INTERCONNECTIONS BETWEEN LAND COVER CHANGE, CLIMATE VARIABILITY, AND LIVELIHOODS IN THE GREATER MAU FOREST COMPLEX, KENYA

By

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A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

Geography – Doctor of Philosophy

2023

ABSTRACT

The Greater Mau Forest Complex (GMFC) is a socio-economically and ecologically significant yet very fragile landscape in southwest Kenya. It hosts an important water catchment for East Africa, includes several protected areas, and has been subject to significant land use land cover (LULC) change over the past decades. However, few studies have comprehensively characterized these changes or their associated implications on livelihoods and sustainability of the system. This dissertation addresses three distinct but connected research questions: (1) What is the nature and magnitude of LULC patterns, and what is the role of biophysical factors in these patterns and processes? (2) How should socio-ecological sustainability be measured in a significant and fragile yet data-sparse landscape? and (3) What is the nature and magnitude of LULC dynamics in the four GMFC counties (Bomet, Kericho, Nakuru, and Narok) and what is the perceived likelihood of LULC changes impacting livelihoods among the forest-adjacent populations?

Study 1 performed robust accuracy assessment and characterized LULC changes in the GMFC under several topographic scenarios using landscape metrics of fragmentation and dominance. The study also applied the Kruskal-Wallis tests to assess statistical significance among the differences. Results showed that despite much conservation focus on deforestation, grasslands in southwest Kenya are more rapidly decreasing in size and becoming more fragmented and that topography has played a significant role in these changes. Improved spatiotemporal LULC characterization and projections are important for managers and policy makers. Study 2 assessed the stability of GMFC system across time using the water-energy-food (WEF) nexus framework. The study used a blend of precipitation, energy consumption, vegetation indices, and crop yield data to examine the WEF synergies

and trade-offs within the GMFC. Results indicate increasing rates of variability among the WEF variables in the GMFC over the last 30 years, suggesting that a paradigm shift would be necessary to ensure sustainability of this ecosystem in the wake of other local and global challenges. Additionally, the research revealed the challenges of measuring sustainability in data-sparse areas. Study 3 investigated LULC change dynamics in the four counties of the GMFC and examined the interconnections between these changes and livelihoods among forest adjacent populations of the GMFC. The study then used data from household surveys and ordinal logistic regression to understand the relationship between LULC changes and livelihoods. Results indicate that land cover varied by county while level of education, household income, and age have statistically significant influence on perceptions regarding the intricate nature-society relations.

This dissertation utilized remote sensing, geographic information systems (GIS), statistical, and qualitative techniques to assess the interconnectedness of land cover change, climate variability, and livelihoods in a significant yet fragile landscape. The robust methods translate well in multiple landscapes and scales. These findings are key for climate change mitigation, adaptation, and resilience discourses because peoples' perceptions influence their behavior towards the environment. This work contributes to nature-society research and policy in the wake of myriad socio-ecological challenges.

This dissertation is dedicated to my beloved late mother Emily Rapando, grandfather Laban Akanga, and grandmother Grace Nyangasi Akanga who did not live long enough to witness this accomplishment. Thank you for the countless prayers and great foundation you gave me!

ACKNOWLEDGEMENTS

In the writing of this dissertation research, I have received immense support. First, I would like to thank my Advisor, Dr. Kyla Dahlin, for welcoming me to her lab! Thank you for the solid mentorship and support throughout my program and dissertation. Despite your busy schedule, you always found time to meet and review my work within a very short time! You also introduced me to numerous opportunities for which I am profoundly grateful. To my doctoral dissertation committee members: Dr. Nathan Moore, Dr. Leo Zulu, and Dr. Robert Richardson: many thanks for your immense support throughout the PhD journey. This research was successful because of your invaluable insights and feedback!

I would also like to acknowledge the following for financial support that enabled me stay enrolled in the graduate program, present at major conferences, and conduct fieldwork in Kenya: MSU Department of Geography, MSU Graduate School, College of Social Science, US NASA Carbon Cycle Science, Owen Gregg Global Climate Change Research Award, Sommers Graduate Fellowship, Michael Graff Dissertation Completion Fellowship, and the Africa Study Center. To the onGEO team, Beth and Juliegh, thank you for the support I received during my onGEO instructor appointments.

Similarly, I would like to thank everyone who supported me during the fieldwork. Specifically, I am grateful to my father, Eliud Akanga, not only for the sacrifices you have made to ensure that my siblings and I had the best education possible, but also for actively supporting and being part of my doctoral journey. Eliud, thank you for taking up the role of my research field assistant with so much grace. I would also like to sincerely thank Mr. Charles Lusweti and Mr. Joseph Mutinda for facilitating access to data that enhanced my research. To all my great friends – thanks for cheering me on. Special gratitude to Dr. Dan

Wanyama for being more than a friend: thank you for journeying with me through undergraduate, masters, and doctoral studies. You have been so supportive in my dissertation writing and among so many things, I cannot thank you enough for helping me troubleshoot the R codes! Finally, to my lovely wife Mercy and my resilient son Bingwa – you have been a great support system. I am grateful and love you both, always!

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CHAPTER 1: INTRODUCTION

1.1 Research Context

Different forms of capital assets (i.e., natural, economic, human, and social) are necessary for individual or societal survival (Krantz, 2001). Earth's resources are finite; hence concepts of sustainability and sustainable development (SD) are important for the long-term functioning of systems. An SD lens helps to find a balance between preserving the ecosystem and meeting human needs (Olawumi & Chan, 2018; World Commission on Environment and Development, 1987) and is essential for fostering livelihoods. Sustainability and SD can be used interchangeably (Olawumi & Chan, 2018; Ruggerio, 2021). Some of the key aspects necessary for dissecting sustainability discourses include what to sustain, how long the system ought to be sustained, and when to measure sustainability (Costanza & Patten, 1995; Daly, 2017; Orr, 2002). Increasing population, consumption, and exploitation of natural capital has led to shrinking resources and impacted livelihoods. A livelihood is defined to encompass the resources, capabilities, and activities required for a means of living. Therefore, a sustainable livelihood is defined as the "ability to cope with and recover from stresses and shocks, maintain, or enhance its capabilities and assets, while not undermining the natural resource base" (Krantz, 2001). The United Nations (UN) Sustainable Development Goals (SDGs) provide a general framework that attempts to define, work towards, and measure SD (Nilsson & Costanza, 2015). To understand whether a region is making progress towards SD, we need to assess how landscapes and their inhabitants have changed over time.

Land use-land cover (LULC) change analysis is a core tool for understanding change in socio-environmental systems and is an essential climate variable (Alemu & Henebry, 2017;

Hollmann et al., 2013; Stehman & Foody, 2019). LULC change can modify atmospheric conditions, influence the carbon cycle and global warming, intensify natural disasters, and alter ecosystem services at local, regional, and global scales (Birhanu et al., 2019; Dahlin et al., 2020; Dwivedi et al., 2005; Lambin et al., 2001; Mas et al., 2004; Zhong et al., 2021). For instance, unabated human encroachment into forest and grassland dominated ecosystems has been shown to have direct and indirect impacts on social and ecological systems such as human-wildlife conflicts, increased droughts, irregular planting seasons, interannual variability, and increasing atmospheric carbon concentration (Ahlström et al., 2015; Riitters, Wickham, & Wade, 2009). Developing countries, particularly Sub-Saharan Africa, are more vulnerable to climate change related impacts partly due to their limited financial and technological capacity to adapt (Bryan et al., 2013). For example, despite being one of the leading economies in Eastern Africa, Kenya has in the recent decades continued to grapple with a workable balance between environment, social, and economic development. Incessant logging, clear felling, human encroachment for settlement and conversion to agriculture have continued to decrease the size of land under forest and grasslands in many ecosystems.

Land-use decisions such as increasing area under cultivation and changing forestry practices often result in unintended consequences (DeFries, Foley, & Asner, 2004). Therefore, reliable monitoring and assessment of LULC dynamics is essential for identification of human induced landscape changes. While most land use decisions are made by people, influenced by economics, policy, and society, the biophysical environment also plays a role in determining where land use changes occur (Dang & Kawasaki, 2017; Msofe et al., 2019; Zhou et al., 2020). For example, topography determines the accessibility, usability, stability, water retention, and composition of a landscape, while geology influences soil properties and arability (Turner et al., 2001). Improved understanding of human and environmental influences on LULC change will enhance assessment and management strategies important to prevent decline in the environmental value of ecosystems (da Silva et al., 2020; Mottet et al., 2006), and can allow for better predictions of where future LULC change may occur. Remote sensing derived LULC change outputs make it possible for use in natural resources mapping and management at local, national, regional, or global scales (Lambin, 1997; Long & Qu, 2018).

The systems approach identifies interconnections where impact on one component in a system can have recurring direct and indirect impacts on others and is necessary to address the complexity of social-ecological systems (Fischer et al., 2015; Lim et al., 2018). For example, the water-energy-food (WEF) nexus is an integrative framework that examines interdependencies between these three sectors to achieve cross-sectoral synergies in attaining SD (Nhamo et al., 2020). These sectors are critical for sustaining human livelihoods and human well-being, yet they are highly susceptible to pressures associated with climate change and other anthropogenic pressures such as population (Golam et al., 2015). Future generations will rely, to a great extent, on the resources that are at the current generation's disposal for their survival. As such, an ecosystem can be adduced to be sustainable if it continues providing various ecosystem services (provisioning, regulating, supporting, and cultural) for next generations without significant disruptions or decline in quality and efficiency (Bennett et al., 2009). The research here employs a systems approach and political ecology framework to understand the interconnections of socio-ecological sustainability by analyzing LULC change, ecological trends, and community livelihoods in the context of SDGs. To assess the status of livelihood sustainability of the target population, I borrow from relevant UN SDG targets and respective metrics used for their measurement (https://sdg-tracker.org/). The scope will be limited to subsets of two out of the seventeen UN SDG targets and indicators that are connected to human livelihoods and whose progress can be measured at the household level: SDG 1, No Poverty and SDG 2, Zero Hunger (United Nations, 2015). A complete list and description of variables used in assessment of livelihood sustainability, connection to SDG indicators, and their rationale is provided in Appendix A and sample household survey questions are in Appendix B. The research will leverage mixed methods including geospatial analysis, spatiotemporal trend quantification, and household surveys.

1.2 Purpose and Objectives

The overarching goal of this dissertation research is to examine interconnections between LULC, climate, and livelihoods in Kenya's GMFC from 1990 to 2021. This time span covers a period where there were three national government regimes and enactment of a new constitution that affected management of natural resources. Therefore, this research addresses the question of how to achieve development that is sustainable for both people and the environment. The study achieves this goal by enhancing the characterization and attribution of the conservation versus livelihoods conundrum that has bedeviled local communities, government, and civil society within the GMFC as well as proposes pragmatic solutions. The study leverages remote sensing, machine learning, spatial analysis, social science, and mixed methods techniques to achieve three main objectives. The dissertation is organized into five chapters: the first chapter constituting this introduction. Each of the next three chapters address specific but interconnected themes (land cover change, socio-ecological sustainability, and livelihoods) and associated objectives. These themes are while the last chapter details the conclusions (Figure 1). The following are the three main themes, each with research objectives and corresponding rationale.

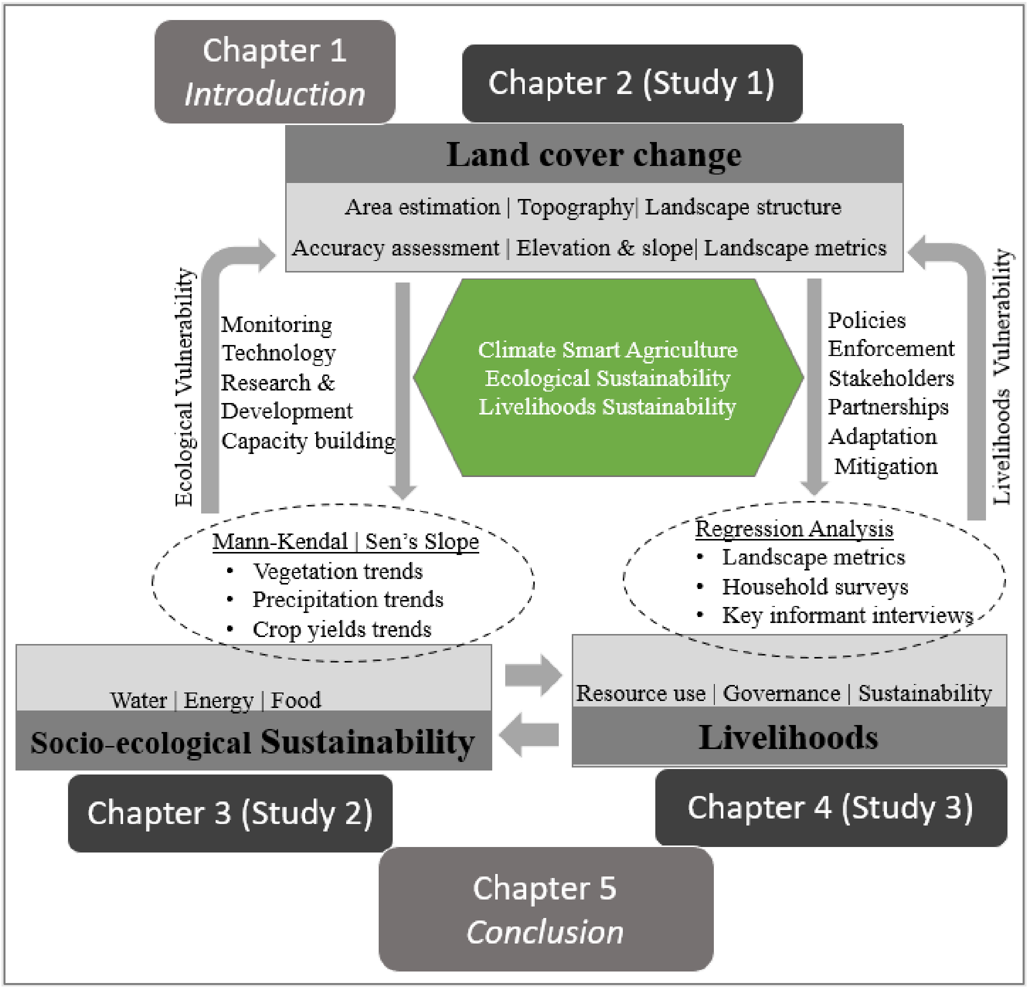

Figure 1. Conceptual framework of dissertation research.

1.3 Objective 1: Land Cover Change by Topography

The objective of this chapter is to assess land cover change dynamics in the GMFC by answering the following question: what is the nature and magnitude of LULC patterns, and what is the role of biophysical factors in these patterns and processes? The GMFC hosts one of the largest water catchments in East Africa and has immense socio-economic and ecological significance. However, it is susceptible to numerous pressures, both natural and anthropogenic. These pressures include deforestation, forest degradation, reserve encroachment, carbon loss, biodiversity loss, threats to sustainable water supply, declining agricultural productivity, and deteriorating livelihoods among the local population. Therefore, there is a need to better understand the structure and patterns of this landscape across time. This chapter analyzes patterns of LULC in GMFC from 1990-2018 based on available remotely sensed land cover data. The chapter also assesses the role of elevation and slope in LULC changes within the topographically heterogeneous region using landscape metrics of fragmentation (number of patches and interspersion and juxtaposition index) and dominance (largest patch index) at the class level. Better characterization of LULC structure, pattern, and change is necessary for improved research and policies for sustainable management of the GMFC.

1.4 Objective 2: Socio-ecological Sustainability

In this chapter, I assess the status of the GMFC using the water-energy-food (WEF) nexus approach. The chapter answers the following question: How do you measure socio-ecological sustainability in a significant and fragile yet data-sparse landscape? Water, energy, and food are critical sectors required to sustain human livelihoods. However, these sectors are highly susceptible to pressures associated with climate change and other anthropogenic pressures which in turn threaten sustainability, as is the case with the GMFC. This chapter leverages mixed methods and the WEF nexus lens to examine the interdependency between these sectors and to assess the status of sustainability. The chapter utilizes various forms of WEF data obtained through remote sensing, field interviews, census, and crop yields to characterize the state of the GMFC from 1990-2021.

1.5 Objective 3: Land Cover Change and Livelihoods through a Political Ecology Lens

Chapter four examines the interconnections between land cover change and livelihoods among forest-adjacent populations. The chapter answers the following question: a) what is the nature and magnitude of LULC dynamics in the four GMFC counties and b) what is the perceived likelihood of forest degradation on livelihoods among the forest-adjacent populations? People living adjacent to natural resources rely on them for their livelihoods. Besides, their routine activities have significant direct and indirect contributions to resource conservation or degradation and are affected by laws and regulations aimed at protecting/restoring these resources (Newton et al., 2016, 2020). Therefore, decisions by residents, policy makers, and law enforcement entities impact natural resources management, climate change, and livelihoods sustainability. The chapter examines (i) how land cover changes vary based on established administrative/governance demarcations across time, and (ii) relationship between LULC changes and livelihoods among people living adjacent to MFC.

CHAPTER 2: ACCELERATING AGRICULTURAL EXPANSION IN THE GREATER MAU FOREST COMPLEX, KENYA[1]

2.1 Introduction

Land use land cover (LULC) change is an essential climate variable (Alemu & Henebry, 2017; Hollmann et al., 2013; Stehman & Foody, 2019) that can modify atmospheric conditions, influence the carbon cycle and global warming, intensify natural disasters, and alter ecosystem services at local, regional, and global scales (Birhanu et al., 2019; Dahlin et al., 2020; Dwivedi et al., 2005; Lambin et al., 2001; Mas et al., 2004; Zhong et al., 2021). The relatively simple and non-technical nature of remote sensing derived LULC change outputs make it possible for use in natural resources mapping and management at various scales (Lambin, 1997; Long & Qu, 2018). Land-use decisions such as increasing area under cultivation and changing forestry practices often result in unintended consequences (DeFries et al., 2004) and so reliable monitoring and assessment of LULC dynamics is essential for identification of human induced landscape changes.

While most land use decisions are made by people, influenced by economics, policy, and society, the biophysical environment also plays a role in determining where land use changes occur (Dang & Kawasaki, 2017; Msofe et al., 2019; Zhou et al., 2020). For example, topography determines the accessibility, usability, stability, water retention, and composition of a landscape, while geology influences soil properties and arability (Turner et al., 2001). Improved understanding of environmental influences on LULC change will enhance assessment and management strategies important to prevent decline in environmental value

[1] Akanga, Donald O., Kyla M. Dahlin, and Nathan J. Moore. "Accelerating agricultural expansion in the greater Mau Forest Complex, Kenya." *Remote Sensing Applications: Society and Environment* 28 (2022): 100860.

of ecosystems (da Silva et al., 2020; Mottet et al., 2006) and can allow for better predictions of where future LULC change may occur.

Globally, much LULC change analysis is aimed at deforestation (e.g., Armenteras et al., 2019; Ayele et al., 2000) and urbanization (e.g., Liu et al., 2019; Mansour et al., 2020; Silva et al., 2018), with less focus on other LULC categories (Yirsaw et al., 2017). For example, emphasis has been placed on forests and forest degradation due to their long-established roles in biogeochemical cycles and climate change (Sun et al., 2019; Yang, Li, & Yan, 2018). Likewise, urban expansion alters LULC regimes, reduces pasture and agricultural land area, and affects ecosystem productivity (Şen et al., 2018; Seto et al., 2012). However, recent research suggests that grasslands and semi-arid savannas are also undergoing high rates of anthropogenic-driven change (Wilcox et al., 2018) and impact interannual variability and trends in atmospheric carbon concentration (Ahlström et al., 2015). Compared to forests, grasslands tend to occur in relatively lower elevations and are easier to clear for agriculture and other human activities. Unabated human encroachment into forest and grassland dominated ecosystems has significant direct and indirect impacts on social and ecological systems (Riitters et al., 2009). Detecting, quantifying, attributing, and monitoring LULC changes at local, regional, and global scales is essential for both understanding current patterns and predicting future processes.

Remote sensing and GIS products such as land cover maps have been used to examine spatiotemporal transitions in LULC (DeFries et al., 2004; Turner et al., 2007) which can inform natural resources management and have significant ecological, economic, and/or social implications (Foody, 2002; Manandhar et al., 2009). However, remotely sensed LULC classifications and pre-existing LULC change maps are prone to errors arising from data quality issues, conversion of spatially and categorically continuous conditions to discrete classes, the minimum mapping unit problem, and classification algorithm decisions (Foody, 2010; Olofsson et al., 2014; Spruce et al., 2020). If unaccounted for, such errors could reverberate in policy and/or research decisions and recommendations and reduce the useability of these LULC products. While most studies stop their analysis of error at computing confusion matrices, overall accuracy, and kappa coefficient of agreement (M. R. Rahman & Saha, 2008; Rwanga & Ndambuki, 2017; Tilahun & Teferie, 2015), good practice recommendations involve rigorous uncertainty analysis and error estimations (Olofsson et al., 2014; Olofsson et al., 2019). If substantial uncertainty is found, then this uncertainty should be taken into consideration in LULC change analyses and any assessment of changes to the geographic structure of the landscape.

Landscape metrics describing the dominance, connectivity, and fragmentation of patches have the capability to depict the geographical structure and functionality of a landscape at various scales (Fichera et al., 2012). The use of landscape metrics, however, needs to be carefully selected since many of them are highly correlated (Cushman et al., 2008). Various natural and anthropogenic factors influence the sizes, dominance, and adjacency of patches on landscapes as well as their utility and sustainability. For instance, spatial metrics that assess the number, size, and evenness of patch adjacencies at landscape level have been leveraged to assess suitability of rainwater harvesting (Albalawneh et al., 2015), freshwater research and management (Kearns et al., 2005), LULC change in heterogenous watersheds (Kumar et al., 2018), and urban sprawl (Das & Angadi, 2021).

Here, we analyze patterns of LULC change in southwestern Kenya from 1990 to 2018 based on available remotely sensed land cover data. This landscape is an important water catchment for the surrounding area, includes several protected areas, and has been subject to significant LULC change over the past decades. We perform rigorous accuracy assessment and area estimation using most recent available high-resolution data (2018) based on recommended good practices (Olofsson et al., 2014). We assess the role of elevation and slope in LULC changes within the topographically heterogeneous region using landscape metrics of fragmentation (number of patches and interspersion & juxtaposition index) and dominance (largest patch index) at the class level. Because this region has been occupied by humans for millennia, and because deforestation has been a recent concern in Kenya (Klopp, 2012), we expected that the proportion of grassland and cropland in the higher slopes and higher elevation topographic gradients would be relatively stable over the past 30 years since these areas are less suited for agricultural development. In contrast, we expected that recent human population increases and changes in governance may have pushed cropland into historically forested regions, especially at lower elevations and in places with lower slopes.

2.2 Study Area

The Greater Mau Forest Complex (GMFC) is located in southwestern Kenya and extends over 30,345 km^2. Here we define the GMFC as the four counties (Bomet, Kericho, Nakuru, and Narok; Figure 2) that include the Mau Forest Complex and surrounding landscape. The GMFC is of immense socio-economic and ecological significance. It is home to the Maasai Mara National Reserve and most of the Mau Forest Complex (MFC), the largest of the five main water catchments in Kenya. Maasai Mara National Reserve is a popular global tourist destination that borders Tanzania's Serengeti and is home to a wide range of wildlife. The MFC has an estimated economic value of over $112 billion and supports more than 10 million people's livelihoods by providing various ecosystem services (Ngigi & Tateishi, 2004;

Ogweno, Opanga, & Obara, 2009; Rwigi, 2014; Swart, 2016; UNEP, 2003, 2008). It is a source to 12 rivers (i.e., Mara, Sondu-Miriu, Nyando, Nzoia, Yala, Turkwell, Rongai, Nderit, Makalia, Kerio, Molo, Naishi, Ewaso Nyiro, and Njoro) which feed important lakes, including lakes Victoria, Turkana, Nakuru, Baringo, and Natron (Ogweno et al., 2009; UNEP, 2003, 2008). These water resources support agriculture, urban and rural water supply, hydropower, tourism, and wildlife habitats throughout East Africa. LULC in the GMFC is important to study because despite its significance, the area has experienced massive deforestation, population increase and natural resources-related conflicts in recent decades.

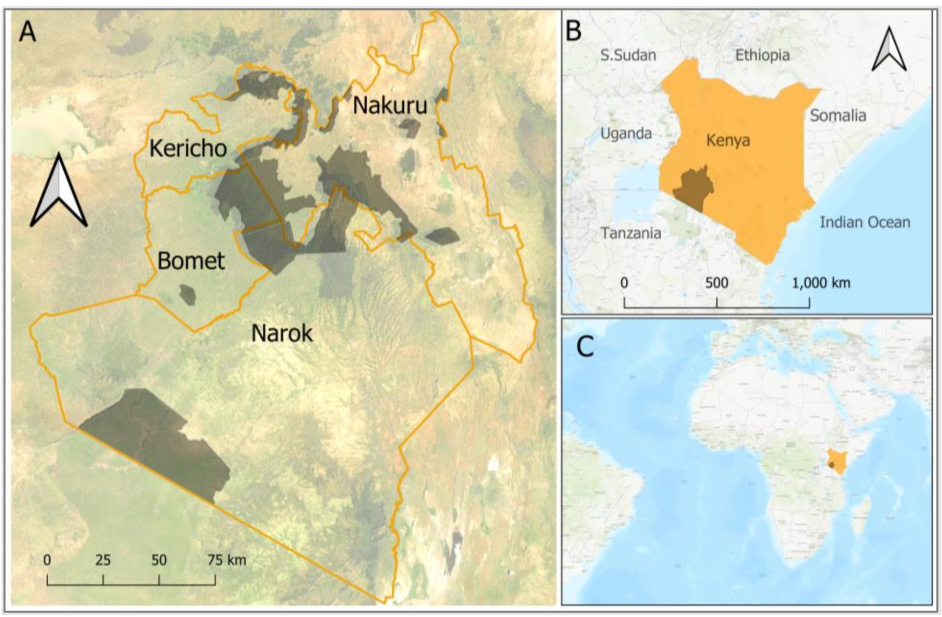

Figure 2. The study area at different geographic scales. A. zoomed in map of the study area (orange boundary) that includes the four counties (Bomet, Kericho, Nakuru, and Narok) and protected areas (gray polygons), B. study area location (brown polygon) within Kenya (orange polygon), and C. GMFC and Kenya's location on the African continent.

The study area consists of wet and dry grasslands, savannas, dense forests, and grasslands or tundra at high altitudes (Mutugi & Kiiru, 2015). The region is characterized by two rainy seasons i.e., long rains which typically extend from March to June and short rains from October to December (Kinyanjui, 2011). Average annual precipitation ranges from approximately 1,000 mm in the east to 2,000 mm in the west of MFC (BirdLife International, 2021). Overall annual mean minimum and maximum temperature are 9° and 24° C, respectively (Baldyga et al., 2008).

2.3 Material and Methods

2.3.1 Image Classification, Accuracy Assessment, and Area Estimation

We obtained land cover classification products for the GMFC for the years 1990, 2000, 2010, and 2018. These years were selected because of data availability. Original digital maps were produced by the Regional Center for Mapping of Resources for Development (RCMRD) using supervised classification of Landsat data (spatial resolution of 30 m X 30 m per pixel). Google Earth and aerial photography were used to obtain high resolution satellite imagery. Calibrated dry season (January and February) Landsat surface reflectance products (Landsat 5, Landsat 7, and Landsat 8 imagery) from 1990 to 2018 were used for image classification. Dry season images were used to allow for better discrimination between trees and grasses or crops and the random forests classifier was employed (RCMRD, 2016).

We reclassified the digital RCMRD land cover products from the initial ten detailed classes to five coarser classes (i.e., forest, grassland, cropland, water, and other) to suit our study area, and to conduct area estimation and independent accuracy assessment. Using the 2018 map classes as strata, we employed a stratified random sampling design to select sample units and allocated the samples size based on good practice recommendations (Olofsson et al., 2014) and our specific interest. Total samples allocation was forest = 100, grassland = 175, Cropland = 130, water = 25, and other = 50. We used Google Earth Pro's freely available high-resolution imagery to identify the classes of the validation sample units for use in accuracy assessment to obtain more accurate representation of reference data compared to the original maps. We conducted the initial accuracy assessment in R statistical software (R Core Team, 2022).

Accuracy assessment and area estimation was based on area proportions of map classes following the approach recommended by Olofsson et al. (2014). Area proportions are preferred to sample units when calculating the final accuracy and estimating area since they are used as input into calculating standard errors of associated classes. Using our sample units, we calculated an error matrix with rows as classified map and columns as the reference. We then used the equation below to calculate standard errors for each class (equation 10 in Olofsson et al 2014).

$$S(\hat{p}_{.k}) = \sqrt{\Sigma_i \frac{W_i \hat{p}_{ik} - \hat{p}_{ik}^2}{n_i - 1}}$$

Where n_{ik} is the sample count at cell (i, k)in the error matrix, W_i is the area proportion of map class i, $\hat{p}_{ik} = W_i \frac{n_{ik}}{n_{i.}}$ (Olofsson et al., 2014). The resultant standard error $S(\hat{p}_{.k})$ was then used to calculate the error-adjusted area estimate.

To obtain the 95% confidence intervals we used $\pm 1.96\sqrt{\hat{V}\left(\widehat{U}_i\right)}$ where 1.96 is the value of the 95th percentile from the standard normal distribution, $\hat{V}$ is the variance of the accuracy measures and $\widehat{U}_i$ is the user's accuracy computed from map proportions. We performed accuracy assessment for the 2018 land cover product due to availability of high-resolution reference data compared to previous time steps where high-resolution imagery is not available. We assumed that the 2018 accuracy assessment confidence intervals and standard errors applied to the earlier classifications as well.

2.3.2 Topographic Data (Elevation and Slope)

To investigate the role of physical environmental factors in LULC change in the study area, we divided the landscape into topographic classes. National-level Shuttle Radar Topography Mission (SRTM) 30 m digital elevation model (DEM) data was obtained from http://geoportal.rcmrd.org/ and clipped to the study area extent, which ranges from 573 m to 3,896 m elevation. We divided the study area into low (<2,100 m) and high (>2,100 m) elevation since most human activity occurs at altitudes below 2000 m (Mottet et al., 2006). We used the SRTM 30 m DEM to calculate slope and divided the study area into low slope (<25%) and high slope (>25%). We then analyzed land cover transitions for these four overlapping landscape classes. We also examined land cover changes for each period based on four combinations of the selected slope and elevation thresholds (e.g., high slope-high elevation, high slope-low elevation, low slope-high elevation, and low slope-low elevation).

2.3.3 Landscape Metrics

To quantify changes to the spatial patterns of the landscape (Cushman, McGarigal, & Neel, 2008; Fichera et al., 2012; Kayiranga et al., 2016) in GMFC, we selected and analyzed three landscape metrics capable of explaining dominance and fragmentation (McGarigal, 2015a) of the LULC classes for 1990, 2000, 2010, and 2018 using the R package 'landscapemetrics' (Hesselbarth et al., 2019). Only three parameters were selected for analysis to avert possible redundancy since many landscape metrics are highly correlated (Cushman et al., 2008; Kumar et al., 2018). Selected parameters include interspersion and juxtaposition index (IJI) which measures evenness of patch adjacencies, number of patches

(NP) which measures the total number of patches per class, and largest patch index (LPI) which indicates the percentage of landscape occupied by the largest patch (Narmada, 2021).

Finally, we conducted Kruskal-Wallis tests to compare statistical significance of selected metrics derived from the different landscape thresholds. Kruskal-Wallis's test is the nonparametric equivalent of one-way analysis of variance (ANOVA) and was selected for this analysis because the data violated assumptions of normality required for ANOVA. Independent variables were the different landscape threshold scenarios while LPI, IJI, and NP metrics were dependent variables. We did a pairwise comparison using Wilcoxon rank sum test to compare the multiple groups and subsequently performed a Dunn post-hoc test with Benjamini-Hochberg correction to identify specific groups that had significant differences after obtaining initial results.

2.4 Results

2.4.1 2018 Map Accuracy Assessment and Area Estimation

The total mapped area was ~30,345 km^2. For the 2018 map, we obtained an overall accuracy of 86% after using map proportions to calculate the final error matrix. All classes resulted in user's accuracy greater than 81% and producer's accuracy greater than 84%, except "other" (Table 1). These values, while not superb, are acceptable given the relatively low ground validation data. The low producer's accuracy of "other" class was compensated when calculating error-adjusted area by excluding errors of commission but including errors of omission. The small standard error bars from calculation of the 95% confidence intervals informed our conclusion of good accuracy and our decision to not carry out subsequent uncertainty analysis in our assessment of LULC change.

Table 1. 2018 error matrix calculated from proportions of map area for all the classes. The total map proportions, area, user's, and producer's accuracies are shown in respective rows and/or columns. The lower section of the table presents results of standard error and 95% confidence interval (CI).

	Forest	Grassland	Cropland	Water	Other	Total	Area (km^2)	User's
Forest	0.111	0.008	0.009	0.000	0.000	0.128	3,622	0.86
Grassland	0.005	0.438	0.046	0.000	0.005	0.495	14,234	0.88
Cropland	0.003	0.023	0.298	0.000	0.040	0.364	10,734	0.82
Water	0.000	0.000	0.000	0.007	0.002	0.008	198	0.81
Other	0.000	0.000	0.000	0.000	0.005	0.005	1,556	1.00
Total	0.119	0.469	0.354	0.007	0.051	1.000	30,344	
Producer's	0.93	0.93	0.84	1.00	0.09			
Std error (km^2)	0.61	3.16	4.22	0.005	1.77			
95% CI	1.20	6.19	8.28	0.01	3.46			

2.4.2 LULC Change and Transition Analysis

In analyzing the LULC change over the 28-year period, we found that, overall, forest and grassland decreased while cropland increased. Cropland expansion occurred mostly around the main forest block in the northern side of the study area (Figure 3A-D). The southmost forest block notably decreased across the study period and some portions transitioned to grassland and the overall size of the forest blocks were largest in 1990 and smallest in 2018.

We also considered the overall patterns of gain and loss for the three main LC types – forest, grassland, and cropland. Forest expansion occurred predominantly in the western part of the GMFC with some expansion in the southern parts (Figure 4A). Forest loss occurred in many parts of the study area but most noticeably around edges of the main forest blocks. Grassland gains were most noticeable in the southern part of GMFC and were mostly converted from forests. Since water and "other" classes occupied the least area and showed very small changes, they were not included in our analyses and discussion. Land use change accelerated across the period of study and revealed an increasing trend in area under cropland in each time period and a decreasing trend in area under forest and grassland (Figure 5).

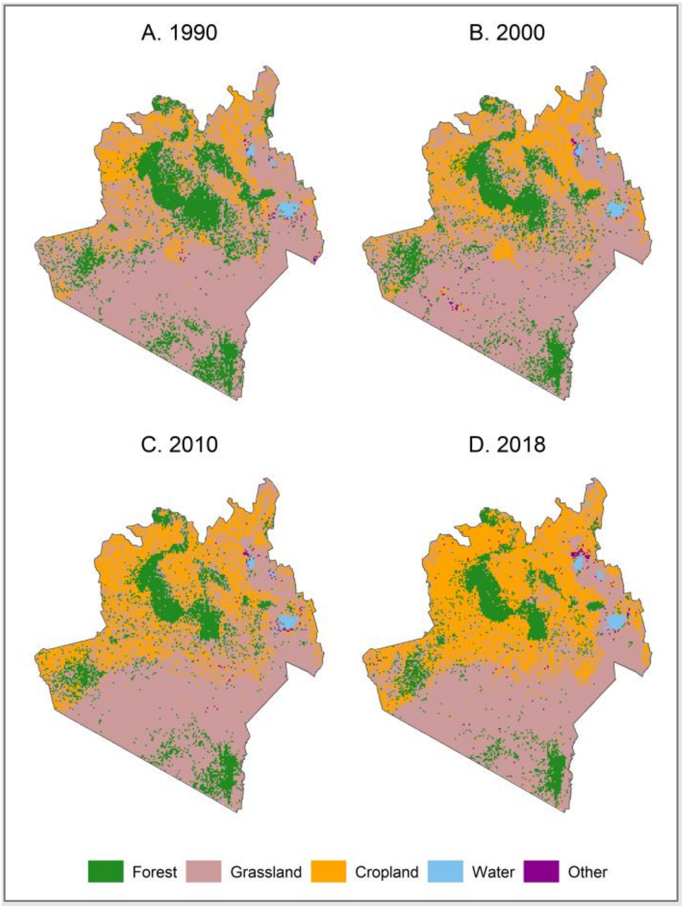

Figure 3. LULC maps of the GMFC from 1990-2018. The maps indicate the years of analysis 1990 (A), 2000 (B), 2010 (C), and 2018 (D) and corresponding spatial distribution. The study area LULC map was reclassified into five classes (forest, grassland, cropland, water, and other). There was a general increase in conversions to cropland and decrease in forest and grassland across the years.

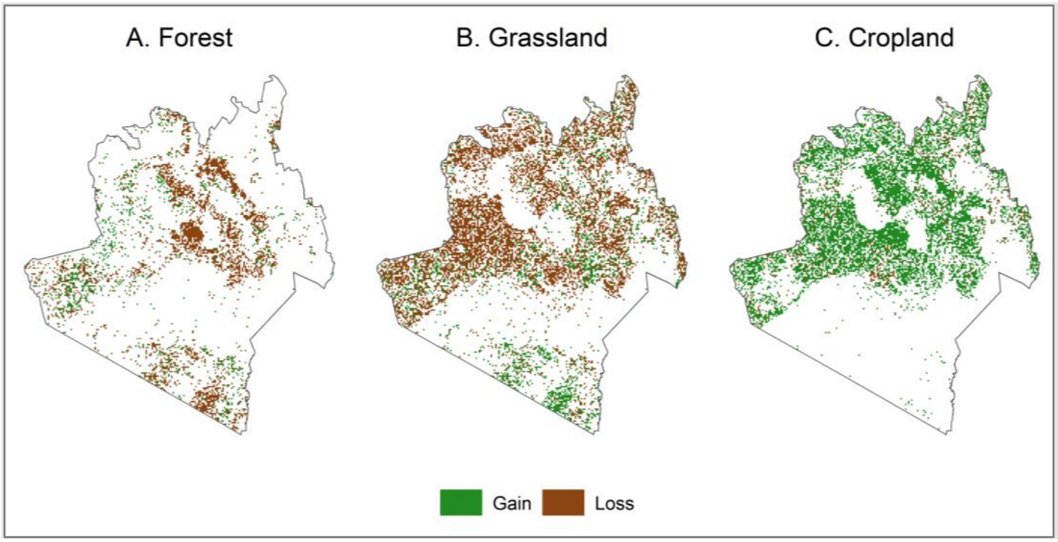

Figure 4. Spatial representation of LULC change transitions from 1990 to 2018. The transitions are represented as net gains and loss for forest (A), grassland (B), and cropland (C) cover types.

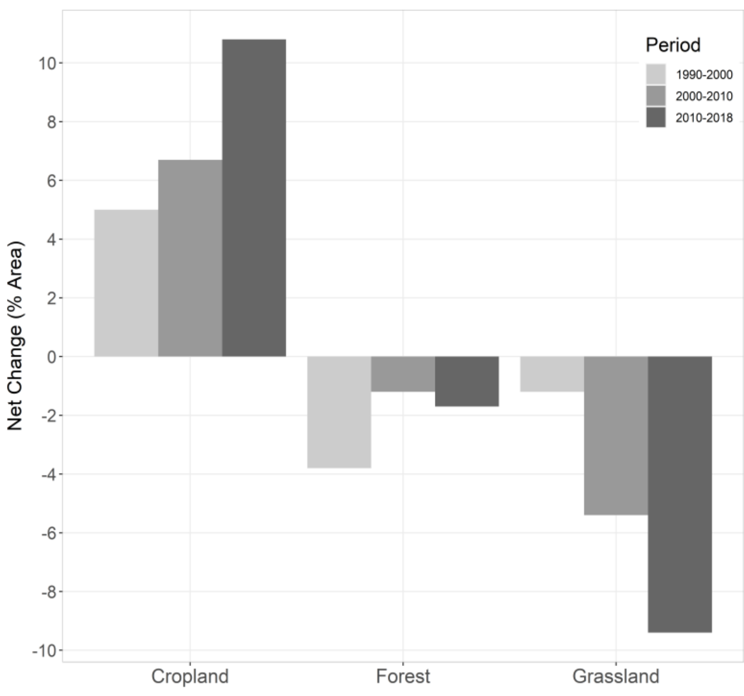

Figure 5. LULC transitions representing the net proportion of change for each category within transition periods. The proportions for the transition periods (1990-2000, 2000-2010, and 2010-2018) were calculated by subtracting the earlier year from the later year hence positive values indicates gain while negative indicates loss.

There was a decrease in forest cover across the three transition periods with the greatest net forest loss observed in the 1990-2000 period (1151 km2). In contrast, the largest decline in grassland (1630 km^2) was observed in the 2010-2018 period while the largest increase in cropland (3272 km2) was observed in the 2010-2018 period. Results from the three transition periods (1990-2000, 2000-2010, 2010-2018) and the overall change (1990-2018) illustrated varying proportions in LULC changes (Table 2).

Table 2. Transition matrices representing percentage of land change from one class to another between different transition periods examined (1990- 2000, 2000-2010, 2010-2018, and 1990-2018).

Land cover class	**Forest**	**Grassland**	**Cropland**	**Water**	**Other**
			1990-2000		
Forest	61.87	31.59	6.49	0.03	0.02
Grassland	4.98	79.65	14.95	0.03	0.39
Cropland	2.54	41.54	55.75	0.03	0.13
Water	2.44	4.08	1.95	91.25	0.28
Other	1.5	59.07	22.22	3.51	13.69
			2000-2010		
Forest	64.17	24.51	11.22	0.08	0.02
Grassland	5.82	74.97	18.94	0.06	0.2
Cropland	3.67	34.88	61.17	0.09	0.19
Water	0.78	10.14	2.29	84.52	2.27
Other	0.63	73.78	8.32	0.33	16.94
			2010-2018		
Forest	57.35	23.06	19.39	0.14	0.06
Grassland	5.42	69.81	24.03	0.28	0.46
Cropland	5.08	19	75.31	0.17	0.44
Water	1	5.04	5.67	88	0.29
Other	1.98	40.87	23.73	8.48	24.94
			1990-2018		
Forest	46.03	25.53	19.39	0.14	0.07
Grassland	5.01	63.99	30.32	0.16	0.51
Cropland	4.07	17.22	78	0.15	0.57
Water	0.82	5.04	5.67	88	0.29
Other	1.67	53.98	25.68	8.95	9.71

For 1990-2000, 31.59% of forest turned to grassland while 6.49% turned to cropland; 14.95% of grassland turned into cropland and 4.98% turned to forest while 2.54% of cropland turned into forest as 41.54% turned into grassland. For 2000-2010, 24.51% of forest turned into grassland while 11.22% turned to cropland; 5.82% of grassland turned to forest while 18.94% turned to cropland; 3.67% of cropland turned to forest while 34.88% turned to grassland. For 2010 to 2018, 23.06% of forest turned to grassland while 19.39% turned to cropland, 5.42% of grassland turned to forest while 24.03% turned to cropland and 5.08% of cropland turned to forest while 19% turned to grassland (Table 2).

2.4.3 Elevation and Slope

Results from elevation and slope were divided into two categories a) analysis on independent slope and elevation gradient and b) analysis on a combination of slope and elevation gradient. The proportion of landscape under independent topographic categories included low slope (89.7%), high slope (10.3%), low elevation (69.4%), and high elevation (30.6%), while proportion of landscape under combined topographic categories included low slope-low elevation (65.3%), low slope-high elevation (24.4%), high slope-low elevation (4.1%), and high slope-high elevation (6.2%). There was less high slope-high elevation area overall than the other landscape types, hence we calculated the net changes as percentage of each topographic class across time.

2.4.3.1 Independent Slope and Elevation Landscape Thresholds

In the high elevation topographic class, forest decreased across the three transition periods while grassland slightly increased between 1990-2000 but decreased between 2000-2010 and 2010-2018 (Figure 6A). Most grassland was lost in 2010-2018. Cropland increased across the transition periods, though the increase was lower between 2000 and 2010. In high slope topographic class, forests decreased between 1990-2000 and 2000-2010 but increased by 0.4% between 2010 and 2018 (Figure 6B), a trend that was not consistent with the overall LULC change pattern in Figure 5. Grassland increased slightly between 1990-2000 then decreased between 2000-2010 and 2010-2018 with the greatest loss in the latter transition period. However, there was continuous cropland expansion across the three transition periods with 2010-2018 registering the most expansion. In low elevation topographic class, area under forest decreased almost evenly across the transition periods (Figure 6C). Grassland decreased and cropland increased across the three transition periods with both classes registering greatest changes between 2010-2018. Low slope regions experienced a decrease in forest coverage across all the three transition periods with the greatest decrease in 1990-2000 and the least in 2000-2010 (Figure 6D). On the other hand, grassland decreased throughout the transition periods with the greatest decrease in 2010-2018. Cropland increased across the three transition periods and the greatest expansion was in 2010-2018. LULC change trends in the low slope landscape category matched the overall LULC change results in section 3.1.

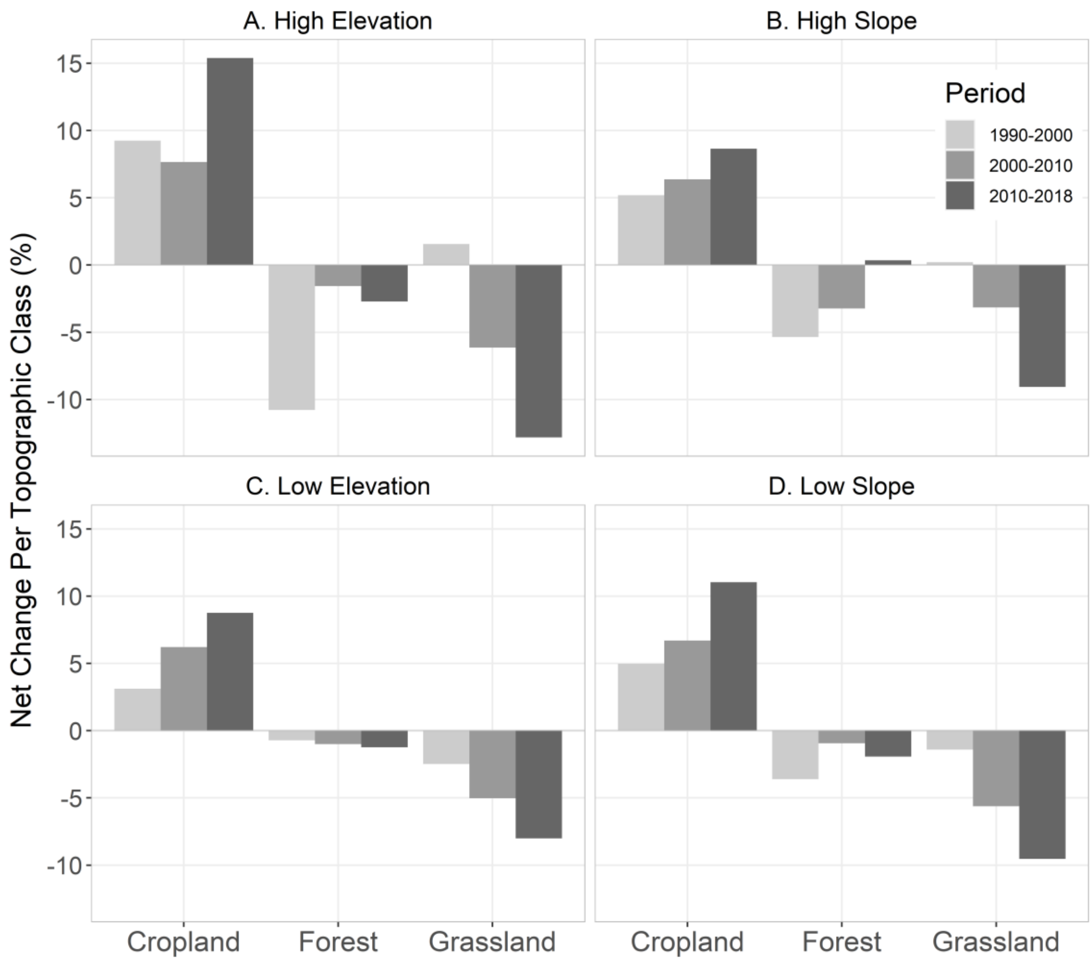

Figure 6. Net changes in LULC types for the different transition periods. The changes presented include forest, cropland, and grassland LULC types for the different transition periods (1990-2000, 2000-2010, and 2010-2018) under high elevation (A), high slope (B), low elevation (C), and low slope (D) topographic classes. The least changes in area occurred in high slope landscape.

2.4.3.2 Slope and Elevation Combinations

Forest decreased across the three transition periods in the high slope-high elevation topographic class. The biggest decline was from 1990 to 2000 (-9%) while the least decline was in 2010-2018 (-1%). Grassland increased slightly (3%) between 1990 and 2000. However, there was a decrease of -2% and -11% in 2000-2010 and 2010-2018 transition periods, respectively (Figure 7A). Whereas area under cropland expanded in each of the three transition periods, the greatest expansion (12%) occurred between 2010 and 2018. In high slope-low elevation regions, forest increased by 0.3% between 1990-2000, decreased by -1.6% between 2000-2010, and had the greatest increase (2.5%) between 2010-2018. Grassland decreased in all transition periods in this topographic class although the greatest decrease occurred between 2010-2018. However, the highest decrease in high slope-low elevation (-6.1%) was comparatively lower than in high slope-high elevation topographic class. Similarly, cropland increased in all the three transition periods, but the greatest was by 6.8% between 2000-2010 (Figure 7B).

In low slope-high elevation, forest decreased across all transition periods, but the largest decrease was -11% between 1990-2000 while the smallest was between 2000-2010 (-0.9%). Grassland increased by 1.3% between 1990-2000 but decreased between 2000-2010 and 2010-2018 by -7.2% and -13.3%, respectively. Cropland increased across the transition periods to a highest of 16.2% between 2010-2018 (Figure 7C). In low slope-low elevation areas, forest decreased gradually and evenly across the three transition periods ranging between -0.8% in 1990-2000 and -1.5% in 2010-2018. Grassland decreased while cropland increased across all the transition periods and the greatest net change for both classes occurred in 2010-2018 (Figure 7D).

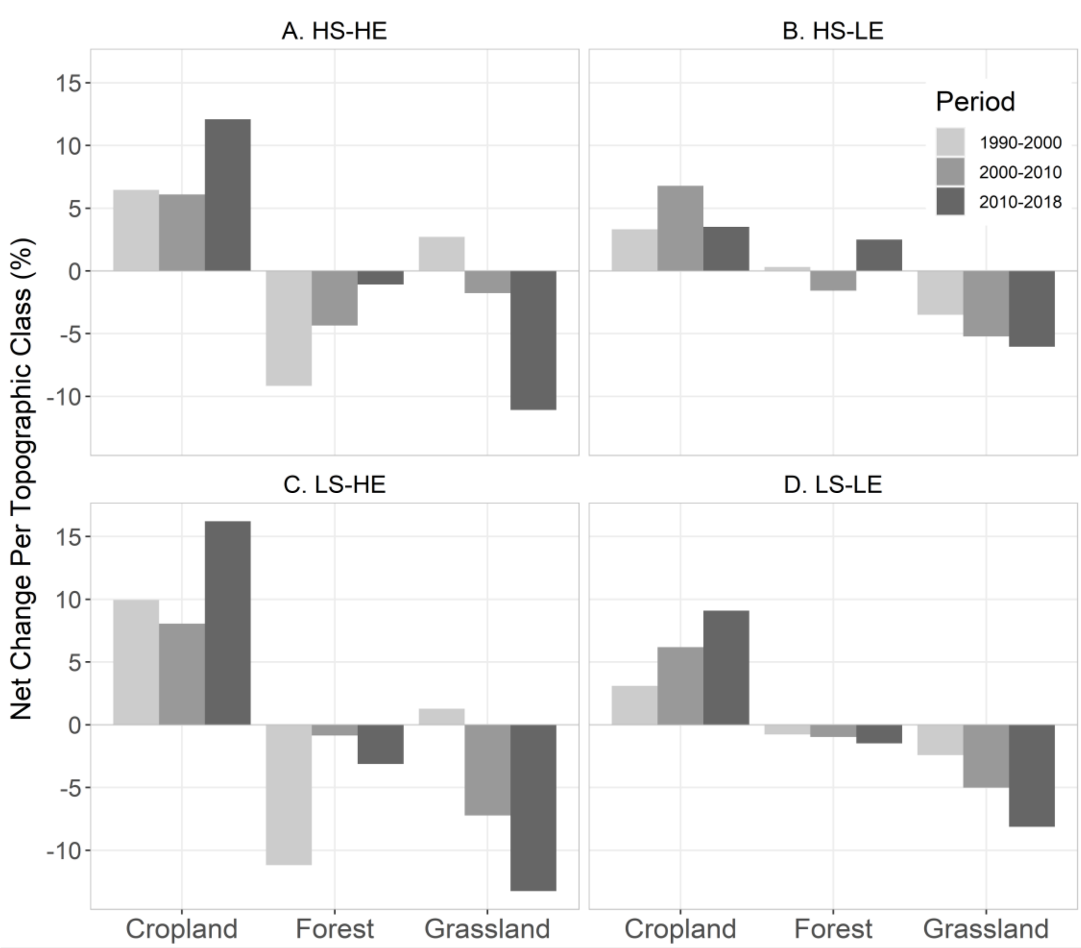

Figure 7. Net changes in LULC types for the three transition periods (1990-2000, 2000-2010, and 2010-2018) under different combinations of slope and elevation. The slope and elevation landscape combination scenarios include HS-HE = high slope-high elevation (A), HS-LE = high slope-low elevation (B), LS-HE = low slope-high elevation (C), and LS-LE = low slope-low elevation (D). The least changes in area occurred in high slope landscape.

2.4.4 Landscape Metrics

To assess how the size and shape of patches changed across the landscape, we calculated three landscape metrics and their change over time within the different topographic classes. Forest and grassland IJI not only increased consistently throughout the period of study but also showed similar trends in most of the topographic classes. However, grassland depicted an overall decrease from 1990-2018 with significant dip between 2000-

2010 transition period (Figure 8A-E). Cropland IJI was lower in all topographic classes compared to forest and grassland IJI but exhibited a steady increase. Forest IJI surpassed grassland IJI in high elevation (Figure 8A), full landscape (Figure 8C), and low slope (Figure 8E) topographic classes but remained lower in low elevation topographic class (Figure 8D).

LPI varied by LULC class, year, and topographic class. The overall LPI trend in high slope (Figure 8G), full landscape (Figure 8H) and low slope (Figure 8J) topographic classes were similar: decreasing grassland, increasing cropland, and plateauing forest. The low elevation topographic class maintained a consistent trend among the three classes with a higher forest LPI compared to cropland and grassland throughout the period of study (Figure 8I). Full landscape, low slope, and high elevation regions experienced a steep increase in cropland LPI from 2010. Comparatively, cropland LPI was greatest among the three LULC classes in high elevation landscape by 2018. Forest LPI was more than corresponding grassland and cropland in 1990 but decreased gradually across all the topographic classes except in high slope. There was a gradual increase in cropland LPI in low elevation compared to full landscape, high elevation, and low slope. Forest had relatively stable LPI across the years but remained the highest in high elevation topographic class.

There was an overall increase in NP in the full landscape for each of the three LULC classes from 1990 to 2010 followed by a decrease from 2010 to 2018 (Figure 8K-O). Forest and cropland in high elevation (Figure 8K), low elevation (Figure 8N), and low slope (Figure 8O) topographic classes showed a similar trend while grassland continually increased in each of the four topographic classes. The NP for all the three LULC classes increased from 1990 to 2018 in high slope regions.

Kruskal-Wallis test at a 95% confidence interval found a significant difference in LPI (χ^2 = 11.70, P = 0.02, DF = 4) and NP (χ^2 = 11.96, P = 0.02, DF = 4) among the five topographic classes (full landscape, high elevation, low elevation, high slope, and low slope) across the study period. Consequently, the post hoc Dunn test revealed that significant differences in LPI occurred between full landscape and high slope (P = 0.02), low elevation and high slope (P = 0.03), and high slope and low slope (P = 0.02) regions (Table 3). NP depicted significant differences between low slope and high elevation topographic classes (P = 0.01) while IJI results did not show statistical differences between any of the topographic classes.

Table 3. Dunn test post hoc result (topography). The results compare the largest patch index (LPI) by landscape group (Benjamini-Hochberg correction). Significant results are denoted by an asterisk.

	Full Landscape	High Elevation	High Slope	Low Elevation
High Elevation	0.33			
High slope	0.01*	0.06		
Low Elevation	0.45	0.34	0.02*	
Low Slope	0.49	0.35	0.01*	0.50

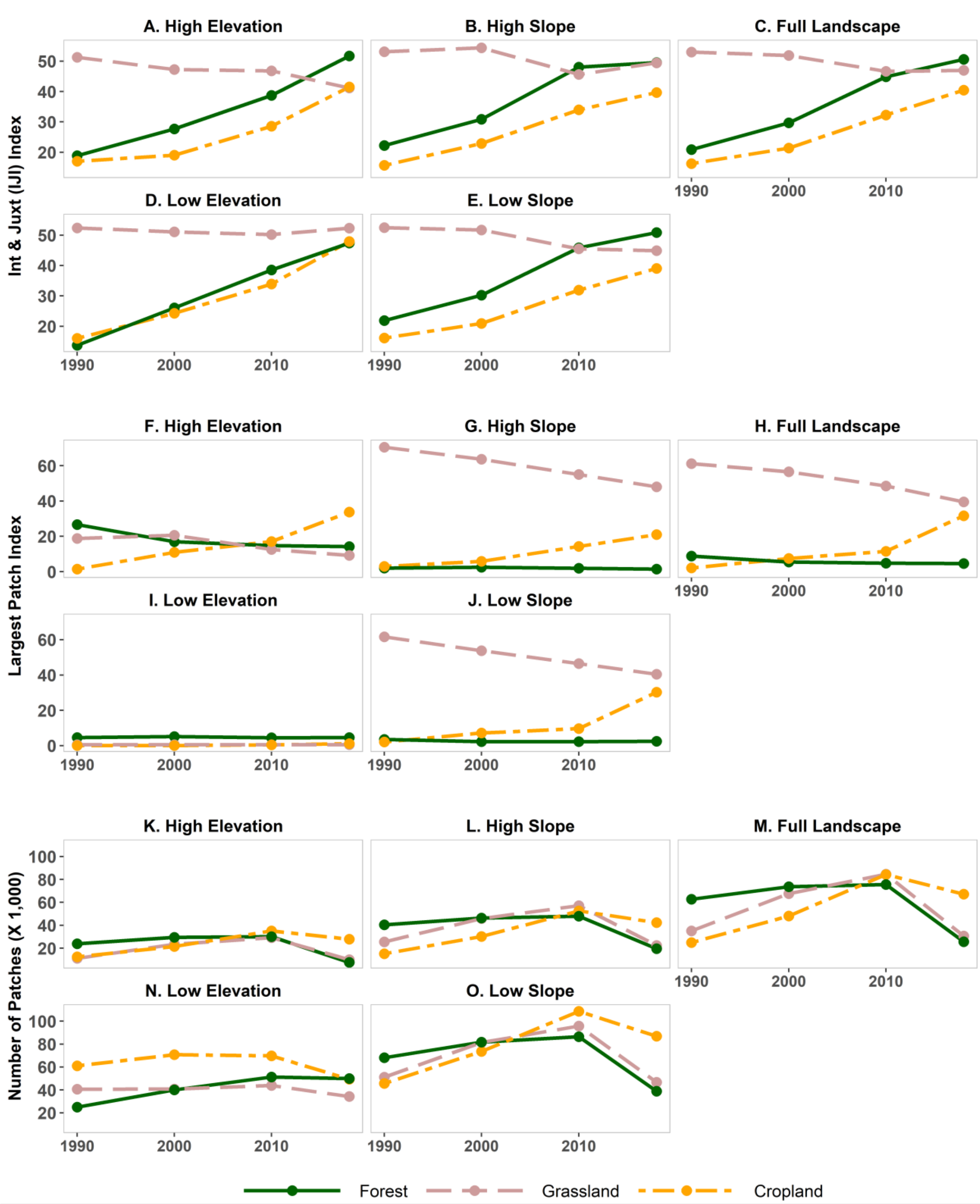

Figure 8. Temporal pattern of landscape metrics from 1990 to 2018. (A – E) interspersion & juxtaposition index (IJI), (F – J) largest patch index (LPI), and (K – O) number of patches (NP) at class level.

2.5 Discussion

The objective of this study was to independently evaluate the uncertainty of existing remotely sensed LULC products, characterize spatiotemporal changes, and examine the influence of slope and elevation on a socioeconomic and ecologically significant landscape across a 28-year period. Here we highlight the relevance of our findings to GMFC and similar ecosystems. The producer's, user's, and overall accuracies and minimal variance in the error-adjusted area obtained from accuracy assessment based on the 2018 data and good practices (Table 1) showed that our accuracies for the forest, grassland, and cropland classes were plausible. Therefore, we did not subject our results to further uncertainty analysis. Understanding uncertainty in LULC research is important for planning for natural resources, prudent climate change mitigation, adaptation, and resilience strategies.

The GMFC experienced LULC changes in varying degrees. The greatest gains were in croplands which are associated with human encroachment. Most farming activities in the study area are practiced on a small scale basis hence the expansion in cropland is indicative of human encroachment into the forest and grasslands. When many adjacent small pieces of farmland associated with small-scale cultivation are aggregated, they form patchwork-type (John & Clark, 2010) of cropland class which become increasingly noticeable through the satellite-based LULC classification hence the spatial patterns in landscape composition. The area is also occupied by several wealthier settlers who tend to colonize larger tracts of land for commercial farming (Mwangi et al., 2017) and are more likely to acquire land in regions of lower elevation and slope gradients that support mechanized farming. Through practices such as land clearing, tilling, and irrigation, continued cropland expansion and agricultural intensification will increase CO_2 emissions (Gray et al., 2014).

Forest degradation has been a major concern for the GMFC in recent decades and since Mau Forest Complex is one of the largest water catchments in East Africa, its degradation has been impacting the region's hydrology and global climate. Forest encroachment was highest between 1990-2000, slowed down in 2000-2010 and slightly increased between 2010-2018, albeit this increase did not surpass the 1990-2000 rate. This can be attributed to the concerted efforts by various stakeholders including government, private sector, and non-governmental organizations, among others, to mitigate the forest loss. Forest configuration decreased in both size and fragmentation due to cropland conversions that occurred at the edges of the forest and isolated forest patches leading to smaller compact block types. Forests were least disturbed in areas of high slope and high elevation as expected because these areas are not suitable for human settlement nor any form of agricultural activities. The strategic, economic, and ecological importance of the GMFC mean that despite the continued decrease in forest cover, more ecological conservation measures should be channeled to areas least likely to be affected by anthropogenic disturbances (e.g., high slope and high elevation topographic regions of the GMFC) as a strategy to conserve the ecosystem and slow down the rate of human induced deforestation.

Grassland exhibited the greatest decline with most being converted to cropland. Grasslands often occur in regions of lower slope and elevation gradient making them prone to anthropogenic disturbances. Furthermore, they are easier to clear for agriculture compared to forests. More people are purchasing and developing land outside the protected savanna region (Serneels & Lambin, 2001). Unabated conversion of grassland to cropland will likely impact interannual variability and trends in atmospheric carbon concentration (Ahlström et al., 2015). Additionally, limited grazing grounds for pastoral communities within the GMFC coupled with changing climate will lead to increased human-wildlife conflicts while also interfering with tourism activities in the Maasai Mara National Reserve (Oduor, 2020).

Elevation and slope gradients play a significant role in the land cover changes. Low slope areas lost most forest and grassland at a more rapid rate than the high slope and elevation areas. The lower slope and elevation areas are traditionally suitable for agricultural activity and therefore experienced more anthropogenic disturbances. In cases where mechanized farming is practiced, these areas have favorable conditions compared to the corresponding steep slopes and high elevation which significantly limit mechanized activity. Statistical results revealed that slope had a higher influence in determining where land cover changes occur, with change more likely on lower slopes. High elevation and slope areas also have periods where the transition and change patterns show decreasing rates of forest loss and instances of forest gain (e.g., Figure 7B) thus increased conservation activities in such regions significantly could reduce deforestation (Bax & Francesconi, 2018). These areas are less likely to be encroached by humans and therefore conservation efforts would face less challenges compared to relatively lower elevation and slope areas.

The spatial metrics revealed decreasing LPI (indicative of decreasing dominance) and increasing NP (indicative of increasing fragmentation) trends in forest and grassland LULC classes within the GMFC in the twenty-eight-year period. Cropland LPI and IJI patterns were inversely proportional to those of forest implying that the forest lost was mostly due to agriculture-related activities. The increase in cropland IJI is likely due to increased cultivation that led to conversion of many small but neighboring pieces of land to cropland. Overall increase in both cropland and forest signified increasing uniform configuration, hence decreasing fragmentation. On the contrary, decreasing grassland IJI implied declining uniformity in configuration, hence increasing fragmentation.

One of the main sources of uncertainty in this study was related to the use of four LULC images over the 28-year period. Such pre-existing LULC products are prone to errors arising from data quality issues, conversion of spatially and categorically continuous conditions to discrete classes, scale of analysis, and classification algorithm decisions (Foody, 2010; Olofsson et al., 2014a; Spruce et al., 2020). Improved access to remote sensing imagery e.g., opening of the Landsat archive (Woodcock et al., 2008) and advancements in computing power and geospatial technologies have mitigated these challenges. Therefore, analysis of LULC change has evolved significantly to incorporate methodologies that detect trends and breakpoints in vegetation time series (Landmann & Dubovyk, 2014; Morrison et al., 2018; Wanyama et al., 2020). Despite shortcomings associated with LULC classification, valuable information continues to be derived from analyses like what has been presented in this study.

2.6 Conclusion

The GMFC has undergone substantial anthropogenic LULC changes in the past 28 years. We conducted rigorous accuracy assessment and area estimation using high spatial resolution reference data and attained an overall classification of 86% with minimum standard errors, leading us to be confident in our assessments of LULC change. Between 1990 to 2018, the proportion of cropland increased by 22.5% while forest and grassland decreased by 6.6% and 16%, respectively. We surmise that these changes could have influenced socio-ecological systems within the study area. Our study illustrated that 1) remote sensing and landscape metrics can be leveraged to assess spatiotemporal dynamics of topographically heterogeneous ecosystems of socioeconomic and ecological significance at varying scales and 2) elevation and slope had significant influence in landscape constitution and transformation. Despite much conservation focus on deforestation, we found that grasslands within the GMFC are more rapidly decreasing in size and becoming more fragmented. This is consistent with recent studies and reinforces the need to better quantify degradation and improve management of forests and grasslands. This type of study can be applied in different regions and at different scales to assess and monitor anthropogenic influence on important yet fragile ecosystems amid the growing challenge of climate change and population increase. Future research should employ long-term and continuous time series analysis algorithms to quantify the influence of LULC changes on climate and carbon storage, investigate drivers of change patterns in the GMFC, and predict future LULC change under different socio-ecological scenarios.

CHAPTER 3: ADVANCING SUSTAINABILITY IN DATA SPARSE LANDSCAPES USING A NEXUS APPROACH

3.1 Introduction

Earth's resources are finite, hence fostering sustainability is important for efficient functioning of systems, preserving the ecosystem, and meeting human needs for bettering livelihoods (Olawumi & Chan, 2018; World Commission on Environment and Development, 1987). Various elements of nature and society are intricately intertwined in deeply coevolutionary relationships (Clark & Harley, 2020; Reyers et al., 2018) and this nature-society dependence influences functioning of systems across the globe. The complexity and delicate nature of these relationships is heightened among populations without adequate financial and technological resources to cushion against dynamic challenges exacerbated by a changing world and climate. Most populations in developing countries depend on natural resources either directly or indirectly for their livelihoods (Jahanger et al., 2022; Maja & Ayano, 2021; Zallé, 2019). For example, a sizable population depends on springs, rivers, and small-scale rainwater harvesting for their domestic needs because most rural households are not connected to tap water. Such populations face perpetual dilemmas that require balancing between conserving the environment and sustaining their livelihoods.

Human perceptions and competing interests influence attitudes and behaviors in relation to environmental stewardship resource exploitation (Bennett, 2016; Breckwoldt et al., 2018; MacDonald et al., 2015; Rogan et al., 2005). These perceptions, attitudes, and behaviors impact the environment at global, regional, national, and local levels. Perceptions, attitudes, and priorities vary depending on stakeholders (and hence competing interests) and may lead to varying priorities relating to conservation and exploitation of natural resources. Therefore, understanding perceptions and priorities of key stakeholders is imperative for fostering integrative and pragmatic sustainability science. Human decisions and actions have direct and indirect impacts on the environment (e.g., through policy formulation and enforcement) at the local level (e.g., through natural resources abstraction and family land subdivisions, clearing land for agriculture, etc.). While such decisions and actions may be well intentioned, the impacts may reverberate across different sectors and result in externalities. Different stakeholders impact socio-ecological sustainability at different levels (Martínez-Fernández et al., 2021; Videira et al., 2016; Weible et al., 2010). For example, experts advise, law makers design policies, government entities enforce the policies, pressure groups like civil society organizations (CSOs) and non-governmental organizations (NGOs) advocate for vulnerable populations while locals are primary actors whose actions contribute immensely to the success and/or failure of the enacted laws and policies. There is need for cooperation and synergies across different sectors to reduce duplication in policy and bolster sustainability efforts.

LULC transformations such as urbanization or conversion of forests to croplands can modify local, regional, and global socio-environmental systems by impacting water resources, energy consumption and supply, and agricultural productivity (Choudhury et al., 2019; Guzha et al., 2018; Liu et al., 2019b; Mello et al., 2018; Näschen et al., 2019). Recent studies indicate that LULC change is an essential climate variable (ECV) which is exacerbated by human activities. For example, unabated human encroachment into water catchments and forest dominated ecosystems can alter the hydrological cycle of a landscape depending on the scale of disturbance. Drying rivers, changing rainfall patterns, shortening of growing seasons, frequent and severe drought among other resultant challenges could have ripple effects on associated social and ecological systems such as human-wildlife conflicts, increased cases of food insecurity, and increases in social upheavals. Studies that quantify the nature, magnitude, and structure of LULC are essential in fostering stable and sustainable environments and societies. Yet, sustainability is a critical characteristic of ecosystems that is difficult to measure due to its spatially specific nature, compounded by data deficiencies (Bali Swain & Yang-Wallentin, 2019; Swain, 2018). Enhancing and measuring socio-ecological sustainability, therefore, requires integrative approaches and multistakeholder partnerships.

Water, energy, and food are critical resources required for sustaining human life, yet they are highly susceptible to climate change and other socio-economic pressures such as population increase (Golam et al., 2015). Besides, management of these resources is often compartmentalized leading to overlap, duplication, and competition that decreases efficiency in attaining sustainability goals (Scott et al., 2015; Weitz et al., 2017). Yet, these resources are interconnected e.g., changes in precipitation (water) are expected to influence agricultural yields (food), which will increase human influence on the environment in terms of energy consumption (e.g., more use of charcoal and wood since people will not be expected to afford cleaner sources of energy). While some perturbations may be short-term, some footprints persist and threaten sustainability of livelihoods and other socio-ecological systems. A nexus approach identifies interconnections where impact on one component in a system can have recurring direct and indirect impacts on others and is necessary to address the complexity of social-ecological systems (Fischer et al., 2015; Lim et al., 2018). The water-energy-food (WEF) nexus is an integrative framework that examines interdependencies between water, energy, and food sectors to achieve cross-sectoral synergies in attaining sustainable development and has increasingly been used to quantify sustainability in recent years (Leemhuis et al., 2017; Mabhaudhi et al., 2021; Nhamo et al., 2020). Since its emergence at the 2011 Bonn Conference (Hoff, 2011), the WEF nexus has been promoted as one of the frameworks to reduce trade-offs, promote synergies, increase system efficiency, and seek strategies for sustainable development (Wu et al., 2021).

Many WEF nexus studies focus on theoretical frameworks while few that highlight practical WEF nexus research are concentrated in the global north because of readily available and accessible data in these regions. To address this research gap in data-sparse regions, there is need for more robust research endeavors that transcend simple linkages among the WEF nexus by blending multiple data streams and techniques including more practical field studies (Albrecht et al., 2018; Dhaubanjar et al., 2017; Endo et al., 2020). Remote sensing and mixed methods techniques can be leveraged to ameliorate WEF studies, most of which rely on the WEF Nexus Tool 2.0 and are limited to areas with readily available data (Daher & Mohtar, 2015). Besides, methods that measure perceptions such as key informant interviews and associated analytic techniques (e.g., multi criteria decision making process; MCDM) can help researchers understand the roles and priorities among sustainability stakeholders across all levels (including policy makers, managers, and locals) and how socio-ecological systems are modified by humans. This study examined the interdependencies among the water, energy, and food sectors which are critical for fostering socio-ecological sustainability in a significant yet fragile landscape in southwest Kenya. We hypothesize that: (1) changes in landscape composition correspond with climate trends over the past three decades and (2) these changes can influence the balance and vulnerability of local communities to climate change impacts. The study leverages a nexus approach, data and techniques from remote sensing, key informant interviews, historical crop yields, and quantitative analyses to characterize the state of the GMFC from 1990 to 2021.

3.2 Study Area

The GMFC landscape is in the Great Rift Valley and consists of four contiguous administrative counties (Bomet, Kericho, Nakuru, and Narok). Total population in the GMFC is approximately 4.8 million people (County Government of Bomet, 2023; County Government of Kericho, 2023; County Government of Nakuru, 2023; County Government of Narok, 2023). The GMFC hosts the largest remaining indigenous forest in East Africa, the Mau Forest. This is the largest water catchment in the region (Klopp & Sang, 2011). Average annual rainfall ranges from approximately 500 mm to 2,000 mm (Akanga et al., 2022; BirdLife International, 2023). The study area experiences two rain seasons, long rains that occur from March to early June and short rains that occur in November and December.

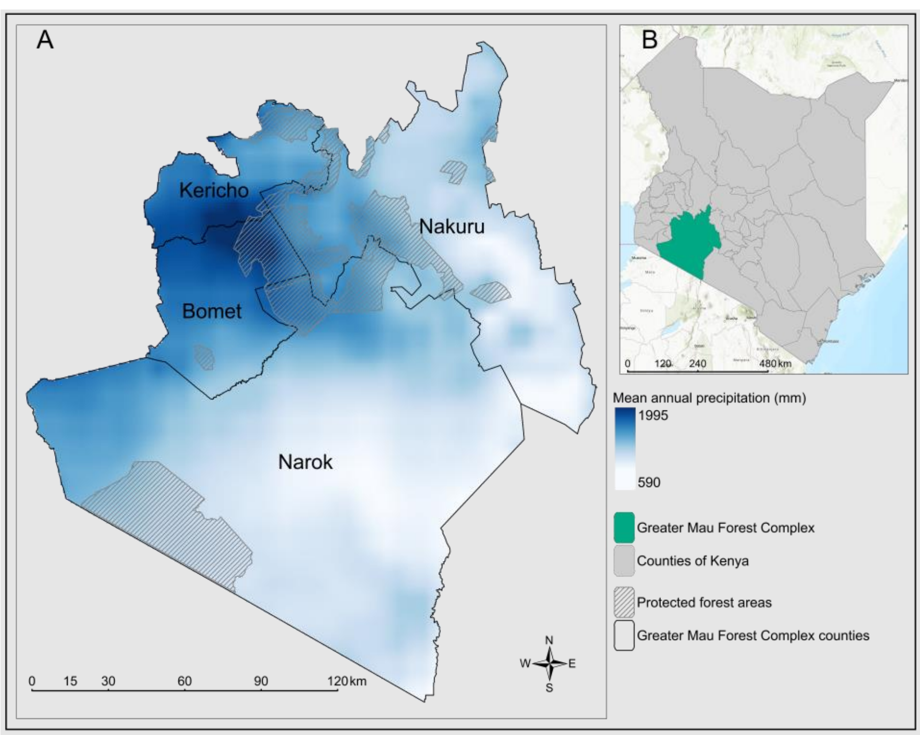

Figure 9. Long term mean annual precipitation for 1992-2021 across the study area (A). The geographic location of GMFC in Kenya is shown in inset figure B.

3.3 Data

3.3.1 Precipitation and Vegetation

Climate Hazards Group InfraRed Precipitation with Stations data (CHIRPS) from 1990-2021 was used to generate proxy variables for the water metric. The CHIRPS data is available through Google Earth Engine (https://earthengine.google.com/) at 5 km spatial resolution and provides global daily and pentad (five day) precipitation rasters from 1981 to present. Increased variability in precipitation has been shown to influence freshwater availability (Rodell et al., 2018) and because GMFC is home to the largest water catchment in Kenya (MFC), variation in precipitation is expected to influence availability and access of water resources in the study area and the East African region.

Data on food was represented by Moderate Resolution Imaging Spectroradiometer Enhanced Vegetation Index (MODIS EVI; MOD13Q1.V6), a 16-day composite with 250m spatial resolution obtained from AppEEARS (https://lpdaacsvc.cr.usgs.gov/appeears/). We used EVI because it performs better than normalized difference vegetation index (NDVI) in the tropics (Phompila et al., 2015). While Landsat has finer spatial resolution and historical coverage, we preferred MODIS due to its daily revisits resulting in less data gaps compared to Landsat's 16-day interval. Additional maize yield data at county scale was obtained from Kenya's Ministry of Agriculture (Government of Kenya, 2022). Data on maize production is best suited for characterizing food in the GMFC because maize is the main food crop grown in the four counties constituting this landscape.

3.3.2 Energy Consumption and Supply

To assess the energy component of WEF, we obtained country-level energy consumption and supply data measured in terajoules (TJ) from The International Energy

Agency (IEA, 2022). We used biofuels consumption, biofuels supply, electricity consumption, and hydropower supply for 2000, 2005, 2010, 2015, and 2020. Additionally, we obtained gridded population dataset at 1 km spatial resolution for the same years from WorldPop (https://hub.worldpop.org/; Tatem, 2017). We unsuccessfully explored the possibility of using alternative data from the Kenya National Bureau of Statistics and Kenya's Ministry of Energy. On the other hand, nighttime lights imagery (NTL) and the Gridded Dataset for Electrification in Sub-Saharan Africa (GDESSA; Falchetta et al., 2019) were not used for this study because the GMFC is predominantly rural with limited electricity and due to the short temporal scale of the GDESSA data.

3.3.3 Data from Fieldwork

Additional data included anecdotal reports from key informant interviews, household surveys, and observations from local communities and the study area. Field data was collected from May to July, 2022 (IRB Number: STUDY00007532, NACOSTI License Number: NACOSTI/P/22/17366), and involved in-depth interviews with five experts per county (20 in total for the GMFC) drawn from the national and county governments as well as non-governmental organizations.

3.4 Methods

We modified the WEF nexus framework by blending remote sensing, geospatial, qualitative, and quantitative techniques to perform analyses that can translate in multiple scales and data sparse landscapes and regions (Albrecht et al., 2018; Dhaubanjar et al., 2017; Endo et al., 2020). Data availability and access challenges prevented us from employing some commonly used tools customized for WEF nexus studies. Precipitation and vegetation analysis was done for the long rainy season because this is when the majority of farmers do most of their agriculture and stock surplus foods. Besides, most of the maize produced in the area is grown during the long rains. Maize is the staple food in most households in this region and is the main ingredient for making the most common meal (ugali).

We processed the 16-day MODIS EVI files from 2002 to 2021 and applied mandatory quality flags and then created monthly composites of mean values for the long rains growing season using R statistical software (R Core Team, 2022). Vegetation indices can indicate the stress of vegetation and it is expected that it will be an indication of how crops will perform in each growing season (Rojas, 2007). Highlights of major methods used are presented in Figure 10.

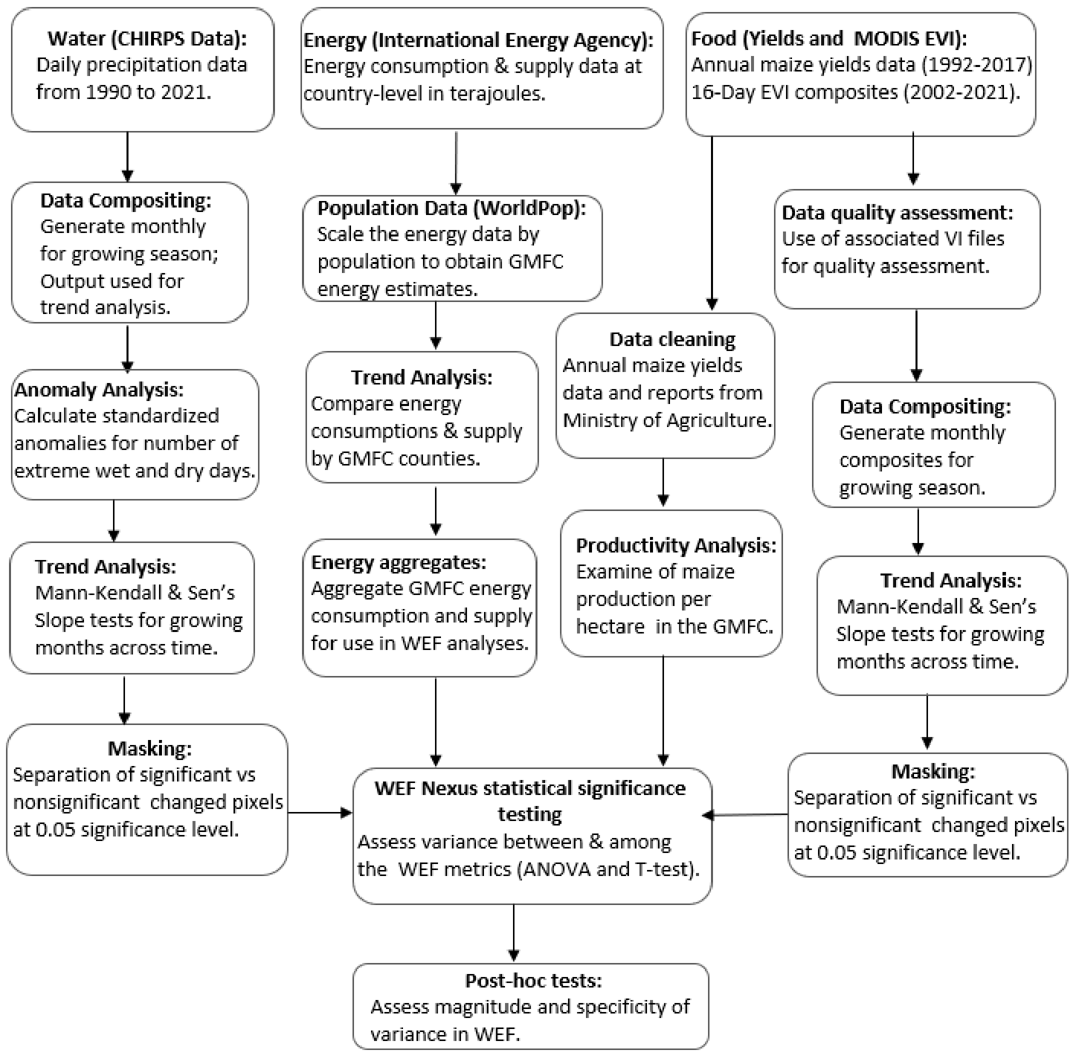

Figure 10. Flow chart of methods for study two.

3.4.1 Precipitation Anomalies

First, we downloaded daily CHIRPS precipitation data from 1990 to 2021 and processed to obtain composites for each month of the long rains growing season (MAMJ). Here, we analyzed precipitation in terms of number of extreme dry days (NXDD) for pixels with less than 2mm of rainfall and number of extreme wet days (NXWD) for pixels with greater than 20mm of rainfall during the long rains season. We used NXDD and NXWD to identify the spatial distribution of rainfall frequency because prolonged absence of rainfall is expected to influence water availability and access as well as crop health. To obtain the standardized anomalies, we calculated the long-term mean and long-term standard deviation and divided the difference by the standard deviation. Negative values indicate less NXDD or NXWD for that year compared to the long-term mean while positive values indicate more NXDD or NXWD for a specific year compared to the long-term mean. We calculated the standard deviation and obtained standardized anomalies for each NXDD and NXWD for the annual growing season. Standardized anomalies provide more information about the magnitude of anomalies (Dabernig et al., 2017).

3.4.2 Trend Analysis on Precipitation and Vegetation

MAMJ time series were assessed for monotonic trends and magnitude of change in precipitation using Mann-Kendall and Sen's slope estimator. First, we performed the non-parametric Mann-Kendall statistic to detect trends in precipitation across the study area. To calculate Mann-Kendal statistic, data values are evaluated as ordered time series and each value compared to subsequent values. The initial Mann-Kendall statistic is 0 and a value of 1 is added if the subsequent value is higher or subtracted from the subsequent value if the latter value is lower (Branco et al., 2019; Priyadarshi et al., 2018; Wanyama et al., 2020). Where values are equal there is no change to the statistic (Khambhammettu, 2005; Wanyama et al., 2020). Mann-Kendall tests were done based on the annual seasonal NXDD and NXWD raster stacks for precipitation and monthly raster stacks for EVI.

$$\mathrm{S} = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} sign(x_j - x_k)$$

where $sign(x_j - x_k)$ $= 1$ if $x_j - x_k > 0$

$= 0$ if $x_j - x_k = 0$

$= -1 \quad$ if $x_j - x_k < 0$ Source: (Khambhammetu, 2005)

To quantify the magnitude of observed monotonic trends in the GMFC greenness, NXDD, and NXWD, we used the Sen's slope estimator (Lamchin et al., 2018; Murthy & Bagchi, 2018; Sen, 1968; Wanyama et al., 2020) and masked significant versus nonsignificant pixels at 95% confidence threshold. We mapped the results to depict areas of increasing greenness as areas of vegetation greening while areas of decreasing greenness as vegetation browning. Mann-Kendall and Sen's slope analysis on precipitation was performed for NXDD and NXWD for the entire time series (1990 to 2021) and 2000 to 2021 to correspond with EVI data availability.

3.4.3 Energy

Energy data was downloaded from the International Energy Agency (IEA, 2022). The data is measured in terajoules and is availed as country averages in five-year intervals. To obtain energy estimates for the study area, we scaled the country-level energy data using county population. Studies indicate that population influences energy consumption and supply (Imasiku & Ntagwirumugara, 2020; Shaari et al., 2013).

3.4.4 WEF Synergies and Trade-offs

We conducted field work from May 2022 to July 2022 to understand how the experts drawn from local and national governments as well as non-governmental organizations perceived the state of WEF in the GMFC. We interviewed experts within the GMFC and asked them to rank the WEF variables (water, energy, and food) based on their perceived relative importance for the functioning and sustainability of the ecosystem and assigned weights based on the ranks (Table 4).

Table 4. Water, energy, and food (WEF) metrics ranking.

WEF Metric Rank	Assigned Weight
First	5
Second	3
Third	1

We used Qualtrics survey tool to record responses, assigned weights based on the ranks and performed the multi criteria decision making process (MCDM) to analyze the synergies and trade-offs associated with WEF. We presented the MCDM results using a radar chart to highlight different perceptions of the interviewed experts from the counties and averaged for the entire study area.

To examine socio-ecological variability in the GMFC, we performed nonparametric Kruskal Wallis and Dunn post-hoc tests on WEF metrics for the years 2000, 2005, 2010, 2015, and 2020. We selected these years for analysis because of energy data availability. We employed Kruskal Wallis tests instead of analysis of variance (ANOVA) because the data violated the assumptions of normality. We subsequently performed the Dunn post-hoc test on the initial statistical results to compare the variances among the WEF metrics in the GMFC.

3.5 Results

3.5.1 Precipitation

We analyzed water resources in the GMFC by examining trends and magnitude of rainfall frequency in terms of number of extreme dry days (NXDD) for pixels with less than 2mm of rainfall per day and number of extreme wet days (NXWD) for pixels with more than 20mm of rainfall per day. The NXDD and NXWD were analyzed for the long rainy season (March, April, May, and June; MAMJ) because this is when most residents undertake intense agricultural practices within the study area. Besides, the long rainy season has traditionally favored the growing of maize, a staple among the GMFC population, compared to the short rains season.

3.5.1.1 Number of Extreme Dry Days (NXDD)

Results of the standardized anomalies revealed variations in extreme rainfall patterns across the thirty-two years. The NXDD anomalies represent the number of days with extreme dryness in a growing season. Negative values indicate less than average long-term mean dry conditions for a specific year and location while positive values indicate more than average long-term mean dry conditions. There were fewer extreme dry days in 2018 than the rest of the years (Figure 11). This coincided with anecdotal field reports which indicated that despite seasonal erratic rain pattern and frequency since the 1990s, the GMFC had registered a slight increase in rainfall after 2018. Seven out of thirty-two years (1993, 1995, 1996, 1999, 2000, 2008, and 2019) had the greatest magnitude of extreme dry days across the entire study area and were expected to have lower than average maize yields and impact food security. The least NXDD occurred in 2012, 2013, 2018, and 2020 while four years (1994, 1997, 2003, and 2016) experienced pockets of extreme dry days albeit at lower magnitude (Figure 11).

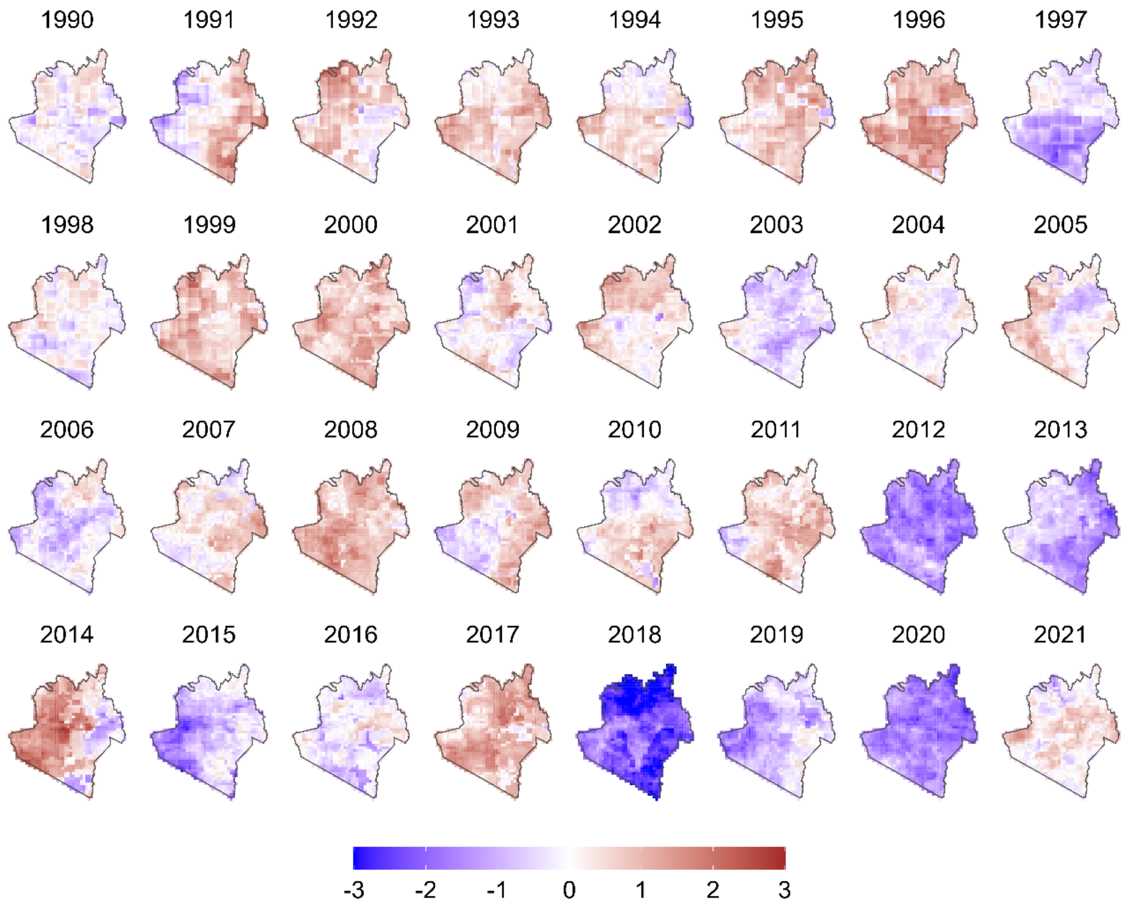

Figure 11. Standardized anomalies of precipitation in the GMFC for extreme dry days from 1990-2021.

The were no consistent patterns in spatial occurrence of NXDD across the study period despite the western region (Bomet and Kericho) traditionally experiencing more rainfall frequency and amounts. In 2014, the western part of the GMFC experienced the greatest number of extreme dry days. Other years with higher standardized anomalies in the western part of the GMFC were 1992 and 2005. The eastern part of the study area experienced the greatest number of extreme dry days in 1991. Years with an overall lower number of extreme dry days include 1990, 1997, 1998, 2004, and 2006. While 2018 had the least number of extreme dry days throughout the period of study, the lowest magnitude was in the north (-3). Other years with the lower number of extreme dry days were 1994 and

2010. Prolonged drier than average conditions have adverse impacts on livelihoods in the GMFC because the food production system relies on rainfall. Key informants noted that rainfall was becoming increasingly erratic, and farmers were being encouraged to adopt drought tolerant crops.

3.5.1.2 Number of Extreme Wet Days (NXWD)

Years with notable number of extreme wet days during the long rains season included 2012, 2015, 2018, 2020, and 2021 (Figure 12). The greatest spatial extent and magnitude of NXWD occurred in 2018 while the least extent and magnitude of extreme wet days occurred in 1999, 2000, 2008, 2011, and 2014 (Figure 12). We present trend analyses results for pixels that met the 95% confidence threshold of Sen's slope. Expectedly, shorter time series exhibited higher magnitude (Figure 13B and D). Most parts of the GMFC experienced a moderate number of dry days per season. The highest magnitude of change during the thirty-two-year period was -0.4 indicating that there was an average increase of approximately 13 days in the number of extreme dry days between 1990 and 2021 (Figure 13 A). The southern part of the GMFC experienced high magnitudes of NXDD in the 1990-2021 time series. This coincided with the loss of sizable patches of forest as found by Akanga et al. (2022). Most of the significant NXDD occurred in the northern half of the GMFC which is dominated by agricultural and forested areas. However, there were a few NXDD occurrences in the grassland-dominated south. The 2000-2021 period experienced a smaller spatial extent of extreme dry day events albeit with higher magnitudes of change compared to the entire time series period (Figure 13B).

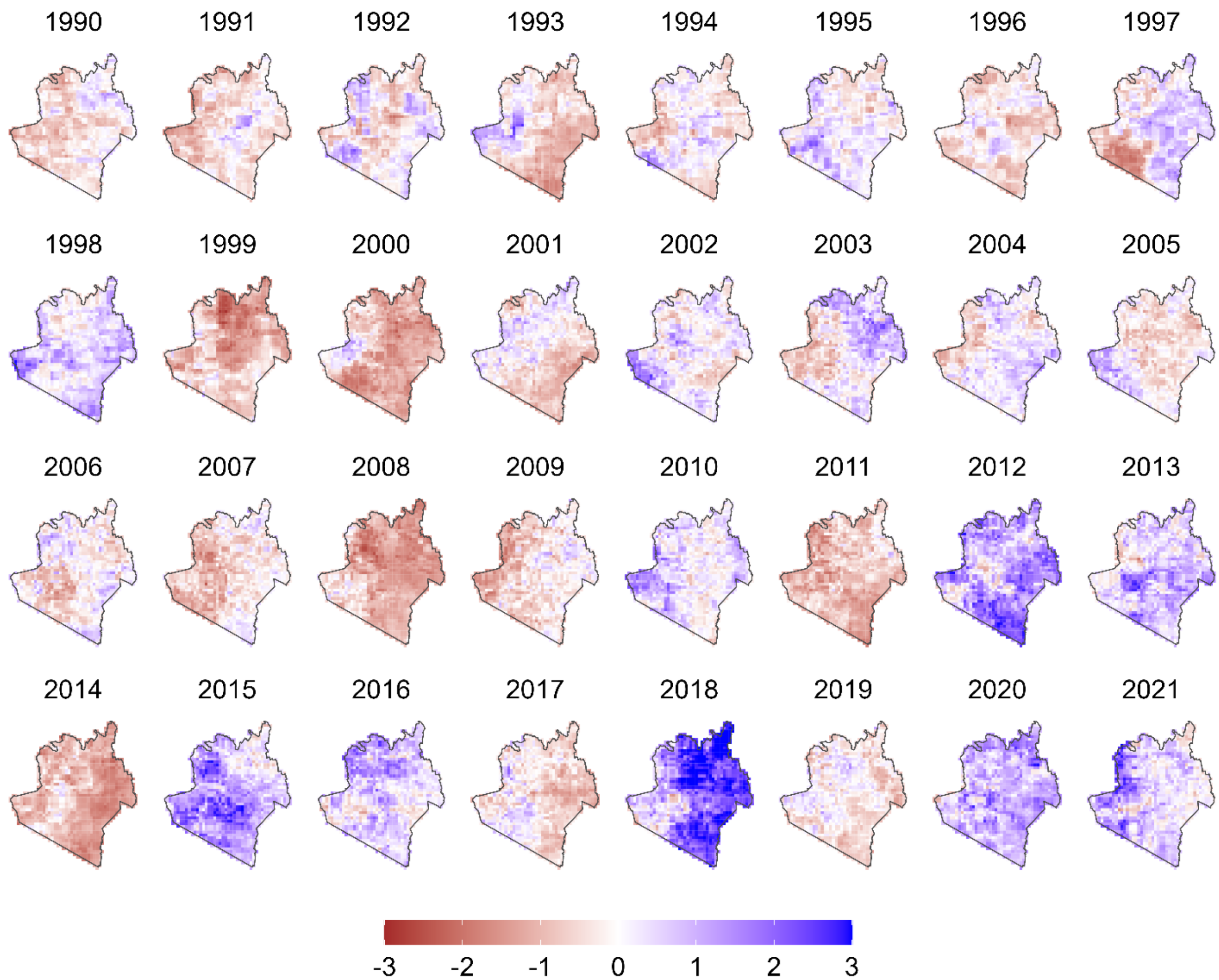

Figure 12. Standardized anomalies of precipitation in the GMFC for extreme wet days from 1990-2021.

The average magnitude was -0.8 days per season implying that the number of dry days increased by approximately 17 days for the 21-year period. The majority of the significant slopes occurred in western, northern, and southern parts of the GMFC. The magnitude of change was highest (-0.9) in the northern part. The majority of the areas without significant changes fall in the grassland-dominated southern parts of the GMFC (Figure 13B).

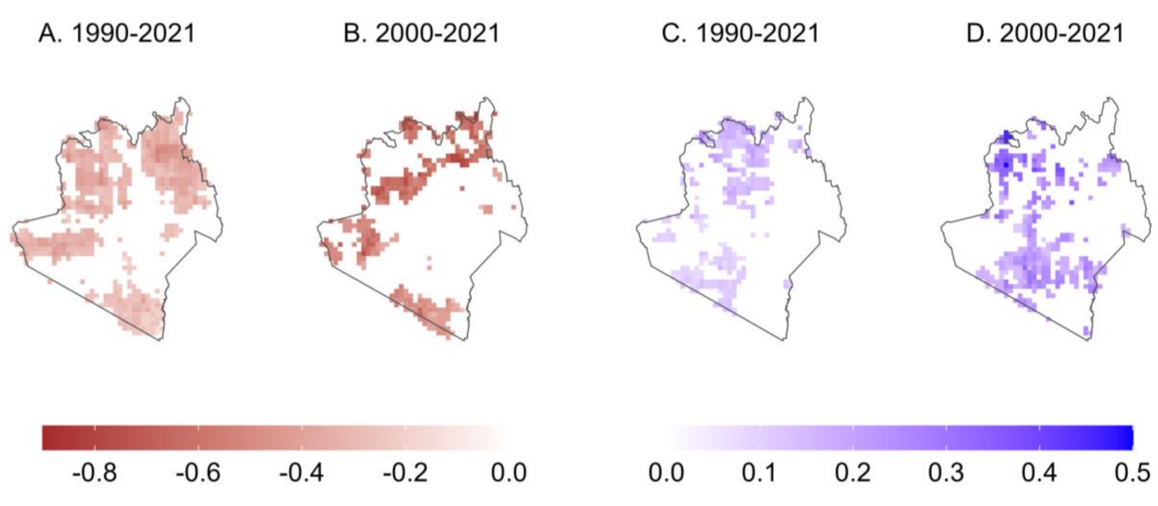

Figure 13. Trend analysis on precipitation patterns in the GMFC for extreme dry days (A-B) and extreme wet days (C-D) for 1990-2021 and 2000-2021.

There was lower spatial coverage in the NXWD trend compared to NXDD trend for the 1990-2021 period. The average significant magnitude of change for the number of extreme wet day events was 0.2 implying that there was an average increase of 6.4 days in the number of extreme wet days for the thirty-two-year period. Sen's slope results for the 1990-2021 time series revealed that significant NXWD trends occurred mostly in the cropland-dominated north and grassland-dominated south with a few pockets in the cropland-dominated western part of the GMFC. There were limited significant changes observed in the eastern parts of the study area. While the NXWD 2000-2021 period depicted higher magnitudes of change in the Sen's slope, the pattern of occurrence was similar to that of NXWD 1990-2021 except with extreme wet day events extending towards the eastern parts of the GMFC (Figure 13 D). The average magnitude of change was about 0.4 for the 2000-2021 period implying that there was an increase of about 9 days of extreme wet events in 2021 compared to 2000. Overall, most of the extreme wet events occurred in the grassland and forested areas with pockets in the cropland. The highest magnitude of change (0.5) occurred in areas under cropland.

Coefficient of variation analysis on the extreme dry days revealed that the northwestern forest dominated areas were more variable than the southern grassland and savannas (Figure 14A). This is expected because the grasslands are more likely to experience drier conditions unlike the dense forest and its environs. The lowest value was ~0.075 (7.5%) while the highest value was ~0.175 (17.5%). Contrary, the extreme wet days revealed a higher range in coefficient of variation with the lowest variation occurring in forested areas (~0.3) and highest variation occurring in the drier grasslands (0.7). Therefore, the extreme wet conditions were more variable compared to extreme dry conditions in the study area (Figure 14B). Total precipitation showed lower variance in the western regions but higher in grassland dominated landscapes (Figure 14C).

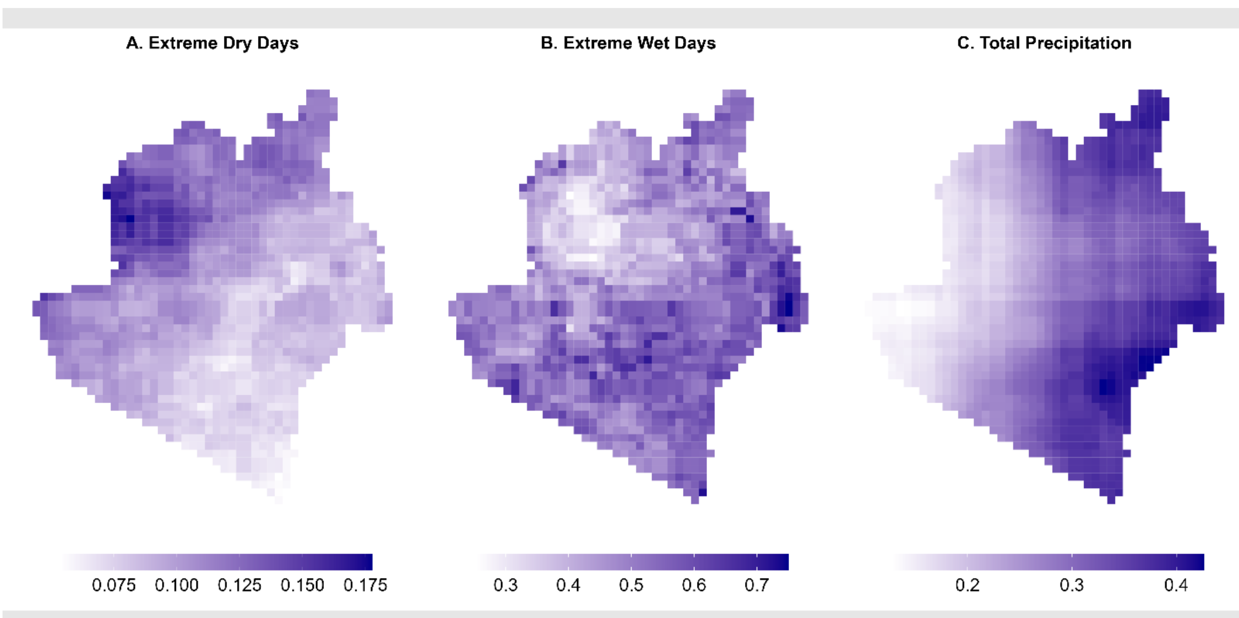

Figure 14. Coefficient of Variation of precipitation for extreme dry days (A), extreme wet days (B), and total precipitation (C) from 1990 to 2021.

3.5.2 Vegetation

Results from EVI trend analysis for three sets of time series (2002-2011, 2012-2021, and 2002-2021) for the individual long rains season months (March, April, May, and June) and the average of the entire season (MAMJ) showed that the magnitude of change ranged from -0.03 for browning to 0.03 for greening (Figure 15). There were minimal changes in the southern part of the study area. Overall, the 2002-2011 period experienced more browning than greening compared to the 2012-2021 period. Sen's slope results in March revealed notable changes in the cropland and forest-dominated central parts of the GMFC. March 2002-2011 depicted more browning than greening. There were a few greening pixels in the northern and southwestern part of the GMFC. Conversely, March 2012-2021 had more greening than 2002-2011 time series. The greening concentrated in the cropland-dominated western half of the GMFC. Trend analysis for the entire time series in March (2002-2021) revealed more browning than greening with most of these changes occurring in croplands and forested areas (Figure 15). However, there were minimal changes in the grassland that dominated the south. The majority of the greening occurred in cropland areas.

April 2002-2011 experienced more widespread browning in most parts of the GMFC albeit there was a small patch of greening in the southwest part. Browning extent increased in the eastern stretch of the study area with more occurrences to the south compared to March of the same time series. Fewer areas depicted significant magnitudes of change in April 2002-2011. While greening and browning were scattered, notable greening occurred in the cropland dominated western part of the GMFC with a few pockets depicted in the northern part. For 2012-2021 April, greening occurred in the western part of the GMFC. Few significant changes occurred in forested areas while there was less browning in April 2012-2022 compared to April 2002-2011. May 2002-2021 depicted larger swaths of greening than April of the same time series. Greening occurred in the northern half and western corner of the study area and spread across the GMFC but was less concentrated in the southern parts.

For May 2002-2011, there was a higher magnitude and spread of browning than greening with the grassland dominated south depicting high magnitudes of browning. There was notable greening in the northwestern and browning in the northeastern parts of the GMFC. For May 2012-2021, significant changes occurred in the northern half of the GMFC and consisted of a mix of browning and greening. There were no significant EVI changes in the southern part of the study area for this period.

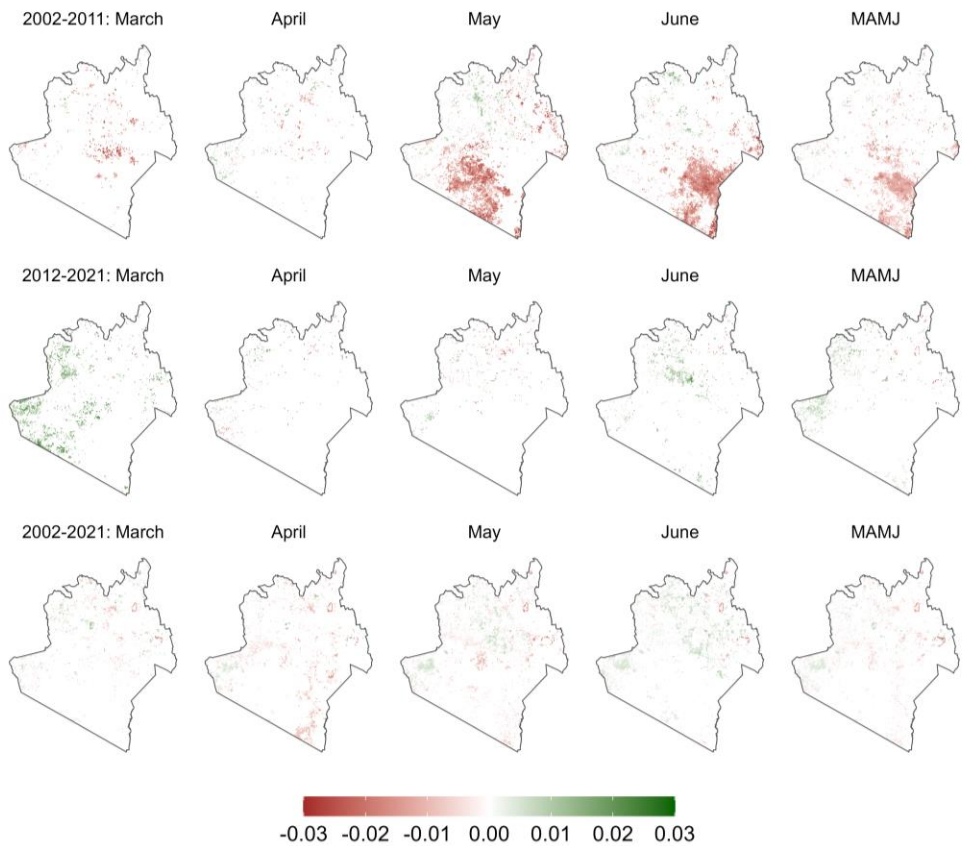

Figure 15. Trend analysis on vegetation greening and browning for long rainy season months from 2002 to 2021.

June 2002-2021 had more greening than browning with most of the significant changes concentrated in the northern half of the study area. For June 2002-2011, there was more browning than greening. Higher magnitudes of browning concentrated in the grassland dominated south and notable greening occurred in the northwest. Surprisingly, June 2012-

2021 depicted more greening than browning. There was notable browning in the northeast. There were few changes in the grassland dominated south, a trend akin to May 2012-2021. MAMJ 2002-2021 depicted more browning than greening. The greening occurred in the cropland dominated west while there were few significant changes in the grassland dominated south parts of the study area. MAMJ 2002-2021 greening and browning patterns showed some similarities with April 2002-2021 trends. There was more browning than greening in MAMJ 2002-2011 with the highest magnitude of browning occurring in the grassland dominated south. There were a few portions of greening in cropland dominated west. MAMJ 2002-2011 EVI patterns were almost similar to June 2002-2011. MAMJ 2011-2021 had more greening than browning with majority of the greening concentrated in the west while browning occurring mostly in the eastern part of the GMFC.

3.5.3 Crop Yields

The GMFC did not see much increase in area under maize production from 1992 to 2003 although the increase was higher between 2004 and 2007, ranging from 200,000 ha to 250,000 ha (Figure 16). While the total area under maize production was consistently above 250,000 ha between 2008 to 2017, there was not much increase in area under maize cultivation. The highest hectarage (~310,000) was in 2010. Total production fluctuated across the years and ranged from ~200,000 tons to ~700,000 tons. Years with peak production include 1994, 2007, 2009, and 2012. While the highest production was recorded in 2009 (~700,000 tons), there was a steep decline of more than ~100,000 in the subsequent year (2010) inferring that the high yields in 2009 may have prompted farmers to increase individual sizes of land tilled in 2010. The lowest production was recorded in 1993 during which the region experienced some of the highest extreme dry events.

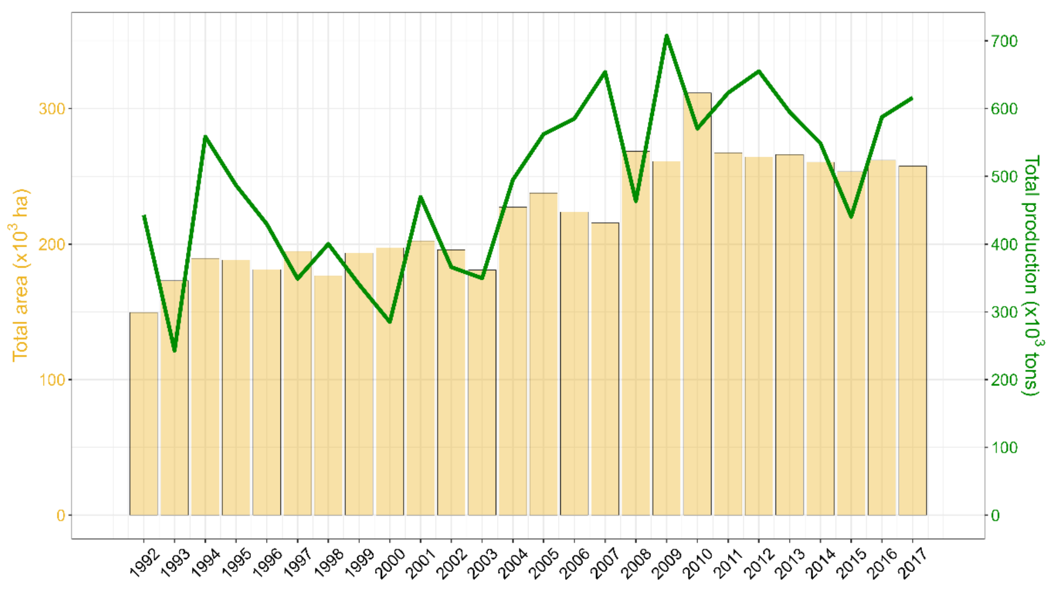

Figure 16. Maize production in the GMFC by total area (in hectares) and total production (in tons).

3.5.4 Energy

Energy data was scaled by population and presented as total consumption and supply by county. Given the abeyance of higher resolution data spatially and temporary, the single national data values for energy variables were split into each administrative unit in proportion to the population size. This assumes that the energy variables are uniform across the country and study region. There was monotonic increase in energy consumption and supply across the period of study. Overall consumption was higher than supply for each of the categories and county. Nakuru had the highest while Kericho had the lowest energy consumption and supply values. The highest demand, supply, and range was on biofuels compared to the other energy types. Energy consumption and supply showed an increasing trend across the period of study. Nakuru depicted the highest while Kericho had the lowest values.

3.5.5 WEF Synergies and Trade-offs

Results from the MCDM analysis revealed competing perceptions among the WEF (Figure 17). Experts suggested that increases in population and urbanization, among other factors had impacted the water, energy, and food sectors. Water was ranked highest while energy ranked low in terms of the relative importance of the WEF for functionality and socio-ecological sustainability of the GMFC and individual counties. Water scarcity meant erratic and decreasing rainfall, declining water volume in major rivers, drying seasonal rivers and water points.

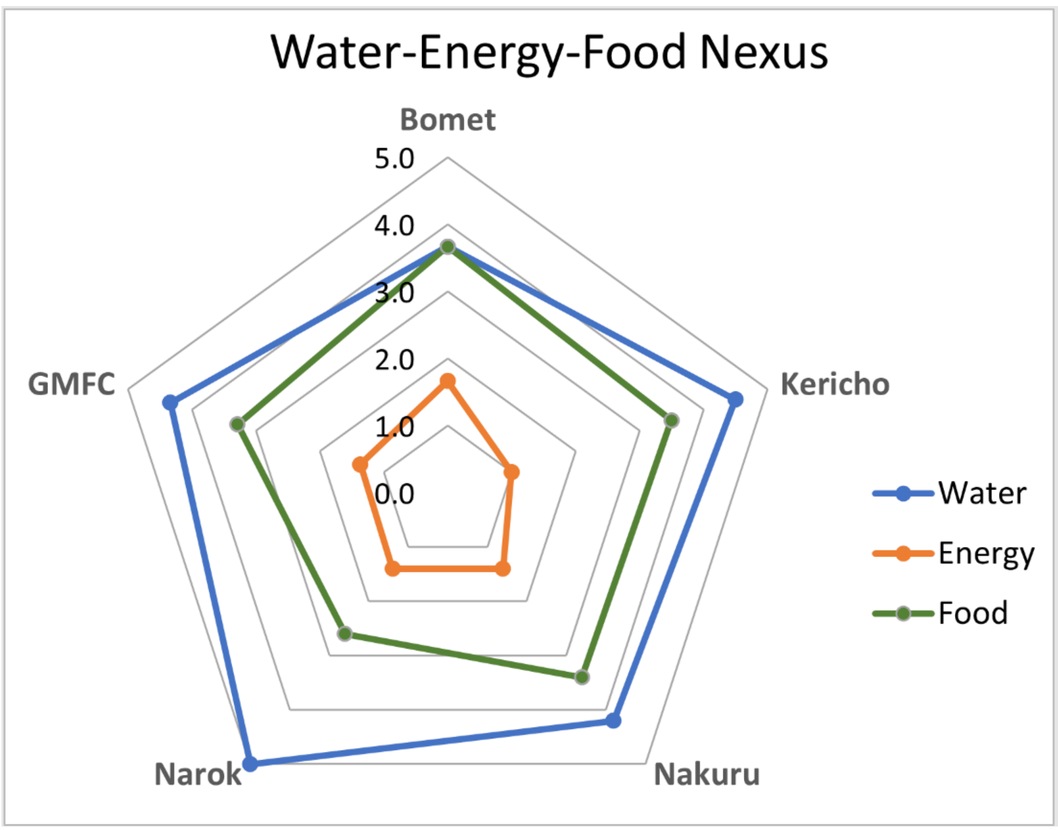

Figure 17. Radar chart from multi criteria decision making (MCDM) process. The MCDM involved key informant interviews with experts in the GMFC during fieldwork.

Narok had the most extreme variability and the WEF were highly separated compared to the rest of the counties. Narok was also the most water stressed followed by Nakuru and Kericho. Food was ranked second. Increasing cases of low crop yields or total crop failure due to changing climatic conditions, pests and diseases were cited as critical threats for the functioning and sustainability of the GMFC. This was reflected across the four counties. Energy was ranked third among most experts despite noting that energy demands had increased tremendously over the past decades. Most rural households in the GMFC use firewood to cook. While the majority of the firewood was initially obtained from adjacent forests, government policies and enforcement in recent decades geared at forest conservation and restoration had led to scarcity in firewood. Households were being encouraged to embrace alternative and sustainable sources of cooking (e.g., biogas) while the government had recently launched rural electrification drive to increase household access to electricity.

Results from Kruskal-Wallis test at 95% confidence revealed significant variability (χ^2 = 12.5, P = 0.002, DF = 2) among the WEF variables. Consequently, the post hoc Dunn test revealed significant differences in the food and energy metrics of the WEF occurred between food and energy (P = 0.0006) among counties while the variance between water versus energy and water versus food did not attain the significance threshold.

3.6 Discussion

The objective of this study was to employ a modified WEF nexus approach in assessing the socio-ecological sustainability of the GMFC using a suite of remote sensing, geospatial, quantitative, and qualitative techniques. In this section, we discuss the significant results and implications on sustainability of the GMFC and similar landscapes.

Rainfall influences water availability especially in areas without comprehensive water infrastructure (Konapala et al., 2020; Panda & Sahu, 2019). Most agricultural activities in the GMFC rely on rainfall hence significant variability in precipitation trends have direct impacts on crop health, domestic water supply, river volumes, etc. The long rains season (MAMJ) accounts for more agricultural production compared to the short rains (SON) in most parts of Kenya. A consistent optimal rainfall range is good for healthy crops, sustained river flow and domestic water supply. Besides uneven rainfall patterns, results from the KIIs revealed that the GMFC is increasingly becoming water stressed partly due to the degradation of the MFC, East Africa's main water catchment. Prolonged dry events result in unexpected delays and/or shortening of planting seasons, poor crop and animal health, low yields, declining water volumes in perennial rivers, and extinction of some seasonal rivers. Recent increases in water tariffs and electricity charges have been attributed to declining water reserves and receding dam levels. Droughts in protected areas increase incidents of human-wildlife conflicts (Abrahms, 2021; Long et al., 2019; Mukeka et al., 2019; Ogutu et al., 2014; Okello, 2006).

Rainfall trends indicated fewer NXDD in 2018 coinciding with field reports. While rain patterns were erratic and overall amounts decreased over the years, there was notable increase in extreme wet conditions between 2018-2021. Most of the significant extreme dry events occurred in the northern parts of the GMFC which is dominated by cropland and forested areas. Here, the average NXDD was -0.8 for the entire time series (2000-2021) implying that the number of extreme dry days decreased by a magnitude of approximately 0.8 days per season. Prolonged extreme dry day events in arable areas directly impact agricultural potential and increase food insecurity through delays in planting, increase in crop pests and diseases, and low yields. Negative NXDD trend could mean significantly lower extreme number of dry days which partly translates to minimal water-related vegetation stress and probable increase in yields for the respective season e.g., 2012 and 2018 (Figure

16). The southern part of the GMFC experienced high magnitudes of NXDD in the 1990-2021 time series which coincided with land cover transformations (Akanga et al., 2022). Extreme water scarcity in the grassland dominated south is expected to impact the pastoral lifestyle and affect the Maasai Mara National Reserve ecosystem leading to an increase in cases of human-wildlife conflicts.

The GMFC also received sporadic cases of extreme wet events. While this may be good for the water sector, unexpected heavy rainfall was associated with pre- and post-harvest losses for produce such as maize, wheat, and potatoes, among others. Poor road networks hinder access to markets whenever it rains. The average NXWD was 0.5 for the 2000-2021 time series implying that the number of extreme wet days increased by one day every two years and a total of about 10 days for the 20-year period. While extreme wet events may benefit the water sector, it may be inconducive for the crops. Notably, some areas experienced both extremely dry and wet days. Warmer atmosphere is expected to have more intense rain and contraction of the growing season. The lower variance in extreme dry conditions and higher range in extreme wet conditions implied that the landscape is continually becoming dry albeit experiencing sporadic wet occurrences. Notable lower values around the forest-dominated areas illustrate that those areas near the MFC experienced more variance in dry conditions compared to grasslands while forests experienced more stable extreme wet conditions compared to grasslands. These results were consistent with studies that illustrate that forests buffer against precipitation variability because of their stable transpiration (O'Connor et al., 2021).

3.6.1 Food/Vegetation

Analysis of vegetation trends against rainfall can detect vegetation stress associated with drought. Trend analysis results revealed overall more browning than greening in most parts of the GMFC. Food production relies mainly on rainfall hence browning indicates vegetation stress including poor health of cultivated crops and portends food insecurity. Field reports depicted the unpredictable starts of seasons, increased crop failures, declining yields, and increased food insecurity at household levels during the period of study. This was corroborated by data from the Ministry of Agriculture which showed increasing area under maize farming yet somewhat plateauing productivity. Flat production (in kg) with expanded area can only indicate that mean yields have declined. Decline in yields in the GMFC has been spatially heterogeneous and was attributed to unpredictable and unfavorable weather patterns, high costs of inputs, and increased pests and diseases e.g., desert locust invasion (Kimathi et al., 2020) and the Maize Lethal Necrosis (MLN) disease that was reported in Bomet County (Government of Kenya, 2022; Jozani et al., 2020; Osunga et al., 2017).

Despite declining production, increasing cost of inputs (e.g., seeds, fertilizers), and unpredictable climate, maize remains the staple food crop in the GMFC hence slow adoption of alternative and/or drought tolerant crops. Most households in the GMFC practice sedentary agriculture thus poor harvests imply that yields will be exhausted sooner leading to higher risk of food insecurity before the next harvest. Kenya government reports indicated more than 6 million citizens were facing famine as of February 2023, making it one of the worst droughts in the country in recent decades. While the entire time series (2002-2021) had more browning than greening, there was more intense browning between 2002-2011 compared to 2012-2021. There were minimal changes in the grassland-dominated southern part of the study area. Most changes (browning) occurred in cropland-dominated areas. The dependence on rainfall means that investment in agriculture is not directly proportional to the output for a small-scale farmer. For example, erratic rainfall patterns make it difficult for farmers to plan. A high-yields season could be followed by a low-yield season despite more investment, causing losses.

Results show increasing pressure on biofuels because the majority of people use firewood as their source of energy. While most firewood had been initially obtained from forests and open bushes, recent government restrictions have reduced exploitation of the protected areas. Charcoal is the second most used source of cooking energy; however, it is dirtier, takes longer to heat, and is more expensive. Energy demand is expected to increase with the increasing population. Increased pressure on biofuels means probable increase in forest degradation for firewood and charcoal despite existing moratoriums. Strict enforcement of forest conservation policies limit supply of firewood and charcoal which in turn increases their prices and drives a few households towards adopting alternative sources of cooking. However, these alternative sources such as liquified petroleum gas and biogas are unaffordable for households without stable income. Based on KII and field observations, sections of the residents have opted to plant their own trees and prune firewood.

3.6.2 WEF Synergies and Trade-offs

This study identified the synergies, trade-offs, and challenges of socio-ecological sustainability from a WEF nexus lens. The MCDM analysis illustrated the intricate connectedness of water, energy, and food resources in sustaining livelihoods in the GMFC. While water was ranked as the most important resource by experts across the four counties, food and energy were seen as essential in the functioning and sustainability of the ecosystem.

Water stress in recent decades was evidenced by drying rivers, low water volumes in rivers and drying springs, erratic rainfall, and shortening growing season, among others. Pressure in water influences food. Lower volumes of streams and rivers hamper irrigation among households living near water points. Statistical analysis showed variability among the WEF variables signaling the need for increased conservation, management, and monitoring of these resources to bolster sustainability and improve livelihoods. The nexus approach revealed existing challenges that are exacerbated by increasing socioeconomic challenges. Gains in one sector may trigger losses in other sectors, hence the need for an integrative approach.

Agroforestry is being encouraged among farmers, individuals growing trees on their farms and pruning them for biofuel use. There is a need to invest in more building awareness of environmental issues – farmers often plant exotic trees (e.g., eucalyptus) on their farms and in riparian areas which have negative impacts on water resources. The residents prefer these exotic species because they grow and mature faster compared to indigenous trees and sprout upon felling. Local tea factories in Kericho and Bomet also provide a ready market for firewood. Based on KIIs, agroforestry and crop diversification is a major synergy in the GMFC counties. Growing both fruit and non-fruit trees will supplement household income and family food supply. Besides, biomass from the trees is used for firewood thus lowering pressure on natural forests hence conserving the MFC water catchment. The non-fruit trees are primarily sold for lumber to supplement household income and used for major household expenses like paying for school fees. Similarly, improving the adoption and diffusion of yield-enhancing technologies (Ogada et al., 2014) is a key WEF synergy. This includes using high quality seeds, diversification from maize to short-term drought tolerant crops, and embracing internet and mobile phone technology for better farming practices. Alternative crops like sorghum and millet can often give better yields under drier conditions which can be sold to obtain funds that can be used to buy and stock maize from other areas based on household needs during harvests when prices are lowest. This will alleviate hunger vulnerability and decrease overreliance on forest resources.

Charcoal is a trade-off between forest resources and energy. Despite existing legislations on charcoal production and logging, approximately 0.35 ha of forest cover is depleted for consumption of one sack (35kg) of charcoal translating to annual loss of 15,174 ha (Onekon & Kipchirchir, 2016). Forest conservation and restoration related policies should involve local communities for more effectiveness and increase survival rate of the trees planted by public and private funded partnerships.

Partnership among government and non-governmental agencies and other stakeholders is necessary to enhance mapping, management, monitoring, and evaluation of resources to enhance sustainability of the GMFC. Coordination among entities like the Kenya Water Towers, Kenya Forest Service, ministries of water, energy, agriculture and livestock, the World Bank, among others will increase efficiency and reduce duplication of conservation roles and curb pilferage of resources. Therefore, changing the energy ladder by promoting alternatives to charcoal and switching to more efficient cooking stoves is an important synergy.

There is a need for concerted efforts to promote adoption and diffusion of yield-enhancing technologies and practices. For instance, rainwater harvesting can reduce the water trade-off in Nakuru and Narok where about 1000 m^2 of roof area can increase yields of fruits and vegetables by 2,350 kg/year in Nakuru (Amos et al., 2020; Korir, 2020; A.

Rahman, 2021). Farmers in our survey reported that they were unwilling to adopt new varieties and technology until they were sure of the success rate. This is consistent with previous studies by Ogada et al. (2014) and Kalele et al. (2021) which report adoption of agricultural technology among smallholder farmers at 10% and 54% respectively (Kalele et al., 2021; Ogada et al., 2014). Integrating technology in planning, management, and monitoring of natural resources will promote socio-ecological sustainability. Underlying all these trade-offs is education and capacity building because farmers practicing agroforestry cut trees on their private farms and sell them to meet crucial household needs including buying food and paying school fees. Finally, if local and national government could mostly pay for school fees it would contribute towards education on these trade-offs, leading to conserving forest resources and water catchment. Additionally, higher levels of formal education have significant positive association with awareness of the interconnectedness between nature and livelihoods among the GMFC population (see Chapter 4).

3.7 Conclusion

Recent studies show increasing changes in land cover with decreasing forests and grasslands and increasing area under cropland (Chapter 2). These changes impact the water, energy, and food security, all of which are essential for sustaining livelihoods. The GMFC is a significant yet fragile ecosystem. This study combined remote sensing, geospatial analyses, key informant interviews, and statistical analyses to assess the sustainability of the GMFC. The WEF nexus approach is important in advancing socio-ecological sustainability among vulnerable populations because it addresses the synergies and trade-offs among these intricately connected sectors. This study found that water, energy, and food sectors are facing unprecedented pressure due to land cover changes, increasing population, climate variability, among other natural and anthropogenic challenges. Analyses revealed increasing dry conditions, unpredictable start of growing season, decreasing crop yields, and high dependency on bioenergy. The majority of the changes occurred in agriculturally viable areas which have more impact on food production. Experts expressed concern about the increasing pressure on the WEF sectors and the need for streamlining operations among the stakeholders to enhance efficiency in the management of these sectors. Synergies and trade-offs, statistically significant variability among the WEF variables reinforce the dependencies among the WEF and emphasize the need for urgent and concerted efforts to bolster sustainability initiatives. Advancing sustainable development research and programs requires robust measuring, monitoring, and evaluation. However, data availability is a key challenge in effective measuring of socio-ecological sustainability in the often data-sparse landscapes in the global south. Despite multiple attempts, we were unable to obtain energy data from the Kenya National Bureau of Statistics (KNBS) for use in this study. Integrative approaches that combine mixed methods and leverage proxy data can help navigate this challenge and support pragmatic research endeavors among vulnerable populations whose livelihoods depend on natural resources.

CHAPTER 4: INTERCONNECTIONS BETWEEN LAND COVER CHANGE AND LIVELIHOODS IN THE GREATER MAU FOREST COMPLEX, KENYA

4.1 Introduction

Nature and society have existed for centuries and continue to influence each other (Rülke et al., 2020) at local, national, regional, and global scales. These systems often result in temporary and/or permanent modifications to the ecological, economic, and social pillars of sustainability. Increasing population pressure and changing climate, among other challenges in recent decades, threaten the sustainability of this mutual relationship (Assan & Kumar, 2009; Barrios et al., 2008; Lockie et al., 2013; Nightingale, 2003). For example, people living adjacent to natural resources rely on them for their livelihoods and their routine activities have significant direct and indirect contributions to resource conservation or degradation (Newton et al., 2016, 2020). Changes may be positive, negative or at times imperceptible. Anthropogenic activities exacerbate landscape transformations and change. These influences are more pronounced among vulnerable populations due to their reliance on natural resources and inadequate ability to cope with adverse natural or human-induced challenges. Balancing between societal, ecological, and economic needs can be onerous especially among populations that live adjacent to and rely on finite natural resources. Therefore, sustainability stakeholders including policy makers, managers, and locals should continually use integrative approaches that address ecological, economic, and social vulnerabilities to achieve appropriate synergies and reduce trade-offs in fostering the sustainability of the entire system.

Land-use land-cover (LULC) change is an essential climate variable that is central to sustainability research. Recent studies indicate some LULC changes involve conversions to cropland at the expense of forests and grasslands (Akanga et al., 2022; Fenta et al., 2020).

Global and regional changes in land cover have resulted in major disturbances that have impacted biodiversity and socio-economic stability (Brink & Eva, 2009) and these impacts affect ecosystem services. For example, Costanza et al. (2014) showed that the global value of ecosystem services decreased by $US 4.3-20.2 trillion per year between 1997 and 2011 while Fenta et al. (2020) found that overall, cropland expansion accounted for an increase of approximately $US 125 billion per year in sub-Saharan Africa 1992-2015 (Costanza et al., 2014; Fenta et al., 2020).

The agricultural sector is integral in East African countries' socio-economic strategic plans, contributing to approximately 33%, 26%, and 24% of gross domestic product (GDP) in Kenya, Tanzania, and Uganda, respectively, where much of the population practice subsistence crop farming, livestock rearing or both on a small scale. However, most agricultural practices in these countries rely on rainfall; hence, changing rain patterns and increasing drought occurrences impact productivity. Besides, increasing cost of inputs (e.g., seeds and fertilizers) and inflation, among other challenges, make it difficult for small scale farmers to maximize agricultural production. Decreasing productivity drives some farmers to increase area under tillage (Van Ittersum et al., 2016) or increase use of fertilizers. Yet, increased use of chemical fertilizers, ever increasing prices, and overall decline in their effectiveness, among other problems, may make fertilizer use not a sustainable solution to poverty and hunger (Jarosz, 2012; Robbins, 2012). Declining soil fertility, erratic rainfall, and increasing cases of prolonged and severe droughts further impede the progress towards eliminating poverty and hunger, two of the seventeen United Nations Sustainable Development Goals (SDGs) among developing countries. For example, more than 5.4 million people in Kenya were likely to experience acute food insecurity by March 2023 as the country experienced one of the worst droughts in decades (International Rescue Committee, 2023). More financial and human resources are required to support vulnerable and small-scale farmers e.g., through subsidized inputs like seeds and fertilizers and field extension services.

Land is a key factor of production (Semin & Namyatova, 2019) and land issues have always been very emotive (Klopp & Lumumba, 2017) in developing countries. Access to farming land and settlement in Kenya is driven by a combination of factors including economic and political ones (Kweyu et al., 2020). The more productive the land the more contested it becomes. Increasing population, increased food demand, and cultural practices (e.g., land inheritance) continue to increase the demand for land, making it more expensive over past decades. The MFC provides some of the most fertile lands in the country and is one of the main water catchments in Kenya. Increasing socio-economic challenges and political patronage have contributed significantly to the degradation of the water catchment. Besides, the adoption of local, regional, and/or global markets and the need to meet the insatiable demand of these markets motivate local communities to engage in practices that are economically beneficial to their livelihoods disregarding other important social or ecological considerations.

Integration of appropriate social and ecological/biophysical dimensions can boost sustainable development research and practice. For example, analysis of remotely sensed imagery could reveal patterns and magnitude of LULC change at varying scales. In contrast, incorporating mixed methods including household surveys and other participatory and integrative approaches can reveal the complexity of socio-ecological systems and driving forces that contribute to land use decisions, particularly where data availability is a challenge. Integrating both quantitative and qualitative approaches including satellite remote sensing, landscape metrics, key informant interviews (KIIs) and household surveys can, therefore, reveal subtle social, cultural, economic, and institutional processes in systems (De Vreese et al., 2016; Getu & Bhat, 2021).

Socio-ecological system challenges are complex and require integrative approaches and robust techniques that focus on analyzing patterns and processes and identifying relevant interventions that have the potential to reduce socio-ecological vulnerability. Siloed approaches leave loose links that compromise the entire socio-ecological system. Integrating land change science and political ecology frameworks accounts for both ecocentric and anthropocentric angles of a socio-ecological system (Thiault et al., 2019). In this study, we investigate the nexus between LULC change and livelihoods among forest-adjacent human populations by a) examining the variance in spatiotemporal trends of LULC changes based on established political administrative demarcations and b) investigating the relationship between LULC changes and livelihoods among people living adjacent to MFC. This study borrows from relevant UN SDGs targets and respective metrics used for their measurement (https://sdg-tracker.org/). I limited the scope to subsets of two out of the seventeen SDG targets and indicators that are connected to human livelihoods and whose progress can be measured at household level: SDG 1, No Poverty, and SDG 2, Zero Hunger (United Nations, 2015).

4.2 Study Area

Agriculture is the mainstay of the economy in the four counties of the GMFC. The northern half receives adequate rainfall (two rainy seasons) that support farming activities. Bomet and Kericho counties are dominated by tea farming both on a small and large scale. The GMFC elevation ranges from approximately 550m to 3100m. Most of the contiguous official gazetted forest blocks and tea plantations are located in high elevation areas found in Bomet and Kericho (County Government of Bomet, 2023; County Government of Kericho, 2023; Figure 18). There are several tea factories that provide a ready market for the tea grown while also employing many locals. However, a bigger percentage of the locals are hired to perform unskilled jobs (Langat, 2017).

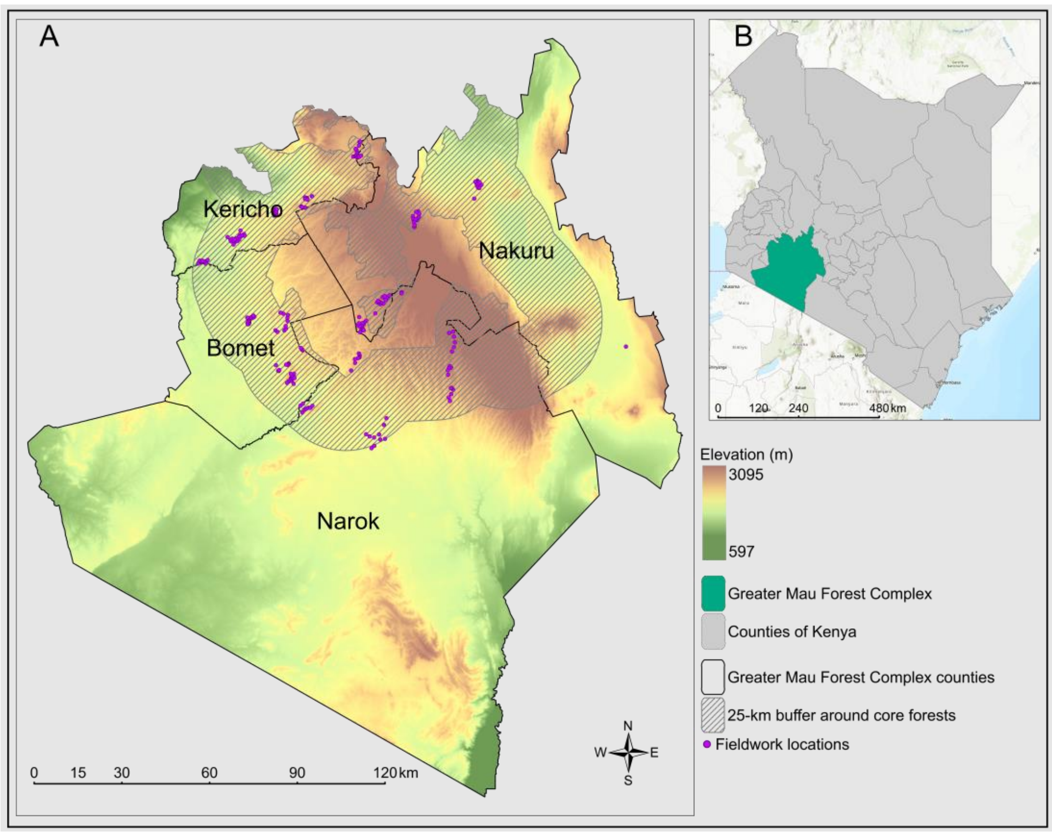

Figure 18. Study area for study 3 showing GMFC counties, elevation, and buffer around the core gazette forest, and sampled locations and points. Sampled locations where samples were drawn during the fieldwork exercise are shown in purple (A) while inset B shows the GMFC location in Kenya and the rest of the county administrative boundaries in Kenya.

4.3 Data and Methods

4.3.1 Data

Land cover datasets were obtained from the Regional Center for Mapping of Resources for Development (RCMRD, 2016) for 1990, 2000, 2010, and 2018. The original raster land-cover data were reclassified to five dominant land cover classes (e.g., cropland, forest, grassland, water, and other) and assessed for accuracy (Akanga et al., 2022).

Household surveys and KIIs were conducted from May to July 2022. Household survey respondents were drawn from people living within 25-km buffer from official gazetted forest boundary (Figure 18A). We selected this distance because people living within this area are more likely to experience direct effects of laws aimed at fostering forest conservation, and there exists a relatively fair road network that facilitated data collection. We used a stratified systematic sampling technique to collect household survey data. First, we overlaid results of the 1990-2018 LULC change analysis (Akanga et al., 2022) on Google Earth Pro to identify GPS locations for five target strata per county based on the following characteristics: forest gains, forest loss, cropland gain, cropland loss, and no change (for control purposes). The sample size consisted of 230 households based on a) 90% confidence interval and 10% margin of error that is acceptable for studies that seek to deduce inferences (Islam, 2018), and b) the minimum requirement of ten samples per independent variable sufficient for ordinal logistic regression analysis (Ottenbacher et al., 2004). The strata were selected prior to site visits. Once in the field, the nearest homestead to the selected GPS location per stratum constituted the first household for the survey. To select participating households, we employed systematic sampling by selecting every tenth homestead starting from the identified origin per stratum. Survey data was keyed into Qualtrics-based questionnaires using tablets, and comprised a mix of nominal, categorial, ordinal and ratio questions (Appendix B).

Surveys were administered in either English or Swahili depending on the respondent's level of language proficiency. English and Swahili are the national languages in

Kenya and are widely used by most of the residents within the GMFC. However, Swahili is most preferred among most people with less than high school-level education. We occasionally sought help from university students from the local community for translation into native languages where necessary. The selected translators were obtained through a snowballing process, after which we trained them in ethical conduct of research, had them observe several interviews, and then took them through practice sessions until we deemed them competent before we allowed to assist with the data collection process. Involving individuals from respective local communities helped ease tensions among some respondents because fieldwork coincided with the country's electioneering period where residents were wary of outsiders.

Survey questions were aimed at investigating the relationship between forest degradation and livelihoods sustainability among people living adjacent to MFC. As such, we focused on five independent variables including income (Achiba, 2018; Fisher et al., 2017), education level (Gebru et al., 2018; Maziya et al., 2017), food security (Mutea et al., 2019; Novienyo & Simatele, 2021), land tenure security (Keovilignavong & Suhardiman, 2020), and age (Mazzone, 2019; Myers & Medley, 2018) (see Table 5). The dependent variable for the study was respondents' perceived likelihood of GMFC degradation to impact livelihoods.

Table 5. Independent variables used for the ordinal logistic regression and the respective levels applied in the study.

Independent variable	**Categories**		
Income	Decreased	No change	Increased
Education level	Primary	Secondary	College
Food secure	No	-	Yes
Land tenure security (binary)	No	-	Yes
Age in years (ratio data)			

The selected independent variables are connected to livelihoods and can be measured at a household scale. Some of the targets incorporated in the questionnaire are subsets of the indicators that are considered important in shaping target outcomes of the following SDG 1, No Poverty and SDG 2, Zero Hunger (Appendix A).

Key informants consisted of representatives from civil society organizations and officials from agriculture, environment, and forestry sectors both at county and national levels. Five KIIs per county (total of 20 KIIs for the entire study area) were conducted to assess the perceptions of experts regarding the introduction of decentralized governance in natural resources management. The KIIs consisted of a blend of closed and open-ended questions to obtain information from experts regarding: (a) opinion about forest cover changes before and after the enactment of new laws on forest governance, (b) opinion about whether the introduction of decentralized system of governance has had positive or negative impact on forest management and accompanying reasons (Appendix C). Each interview lasted for an average of forty minutes. Images/results from LULC change analysis described below formed the basis for discussion and explanation of changes by the key informants. Both the researcher and the field assistant took summary notes during the KIIs. The notes were compared by highlighting key points to identify any omissions and fill the gaps and then grouped by theme, expert, and county.

Fieldwork was conducted after ethical conduct of research approval by Michigan State University Institutional Review Board (IRB; STUDY00007532), Kenya's National Commission for Science, Technology & Innovation (NACOSTI; License No: NACOSTI/P/22/17366), and the County Directors of Education, and County Commissioners of Bomet, Kericho, Nakuru, and Narok (Appendix D).

4.3.2 Methods

4.3.2.1 LULC Change Analysis by County

While recent studies illustrate changes within the GMFC, these studies were limited to biophysical analysis of the landscape including slope and elevation (Akanga et al., 2022). Here, we performed LULC change and fragmentation analysis at the county level (Bomet, Kericho, Nakuru, and Narok) to identify variance in spatiotemporal trends and magnitudes of major land cover classes across the years. Besides, we quantified trends in spatial patterns of LULC classes across the counties by analyzing the IJI to measure evenness of patch adjacencies, LPI to measure the percentage of landscape occupied by the largest patch, and NP to measure the LULC fragmentation across the counties (Akanga et al., 2022; McGarigal, 2015b; Sertel et al., 2018; Singh et al., 2014). Spatial metrics are important in assessing patterns of landscape change across time and space and quantifying landscape degradation. For example, high rates of forest fragmentation are associated with biodiversity loss (Arroyo-Rodríguez et al., 2017). The MFC is the largest water catchment, hence increased fragmentation and decreased dominance will impact the hydrological cycle in the region and across the country.

4.3.2.2 Analysis of Survey and Interview Data

Data from the KIIs was analyzed through cross-tabulation and content analysis (Angessa et al., 2021; Munthali et al., 2019). Key points from the interviews were grouped and tabulated based on thematic similarities and differences to capture the latent or hidden aspects that would be elusive in a strictly remote sensing approach such as peoples' perceptions and awareness of the nature-society interconnectedness. Descriptive statistics for the household survey data were computed to understand the data distribution (Table 8).

4.3.2.3 Mau Forest Complex Degradation and Livelihoods Interconnectedness

We examined the relationship between LULC changes and livelihoods among people living adjacent to the MFC by interrogating the extent to which the locals perceived that their livelihoods would be affected by forest degradation. The dependent/response variable assessed the degree to which respondents believe that forest degradation could negatively affect their livelihood (Appendix B, Question 24). The response variable was measured using a three-level Likert scale i.e., unlikely, not sure, and likely.

To assess the perceptions of residents regarding land cover changes (specifically forest loss) and climate change on livelihoods, we performed ordinal logistic regression using ordinal package of the R statistical software (Christensen, 2022). Ordinal logistic regression is used to model the relationship between an ordinal dependent/response variable and one or more independent/explanatory variables that are either categorial or continuous (Harrell, 2015). The dependent variable was obtained by asking respondents to state their opinion on whether they thought there was a likelihood of their livelihoods being impacted by the depletion of the MFC. Logit is the natural log of the odds ratio expressed as in Equation 1.

$$\mathrm{logit(p)} = \ln\left(\frac{\mathrm{p}}{1-\mathrm{p}}\right) = \upbeta_0 + \upbeta_1\mathrm{x}_1 + \cdots + \upbeta_\mathrm{k}\mathrm{x}_\mathrm{k} \tag{1}$$

Where p is the probability of perceived likelihood of a respondent's livelihood being impacted by forest depletion, β_0 is the intercept, β_1 to β_k are the log odds of the likelihood (and correspond to independent variables) and x_1 to x_k are the independent variables (Table 5). The inverse logit returns the probability of the perceived likelihood (Cox et al., 2018; Kotikot et al., 2020). Computing the antilog of the logit allows us to solve the estimated regression equation (Equation (2)). In an ordinal logistic regression model, an increase in one variable results in a shift towards either end of the spectrum of ordinal responses.

$$\hat{p} = \frac{e^{\beta_0+\beta_1 x_1+\cdots+\beta_k x_k}}{1+e^{\beta_0+\beta_1 x_1+\cdots+\beta_k x_k}} = \frac{1}{1+e^{-(\beta_0+\beta_1 x_1+\cdots+\beta_k x_k)}} \tag{2}$$

Therefore, a significant positive coefficient suggests that as the level of the independent variable increases, the mean of the dependent variable also tends to increase, while a negative coefficient indicates that an increase in the independent variable leads to a decrease in the dependent variable.

4.4 Results

We analyzed LULC change by county administrative boundary to illustrate the changes per class by county. Land cover change trends varied by year and county. While LULC results for the entire GMFC landscape indicated a high rate of forest loss, analysis by county revealed lower rates (i.e., the sum of the changes by each county resulted in the overall landscape change). There were parallels between grassland and cropland LULC change results at the entire landscape and county scale.

4.4.1 Area Estimation and Change

Area under cropland increased continuously during the study period across all the counties albeit at different magnitudes. Cropland was the most dominant land cover in Bomet, Kericho, and Nakuru counties by 2018. In Bomet, cropland increased from 27% in 1990 to 67% by 2018 with a steep increase in 2010 (Figure 19A). Similarly, grassland was the most dominant land cover class in 1990 in Bomet, Nakuru and Narok counties but decreased across all the counties. By 2018, grassland was the least dominant LULC class in Bomet, Kericho, and Nakuru but remained the most dominant in Narok county. Much of the increases in croplands were from grasslands owing to the inverse trends in change across the four counties. There was a small but steady increase in the area under forest in Bomet during the study period going from 22% to 23%, 24%, and 26% for 1990, 2000, 2010, and 2018, respectively (Figure 19A). Grassland accounted for the greatest land cover class in Bomet in 1990 at 51% but shrank to 7% by 2018 making it the least dominant of the three LULC classes. The steepest decrease in grassland was from 2010. In Kericho, both cropland and grassland accounted for approximately 40% of LULC between 1990 and 2000 (Figure 19B). However, cropland increased steeply to 78% while grassland decreased to 8% making it the least dominant among the three LULC classes. There was a 3% decrease in Kericho's forest cover from 17% in 1990 to 14% in 2018.

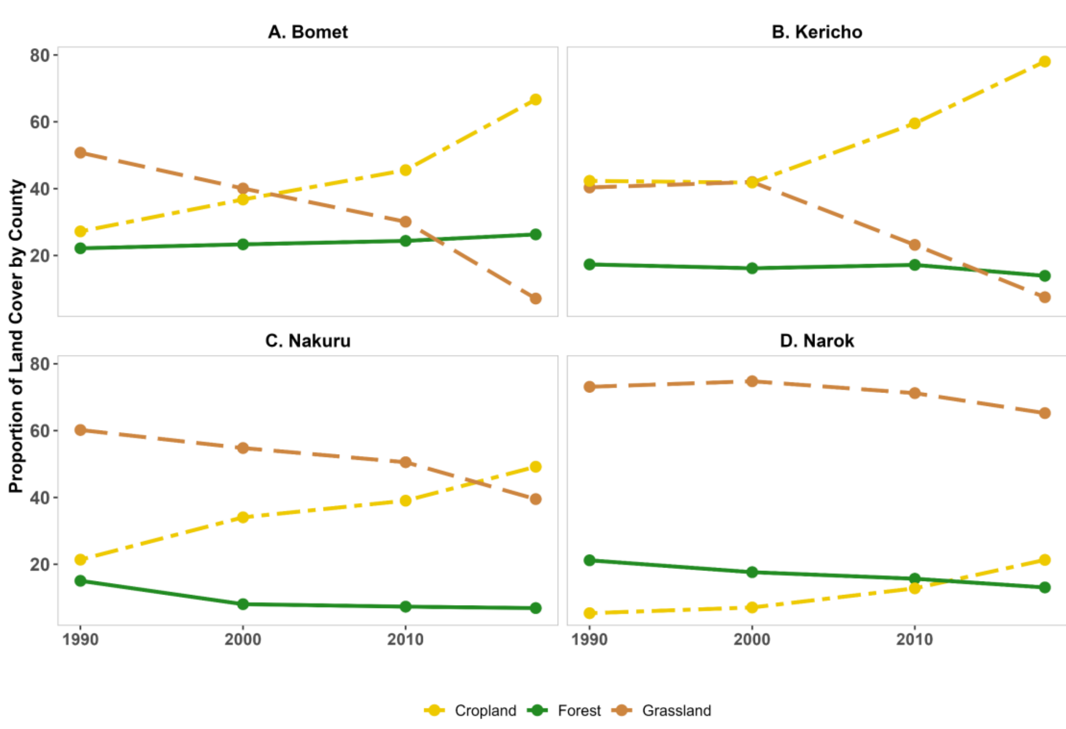

Figure 19. Land cover change trends from 1990 to 2018 by county (A-Bomet, B-Kericho, C-Nakuru, and D-Narok).

In Nakuru, the proportion of cropland increased gradually to more than double from 21% in 1990 to 49% in 2018 constituting the most dominant land cover in the county (Figure 19C). Similarly, grassland decreased gradually from 60% in 1990 to 40% in 2018. However, the decrease in grassland was steeper from 2010. The area under forest decreased from 15%

in 1990 to 8% in 2000 and remained at 7% in 2010 and 2018. Nakuru County experienced a slight decrease in forest cover across the period of study. In Narok County, the area under grassland increased slightly from 73% in 1990 to 75% in 2000 but decreased to 71% in 2010 and 65% in 2018. Narok County also underwent an increase in cropland from 5% in 1990 to 21% by 2018 with an accelerated increase being registered from 2000. In contrast, forest LULC decreased gradually and consistently from 21% in 1990 to 13% by 2018, constituting the least dominant of the three land cover classes.

4.4.2 Landscape Metrics

Cropland IJI increased in all counties across the study period. Bomet and Kericho IJI had a similar trend although Kericho had a steeper increase from 2010 to 2018 (Figure 20B). While cropland IJI was lowest in Bomet and Kericho in 1990, it peaked by 2018 in these two counties. Forest IJI increased gradually across all the counties and decreased from 2010 to 2018 in Bomet and Kericho but increased continuously in Nakuru and Narok counties (Figure 20C-D). Decreasing IJI implies increasing fragmentation. Forest LPI was highest in Nakuru by 2018. Grassland IJI depicted minimal changes across the four counties although Narok had the highest proportion throughout the study period. Similarly, LPI changed across the counties, land cover classes, and year. Cropland LPI increased across all the counties and by 2018 it was the highest of the three land cover classes in Bomet, Kericho, and Nakuru. While there was an overall decrease in grassland LPI, Bomet decreased by the highest magnitude. Grassland LPI accounted for the least land cover classes in Bomet and Kericho by 2018. Narok maintained the highest LPI across the study period (Figure 20H). Forest LPI depicted minimal changes across all the counties and was least in Nakuru and Narok (Figure

20G-H). Increasing LPI implies increasing dominance while decreasing LPI indicates decreasing dominance of the land cover class.

Overall, the NP for cropland and forest LULC classes showed a similar decrease in Bomet County across the study period. NP decreased for Bomet County across the study period. While the cropland NP decreased gradually throughout, forest NP increased gradually from 1990 to 2010 followed by a steep decrease from 2010 to 2018 (Figure 20I).

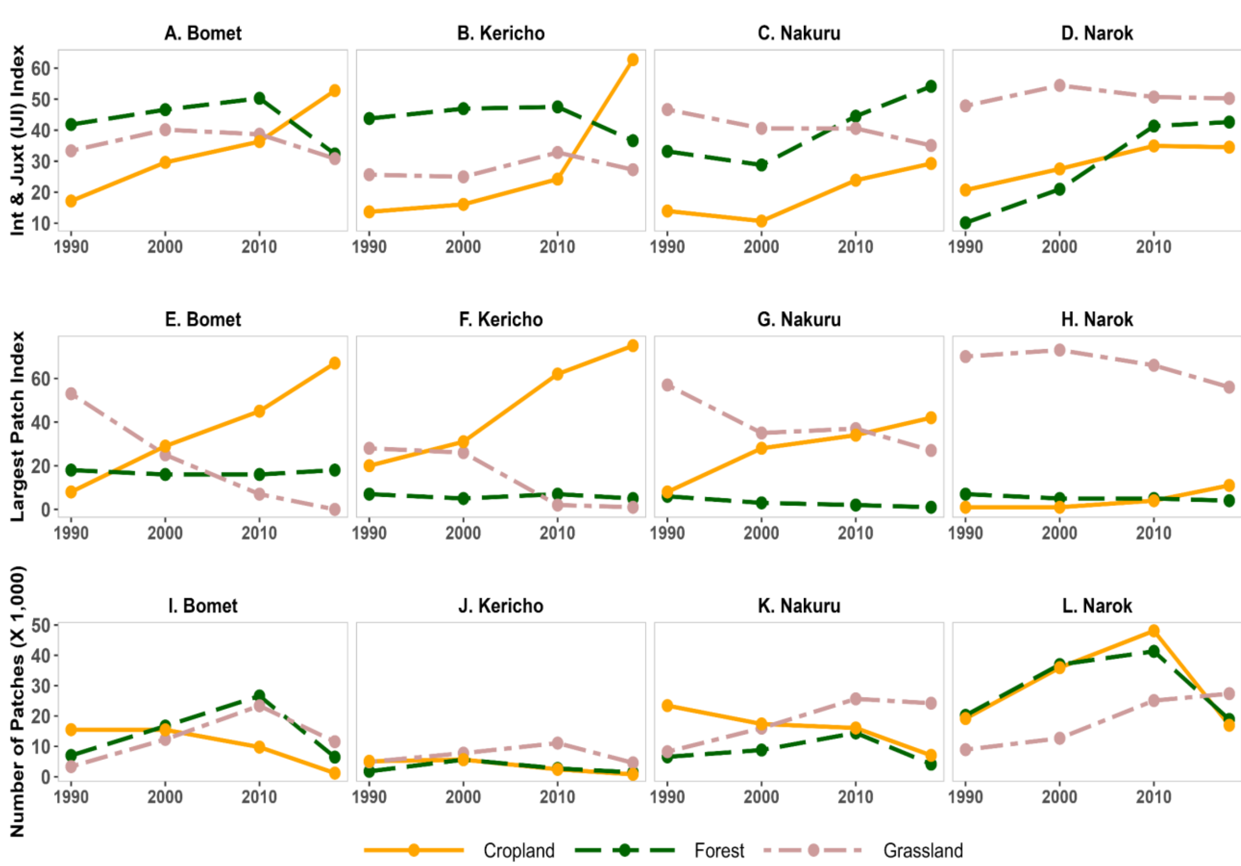

Figure 20. Landscape metrics trends from 1990 to 2018 by county. (A – D) interspersion & juxtaposition index (IJI), (E – H) largest patch index (LPI), and (I – L) number of patches (NP) at class level.

Bomet County's grassland NP showed an overall increase with steady increases between 1990 and 2010 followed by a steep decrease between 2010 and 2018. However, the total count of grassland NP remained higher in 2018 than 1990. Kericho County NP trends depicted a small range among the LULC classes with cropland and forest following a similar flat trend while grassland increased slightly from 1990 to 2010 and decreased afterwards (Figure 20J). Nakuru and Narok cropland and forest NP depicted an overall decrease while grassland increased steadily in both counties (Figure 20K). However, Nakuru cropland decreased steadily across the study period (Figure 20K), Narok cropland increased from 1990 to 2010 before showing a steep decrease between 2010 to 2018. Increasing NP implies increasing dominance while declining dominance is depicted by decreasing NP.

There was a statistically significant difference in NP among the four counties (Bomet, Kericho, Nakuru, and Narok) upon running the Kruskal-Wallis's test for the LULC classes for the entire study period 95% interval (χ^2 = 9.75, P = 0.02, DF = 3). Subsequent Dunn post hoc test showed that the most significant difference occurred between Kericho and Narok counties (Table 6). IJI and LPI did not show significant statistical differences between the four counties.

Table 6. Dunn post hoc test results by county administration for the number of patches (NP) by county administration using Benjamini-Hochberg correction. Significant results are denoted by an asterisk.

	Bomet	Kericho	Nakuru
Kericho	0.21		
Nakuru	0.16	0.04	
Narok	0.06	0.01*	0.25

Overall, these results show that the area of cropland in these four counties is increasing and consolidating into larger tracts of land, but at different rates. Bomet and Kericho have seen the most dramatic landscape changes, while Nakuru and Narok are changing but less rapidly.

4.4.3 Crop Yields

Bomet and Kericho did have lower magnitudes of change in total area under maize production compared to Nakuru and Narok. Similarly, Bomet and Kericho experienced their lowest production more recently (2015 and 2014) compared to Nakuru and Narok (Table 7).

This implies that the steep increase in cropland (Figure 19 A and B) could be because farmers opted to plant alternative crops, including tea, due to the maize failure. Many farmers still grow maize despite the changing climatic conditions, hence need to diversify into other crops. Adoption of drought resistant crops, short term crops like sorghum and potatoes and sell proceeds to buy maize for subsistence consumption.

Table 7. Years of highest and lowest maize productivity in the GMFC counties during the study period.

	Highest Production			Lowest Production		
	Year	Yield (Tons)	Productivity (Tons/Ha)	Year	Yield (Tons)	Productivity (Tons/Ha)
Bomet	1994	126,677	3.16	2015	38,720	1.08
Kericho	2006	188,486	4.52	2014	68,913	1.68
Nakuru	2012	298974	3.33	2000	23,607	0.37
Narok	2009	342250	2.56	1993	55,080	1.62

Despite many respondents increasing the land allotted for agriculture in recent years, yields remained relatively stagnant or even decreased. Diminishing yields were attributed to increasing climate variability, increasing cost of agricultural inputs such as seeds and fertilizer, and outbreak of pests and diseases in recent years. Many of the small-scale farmers indicated that they had resorted to planting poor quality seeds with little or no fertilizers. Most of the farmers in the GMFC who grow maize reported declines in yields despite some increasing total areas under cultivation in recent years. This information was corroborated by results of maize yields and productivity from Ministry of Agriculture, Livestock, and Fisheries (Figure 21) and locals and experts attributed the decline in maize production to the Maize Lethal Necrosis (MLN) that was first reported in the county in 2011. Nakuru and Narok reported better maize yields compared to the other two counties despite the challenges of climate variability and increased cost of inputs across the study area in recent years.

4.4.4 Interview and Household Survey Analysis

4.4.4.1 Key Informant Interviews

Some experts in the KIIs decried the lack of political will in addressing forest conservation challenges. While most of the interviewed experts agreed that the decentralized governance system had resulted in access to more financial and human resources at a local level, some respondents divulged that allocation and access of these resources was prioritized for infrastructural projects. The older farmers averred that prior to transfer of the Ministry of Agriculture functions from the national to county governments, field extension officers would frequently visit farms and/or organize group meetings to offer technical support before and during the growing seasons. However, the relatively younger farmers said that they had rarely received government support from field officers. Nonetheless, there were reports of some partnerships between the national government and several non-governmental organizations to train farmers on climate smart agriculture within the counties. Some of the projects are implemented through Kenya government and World Bank partnerships like the National Agricultural and Rural Inclusive Growth Project (NARIGP), Kenya Climate Smart Agriculture Project (KSCAP), as well as by NGOs e.g., the Rainforest Alliance. Most of the projects were still at a pilot phase as of July 2022, and plans were underway to expand coverage within the respective counties. However, a majority of respondents who reported increases in revenue from agriculture opined that there was no substantial improvement in quality of livelihoods because of the rising cost of living including prices of food, school fees, and other essential expenditures.

4.4.4.2 Household Surveys

4.4.3.2.1 Descriptive Statistics

The total number of household survey respondents was 230 with a minimum, median and maximum age of 19, 44, and 82 years, respectively (Table 8). Data revealed that 45.2% of respondents had primary education or less, 37.4% some college-level education, and 17.4% had attained at least college-level education.

Table 8. Household survey statistics. The total number of observations for the entire GMFC was 230 (Bomet = 61; Kericho = 60; Nakuru = 61; Narok = 48)

Variable	Description	Statistics/Frequency per county							
		Bomet		Kericho		Nakuru		Narok	
		Freq.	%	Freq.	%	Freq.	%	Freq.	%
Age	Categories in years								
Below 40		28	46	26	43	22	36	20	42
41-60		19	31	24	40	25	41	20	42
Above 60		14	23	10	17	14	23	8	17
Education	Highest level of education of education attained								
Primary		20	33	27	45	25	41	32	67
Secondary		26	43	20	33	29	48	11	23
College		15	25	13	22	7	11	5	10
Income									
Decreased		24	39	21	35	23	38	23	48
No Change		7	11	7	12	13	21	11	23
Increased		30	49	32	53	25	41	14	29
Land Secure	Respondents feel their land rights are secure								
No		1	2	0	0	4	7	9	19
Yes		60	98	60	100	57	93	39	81
Food Secure	Respondents can afford a meal when they need to eat								
No		3	5	11	18	12	20	10	21
Yes		58	95	49	82	49	80	38	79

Overall, 93.9% of the respondents in the GMFC did not express concerns of possible evictions as opposed to 6.1% who were concerned about eviction. For income, 39.6% of respondents reported a decrease, 16.5% no change, while 43.9% reported an increase over the last ten years. However, most of the respondents who reported an increase in income opined that these increases did not translate to improved wellbeing because of the soaring cost of living in recent years. Finally, 25.2% of the respondents suggested that the destruction of the MFC was unlikely to impact their livelihoods, 23% were not sure, while 51.7% reported that livelihoods would be impacted if the MFC was severely disturbed. See Table 8 for the detailed distribution of the data by counties.

4.4.3.2.1 Ordinal Logistic Regression Analysis of Household Surveys

We performed ordinal logistic regression on 230 observations based on household survey data collected in Bomet, Kericho, Nakuru, and Narok counties. The results are presented in Table 9. We computed the null model to get an overall measure of the model fit and subsequently compared it with the predictors, which was a significantly better fit (AIC= 440.60; X2 =0.000001; DF = 4) than the null model (AIC = 476.22; p<0.001).

Table 9. Results of the ordinal regression analysis with dependent variable - perceived likelihood of forest degradation to impact livelihoods and five predictors (income, education level, land tenure security, age, and county).

Coefficients:	Estimate	Std. Error	z value	Pr(>|z|)
Income	-0.617169	0.219124	-2.817	0.004855 ***
Education level	1.488143	0.318285	4.676	0.00000293 ***
Land tenure security	-1.481924	0.766728	-1.933	0.053262 **
Age	0.029585	0.009756	3.033	0.002425 ***
County	1.098895	0.308533	3.562	0.000369 ***

Significant codes: <0.01 ***, 0.05 **, 0.1*

There was a significant negative association between income and perceived likelihood of GMFC to impact livelihoods (-0.62), meaning that respondents who had registered an increase in income in recent years were less likely to perceive the degradation of the GMFC as a threat to their livelihoods. On the other hand, level of education indicated a significant positive association with the dependent variable (<0.01), meaning that the higher the respondent's level of education, the more likely they would perceive GMFC degradation to be a threat to their livelihoods. There was a significant positive association between age and perceived likelihood of GMFC degradation to impact livelihoods (0.03). Results indicated that most older respondents who had lived in the area for longer periods of time were more likely to have witnessed varying climate over the years and corresponding effects on agriculture, which is the mainstay of the local and national economy, compared to the relatively younger respondents. The significant positive association between counties and the dependent variable implied that peoples' perceptions regarding impacts of land cover changes on livelihoods are likely to vary based on the county of residence.

4.5 Discussion

Cropland increased in all the four counties with the greatest change occurring in Bomet and Kericho (Figure 19A-B) which have a more conducive climate for agriculture. However, this drastic change was not reflected in the maize yields, implying that farmers may have opted to grow alternative crops other than maize. Tea is widely grown in Kericho and Bomet and is preferred because of the ready market provided by several factories within the county. Overall, Nakuru and Narok had moderate increase in area under cropland (Figure 19c-D) but higher increase in area under maize production (Figure 21C-D).

Figure 21. Maize yields production trends from 1992 to 2017 by county. Total area in ha is illustrated by the bar charts and production in tons depicted by the line graph.

Analysis of landscape metrics revealed a decrease in grassland IJI in all four counties implying declining uniformity in LULC configuration. Lower evenness signifies higher fragmentation while the increasing IJI implied decreasing fragmentation. While we expected that increases in conversion of forest and grasslands to agriculture would result in more fragmentation, we surmise that the numerous small but adjacent pieces of cropland may have influenced the structure of the cropland LULC from a remote sensing perspective. Overall, forest IJI increased (1990-2010) followed by a decline (2010-2018) in Bomet and Kericho counties, implying that forest fragmentation decreased and then increased, respectively. Increasing forest IJI in Nakuru and Narok mean increasing uniformity in the land cover structure, hence decreasing fragmentation. Cropland cover increased in dominance while grassland decreased, likely because of new conversions to croplands.

LULC change is influenced by natural and anthropogenic factors. Because most LULC changes occurred after 2010, we opine that these changes may have been influenced by the adoption of the country's new constitution and enforcement and/or lack of relevant associated policies. KIIs with local and national government officials attributed the increasing climate variability to rampant degradation of the MFC. Several conservation efforts have been put in place to promote conservation in recent decades. Some include involving local communities in forest conserving and restoration efforts through capacity building initiatives led by local administrators. Forest scouts are recruited from communities living next to the cutline (border between forest and tea plantation buffers) and paid by KFS to monitor and report unauthorized entry into the protected forest. Similarly, there is enhanced community surveillance at the Narok/Bomet forest border where locals are encouraged to report any persons entering the forest to the KFS officers who live next to the cutline. Local administrative officers (Chiefs) organize meetings to sensitize community members on the importance of planting indigenous trees as opposed to exotic species like eucalyptus, which impact the hydrological cycle. Despite this awareness, some locals continue to plant the straight fast-growing *Eucalyptus grandis* species (Oballa et al., 2010) because they sprout after harvesting, hence providing a steady revenue stream. Wood products from these trees have high market demand especially in Bomet and Kericho, because they are used for firewood as a source of energy during tea processing in the numerous tea factories within the counties. The slight yet steady increase of forest land cover in Bomet County (22%, 23%, 24%, and 26% in 1990, 2000, 2010, and 2018, respectively) could be attributed to heightened enforcement of forest conservation regulations, increased environmental conservation initiatives, and embracing of an avocado tree planting project within the county. Decreasing forest in Kericho could be attributed to high demand for firewood from numerous tea processing factories.

Results from the ordinal logistic regression analysis revealed that respondents whose income had increased in recent years were less likely to perceive that forest degradation could have an influence on their livelihoods. For as long as they did not "experience direct negative effects" on their livelihoods and their revenue continued to increase, such respondents would not mind carrying on their routine activities. Based on the regression analysis results, a substantial decrease in revenue from agricultural activities among most people would likely prompt such individuals to consider the MFC degradation a significant influence on their livelihoods. Therefore, there is need for creating more awareness among the people living adjacent to the MFC on the interconnectedness of nature and both individual and community livelihoods. The positive association between level of education and perceived likelihood of MFC to impact livelihoods reveals the role of formal education in understanding human-environment relationships because respondents who had higher levels of education could easily understand the relationship between forest degradation, climate variability, and livelihoods. Different courses are offered in primary and secondary school as well as college curricula and these contribute to the broad awareness of nature-society interactions and the interconnectedness of systems. Improved access to education would in the long term likely enlighten future generations and increase their awareness, hence increase the much-needed pragmatism in bolstering the sustainable development agenda.

Land tenure security had a weakly significant negative association – respondents with perceived land tenure security were less likely to report that forest degradation would impact livelihoods. This was an unexpected result because our initial hypothesis was that people with a sense of permanency in the area would be more protective of their resources compared to those living in the area on a temporary basis.

Expectedly, age showed a significant positive association with the dependent variable implying that older respondents had likely witnessed firsthand changes in rainfall patterns, shifting planting seasons, increased droughts, and declining yields, among others. Younger respondents projected contrary perceptions because climate changes often occur gradually and become apparent after a long period of time.

The study revealed the intricacies surrounding nature-society interactions among populations in the GMFC landscape. Future research should leverage robust quantitative and qualitative techniques to examine the human-environment synergies and trade-offs of the GMFC and similar socio-ecological systems. This could result in effective and contextualized programs that can improve the livelihoods of the population while enabling communities to contribute positively to ecological sustainability.

4.6 Conclusion

Nature and society are extremely complex and inextricably connected. While human actions influence landscape dynamics, populations that reside adjacent to natural resources and rely on them for their livelihoods find this complexity more confounding. Area under cropland increased in Bomet, Kericho, Nakuru, and Narok counties as more land was converted from forest and grassland for agricultural use. Forest loss was not as rampant as expected because of myriad conservation initiatives (e.g., tree planting, law enforcement, awareness creation) in the region by multiple stakeholders, most of which prioritize involvement of the GMFC residents. Besides, more residents in Kericho and Bomet are embracing avocado growing projects as others (including tea processing factories) plant eucalyptus trees for use as firewood. These actions, while having different results, contribute to the increasing tree cover in the two counties. This study demonstrated that leveraging mixed methods can reveal the nuances contributing to how anthropogenic activities influence land cover change dynamics. We found that in predicting respondents' perceived likelihood of forest degradation to impact livelihoods, age and level of education had a significant positive association, income and land tenure security had significant negative association, while status of one's food security was not a significant predictor. The robust methods employed in this study including LULC change analysis, fragmentation analysis, and quantitative analyses coupled with in-depth interviews and household surveys can translate well in multiple landscapes, regions, and scales. The findings of this study illustrate that perceptions influence behavior in human-environment interactions and stewardship among populations that rely on natural resources for their livelihoods. The complexity of these interactions is more confounding among vulnerable populations and is influenced by various socioeconomic factors. Comprehensive assessment and nuanced understanding of socioeconomic and ecological dynamics will bolster sustainable development by informing the design of unique programs that address the challenges in the GMFC and similar socio-ecological systems. This study adds new perspectives to the growing literature and methodologies of socio-ecological sustainability research by integrating land change science and political ecology frameworks at different scales.

CHAPTER 5. CONCLUSIONS

5.1 Major Conclusions

This dissertation utilized remote sensing, GIS, statistical, and qualitative techniques to assess the interconnectedness of land cover change, climate variability, and livelihoods in the GMFC. I used the systems approach to address research questions related to three study themes: land change science, sustainability, and livelihoods.

The first study assessed the LULC patterns and processes, including the role of elevation and slope, from 1990 to 2018. Here, I found that the GMFC experienced land cover changes in varying proportions over the last three decades. Cropland increased by 22.5% and became less fragmented, forest decreased by 6.6% and became less fragmented, while grassland decreased by 16% and became more fragmented. There was a statistically significant difference ($p < 0.05$) in LULC change among different topographic classes which implied that elevation and slope influenced patterns and processes in the GMFC. There has been increased encroachment in the past decades as population increase continues to hike food consumption and spur conversions to cropland at the expense of grassland and forests. Improved spatiotemporal LULC characterization and projections are important for managers and policy makers.

In the second study, I measured sustainability in the GMFC using the WEF nexus framework. Here, I used a blend of precipitation, energy consumption, vegetation indices, and crop yield data to examine the WEF synergies and trade-offs within the study area. Results showed that: 1) there has been increasing pressure and variability among the WEF resources over the past 30 years and 2) it is extremely challenging to measure sustainability in a data-sparse landscape. In the wake of a changing climate among other socio-economic challenges, it is imperative to apply integrated approaches to assess, manage, and predict the stability of systems.

The third study investigated LULC change dynamics in the four counties of the GMFC. Besides, I performed ordinal logistic regression on household survey data to examine the interconnections between these changes and livelihoods among forest adjacent populations in the study area. Here, I found that: 1) land cover patterns and processes varied by county administration, 2) education and age had significant positive association on perceptions, and 3) income and land tenure security had significant negative association on perceptions.

My dissertation research revealed that society, economy, and environment are intricately intertwined as evidenced by increasing dry conditions, unpredictable start of growing season, decreasing crop yields, and high dependency on bioenergy. I found that peoples' perceptions regarding nature-society interactions in the GMFC can be positive, negative, or imperceptible, hence there is a need for more interdisciplinary and pragmatic research. The robust methods employed in this study including LULC change, fragmentation, and quantitative analyses coupled with in-depth interviews and household surveys can translate well across landscapes, regions, and scales. Comprehensive analysis of the structure and magnitude of land cover changes, climate variability, and their associations with livelihoods is important for advancing socio-ecological sustainability research and policy. These findings are key for climate change mitigation, adaptation, and resilience discourses because peoples' perceptions influence their behavior towards the environment. This work contributes to nature-society research and policy in the wake of myriad socio-ecological challenges.

5.2 Study Limitations

The interaction with multiple stakeholders from the conceptualization of the research to the execution of fieldwork showed how challenging it is to conduct research in a data-sparse landscape. While most data required for this type of study in developed countries is publicly available and somewhat accessible, most of the crucial data for the GMFC was either unavailable, inaccessible or both. For example, despite multiple attempts and assurances, we were unable to obtain finer scale energy data from the KNBS for use in Chapter 3. Similarly, obtaining necessary approvals for field research from different authorities was time consuming. Multiple overlapping licenses were required before beginning the fieldwork in each of the counties, yet some of the officials responsible for granting approvals were not available when needed. A poor road network and rough terrain also slowed down the data collection exercise in some areas. Some roads were impassable which forced us to trek long distances to access respondents based on the sampling design. Therefore, this research highlighted the need for more fieldwork and better data access protocols to understand control points in a bid to protect such important yet fragile landscapes.

COVID-19 pandemic-related travel restrictions led to delays in starting the field data collection exercise. Consequently, I conducted fieldwork close to the Kenyan general elections when residents were wary of outsiders because of the mistrust associated with political campaigns among neighboring communities. However, incorporating local university students illustrated the importance of partnering with local communities. While a few initial interactions with some respondents were tense because of the timing, most interviews quickly evolved into friendly conversations and residents were willing to participate in the interviews.

This dissertation challenged me to continue furthering sustainable development among vulnerable populations through interdisciplinary and pragmatic science. Despite the data availability and access challenges, there exist many opportunities to contribute to sustainability of systems through integrating various data, methods, and techniques.

5.3 Future Research

Vulnerable populations are disproportionally affected by impacts of climate change such as increasing average temperatures, increasing frequency of extreme weather events, and shifting seasons. Therefore, achieving sustainability requires a holistic approach in research and policy implementation. Besides utilizing robust geospatial, quantitative, and qualitative techniques, future research should focus on engaging local communities in socio-ecological sustainability discourses. This is because while many of the UN SDGs are based on generalized metrics, sustainable development is context-specific, not a one-size-fits-all solution.

Promoting sustainable development in the GMFC will require short-term, mid-term, and long-term interventions by all stakeholders, including local communities, county governments, national government, NGOs, and international partners. Short-term and mid-term interventions include increasing food security through supporting climate smart agricultural practices. For example, growing short-term and drought tolerant food crops will improve yields and decrease cases of hunger and famine in the study area. Additionally, the counties and national government should revive agricultural field extension services to support farmers in making informed decisions that will increase agricultural efficiency by better management of crop pests and diseases and minimizing post-harvest losses.

Long-term interventions include investing in alternative sources of livelihoods (to reduce overreliance on rainfed subsistence agriculture) and alternative sources of energy (to reduce overreliance on biofuels). Besides, there is a need for increased community engagement initiatives to harness local knowledge and improve systems awareness among the GMFC population. This will also facilitate the design of effective and contextualized programs that will bolster local, regional, and global sustainability efforts. Active involvement of communities as well as partnerships among various stakeholders will likely increase the success rate of environment and development related projects.

REFERENCES

Abrahms, B. (2021). Human-wildlife conflict under climate change. *Science*, *373*(6554), 484–485. https://doi.org/10.1126/SCIENCE.ABJ4216

Achiba, G. A. (2018). Managing livelihood risks: Income diversification and the livelihood strategies of households in pastoral settlements in Isiolo County, Kenya. *Pastoralism*, *8*(20). https://doi.org/10.1186/s13570-018-0120-x

Ahlström, A., Raupach, M. R., Schurgers, G., Smith, B., Arneth, A., Jung, M., Reichstein, M., Canadell, J. G., Friedlingstein, P., Jain, A. K., Kato, E., Poulter, B., Sitch, S., Stocker, B. D., Viovy, N., Wang, Y. P., Wiltshire, A., Zaehle, S., & Zeng, N. (2015). The dominant role of semi-arid ecosystems in the trend and variability of the land CO2 sink. *Science*, *348*(6237), 895–899. https://doi.org/10.1126/science.aaa1668

Akanga, D. O., Dahlin, K. M., & Moore, N. J. (2022). Accelerating agricultural expansion in the greater Mau Forest Complex, Kenya. *Remote Sensing Applications: Society and Environment*, *28*, 100860. https://doi.org/10.1016/J.RSASE.2022.100860

Albalawneh, A., Chang, T. K., Huang, C. W., & Mazahreh, S. (2015). Using landscape metrics analysis and analytic hierarchy process to assess water harvesting potential sites in jordan. *Environments - MDPI*, *2*(3), 415–434. https://doi.org/10.3390/environments2030415

Albrecht, T. R., Crootof, A., & Scott, C. A. (2018). The Water-Energy-Food Nexus: A systematic review of methods for nexus assessment. *Environmental Research Letters*, *13*(4), 043002. https://doi.org/10.1088/1748-9326/AAA9C6

Alemu, W. G., & Henebry, G. M. (2017). Land surface phenology and seasonality using cool earthlight in croplands of Eastern Africa and the Linkages to crop production. *Remote Sensing*, *9*(9). https://doi.org/10.3390/rs9090914

Amos, C. C., Rahman, A., Gathenya, J. M., Friedler, E., Karim, F., & Renzaho, A. (2020). Roof-Harvested Rainwater Use in Household Agriculture: Contributions to the Sustainable Development Goals. *Water 2020, Vol. 12, Page 332*, *12*(2), 332. https://doi.org/10.3390/W12020332

Angessa, A. T., Lemma, B., & Yeshitela, K. (2021). Land-use and land-cover dynamics and their drivers in the central highlands of Ethiopia with special reference to the Lake Wanchi watershed. *GeoJournal*, *86*(3), 1225–1243. https://doi.org/10.1007/S10708-019-10130-1/TABLES/7

Armenteras, D., Murcia, U., González, T. M., Barón, O. J., & Arias, J. E. (2019). Scenarios of land use and land cover change for NW Amazonia: Impact on forest intactness. *Global Ecology and Conservation*, *17*, e00567. https://doi.org/10.1016/J.GECCO.2019.E00567

Arroyo-Rodríguez, V., Saldaña-Vázquez, R. A., Fahrig, L., & Santos, B. A. (2017). Does forest fragmentation cause an increase in forest temperature? *Ecological Research*, *32*(1), 81–88. https://doi.org/10.1007/S11284-016-1411-6/FIGURES/2

Assan, J. K., & Kumar, P. (2009). Introduction: Livelihood options for the poor in the changing environment. *Journal of International Development*, *21*(3), 393–402. https://doi.org/10.1002/JID.1565

Ayele, G., Hayicho, H., & Alemu, M. (2000). Land Use Land Cover Change Detection and Deforestation Modeling: In Delomena District of Bale Zone, Ethiopia. *Journal of Environmental Protection*, *10*, 532–561. https://doi.org/10.4236/jep.2019.104031

Baldyga, T. J., Miller, S. N., Driese, K. L., & Gichaba, C. M. (2008). Assessing land cover change in Kenya's Mau Forest region using remotely sensed data. *African Journal of Ecology*, *46*(1), 46–54. https://doi.org/10.1111/j.1365-2028.2007.00806.x

Bali Swain, R., & Yang-Wallentin, F. (2019). Achieving sustainable development goals: predicaments and strategies. *Https://Doi.Org/10.1080/13504509.2019.1692316*, *27*(2), 96–106. https://doi.org/10.1080/13504509.2019.1692316

Barrios, S., Ouattara, B., & Strobl, E. (2008). The impact of climatic change on agricultural production: Is it different for Africa? *Food Policy*, *33*(4), 287–298. https://doi.org/10.1016/J.FOODPOL.2008.01.003

Bax, V., & Francesconi, W. (2018). Environmental predictors of forest change: An analysis of natural predisposition to deforestation in the tropical Andes region, Peru. *Applied Geography*, *91*, 99–110. https://doi.org/10.1016/J.APGEOG.2018.01.002

Bennett, E. M., Peterson, G. D., & Gordon, L. J. (2009). Understanding relationships among multiple ecosystem services. *Ecology Letters*, *12*(12), 1394–1404. https://doi.org/10.1111/J.1461-0248.2009.01387.X

Bennett, N. (2016). Using perceptions as evidence to improve conservation and environmental management. *Conservation Biology*, *30*(3), 582–592. https://doi.org/10.1111/COBI.12681

BirdLife International. (2021). *Important Bird Areas factsheet: Mau forest complex*.

BirdLife International. (2023). *Important Bird Areas factsheet: Mau forest complex*. http://datazone.birdlife.org/site/factsheet/mau-forest-complex-iba-kenya/refs

Birhanu, L., Hailu, B. T., Bekele, T., & Demissew, S. (2019). Land use/land cover change along elevation and slope gradient in highlands of Ethiopia. *Remote Sensing Applications: Society and Environment*, *16*(August), 100260. https://doi.org/10.1016/j.rsase.2019.100260

Branco, E. R. F., Rosa dos Santos, A., Macedo Pezzopane, J. E., Banhos dos Santos, A., Alexandre, R. S., Bernardes, V. P., Gomes da Silva, R., Barbosa de Souza, K., & Moura, M. M. (2019). Space-time analysis of vegetation trends and drought occurrence in domain area of tropical forest. *Journal of Environmental Management*, *246*, 384–396. https://doi.org/10.1016/J.JENVMAN.2019.05.097

Breckwoldt, A., Ratter, B. M. W., & Wang, W. C. (2018). Editorial: Fishing for human perceptions in Coastal and Island Marine resource use systems. *Frontiers in Marine Science*, *4*(FEB), 62. https://doi.org/10.3389/FMARS.2018.00062/BIBTEX

Brink, A. B., & Eva, H. D. (2009). Monitoring 25 years of land cover change dynamics in Africa: A sample based remote sensing approach. *Applied Geography*, *29*(4), 501–512. https://doi.org/10.1016/J.APGEOG.2008.10.004

Bryan, E., Ringler, C., Okoba, B., Roncoli, C., Silvestri, S., & Herrero, M. (2013). Adapting agriculture to climate change in Kenya: Household strategies and determinants. *Journal of Environmental Management*, *114*, 26–35. https://doi.org/10.1016/j.jenvman.2012.10.036

Choudhury, D., Das, K., & Das, A. (2019). Assessment of land use land cover changes and its impact on variations of land surface temperature in Asansol-Durgapur Development Region. *The Egyptian Journal of Remote Sensing and Space Science*, *22*(2), 203–218. https://doi.org/10.1016/J.EJRS.2018.05.004

Christensen, R. H. B. (2022). *ordinal - Regression Models for Ordinal Data* (R package version 2022.11-16). https://CRAN.R-project.org/package=ordinal

Clark, W. C., & Harley, A. G. (2020). An integrative framework for sustainability science. *Sustainability Science: A Guide for Researchers*, 1–22.

Costanza, R., de Groot, R., Sutton, P., van der Ploeg, S., Anderson, S. J., Kubiszewski, I., Farber, S., & Turner, R. K. (2014). Changes in the global value of ecosystem services. *Global Environmental Change*, *26*(1), 152–158. https://doi.org/10.1016/J.GLOENVCHA.2014.04.002

Costanza, R., & Patten, B. C. (1995). Defining and predicting sustainability. *Ecological Economics*, *15*(3), 193–196. https://doi.org/10.1016/0921-8009(95)00048-8

County Government of Bomet. (2023). *About Bomet County*. https://bomet.co.ke/about/

County Government of Kericho. (2023). *About County Kericho*. https://kericho.go.ke/

County Government of Nakuru. (2023). *About County Government of Nakuru*. https://nakuru.go.ke/nakuru-county/#

County Government of Narok. (2023). *About Narok County*. https://narok.go.ke/about-narok/

Cox, D., Hinkley, D., Rubin, D., & Silverman, B. (2018). Analysis of Binary Data. *Analysis of Binary Data, Second Edition*, *7*(2), 27. https://doi.org/10.1201/9781315137391

Cushman, S. A., McGarigal, K., & Neel, M. C. (2008a). Parsimony in landscape metrics : Strength , universality , and consistency. *Ecological Indicators*, *8*(5), 691–703. https://doi.org/10.1016/j.ecolind.2007.12.002

Cushman, S. A., McGarigal, K., & Neel, M. C. (2008b). Parsimony in landscape metrics: Strength, universality, and consistency. *Ecological Indicators*, *8*(5), 691–703. https://doi.org/10.1016/J.ECOLIND.2007.12.002

da Silva, R. F. B., Millington, J. D. A., Moran, E. F., & Batistella, M. (2020). Landscape and Urban Planning Three decades of land-use and land-cover change in mountain regions of the Brazilian Atlantic Forest. *Landscape and Urban Planning*, *204*(August), 103948. https://doi.org/10.1016/j.landurbplan.2020.103948

Dabernig, M., Mayr, G. J., Messner, J. W., & Zeileis, A. (2017). Spatial ensemble post-processing with standardized anomalies. *Quarterly Journal of the Royal Meteorological Society*, *143*(703), 909–916. https://doi.org/10.1002/QJ.2975

Daher, B. T., & Mohtar, R. H. (2015). Water–energy–food (WEF) Nexus Tool 2.0: guiding integrative resource planning and decision-making. *Https://Doi.Org/10.1080/02508060.2015.1074148*, *40*(5–6), 748–771. https://doi.org/10.1080/02508060.2015.1074148

Dahlin, K. M., Akanga, D., Lombardozzi, D. L., Reed, D. E., Shirkey, G., Lei, C., Abraha, M., & Chen, J. (2020). Challenging a Global Land Surface Model in a Local Socio-Environmental System. *Land 2020, Vol. 9, Page 398*, *9*(10), 398. https://doi.org/10.3390/LAND9100398

Daly, H. E. (2017). Toward some operational principles of sustainable development. *Sustainability*, *2*, 291–296. https://doi.org/10.4324/9781315241951-26

Dang, A. N., & Kawasaki, A. (2017). Integrating biophysical and socio-economic factors for land-use and land-cover change projection in agricultural economic regions. *Ecological Modelling*, *344*, 29–37. https://doi.org/10.1016/j.ecolmodel.2016.11.004

Das, S., & Angadi, D. P. (2021). Assessment of urban sprawl using landscape metrics and Shannon's entropy model approach in town level of Barrackpore sub-divisional region, India. *Modeling Earth Systems and Environment*, *7*(2), 1071–1095. https://doi.org/10.1007/s40808-020-00990-9

De Vreese, R., Leys, M., Fontaine, C. M., & Dendoncker, N. (2016). Social mapping of perceived ecosystem services supply – The role of social landscape metrics and social hotspots for integrated ecosystem services assessment, landscape planning and management. *Ecological Indicators*, *66*, 517–533. https://doi.org/10.1016/J.ECOLIND.2016.01.048

Defries, R. S., Foley, J. A., & Asner, G. P. (2004). *Land-Use Choices: Balancing Human Needs and Ecosystem Function*. *2*(5), 249–257.

DeFries, R. S., Foley, J. A., & Asner, G. P. (2004). Land-Use Choices: Balancing Human Needs and Ecosystem Function. *Frontiers in Ecology and the Environment*, *2*(5), 249–257. https://www.jstor.org/stable/3868265

Dhaubanjar, S., Davidsen, C., & Bauer-Gottwein, P. (2017). Multi-Objective Optimization for Analysis of Changing Trade-Offs in the Nepalese Water–Energy–Food Nexus with Hydropower Development. *Water 2017, Vol. 9, Page 162*, *9*(3), 162. https://doi.org/10.3390/W9030162

Dwivedi, R. S., Sreenivas, K., & Ramana, K. V. (2005). Land-use/land-cover change analysis in part of Ethiopia using Landsat Thematic Mapper data. *International Journal of Remote Sensing*, *26*(7), 1285–1287. https://doi.org/10.1080/01431160512331337763

Endo, A., Yamada, M., Miyashita, Y., Sugimoto, R., Ishii, A., Nishijima, J., Fujii, M., Kato, T., Hamamoto, H., Kimura, M., Kumazawa, T., & Qi, J. (2020). Dynamics of water–energy–food nexus methodology, methods, and tools. *Current Opinion in Environmental Science & Health*, *13*, 46–60. https://doi.org/10.1016/J.COESH.2019.10.004

Falchetta, G., Pachauri, S., Parkinson, S., & Byers, E. (2019). A high-resolution gridded dataset to assess electrification in sub-Saharan Africa. *Scientific Data 2019 6:1*, *6*(1), 1–9. https://doi.org/10.1038/s41597-019-0122-6

Fenta, A. A., Tsunekawa, A., Haregeweyn, N., Tsubo, M., Yasuda, H., Shimizu, K., Kawai, T., Ebabu, K., Berihun, M. L., Sultan, D., Belay, A. S., & Sun, J. (2020). Cropland expansion outweighs the monetary effect of declining natural vegetation on ecosystem services in sub-Saharan Africa. *Ecosystem Services*, *45*, 101154. https://doi.org/10.1016/J.ECOSER.2020.101154

Fichera, C. R., Modica, G., & Pollino, M. (2012). Land Cover classification and change-detection analysis using multi-temporal remote sensed imagery and landscape metrics. *European Journal of Remote Sensing*, *45*(1), 1–18. https://doi.org/10.5721/EuJRS20124501

Fischer, J., Gardner, T. A., Bennett, E. M., Balvanera, P., Biggs, R., Carpenter, S., Daw, T., Folke, C., Hill, R., Hughes, T. P., Luthe, T., Maass, M., Meacham, M., Norström, A. V., Peterson, G., Queiroz, C., Seppelt, R., Spierenburg, M., & Tenhunen, J. (2015). Advancing sustainability through mainstreaming a social–ecological systems perspective. *Current Opinion in Environmental Sustainability*, *14*, 144–149. https://doi.org/10.1016/J.COSUST.2015.06.002

Fisher, E., Attah, R., Barca, V., O'Brien, C., Brook, S., Holland, J., Kardan, A., Pavanello, S., & Pozarny, P. (2017). The Livelihood Impacts of Cash Transfers in Sub-Saharan Africa: Beneficiary Perspectives from Six Countries. *World Development*, *99*, 299–319. https://doi.org/10.1016/J.WORLDDEV.2017.05.020

Foody, G. M. (2002). ClassificationArticle_by_Foody_2002.pdf. *Remote Sensing of Environment*, *80*, 185–201. https://doi.org/10.1016/S0034-4257(01)00295-4

Foody, G. M. (2010). Remote Sensing of Environment Assessing the accuracy of land cover change with imperfect ground reference data. *Remote Sensing of Environment*, *114*(10), 2271–2285. https://doi.org/10.1016/j.rse.2010.05.003

Gebru, G. W., Ichoku, H. E., & Phil-Eze, P. O. (2018). Determinants of livelihood diversification strategies in Eastern Tigray Region of Ethiopia. *Agriculture and Food Security*, *7*(1), 1–9. https://doi.org/10.1186/S40066-018-0214-0/TABLES/3

Getu, K., & Bhat, H. G. (2021). Analysis of spatio-temporal dynamics of urban sprawl and growth pattern using geospatial technologies and landscape metrics in Bahir Dar, Northwest Ethiopia. *Land Use Policy*, *109*, 105676. https://doi.org/10.1016/J.LANDUSEPOL.2021.105676

Golam, R., Sharma, B., & Rasul, G. (2015). *Climate Policy The nexus approach to water-energy-food security: an option for adaptation to climate change The nexus approach to water-energy-food security: an option for adaptation to climate change*. https://doi.org/10.1080/14693062.2015.1029865

Government of Kenya. (2022). *Agriculture Statistics – Ministry of Agriculture, Livestock, Fisheries and Co-operatives*. https://kilimo.go.ke/agriculture-statistics/

Gray, J. M., Frolking, S., Kort, E. A., Ray, D. K., Kucharik, C. J., Ramankutty, N., & Friedl, M. A. (2014). Direct human influence on atmospheric CO2 seasonality from increased cropland productivity. *Nature 2014 515:7527*, *515*(7527), 398–401. https://doi.org/10.1038/nature13957

Guzha, A. C., Rufino, M. C., Okoth, S., Jacobs, S., & Nóbrega, R. L. B. (2018). Impacts of land use and land cover change on surface runoff, discharge and low flows: Evidence from East Africa. *Journal of Hydrology: Regional Studies*, *15*, 49–67. https://doi.org/10.1016/J.EJRH.2017.11.005

Harrell, F. E. (2015). *Regression Modeling Strategies With Applications to Linear Models, Logistic and Ordinal Regression, and Survival Analysis Second Edition Springer Series in Statistics*. https://doi.org/10.1007/978-3-319-19425-7

Hesselbarth, M. H. K., Sciaini, M., With, K. A., Wiegand, K., & Nowosad, J. (2019). *landscapemetrics: an open-source R tool to calculate landscape metrics.* (pp. 42:1648-1657). Ecography.

Hoff, H. (2011). Understanding the nexus. *Background Paper for the Bonn2011Conference: The Water, Energy and Food Security Nexus*.

Hollmann, R., Merchant, C. J., Saunders, R., Downy, C., Buchwitz, M., Cazenave, A., Chuvieco, E., Defourny, P., De Leeuw, G., Forsberg, R., Holzer-Popp, T., Paul, F., Sandven, S., Sathyendranath, S., Van Roozendael, M., & Wagner, W. (2013). The ESA climate change initiative: Satellite data records for essential climate variables. *Bulletin of the American Meteorological Society*, *94*(10), 1541–1552. https://doi.org/10.1175/BAMS-D-11-00254.1

IEA. (2022). *World energy statistics and balances*.

Imasiku, K., & Ntagwirumugara, E. (2020). An impact analysis of population growth on energy-water-food-land nexus for ecological sustainable development in Rwanda. *Food and Energy Security*, *9*(1). https://doi.org/10.1002/fes3.185

International Rescue Committee. (2023). Severe drought is projected to leave about 5.4 million people in Kenya without adequate access to food and water between March and June 2023. *International Rescue Committee* . https://www.rescue.org/press-release/irc-severe-drought-projected-leave-about-54-million-people-kenya-without-adequate

Islam, M. R. (2018). Sample size and its role in Central Limit Theorem (CLT). *Computational and Applied Mathematics Journal*, *4*(1), 1–7. http://www.aascit.org/journal/camj

Jahanger, A., Usman, M., Murshed, M., Mahmood, H., & Balsalobre-Lorente, D. (2022). The linkages between natural resources, human capital, globalization, economic growth, financial development, and ecological footprint: The moderating role of technological innovations. *Resources Policy*, *76*, 102569. https://doi.org/10.1016/J.RESOURPOL.2022.102569

Jarosz, L. (2012). Growing inequality: Agricultural revolutions and the political ecology of rural development. *International Journal of Agricultural Sustainability*, *10*(2), 192–199. https://doi.org/10.1080/14735903.2011.600605

John, B., & Clark, F. (2010). *Enhanced processing of SPOT multispectral satellite imagery for environmental monitoring and modelling*. https://helda.helsinki.fi/handle/10138/21224

Jozani, H., Thiel, M., Abdel-Rahman, E. M., Richard, K., Landmann, T., Subramanian, S., & Hahn, M. (2020). Investigation of Maize Lethal Necrosis (MLN) severity and cropping systems mapping in agro-ecological maize systems in Bomet, Kenya utilizing RapidEye and Landsat-8 Imagery. *Https://Doi.Org/10.1080/24749508.2020.1761195*, *6*(2), 125–140. https://doi.org/10.1080/24749508.2020.1761195

Kalele, D. N., Ogara, W. O., Oludhe, C., & Onono, J. O. (2021). Climate change impacts and relevance of smallholder farmers' response in arid and semi-arid lands in Kenya. *Scientific African*, *12*, e00814. https://doi.org/10.1016/J.SCIAF.2021.E00814

Kearns, F. R., Kelly, N. M., Carter, J. L., & Resh, V. H. (2005). A method for the use of landscape metrics in freshwater research and management. *Landscape Ecology*, *20*(1), 113–125. https://doi.org/10.1007/s10980-004-2261-0

Keovilignavong, O., & Suhardiman, D. (2020). Linking land tenure security with food security: Unpacking farm households' perceptions and strategies in the rural uplands of Laos. *Land Use Policy*, *90*, 104260. https://doi.org/10.1016/J.LANDUSEPOL.2019.104260

Khambhammettu, P. (2005). Mann-Kendall analysis for the Fort Ord site. *USACE, HydroGeoLogic, Inc., Memorandum*. http://www. fortordcleanup. com/ar_pdfs/AR-OU1-520C/Appendices/Appendix% 20D. pdf

Kimathi, E., Tonnang, H. E. Z., Subramanian, S., Cressman, K., Abdel-Rahman, E. M., Tesfayohannes, M., Niassy, S., Torto, B., Dubois, T., Tanga, C. M., Kassie, M., Ekesi, S., Mwangi, D., & Kelemu, S. (2020). Prediction of breeding regions for the desert locust Schistocerca gregaria in East Africa. *Scientific Reports 2020 10:1*, *10*(1), 1–10. https://doi.org/10.1038/s41598-020-68895-2

Kinyanjui, M. J. (2011). NDVI-based vegetation monitoring in Mau forest complex, Kenya. *African Journal of Ecology*, *49*(2), 165–174. https://doi.org/10.1111/j.1365-2028.2010.01251.x

Klopp, J. M. (2012). Deforestation and democratization: patronage, politics and forests in Kenya. *Http://Dx.Doi.Org/10.1080/17531055.2012.669577*, *6*(2), 351–370. https://doi.org/10.1080/17531055.2012.669577

Klopp, J. M., & Lumumba, O. (2017). Reform and counter-reform in Kenya's land governance. *Https://Doi.Org/10.1080/03056244.2017.1367919*, *44*(154), 577–594. https://doi.org/10.1080/03056244.2017.1367919

Klopp, J. M., & Sang, J. K. (2011). Maps, Power, and the Destruction of the Mau Forest in Kenya. *Georgetown Journal of International Affairs*, *12*(1), 125–134.

Konapala, G., Mishra, A. K., Wada, Y., & Mann, M. E. (2020). Climate change will affect global water availability through compounding changes in seasonal precipitation and evaporation. *Nature Communications 2020 11:1*, *11*(1), 1–10. https://doi.org/10.1038/s41467-020-16757-w

Korir, J. (2020). Climate Change Adaptation Strategies Adopted for Sustainable Livelihoods by the Pastoral Community in Narok County. *Africa Environmental Review Journal*, *4*(1), 54–73. http://www.aer-journal.info

Kotikot, S. M., Flores, A., Griffin, R. E., Nyaga, J., Case, J. L., Mugo, R., Sedah, A., Adams, E., Limaye, A., & Irwin, D. E. (2020). Statistical characterization of frost zones: Case of tea freeze damage in the Kenyan highlands. *International Journal of Applied Earth Observation and Geoinformation*, *84*, 101971. https://doi.org/10.1016/J.JAG.2019.101971

Krantz, L. (2001). *The Sustainable Livelihood Approach to Poverty Reduction An Introduction*.

Kumar, M., Denis, D. M., Singh, S. K., Szabó, S., & Suryavanshi, S. (2018a). Landscape metrics for assessment of land cover change and fragmentation of a heterogeneous watershed. *Remote Sensing Applications: Society and Environment*, *10*(November 2017), 224–233. https://doi.org/10.1016/j.rsase.2018.04.002

Kumar, M., Denis, D. M., Singh, S., Szabó, S., & Suryavanshi, S. (2018b). Remote Sensing Applications : Society and Environment Landscape metrics for assessment of land cover change and fragmentation of a heterogeneous watershed. *Remote Sensing Applications: Society and Environment*, *10*(November 2017), 224–233. https://doi.org/10.1016/j.rsase.2018.04.002

Kweyu, R. M., Thenya, T., Kiemo, K., & Emborg, J. (2020). The nexus between land cover changes, politics and conflict in Eastern Mau forest complex, Kenya. *Applied Geography*, *114*(November 2019), 102115. https://doi.org/10.1016/j.apgeog.2019.102115

Lambin, E. F. (1997). Modelling and monitoring land-cover change processes in tropical regions. *Progress in Physical Geography*, *21*(3), 375–393. https://doi.org/10.1177/030913339702100303

Lambin, E. F., Coomes, O. T., Turner, B. L., Geist, H. J., Agbola, S. B., Angelsen, A., Folke, C., Bruce, J. W., Coomes, O. T., Dirzo, R., George, P. S., Homewood, K., Imbernon, J., Leemans, R., Li, X., Moran, E. F., Mortimore, M., Ramakrishnan, P. S., Richards, J. F., … Xu, J. (2001). The causes of land-use and land-cover change : Moving beyond the myths. *Global Environmental Change*, *11*(December), 261–269.

Lamchin, M., Lee, W.-K., Woo, S., Sonam, J., Wang, W., Lim, H., Song, C., & Sung, M. (2018). *Long-term trend of and correlation between vegetation greenness and climate variables in Asia based on satellite data*. https://doi.org/10.1016/j.mex.2018.07.006

Landmann, T., & Dubovyk, O. (2014). Spatial analysis of human-induced vegetation productivity decline over eastern Africa using a decade (2001–2011) of medium resolution MODIS time-series data. *International Journal of Applied Earth Observation and Geoinformation*, *33*(1), 76–82. https://doi.org/10.1016/J.JAG.2014.04.020

Langat, C. K. (2017). *Occupational factors for Low Back Pain among tea plantation workers in Kericho County* [Doctoral dissertation]. Jomo Kenyatta University of Agriculture and Technology.

Leemhuis, C., Thonfeld, F., Näschen, K., Steinbach, S., Muro, J., Strauch, A., López, A., Daconto, G., Games, I., & Diekkrüger, B. (2017). Sustainability in the Food-Water-Ecosystem Nexus: The Role of Land Use and Land Cover Change for Water Resources and Ecosystems in the Kilombero Wetland, Tanzania. *Sustainability 2017, Vol. 9, Page 1513*, *9*(9), 1513. https://doi.org/10.3390/SU9091513

Lim, M. M., Jørgensen, P. S., & Wyborn, C. A. (2018). Reframing the sustainable development goals to achieve sustainable development in the Anthropocene—a systems approach. *Ecology and Society*, *23*(3). https://www.jstor.org/stable/26799145?seq=1

Liu, W., Zhan, J., Zhao, F., Yan, H., Zhang, F., & Wei, X. (2019a). Impacts of urbanization-induced land-use changes on ecosystem services: A case study of the Pearl River Delta Metropolitan Region, China. *Ecological Indicators*, *98*, 228–238. https://doi.org/10.1016/J.ECOLIND.2018.10.054

Liu, W., Zhan, J., Zhao, F., Yan, H., Zhang, F., & Wei, X. (2019b). Impacts of urbanization-induced land-use changes on ecosystem services: A case study of the Pearl River Delta Metropolitan Region, China. *Ecological Indicators*, *98*, 228–238. https://doi.org/10.1016/J.ECOLIND.2018.10.054

Lockie, S., Sonnenfeld, D. A., & Fisher, D. R. (2013). *Environmental migration : Nature, society and population movement*. *10233*, 142–153. https://doi.org/10.4324/9780203814550-14

Long, H., Mojo, D., Fu, C., Wang, G., Kanga, E., Oduor, A. M. O., & Zhang, L. (2019). Patterns of human-wildlife conflict and management implications in Kenya: a national perspective. *Https://Doi.Org/10.1080/10871209.2019.1695984*, *25*(2), 121–135. https://doi.org/10.1080/10871209.2019.1695984

Long, H., & Qu, Y. (2018). *Land Use Policy Land use transitions and land management : A mutual feedback perspective*. *74*, 111–120. https://doi.org/10.1016/j.landusepol.2017.03.021

Mabhaudhi, T., Simpson, G., Badenhorst, J., Senzanje, A., W Jewitt, G. P., P Chimonyo, V. G., Mpandeli, S., Nhamo, L., & Badenhorst Jones, J. (2021). *Developing a Framework for the Water-Energy-Food Nexus in South Africa*. https://doi.org/10.1007/978-3-030-61225-2_18

MacDonald, E., Milfont, T., & Gavin, M. (2015). Thinking Globally But Not Acting Locally?: Expert and Public Perceptions of Environmental Threats and Conservation Actions. *Http://Dx.Doi.Org/10.1080/10871209.2015.963748*, *20*(2), 123–132. https://doi.org/10.1080/10871209.2015.963748

Maja, M. M., & Ayano, S. F. (2021). The Impact of Population Growth on Natural Resources and Farmers' Capacity to Adapt to Climate Change in Low-Income Countries. *Earth Systems and Environment 2021 5:2*, *5*(2), 271–283. https://doi.org/10.1007/S41748-021-00209-6

Manandhar, R., Odehi, I. O. A., & Ancevt, T. (2009). Improving the accuracy of land use and land cover classification of landsat data using post-classification enhancement. *Remote Sensing*, *1*(3), 330–344. https://doi.org/10.3390/rs1030330

Mansour, S., Al-Belushi, M., & Al-Awadhi, T. (2020). Monitoring land use and land cover changes in the mountainous cities of Oman using GIS and CA-Markov modelling techniques. *Land Use Policy*, *91*, 104414. https://doi.org/10.1016/J.LANDUSEPOL.2019.104414

Martínez-Fernández, J., Banos-González, I., & Esteve-Selma, M. Á. (2021). An integral approach to address socio-ecological systems sustainability and their uncertainties. *Science of The Total Environment*, *762*, 144457. https://doi.org/10.1016/J.SCITOTENV.2020.144457

Mas, J. F., Velázquez, A., Díaz-Gallegos, J. R., Mayorga-Saucedo, R., Alcántara, C., Bocco, G., Castro, R., Fernández, T., & Pérez-Vega, A. (2004). Assessing land use/cover changes: A nationwide multidate spatial database for Mexico. *International Journal of Applied Earth Observation and Geoinformation*, *5*(4), 249–261. https://doi.org/10.1016/j.jag.2004.06.002

Maziya, M., Mudhara, M., & Chitja, J. (2017). What factors determine household food security among smallholder farmers? Insights from Msinga, KwaZulu-Natal, South Africa. *Http://Dx.Doi.Org.Proxy2.Cl.Msu.Edu/10.1080/03031853.2017.1283240*, *56*(1), 40–52. https://doi.org/10.1080/03031853.2017.1283240

Mazzone, A. (2019). Decentralised energy systems and sustainable livelihoods, what are the links? Evidence from two isolated villages of the Brazilian Amazon. *Energy and Buildings*, *186*, 138–146. https://doi.org/10.1016/J.ENBUILD.2019.01.027

McGarigal, K. (2015a). Fragstats. *Fragstats Help*, *4.2*(April), 1–182. http://www.umass.edu/landeco/research/fragstats/documents/fragstats.help.4.2.pdf

McGarigal, K. (2015b). Fragstats. *Fragstats Help*, *4.2*(April), 1–182. http://www.umass.edu/landeco/research/fragstats/documents/fragstats.help.4.2.pdf

Mello, K. de, Valente, R. A., Randhir, T. O., dos Santos, A. C. A., & Vettorazzi, C. A. (2018). Effects of land use and land cover on water quality of low-order streams in Southeastern Brazil: Watershed versus riparian zone. *CATENA*, *167*, 130–138. https://doi.org/10.1016/J.CATENA.2018.04.027

Morrison, J., Higginbottom, T. P., Symeonakis, E., Jones, M. J., Omengo, F., Walker, S. L., & Cain, B. (2018). Detecting Vegetation Change in Response to Confining Elephants in Forests Using MODIS Time-Series and BFAST. *Remote Sensing 2018, Vol. 10, Page 1075*, *10*(7), 1075. https://doi.org/10.3390/RS10071075

Mottet, A., Ladet, S., Coqué, N., & Gibon, A. (2006). Agricultural land-use change and its drivers in mountain landscapes: A case study in the Pyrenees. *Agriculture, Ecosystems and Environment*, *114*(2–4), 296–310. https://doi.org/10.1016/j.agee.2005.11.017

Msofe, N. K., Sheng, L., & Lyimo, J. (2019). Land use change trends and their driving forces in the Kilombero Valley Floodplain, Southeastern Tanzania. *Sustainability (Switzerland)*, *11*(2), 1–25. https://doi.org/10.3390/su11020505

Mukeka, J. M., Ogutu, J. O., Kanga, E., & Røskaft, E. (2019). Human-wildlife conflicts and their correlates in Narok County, Kenya. *Global Ecology and Conservation*, *18*, e00620. https://doi.org/10.1016/J.GECCO.2019.E00620

Munthali, M. G., Davis, N., Adeola, A. M., Botai, J. O., Kamwi, J. M., Chisale, H. L. W., & Orimoogunje, O. O. I. (2019). Local Perception of Drivers of Land-Use and Land-Cover Change Dynamics across Dedza District, Central Malawi Region. *Sustainability 2019, Vol. 11, Page 832*, *11*(3), 832. https://doi.org/10.3390/SU11030832

Murthy, K., & Bagchi, S. (2018). Spatial patterns of long-term vegetation greening and browning are consistent across multiple scales: Implications for monitoring land degradation. *Land Degradation & Development*, *29*(8), 2485–2495. https://doi.org/10.1002/LDR.3019

Mutea, E., Bottazzi, P., Jacobi, J., Kiteme, B., Speranza, C. I., & Rist, S. (2019). Livelihoods and Food Security Among Rural Households in the North-Western Mount Kenya Region. *Frontiers in Sustainable Food Systems*, *3*, 98. https://doi.org/10.3389/FSUFS.2019.00098/BIBTEX

Mutugi, M., & Kiiru, W. (2015). Biodiversity, Local Resource, National Heritage, Regional Concern, and Global Impact: the Case of Mau Forest, Kenya. *European Scientific Journal*, *1*(January), 1857–7881.

Mwangi, H. M., Lariu, P., Julich, S., Patil, S. D., McDonald, M. A., & Feger, K. H. (2017). Characterizing the Intensity and Dynamics of Land-Use Change in the Mara River Basin, East Africa. *Forests 2018, Vol. 9, Page 8*, *9*(1), 8. https://doi.org/10.3390/F9010008

Myers, C. W., & Medley, K. E. (2018). Electrification as development for sustainable livelihoods at Mt. Kasigau, Kenya. *Https://Doi.Org/10.1080/19376812.2018.1436077*, *38*(4), 326–342. https://doi.org/10.1080/19376812.2018.1436077

Narmada, K. (2021). Landscape metrics to analyze the forest fragmentation of Chitteri Hills in Eastern Ghats, Tamil Nadu. *Journal of Civil Engineering and Environmental Sciences*, 001–007. https://doi.org/10.17352/2455-488X.000038

Näschen, K., Diekkrüger, B., Evers, M., Höllermann, B., Steinbach, S., & Thonfeld, F. (2019). The Impact of Land Use/Land Cover Change (LULCC) on Water Resources in a Tropical Catchment in Tanzania under Different Climate Change Scenarios. *Sustainability 2019, Vol. 11, Page 7083*, *11*(24), 7083. https://doi.org/10.3390/SU11247083

Newton, P., Kinzer, A. T., Miller, D. C., Oldekop, J. A., & Agrawal, A. (2020). The Number and Spatial Distribution of Forest-Proximate People Globally. *One Earth*, *3*(3), 363–370. https://doi.org/10.1016/J.ONEEAR.2020.08.016

Newton, P., Miller, D. C., Byenkya, M. A. A., & Agrawal, A. (2016). Who are forest-dependent people? A taxo nomy to aid livelihood and land use decision-making in forested regions. *Land Use Policy*, *57*, 388–395. https://doi.org/10.1016/J.LANDUSEPOL.2016.05.032

Ngigi, T. G., & Tateishi, R. (2004). Monitoring deforestation in Kenya. *International Journal of Environmental Studies*, *61*(3), 281–291. https://doi.org/10.1080/0020723032000170959

Nhamo, L., Ndlela, B., Mpandeli, S., & Mabhaudhi, T. (2020). The Water-Energy-Food Nexus as an Adaptation Strategy for Achieving Sustainable Livelihoods at a Local Level. *Sustainability 2020, Vol. 12, Page 8582*, *12*(20), 8582. https://doi.org/10.3390/SU12208582

Nightingale, A. (2003). Nature–society and development: social, cultural and ecological change in Nepal. *Geoforum*, *34*(4), 525–540. https://doi.org/10.1016/S0016-7185(03)00026-5

Nilsson, M., & Costanza, R. (2015). Overall framework for the sustainable development goals. Review of Targets for the Sustainable Development Goals: The Science Perspective. In *scholar.ceu.edu*. http://scholar.ceu.edu/sites/default/files/publications/sdg-report.pdf#page=9

Novienyo, L., & Simatele, M. (2021). Food Security and Coping Strategies of Rural Household Livelihoods to Climate Change in the Eastern Cape of South Africa. *Frontiers in Sustainable Food Systems*, *5*. https://doi.org/10.3389/fsufs.2021.692185

Oballa, P. O., Konuche, P. K. A., Muchiri, M. N., & Kigomo, B. N. (2010). *FACTS ON GROWING AND USE OF EUCALYPTUS IN KENYA*. www.kefri.org

O'Connor, J. C., Dekker, S. C., Staal, A., Tuinenburg, O. A., Rebel, K. T., & Santos, M. J. (2021). Forests buffer against variations in precipitation. *Global Change Biology*, *27*(19), 4686–4696. https://doi.org/10.1111/GCB.15763

Oduor, A. M. O. (2020). Livelihood impacts and governance processes of community-based wildlife conservation in Maasai Mara ecosystem, Kenya. *Journal of Environmental Management*, *260*, 110133. https://doi.org/10.1016/J.JENVMAN.2020.110133

Ogada, M. J., Mwabu, G., & Muchai, D. (2014). Farm technology adoption in Kenya: a simultaneous estimation of inorganic fertilizer and improved maize variety adoption decisions. *Agricultural and Food Economics*, *2*(1), 1–18. https://doi.org/10.1186/S40100-014-0012-3/TABLES/3

Ogutu, J. O., Piepho, H.-P., Said, M. Y., & Kifugo, S. C. (2014). Herbivore Dynamics and Range Contraction in Kajiado County Kenya: Climate and Land Use Changes, Population Pressures, Governance, Policy and Human-wildlife Conflicts. *The Open Ecology Journal*, *7*(1), 9–31. https://doi.org/10.2174/1874213001407010009

Ogweno, D. O., Opanga, P., & Obara, A. O. (2009a). Forest landscape and Kenya's Vision 2030. In *Proceedings of the 3rd Annual Forestry Society of Kenya (FSK) Conference and Annual General Meeting held at the Sunset Hotel, Kisumu. 30th September - 3rd October, 2008.*

Ogweno, D. O., Opanga, P., & Obara, A. O. (2009b). Forest landscape and Kenya's Vision 2030. In *Proceedings of the 3rd Annual Forestry Society of Kenya (FSK) Conference and Annual General Meeting held at the Sunset Hotel, Kisumu. 30th September - 3rd October, 2008.*

Okello, M. M. (2006). Land Use Changes and Human–Wildlife Conflicts in the Amboseli Area, Kenya. *Http://Dx.Doi.Org/10.1080/10871200590904851*, *10*(1), 19–28. https://doi.org/10.1080/10871200590904851

Olawumi, T. O., & Chan, D. W. M. (2018). A scientometric review of global research on sustainability and sustainable development. *Journal of Cleaner Production*, *183*, 231–250. https://doi.org/10.1016/J.JCLEPRO.2018.02.162

Olofsson, P., Foody, G. M., Herold, M., Stehman, S. V., Woodcock, C. E., & Wulder, M. A. (2014a). Good practices for estimating area and assessing accuracy of land change. *Remote Sensing of Environment*, *148*, 42–57. https://doi.org/10.1016/j.rse.2014.02.015

Olofsson, P., Foody, G. M., Herold, M., Stehman, S. v., Woodcock, C. E., & Wulder, M. A. (2014b). Good practices for estimating area and assessing accuracy of land change. *Remote Sensing of Environment*, *148*, 42–57. https://doi.org/10.1016/j.rse.2014.02.015

Olofsson, P., Foody, G. M., Stehman, S. V, & Woodcock, C. E. (2013). Remote Sensing of Environment Making better use of accuracy data in land change studies : Estimating accuracy and area and quantifying uncertainty using strati fi ed estimation. *Remote Sensing of Environment*, *129*, 122–131. https://doi.org/10.1016/j.rse.2012.10.031

Onekon, W. A., & Kipchirchir, O. K. (2016). ASSESSING THE EFFECT OF CHARCOAL PRODUCTION AND USE ON THE TRANSITION TO A GREEN ECONOMY IN KENYA Tropical and Subtropical Agroecosystems. *Tropical and Subtropical Agroecosystems* , *19*, 327–335. http://www.redalyc.org/articulo.oa?id=93949148005

Orr, D. W. (2002). Four challenges of sustainability. *Conservation Biology*, *16*(6), 1457–1460. https://doi.org/10.1046/j.1523-1739.2002.01668.x

Osunga, M., Mutua, F., & Mugo, R. (2017). Spatial Modelling of Maize Lethal Necrosis Disease in Bomet County, Kenya. *Journal of Geosciences and Geomatics*, *5*(5), 251–258. https://doi.org/10.12691/jgg-5-5-4

Ottenbacher, K. J., Ottenbacher, H. R., Tooth, L., & Ostir, G. v. (2004). A review of two journals found that articles using multivariable logistic regression frequently did not report commonly recommended assumptions. *Journal of Clinical Epidemiology*, *57*(11), 1147–1152. https://doi.org/10.1016/J.JCLINEPI.2003.05.003

Panda, A., & Sahu, N. (2019). Trend analysis of seasonal rainfall and temperature pattern in Kalahandi, Bolangir and Koraput districts of Odisha, India. *Atmospheric Science Letters*, *20*(10), e932. https://doi.org/10.1002/ASL.932

Phompila, C., Lewis, M., Ostendorf, B., & Clarke, K. (2015). MODIS EVI and LST Temporal Response for Discrimination of Tropical Land Covers. *Remote Sensing 2015, Vol. 7, Pages 6026-6040*, *7*(5), 6026–6040. https://doi.org/10.3390/RS70506026

Priyadarshi, N., Chowdary, V. M., Das, I. C., Chockalingam, J., Srivastava, Y. K., Rao, G. S., Raj, U., & Jha, C. S. (2018). Wavelet and non-parametric statistical based approach for long term land cover trend analysis using time series EVI data. *Https://Doi.Org/10.1080/10106049.2018.1520925*, *35*(5), 512–534. https://doi.org/10.1080/10106049.2018.1520925

R Core Team. (2022). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing.

Rahman, A. (2021). Rainwater Harvesting for Sustainable Developments: Non-Potable Use, Household Irrigation and Stormwater Management. *Water 2021, Vol. 13, Page 3460*, *13*(23), 3460. https://doi.org/10.3390/W13233460

Rahman, M. R., & Saha, S. K. (2008). Multi-resolution segmentation for object-based classification and accuracy assessment of land use/land cover classification using remotely sensed data. *Journal of the Indian Society of Remote Sensing*, *36*(2), 189–201. https://doi.org/10.1007/s12524-008-0020-4

RCMRD. (2016). *Land Cover Change Mapping Program - System for Land Based Emissions Estimation in Kenya (SLEEK)*.

Reyers, B., Folke, C., Moore, M.-L., Biggs, R., & Galaz, V. (2018). *Annual Review of Environment and Resources Social-Ecological Systems Insights for Navigating the Dynamics of the Anthropocene*. https://doi.org/10.1146/annurev-environ

Riitters, K., Wickham, J., & Wade, T. (2009). Evaluating anthropogenic risk of grassland and forest habitat degradation using land-cover data. *Landscape Online*, *13*(1), 1–14. https://doi.org/10.3097/LO.200913

Robbins, P. (2012). Markets and Commodities. In *Political Ecology: A Critical Introduction* (Second Edi). Blackwell Publishers.

Rodell, M., Famiglietti, J. S., Wiese, D. N., Reager, J. T., Beaudoing, H. K., Landerer, F. W., & Lo, M. H. (2018). Emerging trends in global freshwater availability. *Nature 2018 557:7707*, *557*(7707), 651–659. https://doi.org/10.1038/s41586-018-0123-1

Rogan, R., O'Connor, M., & Horwitz, P. (2005). Nowhere to hide: Awareness and perceptions of environmental change, and their influence on relationships with place. *Journal of Environmental Psychology*, *25*(2), 147–158. https://doi.org/10.1016/J.JENVP.2005.03.001

Rojas, O. (2007). Operational maize yield model development and validation based on remote sensing and agro-meteorological data in Kenya. *Http://Dx.Doi.Org/10.1080/01431160601075608*, *28*(17), 3775–3793. https://doi.org/10.1080/01431160601075608

Ruggerio, C. A. (2021). Sustainability and sustainable development: A review of principles and definitions. *Science of The Total Environment*, *786*, 147481. https://doi.org/10.1016/J.SCITOTENV.2021.147481

Rülke, J., Rieckmann, M., Nzau, J. M., & Teucher, M. (2020). How Ecocentrism and Anthropocentrism Influence Human–Environment Relationships in a Kenyan Biodiversity Hotspot. *Sustainability 2020, Vol. 12, Page 8213*, *12*(19), 8213. https://doi.org/10.3390/SU12198213

Rwanga, S. S., & Ndambuki, J. M. (2017). Accuracy Assessment of Land Use/Land Cover Classification Using Remote Sensing and GIS. *International Journal of Geosciences*, *08*(04), 611–622. https://doi.org/10.4236/ijg.2017.84033

Rwigi, S. K. (2014). Assessment of Potential Impacts of Climate Change and Deforestation on Surface Water Yields from the Mau Forest Complex Catchments in Kenya. *PhD Thesis, University of Nairobi, Kenya*, *July*, 204pp.

Scott, C. A., Kurian, M., & Wescoat, J. L. (2015). The Water-Energy-Food Nexus: Enhancing Adaptive Capacity to Complex Global Challenges. *Governing the Nexus: Water, Soil and Waste Resources Considering Global Change*, 15–38. https://doi.org/10.1007/978-3-319-05747-7_2/FIGURES/1

Semin, A. N., & Namyatova, L. E. (2019). Land as a Factor of Production in Agriculture and Features of Agricultural Practices. *International Journal of Mechanical Engineering and Technology (IJMET)*, *10*(02), 1515–1521. http://www.iaeme.com/IJMET/index.asp1515http://www.iaeme.com/ijmet/issues.asp?JType=IJMET&VType=10&IType=02http://www.iaeme.com/IJMET/index.asp1516http://www.iaeme.com/IJMET/issues.asp?JType=IJMET&VType=10&IType=02

Şen, G., Güngör, E., & Şevik, H. (2018). Defining the effects of urban expansion on land use/cover change: a case study in Kastamonu, Turkey. *Environmental Monitoring and Assessment*, *190*(8). https://doi.org/10.1007/s10661-018-6831-z

Sen, P. K. (1968). Estimates of the Regression Coefficient Based on Kendall's Tau. *Journal of the American Statistical Association*, *63*(324), 1379–1389. https://doi.org/10.1080/01621459.1968.10480934

Serneels, S., & Lambin, E. F. (2001). Proximate causes of land-use change in Narok District, Kenya: a spatial statistical model. *Agriculture, Ecosystems & Environment*, *85*(1–3), 65–81. https://doi.org/10.1016/S0167-8809(01)00188-8

Sertel, E., Topaloğlu, R. H., Şallı, B., Algan, I. Y., & Aksu, G. A. (2018). Comparison of landscape metrics for three different level land cover/land use maps. *ISPRS International Journal of Geo-Information*, *7*(10). https://doi.org/10.3390/ijgi7100408

Seto, K. C., Güneralp, B., & Hutyra, L. R. (2012). Global forecasts of urban expansion to 2030 and direct impacts on biodiversity and carbon pools. *Proceedings of the National Academy of Sciences of the United States of America*, *109*(40), 16083–16088. https://doi.org/10.1073/pnas.1211658109

Shaari, S. M., Abdul Rahim, H., & Maizura Abd Rashid, I. (2013). Relationship among population, energy consumption, and economic growth in Malaysia. *The International Journal of Social Sciences*, *13*(1).

Silva, J. S., Silva, R. M. da, & Santos, C. A. G. (2018). Spatiotemporal impact of land use/land cover changes on urban heat islands: A case study of Paço do Lumiar, Brazil. *Building and Environment*, *136*, 279–292. https://doi.org/10.1016/J.BUILDENV.2018.03.041

Singh, S. K., Pandey, A. C., & Singh, D. (2014). *Land Use Fragmentation Analysis Using Remote Sensing and Fragstats*. *November*, 151–176. https://doi.org/10.1007/978-3-319-05906-8_9

Spruce, J., Bolten, J., Mohammed, I. N., Srinivasan, R., & Lakshmi, V. (2020). Mapping Land Use Land Cover Change in the Lower Mekong Basin From 1997 to 2010. *Frontiers in Environmental Science*, *8*, 21. https://doi.org/10.3389/FENVS.2020.00021/BIBTEX

Stehman, S. V, & Foody, G. M. (2019). Remote Sensing of Environment Key issues in rigorous accuracy assessment of land cover products. *Remote Sensing of Environment*, *231*(May), 111199. https://doi.org/10.1016/j.rse.2019.05.018

Sun, J., Zhou, T. C., Liu, M., Chen, Y. C., Liu, G. H., Xu, M., Shi, P. L., Peng, F., Tsunekawa, A., Liu, Y., Wang, X. D., Dong, S. K., Zhang, Y. J., & Li, Y. N. (2019). Water and heat availability are drivers of the aboveground plant carbon accumulation rate in alpine grasslands on the Tibetan Plateau. *Global Ecology and Biogeography*, *March*, 1–15. https://doi.org/10.1111/geb.13006

Swain, R. B. (2018). A Critical Analysis of the Sustainable Development Goals. *World Sustainability Series*, 341–355. https://doi.org/10.1007/978-3-319-63007-6_20/FIGURES/2

Swart, R. (2016). *Monitoring 40 years of land use change in the Mau Forest Complex, Kenya*.

Tatem, A. J. (2017). WorldPop, open data for spatial demography. *Scientific Data 2017 4:1*, *4*(1), 1–4. https://doi.org/10.1038/sdata.2017.4

Thiault, L., Gelcich, S., Marshall, N., Marshall, P., Chlous, F., & Claudet, J. (2019). Operationalizing vulnerability for social–ecological integration in conservation and natural resource management. *Conservation Letters*, *May 2019*, 1–13. https://doi.org/10.1111/conl.12677

Tilahun, A., & Teferie, B. (2015). Accuracy Assessment of Land Use Land Cover Classification using Google Earth. *American Journal of Environmental Protection*, *4*(4), 193–198. https://doi.org/10.11648/j.ajep.20150404.14

Turner, Eric F. Lambin, & Anette Reenberg. (2007). The emergence of land change science for global environmental change and sustainability. *Proceedings of the National Academy of Sciences*, *104*(52), 20666–20671.

Turner, M., Gardner, R. H., & O'neill, R. V. (2001). *Landscape Ecology in Theory and Practice Pattern and Process Second Edition* (Second, Vol. 401). Springer .

UNEP. (2003). *Chapter 4: Environmental Hotspots*. 89–119. http://na.unep.net/atlas/datlas/sites/default/files/unepsiouxfalls/atlasbook_1135/Kenya_Screen_Chapter1.pdf

UNEP. (2008a). *Mau Complex and Marmanet forests; Environmental and economic contributions, current state and trends* (Issue May).

UNEP. (2008b). *Mau Complex and Marmanet forests; Environmental and economic contributions, current state and trends* (Issue May).

United Nations. (2015). *THE 17 GOALS | Sustainable Development*. https://sdgs.un.org/goals

Van Ittersum, M. K., Van Bussel, L. G. J., Wolf, J., Grassini, P., Van Wart, J., Guilpart, N., Claessens, L., De Groot, H., Wiebe, K., Mason-D'Croz, D., Yang, H., Boogaard, H., Van Oort, P. A. J., Van Loon, M. P., Saito, K., Adimo, O., Adjei-Nsiah, S., Agali, A., Bala, A., … Cassman, K. G. (2016). Can sub-Saharan Africa feed itself? *Proceedings of the National Academy of Sciences of the United States of America*, *113*(52), 14964–14969. https://doi.org/10.1073/PNAS.1610359113/SUPPL_FILE/PNAS.201610359SI.PDF

Videira, N., Antunes, P., & Santos, R. (2016). Engaging stakeholders in environmental and sustainability decisions with participatory system dynamics modeling. *Environmental Modeling with Stakeholders: Theory, Methods, and Applications*, 241–265. https://doi.org/10.1007/978-3-319-25053-3_12/FIGURES/7

Wanyama, D., Moore, N. J., & Dahlin, K. M. (2020). Persistent vegetation greening and browning trends related to natural and human activities in the mount Elgon ecosystem. *Remote Sensing*, *12*(13). https://doi.org/10.3390/rs12132113

Weible, C. M., Pattison, A., & Sabatier, P. A. (2010). Harnessing expert-based information for learning and the sustainable management of complex socio-ecological systems. *Environmental Science & Policy*, *13*(6), 522–534. https://doi.org/10.1016/J.ENVSCI.2010.05.005

Weitz, N., Strambo, C., Kemp-Benedict, E., & Nilsson, M. (2017). Closing the governance gaps in the water-energy-food nexus: Insights from integrative governance. *Global Environmental Change*, *45*, 165–173. https://doi.org/10.1016/J.GLOENVCHA.2017.06.006

Wilcox, B. P., Birt, A., Archer, S. R., Fuhlendorf, S. D., Kreuter, U. P., Sorice, M. G., Van Leeuwen, W. J. D., & Zou, C. B. (2018). Viewing woody-plant encroachment through a social-ecological lens. *BioScience*, *68*(9), 691–705. https://doi.org/10.1093/biosci/biy051

Woodcock, C. E., Allen, R., Anderson, M., Belward, A., Bindschadler, R., Cohen, W., Gao, F., Goward, S. N., Helder, D., Helmer, E., Nemani, R., Oreopoulos, L., Schott, J., Thenkabail, P. S., Vermote, E. F., Vogelmann, J., Wulder, M. A., & Wynne, R. (2008). Free Access to Landsat Imagery. *Science*, *320*(May), 1011–1012.

WORLD COMMISSION ON ENVIRONMENT AND DEVELOPMENT. (1987).

Wu, L., Elshorbagy, A., Pande, S., & Zhuo, L. (2021). Trade-offs and synergies in the water-energy-food nexus: The case of Saskatchewan, Canada. *Resources, Conservation and Recycling*, *164*, 105192. https://doi.org/10.1016/J.RESCONREC.2020.105192

Yang, S. J., Li, X. D., & Yan, S. G. (2018). The study for the Spatial Distribution Pattern of NDVI in the Western of Jilin Province. *IOP Conference Series: Earth and Environmental Science*, *113*(1). https://doi.org/10.1088/1755-1315/113/1/012077

Yirsaw, E., Wu, W., Shi, X., Temesgen, H., & Bekele, B. (2017). Land Use/Land Cover Change Modeling and the Prediction of Subsequent Changes in Ecosystem Service Values in a Coastal Area of China, the Su-Xi-Chang Region. *Sustainability 2017, Vol. 9, Page 1204*, *9*(7), 1204. https://doi.org/10.3390/SU9071204

Zallé, O. (2019). Natural resources and economic growth in Africa: The role of institutional quality and human capital. *Resources Policy*, *62*, 616–624. https://doi.org/10.1016/J.RESOURPOL.2018.11.009

Zhong, S., Wang, T., Sciusco, P., Shen, M., Pei, L., Nikolic, J., McKeehan, K., Kashongwe, H., Hatami-Bahman-Beiglou, P., Camacho, K., Akanga, D., Charney, J. J., & Bian, X. (2021). Will land use land cover change drive atmospheric conditions to become more conducive to wildfires in the United States? *International Journal of Climatology*, *41*(6), 3578–3597. https://doi.org/10.1002/JOC.7036

Zhou, Y., Li, X., & Liu, Y. (2020). Land use change and driving factors in rural China during the period 1995-2015. *Land Use Policy*, *99*(December 2019), 105048. https://doi.org/10.1016/j.landusepol.2020.105048

APPENDIX

Selected Variables and their Connection to United Nations SDGs

Variable/ Metric Name	Rationale	Definition and connection to Livelihoods and Sustainable Development Goals (SDGs)
Land tenure security Measured on a Likert scale (Never, Rarely, A few times, Quite regularly, Always) concerned	Determined by whether a respondent perceives their right to land ownership as secure or are concerned about possible evictions by either government or other conflicts. (Question 12 of the household survey)	Land is a major factor of production and central to sustaining livelihoods of most populations in developing countries. This metric is adopted from SDG Indicator 1.4.2 that seeks to ensure all men and women, in particular the poor and vulnerable, have equal rights to economic resources, control over land and other forms of property, and consider their land tenure secure.
Food security Measured on a Likert scale (Definitely No, Probably No, Probably Yes, Definitely Yes).	Lack of food security will be determined by whether a respondent's household has been unable to afford a meal when they were in need at any point in the last ~ 12 months. (Question 20 and 21 of the household survey)	The ability to afford meals when in need is one of the major indicators of sustainable livelihoods among vulnerable populations. This metric is adopted from SDG indicator 2.1.2 that aims at achieving food security by 2030 through ending moderate and severe food insecurity for all. It is based on one of the Food Insecurity Experience Scale (FIES), a statistical scale developed by Food and Agriculture Organization (FAO) to measure unobserved traits (https://www.fao.org/in-action/voices-of-the-hungry/fies/en/).
Income Measured on a Likert scale (Decreased a lot, Decreased a little, remained relatively the same, Increased a little, Increased a lot).	Determined by how a respondent's household income changed in the last ~5 years. Most potential respondents are small-holder farmers who do not keep accurate records of income and expenditure. However, they are expected to be aware of whether their income has increased, decreased, or remained	Income is essential for sustaining the livelihoods of small-scale food producers. This metric is adopted from SDG indicator 2.3.2 whose aim is to double the average income of small-scale food producers by 2030. A substantial increase in income will signify progress towards a sustainable livelihood.

	relatively the same in the last few years. (Question 14 of the household survey)	

Household Survey Questionnaire

These questions have been exported from Qualtrics survey tool.

GMFC Livelihoods Survey, 2022 via Qualtrics

You are being asked to participate in a research study. The purpose of the study is to examine the link between land cover change and local livelihoods. You will be asked to respond to a few questions that will help the researcher to understand the livelihoods of people living close to the Mau Forest. Your participation is voluntary. You can skip any question you do not wish to answer or withdraw at any time. You must be 18 or older to participate. You indicate that you voluntarily agree to participate in this research study by proceeding with the interview.

Start of Block: A. Introduction

Q.1a Name of the County (COUNTY)

- ○ Bomet (1)
- ○ Kericho (2)
- ○ Nakuru (3)
- ○ Narok (4)

Q.1b Name of the Village

____

Q.2a Name of respondent (first and last)

____

Q.2b What is your gender?

- ○ Male (1)
- ○ Female (2)
- ○ Non-binary / third gender (3)
- ○ Prefer not to say (4)

Q.3 What is your year of birth?

____

Q.4 How many people are in your household?

____

Q.5 What is your highest level of education?

- ○ Primary school or less (1)
- ○ High school (2)
- ○ College and above courses (3)

Q.6a How long have you lived on your current farm?

- ○ 0-5 years (1)
- ○ 6-10 years (2)
- ○ 11-15 years (3)
- ○ 16-20 years (4)
- ○ 20+ years (5)

Q.6b Overall, how has the area/size of land you use for farming changed during this period?

- Decreased a lot (1)
- Decreased a little (2)
- Remained relatively the same (3)
- Increased a little (4)
- Increased a lot (5)

Q7a Overall, how can you describe the rain patterns in relation to farming for the period you have lived in this area?
Note: *Can select more than one option*

- Decreased (1)
- Remained relatively the same (2)
- Increased (4)
- Fluctuating (inconsistent by year/season) (3)
- Other (5)

Display This Question:
If: Overall, how can you describe the rain patterns in relation to farming for the period you have li... = Other

Q7b If Other, please state.

____

Start of Block: B. Land Tenure

Q.8 Do you own land?

- ◯ Yes (1)
- ◯ No (2)

Q.9 On average, how much land do you use for farming?
Note: Answer in acres

____

Q.10a How did you acquire the land that you own?
Note: Can select more than one option

- ☐ Purchased (1)
- ☐ Inherited (2)
- ☐ Leased (3)
- ☐ Other (4)

Display This Question:
If: How did you acquire the land that you own? Note: Can select more than one option = Other

Q.10b If Other, please list

____

Q.11 Do you have a title deed for your piece of land?

- ◯ Yes (1)
- ◯ No (2)
- ◯ Not sure (3)

Q.12 How concerned are you about possible eviction from your home/land?

- ◯ Never (1)
- ◯ Rarely (2)
- ◯ A few times (3)
- ◯ Quite regularly (4)
- ◯ Always concerned (5)

Start of Block: C. Income

Q.13a Name your two main economic activities/occupation by their rank/order?
______ Salaried/Wage employment (1)
______ Business (Informal/Registered) (2)
______ Crop production only (3)
______ Livestock production only (4)
______ Both crop and livestock production (5)
______ Other (6)

Display This Question:
If: Name your two main economic activities/occupation by their rank/order? [Other], is Displayed.

Q.13b If Other, please list

____

Q.13c Over the past 12 months, what was the average monthly revenue from your two main economic activities/occupation?

- ◯ Economic activity/Occupation 1 ____
- ◯ Economic activity/Occupation 2 ____

Q.14 Overall, you can say that your average monthly revenue in the last ~5 years has:

- ◯ Decreased a lot (1)
- ◯ Decreased a little (2)
- ◯ Remained relatively the same (3)
- ◯ Increased a little (4)
- ◯ Increased a lot (5)

Start of Block: D. Food Security

Q.15 What type of farming do you practice, if any?

- ◯ Crop production only (1)
- ◯ Livestock production only (2)
- ◯ Both crop and livestock production (3)
- ◯ None (4)

Q.16 Overall, you can say that your crop yields in the last ~5 years have:

- ◯ Decreased by a lot (1)
- ◯ Decreased a little (2)
- ◯ Remained relatively the same (3)
- ◯ Increased a little (4)
- ◯ Increased by a lot (5)

Q.17 What is your main source of food in the household?

- ◯ From family farm (1)
- ◯ Mostly from farm but buy sometimes (2)
- ◯ Mostly buy (3)

Q.18 How many months in a year do you feed the family on homegrown food?

____

Q.19 How many meals do you have in a day?

____

Q.20 During the last 12 months, was there a time when, because of lack of money or other resources:
You were hungry but did not eat?

- ◯ Definitely No (1)
- ◯ Probably No (2)
- ◯ Probably Yes (3)
- ◯ Definitely Yes (4)

Q.21 During the last 12 months, was there a time when, because of lack of money or other resources:
You went without eating for a whole day or slept hungry?

- ◯ Definitely No (1)
- ◯ Probably No (2)
- ◯ Probably Yes (3)
- ◯ Definitely Yes (4)

Start of Block: E. Affordable Energy

Q.22a Is your home connected to electricity?

- ○ Yes (1)
- ○ No (2)

Q22b. Do you have access to biogas or solar energy?

- ○ Yes (1)
- ○ No (2)

Q23a Name two main types of stoves that you use for cooking by their rank/order.
Note: 1. Used to cook most meals in the household; 2. Used occasionally

______ Traditional (3-stone) firewood stove (1)
______ Charcoal stove (2)
______ Kerosene wick stove (3)
______ LPG stove (Gas) (4)
______ Electric stove (5)
______ Other (6)

Display This Question:
If Name two main types of stoves that you use for cooking by their rank/order? Note: 1. Used to cook... [Other], is Displayed.

Q.23b If Other, please list

____

Start of Block: F: Perceptions of residents' interaction with the environment

Q.24 To what extent is a degraded Mau Forest likely to affect your livelihood?

- ○ Extremely unlikely (1)
- ○ Somewhat unlikely (2)
- ○ Neither likely nor unlikely (3)
- ○ Somewhat likely (4)
- ○ Extremely likely (5)

Q.25 To what extent are your actions likely to contribute to environmental degradation?

- ○ Extremely unlikely (1)
- ○ Somewhat unlikely (2)
- ○ Neither likely nor unlikely (3)
- ○ Somewhat likely (4)
- ○ Extremely likely (5)

Guide Questions for Key Informant Interviews

Interconnections between land use-land cover change, climate variability, and livelihoods in the Greater Mau Forest Complex, Kenya

You are being asked to participate in a research study. The purpose of the study is to examine the link between land cover change and local livelihoods. You will be asked to do respond to a few questions that will help the researcher to understand the livelihoods of people living close to the Mau Forest and the interviews will be focused on sustainable forest management theme. Your participation is voluntary. You can skip any question you do not wish to answer or withdraw at any time. You must be eighteen (18) years or older to participate. You indicate that you voluntarily agree to participate in this research study by proceeding with the interview.

Guide questions for key informant interviews

Start of Block: 1. Introduction

Q1 Name of the County

○ Bomet (1)

○ Kericho (2)

○ Nakuru (3)

○ Narok (4)

Q2a Name of the Department/Agency

○ County Agriculture Office (1)

○ National Environment Management Authority (NEMA) (2)

○ Kenya Forest Service (3)

○ NGO (4)

○ Other (5)

Display This Question:

If Name of the Department/Agency = Other

Q2b Name of department/agency/entity if "Other" was selected in Q2a.

____

Q2c Name and title of official

____

Q3 Please rank the following resources in terms of their relative influence on the functioning, livability, and sustainability of the GMFC.

Water (1)
Energy (2)
Food (3)

Q4a Please describe the state of forest coverage in your county.

	Decreased a lot (1)	Decreased a little (2)	Remained the same (3)	Increased a little (4)	Increased a lot (5)
Past 10 years (1)	○	○	○	○	○
Past 20 years (2)	○	○	○	○	○
Past 30 years (3)	○	○	○	○	○

Q4b Please give the main reasons for your answer above i.e., How do you determine or conclude that pattern as changed?

- ◯ 1. (1) ________________________________
- ◯ 2. (2) ________________________________
- ◯ 3. (3) ________________________________
- ◯ 4. (4) ________________________________
- ◯ 5. (5) ________________________________
- ◯ 6. (6) ________________________________
- ◯ 7 (7) ________________________________
- ◯ 8 (8) ________________________________

Q4c What are the key drivers of the pattern you have stated above?

- ◯ 1. (1) ________________________________
- ◯ 2. (2) ________________________________
- ◯ 3. (3) ________________________________
- ◯ 4. (4) ________________________________
- ◯ 5. (5) ________________________________
- ◯ 6. (6) ________________________________
- ◯ 7 (7) ________________________________
- ◯ 8 (8) ________________________________

Q5a Overall, the impact of decentralized governance of forest management has been:

- ○ Definitely positive (1)
- ○ Somewhat positive (2)
- ○ Neither positive nor negative (3)
- ○ Somewhat negative (4)
- ○ Definitely negative (5)

Q5b Please give reasons for your answer above.

- ○ 1. (1) ____
- ○ 2. (2) ____
- ○ 3. (3) ____
- ○ 4. (4) ____
- ○ 5. (5) ____
- ○ 6. (6) ____
- ○ 7 (7) ____
- ○ 8 (8) ____

Q6 List some factors that are/can be promoted to conserve the forest and/or the environment while improving livelihoods of the residents living adjacent to the forests.

- ○ 1. (1) ____
- ○ 2. (2) ____
- ○ 3. (3) ____
- ○ 4. (4) ____
- ○ 5. (5) ____
- ○ 6. (6) ____
- ○ 7 (7) ____
- ○ 8 (8) ____

Approvals for Field Research

REPUBLIC OF KENYA

NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Ref No: 656455

Date of Issue: 09/May/2022

RESEARCH LICENSE

This is to Certify that Mr.. Donald Akanga of Michigan State University, has been licensed to conduct research in Bomet, Kericho, Nakuru, Narok on the topic: Interconnections between land cover change, climate variability, and livelihoods in the Greater Mau Forest Complex, Kenya for the period ending : 09/May/2023.

License No: **NACOSTI/P/22/17366**

656455

Applicant Identification Number

Director General

NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Verification QR Code

NOTE: This is a computer generated License. To verify the authenticity of this document, Scan the QR Code using QR scanner application.

Figure 22. NACOSTI research license.

REPUBLIC OF KENYA

MINISTRY OF EDUCATION
State Department of Early Learning and Basic Education

Email:cdekerichocounty@gmail.com
When Replying Please Quote:

County Education Office
P.O BOX 149
KERICHO

Ref: KER/C/ED/RC/VOIII/2/20

6th June 2022

TO WHOM IT MAY CONCERN.

RE: RESEARCH AUTHORIZATION: MR. DONALD AKANGA NO.NACOSTI/P/22/17366.

I refer to the Director General NACOSTI Letter Ref: No. 656455 dated 9th May 2022 granting the above student authority to proceed for field work. His area of study is titled: ***"INTERCONNECTIONS BETWEEN LAND COVER CHANGE, CLIMATE, VARIABILITY, AND LIVELIHOODS IN THE GREATER MAU FOREST COMPLEX, KENYA."*** for the period ending 9TH May 2023.

This is to request your office to accord him the necessary support during the data collection process.

Thank you.

COUNTY DIRECTOR OF EDUCATION
KERICHO COUNTY
06 JUN 2022
P.O. BOX 149 – 20200,
KERICHO.

ROSE K SAGARA
COUNTY DIRECTOR OF EDUCATION
KERICHO.

Figure 23. County Director of Education research authorization, Kericho.

THE PRESIDENCY
MINISTRY OF INTERIOR AND CO-ORDINATION OF NATIONAL GOVERNMENT

Telegrams: ....
Telephone: Kericho 20132
When replying please quote
kerichocc@yahoo.com

COUNTY COMMISSIONER
KERICHO COUNTY
P.O. BOX 19
KERICHO

REF: MISC.19 VOL.VIII (30)

6th June, 2022

Donald Akanga
Michigan State University

RE: RESEARCH AUTHORIZATION

I am pleased to inform you that you are authorized to undertake research vide letter Ref. No. NASCOTI/P/22/17366 dated 9th May, 2022 on "***Interconnections between land cover change, climate variability, and livelihoods in the Greater Mau Forest Complex, Kericho County, Kenya"*** for a period ending 9th May, 2023.

EDNA J.CHESARO
FOR: COUNTY COMMISSIONER
KERICHO COUNTY

Figure 24. County Commissioner research authorization, Kericho.

THE PRESIDENCY

MINISTRY OF INTERIOR AND COORDINATION OF NATIONAL GOVERNMENT

Telegrams: "DISTRICTER", Bomet
Telephone: (052) 22004/22077 Fax 052-22490
When replying please quote

COUNTY COMMISSIONER
P.O BOX 71- 20400
BOMET

REF: EDU.12.1 VOL. IV/ (6)

27TH MAY, 2022

The Deputy County Commissioners
Bomet Central Sub County,
Bomet East Sub County,
Sotik Sub County,
Konoin Sub County,
Chepalungu Sub County

RE: RESEARCH AUTHORIZATION – DONALD AKANGA OF MICHIGAN STATE UNIVERSITY

The above named person has been authorized to conduct research on **"Interconnections between land cover change, climate variability, and livelihoods in the Greater Mau Forest Complex, Kenya** by the National Commission for Science, Technology and Innovation vide their letter **Ref. No. 656455** dated **9th May, 2022** for the period ending **9th May, 2023.**

Any assistance accorded would be appreciated.

Rehema Kiteto
For County Commissioner
BOMET

COUNTY COMMISSIONER
BOMET COUNTY
27 MAY 2022
P. O. Box 71-20400, BOMET

Figure 25. County Commissioner research authorization, Bomet.

REPUBLIC OF KENYA
MINISTRY OF EDUCATION
STATE DEPARTMENT OF EARLY LEARNING AND BASIC EDUCATION

Telegrams: "ELIMU",
Telephone: 052-22265
When replying please quote
email:cdebometcounty@gmail.com
Ref/CDE/BMT/ED/AUTH/74/VOL.II/27

COUNTY EDUCATION OFFICE,
BOMET COUNTY,
P.O. BOX 3-20400,
BOMET.

27th May, 2022

Mr. Donald Akanga
Michigan State University

TO WHOM IT MAY CONCERN

RE: RESEARCH AUTHORIZATION.

Reference is made to the letter dated 9th May, 2022 Ref: No. NACOSTI P/22/17366/656455 from NACOSTI requiring the above-mentioned person to conduct research on **"Interconnections between land cover change, climate variability, and livelihoods in the Greater Mau Forest Complex, Kenya,"** for the period ending 9th May, 2023.

The purpose of this letter is to inform you that authority has been granted for him to carry out the study in Bomet County, including learning Institutions among others.

Kindly accord him the assistance he requires to carry out the exercise.

COUNTY DIRECTOR OF EDUCATION
BOMET
P.O. Box 3 - 20400, BOMET
27-5-2022

APOLLO APUKO
COUNTY DIRECTOR OF EDUCATION
BOMET COUNTY.

Copy

CEO- NACOSTI

SYSTEM CERTIFICATION ISO 9001 SGS

Figure 26. County Director of Education research authorization, Bomet.

OFFICE OF THE PRESIDENT
Ministry of Interior and Coordination of National Government

Email: ccnakurucounty@yahoo.com
ccnakurucounty@gmail.com

COUNTY COMMISSIONER
NAKURU COUNTY
P. O. BOX 81
NAKURU

When replying please quote:

Ref. No. CC. SR. EDU 12/1/2/VOL.VI/94

9th June, 2022

DEPUTY COUNTY COMMISSIONERS
MOLO
NJORO
KURESOI NORTH
KURESOI SOUTH

RE: RESEARCH AUTHORIZATION – DONALD AKANGA - ID. NO - 27281948

The above named who is a PhD candidate in the Department of Geography, Environment and Spatial Sciences at Michigan State University has been authorized to carry out research on **Interconnections between land cover change, climate variability and livelihoods in the Greater Mau Forest Complex, Kenya** in Nakuru County, for the period ending: 9th May, **2023.** NACOSTI License No. is NACOSTI/P/22/17366.

Please accord him all the necessary support to facilitate the success of his research.

MWANGI NYAGA
FOR: COUNTY COMMISSIONER
NAKURU COUNTY

Figure 27. County Commissioner research authorization, Nakuru.

MINISTRY OF EDUCATION

STATE DEPARTMENT OF EARLY LEARNING AND BASIC EDUCATION

Telegrams: "EDUCATION",
Telephone: 051-2216917
Fax: 051-2217308
Email: cdenakurucounty@gmail.com
When replying please quote

COUNTY DIRECTOR OF EDUCATION
NAKURU COUNTY
P. O. BOX 259,
NAKURU.

Ref. NO. CDE/NKU/GEN/4/1/21/VOL.VII/22

8th June, 2022

TO WHOM IT MAY CONCERN

RE: RESEARCH AUTHORIZATION – DONALD AKANGA NACOSTI/P/22/17366

Reference is made to the above-mentioned permit dated 9th May, 2022.

Authority is hereby granted to the above-named individual to carry out research on: **"Interconnections between land cover change climate variability and livelihoods in the greater Maut Forest complex in Nakuru County Kenya"** for the period ending **09/05/ 2023.**

Kindly accord him necessary assistance.

COUNTY DIRECTOR OF EDUCATION NAKURU COUNTY P. O. Box 259 NAKURU

RUTH KAMAU
FOR COUNTY DIRECTOR OF EDUCATION
NAKURU

Copy to:

- Michigan State University

Figure 28. County Director of Education research authorization, Nakuru.

REPUBLIC OF KENYA
MINISTRY OF EDUCATION
State Department of Early Learning and Basic Education

FAX NO. 050-22391
When replying please quote;

Ref. CDE/NRK/RES/VOL1/268

COUNTY DIRECTOR OF EDUCATION
NAROK COUNTY
P.O BOX 18
NAROK

DATE: 23RD MAY, 2022

TO WHOM IT MAY CONCERN

RE: RESEARCH AUTHORIZATION – MR. DONALD AKANGA.

The above named is of Student of Michigan State University.
He has been authorized to carry out research in Narok on "***Interconnections between land cover change, climate variability, and livelihoods" in the Greater Mau Forest Complex, Kenya*** *for the period ending* **09/05/2023.**

Please accord him the necessary assistance.

COUNTY DIRECTOR
OF EDUCATION
NAROK

JANE W. NJOGU
COUNTY DIRECTOR OF EDUCATION
NAROK

C.C
- County Commissioner – Narok
- Mr. Donald Akanga

SGS

Figure 29. County Director of Education research authorization, Narok.

OFFICE OF THE PRESIDENT
MINISTRY OF INTERIOR
AND
COORDINATION OF NATIONAL GOVERNMENT

Telegram: **"COUNTY"**, Narok County
Telephone: Narok [050] 22305/22435
Fax: [050] 22588/22305/22127
If calling or telephoning ask for the undersigned.
When replying please quote;
RE: SR.ADM.15/6/VOL.II/106

County Commissioner
Narok County
P O Box 4-20500
Narok

24th May, 2022

Deputy County Commissioners
Narok North
Narok South

RE: RESEARCH AUTHORIZATION – MR. DONALD AKANGA

Mr. Donald Akanga of Michigan State University has been authorized to carry out research on "**Interconnections between land cover change, climate variability , and livehoods"in greater Mau Forest Complex , Kenya** for the period ending 9th May, 2023.

Please accord him necessary support.

INIMAH GARY
FOR: COUNTY COMMISSIONER
NAROK COUNTY

CC
Mr. Donald Akanga

Figure 30. County Commissioner research authorization, Narok.