

**EFFECTS OF FOREST COVER CHANGE ON CARBON STOCK IN MIOMBO
WOODLANDS: A CASE OF MBIWE FOREST RESERVE IN MBEYA REGION,
TANZANIA**

BY

SIMON KITEREJA

**A DISSERTATION SUBMITTED IN PARTIAL FULFILMENT OF THE
REQUIREMENTS FOR THE DEGREE OF MASTER OF SCIENCE IN FOREST
RESOURCES ASSESSMENT AND MANAGEMENT OF THE SOKOINE
UNIVERSITY OF AGRICULTURE. MOROGORO, TANZANIA.**

2015

ABSTRACT

Most changes in forest cover affect the amount of carbon held in vegetation and soil, thereby, either releasing carbon dioxide (a greenhouse gas) to, or removing it from the atmosphere. A study on effects of forest cover change on carbon stock in miombo woodlands was carried out in Mbeya region at Mbiwe Forest Reserve. Landsat MSS, TM and ETM+ image data acquired on June 1984, June 1990 and June 2013 were obtained and used for forest cover change analysis. Inventory data on systematically laid plots were used to compute the biomass. The forest cover change from the satellite imagery of 1984, 1990 and 2013 (the dependent variables) and road network, villages and cultivated areas (the independent variables) were used for determining factors of forest cover change and a logistic linear model was used. Sample plots were established and biomass per hectare of each measured plots were used as dependent variables and vegetation indices from the satellite imageries were used as independent variables to formulate models that were used to estimate biomass of the whole area of Mbiwe Forest Reserve. Finally, the difference of biomass between 1984 and 1990 and between 1990 and 2013 were computed to obtain the gain or loss in biomass. The coefficient of 0.50 was used for conversions of biomass to carbon stock. The results show that there is a change of forest cover and hence carbon stock between periods under consideration. During the period 1984-1990, closed woodland decreased by 2 306.2 ha (-4.7%) and 12 748.2 ha (-26%) for the period 1990-2013. Similarly, in the period 1984-1990, open woodland increased by 2 420.7 ha (5%) and decreased by 723.3 ha (-1.5%) between 1990 and 2013. Meanwhile, in the period 1984 – 1990, the bushland increased by 436.5 ha (0.9%) and 12 476 (25%) for the period 1990 – 2013. The results revealed that the year 1984 had the highest average carbon stock 58.5 tC/ha followed by year 1990, with 55.7 tC/ha and 2013 had the lowest carbon stock of 54.8 tC/ha, varying from 0.5 to 199.9 tC/ha. It was revealed that presences of roads and village centres in and around forest reserves also presences of cultivated areas in the forest

reserves have high effects on forest cover change. This study recommends that forest reserves need to be protected as for 19 years (1984 – 2013) a total of 15 779.4 ha out of 49 147.7 ha were changed from closed and open woodland to bushland, cultivated land or bare soil and at the same period a total of 1 796.80 tC were lost as a results of forest cover change. On the other hand from 1990 – 2013 closed woodland decreased at a rate of 554.3 ha/year, assuming a linear decline. If this continues unabated, it is likely that in the next 10 years the closed woodland will be completely converted to other covers. Therefore more effort is needed to protect the forest.

DECLARATION

I, Simon Kitereja, do hereby declare to the Senate of Sokoine University of Agriculture that, this dissertation is my own original work and that it has neither been submitted nor concurrently being submitted in any other Institution.

Simon Kitereja

MSc. Candidate

Date

The above declaration is confirmed by:

Professor J. J. Kashaigili

(1st Supervisor)

Date

Dr. J. Z. Katani

(2nd Supervisor)

Date

COPYRIGHT

All rights reserved. No part of this work may be reproduced, stored in any retrieved system or transmitted in any form or by any means without prior permission of the author or Sokoine University of Agriculture in that behalf.

AKNOWLEDGEMENTS

I wish to express my sincere gratitude to the Ministry of Natural Resources and Tourism in particular the Tanzania Forest Services (TFS) for providing financial support throughout the study. Special thanks should also go to my supervisors Professor J. J. Kashaigili and Doctor J. Z. Katani of the Department of Forest Mensuration and Management for their constant and tireless efforts in guiding me during this study. Their constructive criticisms and broad knowledge have enabled me to accomplish this study.

My sincere thanks go to the Department of Natural Resources and Land, Chunya Office Mbeya, especially the District Natural Resources and Land Officer (DNRLO), Mr. Edward Ambilikile Syadala. Chunya District Forest Office Officials, specifically Mr. Jumanne James and the District Forest Manager (TFS), Mr. Noel Maeda for their moral and material support.

This study could not have been possible without the generous time and cooperation of my fellow students in the Faculty of Forestry and Nature Conservation.

Special thanks go to my sister in law Aleningwa Jonas Swai and her daughter Helena Mosha for their encouragement and endlessly support rendered to me during this study.

I am very grateful to my beloved wife Rahel Jonas Swai for her encouragement, patience, and tolerance and for taking care of our children during my absence for this study. My children Derrin and Perrin missed me so much during my study. I thank them very much for their tolerance to the hardships which they might have faced while I was away for studies. I thank the almighty “GOD”, the most merciful and the most beneficent deserves full thanks for granting me life, strength and blessings to pursue the study.

DEDICATION

This dissertation is dedicated to my parents Mr. Sylvester Nsinda and Mrs. Carolina Bwire who not only tirelessly endured to lay down the foundation of my education, but also devoted much of their moral support and financial resources to pay for my education.

TABLE OF CONTENTS

ABSTRACT	ii
COPYRIGHT	v
AKNOWLEDGEMENTS	vi
DEDICATION.....	vii
TABLE OF CONTENTS	viii
LIST OF TABLES	xi
LIST OF FIGURES	xii
CHAPTER ONE	1
1.0 INTRODUCTION	1
1.1 Background	1
1.2 Problem Statement	2
1.3 Justification of the Study	3
1.4 Objective	3
1.4.1 Main Objective	3
1.4.2 Specific Objective	3
1.5 Research Questions	4
1.6 Conceptual Framework of Research	4
CHAPTER TWO	6
2.0 LITERATURE REVIEW	6
2.1 Definition of Key Terms	6
2.2 Remote Sensing for above Ground Biomass Estimation	8
2.3 Carbon Stock Estimation.....	9
2.4 Causes of forest cover change	11

2.4.1 Proximate causes	14
2.4.2 Underlying Causes	15
CHAPTER THREE	17
3.0 MATERIALS AND METHODS	17
3.1 Materials	17
3.1.1 Description of the Study Area	17
3.1.2 Location	17
3.1.3 Climate	17
3.1.4 Vegetation	18
3.1.5 Social-economic activities	19
3.2.1 Data collection	19
3.2.1.1 Remote sensing data	19
3.2.1.1 Factors causing forest cover change	22
3.2.2 Data analysis	24
CHAPTER FOUR	39
4.0 RESULTS AND DISCUSSION	39
4.1 Forest cover for Mbiwe Forest Reserve from 1984, 1990 and 2013	39
4.3 Changes in forest cover for Mbiwe Forest Reserve from 1984, 1990 and 2013	43
4.4 Carbon stock change for Mbiwe Forest Reserve from 1984, 1990 and 2013	47
4.4.1 Above ground biomass	47
4.4.2 Above ground carbon stock	47
4.5 Factors of Forest Cover Change	50

CHAPTER FIVE	55
5.0 CONCLUSION AND RECOMMENDATIONS.....	55
5.1 Conclusion	55
5.1.1 Change in forest cover for Mbiwe Forest Reserve from 1984, 1990 and 2013	55
5.1.2 Changes in carbon stock for Mbiwe Forest Reserve from 1984, 1990 and 2013	56
5.1.3 Factors of influencing Forest Cover Change.....	56
5.2 Recommendations.....	56
REFERENCES.....	57
APPENDICES	71

LIST OF TABLES

Table 1: The Landsat MSS and ETM Image Scenes used in this study	19
Table 2: Classification results	43
Table 3: Cover area, change area and annual rate of change between 1984 - 1990 and 1990 - 2013	46
Table 4: Carbon stock for the year 1984, 1990 and 2013	48
Table 5: Factors significantly associated with forest cover change during the period 1990 to 2013	54

LIST OF FIGURES

Figure 1:	Conceptual framework of research.	5
Figure 2:	A Map showing location of Mbiwe Forest Reserve in Chunya District.	18
Figure 3:	Concentric Circular Plots.	22
Figure 4:	Sample plots distribution.	23
Figure 5:	DVI 1984.	31
Figure 6:	DVI 1990.	32
Figure 7:	DVI 2013.	33
Figure 8:	RSR 1984.	34
Figure 9:	RSR 1990.	35
Figure 10:	RSR 2013.	36
Figure 11:	Forest Cover for Mbiwe Forest Reserve in year 1984.	40
Figure 12:	Forest Cover for Mbiwe Forest Reserve in year 1990.	41
Figure 14:	Forest cover change for Mbiwe Forest Reserve for the period 1984 – 1990.	44
Figure 16:	Carbon Stock in 1984.	48
Figure 17:	Carbon Stock in 1990.	49
Figure 18:	Carbon Stock in 2013.	50
Figure 19:	Spatial distribution of forest covers loss due to distance from the village centres to the degraded areas.	51
Figure 20:	Spatial distribution of forest covers loss due to distance from the roads to the degraded areas.	52
Figure 21:	Spatial distribution of forest covers loss due to distance from the cultivated areas to the degraded areas.	53
Figure 22:	Spatial distribution of forest covers changes due to the distance from the village centers, roads and cultivation areas to the degraded areas.	54

LIST OF ABBREVIATIONS AND SYMBOLS

C	Carbon
CO ₂	Carbon Dioxide
FAO	Food and Agriculture Organization of the United Nations
FBD	Forestry and Beekeeping Division
MNRT	Ministry of Natural Resources and Tourism
RS	Remote Sensing
SUA	Sokoine University of Agriculture
UNEP	United Nations Environment Programme
URT	United Republic of Tanzania
VPO	Vice President's Office
WWF	Worldwide Wildlife Fund

CHAPTER ONE

1.0 INTRODUCTION

1.1 Background

The Miombo ecosystem is one of the tropical wildernesses in the world covering about 3.6 million km² and spanning ten countries in East and Central Africa (Munishi *et al.*, 2010). In Africa, miombo woodlands cover an area of 3.6 million km² extending from Angola, Kongo, Zambia, Malawi, Mozambique, Tanzania and Zimbabwe (Campbell *et al.*, 2007; VPO, 2009; Munishi *et al.*, 2010). It is estimated that in 2013, Tanzania mainland had 48 million ha of forests and miombo woodland, representing 55% of total land area. Miombo woodland is 44 million ha representing 51% of Tanzania mainland land area (NAFORMA, 2013) which is 92% of the forest ecosystem in Tanzania.

The forest vegetation in Tanzania is primarily woodland, dominated by trees in the legume sub-family *Ceasalpinoideae* with the genera *Brachystegia*, *Julbernardia* and *Isoberlinia* dominating and a well-developed underlying layer of grass. The dominance of one family of trees provides the unifying feature for this ecosystem (WWF, 2003; Munishi *et al.*, 2010). Although the Miombo woodlands ecosystems of Tanzania are likely to have high potential for carbon storage and mitigating CO₂ emissions, reliable estimates for their potential are few and inadequate (Munishi *et al.*, 2010).

Worldwide reduction of forest cover was partially offset by gains in forest area through afforestation and natural forest expansion of 6.8 million ha per year between 1990 and 2000 and 7.3 million ha per year between 2000 and 2005. Thus, the rate of annual net forest loss increased significantly from 2.7 million ha between 1990 and 2000 to 6.2 million ha between 2000 and 2005 (FAO, 2012). Most changes in forest cover affect the

amount of carbon held in vegetation and soil, thereby, either releasing carbon dioxide “a greenhouse gas” to, or removing it from the atmosphere. Hence, forest cover changes can increase C loss rates which are extremely difficult to reverse, in the short term, opposite to organic carbon (OC) which accumulates in soil in the long-term. In other hand, forest cover changes can increase C sequestration rates and hence mitigate the problem of global warming (Muñoz *et al.*, 2011). This study aimed at finding out the effects of forest cover change on carbon stock in miombo woodlands.

1.2 Problem Statement

Quantifying the vegetation carbon stocks of forest ecosystems and how they change over time is extremely important for understanding current trends in the global, regional, country and local carbon cycle (McNicol *et al.*, 2013). In the 2010 Global Forest Resources Assessment, many countries were unable to report on a wide range of forest-related parameters. In some cases data have not been collected and in others they have not been processed (FAO, 2010). Data on deforestation are likely to be even more difficult to obtain (FAO, 2011). Mbiwe Forest Reserve is one of the forests in Tanzania which its data on forest cover change over a period of time is not known. The forest is under the influence of mining, cultivation and settlement, but it is not known to what extent these activities have contributed to the change in forest cover. Therefore these and other socioeconomic activities may become factors of forest cover change. This is because forest cover change result from a complex socioeconomic process and in many cases it is impossible to isolate single causes (Geist and Lambin, 2001). It is also being postulated that the existence of the forest in the proximity of the three town centers namely Chunya, Makongorosi and Mkwajuni have accelerated high demand for timber, poles and charcoal. It is estimated that the annual district wood demand is 2 620 580/ m³ as compared to the available supply of 1 609 266 m³. This high demand of forest

products depicts the widespread felling of trees which lead into loss of forest cover (PC, 1997). While that has been said, no quantification has been carried out. Therefore, this study investigated the forest cover change of Mbiwe Forest Reserve. The study revealed the forest cover changes that occurred overtime and how changes influenced carbon stock changes. The study also explored the factors for the changes.

1.3 Justification of the Study

Information on forest condition and the extent of forest degradation will enable the prioritization of human and financial resources to prevent further degradation and to restore and rehabilitate degraded forests (FAO, 2011). The findings from this study will serve as baseline for other forthcoming studies dealing with carbon credits. The findings will inform the government to take appropriate and effective management measures for sustainable management of the Mbiwe Forest Reserve and other forest reserves in Tanzania. The findings also will assist to know the trend of carbon stock in Mbiwe Forest Reserve which when aggregated with other forests will help to inform the available carbon nationally, and hence regional and global levels.

1.4 Objective

1.4.1 Main Objective

To assess the effects of forest cover change on carbon stock from 1984 to 2013 in miombo woodlands of Mbiwe Forest Reserve.

1.4.2 Specific Objective

- i. To assess forest cover change in miombo woodlands of Mbiwe Forest Reserve from 1984 to 1990 and from 1990 to 2013;

- ii. To assess changes in carbon stock following change in forest cover of Mbiwe Forest Reserve from 1984 to 1990 and from 1990 to 2013;
- iii. To assess the factors influencing forest cover change.

1.5 Research Questions

- i. How many hectares of forest cover have changed from 1984 to 2013?
- ii. How many tons of carbon stock have changed due to forest cover change from 1984 to 2013?
- iii. What are the factors influencing forest cover changes?

1.6 Conceptual Framework of Research

Forest cover change may either causes loss in biomass and eventually leads into loss in carbon or increases in biomass and eventually into carbon stock gain. The forest cover changes are caused by factors of forest cover change. Therefore if there is an increase of biomass in the forest due to forest cover gain there will be a carbon stock gain but if there is a decreases of biomass in the forest due to forest cover loss there are will be carbon loss.

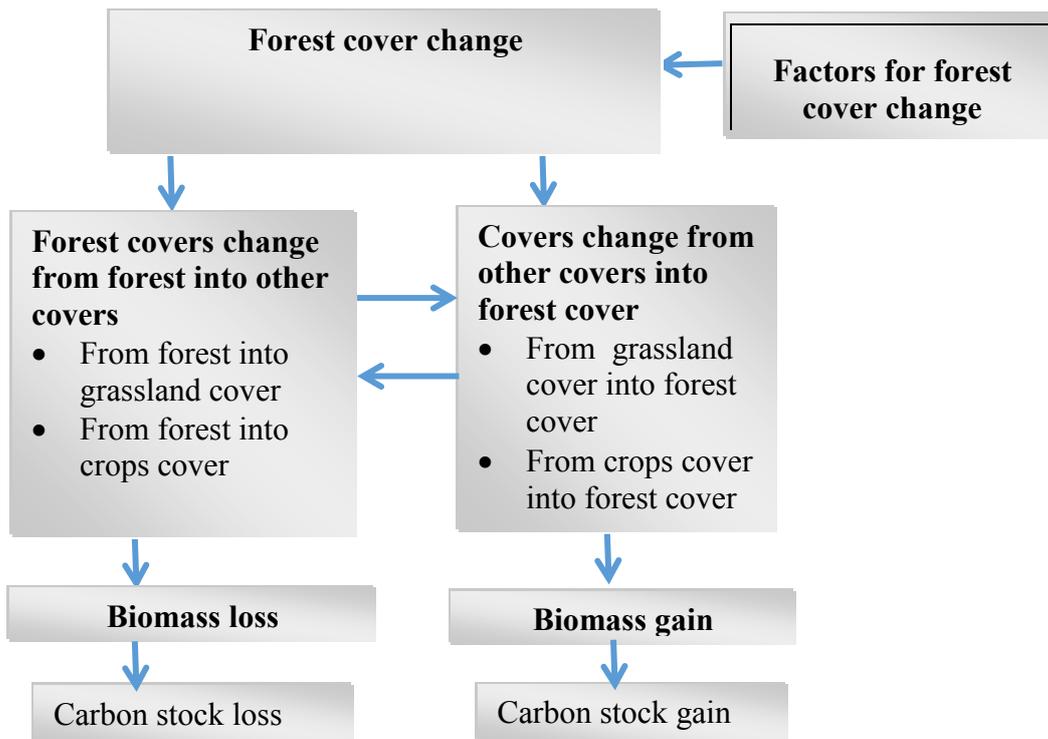


Figure 1: Conceptual framework of research.

CHAPTER TWO

2.0 LITERATURE REVIEW

2.1 Definition of Key Terms

Forest reserve

Forest reserve is a forest area, either for production of timber and other produce or protective for the protection of forests and important water catchments, controlled under the Forest Ordinance and declared by the Minister for Ministry of Natural Resources and Tourism (URT, 1998). Forest reserves provide numerous services to the populations and animals. For example, in sub-sahrian regions of Africa, numerous temporary ponds observed within the nature including reserves (Zongo *et al.*, 2001).

Forest cover

Forest cover is defined as an area more than 1 ha in extent and having tree canopy density of 10 percent and above (Miranda *et al.*, 2014).

Forest cover change

Forest cover change is on the negative side, when it leads into deforestation and degradation of natural forests and on the positive side, when it leads into afforestation and reforestation, either naturally or by planting (FAO, 2000). These forests are, however, faced with deforestation at a rate of between 130 000 and 500 000 hectares per year, which results from heavy pressure from agricultural expansion, livestock grazing, wild fires, overexploitation, and unsustainable utilization of wood resources and other human activities, mainly in the general lands. Two of the eight biodiversity hotspots in Africa are in Tanzania (Dallu, 2002). There is a widespread assumption that forests provide useful ecosystem functions in maintaining constant supplies of good quality

water. Loss of forests has been blamed for everything from flooding to aridity and for catastrophic losses to water quality (Dudley and Stolton, 2003).

Woodlands

Woodland is a land with an open cover of trees, with the crown not forming a thickly interlaced canopy. Scattered evergreen shrubs may often be present, but are not conspicuous. Grasses and herb form the dominant ground cover, the grasses consisting of perennial species, usually with a tufted form and growth up to a height of 2 meters, rarely more. Epiphytes, especially ferns, are rare, but lichens may be present. Two types of woodland follow, the second type being the most extensive is divided floristically into various subtypes (Holmes, 1995). Woodlands can be divided into two main types, coniferous and broadleaf. Within these two general categories are many other different types. These are usually classified according to the dominant tree species making up the woodland (http://www.countrysideinfo.co.uk/woodland_manage). In Tanzania these forests have very rich biodiversity with stocking of 200-to 400 m³/ha. Woodland is the dominant forest type covering large areas in the western and southern parts of the country. Its stocking is estimated to be between 20 to 100 m³/ha. The estimated annual increment of harvestable volume in the woodlands is about 70 million m³ while the annual extraction of wood is approximately 30 million m³. Wood growth is unevenly distributed, particularly in central Tanzania with its low rainfall and sparse vegetation (Dallu, 2002).

Carbon stock

Carbon stock is the quantity of carbon in a “pool”, meaning a reservoir or system which has the capacity to accumulate or release carbon (FAO, 2005). Tropical forests play an important role in the global carbon cycle. They contain about 40% of global terrestrial

carbon, account for more than half of global gross primary productivity, and sequester large amounts of CO₂ from the atmosphere (Ngo, 2013).

2.2 Remote Sensing for above Ground Biomass Estimation

Different approaches have been applied to forest biomass estimation. Traditionally, field measurements are the most accurate methods for estimation. However, these approaches are usually time consuming and labor intensive, and also cannot provide the continuous spatial distribution of biomass at large scales. Remote sensing enables the estimation of forest biomass at multiple scales with large spatial and temporal coverage (Du *et al.*, 2014).

Remotely sensed data are data generated by sensors from a platform not directly touching or in close proximity to the forest biomass (Hernandez *et al.*, 2004). The remote sensing-based biomass estimation methods assume that forest stand information captured by sensors is highly correlated with aboveground biomass (Dengsheng *et al.*, 2012). Remote sensing imagery can be extremely useful, particularly where validated or verified with ground measurements and observations (i.e. “ground truth”) (Hernandez *et al.*, 2004).

There are different approaches, tools and techniques for biomass estimation (Baral, 2011). Estimation of forest biomass can be measured by using; field measurement, Remote Sensing (RS) and Geographic Information System (GIS).

Remote-sensing images can be used in the estimation of aboveground biomass in at least three ways:

- (i) Classification of vegetation cover and generation of a vegetation type map. This partitions the spatial variability of vegetation into relatively uniform zones or

vegetation classes. These can be very useful in the identification of groups of species and in the spatial interpolation and extrapolation of biomass estimates.

- (ii) Indirect estimation of biomass through some form of quantitative relationship (e.g. regression equations) between band ratio indices such as normalized difference vegetation index, green vegetation index (NDVI, GVI, etc.) or other measures such as direct radiance values per pixel or digital numbers per pixel, with direct measures of biomass or with parameters related directly to biomass, e.g. leaf area index (LAI).
- (iii) Partitioning the spatial variability of vegetation cover into relatively uniform zones or classes, which can be used as a sampling framework for the location of ground observations and measurements (Hernandez *et al.*, 2004).

The remote sensing-based biomass estimation methods assume that forest stand information captured by sensors is highly correlated with aboveground biomass (Dengsheng *et al.*, 2012; Lu *et al.*, 2012; Baral, 2011). According to this assumption, the key principles for biomass estimation are to use appropriate variables and to develop suitable estimation models if sufficient sample plots are available. Many new variables such as vegetation indices and textures can be calculated from the multispectral bands (Dengsheng *et al.*, 2012). Several studies have been done using this technique such as Yukon in Alaska (Lei *et al.*, 2012) and Northern Wisconsin in USA (Zheng *et al.*, 2004).

2.3 Carbon Stock Estimation

To monitor aboveground carbon stocks, including carbon losses and gains caused by deforestation, forest degradation and forest recovery, a combination of data is required:

- (i) the rate of change in forest cover and disturbance; and (ii) the amount of carbon stored

in the forest ('carbon density' in units such as tons of carbon per hectare: tons C ha⁻¹) (Asner, 2009).

The rates of carbon emission are considered as the largest source of uncertainty in climate change scenarios due to the difficulty in spatially explicitly estimating the carbon stocks and dynamic changes. One solution is to develop robust approaches for estimating biomass/carbon changes in forest cover using remotely sensed data (Dengsheng *et al.*, 2005). The past three decades have produced significant advances in estimating forest biomass including the application of different sensor data (e.g., Landsat, radar, and LiDAR) and the development of advanced techniques such as regression analysis, neural network, and process-based ecosystem models (Dengsheng *et al.*, 2012).

Various satellites measure forest cover, canopy loss and disturbance, and metrics of forest structure (Chambers *et al.*, 2007), but no satellite technology can directly measure carbon density (Baral, 2011). Satellites thus provide an opportunity to monitor changes in forest carbon caused by deforestation and degradation but only if carbon densities have been assessed. Traditionally, carbon densities have been assessed using field-based inventory plots, which are valuable but also expensive, time consuming and inherently limited in geographic representativeness (Baral, 2011).

Forest inventory and Remote Sensing (RS) are two principal data sources used to estimate AGB and hence ultimately carbon stocks (Krankina *et al.*, 2004). A common practice is to develop a statistical relationship between ground-based measurements and satellite imagery to estimate biomass and then carbon stock. Various types of satellite images are used to map carbon (Baral, 2011).

The carbon stocks for various years e.g, 1984, 1990 and 2013 are obtained by assuming that carbon stock of the forest area does not change very much within such short time period (Kashaigili *et al.*, 2013; Gibson *et al.*, 2005). This is because growth rates for miombo are low and this is due to the facts that they are located on some of the poorest soils in Africa (Campbell, 1996 and Campbell *et al.*, 2007). Dry miombo coppice plots in Zambia had yields of about 2 m³ per ha per year. Expressed in biomass terms, yields varied between 1.4-2.0 Mg per ha per year in dry miombo woodland, and between 2.1-3.4 Mg per ha per year in wet miombo (Campbell *et al.*, 2007). In Tanzania, Misana *et al.* (2005) estimated 2.3 m³per ha per year from regrowth of miombo woodland.

2.4 Causes of forest cover change

Forest cover change may lead into negative side as deforestation and degradation of natural forests and on positive side as afforestation (Lambin *et al.*, 2003). Identifying the causes of forest cover change requires an understanding of how people make use of forest and how various factors interact in specific contexts to influence decision making on forest uses (Nagendra, 2007). There is high variability in time and space in biophysical environments, socioeconomic activities, and cultural contexts that are associated with forest cover change. Forest cover change results from complex socio-economic processes and in many situations it is impossible to isolate a single cause (Geist and Lambin, 2001). These among others include demographic factors, government policies, institutional factors, economic factors, socio-cultural factors, technological factors as well as infrastructure development (Misana *et al.*, 2012). Forest cover change has multiple causes with the particular mix of causes varying from place to place (Rudel and Roper, 1996). There is no consensus on the underlying causes of forest cover change (Angelsen, 1995). So, despite the existence of knowledge about drivers of deforestation, the question “what causes deforestation in a particular geographic location still remains unanswered.

Addressing this question begs the acquisition of location specific information for fine-tuning existing knowledge (Odada *et al.*, 2009) necessary for developing useful policy interventions to reverse location-specific deforestation (Nagendra, 2007).

Since the 1990s, a number of studies have attempted to explicate the dynamics of forest cover change in local and regional-scale analyses by combining remote sensing data with spatially referenced biophysical, social and economic information. Many of these spatially explicit studies have the ultimate goal of understanding not merely the location and nature (proximate cause) of forest change, but also identifying the fundamental driving forces of that change (Chowdhury, 2006).

Regression technique examines the relationship between each forest cover type changes and its underlying causes (Phong, 2004). In regression models of deforestation processes, for instance, the products of satellite image classification yield the dependent variable, such as locations and/or area of deforestation. Image classification may also yield rich ancillary datasets (independent variables) that can be used to test specific hypotheses about deforestation dynamics (Chowdhury, 2006). Classified land cover maps from satellite imagery can be used in GIS to produce additional data, such as indices of landscape structure and distances to particular cover classes (e.g. roads, water or nearest cleared land) (Chowdhury, 2006). As indicated by Geoghegan *et al.* (1997; 2001) one of the advantages of modeling with satellite imagery and Geographic Information Systems (GIS) data lies in the possibility of generating relevant, spatially explicit variables for analysis. Approach of using spatial modeling allows preliminary assessments of exactly which factors matter for what kinds of forest cover changes and at what scales (Chowdhury, 2006).

Geist and Lambin (2001) recognize and divide the causes of forest cover change on three groups, proximate cause, underlying causes and other causes (like biophysical).

The prominent proximate factors found in the literature included agricultural expansion, wood extraction and infrastructure extension while the underlying factors include economic factors, demographic factors, institutions, national policies, socio-cultural factors and remote influences (Basu, 2011).

The factors influencing forest cover change are different in different places. It may be difficult to generalise that one or several factors are the most important (Geist and Lambin, 2001). This is revealed by the following findings of Bawa and Dayanandan (1997) examined the correlations between tropical deforestation and socioeconomic variables across sites in Latin America, Africa and Asia. They found deforestation to be positively correlated with population density, per capita external debt, cattle density, cropland area/total land area, land in other use/total land area, forest products (fuelwood, charcoal, round wood and panel products) extracted per unit forest area, and per capita energy consumption. Another study about drivers of deforestation is reported in Nagendra (2007). This study was aimed at evaluating hypothesized drivers of forest cover change and identifying significant variables that appeared to impact forest clearing or regeneration in Nepal. Results showed tenure regimes, monitoring and user group size per unit of forest area were significantly associated with forest cover change while leadership was not.

Place and Otsuka (2000) determined factors driving tree cover change around Lake Kyoga in Uganda in which they found the important factors to be population pressure,

market access and land tenure. Vogt *et al* (2006) also found land tenure to have significant influence on land-cover changes in Uganda

2.4.1 Proximate causes

Proximate (or direct) causes of forest cover change constitute human activities or immediate actions that originate from intended forest use and directly affect forest cover (Geist and Lambin, 2001). They involve a physical action on forest cover. Proximate causes are the one of the group of factors that causes forest cover change. Proximate causes generally operate at the local level (individual farms, households or communities). Some of these are such as agriculture, infrastructure and wood extraction.

Over the years, researchers have identified agricultural expansion as a major proximate cause in almost all studies on deforestation. In the 1990s, according to the United Nations Environment Programme (UNEP), 70% of total deforested areas were converted to permanent agriculture systems (Cleveland, 2008).

Infrastructure development (road construction, dams, mining, power stations, etc.) is an important proximate cause of forest-related land cover change. Road construction particularly, is a key factor in triggering deforestation as it tends to open up areas of undisturbed, mature forests to pioneer settlements, logging, and occasionally unsuitable forms of agriculture (Cleveland, 2008).

Wood extraction from natural forests is another proximate cause of forest cover change. Despite the growing importance of plantations as a source of wood supply, wood extraction in the form of commercial timber, poles, fuel-wood, and charcoal continues to degrade mature natural forests in many parts of the world (Cleveland, 2008).

2.4.2 Underlying Causes

Underlying (or indirect or root) causes are fundamental forces that underpin the more proximate causes of land-cover change. They operate more diffusely (i.e., from a distance), often by altering one or more proximate causes. Underlying causes are formed by a complex of social, political, economic demographic, technological, cultural, and biophysical variables that constitute initial conditions in the human-environment relations and are structural (or systemic) in nature (Geist and Lambin, 2001). Underlying causes are often exogenous to the local communities managing forest and are thus uncontrollable by these communities.

Some of the underlying causes are direct regulation of access to land resources, market adjustments, or informal social regulations (e.g. shared norms and values that give rise to shared land management practices). Some of these factors are population, poverty and distance to the market, town, road, river and center (Waiswa, 2009).

Market, town, road, river and center distance have shown to have positive effects on forest cover change (Phong, 2004). This is because the presence of all those factors increases accessibility of a particular forest hence degradation of which at the end of the day will lead into forest cover change.

Population is important underlying cause that exerts significant impact on the total forest cover. Increase in population density leads to depletion of forest cover (Basu, 2011). At longer timescales, both increases and decreases of a given population also have a large impact on land use. Demographic change does not only imply the shift from high to low rates of fertility and mortality (as suggested by the demographic transition), but it is also

associated with the development of households and features of their life cycle (Geist and Lambin, 2001).

The higher the level of rural poverty, the lower the total forest cover is likely to be (Basu, 2011). Poverty is popularly cited as a principal underlying cause of forest loss and degradation (Cleveland, 2008). Increase in poverty causes a decrease in open forest cover since the forest-dependent communities stay near or inside open forests and their livelihood is dependent on these forests. Be it the extraction of firewood or forest clearing for agriculture, the poor relies on the open forests, which are easily accessible (Basu, 2011).

2.4.3 Other Causes

The group of other factors associated with deforestation is composed of pre-disposing environmental factors (land characteristics, features of the biophysical environment), biophysical drivers and social trigger events. Land characteristics such as soil quality, topography, and forest fragmentation are increasingly recognized not to drive, but rather to shape deforestation (Rudel and Roper, 1997). Biophysical drivers (triggers) and social trigger events have been introduced to identify such forces or events that often work as catalytic factors leading to sudden shifts in the human-environment condition. These shifts could be of social nature (such as wars, abrupt economic changes or policy interventions), or operate in the form of biophysical drivers (such as droughts or forest fires), while the difference between the social and natural sphere cannot always be clearly drawn (Geist and Lambin, 2001).

CHAPTER THREE

3.0 MATERIALS AND METHODS

3.1 Materials

During this study I used GPS, caliper, compass and tape measure for data collection.

3.1.1 Description of the Study Area

3.1.2 Location

Mbiwe Forest Reserve is one of the forest reserves in Chunya District in Mbeya Region. The forest lies between 8°24'36.84" and 8°39'44.27" Latitudes South of the Equator, and between 33°02'57.72" and 33°20'14.96" Longitudes East of Greenwich (Fig. 2). The area of the forest reserve is 49 147.7 ha with 475 – 2 981 m asl. The forest is under the influence of mining, cultivation and settlement, but it is not known to what extent these activities have contributed to the change in forest cover. It is also being postulated that the existence of the forest in the proximity of the three town centers namely Chunya, Makongorosi and Mkwajuni have accelerated high demand for timber, poles and charcoal. It is estimated that the annual district wood demand is 2 620 580/ m³ as compared to the available supply of 1 609 266 m³. This high demand of forest products depicts the widespread felling of trees which lead into loss of forest cover (PC, 1997).

3.1.3 Climate

The average temperature ranges between 21° centigrade and 23° centigrade annually and this is very much influenced by physiography and altitude. Mean annual rainfall ranges from 600 mm to 1 000 mm, and normally the peak period of heavy rains are recorded during the months of December and March almost every year (PC, 1997).

3.1.4 Vegetation

Mbiwe Forest Reserve is composed of miombo woodland, mixed dry forest, legume-dominated dry forest and mixed scrub. The most predominant natural vegetation is miombo woodlands. Common vegetative species include those of *Brachystegia spiciformis*, *Brachystegia boehmii*, *Pterocarpus angolensis*.

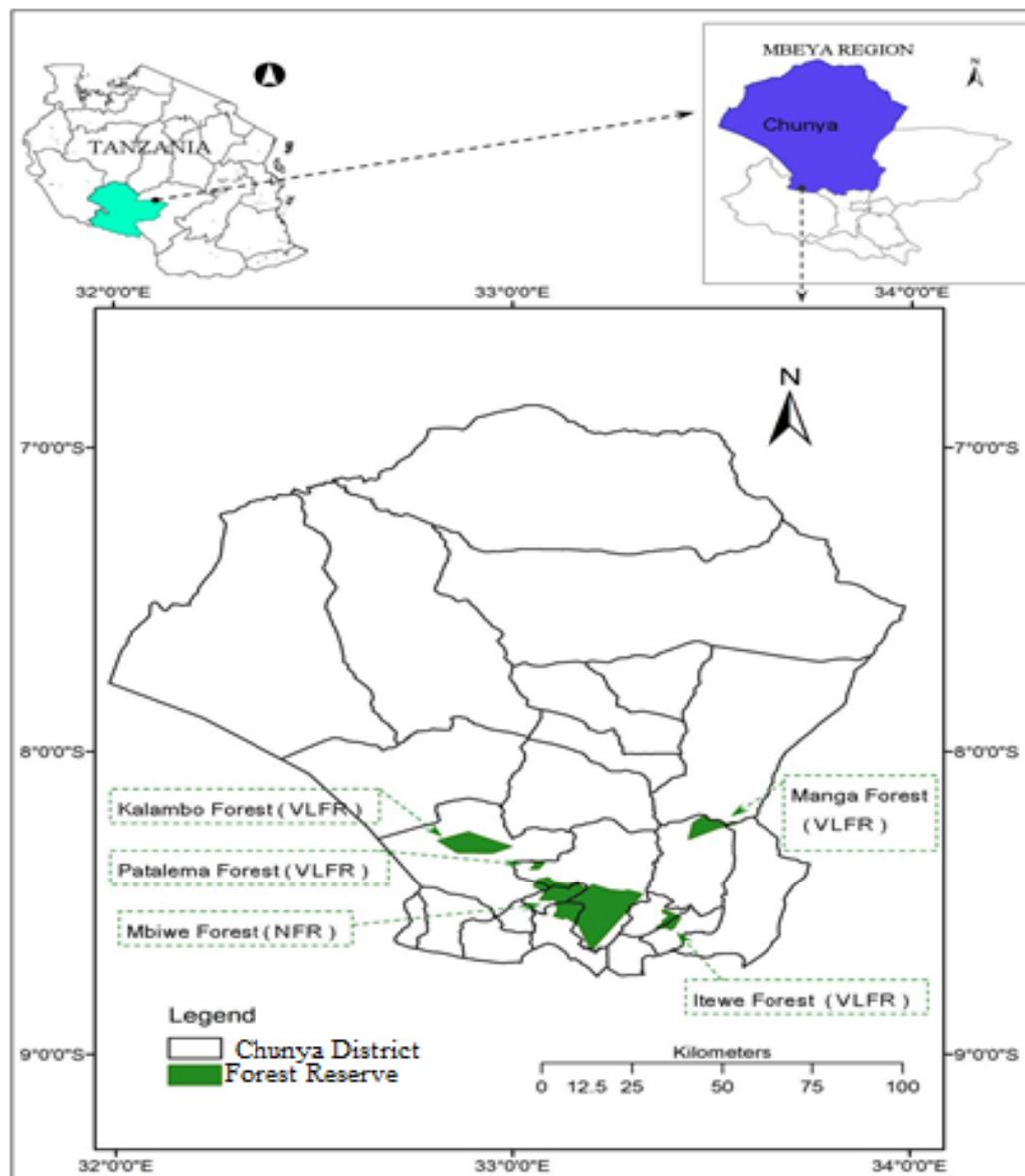


Figure 2: A Map showing location of Mbiwe Forest Reserve in Chunya District.

3.1.5 Social-economic activities

The major threats to the forest reserve are settlement, charcoal, overgrazing, gold mining and agriculture. Settled areas are now coming up with siamea (mijohoro) trees which are planted by the community. There are two big licensed gold mining companies in the forest which are Gold trees mining company and Matunda ASM and a number of small scale miners (PC, 1997). The closest settlements to Mbiwe Forest Reserve are Matundasi, Makongorosi, Mkwajuni and Infwenkenya wards.

3.2 Methods

3.2.1 Data collection

3.2.1.1 Remote sensing data

Landsat MSS and TM data acquired on June 1984, June 1990 and June 2013 was used. In consideration of cloud cover, the seasonality and phenological effects (Kashaigili, 2006), image listed in Table 1 were selected for image processing and change analysis.

Table 1: The Landsat MSS and ETM Image Scenes used in this study

Satellite Sensor	Path/Row	Date of acquisition	Season	Cloud cover
Landsat MSS	169066	20/06/1984	Dry	10
Landsat MSS	170066	31/08/1984	Dry	10
Landsat TM	169066	22/08/1990	Dry	10
Landsat TM	170066	09/07/1990	Dry	10
Landsat ETM+	169066	18/08/2013	Dry	10
Landsat ETM+	170066	22/06/2013	Dry	10

TM = Thematic Mapper; ETM+ = Enhanced Thematic Mapper Plus; MSS = Multi Spectral Scanner.

Inventory data

Reconnaissance survey was conducted to get the data for determining number of sample plots. During reconnaissance survey the number of sample plots must be predetermined according to the required measurement accuracy and confidence interval (Schindele, 1995; Jarvis, 2013). In most cases confidence interval of 68% and accuracy of $\pm 10\%$ are used (Jarvis, 2013). In order to increase accuracy and confidence interval, the number of measurement points must be added. In case of significantly irregular allocation of trees in the forest stand it is recommended to use more measurement points than prescribed above. If higher measurement accuracy is expected, the confidence interval of 95% should be used. When confidence interval is increased from 68% to 95% or permitted error is reduced twice, the minimum number of measurement points grows four times (Jarvis, 2013). Confidence interval of 95% was used which lead to 60 sample plots where data was collected.

After reconnaissance survey determination of number of sample plots was done whereby the consideration was done on the facts that a larger number of plots allow the estimate of spatial variability of carbon stocks, which increases the confidence in carbon estimates. Thus, to ensure enough number of sample plots the formula (1) was used to get the number of sample plots in the entire area of the forest reserve and their data recorded in different concentric plots as shown in (Fig. 3). The plots were allocated systematically all over the area of the forest reserve (Fig. 4) hence enabling to cover all vegetation cover types in that particular forest. This distribution of plots systematically enabled to get biomass data from all vegetation covers.

$$n = \frac{t^2 CV^2}{AE^2} \quad (\text{Baral, 2011}) \dots\dots\dots(1)$$

Where:

n = Minimum number of samples plots required

t = t value associated with specific probability

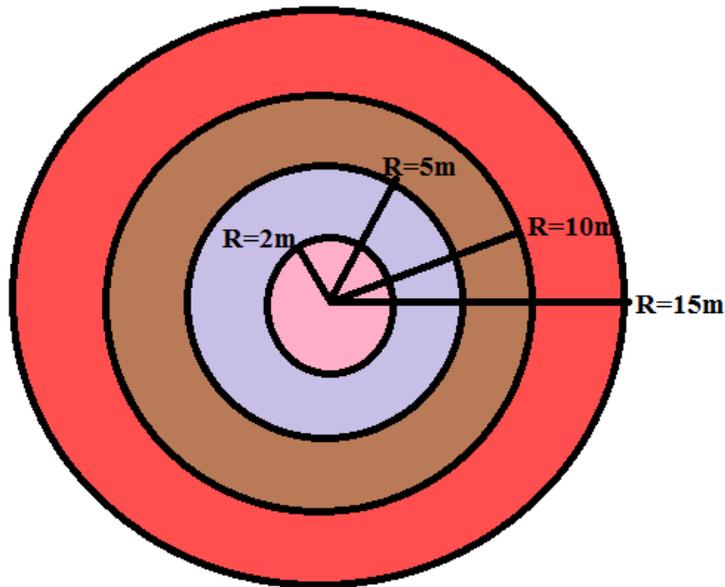
CV= Coefficient of Variation

AE= Allowable error

The first plot was established randomly and then systematic sampling was used to establish other sample plots. The concentric plot of 2m, 5m, 10m and 15m radius was established. In the radius of 2m regeneration of tree species were recorded and the rest radii the data were recorded as shown in Fig. 3. According to the IPCC (2003) a sampling error (E) of 5% is recommended for Land Use, Land Use Change and Forestry (LULUCF) projects. However according to Zahabu (2008) under certain circumstances a 10% sampling error can be used to reduce cost while maintaining estimates within the precision of ± 10 of the mean with a 95% confidence interval. Therefore regarding to the 10% sampling error was used and a total of 64 plots were established. Distance between plots were 2 km and between transects were 4 km. Every plot was registered with a global positioning system to allow further integration with spatial data in geographic information systems and image processing systems.

The use of concentric plots in forest inventory aims at increasing the accuracy of the measurement and sampling intensity of large trees, and simultaneously at saving time. Tropical natural forests are characterized with having negative exponential diameter distribution such that there are several small size trees and the number of trees decreases with increasing tree size. The concentric plot design ensures that small trees are measured in small plots and large trees (which constitute most of the biomass per unit area) are

measured in large plots. This arrangement results in measuring approximately the same number of trees for the different size classes (NAFORMA, 2010).



Radius = 15m: Trees DBH \geq 20cm

Radius = 10m: Trees DBH \geq 10cm

Radius = 5m: Trees DBH \geq 5cm

Radius = 2m: Trees DBH \geq 1cm

(MNRT, 2010). (2)

Figure 3: Concentric Circular Plots.

3.2.1.1 Factors causing forest cover change

To determine factors of forest cover change logistic regression was used as it allows examining the relationship between two variables which are binary. In this study, data on independent and dependent variables were collected and used to develop logistic model. The dependent variables were forest cover change, as detected from the satellite imagery of 1984 and 1990 and 2013. Independent variables were road network, villages around Mbiwe Forest Reserve and cultivated areas within the forest reserve. Those independent variables were used due to its availability with regards to the time and availability of the

data but if were easily available more independent variables could be added as much as possible.

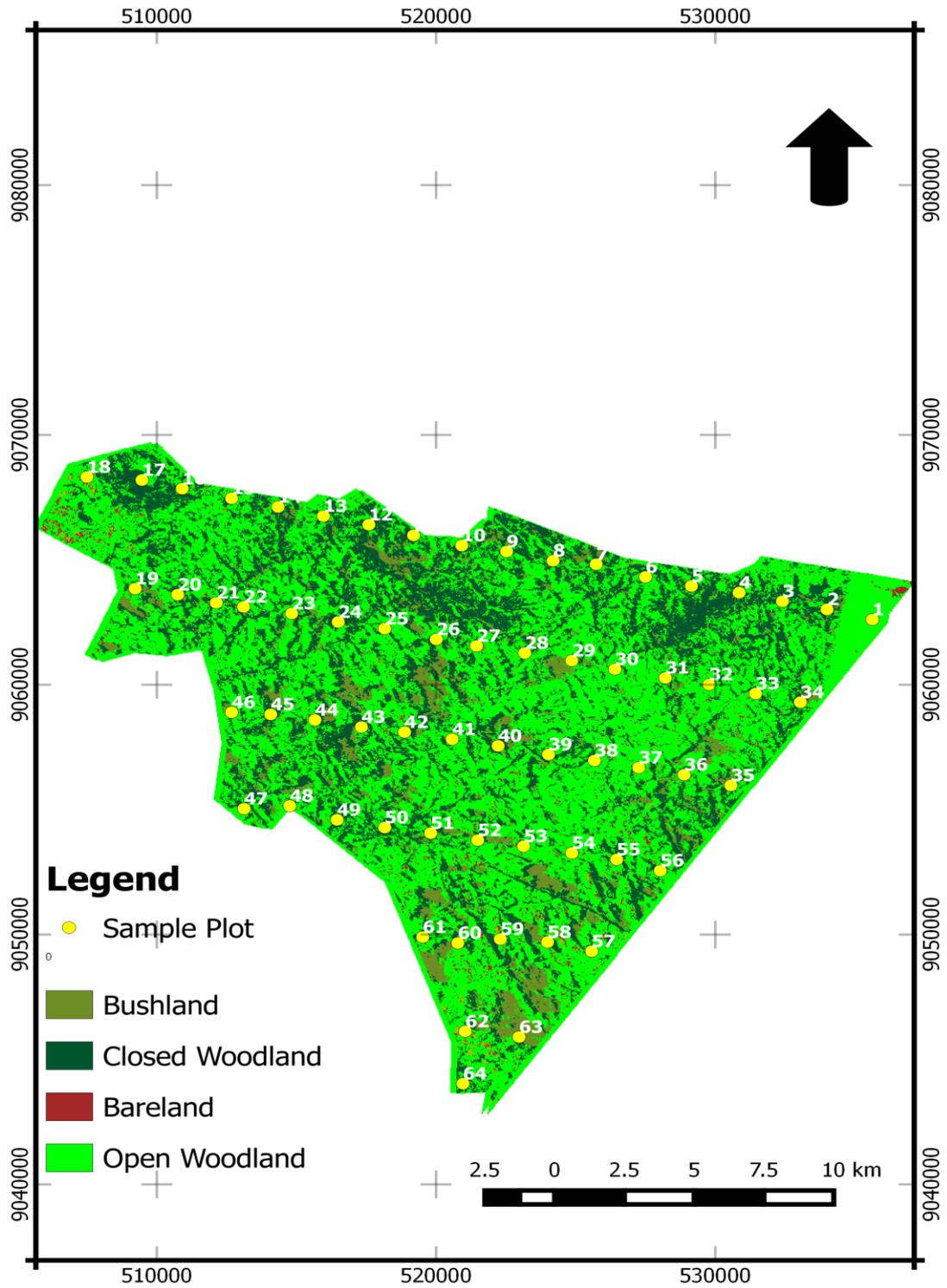


Figure 4: Sample plots distribution.

Therefore roads network, villages that are around Mbiwe Forest Reserve were manually digitized from the satellite image of 2013. In order to get cultivated areas a variable cultivated area was used. All data were brought together in a raster GIS and resampled to a common spatial resolution. The approach of Phong (2004) was adopted whereby the buffer zone of 100 m was created along the road networks and around villages which are around Mbiwe Forest Reserve.

In order to get dependent variables, the forest cover change, as detected from the satellite imagery of 1984, 1990 and 2013 was used. The Landsat images of 1984, 1990 and 2013 were classified and then change detection was done in order to get forest cover change. Forest cover change obtained from change detection was taken as dependent variables to logistic regression model. According to Chowdhury (2006) statistical method has been employed in a spatially explicit manner in which the driving factors of forest cover change are correlated with major classes of forest cover.

3.2.2 Data analysis

3.2.2.1 Image Processing

Image preprocessing

To ensure accurate identification of temporal changes and geometric compatibility with other sources of information, image to image geo-correction was conducted to rectify the 1984 and 1990 images based on 2013 image. The first order polynomial transformation and nearest neighborhood interpolation was applied to geometrically rectify the 1984 and 1990 imagery and registered to the UTM map coordinate system, Zone 36 South, Datum Arc 1960.

Image enhancement

Images enhancement was performed using a 4, 5, 3 color composite band combination and its contrast was stretched using the Gaussian distribution function followed by high pass filter 3×3 to increase the visibility of the ground control points in both images.

3.2.2.2 Preliminary image classification and ground truthing

Image classification analyzes the numerical properties of various image features and organizes data into categories (Fisher *et al.*, 2003). Supervised Image classification, using Maximum Likelihood Classifier (MLC) was performed in ILWIS software. Training fields were identified by inspecting an enhanced color composite imagery. Areas with similar spectral characteristics were trained and classified.

Ground truthing was done in order to verify and modify land covers obtained during preliminary image interpretation. Before going to the field, to implement ground truthing, preliminary image classification was performed to roughly identify vegetation types and other land cover classes. Sets of hardcopy of colour composite images with overlays of roads and UTM coordinates were produced using image acquired on 08th August 2013 and used as a base-map during the ground truthing. A hand-held GPS was used to locate sampled land cover observations. During the ground truthing, the following major land cover classes were identified: closed woodland, open woodland, cultivated land, Bushland and Bareland and mining.

3.2.2.3 Final image classification

The approach used by Kashaigili (2006) was adopted whereby supervised image classification using maximum likelihood classifier was used in order to provide efficient, consistent and repeatable routines for mapping large areas. Training sites were generated

by on-screen digitizing of selected areas for each land cover class identified on the colour composite. Training was iterative process, whereby the selected pixels were evaluated by performing an estimated classification. Based on the inspection, training samples were refined until a satisfactory result was obtained. The objective was to produce thematic classes that resemble or can be related to the actual land cover types on the earth's surface.

3.2.2.4 Classification accuracy assessment

Land cover maps derived from classification of images usually contain some sort of errors due to several factors that range from classification techniques to methods of satellite data capture. Hence, evaluation of classification results is an important process in the classification procedure (Yesserie, 2009). During data collection forest cover of each plot centers were recorded. Then those points were visually classified in respect to forest cover classes. Therefore error/confusion matrix was used as it is among the common measures used for measuring the accuracy of thematic maps derived from multispectral imagery. An error matrix is a square assortment of numbers defined in rows and columns that represent the number of sample units assigned to a particular category relative to the actual category as confirmed on the ground. In conformance with standard accuracy assessment techniques, error matrices were produced and used to compute user's accuracy, producer's accuracy and overall accuracy for each classification. kappa (k) was computed using equation (3) (Waisa, 2009) to determine how much better the classification was than chance alone

$$k = \frac{Observed - Expected}{1 - Expected} \quad (2)$$

Whereby: Observed = Overall value for percent correct and

$$\text{Expected} = \text{Estimate of the contribution of chance agreement to the observed percent correct} \quad (3)$$

3.2.2.5 Forest cover change

To analyze the changes between different time epochs, change detection analysis was performed. Many change detection methods have been developed and used for various applications. However, they can broadly be divided into: post classification approaches and spectral change detection approaches (Kashaigili *et al.*, 2013). The post classification change detection method was applied followed by spatial overlay analysis in QGIS resulting into attribute table. The table was exported to R software to compile area change detection matrix for 1984-1990 and 1990- 2013 period.

3.2.2.6 Rates of forest cover change

The forest cover change rates that were computed covered the periods 1984 to 1990 and 1990 to 2013. Estimation for the rate of change for different forest covers was computed based on the following formulae (Kashaigili and Majaliwa, 2010).

$$\% \text{ Change}_{\text{year } x} = \frac{\text{Area}_{i \text{ year } x} - \text{Area}_{i \text{ year } x+1}}{\sum_{i=1}^n \text{Area}_{i \text{ year } x}} \times 100 \quad \dots\dots\dots (4)$$

$$\text{Annual rate of change} = \frac{\text{Area}_{i \text{ year } x} - \text{Area}_{i \text{ year } x+1}}{t_{\text{years}}} \quad \dots\dots\dots (5)$$

$$\% \text{ Annual rate of change} = \frac{\text{Area}_{i \text{ year } x} - \text{Area}_{i \text{ year } x+1}}{\sum_{i=1}^n \text{Area}_{i \text{ year } x} \times t_{\text{years}}} \times 100 \quad \dots\dots\dots (6)$$

Where;

$Area_{i\ year\ x}$ = area of cover i at the first date,

$Area_{i\ year\ x+1}$ = area of cover i at the second,

$\sum_{i=1}^n Area_{i\ year\ x}$ = the total cover area at the first date and

t_{years} = period in years between the first and second scene acquisition dates.

3.2.2.7 Above Ground Biomass estimation

The aboveground biomass was estimated by using formula (7) (Mugasha *et al.*, 2004).

$$Biomass = \exp^{[-1.83322+2.40156 \ln (dbh)]} \dots\dots\dots(7)$$

Whereby:

B= Biomass (kg)

D= DBH (cm)

This model (equation 7) was developed for Mpanda District which has the same climatic condition and vegetation types of miombo woodland as Mbiwe Forest Reserve in Chunya District. The carbon stocks for 1984, 1990 and 2013 were obtained by assuming that carbon stock of the forest area didn't change (Kashaigili *et al.*, 2013; Gibson *et al.*, 2005). This is because growth rates for miombo are low due to the facts that they are located on some of the poorest soils in Africa (Campbell, 1996 and Campbell *et al.*, 2007).

Biomass was aggregated at the plot level then estimated per hectare. The techniques of Ji *et al.*, (2012) of estimating biomass for formulating the model was adopted where the biomass per hectare of each measured plot was used later as dependent variables to formulate models that were used to estimate biomass of the whole area of Mbiwe Forest

Reserve. The data of biomass per hectare of each measured plots was used because during biomass data collection all forest cover were covered, therefore all forest cover types in Mbiwe Forest Reserve were represented.

There are basically three different approaches used in forest inventory with remote sensing to assess biophysical variables from spectral signals provided by optical satellite images (1) statistical (empirical) (2) physically based, and (3) various combinations of them (e.g., neural networks). In this study biophysical model was used. This model uses spectral bands which were formulated mathematically into vegetation indices models. The techniques of Lu *et al.* (2012); Zheng *et al.* (2004) of estimating vegetation indices was adopted whereby four individual bands [blue, green, red and near-infrared (NIR)] were used to calculate three vegetation indices.

$$DVI = NIR - Red \dots\dots\dots(8)$$

$$NDVI = \frac{(NIR - red)}{(NIR + red)} \dots\dots\dots(9)$$

$$RSR = \frac{NIR}{red} ; \dots\dots\dots(10)$$

These vegetation indices were obtained by using ILWIS MAP CALCULATOR. After running collinearity Normalized Difference Vegetation Index (NDVI) was left out and only two indices i.e Difference Vegetation Index (DVI) and Reduced Simple Ratio (RSR) were used. According to Zakaria (2010) since there is a relationship between vegetation indices and biophysical variables (e.g. stand parameters) the models were established using vegetation indices as independent variables and biomass per hectare of each measured plots as dependent variables. Statistically, the model is generally expressed as shown in model (Equation 11).

$$Y = b_0 + b_1 X_1 \dots\dots\dots (11)$$

Whereby

Y = the dependent variable (Biomass of each plot);

X_i = the independent variable (Vegetation indices i.e DVI and RSR);

$b_0, b_{1,i}$ =constant parameters that need to be determined (Zheng *et al.*, 2004)

According to Zheng *et al.* (2004) the models were used to estimate the biomass of the whole Mbiwe Forest Reserve for the image of year 1984, 1990 and then for the image of the year 2013. Finally the difference of biomass between 1984 and 1990 and between 1990 and 2013 were computed to obtain the gain or loss of biomass.

After using DVI and RSR as independent variables the following equations were obtained.

$$\text{Biomass}_{1984} = 212.533(\text{RSR}_{1984}) - 15(\text{DVI}_{1984}) - 41.851 \dots \dots \dots (12)$$

$$\text{Biomass}_{1990} = 260.503(\text{RSR}_{1990}) - 8.624(\text{DVI}_{1990}) - 178.037 \dots \dots \dots (13)$$

$$\text{Biomass}_{2013} = 377.35436(\text{RSR}_{2013}) - 0.12495(\text{DVI}_{2013}) - 261.95712 \dots \dots \dots (14)$$

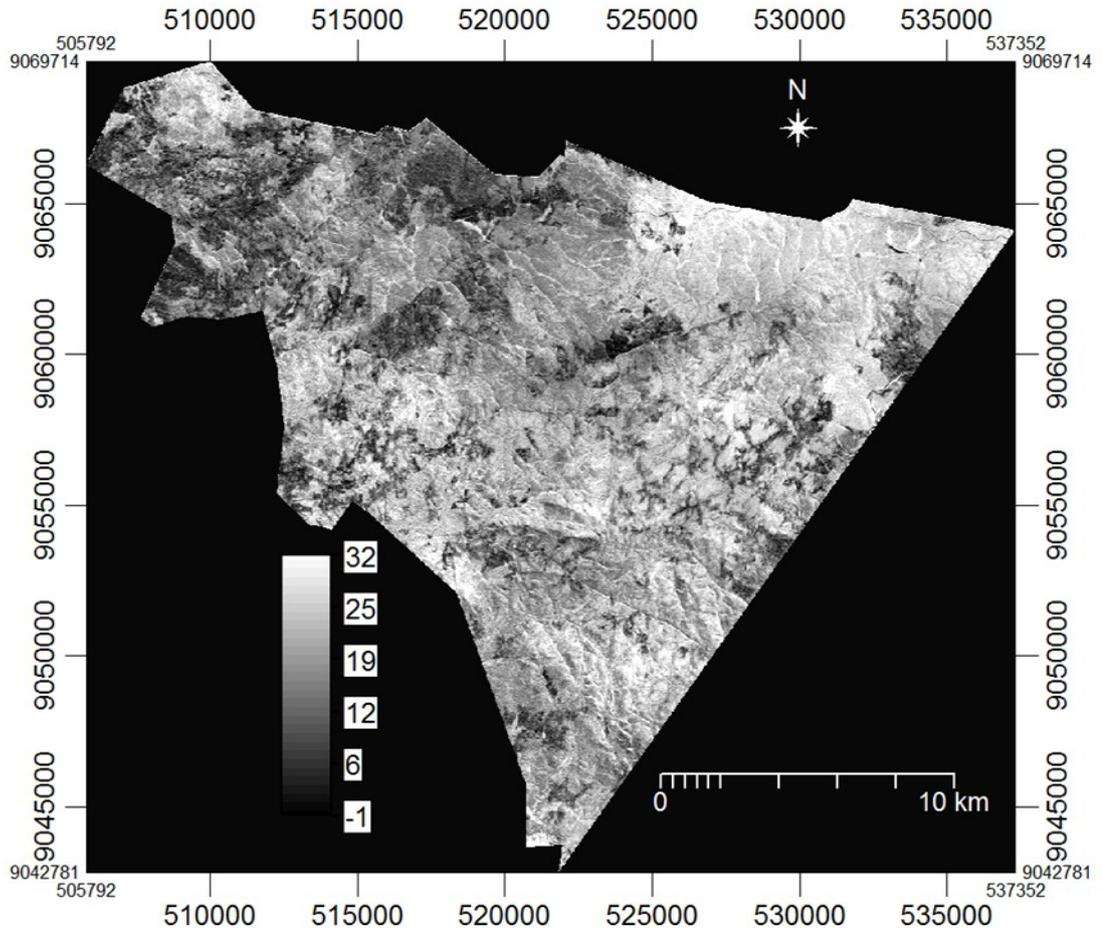


Figure 5: DVI 1984.

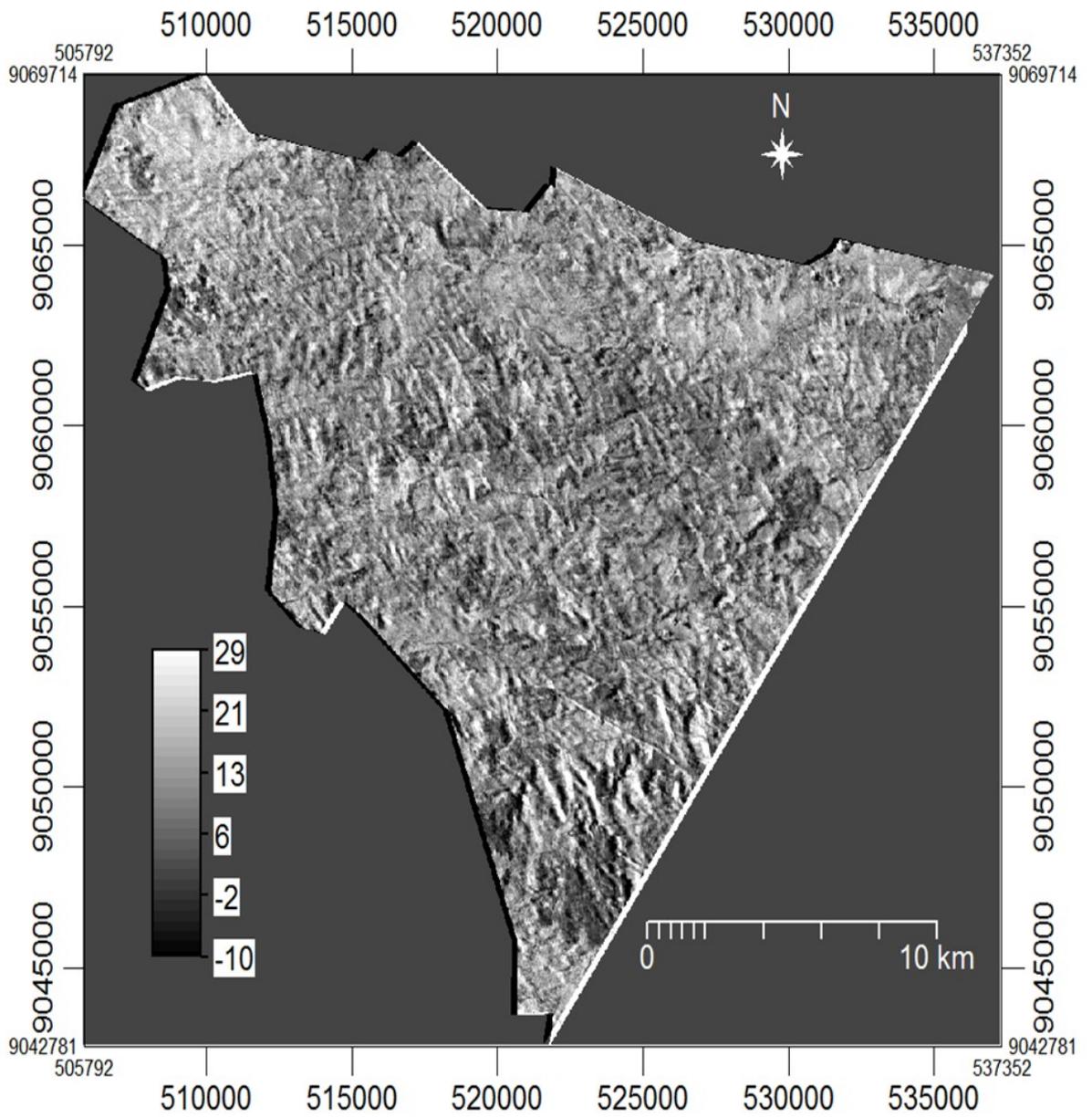


Figure 6: DVI 1990.

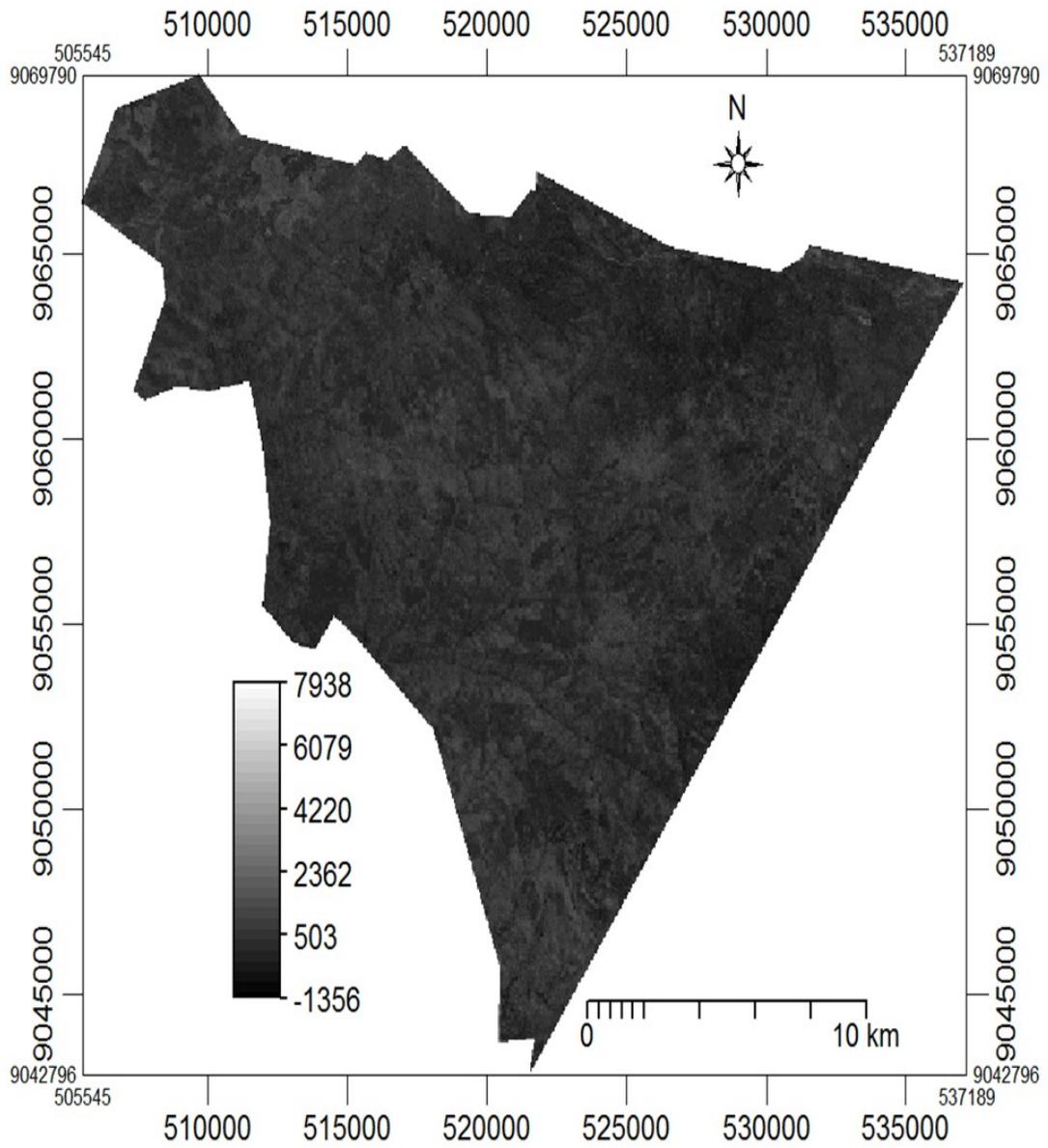


Figure 7: DVI 2013.

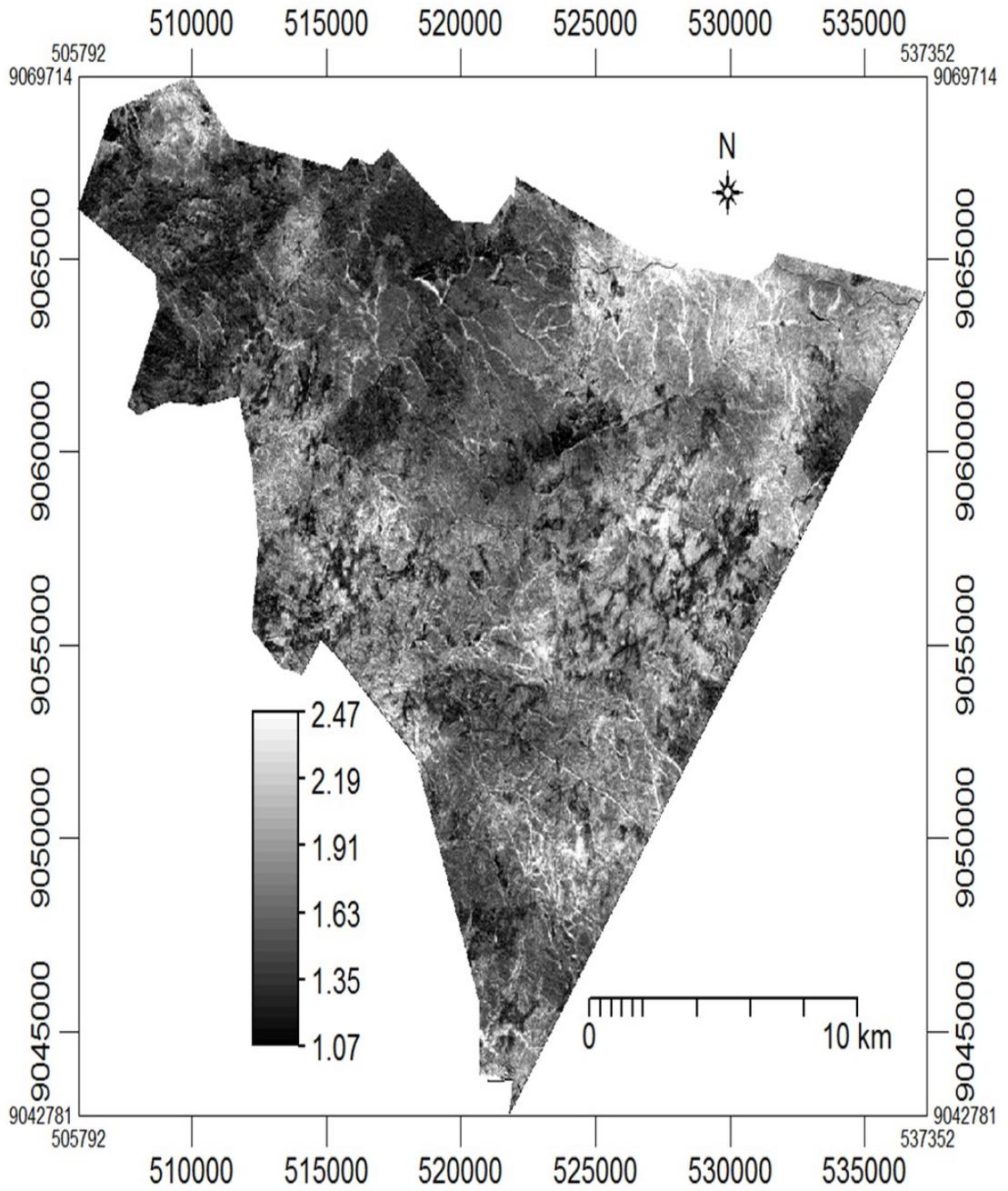


Figure 8: RSR 1984.

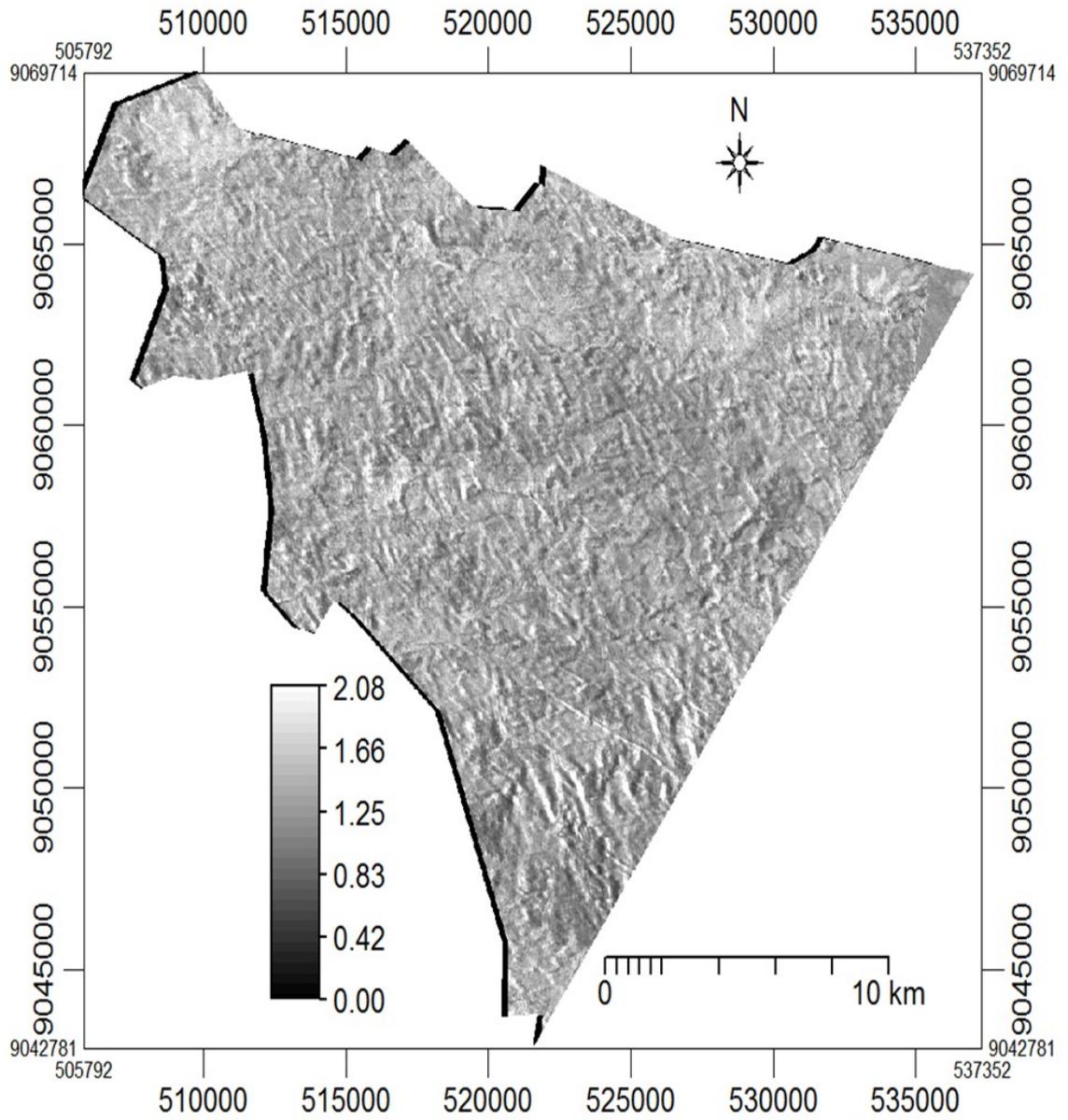


Figure 9: RSR 1990.

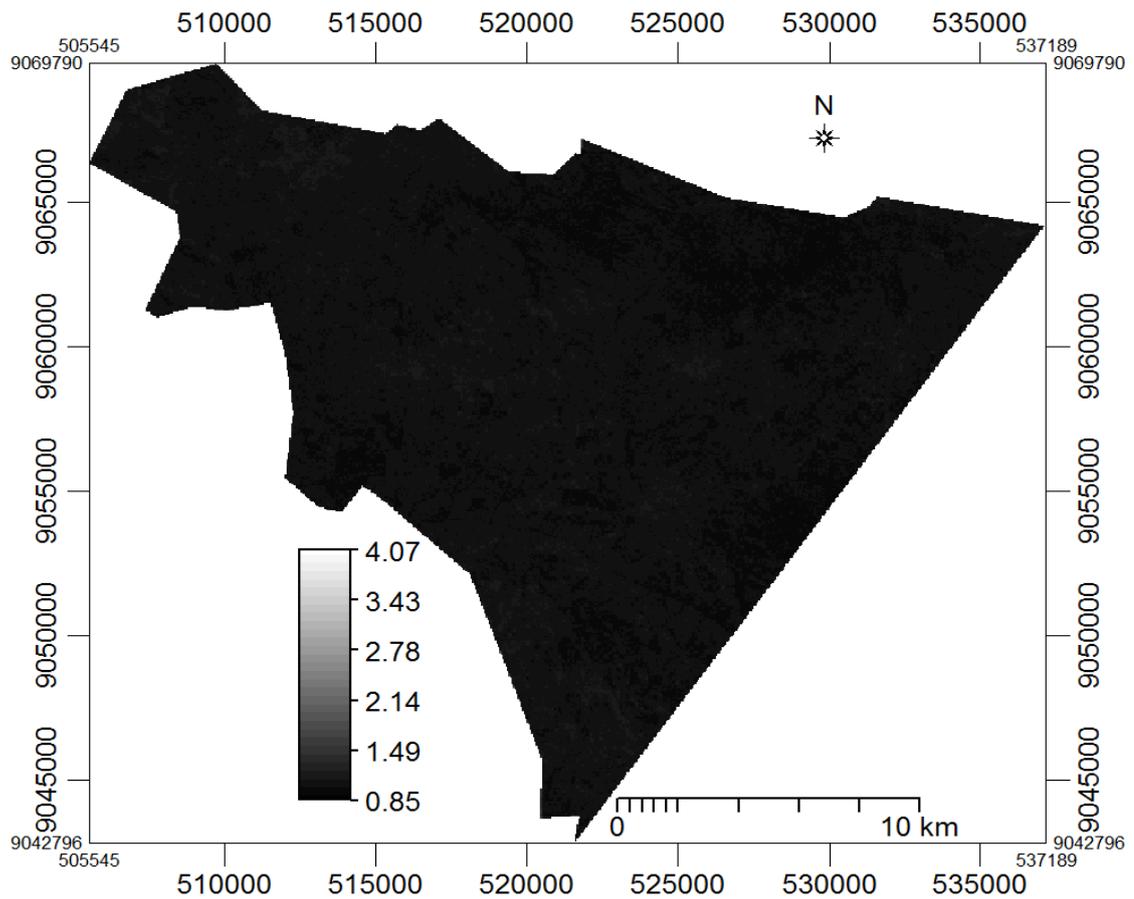


Figure 10: RSR 2013.

3.2.2.8 Carbon stock estimation

The coefficient of 0.50 as suggested by Munishi *et al.*, (2010); Gibson *et al.*, (2005), was used for conversions of biomass to carbon stock:

$$C = 0.50 \times \text{biomass} \dots\dots\dots(15)$$

3.2.2.9 Carbon mapping

Using ILWIS calculator mapping of tree above ground carbon was done by multiplying biomass of each year by coefficient of conversion which was 0.50.

3.2.2.10 Factors causing forest cover change

(i) Dependent variables

The forest change cover map obtained after change detection was used as dependent variable and was overlaid on the independent variable maps (distance from the forest cover changes as detected on the forest cover change map to roads, village center and cultivated areas in the forest reserve, these were calculated as maps using GIS tools) and the type of changes that occurred on each location was recorded. This information was consolidated into a common table containing dependent and independent variables. For logistic regression analysis dependent variables were then transformed to binary variables i.e. 1, 0 representing “change”, “no changes” respectively.

(ii) Independent variables

In order to determine which factors contribute most to forest cover change the variables, distance from roads, villages and cultivated areas in the forest reserve to the areas where the cover changes occurred in the forest reserve was used.. Therefore distance from the areas where the cover changes occurred in the forest reserve to roads was calculated as a series expanding from each arc of the road network, villages the nearest settlement was calculated as a series expanding from each center and cultivated areas in the forest was calculated as a series expanding from each cultivated areas. The above dependent and independent variables were used in the logistic linear model (16). According to Wickramaarachchi *et al.* (2013) logistic regressions was successfully applied to analyze the causes of forest cover change.

According to Phong (2004) before variables being used collinearity between the independent variables and the coefficients of determination (R^2) of the multivariate

relationships between one of the independent variables against all the others were calculated in order to find if they are below the critical value of 0.8.

The logistic regression was used because it measures the relationship between a categorical dependent variable and one or more independent variables, which are usually (but not necessarily) continuous, by using probability scores as the predicted values of the dependent variable.

The output from a logistic is the relationship of the occurrence of an event, using the independent variables as predictor values (Garson, 2000). In this study the occurrence of the changes of the forest cover (dependent variable) was predicted with the independent variables (driving factors) to see which among independent variables predict more the occurrence of change of the forest cover. Using the logistic regression analysis, relationship between the spatial distribution of the change of forest cover and its driving factors was determined.

$$\log \text{it}(p) = \left[\frac{\log p}{1-p} \right] \quad (\text{Serneels and Lambin, 2001})$$

$$= \alpha + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n$$

Whereby

α = intercept

β_{1-n} = Parameter values.

X_{1-n} = Predictor variables

p = Probability of success(16)

CHAPTER FOUR

4.0 RESULTS AND DISCUSSION

4.1 Forest cover of Mbiwe Forest Reserve for 1984, 1990 and 2013

The forest cover maps for the period 1984, 1990 and 2013 are shown in Fig. 11, Fig.12 and Fig. 13 respectively and their cover areas are shown in Table 3. The maps show that there is a significant change between periods under consideration. Results indicate that in 1984, Open Woodland occupied 28 221.3ha (57.4%) which was the largest cover in that year, Closed Woodland 16 501.7 ha (33.6%) was the second largest forest cover, Bushland 3 206.2ha (6.5%) was the third largest cover, while Bareland and mining was 1 218.5 ha (2.5%) (Table 3). In 1990, Open Woodland occupied 30 642 ha (62.4%) the largest forest cover as it was 1984, Closed Woodland 14 195.5 ha (28.9%) continued to be the second largest forest cover compared to 1984, Bushland 3 642.7ha (7.4%) continued to be the third largest forest cover compared to 1984, Bareland and mining 552.6 ha(1.1%) continued to persist although at low rate compared to forest cover of 1984, and Cultivated land occupied 114.9ha (0.2%). This shows that encroachment in the forest reserve started around 1990. Finally in 2013 Open Woodland (29 918.7 ha which is 60.9%) continued to dominate the forest cover, Closed Woodland which was 1 447.3 ha (2.9%), decreased dramatically compared to that of 1984 and 1990, Bushland (16 118.7ha which is 32.8%) increased dramatically compared to 1984 and 1990. This indicates that there was a change of Closed and Open Woodland into bushland. Bareland and mining (882.7 ha which is 1.8%) increased compared to 1984 and 1990, this indicates that there was a change from Closed and Open Woodland into Bareland and mining. Cultivated land (780.3ha which is 1.6%) increased compared to 1984 and 1990, this indicates that there was a change from Closed and Open Woodland into Cultivated land.

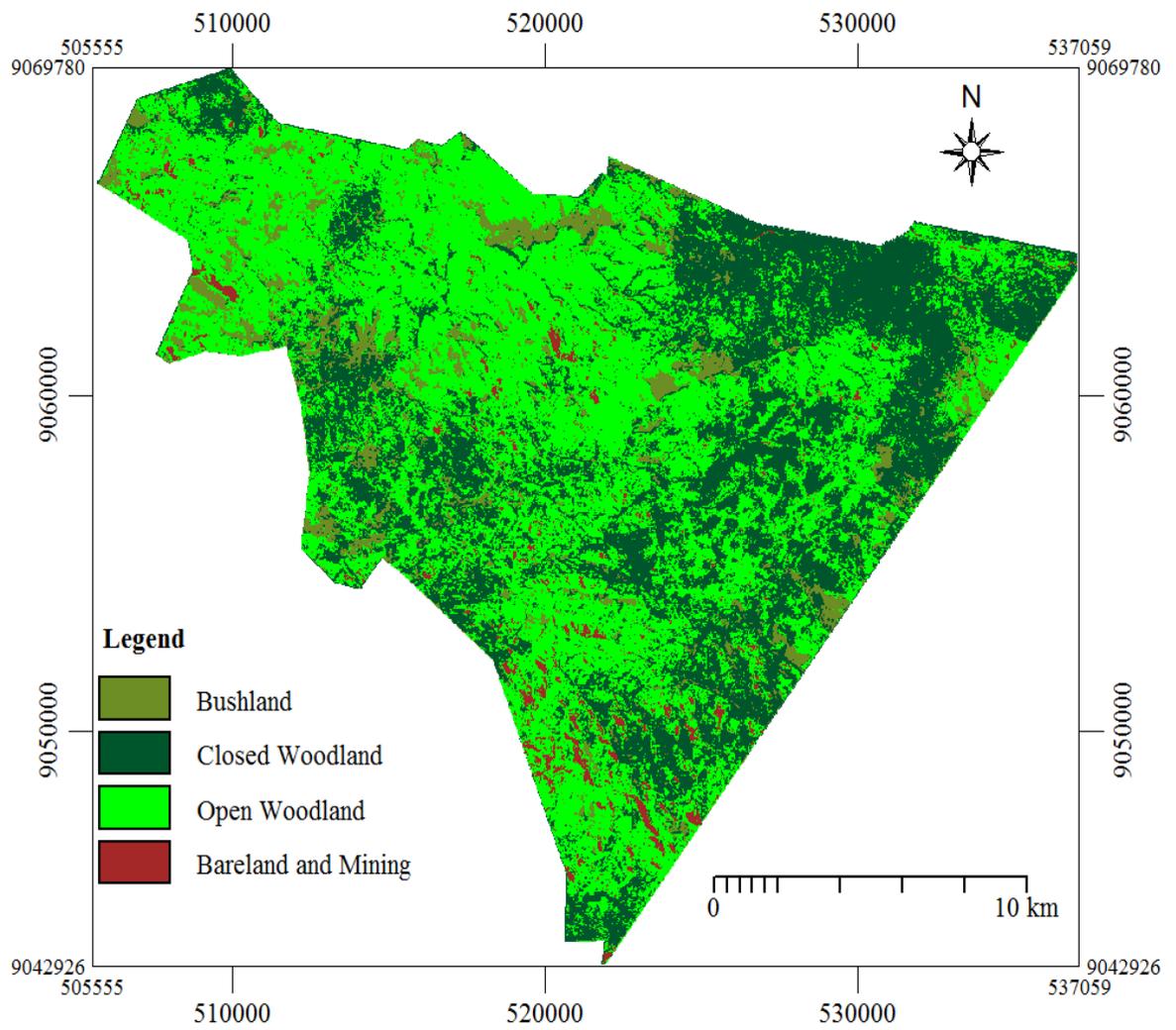


Figure 11: Forest Cover for Mbiwe Forest Reserve in year 1984.

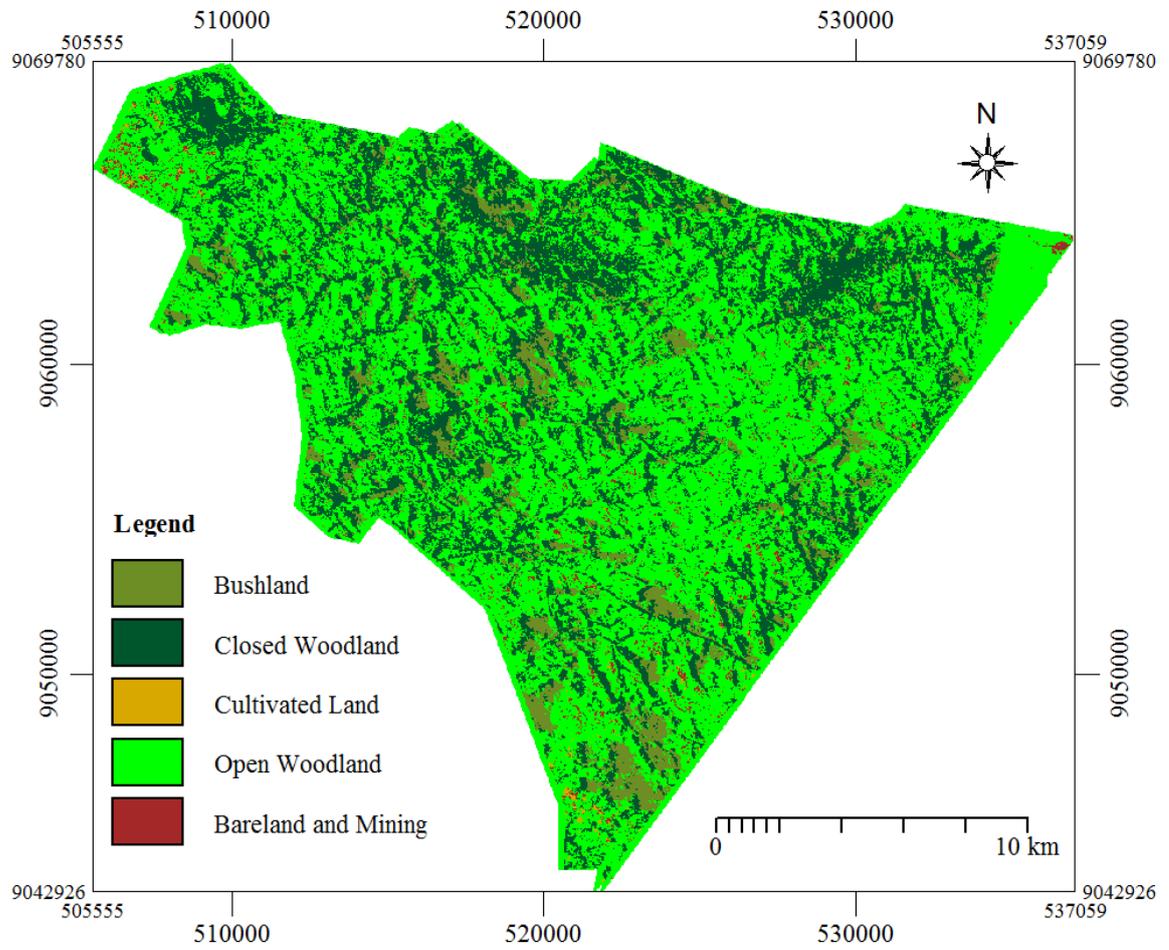
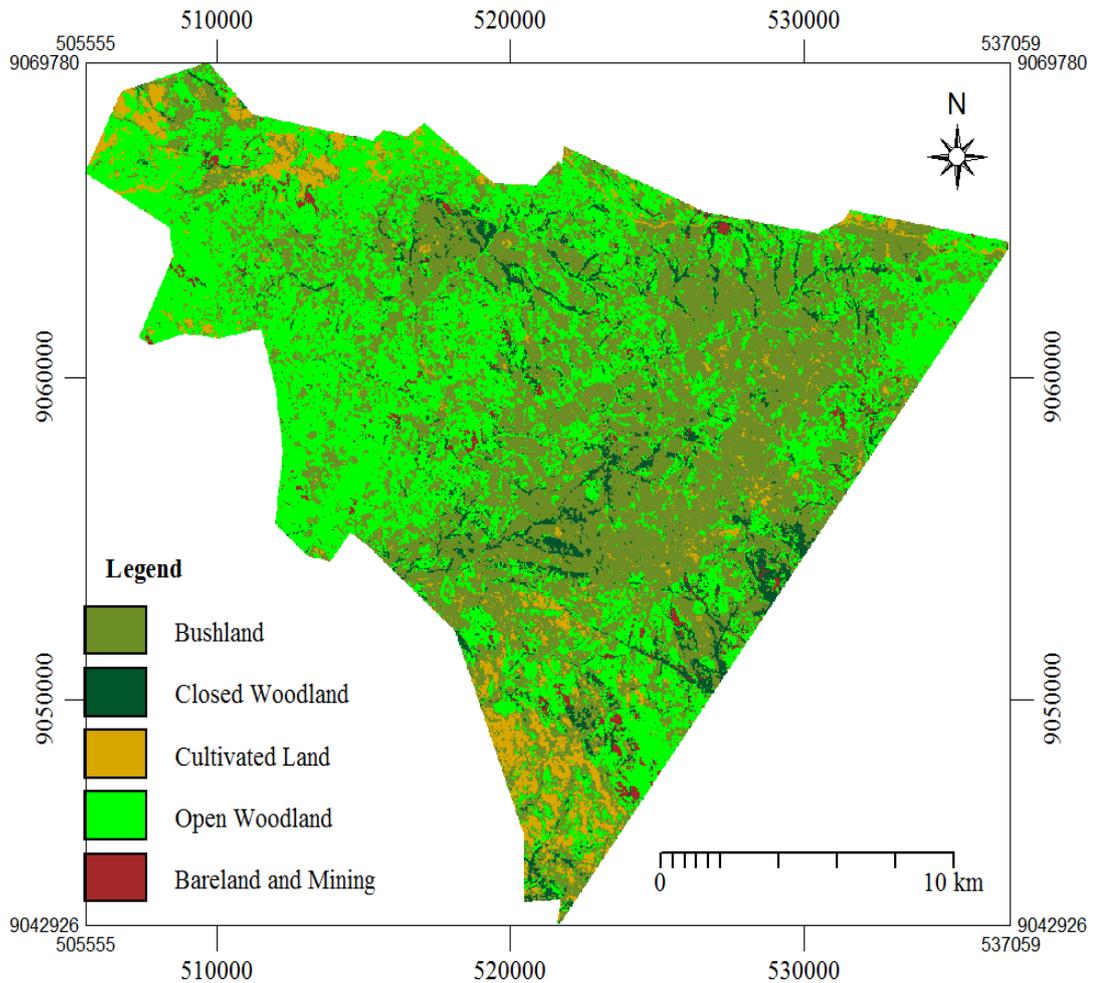


Figure 12: Forest Cover for Mbiwe Forest Reserve in year 1990.



Fi

Figure 13: Forest Cover for Mbiwe Forest Reserve in year 2013.

4.2 Accuracy Assessment for Images Classification

The user's accuracy (average accuracy), producer's accuracy (reliability) and overall accuracy assessment for Mbiwe Forest Reserve after classification revealed to be 74.86%, 71.92% and 81.81% respectively. According to Kashaigili *et al.*, (2013), the overall accuracy assessment is accepted if it is greater than 80%. The figures in column Unclassified represent the ground truth pixels that were found not classified in the classified image.

Table 2: Classification results

	BuL	CW	CuW	OW	Bal	Uc	ACC
Bul	165453	8980	0	11420	1651	3810	0.87
CW	3491	16071	0	2923	0	708	0.69
CuW	633	0	6794	571	2321	662	0.62
OW	30194	10710	831	222377	628	11081	0.81
Bal	201	0	1185	710	7305	210	0.76
REL	0.83	0.45	0.77	0.93	0.61		

Bul = Bushland; CW = Closed Woodland; CuW = Cultivated land; OW = Open Woodland; Bal = Bareland and mining; REL= Reliability; Uc= Unclassified; ACC= Accuracy

4.3 Changes in forest cover for Mbiwe Forest Reserve from 1984, 1990 and 2013

The forest cover change maps between 1984 and 1990 and between 1990 and 2013 are shown in (Fig. 14: and Fig. 15): respectively and their cover area changes in the same period are shown in (Table 3).

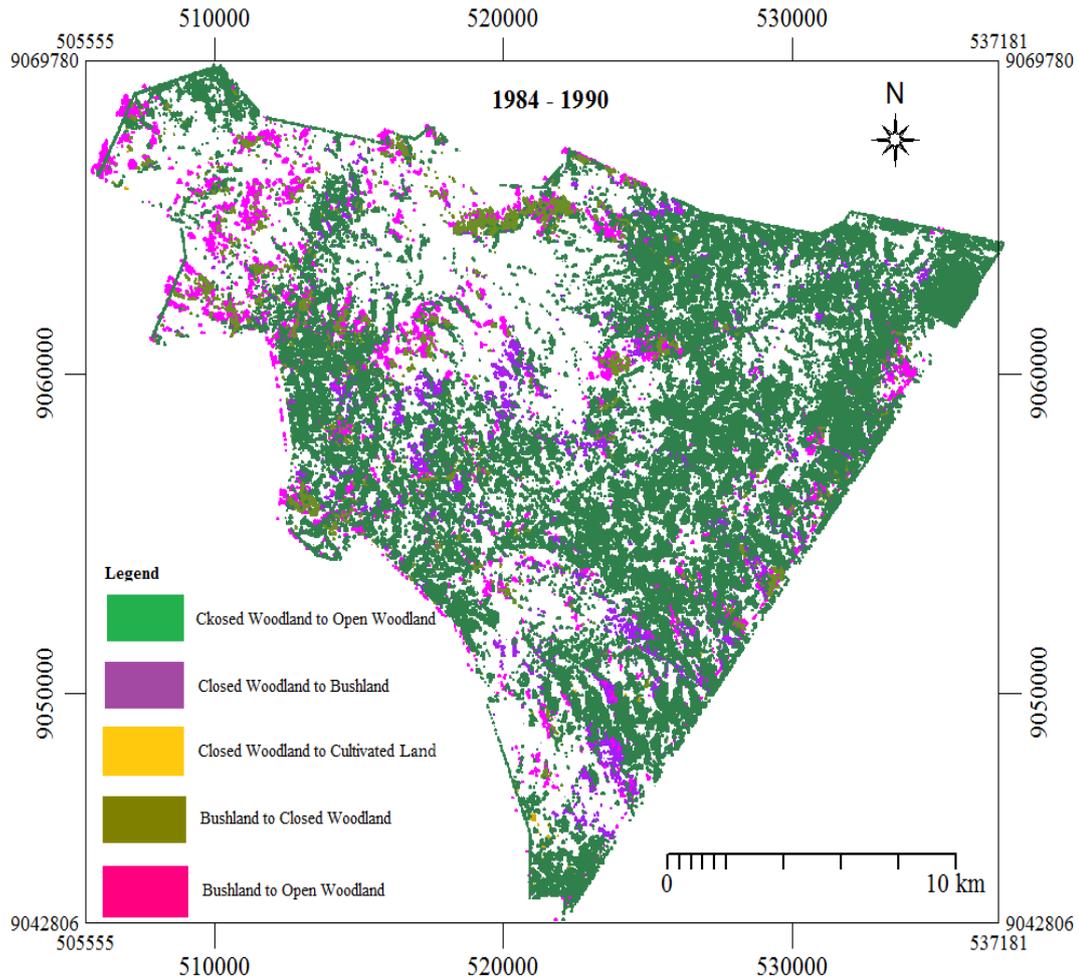


Figure 14: Forest cover change for Mbiwe Forest Reserve for the period 1984 – 1990.

The result in Table 3 revealed that closed woodland decreased by 2 306.2 ha (–4.7%) and 12 748.2 ha (–26%) for the period between 1984-1990 and 1990–2013 respectively. This shows that there was a sharp decrease of closed woodland probably due to timber harvesting or mining activities. Similarly, in the period 1984-1990, open woodland increased by 2 420.7 ha (5%) and decreased by 723.3 ha (–1.5%) between 1990-2013. During the period of 1984-1990 there was increase of open woodland cover due to the facts that there was a decrease of closed woodland in the same period hence conversion of closed woodland into open woodland. Meanwhile, in the period 1984 – 1990, the bushland increased by 436.5 ha (0.9%) and 12 476 (25%) for the period 1990 – 2013.

There was an increase of bushland in both periods because 1984-1990 and 1990-2013 there was a change of closed and open woodland into other classes and one of them being bushland. However, for the year 1984 there was no cultivated land but by 1990 there was cultivated land therefore for the period of 1984 – 1990 the cultivated land was 114.9 ha (0.2) and for the period 1990 – 2013 cultivated land area increased by 665.4 ha (1.4%). Absence of cultivated land during 1984 was probably due to low population around the Mbiwe Forest Reserve and serious law enforcement on the management of that particular forest and vice versa for the period of 1990-2013. The Bareland and mining area decreased by 665.9 ha (-1.4%) for the period 1984 – 1990 and increased by 330.1 ha (0.7%) for the period 1990 - 2013. Decrease of Bareland and mining during 1984-1990 may be was due to serious law enforcement on the management of that particular forest and vice versa for the period of 1990-2013.

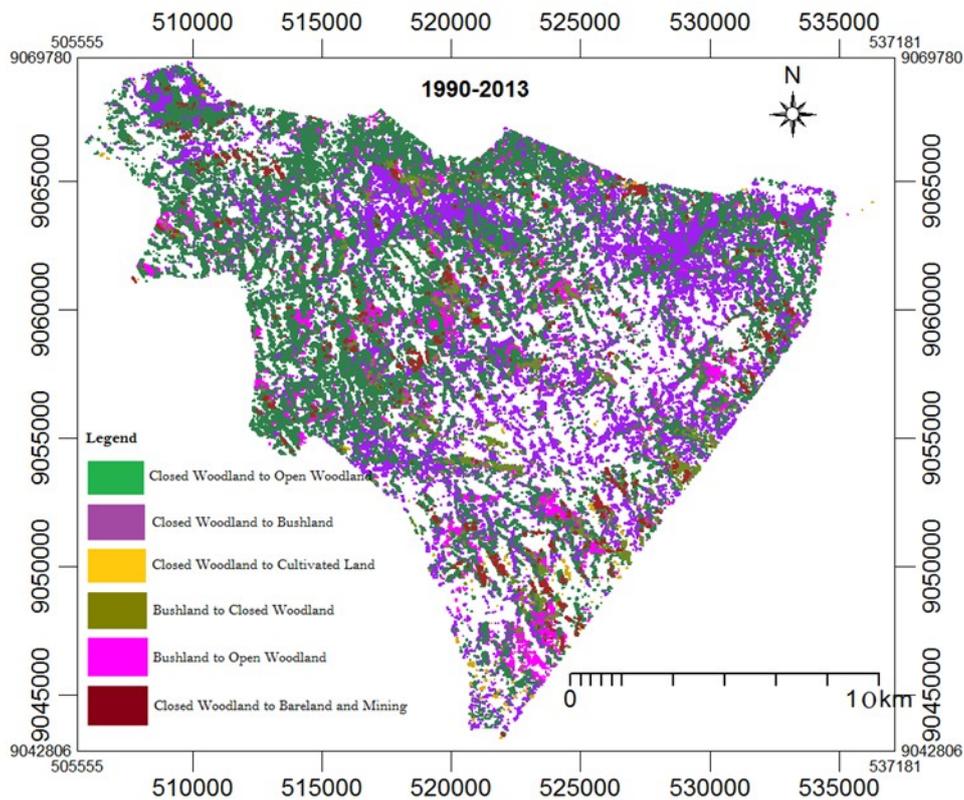


Figure 15: Forest cover change for Mbiwe Forest Reserve for the period 1990 – 2013.

Table 3: Cover area, change area and annual rate of change between 1984 - 1990 and 1990 - 2013

Forest Cover Type	Forest cover						Change area				Annual rate of change	
	1984		1990		2013		1984 - 1990		1990 - 2013		1984 - 1990	1990 - 2013
	Area (ha)	%	Area (ha)	%	Area (ha)	%	Area (ha)	%	Area (ha)	%	(ha/year)	(ha/year)
BL	3206.2	6.5	3642.7	7.4	16118.7	32.8	436.5	0.9	12476	25.4	72.8	542.4
CW	16501.7	33.6	14195.5	28.9	1447.3	2.9	-2306.2	-4.7	-12748.2	-26	-384.4	-554.3
CuW	0	0	114.9	0.2	780.3	1.6	114.9	0.2	665.4	1.4	19.2	28.9
OW	28221.3	57.4	30642	62.4	29918.7	60.9	2420.7	5	-723.3	-1.5	403.5	31.4
Bal	1218.5	2.5	552.6	1.1	882.7	1.8	-665.9	-1.4	330.1	0.7	-111	14.4
Total	49147.7	100	49147.7	100	49147.7	100						

BL= Bushland CW= Closed Woodland CuW= Cultivated land OW= Open Woodland Bal= Bareland and mining

4.4 Carbon stock change for Mbiwe Forest Reserve from 1984, 1990 and 2013

4.4.1 Above ground biomass

The results revealed that by 2013 the average above ground biomass was 66.6 t/ha this result is within the range of $59 \text{ Mg ha}^{-1} \pm 26.15$ (ranging from 15 to 165 Mg ha^{-1}) by the study conducted in 2009 in Niassa National Reserve (NNR) in northern Mozambique (Ribeiro *et al.*, 2013). However according to Ryan (2013), in dry miombo aboveground woody biomass averages around $55 \text{ t dry matter ha}^{-1}$, whilst in wet miombo 90 t ha^{-1} (dry matter) is typical.

4.4.2 Above ground carbon stock

Carbon maps for the year 1984, 1990 and 2013 are shown in Fig. 16, 17 and 18. It was revealed that 1984 had the highest average carbon stock 58.5 tC/ha followed by 1990, 55.7 tC/ha and 2013 had the lowest 54.8 tC/ha , varying from the lowest 0.5 to 199.9 tC/ha the highest (Table 4). This is slightly lower compared to the total of Carbon Stock Density 67 Mg C h a^{-1} (Stdev ± 24.85) in miombo woodland of Niassa National Reserve in northern Mozambique (Ribeiro *et al.*, 2013) which is the same wet miombo woodland as Mbiwe forest reserve. This is probably due to the difference of forest cover between the two forest reserves.

Tanzania has reported an average forest biomass value of 60 tC ha^{-1} to the Food and Agriculture Organization (FAO, 2010; Godoy *et al.*, 2011). The national Forest and Beekeeping Division (FBD) reported an average biomass value of 157 tC ha^{-1} for eastern lowland forest with low to medium levels of degradation, and 33 tC ha^{-1} for highly-degraded lowland forest (FBD, 2007). Another studies conducted by Shrima *et al.* (2011) on carbon stock on Eastern Arc Mountain, a dry miombo woodland, revealed a weighted mean of 23.3 Mg ha^{-1} and this was slightly higher compared with results from Zahabu

(2008), Chamshama Mugasha & Zahabu (2002) and Munishi *et al.* (2010), which were 22.5, 19.04 and 19.12 Mg ha⁻¹, respectively, from the same miombo vegetation type.

Table 4: Carbon stock for the year 1984, 1990 and 2013

Year	Total Carbon (tC) (Mbiwe Forest, 49,147.7ha)	Average (Carbon tC/ ha)
1984	14 516.60	58.5
1990	12 910.80	55.7
2013	12 719.80	54.8

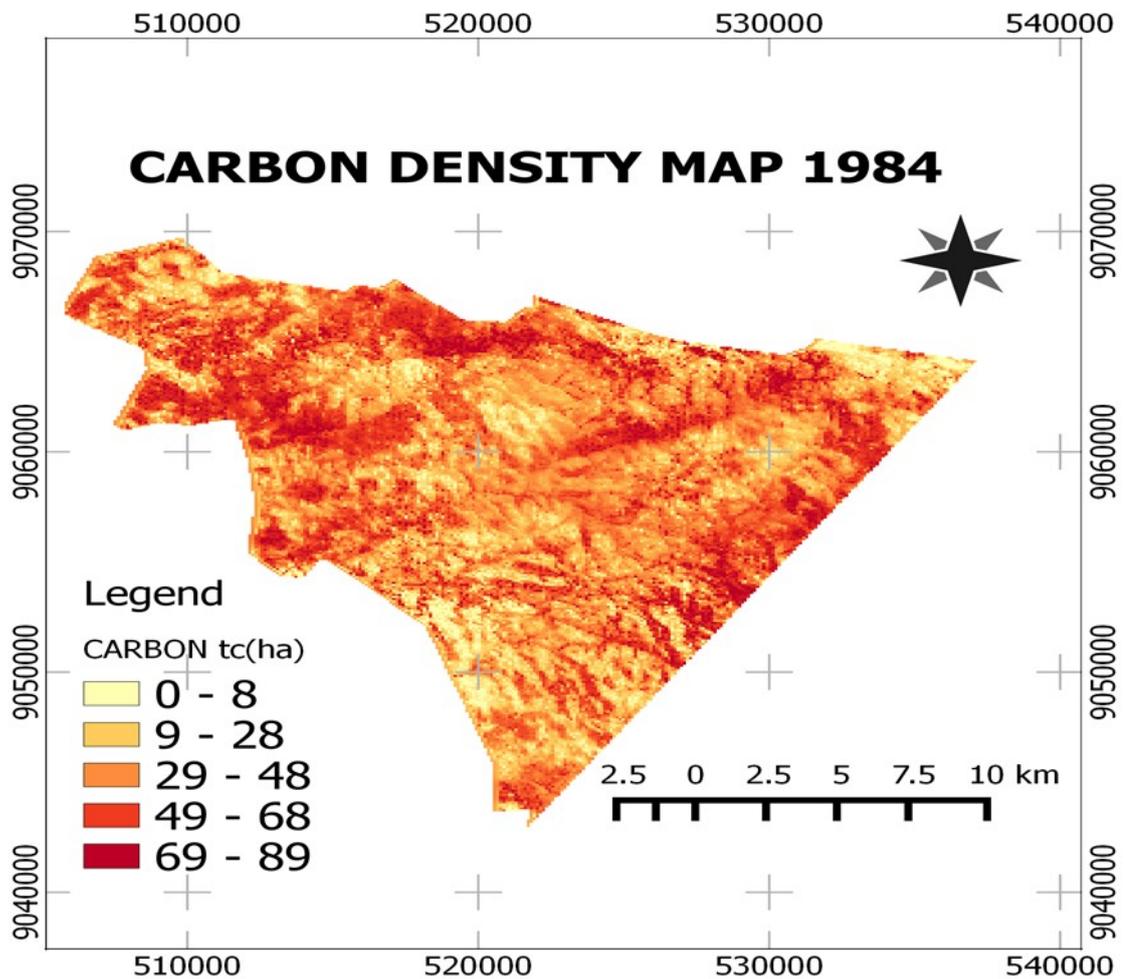


Figure 16: Carbon Stock in 1984.

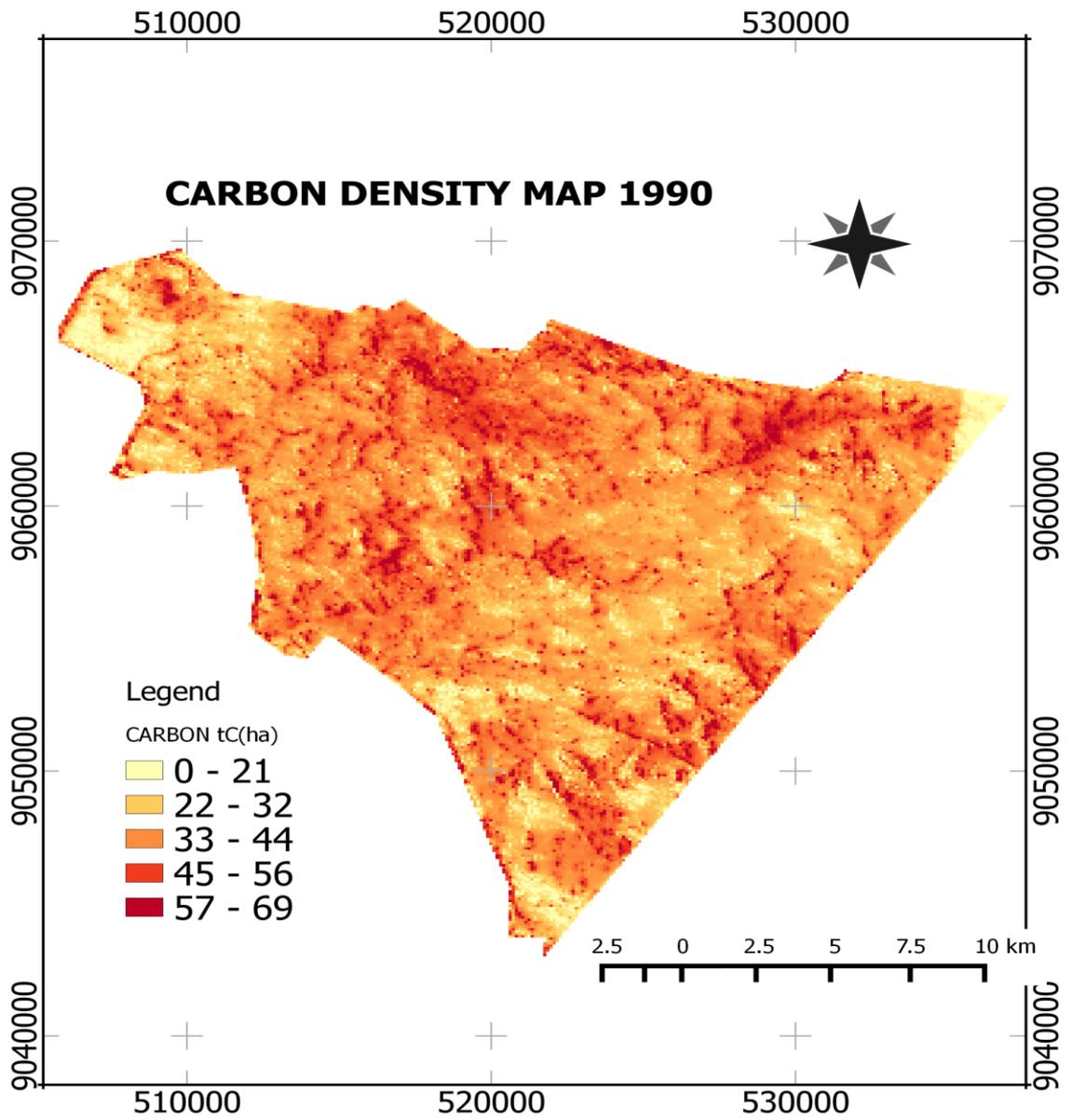


Figure 17: Carbon Stock in 1990.

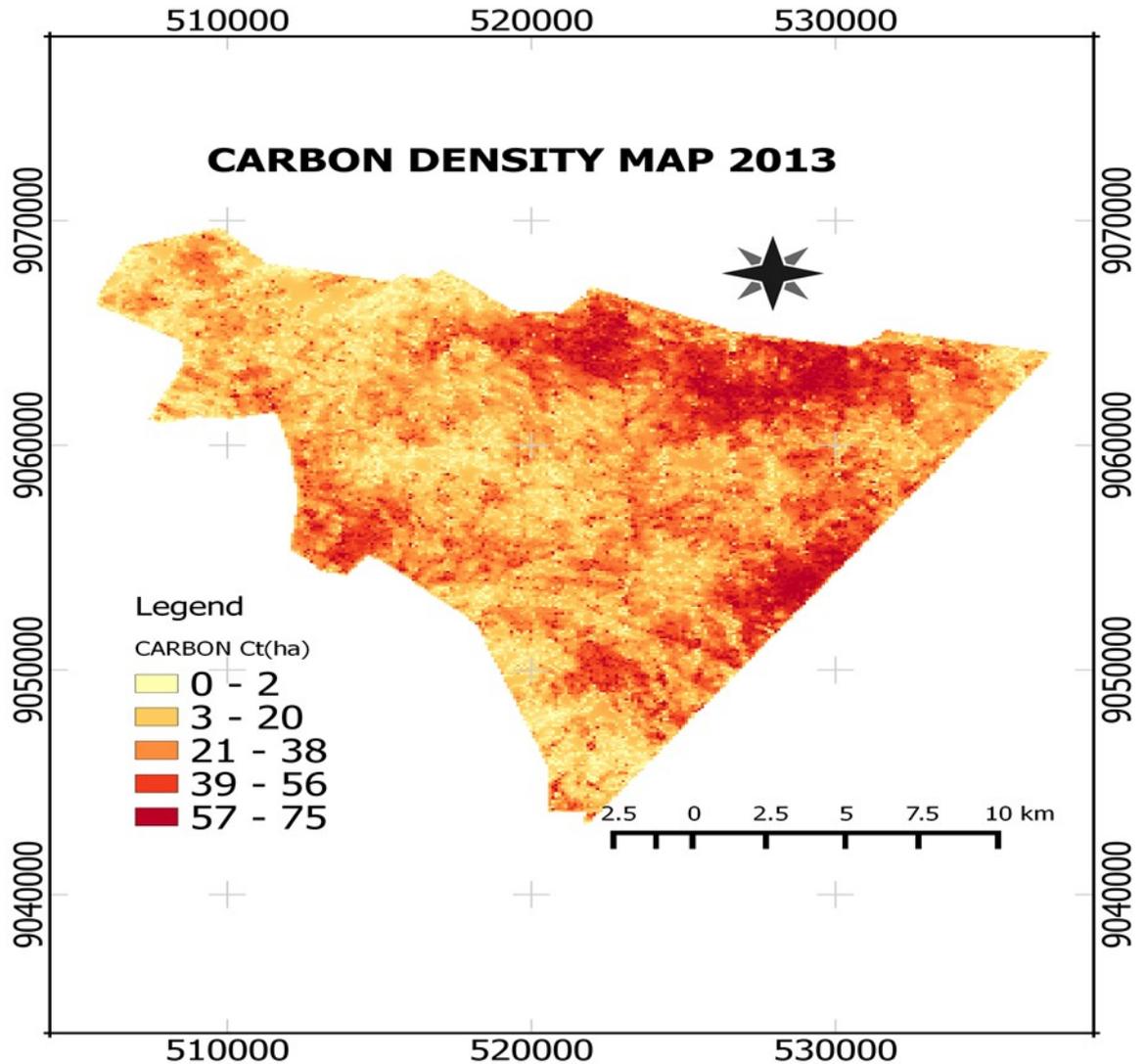


Figure 18: Carbon Stock in 2013.

4.5 Factors of Forest Cover Change

Spatial distribution of forest cover loss due to factors of forest cover change is shown in Fig. 20 – 23 and it is revealed in Table 5 that distance from degraded areas to village centers and to the cultivation areas have high effects on forest cover change followed by distance to the road. This result on cultivation to be one of the leading factors of forest change is the same as of Mwavu and Witkowski (2008) analyzed land-use and cover changes within and around Budongo Forest Reserve in Uganda. Deforestation was found to be driven by a number of socioeconomic factors including agricultural expansion,

increasing human population, unclear land tenure, conflicts of interest and political interference in addition to local people's perception that the forest was an obstacle to agriculture.

However, on road and village distance results are the same as Phong, (2004) when analyzing deforestation for the period 1989 – 1996 in Bach Ma National Park and its buffer zones; it was found that Management effects (zone), distance to village and road are positively related with deforestation while slope and population density are negatively related with deforestation.

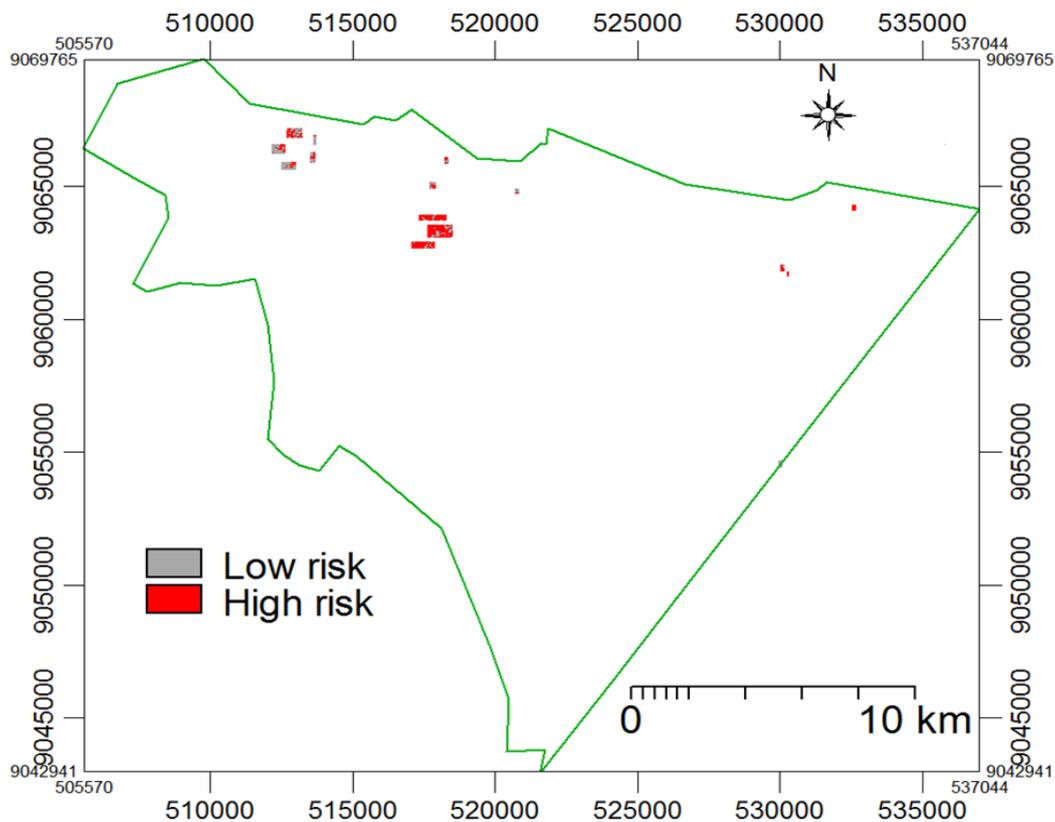


Figure 19: Spatial distribution of forest covers loss due to distance from the village centres to the degraded areas.

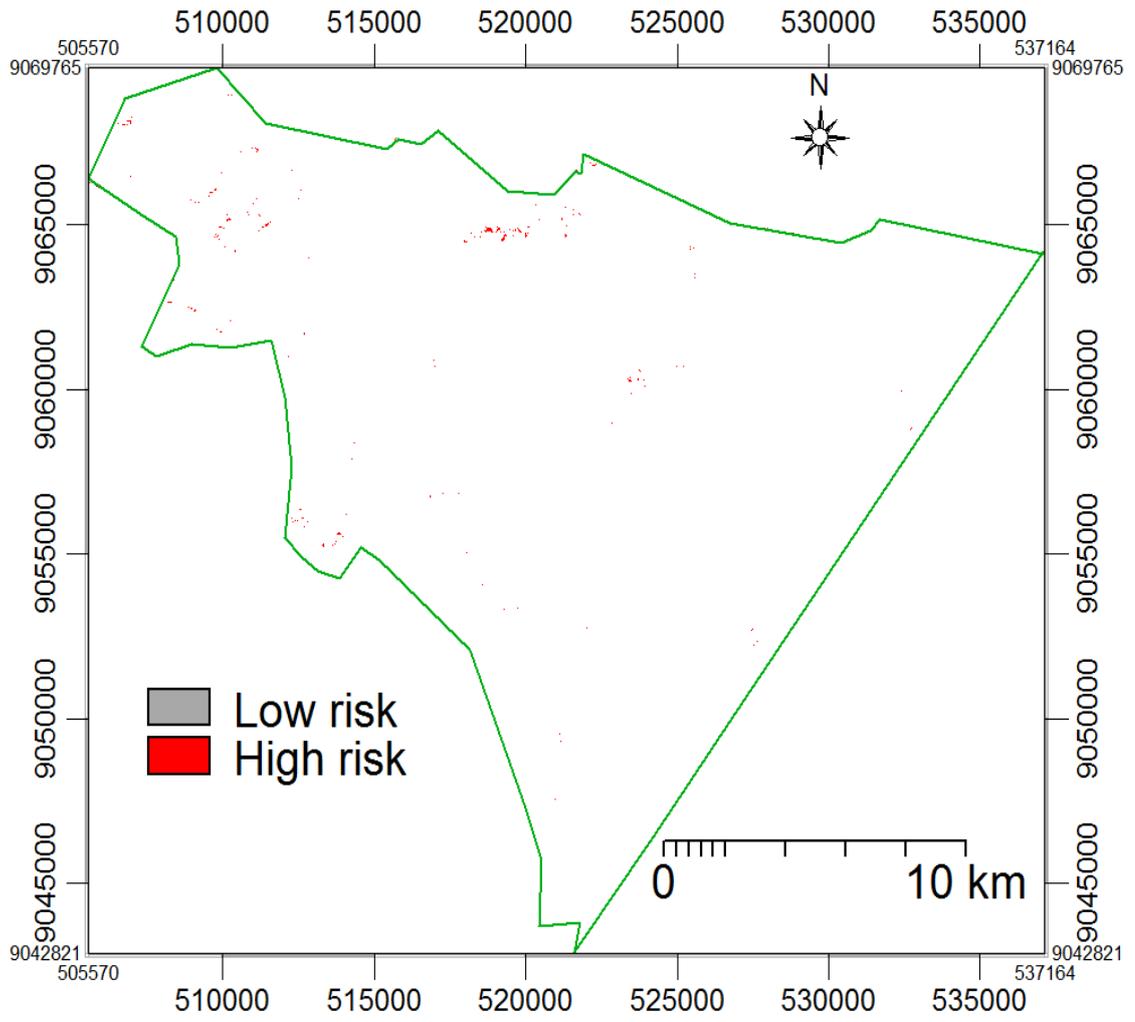


Figure 20: Spatial distribution of forest covers loss due to distance from the roads to the degraded areas.

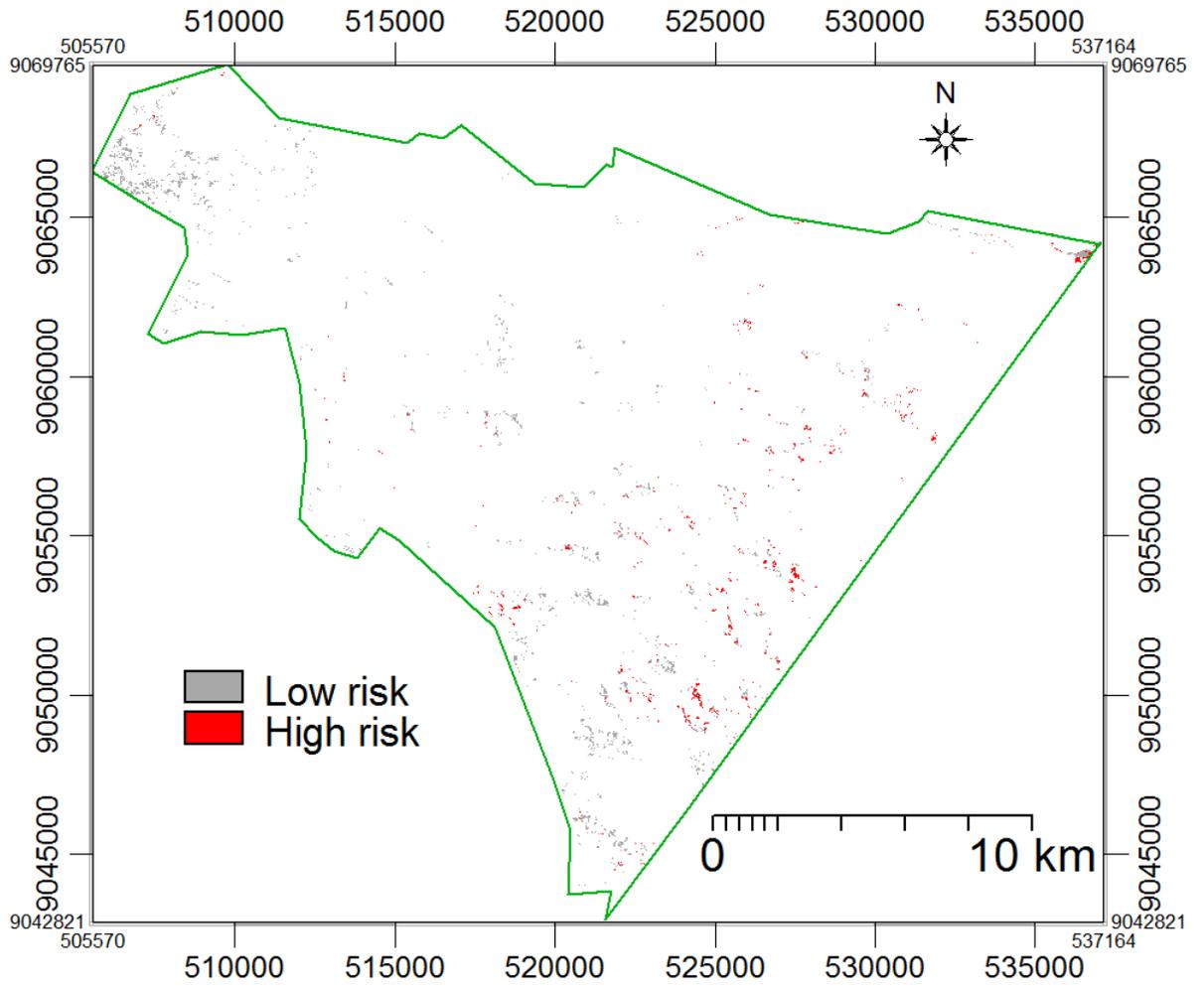


Figure 21: Spatial distribution of forest covers loss due to distance from the cultivated areas to the degraded areas.

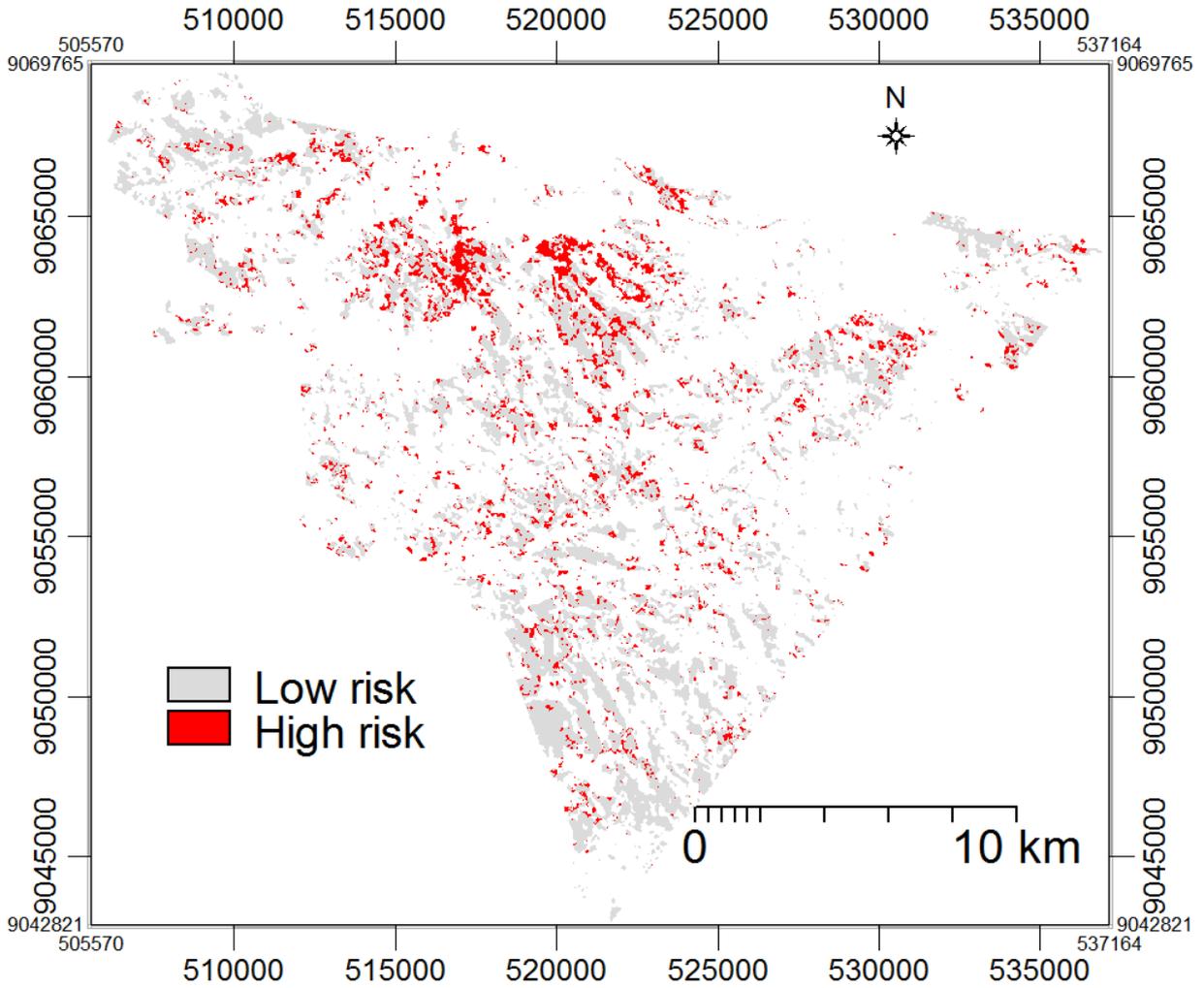


Figure 22: Spatial distribution of forest covers changes due to the distance from the village centers, roads and cultivation areas to the degraded areas

Table 5: Factors significantly associated with forest cover change during the period 1990 to 2013

Coefficients	Estimate	Std. Error	Z value	Pr(> z)
(Intercept)	2.657e-01	9.215e-04	26.299	3e-12 ***
Distance to village center	4.200e-10	2.314e-01	7.210	1.10e-03 ***
Distance to road	1.124e-10	1.605e-01	1.004	1.10e-13***
Distance to cultivation area	2.310e-10	1.201e-01	3.191	1.10e-07

This distance is from degraded areas to the village center, roads and cultivation areas.

CHAPTER FIVE

5.0 CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

The following conclusion can be drawn from the assessment of the effects of forest cover change on carbon stock between 1984, 1990 and 2013 in miombo woodlands of Mbiwe Forest Reserve.

5.1.1 Change in forest cover for Mbiwe Forest Reserve from 1984, 1990 and 2013

Closed woodland has been changing to other forest cover as 1984 – 1990 changing was by 4.7% (2 306.2 ha) and 1990 – 2013 changing was by 26% (12 748.2 ha) while bushland and cultivated woodland have been expanding as 1984 – 1990 closed woodland expanded by 0.9% (436.5 ha) and 1990 – 2013 closed woodland expanded by 25.4% (1 247.6 ha) meanwhile 1984 – 1990 cultivated woodland expanded by 0.2% (114.9 ha) and 1990 – 2013 cultivated woodland expanded by 1.4% (665.4 ha). Open woodland and bareland and mining were not constantly increasing or decreasing as 1984 – 1990 open woodland expanded by 5% (2 420.7 ha) and 1990 – 2013 open woodland shrinking was by 1.5% (723.3 ha) meanwhile 1984 – 1990 bareland and mining changing was by 1.4% (665.9 ha) and 1990 – 2013 bareland and mining expanded by 0.7% (330.1 ha).

On the other hand from 1990 – 2013 closed woodland decreased at a rate of 554.3 ha/year assuming a linear decline. If this continues unabated, it is likely that in the next 10 years from now the closed woodland will be completely converted to other covers. Therefore more effort is needed to protect the forest.

5.1.2 Changes in carbon stock for Mbiwe Forest Reserve from 1984, 1990 and 2013

It is revealed from this study that by 2013 the average above ground biomass was 66.6 t/ha and 1984 had the highest average carbon stock 58.5 tC/ha followed by 1990 55.7 tC/ha and 2013 had the lowest 54.8 tC/ha. This change of carbon from the highest 58.5 tC/ha to 54.8 tC/ha for 1984 to 2013 respectively was due to the decreases of closed woodland and open woodland, which contribute highly on biomass of a tree.

5.1.3 Factors of influencing Forest Cover Change

Cultivation in the forest reserves and establishment of villages and roads in and around forest reserves have been found to be the main causes for the change in forest cover.

5.2 Recommendations

Based on the findings from this study it is recommended that:

More efforts on protection of forest reserves is needed especially to the forest reserves which are close to the good infrastructures such as main roads, railways and town centers as those infrastructures accelerate forest cover changes. Also law enforcement should be enforced to to protect forests; this will lead villagers who are living around forest reserves to refrain from getting into forest reserves for cultivation and clearfelling trees for their various uses.

REFERENCES

- Abdallah J. M. and Monela, G. G. (2007). MITMIOMBO-Management of Indigenous Tree Species for Ecosystem Restoration and Wood Production in Semi-Arid Miombo Woodlands in Eastern Africa. In: *Proceedings of the First MITMIOMBO Project Workshop*, held in Morogoro, Tanzania 6 – 12 February 2007. pp. 9-23.
- Angelsen, A. (1995). Shifting Cultivation and Deforestation. A Study from Indonesia. *World Development* 23(10): 1713 – 1723.
- Asner, P. G. (2009). Tropical forest carbon assessment: integrating satellite and airborne mapping approaches. *The Environmental Research Letters* 4: 1 – 11.
- Baral, S. (2011). Mapping carbon stock using high resolution satellite images in subtropical forests of Nepal. Dissertation for Award of MSc Degree at University of Twente, 60pp.
- Basuki, T. M., Laake van, P. E., Skidmore, A. K. Y. and Hussin, A. (2009). Allometric equations for estimating the above-ground biomass in tropical lowland Dipterocarp forests. *Forest Ecology and Management* 257(8): 1684 – 1694.
- Basu, A. and Nayak, C. N. (2011). Underlying causes of forest cover change in Odisha, India. *Forest Policy and Economics* 13(7): 563 – 569.
- Bawa, K. S. and Dayanandan, S. (1997). Socioeconomic factors and tropical deforestation. *Nature* 386: 562 – 563.

- Blomley, T. and Iddi, S. (2009). *Participatory Forest Management in Tanzania: 1993 – 2009 Lessons Learned and Experiences to Date*. Ministry of Natural Resources and Tourism, Dar es Salaam, Tanzania. 69pp.
- Burges, S. N., Bahane, B., Clair, T., Danielsen, F., Dalsgaard, S., Funder, M., Hagelberg, N., Harrison, P., Haule, C., Kabalimu, K., Kilahama, F., Kilawe, E., Lewis, S. L., Lovett, J. C., Lyatuu, G., Marshall, A. R., Meshack, C., Miles, L., Milledge, S. A.H., Munishi, P. K. T., Nashanda, E., Shirima, D., Swetnam, R. D., Willcock, S., Williams, A. and Zahabu, E. (2010). Getting ready for REDD+ in Tanzania: a case study of progress and challenges. *Fauna and Flora International Oryx* 44(3): 339 – 351.
- Campbell, B. M., Angelsen, A., Cunningham, A., Katerere, Y., Stone, A. and Wunder, S. (2007). Miombo Woodlands- opportunities and barriers to sustainable forest management. [http://www.cifor.org/miombo/docs/Campbell_BarriersandOpportunities.pdf] site visited on 2/2/2013.
- Campbell, B. (1996). *The Miombo in Transition: Woodlands and Welfare in Africa*. Center for International Forestry Research Bogor, Indonesia. 267pp.
- 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.
- Country Side Information (2014). Types of Woodland. [www.countrysideinfo.co.uk/woodland_manage] site visited on 6/5/2014.

- Dallu, A. I. M. (2002). Tanzania Secondary Forest Management in Africa: Reality and perspectives Tanzania Country Paper. In: *Proceedings Workshop on Tropical Secondary Forest Management in Africa. Reality and Perspectives - In Collaboration with ICRAF and CIFOR*, Nairobi, Kenya, 9 – 13 December 2002. pp. 1 – 12.
- Dengsheng, L., Batistella, M. and Moran, E. (2005). Satellite Estimation of Aboveground Biomass and Impacts of Forest Stand Structure. *Photogrammetric Engineering and Remote Sensing* 71(8): 967 – 974.
- Dengsheng, L., Qi, C., Guangxing, W., Moran, E., Mateus, B., Maozhen, Z., Gaia, V., L. and David, S. (2012). Aboveground forest biomass estimation with landsat and LiDAR data and uncertainty analysis of the estimates. *International Journal of Forestry Research* 2012: 1 – 16.
- Du L., Zhou T., Zou Z., Zhao X. Huang K. and Wu H. (2014). Mapping forest biomass using remote sensing and national forest inventory in China. *Forests* 5: 1267 – 1283.
- Dudley, N. and Stolton, S. (2003). *The Importance of Forest Protected Areas to Drinking Water. Alliance for Forest Conservation and Sustainable Use*. The World Bank, Washington DC. 114pp.
- Escobedo, F., Seitz, J. A. and Zipperer, W. (2010). Carbon Sequestration and Storage by Gainesville's Urban Forest. University of Florida. [<http://www.edis.ifas.ufl.edu>] site visited on 12/2/2013.

FAO (1995). Forest resources assessment 1990. Global synthesis. Food and Agriculture Organization, Rome, Italy. www.fao.org/007/v5695e/htm] site visited on 24/10/2012.

FAO (2000). *Land Cover Classification System Classification Land Cover Concepts and User Manual*. Food and Agriculture Organization, Rome, Italy. 67pp.

FAO (2004). *Assessing Carbon Stocks and Modeling Win–Win Scenarios of Carbon Sequestration through Land-Use Changes*. Food and Agriculture Organization, Rome, Italy. 156pp.

FAO (2005). *Global Forest Resources Assessment Update 2005 Terms and Definitions Final Version*. Food and Agriculture Organization, Rome, Italy. 34pp.

FAO (2009). *State of the World's Forests*. Food and Agriculture Organization, Rome, Italy. 152pp.

FAO (2010). *Global Forest Resources Assessment Country Report*. Food and Agriculture Organization, Rome, Italy. 56pp.

FAO (2011). *Assessing Forest Degradation towards the Development of Globally Applicable Guidelines*. Food and Agriculture Organization, Rome, Italy. 99pp.

FAO (2012). *Global Forest Land-Use Change 1990–2005*. Food and Agriculture Organization, Rome, Italy. 46pp.

FBD (2007). *Establishing Mechanisms for Payments For Carbon Environmental Services In The Eastern Arc Mountains, Tanzania*. Forest Beeping Department, Dar es Salaam, Tanzania. 25pp.

Fisher, R., Perkins, S., Walker, A. and Wolfart, E. (2003). Ground Truthing. [<http://www.orionmagazine.org/index.php/articles/article/141/>] site visited on 15/5/2013.

Garson, G. B. (2000). PA 765 Statnotes: An Online Textbook. [<http://faculty.chass.ncsu.edu/garson/PA765/logistic.htm>] site visited on 25/9/2014.

Geist, H. J. and Lambin, E. F. (2001). *What Drives Tropical Deforestation? A Meta-Analysis of Proximate And Underlying Causes of Deforestation Based on Subnational Case Study Evidence*. International Project Office University of Louvain, Belgium. 118pp.

Geist, H. J. and Lambin, E. F. (2002). Proximate causes and underlying driving forces of tropical deforestation. *BioScience* 52(2): 140 – 143.

Geoghegan, J., Wainger, L. and Bockstael, N. (1997). Spatial landscape indices in a hedonic framework: an ecological economics analysis using GIS. *Ecological Economics* 23: 251 – 264.

Geoghegan, J., Cortina, Villar, S. and Klepeis, P. (2001). Modelling tropical deforestation in the southern Yucatán peninsular region: comparing survey and satellite data. *Agriculture, Ecosystems and Environment* 85: 25 – 46.

- Godoy, F., Tabor, K., Burgess, N. D., Mbilinyi, B. P., Kashaigili, J. J. and Steininger, M. K. (2011). Deforestation and CO₂ emissions in coastal Tanzania from 1990 to 2007. *Environmental Conservation* 39(1): 62 – 71.
- Hernandez, R. P., Koohafkan, P. and Antoine, J. (2004). *Assessing Carbon Stocks And Modelling Win–Win Scenarios Of Carbon Sequestration Through Land-Use Changes*. Food and Agriculture Organization, Rome Italy. 166pp.
- Holmes J. (1995). *Natural Forest Handbook for Tanzania*. Forest Ecology and Management, Dar es Salaam, Tanzania. 526pp.
- Hosonuma, N, Herold, M., Sy, V., De, Fries, R. S. D., Brockhaus, M., Verchot, L., Angelsen, A. and Romijn, E. (2012). *An Assessment of Deforestation and Forest Degradation Drivers in Developing Countries*. Environmental Research Letter, The Netherlands 13pp
- Houghton, R. A. and Goodale, C. L. (2004). *Effects of Land-Use Change on the Carbon Balance of Terrestrial Ecosystems*. Cornell University, Ithaca, New York. 14pp.
- IPCC (2003). *Good Practice Guidance for Land Use, Land-Use Change and Forestry*. (Edited by Penman, J., Gytarsky, M., Hiraishi, T., Krug, T., Kruger, D., Pipatti, R., Buendia, L., Miwa, K., Ngara, T., Tanabe, K. and Wagner F.), Institute for Global Environmental Strategies, Japan. 6pp.

Järvis J. (2013). *Forest Measurement With Relascope. Practical Description for Fieldwork with Examples for Estonia*. Estonia Environment Information Centre, Estonia. 11pp.

Ji, L., Wylieb, B. K., Nossocv, D. R., Petersona, B., Waldropd, M. P., McFarlandd, J. W., Roverb, J. and Hollingsworthe, T. N. (2012). Estimating aboveground biomass in interior Alaska with Landsat data and field measurements. *International Journal of Applied Earth Observation and Geoinformation* 18: 451– 461.

Karna,Y. K. (2012). Mapping above ground carbon using worldview satellite image and Lidar data in relationship with tree diversity of forests. Dissertation for Award of MSc Degree at University of Twente, 79pp.

Kashaigili J. J., Mdemu, M. V., Nduganda, A. R., Mbilinyi, B. P. (2013). Integrated Assessment of Forest Cover Change and Above-Ground Carbon Stock in Pugu and Kazimzumbwi Forest Reserves, Tanzania. *Advances in Remote Sensing* 2: 1 – 9.

Kashaigili, J. J. and Majaliwa, A. M. (2013). Implications of land use and land cover changes on hydrological regimes of the Malagarasi River, Tanzania. *Journal of Agricultural Science and Application* 2(1): 45 – 50.

Kashaigili, J. J. (2006). Land covers dynamics and hydrological functioning of wetlands in the Usangu Plains, Tanzania. Thesis for Award of PhD Degree at Sokoine University of Agriculture, Morogoro, Tanzania, 299pp.

- Krakina, O. N., Harmon, M. E., Cohen, W. B., Oetter, D. R., Olga, Z. and Duane, M. V. (2004). Carbon Stores, Sinks and Sources in Forest of Northwestern Russia: Can We Reconcile Forest Inventories with Remote Sensing Results? *Climate Chang*, 67(2): 257 – 272.
- Lal, R. (2007). An Introduction to British Woodlands and their Management: Carbon management and sequestration center. *Philosophical Transaction Royal Society* 363: 815 – 830.
- Lambin, E. F., Geist, H. J. and Lepers, E. (2003). Dynamics of land-use and land-cover change in tropical regions. *Annual Review Environment Resource* 28: 205 – 241.
- Lei, J., Bruce, K. W., Dana, R. N., Birgit, P., Mark, P. W., Jack, W. M., Jennifer, R. and Teresa, N. H. (2012). Estimating aboveground biomass in interior Alaska with Landsat data and field measurements. *International Journal of Applied Earth Observation and Geoinformation* 18: 451 – 461.
- Lovett, J. C. and T. Pócs (1993). Assessment of the condition of the Catchment Forest Reserves, a botanical appraisal. Arusha Region. [<http://easternarc.or.tz/downloads/eastern-arc/arusha.pdf>] site visited on 12/4/2013.
- Lu, D., Mateus, B. and Emilio, M. (2005). Satellite estimation of aboveground biomass and impacts of forest stand structure. *Photogrammetric Engineering and Remote Sensing* 71(8): 967 – 974.

- Mawalla, N. P., Clark, K. and Bartholomew, L. (2011). *Directory of Natural Resources and Land in Tanzania*. (Editors by Krissie, C. and Wayne, L.), PAMS Foundation. Dar es Salaam, Tanzania. 90pp.
- Miranda, J. J., Corral, L., Blackman, A., Asner, G. and Lima, E. (2014). *Effects of Protected Areas on Forest Cover Change and Local Communities: Evidence from the Peruvian Amazon*. Washington DC. 37pp.
- Misana, B. S., Sokoni, C. and Mbonile, J. M. (2012). Land-use/cover changes and their drivers on the slopes of Mount Kilimanjaro, Tanzania. *Journal of Geography and Regional Planning* 5(6):151 – 164.
- Miya, M., Ball, S. M. J. and Nelson, F. D. (2012). Drivers of Deforestation and Forest Degradation in Kilwa District. *Proceedings of National Forest Monitoring Systems and Measurement, Reporting and Verification of Carbon Stocks*, Arusha, Tanzania, 25 February - 1 March 2013. 34pp.
- Mugasha, W. A., Eid, T., Bollandsås, O. M., Malimbwi, R. E., Chamshama, S. A. O., Zahabu, E. and Katani, J. Z. (2012). Allometric models for prediction of aboveground biomass of single trees in miombo woodlands in Tanzania: In: *Proceedings of the first Climate Change Impacts, Mitigation and Adaptation Programme Scientific Conference*, 2012. pp. 8 – 17.
- Munishi, P. K. T., Mringi, S., Shirima, D. D. and Linda, S. K. (2010). The role of the Miombo Woodlands of the Southern Highlands of Tanzania as carbon sinks. *Journal of Ecology and the Natural Environment* 2(12): 261 – 269.

- Muñoz-Rojas, M., De la Rosa, D., Zavala, L.M., Jordán, A. and Anaya-Romero, M. (2011). Changes in land cover and vegetation carbon stocks in Andalusia, Southern Spain (1956 – 2007). *Science of the total Environment* 409(15): 2796 – 2806.
- Mwavu, E. N. and Witkowski, E. T. F. (2008). Land-use and cover changes (1988–2002) around Budongo Forest Reserve, NW Uganda: Implications for forest and woodland sustainability. *Land Degradation and Development* 19: 606 – 622.
- MNRT (2010). *National Forestry Resources Monitoring And Assessment Of Tanzania Field Manual Biophysical Survey*. Government Printers, Dar es Salaam, Tanzania. 108pp.
- NAFORMA (2013). *National Forestry Resources Monitoring and Assessment of Tanzania Field Manual*. Biophysical survey Forestry and Beekeeping Division, Dar es Salaam, Tanzania. 108pp.
- Nduwamungu, J., Bloesch, U., Munishi, P. K. T., Hagedorn, F. and Lulu, K. (2009). Recent land covers and uses changes in Miombo woodlands of eastern Tanzania. *Tanzania Journal of Forestry and Nature Conservation* 78(1): 1856 – 0315.
- Nagendra, H. (2007). Drivers of reforestation in human-dominated forests. *Proceedings of the National Academy of Sciences* 104(39): 15218 – 15223.
- Ngo, K. M., Benjamin, L. T., Helene, C. M., Stuart, J. D., Markku, L., Nik, F. N. H. and Shawn, L. (2013). Carbon stocks in primary and secondary tropical forests in Singapore. *Forest Ecology and Management* 296: 81 – 89.

NOAA Coastal Services Center (2009). Land cover and land use classification.

[<http://oceanservice.noaa.gov/facts/lclu.html>] site visited on 5/3/2013.

Odada, E. O., Ochola, W. O. and Olago, D. O. (2009). Drivers of ecosystem change and their impacts on human well-being in Lake Victoria Basin. *African Journal of Ecology* 47(1): 46 – 54.

Phong .T. L. (2004). Analysis of forest cover dynamics and their driving forces in Bach ma National Park and its buffer zone using remote sensing and GIS. Dissertation for Award of MSc Degree at University of Twente, 66pp.

Place, F. and Otsuka, K. (2000). Population pressure, land tenure and tree resource management in Uganda. *Land Economics* 76(2): 233 – 251.

Planning commission Dar es Salaam and Chunya District Council (1997). *Socio-economic profile of Chunya District*. Planning Commission Dar es Salaam and Chunya District council, Tanzania. 147pp.

Ribeiro, N. S., Matos, C. N., Moura, I. R., Washington-Allen, R. A. and Ribeiro, A. I (2013). Monitoring vegetation dynamics and carbon stock density in miombo woodlands. [<http://www.cbmjournal.com/content/8/1/2011>] site visited 20/4/2012.

Rude, L. T. and Roper, J. (1996). Regional patterns and historical trends in tropical deforestation, 1976-1990. *A Qualitative Comparative Analysis*. – *Ambio* 25(3): 160 – 166.

- Serneels, S. and Lambin, E. F. (2001). Proximate causes of land-use change in Narok District, Kenya: A spatial statistical model. *Agriculture, Ecosystems and Environment* 85: 65 – 81.
- Schindele W. (1995), Guidelines for a Reconnaissance Forest Inventory. *Working Paper Report on Forest Resources Assessment and Forest Management within the Scope of the Integrated Forest Management Project*. Bhutan, German pp. 1 – 48.
- Singh, S. (2000). Change detection using remote sensing land cover change analysis of the Teba catchment in Spain. Dissertation for Award of MSc Degree at University of Twente, 76pp.
- 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 for Ecology* 49: 332 – 342.
- United Republic of Tanzania (1998). *National Forest Policy*. Government Printers, Dar es Salaam, Tanzania. 59pp.
- United Republic of Tanzania (2009). *Fourth National Report on Implementation of Convention on Biological Diversity*. Vice President's Office, Dar es Salaam, Tanzania. 81pp.
- Vogt, N., Bahati, J., Unruh, J., Green, G., Banana, A., Gombya-Ssembajjwe, W. and Sweeney, S. (2006). Integrating remote sensing data and rapid appraisals for

landcover change analyses in Uganda. *Land Degradation and Development* 17: 31 - 43.

Waiswa, D. (2009). Dynamics of forest cover extent, forest fragmentation and their drivers in the Lake Victoria crescent, Uganda. Thesis for Award of PhD Degree at State University of Blacksburg, Virginia, 102pp.

Wickramaarachchi, T. N., Ishidaira, H. and Wijayarathna, T. M. N. (2013). Projecting Land Use Transitions in the Gin Catchment, Sri Lanka. *Research Journal of Environmental and Earth Sciences* 5(8): 473 – 480.

Yesserie, A. G. (2009). Spatio-Temporal Land Use/Land Cover Changes Analysis and Monitoring in the Valencia Municipality, Spain. Dissertation for Award of MSc Degree at Universitat Jaume I, Castellón, Spain, 69pp.

Zheng, D. R., Chen, J., Crow, J., Bresee, T., Le, M. M., Ryu, J. and Ryoul, S. (2004). Estimating aboveground biomass using Landsat 7 ETM+ data across a managed landscape in northern Wisconsin, USA. *Remote Sensing of Environment* 93: 402 – 411.

Zahabu, E. (2008). Sinks and sources a strategy to involve forest communities in Tanzania in global climate policy. Thesis for Award of PhD Degree at University of Twente, 249pp.

Zakaria, H. E. A. (2010). Integration of Remote Sensing and GIS in Studying Vegetation Trends and Conditions in the Gum Arabic Belt in North Kordofan, Sudan. Thesis for Award of PhD Degree at Technische Universität Dresden, 165pp.

Zongo, B., Zongo, F. and Boussim, J. I. (2001). *Importance of Forestry Reserves to The Regulation of Water Quality and Microalgae Structure of Temporary Ponds*. Burkina Faso. 35pp.