrition security: implementation of sustainable land management (SLM) increased for agricultural production: support the reclamation of 60,000 ha of degraded land; area under integrated soil nutrient management increased by 250,000 acres; farm area under conservation agriculture increased to 250,000 acres, incorporating minimum/no tillage; total area under agroforestry at farm level increased by 200,000 acres (pg. 45) Forestry, wildlife and tourism (pg. 52):	* Mainstream climate change into environment audits, environmental impact assessments and strategic environmental assessments * Provide information through the MRV+ system for measuring, monitoring, evaluating, verifying and reporting results of mitigation actions, adaptation actions and the synergies between them, and support received (pg. 80) * M&E will focus on demonstrating that investment in adaptation and mitigation actions leads to real climate results and development benefits and provide the evidence base for planning and implementing future actions, seeking support, and domestic and international reporting (pg. 87) $ Operationalise the Climate Change Fund; pilot the issuance of Green Bonds; participate in the development of market-based mechanisms domestically and internationally (pg. 79)

	Policies, strategies, and plans	LDN response hierarchy Avoid (+) Reduce & Reverse (++)	Means of implementation (*) (financial measures: $)
		+ reduce deforestation and forest degradation in 100,000 million ha of natural forests through: community/participatory forestry management; limiting access to forests: preventing disturbances through improved enforcement and monitoring ++ restoration of up to 200,000 ha of forest on degraded landscapes (ASALs, rangelands) ++ Conserve 30,000 hectares of wildlife habitats	
sector / area based	**National Policy for the Sustainable Development of Northern Kenya and other Arid Lands (2012)**	Policy interventions by sector (Annex 1, 2): + Promote water harvesting to ensure food security in collaboration with Regional Development Authorities + Ensure that all investment and economic development protects the environment, provides compensation where required, and delivers maximum benefits to communities ++ Protect and increase forest cover, riverine vegetation and critical water catchment areas in the ASALs	* To strengthen the climate resilience of communities in the ASALs and ensure sustainable livelihoods (para. 4.2) Policy interventions by sector (Annex 1, 2): * Strengthen research and extension systems relevant to rain-fed crop production, including soil and water conservation, organic farming and agroforestry * Increase access to the skills and technologies needed for irrigated agriculture, particularly when community-managed * Protect and promote indigenous knowledge & practice, promote environmental education & awareness, and intensify environmental conservation efforts $ Develop and support financial services and products appropriate to the needs of the region, including insurance schemes to buffer production against risk
	Forest Policy (2014)	+ Sustainable Forest Management (SFM): All forest resources shall be managed sustainably to yield social, economic and ecological goods and services for the current generation without compromising similar rights of future generations (para. 3.3) ++ Promote the rehabilitation and management of water catchment areas (para. 4.1)	* Monitor, assess and prepare periodic report on the integrity of forests including water towers (para. 4.1) * Design appropriate capacity development plans through continuous assessment of professional and technical capacity needs (para. 6.1) * Mainstreaming forestry into sector policies, such as wildlife, agriculture, housing, national security, water, tourism, industry, energy, education (para. 8.1) $ Contribute financial resources for the Forest Management and Conservation Trust Fund (para. 7.3) $ Enhance resource mobilization strategies through carbon financing, payment for environmental services and other appropriate mechanisms (para. 7.3)

Policies, strategies, and plans	LDN response hierarchy Avoid (+) Reduce & Reverse (++)	Means of implementation (*) (financial measures: $)
	++ Promote species diversification through planting of indigenous and exotic species with proven potential (para. 4.2)	
Mining and Minerals Policy (2014)	+ Integrating sound environmental protection, safety and health considerations in mineral resources development (para. 3.2) ++ Establish a clear legal framework, procedures and obligations concerning rehabilitation at mine closure by mining licence and permit holders (para. 3.4)	Policy Strategies (para. 3.4): * Enhance collection and access to geological data: conduct a nationwide airborne geophysical survey, acquire spatial data, and undertake ground surveys to identify potential mineralised zones * Develop and implement mechanisms to enhance participation of Government (National & County), affected communities and other stakeholders in mining investments $ Requirement for mining rights holders to set aside an environmental deposit bond to meet rehabilitation and mine closure obligations
Climate Smart Agriculture Strategy: 2017-2026 (2017)	Activities within thematic areas (Annex 1): ++ Promote sustainable natural resource management through: integrated soil fertility management (ISFM); restoration of degraded soils and conservation of soil biodiversity ++ Promotion of agroforestry for reduction of emissions from deforestation and forest degradation plus, forest conservation, sustainable management of forests and enhancement of carbon stocks, including range management + Minimize use of fires in rangelands and croplands management + Establish oversight and accountability systems for enforcement + Promote partnerships between stakeholders to enhance joint planning and implementation of CSA programs	Activities within thematic areas (Annex 1): * Mainstream CSA activities into the government budget cycle * Formulate proposals for joint programs and projects for CSA with private, sector and development partners to enhance funding for CSA * Promote strategic partnerships with private sector and development partners * Establish and maintain a data and information management system that is interlinked to counties and other stakeholders $ Establish mechanisms for accessing climate finance for CSA activities, for e.g. through enhancing access to the Climate Change Fund provided for in the Climate Change Act(2016) and ensure that climate activities are mainstreamed in the MTP

Policies, strategies, and plans	LDN response hierarchy Avoid (+) Reduce & Reverse (++)	Means of implementation (*) (financial measures: $)
Wildlife Conservation and Management Policy (2017)	+ Ecosystem approach: management of wildlife resources with the objective of maintenance of ecosystem functions and ecological processes, and explicitly accounting for the impact of interventions on ecological patterns and processes at the landscape scale (para. 3.3) ++ Rehabilitate and restore wildlife habitats, including in threatened, sensitive or critical areas and degraded areas in the protected areas (para. 5.2)	* Policy Integration: the wildlife policy will be linked to and harmonised with other relevant policy areas and instruments (para. 3.3) * Support conservation education, public awareness and capacity building, in order to foster wildlife conservation and change of attitudes amongst local communities, schools and other interested groups (para. 5.3) $Establish and manage a Wildlife Endowment Fund to promote wildlife conservation and management (para. 5.4) $ Develop economic modalities for appropriate economic instruments, including payment of ecosystem services (PES), to support the conservation of important wildlife areas (para. 5.4)
REGIONAL		
Ewaso Ng'iro South Development Authority Strategic Plan (2017-2022)	Strategic pillars: (Chap. 4) + Undertake review of master plan + On-farm water harvesting + Promotion of smallholder irrigation ++ Rehabilitation of degraded catchment areas	Strategic pillars: (Chap. 4) * Partner with learning institutions in research and innovation development * Partner with local community in implementation and management of projects $ Establish resource mobilisation strategy: mapping of donors and development partners; implement selected projects under the public private partnership framework * Strengthen M&E: Systematic data collection of the planned activities, outputs and outcomes
Kerio Valley Development Authority Strategic Plan (2014-2018)	Strategic objectives: (Chap. 4) + Protection of riparian areas along river banks + Promote farm forestry (woodlots establishment) + Construction of water pans/small dams ++ Support mitigation measures on landslide prone areas	Strategic objectives: (Chap. 4) * Promote climate change adaptation and mitigation * Undertake detailed studies on mapped resources (GIS based) * Establish data resource centre * Explore Public Private Partnership (PPP) arrangements to attract a wide a wide range of both local and International investors $ Undertake resource mobilization and organise investment forums $ Generate revenues from greening technologies such as carbon credit and climate change global adaptation funds

Policies, strategies, and plans	LDN response hierarchy Avoid (+) Reduce & Reverse (++)	Means of implementation (*) (financial measures: $)
COUNTY		
Makueni Vision 2025 (2016)	+ development of a county environmental policy and greening regulations, and environmental management framework ++ rehabilitation and protection of ecosystems (wetlands, forests, rangelands and water catchments) through reclaiming river banks, water catchments, re-afforestation and tree planting: increase forest cover to at least 10 per cent	* Strengthening the role of communities in management and conservation of environment and sustainable waste management systems * Mainstreaming climate change and disaster management in development planning * Continuously invest in awareness creation and sensitization on climate change and disaster reduction $ Develop the county investment marketing and promotion bill and the appropriate policy as a strategy to help bridge the financial resources gap, by marketing the county as an ideal investment destination (para. 7.4)
Lamu County Spatial Plan: 2016-2026 (2017)	Measures identified across strategic zones: + discourage encroachment onto sand dunes ++ propose a 100-meter buffer zone on Lamu Island along the sand dune strip + promote conservation of the sand dunes as breeding grounds for the turtles (CBD) ++ preventing encroachment by providing a buffer zone of at least 100 meters along the edges of the mangrove ring + promote mutually compatible land uses that enhance the conservation of the Mangrove Forests, e.g. eco-lodges in Manda Island and Pate Island around the mangrove rings ++ maintain at least the 70% mangrove cover in the county	* Form Community Forest Organizations to collaborate with relevant organisations in the management and use of the mangrove forests * Establish training institutes to do research and train personnel on mangrove and marine life * Promote inter-agency cooperation in the management and conservation of mangrove forests $ The Capital Investment Plan (CIP) developed as a process of planning and funding capital investment as a regular activity integrated within the county (Chap. 16) * Monitoring and evaluation framework: for the purposes of accountability and reporting of progress on the implementation of the spatial plan, and as a basis for adaptive management and continued improvement of the environmental conditions of the County (Chap. 17)
Lamu County Integrated Development Plan: 2018-2022 (2018)	+ Improving range resource management and conservation + Policy formulation and research: laws, policies, strategies and regulations on use of land and other resources; resettlement action plan	* Mainstreaming climate change and other cross cutting issues in agriculture and rural development (p. 66) * Survey and mapping, including accessible spatial information to users with data reliability and uniformity (p. 66): * Secure rights in land and natural resources

Policies, strategies, and plans	LDN response hierarchy Avoid (+) Reduce & Reverse (++)	Means of implementation (*) (financial measures: $)
	++ Storm water infrastructure development to improve drainage	* Enhance evidence-based policy development through monitoring, evaluation and reporting (p. 102) * Increase stakeholder involvement in tourism product development and marketing * Flood management: conduct floods risk assessments, floods vulnerability sensitization campaigns (p. 132) $ Ensure adequate and sufficient funding for projects and programs by enforcing revenue collection and increase revenue points, revenue resource mapping
Makueni County Integrated Development Plan: 2018-2022 (2018)	+ facilitate gazetting of 20 water catchment areas and towers + develop a water policy, county water master plan, rain water harvesting policy ++ rehabilitate 10 rivers	* community sensitization campaigns and advocacy on environment conservation * awareness and advocacy on climate change * strengthening the capacity of community members on water governance * issuance of new 10,000 tittle deeds $ establish a fund to support activities for green energy development $ Resource Mobilization Framework: the internal strategy focuses on enhancing the county's own source revenue, while the external strategy focuses on engaging external partners to finance implementation of the CIDP
Makueni County Spatial Plan: 2019-2029 (2019)	Measures identified in the Implementation Matrix (section 6.3): ++ Afforestation and re-afforestation of all degraded forests + Preparation of forest management plans for all gazetted forests ++ Promotion of soil conservation + Prepare detailed feasibility study along the major rivers to establish the viability and suitable locations for medium and small sand dams + Map out and prohibit development in environmentally sensitive areas + Increasing number of extension officers in the whole county	Measures identified in the Implementation Matrix (section 6.3): * Development of community awareness programs on benefits of forest resources * Enhancement of community training programs on the appropriate and standardized methods of terracing within the steep sloping areas * Titling of the un-surveyed land in the rural areas * Developing a comprehensive Geographical Information System (GIS) based database on land information * Encouraging research in farm inputs e.g. improved seed varieties $ The Capital Investment Plan (CIP) is a five-year planning tool intended to, inter alia, identify all capital needs, and Identify appropriate actors to fund selected development projects (Chapter 7)

4.6.3 Appendix 4.C: Key public institutions at the national, regional and county level with a mandate relevant to LDN

		Ministry of Environment and Forestry	Ministry of Lands and Physical Planning	Ministry of Agriculture, Livestock, Fisheries and Irrigation	Ministry of Devolution and ASALs		Ministry of Tourism and Wildlife	Ministry of Water and Sanitation	Ministry of Mining	Ministry of East African Community and Regional Development	The National Treasury
NATIONAL	Policy	- Kenya Meteorological Department - Directorate of Environment - Directorate of Natural Resources	Department of Physical Planning		Devolution Department	ASAL Department			- Directorate of Mines - Directorate of Geological Survey		State Department for Planning
		Climate Change Secretariat	National Land Commission	Agricultural Sector Coordination Unit	Intergovernmental Relations Technical Committee	ASAL Transformation Secretariat					Vision 2030 Delivery Secretariat
		National Climate Change Steering Committee (NCCSC)	National Technical Committee - Spatial Planning - Land Use Policy	Inter-Ministerial Coordination Committee	Council of County Governors	ASAL Cabinet Sub-Committee					
		State Department Climate Change Units	National Council - Land Use Policy - Physical Planning		National and County Government Coordinating Summit	ASAL Inter-Ministerial Committee					
					Intergovernmental Consultative Sectoral Forum						
	Multi-stakeholder Forum	National Climate Change Council				ASAL Stakeholders' Forum (national)			Mining Forum		
	Regulatory	National Environmental Management Authority		Agriculture and Food Authority		National Drought Management Authority		Water Resources Authority	Mineral Rights Board		
		National Environment Tribunal						Water Services Regulatory Board			
		Environment and Land Court						Water Tribunal			
	Research/ Training	Kenya Forestry College		Kenya Agricultural & Livestock Research Organization		National Council on Nomadic Education	Wildlife Research and Training Institute				
		Kenya Forestry Research Institute				Northern Kenya Education Trust					
	Service provision/ Coordination/ Technical	Kenya Water Towers Agency	Kenya Institute of Surveying and Mapping	Agricultural Development Corporation			Kenya Wildlife Service	National Water Harvesting and Storage Authority	National Mining Corporation		
		Kenya Forest Service		National Irrigation Board					Minerals and Metal Commodity Exchange		
REGIONAL	Multi-stakeholder Forum	Forest Conservation Committee						Basin Water Resources Committee			
	Service provision/ Coordination/ Technical							Water Works Development Agencies		6 Regional Development Authorities	
COUNTY	Legislative				County Assemblies						
	Multi-stakeholder Forum	County Environment Committee			Village council	ASAL Stakeholders' Forum (county)					
	Service provision/ Coordination/ Technical	County Climate Change Units	County Physical Planning Committee		Citizens' Service Centre (at the county; the sub-county; the Ward; and any other decentralized level)		County Wildlife Conservation and Compensation Committees	Water service providers	Artisanal Mining Committee		
			County Technical Implementation Committees (Land Use Policy)		County executive committee		Community wildlife associations				
			Community land management committee		County Development Board						
					Office of Village Administrator						
					Office of Ward Administrator						
	USERS	Community Forest Associations	Registered community	Irrigation Water Users Associations				Water resource users associations			

Chapter

5

A CLIMATE-SMART APPROACH TO THE IMPLEMENTATION OF LAND DEGRADATION NEUTRALITY WITHIN A WATER CATCHMENT AREA IN KENYA

Based on the published manuscript:

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Abstract

At the sub-national level, the United Nations Convention to Combat Desertification (UNCCD) proposes the analysis and contextualization of land degradation-neutrality (LDN) at a water catchment scale to provide decision support for the formulation of policies and programmes towards transformative LDN interventions. Building on a number of national LDN studies in Kenya, an approach for the implementation of LDN that is based on the spatial and temporal characterization of key land degradation and climate change variables was defined. For a selected water catchment area, the LDN baseline was computed, the drivers that affect land degradation and regeneration trends within the main land cover types were identified and described, the trends of key climate change variables were described, and appropriate sustainable land management interventions for the main land cover types were identified. A climate-smart landscape approach that delineated the catchment area into zones focused on adaptation, and both adaptation and mitigation objectives was then proposed. The operationalization of a climate-smart landscape will require significant investment to not only provide an understanding of the bio-physical processes and interactions occurring at the catchment level but also to develop the institutional and technical capacities of relevant actors. The landscape approach proposed for the catchment area has the potential to improve livelihoods and the productivity of ecosystems while concurrently facilitating synergies between land degradation, climate change, and other development objectives.

***Keywords**: land degradation-neutrality; climate change; climate-smart-landscape; water catchment; Kenya*

5.1 Introduction

Land degradation and climate change are two of the most pressing global problems affecting terrestrial ecosystems. According to the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES), land degradation is occurring in all parts of the terrestrial world, and is negatively impacting the well-being of at least 3.2 billion people, and costing more than 10% of the annual global gross product in loss of biodiversity and ecosystem services (IPBES, 2018). In addition, the Intergovernmental Panel on Climate Change (IPCC) states that in recent decades, changes in climate have caused impacts on natural and human systems on all continents by altering hydrological systems, affecting the quantity and quality of water resources, causing, inter alia, mainly negative impacts on crop yields, and the shift of geographic ranges, seasonal activities, migration patterns, and abundances of many terrestrial and freshwater species (IPCC, 2014). Furthermore, land degradation and climate change are inextricably linked. Soils contain vast reserves of organic carbon, which are estimated to be three times the amount of carbon in vegetation and twice the amount in the atmosphere (Smith, 2012). When land is degraded, carbon dioxide (CO_2) is released from cleared and dead vegetation, and through the reduction of the carbon sequestration potential of the degraded land (Sivakumar & Stefanski, 2007). Over the period 1970 to 2010, CO_2 from forestry and other land use (FOLU) generated approximately 15% of total annual anthropogenic greenhouse gas (GHG) emissions (IPCC, 2014). Moreover, climate change may exacerbate land degradation through alteration of spatial and temporal patterns in temperature, rainfall, solar radiation, and winds (Sivakumar & Stefanski, 2007), which could adversely affect both above and below-ground fauna and flora. The inter-linkages between land degradation and climate change (as well as biodiversity loss) has been recognised and conceptualised in the Millennium Ecosystem Assessment (MEA) (MEA, 2005).

The Sustainable Development Goals (SDGs), adopted by the global community in 2015, include goals and targets related to land degradation and climate change. Specifically, goal 15.3 of the SDGs states: “By 2030, combat desertification, restore degraded land and soil, including land affected by desertification, drought and floods, and strive to achieve a land degradation-neutral world" (UN, 2017). The United Nations Convention to Combat Desertification (UNCCD) defines land degradation-neutrality (LDN) as a "state whereby the amount and quality of land resources necessary to support ecosystem functions and services and enhance food security remain stable or increase within specified temporal and spatial scales and ecosystems" (UNCCD, 2015). SDG 13 is expressed as a clarion call to "take urgent action to combat climate change and its impacts" with targets related to: strengthening resilience; integrating climate change measures into national policies and planning; improving human and institutional capacity on climate change, particularly in vulnerable groups; and monitoring progress towards climate financial commitments (UN, 2017).

Notwithstanding the complex interconnections between land degradation and climate change (MEA, 2005), concurrently addressing these two phenomena is not an insurmountable problem. The IPBES seminal assessment report on land degradation and restoration emphasises that not only will the adoption of sustainable land management (SLM) practices avoid, reduce and reverse land degradation (also know as the LDN response hierarchy, as elaborated by Cowie et al. (2018) in an article that summarises the key features of the scientific conceptual framework for LDN), but SLM practices may also substantially contribute to the adaptation and mitigation of climate change (IPBES, 2018). SLM as broadly defined by FAO/TerrAfrica in Liniger et al. (2011) is "the adoption of land use systems that, through appropriate management practices, enables land users to maximise the economic and social benefits from the land whilst maintaining or enhancing the ecological support functions of the land resources." The IPBES (2018) message above, that actions to address land degradation can also contribute to addressing climate change, is aligned with the recommendations by the IPCC (2014), that the most cost-effective mitigation options in forestry are afforestation, sustainable forest management and reducing deforestation, and in agriculture, cropland management, grazing land management and restoration of organic soils. Further, included in the suite of low-cost and simple low-regrets adaptation measures proposed by the IPCC for Africa (Niang et al., 2014) are i) harnessing Africa's longstanding experiences with natural resource management, biodiversity use, and ecosystem-based responses such as afforestation, rangeland regeneration, catchment rehabilitation, and community based natural resource management to develop effective and ecologically sustainable local adaptation strategies; and ii) technological and infrastructural approaches in agricultural and water management, such as planting crop varieties that are better suited to shorter and more variable growing seasons, constructing bunds to more effectively capture rainwater and reduce soil erosion.

A growing body of literature has documented that many SLM practices can lead to both mitigation and adaptation outcomes (Liniger et al., 2011; Delgado et al., 2011; Branca et al., 2011; Harvey et al., 2014; Locatelli et al., 2015). The framing of practices in terms of their potential to attain both adaptation and mitigation benefits has resulted in the emergence of the term "climate-smart" as a development concept. The term was first used by the Food and Agricultural Organization of the United Nations (FAO) to describe the needed transformation and reorientation of agricultural production systems in the face of climate change (Rosenstock et al., 2016). The term is now broadly used to express the pursuit of adaptation and mitigation objectives simultaneously across various ecosystems e.g. climate-smart forests (Nabuurs et al., 2017), climate-smart soils (Paustian et al., 2016), and climate-smart landscapes (Harvey et al., 2014). The three main concepts that define a climate-smart approach are: sustainably increasing productivity and incomes; adapting and building resilience to climate change; and reducing and/or removing greenhouse gas emissions.

The UNCCD LDN Target-Setting Programme (TSP) provides technical and financial support to over 120 countries, including Kenya, in three key areas: accessing the best available data for target setting; conducting multi-stakeholder consultation processes to mainstream LDN into national SDG agendas; and identifying investment opportunities for LDN implementation (UNCCD, 2019). At the sub-national level, the UNCCD TSP proposes the analysis and contextualisation of LDN at the watershed scale to provide decision support for the formulation of policies and programmes towards transformative LDN interventions (UNCCD, 2017). A watershed is an area that drains to a common outlet (stream, river, wetland, lake, or ocean), and where water, soil, geology, flora, fauna, and human land-use practices interact (Darghouth et al., 2008). The use of watersheds as a socioeconomic-political unit for management, planning and implementation is not a new concept, and has evolved from a focus on water resource management and the hydrological cycle, to the current integrated multidisciplinary approach of broadly managing ecosystems using the boundaries of the watershed, and now commonly known as integrated watershed management (Wang et al., 2016).

To reduce the impacts of degradation and enhance the resilience of both ecosystems and rural livelihoods, one of the urgent step changes recommended by the IPBES (2018) is the implementation of integrated landscape-wide approaches. The term 'landscape approach' has been applied in many different contexts, but can generally be termed to refer to a set of concepts, tools, methods and processes used in landscapes to achieve multiple economic, social, and environmental objectives (multifunctionality), involving different actors (Minang et al., 2015a). Landscape initiatives at the watershed level are among the oldest landscape approaches (van Noordwijk et al., 2015), with the first written reference to watershed management dating to as far back as 800 BC (Wang et al., 2016). As the terms water catchment and watershed are generally used synonymously (Darghouth et al., 2008), in the current study the term water catchment will be used.

The operability of the LDN concept at the national level is an area of recent and growing research, resulting in a number of publications on the characterisation of LDN, e.g.: Gichenje and Godinho (2018) established the LDN baseline for Kenya (580,000 km^2) in terms of the three LDN indicators (land cover, land productivity, and soil organic carbon (SOC)) using trends in Normalised Difference Vegetation Index (NDVI) and land cover datasets over the 24-year period from 1992 to 2015; Nijbroek et al. (2018) derived SOC baseline maps by comparing different digital soil mapping methods and sampling densities in the Otjozondjupa Region (150,000 km^2) in Namibia to provide new insights and guidance for future LDN SOC baseline mapping in other areas; Solomun et al. (2018), for the Entity Republic of Srpska (a 25,024 km^2 region that is part of Bosnia and Herzegovina), derived the baseline condition based on trends for land cover, land productivity dynamics and SOC, based on a global dataset provided by the UNCCD for the three indicators. More recently, Al Sayah et al. (2019)

examined the impact of land use and land cover changes, surface runoff and soil types to establish land capability maps to determine the extent of land degradation in the Awali basin (301 km^2) in Lebanon.

Given this background, the present study aimed to propose an approach for the implementation of LDN at a water catchment level that is based on the spatial and temporal characterisation of key land degradation and climate change variables. The present study builds on the results obtained from the following national level studies in Kenya: LDN baseline assessment (Gichenje and Godinho, 2018); the identification of the key drivers of land degradation and regeneration (Gichenje et al., 2019a); and the assessment of the potential of the current land-use policy framework in Kenya to achieve LDN (Gichenje et al., 2019b). For a selected water catchment area in Kenya, the specific objectives of this study were as follows: i) compute the LDN baseline; ii) identify and describe the drivers that affect greening and browning trends within the main land cover types, and make a comparison with the results obtained at the national level; iii) characterise the water catchment area using key climate change variables; iv) identify appropriate SLM interventions for the main land cover areas; and v) conceptualise a climate-smart landscape and reflect on the possible benefits, challenges, and policy implications of LDN implementation therein.

5.2 Materials and methods

5.2.1 Study area

Kenya is located on the eastern coast of Africa and has a total area of 582,646 km^2. The terrain and climate of the country varies considerably, and it is hot and humid along the coast, temperate inland, and very dry in the north and northeast parts of the country (GoK, 2015). According to the National Water Master Plan 2030 (GoK, 2013), the country can be delineated into 6 main catchment areas. As the major rivers in the two smallest and contiguous catchment areas, Lake Victoria North and Lake Victoria South, drain into Lake Victoria (GoK, 2013), we merged these two water catchment areas into one. The merged area was termed the Lake Victoria Water Catchment (LVWC) and is the focus of our analysis (Figure 5.1).

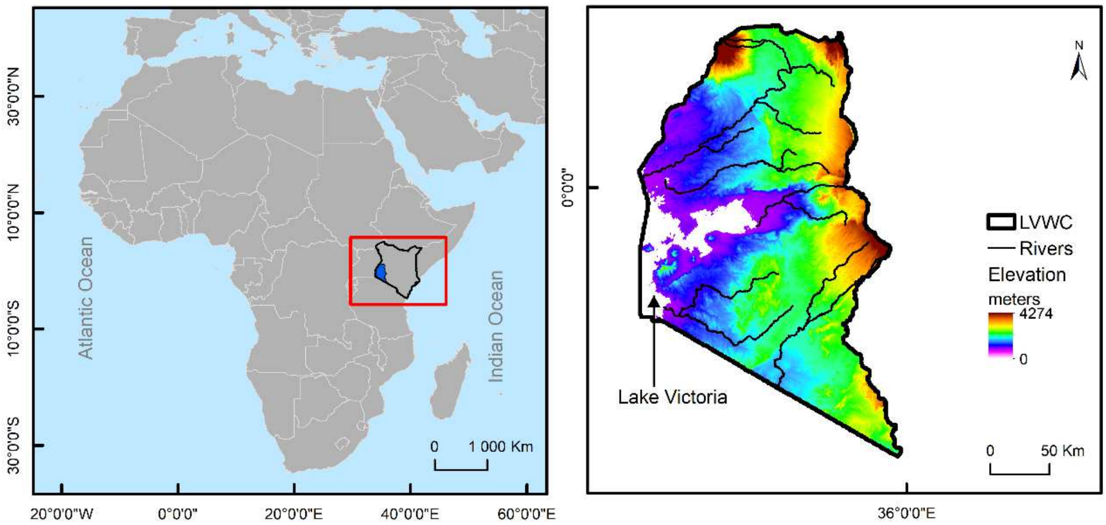


Figure 5.1: Study area (with elevation and rivers illustrated for the LVWC).

LVWC is located at the western most part of the country as shown in Figure 5.1. It borders Uganda in the north, Tanzania in the south, and the Rift Valley catchment area in the east. Lake Victoria, which is the second largest fresh water lake in the world, forms the most western extent of the LVWC. The total area of the catchment area is 49,292 km^2, corresponding to 8.5% of the country's total area. Based on the population projections for 2017, the population of the area is estimated at 17.7 million, or 37.6% of the total population of Kenya (GoK, 2018a). The average population density is approximately 500 persons/km^2, and ranges from 62 persons/km^2 (in Narok county) to as high as 1202 persons/km^2 (in Vihiga county). The LVWC encompasses 18 counties, of which 4 counties are partially located in the catchment area). An illustration of the county boundaries within the LVWC is provided in Appendix 5.A.

According to the National Water Master Plan (GoK, 2013) the catchment area can be described as follows. The topography of the catchment area varies, peaking at an altitude of 4,321 m above mean sea level (amsl) in Mt. Elgon, to Lake Victoria at 1,134 m amsl. The major rivers in the catchment area are the Nzoia, Yala, Malaba, Malikisi, Sio, Nyando, Sondu, Kuja and Mara rivers. The source of a number of these rivers is a large forest area in the eastern part of the catchment area, known as the Mau Forest Complex. LVWC has been the most vulnerable area to flood disasters in Kenya. The majority of the LVWC is classified as a humid area, and the mean annual rainfall ranges between 1,200 mm to 1,800 mm. The northern half of the catchment area has ample annual rainfall and is wet, but the lower southern part has less rainfall. Major crops cultivated are rain-fed and include horticultural crops and food crops such as maize. Rice cultivation is active at the low-lying area near Lake Victoria. The share of irrigation area against cropping area ranges is low (less than 3%).

5.2.2 Data

Water catchment area

Vector data for the river basins of Kenya was downloaded from the Intergovernmental Authority on Development (IGAD) Climate Prediction and Applications Centre (ICPAC) GeoPortal (http://geoportal.icpac.net/layers/geonode%3Aken_riverbasins) (ICPAC, 2019). The data were cropped to the extent of the LVWC, and projected to the WGS84 coordinate system.

LDN baseline

The LDN national baseline for Kenya (Gichenje & Godinho, 2018) was established as follows: The state in 2015 of each of the 3 LDN indicators (i.e. land cover, land productivity, and SOC) across the main land cover classes, and the trends in Global Inventory Monitoring and Modeling System (GIMMS) Normalised Difference Vegetation Index (NDVI) and land cover data for the 1992-2015 period. The LDN baseline is the reference state of the three LDN indicators at time zero (i.e., the year 2015 when the SDGs were adopted) against which the LDN target will be assessed in 2030 (the target date for the SDGs) (Gichenje & Godinho, 2018). The following layers (at 300m resolution), as derived from the Gichenje & Godinho (2018) study, were cropped to the extent of the LVWC.

- Land cover: The land cover maps for the period 1992 – 2015.
- Net Primary Productivity (NPP): MODIS annual NPP data for 2015.

- Soil organic carbon (SOC): SOC at the standard fixed depth interval of 0–30 cm (ton/ha).
- Greening and browning NDVI trends: Trends in the Normalised Difference Vegetation Index (NDVI) were used as a proxy for trends in land productivity. Persistent negative NDVI trends (an indication of land degradation) were termed as browning trends, while persistent positive NDVI trends (an indication of land regeneration) were termed as greening trends.

Drivers of greening and browning trends

Dependent variable: The NDVI trends layer described above was used to derive the dependent variable. In 2015, the main land cover classes in the LVWC were agriculture (75%) and forests (13%). The share of greening and browning trends within the agriculture and forest layers (at 300m resolution), as well as the number of observations, were presented in Table 5.1.

Table 5.1: Share of greening and browning trends within the different datasets.

NDVI trend	Agriculture	Forest
	300m resolution	
Greening	7.8%	9.3%
Browning	92.2%	90.7%
Total observations	103,062	17,284

Explanatory variables: On the basis of the study undertaken by Gichenje et al. (2019a) on the analysis of the drivers that affect greening and browning trends in Kenya, the same dataset of 28 explanatory variables (broadly grouped into natural and anthropogenic variables) were used to identify the key drivers affecting greening and browning trends in the LVWC. A full description of the explanatory variables, the sources of data, and the SDG each variable most closely represents are contained in Gichenje et al. (2019a).

Climate change variables

The following 3 climate change variables were selected to characterise the water catchment area.

Soil moisture: Soil moisture refers to the amount of water stored in the unsaturated soil zone (Seneviratne et al., 2010). Soil moisture is a slowly varying component of the Earth system, which can influence weather through its impact on evaporation and other surface energy fluxes (Koster et al., 2004). In a review of soil moisture–climate interactions, Seneviratne et al. (2010) highlight that soil moisture constrains plant transpiration and photosynthesis in several regions of the world, with consequent impacts on the water, energy and biogeochemical cycles. Soil moisture is a key variable of the climate system, through its action as a storage component for precipitation and radiation anomalies, thus inducing persistence in the climate system (Seneviratne et al., 2010). The soil moisture data was obtained from the combined active–passive microwave data set of the European Space Agency Climate Change Initiative (ESA-CCI) (https://www.esa-soilmoisture-cci.org/node/145). The combined ESA-CCI soil moisture data (CCI SM v04.4) (in m^3/m^3 volumetric units, at a resolution of 0.25 degrees, and flag 0 pixels indicating no data inconsistency detected) for the period January 1992 to December 2017 was used in this study. The global daily data were cropped to the extent of Kenya, and then cropped again to the extent of the LVWC, and aggregated to monthly and annual mean values.

Vegetation condition index: Since 2014, Kenya's National Drought Management Authority (NDMA) uses the vegetation condition index (VCI) as the basis for providing disaster contingency funds to counties in drought conditions (Klisch & Atzberger, 2016). The VCI is a NDVI-based index that serves as a proxy for moisture vegetation health, and ranges from zero (representing extreme vegetation stress) to 100 (indicating optimal conditions) (Kogan & Guo, 2015). The NDMA uses the following thresholds to indicate the category of drought: ≥ 50 = wet; 35–50 = normal; 21-34 = moderate drought; 10-20 = severe drought; and < 10 = extreme drought (Klisch & Atzberger, 2016). The VCI data at a resolution of 4-km, were derived from the National Oceanic and Atmospheric Administration (NOAA) and the Advanced Very High Resolution Radiometer (AVHRR) dataset (NOAA, 2019). The weekly records for the period 2005 - 2018 (prior to 2005 there are years with missing data) were cropped to the extent of Kenya, and then cropped again to the extent of the LVWC, and aggregated to monthly and annual mean values.

Vulnerability index: The degree to which human and natural systems are susceptibility to, and unable to cope with the adverse effects of climate change, including climate variability and extremes, is referred to as vulnerability (IPCC, 2007). The vulnerability index spatial dataset (30 arc/sec spatial resolution) indicating the level of vulnerability to climate change impacts in 2010, was downloaded from the FAO GeoNetwork site (http://www.fao.org/geonetwork/srv/en/main.home) (FAO, 2019).

5.2.3 Methods

LDN baseline

Using the extent for the LVWC, and following Gichenje & Godinho (2018), we calculated the baseline state of each of the 3 LDN indicators per land cover type as follows: the area of each land cover class using the land cover map for 2015; the annual MODIS NPP in 2015; and the mean SOC in 2000. We also computed the change from year to year for each the land cover classes over the 24-year period (increase or decrease in km^2).

Drivers of greening and browning trends

Following Gichenje et al. (2019a), the methodological approach used to identify the key drivers of greening and browning trends in the LVWC was the random forest (RF) machine learning algorithm. The methodological steps, outputs (variable importance (VI) plots using the mean decrease in accuracy (MDA) measure; and relative importance plots by SDG group) and performance metrics (accuracy; and Kappa) are described in Gichenje et al. (2019a).

However, the current study differs from the Gichenje et al. (2019a) study in the method used to balance the data. As indicated in Table 5.1, browning trends are predominant (more than 90%) in agriculture and forest areas. As the RF algorithm performs poorly for classification of imbalanced data (Chen et al., 2004), we used the synthetic minority oversampling technique (SMOTE) to balance the data. The SMOTE algorithm, instead of replicating and adding observations from the minority class (in our case the greening class), it generates artificial data through a combination of over-sampling of the minority class, and under-sampling of the majority class (Chawla et al., 2002). We split the dataset into a training set (80%), and a test set (20%). Using the training set and the DMwR package (Torgo, 2010), we created a SMOTE training set by setting perc.over = 100 to double the greening cases, and setting perc.under = 200 to keep half of what was created as browning cases. The SMOTE training set was used as input to the RF model, while the test set was used to score the model.

Trends of the climate change variables

Soil moisture trends and monthly variability: Using the *greenbrown* R package (Forkel et al., 2015; Forkel et al., 2013), we computed the pixelwise trend analysis on annual mean aggregated soil moisture time series (1992-2017) to extract significant trends (at a confidence level of 95%) for the water catchment area. The output was a single layer classified into 3 areas: non-significant trends, positive significant trends and negative significant trends. The trends layer was then resampled and projected to match the 300m land cover data using the nearest-neighbour algorithm. We also examined the monthly variability of the soil moisture data by generating boxplots.

VCI trends and monthly variability: Using the monthly aggregated data and the NDMA drought categories, the drought dynamics at the water catchment level was calculated as the per cent of the area affected by drought as follows: VCI ranging from 21 to 50 indicates moderate-to-normal drought intensity; and VCI ≤ 20 indicates extreme-to-severe drought intensity. Linear trend lines were plotted to illustrate the direction of change of the proportion of the areas affected by drought. We also examined the monthly variability of the VCI data by generating boxplots.

Vulnerability index: Based on the quantiles assigned to the vulnerability index layer (FAO, 2019), the values in the layer were grouped into the following three categories: low: <0.9; medium: 0.9 to 1.1; and high: >1.1. The vulnerability index layer was then cropped to the extent of the water catchment area. This layer was then resampled and projected to match the 300m land cover data using the nearest-neighbour algorithm.

SLM interventions

A qualitative assessment of the potential of the current land-use policy framework to effectively implement LDN objectives was undertaken by Gichenje et al. (2019b). One of the key findings of the aforementioned study was that the National Climate Change Action Plan (NCCAP) (GoK, 2018b) contained targeted land based interventions, which while aimed at mainstreaming adaption and mitigation actions into sector functions, could also comprehensively support the implementation of LDN. In this regard, Gichenje et al. (2019b) recommended that this 5-year action plan could be used as a first step towards implementing LDN, and as a tool for addressing synergies between climate change and land degradation. In this step of the analysis, we first identified SLM initiatives from the NCCAP (GoK, 2018b) that could be implemented within the main land cover areas in the LVWC. Using the population density and land area of the LVWC, we then scaled down the national targets. For each broad cluster of SLM practices (e.g. water management, agroforestry, soil fertility management), we described the potential to address the three climate-smart objectives (i.e. increasing productivity and incomes; adapting and building resilience to climate change; and reducing and/or removing greenhouse gas emissions).

5.3 Results

5.3.1 LDN baseline

The LDN baseline is provided in Table 5.2. The highest values of NPP and SOC occur in forests and wetlands. In the LVWC the predominant land cover class is agriculture (75%), followed by forest (13%) and water bodies (7%) (Figure 5.2a). The annual change in area (increase or decrease in km^2) within each land cover class was examined and showed that the magnitude of change was more pronounced during the first half of the 24-year period (Figure 5.2b). Of note is that at the national level, a high rate of land cover change was also observed in the first half of the 24-year period from 1992 to 2015 (Gichenje & Godinho, 2018). The largest annual change in area occurred in 2001, whereby approximately 940 km^2 of agriculture areas increased at the expense of forest areas and shrublands.

In the catchment area, 67% of the area is characterised by non-significant NDVI trends (Figure 5.2c). Browning trends account for approximately a quarter of the area (with strong browning = 13%, and moderate browning = 11%). Greening trends (predominantly moderate greening), account for only 2% of the area (Figure 5.2c). Of note is that the trends illustrated in Figure 5.2c refer to human-induced trends, as the climate influence was removed from the NDVI trends (Gichenje & Godinho, 2018).

Table 5.2: Status of the 3 LDN indicators in the baseline year (2015).

Land cover classes	Land cover (area)		MODIS NPP	Soil organic carbon[1] (0-30cm)
	km^2	%	g C/m^2	ton/ha
Agriculture	36,928	74.9%	996	90
Forest	6,553	13.3%	1170	118
Grassland	226	0.5%	754	62
Shrubland	1,955	4.0%	816	72
Wetland	179	0.4%	1146	121
Settlement	68	0.1%	806	94
Water	3,382	6.9%	-	-

1. The SOC is for the year 2000. In the absence of a national SOC database, the UNCCD recommends that SoilGrids250m can be used to compute the SOC stocks as representing data for the year 2000 (UNCCD, 2017).

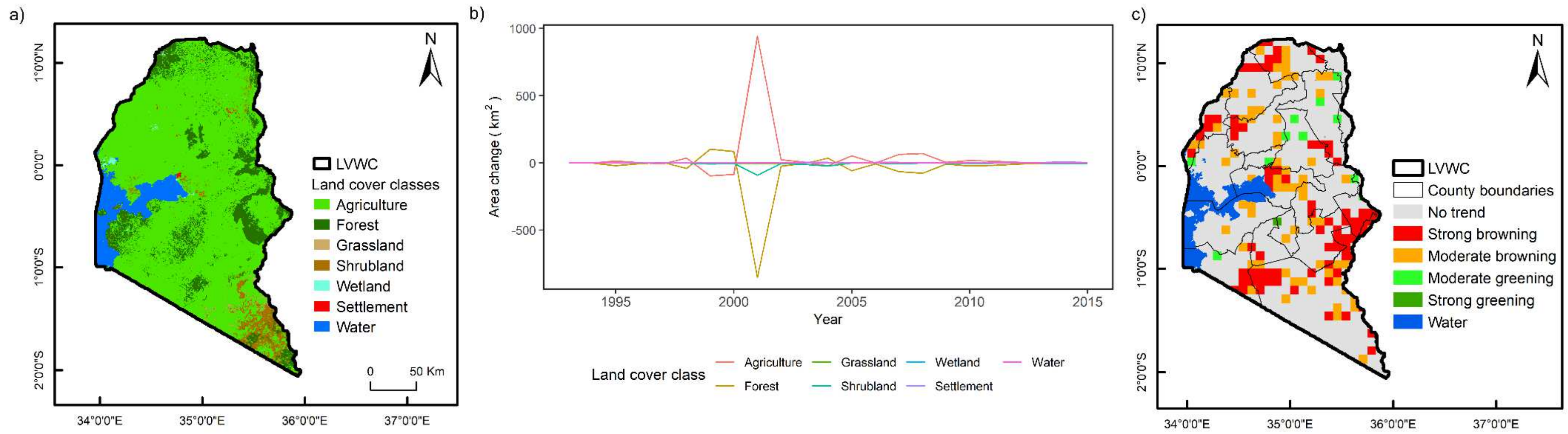


Figure 5.2: Land Degradation Neutrality (LDN) baseline for the Lake Victoria Water Catchment (LVWC): a) land cover map for 2015; b) annual change in area (km^2) for each land cover class from 1992 to 2015; and c) distribution of human-induced greening and browning trends.

5.3.2 Drivers of greening and browning trends and comparison with national level results

For the agriculture dataset, none of the 28 explanatory variables were rejected from the Boruta procedure (i.e. step 1 of the methodology as described in Gichenje et al. (2019a). However, for the forest dataset, the variable night-time lights was rejected from the Boruta procedure. Hence, the RF analysis involved the use of all 28 explanatory variables in the agriculture dataset, and the use of 27 explanatory variables in the forest dataset. The two RF models showed strong performance, and the mean values for accuracy and Kappa are provided in Table 5.3.

Table 5.3: Mean performance metrics from 100 random forest iterations for the two datasets.

Metric	Agriculture	Forest
Accuracy	0.9925	0.9968
Kappa	0.9501	0.9813

The VI plots for the two datasets were derived from the mean of the 100 classifications. As depicted in the two VI plots (Figure 5.3, 5.4), the most important variables can be grouped as those with a MDA greater than the mean MDA (illustrated in Figure 5.3, 5.4 as the vertical red dashed line). In agricultural areas the most important variables in the LVWC (Figure 5.3a), were primarily the natural variables (slope, landform and vulnerability), and the variables representing accessibility to markets both for the inputs and outputs of agricultural production (distance to roads, distance to towns, and travel time). For the most part, the most important variables at the national level (Figure 5.3b, (Gichenje et al., 2019a)) coincide with those at the LVWC. However the differences between the two levels are as follows. At the national level, soil type and zone are above the mean MDA, while in the LVWC these two variables are below the mean MDA. Further, in the LVWC the potential of agricultural land (i.e. the variable LowAgric) has a strong influence on greening and browning trends, unlike at the national level where this variable is ranked the lowest. Most of the LVWC falls within the humid moisture zone. Agricultural areas in the LVWC have a predominant soil type (i.e. acrisols), and are mainly of medium or high potential.

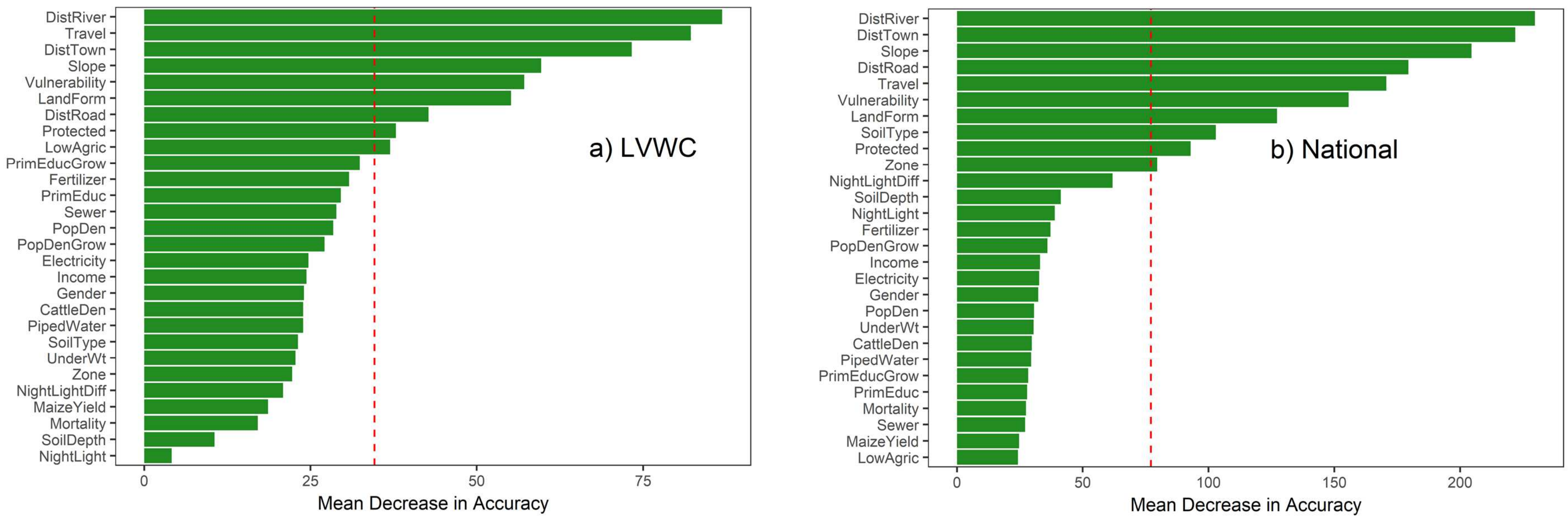


Figure 5.3: Comparison of the variable importance (VI) plots for agriculture areas: (a) VI plot for the LVWC; and (b) VI plot at the national level (note: the national plot is obtained from Gichenje et al. (2019a); and the average Mean Decrease in Accuracy (MDA) is represented by the vertical red-dashed line).

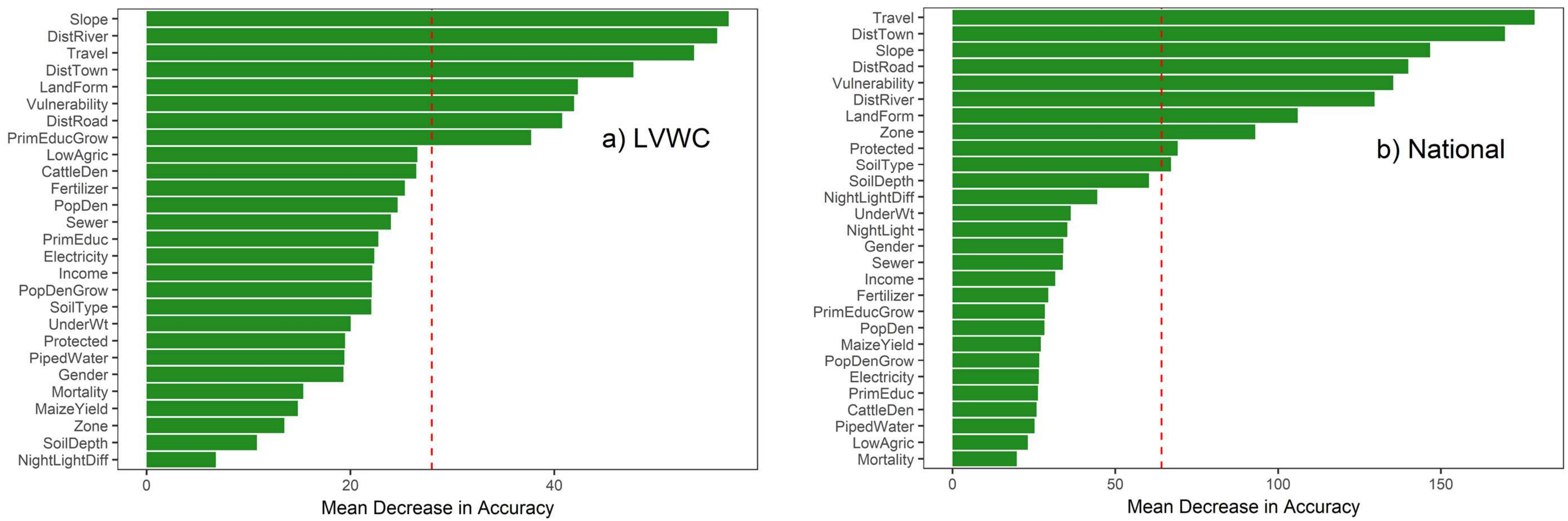


Figure 5.4: Comparison of the variable importance (VI) plots for forest areas: (a) VI plot for the LVWC; and (b) VI plot at the national level (note: the national plot is obtained from Gichenje et al. (2019a); and the average MDA is represented by the vertical red-dashed line).

Similar to agricultural areas in the LVWC, the most important variables in forest areas were primarily the natural variables and the variables representing accessibility to markets (Figure 5.4a). As well, the most important variables in forest areas at the national level (Figure 5.4b, (Gichenje et al., 2019a)) coincide with those at the LVWC. However, the differences between the two levels are as follows. At the national level, zone, soil type, and protected areas are above the mean MDA, while in the LVWC these three variables are below the mean MDA. Of note is that in the LVWC, one social development variable, the growth in primary school enrolments between 1992 and 2015, has a strong influence on greening and browning trends. Andosols are the predominant soil type group in forest areas in the LVWC. Unlike at the national level where most of the forest areas are not within protected areas, in the LVWC forests are equally distributed within both protected and non-protected areas.

When the variables were grouped by SDGs, we note the similarity of the results obtained across the two datasets in the LVWC. In both agricultural and forest areas in the LVWC, the variables grouped under the SDGs 15 (life on land) and 8 (economic growth) cumulatively account for over 50% of the prediction of the greening and browning trends (Figure 5.5a, 5.6a). The main difference between the national level results (as obtained from Gichenje et al. (2019a)) and the results in the catchment area in both agricultural and forest areas, was the higher relative importance of the social dimensions of sustainable development, and in particular education (SDG 4), in contributing to greening and browning trends.

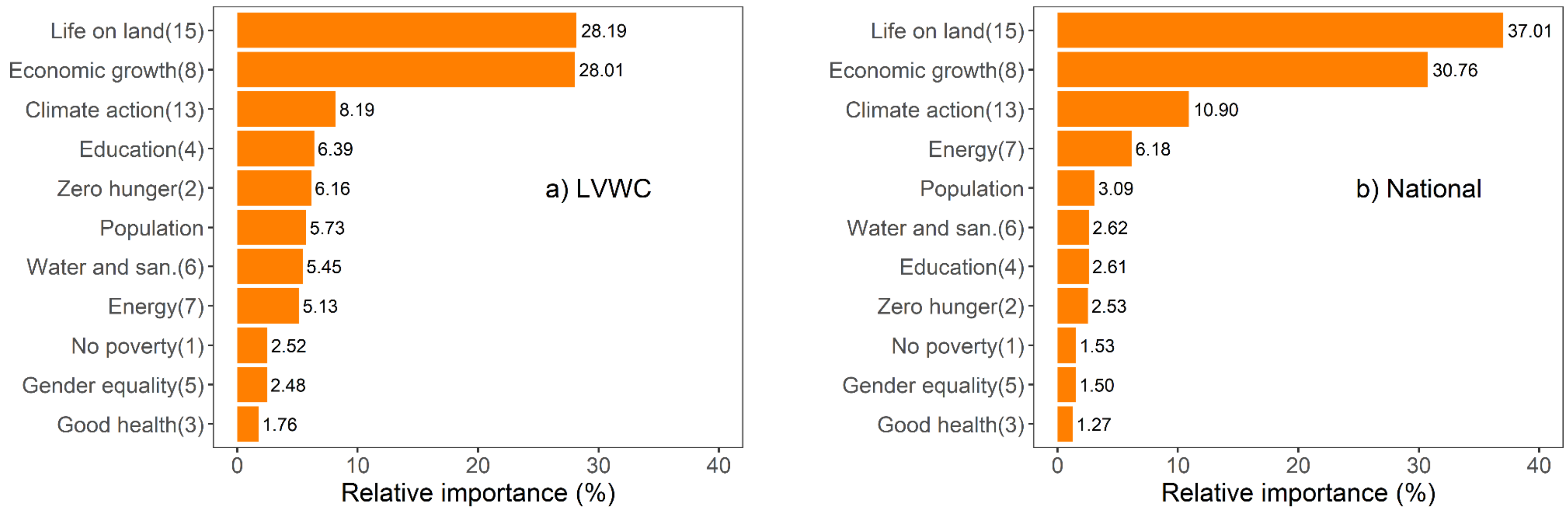


Figure 5.5: Comparison of the relative importance by SDGs for agriculture areas: (a) relative importance for the LVWC; and (b) relative importance at the national level (note: the national plot is obtained from Gichenje et al. (2019a)).

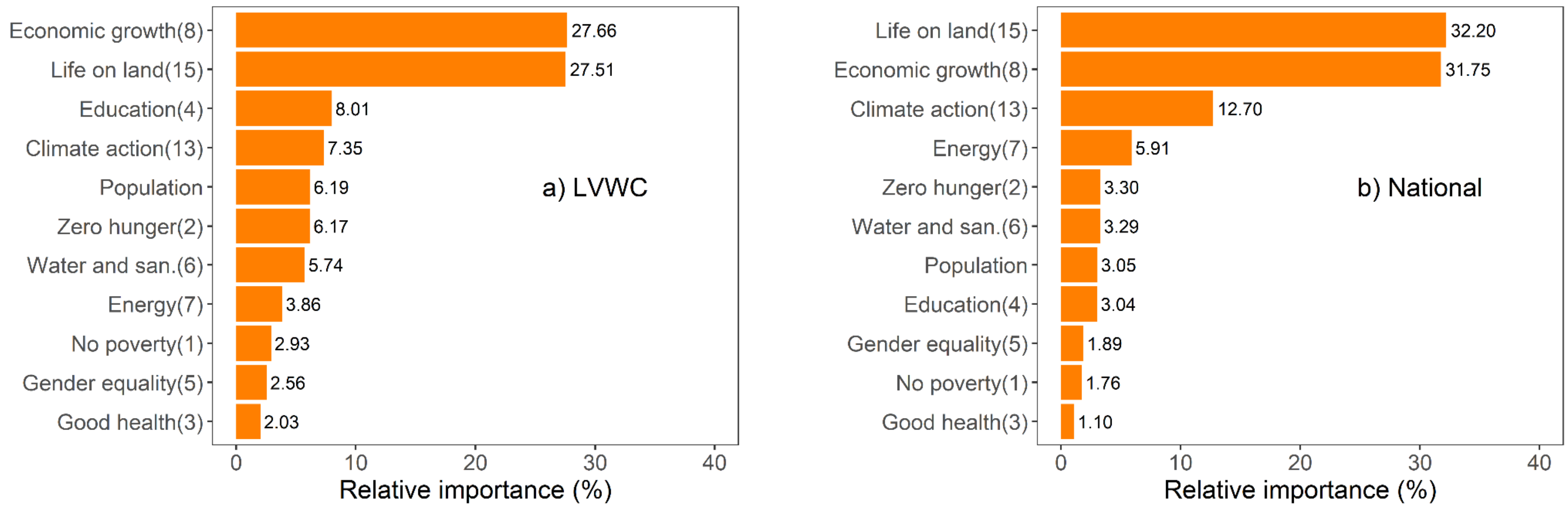


Figure 5.6: Comparison of the relative importance by SDGs for forest areas: (a) relative importance for the LVWC; and (b) relative importance at the national level (note: the national plot is obtained from Gichenje et al. (2019a)).

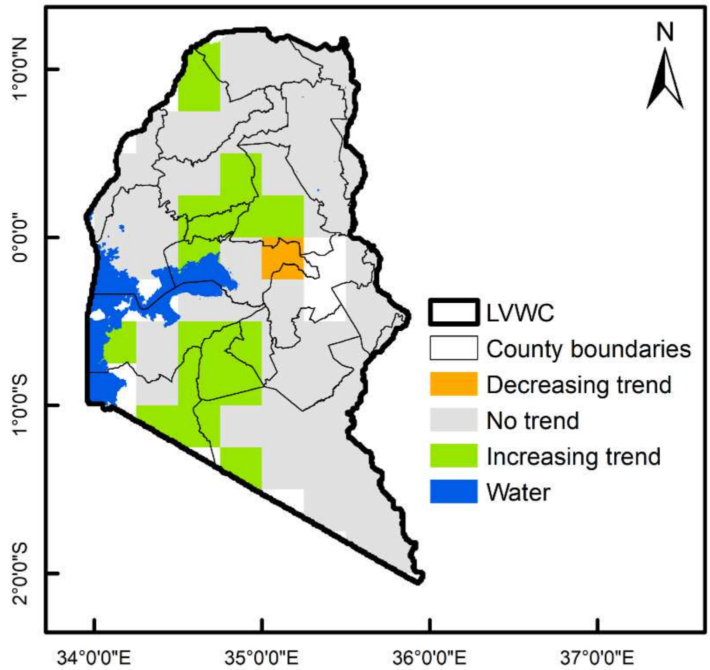
5.3.3 Trends of the climate change variables

Non-significant soil moisture trends account for the largest share of the area (70%) (Figure 5.7a). Increasing soil moisture trends account for approximately a fifth of the area (22%), and occur both north and south of Lake Victoria. Decreasing soil moisture trends are a very small share of the area (< 2%). The boxplot depicting the monthly soil moisture variability indicates that over the 26-year period (1992-2017) there was considerable variability in the range of soil moisture values in each month (Figure 5.7b). May is the month with the maximum mean soil moisture. Outlier values (i.e. those points that are outside 1.5 times the interquartile range either above the upper quartile or below the lower quartile) occurred in the upper quartile in April, and below the lower quartile in March and September.

Figure 5.8a shows the drought dynamics expressed as a per cent of the drought affected area to the area of the entire region, for the 14-year period (2005-2018) using the VCI. In general, extreme to severe drought does not cover more than 25% of the LVWC. However, there were two main peaks in the areas with extreme to severe drought: late 2005 and early 2006; and over the first half of 2015. As per the NDMA classification, most of the area can be characterised as being wet (i.e. VCI ≥ 50). However, as illustrated in Figure 5.8a, the increasing linear trend lines indicate that the proportion of the area in the LVWC under extreme-severe and moderate-normal have been increasing over the 14-year period. The boxplot illustrating the monthly VCI variability also indicates that over the 14-year period each month was wet (minimum mean VCI was 51.15 in the month of February) (Figure 5.8b). There was considerable variability in the range of VCI values, particularly in the months of January, February and April. The maximum mean VCI occurred in October (66.84). Outlier values occurred both above the upper quartile and below the lower quartile in March and December, and above the upper quartile in July.

The spatial distribution of the vulnerability index indicates the predominance of low vulnerability (47%) and medium vulnerability (43%) areas (Figure 5.9). High vulnerability areas account for approximately 4% of the area and are located primarily north of Lake Victoria.

a)



b)

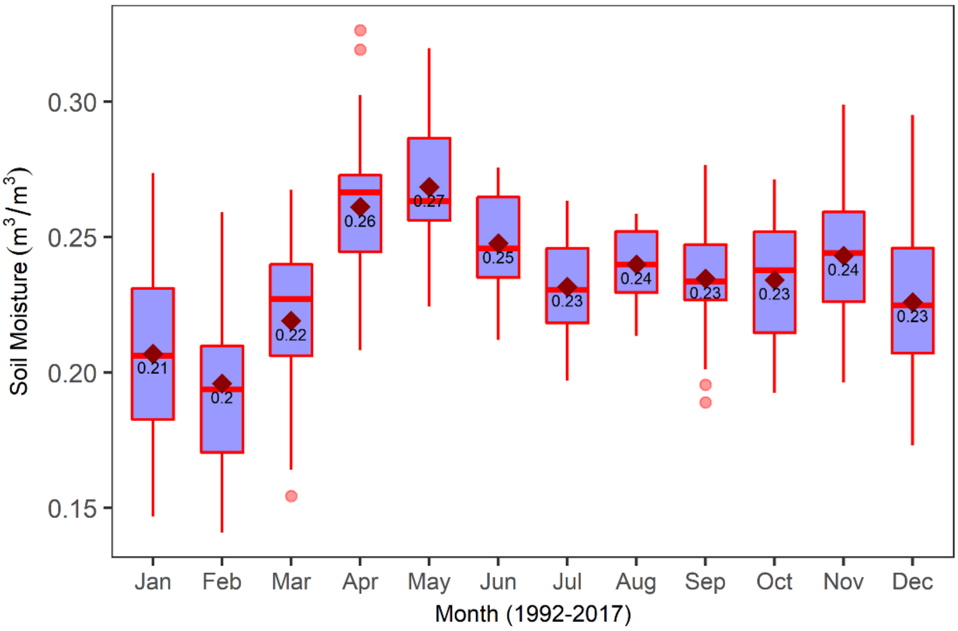


Figure 5.7: Soil moisture: a) spatial distribution of trends (white patches denote no data); and b) monthly variability.

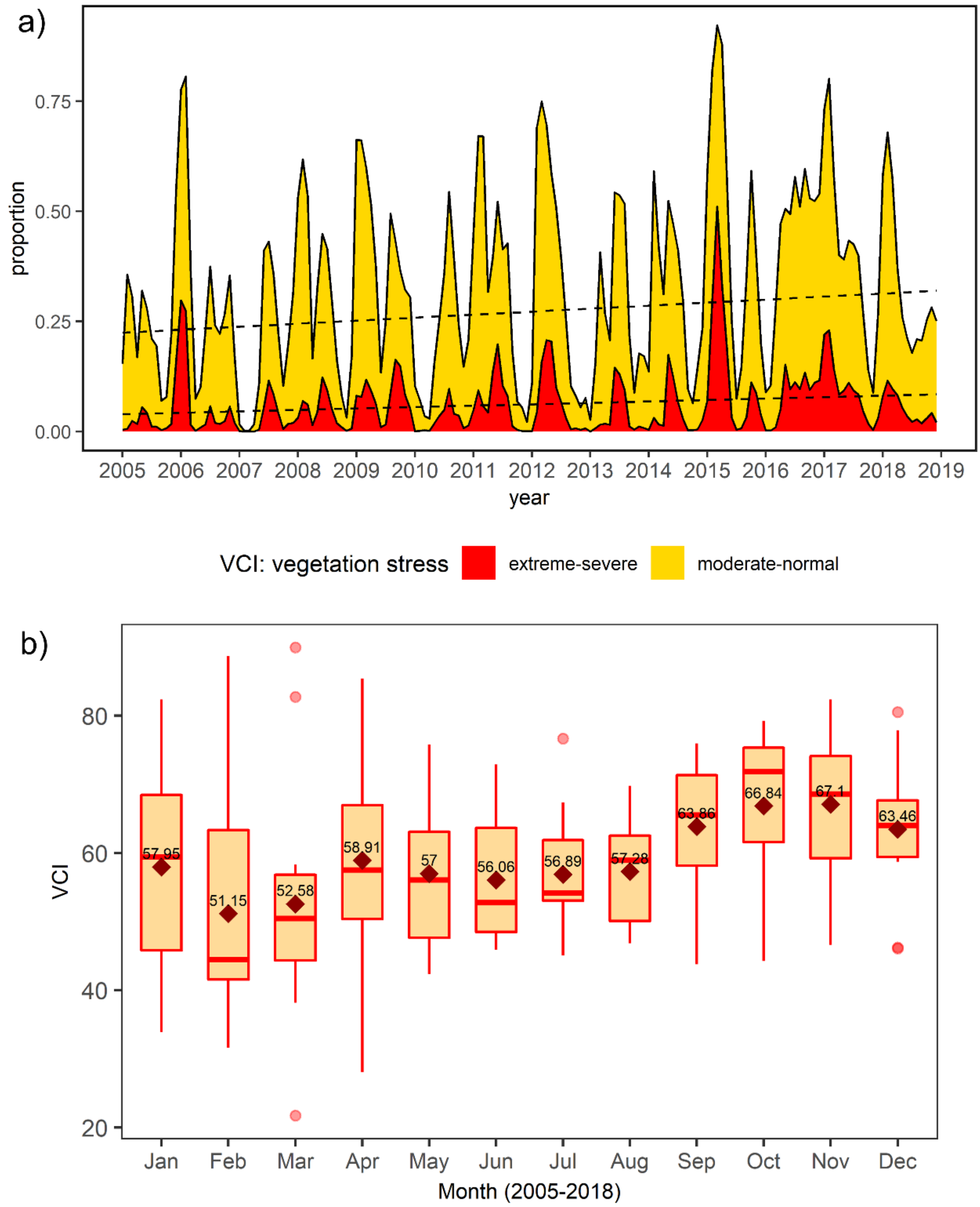


Figure 5.8: Vegetation Condition Index (VCI): a) percent of the LVWC under extreme-severe and moderate-normal vegetation stress (trend line for the two areas represented as the dashed line); and b) monthly variability.

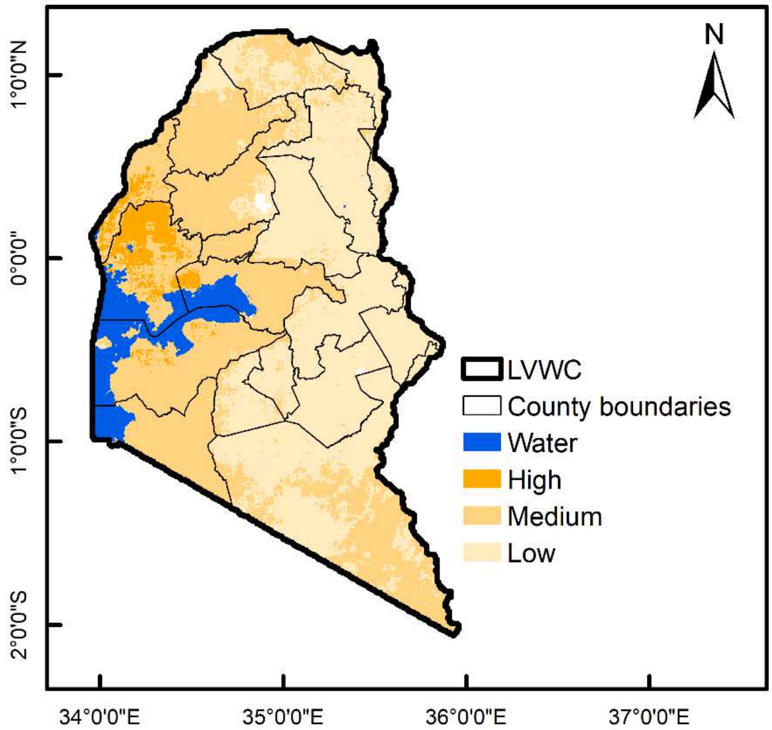


Figure 5.9: Vulnerability index.

5.3.4 SLM interventions

The main SLM initiatives identified in the NCCAP (GoK, 2018b) that could be implemented within the LVWC are provided in Table 5.4. These SLM interventions were obtained from the following four main priority areas of the NCCAP (GoK, 2018b): food and nutrition security; water and the blue economy; forestry, wildlife and tourism; and energy. We focused on those land based SLM interventions with clear quantifiable targets, and the national targets were scaled down using the population density and land area of the LVWC. The SLM practices broadly fall into the following clusters: minimum soil disturbance, soil fertility management, agroforestry, water management, and planted forests. The potential for each broad cluster of SLM practices to address the 3 climate-smart objectives (i.e. increasing productivity and incomes; adapting and building resilience to climate change; and reducing and/or removing greenhouse gas emissions) is described in Table 5.4.

Table 5.4: Sustainable Land Management (SLM) interventions and their potential to address the 3 climate-smart objectives.

SLM intervention[1]	Land degradation addressed[2]	Potential to address climate smart objectives[2] Productivity	Adaptation (A) and Mitigation (M)	
Forest				
Plant one million trees per county per year Deforestation and forest degradation reduced through enhanced protection of additional 8,000 ha of natural forests Area under private sector-based commercial and industrial plantations increased by at least 4,000 ha	Planted forests can rehabilitate degraded land (e.g. eroded or overgrazed areas), particularly if replanted and/or left to coppice after the mature trees are harvested.	In some locations in the central highlands of Kenya, the average gross margin from trees per farm per year was US$ 734, which includes the contribution of: coffee and tea (65%); fruits (28%); and timber and firewood contribute (7%). For 70-80% of the households the trees grown on farms function also as major sources of fuelwood.	A: Planted forests can positively influence the microclimate, which can enhance the resilience to climate variability; increased availability of wood products, fuelwood, and some non-wood forest products, that can lead to employment and income generation. M: Planted forests are carbon sinks, especially on marginal agricultural land and degraded soils.	**Planted forests**
Agriculture				
Farm area under conservation agriculture increased to 8,000 ha, incorporating minimum/no tillage	Reduced physical soil deterioration increase the soil's capacity to absorb and hold water due to the improvement of the soil structure.	Positive effects on crop yields are widely reported and the average for SSA is 134 % (Branca et al., 2013).	A: Increases tolerance to changes in temperature and rainfall including incidences of drought and flooding. M: Leads to a build-up of SOM (less exposure to oxygen and thus less SOM mineralization)	**Minimum soil disturbance**
Area under integrated soil nutrient management increased by 8,000 ha Manure management improved by adoption of biogas technology by 28,240	Nutrient-rich sludge from biogas plant can be used as fertilizer for plants. Reduced chemical soil degradation due to increased SOM and biomass, which increases	Organic fertilization (compost, animal, and green manure) is widely found to have positive effects on the yields. For example, maize yields increased by 100 % (from 2 to 4 t/ha) in Kenya in 2005 (Branca	A: Soils with better water holding capacity can support more drought-tolerant cropping systems. M: Increases SOM.	**Soil fertility management**

SLM intervention[1]	Land degradation addressed[2]	Potential to address climate smart objectives[2] Productivity	Adaptation (A) and Mitigation (M)	
households and at least 70 abattoirs	the water holding capacity of soils.	et al., 2013).		
Total area under agroforestry (AF) at farm level increased by 6,500 ha	AF can help stop and reverse land degradation by providing a favourable micro-climate, providing permanent cover, improving organic carbon content, improving soil structure, increasing infiltration, and enhancing fertility and biological activity of soils.	In Kitui district, Kenya, over an 11-year rotation growing *Melia volkensii* trees in croplands, the accumulated income from tree products exceeded the accumulated value of crop yield lost by 42% during average years, and by 180% with the assumption of 50% crop failure due to drought.	A: AF systems are characterised by creating their own micro-climates, and buffering extremes (excessive storms or dry and hot periods); great potential to diversify food and income sources. M: AF can sequester significant amounts of C from the atmosphere; integrated with bioenergy production it can also reduce GHG emissions (Delgado et al., 2011).	**Agroforestry**
Number of institutions/value chain actors and households harvesting water for agricultural production increased to 176,500 Livelihood systems improved on 4,800 ha of degraded land through the development of water pans and ponds: 105,900 farm ponds installed Acreage under irrigation increased by 22,720 ha **Cross cutting** Increase annual per capita water availability (harvested, abstracted and stored) by	Proper water management can reduce erosion by water, which leads to a loss of fertile topsoil. Sediment may be captured from the water catchment area and conserved within the cropped area.	More water available to crops is crucially important for increased agricultural production; e.g. water conservation techniques resulted in a 50 % increase in productivity in Kenya in 2001 (Branca et al., 2013).	A: The storage of excess rainfall and the efficient use of irrigation are critical in view of growing water scarcity, rising temperatures and climatic variability; reduces risks of production failure due to water shortage associated with rainfall variability and helps cope with more extreme events; enhances aquifer recharge; irrigation can increase incomes of the farmers by producing more, and higher-value crops. M: Irrigation can improve the soil organic carbon sequestration potential by increasing the available water in the root zone. M: Protecting watershed can benefit hydropower and clean energy production (Locatelli et al., 2015).	**Water management**

SLM intervention[1]	**Land degradation addressed[2]**	**Potential to address climate smart objectives[2]**	
		Productivity	**Adaptation (A) and Mitigation (M)**
construction of 2 multipurpose dams (Radat and Gogo dams) Conserve and rehabilitate water catchment areas by protecting water catchment areas feeding the hydro-power dams The annual number of climate-proofed water harvesting, flood control and water storage infrastructure increased by 460			

Note: 1. NCCAP (GoK, 2018b); 2. Liniger et al. (2011) unless otherwise cited.

5.4 Discussion

5.4.1 A climate-smart landscape for the LVWC

Following the characterisation of the LVWC by key land degradation and climate change variables, the identification of the key drivers that affect greening and browning trends within the 2 main land cover types (agriculture and forest), and the identification of appropriate SLM practices from the NCCAP (GoK, 2018b), we now propose a climate-smart landscape (Harvey et al., 2014) for the LVWC, followed by a discussion of the benefits, challenges, and policy implications of LDN implementation therein. The proposed climate-smart landscape for the LVWC is based on the delineation of land units to provide benefits for adaptation, mitigation, and for both adaptation and mitigation, as exemplified by Torquebiau (2015). As illustrated in Figure 5.10, the climate-smart landscape for the LVWC is composed of the following 3 distinct zones: i) the highland areas (> 2,200 m) forming part of the northern and eastern border of the water catchment are to be reserved for forest protection and restoration (combined focus on mitigation and adaptation); ii) the central part is to be reserved for annual crops or livestock (adaptation focus); and iii) the lowlands (< 1,500 m) around Lake Victoria are to be reserved for perennial crops (combined focus on mitigation and adaptation).

The forest zone corresponds primarily to the areas within the LVWC with a high forest cover (Figure 5.2a). There are strong browning trends located in the protected areas around Mt Elgon and the Mau Forest Complex (Figure 5.2c). These protected areas should be the first priority for implementation of the enhanced protection of natural forests to curb deforestation and forest degradation, as identified in Table 5.4. To increase tree cover outside of the protected areas, two other interventions identified in Table 5.4 that can be implemented in this zone are the establishment of plantations by the private sector, and the planting of 1 million trees per county per year. Apart from the latter target, more ambitious targets are proposed for the other two interventions as browning trends account for 26% of forest areas or 172,500 ha in the LVWC. Increasing soil moisture trends around Mt. Elgon indicate more favourable conditions for increasing forest cover, as compared to other areas in the forest protection zone with non-significant soil moisture trends (Figure 5.7a). The forest zone is primarily characterised as an area with low vulnerability to climate change (Figure 5.9), and the proposed SLM interventions in this zone could be sufficient to maintain and even reinforce resilience of the socio-ecological systems to undesirable change.

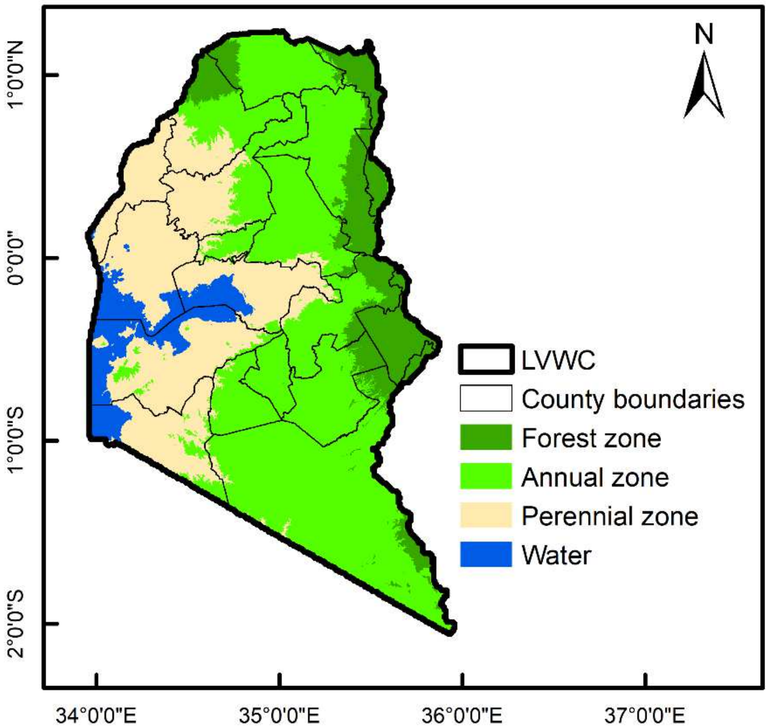


Figure 5.10: Climate-smart landscape for the LVWC.

Both the annual and perennial zones are located in areas within the LVWC where the predominant land cover class is agriculture (Figure 5.2a). SLM interventions identified in Table 5.4 for agricultural areas are all suitable measures that can be implemented in the annual and perennial zones. As a priority, these interventions should target those areas with browning trends, which account for 26% or approximately 1 million ha of agricultural land in the LVWC. As noted above for the SLM interventions proposed for forest areas, more ambitious targets are also needed within agricultural areas.

The annual zone of LVWC (i.e. areas with an altitude ranging from > 1,500 m and < 2,200 m), is characterised by areas with increasing soil moisture trends in a number of counties (Figure 5.7a), indicating favourable conditions for growing annual crops, pastures and establishing agroforestry. Some examples of the main annual crops grown in the LVWC are maize, beans, sorghum, millet, rice, sweet potato, and various vegetables (GoK, 2019). The main area with strong browning trends is in the western area of Narok county (Figure 5.2c). The annual zone is also characterised as an area with low to medium vulnerability to climate change (Figure 5.9), and the proposed SLM interventions could be sufficient to strengthen the resilience of agricultural and livelihood systems in this zone.

The lowland areas (i.e. elevation of < 1,500 m) are proposed for perennial crops primarily because there are several locations with strong browning trends (in Busia, Kakamega, Kisumu, and Migori counties) (Figure 5.2c), and because the lowlands contain areas with decreasing soil moisture trends (in the eastern part of Kisumu county) (Figure 5.7a). The planting of perennial crops with the incorporation of minimum and/or no tillage has the potential to reduce physical soil deterioration, resulting in an increase of the soil's capacity to absorb and hold water due to the improvement of the soil structure (Table 5.4). Some examples of perennial crops grown in the LVWC are sugarcane, cassava, groundnuts, cotton, tea, bananas, and tobacco (GoK, 2019). The perennial zone is also characterised as an area with medium to high vulnerability, with the latter occurring in areas north of Lake Victoria (Figure 5.9). Hence to bolster the resilience of agricultural and livelihood systems in this zone, consideration should also be given to alternative livelihood systems that have minimal dependence (and pressure) on land resources (Méndez, 1993) and to social protection programmes that guarantee minimum incomes or food access (Lipper et al., 2014).

The bimodal rainfall pattern that is typical for the country (with long rains from March to May, and short rains are from October to December (Gichangi et al., 2015)), is not exhibited in the LVWC, as illustrated in the monthly boxplots for the variables soil moisture and VCI (Figure 5.7b, 5.8b). Further, for the 14-year period from 2005-2018, most of the land area of the LVWC can be categorised to be in a wet state, but with increasing trends in the proportion of the area in the LVWC under extreme-severe and moderate-normal drought (Figure 5.8a). Thus, the water management measures identified in Table 5.4 will be instrumental in not only enhancing the resilience of an area that is the most vulnerable to flooding in Kenya (GoK, 2013), but also in providing water storage to address incidences of increasing water scarcity.

By computing the relative importance of variables grouped by SDGs (Figure 5.5, 5.6), we provided an alternative way for policy makers to understand the interconnectedness of social, environmental and economic factors in addressing LDN. As compared to the national level, at the water catchment level, we demonstrated that the social dimensions of sustainable development account for a greater weight in influencing greening and browning trends. This result reinforces the message that achieving LDN will require integrated approaches through greater alignment and closer coordination across social, economic and environmental development priorities (e.g. food, energy, water, climate change, health, education, etc.) (IPBES, 2018).

5.4.2 Implications of LDN implementation in the climate-smart landscape.

The operationalisation of a climate-smart landscape for the implementation of measures to address LDN in the LVWC could contribute to building what Denton et al. (2014) terms as "climate-resilient" pathways, which are iterative, continually evolving processes within complex systems that combine adaptation and mitigation to realize the goal of sustainable development. The concept of pathways is not new, and has been used to describe potential trajectories of future development that communities could take in response to local and global environmental, economic, political, and social changes (Eisenhauer, 2016). In this regard, different studies (e.g. Lipper et al., 2014; Harvey et al., 2014, Sayer et al., 2013) have conceptualised various approaches to address complex ecological challenges (e.g. climate change, land degradation, biodiversity loss) within landscapes. In general these approaches can be broadly clustered around 4 key pillars, as described by Sapkota et al. (2018) in their identification of the governance components of an integrated approach for ecosystem restoration: political (laws, jurisdictions, and institutions); economic (financial resources); social (collaboration, coordination, and participation) and research (science, technology and information).

In a study that examined whether the current land-use policy framework in Kenya has the potential to implement LDN objectives (Gichenje et al., 2019b), the first two components of an integrated approach for ecosystem management (i.e. political and economic) were discussed extensively. The aforementioned study highlighted that the main shortcoming is the disjointed approach on the management and protection of soil and land resources, which is scattered across various policy areas. To address this shortcoming, Gichenje et al. (2019b) recommended a number of key policy and institutional improvements, including: a national soil policy on the management and protection of soil and land resources; a systematic and coordinated data collection strategy on soils; mobilisation of adequate and sustained financial resources; and streamlined responsibilities and governance structures across national, regional and county levels. These recommendations are also of relevance to support the implementation of climate-smart LDN interventions at the water catchment level. We devote the remainder of the discussion to issues pertaining to coordination/collaboration and research.

Given the complex and changing nature of landscape processes, competent and effective institutions and representation that are able to engage with all the issues raised in dynamic landscapes are critically required (Sayer et al., 2013). Within landscapes, there are multiple stakeholders (represented by public, private, and civic entities) who operate at different levels (e.g. national, regional, and county), and who often have conflicting objectives and perspectives (Minang et al., 2015b). The implementation of a climate-smart landscape as proposed for the LVWC would require that first and foremost a shared vision for the landscape be agreed upon by the stakeholders, with a broad consensus on general goals, challenges, and concerns, as well as on options and opportunities (Sayer et al., 2013).

The LVWC falls under the mandate of the Lake Basin Development Authority (LBDA), which is one of the 6 regional development authorities (RDAs) established by acts of parliament on the basis of river basins and large water bodies. The main mandate of the RDAs, which exist at a governance level between the national and county governments, is to plan and co-ordinate the implementation of development projects within river basins. Other government actors at the LVWC level would be the 18 county governments, and key national line ministries and their specialised agencies.

A number of formalised multi-stakeholder forums exist at the sub-national level that could facilitate the coordination of actors at the LVWC, e.g.: the Basin Water Resource Committee (established under the Water Act (GoK, 2016a), and responsible for the management of the water resources within a respective basin area); and the Forest Conservation Committee (established under the Forest Conservation and Management Act (GoK, 2016b), and responsible for making recommendations to the relevant national and county government organisations in relation to the conservation and utilisation of forests). Both these committees are to be represented by each county government whose area falls within the basin or forest conservation area, the responsible national government ministry, and non-governmental actors (farmers or pastoralists, business community, organisations involved in water resource or forest management programmes). Significant investment will be required to sufficiently develop the institutional and technical capacities of all actors operating within the water catchment.

Watersheds, and more broadly landscapes, are complex and dynamic systems in which a diverse range of influences and constraints (water, soil, geology, flora, fauna, etc.) interact with human natural resource use practices (Sayer et al., 2013; Darghouth et al., 2008). Scientific and experiential research is necessary not only to provide an understanding of the bio-physical components and interactions within the landscape, the drivers of change at different scales, and on the interventions that encourage resilience within ecosystems (Sayer et al., 2013). This type of focused research for the LVWC could be undertaken by a number of government specialised agencies, including the Kenya Agricultural and Livestock Research Organization (KALRO) (which has a number of specialised institutes located within LVWC e.g. the Sugar Research Institute in Kisumu; Food Crops Research Centre in Kisii; Non-Ruminant Research Institute in Kakamega; Food Crops Research Centre in Busia), the Kenya Forest Service, and the Kenya Wildlife Services.

To guide the implementation of climate-smart interventions across the three climate-smart zones proposed in this study, it is paramount that field level assessments be undertaken. In particular, although NDVI can serve as a proxy for land degradation, it does not tell us anything about the kind of degradation or regeneration processes (Bai et al., 2008). In this regard, field studies in selected sites with browning trends will provide information on the types of land degradation occurring in the LVWC (e.g. water erosion, wind erosion, plough and mechanical erosion, chemical degradation, and biological degradation that are all induced or aggravated by human activities (Brabant, 2010)). Further, combining the results of the current study that has used spatially explicit information on key climate change and land degradation variables, with participatory approaches involving key governmental and non-governmental stakeholders (e.g. Willemen at al., 2018; Stringer & Reed 2007), would enable the articulation of a guiding vision for the landscape and thus identify and prioritise entry points for stakeholders to begin to work together (Sayer et al., 2013), as well as help to clarify the facilitation processes that best foster effectiveness, efficiency and equity in decision-making by actors within the catchment area (Minang et al., 2015c).

5.5 Conclusions

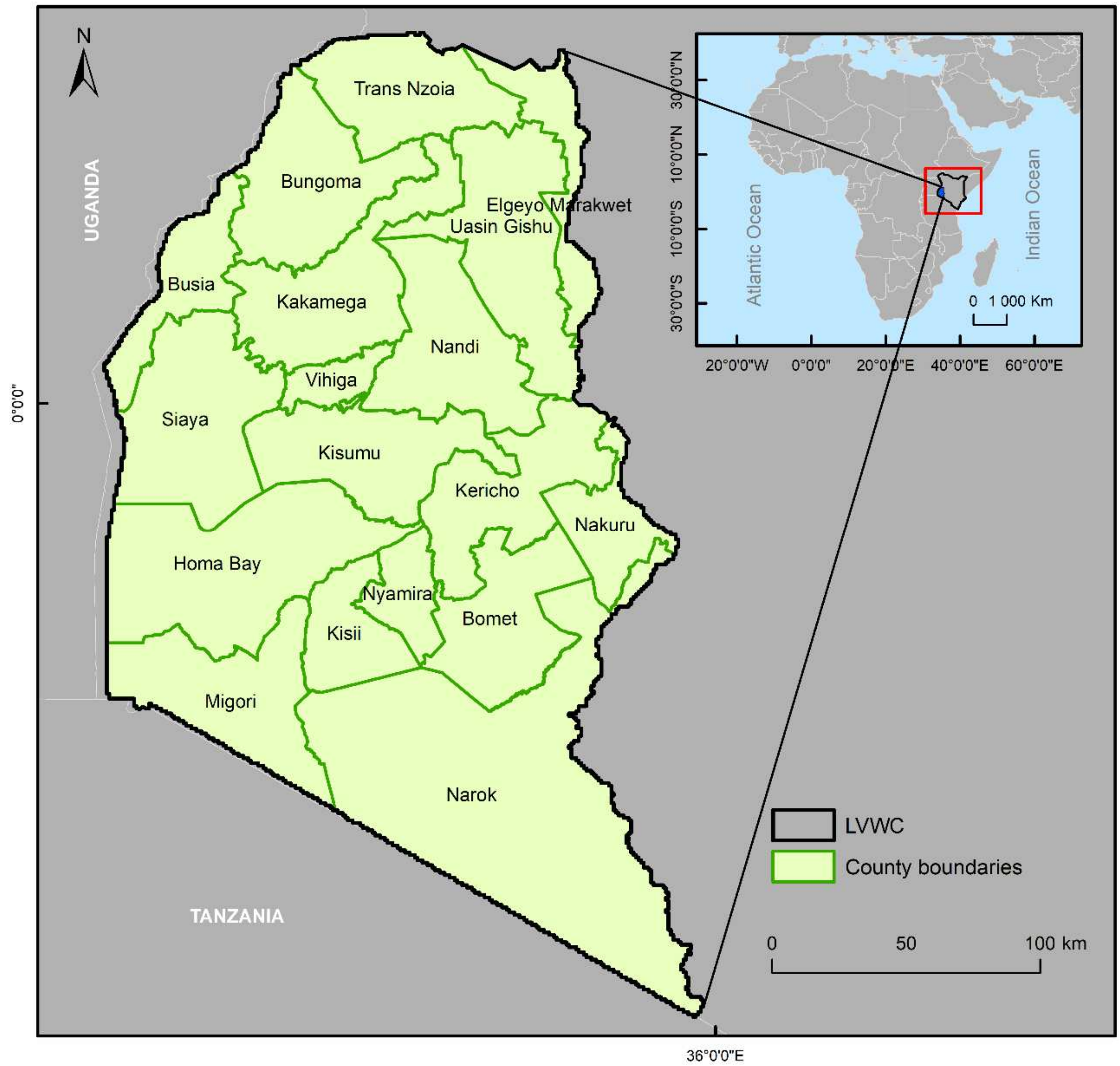
The operationalisation of LDN at the landscape scale can be initiated in water catchment areas using climate change as a specific policy entry point. For the LVWC in Kenya we documented how operational synergy between land degradation and climate change can be pursued through the implementation of targeted land based climate change adaptation and mitigation interventions articulated in the NCCAP (GoK, 2018b) that broadly address soil fertility management, minimum soil disturbance, water management, agroforestry, and planted forests. Further, we proposed a climate-smart landscape that delineated the LVWC area into three zones that are dedicated to forest protection and restoration, annual crops or livestock, and perennial crops.

To support for the implementation LDN interventions at the landscape scale, Kenya has the unique advantage in that dedicated institutions (i.e. the regional development authorities) and multi-stakeholder forums (e.g. forest and water basin committees) exist at the sub-national level. However, significant investment will be required to create competent and effective institutions and representation, as well as to support scientific and experiential research to foster broad-scale adoption of climate-smart approaches at the landscape scale. Complementing the results of the current study that focused on providing spatially explicit information on key climate change and land degradation variables, with participatory approaches involving key governmental and non-governmental stakeholders, may provide a mechanism for building consensus on oft-competing objectives, as well as for identifying starting points for stakeholders to begin to work together at the landscape scale.

Substantial action is needed in the next decade to achieve the LDN target, and more broadly the SDGs. The landscape approach is an emerging and expanding practice that holds promise for allocating and managing land to achieve multiple objectives such as food security, poverty alleviation, climate change mitigation, biodiversity conservation and other goals. We recommend that Kenya, in identifying how the country will achieve the LDN target by 2030, include programmes that can test how water catchment areas can provide an operating space where synergies between land degradation, climate change and other development objectives can concurrently be exploited to improve livelihoods and the productivity of ecosystems.

5.6 Appendices

5.6.1 Appendix 5.A: County boundaries within the LVWC.



Chapter 6

SYNTHESIS

The primary objective of this doctoral research was to operationalize the LDN target at the national level using Kenya as the case study. In this regard, the following four research objectives were pursued: i) define the LDN baseline in terms of the three LDN indicators (land cover, land productivity, and carbon stocks) (Chapter 2); ii) identify and characterise the drivers that affect land degradation and regeneration within the 4 main land cover types (agriculture, forest, shrubland and grassland) and the area characterised by land cover change (Chapter 3); iii) assess the potential of the current land-use policy framework to effectively implement LDN (Chapter 4); and iv) propose an approach for the implementation of LDN at the sub-national level (Chapter 5). This final chapter synthesises the main findings while highlighting the innovative character of the research developed, and discusses the significance and implications of the results obtained for LDN policy and practice. To conclude, the main research limitations and suggestions for further research are proposed.

6.1 Overview of main findings

6.1.1 LDN baseline (Research Question 1)

The first task of this research was to define the LDN baseline in terms of the three LDN indicators (land cover, land productivity, and carbon stocks). The LDN baseline is an integral component of the UNCCD LDN conceptual framework (Cowie et al., 2018) as it defines the reference state of the LDN indicators at time zero (i.e. the year 2015 when the SDGs were adopted) against which the LDN target will be assessed in 2030 (the target date for the SDGs). The key contribution of the LDN baseline study was the use of long-term NDVI and land cover datasets over the 24-year period from 1992-2015 to capture significant human-induced land degradation (browning) and regeneration (greening) NDVI trends, and the trajectory of land cover change, as well as the long-term association between them. Further, this analysis demonstrated that the Mann-Kendall significance test (Kendall's tau) could be used to describe quantitative classes of human-induced greening and browning trends. The results of this analysis provided a spatial distribution of greening, browning, and non-significant NDVI trend areas, and land cover change sites. Non-significant NDVI trend areas account for the largest share of the land area. Given the precautionary principle underlying the LDN response hierarchy (Cowie et al., 2018), and that it will become more difficult and costly over time to implement land restoration measures (IPBES, 2018), the overarching strategy in Kenya should be to avoid land degradation through the use of proactive measures such as appropriate regulation and planning. This entails targeted enforcement of environmental legislation to deter processes and activities that are likely to lead to the degradation of land, and will require the strengthening of the capacity of regulatory, enforcement and coordination agencies. Targeted field level assessments in selected browning, greening, and land cover change sites should be undertaken to shed light on the processes and factors driving vegetation cover changes and dynamics, which can then inform policy development on the planning of LDN interventions. Given the paucity of SOC data in Kenya, and the centrality of SOC in a range of soil functions across several of the SDGs (e.g. food security, human health, biodiversity preservation, water security, and climate change) (Stockmann et al., 2015), investments will be required in mapping of SOC and other soil properties.

6.1.2 Drivers of greening and browning trends (Research Question 2)

In the context of pursuing LDN, the identification of the important drivers of land degradation as well as land restoration is crucial for planning appropriate sustainable land management measures aimed at reducing and preventing land degradation, and incentivising land restoration. The focus under the second research question was to identify the key drivers that affect greening and browning trends within the 4 main land cover types (agriculture, forest, grassland and shrubland) and within an area characterised by land cover change. The methodological approach was based on machine learning, using the random forest classification algorithm. The key contribution of this study was to identify and demonstrate the influence of the key human-environment drivers of land degradation and regeneration, using a large set of explanatory variables, including proxies for broad socio-economic development that represent the SDGs. The results obtained indicate that while the explanatory variables can be grouped into two tiers using the variable importance measure, no explanatory variable was considered unimportant from the analysis. This result reinforces the well-established view in the published literature that land degradation and regeneration are products of complex interactions between both the biophysical environment and human actions (MEA, 2005). Thus LDN implementation in Kenya will require integrated approaches through greater alignment and closer coordination across the environmental, social and economic dimensions of sustainable development. Further, as environmental variables were responsible for 50% of the influence on greening and browning trends, targeted enforcement of environmental legislation is required, particularly to avoid land degradation and to confer resilience to land that is not degrading.

6.1.3 Potential of the current land-use policy framework to address LDN (Research Question 3)

The third task of this dissertation involved the assessment of the potential of the current policy instruments that directly or indirectly impact on the use of land in a rural context to implement LDN objectives. The main contribution of this study was in its approach to analyse the appropriateness of the existing national policy frameworks and institutional set ups that are anchored on the recently developed science-based LDN conceptual framework (Cowie et al., 2018). The qualitative content analysis of various policy instruments was framed around an LDN operational approach for Kenya that was based on the LDN response hierarchy, as well as on sustainable land management (SLM) practices that are appropriate to the country’s main land cover types, and on a set of enabling conditions that aim to strengthen SDG implementation. The results obtained, demonstrated that the policy instruments were rich with specific and pertinent legal provisions and measures, and also indicated the presence of relevant institutions and structures across governance levels. However, the main shortcoming is the disjointed approach on the management and protection of soil and land that is scattered across various policy areas. To support the effective implementation of LDN, the main policy and institutional improvements recommended are in relation to: data collection on the existing soil and land conditions, and on socio-economic factors; adequate and sustained financial resources; and the delineation of responsibilities across various levels of government.

6.1.4 LDN implementation at a sub-national level for a selected water catchment area (Research Question 4)

At the sub-national level, the UNCCD proposes the analysis and contextualisation of LDN at the water catchment scale to provide decision support for the formulation of policies and programmes towards transformative interventions (UNCCD, 2017). Building on the three aforementioned studies described above (i.e. Research Question 1, 2, and 3), based on the spatial and temporal characterisation of key land degradation and climate change variables, an approach for the implementation of LDN for a selected water catchment area was defined. The main contribution of this study was to demonstrate how LDN could be operationalised using climate change as a specific policy entry point. For the Lake Victoria Water Catchment area, a climate-smart landscape approach that delineated the catchment area into zones focused on adaptation, and both adaptation and mitigation objectives was proposed. At the sub-national level there is an increased importance in the contribution of social factors on browning and greening trends, as compared to the national level results. This not only reinforces the message that LDN implementation in Kenya will require integrated approaches (as emphasised under Research Question 2), but that at the local level a better understanding is required of the relationship between public policies (particularly social policies), farmers' decisions, and land degradation and regeneration dynamics. While the landscape approach proposed for the catchment area has the potential to improve livelihoods and the productivity of ecosystems, it will require significant investment to not only provide an understanding of the bio-physical processes and interactions occurring at the catchment level, but also to develop the institutional and technical capacities of relevant actors.

6.2 Research limitations

The main limitations stemming from this research were as follows:

- The coarse spatial resolution GIMMS NDVI data used in the LDN baseline study was determined by the availability of NDVI data with the same temporal scale as the time series of the land cover maps from 1992 to 2015. While deriving significant trends from NDVI time series requires a long temporal resolution, the coarse spatial resolution the GIMMS NDVI data limits its usefulness for detailed studies (Pettorelli et al., 2005). In this regard, future studies of the complex processes underlying vegetation dynamics would benefit from higher resolution satellite data.
- Validating the results of the LDN baseline study through field studies is challenging given the spatial and temporal extent of the analysis, and that there is no country-wide programme for the monitoring of biomass resources in Kenya. Complementing the results of the remote-sensing analysis with participatory approaches involving key governmental and non-governmental stakeholders, and with targeted field level assessments in selected browning, greening, and land cover change sites, would provide information on the kind of land degradation or regeneration processes occurring at the local level.
- The qualitative content analysis of the official government legal, policy and planning documents provided valuable insights on the potential of the current land-use policy framework to implement LDN objectives. However, an assessment of policy effectiveness would require an analysis of management results at the scale at which actions to address land degradation are taken, i.e. landscape, farm or plot. Empirical observations of policy impact would offer guidance to governments and policymakers on how best to strengthen and support LDN policy and implementation.

6.3 Future research directions

The 2030 agenda on sustainable development as articulated in the SDGs, is an ambitious universal vision that aims to end poverty, promote prosperity and well-being, while protecting the environment. Over the next decade, substantial action is needed in Kenya (and across all countries and communities) to achieve the LDN target of the SDGs. Operationalising the LDN target at the national level is not an insurmountable challenge, but will require concerted and coordinated action across the following four broad governance components of an integrated approach for ecosystem restoration, as outlined by Sapkota et al., 2018: political (laws, jurisdictions, and institutions); economic (financial resources); social (collaboration, coordination, and participation); and research (science, technology and information).

In consideration to the limitations discussed above, this research has opened a number of areas for further research. Given the local-scale and biophysical and socioeconomic contexts within which land degradation and regeneration occurs, and that most land management decisions take place at individual farm scale, further research is needed at the local level in the following areas:

- **High resolution Earth Observation (EO) data and machine learning:** Recent advances in EO systems have resulted in the collection of multitemporal, multispectral, and multifrequency imagery and data with increasing spatial resolution. For example, the up-coming European Space Agency FLEX mission in 2022, will provide solar-induced chlorophyll fluorescence (SIF) data at 300 meters spatial resolution. The SIF data has the potential of providing a more direct proxy for photosynthetic activity and, thus there is a need to test the usefulness of this product as a reliable data source for land degradation and regeneration monitoring. Hence, an area of research at the local level is the combination of high resolution EO datasets with modern data analytics, such as machine learning, to support communities and countries in better monitoring progress and reporting on the LDN indicators.

- **Field validation of remote-sensing analysis:** While the NDVI data used in this dissertation served to measure temporal changes in vegetation and as a proxy for land degradation, it does not provide information on the kind of land degradation or regeneration processes. More research is needed on ground-based measurements that overlap with remote-sensing analysis to not only provide information on the reliability of the remote-sensing products, but also to provide insights into the different types of land degradation and regeneration processes occurring at the local scale.

- **Inter-disciplinary research to promote multifunctional landscapes:** For the vast majority of farmers across Sub-Saharan Africa, water and food security, livelihood opportunities, and other developmental issues are inextricably linked to land degradation and climate change. Each development issue can only be effectively addressed through integrated programmes or approaches that recognise and address the interconnections between these issues. The landscape approach is an emerging and expanding practice that holds promise for allocating and managing land to achieve multifunctionality, i.e. the attainment of multiple objectives simultaneously. More focused inter-disciplinary research is required at the landscape scale on new ideas and on LDN policies and practices, in which synergies across multiple development priorities are exploited, and on how multiple agents of change (i.e. citizens, civil society, academia, businesses and government) can be mobilised to effectively work together.

Chapter

7

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