Analysis of vegetation fragmentation and impacts using remote sensing techniques in the Eastern Arc Mountains of Tanzania

Mercy Mwanikah Ojoyi

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Abstract

The Eastern Arc Mountains of Tanzania forms part of the Eastern Afromontane Biodiversity Hotspots, listed among the global World Wide Fund for Nature's (WWF) priority ecoregions. However, the region is threatened by fragmentation and habitat modification resulting from competing forms of land uses, which is in turn threatening biodiversity conservation, planning and management efforts. To determine vulnerability that can inform long-term conservation and management of the biodiversity hotspots, an in-depth understanding of the qualitative and quantitative nature of ecosystems is a pre-requisite. The overall goal of this study was to quantify fragmentation, investigate its impacts on tree species diversity, abundance and biomass and to identify management interventions in the Eastern Arc Mountains of Tanzania. Using ecological field based measurements and a series of LANDSAT and RapidEye satellite imagery, fragstats metrics showed dynamic fragmentation patterns at both spatial and temporal scales. Furthermore, species diversity was predicted better with customized environmental variables using the Generic Algorithm for Rule-Set Prediction (GARP) model, which recorded an Area under Curve (AUC) of 0.89. In addition, Poisson regression results showed different responses by individual tree species to patch area dynamics, habitat status and soil nitrogen. Partial Least Squares and Random Forest models were used to determine above ground biomass prediction based on a combination of edaphic variables and vegetation indices. Total biomass estimations decreased from 1162 ton ha-^{1} in 1980 to 285.38 ton ha-^{1} in 2012. As a reference point in formulation of policy insights based on strong scientific and empirical knowledge, socio-economic factors influencing vulnerability of ecosystems and management interventions were examined using remotely sensed and empirical data from 335 households. The multiple logistic regression model indicated habitat fragmentation and forest burning as key conservation threats while low income

level (54.62%) and limited knowledge on environmental conservation (18.51%) were identified as major catalysts to ecosystem vulnerability. The study identified livelihood diversification, effective institutional frameworks and afforestation programmes as major intervention measures. The overall study shows the effectiveness of remote sensing techniques in ecological studies and how results can be used to inform decisions for addressing complex ecological challenges in the tropics.

Preface

This study was carried out in the School of Agricultural, Earth and Environmental Sciences, University of KwaZulu-Natal, Pietermaritzburg, South Africa, from June 2011 to October 2014, under the supervision of Professor Onisimo Mutanga and Dr. John Odindi.

I declare that the work reported in this thesis has never been submitted in any form to any other institution. This work represents my original work except where due acknowledgments are made.

Mercy Mwanikah Ojoyi Signed: ________________________ Date:_________________

As the candidate's supervisors, certify the above statement and have approved this thesis for submission.

1. Prof. Onisimo Mutanga Signed:__________________ Date: _________________

2. Dr. John Odindi Signed:___________________ Date: _________________

Declaration 1 – Plagiarism

I, **Mercy Mwanikah Ojoyi**, declare that:

1. The research reported in this thesis, except where otherwise indicated, is my original research.

2. This thesis has not been submitted for any degree or examination at any other institution.

3. This thesis does not contain other persons data, pictures, graphs or other information, unless specifically acknowledged as being sourced from other persons.

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Declaration 2 – Publications and manuscripts

1. Ojoyi, M.M., Mutanga, O., Odindi, J., Ayenkulu, E., Abdel-Rahman, E.M. (2015). The effect of forest fragmentation on tree species abundance and diversity in the Eastern Arc Mountains of Tanzania. *Applied Ecology and Environmental Research*, 13, 307-324.

2. Ojoyi M. M, Mutanga O., Odindi J., Abdel-Rahman E. (2014). Analyzing fragmentation in vulnerable biodiversity hotspots using remote sensing and frag stats in Tanzania. *Landscape Research* (under revision).

3. Ojoyi M. M, Mutanga O., Odindi J., Abdel-Rahman E., (2014). Ecosystem disturbance: assessing impacts on above ground biomass & spatial structure using Rapid eye imagery. *Geocarto International* (under revision).

4. Ojoyi M. M, Mutanga O., Odindi J., Antwi-Agyei P., Abdel-Rahman E., (2014). Managing fragile landscapes: empirical insights from Tanzania. *Journal of Nature Conservation* (under review).

Dedication

To family ~ for all your extraordinary encouragement, support and prayers.

In deed family is a haven in a heartless world ~ Christopher Lasch

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CHAPTER ONE

General Introduction

Human encroachment in Nguru Montane forest

1.1 General overview

Tropical forests are widely recognized for their important role in the conservation of flora and fauna (Gentry, 1992). Their reputation lies with their rich predominant massive woody plants, and high diversity extending over large scales (Geist and Lambin, 2002; Gentry, 1992). They support large carbon stores worldwide (Jiménez *et al*., 2014; Shirima *et al*., 2011; Swetnam *et al*., 2011). Unfortunately, great potential vested in these forests is not well explored, with less focus embedded on biodiversity conservation and related challenges (Green *et al*., 2013a; Hall *et al*., 2009).

Tropical forests experience climate similar to Mediterranean climate, stable and conducive for farming and other subsistence livelihood resources (Geist and Lambin, 2002; Tabarelli *et al*., 2005). They are therefore characterized by an exponential increase in population, coupled with the intensification of economic activities resulting in huge volumes of forests destroyed through grazing, development of settlement, and agriculture (Holmberg, 2008). This leads to ramifying impacts such as habitat destruction, land and soil degradation, an increase in species losses and extinctions (Cushman, 2006; McGarigal and Cushman, 2002) and forest fragmentation (Ojoyi *et al*., 2015).

Fragmentation in the tropics is an ongoing debate in conservation biology and ecological research (Lindenmayer and Fischer, 2006; Lung and Schaab, 2006; Pardini *et al*., 2005; Reid *et al*., 2004; Tabarelli *et al*., 1999; Wiens, 1995). It is the most important threat to biodiversity conservation (Laurance and Cochrane, 2001). Not only does it affect habitat structure, but also makes it a challenge for species survival (Platts *et al*., 2008). It increases risks associated with changes in demography and genetic events (Cushman, 2006). It has been linked to modification of landscapes with conservation competing invariably with other forms of land use such as farming, settlement and infrastructural development.

The fragmentation concept has been defined in various different contexts. In this study, ecological definitions have been adopted. Forman and Collinge, (1997) describe the fragmentation concept as a process by which the quality of a habitat declines through dis-integration into smaller and isolated patches. Franklin *et al*., (2002) refers to the term fragmentation as a form of discontinuity which results from a set of mechanisms in the spatial distribution of resources and conditions present in an area, at a certain scale distorting the occupancy, reproduction and species existence. It refers to the spatial patchiness of a habitat or the process that leads to such patterns (Wiens, 1995; Wiens, 2000). Commonly, it is driven by dynamic relationships between increases in human-related needs on the scarce land resource, creating a mosaic of both fragmented and natural environment (Fahrig, 2003; McGarigal, 2002; Wiens, 1995), which occurs when intact continuous strands of ecosystems are divided due to underlying human factors (Wade *et al*., 2003). Generally, fragmentation is a universal form of habitat modification closely linked to growth in human population, urban sprawl, farming, and settlements, which interfere with biota composition and ecological procedures (Fahrig, 2003; Honnay *et al*., 2005; Tabarelli *et al*., 1999; Turner, 1996). It also alters the biophysical structure of ecosystems, including moisture balance, temperature regimes and net solar radiation reaching the ecosystem (Saunders *et al*., 1991).

To date, the subject on landscape-human interactions, species distribution and interactions is a subject not well understood in the tropics (Turner *et al*., 2003). This information is valuable for conservation experts in the tropics for optimal resource allocation (Gould, 2000; Kerr and Ostrovsky, 2003). Development of space-based systems presents unprecedented opportunities relevant for use in monitoring, planning and other biodiversity conservation activities (Shirk *et al*., 2014). Thereto, a research study was developed with a goal to address this quest. The study aimed at addressing the question on patterns of fragmentation, impacts on vegetation and harnessing of factors that strongly affect stability of ecosystems. This dissertation is contextualized in the Eastern Arc Mountains, a global biodiversity hotspot subjected to different conservation challenges in East Africa. The thesis first introduces the global hotspot, focusing on exploring the effectiveness of remote sensing as a tool for determining the frequency and impacts of fragmentation on vegetation. The potential of remote sensing is outlined in each of the analytical chapters presented at the end of the chapter. The discussion is limited to the case studies used where more knowledge was obtained from research-oriented experiences.

1.2 The potential of remote sensing in conservation of the Eastern Arc Mountains

The Eastern Arc Mountain blocks support important ecosystem functions, contribute to the global terrestrial carbon storage (Swetnam *et al*., 2011) and account for a high number of the world's endemic species (Burgess *et al*., 2007a). They remain prone to a series of anthropogenic disturbances (Green *et al*., 2013b;Swetnam *et al*., 2011). Forest structures have been altered (Newmark, 1998) with more endemic species subjected to extinction (Lovett, 1999). Previous studies associated occurrence of historical isolation processes to the instability of habitat conditions in the Eastern Arc Mountains (Jetz *et al*., 2004). For instance, over time, the scattered distribution of forest blocks exposes intact areas to fragmentation (Burgess *et al*., 2007b) while the capacity of endemic species is often unable to withstand growing external human pressure (Burgess *et al*., 2007a; Green *et al*., 2013b; Hall *et al*., 2009; Newmark, 1998).

The scarcity of knowledge on cost-effective methods in the management of ecological challenges necessitates an exploration of other reliable techniques. Space-based platforms serve as a key option in the development of viable options in tropical forest conservation (Horning *et al*., 2010). With advances in sensor resolutions, ecologists can easily extract important details on the characteristics of natural resources of interest (Turner *et al*., 2003). Remotely sensed datasets offer a viable option for measurement and identification of important environmental information in large areas synoptically (Pelkey *et al*., 2000;Wiens *et al*., 2009). A combination of satellite imagery, aerial photographs and ground-based data is a good measure of depicting changes, estimating the quantity and quality of features, and their distribution at the landscape scale. Remotely sensed datasets are also valuable in maximizing multi-temporal monitoring efforts (Wiens *et al*., 2009). Aerial photographs, satellite imagery and ground truth data can be useful in resource inventory and recognition of vegetation patterns and is an effective and reliable source of information for risk and threat estimation (Cunningham, 2006; Cunningham *et al*., 2009; Millington *et al*., 2003). Generally, remotely sensed datasets, unlike field based techniques, are valuable in monitoring areas that would otherwise be expensive and time consuming (Wiens *et al*., 2009).

Remotely sensed data at different spectral and spatial resolution provide detailed information at both small and large scales (Rindfuss and Stern, 1998). Due to complexity of vegetation and forest structure in the Eastern Arc Mountains, a relatively good resolution dataset is needed to effectively determine conservation priorities (Platts, 2012). It could be considered as a more reliable approach in understanding closely related subjects such as habitat modification, habitat fragmentation and loss, which have been placed under one umbrella for years (Lindenmayer and Fischer, 2006). Moreover, the utility of remote sensing technology has the capacity to demonstrate species responses to habitat interactions with changing environmental needs. Mounting evidence shows how species models have been used to map species distribution and possible frequency of occurrence (Donoghue *et al*., 2007; Gould, 2000; Kerr and Ostrovsky, 2003; Thenkabail *et al*., 2012). Unfortunately, this is a subject not well explored in the Eastern Arc Mountains (Platts, 2012). The region still demands a quest for better technological approaches in managing complex conservation challenges.

1.3 Study goal and objectives

The overall goal of this study was to investigate fragmentation as a conservation challenge in the tropics using space-based technology. The use of remote sensing was instrumental in the performance of heuristic roles of assessing the spatial and temporal vegetation patterns, impacts on species, and above ground biomass. A socio-ecological model was developed to establish driving forces and intervention measures. The following objectives were investigated:

1. To analyze vegetation fragmentation patterns using remote sensing and fragstats
2. To investigate impacts of fragmentation on species abundance, diversity and biomass
3. To assess application of remote sensing techniques in biomass prediction in fragmenting landscapes within the Eastern Arc Mountains
4. To establish potential social-ecological elements contributing to increased vulnerability of ecosystems and viable long term intervention measures

1.4 Research scope of the study

A conceptual framework was built with a goal to establish relationships between fragmentation and impacts on vegetation in the Eastern Arc Mountains. The study aimed at addressing the question on the status of fragmentation trends, impacts and harnessing of factors that strongly affected stability of ecosystems (Figure 1.1). The framework used was instrumental in problem identification, conservation linked complexities and potential solutions in the case studies applied.

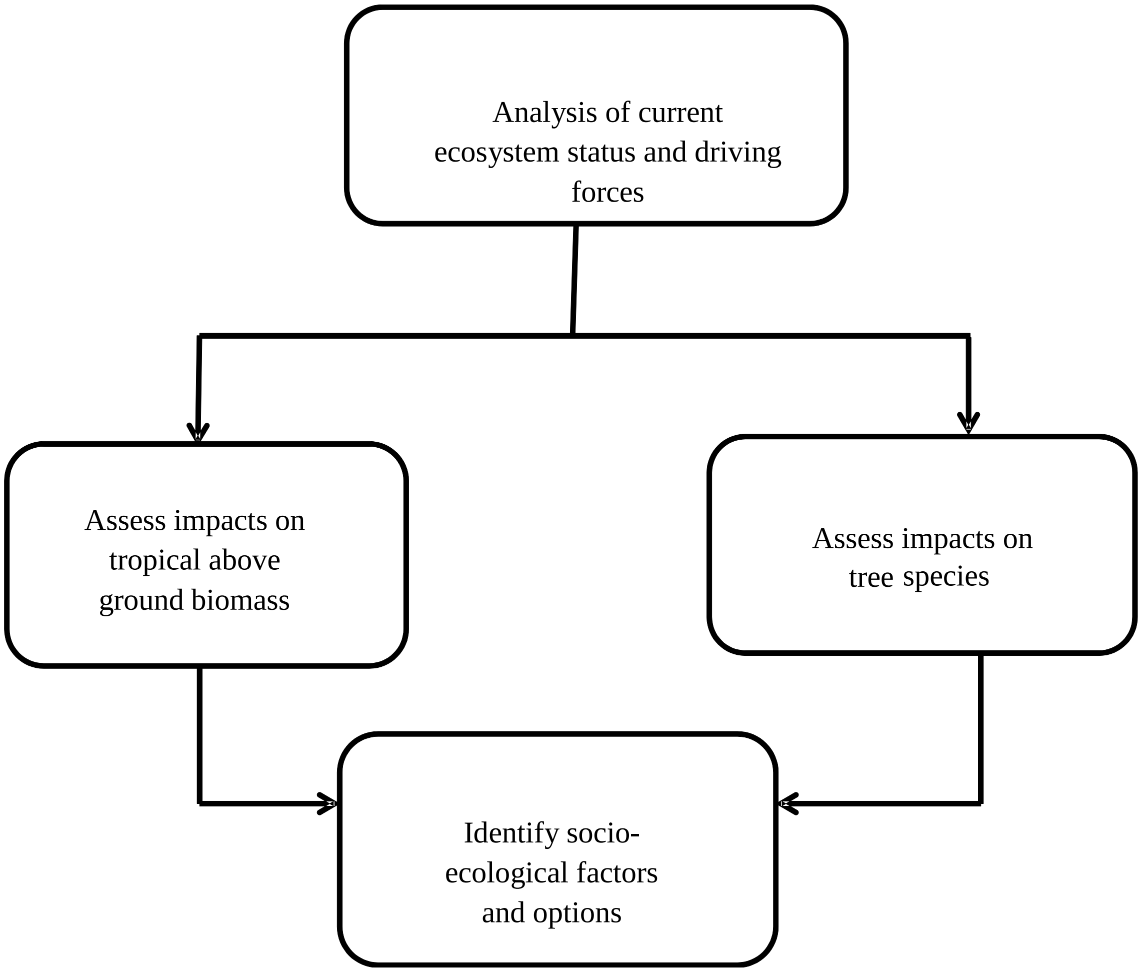


Figure 1.1: The main conceptual framework

1.5. Study area

1.5.1 Location and climate

The Eastern Arc Mountains consist of a chain of thirteen forest blocks that stretch from Taita Hills in Southern Kenya to the Udzungwa Mountains in Southern Tanzania (Burgess *et al*., 2007a; Newmark, 2002). They are located 3˚ 20' to 8˚ 45'S latitude and 35˚ 37' to 38˚ 48'E longitude (Newmark, 2002). The elevation ranges between 121 and 2636 meters above sea level (Platts, 2012). These mountain blocks include: Taita Hills, North and South Pare, West and East Usambara, North and South Nguru, Ukaguru, Uluguru, Rubeho, and Udzungwa (Figure 1.2).

Climatic patterns are influenced by the Indian Ocean (Lovett and Ihlenfeldt, 1990). An average annual temperature of 18°C and rainfall ranging from 1700 to 2000 mm per year is experienced (Mumbi *et al*., 2008). The Ukaguru, Rubeho and Udzungwa mountain blocks experience lengthy dry spells with less precipitation (Platts, 2012).

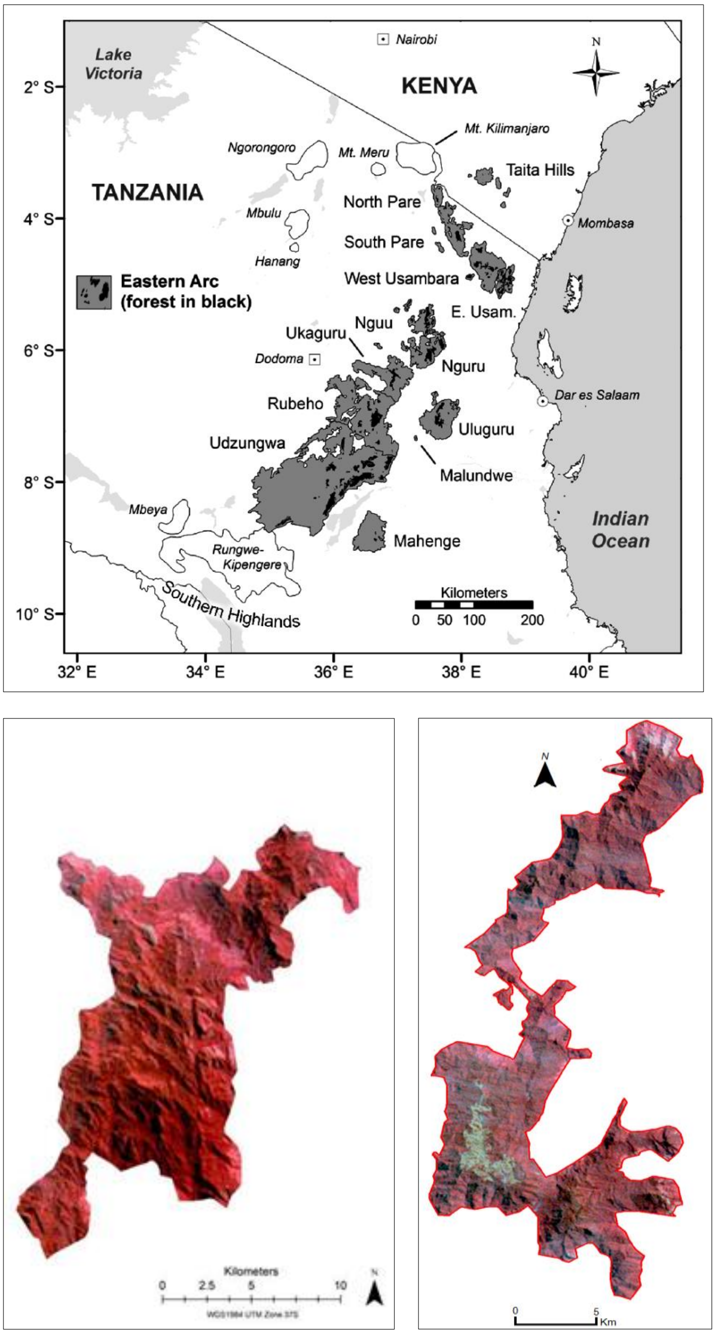
1.5.2 Biological significance

As aforementioned, the Eastern Arc Mountains form part of the Eastern Afromontane Biodiversity Hotspot, and is among the leading World Wide Fund's (WWF's) 200 priority ecoregions (Burgess *et al*., 2007a; Platts, 2012). The thirteen forest blocks cover approximately 5400 km^2 (Mumbi *et al*., 2008). These forest blocks were categorized in 1988 as leading regions of global conservation importance (Lovett and Ihlenfeldt, 1990). They host the world's endemic flora and fauna based on the International Union for Conservation of Nature and Natural Resources (IUCN) red list criteria (Burgess *et al*., 2007a; Hall *et al*., 2009; Newmark, 1998). Approximately eight-hundred tree species found in the region are listed as endemic with others threatened to near extinction (Hall, 2009; Newmark, 1998). These blocks remain vulnerable to dynamic habitat patterns (Shirk *et al*., 2014), growth in rural population and subsistence farmlands (Burgess *et al*., 2007b).

1.5.3 Study site selection

Selection of case studies was based on a detailed synthesis of literature review conducted in the region, which showed a dearth in knowledge on challenges of habitat modification and fragmentation (Green *et al*., 2013b; Newmark, 1998; Platts, 2012; Shirk *et al*., 2014). Case studies were conducted in the Nguru North forest block and the Uluguru forest block including outlying hills such as Mindu, Nguru ya Ndege, Mkungwe, Dindili and Kitulangalo. Uluguru forest was selected as an important block in Morogoro region.

Previous studies showed a decline in forest cover in the Uluguru forest block ranging from 300 km^2 in 1955 to 220 km^2 in the year 2000 (Burgess *et al*., 2002). This forest block is regarded as vulnerable to fragmentation, influencing biodiversity conservation in the region (Burgess *et al*., 2007a; Burgess *et al*., 2002). Nguru forest block was selected as a forest fragment subjected to intense human pressure and suffers from data scarcity due to its remoteness and difficulties in accessibility (Burgess *et al*., 2007a; Platts, 2012).



Nguru south forest block

Uluguru forest block

Figure 1.2: Location of select study sites in Tanzania based on LANDSAT ETM; the Eastern Arc Mountain blocks map modified from Platts *et al*., 2011)

1.6 Thesis structure

The dissertation is structured in form of scientific articles, which have been published or under review. Each of the chapters is presented independently in accordance with journal publications. There is however some overlap in introductory sections.

Chapter 1 – General Introduction

Growth in space-based technology is regarded as an important development trajectory in solving complex ecological challenges. The introductory chapter shows the need to integrate space-based technology in managing conservation challenges in the Eastern Arc Mountains. The chapter provides some important information that could guide scientists who wish to pursue space-based technology as an important source of information in understanding conservation challenges and informing decisions and decision making procedures. The chapter provides a justification of the study, and its importance. In addition, a detailed look at the study objectives; methods used and research questions is provided.

Chapter 2 – Analyzing fragmentation in vulnerable biodiversity hotspots using remote sensing and frag stats in Tanzania

Generally, vegetation fragmentation in the Eastern Arc Mountains in Tanzania has not kept pace with the on-going patterns at the spatial and temporal scales. Specifically, how individual habitats respond to spatial heterogeneity across diverse fragmenting ecosystems remains largely unexplored. Three sets of satellite data and fragstats metrics were used to investigate changes in the biophysical landscape characteristics. Spatial and temporal fragmentation patterns were modelled. Moreover, lessons on effective conservation and management of the forests in Tanzania were articulated.

Chapter 3 – Impacts of fragmentation on the species abundance and diversity

Despite the many ecological studies conducted in the Eastern Arc Mountains, this chapter features one of the few studies that utilize remote sensing technology and other biophysical variables, including soil factors to model distribution of species diversity in threatened and less threatened areas. Species models generally provide important information that shows distribution of species frequency of occurrence. The chapter investigates responses of species abundance and diversity to fragmentation. Specifically, the chapter explores richness and species distribution in the study area using the Generic Algorithm for Rule-Set Prediction (GARP) algorithm. Further investigations are conducted on impacts of spatial attributes on individual species based on generalized linear models to determine sensitivity of individual species to fragmentation.

Chapter 4 – Predicting biomass in fragmenting landscapes in the Eastern Arc Mountains using remote sensing data

In order to minimize uncertainties in the degree of disturbance and to enhance planning and monitoring efforts, regular assessments of biomass is essential. Quantifying structural aspects of ecosystems is vital in describing the qualitative and quantitative nature and state of ecosystems. Above ground biomass can be useful in highlighting the state of these ecosystems. In this chapter, the potential of remotely sensed data and topo-edaphic factors are explored. High resolution RapidEye satellite data and field measurements are utilized. In addition, topo-edaphic factors are integrated as they influence the spatial distribution of biomass.

Chapter 5 – Bridging science and policy: an assessment of ecosystem vulnerability and management scenarios in Tanzania

In most case scenarios, scientific concepts are known to operate from knowledge creation angle while policy development has been associated with a civil obligation (Hoppe, 2005).

This chapter shows the need for researchers to engage proactively with policy experts. This chapter attempts to bridge the space based knowledge from the scientific perspective “science view” with socio-economic model and community responses with a strong basis on the “civic perspective”. Hence merging of the two fosters the relationship between the two diverse domains. Ecosystem vulnerability is assessed based on changes in cover, while potential drivers to habitat loss are analyzed using the logistic regression on data from 335 respondents from 11 villages from Nguru, Uluguru and surrounding hills. Socio-ecological factors driving ecosystem vulnerability and policy implications of the research are discussed.

Chapter 6 – Vegetation fragmentation and impacts using multispectral data in the Eastern Arc Mountains of Tanzania: a synthesis

The overall contribution of the thesis goal and objectives met is described in this chapter. An in-depth synthesis of the work and its contribution to conservation and management of the Eastern Arc Mountains is elucidated. This chapter shows the effectiveness of applying remotely-sensed techniques in ecological studies from diverse analytical chapters. In addition, the importance of integrating relatively good resolution data in conservation and management of the complex forest blocks in the Eastern Arc Mountains is discussed. Relevance to policy and management is highlighted. Research reflections and future recommendations in the management of the Eastern Arc Mountains are presented.

CHAPTER TWO

Analysing fragmentation in vulnerable hotspots using remote sensing and frag stats

Human-dominated landscape in the Uluguru montane forest

This chapter is based on:

Ojoyi M. M, Mutanga O., Odindi J., Abdel-Rahman E. (2014). Analyzing fragmentation in vulnerable biodiversity hotspots using remote sensing and frag stats in Tanzania. *Landscape research* (under revision).

Presented at **International Conservation for Conservation Biology** 22-7-2014 Baltimore, USA.

Abstract

Habitat fragmentation is a threat to conservation of biodiversity hotspots in Morogoro region, Tanzania. Despite this threat, research on fragmentation has not kept pace with the on-going fragmentation along spatial and temporal domains, particularly how individual habitats respond to the spatial heterogeneity. This study sought to model spatial and temporal fragmentation patterns. Satellite data were used to characterize the biophysical landscape characteristics and fragstats metrics were used to quantify the magnitude of fragmentation in the study area. Results show an increase in the frequency of patches by 391 and 412 in woodland and dense forest, respectively, between 1995 and 2012. Patch number in grasslands increased by 1039 between 1975 and 1995. In less dense forest, the number increased by 12 between 1975 and 2012. Games-Howell results showed a high significance in the fragmentation trend ($p \leq 0.05$). The paper underscores the need to incorporate management plans in protecting fragile habitats.

Key words: habitat, fragmentation, fragstats, remote sensing, Tanzania

2.1 Introduction

Habitat fragmentation is a phenomenon of great concern globally (McGarigal and Cushman, 2002; Nagendra *et al.*, 2004). It refers to habitat breakages or the degree of patchiness of a habitat (Fahrig, 2001; Fahrig, 2003; McGarigal and Cushman, 2002; Wiens, 1995) mainly as a result of human activities (Neel *et al.*, 2004). Habitat fragmentation interferes with the structural configuration of natural ecosystems and their ecological functioning (Abdullah and Nakagoshi, 2007; Echeverria *et al.*, 2006; Echeverria *et al.*, 2008; Iida and Nakashizuka, 1995) such as metapopulations. Spatially isolated habitat fragments in a landscape could lead to a metapopulation structure (Hanski, 1998), leading to relatively smaller and isolated patches and consequent increase in extinction rate and less colonization (Opdam, 1991). Habitat fragmentation also affects biodiversity, particularly in areas where the largest fragmentation is prevalent (Cushman *et al.*, 2012; Millington *et al.*, 2003) through reduction of the total habitat size, threatening species survival (Murcia, 1995). It has long term impacts on species numbers (Aguilar *et al.*, 2008; Cushman, 2006), species abundance (Debinski and Holt, 2000; Fahrig, 2003; Jha *et al.*, 2005; Jorge and Garcia, 1997; Vogelmann, 1995) as well as exposing natural ecosystems to external risks, parasitism and dominance of invasive species (Wiens, 1995).

Habitat fragmentation is an explicit challenge to conservation in the tropics (Pelkey *et al.*, 2000). It is considered a threat to species endemism (Adams *et al.*, 2003; Bjorndalen, 1992; Burgess *et al.*, 2002; Burgess *et al.*, 2001; Erik Bjørndalen, 1992). In Africa, approximately 310,000 hectares of forest is converted annually to agriculture, while 200,000 hectares is converted into woodlands annually, leading to conversion of intact areas into patchy habitats (Achard *et al.*, 2002). Fragmentation acts synergistically with other factors such as solar radiation effects, leading to dominance of other invasive species.

Ecosystems in Morogoro region, Tanzania contribute to the world's climate regulation through large carbon stores (Burgess *et al*., 2007; Swetnam *et al*., 2011). These ecosystems are listed among the most threatened biodiversity hotspots globally with a significant effect on species extinction (Brooks *et al*., 2006; Burgess *et al*., 2007; Myers *et al*., 2000; Swetnam *et al*., 2011). An increase in the anthropogenic disturbances pose significant threats to their long term conservation (Hall *et al*., 2009; Hall, 2009; Newmark, 1998). The region is estimated to have lost forest cover between 1955 and 2000, from 300 km^2 to 220 km^2 respectively, causing adverse impacts on species survival (Burgess *et al*., 2007). This finding was recently confirmed by Ojoyi *et al*. (2015) who established adverse impacts of fragmentation on species abundance and diversity in the Uluguru Mountains in Morogoro region.

Despite global value of natural forest ecosystems in the Eastern Arc Mountains, very little research has been conducted with focus on the landscape's spatial heterogeneity (Newmark, 1998). In addition, there is limited knowledge on spatial effects on the magnitude and extent of fragmentation of these ecosystems (Burgess *et al*., 2002; Burgess *et al*., 2001; Luoga *et al*., 2000; Yanda and Shishira, 1999). Furthermore, mechanisms by which natural habitats in the Eastern Arc Mountains respond to the spatial heterogeneity across diverse fragmenting ecosystems remain largely unexplored (Swetnam *et al*., 2011; Yanda and Shishira, 1999). Though single habitats may differ in their degree of response to fragmentation (McGarigal, 2006; Neel *et al*., 2004), the robustness of fragmentation is expected to vary (Fahrig, 2003; Echeverría *et al*., 2007). For instance, what could be termed as fragmentation in homogeneous landscapes may be interpreted differently in a heterogeneous landscape (Fischer and Lindenmayer, 2007; Wiens, 2000). This could be due to differences in the habitat's structural complexity and biological processes (Murcia, 1995).

This study was therefore conducted with an overarching aim of assessing the spatial extent and magnitude of fragmentation across dominant heterogeneous landscapes within Morogoro region. Remote sensing was applied due to its great ability to quantify spatio-temporal patterns in diverse landscapes (Nagendra *et al*., 2004). The present study sought to specifically; (1) determine the magnitude of change in each of the individual habitats; (2) assess the temporal and spatial extent of fragmentation in major habitats over years; and (3) identify management implications in the region. This study has a strong relevance to the region's ecology. It is important to note that, an explicit assessment of spatial changes over varying time spans has the ability to provide an important platform for detailed landscape change assessments and identification of potential drivers (Lung and Schaab, 2006; Southworth *et al*., 2002). It is also considered a prerequisite for knowledge generation, essential in future monitoring and management of fragmenting landscapes in Tanzania (Fjeldså, 1999; Hall *et al*., 2009; Swetnam *et al*., 2011). The study provides an important basis for a holistic thinking on the need to protect the rapidly fragmenting landscapes.

2.2 Study area

Most rich biodiversity hotspots in Tanzania are located in the Eastern Arc Mountains (Burgess *et al*., 2007; Hall *et al*., 2009; Hall, 2009; Myers *et al*., 2000; Newmark, 1998; Olson and Dinerstein, 1998). The study area forms part of the Eastern Arc Mountains. Specifically, part of ecosystems dominated by four dominant habitat types along adjoining tracts of natural forest ecosystems were selected in Morogoro region (Figure 2.1). The study site selection was based on previous ecological studies that attributed species losses to fragmentation (Burgess *et al*., 2002; Burgess *et al*., 2001; Hall, 2009; Luoga *et al*., 2000; Yanda and Shishira, 1999). The four main habitats considered for the study were woodland, dense forest, less dense forest and grassland. Dense forest, grassland and less dense forest form part of the Uluguru Mountains which is underlain by pre-cambrian metamorphic rock types (Burgess *et al*., 2007; Hall, 2009; Shirima *et al*., 2011). Dominant tree species in the region include: *Bersama abyssinica*, *Cassipourea malosana*, *Cornus volkensii*, *Cussonia lukwangulensis*, *C. spicata*, *Dombeya torrida*, *Draceana afromontana*, *Garcinia volkensii*, and *Xymalos monospora*. Bamboo thickets form dense stands of *Sinarundinaria alpina* 12-15 m tall and 15 cm diameter, (Bjørndalen, 1992; Lovett, 1993). The grassland habitat consists of *Panicum lukwangulense* and *Andropogon thystinus*, with scattered trees of *Agauria saliciflora*, *Adenocarpus mannii*, *Myrica salicifolia* and *Berberis sp.*, which are thought to have replaced upper montane forest following the occurrence of fires (Bjorndalen, 1992). Kitulanghalo forest forms part of Miombo, which covers 90% of the total forested ecosystem in Tanzania (Mugasha *et al*., 2013). They are dominated by *Brachystegia*, *Isoberlinia*, and *Julbernardia*, *Pterocarpus angolensis*, *Afzelia quanzesis and Albizia species* (Munishi *et al*., 2010). It is a semi-natural Miombo woodland which receives less than 1000 mm of rainfall per annum. It is also important to note that proximity of these forests to Morogoro urban increases their susceptibility to anthropogenic influence interfering with their functioning and long term management (Mugasha *et al*., 2013).

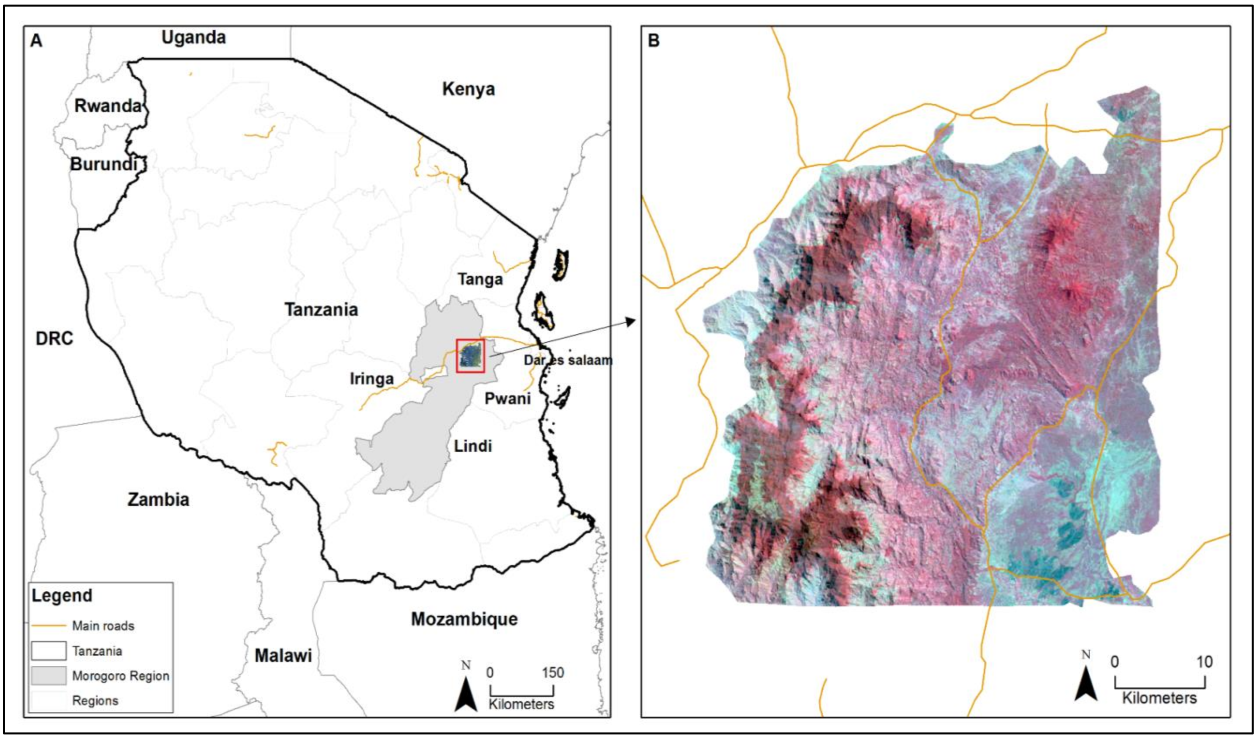


Figure 2.1: Study area (left) location based on a Landsat 1975 composite (right) in Morogoro, Tanzania.

2.3 Materials and methods

2.3.1 Image pre-processing

Satellite images with less than 15% cloud cover were used for the study. Landsat MSS (20/08/1975), Landsat TM (30/09/1995) and Landsat ETM (20/07/2012) from the Global Landcover Facility were selected. Datum was set to WGS 84 and referenced to Universal Transverse Mercator (UTM) Zone 37 South. All images were orthorectified using ground validation points, DEM, and aerial photos as a reference. Landsat images were resampled to a common resolution pixel by use of bilinear resampling to ensure consistency of the resolution with all image scenes. First order polynomial transformation was applied in image registration to correct for any shifts. Atmospheric correction involved the use of the radiative transfer model to remove atmospheric effects using the ATCOR (Atmospheric and topographic correction) module in Erdas Imagine 2013. This procedure was considered useful in simulating atmospheric interactions between the sun surface and sensor pathways. ATCOR masks haze, cloud, water and enhances pixel visibility. DN values were converted to reflectance values (Chander *et al*., 2009) using the metadata provided with the Landsat images (Richter and Schlaepfer, 2011; Richter and Schläpfer, 2004).

2.3.2 Image classification

Supervised classification using the maximum likelihood classifier was adopted as the most preferred parametric classification technique (Liu *et al*., 2002; Manandhar *et al*., 2009; Tseng *et al*., 2008; Xi, 2007). It is based on the Bayes theorem that utilizes a discriminant function which assigns pixel values to the category with the highest likelihood (Aldrich, 1997; Ince, 1987). Spectral signatures were created and applied in categorizing similar pixels in the entire image using 8 polygons representing training data sets for each habitat class. A color composite consisting of 3, 4 and 5 bands facilitated visual interpretation process while the Gaussian distribution function was applied in the stretching process. The image was classified into four class categories, namely: woodland, grassland, dense forest and less dense forest. These are the main dominant vegetation types in the study area. These land cover classes are defined and described by United States Geological Survey (USGS, 2006) as shown in Table (2.1).

A total of 82 field ground data points were used to validate the classified 2012 image. A confusion matrix was then created to compare ground truth data with the maximum likelihood prediction and to determine the overall accuracy, producer's accuracy and user's accuracies e.g. (Stehman and Czaplewski, 1998). Overall accuracy is a percentage (%) between correctly classified classes and the total number of test ground truth samples, while PA is the probability of a specific class being correctly classified. The User Accuracy (UA) is the possibility that a sample of a specific class and maximum likelihood assigns that class.

2.3.3 Modelling habitat fragmentation

Fragstats metrics (Table 2.2) were extracted from processed Landsat images. All classified images were converted to ASCII format in ArcGIS 10.2. The raster version of the C program in Fragstats was applied using the 8 cell rule (McGarigal and Marks, 1995). All ASCII format scenes were imported into Fragstats, then ASCII built-in-algorithm selected for running analyses in the Fragstats model. Fragstats has a distinct nature and capacity to estimate landscape behavior characteristics (Saikia *et al.*, 2013; Millington *et al.*, 2003), and therefore relevant in forest fragmentation studies (Vogelmann, 1995). Metrics relevant in explaining the magnitude and extent of fragmentation were selected (Saikia *et al.*, 2013; Millington *et al*. 2003; Cushman, 2006; Cushman *et al.*, 2012). All metrics were selected from the 1975, 1995 and 2012 image scenes. A total of 155 samples were randomly selected and extracted. For the statistical analyses, two metrics i.e. perimeter area relationship and patch area were used for testing the magnitude of fragmentation. Patch area is a useful metric in landscape analysis, and very relevant in ecological research (McGarigal and Marks, 1995). The Kolmogorov-

Smirnov test was used for evaluating data normality in both perimeter area ratio (PARA) and patch area. The perimeter area data and mean patch area data (n=155) were normally distributed. Mann-Whitney U-tests were selected and used to assess differences between patch areas across the years using STATA Software 12. However, it is important to note that, the fragmentation indicators used in this study should be interpreted as empirical (mechanic) and not ecological measures. For instance, a fragmented (patchy) landscape with the four dominant vegetation types could be one contiguous habitat for forest generalist like a Duiker species that could live in a matrix of all these vegetation types.

Table 2.1: Definition of land cover classes based on USGS (2006)

Land cover	**Definition**
Dense Forest	Dominantly native forest consisting of >60% ground surface covered by trees with a dense canopy cover. The trees are green throughout the year
Less dense forest	Vegetation in this cover class consists of natural vegetation >6m tall with a crown density of <30%. However, the canopy is not as dense as that of dense forest with scattered foliage cover.
Woodland	Refers to woody vegetation type with scattered foliage cover <30% with stunted growth. Mature vegetation consists of <5m woody savannas and in this region, they are located in drier parts of the case study region
Grassland	Consists of land cover dominated by more than 60% grass like vegetation with scattered shrubs and scrubs

Table 2.2: Fragmentation indices used in the present study

Fragstats matrix	**Description**
Patch Density (PD)	Number of patches of the corresponding patch type
Largest Patch Index (LPI)	It's an index used to quantify the percentage of total landscape area characterized by the largest patch.
Edge density (ED)	Used to assess edge length per unit area
Patch Number (NP)	It's a measure of the magnitude of fragmentation of patches
Interspersion Juxtaposition Index (IJI)	The index is used in isolating the interspersion of different patch types.
Patch Area (MN)	Refers to the sum, across all patches in the landscape, of the corresponding patch metric values, divided by the total number of patches in (ha).
Perimeter Area Ratio-PARA	Refers to the ratio of the patch perimeter (m) to area (m^2).
Total Area (CA)	Refers to the sum of areas (m^2) of all patches for the patch type
Percentage of Landscape (PLAND)	Useful in computing the proportional abundance for each of the patch type across the landscape

2.3.4 Secondary data

Secondary data were collected from government office within Morogoro region. This included population statistics and other conservation data on impacts from previous reports and publications in the case study region.

2.4 Results

2.4.1 Classification and accuracy assessment

The overall accuracy for 1975, 1995 and 2012 image scenes was 78.26%, 84% and 76.54%, respectively (Table 2.3). Changes in total area coverage were observed in all years (Figures 2.2A, B and C).

Table 2.3: Individual accuracy measures of the four dominant land cover classes

	1975		**1995**		**2012**	
Habitat Class	**Producer's Accuracy (%)**	**User's Accuracy (%)**	**Producer's Accuracy (%)**	**User's Accuracy (%)**	**Producer's Accuracy (%)**	**User's Accuracy (%)**
Dense Forest	100.00	75	100.00	100.00	80.77	95.45
Less Dense Forest	066.67	100	100.00	100.00	100.00	60.00
Woodland	066.67	100	066.67	066.67	075.00	58.54
Grassland	100.00	100	100.00	100.00	084.62	91.67
Overall Accuracy	78.26		84		76.54%	
Kappa co-efficient	0.74		0.81		0.73	

2.4.2 Change detection

Findings showed that land modification and change occurred over the years. Most habitats declined significantly i.e. dense forest (38,675.70 hectares), woodland (78,884.46 hectares), grassland (3230.01 hectares). However, the study showed a significant increase in the less dense forest cover, by 43,267.38 hectares. The considerable increase in woodland area could be due to the mapping method. The maximum producer's accuracy in 1975 and 1995 (about 66%) was for woodland class, which is relatively smaller compared to the accuracy of other classes.

2.4.3 Quantifying the magnitude of change

Dense forest, woodland and grassland are undergoing a negative change at an annual rate of 1.6%, 1.6% and 0.7%, respectively (Table 2.4).

Table 2.4: Habitat annual rate of change

Habitat	**1975 (ha)**	**Total %**	**1995 (ha)**	**Total %**	**2012 (ha)**	**Total %**	**Annual rate of change in % 1975-2012**
Dense Forest	64813.68	17.7	27742.68	07.6	26137.98	07.1	-1.6
Less dense forest	74493.72	20.4	144648.4	39.5	117761.1	32.2	+1.6
Woodland	137289.24	37.6	98242.83	26.8	58404.78	16.0	-1.6
Grassland	13223.16	03.6	07163.91	02.0	09993.15	02.7	- 0.7

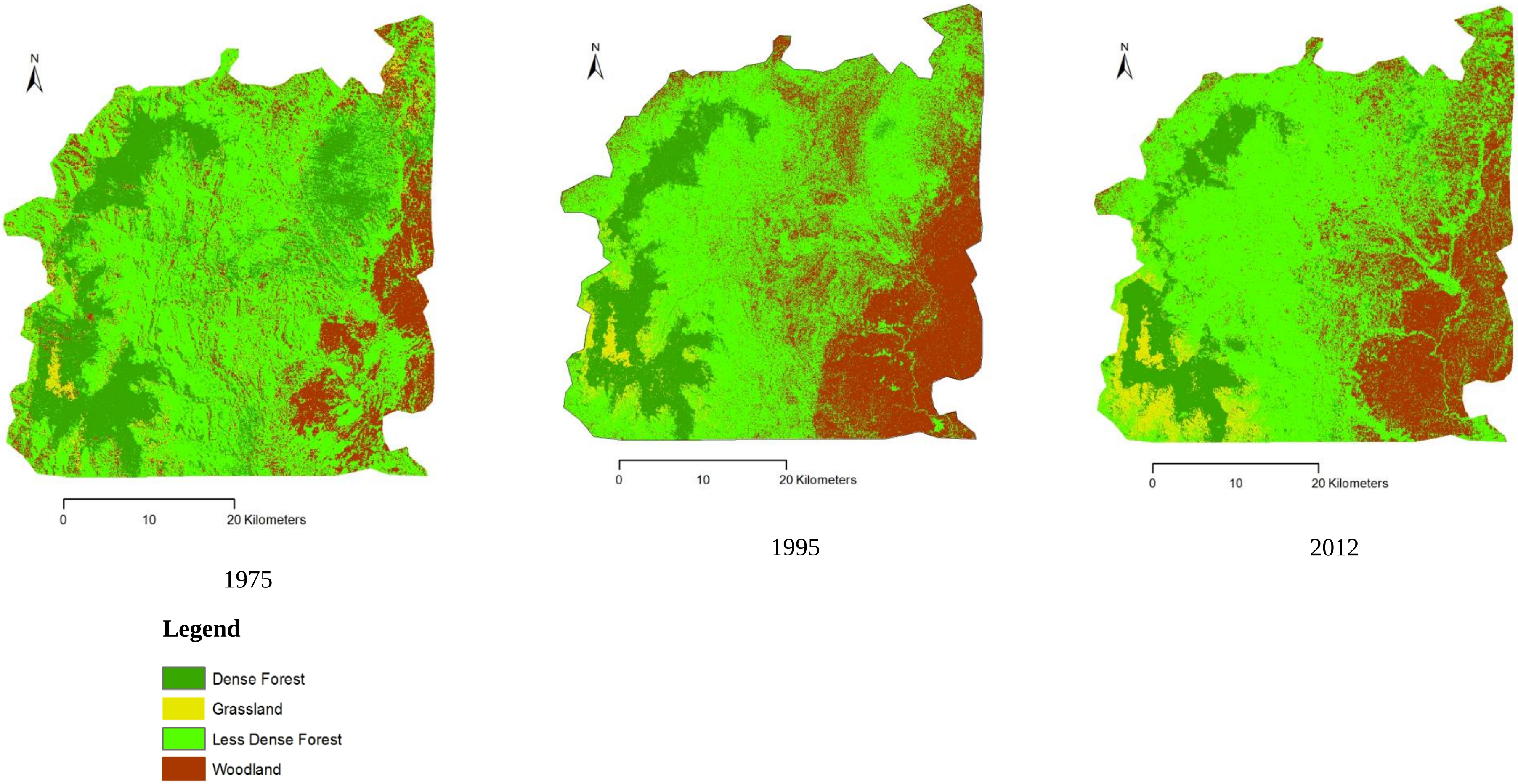


Figure 2.2: Land use/ land cover (LULC) maps in 1975, 1995 and 2012.

2.4.4 Fragmentation patterns

2.4.4.1 Temporal variation in fragmentation

Analyses showed dynamic temporal trends (Table 2.4). Patch number was relatively higher in dense forest and woodland in 1975, 1995 and 2012 than in less dense forest and grassland. An analysis of the percentage of landscape (PLAND) and edge density parameters, showed that less dense forest had the highest number compared to the rest of the habitats. Woodland and less dense forest habitats had the highest edge density values (Figure 2.5).

In addition, patch number was least in both dense forest between 1975 and 1995. A decrease in total core area, percentage of landscape and edge density was observed in both woodland and less dense forest classes between 1975 and 2012 (Figures 2.3-2.5). Woodland area increased in 1995 and then decreased in 2012. The largest patch index (LPI) was observed in less dense forest, while woodland, dense forest and grassland had the least values below five. Woodland and grassland had the highest PARA compared to less dense and dense forest (Table 2.4).

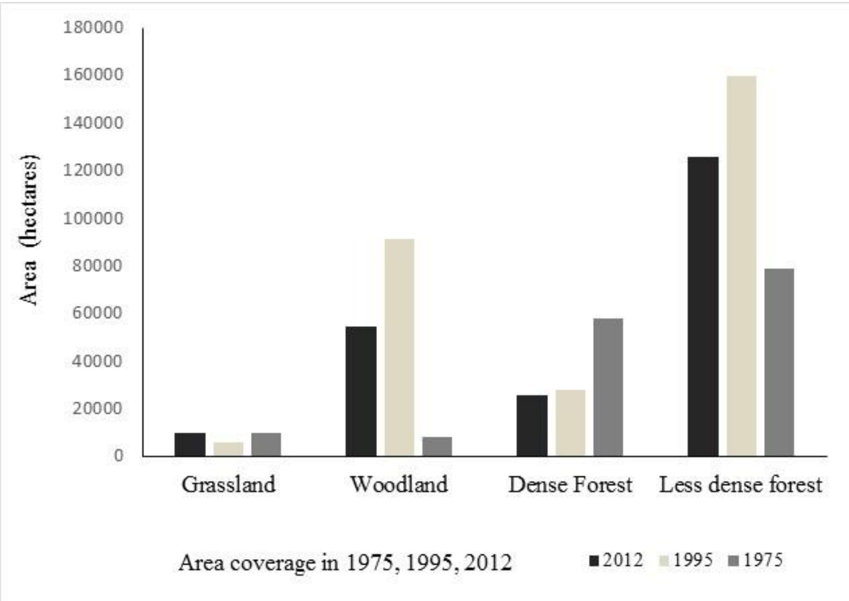


Figure 2.3: Temporal patterns of core area.

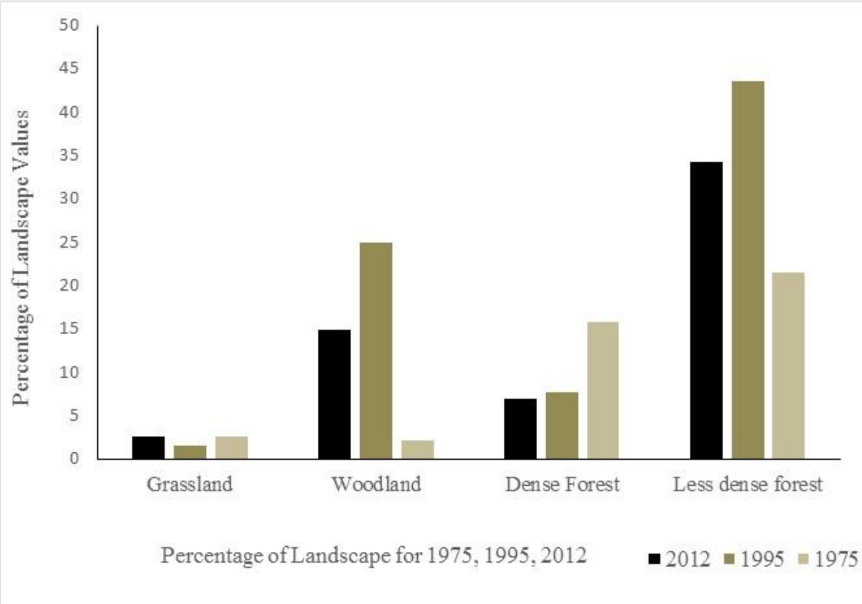


Figure 2.4: Temporal percentage of landscape patterns.

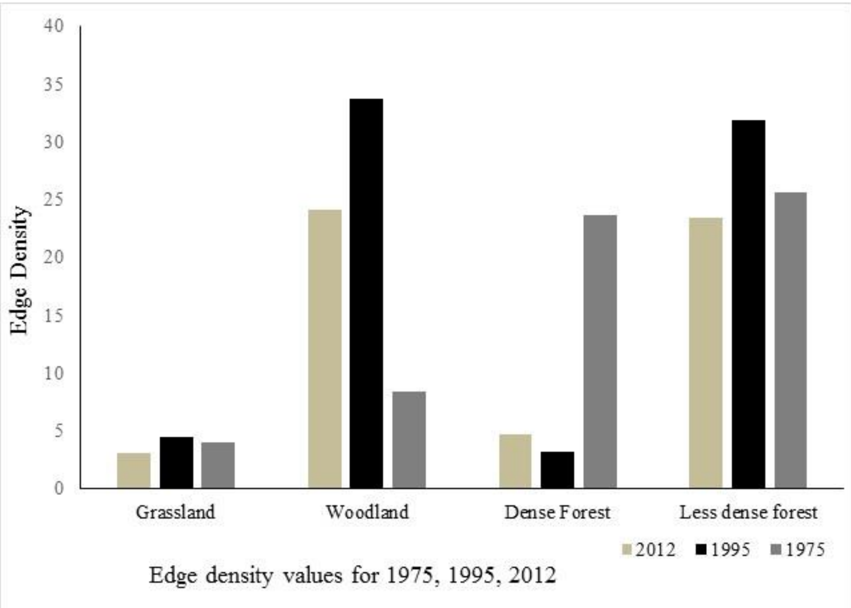
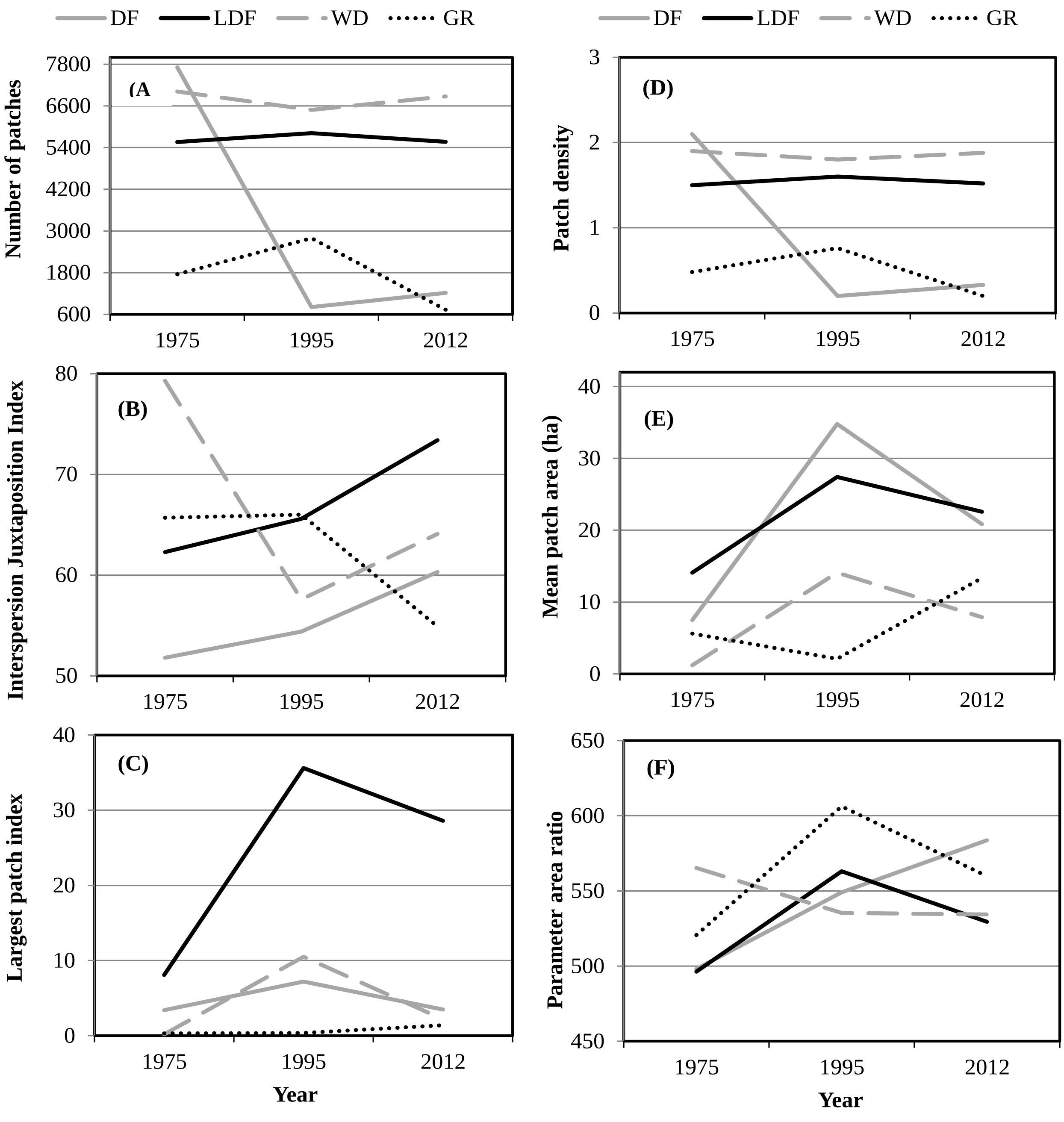


Figure 2.5: Temporal edge density patterns.

2.4.4.2 Spatial variation in fragmentation

Spatial analyses showed a greater probability of dispersion in the woodland and less dense forest habitats. The Interspersion Juxtaposition Index (IJI) ranged between 0 (for clumped patches) and 100 (for grassland). In 1975 and 1995, the grassland habitat had the highest IJI.

In 2012, less dense forest had the highest IJI. Furthermore, results indicated the largest patch number and mean patch area in dense forest in the year 1975 and woodland in 2012 (Figure 2.6).



DF- dense forest, LDF-less dense forest, WD-woodland, GR-grassland

Figure 2.6: Spatial variability in the six fragmentation indices (A, B, C, D, E, and F) in 1975, 1995, and 2012.

2.4.5 Mann-Whitney results

Based on the Kolmogorov-Smirnov tests, data were not normally distributed ($p \leq 0.05$). The non-parametric statistics (Mann-Whitney tests) were then applied. Mann-Whitney test results showed distinct differences in patch area ($p<0.01$) between 1975 and 1995 for all habitats and 1995-2012 for all habitats except dense forest (Table 2.5), indicating a rapidly fragmenting landscape.

Table 2.5: Patch area compared by Mann-Whitney Tests

Class	**Year**	**z-value (1975-1995)**	***Prob* > |*z*|**	***z-value (1995-2012)***	***Prob*> |*z*|**
Dense forest	1975	*9.495****	0.0000	-6.872 NS	0.1895
	1995				
	2012				
Grassland	1975	13.680***	0.0000	-7.441***	0.0000
	1995				
	2012				
Less dense forest	1975	16.728***	0.0000	-8.268***	0.0000
	1995				
	2012				
Woodland	1975	-16.63***	0.0000	2.461***	0.0000
	1995				
	2012				

NS= not significant ($p<0.01$), *** = significant ($p<0.001$)

2.4.6 Games Howell test results for perimeter area relationship

Games Howell results indicated very significant patterns of fragmentation between 1975 and 1995 within all habitats ($p \leq 0.05$). In 1975 and 2012, the trend was significant in less dense forest and woodland ($p \leq 0.05$), while in 1995 and 2012, the trend was significant in grassland, dense forest and less dense forest ($p \leq 0.05$) (Table 2.6). A highly significant trend was observed with perimeter area relationship in the less dense forest across the years.

Table 2.6: Games-Howell results for mean parameter area ratio (PARA) in 1975, 1995, 2012

Class	**Mean**			***p* value**		
	1975	**1995**	**2012**	**1975 vs 1995**	**1975 vs 2012**	**1995 vs 2012**
Grassland	565.28	606.21	560.00	0.0001	0.5960	0.0001
Dense forest	498.12	549.14	483.72	0.0001	0.3000	0.0001
Less dense forest	496.29	563.06	529.53	0.0001	0.0001	0.0001
Woodland	498.58	535.43	534.26	0.0001	0.0001	0.8930

2.4.7 Population trends in the region

Statistics in the area show an increasing population trend in the region (Table 2.7).

Table 2.7: Dynamic population trends in Morogoro region

District	1967	1988	2002	2013
Morogoro Urban	24,999	117 601	227 921	315 866
Morogoro rural	291 373	430 202	263 012	286 248
Mvomero			259 347	312 109
Kilosa	193 810	346 526	488 191	631 186
Kilombero	74 222	187 593	321 611	407 880
Ulanga	100 700	138 642	193 280	265 203
Total in Morogoro	685 104	1 220 564	1 753 362	2 218 492

Source: United Republic of Tanzania (1997; 2013)

2.5 Discussion

Fragmentation patterns are evident at both the spatial and temporal domains. Distinct differences in fragmentation indicated how each individual habitat responded to fragmentation in Morogoro region. The reason could be attributed to the topography of the area and resource accessibility essential for livelihood support initiatives such as agriculture, urbanization/settlement, and infrastructure development. These have been considered as key drivers of land modification and fragmentation for natural ecosystems in the region. Conservation implications provided form an important platform for future monitoring and management of the fragile landscape.

2.5.1 Spatial and temporal patterns in Morogoro region

The negative trend in habitat area for habitats decreasing in total area size is prevalent in the region (Table 2.2). Negative trend patterns in the extent of total habitat coverage have close relations with deleterious fragmentation effects (Cushman, 2006). However, effects of fragmentation are dependent on habitat size (Fahrig, 2003). Perimeter-area results showed very distinct differences in the woodland and grassland habitat patterns. A high perimeter-area relationship characterizes the rapid rate of fragmentation underlying the two landforms (Jorge and Garcia, 1997; McGarigal, 2006). Woodland habitat displays a patchy type of deforestation, which is characterized by an increase in patch number between 1995 and 2012. The patchy type of fragmentation is driven by economic and demographic reasons (Green *et al*., 2013a).

Changes in mean patch area patterns were recorded on woodland and less dense forest habitats. Furthermore, patch number increased by 412 and 391 in dense forest and woodland respectively. This is an indication of the fragmentation level in the area (Jorge and Garcia, 1997). Furthermore, patch area has been ideal in characterizing distinct areas with analogous environmental scenarios whereby patch boundaries are distinguished by discontinuities in environmental character state relevant to organisms or the ecological phenomenon being considered (Wiens, 1985). A combination of patch density (PD), PARA (perimeter to area ratio) and mean nearest neighbor distance are considered profound in estimation of the extent of fragmentation in each of the habitats analyzed (Jorge and Garcia, 1997). Patch density and perimeter to area ratio (PARA) have been profound in fragmentation assessments as they have a strong influence on ecosystem functioning and ecological processes (McGarigal, 2006). Woodland and less dense forest had the highest patch number over the years, which are attributed to fragmentation emerging from resource accessibility in the two forest habitats. It could be also an aspect related to their vicinity to Morogoro town and management by local authorities. Such challenges are potential drivers enhancing susceptibility to habitat fragmentation (Fahrig, 2001; Fahrig, 2003; McGarigal, 2006; Wiens, 1995). Undisturbed areas have larger patch sizes compared to disturbed areas (Fischer and Lindenmayer, 2007). Similar findings were explained by dynamics in mean patch area which was driven by pressure from anthropogenic disturbances (Stoms and Estes, 1993).

The interspersion juxtaposition index (IJI), was profound in characterizing the degree of adjacency for each patch type. Less dense forest had the highest IJI in 2012 compared to the rest of the habitats. Woodland had a greater patch density, signifying higher spatial heterogeneity. In addition, the largest patch index was associated with less dense forest while least values were associated with grassland. This indicates the fragmented nature of less dense forest and grassland as it provides information on least and most fragmented landscapes (McGarigal, 2006). In addition, the largest patch index for less dense forest was significant compared to the rest of the habitats, an indicator of the minimum area requirements for species survival (Rutledge, 2003).

Dense forest, grassland and woodland had the largest edge density, attributed to increasing exposure to farmlands and settlements. Edge effects characterize the biophysical state of ecosystems at the periphery or in the neighborhood and have deleterious effects in the long term (Hargis *et al*., 1998). This is because disintegration of habitats intensifies the response of abiotic edge effects on ecosystem functioning (Murcia, 1995) and reduces a habitat's ability to sustain a population (Fahrig, 2003). It also affects occurrence of species populations (Murcia, 1995) and ensures that the interaction of species in disturbed environments remains restricted enhancing the mortality risk (Kupfer *et al*., 2006). Other similar studies established a great intensity of fragmentation associated with more edge effects through exposure of contiguous habitats to solar radiation and soil moisture to drier heat conditions (Rutledge, 2003).

Games-Howell test results showed a significant level in the perimeter area relationship ($p \leq 0.05$). This could be explained by the fact that less dense forest adjoins dense forest, taking up the region dominated by woodland. Other possible causes are linked to expansion of Morogoro town and extensive farmlands in Fulwe, Mkuyuni and Mlali regions in Morogoro rural district. Similarly, other studies showed how adjoining activities altered intact habitat ecosystems (Echeverría *et al*., 2007). However, the significant differences found for almost all fragmentation indices should be interpreted with caution as there were no absolute agreements (100%) between the reference classes on the ground and the predicted ones in the images as indicated by the classification accuracy and maps quality.

2.5.2 Potential driving forces and conservation impacts

An increase in population density may be one of the factors for habitat modification in four individual habitats analyzed (URT, 2013 – see Table 2.7). This confirms other studies that relate massive losses of natural tropical ecosystems due to external human perturbations (de Chazal and Rounsevell, 2009; Foley *et al*., 2005; Haines-Young, 2009; Nagendra *et al*., 2013; Pérez-Vega *et al*., 2012; Reidsma *et al*., 2006; Wasige *et al*., 2013; Zebisch *et al*., 2004). In addition, extensive farming and urban regrowth are possible drivers to habitat modification and fragmentation in the region. Uluguru forest montane forests have a conducive montane climate that supports subsistence farming, an activity which most communities practice (Burgess *et al*., 2007b; Swetnam *et al*., 2011; Yanda and Shishira, 1999).

Another possible cause is linked to expansion of agricultural fields and urban set-ups in Morogoro rural and urban districts. This confirms previous findings which established how a substantial amount of dense forest had been lost in Uluguru Mountains, due to expansion of urban settlements and agricultural farms (Burgess *et al*., 2002; Burgess *et al*., 2001). Furthermore, a decrease in the woodland could be attributed to wood harvesting for commercial purposes in Kitulanghalo forest (Theilade *et al*., 2007). In other parts of Tanzania, related studies established effects of woodland loss to land modification (Munishi *et al*., 2010; Ntongani *et al*., 2010; Yanda and Shishira, 1999).

Fragmentation studies are relevant in assessing ways in which species respond to varying levels of fragmentation (Wiens, 1995). This study provides an important foundation upon which conservation and management principles can be established particularly in dense and less dense forests with leading records of endangered and vulnerable species (Burgess *et al*.,; 2007; Hall *et al*., 2009). This is because impacts of fragmentation seem to be impacting heavily on natural ecosystems in Morogoro region. A previous study in Uluguru montane ecosystem also established a decrease in species abundance and diversity in fragmented areas (Ojoyi *et al*., 2015). Intensification of the human population growth may have extirpated important fauna and flora in the Ulugurus (Burgess *et al*., 2002; Burgess *et al*., 2001). This could be a result of expanding settlements and farming in the area (Burgess *et al*., 2007; Hall, 2009; Swetnam *et al*., 2011; Yanda, 2010). This may lead to losses of genetic diversity and useful genes in areas originally covered by intact forest ecosystems (Burgess *et al*., 2007; Hall, 2009; Shirima *et al*., 2011; Swetnam *et al*., 2011; Theilade *et al*., 2007; Yanda and Shishira, 1999). Other studies linked species losses to habitat modification of natural landscapes into other forms due to changes in a habitat's spatial configuration (Fischer and Lindenmayer, 2007).

To forestall some of the problems earlier highlighted, forested areas identified as biodiversity hotspots such as the four habitats, with important functions for groundwater recharge, surface water runoff, biotopes for instance, need to be protected from the impacts of land modification and fragmentation (Byron and Arnold, 1999; Janzen, 1970; Montagnini and Jordan, 2005; Wright, 2005; Wunder, 2001). Implications of habitat modification and fragmentation in Morogoro region can be better deciphered through the impact on habitat structure and species losses. Impacts of fragmentation need to be understood by the local population in order to curtail inappropriate destructive practices. It will be useful if policy measures and sustainable bottom-up approaches in management and conservation of forest resources are instituted in the region.

2.6 Conclusions

In conclusion, the study has provided spatial and temporal information regarding fragmentation trends in the region. Distinct differences in magnitude are evident for each of the individual habitats analyzed. The magnitude of fragmentation was significant in less dense forest. One important aspect which stands out from the study is that fragmentation seems to be driven by closeness to livelihood support resources such as access to agricultural land and roads. Agricultural farming, population pressure and urban growth are identified as major driving forces to habitat modification and fragmentation.

Despite the diversity in the results obtained, this study provides an important knowledge on spatio-temporal vegetation patterns and ecological functions of forests in Morogoro region. Each of the results has a fundamental role to play on the ongoing conservation work implemented by the Critical Endangered Ecosystem Partnership Programme and Birdlife International aimed at protecting fragile ecosystems subjected to anthropogenic disturbances in different parts of East Africa. It is expected that findings from this study will offer an ideal platform for government authorities and other conservation organizations in the region.

CHAPTER THREE

Impacts of forest fragmentation on species abundance and diversity in the Eastern Arc Mountains in Tanzania

Habitat destruction in Nguru Montane forest ecosystem

This chapter is based on:

Ojoyi, M.M., Mutanga, O., Odindi, J., Ayenkulu, E., Abdel-Rahman, E.M. (2015). The effect of forest fragmentation on tree species abundance and diversity in the Eastern Arc Mountains of Tanzania. *Applied Ecology and Environmental Research*, 13, 307-324.

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Abstract

Habitat fragmentation is considered a threat to biodiversity conservation. Uluguru forest block, a section of the Eastern Arc Mountains in Tanzania remains highly vulnerable to fragmentation. However, to date, fragmentation effects on species abundance and diversity have not been investigated. This study aimed at investigating effects of fragmentation on species abundance and diversity in Uluguru forest block, Morogoro region, Tanzania. A RapidEye satellite image was analysed using the maximum likelihood classifier (MLC) to map the fragmented forest. Remotely sensed variables with data on species diversity were modelled using the Generic Algorithm for Rule-Set Prediction (GARP) algorithm while fragmentation parameters were extracted using Fragstats software, which were then linked to species and edaphic factors. Results showed that species diversity was predicted better with customized environmental variables which recorded an Area Under Curve (AUC) of 0.89. The Poisson regression results showed that individual tree species responded differently to patch area dynamics, habitat status and soil nitrogen. Generally, the abundance of dominant species like *Mytenus undata Thunb* (p < 0.001), *Zenkerella capparidacea* (Taub.) *J. Leon* (p < 0.001) and *Oxyanthus specious* DC. (p = 0.023) decreased with a reduction in patch area. The present study suggests the need to integrate comprehensive plans and other intervention measures into long-term intervention initiatives.
Keywords: RapidEye, habitat fragmentation, soil, species abundance

3.1 Introduction

Species abundance and richness are important measures of biodiversity (Gould, 2000). They vary from one spatial range to another, which is a function of habitat heterogeneity (Kerr *et al.*, 2001) fragmentation (Murcia, 1995; Benítez-Malvido and Martínez-Ramos, 2003; Echeverría *et al.*, 2007; Hobbs *et al.*, 2008) and modification (Osborne *et al.*, 2001). Habitat modification interferes with ecosystem configuration (Stoms and Estes, 1993), species distribution and numbers (Griffiths and Lee, 2000), structural complexity of ecosystems and their functioning (Debinski *et al.*, 1999), patch and landscape ecosystem processes (Didham, 2001) and alters the biological trait of individual species (Helm *et al.*, 2006). It also interacts synergistically with anthropogenic threats (Laurance, 2007), interferes with the occurrence of species, their composition and density (Stoms and Estes, 1993). Literature shows that habitat fragmentation also condenses habitat area coverage enhancing the species extinction debt (Bogich *et al.*, 2012). By reducing the total habitat area requirements of species (Murcia, 1995; Fahrig, 2003; Echeverría *et al.*, 2007), the rate of species extinction and endemism is enhanced (Burgess *et al.*, 2001; Burgess *et al.*, 2002; Adams *et al.*, 2003; Tøttrup *et al.*, 2004). In low montane ecosystems, fragmentation is known to affect species loss due to deforestation (Hall *et al.*, 2009). Various studies indicate significant variability in the abundance of alien invasive plant species, due to fragmentation. For instance, Mumbi *et al*., (2008) showed that fragmentation affects the abundance of coprophilous fungi and algal blooms as a result of reduction in the population of *Podocarpus* and *Psychotria* tree species.

The intensity of fragmentation is dependent on different factors (Benítez-Malvido and Martínez-Ramos, 2003; Fahrig, 2003; Echeverría *et al.*, 2006). For instance, dynamics in land use and elevation has an effect on individual species (Murcia, 1995; Benítez-Malvido and Martínez-

Ramos, 2003; Fahrig, 2003; Burgess *et al.*, 2007b; Echeverría *et al.*, 2008). It may also be a function of varying patch sizes (Echeverría *et al.*, 2008) and structural complexity (Murcia, 1995; Benítez-Malvido and Martínez-Ramos, 2003; Fahrig, 2003; Fischer and B. Lindenmayer, 2006; Burgess *et al.*, 2007b). However, the effect of fragmentation on tree species at local scales is not widely explored (Ylhäisi, 2004; Zotz and Bader, 2009). Whereas a series of studies have used bioclimatic variables to ecologically model species diversity (Pearson and Dawson, 2003; Martínez-Meyer *et al.*, 2004; Thuiller *et al.*, 2006), the validity of this approach, particularly at local scales, remains unresolved (Araújo and Luoto, 2007).

As aforementioned, habitat fragmentation is a threat to biodiversity and conservation (Achard *et al.*, 2002; DeFries *et al.*, 2002; Benítez-Malvido and Martínez-Ramos, 2003; Fahrig, 2003; Fischer and Lindenmayer, 2006; Burgess *et al.*, 2007b; Echeverría *et al.*, 2008; Hobbs *et al.*, 2008). This is the case for the Eastern Arc Mountains in Tanzania, a highly ranked global biodiversity hotspot (Olson and Dinerstein, 1998; Hall, 2009). They host approximately 100 endemic vertebrates (10 mammals, 20 birds, 38 amphibians, 29 reptiles) and approximately 1500 plant species including, 68 tree endemics (Burgess *et al.*, 2007b). Despite their global importance, the region remains highly vulnerable to anthropogenic influence (Bjørndalen, 1992; Burgess *et al.*, 2002). The extent of habitat loss and fragmentation has been deleterious (Newmark, 1998; Fjeldså, 1999; Hall *et al.*, 2009; Swetnam *et al.*, 2011). Key threats include settlements, logging, farming and urban sprawl (Burgess *et al.*, 2007b), consequently, approximately 80% of forest cover has been lost in recent years (Hall *et al.*, 2009). A substantial area and the highest number of extinct species were recorded in lowland montane forest between 1975 and 2000 (Hall, 2009).

A shift in an ecosystem's stability transforms it to an undesired state, compromising its capacity to support normal functions and increasing the rate of endemism and extinction (Şekercioğlu *et al.*, 2004). Although species vary in their geographic occurrence, distribution and response to dynamic environmental conditions (Fischer *et al.*, 2004), modelling their diversity is a prerequisite in conservation monitoring, planning and management (Carlson *et al.*, 2007). This forms a basis for knowledge generation, specifically on species-habitat relationships in space, time and future risk management (Olson *et al.*, 2014). To date, this subject remains unexplored in natural fragmenting ecosystems in Morogoro region, Tanzania (Hall *et al.*, 2009).

Up to date, the subject on how landscape-modification and species interactions is not well explored (Turner *et al*., 2003). The information is ideal in resource planning and management of natural resources in the tropics. Advancement in remotely sensed data presents an unprecedented opportunity in monitoring and planning efforts. The use of remote sensing technology has the capacity to show species responses to habitat interactions with changing environmental needs. This study features one of the few studies that utilize remote sensing technology and other biophysical variables, including soil factors to model distribution of species diversity in threatened and less threatened areas. Specifically, how forest fragmentation affects species abundance and diversity in a heterogeneous landscape in the Uluguru forest block. Edaphic factors such as NPK, pH and C were used as indicators to soil health (Solomon *et al.*, 2000; Fageria, 2010). Species models generally provide important information that shows distribution of species frequency of occurrence.

3.2 Materials and methods

3.2.1 Study area

Uluguru tropical forest is located at ($7^o 2´$ - 7^o 16´S) and (38^o 0´ - 38^o 12´E) in Tanzania and forms part of the Eastern Arc Mountains blocks, which is a series of crystalline mountains in Kenya and Tanzania (Burgess *et al*., 1998). These mountains range from lowland rain forests to elfin montane forests and are separated by lowlands whose origin is said to have been caused by faulting (Olson and Dinerstein, 1998). The area experiences bimodal rainfall in April and November, ranging from 2900-4000 mm on windward slopes and 1200-4000 mm on the leeward (Burgess et al., 1998). The Uluguru forest block (Figure 3.1) hosts approximately 135 plant species (Fjeldså, 1999; Lovett 1993; Burgess *et al*., 2007b), however, the forest cover has declined from 300 km^2 in 1955 to 220 km^2 in 2000. Consequently, Uluguru montane forest ecosystem is regarded to as highly vulnerable to fragmentation, negatively affecting species abundance and increasing risk of extinction of rare species like the Uluguru Bush Shrike (Bjorndalen, 1992; Bjørndalen, 1992; Burgess *et al*., 2001; Burgess *et al*., 2002; Fuchs *et al*., 2005).

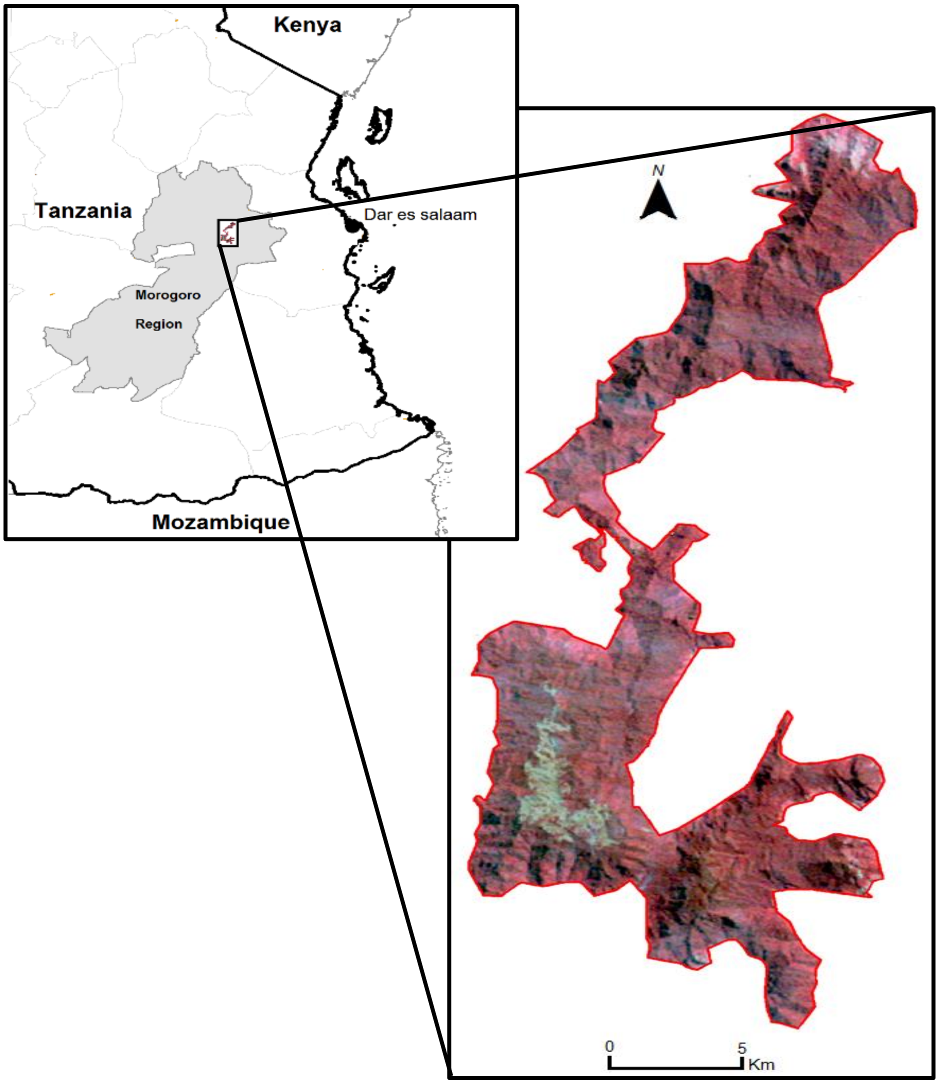

Figure 3.1: Location of Uluguru forest: delineation based on Landsat MSS captured in 1975.

3.2.2 Field data collection

Tree measurements were collected randomly within 10 m × 10 m plots in August 2012, in the same month of image acquisition. Data was collected from 80 plots located in the field using a Global Positiong System (GPS) of submeter accuracy. Major tree species with more than five centimeters diameter at breast height (dbh) were sampled. Data on species names, genera, families, density, basal height, and canopy cover were recorded. Additionally, elevation points for each plot was taken. Soil data (C, N, P, ph and K) was collected within the 0-15cm depth.

The status of the habitat in Uluguru forest blocks was categorised into two classes; fragmented and intact (82 data ground data points were used).

3.2.3 Image acquisition and pre-processing

RapidEye satellite imagery for the Uluguru forest block was acquired on 23/10/2012. RapidEye has a spatial resolution of 5 metre and 5 bands covering the spectral regions: Blue: 440-510 nm, Green: 520-590 nm, Red: 630-685 nm, Red Edge: 690-730 nm and NIR: 760-850 nm. The red edge band has the potential to detect chlorophyll concentration in the visible region of the spectrum; which allows use of different vegetation indices in above ground biomass prediction. It has great potential in discriminating varied and stressed vegetation types. The image was first geometrically corrected (Universal Transverse Mercator: UTM, zone 37 South projection) using 30 identifiable ground control points (GCPs) distributed across the image. The GCPs were recorded on 1:50000 topographic maps of various years. A nearest-neighbour algorithm and first order polynomial transformation were applied to resample the image to its original pixel size. The nearest neighbor is a resampling method that assigns a value to each "corrected" pixel from the nearest "uncorrected" pixel. Its advantage is simplicity and the capability to preserve original values in the unaltered image scene. The advantage of using first-order transformations is that it can easily project raw imagery to a planar map projection, convert a planar map projection to another planar map projection, and very efficient when rectifying relatively small image areas. The root mean square error of less than half a pixel was obtained, indicating a reliabe geometric correction. The imagery was then atmospherically corrected using ATCOR module built in Earth Resources Data Analysis System software (Erdas Imagine 2013) and digital number values converted to surface reflectance. ATCOR is useful in computation of the ground reflectance image for the reflective spectral bands, and emissivity images for the thermal bands.

3.2.4 Soil chemical analysis

A total of 80 samples of soil taken at 0-15 cm depth were collected from 10m by 10m plots. Samples were air dried and sieved using a 2 mm sieve prior to analysis. Scanning of soil samples was conducted using atomic absorption spectrometer to get soil reflectance values. The spectrometer is designed to effectively determine the concentrations of trace and major elements in solution under observation. The spectrometer was then used to extract reflectance values for each of the elements (N, P, K, ph, C) which were then taken for wet chemistry analysis. The contents of nutrient elements were used to correlate bands with actual mineral values. These were then used to estimate for the rest of the samples.

3.3 Data analysis

3.3.1 Image classification

Maximum Likelihood (ML) supervised classifier, one of the most commonly used methods for classifying remotely-sensed data as a statistical decision criterion that facilitates classification of overlapping signatures whereby pixels are assigned to the highest class of probability based on the Bayesian Probability Function which is computed from class inputs obtained from training sites (Strahler, 1980; Conese and Maselli, 1992; Foody *et al.*, 1992; Wei and Mendel, 2000; Bruzzone and Prieto, 2001; Seto and Liu, 2003). It was used to delineate the fragmented and intact forest classes. Based on the developed class signatures, a thematic map was produced and smoothed using the majority filter rule. A total of 82 ground truth points were used to generate a confusion matrix to determine the overall (OA), producer's (PA) and user's (UA) accuracies.

3.3.2 Modelling fragmentation

Fragmentation in the Uluguru forest block was modelled using Fragstats metrics. Fragstats is a spatial statistics program useful in computing metrics at patch, class and landscape level (McGarigal and Marks, 1995). It is distinct in nature and has the capacity to estimate landscape behaviour characteristics (Millington *et al.*, 2003; Saikia *et al.*, 2013). In this study, the classified RapidEye image was converted to ASCII format and analyzed to get different patch parameters. According to Didham, (2001) patch metrics are valuable in characterizing fragmentation, consequently, patch metrics were combined with species data for further analysis.

3.3.3 Statistical analyses

Poisson regression was used to investigate significant differences in species abundance between fragmented and intact habitats. Student t-tests were used to determine differences between intact and fragmented habitats in relation to elevation, patch area and soil nitrogen content. Relationships between patch area and soil nitrogen content and patch area and elevation were investigated. Elevation and patch area are considered important estimators of habitat heterogeneity and fragmenting landscape respectively (Kerr *et al.*, 2001).

3.3.3.1 Calculation of species diversity

Species diversity was calculated from field measurements using the Shannon-Weaver diversity index. The analyses were performed using the R version 2.10.0 (R Development Core Team, 2009) for field data collected from the Ulugurus. Shannon-Weaver diversity index is a measure of the diversity index of a species community and combines richness and evenness. It is a non-parametric statistical parameter based on the proportion of species relative (qi) to the total number of species (Q) (Chao and Shen, 2003). Species diversity was calculated, taking into account the number of species per family present in the forest ecosystem and was computed using the equation;

$$H' = -\sum_{i=1}^{S} \left(\frac{qi}{Q}\right) \log \left(\frac{qi}{Q}\right) \qquad \text{(Eq. 1)}$$

Where: H' is the Shannon-Weaver diversity index, qi is the fraction of individuals belonging to the i species, Q is the total number of individual species in the sample, and *S* is the species richness (Shannon and Weaver, 1963). Species diversity was then categorized in two groups: low and high values, which were converted to readable text file format with geographic co-ordinates for processing in GARP.

3.3.3.2 Species niche modelling using GARP

GARP basically is an algorithm which helps in the identification of the best ecological niche for species occurrence or survival. The model describes ecological suitability within which species can sustain their population. The model utilizes point locations for species occurrence concurrent with environmental factors, represented as layers. In the study, tree species collected were input into the model. The best subset procedures using open modeller for the runs. Remote sensing variables were extracted based on the high resolution RapidEye satellite data and measurements linked to species habitat requirements. Kriging was applied to the rest of variables i.e. N, P, K, C then converted into ASCII format, a format accepted by GARP model. An ASTER digital Elevation Model (DEM) was also converted to the ASCII format. This was used to establish relationships between species diversity and other environmental variables including N, P, K, C, pH, DEM, and RapidEye satellite data. All variables used in the model were screened to test for highly correlated variables using the Pearson correlation tests. With values $r<0.7$ shows no correlation (Olson *et al.*, 2014). A Pearson correlation test was employed to assess relationships between Shannon wiener index and each of the environmental parameters.

3.3.3.3 Jack Knife tests

Jack Knife tests were used to assess the importance of the variables used in running the model (Saatchi *et al.*, 2008). This test is in-built in the GARP model which is important in testing the significance of each of the environmental variables used. It generates a model that estimates the accuracy for the entire layer set. Then for each layer, a new model is generated without that particular layer and the accuracy determined. All models were trained with similar points randomly selected from given occurrence points, and the accuracy calculated with the rest of the test points using 75% of the data. The area under curve (AUC) was used in assessing the level of significance of the curve whereby, values less than 0.5 are regarded as uninformative, between 0.7 and 0.8 as acceptable and above 0.8 signify a good fit (Bell, 1999).

3.3.3.4 Further model validation

The model was further validated using the partial receiver operating curve (ROC). We integrated species presence data and area dependent suitability file generated as an ASCII file in GARP. This was then converted as a grid format and points extracted in ArcGIS 10.2. The two data sets were run in partial roc setup and run with a proportion of points set at 50.

3.4 Results

Figure 3.2 shows a thematic map obtained using ML classifier. An overall classification accuracy of 84% was obtained with individual accuracies for both classes being more than 80%, except the producer’s accuracy for intact forest (Table 3.1). The classifications show that North Uluguru has relatively more intact forest than South Uluguru (Figure 3.2).

Table 3.1: Classification accuracy measures for the thematic map

Class name	Correctly classified	Misclassified	Total	PA (%)	UA (%)
Fragmented Forest	54	2	56	96.43	83.08
Intact forest	15	11	26	57.69	100.00
OA (%)	84.15				

3.4.1 Estimating tree species abundance

A total of 1,394 trees, comprising 55 different species categories were found in Uluguru forest block. The species discovery curve (Figure 3.3) shows relations between discovered and sampled species.

The *Syzygium cordatum Hochst.ex C.Krauss* was the most dominant tree species, constituting 18% of the total trees measured (Figure 3.4). On average, elevation for Uluguru forest was 1,951.63 m. There was no significant difference ($p \geq 0.05$) in elevation status between intact (1901 m) and fragmented (2056 m) habitats in Uluguru forest (t = -1.515, p = 0.134).

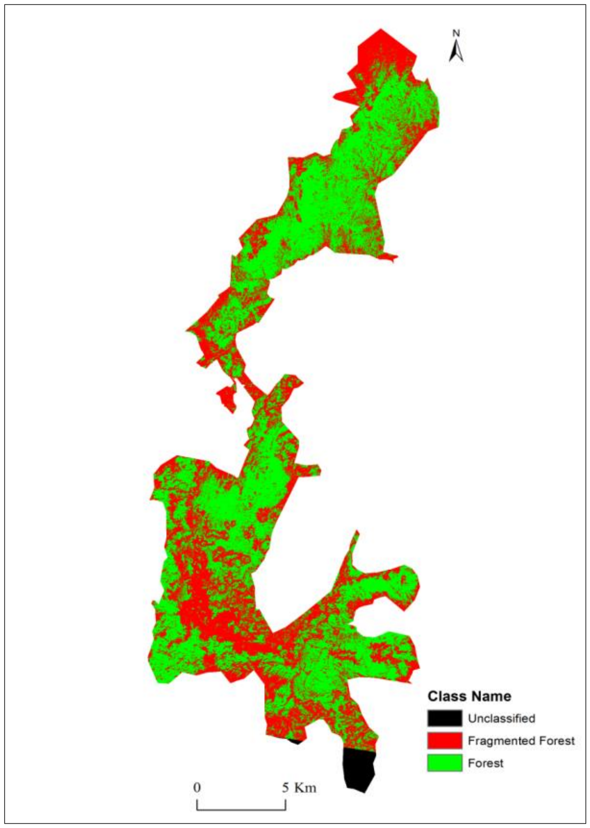

Figure 3.2: Fragmented and intact forests in the study area.

3.4.2 Impacts of forest fragmentation on patch area and soil health

The mean patch area was 41,108 m^2, which varied significantly (t = 2.781, p = 0.007) between intact (52,665m^2) and fragmented (17,106m^2) habitats. There was no significant difference in nitrogen content between intact and fragmented forests (p=0.242). The average soil nitrogen level for Uluguru was 0.50 mg/g, which was relatively similar in intact (0.53) and fragmented (0.45) habitats.

3.4.3 Impacts of forest fragmentation on species abundance and soil health

Individual species responded differently to changes in patch area, habitat status and soil nitrogen content (Table 3.2). The abundance of some species increased (a positive estimate value) with an increase in patch area while others decreased (a negative estimate value). For instance, the abundance of *Syzygium cordatum Hochst.ex C.Krauss* (p < 0.001), *Allanblackia uluguruensis Engl* (p < 0.001), and *Maesa lanceolata Forssk* (p < 0.001) increased significantly with an increase in patch area. While the abundance of *Mytenus undata Thunb* (p < 0.001), *Zenkerella capparidacea (Taub.) J.Leon* (p < 0.001) and *Oxyanthus specious DC*. (p = 0.023) decreased significantly. Some tree species were more abundant in intact areas than in fragmented areas, after adjusting for the effect of patch area and nitrogen level and vice versa. *Syzygium cordatum Hochst.ex C.Krauss* (p < 0.0001), *Allanblackia uluguruensis Engl* (p = 0.003), and *Maesa lanceolata Forssk* (p = 0.047) were more abundant in fragmented habitats, while Myte*nus undata Thunb* (p < 0.001), *Zenkerella capparidacea* (Taub.) J.Leon (p < 0.001), and *Oxyanthus specious DC.* (p = 0.008) were more abundant in intact areas (Table 3.2). Results also showed that soil nitrogen content varied with a change in habitat status which also influenced the abundance of species in both fragmented and non-fragmented areas. For instance, adjusting the effect of patch area and habitat status, the abundance of species intensified in some dominant tree species, while others decreased with higher levels of nitrogen (Table 3.2). Species populations also correlated inversely with changes in nitrogen. For instance, the abundance of *Zenkerella capparidacea* (*Taub*.) *J.Leon* (p<0.001) and *Psychotria goetzei (K.Schum.) E.M.A* was lowest under low nitrogen conditions (p = 0.049).

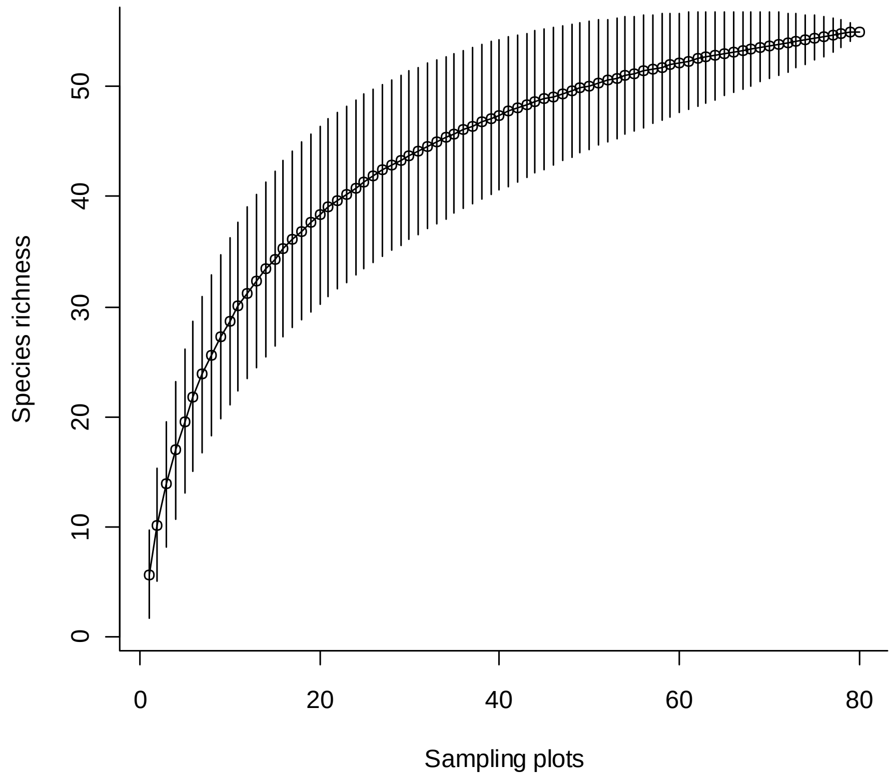

Figure 3.3: Species discovery curve (accumulation curve).

3.4.4 GARP model AUC KAPPA results

The model was run producing a high total area under curve (AUC) accuracy of 0.89, which signifies a good fit of the model. In further validation of the model in Partial Roc, a value of 1.27 was generated. This is within the 1-1.5 range which is an indicator of a very good model prediction. The Jackknife test results generated an overall internal test accuracy of 72.31% and a Roc score of 0.8875 while the external test accuracy was 81.82% and a Roc score of 0.94. The total area under curve (AUC) was 0.89.

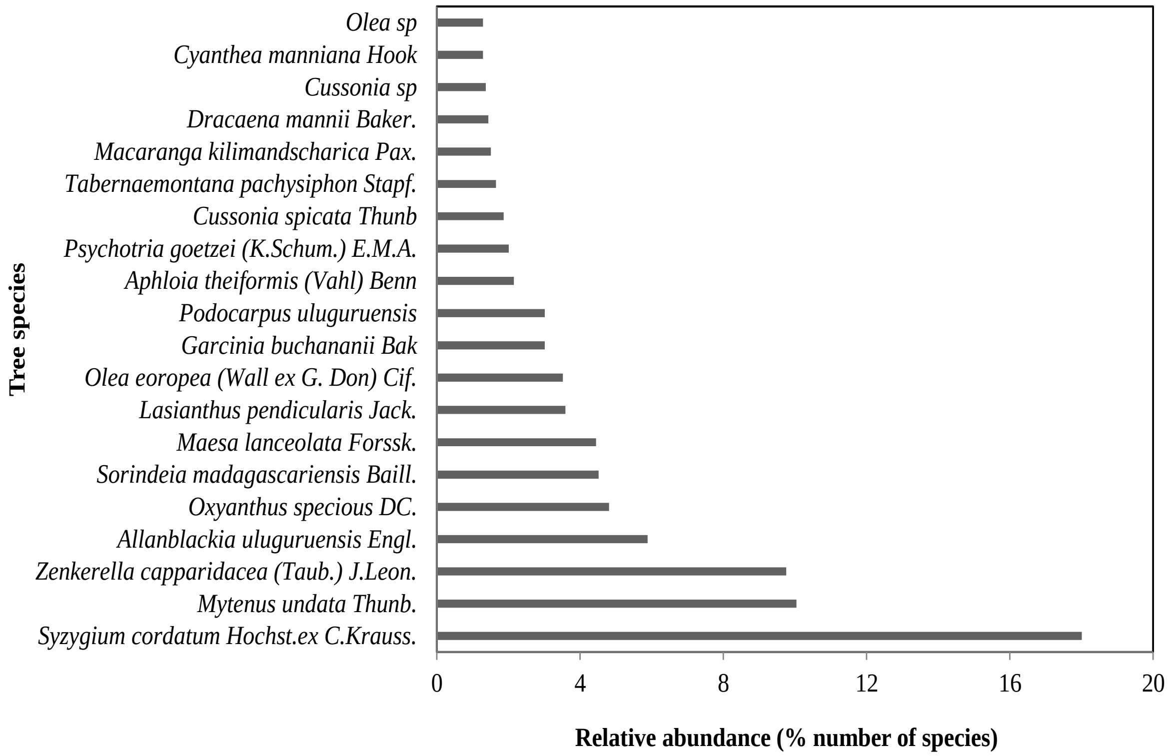

Figure 3.4. Rank-abundance curve for dominant tree species.

3.4.5 Species diversity

A total of 1,394 trees, comprising 55 species, were recorded. There was higher species diversity in Uluguru South than Uluguru North (p-value: 6.026e-05). No variables used in the model were highly correlated i.e. $r < 0.7$. Pearson correlations between the Shannon wiener index and each of the environmental variables showed a positive correlation between most of the variables (C: $r=0.26$, N: $r=0.25$, P: $r=0.22$, DEM: $r=0.37$) except K: $r= -0.25$. DEM, C, N, Ph, P had a significant influence on the model. However, the digital elevation model had the greatest effect on the model.

High species diversity was dominant in intact areas located in the central region of the Uluguru forest (Figure 3.5A) while low species diversity was widespread in fragmented areas (Figure

3.5B). Areas characterized by zero values are not well placed to support high species diversity due to the extent of fragmentation beyond the threshold (see Figure 3.5).

3.5 Discussion

This study provides important findings on effects of fragmentation on species abundance in the Uluguru forest area based on field measurements and remotely sensed data. The relatively high overall accuracy (see Table 3.1) of mapping fragmented and intact forest in the study area provided an important basis for investigating the impact of habitat fragmentation on species abundance and diversity. Results show that fragmentation is intensive on the outskirts of the Uluguru forest (see Figure 3.3). The results are discussed in the context of how fragmentation affects species abundance and diversity and related conservation implications.

Table 3.2: Poisson regression model results for the relationship between abundance of tree species and mean patch area (ha), habitat status and soil nitrogen content for the dominant species in Uluguru forest area

	Patch area (ha)		**Habitat Status**		**Nitrogen level (g kg-1)**	
Species	Estimate±se	*P* value	Estimate±se	*P* value	Estimate±se	*P* value
Syzygium cordatum Hochst.ex C.Krauss.	0.00001±0.000001	<0.001	1.17±0.14	<0.001	0.58±0.16	<0.001
Mytenus undata Thunb.	-0.00004±0.000007	<0.001	-2.40±0.33	<0.001	0.76±0.33	0.020
Zenkerella capparidacea (Taub.) J.Leon.	-0.00002±0.000006	<0.001	-0.81±0.21	<0.001	-1.91±0.53	<0.001
Allanblackia uluguruensis Engl.	0.00001±0.000002	<0.001	0.75±0.25	0.003	0.71±0.27	0.008
Oxyanthus specious DC.	-0.00003±0.000015	0.023	-2.74±1.03	0.008	0.28±0.95	0.769
Sorindeia madagascariensis Baill.	-0.00004±0.000013	0.001	-0.92±0.30	0.002	0.74±0.43	0.086
Maesa lanceolata Forssk.	0.00001±0.000003	<0.001	0.61±0.31	0.047	0.79±0.29	0.007
Lasianthus pendicularis Jack.	-0.00004±0.000013	<0.001	-1.89±0.48	<0.001	-0.39±0.69	0.578
Olea eoropea (Wall ex G. Don) Cif.	0.00001±0.000003	0.008	1.22±0.31	<0.001	0.003±0.44	0.995
Garcinia buchananii Bak	0.00001±0.000003	<0.001	2.14±0.37	<0.001	1.16±0.36	0.001
Podocarpus uluguruensis	0.00004±0.000003	0.244	1.84±0.37	<0.001	0.38±0.43	0.382
Aphloia theiformis (Vahl) Benn	0.00011±0.000003	0.002	0.43±0.41	0.301	-0.29±0.61	0.634
Psychotria goetzei (K.Schum.) E.M.A.	-0.00001±0.000007	0.17	0.35±0.38	0.362	-2.08±1.06	0.049
Cussonia spicata Thunb	0.00003±0.000006	<0.001	1.53±0.53	0.004	2.08±0.36	<0.001
Tabernaemontana pachysiphon Stapf.	-0.00001±0.000011	0.235	-1.91±0.74	0.010	-4.48±1.91	0.019
Macaranga kilimandscharica Pax.	0.000018±0.00001	0.066	-2.32±0.76	0.002	-19.21±3.94	<0.001
Dracaena mannii Baker.	0.00002±0.000006	0.003	-0.002±0.69	0.998	-1.02±1.12	0.363
Cussonia sp	-0.00004±0.000033	0.217	0.264±0.46	0.570	-1.562±1.19	0.190
Cyanthea manniana Hook	0.00002±0.000011	0.840	-1.815±0.76	0.017	-10.395±3.07	0.001
Olea sp	-0.000003±0.00002	0.170	-1.667±0.75	0.027	-2.724±1.77	0.123

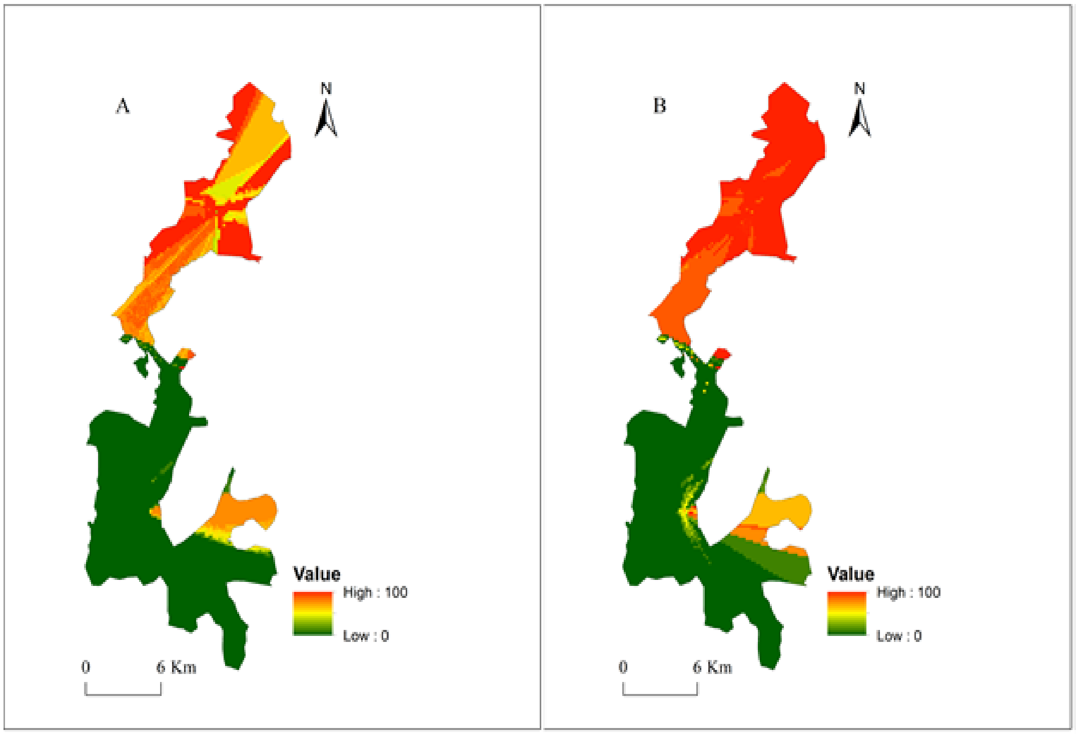

Figure 3.5: Probability for high (A) and low (B) species diversity.

3.5.1 Fragmentation impacts on species abundance and soil health conditions

Individual species responded differently to changes in patch area. Species abundance of some tree species declined with an increase in patch area, while others decreased. For instance, the abundance of *Syzygium cordatum Hochst.ex C.Krauss*, *Allanblackia uluguruensis Engl*, and *Maesa lanceolata Forssk* increased in disturbed areas compared to intact areas. These species prefer abundant light associated with forest fragmentation (Cunningham, 2001). Other species such as *Mytenus undata Thunb*, *Zenkerella capparidacea (Taub*.) *J.Leon*, and *Oxyanthus specious DC* were more abundant in intact habitats than fragmented areas. This suggested that such species are prone to forest disturbance and therefore need to be prioritized for conservation.

More tree species were scattered with a low similarity along study plots with frequent occurrence of tree stumps where field assessments were conducted. A negative correlation was established on the abundance of species like *Oxyanthus specious* which decreased with an increase in patch area while *Mytenus undata Thunb*, *Zenkerella capparidacea (Taub.) J.Leon* and *Oxyanthus specious DC* significantly decreased. A decrease in patch area provides an indication that a habitat undergoing fragmentation (McGarigal and Cushman, 2002; Wu *et al.*, 2002; McGarigal, 2006). It opens up other avenues for increasing edge effects caused by human settlements and tree logging which in turn interferes with the habitat configuration of species through increased exposure to soil erosion and drying up of soil moisture and erosion of nutrients (Gould, 2000; Burgess *et al.*, 2007b). The findings are consistent with an ecological study by Echeverría *et al*., (2007) which established fragmentation effects on vegetation species in southern Chile. Fragmentation also escalates the degree of patchiness of a habitat which has an effect on an ecosystem's configuration and biophysical processes (Lovett *et al.*, 2006; Maeda *et al.*, 2010).

Furthermore, species abundance varied significantly, which could be attributed to changes in soil in both intact and fragmented areas. The threat posed to soil is an aspect that suggests progressive fragmentation could intensify the susceptibility of important ecosystem soil elements to attrition. The level of soil nitrogen in fragmented areas was less compared to that in less fragmented areas. Typically, a fragmenting habitat is characterized by low nitrogen content (Billings and Gaydess, 2008). Changing land use play a role as they influence soil health properties (Davidson *et al.*, 2004; Amazonas *et al.*, 2011). Frequent habitat disturbances open up intact habitats to soil erosion, loss of organic matter and other necessary elements useful for vegetation growth (Guggenberger *et al.*, 1994; Foley *et al.*, 2005).

3.5.2 Impacts of fragmentation on species diversity

Applying remote sensing variables such as the fragmentation index map, DEM and edaphic factors were useful in species diversity prediction. In this study, species diversity was better predicted using customized variables with an AUC of 0.86 when the model was tested using partial ROC value of 1.27. High species diversity was associated with less fragmented land use type, high terrain and good soil conditions not exposed to harsh environmental conditions and heat. This was reflected with Jackknife analysis that showed variables with the highest effect on the model. The soil variables and DEM influenced the model by 72%. The GARP model result produced an AUC of 0.89. GARP model has the advantage of predicting entire species diversity distribution as opposed to Maxent which only predicts the distribution of input occurrence data (Peterson *et al.*, 2007). It has also been successfully used in other studies targeting regional or local scale predictions (Woodward and Beerling, 1997).

High species diversity was evident in intact non-fragmented areas. Areas characterized by zero values were not well placed to support high species diversity due to the wide extent of fragmentation. Low species diversity was prevalent in fragmented areas associated with low values of nitrogen, carbon, potassium and phosphorus in the Uluguru North. This is attributed to increased anthropogenic activities in the area (Shirima *et al.*, 2011). This further confirms a similar study finding which associated high species diversity with intact areas attributed to less human disturbances (Rashid *et al.*, 2013). Other related studies established less species in sites exposed to predation (Olson *et al.*, 2014).

Based on the GARP algorithm, generally, Uluguru forest block has a high potential for high species diversity. It is possible to restore the entire region into a high species diversity site despite the increasing rate of external perturbations from anthropogenic activities. Ecologists support the argument that disturbed ecosystems with a high diversity response have a better chance of restoration after disturbance, as opposed to ecosystems with low diversity (Folke *et al.*, 2004). If the habitat is conserved, most likely endemic and vulnerable species will be protected from more exposure to harsh environmental conditions (Armenteras *et al.*, 2003; Burgess *et al.*, 2007b; Buermann *et al.*, 2008; Burgess *et al.*, 2013) and other ecological risks (Folke *et al.*, 2004). This could significantly contribute to low endemism and extinction rates (Şekercioğlu *et al.*, 2004).

3.5.3 Conservation implications

Anthropogenic activity affects species occurrences and survival rates (Tilman and Lehman, 2001; Pineda and Halffter, 2004; MacDougall *et al*., 2013). The site portrays a strong probability of high species diversity with a great ecological resilience capacity. Conservation organizations and decision makers need to encourage good conservation practices that will counteract loss of vegetation in the area. One of the challenges facing management of fragile ecosystems is development of socio-ecological resilience that can in principle contain dynamic landscapes (Daily, 2000; Fischer *et al*., 2004; Folke *et al*., 2003; Foley *et al*., 2005). The need for example, to support development of appropriate scenarios with the capacity to support sustainable livelihoods while conserving the habitat need to be strengthened. The other factor which may account for species losses is poor institutional frameworks. A previous finding indicated that institutions, which are lacking in Uluguru region, play a critical role in fostering community response to sustainable use of natural resources. Based on field observations, most communities are not motivated into sustainable forest conservation activities. Therefore, pursuing sustainable forest management while integrating local institutional frameworks can be a sound and a better step in strengthening governance frameworks in biodiversity conservation (Lopa *et al.*, 2012).

Based on findings of this study, habitat fragmentation can be considered to be a major threat to conservation in the region. Findings showed that in areas of high terrain, the intensity of fragmentation was relatively high. This could be associated with rich biodiversity resources in high terrain areas in the Ulugurus (Swetnam *et al.*, 2011). Though the abundance of species varied with changes in habitat status, it emerged that most dominant species were affected. It will be appropriate if decision makers and conservation biologists could support conservation efforts in the region as it still remains susceptible to increased endemism and extinction. This is due to the increasing population leading to clearing of the Uluguru slopes in search of greener pastures (Burgess *et al.*, 2007b). Furthermore, expansion of the urban set-ups at Morogoro town and surrounding smaller towns facilitate easy accessibility to markets in Morogoro region which drive forest loss in Uluguru.

Generally, the Eastern Arc mountains have a very conducive and reliable climate (Mumbi *et al.*, 2008). This is useful in establishment of agricultural systems and therefore attractive to subsistence farmers in Tanzania (Burgess *et al.*, 2007a). Intensification of agricultural systems and settlements presents a key threat to species abundance and survival in the Ulugurus (Burgess *et al.*, 2007b). Although population density is projected to intensify in the coming decades, the worst case scenario is expected (Fjeldså, 1999; Hall *et al.*, 2009; Swetnam *et al.*, 2011). Most likely species existence might become irreplaceable in the long-term if the trend persists (Rondinini *et al.*, 2006).

3.6 Conclusions

The present study has yielded valuable insights regarding the ecological importance of forest fragmentation on the abundance and diversity of fundamental species in Tanzania. Overall, fragmentation presents a great challenge to species abundance and diversity in the Uluguru forest block. We make important observations from the study: 1) Fragmentation is having an impact on species abundance under changing soil conditions, and 2) The use of Genetic Algorithm for Rule-Set Prediction (GARP model) and remote sensing variables are useful in discerning impacts of fragmentation on species diversity in the Uluguru forest block. Our study results suggest the need to accord priority to habitat restoration and conservation efforts in the long term plans for the fragmenting habitat.

CHAPTER FOUR

Forest biomass prediction in fragmenting landscapes in Tanzania based on remote sensing data

Field based measurements with forest guard and research assistants George (center), Munuo (right)

This chapter is based on:

Ojoyi M. M, Mutanga O., Odindi J., Abdel-Rahman E., (2014). Ecosystem disturbance: assessing impacts on above ground biomass and spatial structure using Rapid eye imagery. *Geocarto international* (under revision).

Abstract

Estimating tropical biomass is critical for establishment of conservation inventories and landscape monitoring. However, monitoring biomass in a complex and dynamic environment using traditional methods is challenging. Recently, biomass estimates based on remotely sensed data and ecological variables have shown great potential. The present study explored the utility of remotely sensed data and topo-edaphic factors to improve biomass estimation in Tanzania. Twenty nine vegetation indices were calculated from RapidEye data, while topo-edaphic factors were taken from field measurements. Results showed that using either, topo-edaphic variables or vegetation indices, biomass could be predicted with an R^2 of 0.4. A combination of topo-edaphic variables and vegetation indices improved the prediction accuracy to an R^2 of 0.6. Results further showed a decrease in biomass estimates from 1162 ton ha^{-1} in 1980 to 285.38 ton ha^{-1} in 2012. The study demonstrates the value of combining remotely sensed data with topo-edaphic variables in biomass estimation.

Keywords: biomass, topo-edaphic factors, heterogeneous, management, RapidEye

4.1 Introduction

Tropical forests are the most extensive terrestrial global ecosystems (Lead *et al*., 2000). These ecosystems are valuable social and ecological assets as they contain large carbon storage capacity (Howell *et al*., 2006). Consequently, assessing tropical forest's biomass quantity is vital in understanding their health and designing optimal sustainable management strategies (Aerts and Chapin III 2000; Clark and Clark 2000; Laurance *et al*. 1999; Mani and Parthasarathy 2007). Quantifying biomass is also an important requirement in effective execution of carbon credit markets (Con *et al*., 2013; Munishi and Shear 2004a; Swai *et al*., 2014).

To date, existing studies on tropical forest above ground biomass estimations have commonly used various environmental variables based on field measurements (Brown 2002; Brown *et al*. 1991; Brown and Lugo 1992; Chave *et al*. 2008; Gough *et al*. 1994; Miguez *et al*. 2008; Shirima *et al*. 2011; White *et al*. 1991). However, such field based techniques are often time consuming, relatively expensive and inaccurate, especially over large spatial extents (Baskerville, 1972; Ketterings *et al*. 2001; Malimbwi *et al*. 1994; Nelson *et al*. 1999). However, the emergence of higher spatial and spectral resolution sensors such as Worldview, Pleades, RapidEye and GeoEye, offer great potential for cost effective and reliable large scale biomass estimation (Cho *et al*., 2007; Popescu, 2007; Popescu *et al*., 2003; Wulder *et al*., 2004). The RapidEye sensor for instance consists of strategically located bands such as the red edge which is valuable in vegetation mapping (Ayanu *et al*., 2012; Li *et al*., 2012; Ramoelo *et al*., 2012; Tapsall *et al*., 2010; Vo *et al*. 2013). Such data could also have potential use in estimating above ground biomass in a heterogeneous tropical forest.

Due to variability in topo-edaphic characteristics, studies have shown that biomass in tropical forests vary across landscapes (Schulp *et al.*, 2008). Topographic factors such as elevation and slope affect biomass productivity. Soil nutrients on the other hand play a vital role in regulating and maintaining the biophysical processes in vegetation (Aerts and Chapin III 2000; Chapin, 1980; Fageria 2010; Marschner and Rimmington, 1988). Consequently, due to their direct roles in the photosynthetic process, organic carbon, nitrogen, potassium and phosphorous are particularly known to influence biomass production (Chapin, 1980). Furthermore, studies have shown that plant species have a complimentary role in edaphic resource exploitation, particularly in heterogeneous landscapes (Tilman, and Lehman, 2001). For instance, habitats with a relatively higher species diversity facilitate biomass accumulation in plants exposed to carbon dioxide and nitrogen (Reich *et al*., 2001).

Whereas remotely sensed data have become valuable in mapping landscapes, their reliability in mapping tropical forest landscapes is often impeded by dynamic ecosystem characteristics and functioning, heterogeneous vegetation types, composition and structural complexity (Kerr and Ostrovsky, 2003). These factors result in complex remotely sensed variables which may not result in accurate tropical forest above ground biomass estimates. Integration of multiple vegetation indices derived from remotely sensed data; for instance, result in a huge data dimensionality, leading to over fitting and multi-colinearity. This may result in challenges as well as failure to select optimum uncorrelated variables that physically explain biomass variability. Researchers have advocated for statistical methods that do not encounter such kind of problems. Partial least squares regression (PLSR) is one of the effective statistical methods that can transform the spectral vegetation indices to a fewer orthogonal (perfectly uncorrelated) number of components (Wold, 1995) and relate those components to tropical forest biomass.

Previous studies have demonstrated that vegetation indices generated from multispectral data are fairly related to forest above ground biomass e.g. (Box *et al*., 1989; Das and Singh, 2012; Lu, 2006; Van der Meer *et al*., 2001). However, to the best of our knowledge none of these studies have examined the integration of topo-edaphic and remotely sensed variables for forest above ground biomass prediction. In the current study, we hypothesized that complementing topo-edaphic factors with remotely sensed variables could provide a better assessment in estimating above ground forest biomass in a heterogeneous tropical landscape. The present study therefore aimed at exploring the value of complementing topo-edaphic variables with remotely sensed vegetation indices in improving estimation of biomass in Morogoro region, Tanzania.

4.2 Materials and methods

4.2.1 Study area

The study was conducted in Uluguru (7^{o} 2' 7^{0} 16´ S and 38^{0} 0´ 38^{0} 12´ E) and Kitulanghalo (6° 41'S and 37° 57' E) forest blocks located in Morogoro region, Tanzania (Figure 4.1). Uluguru forest block is located in the Eastern Arc Mountains, one of the biodiversity hotspot in the world (Burgess *et al*., 2007; Shirima *et al*., 2011; Swetnam *et al*. 2011). The area is characterized by a mountainous terrain and supports important ecosystem that includes the world's endemic plant and animal species (Brooks *et al*., 2006; Burgess *et al*., 2007; Myers *et al*., 2000; Shirima *et al*., 2011; Swetnam *et al*., 2011). The area receives approximately 1200 mm of rain per year on the eastern and 2900-4000 mm on the western slopes respectively. Forest cover has been lost from 300 km^2 in 1955 to 220 km^2 in 2000 (Burgess, *et al*., 2007; Hall, 2009). This has enhanced endemism and extinction of rare species such as the Uluguru Bush Shrike (Burgess, *et al*., 2007).

Miombo woodlands cover approximately 90% of the total forested terrestrial ecosystem in Tanzania and contribute to the largest carbon storage capacity (Mugasha, *et al*., 2013). Kitulangalo forest, a semi-natural Miombo woodland is located between Morogoro and Dar es

Salaam. The area receives approximately 1000 mm of rainfall per annum and is dominated by *Brachystegia*, *Isoberlinia*, and *Julbernardia*, *Pterocarpus angolensis, Afzelia quanzesis and Albizia species*. Miombo woodlands are well valued by communities which proliferates their commercialisation in adjacent urban areas (Theilade *et al*., 2007). Their proximity to the surrounding urban areas therefore enhances its susceptibility to anthropogenic influence.

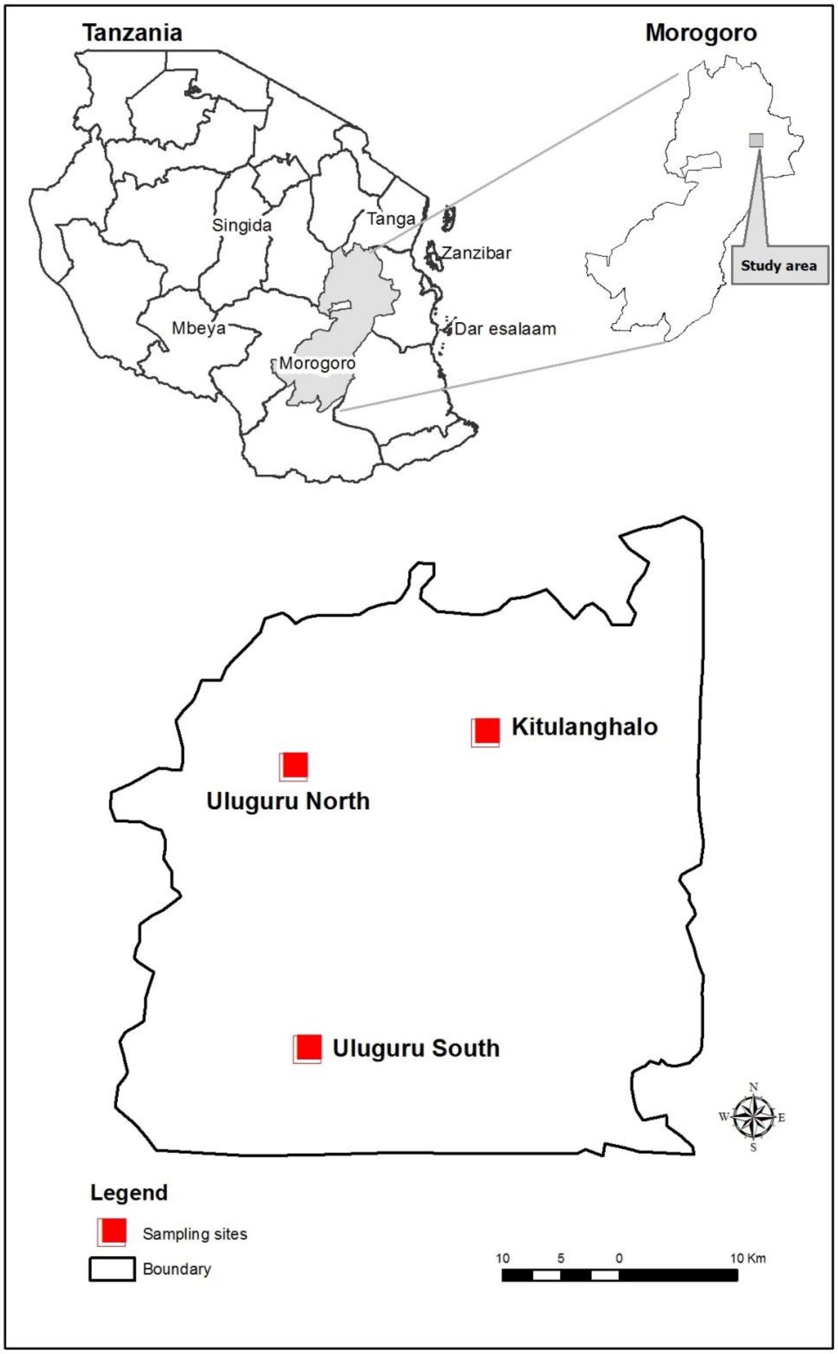

Figure 4.1: Location of the study area.

4.2.2 Biomass estimation based on field allometric equations

Above ground biomass tree measurements were randomly collected from 115 plots each measuring 10 m by 10 m. Hawth's analysis tool extension for ArcMap software was used to generate the random plots. Based on the methods described by Chave *et al*., (2005), trees with more than five cm in diameter at breast height (dbh) were sampled. For this study, 2014 trees of different species were measured. The existing allometric model by Chave *et al*., 2005 was then used to estimate above ground biomass. The model was specifically developed for tropical forests in mountainous areas and therefore suits Uluguru forest and expressed as;

$$\text{Above Ground Biomass} = (0.0509^{*}(\text{wd}^{*}\text{d}^{2*}\text{ht})$$

Where: wd is wood density, d is number of trees per unit area and 'ht' is height.

In this study, an average wood density value of 0.57 was used which is a value for wood density in the Eastern Arc Mountains (Munishi and Shear, 2004a). With regard to biomass estimations in Kitulanghalo forest, an equation developed by Chamshama *et al*., (2004) was applied. This equation has been developed and used in a woodland forest ecosystem (e.g. the Kitulanghalo forest). The model states that above ground biomass equals $0.0625*dbh^{2.553}$. The total above ground biomass was estimated in each of the 115 plots sampled. Individual tree species numbers with more than five centimetres dbh were recorded in each plot.

4.2.3 Soil analysis and topographic variables

A total of 115 soil samples were collected from the center of the 10 m by 10 m plots. Samples were air dried and sieved using a 2 mm sieve, prior to analysis. Scanning of soil samples was conducted using the atomic absorption spectrometer to obtain soil reflectance values. The spectrometer was used to extract reflectance values for five elements (N, P, K, pH, and C). These soil elements were further analyzed by wet chemistry analysis and the results later used to correlate bands with actual mineral values. Digital Elevation Model and slope were extracted from the freely available ASTER data.

4.2.4 Image acquisition and pre-processing

RapidEye satellite imagery covering the study area was acquired on 23/10/2012. The imagery has a five metre and five bands spatial and spectral resolutions, respectively. RapidEye bands are centered at blue: 440-510 nm, green: 520-590 nm, red: 630-685 nm, red edge: 690-730 nm and near infrared: 760-850 nm. The image was first geometrically corrected (Universal Transverse Mercator: UTM, zone 37 south projection) and resampled to its original pixel size using nearest-neighbour algorithm and first-order polynomial transformation method. The nearest neighbor is a resampling method that assigns a value to each "corrected" pixel from the nearest "uncorrected" pixel. It has the capacity to preserve original values in the unaltered image scene. A root mean square error of less than a pixel was obtained, indicating a reliable geometric correction. Atmospheric correction was then applied using ATCOR module built into Earth Resources Data Analysis System software (ERDAS Imagine 2013) that converts the data to surface reflectance.

4.3 Data analysis

To co-relate forest above biomass and RapidEye data, a partial least squares regression (PLSR) was utilized. Generally, when a feature of interest like forest biomass is modelled using remotely sensed data, there are many possible correlated (co-linearity phenomenon) spectral bands or vegetation indices and relatively fewer field measurements (Hughes phenomenon). Therefore, PLSR creates a small number of orthogonal components (tolerate co-linearity problem) from the predictor variables (X) that are also related to the response (Y) variable and therefore reduces the dimensionality of the “X” variables (Wold, 1995). PLSR then extracts the components which serve as new predictors and relates them to the response variable (Huang *et al*., 2004; Abdi, 2007). The PLS components creation process utilizes the principles of principal component anaysis and a multiple linear regression step and utilizes the components to predict “Y” (Wold, 1995). However, PLSR model can poorly perform if a high number of components are included in the model (Mevik and Wehrens, 2007). Therefore, in the present study, the optimal number of components was selected using a leave-one-cross validation method. A number of components that resulted in the first minimum root mean square error (RMSE) were selected. Eight variables (NPK, C, pH, DEM, slope) were employed to estimate forest above ground biomass using PLSR. The use of twenty nine spectral vegetation indices (Table 4.1) in estimating of above ground biomass in the study area was also tested. The indices are sensitive to chlorophyll and moisture content. Additionally, edaphic and topographic factors were integrated with the rest of the twenty nine spectral vegetation indices to estimate above ground forest biomass. The ASTER DEM is a highly accurate DEM covering all the land on earth. It is available to users in different locations and displays a bird’s-eye-view map which enables users perform advanced analysis of choice across diverse fields.

Table 4.1: Spectral vegetation indices used in the study

INDEX	NAME	FORMULA	REFERENCE
NDVI	Normalized difference vegetation Index	$(\rho nir - \rho r) / \rho(nir + \rho r)$	(Tucker, 1979)
SR	Simple ratio	$\rho nir/\rho red$	(Birth and McVey, 1968)
EVI	Enhanced vegetation Index	$G \times ((\rho nir - \rho R)/\rho nir + CI \times \rho R - C2 \times \rho B + L))$ $\rho B = reflectance\ of\ blue\ band$	(Huete *et al*., 1997)
NDVIred edge	NDVI red edge index	$(\rho nir - \rho Red\ edge) / \rho(nir + \rho Red\ edge)$	
SR red edge		$\rho nir/\rho red\ edge$	
Red/ Green	Red to green ratio	$(\rho red/(\rho green)$	(Gamon and Surfus, 1999)
Red edge / Green	Red edge to green ratio	$(\rho red\ edge/(\rho green)$	
CI	Red edge chlorophyll index	$\frac{\rho nir}{\rho red - edge} - 1$	(Gitelson *et al*., 2005)
SAVI	Soil Adjusted vegetation index	(1+L)$(\rho nir - \rho r)/(\rho nir + \rho r + L)$	(Huete, 1988)
Sqrt SR	Square root of simple ratio	$\left(\frac{\rho nir}{\rho red}\right)$ ½	(Tucker, 1979)
SgRSRred edge		$\left(\frac{\rho nir}{\rho red\ edge}\right)$ ½	
MSR	Modified simple ratio	$\frac{(\frac{\rho nir}{\rho red} - 1)}{\left(\frac{\rho nir}{\rho red}\right) ½ + 1}$	(Chen and Cihlar, 1996)
NDVIgreen	Green NDVI index	$(\rho nir - \rho green)/(\rho nir + \rho green)$	(Gitelson *et al*., 1996)
GDI	Green difference index	$\rho nir + \rho r + \rho green$	(Vescovo and Gianelle, 2008)
GRDI	Green red difference index	$(\rho green - \rho red)/(\rho green + \rho red)$	(Vescovo and Gianelle, 2008)
VI	Vegetation Index	$\rho nir - \rho red$	(Tucker, 1979)
NLI	Non-linear vegetation index	$(\rho^2 nir - \rho r)/(\rho^2 nir + \rho r)$	(Goel and Qin, 1994)
RDVI	Re-normalized difference vegetation index	$\rho nir - \rho red)/(\rho nir + \rho red)$½	(Roujean and Breon, 1995)

MNLI	Modified non-linear vegetation index	$\frac{(R^2nir - Rred)(1+L)}{(R^2nir + Rred + L)}$	(Gong *et al*., 2003; Viña *et al*., 2011)
SR*NDVI	SR*NDVI	$(R^2nir - Rred)/(Rnir + (R^2red)$	(Gong, *et al*., 2003; Viña *et al*., 2011)
SRred edge * NDVIred edge			
SAV *SR	SAVI*SR	$(R^2nir - Rred)/(Rnir + Rred + L)\ Rred$	(Gong *et al*., 2003; Viña *et al*., 2011)
WDR I	wide-dynamic range vegetation index	$(a \times \rho nir - \rho r) / (a \times \rho nir + \rho r)$	(Gitelson, 2004)
CI*Green*	Green chlorophyll index	$\frac{\rho nir}{\rho green} - 1$	(Gitelson, 2004)
MTCI	MERIS Terrestrial chlorophyll Index	$\frac{\rho nir - \rho red - \rho\ red\ edge}{\rho red\ edge - \rho red}$	(Dash and Curran, 2004)
NIR/G	Near infrared to green ratio index	$(\rho nir/(\rho green)$	(Almeida and Filho, 2004)
GDVI^n	Generalized Difference VI	$(\rho^n nir - \rho^n r)/ (\rho^n nir + \rho^n r)$	(Wu, 2014)
GDVIred edge^n	Generalized Difference VI red edge	$(\rho^n nir - \rho^n red\ edge)/ (\rho^n nir + \rho^n red\ edge)$	
EVI2	Enhanced vegetation index 2	$2.5(\rho nir - \rho r) / (\rho nir + 2.4\rho R + L)$	(Jiang *et al*., 2008)

$\rho Green$, ρRed, and ρNIR are surface reflectance values at green (Band 2), red (band 3), NIR (band 4), and red edge (band 5) of RapidEye.

For SAVI, the slope of the soil line (L) = 0.05, while for GDVI, $a = 2$.

4.4 Results

4.4.1 Species and trends in above ground forest biomass contribution

The overall mean and standard deviation of the above ground biomass data used in the present study were 3.30 and 5.78 ton ha-1, respectively. Dominant species recorded in each plot were recorded. Table (4.2) shows the means and standard deviations of the dominant tree species in the study area. Tree species which contributed the highest biomass estimates in Uluguru forest were *Zenkerella capparidacea (Taub.) J.Leon*, *Syzygium cordatum Hochst.ex C.Krauss,* and *Allanblackia uluguruensis Engl.* While, *Sterculia quinqueloba (Garcke) K. Schum*, *Lannea schimperi (Hochst. Ex A. Rich) Egl. Tamarindus indica L., Turraea robusta Gürke, Acacia mellifera (Vahl.) Benth, Brachystegia boehmii Taub* and *Brachystegia microphylla Harms* contributed the most in Kitulanghalo forest block.

Table 4.2: Mean and standard deviation of biomass (ton ha^{-1}) for the dominant tree species

Species	**Mean**	**Standard deviation**
Zenkerella capparidacea (Taub.) J.Leon.	0.42	0.96
Syzygium cordatum Hochst.ex C.Krauss.	0.27	0.616
Allanblackia uluguruensis Engl.	1.37	4.07
Combretum sp	0.06	0.07
Julbernardia globiflora (Benth.) Troupin	0.19	0.23
Lannea schimperi (Hochst. Ex A. Rich) Egl.	0.55	0.77
Pterocarpus tinctorius Welw.	0.15	0.71
Sterculia quinqueloba (Garcke) K. Schum	2.88	2.73
Tamarindus indica L.	1.33	0.68
*Xeroderris stuhlmannii (*Taub.) *Mendonça* & E.P. Sousa	0.56	0.10

4.4.2 PLS predictive models

Table (4.3) shows results of PLSR analysis. All models resulted in selection of two components. When only eight topo-edaphic variables were used, that is (DEM, slope, Shannon, N, P, K, ph, C), the PLSR model showed only 44% of the variability in the above ground forest biomass. Approximately similar amount of variation (43%) was explained using 29 vegetation indices. On the other hand, a PLSR model with a total of 29 vegetation indices and the 8 topo-edaphic factors explained 60% of the above ground forest biomass variability. Figure (4.3) highlights the influence of each vegetation index or topo-edaphic factor on PLSR models. Generally, N, P and C contributed the most on the model components while SAVI, MSR, and GDI were the most influential indices in both models. After integrating topo-edaphic factors together with vegetation indices in the estimation of above ground biomass, their influence on the components of the model was relatively higher than most of the vegetation indices (Figure 4.3c).

Relatively high RMSE values were obtained for all models. The performance of PLSR models is presented in Figure (4.4). Results demonstrated that when remotely sensed data were utilized, biomass values of less than 2 ton ha^{-1} were accurately estimated as the slope of the relationship between the measured and predicted biomass values of more than 2 ton ha^{-1} was deviated from the expected one-to-one line. The inclusion of topo-edaphic factors in remote sensing-based model improved the predictability of above ground forest biomass by reducing the RMSE by approximately 20% (Figure 4.4c).

Table 4.3: Coefficient of determination intercepts and number of components of the PLSR models for estimating forest above ground biomass. See Figure 4.3 for the PLSR regression coefficients.

Variables	**Number of components**	**Intercept**	$\mathbf{R^2}$
8 topo-edaphic factors	2	0.384	0.44
29 vegetation indices	2	-0.504	0.43
29 vegetation indices + 8 topo-edaphic factors	2	6.721	0.6

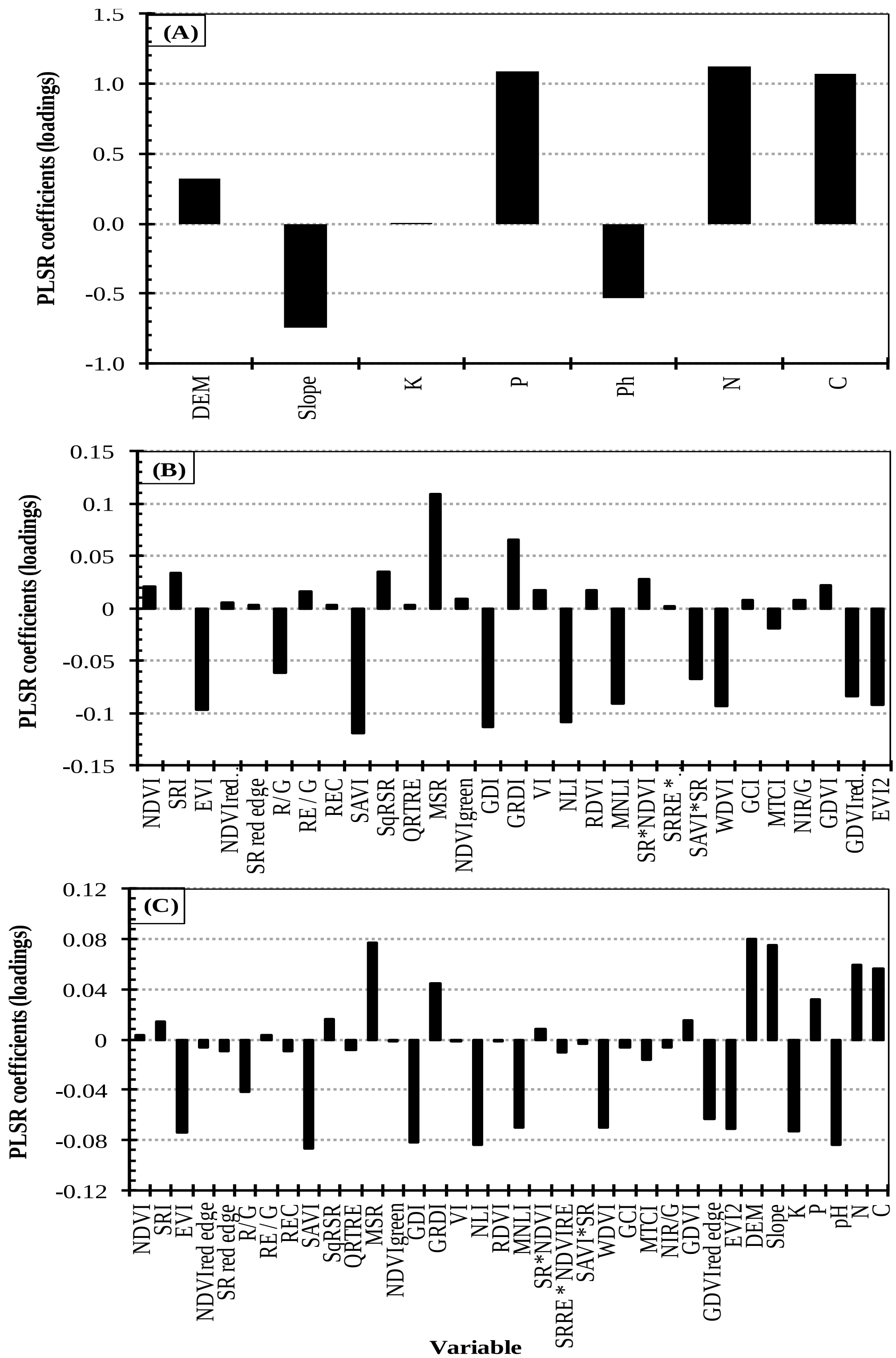

Figure 4.3: PLSR coefficients (loadings) for the variables used in the present study. (A): topo-edaphic factors, (B): vegetation indices, and (C): vegetation indices and topo-edaphic factors.

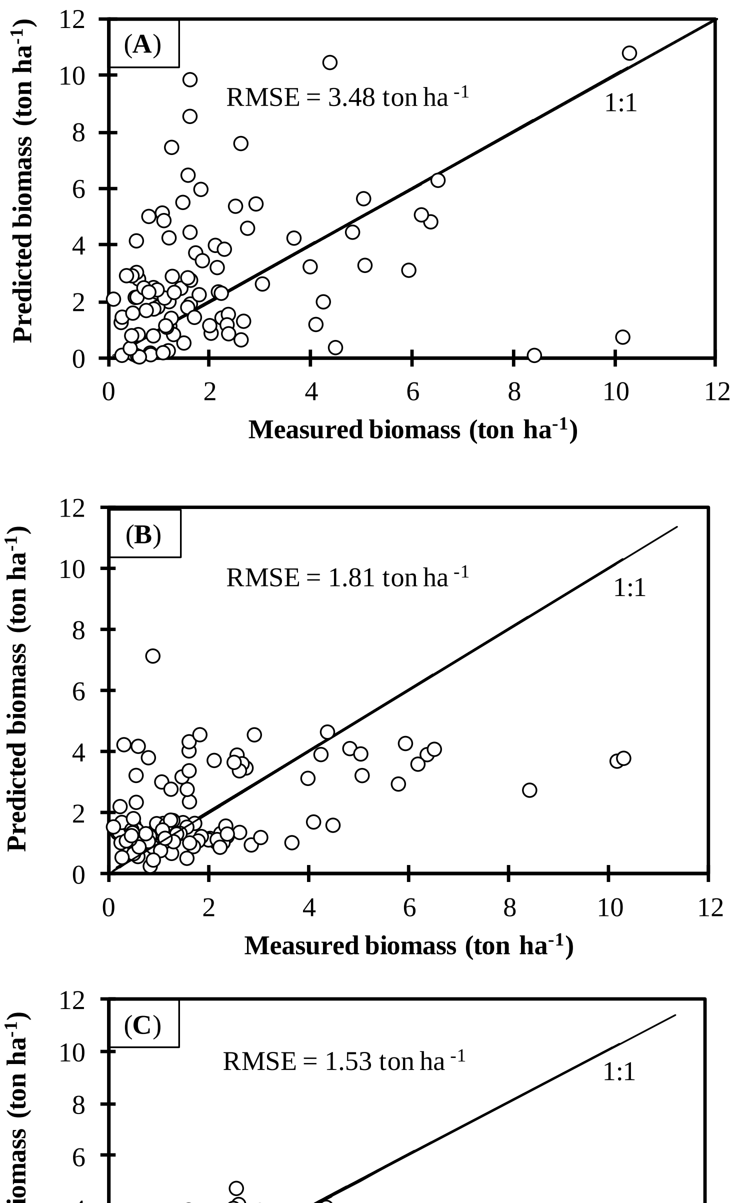

Figure 4.4: One-to-one relationship between measured and predicted above ground biomass for the sample data set using leave-one-out cross validation model. (A): Using eight topo-edaphic factors, (B) using 29 vegetation indices, and (C) using 29 vegetation indices plus the eight topo-edaphic factors based on 115 samples.

4.5 Discussions

The study presents an important finding on the vital role played by topo-edaphic factors in biomass estimation. Overall, the results revealed that a combination of edaphic factors and 29 vegetation indices relatively reduced biomass prediction error by approximately 20%, with an underestimation of biomass above 4 ton ha^{-1}.

4.5.1 Use of vegetation indices on above ground biomass estimation

The present study indicated that SAVI, MSR, and GDI were the most influential variables in biomass estimation (highest PLS loadings in Figure 4.3). The effect of MSR and GDI can be attributed to their sensitivity to chlorophyll content which is directly related to biomass productivity (Loris and Damiano, 2006;Xue and Yang, 2009). The value of SAVI on biomass estimation, on the other hand, confirms a previous finding that shows Uluguru forest is subjected to fragmentation (Hall *et al*., 2009; Kacholi, 2014). Therefore, the effect of soil background on the remotely sensed variables was reduced by the advent of SAVI (Huete, 1988). All topo-edaphic factors had relatively higher PLSR loadings (Figure 4.3b). This confirms the importance of these factors in above ground biomass estimation.

Possible reasons for the high error values when biomass was modelled using only vegetation indices could be due to the relatively coarser spatial resolution (5 m x 5 m) of the RapidEye sensor. Since the study area is a heterogeneous landscape, within (5 m x 5 m), a mixture of tree species may exist. In combination with ground truth data, higher resolution remotely sensed data could help resolve effects of structural variability at finer and complex vegetation structures (Houghton *et al*., 2001). The low biomass prediction accuracy could also be due to the saturation problem that results when data from broader spectral resolution sensors like RapidEye are used to estimate biomass of densely vegetated sites (Adam *et al*., 2014; Avitabile *et al*., 2012; Lu and Batistella, 2005; Powell *et al*., 2010). This is supported by the deviation of the regression model slope from one-to-one relation at higher biomass values in Figure (4.4B). We suggest that future biomass estimation studies should adopt finer resolution satellite imagery such as WorldView-2, WorldView-3 and Sentinel-2 sensors. Such sensors contain the red edge band which has been proven to be less sensitive to high biomass saturation problem (Mutanga and Skidmore, 2004). Another possible reason of high error in biomass estimates using vegetation indices is that only trees of more than five centimeter in diameter were measured while remotely sensed data integrated spectral features of all the trees in the study site. Moreover, our study used a snapshot of specific variables in the study area. Since above ground forest biomass is a result of a cumulative effect of biotic and abiotic variables on tree growth and development (Chuine and Beaubien, 2001; Duchesneau *et al*., 2001; Thomas *et al*., 2002; Utkhede and Smith, 1993; Vollenweider and Günthardt-Goerg, 2005), the use of multi-temporal data sets would capture the variation in above ground biomass more accurately.

Results of the present study showed that variance in above ground biomass data were relatively high. This may have affected RMSE values since they were calculated from mean deviations. Furthermore, other studies note that vegetation indices calculated from broadband spectral data tend to saturate at high biomass level (Gao *et al*., 2000). To overcome this problem, Mutanga and Skidmore (2004) recommended the use of narrow-band vegetation indices for estimating above ground biomass in densely vegetated areas. Narrow-band vegetation indices are commonly calculated from hyperspectral data which are costly and not readily available. Improved spatial resolution in concert with edaphic and topographic factors could therefore significantly improve the accuracy of biomass estimation in heterogeneous landscapes like the Uluguru and Kitulanghalo forests in Tanzania.

4.5.2 Effects of edaphic factors on above ground biomass estimation

This study contributes to an important element that integrates both remotely sensed data and topo-edaphic factors in forest above ground biomass estimation. As aforementioned, to the best of our knowledge, previous studies that employed remote sensing techniques did not incorporate topo-edaphic factors in biomass estimation. In Uluguru region, previous studies have only applied field allometric equations in estimating above ground biomass (Mugasha *et al*., 2013; Munishi *et al*., 2010; Munishi and Shear, 2004b; Swai *et al*., 2014).

Results in the present study indicate the value of topo-edaphic variables in above ground forest biomass estimation in a heterogeneous forest landscape. This is shown by an improved R^2 value from 0.43 to 0.6. Edaphic factors (NP and C) and topographic factors account for a significant contribution in the PLS loadings and hence in estimating above ground biomass estimation (Figure 4.3a and 4.3c). This finding is congruent with other study findings which show the effect of topo-edaphic factors on above ground biomass productivity (Colgan *et al*., 2012). However, K either contributed the least or negatively influenced biomass estimation; consequently, the role of K in Morogoro forests requires further investigation.

Elevation also influenced biomass prediction accuracy (Figure 4.3c). This finding is consistent with other study findings which note that variation in topography and slope in heterogeneous landscapes influences vegetation productivity (Brown *et al*., 1991; Brown *et al*., 1999). Furthermore, related studies in the region indicate how variation in topography affected the complexity and composition of vegetation in the region (Burgess *et al*., 2007, Shirima *et al*., 2011).

4.5.3 Comparing biomass estimates with previous studies

Total above ground biomass obtained in the Uluguru forest was relatively lower than biomass obtained from previous studies. For instance, in the present study a total of 285.38 ton ha^{-1} biomass was obtained for Uluguru forest. This differed considerably from the total biomass estimated in previous studies. Munishi and Shear (2004b), recorded a total of 648 ton ha^{-1}, while Hall (1980) estimated a value of 1162 ton ha^{-1}. This can be explained by a recent finding in the region (Ojoyi *et al*. 2014, under revision) which showed an increasing fragmentation trend pattern in the Uluguru montane ecosystem. In Kitulanghalo, the current study obtained a total of 94.3 ton ha^{-1}, while Shirima, *et al*., (2011) recorded 76.6 ton ha^{-1} in total. Above ground biomass in Kitulanghalo was also estimated in 2010 at a total value of 38.24 ton ha^{-1} (Munishi *et al*. 2010), in 2004 at 29 ton ha^{-1} (Chamshama *et al*., 2004) and in 1994 at a value of 12.90 ton ha^{-1} (Malimbwi *et al*., 1994). Tropical montane forests like Uluguru are often more fertile and hence increased biomass productivity than woodland (Kitulanghalo) ecosystems. Furthermore, chemical properties of soil in disturbed habitats would be less productive, hence, low biomass than soil found in intact forest environments (Laurance *et al*., 1999).

The average above ground biomass for Kitulanghalo forest was 14.57 ton ha^{-1}, which was relatively higher than the estimated 12.90 ton ha^{-1} attained by Malimbwi *et al*. (1994). This could be attributed to regenerating trees and an increase in the productivity rate particularly in high productive sites in Kitulanghalo forest (Chamshama *et al*., 2004). However, former studies attained 38.4 ton ha^{-1} average above ground biomass in Miombo forest ecosystem in Longisonte forest reserve and Zelezeta village forest reserve, in Southern highlands of Tanzania (Munishi *et al*., 2010).

The approach used in estimating above ground biomass may have contributed to variation in the results obtained. For instance, Shirima *et al*., (2011) targeted woodlands with a closed canopy and less disturbance. Other studies considered dbh only, while others considered both dbh and height (Mugasha *et al*., 2013). Malimbwi *et al*., (1994), applied tree measurements of more than ten cm in diameter; while Chamshama *et al*., (2004) included all tree stems and branches. In this study, the model developed by Chamshama *et al*., (2004) was utilized. Measurements were taken from trees of more than five centimeters in diameter.

4.5.4 Management implications

Uluguru montane forest is a global carbon storage block (Burgess *et al*., 2007; Shirima *et al*., 2011; Swetnam *et al*., 2011). Despite the global significance, decline in productivity is expected to continue in the next decades due to expansion of farmlands and urban sprawl (Burgess *et al*., 2007; Lopa *et al*., 2012; Yanda and Shishira 1999). In addition, deforestation is considered a serious threat in the region. Deforestation contributes to habitat loss in the tropics with more than 50% global rates in Africa; at an annual rate of more than 10 million hectares (Lead *et al*., 2000). Reinforcement of conservation efforts in Tanzania is a pre-requisite in counteracting future anthropogenic threats (Meehl *et al.*, 2007; Mertz *et al*., 2009; Paavola, 2008; Sokona and Denton 2001). The paper recommends the need for conservation and management programmes to formulate strategies that would safeguard forest remnants from further human destruction. It will be useful if policy agenda took into consideration the need for regular monitoring and management efforts of biomass production since biomass accumulation is expected to vary regularly due to ecosystem changes attributed to anthropogenic influence and climate change

(Swai *et al*., 2014). Regular biomass estimation studies are considered as a pre-requisite in effective quantification of carbon stocks and fluxes (Ketterings *et al*., 2001). It is envisaged that the current results provide information on the current biomass status but also inform decision makers on the need to conduct regular conservation monitoring frameworks in Morogoro region.

4.6 Conclusions

The use of remote sensing data in concert with field based measurements significantly improved the accuracy of biomass estimation in the heterogeneous landscapes. The study has shown the vital role played by topo-edaphic factors in complementing remotely sensed variables towards above ground estimation in a heterogeneous landscape. A combination of edaphic factors and 29 vegetation indices relatively increased biomass predictions by 20%. However, the error of estimates was relatively high and this could be attributed to saturation problems.

Biomass prediction using remotely sensed variables and topo-edaphic factors is a technique which has not been applied in heterogeneous landscapes in Africa. Though the results are limited by the saturation challenge, the overall result obtained is reliable and sound. Therefore, improving the resolution of the input data can greatly improve results and enhance reliability of the estimates.

The paper further augments recommendations by previous studies that emphasize the need for reliable advanced technology such as remote sensing to predict biomass. Such studies contribute to monitoring programmes critical for supporting climate change mitigation and biodiversity conservation.

CHAPTER FIVE

Bridging science and policy: an assessment of ecosystem vulnerability and management scenarios in Tanzania

Small scale farming in Uluguru montane ecosystem

This chapter is based:

Ojoyi M. M, Mutanga O., Odindi J., Antwi-Agyei P., Abdel-Rahman E., (2014). Managing fragile landscapes: empirical insights from Tanzania. *Journal of Nature Conservation* (under review).

Presented at **Humboldt Foundation conference** in Pietermaritzburg on the 30-9-2014

Abstract

Ecosystems in sub-Saharan Africa remain highly vulnerable to external perturbations. An in-depth understanding of the socio-ecological mechanisms provides an important platform for effective management of vulnerable ecosystems. Using remotely sensed data and empirical data from 335 households, a model was developed to understand how different ecological and socio-economic factors influenced ecosystem vulnerability in the region. Remotely sensed data indicated negative patterns of change in ecosystem health. The multiple logistic regression analysis showed habitat fragmentation and forest burning as key threats ($p \leq 0.05$). From a social point of view, low income level (54.62%) and limited knowledge on environmental conservation (18.51%) are considered as major catalysts enhancing ecosystem vulnerability. Statistical results showed livelihood diversification (45.1%), effective institutional frameworks (30.7%) and afforestation programmes (24.2%) as key intervention measures. The methodology and policy reflections emerging from this research have a wider applicability in managing vulnerable landscapes.

Keywords: ecosystems, vulnerability, planning, management, Tanzania

5.1 Introduction

Many factors play a vital role towards increased ecosystem vulnerability. Human related aspects such as population growth are critical socio-economic factors altering planning and management of ecosystems (Giliba *et al*., 2011). Furthermore, ecological threats such as habitat fragmentation and fires are considered major threats to conservation planning and management of most ecosystems (Achard *et al*., 2002; Benítez-Malvido and Martínez-Ramos, 2003; Burgess *et al*., 2007b; DeFries *et al*., 2002; Echeverría *et al*., 2007; Fahrig, 2003; Fischer and Lindenmayer, 2006; Hobbs *et al*., 2008; Murcia, 1995). The process of habitat fragmentation is known to be a significant threat to ecological functioning, biodiversity conservation and proximate threats to ecosystems respectively (MacDougall *et al*., 2013).

A comprehensive assessment of ecosystem vulnerability is a pre-requisite in determining the relative effectiveness of conservation and management efforts (Wilson *et al*., 2005). Mapping ecosystem vulnerability is particularly useful in monitoring trends and predicting likely future impacts (Antwi-Agyei *et al*., 2012). To date, very few studies have taken into account the vulnerability status of fragile ecosystems and potential threats (Chapin III *et a*l., 2004, Folke *et al*., 2003). A review by Giliba *et al*., (2011) highlights challenges associated with incorporating vulnerability into conservation planning and management due to the lack of effective vulnerability frameworks. Ecosystem vulnerability is a highly contested term. Commonly, it is used to describe a state of susceptibility to stress or harm and revolves around aspects of change or disaster occurrences (Adger, 2006). It is often an indication of a lack of adaptive capacity of any given ecosystem to recover from shock or stress imposed by humans or the external environment (Füssel and Klein, 2006). An ecosystem is considered vulnerable when it displays a high level of sensitivity to change in structure and functioning. The vulnerability concept consists of the socio-economic, physical, infrastructural, political and environmental dimensions (Fraser *et al*., 2003; Adrianto and Matsuda, 2002) and denotes changes in the socio-ecological systems (Holling and Gunderson, 2002). Vulnerability has been linked directly to sensitivity to change, exposure level and coping capacity (Kasperson *et al*., 2005; Gallopín 2006). Differences in vulnerability may be driven by the geographic position, economic structure, access to human, social, natural and financial capitals (Antwi-Agyei *et al*., 2013). Vulnerability is broadly used in different fields including climate studies (Antwi-Agyei *et al*., 2012) and the social system (Adger, 2006).

Diverse system variables portray a system's capacity to develop resilience, thresholds, feedback loops and disturbance regimes (Walker and Salt, 2006). This has an important bearing on the maintenance of ecosystems along a desirable development trajectory (Gunderson, 2000, Walker and Salt, 2006). While any single element of the global sphere could be supported by mutually reinforcing feedbacks, the verge can change its course into other spheres with diverse reactions and impacts (Folke *et al*., 2004). If a set threshold is reached, it is expected that alterations in feedbacks make it almost impossible to return to its original state (Carpenter *et al*., 2001). The dynamic nature of most ecosystems (Tabarelli and Gascon, 2005) coupled with other biophysical and socio-economic factors, enhances the degree of vulnerability (Adger, 2006; Simelton *et al*., 2009). Therefore, appropriate conservation measures targeting reinstatement of affected areas need to first develop vulnerability frameworks necessary in monitoring and restoration efforts (Walker and Salt, 2006). In addition, incorporating regional and local stakeholders in the development of policies that advocate for collective social responsibility can support long term management of fragile and vulnerable landscapes (Daily, 2000). For instance, putting into place effective governance frameworks and institutional settings can foster long term biodiversity conservation and management efforts (Paavola *et al*., 2009). The demand for up to date knowledge on ecological and social factors is vital for policy makers and resource managers in formulating appropriate management interventions (Dolisca *et al*., 2006).

Natural ecosystems in sub-Saharan African face undesirable and rapid stresses due to the increasing external perturbations (Dixon *et al*., 2003; Fa *et al*., 2005; Lavorel *et al*., 2007; Rouget *et al*., 2003). In particular, ecosystems in Morogoro region, Tanzania are characterized by past threats and high dependency level increasing their sensitivity and exposure level to human encroachment that compromises their capacity to perform important functions (Burgess *et al*., 2007a; Hall *et al*., 2009; Newmark, 2002; Tabor *et al*., 2010). It is expected that if impacts associated with increased ecosystem vulnerability are not addressed, then most likely, adverse impacts will translate into loss of habitats and negative effects on important ecosystem functions. Although the decentralization policy in Tanzania has led to an increase in the local communities' knowledge by shifting planning to local governmental authorities, the system still suffers from limited accessibility to important information on appropriate landscape management (Sanga *et al*., 2013). A knowledge gap, and best ways of bridging science and policy can hinder effective management interventions (Giliba *et al*., 2011). Therefore, we argue that governance structures need to promote interventions that contribute towards an increase in the vulnerability of ecosystems. This however requires widespread vulnerability assessments, potential threats and feedback mechanisms (Adger, 2006; Holling and Gunderson, 2002). Such information can be acquired from up to date geographic and region specific data (Adger, 2006), such as that provided in this paper.

Consequently, the overarching goal of this paper is to apply a combination of social and ecological indicators to assess vulnerability of ecosystems and management interventions in biodiversity hotspots in Morogoro region, Tanzania. In doing that, this paper contributes to the on-going debate on development of successful vulnerability frameworks needed for effective conservation and management interventions particularly in complex and dynamic environments with inadequate geographic data (Walker and Salt, 2006). We apply a combination of time series satellite imagery and empirical data from 335 households as a reference point in formulation of policy recommendations for habitat management of fragile landscapes. A model was developed to understand how different factors influenced ecosystem vulnerability in the region. A lack of region specific policy and management guidelines is one of the leading factors constraining conservation and management efforts, particularly in sub-Saharan Africa, where there are multiple drivers of change (Dolisca *et al*., 2006; Giliba *et al*., 2011). This paper attempts to contribute to unresolved management issues and knowledge generation aspects by providing guidance as leverage points for resource planners and managers in enactment of policy guidelines towards long term management of vulnerable landscapes.

5.2 Materials and methods

5.2.1 Study area

The Morogoro region is one of the twenty main regions in Tanzania. It lies between 5°58' and 10°00' South and 35°25' and 38°30' East (Figure 5.1). The oceanic climate of the region translates into a bimodal rainfall distribution characterized by two rainfall peaks per year with a dry spell separating the short rains (October–December) from the long rains (March–May) (Kacholi, 2014). Rainfall exceeds 1000 mm per annum in high altitudes of the Eastern slopes of the Uluguru Mountains and decreases in a gradient to 600 mm per annum in the low altitude plains. The area receives an average rainfall between 800-1000 mm per year. Moderate temperatures of around 25^{o}C are experienced throughout the year. August is the coldest month (average of 18 ºC) while the hottest is February (32 ºC).

Natural ecosystems in Morogoro region have been subjected to forest fragmentation over the years (Burgess *et al*., 2002; Burgess *et al*., 2001; Hall, 2009; Luoga *et al*., 2000b; Yanda and Shishira, 1999). Between 1955 and 2000 for instance, Burgess *et al*. (2007b) note that natural forest cover decreased from 300 km^2 to 220 km^2 and the rate of endemism and extinctions increased. This is attributed to an increase in the settlements and farming activities in the region.

Morogoro region is made up of five districts, namely; Morogoro rural, Morogoro urban, Ulanga, Kilombero and Kilosa districts (Figure 5.1). The Morogoro region has an estimated total population of 2,218,492 and 157 villages (United Republic of Tanzania, 2013). The study was implemented across 11 villages randomly selected in Nguru, Kitulangalo and Uluguru forest ecosystems (sampled across four districts namely: Kilosa, Mvomero, Morogoro urban and Morogoro rural).

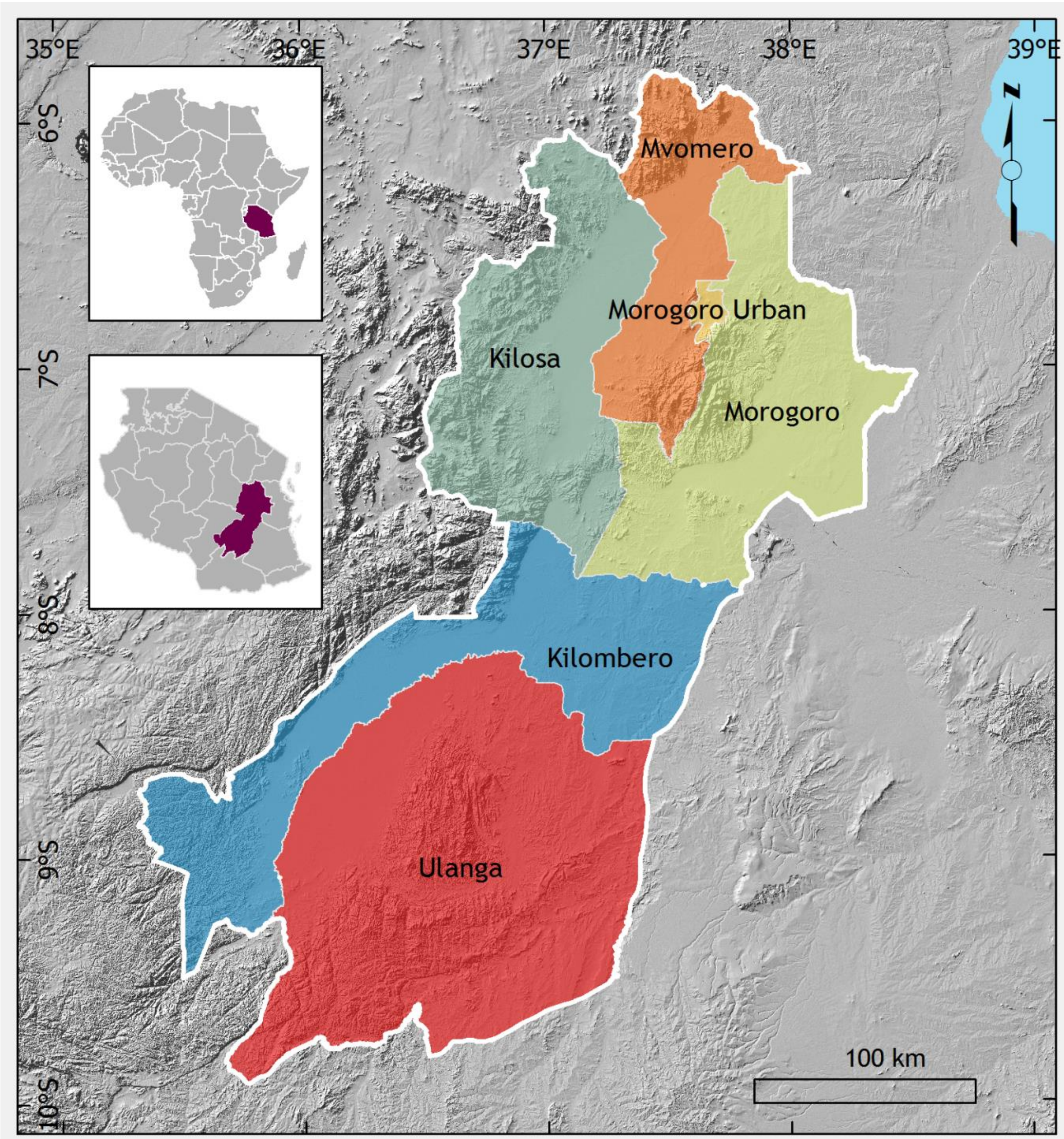

Figure 5.1: Location of the five districts within Morogoro region, Tanzania.

5.2.2 Field data collection

5.2.2.1 Assessing indicators of vulnerability based on spatial mapping

Regions considered ecologically vulnerable to changes in total habitat coverage were assessed using satellite imagery. Landsat TM (30/09/1995) and Landsat ETM+ (20/07/2012) were utilized. Supervised image classification using the maximum likelihood classifier, the most popular parametric classification technique was adopted (Liu *et al*., 2002; Manandhar *et al.*, 2009; Tseng *et al*., 2008). It is based on the Bayes theorem that utilizes a discriminant function which assigns pixel values to the category with the highest likelihood (Aldrich, 1997; Dean and Smith, 2003; Ince, 1987). The images were classified into natural intact forest cover and developed areas. A total of 82 field ground data points were used to validate the classified 2012 image. Change difference in forest cover between the 2012 and 1995 were conducted using the land change modeler.

5.2.2.2 Social data sampling strategy

Household data was collected between July and October 2012 from 335 households randomly sampled from 11 villages. The villages included Kitulangalo (8.3%), Mikese (9.9%), Ruvuma (8.2%), Mbete (9.8%), Tangeni (8.8%), Mafuta (9.9%), Ubiri (9.3%), Tulo (8.8%), Chanzema (9.3%), Kwelikwiji (9.7%), and Choma (8%). To facilitate relevance of responses to the research questions, only villages adjacent to the natural cover sites were sampled. Interviews were administered by the primary investigator and three trained research assistants. All interviews were administered in Swahili, the widely spoken national language in Tanzania. Interviews investigated information on household socioeconomic characteristics, on-going development activities in the region, perceptions on changes to forest cover in the past 20 years, and appropriate strategies for managing fragile landscapes.

5.2.2.3 Secondary data

Secondary data was collected from local government extension officers and leaders across districts within Morogoro region.

5.3 Data analysis

A multiple logistic regression model was used to investigate factors associated with ecosystem vulnerability. These were classified into three groups: (i) Household socioeconomic characteristics (such as age, gender, education); (ii) Economic development activities (farming, charcoal production, timber sawing, firewood collection, settlement, infrastructure development); and (iii) Perception regarding change in forest cover (i.e. whether there is a decrease in size of forest cover). The following model was developed to understand how different factors influenced ecosystem vulnerability in the Morogoro region.

$$Vulnerability = f(Household\ characteristics + human\ activities + perceptions\ on\ forest\ cover\ changes) \text{ Equation}$$

Variables with a strong relationship (*p<0.1*) on univariate (used here to mean a single covariate) analyses were included in a backwards, stepwise regression model and rejected at the $p \geq 0.05$ level based on likelihood ratio tests. Selection of variables was based on literature and expert knowledge. One-Way ANOVA analysis was used for testing significant differences associated with driving forces and management interventions. Duncan post-hoc tests were used to assess significant differences ($p \leq 0.05$) within and between group means.

5.4 Results

5.4.1 Forest cover change - an indicator of ecosystem vulnerability

Based on the logistic regression results, a decrease in forest size and burning were considered as key driving forces towards an increase in ecosystem vulnerability (p-values < 0.0001 and 0.021, respectively, Table 5.2). An expansion in development is a major contributing factor to ecosystem dynamics across the region (Figure 5.2a and 5.2b).

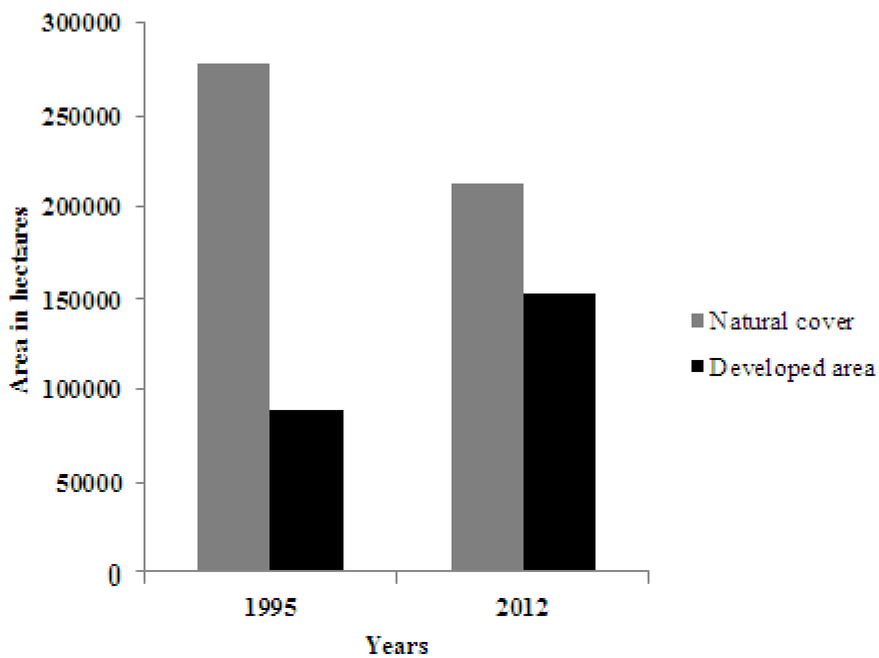

Figure 5.2a: Patterns of change in natural cover.

Figure 5.2b: Change analysis (1995-2012) with forest patches (green) and developed areas (grey).

5.4.2 Ecosystem vulnerability as perceived by respondents

The proportion of respondents was similar among females (32.6%) and males (33.0%; with no significant difference ($p \geq 0.05$). Approximately 32.8% (95% CI: 27.8-38.1%) of respondents indicated the high extent of ecosystem vulnerability. Vulnerability of ecosystems in Morogoro region significantly varied across villages ($p \leq 0.05$). The greatest vulnerability was significant among respondents in Mbete, Mafuta, Ubiri and Kwelikwiji villages compared to the rest of the other villages (Table 5.2).

Table 5.2: A logistic regression model showing ecosystem vulnerability

Variable	Odds ratio	95% CI	P-value
Villages			
Kitulangalo	1	_	_
Mikese	0.514	0.19-1.37	0.183
Ruvuma	0.852	0.15-4.97	0.859
Mbete	0.238	0.06-1.00	**0.049**
Tangeni	0.700	0.12-3.99	0.688
Mafuta	0.191	0.06-0.60	**0.005**
Ubiri	0.129	0.03-0.57	**0.007**
Tulo	0.402	0.09-1.78	0.230
Chanzema	1.411	0.44-4.53	0.563
Kwelikwiji	0.289	0.10-0.84	**0.023**
Choma	0.302	0.03-3.41	0.333
Forest size decrease	8.117	3.89-16.92	**0.001**
Forest burning	0.330	0.13-0.85	**0.021**

5.4.3 Socio-economic factors influencing ecosystem vulnerability

In total, 335 respondents were interviewed across 11 villages with approximately 39.4% females and 60.6% males; aged above 18 years. Majority (48.96%) of the respondents were in the middle age group between 35-55 years. Approximately 16.7% of the participants did not have any form of formal education, 76.7% had primary education and 6.57% had secondary education. All respondents reported farming as the most highly practiced economic activity. Main activities associated with forest loss included charcoal production (35.4%), farming (26.8%), timber sawing (17.0%), forest burning (13.4%) and settlement (5.5%). Driving forces leading to habitat loss and fragmentation included poor income (54.62%) and lack of capacity building on conservation (18.51%). Duncan post-hoc test showed statistical significance within and between group differences across the different villages (Figure 5.3). Tangeni and Ubiri village respondents seem to be more knowledgeable on major drivers of change compared to the rest of the villages.

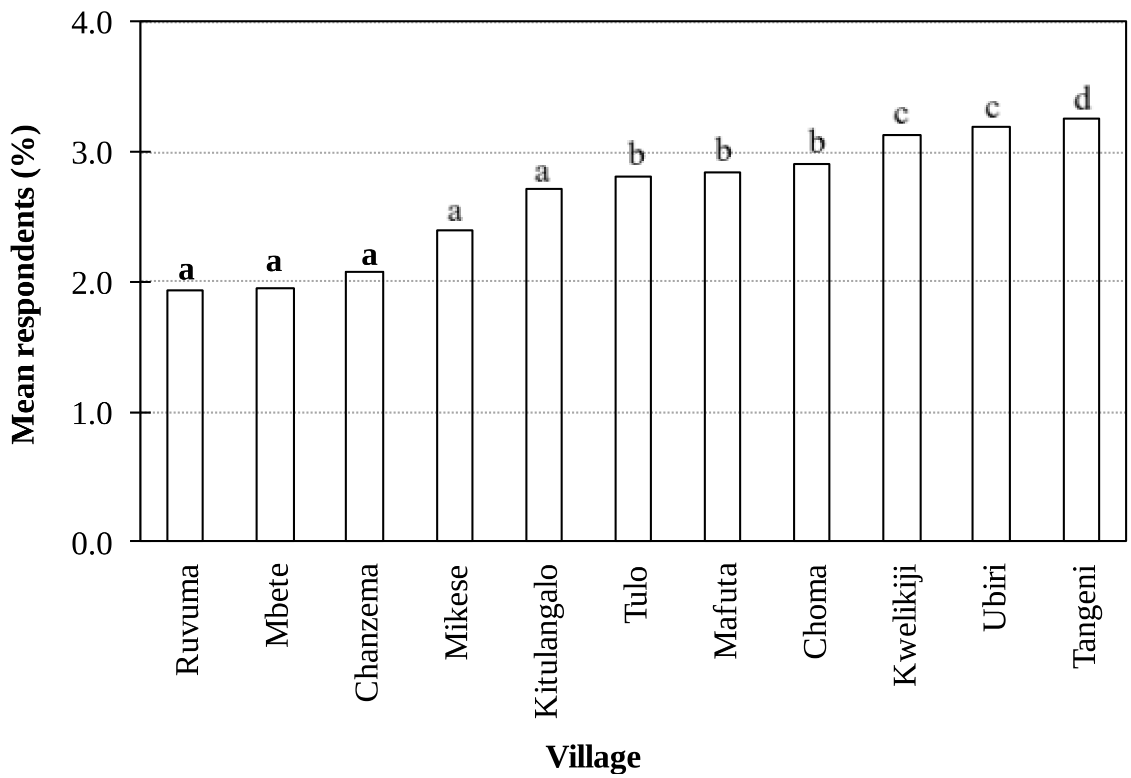

Figure 5.3: Mean percent respondents in each village who perceived poor income and lack of capacity building on conservation as driving forces to habitat loss. Bars with similar letters are not significantly different (p≤0.05) based on Duncan post hoc tests.

5.4.4 Management interventions

Respondents prioritized livelihood diversification (45.1%) as essential in effective management of vulnerable ecosystems in Morogoro region. Effective institutional frameworks (30.7%) and afforestation programmes (24.2%) emerged as useful intervention measures. Furthermore, one way ANOVA test indicated a high level of significance ($p<0.005$; $F=5.7$) at a 5% level of significance for the mean between villages, and management intervention measures. Duncan post-hoc test results showed statistical significance within and between group differences across different villages (Figure 5.4). Mikese and Ubiri villages had the highest appreciation concerning the need to integrate livelihood diversification and effective institutional frameworks as key intervention strategies.

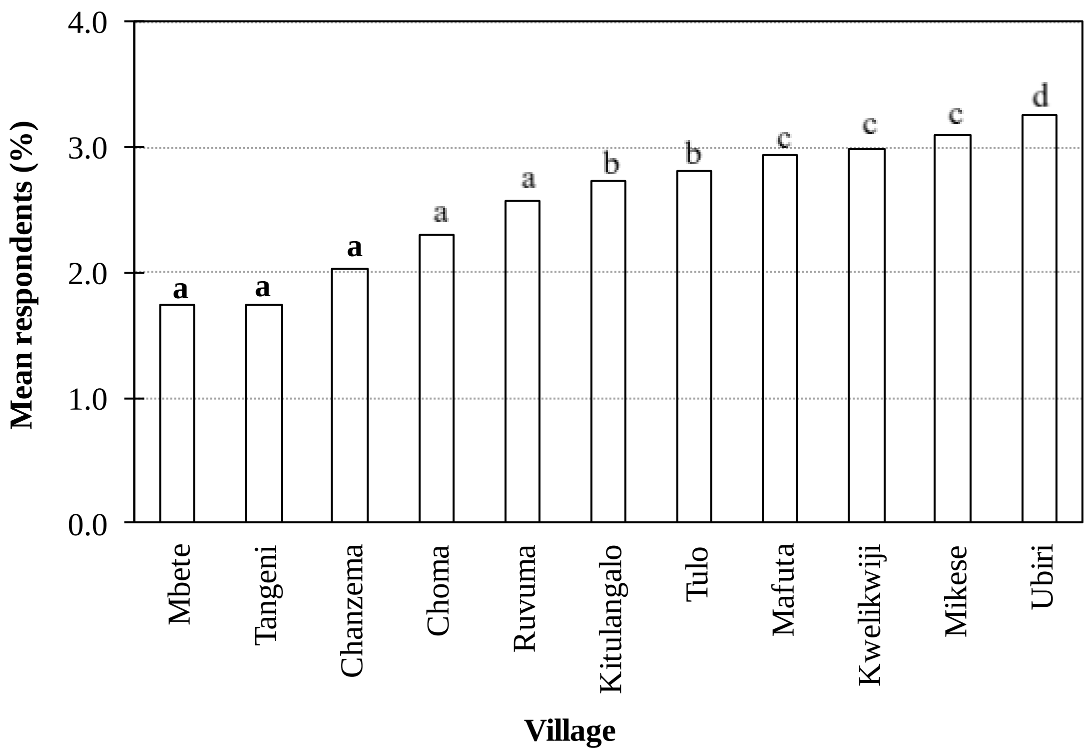

Figure 5.4: Mean percent respondents in each village who appreciate livelihood diversification, institutional frameworks and afforestation programmes as useful intervention measures. Bars with similar letters are not significantly different ($p \leq 0.05$) based on Duncan post hoc tests

5.4.5 Population trend statistics in the region

Statistics obtained from secondary data show an increasing population trend in the region (Table 5.3).

Table 5.3: Population trends in Morogoro region

District	1967	1988	2002	2013
Morogoro Urban	24,999	117 601	227 921	315 866
Morogoro rural	291 373	430 202	263 012	286 248
Mvomero	*	*	259 347	312 109
Kilosa	193 810	346 526	488 191	631 186
Kilombero	74 222	187 593	321 611	407 880
Ulanga	100 700	138 642	193 280	265 203
Total in Morogoro	685 104	1 220 564	1 753 362	2 218 492

* *Represents missing data*

Source: United Republic of Tanzania (1997; 2013)

5.5 Discussion

Important results emerge from the study. First, changing patterns in natural forest cover is a good indicator of the high level of vulnerability. We also investigated important issues to be considered in the conservation agenda of fragile landscapes. Two socio-economic factors namely: low economic capacity and poor knowledge on environmental conservation stand out as major drivers of the high level of ecosystem vulnerability in the study area. However, this varied considerably across the study villages with highest significance evident with Tangeni and Ubiri villages. It is important to note that appropriate management of landscapes is heavily driven by socio-economic factors. Results showed Ubiri and Mikese villages to be leading in prioritization of livelihood diversification and institutional frameworks. To account for significant differences across the different villages, we present our discussion and policy implications based on the results obtained.

5.5.1 Natural ecosystem vulnerability in Morogoro region

Generally, a negative modification in natural forest cover change is evident in the area which characterizes the high vulnerability extent of exposure and threats for most ecosystems in the region. Demand for this resource has led to its decrease over the past years as a result of population growth and changes in land uses. Hence, the magnitude of relationships between categories of the significant variables confirms the importance of three drivers of change (i.e. population growth, climate change and habitat encroachment) with regard to their effect on changing patterns as established in a previous study in the area (Ojoyi and Kahinda, 2015).

Wilson *et al*., (2005), characterizes areas exposed to past threats based on quantitative spatial models to predict the extent of future vulnerability. Potential explanations leading to the increased extent in exposure could be attributed to habitat transformation into human activities such as agriculture and built-up areas (Burgess *et al*., 2007a; Hall *et al*., 2009; Newmark, 2002). An increase in settlements and farmlands may have led to a decline in natural land cover (Abdallah and Monela, 2007; Luoga *et al*., 2000a). In addition, most people in Morogoro region are subsistence farmers who rely heavily on rain-fed agriculture which could be a principal factor to natural forest cover loss (Yanda, 2010). The extent of deforestation in most woodlands in Tanzania makes conservation very challenging (Kideghesho *et al*., 2013). Other studies relate to farming and urban sprawl among leading causes to natural forest loss (Qasim *et al*., 2011). It is also possible that dynamic spatial patterns may have heightened as a result of high growth in population in the region contributing to detrimental forest cover losses (as shown by results in Table 5.3).

5.5.2 Emerging factors

5.5.2.1 Impacts of poor economic capacity and conservation knowledge

Income and improved conservation capacity are critical in shaping the behavior of communities in supporting conservation efforts. Results presented in this paper showed poor income (54.62%) and lack of conservation capacity (18.51%) as leading factors to the increase in the extent of ecosystem vulnerability in Morogoro region. Respondents from Tangeni and Ubiri villages were more knowledgeable on driving forces to ecosystem vulnerability as opposed to the rest of the villages. Differences in perceptions regarding the extent of vulnerability could partly be attributed to better knowledge on the significance of conservation in Tangeni and Ubiri than the rest of the villages. The possible reason could be attributed to better access to conservation programmes in Morogoro urban and rural districts. The presence of conservation support programmes initiated by Sokoine University and the Eastern Arc Mountains Critical Ecosystem Partnership Fund (CEPF) programmes in Morogoro urban districts for instance may offer better access to knowledge on environmental conservation. In addition, accessibility to such institutions harnesses introduction of development programmes to low income households. As such, these programmes present unique growth and development opportunities. These findings are in agreement with Dolisca *et al*., (2006) who established that participatory management of ecosystems could be enhanced by socio-economic factors such as increase in the annual income and increased awareness. Similarly, other studies also established how communities with better income levels and environmental capacity had more concern for environmental conservation activities (Solecki, 1998).

5.5.2.2 The role of livelihood diversification and institutional frameworks

The concept of livelihood diversification emerged as a critical management intervention avenue (45.1%). The role of the intervention measures was most appreciated in Ubiri and Mikese than the rest of the study villages. Livelihood diversification combines three linked concepts of capability, equity and sustainability (Chambers and Conway, 1992). This is supported by the prevailing scenario in Morogoro region where, most communities live under poor economic conditions (Ellis and Mdoe, 2003; Paavola, 2008). This constrains conservation efforts in the region (Burgess *et al*., 2007b). Many individuals living adjacent to natural forest ecosystems are subsistence farmers who practice small-scale farming (Burgess *et al*., 2007a; Hall *et al*., 2009). Increased incidences of poverty and high population growth rates in Morogoro region (Table 5.3) play a vital role towards habitat loss and fragmentation in Tanzania (Kashaigili and Majaliwa, 2010; Kideghesho *et al*., 2013; Njana *et al*., 2013). It is important therefore that resource managers and policy makers first plan to integrate policy measures on sustainable livelihood options. Raising levels of human and social capital are critical to establishing the appropriate governance structures as a key intervention strategy (Mertz *et al*., 2009; Vincent, 2007). Appropriate legislative measures need to be formulated consonant with natural forest resources available and socio-economic patterns of the local people living adjacent to the region.

In addition, it will useful if communities had access to incentives as a way to encourage their full participation in the conservation agenda. Supporting alternative community projects can assist resolve the social-ecological crisis facing environmental conservation (Daily, 2000; Ferraro, 2009). For instance, sustainable livelihood options holds greater promise with regard to better livelihood options (Lopa *et al*., 2012). The social and capital elements need to be considered if such an approach is to be effected in the long term (Brown *et al*., 2000). A long term plan of action should be put in place to facilitate conservation planning and management in the long term. Our present study results support previous studies which showed the need to strengthen institutional frameworks and livelihood diversification programmes as an important asset in sustainable conservation and management efforts (Serageldin *et al*., 1994). Furthermore, this study adds to arguments made by Neufeldt *et al*., (2011) who asserts that development programmes need to prioritize effective institutional frameworks which support economic capacity of communities while supporting livelihood diversification.

The study showed that approximately 30.7% of the respondents in Morogoro region prioritize effective institutional frameworks as an important management approach. Though the United Republic of Tanzanian government is the main provider of extension services, several non-governmental organizations (NGOs) have, over time, supplemented these services (Rutatora and Mattee, 2001). To an extent, local communities in the region lack confidence in their national governments with regard to policy planning and management (Sanga *et al*., 2013). Hence, pursuing bottom up planning procedures with local communities would be an effective way to boost their confidence in existing governance structures. Results on the role of effective institutional frameworks presented show a great opportunity for positive change if programmes and policies are developed and implemented along with local institutional arrangements to ensure effective decision making procedures. Policy makers and regional planners must realize that an effective institutional framework is an effective mechanism that can help in the long term resilience development against external perturbations. Knack and Keefer, (1997) explain the importance of effective institutional frameworks towards increased economic performance at the local scale.

Encouraging community participatory initiatives was considered as key in shaping future conservation planning and management efforts. A relatively good proportion of respondents in the region (24.2%) showed the need for long term re-afforestation programmes. The move towards participatory forest management is an approach that has seen designation of forest management by local communities (Abdallah and Monela, 2007). Indeed, it has been argued that involving local people who directly or indirectly benefit from conservation projects may increase their participation in such projects (Studsrød and Wegge, 1995).

5.6 Conclusions and recommendations

A better understanding of the socio-ecological mechanisms responsible for ecosystem vulnerability is critical for the effective management of such ecosystems. This is particularly important for dryland dynamic environments that characterize sub-Saharan Africa where there are multiple drivers of change. Using socioeconomic and remotely sensed data, this paper has provided a great understanding of the key factors driving ecosystem vulnerability. Importantly, the results highlight the influence of forest fragmentation and fires on vulnerability of natural ecosystems in Morogoro region, Tanzania. Results presented show that the major socio-economic factors driving ecosystem vulnerability include low income levels of the communities and poor knowledge pertaining environmental conservation in the study villages. One key result emerging from this study is that different villages within the same geographical locations may perceive different factors driving ecosystems vulnerability. This is significant as it demonstrates the need for policy makers to design region-specific policies and programmes aimed at reducing ecosystem vulnerability. Despite the challenges associated with management of vulnerable ecosystems, our results present a window for positive change by pointing out the need to strengthen livelihood diversification needs and effective institutional frameworks. It is expected that results in this study will be well translated by resource and conservation planners in the long term conservation and management agenda against external perturbations. It is of utmost significance that management of vulnerable landscapes integrates policy guidelines aligned to effective institutional and livelihood diversification frameworks. It should be pointed out that the methodological approach and findings from this paper may have wider applications for the management of vulnerable ecosystems in Tanzania and across ecosystems in sub-Saharan Africa more widely.

CHAPTER SIX

Determining vegetation fragmentation and impacts using multispectral remotely sensed data in the Eastern Arc Mountains, Tanzania: a synthesis

A human-dominated landscape with farmlands at the foot of Uluguru mountain forest

6.1 Introduction

Ecological research on vegetation fragmentation is critical for detailed assessment of structural aspects of ecosystems and species responses to anthropogenic and non-anthropogenic pressure (Wiens, 1995). Such research also provide an ideal basis for establishment of conservation and management principles (Burgess *et al*., 2007; Hall *et al*., 2009).

In the tropics, overwhelming evidence indicates mounting pressure on forest ecosystems. It has therefore become necessary to know how and where these resources are threatened. Previous ecological research conducted in the Eastern Arc Mountain blocks acknowledged their exceptional conservation relevance (Burgess *et al*., 2007; Shirk *et al*., 2014). However, encroachment caused by increasing rates of fragmentation remain unexplored (Hall, 2009). Specifically, there is a dearth of spatial knowledge on changing patterns and effects caused on these ecosystems (Burgess *et al*., 2002; Green *et al*., 2013b; Hall, 2009). Fragmentation interferes with flora and fauna and ecological functioning of ecosystems (Fahrig, 2003; Tabarelli *et al*., 1999; Turner, 1996). The worst case scenario is inevitably expected in the coming decades (Green *et al*., 2013a). While there is an increasing need for such knowledge, the use of reliable techniques to generate the required information is inadequate (Platts, 2012).

Growth in space-based techniques, with reliable data, presents a better alternative to the often labor intensive, time-consuming and costly traditional techniques (Vuolo *et al*., 2010). In the recent past, there has been a growing interest in the use of remotely-sensed imagery in a range of applications that include vegetation mapping, vegetation quality assessments and other conservation needs (Schmidt and Skidmore, 2003). Recently launched sensors like RapidEye, with improved spatial and spectral characteristic allow for detailed mapping of vegetation attributes at species level (Ramoelo *et al*., 2012; Schuster *et al*., 2012). The red edge section of the spectrum (690-730 nm) that characterize some of the recent new generation sensors offer great potential in discriminating varied and stressed vegetation types (see Figure 6.1) (Eitel *et al*., 2011).

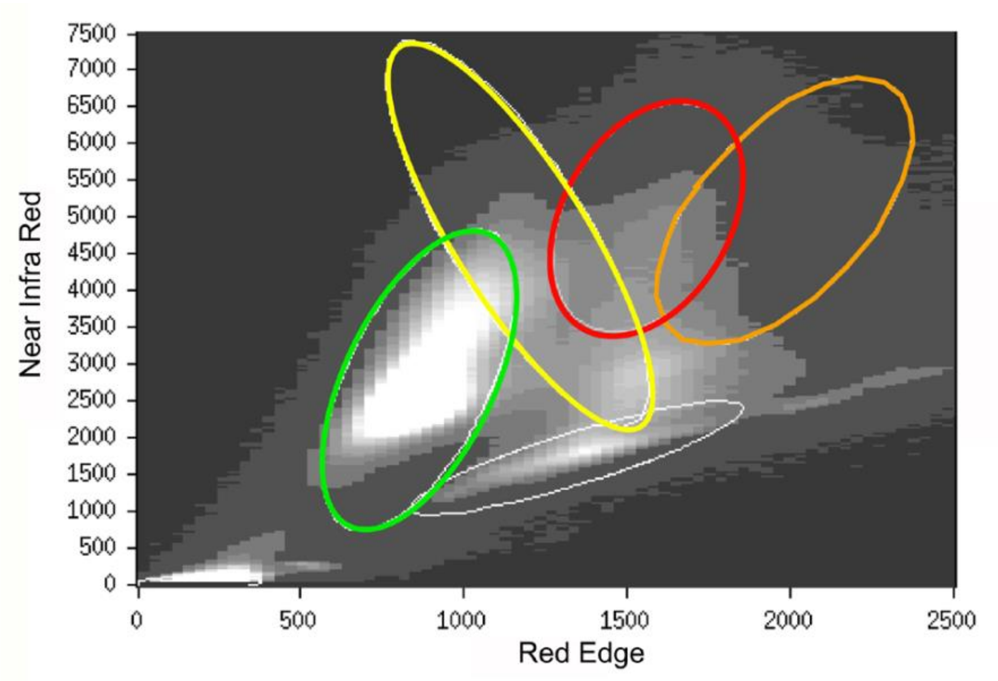

Figure 6.1: Detection of diverse vegetation types based on RapidEye bands (2013) combinations; colors represent red (grassland), green (forest), yellow/orange (2 crops), soil (grey), (RapidEye, 2013)

To date, the use of remotely-sensed data in ecological applications in Tanzania remain limited (Platts, 2012). This includes lack of information on, the rate and impact of fragmentation in the forest blocks of Eastern Arc Mountains (Green *et al*., 2013b; Shirk *et al*., 2014). Despite their global significance, these blocks have been subjected to a wide array of biophysical modifications. Scarcity of information could be a result of their complex nature, making it difficult for adoption of traditional field based techniques to monitor and estimate spatial variation and potential drivers respectively. Hence, this research justified the need to integrate remotely-sensed data in ecological applications. This is explained in the discussion section with reference to conservation of the Eastern Arc blocks. Important aspects of each of the case studies are highlighted as models for future research. In all cases, procedures applied are universal and replicable and/or transferable to tropical forest landscapes.

6.2 Effectiveness of remotely-sensed data in the study

6.2.1 Analysis of vegetation fragmentation

In a retrospective application, Landsat satellite imagery and fragstats metrics were found to be useful in modelling the magnitude of change and trend patterns. Fragstats program was able to account for fragmentation patterns due to its capacity to estimate landscape behavior characteristics (Saikia *et al.*, 2013; Millington *et al*., 2003). Findings based on Games-Howell showed high significance in fragmentation trends ($p \leq 0.05$). There was an increase in patch frequency by 391 and 412 in woodland and dense forest respectively between 1995 and 2012. In accounting for temporal and spatial patterns, patch metrics were effective indicators of vegetation fragmentation. Mann-Whitney test showed distinct differences in patch area ($p<0.01$) between 1975 and 1995 for all habitats except for dense forest between 1995-2012 (Table 6.1). Overall, the patchy nature of forest fragments was a clear indicator of a fragmenting ecosystem.

Table 6.1: Patch area results based on Mann-Whitney tests

Class	**Year**	**z-value (1975-1995)**	***Prob* > |*z*|**	***z-value (1995-2012)***	***Prob*> |*z*|**
Dense forest	1975	*9.495****	0.0000	-6.872 NS	0.1895
	1995				
	2012				
Grassland	1975	13.680***	0.0000	-7.441***	0.0000
	1995				
	2012				
Less dense forest	1975	16.728***	0.0000	-8.268***	0.0000
	1995				
	2012				
Woodland	1975	-16.63***	0.0000	2.461***	0.0000
	1995				
	2012				

NS= not significant (p<0.01), *** = significant (p<0.001)

6.2.2 An analysis of impacts on vegetation species

Few researches in the Eastern Arc mountains have made use of remotely-sensed data and other biophysical variables in understanding species diversity patterns and threats in each of the forest blocks (Platts *et al*., 2008). The current project forms an important basis in demonstrating the vital role of high resolution satellite data in modelling the impacts of fragmentation on individual tree species.

Remotely-sensed variables with data on species diversity were modelled by applying the Generic Algorithm for Rule-Set Prediction (GARP) algorithm while patch area metrics were extracted using Fragstats software, which were then linked to species and edaphic factors. The model allowed for detection of tree species diversity and variables accounting for differences in species occurrences. Research findings indicated how species diversity was better predicted with customized environmental variables with an Area under Curve (AUC) of 0.89, while the Poisson regression showed that individual tree species responded differently to patch area dynamics, habitat status and soil nitrogen. Generally, application of the GARP model which is compatible with remote sensed data showed how ecologists could use different data sets to establish the best ecological niche for species survival. Uluguru montane forest ecosystem outskirts were found to be more vulnerable to fragmentation. Elevation was a factor with most effects on the model. This could be due to the fact that elevation determines the abundance of species in the Uluguru montane ecosystem. Species found in low elevations mostly experienced interference from fragmentation. Underlying factors such as rapid increase in population growth and agriculture have a strong presence in the former intact areas, significantly affecting vegetation species (Figure 6.2).

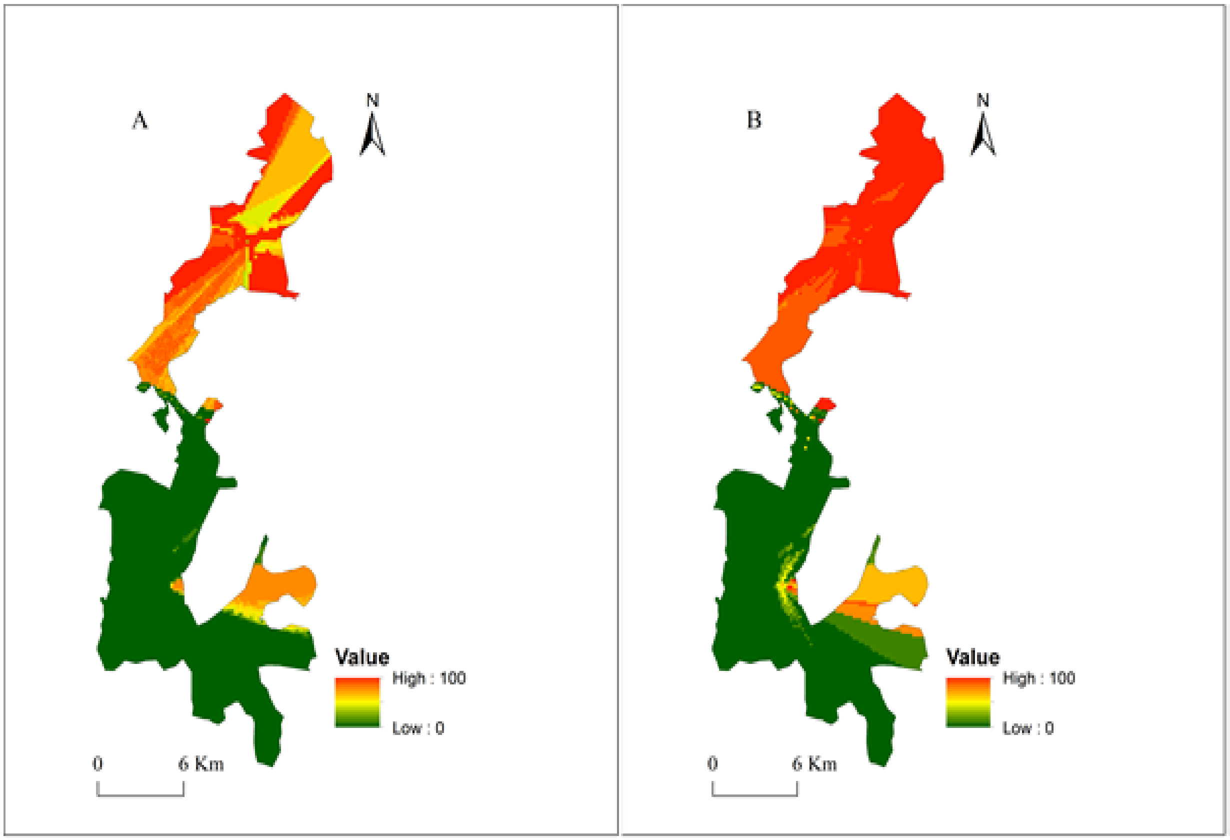

Figure 6.2: High (A) and low (B) species diversity.

6.2.3 The potential utility of remote sensing in biomass estimation

Constant and precise biomass estimation initiatives in forestry are considered a pre-requisite in the successful development of plausible forest inventories and landscape monitoring procedures (Berndes *et al.*, 2003; Mumby *et al.*, 2004). It supports vegetation productivity assessments, determination of vegetation quality and the general structure of ecosystems.

Mapping biomass has been a challenging task using traditional methods in complex heterogeneous forest landscapes. The red edge band has the potential to detect chlorophyll concentration in the visible region of the spectrum; which allows use of different vegetation indices in above ground biomass prediction. The study applied a combination of different vegetation indices derived from RapidEye imagery and topo-edaphic factors to determine the ability of utilizing high resolution satellite imagery to predict above ground forest biomass. A partial least squares regression (PLSR) was used for establishment of the relationship between biomass and RapidEye data. A PLSR model with a total of twenty-nine spectral vegetation indices and eight topo-edaphic factors explained 60% of the above ground forest biomass variability (see Figure 6.3). While, PLSR models consisted of either topo-edaphic or spectral vegetation indices yielded R^2 values of 0.44 and 0.43, respectively. Fragmentation was found to be a contributing factor to low biomass.

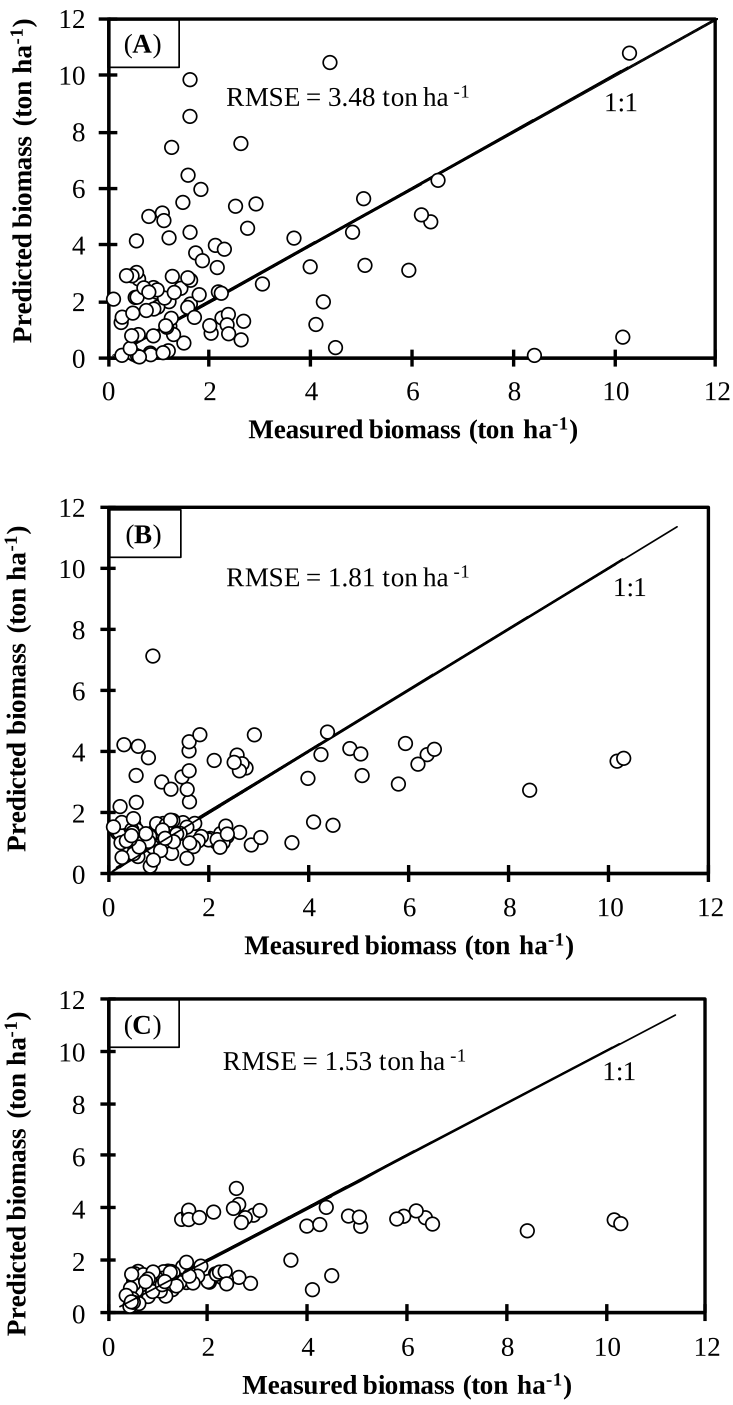

Figure 6.3: One-to-one relationship between measured and predicted above ground biomass for the sample data set using leave-one-out cross validation model. (A): Using eight topo-edaphic factors, (B) using 29 vegetation indices, and (C) using 29 vegetation indices plus the eight topo-edaphic factors based on 115 samples.

6.2.4 Analyzing potential threats and opportunities

Universally, no policy has been conceived that can facilitate control of human-ecosystem transformation in the tropics (Geist and Lambin, 2002). However, an in-depth understanding on potential threats to conservation is a pre-requisite in establishing case specific policy interventions (Chowdhury, 2006; Geist and Lambin, 2001).

This study also tested how science-based interpretation could guide policy makers into ameliorative decision making processes. Combining remotely-sensed data and socio-ecological factors were profound in meeting this noble goal. Findings showed low income (52.62%) and low education (18.51%) among main contributors of ecosystem vulnerability. The study suggests the need for ongoing research to investigate appropriate and innovative mechanisms including livelihood diversification (45.1%), effective institutional frameworks (30.7%) and afforestation measures (24.2%). It could be useful if conservation experts engaged programmes that supported alternative livelihood initiatives, effective institutional frameworks and restoration of disturbed habitats.

6.3 Discussions

Application of remotely-sensed data was effective in determining the general state of dominant forest ecosystems. Primarily, human encroachment activities leading to fragmentation and habitat modification had significant effects on species and overall biological conservation. Empirical findings project that in the long term, species and ecological functions of ecosystems will diminish.

GARP model was a better predictor of species diversity in both fragmented and intact areas. While the results established the links between main biophysical variables contributing to the model, the use of bioclim data would have been worth exploring to determine the effect of other bioclim variables. However, this study was limited to Uluguru forest, which might not have had much effect. This is however an important research aspect that could be investigated. Furthermore, the research work on biomass estimation also confirms the need to integrate remote sensing techniques in supporting biodiversity conservation initiatives.

Conservation of the Eastern Arc Mountains demands an in-depth knowledge on driving forces and plausible solutions for management of un-desirable shifts. A significant proportion of respondents interviewed were primarily immigrants from other parts of Tanzania. Despite government decentralization policies, there is an apparent scarcity of knowledge and resource accessibility (Sanga *et al*., 2013). Emphasis should be placed on capacity building, an aspect still lacking in Morogoro region. Conservation and education awareness needs to be enhanced as a long term strategy to contain human encroachment activities. It will be valuable if government authorities in Tanzania learnt to capitalize on the social system as a useful platform in reaching out to as many communities as possible.

The need to appraise conservation and management policies that are/have not been executed is one aspect that strongly emerged from the management perspective of this study. It will be useful if priority is accorded to policies that promote habitat restoration and conservation measures in the fragile status of these ecosystems. Many local people residing in Morogoro region practice small scale farming with others engaging in ecologically destructive activities such as charcoal production for their livelihoods. Therefore, conservationists and other natural resource experts need to establish other options for local communities living adjacent to natural sites. This should include development of tangible benefits and incentives in a manner that could attract their full engagement in conservation of remnant forests. Such information could also be integrated in long term development of conservation programmes and other agenda.

6.4 Conclusions and future research opportunities

The core of this study was to investigate the utility of remotely-sensed data in modelling fragmentation and impacts in the Eastern Arc Mountains. It also gave an insight on the significance of incorporating scientific concepts in decision making. The following conclusions can be drawn:

1. The use of remotely-sensed imagery indicated its spatial significance in computing the patterns and magnitude of fragmentation. Consistent monitoring procedures based on advanced remote sensing techniques could guide development of better conservation and management plans of the forest remnants.

2. Fragmentation is a great threat to biodiversity conservation in the Eastern Arc Mountains. This is exhibited by increases in the patchy nature of the forest fragments.

3. Fragmentation analytical results showed a negative impact on species abundance and diversity. The abundance of tree species in intact areas was found to be more than areas disturbed. This means that if fragmentation persists, less species are expected in the rest of the forest fragments.

4. Inclusion of edaphic factors strongly improved biomass prediction in heterogeneous landscape using Partial Least Squares. It also revealed adverse impacts of fragmentation to above ground forest biomass.

5. From a conservation perspective, establishing habitat restoration for areas prone to fragmentation requires quick conservation effort. Conservation managers may need to incorporate livelihood diversification, effective institutional frameworks and afforestation in their programmes as long term strategies to conserve the forest blocks in the Eastern Arc Mountains.

The current study attests to the urgent need for quick action to be accorded to conservation of the Eastern Arc Mountain blocks. Fragmentation is expected to lead to more disastrous impacts. If the current patterns persist, it could inevitably lead to increase of forest fragments and a further decline in species abundance and diversity. It is critical that sustainable and viable options be sourced, and strengthened in a way that could help minimize people's dependence on these resources.

The rate of species endemism has frequently been mentioned in literature. The use of high resolution remotely-sensed data and Maxent or GARP might be useful in the spatial analysis of endemic and vulnerable species. In addition, fauna is an important component of biodiversity in the Eastern Arc Mountains. The increasing rate of endemic species is also associated with the animal kingdom. Although the scope of this study did not cover this important research component, future researches might find it valuable to establish the interaction between animals and habitat disturbances.

References

Abdallah, J., and Monela, G. (2007). Overview of Miombo woodlands in Tanzania. *Mitmiombo– management of indigenous tree species for ecosystem restoration and wood production in semi-arid Miombo woodlands in eastern Africa. Working Papers of the Finnish Forest Research Institute,* 50**,** 9-23.

Abdullah, S.A., and Nakagoshi, N. (2007). Forest fragmentation and its correlation to human land use change in the state of Selangor, peninsular Malaysia. *Forest Ecology and Management,* 241**,** 39-48.

Achard, F., Eva, H.D., Stibig, H.J., Mayaux, P., Gallego, J., Richards, T. and Malingreau, J.P. (2002). Determination of Deforestation Rates of the World's Humid Tropical Forests. *Science,* 297**,** 999-1002.

Adam, E., Mutanga, O., Abdel-Rahman, E.M, Ismail, R., (2014). Estimating standing biomass in papyrus (*Cyperus papyrus L.*) swamp: exploratory of in situ hyperspectral indices and random forest regression. *International Journal of Remote Sensing,* 35:693-714.

Adams, M., Cooper, J. and Collar, N. (2003). Extinct and endangered (E&E') birds: a proposed list for collection catalogues. *Bulletin-British Ornithologists Club,* 123**,** 338-354.

Adger, W.N., (2006). Vulnerability. *Global Environmental Change,* 16**,** 268-281.

Adrianto, L., and Matsuda, Y., (2002). Developing economic vulnerability indices of environmental disasters in small island regions. *Environmental Impact Assessment Review,* 22**,** 393-414.

Aerts R, and Chapin, III F. (2000). The mineral nutrition of wild plants revisited. *Advances in Ecological Research,* 30,1-67.

Aguilar, R., Quesada, M., Ashworth, L., Herrerias-Diego, Y. and Lobo, J., (2008). Genetic consequences of habitat fragmentation in plant populations: susceptible signals in plant traits and methodological approaches. *Molecular Ecology,* 17**,** 5177-5188.

Aldrich, J. (1997). RA Fisher and the making of maximum likelihood 1912-1922. *Statistical Science,* 12**,** 162-176.

Almeida T, Filho D.S. (2004). Principal component analysis applied to feature-oriented band ratios of hyperspectral data: a tool for vegetation studies. *International Journal of Remote Sensing*,25,5005-5023.

Amazonas, N.T., Martinelli, L.A., Piccolo, M.d.C., Rodrigues, R.R. (2011). Nitrogen dynamics during ecosystem development in tropical forest restoration. *Forest Ecology and Management*, 262, 1551-1557.

Antwi-Agyei, P., Dougill, A.J., Fraser, E.D. and Stringer, L.C. (2013). Characterising the nature of household vulnerability to climate variability: empirical evidence from two regions of Ghana. *Environment, Development and Sustainability,* 15**,** 903-926.

Antwi-Agyei, P., Fraser, E.D., DougilL, A.J., Stringer, L.C. and Simelton, E. (2012). Mapping the vulnerability of crop production to drought in Ghana using rainfall, yield and socioeconomic data. *Applied Geography,* 32**,** 324-334.

Araújo, M.B., and Luoto, M. (2007). The importance of biotic interactions for modelling species distributions under climate change. *Global Ecology and Biogeography*,16,743-753.

Armenteras, D., Gast, F., Villareal, H. (2003). Andean forest fragmentation and the representativeness of protected natural areas in the eastern Andes, Colombia. *Biological Conservation*,113,245-256.

Avitabile, V., Baccini, A., Friedl, M.A, Schmullius, C. (2012). Capabilities and limitations of Landsat and land cover data for aboveground woody biomass estimation of Uganda. *Remote Sensing of Environment,*117,366-380.

Ayanu Y.Z, Conrad, C, Nauss, T, Wegmann, M, Koellner, T. (2012). Quantifying and mapping ecosystem services supplies and demands: a review of remote sensing applications. *Environmental Science and Technology,* 46,8529-8541.

Baskerville, G. (1972). Use of logarithmic regression in the estimation of plant biomass. *Canadian Journal of Forest Research,* 2,49-53.

Bell, J. (1999). Tree-based methods. *In:* Fielding, A. (ed.) *Machine Learning Methods for Ecological Applications.* Springer US.

Benítez-Malvido, J., Martínez-Ramos, M. (2003). Impact of forest fragmentation on understory plant species richness in Amazonia. *Conservation Biology,* 17, 389-400.

Berndes, G., Hoogwijk, M., and Van Den Broek, R. (2003). The contribution of biomass in the future global energy supply: a review of 17 studies. *Biomass and Bioenergy*, 25, 1-28.

Birth, G.S, McVey, G.R. (1968). Measuring the color of growing turf with a reflectance spectrophotometer. *Agronomy Journal*, 60,640-643.

Billings, S.A., Gaydess, E.A. (2008). Soil nitrogen and carbon dynamics in a fragmented landscape experiencing forest succession. *Landscape Ecology*, 23, 581-593.

Bjorndalen, J.E. (1992). Tanzania's vanishing rain forests—assessment of nature conservation values, biodiversity and. *Biotic Diversity in Agroecosystems*, 313.

Bogich, T.L., Barker, G.M., Mahlfeld, K., Climo, F., Green, R., Balmford, A. (2012). Fragmentation, grazing and the species–area relationship. *Ecography*, 35, 224-231.

Box, E.O., Holben, B.N., Kalb, V. (1989). Accuracy of the AVHRR vegetation index as a predictor of biomass, primary productivity and net CO2 flux. *Vegetatio*,80,71-89.

Brooks, T.M., Mittermeier, R.A., Da Fonseca, G.A.B., Gerlach, J., Hoffmann, M., Lamoreux, J. F., Mittermeier, C.G., Pilgrim, J.D. and Rodrigues, A.S.L. (2006). Global Biodiversity Conservation Priorities. *Science*, 313**,** 58-61.

Brown, D.G., Pijanowski, B.C., and Duh, J.D. (2000). Modeling the relationships between land use and land cover on private lands in the Upper Midwest, USA. *Journal of Environmental Management*, 59**,** 247-263.

Brown, S. (2002). Measuring carbon in forests: current status and future challenges. *Environmental Pollution*. 116, 363-372.

Brown, S., and Lugo, A.E. (1992). Aboveground biomass estimates for tropical moist forests of the Brazilian Amazon. *Interciencia. Caracas*,17,8-18.

Brown, S.L., Schroeder, P., Kern, J.S. (1999). Spatial distribution of biomass in forests of the eastern USA. *Forest Ecology and Management*, 123,81-90.

Brown, S, Gillespie, A.J.R, Lugo, A.E. (1991). Biomass of tropical forests of south and southeast Asia. *Canadian Journal of Forest Research*. 21,111-117.

Bruzzone, L., Prieto, D.F. (2001). Unsupervised retraining of a maximum likelihood classifier for the analysis of multitemporal remote sensing images. Geoscience and Remote Sensing, *IEEE Transactions on Geosciences and Remote Sensing*, 39, 456-460.

Buermann, W., Saatchi, S., Smith, T.B., Zutta, B.R., Chaves, J.A., Milá, B., Graham, C.H. (2008). Predicting species distributions across the Amazonian and Andean regions using remote sensing data. *Journal of Biogeography,* 35, 1160-1176.

Burgess, N.D., Balmford, A., Cordeiro, N.J., Fjeldså, J., Küper, W., Rahbek, C., Sanderson, E.W., Scharlemann, J.P.W., Sommer, J.H., Williams, P.H. (2007a). Correlations among species distributions, human density and human infrastructure across the high biodiversity tropical mountains of Africa. *Biological Conservation*, 134,164-177.

Burgess, N.D., Butynski, T.M., Cordeiro, N.J., Doggart, N.H., Fjeldså, J., Howell, K.M., Kilahama, F.B., Loader, S.P., Lovett, J.C., Mbilinyi, B., Menegon, M., Moyer, D.C., Nashanda, E., Perkin, A., Rovero, F., Stanley, W.T., Stuart, S.N. (2007b). The biological importance of the Eastern Arc Mountains of Tanzania and Kenya. *Biological Conservation*, 134, 209-231.

Burgess, N., Doggart, N., and Lovett, J.C. (2002). The Uluguru Mountains of eastern Tanzania: the effect of forest loss on biodiversity. *Oryx,* 36**,** 140-152.

Burgess, N.D., Fjeldså, J., Botterweg, R. (1998). Faunal Importance of the Eastern Arc Mountains of Kenya and Tanzania. *Journal of East African Natural History*, 87, 37-58.

Burgess, N.D., Mwakalila, S., Munishi, P., Pfeifer, M., Willcock, S., Shirima, D., Hamidu, S., Bulenga, G.B., Rubens, J., Machano, H., Marchant, R. (2013). REDD herrings or REDD menace: Response to Beymer-Farris and Bassett. *Global Environmental Change*, 23, 1349-1354.

Burgess, N., Romdal, T.S. and Rahner, M. (2001). Forest loss on the Ulugurus, Tanzania and the status of the Uluguru Bush Shrike Malconotus alius. *Bulletin of the African Bird Club*, 8**,** 89-90.

Byron, N., and Arnold, M. (1999). What futures for the people of the tropical forests? *World Development,* 27**,** 789-805.

Carlson, K., Asner, G., Hughes, R.F., Ostertag, R., Martin, R. (2007). Hyperspectral Remote Sensing of Canopy Biodiversity in Hawaiian Lowland Rainforests. *Ecosystems*, 10, 536-549.

Chamshama, S.A.O, Mugasha A.G, Zahabu E. (2004). Stand biomass and volume estimation for Miombo woodlands at Kitulangalo, Morogoro, Tanzania. *The Southern African Forestry Journ*al, 200,59-70.

Chambers, R. and Conway, G. (1992). Sustainable rural livelihoods: practical concepts for the 21st century, Institute of Development Studies (UK).

Chander, G., Markham, B.L. and Helder, D.L. (2009). Summary of current radiometric calibration coefficients for Landsat MSS, TM, ETM+, and EO-1 ALI sensors. *Remote Sensing of Environment*, 113**,** 893-903.

Chao, A., Shen, T.J. (2003). Nonparametric estimation of Shannon's index of diversity when there are unseen species in sample. *Environmental and Ecological Statistics*, 10, 429-443.

Chapin, F.S. (1980). The mineral nutrition of wild plants. *Annual Review of Ecology and Systematics*, 11,233-260.

Chapin III, F., Peterson, G., Berkes, F., Callaghan, T., Angelstam, P., Apps, M., Beier, C., Bergeron, Y., Crépin, A. and Danell, K. (2004). Resilience and vulnerability of northern regions to social and environmental change. *AMBIO:A Journal of the Human Environment*, 33**,** 344-349.

Chave, J., Andalo, C., Brown, S., Cairns, M., Chambers, J., Eamus, D., Fölster, H., Fromard, F., Higuchi, N., Kira, T., (2005). Tree allometry and improved estimation of carbon stocks and balance in tropical forests. *Oecologia*,145,87-99.

Chave, J., Condit, R., Muller-Landau, H.C., Thomas S.C., Ashton P.S., Bunyavejchewin, S., Co, L.L., Dattaraja, H.S., Davies, S.J., Esufali, S., et al., (2008). Assessing Evidence for a Pervasive Alteration in Tropical Tree Communities. *PLoS Biology*,6,455-462.

Chen J.M., and Cihlar, J. (1996). Retrieving leaf area index of boreal conifer forests using Landsat TM images. *Remote Sensing of Environment*,55,153-162.

Cho, M.A., Skidmore, A., Corsi, F., van Wieren, S.E., Sobhan, I. (2007). Estimation of green grass/herb biomass from airborne hyperspectral imagery using spectral indices and partial least squares regression. *International Journal of Applied Earth Obserservation and Geoinformatics*,9,414-424.

Chowdhury, R.R. (2006). Driving forces of tropical deforestation: The role of remote sensing and spatial models. *Singapore Journal of Tropical Geography*, 27, 82-101.

Chuine, I, and Beaubien, E.G. (2001). Phenology is a major determinant of tree species range. *Ecology Letters,* 4,500-510.

Clark, D.B., and Clark, D.A. (2000). Landscape-scale variation in forest structure and biomass in a tropical rain forest. *Forest Ecology and Management*,137,185-198.

Colgan, M, Asner, G, Levick, S, Martin, R, Chadwick, O. (2012). Topo-edaphic controls over woody plant biomass in South African savannas. *Biogeosciences Discussions,9,* 957-987.

Conese, C., and Maselli, F., (1992). Use of error matrices to improve area estimates with maximum likelihood classification procedures. *Remote sensing of Environment* ,40, 113-124.

Con, T.V., Thang, N.T, Ha, D.T.T, Khiem, C.C, Quy, T.H, Lam, V.T, Van Do, T, Sato, T. (2013). Relationship between aboveground biomass and measures of structure and species diversity in tropical forests of Vietnam. *Forest Ecology and Management*, 310,213-218.

Cunningham, A., (2001). Applied Ethnobotany:" People, Wild Plant Use and Conservation". Earthscan Publications Limited, United Kingdom.

Cunningham, M.A. (2006). Accuracy assessment of digitized and classified land cover data for wildlife habitat. *Landscape and Urban Planning,* 78**,** 217-228.

Cunningham, S., Mac Nally, R., Read, J., Baker, P., White, M., Thomson, J. and Griffioen, P. (2009). A robust technique for mapping vegetation condition across a major river system. *Ecosystems,* 12**,** 207-219.

Cushman, S.A. (2006). Effects of habitat loss and fragmentation on amphibians: A review and prospectus. *Biological Conservation,* 128**,** 231-240.

Cushman, S.A., Shirk, A. and Landguth, E.L. (2012). Separating the effects of habitat area, fragmentation and matrix resistance on genetic differentiation in complex landscapes. *Landscape Ecology*, 27**,** 369-380.

Daily, G.C. (2000). Management objectives for the protection of ecosystem services. *Environmental Science and Policy* 3, 333-339.

Dash J, Curran P. (2004). The MERIS terrestrial chlorophyll index. de Castilho CV, Magnusson WE, de Araújo RNO, Luizão RCC, Luizão FJ, Lima AP, Higuchi N. 2006. Variation in aboveground tree live biomass in a central Amazonian Forest: Effects of soil and topography. *Forest Ecology and Management*. 234,85-96.

Das S, and Singh, T. (2012). Correlation analysis between biomass and spectral Vegetation indices of forest ecosystem. *Proceedings of the International Journal of Engineering Research and Technology*,1,5. ESRSA Publications.

Davidson, E.A., Reis de Carvalho, C.J., Vieira, I.C., Figueiredo, R.d.O., Moutinho, P., Yoko Ishida, F., Primo dos Santos, M.T., Benito Guerrero, J., Kalif, K., Tuma Sabá, R. (2004). Nitrogen and phosphorus limitation of biomass growth in a tropical secondary forest. *Ecological Applications*, 14, 150-163.

Debinski, D.M., Kindscher, K., Jakubauskas, M.E. (1999). A remote sensing and GIS-based model of habitats and biodiversity in the Greater Yellowstone Ecosystem. *International Journal of Remote Sensing*, 20, 3281-3291.

De Chazal, J. and Rounsevell, M.D.A. (2009). Land-use and climate change within assessments of biodiversity change: A review. *Global Environmental Change,* 19**,** 306-315.

Dean, A.M. and Smith, G.M. 2003. An evaluation of per-parcel land cover mapping using maximum likelihood class probabilities. *International Journal of Remote Sensing,* 24**,** 2905-2920.

Debinski, D.M. and Holt, R.D. (2000). A Survey and Overview of Habitat Fragmentation Experiments Sondeo y Revisión de Experimentos de Fragmentación de Hábitat. *Conservation Biology,* 14**,** 342-355.

DeFries, R.S., Houghton, R.A., Hansen, M.C., Field, C.B., Skole, D., Townshend, J. (2002). Carbon emissions from tropical deforestation and regrowth based on satellite observations for the 1980s and 1990s. *Proceedings of the National Academy of Sciences* 99, 14256-14261.

Didham, R.K. (2001). Ecological Consequences of Habitat Fragmentation. eLS. John Wiley & Sons, Limited.

Dixon, R. K., Smith, J. and Guill, S. (2003). Life on the edge: vulnerability and adaptation of African ecosystems to global climate change. *Mitigation and Adaptation Strategies for Global Change,* 8**,** 93-113.

Dolisca, F., Carter, D.R., Mcdaniel, J.M., Shannon, D.A. and Jolly, C.M. (2006). Factors influencing farmers' participation in forestry management programs: A case study from Haiti. *Forest ecology and management,* 236**,** 324-331.

Donoghue, D.N., Watt, P.J., Cox, N.J. and Wilson, J. (2007). Remote sensing of species mixtures in conifer plantations using LiDAR height and intensity data. *Remote Sensing of Environment,* 110**,** 509-522.

Duchesneau, R, Lesage, I, Messier C, Morin H. (2001). Effects of light and intraspecific competition on growth and crown morphology of two size classes of understory balsam fir saplings. *Forest Ecology and Management,* 140,215-225.

Echeverria, C., Coomes, D., Salas, J., Rey-Benayas, J. M., Lara, A. and Newton, A. (2006). Rapid deforestation and fragmentation of Chilean Temperate Forests. *Biological Conservation,* 130**,** 481-494.

Echeverria, C., Coomes, D. A., Hall, M. and Newton, A. C. (2008). Spatially explicit models to analyze forest loss and fragmentation between 1976 and 2020 in southern Chile. *Ecological Modelling,* 212**,** 439-449.

Echeverría, C., Newton, A.C., Lara, A., Benayas, J.M.R. and Coomes, D.A. (2007). Impacts of forest fragmentation on species composition and forest structure in the temperate landscape of southern Chile. *Global Ecology and Biogeography,* 16**,** 426-439.

Eitel, J.U., Vierling, L.A., Litvak, M.E., Long, D.S., Schulthess, U., Ager, A.A., Krofcheck, D.J. and Stoscheck, L. (2011). Broadband, red-edge information from satellites improves early stress detection in a New Mexico conifer woodland. *Remote Sensing of Environment*, 115, 3640-3646.

Ellis, F. and Mdoe, N. (2003). Livelihoods and rural poverty reduction in Tanzania. *World Development,* 31**,** 1367-1384.

Fa, J.E., Ryan, S.F. and Bell, D.J. (2005). Hunting vulnerability, ecological characteristics and harvest rates of bushmeat species in afrotropical forests. *Biological conservation,* 121, 167-176.

Fageria, N.K. (2010). The use of nutrients in crop plants. CRC Press, Taylor and Francis Group.

Fahrig, L. (2001). How much habitat is enough? *Biological Conservation,* 100**,** 65-74.

Fahrig, L. (2003). Effects of Habitat Fragmentation on Biodiversity. *Annual Review of Ecology, Evolution, and Systematics,* 34**,** 487-515.

Ferraro, P.J. (2009). Regional Review of Payments for Watershed Services: Sub-Saharan Africa. *Journal of Sustainable Forestry,* 28**,** 525-550.

Fischer, J. and B. Lindenmayer, D. (2006). Beyond fragmentation: the continuum model for fauna research and conservation in human-modified landscapes. *Oikos*, 112**,** 473-480

Fischer, J. and Lindenmayer, D.B. (2007). Landscape modification and habitat fragmentation: a synthesis. *Global Ecology and Biogeography,* 16**,** 265-280.

Fischer, J., Lindenmayer, D.B., Fazey, I. (2004). Appreciating Ecological Complexity: Habitat Contours as a Conceptual Landscape Model Valorando la Complejidad Ecológica: Contornos de Hábitat como un Modelo Conceptual del Paisaje. *Conservation Biology*, 18, 1245-1253.

Fjeldså, J. (1999). The impact of human forest disturbance on the endemic avifauna of the Udzungwa Mountains, Tanzania. *Bird Conservation International,* 9**,** 47-62.

Foley, J.A., Defries, R., Asner, G.P., Barford, C., Bonan, G., Carpenter, S.R., Chapin, F.S., Coe, M.T., Daily, G.C., Gibbs, H.K., Helkowski, J.H., Holloway, T., Howard, E.A., Kucharik, C.J., Monfreda, C., Patz, J.A., Prentice, I.C., Ramankutty, N. and Snyder, P.K. (2005). Global consequences of land use. *Science,* 309**,** 570-574.

Folke, C., Carpenter, S., Walker, B., Scheffer, M., Elmqvist, T., Gunderson, L., Holling, C.S. (2004). Regime shifts, resilience, and biodiversity in ecosystem management. *Annual Review of Ecology, Evolution, and Systematics,* 35, 557-581.

Folke, C., Colding, J. and Berkes, F. (2003). Synthesis: building resilience and adaptive capacity in social-ecological systems. *Navigating social-ecological systems: Building resilience for complexity and change***,** 352-387, Cambridge University Press.

Foody, G.M., Campbell, N., Trodd, N., Wood, T. (1992). Derivation and applications of probabilistic measures of class membership from the maximum-likelihood classification. *Photogrammetric Engineering and Remote Sensing*, 58, 1335-1341.

Forman, R.T., and Collinge, S.K. (1997). Nature conserved in changing landscapes with and without spatial planning. *Landscape and Urban Planning,* 37**,** 129-135

Fraser, E.D., Mabee, W. and Slaymaker, O. (2003). Mutual vulnerability, mutual dependence: The reflexive relation between human society and the environment. *Global Environmental Change,* 13**,** 137-144.

Franklin, A.B., Noon, B.R., and George, T.L. (2002). What is habitat fragmentation? *Studies in Avian Biology,* 25**,** 20-29.

Fuchs, J., Fjeldså, J., Pasquet, E., (2005). The use of mitochondrial and nuclear sequence data in assessing the taxonomic status of the endangered Uluguru Bush Shrike Malaconotus alius. *Ibis*, 147, 717-724.

Füssel, H.M. and Klein, R.J. (2006). Climate change vulnerability assessments: an evolution of conceptual thinking. *Climatic change,* 75**,** 301-329.

Gamon J, and Surfus, J. (1999). Assessing leaf pigment content and activity with a reflectometer. *New Phytologist*,143,105-117.

Gao, X, Huete, A.R, Ni, W., Miura, T. (2000). Optical–biophysical relationships of vegetation spectra without background contamination. *Remote Sensing of Enviro*nment,74,609-620.

Geist, H.J. and Lambin, E.F. (2001). What drives tropical deforestation. LUCC Report series, 4, 116. Ciaco, Louvain-la-Neuve, Belgium.

Geist, H.J. and Lambin, E.F. (2002). Proximate Causes and Underlying Driving Forces of Tropical Deforestation Tropical forests are disappearing as the result of many pressures, both local and regional, acting in various combinations in different geographical locations. *BioScience*, 52, 143-150.

Gentry, A.H. (1992). Tropical Forest Biodiversity: Distributional Patterns and Their Conservational Significance. *Oikos,* 63**,** 19-28.

Giliba, R.A., Boon, E.K., Kayombo, C.J., Chirenje, L.I. and Musamba, E.B. (2011). The influence of socio-economic factors on deforestation: a case study of the Bereku Forest Reserve in Tanzania. *Biodiversity,* 2**,** 31-39.

Gitelson, A.A. (2004). Wide dynamic range vegetation index for remote quantification of biophysical characteristics of vegetation. *Journal of Plant Physiology,*161,165-173.

Gitelson, A.A., Kaufman, Y.J., Merzlyak, M.N. (1996). Use of a green channel in remote sensing of global vegetation from EOS-MODIS. *Remote Sensing of Environment*, 58,289-298.

Gitelson, A.A., Vina, A., Ciganda, V., Rundquist, D.C, Arkebauer, T.J. (2005). Remote estimation of canopy chlorophyll content in crops. *Geophysical Research Letters*, 32, L08403.

Goel, N.S., and Qin, W. (1994). Influences of canopy architecture on relationships between various vegetation indices and LAI and FPAR: A computer simulation. *Remote Sensing Reviews*,10,309-347.

Gong, P, Pu, R., Biging, G.S, Larrieu, M.R. (2003). Estimation of forest leaf area index using vegetation indices derived from Hyperion hyperspectral data. *IEEE Transactions on Geoscience and Remote Sensing*, 41,1355-1362.

Gough, L, Grace, J.B, Taylor, K.L. (1994). The relationship between species richness and community biomass: the importance of environmental variables. *Oikos*, 70, 271-279.

Gould, W. (2000). Remote sensing of vegetation, plant species richness, and regional biodiversity hotspots. *Ecological Applications*, 10, 1861-1870.

Green, J.M.H., Larrosa, C., Burgess, N.D., Balmford, A., Johnston, A., Mbilinyi, B.P., Platts, P. J. and Coad, L. (2013b). Deforestation in an African biodiversity hotspot: Extent, variation and the effectiveness of protected areas. *Biological Conservation*, 164, 62-72.

Griffiths, G.H., and Lee, J., (2000). Landscape pattern and species richness; regional scale analysis from remote sensing. *International Journal of Remote Sensing*, 21, 2685-2704.

Guggenberger, G., Christensen, B.T., Zech, W. (1994). Land-use effects on the composition of organic matter in particle-size separates of soil: I. Lignin and carbohydrate signature. *European Journal of Soil Science*, 45, 449-458.

Gunderson, L.H. (2000). Ecological Resilience-In Theory and Application. *Annual Review of Ecology and Systematics*, 31**,** 425-439.

Haines-Young, R. (2009). Land use and biodiversity relationships. *Land Use Policy*, 26, S178-S186.

Hall, J. (1980). Practical training program-forest biology: exercises in forest botany. Division of Forestry, University of Dar es Salaam. Morogoro, Tanzania.

Hall, J., Burgess, N.D., Lovett, J., Mbilinyi, B. and Gereau, R.E. (2009). Conservation implications of deforestation across an elevational gradient in the Eastern Arc Mountains, Tanzania. *Biological Conservation,* 142**,** 2510-2521.

Hall, J.M. (2009). Ecological change in Tanzanian montane rainforests: From species to landscape. Doctoral dissertation. University of Florida.

Hanski, I. (1998). Metapopulation dynamics. *Nature,* 396, 41-49.

Hargis, C., Bissonette, J. and David, J. (1998). The behavior of landscape metrics commonly used in the study of habitat fragmentation. *Landscape Ecology,* 13**,** 167-186.

Helm, A., Hanski, I., Pärtel, M. (2006). Slow response of plant species richness to habitat loss and fragmentation. *Ecology Letters*, 9, 72-77.

Hobbs, N.T., Galvin, K.A., Stokes, C.J., Lackett, J.M., Ash, A.J., Boone, R.B., Reid, R.S., Thornton, P.K. (2008). Fragmentation of rangelands: Implications for humans, animals, and landscapes. *Global Environmental Change*, 18, 776-785.

Holling, C.S., and Gunderson, L.H. (2002). Resilience and adaptive cycles. *Panarchy: Understanding transformations in human and natural systems***,** 25-62, Island Press, Washington DC.

Holmberg, J. (2008). Natural resources in sub-Saharan Africa: Assets and vulnerabilities. Elanders Sverige AB, Sweden.

Honnay, O., Jacquemyn, H., Bossuyt, B. and Hermy, M. (2005). Forest fragmentation effects on patch occupancy and population viability of herbaceous plant species. *New Phytologist,* 166**,** 723-736.

Hoppe, R. (2005). Rethinking the science-policy nexus: from knowledge utilization and science technology studies to types of boundary arrangements. *Poiesis and Praxis,* 3**,** 199-215.

Horning, N., Robinson, J., Sterling, E., Turner, W. and Spector, S. (2010). *Remote sensing for Ecology and Conservation*, Oxford University Press.

Houghton, R.A., Lawrence, K.T., Hackler, J.L., Brown, S. (2001). The spatial distribution of forest biomass in the Brazilian Amazon: a comparison of estimates. *Global Change Biology,*7,731-746.

Huete, A. (1988). A soil-adjusted vegetation index (SAVI). *Remote Sensing of Environment,* 25, 295-309.

Huete, A., Liu, H., Batchily, K., Van Leeuwen, W. (1997). A comparison of vegetation indices over a global set of TM images for EOS-MODIS, *Remote Sensing of Environment*, 59,440-451.

Iida, S., and Nakashizuka, T. (1995). Forest fragmentation and its effect on species diversity in sub-urban coppice forests in Japan. *Forest Ecology and Management,* 73**,** 197-210.

Ince, F. (1987). Maximum likelihood classification, optimal or problematic? A comparison with the nearest neighbour classification. *Remote Sensing,* 8**,** 1829-1838.

Janzen, D.H. (1970). Herbivores and the number of tree species in tropical forests. *American Naturalist***,** 501-528.

Jetz, W., Rahbek, C. and Colwell, R.K. (2004). The coincidence of rarity and richness and the potential signature of history in centres of endemism. *Ecology Letters,*7**,**1180-1191.

Jha, C.S., Goparaju, L., Tripathi, A., Gharai, B., RaghubanshI, A. S. and Singh, J.S. (2005). Forest fragmentation and its impact on species diversity: an analysis using remote sensing and GIS. *Biodiversity and Conservation,*14**,** 1681-1698.

Jiang, Z, Huete, A.R., Didan, K., Miura, T. (2008). Development of a two-band enhanced vegetation index without a blue band. *Remote Sensing of Enviro*nment,112,3833-3845.

Jiménez, E.M., Peñuela-Mora, M.C., Sierra, C.A., Lloyd, J., Phillips, O.L., Moreno, F.H., Navarrete, D., Prieto, A., Rudas, A., Álvarez, E., Quesada, C.A., Grande-Ortíz, M.A., García-AbriL, A. and Patiño, S. (2014). Edaphic controls on ecosystem-level carbon allocation in two contrasting Amazon forests. *Journal of Geophysical Research: Biogeosciences,* 119**,** 1820-1830.

Jorge, L.A.B., and Garcia, G.J. (1997). A study of habitat fragmentation in Southeastern Brazil using remote sensing and geographic information systems (GIS). *Forest Ecology and Management,* 98**,** 35-47.

Kacholi, D.S. (2014). Edge-Interior Disparities in Tree Species and Structural Composition of the Kilengwe Forest in Morogoro Region, Tanzania. ISRN Biodiversity, 8.

Kashaigili, J.J., and Majaliwa, A.M. (2010). Integrated assessment of land use and cover changes in the Malagarasi river catchment in Tanzania. *Physics and Chemistry of the Earth, Parts A/B/C,* 35**,** 730-741.

Kerr, J.T., and Ostrovsky, M. (2003). From space to species: ecological applications for remote sensing. *Trends in Ecology and Evolution,*18,299-305.

Kerr, J.T., Southwood, T.R.E., Cihlar, J. (2001). Remotely sensed habitat diversity predicts butterfly species richness and community similarity in Canada. *Proceedings of the National Academy of Sciences*, 98, 11365-11370.

Ketterings Q.M., Coe., R., van Noordwijk, M., Ambagau, Y, Palm, C.A. (2001). Reducing uncertainty in the use of allometric biomass equations for predicting above-ground tree biomass in mixed secondary forests. *Forest Ecology and Management,*146,199-209.

Kideghesho, J., Rija, A., Mwamende, K. and Selemani, I. (2013). Emerging issues and challenges in conservation of biodiversity in the rangelands of Tanzania. *Nature Conservation,* 6**,** 1-29.

Knack, S. and Keefer, P. (1997). Does Social Capital Have an Economic Payoff: A Cross-Country Investigation. *Quarterly Journal of Economics*, 112, 1251-1288.

Kupfer, J.A., Malanson, G.P. and Franklin, S.B. (2006). Not seeing the ocean for the islands: the mediating influence of matrix-based processes on forest fragmentation effects. *Global Ecology and Biogeography,* 15**,** 8-20.

Laurance, W. (2007). Ecosystem decay of Amazonian forest fragments: implications for conservation. In: Tscharntke, T., Leuschner, C., Zeller, M., Guhardja, E., Bidin, A. (Eds.), Stability of Tropical Rainforest Margins. Springer Berlin Heidelberg, 9-35.

Laurance, W.F. and Cochrane, M.A. (2001). Special section: Synergistic effects in fragmented landscapes. *Conservation Biology,* 15**,** 1488-1489.

Laurance, W.F., Fearnside, P.M., Laurance, S.G., Delamonica, P, Lovejoy T.E., Rankin-de Merona, J.M., Chambers, J.Q., Gascon, C. (1999). Relationship between soils and Amazon forest biomass: a landscape-scale study. *Forest Ecology and Management,* 118,127-138.

Lavorel, S., Flannigan, M.D., Lambin, E.F., and Scholes, M.C. (2007). Vulnerability of land systems to fire: interactions among humans, climate, the atmosphere, and ecosystems. *Mitigation and Adaptation Strategies for Global Change,* 12**,** 33-53.

Lindenmayer, D.B. and Fischer, J. (2006). Habitat Fragmentation and Landscape Change: An Ecological and Conservation Synthesis, CSIRO Publishing, Victoria.

Liu, X.-H., Skidmore, A. and Van Oosten, H. (2002). Integration of classification methods for improvement of land-cover map accuracy. *ISPRS Journal of Photogrammetry and Remote Sensing,* 56**,** 257-268.

Li X., Gao, Z., Bai, L., Huang, Y. (2012). Potential of high resolution RapidEye data for sparse vegetation fraction mapping in arid regions. Paper presented at: *Geoscience and Remote Sensing Symposium (IGARSS),* 2012 IEEE International, Munich, Germany.

Lopa, D., Mwanyoka, I., Jambiya, G., Massoud, T., Harrison, P., Ellis-Jones, M., Blomley, T., Leimona, B., van Noordwijk, M., Burgess, N.D. (2012). Towards operational payments for water ecosystem services in Tanzania: a case study from the Uluguru Mountains, *Oryx*, 46, 34-44.

Loris V, and Damiano, G. (2006). Mapping the green herbage ratio of grasslands using both aerial and satellite-derived spectral reflectance. *Agriculture, Ecosystems and Environment,* 115,141-149.

Lovett, J. (1993). Eastern Arc moist forest flora. *Biogeography and Ecology of the Rain Forests of Eastern Africa***,** 33-55.

Lovett, J. and Ihlenfeldt, H. (1990). Classification and status of the moist forests of Tanzania. *Mitteilungen aus dem Institut für Allgemeine Botanik Hamburg,* 23**,** 287-300.

Lovett, J.C. (1999). Tanzanian forest tree plot diversity and elevation. *Journal of Tropical Ecology,* 15**,** 689-694.

Lovett, J.C., Marshall, A.R., Carr, J. (2006). Changes in tropical forest vegetation along an altitudinal gradient in the Udzungwa Mountains National Park, Tanzania. *African Journal of Ecology,* 44, 478-490.

Lu D. (2006). The potential and challenge of remote sensing-based biomass estimation. *International Journal of Remote Sensing,* 27,1297-1328.

Lu D, and Batistella, M. (2005). Exploring TM image texture and its relationships with biomass estimation in Rondônia, Brazilian Amazon. *Acta Amazonica*, 35,249-257.

Lung, T. and Schaab, G. (2006). Assessing fragmentation and disturbance of west Kenyan rainforests by means of remotely sensed time series data and landscape metrics. *African Journal of Ecology,* 44**,** 491-506.

Luoga, E.J., Witkowski, E., and Balkwill, K. (2000). Differential utilization and ethnobotany of trees in Kitulanghalo forest reserve and surrounding communal lands, eastern Tanzania. *Economic Botany*, 54**,** 328-343.

Luoga, E., Witkowski, E., and Balkwill, K. (2000a). Economics of charcoal production in miombo woodlands of eastern Tanzania: some hidden costs associated with commercialization of the resources, *Ecological Economics,* 35**,** 243-257.

Maeda, E.E., Pellikka, P.K., Siljander, M., Clark, B.J. (2010). Potential impacts of agricultural expansion and climate change on soil erosion in the Eastern Arc Mountains of Kenya. *Geomorphology*, 123, 279-289.

Malimbwi R., Solberg, B., Luoga, E. (1994). Estimation of biomass and volume in miombo woodland at Kitulangalo Forest Reserve, Tanzania, *Journal of Tropical Forest Science,*7,230-242.

Manandhar, R., Odeh, I. O., and Ancev, T. (2009). Improving the accuracy of land use and land cover classification of Landsat data using post-classification enhancement. *Remote Sensing*, 1**,** 330-344.

Mani, S., and Parthasarathy, N. (2007). Above-ground biomass estimation in ten tropical dry evergreen forest sites of peninsular India. *Biom and Bioenergy*. 31:284-290.

Marschner, H., and Rimmington, G. (1988). Mineral nutrition of higher plants. *Plant, Cell and Environment,*11,147-148.

Martínez-Meyer, E., Townsend-Peterson, A., Hargrove, W.W. (2004). Ecological niches as stable distributional constraints on mammal species, with implications for Pleistocene extinctions and climate change projections for biodiversity. *Global Ecology and Biogeography*, 13, 305-314.

MacDougall, A.S., McCann, K.S., Gellner, G., Turkington, R., (2013). Diversity loss with persistent human disturbance increases vulnerability to ecosystem collapse, *Nature*, 494, 86-89.

Mcgarigal, K. (2002). *Landscape Pattern Metrics*. *Encyclopedia of environmetrics*. John Wiley and Sons, Limited.

Mcgarigal, K. (2006). *Landscape Pattern Metrics*. *Encyclopedia of Environmetrics.* John Wiley and Sons, Limited.

Mcgarigal, K. and Cushman, S.A. (2002). Comparative evaluation of experimental approaches to the study of habitat fragmentation effects. *Ecological Applications,* 12**,** 335-345.

Mcgarigal, K., and Marks, B.J. (1995). Spatial pattern analysis program for quantifying landscape structure. USDA Forest Service General Technical Report. *PNW-GTR-351. US Department of Agriculture, Forest Service, Pacific Northwest Research Station*.

Meehl, G.A., Stocker, T.F., Collins, W.D., Friedlingstein, P., Gaye, A.T., Gregory, J.M., Kitoh, A., Knutti, R., Murphy, J.M., Noda, A. (2007). Global climate projections. *Climate Change,*747-845.

Mertz, O, Halsnæs, K, Olesen, J.E, Rasmussen, K. (2009). Adaptation to climate change in developing countries. *Environmental Management*, 43,743-752.

Mertz, O., Mbow, C., Reenberg, A. and Diouf, A. (2009). Farmers' Perceptions of Climate Change and Agricultural Adaptation Strategies in Rural Sahel. *Environmental Management,* 43**,** 804-816.

Mevik, B.H., and Wehrens, R. (2007). The pls package: principal component and partial least squares regression in R. *Journal of Statistical Software,* 18**,** 1-24.

Miguez, F.E., Villamil, M.B., Long, S.P., Bollero, G.A. (2008). Meta-analysis of the effects of management factors on Miscanthus giganteus growth and biomass production. *Agricultural and Forest Meteorology,*148,1280-1292.

Millington, A.C., Velez-Liendo, X.M., Bradley, A.V. (2003). Scale dependence in multitemporal mapping of forest fragmentation in Bolivia: implications for explaining temporal trends in landscape ecology and applications to biodiversity conservation. *ISPRS Journal of Photogrammetry and Remote Sensing*, 57*,* 289-299.

Montagnini, F., and Jordan, C.F. (2005). Importance of tropical forests. *Tropical Forest Ecology: The Basis for Conservation and Management***,** 1-17.

Mugasha WA, Bollandsås OM, Eid T. (2013). Relationships between diameter and height of trees in natural tropical forest in Tanzania. *Southern Forests: a Journal of Forest Science*.75:221-237.

Mugasha, W.A., Eid, T., Bollandsås, O.M., Malimbwi, R.E., Chamshama, S.A.O., Zahabu, E., Katani, J.Z. (2013). Allometric models for prediction of above- and belowground biomass of trees in the miombo woodlands of Tanzania. *Forest Ecology and Management*, 310, 87-101.

Mumbi, C., Marchant, R., Hooghiemstra, H., Wooller, M. (2008). Late Quaternary vegetation reconstruction from the Eastern Arc Mountains, Tanzania. *Quaternary Research*, 69, 326-341.

Mumby, P.J., Edwards, A.J., Arias-gonzález, J.E., Lindeman, K.C., BlackwelL, P.G., Gall, A., Gorczynska, M.I., Harborne, A.R., Pescod, C.L., Renken, H. (2004). Mangroves enhance the biomass of coral reef fish communities in the Caribbean. *Nature*, 427, 533-536.

Munishi, P., Mringi, S., Shirima, D., and Linda, S. (2010). The role of the Miombo woodlands of the Southern Highlands of Tanzania as carbon sinks. *Journal of Ecology and the Natural Environment*, 2, 261-269.

Munishi, P., and Shear, T. (2004a). Carbon storage in afromontane rain forests of the Eastern Arc Mountains of Tanzania: their net contribution to atmospheric carbon. *Journal of Tropical Forest Science*,78-93.

Murcia, C. (1995). Edge effects in fragmented forests: implications for conservation. *Trends in Ecology and Evolution*, 10**,** 58-62.

Mutanga, O., Skidmore, A.K. (2004). Narrow band vegetation indices overcome the saturation problem in biomass estimation. *International Journal of Remote Sensing*,25,3999-4014.

Myers, N., Mittermeier, R.A., Mittermeier, C.G., Da Fonseca, G.A.B., and Kent, J. (2000). Biodiversity hotspots for conservation priorities. *Nature*, 403**,** 853-858.

Nagendra, H., Munroe, D.K., and Southworth, J. (2004). From pattern to process: landscape fragmentation and the analysis of land use/land cover change. *Agriculture, Ecosystems and Environment*, 101**,** 111-115.

Nagendra, H., Reyers, B. and Lavorel, S. (2013). Impacts of land change on biodiversity: making the link to ecosystem services. *Current Opinion in Environmental Sustainability,* 5**,** 503-508.

Neel, M., Mcgarigal, K., and Cushman, S. (2004). Behavior of class-level landscape metrics across gradients of class aggregation and area. *Landscape Ecology,* 19**,** 435-455.

Nelson, B.W., Mesquita, R., Pereira J.L., Garcia Aquino de Souza, S., Teixeira Batista, G., Bovino Couto, L. (1999). Allometric regressions for improved estimate of secondary forest biomass in the central Amazon. *Forest Ecology and Management*, 117,149-167.

Neufeldt, H., Kristjanson, P., Thorlakson, T., Gassner, A., Norton-Griffiths, M., Place, F. and Langford, K. (2011). Making climate-smart agriculture work for the poor. *ICRAF Policy Brief,* 12.

Newmark, W.D. (2002). Conserving biodiversity in East African forests: a study of the Eastern Arc Mountains, Springer-Verlag Berlin.

Newmark, W.D. (1998). Forest Area, Fragmentation, and Loss in the Eastern Arc Mountains: Implications For the Conservation of Biological Diversity. *Journal of East African Natural History,* 87**,** 29-36.

Njana, M.A., Kajembe, G.C., and Malimbwi, R.E. (2013). Are miombo woodlands vital to livelihoods of rural households? Evidence from Urumwa and surrounding communities, Tabora, Tanzania. *Forests, Trees and Livelihoods,* 22**,** 124-140.

Ntongani, W.A., Munishi, P.K.T., and Mbilinyi, B.P. (2010). Land use changes and conservation threats in the eastern Selous–Niassa wildlife corridor, Nachingwea, Tanzania. *African Journal of Ecology,* 48**,** 880-887.

Ojoyi M.M., and Kahinda J. (2015). An analysis of climatic impacts and adaptation strategies in Morogoro region, Tanzania. *International Journal of Climate Change Strategies and Management*, 7, 97-115.

Ojoyi, M.M., Mutanga, O., Odindi, J., Abdel-Rahman, E. (2014). Analyzing fragmentation in vulnerable biodiversity hotspots using remote sensing and frag stats in Tanzania. *Landscape research* (under revision).

Ojoyi, M.M., Mutanga, O., Odindi, J., Ayenkulu, E., Abdelrahman, E.M. (2015). The effect of forest fragmentation on tree species abundance and diversity in the Eastern Arc Mountains of Tanzania. *Applied Ecology and Environmental Research*, 13, 307-324.

Olson, D. M., and Dinerstein, E. (1998). The Global 200: A Representation Approach to Conserving the Earth's Most Biologically Valuable Ecoregions. *Conservation Biology*, 12**,** 502-515.

Olson, L.E., Sauder, J.D., Albrecht, N.M., Vinkey, R.S., Cushman, S.A., Schwartz, M.K. (2014). Modeling the effects of dispersal and patch size on predicted fisher (Pekania [Martes] pennanti) distribution in the U.S. Rocky Mountains. *Biological Conservation*, 169, 89-98.

Opdam, P. (1991). Metapopulation theory and habitat fragmentation: a review of holarctic breeding bird studies. *Landscape Ecology*, 5, 93-106.

Osborne, P.E., Alonso, J.C., Bryant, R.G. (2001). Modelling landscape-scale habitat use using GIS and remote sensing: a case study with great bustards. *Journal of Applied Ecology*, 38, 458-471.

Paavola, J. (2008). Livelihoods, vulnerability and adaptation to climate change in Morogoro, Tanzania. *Environmental Science and Policy*, 11**,** 642-654.

Paavola, J., Gouldson, A. and Kluvánková-oravská, T. (2009). Interplay of actors, scales, frameworks and regimes in the governance of biodiversity. *Environmental Policy and Governance*, 19**,** 148-158.

Pardini, R., De Souza, S.M., Braga-neto, R. and Metzger, J.P. (2005). The role of forest structure, fragment size and corridors in maintaining small mammal abundance and diversity in an Atlantic forest landscape. *Biological Conservation*, 124**,** 253-266.

Pearson, R.G., and Dawson, T.P. (2003). Predicting the impacts of climate change on the distribution of species: are bioclimate envelope models useful? *Global ecology and biogeography*, 12, 361-371.

Pelkey, N.W., Stoner, C.J. and Caro, T.M. (2000). Vegetation in Tanzania: assessing long term trends and effects of protection using satellite imagery. *Biological Conservation*, 94**,** 297-309.

Peterson, A., Papeş, M., Eaton, M. (2007). Transferability and model evaluation in ecological niche modeling: a comparison of GARP and Maxent. *Ecography*,30, 550-560.

Pérez-Vega, A., Mas, J.F. and Ligmann-Zielinska, A. (2012). Comparing two approaches to land use/cover change modeling and their implications for the assessment of biodiversity loss in a deciduous tropical forest. *Environmental Modelling and Software*, 29**,** 11-23.

Pineda, E., and Halffter, G. 2004. Species diversity and habitat fragmentation: frogs in a tropical montane landscape in Mexico. *Biological Conservation*, 117, 499-508.

Platts, P. (2012). Spatial modelling, phytogeography and conservation in the Eastern Arc Mountains of Tanzania and Kenya. PhD thesis, The University of York, UK.

Platts, P.J., Burgess, N.D., Gereau, R.E., Lovett, J.C., Marshall, A.R., McClean, C.J., Pellikka, P.K.E., Swetnam, R.D., Marchant, R. (2011). Delimiting tropical mountain ecoregions for conservation. *Environmental Conservation*, 38, 312-324.

Platts, P.J., Mcclean, C.J., Lovett, J.C. and Marchant, R. (2008). Predicting tree distributions in an East African biodiversity hotspot: model selection, data bias and envelope uncertainty. *Ecological Modelling*, 218, 121-134.

Popescu, S.C. (2007). Estimating biomass of individual pine trees using airborne lidar. *Biomass and Bioenergy,* 31, 646-655.

Popescu, S.C, Wynne R.H, Nelson R.F. (2003). Measuring individual tree crown diameter with lidar and assessing its influence on estimating forest volume and biomass. *Canadian Journal of Remote Sensing*, 29,564-577.

Powell, S.L, Cohen, W.B., Healey, S.P, Kennedy, R.E, Moisen G.G., Pierce K.B., Ohmann, J.L. (2010). Quantification of live aboveground forest biomass dynamics with Landsat time-series and field inventory data: A comparison of empirical modeling approaches. *Remote Sensing of Environment,* 114,1053-1068.

Qasim, M., Hubacek, K., Termansen, M., and Khan, A. (2011). Spatial and temporal dynamics of land use pattern in District Swat, Hindu Kush Himalayan region of Pakistan. *Applied Geography,* 31**,** 820-828.

Ramoelo, A, Skidmore, A.K, Cho, M.A, Schlerf, M., Mathieu, R., Heitkönig, I.M. (2012). Regional estimation of savanna grass nitrogen using the red-edge band of the spaceborne RapidEye sensor. *International Journal of Applied Earth Observation and Geoinformation,*19,151-162.

RapidEye. (2013). The RapidEye Red Edge. Whitepaper.

Rashid, I., Romshoo, S., Vijayalakshmi, T. (2013). Geospatial modelling approach for identifying disturbance regimes and biodiversity rich areas in North Western Himalayas, India. *Biodiversity and Conservation*, 22, 2537-2566.

Reich, P.B., Knops, J., Tilman, D., Craine, J., Ellsworth, D., Tjoelker, M., Lee, T., Wedin, D., Naeem, S., Bahauddin, D. (2001). Plant diversity enhances ecosystem responses to elevated CO2 and nitrogen deposition. *Nature*, 410, 809-810.

Reid, R.S., Thornton, P.K., and Kruska, R.L. (2004). Loss and fragmentation of habitat for pastoral people and wildlife in East Africa: Concepts and issues. *African Journal of Range and Forage Science*, 21**,** 171-181.

Reidsma, P., Tekelenburg, T., Van Den Berg, M. and Alkemade, R. (2006). Impacts of land-use change on biodiversity: An assessment of agricultural biodiversity in the European Union. *Agriculture, Ecosystems and Environment,* 114**,** 86-102.

Richter, R., and Schlaepfer, D. (2011). Atmospheric/topographic correction for satellite imagery: ATCOR-2/3 User Guide Vers. 8.0. 2. *DLR—German Aerospace Center, Remote Sensing Data Center*.

Richter, R., and Schläpfer, D. (2004). Atmospheric/topographic correction for airborne imagery. *ATCOR-4 User Guide Version* 3.

Rindfuss, R.R., and Stern, P.C. (1998). Linking remote sensing and social science: The need and the challenges. *People and pixels: Linking remote sensing and social science***,** 1-27.

Rondinini, C., Chiozza, F., Boitani, L., (2006). High human density in the irreplaceable sites for African vertebrates conservation. *Biological Conservation*, 133, 358-363.

Rouget, M., Richardson, D.M., Cowling, R.M., Lloyd, J.W. and Lombard, A.T. (2003). Current patterns of habitat transformation and future threats to biodiversity in terrestrial ecosystems of the Cape Floristic Region, South Africa. *Biological Conservation,* 112**,** 63-85.

Roujean, J-L, Breon, F.M. (1995). Estimating PAR absorbed by vegetation from bidirectional reflectance measurements. *Remote Sensing of Environment,* 51,375-384.

Rutatora, D.F., and Mattee, A.Z. (2001). Major agricultural extension providers in Tanzania. *African Study Monographs*, 22**,** 155-173.

Rutledge, D.T. (2003). Landscape indices as measures of the effects of fragmentation: can pattern reflect process? Doc Science Internal Series 98. *Department of Conservation, Wellington, Newzealand.*

Saatchi, S., Buermann, W., ter Steege, H., Mori, S., Smith, T.B. (2008). Modeling distribution of Amazonian tree species and diversity using remote sensing measurements. *Remote Sensing of Environment*, 112, 2000-2017.

Shannon, C.E., and Weaver, W. (1963). The Mathematical Theory of Communication. University of Illinois Press, Champaign, IL.

Saikia, A., Hazarika, R. and Sahariah, D. (2013). Land-use/land-cover change and fragmentation in the Nameri Tiger Reserve, India. *Geografisk Tidsskrift-Danish Journal of Geography,* 113**,** 1-10.

Sanga, C., Kalungwizi, V., and Msuya, C. (2013). Building an agricultural extension services system supported by ICTs in Tanzania: Progress made, Challenges remain. *International Journal of Education and Development,* 9, 80-99.

Saunders, D.A., Hobbs, R.J. and Margules, C.R. (1991). Biological consequences of ecosystem fragmentation: a review. *Conservation biology,* 5**,** 18-32.

Schmidt, K.S., and Skidmore, A.K. (2003). Spectral discrimination of vegetation types in a coastal wetland. *Remote Sensing of Environment*, 85, 92-108.

Schulp, C.J, Nabuurs G.J., Verburg, P.H., de Waal, R.W. (2008). Effect of tree species on carbon stocks in forest floor and mineral soil and implications for soil carbon inventories. *Forest Ecology and Management*, 256,482-490.

Schuster, C., Förster, M. and Kleinschmit, B. (2012). Testing the red edge channel for improving land-use classifications based on high-resolution multi-spectral satellite data. *International Journal of Remote Sensing*, 33, 5583-5599.

Şekercioğlu, Ç.H., Daily, G.C., Ehrlich, P.R. (2004). Ecosystem consequences of bird declines. *Proceedings of the National Academy of Sciences*, 101, 18042-18047.

Serageldin, I., Steer, A. D. and Cernea, M.M. (1994). *Making development sustainable: from concepts to action*, World Bank Publications.

Seto, K.C., Liu, W. (2003). Comparing ARTMAP neural network with the maximum-likelihood classifier for detecting urban change. *Photogrammetric Engineering and Remote Sensing*, 69, 981-990.

Shirima, D.D., Munishi, P.K.T., Lewis, S.L., Burgess, N.D., Marshall, A.R., Balmford, A., Swetnam, R.D. and Zahabu, E.M. (2011). Carbon storage, structure and composition of miombo woodlands in Tanzania's Eastern Arc Mountains. *African Journal of Ecology*, 49**,** 332-342.

Shirk, P.L., Linden, D.W., Patrick, D.A., Howell, K.M., Harper, E.B., and Vonesh, J.R. (2014). Impact of habitat alteration on endemic Afromontane chameleons: evidence for historical population declines using hierarchical spatial modelling. *Diversity and Distributions,* 20, 1186-1199.

Simelton, E., Fraser, E.D., Termansen, M., Forster, P.M. and Dougill, A.J. (2009). Typologies of crop-drought vulnerability: an empirical analysis of the socio-economic factors that influence the sensitivity and resilience to drought of three major food crops in China (1961–2001). *Environmental Science and Policy,* 12**,** 438-452.

Sokona, Y, Denton, F. (2001). Climate change impacts: can Africa cope with the challenges? *Climate Policy,* 1,117-123.

Solecki, W.D. (1998). Local attitudes on regional ecosystem management: A study of New Jersey pinelands residents. *Society and Natural Resources,* 11**,** 441-463.

Solomon, D., Lehmann, J., Zech, W. (2000). Land use effects on soil organic matter properties of chromic luvisols in semi-arid northern Tanzania: carbon, nitrogen, lignin and carbohydrates. *Agriculture, Ecosystems and Environment*, 78, 203-213.

Southworth, J., Nagendra, H. and Tucker, C. (2002). Fragmentation of a Landscape: Incorporating landscape metrics into satellite analyses of land-cover change. *Landscape Research,* 27**,** 253-269.

Stehman, S.V., and Czaplewski, R.L. (1998). Design and Analysis for Thematic Map Accuracy Assessment: Fundamental Principles. *Remote Sensing of Environment,* 64**,** 331-344.

Stoms, D.M., and Estes, J.E. (1993). A remote sensing research agenda for mapping and monitoring biodiversity. *International Journal of Remote Sensing,* 14**,** 1839-1860.

Strahler, A.H. (1980). The use of prior probabilities in maximum likelihood classification of remotely sensed data. *Remote Sensing of Environment*, 10, 135-163.

Studsrød, J.E. and Wegge, P. (1995). Park-people relationships: the case of damage caused by park animals around the Royal Bardia National Park, Nepal. *Environmental Conservation*, 22**,** 133-142.

Swai, G, Ndangalasi H.J., Munishi, P.K, Shirima, D.D. (2014). Carbon stocks of Hanang forest, Tanzania: An implication for climate mitigation. *Journal of Ecology and The Natural Environment*, 6, 90-98.

Swetnam, R.D., Fisher, B., Mbilinyi, B.P., Munishi, P.K.T., Willcock, S., Ricketts, T., Mwakalila, S., Balmford, A., Burgess, N.D., Marshall, A.R. and Lewis, S.L. (2011). Mapping socio-economic scenarios of land cover change: A GIS method to enable ecosystem service modelling. *Journal of Environmental Management,* 92**,** 563-574.

Tabarelli, M., Mantovani, W. and Peres, C.A. (1999). Effects of habitat fragmentation on plant guild structure in the montane Atlantic forest of southeastern Brazil. *Biological Conservation*, 91, 119-127.

Tabarelli, M., and Gascon, C. (2005). Lessons from Fragmentation Research: Improving Management and Policy Guidelines for Biodiversity Conservation. *Conservation Biology*, 19, 734–739.

Tabarelli, M., Pinto, L.P., Silva, J., Hirota, M. and Bede, L. (2005). Challenges and opportunities for biodiversity conservation in the Brazilian Atlantic Forest. *Conservation Biology,* 19**,** 695-700.

Tabor, K., Burgess, N.D., Mbilinyi, B.P., Kashaigili, J.J. and Steininger, M.K. (2010). Forest and woodland cover and change in coastal Tanzania and Kenya, 1990 to 2000. *Journal of East African Natural History*, 99**,** 19-45.

Tapsall, B, Milenov., P, Tasdemir, K. (2010). Analysis of RapidEye imagery for annual landcover mapping as an aid to European Union (EU) common agricultural policy. In: Wagner W, Székely, B, editors. Proceedings of the ISPRS TC VII Symposium- 100 Years; 2010 July 5-7; Vienna, Austria: Vienna University of Technology.

Theilade, I., Hansen, H.H., Krog, M. and Ruffo, C.K. (2007). Use-values and relative importance of trees to the kaguru people in semi-arid Tanzania: part ii woodland species. *Forests, Trees and Livelihoods*, 17**,** 109-123.

Thenkabail, P.S., Lyon, J.G., and Huete, A. (2012). *Hyperspectral remote sensing of vegetation*, CRC Press Boca Raton, FL.

Thomas, F., Blank, R., Hartmann, G. (2002). Abiotic and biotic factors and their interactions as causes of oak decline in Central Europe. *Forest Pathology,* 32,277-307.

Thuiller, W., Lavorel, S., Sykes, M.T., Araújo, M.B. (2006). Using niche-based modelling to assess the impact of climate change on tree functional diversity in Europe. *Diversity and Distributions*, 12, 49-60.

Tilman, D., Lehman, C. (2001). Human-caused environmental change: Impacts on plant diversity and evolution. *Proceedings of the National Academy of Sciences*, 98, 5433-5440.

Tøttrup, A.P., Larsen, J.L., Burgess, N.D. (2004). A first estimate of the population size of Loveridge's Sunbird Nectarinia loveridgei, endemic to the Uluguru Mountains, Tanzania. *Bird Conservation International*, 14, 25-32.

Tseng, M.H., Chen, S.J., Hwang, G.H. and Shen, M.Y. (2008). A genetic algorithm rule-based approach for land-cover classification. *ISPRS Journal of Photogrammetry and Remote Sensing,* 63**,** 202-212.

Tucker, C.J. (1979). Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sensing of Environment,* 8,127-150.

Turner, I. (1996). Species loss in fragments of tropical rain forest: a review of the evidence. *Journal of Applied Ecology*, 33,200-209.

Turner, W., Spector, S., Gardiner, N., Fladeland, M., Sterling, E., and Steininger, M. (2003). Remote sensing for biodiversity science and conservation. *Trends in Ecology and Evolution,* 18**,** 306-314.

United Rebublic of Tanzania (URT). (1997). Morogoro Region Socio-Economic Profile. The Planning Commission, Dar es Salaam and Regional Commissioner's Office, Morogoro.

United Republic of Tanzania. (2013). Population Distribution by Age and Sex. National Bureau of Statistics Ministry of Finance Dar es Salaam.

Utkhede, R, Smith, E. (1993). Biotic and abiotic causes of replant problems of fruit trees. In: Utkhede RS, editor. ISHS Acta Horticulturae 363. *Proceedings of the III International Symposium on Replant Problems.* Penticton, Canada,Sandman Inn.

Van der Meer, F., Bakker, W., Scholte, K., Skidmore, A., De Jong, S., Clevers, J., Addink, E., Epema, G. (2001). Spatial scale variations in vegetation indices and above-ground biomass estimates: implications for MERIS. *International Journal of Remote Sensing,* 22, 3381-3396.

Vescovo, L., and Gianelle, D. (2008). Using the MIR bands in vegetation indices for the estimation of grassland biophysical parameters from satellite remote sensing in the Alps region of Trentino (Italy). *Advances in Space Research,* 41,1764-1772.

Viña, A., Gitelson, A.A., Nguy-Robertson, A.L., Peng, Y. (2011). Comparison of different vegetation indices for the remote assessment of green leaf area index of crops. *Remote Sensing of Environment*, 115, 3468-3478.

Vincent, K. (2007). Uncertainty in adaptive capacity and the importance of scale. *Global Environmental Change,* 17**,** 12-24.

Vo Q.T., Oppelt, N., Leinenkugel, P., Kuenzer, C. (2013). Remote sensing in mapping mangrove ecosystems—An object-based approach. *Remote Sensing,* 5,183-201.

Vogelmann, J.E. (1995). Assessment of Forest Fragmentation in Southern New England Using Remote Sensing and Geographic Information Systems Technology.*Conservation Biology, 9, 439-449.*

Vollenweider, P., Günthardt-Goerg, M.S. (2005). Diagnosis of abiotic and biotic stress factors using the visible symptoms in foliage. *Environmental Pollution*,137,455-465.

Vuolo, F., Atzberger, C., Richter, K., D'urso, G. and Dash, J. (2010). Retrieval of biophysical vegetation products from RapidEye imagery, na.

Wade, T.G., Riitters, K.H., Wickham, J.D. and Jones, K.B. (2003). Distribution and causes of global forest fragmentation. *Conservation Ecology,* 7, 7.

Walker, B., and Salt, D. (2006). *Resilience thinking: sustaining ecosystems and people in a changing world*, Island Press, Washington DC.

Wasige, J.E., Groen, T.A., Smaling, E., and Jetten, V. (2013). Monitoring basin-scale land cover changes in Kagera Basin of Lake Victoria using ancillary data and remote sensing. *International Journal of Applied Earth Observation and Geoinformation,* 21**,** 32-42.

Wei, W., Mendel, J.M., (2000). Maximum-likelihood classification for digital amplitude-phase modulations. *IEEE Transactions on Communications*, 48, 189-193.

White, P.A., Kalff, J., Rasmussen, J.B., Gasol, J.M. (1991). The effect of temperature and algal biomass on bacterial production and specific growth rate in freshwater and marine habitats. *Microbial Ecology,* 21,99-118.

Wiens, J.A. (1985). Chapter 10 - Vertebrate Responses to Environmental Patchiness in Arid and Semiarid Ecosystems. *In:* Steward, T. P. and White, P. S. (eds.) *The Ecology of Natural Disturbance and Patch Dynamics.* San Diego, Academic Press.

Wiens, J.A. (1995). Habitat fragmentation: island v landscape perspectives on bird conservation. *Ibis*, 137**,** S97-S104.

Wiens, J. (2000). Ecological heterogeneity: an ontogeny of concepts and approaches. *The Ecological Consequences of Environmental Heterogeneity***,** 2, 9-31.

Wiens, J., Sutter, R., Anderson, M., Blanchard, J., Barnett, A., Aguilar-AmuchasteguI, N., Avery, C. and Laine, S. (2009). Selecting and conserving lands for biodiversity: The role of remote sensing. *Remote Sensing of Environment,* 113**,** 1370-1381.

Wilson, K., Pressey, R., Newton, A., Burgman, M., Possingham, H., and Weston, C. (2005). Measuring and Incorporating Vulnerability into Conservation Planning. *Environmental Management,* 35**,** 527-543.

Wold, S., 1995. PLS for multivariate linear modeling. In: van de Waterbeemd, H. (Ed.), Chemo metric Methods in Molecular Design. VCH, Weinheim, Gemany, pp. 195–218

Woodward, F.I., and Beerling, D.J. (1997). The dynamics of vegetation change: health warnings for equilibrium'dodo'models. *Global Ecology and Biogeography Letters*, 413-418.

Wright, S.J. (2005). Tropical forests in a changing environment. *Trends in Ecology and Evolution,* 20**,** 553-560.

Wu, J., Shen, W., Sun, W., Tueller, P. (2002). Empirical patterns of the effects of changing scale on landscape metrics. *Landscape Ecology*, 17, 761-782.

Wu, W. (2014). The Generalized Difference Vegetation Index (GDVI) for Dryland Characterization. *Remote Sen*sing, 6,1211-1233.

Wunder, S. (2001). Poverty alleviation and tropical forests—what scope for synergies? *World Development,* 29**,** 1817-1833.

Wulder M.A., Hall, R.J., Coops N.C., Franklin, S.E. (2004). High spatial resolution remotely sensed data for ecosystem characterization. *Bioscience,*54,511-521.

Xi, Z. (2007). Integration of multi–source data for the detection and analysis of long term land cover change. *Masters Thesis, Enschede, The Netherlands, The International Institute for Geo-Information Science and Earth Observation (ITC).*

Xue, L., and Yang, L. (2009). Deriving leaf chlorophyll content of green-leafy vegetables from hyperspectral reflectance. *ISPRS Journal of Photogrammetry and Remote Sensing,* 64,97-106.

Yanda, P., and Shishira, E. (1999). Land Cover Changes and their Influencing Factors in Tanzania. *In*: Ravichandran V. *Regional Land Cover Changes, Sustainable Agriculture and Their Interactions with Global Change***,** 49, Universities Press (India) Limited.

Yanda, P.Z. (2010). Impact of small scale tobacco growing on the spatial and temporal distribution of Miombo woodlands in Western Tanzania. *Journal of Ecology and the Natural Environment,* 2**,** 10-16.

Ylhäisi, J. (2004). Indigenous forests fragmentation and the signifi cance of ethnic forests for conservation in the North Pare, the Eastern Arc Mountains, Tanzania. *Fennia-International Journal of Geography*, 182, 109-132.

Zebisch, M., Wechsung, F., and Kenneweg, H. (2004). Landscape response functions for biodiversity assessing the impact of land-use changes at the county level. *Landscape and Urban Planning,* 67**,** 157-172.

Zotz, G., Bader, M.Y. (2009). Epiphytic Plants in a Changing World-Global: Change Effects on Vascular and Non-Vascular Epiphytes. In: Lüttge, U., Beyschlag, W., Büdel, B., Francis, D. (Eds.), Progress in Botany. Springer Berlin Heidelberg, pp. 147-170.