CHARACTERIZATION OF THE ENVIRONMENTAL EFFECTS OF CLIMATE CHANGE AND VARIABILITY ON THE BIOPHYSICAL AND SOCIO-ECONOMIC SYSTEMS USING GEO-INFORMATION TECHNOLOGY AT THE MAU FOREST COMPLEX, NAROK COUNTY, KENYA

SIMEON ORUKO OYIEKO

A RESEARCH THESIS SUBMITTED TO THE SCHOOL OF NATURAL RESOURCES, TOURISM AND HOSPITALITY IN PARTIAL FULFILLMENT OF THE REQUIREMENT FOR THE AWARD OF MASTER OF SCIENCE IN ENVIRONMENTAL STUDIES OF MAASAI MARA UNIVERSITY

JULY, 2021

DECLARATION

This research thesis is my original work and has not been submitted in part or full for the award of a degree in this or any other University for examination. In cases where explicit ideas and references are made to the contribution of others herein, they have been duly acknowledged. All the rights reserved, no part of this research should be reproduced without my consent or that of the Maasai Mara University.

Simeon Oruko Oyieko
(MES10/1014/2014)

Signature: **Date: 14th June, 2021**

APPROVAL

This research thesis has been submitted for examination with our approval as the University supervisors.

Prof. Simon Ole Seno

Department of Environmental Studies, Geography and Agriculture

Maasai Mara University, Kenya.

Signature: **Date: 15th. June, 2021**

Dr. Samson Okongo Mabwoga

Department of Environmental Studies, Geography and Agriculture

Maasai Mara University, Kenya.

Signature: **Date: 15th. June, 2021**

DEDICATION

Dedicated to my late father who passed on during the course of this study, for his wise counsel and support, to my wife, for her perseverance and inexorable support, and to my cheerful son, Raylan Meier Oyieko born during the course of this study.

ACKNOWLEDGEMENTS

I am deeply indebted to acknowledge the unwavering and relentless guidance, advice, expertise and support from my supervisors Prof. Simon Ole Seno and Dr. Samson Mabwoga which culminated in the successful completion of this study. My heartfelt gratitude to Prof. Romulus Abila, Dean, School of Natural Resource Management and Animal Science, Dr. Samson Mabwoga, Chair, Department of Environmental Studies, Geography and Agriculture and the entire academic and non-teaching staff for their kind and constant assistance and research facilitation.

My profound appreciation to the African Forest Forum (AFF) for funding this research and Maasai Mara University (MMU) for collaboratively facilitating the study. Special thanks to the AFF for awarding me the research grant. Many thanks to Dr. Dickson Makanji whose advice fundamentally assisted me to secure AFF grant for this study.

This research would not have been successful without the help of various government departments and private sector. Many thanks to KFS, KWS, NEMA, KNBS, RCMRD and NCG for their technical and logistical support during my research period. My sincere gratitude goes to Mr. James Muthoka, Data Dissemination Officer at RCMRD, for his scientific and technical assistance and unconditional data provision. Many thanks to Narok County Government, Environment and Water Department for allowing me to undertake this research.

I am grateful for the kind assistance of my field research team, many thanks to Sogoo Community Forest Association (CFA), Olololunga CFA and Olpusimoru CFA for their logistical support during data collection period. Finally, I am very grateful to my family and friends whose support and encouragements propelled me to the successful completion of this study.

Table of Contents

DECLARATION ...... **II**

DEDICATION ...... **III**

ACKNOWLEDGEMENTS ...... **IV**

TABLE OF CONTENTS ...... **V**

LIST OF TABLES ...... **IX**

LIST OF FIGURES ...... **X**

ACRONYMS ...... **XII**

ABSTRACT ...... **XIII**

CHAPTER 1: INTRODUCTION **1**

1.1 Background **1**

1.2 Problem Statement **4**

1.3 Research Objectives **6**
- 1.3.1 General Objective 6
- 1.3.2 Specific Objectives 6

1.4 Research Questions **6**

1.5 Justification of the Research **7**

1.6 Scope and Limitation of the Study **8**

CHAPTER 2: LITERATURE REVIEW **10**

2.1 Global Climate Change and Variability **10**

2.2 Regional Climate Change and Variability **11**

2.3 Climate Change Impacts and Vulnerability **12**

2.4 Climate Change and Variability in Kenya **13**
- 2.4.1 Climate Change and Variability Projections in Kenya 13
- 2.4.2 Climate Change Impacts, Risks and Vulnerability in Kenya 14
- 2.4.3 Effects of CCV on Forestry Resources 16

2.5 Climate Change and Variability is a Geographic Problem **17**

2.6 Remote Sensing (RS) of the Earth Resources **18**
2.6.1 Satellite Remote Sensing (SRS) of the Earth Resources 19
2.6.2 Satellite Remote Sensing and Climate Change and Variability.. 23
2.6.3 Remote Sensing in Forestry and Vegetation Mapping 23
2.6.4 Remote Sensing and Land Cover/use Change Detection 27

2.7 Theoretical and Conceptual Framework **28**

CHAPTER 3: RESEARCH METHODOLOGY **30**

3.1 Study Area **30**
3.1.1 Geographical Location of the Study Area 30
3.1.2 Biophysical Description 32
3.1.2.1 Topography 32
3.1.2.2 Climate 33
3.1.2.3 Geology and Soils 34
3.1.2.4 Hydrology 34
3.1.2.5 Vegetation 35
3.1.3 Threats to the Forests... 35
3.1.4 Socio-economic Characterization... 36
3.1.4.1 Settlement... 36
3.1.4.2 Communities Adjacent to the Forests 36
3.1.4.3 Economic Activities 36

3.2 Research Design **37**

3.3 Spatial Survey and Climate Variability in the Study Area **37**
3.3.1 Spatial Survey and Climate Variables Data 37

3.4 Satellite Remote Sensing of the Study Area **38**
3.4.1 Satellite Imagery Data 38
3.4.2 Selection of Satellite Images for the Study Area 39
3.4.3 Landsat Images Characteristics 40
3.4.4 Satellite Images Processing 42
3.4.4.1 Images Import 43
3.4.4.2 Geometric Correction.. 43
3.4.4.3 Radiometric Calibration 45
3.4.4.3.1 Conversion of DN Values to Physical Units... 45
3.4.4.4 Atmospheric Correction 49
3.4.4.5 Image Composite and Mosaicking 49
3.4.4.6 Image Sub-setting.. 50
3.4.5 Image Classification 52
3.4.6 Classification Accuracy Assessment 53
3.4.7 Normalized Difference Vegetation Index (NDVI) 53
3.4.8 Change Detection 54
3.4.8.1 Post Classification Change Detection 55
3.4.8.2 NDVI Change Detection 55
3.4.9 Ground Truthing.. 55
3.4.10 Software... 56

3.5 Household (HH) Survey of the Study Area **56**
3.5.1 Study Setting 56
3.5.2 Household Survey Sampling Procedure 57
3.5.3 Study Population Sampling 59
3.5.4 Household (HH) Survey Data 60
3.5.5 Data Collection Instruments 61
3.5.6 Validation and Reliability of the Instruments 61
3.5.7 Ethical Concerns of the Study 62
3.5.8 Household Survey Data Analysis 62

CHAPTER 4: RESULTS AND DISCUSSION **63**

4.1 Trends in Observed Precipitation **63**

4.2 Trends in Observed Temperature **65**

4.3 Characterization of Land Cover / Use Changes in MFC using Remote Sensing Techniques **67**
4.3.1 Images Classification 67
4.3.2 Classification Accuracy Assessment 77
4.3.3 Normalized Difference Vegetation Index (NDVI) 83
4.3.4 Change Detection 85
4.3.4.1 NDVI Change Detection 85

4.4 Assessment of Vulnerability of the Forest Resources and People to CCV **89**
4.4.1 Socio-Demographic Characteristics and Education 89
4.4.2 CCV awareness 90
4.4.3 Perception of the Study Population on CCV 93
4.4.3.1 Perception on Causes of CCV 93
4.4.3.2 Perception on the Evidence for CCV 94
4.4.3.3 Perception on Adaptation and Mitigation of CCV 95
4.4.3.4 Perception on CCV Impacts and Vulnerability 95
4.4.4 Assessment of CCV Vulnerability 96
4.4.4.1 Exposure 96
4.4.4.2 Sensitivity 98
4.4.4.2.1 Forestry and Forest Resources 98
4.4.4.2.2 Food security 99
4.4.4.2.3 Health 101
4.4.4.2.4 Livelihoods of the Study Population 103
4.4.4.2.5 Water sources 106
4.4.4.3 Adaptive Capacity of the Households 108
4.4.5 Household Survey Discussion 109

CHAPTER 5: CONCLUSION AND RECOMMENDATION **114**

5.1 Summary of the Key Findings **114**
5.1.1 Spatio-temporal variability in the state of climate variables in the study area 114
5.1.2 Characterization of the land cover/use changes in the study area 114
5.1.3 Impacts of climate variability and land cover/use changes in the study area 114
5.1.4 Vulnerability of the people and forest resources to the impacts of CCV 115

5.2 Recommendations 117
5.2.1 Suggestions for further research 117

REFERENCES 118

APPENDICES... 134

LIST OF TABLES

Table 2.1: Landsat Missions…………………………………………………..21
Table 3.1: Landsat 5, 7 and 8 (OLI/TIRS) data used for the study……………...39
Table 3.2: Image Characteristics of the Landsat sensors………………………..42
Table 4.1: Land cover classes in the study area and their descriptions …..……...68
Table 4.2: Land Cover Classes Area (in Ha) and their Respective Percentages...74
Table 4.3: Accuracy Assessment Error Matrix for 1990……………………….. 77
Table 4.4: Accuracy Assessment Error Matrix for 2000 ………………………..78
Table 4.5: Accuracy Assessment Error Matrix for 2010 ………………………..78
Table 4.6: Accuracy Assessment Error Matrix for 2016 ……………………….78
Table 4.7: Accuracy Assessment Totals for 1990………………………………..81
Table 4.8: Accuracy Assessment Totals for 2000………………………………..81
Table 4.9: Accuracy Assessment Totals for 2010………………………………..81
Table 4.10: Accuracy Assessment Totals for 2016………………………………82
Table 4.11: Gender proportions by age categories of the respondents……….....89
Table 4.12: Cross tabulation of education levels and employment status of the respondents……………………………………………………….90
Table 4.13: Awareness of CCV in different age categories of the respondents....91
Table 4.14: Awareness of CCV by years of residence of the respondents………92
Table 4.15: Awareness of CCV against the respondent’s occupation and employment status.…………………………………………………93
Table 4.16: Respondents opinion about occurrence of natural disasters………...97
Table 4.17: Accessibility of medical facilities by gender……………………....101
Table 4.18: Correlation matrix on relationship between occurrence of EWEs and diseases/infections…………………………………………………103
Tables 4.19: Primary livelihood activities and climate aspects………………...105
Table 4.20: Respondent’s CCV adaptation and mitigation strategies…………108

LIST OF FIGURES

Figure 2.1: Pressure State Effects Response (PSER) Model…………………….....29
Figure 3.1: Location of the Study Area……………………………………….....32
Figure 3.2: Monthly precipitation for the study area……………………………33
Figure 3.3: Mean monthly rainfall and temperature for the study araea…………34
Figure 3.4: Satellite Imagery Study Design (Images Processing and Analysis)…44
Figure 3.5: Composite subset image of the study area for the year 1990………..50
Figure 3.6: Composite subset image of the study area for the year 2000………..51
Figure 3.7: Composite subset image of the study area for the year 2010………..51
Figure 3.8: Composite subset image of the study area for the year 2016………..52
Figure 3.9: Map for the administrative locations used in the study……………...57
Figure 3.10: Overall methodological framework and sampling design…….........59
Figure 4.1: The trends of mean monthly rainfall and temperature variation…......63
Figure 4.2: The trends of monthly rainfall variability from 1990 – 2013……… 64
Figure 4.3: The trends of mean monthly min, average and max, temperature......65
Figure 4.4: The trends of monthly maximum temperature from 1995 – 2013…..66
Figure 4.5: The trends of monthly minimum temperature from 1995 – 2013…...66
Figure 4.6: The trends of mean annual rainfall and temperature variation from 1990 – 2014...67
Figure 4.7: Land cover/use thematic map of the study area for the year 1990.... 68
Figure 4.8: Land cover/use thematic map of the study area for the year 2000......69
Figure 4.9: Land cover/use thematic map of the study area for the year 2010......69
Figure 4.10: Land cover/use thematic map of the study area for the year 2016…70
Figure 4.11: Land Cover Classes Trends from 1990 – 2016…………………....71
Figure 4.12: Land Cover Classes Trends from 1990 – 2016…………………....72
Figure 4.13: Percentage Land Cover Changes (1990-2016).……………………75
Figure 4.14: Percentage Land Cover Changes from 1990 – 2016……………....76
Figure 4.15: Overall Change in Forested Land Cover Areas.…………………....77
Figure 4.16: Overall Change in Non-forested Land Use….……………………..77
Figure 4.17: The study area NDVI thematic map for the year 1990………….....83
Figure 4.18: The study area NDVI thematic map for the year 2000…………….84
Figure 4.19: The study area NDVI thematic map for the year 2010………….....84
Figure 4.20: The study area NDVI thematic map for the year 2016………….....85
Figure 4.21: NDVI changes highlight map of the study area for 1990 – 2000….86
Figure 4.22: NDVI changes highlight map of the study area for 2000 – 2010….87
Figure 4.23: NDVI changes highlight map of the study area for 2010 – 2016….87
Figure 4.24: NDVI changes highlight map of the study area for 1990 – 2016….88
Figure 4.25: Awareness of CCV by gender of the respondents………………....91
Figure 4.26: Awareness of CCV by age……………..92
Figure 4.27: Awareness of CCV by level of education.......................................92
Figure 4.28: CCV is just natural fluctuation in Earth's temperature………….....94
Figure 4.29: Human activities have no significant impacts on global temp……..94
Figure 4.30: Pollution from industries is the main cause of CCV……………....94
Figure 4.31: Developing countries should take most of the blame for CCV…....94
Figure 4.32: The evidence for CCV is unreliable..…………………………........95

Figure 4.33: It is too early to say whether CCV is really a problem…………....95
Figure 4.34: It is already too late to do anything about CCV…………………...95
Figure 4.35: The government is not doing enough to tackle CCV……………...95
Figure 4.36: Flooding is not increasing, there is just more reporting of it in the media these days…………………………………………………...96
Figure 4.37: The effects of CCV are likely to be catastrophic…………………96
Figure 4.38: The ability to make accurate weather prediction……………….....97
Figure 4.39: Rainfall consistency………………………...........................97
Figure 4.40: Length of growing period (seasonality)……………………......98
Figure 4.41: Floristic composition of vegetation (indicator of habitat quality)...98
Figure 4.42: Percentage of respondents on changes in forestry………………...98
Figure 4.43: Effects on livelihood if the exposure of forestry and forest resources continued...99
Figure 4.44: Livelihood portion that directly or indirectly rely on forestry and forest resources..…………………………………………………99
Figure 4.45: Percentages of respondent's rating on livelihood resources……...100
Figure 4.46: Percentages of respondent's rating on livelihood resources……...101
Figure 4.47: Incidences of crops diseases and infections……………...........102
Figure 4.48: Human diseases, deaths and infections…………………………..102
Figure 4.49: Incidences of livestock diseases and deaths……………………...102
Figure 4.50: Activities primarily depended upon for livelihoods……………...104
Figure 4.51: Proportion of primary livelihood activities that are directly reliant on climate/weather……………………………………………………102
Figure 4.52: Aspect of climate that poses the greatest livelihood problems…..102
Figure 4.53: Primary source of lighting to the home………….......................106
Figure 4.54: Primary source of energy for cooking…………………….........106
Figure 4.55: Primary source of energy for heating…………………..............106
Figure 4.56: Water resources status……………………………………...107

Acronyms

CAD	Computer Aided Design
CCV	Climate Change and Variability
CFC	Chloroflouro Carbon
DN	Digital Number
DOS	Dark Object Subtraction
EOS	Earth Observation Satellites
ERDAS	Earth Resources Data Analysis System
ESRI	Environmental Systems Research Institute
ETM+	Enhanced Thematic-Mapper Plus
EWE	Extreme Weather Events
GHG	Greenhouse Gas
GIS	Geographic Information System
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
ITCZ	Inter-Tropical Convergence Zone
KFS	Kenya Forest Service
KMD	Kenya Meteorological Department
KNBS	Kenya National Bureau of Statistics
KWS	Kenya Wildlife Service
MEMR	Ministry of Environment and Mineral Resources
MFC	Mau Forest Complex
MRB	Mara River Basin
MSS	Multi-Spectral Scanner
NCG	Narok County Government
NDVI	Normalized Difference Vegetation Index
NEMA	National Environment Management Authority
OLI	Operational Land Imager
RCMRD	Regional Centre for Mapping of Resources for Development
RS	Remote Sensing
SPSS	Statistical Package for Social Scientists
TIRS	Thermal Infrared Sensor
TM	Thematic-Mapper
USGS	United States Geologic Survey

Abstract

Climate change and variability are immediate and severe threats to the environment and socio-economic systems. The study was carried out within the Mau Forest Complex (MFC), Narok County to characterize the effects of climate change and variability (CCV) on biophysical and socio-economic systems. The MFC is the largest remnant closed canopy Afromontane forest in East Africa and a critical catchment area for many river basins. Unfortunately, this socio-ecological system is faced with unprecedented onslaught threatening its existence. The study was undertaken based on the premise that such resources are highly susceptible to climatic variations and unsustainable anthropogenic activities triggered by such variations and extreme weather events. Longitudinal and cross-sectional research designs with mixed methods were used to infer results on Landsat imagery, climate variables and household survey data. Climate and satellite imagery data spanning 26 years were obtained from Kenya Meteorological Department and United States Geologic Survey respectively. The satellite images were processed and subjected to unsupervised classification and NDVI thematic maps creation. Change detection analyses were performed through post classification and NDVI image differencing methods to produce land cover/use thematic maps. Household survey sample size was calculated based on probability proportional to estimated size. Proportionate stratified multistage clustered sampling and snowball sampling for key informant interviews were used to determine the sample respondents. Evidence of association and significance tests between variables were measured using Spearman's Chi-square (χ^2) test of independence and generalized linear model. The results indicated increasing precipitation variability and declining overall precipitation trend. The observed variability in extreme temperature events indicated warming tendencies with an increasing overall trend in mean annual temperature. Satellite imageries classification results showed that dense forest cover significantly reduced while other land cover/use showing an increasing trend. NDVI thematic maps revealed a reduction in vegetation vigour. Household survey results revealed that majority of the respondents were aware of CCV while the socio-economic systems are vulnerable to the impacts of CCV as evidenced by existence of extreme climate related events such as flash floods, droughts, land/mudslides and extreme temperatures leading to environmental degradation, deforestation, agricultural land expansion and other unsustainable land uses. The resulting impacts to the biophysical and socio-economic systems in the area were linked to crops yield failure, land use conflicts, high prices and shortage of farm produce, food insecurity, diseases and deaths. The national and Narok County government must devote their resources in educating and informing the communities about all CCV's aspects in all sectors through tailor made educational programmes, awareness and sensitization campaigns, incentive environmental conservation programmes, strengthening adaptive capacity and mitigation strategies, formulation and implementation of adequate adaptation and mitigation policies such as afforestation and reforestation, relocating people from the encroached and areas with contested settlement, enhance sustainable charcoal production, boost food production with minimum impacts, agroforestry, enhance the use of traditional knowledge, poverty alleviation and livelihoods improvement strategies, invest in social capital systems and adopt measures to curb soil erosion and climate smart technologies to help cope with the adverse impacts of CCV.

CHAPTER 1: INTRODUCTION

1.1 Background

Climate change and variability (CCV) are the most complex, immediate and severe threats to the environment, socio-economic systems and humanity; discussed in many scientific domains, workshops and conferences (Chukwu & Asiegbu, 2011; IPCC, 2013; Mngumi, 2016; IPCC, 2018; Leippert *et al.*, 2020). Global warming, as the topic connotes, is a world-wide phenomenon in which the earth's surface is gradually being heated up due to natural and man-made actions (FAO, 2010; Chukwu & Asiegbu, 2011; Baral, 2012). The scientific sphere reiterates that CCV have caused significant biophysical and socio-economic effects across most sectors with the most vulnerable being forestry, biodiversity, agriculture and livestock, water, health, fisheries, energy and tourism (GoK, 2010; NEMA, 2013; Alireza & Peyman, 2014).

Climate change, including increases in frequency and intensity of extremes, has adversely impacted food security and terrestrial ecosystems as well as contributed to desertification and land degradation in many regions (IPCC, 2018; IPCC, 2019). Extremes of climate variables have direct and indirect effects on forests and people. Changes in spatio-temporal patterns of temperature and precipitation are associated with extreme weather events (EWE) such as floods, droughts, landslides, heat and cold waves, wind storms, wildfires and vegetation shift (IPCC, 2007; 2013). The Intergovernmental Panel on Climate Change (IPCC, 2014) indicates that the most hit are the poorest and vulnerable people in developing countries. Natural calamities like the glacial retreat, deprivation of the soil quality, depletion of the ozone layer, snow avalanches, abrupt variations in weather patterns, changes in population dynamics, perishing of species (in particular endemic species up to 34%) and the substantial damage to the natural resources are some of the severe challenges laid forth by climate change and variability (Dyurgerov & Meier, 2005).

The major reason adduced for CCV is the intensification of greenhouse gasses (GHGs) emission (Chukwu & Asiegbu, 2011; Baral, 2012; IPCC, 2014; IPCC, 2018). Global warming is a phenomenon which occurs as the energy from the sun warms the earth when its radiant heat is absorbed by GHGs and become trapped in the atmosphere (Chukwu, 2008). Some of the most common GHGs are water vapour, carbon dioxide, chlorofluorocarbon (CFC) and methane (CH_4). The gradual temperature rise warms up the earth and causes vital climatic variations across the globe. Several scientists believe that human activities are some of the primary causes of global warming which may have devastating consequences on the climate, environment and societies (IPCC, 2007; Alireza & Peyman, 2014). Human activities are estimated to have caused approximately 1.0°C of global warming above pre-industrial levels, with a likely range of 0.8°C to 1.2°C. Global warming is likely to reach 1.5°C between 2030 and 2052 if it continues to increase at the current rate (IPCC, 2018). Climate-related risks for natural and human systems are higher for global warming of 1.5°C than at present (IPCC, 2018).

Climate change being a long term phenomenon is manifested in the short term by climate variability in the form of weather uncertainties (unpredictable seasons), persistent climatic abnormalities (drought and floods), rampant environmental degradation and eminent food insecurity occurring at various levels, and low adaptive capacity to the impacts of these climate related events (Boko *et al.*, 2007). Some places may experience more sudden and stormy rains resulting to floods, while others less rain resulting to persistent and severe drought. Warmer temperatures will cause a greater amount of evaporation from lakes, rivers, and oceans. In some areas this could be good, and in others it could be considered adverse. Global warming would lead to tropical storms appearing with greater frequencies (Murck *et al*., 1999; IPCC, 2007; FAO, 2010). Increased precipitation and evaporation also force plant life to adjust and shift (Cavaliere, 2009).

As CCV impacts intensify, affected communities resort to unsustainable activities such as forest encroachment and settlement, logging, expansion of agricultural land, charcoal burning, fuel wood collection, increased use of fertilizers and hazardous substances to boost food production resulting to terrestrial and aquatic pollution from point and non-point sources and atmospheric pollution from industrial and automobile emissions (FAO, 2019a). Climate change has severe negative impacts on livelihoods and food systems worldwide. Our future climate according to latest scenarios seriously undermine current efforts to improve the state of food security and nutrition, especially in sub-Sahara Africa (IPCC, 2018; IPCC, 2019). In addition, as CCV impacts intensify, women, elderly, sick, children and other marginalized groups become more vulnerable (FAO, 2010; Lasco *et al*., 2010).

Intensification of CCV impacts exacerbate socio-economic challenges such as water scarcity, poor healthcare, resources-use conflicts and inequity, diminishing ecological resilience, natural and human displacements, poverty and lose of livelihoods, transport and infrastructural destruction, food insecurity (crops yield failure), diseases and even deaths (IPCC, 2007; UNEP, 2009; Wondimagegn & Lemma, 2016). Unprecedented and unusual rates of change continue to affect major earth systems including hydrological cycle, carbon and nutrients cycles, ecosystems (water, food and fiber) and accelerate environmental stressors (Lasco *et al*., 2010).

Kenya's Narok County has continued to experience various extreme weather events (EWEs) recently. There have been unpredictable and unreliable changes in precipitation occasioning persistent floods and droughts. The frequent and intensified occurrence of flash floods and land/mudslides in the County have led to destruction of crop fields, infrastructure and properties; human displacement and/or deaths. The shorter and intermittent growing seasons due to drought have led to decline or failure in crops yield causing food insecurity, higher prices in food and farm produce, loss of income, resources-use conflicts and political disorder (Wondimagegn & Lemma, 2016). The pastoralists have also suffered a great loss of livestock to severe and frequent droughts. In addition, they have also led to decline in, and even loss of biodiversity and environmentally induced migration and displacements (FAO, 2010; NEMA, 2013). The impacts are exacerbated by weak adaptive capacity and resilience, lack of adequate knowledge, gender insensitivity and weak policies and response strategies to the impacts. Sufficient societal, forestry and forest resources adaptive capacity and resilience strategies need to be put in place in order to enhance biodiversity sustainability, improved environmental quality and social well-being and reduce gender disparities, intergenerational inequity and marginalization (Richard *et al.*, 2016; Sinclair *et al.,* 2019). Therefore, with the advancement in geo-information technology, researchers should venture into studies that utilize the advancements to the benefit of the people and environment; and help minimize the environmental threats of CCV.

CCV is a geographic problem thus needs a geographic solution. There is a need to exploit the advancements in the field of geo-information technology (Remote Sensing and GIS) to study the climatological trends and their effects on biophysical and socio-economic systems. Geographic Information System (GIS) is a toolset that captures, stores, analyzes, manages and presents data that are linked to location(s). According to Fotheringham *et al*. (2000), GIS is simply incorporation of statistical analysis, cartography and database technology. Given the vast range of spatial analysis techniques that have been developed recently, this could just be the state of the art technology to help unravel the environmental effects of climate change and variability. The GIS packages are rapidly and increasingly emerging and integrating analytical toolsets as standard built-in facilities (Fotheringham *et al*., 2000). Therefore, GIS is described as any system with capability to integrate, store, analyze, edit, share and display geographic information using spatio-temporal location as the main index variables for the rest of all other geographic information (Goodchild, 1987). GIS can be used to spatially and temporally reference and locate variables.

The earth's surface, subsurface and atmospheric conditions can be studied by feeding satellite data into a GIS platform. It gives researchers the ability to investigate the variations in earth's processes over time. For example, changes in vegetation vigour during growing season can be simulated to determine the intensity and severity of drought in a given area. The resulting graphical maps known as normalized difference vegetation index (NDVI) are indicative of vegetation health which can be used to detect regional interruption in rainfall and its effect on vegetation cover (Goodchild, 1987).

This study explored the integrative analytical toolsets in the geo-information technology to link the characterized spatio-temporal land cover/use changes and changes in the state of climate variables (temperature and precipitation) to the environmental impacts of climate change and variability in the area using remote sensing imageries and climate data for a period of 26 years (1990 – 2016). Temporal range was chosen due to availability of quality satellite imageries and the fact that most changes in land cover/use in the area were experienced since early 1990s (Ministry of Forestry and Wildlife, 2010). The study also assessed the vulnerability of the biophysical and socio-economic systems to the impacts of climate change and variability with particular emphasis on gender, age and marginalized groups using household survey. Finally, based on the findings, the study recommended appropriate and adequate adaptive strategies and policies, resilience building, prioritization on sensitivity and response strategies.

1.2 Problem Statement

Perusal of literature reveals insufficient information on trends of climate change and variability; and its impact on the critical biophysical and socio-economic systems in Narok County, Kenya. Little work has been done in the area, with most studies reporting work at regional or national level. Stephen &

Rachel (2013) assessed the coherent and cost-effective policy response to climate change in Kenya but not at the technological and applied level. FAO (2010) analyzed the risks of climate change and variability in the smallholders sector, a case study of the Laikipia and Narok districts representing major agro-ecological zones of Kenya. Through the available analytical toolsets in GIS and Remote Sensing (RS), these knowledge gaps can be bridged. In view of this, the fast growing field of geo-information technology offers invaluable possibilities to capture and analyze the trends of environmental effects of climate change and variability in the area. RS and GIS can be used to study these environmental effects of climate change and variability; and assist to put in place adequate adaptive strategies, resilience and mitigation measures to help reduce and/or control the impacts.

Extreme weather events and natural disasters such as the prolonged droughts, flash floods, land/mudslides, warm and cold spells are currently and increasingly being experienced in Narok County. These extreme weather events can be directly or indirectly linked to the environmental impacts of climate change and variability which often result to decline in crops yield, increased crops failure, decline in, and even loss of biodiversity, food insecurity, higher farm produce prices, higher rates of unemployment, loss of income, resource use conflicts and political instability with adverse impacts on biophysical integrity and social fabric of the people.

Traditionally, the livelihoods of the Maasai community who are the majority in Narok County is structured around pastoralism. Sub-Saharan African pastoralism involves highly fluid production systems responding flexibly to variable and unpredictable arid and semi-arid rangeland environments (Homewood *et al*., 2006). As such, the impacts of global CCV will restrict access to key resources of pasture and water, exacerbating pastoralist vulnerability to drought herd loss and threaten the sustainability of the pastoral production systems. In addition, the County has witnessed its fair share of drought and famine due to changes in the climatic patterns of the area caused by massive deforestation and environmental degradation of the Mau Forest Complex (MFC).

Therefore, this study explored how geo-information technology (RS and GIS) can be used to characterize the impacts of climate change and variability on the biophysical and socio-economic systems in the area. The study characterized the land cover/use changes, assessed the spatio-temporal variability in the state of climate (precipitation and temperature), and assessed the impacts of the characterized land cover/use changes and spatio-temporal climate variability on the biophysical and socio-economic systems. The study also assessed how vulnerable the people and the forests are to the impacts of climate change and variability and the coping strategies (adaptation and mitigation) to the impacts.

1.3 Research Objectives

1.3.1 General Objective

The general objective of this study was to characterize and assess the environmental effects of climate change and variability using geo-information (RS and GIS) and household survey techniques in Mau Forest Complex of Narok County. In addition, assess the vulnerability of the socio-economic systems with particular emphasis on gender, age and marginalized groups in the area.

1.3.2 Specific Objectives

1. To assess the spatio-temporal variability of climate variables (precipitation and temperature) in the Mau Forest Complex over the last 26 years (1990 – 2016).
2. To characterize the land cover/use changes in Mau Forest Complex over the last 26 years (1990 – 2016).
3. To assess the impacts of spatio-temporal climate variability and the characterized land cover/use changes on the biophysical and socio-economic systems in the area.
4. To assess the vulnerability (exposure, sensitivity and adaptive capacity) of the people and forest resources to the impacts and what has been done to cope (adapt and mitigate) with such impacts.

1.4 Research Questions

1. What are the spatio-temporal variability of climate variables (precipitation and temperature) in the area?
2. How can geo-information technology (RS and GIS) be used to characterize the land cover/use changes in the area?
3. What are the impacts of the characterized land cover/use changes and spatio-temporal climate variability on the biophysical and socio-economic systems in the area?

4. How vulnerable (exposure, sensitivity and adaptive capacity) are the people and the forest resources to the impacts and what have been done to cope (adapt and mitigate) with the impacts in the area?

1.5 Justification of the Research

Several studies involving climatological data and the results of the simulation models revealed that the average temperature of the earth is increasing (IPCC, 2001; 2007; Baral, 2012; IPCC, 2013; NEMA, 2013; IPCC, 2014). Therefore, CCV negatively affects the earth's critical systems, mainly by rising temperature as a consequence of global warming (Sheffield & Wood, 2008). The critical biophysical and socio-economic systems in Narok County include the Maasai-Mau, Trans-Mara and Olpusimoru forest blocks which form part of the larger MFC, the largest remnant montane forest in East Africa and the major catchment area for many river basins including the famous Mara River Basin and Ewaso Nyiro South River Basin; the woodland and savanna forests of the Maasai Mara National Reserve and the adjacent conservancies and ranches supporting a great array of wildlife and biodiversity; and the agro-ecological zones known for wheat, beans and maize production. The socio-economic wellbeing of the County greatly depends on these resources for their livelihood support.

Forests, tree resources and the people are very important features of the communities though faced with many challenges for their survival as a result of weak and inadequate knowledge based adaptive capacity, resilience and mitigation strategies to the impacts of CCV. There is urgent need to enhance the role of African forestry and its adaptive capacity to the adverse effects of climate change and variability so as to sustain biodiversity and improve environmental quality and livelihoods. There is also a need to integrate the gender sensitivity, policy responses and strategies with the adaptive capacity to CCV.

Now, as the scientific fraternity recognizes the environmental concerns of anthropogenic activities influencing CCV; RS combined with GIS technologies are becoming essential tools to understand the impacts of these variations over time. GIS enables the combination of various sources of data with existing maps and up-to-date information from earth observation satellites (EOS) along with the outputs of climate change models (Sheffield & Wood, 2008). This can help in understanding the effects of climate change and variability on the complex biophysical and socio-economic systems. The outputs from a

GIS in the form of thematic maps combined with satellite imagery allow researchers to view their subjects in ways that literally have never been seen before (Stein *et al*., 2002). The images are also invaluable for conveying the effects of climate change and variability to non-scientists.

The GIS technology has been used in natural resource management and environmental planning, monitoring and modeling which makes it preferably applicable in this study. It can also be used for an earth-surface-based environmental impacts study. It is the science underlying the geographic concepts, applications and systems (Fotheringham & Rogerson, 1993). The technological application would be very vital to assist, minimize and/or control further environmental degradation and socio-economic issues as global warming and its consequences can affect critical systems.

1.6 Scope and Limitation of the Study

This research was executed at the Mau Forest Complex (MFC) of Narok County to examine the environmental effects of CCV. Specifically, the general goal of this research was to characterize and assess the effects of climate change and variability on the biophysical and socio-economic systems at the MFC, a largest remnant closed canopy forest in Eastern Africa, using RS and GIS. Finally, determine the vulnerability of these systems to the impacts of climate change and variability, and the adaptation strategies to the impacts. The study was undertaken based on the premise that such remnant Afromontane forests are highly susceptible to climatic variations and unsustainable anthropogenic activities triggered by such variations and extreme weather events (natural disasters).

However, land cover/use changes are influenced by physical location, demographic, cultural and socio-economic factors at the household, community, national and global level; therefore every land use system adopted differs from the rest in the extent of the applied inherent driving forces. Thus the results of this study might only be applicable to areas which have the same climatic and physical location characteristics as those of the study area. Furthermore, the factors influencing the land cover/use systems are dynamic depending on political and institutional setup around the study area. Therefore, the results from this study should be supported by global and national institutional and political arrangements.

The satellite imageries and climate variables data was limited to quality, cost and accessibility of the available data in the respective institutional repositories and analysis software. The spatial survey information acquired during ground truthing was limited due to poor infrastructural development, financial constraints, human resources, geographical area and existing forest morphometry, language barrier and socio-demographic characteristics in the area. Finally, the study was limited to only the sampled locations and three forest blocks of the expansive Mau Forest Complex due to inadequacy of time and funds, therefore, any generalization to other contexts should be done with these limitations in mind.

CHAPTER 2: LITERATURE REVIEW

2.1 Global Climate Change and Variability

Warming of the climate systems is unequivocal, as is now evident from observations of increases in global average air and ocean temperatures, widespread melting of snow and ice, and rising global average sea level – IPCC AR5 (Cubasch *et al*., 2013; IPCC, 2013; 2014; 2018; 2019). Eleven of the last twelve years (1995–2006) rank among the 12 warmest years in the instrumental record of global surface temperature (since 1850). Global surface temperatures have typically varied by (5 – 7)℃ through these cycles, with large changes in ice volume and sea level, and temperature changes as great as (10 – 15)℃ in some middle and high latitude regions of the Northern Hemisphere (Cubasch *et al*., 2013). Since the end of the last ice age, about 10,000 years ago, global surface temperatures have probably fluctuated by little more than 1℃. Some fluctuations have lasted several centuries, including the little ice age which ended in the nineteenth century and which appears to have been global in extent (IPCC, 2018; IPCC, 2019).

The rate of CCV anticipated during the 21st century is unparalleled in human era. The average global temperature has typically varied by 5℃ over interlude of millions of years throughout the geologic period. Scientists have now realized that the earth's surface temperature, which has already varied by 0.8℃ since the late 1800s is likely to rise by another (1.4 - 5.8)℃ in the course of the 21st century (IPCC, 2013; 2014); changing spatial and temporal pattern of temperature and precipitation, and the frequency of the extreme climate events around the globe. Fundamental earth systems including ocean circulation and the hydrological, carbon and nutrient cycles upon which our lives are dependent will be adversely affected by such unprecedented rapid rate of change (Tao *et al.*, 2003). Natural and managed ecosystems providing us with food, water and fiber are disrupted exacerbating existing environmental stressors such as stratospheric ozone depletion, urban air pollution, desertification, declining water quality and deforestation (IPCC, 2001). Enormous efforts have been devoted by researchers to analyze how climate change and variability has influenced the natural environment and human society.

According to IPCC (2007), global atmospheric concentration of greenhouse gases (GHGs) such as carbon dioxide (CO_2), nitrous oxide (N_2O) and methane (CH_4) have increased remarkably due to anthropogenic activities since 1750s. Their levels have surpassed pre-industrial values as determined from ice cores straddling several thousands of years. Observational evidence from all continents have shown that warming has affected many natural systems as the global temperature rise of less than 1℃ has already triggered substantial changes in several natural systems and the imminent effects of much higher projected temperature rise by the end of the 21st century is startling (Fredolin *et.al.*, 2012).

2.2 Regional Climate Change and Variability

The IPCC (2007) AR4 portrays a situation that, Africa is one of the most vulnerable continent to climate change. The IPCC (2013; 2014) AR5 also gives convincing evidence that climate change is real and it is happening now, and that it will become worse and that the poorest in developing countries and most vulnerable people will be the worst affected. Climate change being a long term phenomenon is manifested in the short term by climate variability in the form of weather uncertainties (unpredictable seasons), imminent food insecurity occurring at various levels, persistent climatic abnormalities (drought and floods), low adaptive capacity to the impacts of these climatic related events and rampant environmental degradation (Pearce 1996; Tol, 2002; Mendelsohn & Williams, 2004; Boko *et al.*, 2007).

Africa has warmed by 0.7℃ in the 20th century and general circulation models (GCM) project warming across Africa ranging from 0.2℃ per decade (low scenario) to more than 0.5℃ per decade (high scenario) (Hulme *et al*., 2001; IPCC, 2007; 2013; 2014). The climate model scenarios show an increase in future mean annual temperature with projections from (1 - 3.5) ℃ by 2050 (SEI, 2009). A recent study report a rise of about 1℃ by 2030 to around 1.5℃ by 2050 for a mid-range emission scenario. Based on the Multi-Model-Dataset (MMD) of 21 global models and on the A1B-scenario, the projections for East Africa indicate that the median near-surface temperature in the 2080 - 2099 period will increase by (3 – 4) ℃ compared to the 1980 –1999 period (IPCC, 2007).

Precipitation in East Africa on the other hand is more variable; under intermediate warming scenarios, parts of Equatorial East Africa will likely experience (5 – 20)% increased rainfall from December – February and (5 – 10)% decreased rainfall from June - August by 2050 (Hulme, 2001; IPCC, 2007). Generally, climatic changes of this magnitude will have far reaching negative impacts on the availability of water resources, food security, agricultural resources, biodiversity, tourism, coastal development and human health. Although, the crops yield projections varies from one study to another depending on model used, majority of global and regional scale studies points to yield decline especially to the staple food. In some African countries (Kenya included), yields from rain fed agriculture could be halved by 2020 and the net revenues from agriculture could fall by 90% by 2100 (IPCC, 2007).

While many regions are likely to experience the adverse impacts of climate change, of which some are potentially irreversible, some effects of climate change are likely to be beneficial. For instance, crop production in the mid and high latitudes is projected to increase at a local mean temperature increase of (1 – 3) ℃ (IPCC, 2007). Clearly, it is important to understand the nature of climate change risks, where natural and human ecosystems are likely to be most vulnerable, and what may be achieved by adaptive responses (Lasco *et.al*, 2010).

2.3 Climate Change Impacts and Vulnerability

The biophysical and socio-economic systems are confronted with a number of threats, such as environmental degradation, climate change and socio-economic challenges. These changes which may dampen or amplify the significance of the environmental challenges do not occur in seclusion and often reflect changes in the global markets (UNEP, 2009). Countries, vital ecosystems and other sectors such as forestry, health, agriculture, biodiversity and local economic activities are faced with very serious risks emanating from the impacts of climate change. Intertwined with other pressures, the impacts of climate change could also aggravate other serious local and regional socio-economic challenges such as inequitable distribution of resources, poor healthcare, poverty, reducing ecological resilience and energy uncertainty (UNEP, 2009). Climate change and variability poses varying threats, direct or indirect, both to natural and human systems. Ecosystems, human health and socio-economic sectors are all vital to sustainable development as indicated by several scientific studies though very sensitive to climate changes and variability (IPCC 2001; 2007).

The impacts of global climate change on agriculture and environment could change the photosynthesis process and crops yield. Such evidence resulted into a wide number of reports that present agroecology as a promising systemic approach to address climate change by unlocking adaptation and mitigation potentials in agriculture and food systems, which would ultimately build resilience and stimulate sustainable development (Baker, *et al.*, 2019). The changes observed in climate might be attributed to its long-term natural fluctuations or to the human activities like land use changes and greenhouse gases emission (Alireza & Peyman, 2014). The effects of climate change and variability on vegetation cover and agricultural products were investigated by Anyamba & Eastman (1996) and Li & Kafatos (2000), showing that global warming and climate change have undesirable effects on many countries with approximately 50% of the associated total losses and damages being observed in agricultural section. Sheffield & wood (2008) iterated that the anticipated climate change may affect the future drought characteristics by altering the severity, duration and frequency of droughts due to the induced changes in climate variables, mainly by rising temperature as a consequence of global warming.

2.4 Climate Change and Variability in Kenya

CCV presents a number of economic, social and environmental challenges and opportunities to Kenya that should be addressed and harnessed to avoid slowing development gains and realization of Vision 2030 (Ongoma & Onyango, 2014). Weather and climate play an important role in daily activities of the societies across the globe and any shift in the two may be advantageous or may pose a negative impact to life, infrastructures and economy. Understanding the magnitude and frequency of extreme events related to weather and climate is paramount especially when building societal resilience (Ongoma & Onyango, 2014).

2.4.1 Climate Change and Variability Projections in Kenya

FAO (2010) indicated that Kenya's climate is expected to warm across all seasons during this century. The annual mean surface air temperatures are expected to rise between 3℃ and 4℃ by 2099 under medium emission scenario, an indication of temperature rise at the rate of 1.5 times compared to that of the global average (Boko *et al.*, 2007). As a result, the overall annual rainfall is expected to rise by around 7% during the same period though the increase will not be uniformly experienced spatially and temporally (FAO, 2010).

Rainfall variability is expected to rise and intensity and frequency of extreme weather events in the region are likely to be increased by warmer temperatures, meaning that many areas in East Africa will be faced with elevated risk of longer dry spells and heavier storms (FAO, 2010). The climate projections in Kenya are largely a reflection of these regional trends. The country's mean annual temperatures are expected to rise by (1 - 2.8)℃ by 2060s and (1.3 - 4.5)℃ by 2090s (IPCC, 2007). Such increase in temperature will be accompanied by up to 48% rise in mean annual rainfall with the greatest increase in the total rainfall occurring between October and December while the largest rainfall variation is expected to occur between January and February. The increase in rainfall is expected to be concentrated in the Lake Victoria region to the central highlands east of the Rift Valley based on regional variation within the country (FAO, 2010).

2.4.2 Climate Change Impacts, Risks and Vulnerability in Kenya

The impacts of climate change in Kenya is unmistakable as evidenced by extreme and harsh weather events. More specifically, since the early 1960s, both minimum (night time) and maximum (day time) temperatures have been on an increasing (warming) trend. The minimum temperature has generally increased by (0.7 – 2.0)℃ and the maximum by (0.2 – 1.3)℃, depending on the season and the region (GoK, 2010).

The pressure of CCV makes Kenya highly vulnerable to the impacts. The vulnerability is further aggravated by the fact that Kenya's economy is reliant on climate sensitive natural resources such as agriculture, forestry, wildlife-based tourism and water for socio-economic sustenance (Stephen & Rachel, 2013). Stern (2009) estimates that the central economic costs of climate change could be equivalent to 2.6% of GDP each year by 2030 for Kenya. The impacts of climate change and variability thus trigger a series of events with undesirable outcomes making the country unable to build the necessary adaptive capacity and resilience against climate change (Stephen & Rachel, 2013).

The dry lands of Kenya including Narok County are most vulnerable to CCV phenomenon. This has been caused by fragile nature of the environment exacerbated by the expansion of agricultural activities, forests encroachment and unsustainable land-use associated with swelling human population. The frequency and severity of both droughts and floods is already high and is expected to increase in coming years (FAO, 2010). Abnormal and abrupt onset of rainfall cause floods and destroy infrastructure, hamper physical mobility, damage crop fields, increase disease epidemics, death to livestock, and severe impact on livelihoods. These climate related events have led to rampant environmental degradation, resource use conflicts and desertification (GoK, 2009). The aridity of the dry lands has been aggravated by the increased frequency and severity of droughts which in turn is adversely affecting ecosystems balance, community's livelihoods, rain fed agriculture and overall food security. The elderly, women and children are adversely subjected to famine as a result of prolonged droughts which ultimately lead to severe malnutrition, diseases and eventual deaths (FAO, 2010).

Increasing human population and expansion of agricultural land for food production have been the major cause of destruction of vegetation cover and subsequent rampant environmental degradation. The demand for food, fuel wood (charcoal and firewood) and other forest products (including timber and poles for building and construction) exacerbate the problem (GoK, 2009). It is worthwhile noting that rising human population, deforestation and associated water catchments destruction significantly contributed to environmental degradation and depletion of Kenyan resources base (UNEP, 2008). For instance, the recent expansion of agricultural land for large scale wheat production, escalating rates of deforestation (mainly conversion of forests and bush lands to smallholder farms, charcoal burning and illegal logging upstream) and rapid encroachment in the MFC have been linked to the rising frequency of droughts and floods in Narok area (UNEP, 2008).

Kenya being no exception, adverse effects of climate change have been experienced all over the world and it has caused negative socio-economic effects in many sectors (GoK, 2009). Weather pattern variations (reduced rainfall and failed seasons), prolonged and frequent droughts, flash floods and landslides, shrinking water resources, environmental degradation and destruction of habitats, biodiversity loss, resurgence of pests and diseases, severe famine and hunger as a result of food insecurity and resource use conflicts are some of the general adverse effects of climate change experienced in Kenya (NEMA, 2013). Strong evidence suggests that many rural subsistence or smallholder farmers are left trapped in a vicious cycle of poverty and vulnerability due to recurrent droughts and frequent floods (Phiri *et al.*, 2005; KMD, 2008). UNEP (2005) established that rains used to fail every nine or ten years but currently the cycle seem to have change to five years. The country is experiencing droughts every two or three years recently (KMD, 2008).

More frequent and intense storms, floods, droughts and cyclones will also harm human health. These natural hazards can lead directly to death, injury and mental stress. Indirect effects would result from the loss of shelter, contamination of water supplies, reduced food supplies, heightened risk of infectious disease epidemics (such as diarrhea and respiratory disease), damage to health services infrastructure and the displacement of people. Higher temperatures and changes in precipitation and climate variability would alter, and in some cases extend, the geographic range and seasonality of vector-borne diseases. The temporal and spatial changes in temperature, precipitation and humidity that are expected to occur under different climate change scenarios would affect the biology and ecology of disease vectors and, consequently, the risk of disease transmission such as malaria, meningitis and other parasitic disease, and parasites, such as tsetse fly.

2.4.3 Effects of CCV on Forestry Resources

Kenya has 3.467 million ha of forest cover which is equivalent to 5.9% of land area. Out of which 2.4 % of total land area comprises of indigenous closed canopy forests, mangroves and plantations in both public and private lands (Ministry of Forestry and Wildlife, 2009). The areas covered by indigenous forests are considered to be significant water catchment areas with high levels of biodiversity and providing ecosystem goods and services to millions of people. Some of the indigenous forests have been cleared to give way to the establishment of plantation forests, originally meant to be buffer zones planted with quick growing trees for neighboring communities' wood requirements and industrial wood sources (IUCN, 1995).

Twenty years ago, Kenya's closed-canopy forests covered approximately 2% of the country (KIFCON, 1994). Ten years later, remote sensing data indicated that compared to global and African forest cover of 21.4 and 9.25% respectively, Kenya's closed canopy forest cover stood at less than 1.7% (UNEP, 2005). Today this figure is still falling, and this will have major negative socio-economic effects in the country (GoK, 2009). At a time when the world is confronted by climate change, forest cover can help to mitigate the effects of droughts and floods. Forests trap, store and slowly release rain water, the life blood of the economy. They support agriculture, fisheries, electricity production and urban and industrial development. Forests also produce wood and medicines, moderate climate, reduce erosion, shelter a disproportionate share of Kenya's biodiversity, and have religious and cultural significance. Yet Kenya's forests have been and remain the target of unabated destruction and degradation, over-exploitation, uncontrolled and unplanned development (Akotsi *et al*., 2006).

Climate has a direct influence on forest distribution, typically through extremes in temperature and precipitation amounts (Rogan & Miller, 2006). Despite the key structural and functional roles played by forestry resources in Kenya, there has been extensive forest ecosystem destruction through encroachment, unsustainable exploitation, fires, and agricultural land expansion. The forests are under increasing threats from irregular and ill-planned settlements and illegal forest resource exploitation. Over the last decades, approximately 25% of Mau forest has been lost to excisions and encroachment (GoK, 2009).

The 2003 –2005 forest cover change analysis findings reveal that Mau forests continue to be destroyed at an alarming rate. About 9,813 ha (9,295.72 ha indigenous forest and 517.87 ha plantation forests) were cleared, compared to 7,084.24 ha (most of it plantation) between 2000 and 2003. The other disturbing observation from Mau is that there are a number of new sites that show deforestation. Out of the 14 sites identified, eight were new, meaning that destruction is spreading. Most of the indigenous clearings, totaling 5,546.71 ha, occurred in old sites. Loss in new sites amounted to 3,749.01 ha. The Mau Complex forests therefore are clearly an ecosystem that requires urgent attention to curb rampant destruction of indigenous forest (Akotsi *et al.*, 2006).

The continued destruction of the Mau forests threatens the livelihood of many people. Most of the loss is attributed to continued irrational settlement of people within Mau in areas including those which are prone to erosion and unsuitable for agriculture (GoK, 2009). Kenya is already experiencing what scientists explain as the extensive impacts of climate change; persistent food problems as a result of decreased yields, habitat change in some areas leading to species range shifts, and changes in plant diversity which includes indigenous foods and plant-based medicines. During this century, this warming trend and changes in precipitation patterns are expected to continue accompanied by a rise in sea level and increased frequency of extreme weather events. Reduction in water quantity will lead to a reduction in water available for tree and forest growth, leading to reduced forest productivity and yields that would bring a gradual decrease in forest cover (Muoghalu, 2014).

2.5 Climate Change and Variability is a Geographic Problem

Radical changes experienced in earth's climate in the distant and recent past will most certainly occur in the near future. As the world’s population, industrialization and urbanization continue to rise, so too will environmental stressors such as pollution increase. These factors would trigger enormous consequences in quality of life on earth because they exacerbate change in climate and environmental quality (Dangermond & Matt, 2010). Both observations and predictions in the past and future are useful in studying climate change. Dangermond & Baker (2010) iterated that GIS with its ability to infinitely combine diverse datasets in a number of ways, is a useful platform for almost all field of knowledge from archaeology to zoology. Global climate change is a difficult, complex, politically charged and vitally important issue. Every aspect of climate change affects or is affected by geography, be it at a global, regional, or local level. To help us better understand such geographies, GIS is the single most powerful integrating tool for inventorying, analyzing, and ultimately managing this extremely complex problem (Dangermond & Matt, 2010).

2.6 Remote Sensing (RS) of the Earth Resources

Remote sensing is the practice of deriving information about the Earth's land and water surfaces using images acquired from an overhead perspective, using electromagnetic radiation in one or more regions of the electromagnetic spectrum, reflected or emitted from the Earth's surface (Campbell & Wynne, 2011). The term was coined when aerial photography no longer accurately described the many forms of imagery collected using radiation outside the visible region of the spectrum (Campbell, 2008). It has become a very powerful tool for gathering information on various resources and phenomena on the surface of the earth, depending on how they reflect the electromagnetic radiations falling on them (Mabwoga, 2013). It has been used in different fields of ecological research for mapping vegetation, species distribution, modeling, land use status and change, estimating environmental processes, developing landscape ecology metrics, assessing community biodiversity, and estimating climatic parameters (Rocchini, 2010).

Earth Observation (EO) data have become an important tool for characterizing the main processes and estimating key variables governing the earth (Hayman *et al.,* 2012). It has become one of the most effective and promising methods to study the earth because of its efficiency, authenticity, safety, accessibility, ability to study huge territories, and applications in different fields of science and national economy (Dolinets & Mozgovoy, 2009). The data collected by earth observation remote sensing is also a powerful tool for conservation, and it is essential that conservationists working with satellite imageries and the experts behind it work together to make use of the technology and convert the results into action for conservation. Green *et al.* (2011) discussed the latest developments in remote sensing technology as to how these could be applied to conservation including the identification of the information that conservation, practitioners actually need from earth observation remote sensing data. It helps in maintenance and exploitation of data describing our environment, which contribute to sound decision making and better management of our environment. Imagery from the RS platforms has been used to classify vegetation and restoration monitoring.

A number of factors have contributed to the development of remote sensing, as we know it today. These include the invention and development of multi-spectral scanners producing digital information, advances in computer processing and its applications to remote sensing, development of stable high-altitude aircraft and satellites to carry the sensors, and scientific interest in using these tools (Botkin *et al.*, 1984). These advances in both remote sensing systems and computer technology have given ecologists new tools for monitoring and understanding changes in the earth's biota. Remote sensing is presently used by geologists, foresters, geographers, agriculturalists and engineers for evaluating natural and agricultural resources (Greegor, 1986). Optimization of the benefits of remote sensing will rest not only in technological advances, but also in shifts in approaches to information requirements and the development of information systems that will fulfill those needs (Boivin *et al*., 2003), identifying priority areas which should allow for better characterization of particular environments of interest (Sanchez-Azofeifa *et al.*, 2003), especially where there is lack of the fundamental scientific understanding.

2.6.1 Satellite Remote Sensing (SRS) of the Earth Resources

The first Earth observation satellite was a meteorological satellite known as the Television and Infrared Observation Satellite (TIROS-1), was launched in 1960. This satellite was designed for climatological and meteorological observations but provided the basis for later development of land observation satellites (Campbell and Wynne, 2011). In 1972, the launch of Landsat 1, the first of many Earth-orbiting satellites designed for observation of the Earth's land areas, marked another milestone (Lauer *et al.*, 1997; Markham, 2004). Since the launch of the first Landsat series of remote sensing satellites, a continuous record of Earth observation for almost 46 years has been obtained (Table 2.1).

Landsat provided, for the first time, systematic repetitive observation of the Earth's land areas. Each Landsat image depicted large areas of the Earth's surface in several regions of the electromagnetic spectrum, yet provided modest levels of detail sufficient for practical applications in many fields (Williams *et al.*, 2006). By the early 1980s, a second generation of instruments for collecting satellite imagery provided finer spatial detail at

30m, 20m, and 10m resolutions and, by the 1990s, imagery at meter and sub-meter resolutions (Li, 1998). Finally, by the late 1990s, development of commercial capabilities (e.g., Geoeye, IKONOS, QuickBird, WorldView-1 and 2, and RapidEye) for acquiring fine-resolution satellite imagery (initially at spatial resolutions of several meters but eventually sub-meter detail) opened new civil applications formerly available only through uses of aerial photography (Li, 1998; Surazakov & Aizen, 2010). Fine resolution satellite imagery has found important application niches for mapping of urban utility infrastructure, floodplain mapping, engineering and construction analysis, topographic site mapping, change detection, transportation planning, and precision agriculture (Ryerson & Aronoff, 2010).

Landsat's full potential may not yet be fully acknowledged, but three of its most significant contributions can be possibly recognized. First, the routine availability of multispectral data for large regions of the earth's surface greatly expanded the number of people who acquired experience and interest in analysis of multispectral data (Lauer *et al.*, 1997; Markham, 2004). Secondly, Landsat created an incentive for the fast and wide expansion for use of digital analysis for remote sensing. A third contribution of the Landsat program was its role as a model for development of other land observation satellites designed and operated by diverse organizations throughout the world (Williams *et al.*, 2006; Wulder *et al.*, 2008).

Satellite remote sensing systems is today operated by many corporations and national governments specifically designed for observation of the earth's surface to collect information concerning topics such as crops, forests, water bodies, land use, cities, and minerals (Jensen, 2007; Campbell & Salomonson, 2010). Satellite sensors offer several advantages over aerial platforms: They can provide a synoptic view (observation of large areas in a single image), fine detail, and systematic, repetitive coverage. Such capabilities are well suited to creating and maintaining a worldwide cartographic infrastructure and to monitoring changes in the many broad-scale environmental issues that the world faces today (Ryerson & Aronoff. 2010).

Table 2.1 Landsat Missions

Satellite	Launch	Decommissioned	Principal Sensors
Landsat 1	July 23, 1972	January 6, 1978	MSS/RBV
Landsat 2	January 22, 1975	July 27, 1983	MSS/RBV
Landsat 3	March 5, 1978	September 7, 1983	MSS/RBV
Landsat 4	July 16, 1982	*/ June 15, 2001	MSS/TM
Landsat 5	March 1, 1984	2013	MSS/TM
Landsat 6	October 5, 1993	Did not Achieve Orbit	ETM
Landsat 7	April 15, 1999	**/ Operational	ETM+
Landsat 8	February 11, 2013	Operational	OLI / TIRS

*- Transmission of TM data failed in August 1993.
**- Malfunction of ETM+ scan line corrector has limited the quality of imagery since May 2003.

The success of Landsat program is due to the rigorous geometric and radiometric standards, large on-board capacity and spatial, spectral, temporal and radiometric image characteristics that are well known and established in land cover mapping and dynamic studies. Different sensors have been developed for environmental and natural resources mapping, and data acquisition (Melesse *et al*., 2007). The key features of a Landsat program that have resulted in the extensive use of Landsat data for large scale land cover mapping and monitoring are its satisfaction in meeting the data needs for land cover monitoring. Landsat sensors have played important role in ecology and for characterizing land cover and vegetation attributes. Because of its long data record and free data availability, Landsat has a unique role in RS (Cohen & Goward, 2004).

Despite the success, the resolution of Landsat imagery is too low to detect finer details of forestry and ecological components. High-resolution imagery from satellites such as GeoEye, IKONOS and QiuckBird offer more detailed results but their high cost and the lack of long term data records are at present restricting factors for their use by ecologists (De Roeck *et al*., 2008). Therefore, there is need for moderate resolution imagery that is economical. New generation of fine spatial resolution provide an opportunity for detailed and accurate ecological studies which reduces the need for expensive ground surveys. As a result, there have been improvements in imaging capabilities in terms of spectral, radiometric, temporal and spatial resolutions from other satellites, which have been made available at reasonable cost. On the current status, remote sensing data of sub-metre spatial resolution has been made available and can be used to detect even small features from plants, to species level (Dahdouh-Guebas *et al*., 2004). These advances in technology and decrease in cost are now making RS and GIS practical and attractive for use in resource management (Klemas, 2001). They are also allowing researchers and managers to take a broader view of ecological patterns and processes.

There is a need for developing more comprehensive approaches to deal with application of new RS technologies, and analysis in a GIS environment. RS and GIS are essential and excellent tools used in studies for the sustainable use and management of important ecosystems (Campbell & Salomonson, 2010). RS technology and other scientific tools can be integrated in long-term studies, both retrospective and predictive, in order to take effective measures to manage ecosystems at early stages of their degradation (Dahdouh-Guebas, 2002). RS techniques now offer the ability to estimate total biomass, to differentiate green vegetative tissue from woody tissue, and to differentiate this from the water in plants (Botkin *et al.*, 1984). The systems generate information on land use/land cover changes, and indicators can be developed from remote sensing data to monitor environmental change, facilitating comparison and assessment of trends useful for environmental monitoring (Tinner, 2004).

Boit (2016) used satellite imagery from Landsat-5 Thematic Mapper (TM) and Landsat-7 Enhanced Thematic Mapper (ETM+) to study the impacts of Mau Forest catchment on the Great Rift Valley Lakes in Kenya. The study investigated the relationship between the increasing rate of deforestation and the reduction of the volumes of water in the neighbouring lakes and showed that there has been a reduction of Mau Forest due to deforestation and irregular dynamics in the water bodies. Chen *et al*. (2003) used Landsat TM and ETM+ to study land use/land cover changes in a river bed dominated by grasslands and where crop cultivation, livestock grazing, urban development construction of infrastructure have caused changes in inland cover. They identified and quantified the spatial extent of land use /cover in the basin.

RS and GIS applications are being widely used for various projects relating to natural resource management. Forests are very important national assets for economic, environmental protection, social and cultural values and should be conserved in order to realize all these benefits. Kenya’s forests are rapidly declining due to pressure from increased population, technological innovation, urbanization, human development and other land uses (Boitt, 2016). Mundia & Murayama (2009) used Landsat MSS, Landsat TM and ALOS AVNIR-2 to analyze long-term land use/cover changes and wildlife population dynamics. The study used multi-temporal satellite images, together with physical and social economic data in a post classification analysis with GIS to analyze outcomes of different land use practices and policies, and found a rapid land cover conversions and a drastic decline for a wide range of wild species.

2.6.2 Satellite Remote Sensing and Climate Change and Variability

Satellite remote sensing has provided major advances in understanding the climate system and its changes, by quantifying processes and spatio-temporal states of the atmosphere, land and oceans. SRS which acquires information about the earth's surface, subsurface and atmosphere remotely from sensors on board satellites (including geodetic satellites) is an important component of climate system observations (Jun *et al*., 2013). Since the first space observation of solar irradiance and cloud reflection was made with radiometers on-board the Vanguard-2 satellite in 1959 (Yates, 1977), SRS has gradually become a leading research method in climate change studies (Li *et al*., 2011). The use of satellites allows the observation of states and processes of the atmosphere, land and ocean at several spatio-temporal scales. For instance, it is one of the most efficient approaches for monitoring land cover and its changes through time over a variety of spatial scales (Bontemps, 2011; Gong, 2013). Satellite data are frequently used with climate models to simulate the dynamics of the climate system and to improve climate projections (Ghent *et al.*, 2011).

2.6.3 Remote Sensing in Forestry and Vegetation Mapping

Since it was first introduced, remote sensing (RS) has been assumed to contribute to forest and landscape management. The technology – sensors, processing and analysis – has been the subject of a vast amount of research and development, and studies using RS have improved understanding of the sites studied. At the strategic level of forest planning, or of general planning of forest resource allocation over a wide area, RS has often played an important role in estimating and monitoring the forest cover (Takao *et al*., 2010). Remote sensing and GIS are complementary technologies that, when combined, enable improved monitoring, mapping, and management of forest resources (Franklin, 2001). The use of remote sensing by forest managers has steadily increased, promoted in large part by better integration of imagery with GIS technology and databases, as well as implementations of the technology that better suit the information needs of forest managers (Wulder & Franklin, 2003).

Remotely sensed images can be used to provide unique information about vegetation characteristics (Botkin *et al.*, 1984). Application of remote sensing techniques to vegetation studies and the estimation of various vegetation properties such as biomass and density have been undertaken. Many vegetation characteristics can be estimated from reflectance measurements, such as species composition, vegetation structure, biomass and plant physiological parameters. However, proper use of these methods requires an understanding of the physical processes behind the interaction between electromagnetic radiation and vegetation, in order to obtain successful results (Mabwoga, 2013).

Reflectance from satellite imagery is highly correlated with leaf area, biomass, leaf water content, and chlorophyll content (Lorenzen & Jensen, 1988). Chlorophyll present in green plants strongly absorbs energy in the wavelength bands centered on 0.45 μm and 0.65 μm. Healthy green vegetation intercepts radiation from the sun and this electromagnetic energy interacts with pigments, water, and intercellular air spaces within the plant (Jensen, 2007). The red and blue energies are heavily absorbed by plant leaves, whereas the green energy is strongly reflected. Green vegetation usually has high reflectance at near infrared wavelengths (Band 4 of Landsat (TM/ETM+) and a low reflectance at the red wavelengths (band 3 Landsat TM). At 0.7 to 1.3 μm, plant reflectance is mainly due to the internal structure of plant leaves, which varies greatly from one plant species to another. Hence the reflectance values in this range permit us to discriminate one plant species from another. Differences in reflectance among vegetation cover types are attributed to variable foliage coloration and vegetative density (Everitt *et al.*, 2002). At 1.4, 1.9 and 2.7 μm wavelengths, a decrease in reflectance is observed because water molecules in the leaves absorb strongly these radiations.

Kinyanjui (2010) used SPOT-VEGETATION sensor to study NDVI-based vegetation monitoring in Mau forest complex, indicating that NDVI patterns within a year follow cyclic trends with a strong dependence on rainfall seasons. The forest vegetation indicated negligible changes over the study period but effects of extended dry periods in 2000 and 2009 were evident. Zhang *et al.* (2011) used Landsat TM for classifying coastal vegetation into different land cover classes. Tuxen *et al.* (2011) mapped vegetation at tidal marshes using detailed vegetation field surveys and high spatial-resolution color-infrared aerial photography and identified different vegetation classes. Bwangoy *et al*. (2010) reported results of a classification approach to mapping the wetlands of the Congo Basin, using optical remotely sensed imagery of the Landsat Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+) sensors, JERS-1 active radar L-band imagery, and topographical indices derived from elevation data. Arieira *et al.* (2011) integrated field sampling and remote sensing data to map vegetation communities which helped to reduce the uncertainties occurring when only remote sensing data is used. Mapping improved by field observation.

Due to enhancements achieved with Landsat-8 in the scanning technology (replacing whisk-broom scanners with two separate push-broom OLI and TIRS scanners), an extended number of spectral bands (two additional bands provided) and narrower bandwidths; it is necessary to perform cross-comparative analysis for the combined use of multi-decadal Landsat imagery. Peng *et al*., (2013) used independent sample points of four major land cover types (primary forest, unplanted cropland, swidden cultivation and water body) to carry out cross-comparison for the spectral bands of vegetation indices derived from Landsat-7 Enhanced Thematic Mapper Plus (ETM+) and Landsat-8 Operational Land Imager (OLI) Sensors. Eight sample plots with different land cover types were manually selected for comparison with the Normalized Difference Vegetation Index (NDVI), the Modified Normalized Difference Water Index (MNDWI), the Land Surface Water Index (LSWI) and the Normalized Burn Ratio (NBR). Comparative results indicated high degree of similarities between both sensors with slight difference in average surface reflectance of each band. It demonstrated that ETM+ and OLI imagery can be used as complementary data due to both sensors subtle vegetation indices differences and their high linear correlation coefficient ($R2$ > 0.96). Cross-comparison analysis of satellite sensors revealed that LSWI and NBR performed better than NDVI and MNDWI due to the spectral band difference effects.

Kinyanjui *et al*. (2014) used ALOS (Advanced Land Observation Satellite) AVNIR-2 (Advanced Visible and Near Infrared Radiometer type 2) a 10 m spatial resolution Japanese satellite image to carry out an inventory of the above ground biomass in the Mau Forest Ecosystem, and revealed that degradation that converts dense forests into open and moderately dense forests contributed to a biomass loss. In a study to assess the hydrological impacts of Mau Forest, Chrisphine *et al*. (2016) used Landsat TM satellite imagery to carry out comparative analysis of land use land-cover (LULC) changes and demonstrated that as a result of deforestation and agricultural activities carried out within the Mau forest areas, the Mau forest cover has changed. Nabutola (2010) stated that remote-sensing-based detection of forest degradation is not easy because subtle degradation signals are difficult to detect in the first place and quickly lost with time due to fast regeneration. A time series analysis has been advanced with frequent updates based on Landsat data to monitor and map forest degradation over a long period of time to overcome these shortcomings.

To improve land-cover classification accuracy Li *et al.* (2011) examined the use of different remote sensing-derived variables and classification algorithms. Different scenarios based on Landsat Thematic Mapper (TM) spectral data and derived vegetation indices and textural images, and different classification algorithms were explored and the results indicated that the combination of both vegetation indices and textural images into TM multispectral bands improved overall classification accuracy. Shoshany (2000) has reviewed the current status of applying satellite remote sensing in regions characterized by high spatio-temporal heterogeneity of vegetation patterns. Vegetation mapping was achieved using phenological classification of vegetation indices derived mainly from NOAA AVHRR images, with detailed mapping being conducted using multispectral techniques and Landsat TM images. Du *et al.* (2008) applied NDVI and other VIs, vegetation analysis by land cover classification, and the greenness component derived from K-T transform, which are widely used to extract vegetation information from Landsat TM image. Analysis found that there was association among NDVI, vegetation abundance and greenness.

Satyanarayana *et al.* (2011) used ground-truth and remote sensing measurements to assess the mangrove vegetation composed of several species. Recent high-resolution multispectral satellite data from QuickBird with 2.4 m spatial resolution were used to produce land-use/ cover classification and Normalized Differential Vegetation Index (NDVI) mapping for the delta. Using NDVI ranges for different vegetation classes an image was developed with distribution of the mangroves at different site. The sites with young/growing and also mature trees with lush green cover showed greater NDVI values (0.40–0.68) indicating healthy vegetation, while mature forests under environmental stress due to sand deposition and/or poor tidal inundation showed low NDVI values (0.38–0.47) and an unhealthy situation. Fraser *et al.* (2011) derived NDVI and tasseled cap indices to predict changes in shrub and other vegetation covers and to investigate changes to vegetation using Landsat TM and ETM+ satellite images.

The use of remote sensing for environmental policy development is now quite common and well documented, as images from remote sensing platforms are often used to focus attention on emerging environmental issues and spur debate on potential policy solutions. Mayer & Lopez (2012) have discussed several national and regional examples of how remote sensing for forest and wetland conservation has been effectively integrated with policy decisions, along with barriers to further integration. The range of successful applications from remote sensing analyses has increased with the launch of many new instruments that record data across the electromagnetic spectrum. Applications such as studies of the landscape properties, water properties and measuring heterogeneity have made use of RS (Mertes, 2002).

2.6.4 Remote Sensing and Land Cover/use Change Detection

Change detection is the process of identifying differences in the state of an object, or a phenomenon over a span of time (Singh, 1989). Many techniques are available on change detection which include image differencing, principal components analysis (PCA), spectral mixture analysis, artificial neural networks, integration of multisource data and post-classification comparison (Lu *et al.*, 2004). There are also different aspects of change detection from land use land cover, forest or vegetation changes to forest mortality, defoliation and damage assessment. Regardless of the method used, good change detection technique should give change and change rate, spatial distribution of change types, change trajectory of land cover types, and an accuracy assessment of the change results (Mabwoga, 2013).

The process of change detection involves the sensing of environmental changes by way of using two or more scenes covering the same geographic area acquired over a period of time. These changes could be the seasonal variations in a phenomenon or land use/cover changes or other changes, and thus offer a good potential for characterizing and understanding changes occurring over time. The basic assumption for change detection is that any change in land cover results in changes in radiance values, and that the change in radiance due to land cover change are relatively large as compared to the radiance changes caused by external factors such as differences in atmospheric conditions, soil moisture and sun angles (Mas *et al*., 1999).

It is imperative to note that such progress in the field of RS advanced in tandem with advances in GIS, which provided the ability to bring remotely sensed data and other geospatial data into a common analytical framework, thereby enhancing the range of products and opening new markets mapping of urban infrastructure, supporting precision agriculture and support of floodplain mapping (Burrough & McDonnell, 1998; Madden, 2009; Campbell *et al*., 2010).

2.7 Theoretical and Conceptual Framework

Climate change is a long-term shift in weather conditions as a result of natural factors (volcanic activities, solar output – earth's energy balance, and earth's orbit around the sun); human activities and other short lived and long lived climate forcers. Climate change can involve both changes in average conditions and changes in variability, including extreme events (Jennifer, 2014). Indicators are observations or calculations that can be used to track conditions and trends. Indicators are used to measure progress towards a desired goal. Indicators related to climate change, which may be physical, ecological or societal can be used to understand how the environment is changing, assess the climate change trends and progression, determine the risks and vulnerabilities, and inform decision about climate preparedness (Bours *et al*., 2014; USEPA, 2016).

The climate change related research in the country can be limited by a number of issues including lack of regionally, nationally and/or area specific climate change indicators suite models. Indicators relating to climate change are at different stages of development and usage (EEA, 2012). Climate change indicators and climate impact indicators are at a more advanced stage of development. Vulnerability, resilience and climate adaptation indicators are still in the early stages of development (Jennifer, 2014). For instance, Germany adopted the approach of using the Drivers-Pressure-State-Impacts-Response (DPSIR) model; U.K. Department of Environment, Food and Rural Affairs (DEFRA) uses Pressure-State-Impact (PSI) model; while the California Environment Protection Agency (Cal/EPA) uses Pressure-State-Effects-Response (PSER) model adopted from Organization for Economic Cooperation and Development (OECD) (EEA, 2012; OEHHA, 2013; Jennifer, 2014). In this model, human activities and natural phenomena exert pressures on the climate that alter the state of the climate, and the changes in state lead to adverse effects on human and ecological health. Responses are actions taken to alleviate the pressure or remediate the state (Jennifer, 2014).

Climate change, climate impacts, climate adaptation and vulnerability indicators (measuring exposure, sensitivity and adaptive capacity) were used to assess the interrelationships between climate, biophysical and socio-economic systems. Pressure-State-Effects-Response (PSER) model (Fig. 2.1) was adopted for the development and customization of the Narok County Climate Change Indicators (NCCCI) suite (Annexure Table 1.1 and 1.2) due to its broadness, comprehensive nature and overall climate change indicators inclusivity (Erhard *et al*., 2002; Cannell *et al*., 2003; UNFCCC, 2010; Schönthaler *et al.*, 2011). Variably this model has been modified by different countries and organizations to fit their needs. For example, Germany adopting DPSIR model: socio-economic Driving force-Pressure-State-Impacts and policy-Responses.

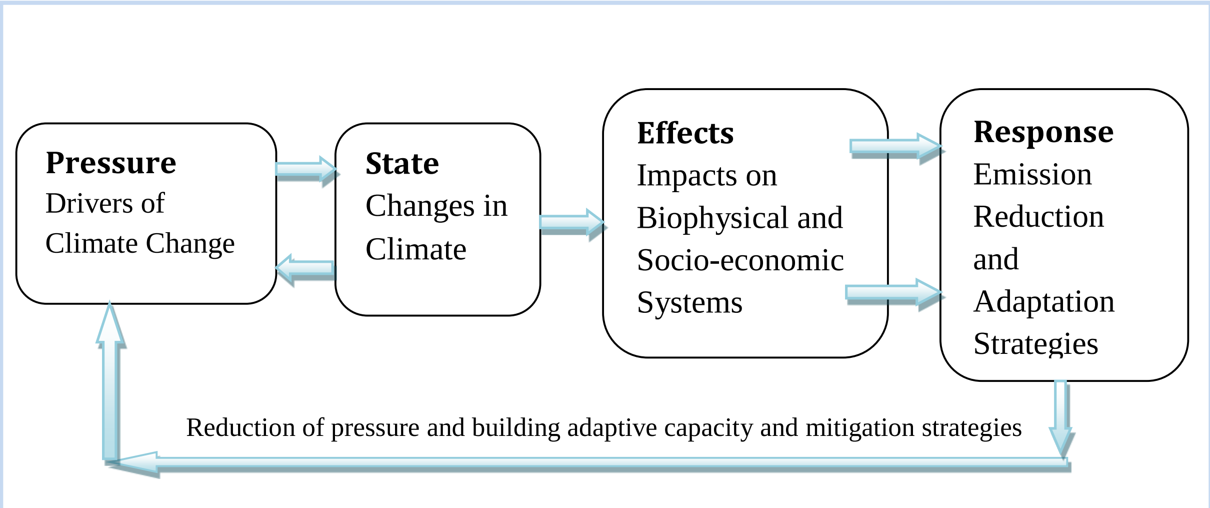


Fig. 2.1: Pressure – State – Effects – Response (PSER) Model

The need to develop localized indicators model for the study was due to lack of locally standardized climate change and adaptation indicators model and the fact that internationally standardized indicators may not reflect the local context. Indicators were selected based on data availability, representativeness, sensitivity and decision-support criteria (Bours *et al*., 2014; USEPA, 2016).

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Study Area

3.1.1 Geographical Location of the Study Area

The study area is located within Mau Forest Complex in Narok County lying between Latitudes $0^o25'$ and $0^o58'$ S; and Longitudes $35^o20'$ and $35^o58'$ E. The three forest blocks that comprised the study area included: the Maasai Mau forest, Trans-Mara forest and Ol Pusimoru forest covering a total area of 148,607 ha (NMK & KIFCON, 1993a; MEMR, 2009; Ministry of Forestry and Wildlife, 2010). The three forest blocks were particularly chosen for the study because of their socio-economic significance to the people of Narok County. They almost entirely form the upper catchment for the rivers supplying much needed water to the agro-pastoralist communities in both Narok and neighbouring Kajiado counties alongside provision of other essential ecosystem goods and services. They are also the only permanent source of water to the lower lying wildlife dominated plains of Maasai Mara and Serengeti, both world famous protected areas and major source of revenue to the County through tourism. The forest blocks are also important buffer to the impacts of CCV in the area. A part from the biophysical and socio-economic roles, the forest blocks were chosen for the study because they fully lie within the administrative boundaries of Narok County.

Nevertheless, the forest blocks have experienced unabated destruction and degradation due to encroachment, deforestation, agricultural expansion, illegal logging, fuel wood collection and illegal extraction of forest resources (Baldyga *et al*., 2007; Kinyanjui, 2009). Akotsi *et al*. (2006) reported that the accelerated rates of forest destruction and degradation rising from 2,010 ha per year between 2000 – 2003 to 4, 670 ha per year between 2003 – 2005 was a cause of concern due to unabatedly increasing forest cover loss.

The MFC is considered the most important of the five main watershed areas in Kenya because of its environmental and socio-economic contribution to the country. It has the distinction of being the largest remnant indigenous closed-canopy montane forest in Eastern Africa, occupying an area of 416,542 ha (MEMR, 1994; GoK, 2009). It is home to 400 species of birds, 50 species of mammals and 300 species of plants (NMK and KIFCON, 1993b). The MFC comprises 22 separate blocks of forest within which the three forest blocks (Maasai Mau, Trans-Mara and Olpusimoru) constituting the study area are situated (Fig. 3.1).

It is a watershed of national, regional and international importance contributing directly and indirectly to the survival of millions of people and to the maintenance of diversity of wetland and terrestrial ecosystems that support unique assemblages of biodiversity and social systems outside the forest areas. The importance of MFC is related to the ecosystem services it provides, such as river flow regulation, flood mitigation, water storage, water purification and recharge of groundwater, reduction and control of soil erosion and siltation, protection of biodiversity, carbon sequestration, carbon reservoir and regulation of microclimate which provides favourable conditions for optimum crop production (GoK, 2009). The country's tourism, agriculture and energy sectors rely heavily on the MFC and as such it is an important forest cover.

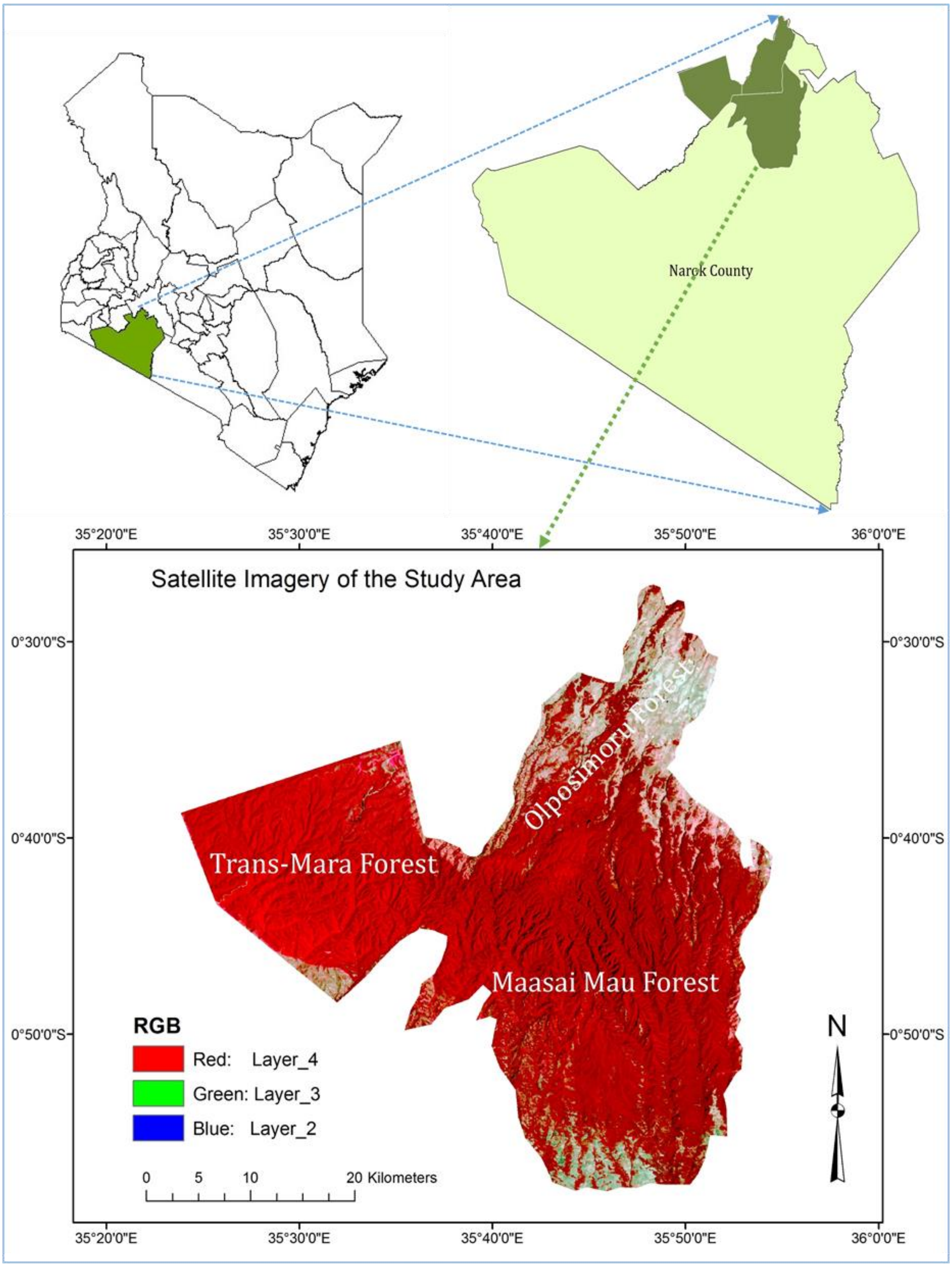


Fig. 3.1: Location of the Study Area

3.1.2 Biophysical Description

3.1.2.1 Topography

The study area has diverse topography which ranges from a plateau with altitudes ranging from 1000 – 2350 m above sea level at the Southern parts to mountainous landscape ranging to about 3098 m above sea level at the highest peak of Mau escarpment (Mau Forest Complex) in the North (MEMR, 2009; Ministry of Forestry and Wildlife, 2010). The study area lies at an altitude of between 2000 – 2800 m above the sea level.

3.1.2.2 Climate

Narok County experiences bi-modal pattern of rainfall with long rains in (March – May) and short rains in (October - December). The amount of rainfall is influenced by bi-annual passage of Inter-Tropical Convergence Zone (ITCZ). Rainfall distribution is uneven with high potential areas receiving the highest amount of rainfall ranging from 1200 mm – 2000 mm annually, while the lower and drier areas of Loita plains and Maasai Mara plains classified as semi-arid receiving 500 mm or less and 1100 mm annually, respectively (KIFCON, 1994; MEMR, 2009). The County experiences a wide variation of temperatures throughout the year with mean annual temperatures varying from 10^{o}C in Mau escarpment to about 20^{o}C in the lower drier areas (MEMR, 2009; Ministry of Forestry and Wildlife, 2010). Temperatures are closely related to altitude with minimal variation throughout the year (Fig. 3.2 and 3.3).

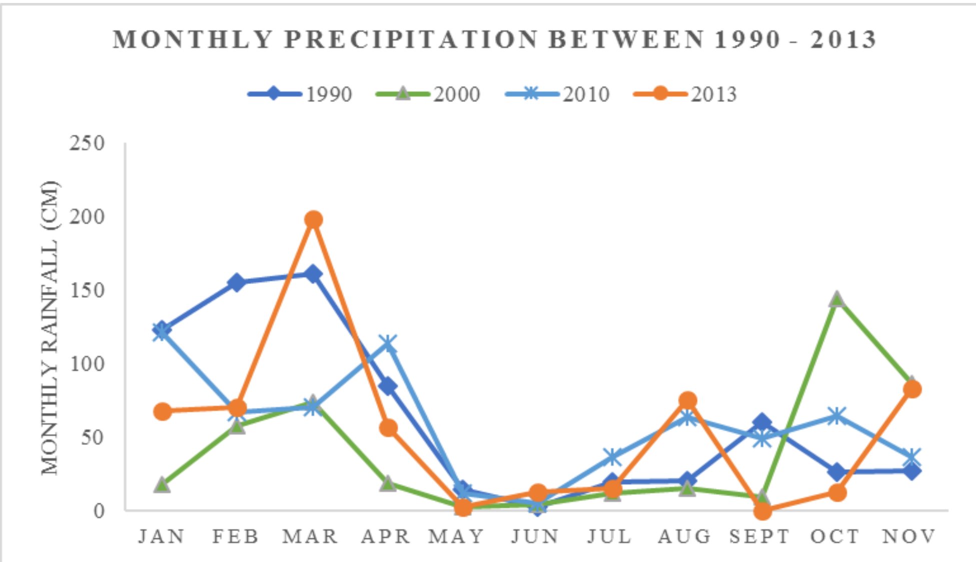


Fig. 3.2: Monthly precipitation for the study area

Climate Data from Kenya Meteorological Department (KMD) 1990 – 2013

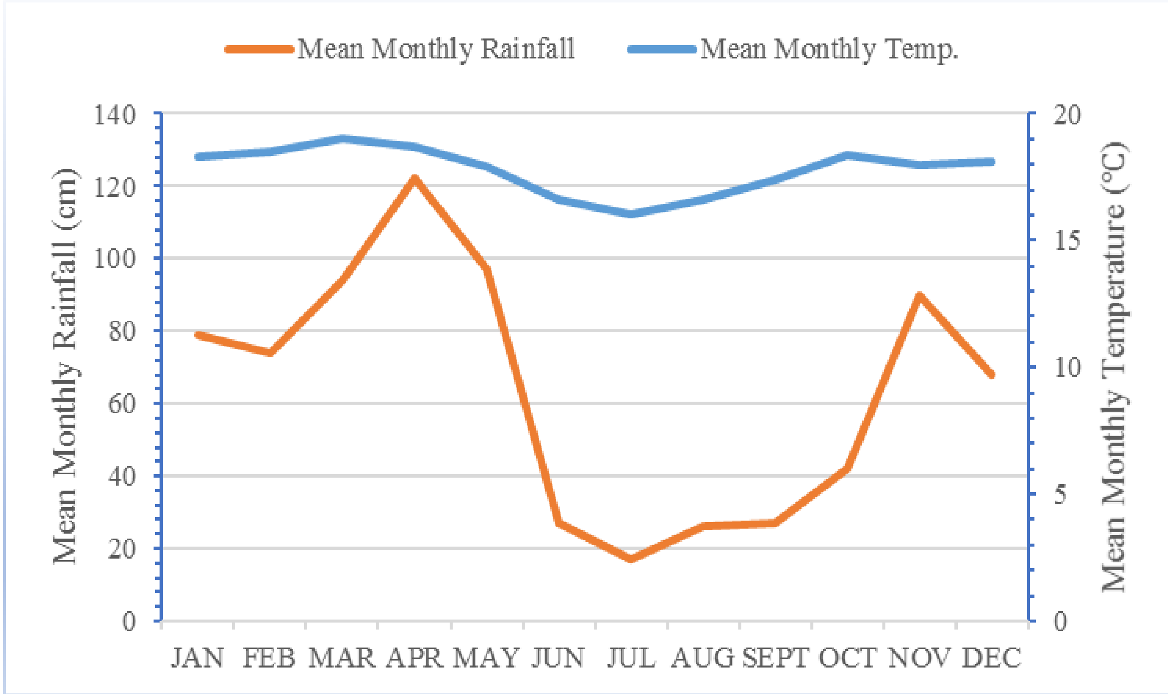


Fig. 3.3: Mean monthly rainfall and temperature for the study araea

Climate Data from Kenya Meteorological Department (KMD) 1990 – 2013

3.1.2.3 Geology and Soils

The volcanic geological formations dominate the eastern and northern parts of the county. The hilly and mountainous areas such as the Mau escarpment have deep and well-formed soils. The main soil types include luvisols, luvic and andolivic phaezems, chromic vertisols and chromic aerosols. The other soil types also found are Mollic andosols, derived from Tertiary volcanic material, with inclusions of cambisols on the steepest slopes and humic notosols in the North. The Soils have high potential for agriculture since they have high available water capacity, well drained with fine texture and a high natural fertility (KIFCON, 1994; NEMA, 2013).

3.1.2.4 Hydrology

The study area has a drainage pattern of parallel rivers running in straight courses in south western and eastern direction. Most of these rivers and streams flow from the forest reserves discharging into the Mara River tributaries Amala and Nyangores. The streams which include Isei, Mosiro, Amalo, Cheptaburbur and Cheimon drain into the Amala passing through the Trans-Mara forest reserve. Amala and Nyangores are the two major tributaries passing through Trans-Mara and have their main source beyond the Trans-Mara forest in the Eastern Mau forest. Nairotia and Olenguruone forests are the start of the head waters of the Mara River which is the only permanent source during the dry season in the protected area complex of the Maasai Mara National Reserve and the Serengeti National Park, both world famous for wildlife and sprawling savannah grassland; and eventually flows into Lake Victoria (FAO, 2010; NEMA, 2013).

Almost the entire Maasai Mau forest forms the upper catchment for the Ewaso Ngiro River, while the western part of the forest is part of the upper catchment of the Mara River. The Ewaso Ngiro River flows into Lake Natron, the main breeding ground for the flamingoes in the Rift Valley. Both are also Important Bird Areas (IBA) with 450 and 540 bird species, respectively. The Ewaso Ngiro and Mara Rivers provide the much needed water to pastoralist communities, agriculture and urban areas in Narok and Kajiado Counties (Ministry of Forestry and Wildlife, 2010).

3.1.2.5 Vegetation

The vegetation in the area is characterized by dense indigenous woodland, riverine forests and high altitude grasslands. The Afro-montane forest formations found in the area attract sufficient precipitation supporting forest vegetation similar to the one found in Mount Kenya and Aberdares. This moist forest is predominantly evergreen forest type with an average canopy height of 20m. The Afro-montane forest formation stretch from West Africa to Kenya and support many different types of forest tree species and forest types. The forest formations found in the area include *Podocarpus* forest, *Juniperous* forest and *Aningeria – Strombosia – Drypetes* vegetation forest formations. The most threatened tree species are *Juniperus procera*, *Prunus Africana*, *Olea capensis*, *Olea Africana*, *Hagenia abyssinica* and *Podocarpus latifolia*. Five major plant communities found include *Podocarpus-Maytenus-Juniperus* community, *Podocarpus-Dombeya* community, *Podocarpus-maytenus* community, *Trichocladus-Allophyllus* community and *Trichocladus* community (KIFCON 1992; MEMR, 1994).

3.1.3 Threats to the Forests

According to KIFCON (1994), the area has been used for subsistence purposes such as hunting wild animals for bush meat, honey collection, cultivation, grazing, pole wood, bamboo, fuel wood, charcoal production, collection of medicinal plants and collection of grasses and vines for basket making and thatching by the people living adjacent to the forests; and over time turned commercial as population increases and alternative sources for these products diminish leaving the forests as the only source. Although listed among the subsistence usage, fuel wood extraction comprise of over 70% of total wood cut from the forests both for substance and for sale to distant merchant by adjacent communities (MEMR, 1994; GoK, 2009).

There is illegal commercial extraction of timber targeting highly valued commercial trees species like *Juniperus procera*, *Podocarpus latifolius, Olea spp.* and *Zanothoxylum gilletti*. Pit sawing, a semi commercial mode of timber extraction has contributed significantly to the illegal removal of timber tree species. Use of tree in manufacture of bee hives and removal of tree bark for use as beehive covers is another cause of trees removal targeting *Podocarpus latifolia*, *Olea europaea* and *Juniperus procera* (KIFCON 1992; Ministry of Forestry and Wildlife, 2010).

3.1.4 Socio-economic Characterization

3.1.4.1 Settlement

To the South are the Mara plains occupied by the pastoral Maasai communities. Due to their nature of life, Maasai people did not live inside the forests except during dry season in search of forest pastures. This was temporary and during the rainy season they left for the lower plains. Settlement around the forests by Kipsigis communities was very gradual until the 1960’s when over 20% of the respondents settled in the area (Socio-economic Survey Findings, 2010). This continued to the maximum influx in the 1980’s and 1990’s. However, dominance varies with the eastern and southern side being dominated by Maasai, while the western side is dominated by Kipsigis. Ogiek are strongly present on the eastern side, though their presence is also evidenced on the western and southern side. The area is termed as trust land for the adjacent communities.

3.1.4.2 Communities Adjacent to the Forests

The study area is located within ten (10) administrative locations. These locations are Lower Melili, Enabelibel, Nayituyupaki, Olokurto, Olpusimoru, Nkareta, Endonyo Ngiro, Melelo, Sogoo and Sagamia. The composition and structure of households around the area varies widely. For example, the area is inhabited by different ethnic groups including Maasai, Kipsigis, Ogiek and Kisii among others.

3.1.4.3 Economic Activities

During reconnaissance survey, the economic activities in the study area were noted mainly as agriculture (wheat, maize and beans farming), pastoralism (livestock husbandry) and quarrying. Narok County is known for wheat production due to the fertile soils, water availability and favourable forest microclimate conditions. Timber and non-timber forest products including medicinal plants, wild honey and fruits are also found. Livelihood activities include farming and livestock husbandry during wet season, honey collection, timber extraction, business and charcoal burning. Dependence on the resources is through water sources, building materials, animals cropping, wildlife habitat, grazing, fuel-wood collection, charcoal, herbal medicine, farming, honey and forage. Water consumption, fuel-wood collection and grazing are the key values common among households as compared to honey harvesting, charcoal burning and timber extraction.

3.2 Research Design

This study employed longitudinal and cross-sectional survey research designs with mixed (quantitative and qualitative) methods to measure the variables (Russell, 2006; Lynn, 2009). Longitudinal research designs describe patterns of change and help establish the direction and magnitude of causal relationships. Measurements are taken on each variable over two or more distinct time periods. This allows the researcher to measure change in variables over time. The longitudinal survey was carried for the analysis of Landsat imageries to provide the trends in land cover/use change and the analysis of changes in the state of climate variables for the period 1990 – 2016. Mixed methods research refers to the use of data collection methods that collect both quantitative and qualitative data in such a way as to bring different perspectives to bear in the inquiry and therefore support triangulation of the findings in answering the research questions (Johnson *et al.*, 2007).

3.3 Spatial Survey and Climate Variability in the Study Area

3.3.1 Spatial Survey and Climate Variables Data

Preliminary spatial survey data was gathered using digital data collection systems. An eTrex, Garmin GPS receiver with an accuracy of ± 3 m was used to determine the geo-coordinates of the area in terms of its latitude and longitude. All GPS geo-coordinates were recorded and downloaded to be used as ground control points (GCP) to geo-reference satellite images. Spatial sampling in selected synoptic locations was used to determine the geo-coordinates of the area during ground-truthing and reconnaissance survey. The forests and administrative boundaries were set using shape files acquired from World Database for Protected Areas (WDPA) (http://protectedplanet.net), Kenya GIS Data (http://arcgis.org), and International Livestock Research Institute (ILRI) GIS data (http://ilri.org/GIS). In addition, they were to create base maps to be used in the study by overlaying the shape files on the satellite images to subset or clip the area of interest (AOI). Climate variables (temperature and precipitation) data for the study area obtained from Kenya Meteorological Department (KMD) collected between 1990 and 2014 were used to generate climate variability trends. The climate data was used to calculate mean monthly rainfall and temperature, mean annual rainfall and temperature, and monthly maximum and minimum temperature.

3.4 Satellite Remote Sensing of the Study Area

3.4.1 Satellite Imagery Data

The satellite imagery data used in this study was acquired from Landsat. Landsat imagery with spatial resolution of 30m and 15m panchromatic band (Landsat-7 & 8), spanning twenty six (26) years (1990 – 2016) was obtained from Regional Centre for Mapping of Resources for Development (RCMRD) and United States Geologic Survey (USGS) download site (http://glovis.usgs.gov/). All Landsat standard data products are processed using the Level-1 Product Generation System (LPGS) with .GeoTIFF output format, Cubic Convolution (CC) resampling method, Universal Transverse Mercator (UTM) map projection, World Geodetics System (WGS) 84 datum and MAP (North-up) image orientation with a very few exceptions of Landsat TM scenes processed using the National Land Archive Production System (NLAPS) (https://landsat.usgs.gov/). Landsat Level-1 data products are created using the best available processing level for each particular scene. The processing level used is determined by the existence of ground control points (GCP), elevation data provided by a Digital Elevation Model (DEM), and/or data collected by the spacecraft and sensor (Payload Correction Data (PCD)) (https://landsat.usgs.gov/geometry).

Landsat images utilized in this study were all Level-1 Terrain corrected Products (L1TP). The Landsat images under this processing level L1TP are already radiometrically calibrated and orthorectified (terrain corrected) for relief displacement, sensors inclination and elevation using GCP and DEM data (https://landsat.usgs.gov/geometry). These are the highest quality Level-1 products suitable for pixel-level time series analysis. The L1TP correction process utilizes both GCP and DEM to attain absolute geodetic accuracy. The WGS 84 ellipsoid is employed as the Earth model for the UTM coordinate transformation. The end result is a geometrically rectified product free from distortions related to the sensor (e.g. jitter, view angle effects), satellite (e.g. attitude deviations from nominal), and Earth (e.g. rotation, curvature, relief, terrain). The 2005 Global Land

Survey is used as the source for GCPs while the primary terrain data is the Shuttle Radar Topographic Mission DEM (USGS, 2015; 2016).

3.4.2 Selection of Satellite Images for the Study Area

Landsat satellite images for four epochs (1990, 2000, 2010 and 2016) taken by Landsat-5 Thematic Mapper (TM), Landsat-7 Enhanced Thematic Mapper Plus (ETM+) and Landsat-8 Operational Land Imager (OLI/TIRS) sensors respectively were obtained, selected and processed. The use of Landsat 7 (ETM+) data was limited due to lack of suitable images in the archives, as a result of the May, 2003 instrument malfunction (Chander *et al*., 2009). The use of Landsat 8 (OLI/TIRS) data was also limited because the spacecraft became operational in February, 2013 hence short imageries span in the archives.

The Landsat satellite images for the study were identified by path and row of the respective Landsat sensor coverage. The WRS Path 169, Row 060 and Path 169, Row 061 were selected for satellite imagery data acquisition because the study area traversed two adjoining scenes. These scenes were selected because they provided sufficient coverage of the geographical location of the study area. The selected images for the four epochs were relatively taken at the same time period for each pair of images of a given year to avoid seasonal variations due to vegetation vigour, atmospheric conditions and solar angle hence eliminate the biasness during comparison with the corresponding previous images to enhance change detection. The selection of dates and time intervals was limited to availability of suitable imagery in terms of low or no cloud cover and high quality images (Table 3.1).

Table 3.1: Landsat 5 (TM), 7 (ETM+) and 8 (OLI/TIRS) data used for the study

Spacecraft	Sensor	Acquisition Date	Day of the Year (Julian)	Scenes (Path/Row)
Landsat 5	TM	06 – Feb – 1990	037	169/060; 169/061
	TM	30 – Jan – 2010	030	169/060; 169/061
Landsat 7	ETM+	12 – Feb – 2000	043	169/060; 169/061
Landsat 8	OLI / TIRS	16 – Feb – 2016	047	169/060; 169/061

3.4.3 Landsat Images Characteristics

The USGS has been involved in the collection and archiving of remote sensing data since the year 1972, using the RBV, MSS, TM, ETM+ and OLI/TIRS sensors onboard the Landsat satellite series Landsat 1-3, Landsat 4-5, Landsat 6 and 7, and Landsat 8 (Appendix 1). Landsat-6 failed to acquire orbit. The global scale remote sensing data covers nearly 46 years record of global satellite observations of the earth at 15m, 30m, 60m, 100m and 120m resolutions (Campbell & Wynne, 2011; USGS, 2015).

Landsat-5 was equipped with a multispectral scanner (MSS) to observe solar radiation reflected from the Earth's surface in four different spectral bands, while the Thematic Mapper (TM), an advanced version of the observation equipment used in the MSS, observes the Earth's surface in seven spectral bands ranging from visible to thermal infrared regions. TM was designed to achieve higher image resolution, sharper spectral separation, improved geometric fidelity, and greater radiometric accuracy and resolution than that of the MSS sensor (Mabwoga, 2013).

Each pixel in a TM scene represents a 30m by 30m ground area, except the thermal infrared band 6, using a larger 120m by 120m pixel. The TM sensor has seven bands that simultaneously record reflected or emitted radiation from the Earth's surface in the blue-green (band 1), green (band 2), red (band 3), near-infrared (band 4), mid-infrared (bands 5 and 7), and the thermal-infrared (band 6) portions of the electromagnetic spectrum (Table 3.2).

TM band 1 is a short wavelength of light which penetrates water better than the other bands, and it is often the band of choice for monitoring aquatic ecosystems (bathymetric (water depth) mapping along coastal areas). However, it is the “noisiest” of the Landsat bands since it is most susceptible to atmospheric scatter (http://gif.berkeley.edu). TM band 2 has similar qualities to band 1 but not as extreme and can detect green reflectance from healthy vegetation. Since vegetation absorbs nearly all red light, band 3 is sometimes called the chlorophyll absorption band. It is designed for detecting chlorophyll absorption in the vegetation and monitoring vegetation health. TM band 4 is ideal for NIR reflectance peaks in healthy green vegetation, and for detecting water-land interfaces since water absorbs nearly all light at this wavelength. Indices like NDVI are generated when it’s compared with other bands which are useful to precisely measure the vegetation health than using visible greenness alone. The two mid-infrared bands on TM are useful for vegetation and soil moisture studies, differentiating between clouds and snow, and discriminating between rock and mineral types. The TIR band on TM is designed to assist in thermal mapping, and for soil moisture and vegetation studies.

Landsat-7 is equipped with the Enhanced Thematic Mapper Plus (ETM+), an advanced successor of the TM sensor with essentially similar observation bands and a newly added high resolution (15m) panchromatic band 8. All the Landsat 7 scenes acquired since July 14, 2003 are collected in "SLC-off" mode because of the instrument malfunction which occurred in May 31, 2003. Although images from the ETM+ sensor have several advances over images from the TM sensor, they are identical in spectral and spatial sensitivity within the six bands used in this study (Table 3.2) and are therefore readily comparable (Mabwoga, 2013).

Landsat 8 is equipped with two sensors, the OLI 15m pan and 30m multi-spectral spatial resolution along a 185 km wide swath and TIRS sensitive to two thermal bands which helps it separate the temperature of the earth’s surface from that of the atmosphere. It has 11 bands with additional band 1 sensing the deep blues and violets. Blue light is hard to collect from space because it’s scattered easily by tiny bits of dust and water vapour in the air, and even by air molecules themselves. This is one reason why very distant things (like mountains on the horizon) appear bluish, and why the sky is blue. Band 1 is the only instrument of its kind producing open data at this resolution. It is called the coastal/aerosol band because it’s used to image shallow water and track fine particles like dust and smoke (http://landsat.gsfc.nasa.gov/). Bands 2, 3, 4 and 5 now measures the Blue, Green, Red and NIR respectively as its predecessor’s bands 1, 2, 3 and 4.

Bands 6 and 7 cover different slices of shortwave Infrared (SWIR) and are useful for telling wet earth from dry earth, and for geology: rocks and soils that look similar in other bands often have strong contrasts in SWIR. Band 8 is panchromatic band or pan used for sharpening visible colours by combining them into one channel. It can see more light at once hence the sharpest of all bands with a resolution of 15m. Band 9 cover a very thin wavelength missed by all other satellites because the atmosphere absorbs all of it. Precisely because the ground is barely visible in this band, anything that appears clearly in it must be reflecting very brightly and/or be above most of the atmosphere such as the clouds (http://landsat.gsfc.nasa.gov/). Bands 10 and 11 are TIR and are used to measure heat.

Table 3.2: Image Characteristics of the Landsat TM, ETM+ and OLI/TIRS sensors.

Sensor (Path/Row)	Resolution					Swath (Km)
	Spectral		Spatial (m)	Radio-metric	Temporal (Days)	
	Bands	Wavelength (µm)				
Landsat TM (169/060); (169/061)	Band 1 (Blue-Green)	0.45 – 0.52	30	8 bit	16	185
	Band 2 (Green)	0.52 – 0.60	30			
	Band 3 (Red)	0.63 – 0.69	30			
	Band 4 (NIR)	0.76 – 0.90	30			
	Band 5 (Mid-IR)	1.55 – 1.75	30			
	Band 6 (TIR)	10.4 – 12.5	120			
	Band 7 (M-IR)	2.08 – 2.35	30			
Landsat ETM+ (169/060); (169/061)	Band 1 (Blue)	0.450 – 0.515	30	8 bit	16	185
	Band 2 (Green)	0.525 – 0.605	30			
	Band 3 (Red)	0.630 – 0.690	30			
	Band 4 (NIR)	0.760 – 0.900	30			
	Band 5 (Mid-IR)	1.550 – 1.750	30			
	Band 6 (TIR)	10.40 – 12.50	60			
	Band 7 (M-IR)	2.080 – 2.350	30			
	Band 8 (Pan)	0.520 – 0.920	15			
Landsat OLI/TIRS (169/060); (169/061)	Band 1 (Deep Blue)	0.433 – 0.453	30	16 bit	16	185
	Band 2 (Blue)	0.450 – 0.515	30			
	Band 3 (Green)	0.525 – 0.600	30			
	Band 4 (Red)	0.630 – 0.680	30			
	Band 5 (NIR)	0.845 – 0.885	30			
	Band 6 (SWIR)	1.560 – 1.660	60			
	Band 7 (SWIR)	2.100 – 2.300	30			
	Band 8 (Pan)	0.500 – 0.680	15			
	Band 9 (Clouds)	1.360 – 1.390	30			
	Band 10 (TIR)	10.60 – 11.20	100			
	Band 11 (TIR)	11.50 – 12.50	100			

3.4.4 Satellite Images Processing

The satellite images were pre-processed using standardized formulas/methods and converted to real geographical variables. Ortho-rectified satellite images in which distortions due to topographic variation and sensors inclination have been removed were subset or clipped to match the area of interest (AOI) and ease image processing. Prior to sub-setting, a reconnaissance survey was done to develop baseline information on the extent of the study area. A base map for the study area was prepared using ERDAS Imagine and ArcGIS. During the field reconnaissance survey, major vegetation mosaics were noted and their position recorded with GPS. This was done to aid in verification of land cover types during images classification. The resulting geometrically corrected images were subjected to radiometric calibration. The graphical models in ERDAS Imagine were used to convert DN values to radiance and then to reflectance. The radiometrically calibrated images were further atmospherically corrected using dark object subtraction (DOS) technique. Finally, the outputs were rescaled back to DN values.

The atmospherically corrected and rescaled images were further subjected to unsupervised classification in ERDAS Imagine and processed at iteration of 6 and a threshold of 0.950. The images were then subjected to post-classification change detection processes to produce land cover change matrices. The classified images were used in forest cover characterization and trends analysis. Other processing steps included the calculation of NDVI for the forest cover change characterization. This was performed to produce NDVI thematic maps useful in detecting changes in vegetation vigour during the study period. The step by step pre-processing procedures are briefly described below. A schematic flow chart of the image processing techniques is given in (Fig. 3.4).

3.4.4.1 Images Import

The first step in image processing is the extraction of individual bands from the raw image which comes in compressed format. The compressed image files are downloaded in .GeoTIFF format and decompressed or unzipped. The image bands were separately imported and stacked into a single image in ERDAS Imagine to be converted to imagine (.img) file format which are lighter and easier to use in processing.

3.4.4.2 Geometric Correction

The Landsat images used in this study were already radiometrically and geometrically orthorectified using GCPs and DEM to remove distortions due to topographic variations and relief displacements.

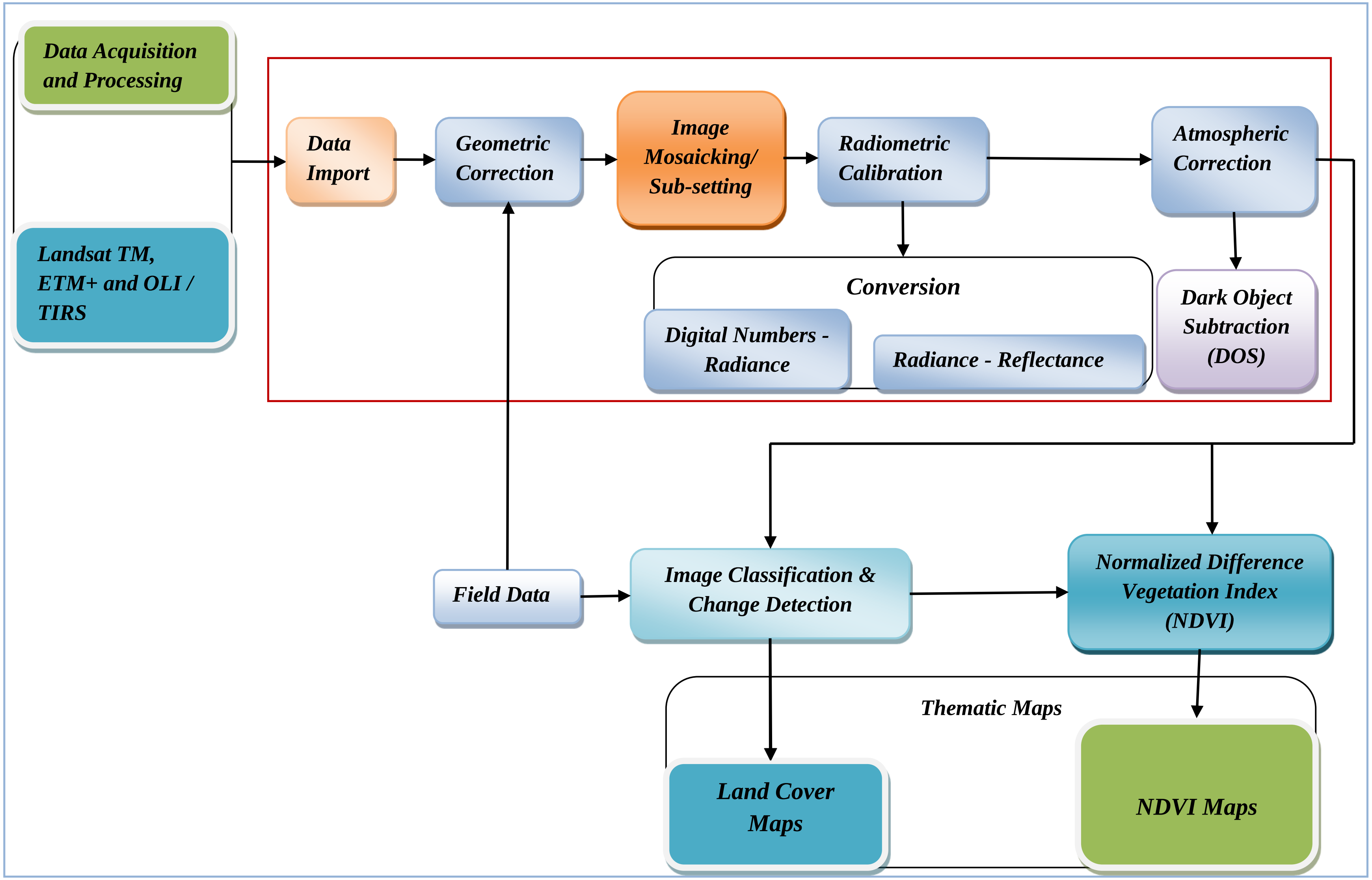


Fig. 3.4: Satellite Imagery Study Design (Images Acquisition, Processing and Analysis)

3.4.4.3 Radiometric Calibration

The Landsat data obtained from USGS archive had already undergone correction for radiometric and geometric accuracy. However, they were scaled to byte value prior to the media output and were formatted to fit in an 8-bit digital number (ranges from 0 – 255) for TM and ETM+ sensors and 16-bit number (from 0 – 65535) for the OLI/TIRS sensor. Data in such a format is referred to as "digital number," (DN values). The DN values had to be converted to reflectance, a physical measurement, before they were used for further image processing.

An image comprises of a series of spectral bands, the pixels of which each have a DN value. Image spectrometric studies and atmospheric correction operations, however, need at-sensor radiance. Radiometric calibration of the sensors involves converting the raw DN transmitted from the satellite to units of absolute spectral radiance (Chander *et al*., 2009). As pixel DN is a simple linear transformation of radiance, the gain and offset of this linear transformation can be used to calculate radiance. These gain and offset values are unique for each spectral band acquired by a particular sensor. These values change over the life span of a sensor according to its sensitivity changes, so their most recent values should be used (Nasr *et al*. 2012).

3.4.4.3.1 Conversion of DN Values to Physical Units

a) Conversion of DN to at-sensor Spectral Radiance of TM & ETM+ sensors ($\mathbf{Q_{Cal}}$ - $\mathbf{L_\lambda}$)

Calculation of at-sensor spectral radiance is the fundamental step in converting image data from multiple sensors and platforms into a physically meaningful common radiometric scale (Chander *et al*., 2009). It involved rescaling the raw digital numbers (Q) transmitted from the satellite to calibrated digital numbers (Qcal) (Chander *et al*., 2004), which have the same radiometric scaling for all scenes processed on the ground for a specific period.

$$\mathbf{L_\lambda = G_{rescale} * Q_{Cal} + B_{rescale}}$$

Where:

$$\mathbf{G_{rescale} = \left(\frac{(LMAX_\lambda - LMIN_\lambda)}{(Q_{Calmax} - Q_{Calmin})}\right)}$$

$$\mathbf{B_{rescale} = LMIN_\lambda - \left(\frac{(LMAX_\lambda - LMIN_\lambda)}{(Q_{Calmax} - Q_{Calmin})}\right) * Q_{Calmin}}$$

Hence:

$$\mathbf{L_\lambda = \left(\frac{(LMAX_\lambda - LMIN_\lambda)}{(Q_{Calmax} - Q_{Calmin})}\right) * (Q_{Cal} - Q_{Calmin}) + LMIN_\lambda}$$

Where:

Variable	Meaning	Measurement units
$\mathbf{L_\lambda}$	Spectral Radiance at the sensor's aperture	W/(m^2 * sr * μm)
$\mathbf{Q_{Cal}}$	Quantized calibrated pixel value – the input file	DN
$\mathbf{LMIN_\lambda}$	Spectral at-sensor Radiance that is scaled to $\mathbf{Q_{Calmin}}$	W/(m^2 * sr * μm)
$\mathbf{LMAX_\lambda}$	Spectral at-sensor Radiance that is scaled to $\mathbf{Q_{Calmax}}$	W/(m^2 * sr * μm)
$\mathbf{Q_{Calmin}}$	Minimum quantized calibrated pixel value corresponding to $\mathbf{LMIN_\lambda}$ **(DN = 1)**	DN
$\mathbf{Q_{Calmax}}$	Maximum quantized calibrated pixel value corresponding to $\mathbf{LMAX_\lambda}$ **(DN = 255)**	DN
$\mathbf{G_{rescale}}$	Band-specific rescaling gain factor	(W/(m^2 * sr * μm))/DN
$\mathbf{B_{rescale}}$	Band-specific rescaling bias factor	W/(m^2 * sr * μm)

The latest gain and bias numbers and the LMINλ, LMAXλ, for the Landsat 5 TM and Landsat 7 ETM+ sensors are given in Chander *et al*. (2009). The LMINλ and LMAXλ for a particular scene are given in a metadata file (MTL.txt) accompanying the image (Appendix 2.1&2.2). The graphical model used for the conversion of DN values to radiance is given in (Appendix 3).

b) Conversion to at-sensor Spectral Radiance of OLI / TIRS sensors ($\mathbf{Q_{Cal}}$ - $\mathbf{L_\lambda}$)

Images are processed in units of absolute radiance using 32-bit floating point calculations. These values are then converted to 16-bit integer values in the finished level 1 product (USGS, 2015; USGS, 2016). These values were then converted to spectral radiance using the radiance scaling factors provided in the metadata file (MTL.txt) as shown in (Appendix 4) (http://landsat.usgs.gov/tools.php).

$$\mathbf{L_\lambda = M_L * Q_{Cal} + A_L}$$

Where:

Variable	Meaning	Measurement units
L_λ	Spectral Radiance at the sensor's aperture	$W/(m^2 * sr * \mu m)$
Q_{Cal}	Quantized calibrated level 1 pixel value – the input file	DN
M_L	Radiance Multiplicative scaling factor for the band (RADIANCE_MULT_BAND_n from the metadata)	$W/(m^2 * sr * \mu m)/DN$
A_L	Radiance Additive scaling factor for the band (RADIANCE_ADD_BAND_n from the metadata)	$W/(m^2 * sr * \mu m)$

The graphical model used for the conversion of DN values to radiance is given in (Appendix 5)

c) Conversion of TM and ETM+ Radiance to TOA Reflectance (L_λ - ρ_λ)

A reduction in scene-to-scene variability can be achieved by converting the at-sensor spectral radiance to exoatmospheric TOA reflectance, also known as in-band planetary albedo (Chander *et al*., 2009). Conversion to TOA reflectance is necessary because it removes the cosine effect of different solar zenith angles due to the time difference between data acquisitions; compensates for different values of the exoatmospheric solar irradiance arising from spectral band differences; and corrects for the variation in the Earth–Sun distance between different data acquisition dates. These variations can be significant geographically and temporally (Chander *et al*., 2009). The TOA reflectance of the Earth is computed according to the equation:

$$\rho\lambda = \frac{\pi * L_\lambda * d^2}{ESUN_\lambda * \cos\theta_s}$$

Where:

Variable	Meaning	Measurement units
$\rho\lambda$	Planetary TOA reflectance	(Unitless)
π	Mathematical constant ~3.14159	(Unitless)
L_λ	Spectral Radiance at the sensor's aperture	$W/(m^2 * sr * \mu m)$
d^2	Earth–Sun distance	Astronomical units
$ESUN_\lambda$	Mean exoatmospheric solar irradiance	$W/(m^2 * sr * \mu m)$
θ_s	Solar zenith angle	Degrees

Note that the **cos θ** of the solar zenith angle is equal to the **sin θ** of the solar elevation angle. The Earth sun distance (d^2) and the solar elevation angle (**sin θ**) are shown in

(Appendix 6). The graphical model used for the conversion of radiance to reflectance is given in (Appendix 7).

d) Conversion of OLI Radiance to Top of Atmosphere (TOA) Reflectance

Similar to the conversion to radiance, the 16-bit integer values in the level 1 product can also be converted to TOA reflectance (http://landsat.usgs.gov/tools_project.php). The following equation was used to convert level 1 DN values to TOA reflectance.

$$\boldsymbol{\rho\lambda' = M\rho * Qcal + A\rho}$$

Where:

Variable	Meaning	Measurement units
$\boldsymbol{\rho\lambda'}$ =	Top-of-Atmosphere Planetary Spectral Reflectance, without correction for solar angle	(Unitless)
$\mathbf{Q_{cal}}$ =	Quantized calibrated level 1 pixel value – the input file	DN
Mρ =	Reflectance Multiplicative scaling factor for the band (REFLECTANCE_MULT_BAND_n from the metadata)	DN^{-1}
Aρ =	Reflectance Additive scaling factor for the band (REFLECTANCE_ADD_BAND_n from the metadata).	DN^{-1}

NB: n = Band numbers in both cases (e.g. Band 1, 2, 3 and so on)

Note that $\boldsymbol{\rho\lambda'}$ is not the true TOA Reflectance, because it does not contain a correction for the solar elevation angle. This correction factor is left out of the level 1 scaling at the users' request; some users are contented with the scene-centre solar elevation angle in the metadata, while others prefer to calculate their own per-pixel solar elevation angle across the entire scene (USGS, 2015). Once a solar elevation angle is chosen, the conversion to true TOA Reflectance is:

$$\boldsymbol{\rho\lambda = \frac{\rho\lambda'}{\sin(\theta)}}$$

Where:

$\boldsymbol{\rho\lambda'}$ = Top-of-Atmosphere Planetary Reflectance (Unitless)

θ = Solar Elevation Angle (from the metadata – for this study).

The graphical model used for the conversion of radiance to reflectance is given in (Appendix 8).

3.4.4.4 Atmospheric Correction

Atmospheric correction was necessary to correct the images for first degree atmospheric effects (Nasr *et al*. 2012). Atmospheric correction is the process of compensating for atmospheric distortions from Rayleigh or molecular scatter, and radiance that results from aerosols or haze influencing the signal at the top of the atmosphere. Graphical model in ERDAS Imagine software was used to correct for atmospheric effects associated with the Landsat images using the estimated calibration coefficients. This model accounts for the effects of atmospheric water vapour and influence of adjacent ground measurements (Nasr *et al*. 2012). The images were atmospherically corrected using the dark object subtraction (DOS) method (Song *et al.*, 2001). DOS is one of the most commonly used method for atmospheric correction which requires identification of the darkest object with negligible reflectance within the image. The signal level over that object is estimated and subtracted from every pixel in the image.

The procedure is often referred to as DOS because it assumes that within a satellite image there are features that have near-zero percent reflectance. The signals recorded by the sensor from those features are believed to be as a result of atmospheric scattering, which must be removed. Dark objects in an image are usually deep, clear water features such as lakes, shadows, asphalt paving and dense forests. Minimum values in the bands in the image are assumed to be due to the additive effects of the atmosphere (Munyati, 2004). The study area image scenes contained several deep water features such as lakes, rivers, dense forests and trees canopy shadows making DOS approach suitable to be used for atmospheric correction as areas with negligible reflectance in all bands could be found.

Atmospheric correction values were selected through histogram evaluation. The values were input in the conditional statement of the Spatial Modeler and subtracted from each band. The graphical model used for DOS is given in (Appendix 9).

3.4.4.5 Image Composite and Mosaicking

Composite images of the scenes were created by layer staking respective satellite images colour bands together for a multi-layer or band combinations. The composite images were mosaicked by stitching or combining together the two scenes because the study area traversed or spanned across these scenes. The mosaic process offers the capability to stitch images together so one large, cohesive image of an area can be created. Images enhancement and colour balancing was performed to ensure that the brightness and contrast of pixels are uniform. This was done to facilitate visual interpretation of the images and colour contrast. Layer stacking or bands combination and mosaicking was done in ERDAS Imagine.

3.4.4.6 Image Sub-setting

The spatial extent of the mosaicked images was greater than the study area, therefore, these images were subset to create an area of interest (AOI). This was done to make image processing easier and to extract the study area. Shape files of the study area downloaded from World Database for Protected Areas (WDPA) (http://protectedplanet.net) was overlaid on the mosaicked satellite images to subset or clip the area of interest (AOI). Sub-setting was done with the help of ERDAS's AOI tools in the Imagine Viewer using an AOI file that was created using the study area shape file (Figs. 3.5 – 3.8).

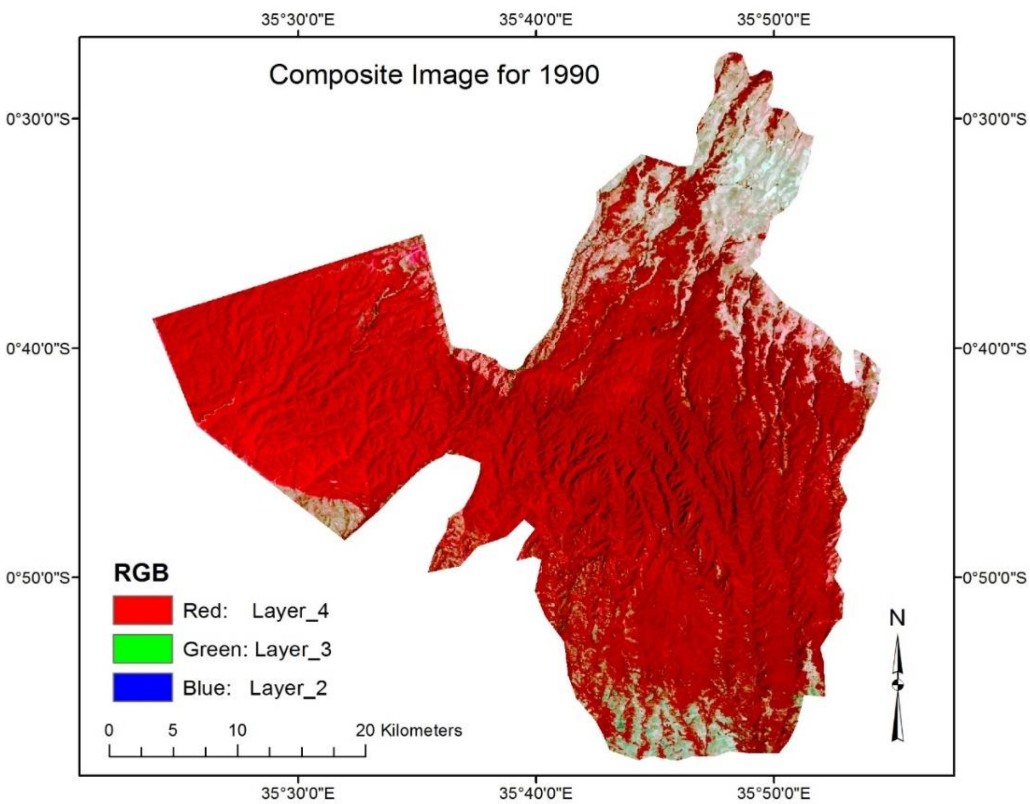


Fig. 3.5: Composite subset image of the study area for the year 1990

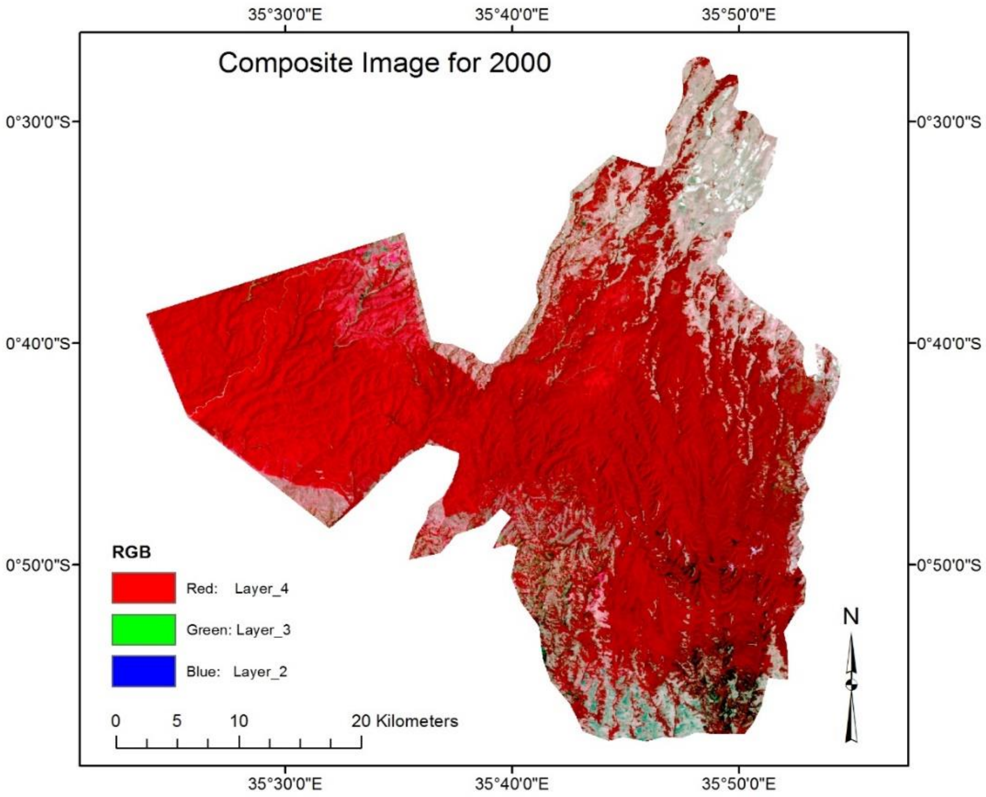


Fig. 3.6: Composite subset image of the study area for the year 2000

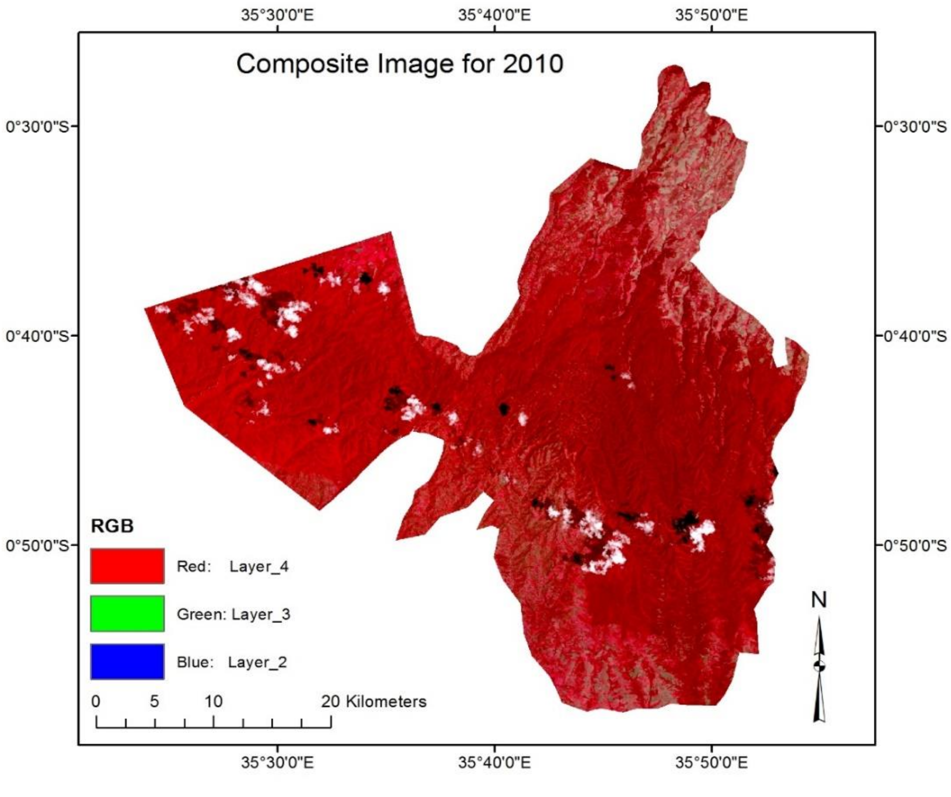


Fig. 3.7: Composite subset image of the study area for the year 2010

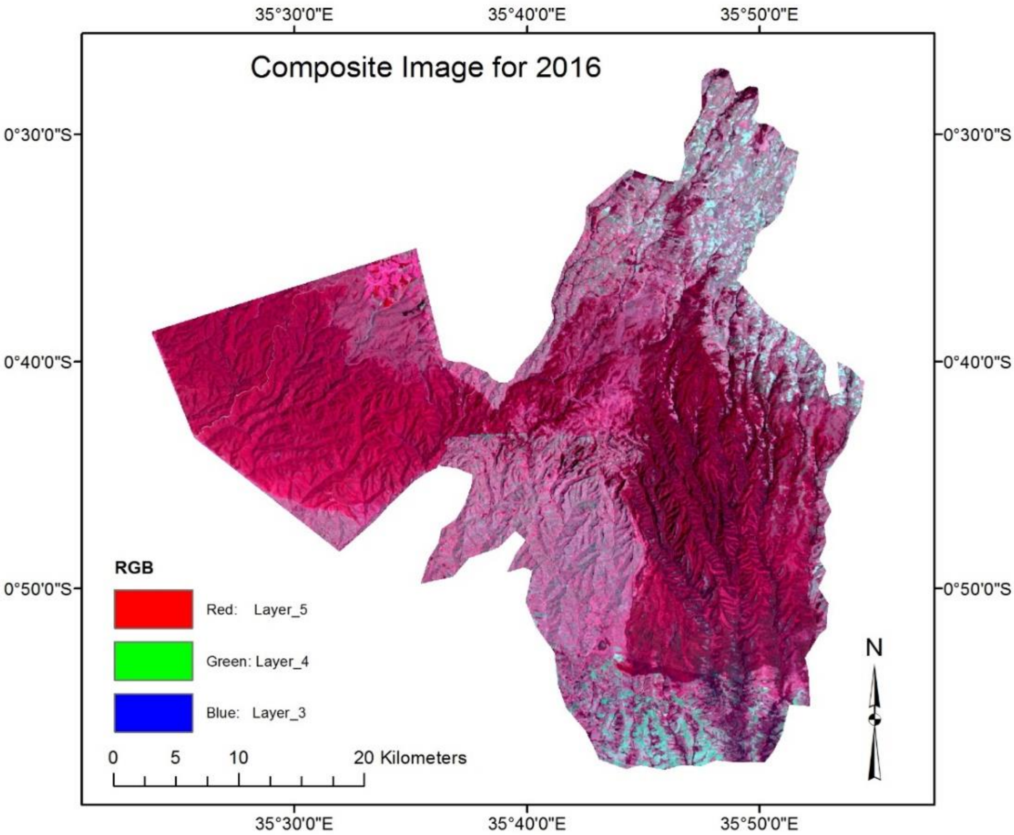


Fig. 3.8: Composite subset image of the study area for the year 2016

3.4.5 Image Classification

Pre-processed images were used in image classification. Each image was classified separately using the unsupervised classification method in ERDAS Imagine 2014 software. The unsupervised classification was done at maximum iteration of 10 and convergence threshold of 0.950. The ISODATA clustering algorithm examines the unknown pixels in an image and groups them based on the premise that values within a given cover type should be close together in the measurement of space (Lillesand *et al*., 2008). It defines the spectral classes using spectral distance and iteratively classifies the pixels, redefines the criteria for each class, and classifies again, so that the spectral distance patterns in the data gradually emerge (ERDAS, 2009). The classes were interpreted based on field work and data obtained by a handheld Garmin GPS, and through visual interpretation. To simplify the images interpretation of change, the classes were recorded from the initial clusters. Due to visual interpretation of the original images and familiarity of the study area, the expected classes were identified on the basis of the prior knowledge. Based on the existing knowledge of the study area, 5 classes were identified as agricultural land, bare grounds, tea plantations, degraded forest and forest.

3.4.6 Classification Accuracy Assessment

Images classification for land cover classes is never conclusive without accuracy assessment. The accuracy assessment task was done by comparing two sources of information, one based on analysis of remotely sensed data (the map) and ground information, the reference data. Therefore, an essential measure of the efficiency is the ability to successfully extrapolate data from the field to the mapped area. One such measure is to perform classification accuracy, to be able to quantify a confidence level, so that the classification data can be related to the actuality over the classified area (Reddy, 2001). The most common method for assessing the accuracy of a classification is the use of an error matrix or the confusion matrix, as described by Foody (2002; 2009) and Congalton and Green (2009). Error matrices are useful analytical tools for assessing and comparing classified map accuracy (Congalton & Green, 1999; Lillesand & Kiefer, 2004). Compilation of an error matrix is required for any serious study of accuracy. The details on the construction and evaluation of the error matrices were referred from Campbell & Wynne (2011).The classified images were compared with field data and topographical information of the study area to ascertain how ground measurements as observed during ground truthing was classified on the images.

3.4.7 Normalized Difference Vegetation Index (NDVI)

Generally, healthy vegetation absorbs most of the visible light that falls on it, and reflects a large portion of the near-infrared light. Unhealthy or sparse vegetation reflects more visible light and less near-infrared light. Bare soils on the other hand reflect moderately in both the red and infrared portion of the electromagnetic spectrum (Holme *et al.,* 1987). Overall, NDVI provides a crude estimate of vegetation health and a means of monitoring changes in vegetation over time. Although there are several vegetation indices, NDVI remains one of the most widely used and well-known index to detect live green vegetation in multispectral remote sensing data. It is preferred to the simple indices because it compensates for illumination conditions such as surface slope and orientation.

The NDVI is a numerical indicator that uses the visible and near-infrared (NIR) bands of the electromagnetic spectrum. It is a ratio often used to determine the density of vegetation in an area based on visible and NIR sunlight reflected by plants. The pigments in plant leaves, the chlorophyll, strongly absorbs visible light from (0.4 - 0.7) µm for use in photosynthesis. The cell structure of the leaves, on the other hand, strongly reflect near infrared light from (0.7 - 1.3) μm. The more leaves a plant has, the more of these wavelengths of light are reflected.

Vegetation have a reflectance of 20% or less in the 0.4 - 0.7 μ (green to red) and about 60% in the 0.7 - 1.3 μ (NIR). These spectral reflectance are themselves ratios of the reflected over the incoming radiation in each spectral band individually; hence, they take on values between 0.0 and 1.0. Thus, the NDVI ranges from +1.0 to -1.0. Negative values of NDVI (values near -1) correspond to deep water. Values close to zero (-0.1 to 0.1) generally correspond to barren areas of rock, sand, or snow. Sparse vegetation such as shrubs and grasslands or senescing crops may result in moderate positive NDVI values (approximately 0.2 to 0.5). High NDVI values (approximately 0.6 to 1) correspond to dense vegetation such as that found in temperate and tropical forests or crops at their peak growth stage.

Vegetated areas give positive values due to their high reflectance in the NIR and low reflectance in the visible spectrum. On the other hand, bare areas or areas with very sparse vegetation cover have higher reflectance in the visible spectrum than in the NIR, leading to negative or near zero NDVI values. It was calculated in ERDAS Imagine spatial modeler using the following formula. The graphical model for NDVI is given in (appendix 10).

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)}$$

The resultant values were correlated to the characterized time-series changes in forest cover and land cover/land use. This was also correlated to climate variability in the area to determine when drought was most severe and so on depending on the magnitude of climate change and variability impacts at the same period.

3.4.8 Change Detection

The detection of changes involves the comparison of satellite images taken in different years but at the same or nearly the same time period (Akotsi *et. al*, 2006). This study used post classification and NDVI change detection analysis methods to evaluate changes in land cover/land use by comparison of corresponding time-series images. Change detection was performed by taking the year 1990 classified image as the reference year, and changes occurring until 2016 were determined. Observation of changes were done during the three periods (1990 – 2000, 2000 – 2010 and 2010 – 2016) and overall changes in land cover in the study area for the study period of 26 years (1990 – 2016) noted.

3.4.8.1 Post Classification Change Detection

Post classification change detection involves comparing images subsequent to their classification. It consists only of comparing the "from" and "to" class for each pixel or segment and has advantage of giving "from-to" detection suitable when training data is available (Lu *et al*., 2004; Campbell & Wynne, 2011). It is conceptually one of the most simple change detection methods which involves an initial, independent classification of each image, followed by a thematic overlay of the classifications resulting in a complete "from-to" change matrix of the transitions between each class on the two dates (Almutairi & Warner, 2010). The method has also been found to be the least sensitive to changes in the image properties of class separability, radiometric normalization error and band correlation. By using the change matrix, an advantage of "from-to-" to interpret change information can be taken (Alphan *et al.,* 2009).

3.4.8.2 NDVI Change Detection

The method applied in this study was known as image differencing, where the value of the pixels in the previous NDVI image was simply subtracted from the value of the corresponding pixels in the subsequent NDVI image. NDVI image differencing was computed using ERDAS Imagine® 2014. In this case, the situation in 1990 NDVI image was compared with that in 2000, 2000 with 2010, 2010 with 2016 and finally image pixels in 1990 was subtracted from those in 2016 to determine overall changes during the study period. In order to distinguish areas of significant changes from areas with no significant changes, a meaningful threshold of changes must be applied. Therefore, changes in this study were determined at a threshold of 15% as either increased or decreased. In areas with no significant change, the difference value was zero or close to zero. On the other hand, in areas where major changes occurred, the difference gave large positive (increase in vegetation density) or negative (decrease in vegetation density) values.

3.4.9 Ground Truthing

After image classification, the study area was revisited to verify the information collected by remote sensed images and the real situation on the ground, specifically targeting areas where major forest changes were observed to ascertain the cause of the forest cover changes observed. It involved identifying and verifying different categories of land cover/use classes on the ground and compare with the information obtained from the images. The GPS coordinates taken during spatial and reconnaissance survey, field observations and visual interpretation of the available study area maps were used to determine how each points characterized on the ground as observed during ground truthing was classified on the image.

3.4.10 Software

Satellite images processing and geo-spatial analysis was performed using ERDAS Imagine® 2014, a digital image processing software developed by Leica Geo-systems, Atlanta, USA and ArcGIS 10.3 developed by ESRI. MS-Excel was used to export and import field data into a GIS platform. Thematic and NDVI maps were prepared using ERDAS Imagine® and ArcGIS. In addition, MS-Excel and SPSS ver. 23 software were used for statistical analyses for HH survey.

3.5 Household (HH) Survey of the Study Area

3.5.1 Study Setting

This community-based cross-sectional study was carried out between April - September, 2016 in ten (10) purposively selected locations of Narok County, namely; Lower Melili, Nkareta, Olokurto, Naituyupaki, Enabelibel, Ol Pusimoru, Melelo, Endonyo Ngiro, Sogoo, and Sagamian (Fig. 3.9). These locations were conveniently selected because they are administratively situated partly within and adjacent to the forest blocks forming the community-forest interphase constituting the most vulnerable areas to CCV (Ministry of Forestry & Wildlife, 2010). The total population of the ten (10) locations is estimated at 127,966 as per the national population census (KNBS, 2009). Geographic areas or administrative boundaries were used to collect the socio-economic data due to lack of proper residential address system in the study area, therefore, it provided the best alternative for demarcating areas for HH survey (UN, 2005).

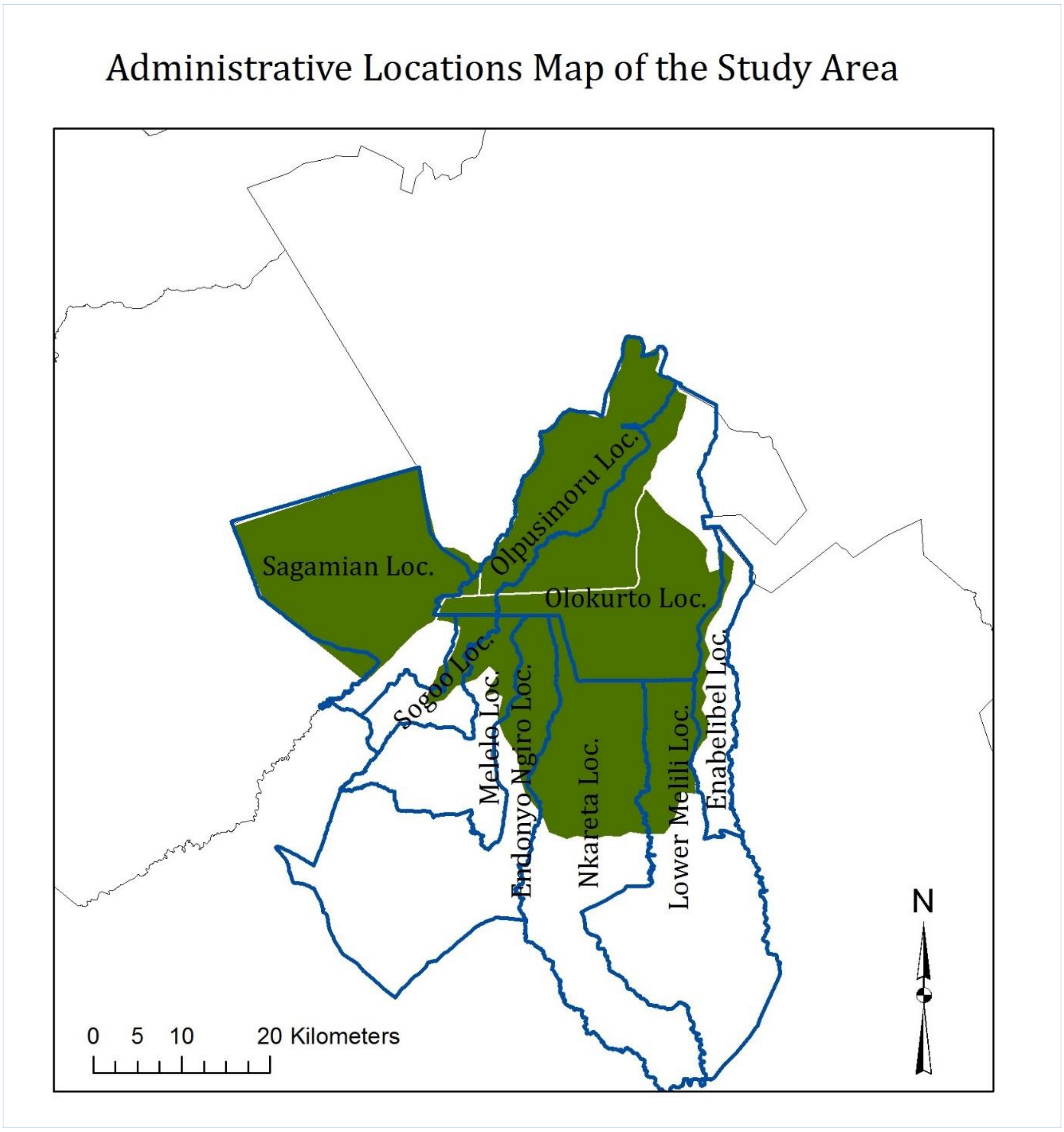


Fig. 3.9: Map for the Administrative Locations used in the Study

3.5.2 Household Survey Sampling Procedure

The sample size calculation was based on probability proportional to estimated size (PPES). Proportionate stratified multistage clustered sampling was used to determine the sample design frame. Clustered sampling method was adopted because it reduces the cost of survey by grouping the respondents together (UN, 2005). The population was stratified into homogeneous groups and then simple random samples were drawn from within each stratum. Stratification was applied at each stage of sampling. Administrative locations were explicitly stratified into mutually exclusive and collectively exhaustive strata before selection and separate samples selected from each stratum. They were used for the study as the first strata and then implicitly stratified to establish sub-locations as the primary sampling units (PSUs). HHs were listed within each PSU to determine the sample frame and the number of persons within each HH was recorded according to the latest enumeration report for the area. The total number of HHs or persons within the study area was treated as the target population size. The persons within each HH were the ultimate sampling units (USUs) and the final stratification stage (Fig. 4.0). The samples were drawn from each PSU with PPES by randomly selecting the number of HHs at a fixed rate (UN, 2005). The formula by UN (2005), Kothari (2006) and Kalton (2009) was used to calculate the study sample size with a confidence interval of 95%.

$$ME = z\sqrt{\frac{p(1-p)}{n}}$$

$$n = \frac{p(1-p)z^2}{ME^2}$$

Where:

- ME is the desired margin of error (95%) CI, α = 0.05
- z is the desired z-score (1.96 for a 95% CI) yielding the desired degree of confidence
- p is an estimate of the population proportion.
- n is the sample size

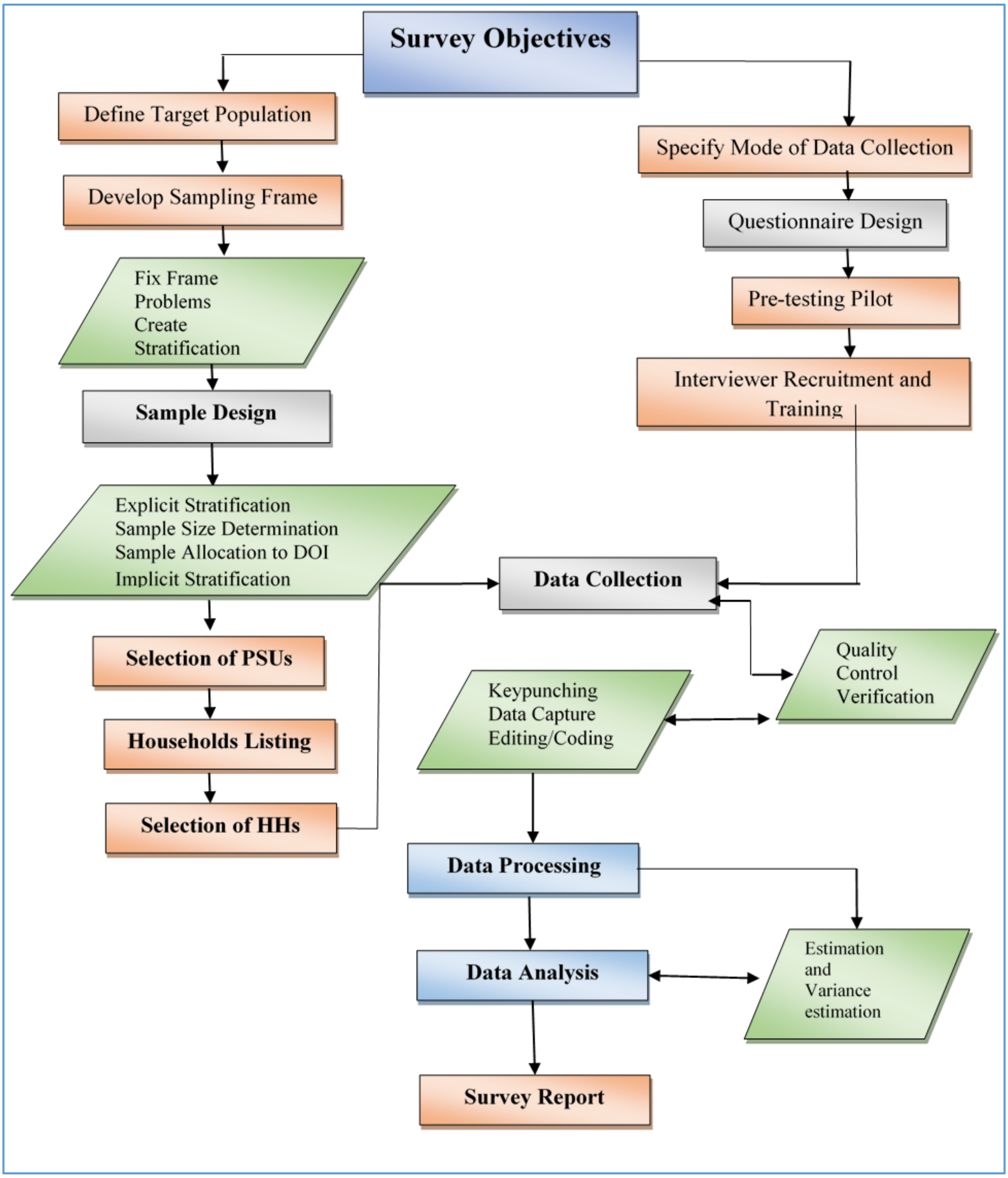


Fig. 3.10: Overall Methodological Framework and Sampling Design

Adopted and modified from (UN, 2005)

3.5.3 Study Population Sampling

The target study population was the communities in the ten (10) vulnerable locations comprised of twenty three (23) sub-locations. A total of seventeen (17) sub-locations were randomly selected as PSUs. The Kenya National Bureau of Statistics (KNBS) uses sub-locations as standard Enumeration Areas (EA) and HH listing for its census, which was used for HHs listing and selection. From the selected sub-locations (PSUs), 24,072 HHs were listed and finally a total of 405 HHs (Appendix 11) were randomly sampled as adequate representative of the target population. From each sampled HH, the head of the HH, or a member of the HH who could act in the capacity of HH's head in case of absence or incapacitation, or a nominee of the HH's head was selected as the eligible participant. The selected participant's consent was obtained, and the questionnaires were administered to the consented individuals to acquire the information.

In addition, Key Informants (n = 34) were also purposively selected to be interviewed. Key Informants (KI) comprised of experts or people knowledgeable in a particular field of interest and included opinion experts such as community leaders, rainmakers, traditional medicine men, spiritual leaders, local NGOs and government officials with specific information or vast knowledge in the study subject. Snowballing sampling method was also used to select respondents in cases where KI would refer the interviewer to someone considered to have special information about the subject of study.

3.5.4 Household (HH) Survey Data

A pretested, structured/unstructured interviewer-administered questionnaire was used for the study. Secondary literature and information from Key Informant Interviews (KIIs) was also used to gather preliminary literature and information on CCV which was ultimately used to develop questionnaire on CCV knowledge, perception, and vulnerability (Kabir *et al*., 2016).

A draft questionnaire was developed and finalized after pre-testing. The finalized questionnaire (Appendix 12) was used to collect information on CCV. One week training for the data enumerators and questionnaires pre-testing was carried out, after which seventeen (17) trained data enumerators administered the questionnaires at HH level for four (4) weeks under strict supervision of five (5) experienced Community Forest Association (CFA) officials from the study area. Data enumerators/translators were recruited from individuals acquainted with the specific local dialects in the area so as to comprehensively translate the questions to the respondents and record appropriately. The data collation process was supervised by the investigators. Regular observations at HH level was done and the data checked for completeness. Each filled-up questionnaire was checked and missing information as well as any error detected was corrected and/or accounted for immediately. The collected data was then categorized, numerically coded and fed into IBMs Statistical Package for Social Scientist (SPSS ver. 23) for statistical analysis.

3.5.5 Data Collection Instruments

The main data collection instruments used in this study was a pretested, structured/unstructured interviewer-administered questionnaires. Secondary literature or desktop review and Key Informant Interviews (KIIs) were used to gather preliminary literature and information on CCV which were ultimately used to develop questionnaire on CCV knowledge, perception, attitudes and vulnerability. Responses were acquired using various Likert-type answers on nominal (dichotomous and categorical) and ordinal scale. A KII schedule was also developed to gather data from Key Informants using a short semi-structured interview schedules. Experts were contacted to validate the available data collection tools for assessment of the impacts of CCV on the vulnerable biophysical and socio-economic systems. Observation checklists about the HHs and community characteristics were also developed and used by the interviewers.

3.5.6 Validation and Reliability of the Instruments

The accuracy and precision of the instruments to capture and measure the variables studied and achieve desired responses and output was ensured through:-

- Adequate background information and relevant literature in the field of study subjects.
- Pre-testing of the instruments and review of the shortfalls by correcting to clarify and use proper wording for general acceptability.
- Reconnaissance and pilot surveys to verify the mood on the ground and collect preliminary information.
- Expert’s opinions in validity and reliability of the instruments.
- Alignment of the instruments with specific objectives to capture relevant information and achieve desired results.
- Proper identification of the methods and type of data to be collected (quantitative, qualitative or both); and scale of measurements (nominal, categorical, ordinal or ratio).
- Ensure anonymity and confidentiality of the respondents by consent approval to boost honesty and willingness to participate.
- Ensuring availability of satellite imagery of the required scenes for the specified time and selection of quality images for processing in terms of path and row.

Spatial, spectral and radiometric resolutions of the selected images were also verified.

- Ensuring that the selected images have the scene metadata with valid scene information.

These validity and reliability measures ensured how well the instruments were able to capture the variables and yield desired results.

3.5.7 Ethical Concerns of the Study

The study was approved by the directorate for Board of Postgraduate Studies (BPS) and approvals obtained from National and County government departments including Kenya Forest Service (KFS), County Commissioner and County Department of Environment, Water and Energy. An informed participant's consent was obtained from the HH's head after a written introductory information note was read out before the interview commenced. The heads of the HHs were assured that the data collected were confidential and that none of their household status or information will be revealed to the public or private entities.

3.5.8 Household Survey Data Analysis

Data from the survey was coded and fed into the computer and validated using SPSS by logical and range checks. Qualitative data from interviews were coded and indexed through intensive content analysis in order to identify major themes and dominant narratives. Summary statistics were exported to excel worksheets to produce graphical figures and tables. The summary statistics were reported as frequencies and percentages with α-value = 0.05 (95%) Confidence Interval (CI) for nominal or categorical and ordinal variables. The results were summarized and presented using frequency and/or percentage tables and figures. Evidences of association and significance tests between variables, knowledge and perception of CCV were explored by cross-tabulation and measured using Spearman's Chi-square (χ^2) test of independence, correlation statistics and simple Generalized Linear Models (GzLM). The Logistic Regression Model (Logit) of GzLM was applied to explore the response and predictor (explanatory) variables that had significant relationship using multinomial distribution and logit link functions analysis. The effects of predictor variables were evaluated by checking whether the Wald 95% CI for each coefficient included zero.

CHAPTER 4: RESULTS AND DISCUSSION

4.1 Trends in Observed Precipitation

Based on records from one synoptic station in Narok, the mean monthly rainfall ranges between less than 20cm to more than 120cm, with two seasonal rainfall peaks receiving the highest amount of precipitation in March – May and October – December. The spatial and temporal variation in precipitation indicated low rainfall reliability. Most of the months are characterized by high incidences of droughts indicating that several areas in the county are prone to dry spells. The rainfall trends in the area exhibit very sharp onset and offset of monthly rainfall with shorter rainy seasons dropping very abruptly to drier seasons. This requires farmers to be very selective in their choices for crop breeds and plant crops which require shorter rainy seasons and drought resistant (Fig. 4.1).

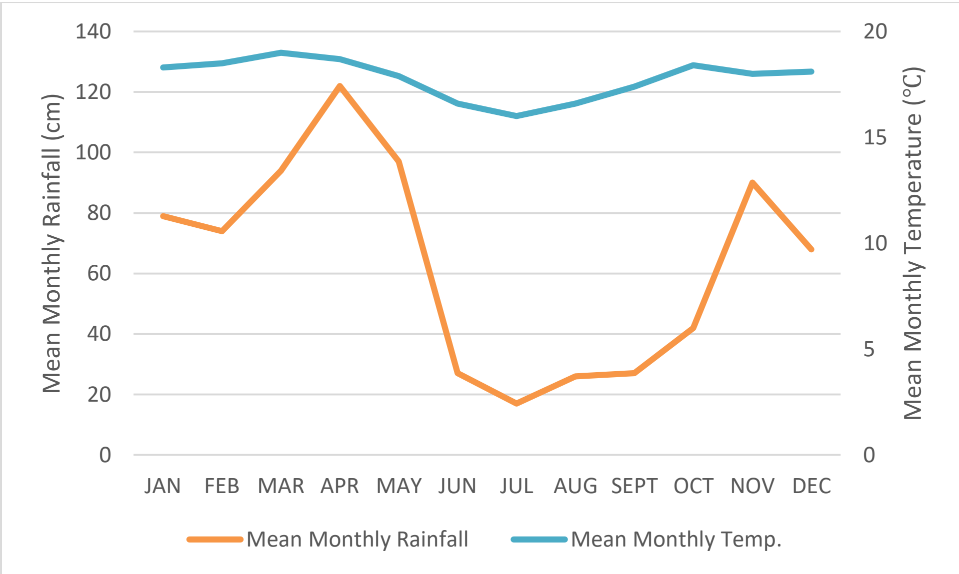


Fig. 4.1: The trends of mean monthly rainfall and temperature variation.

The onset of rainy season usually falls between March and May which is normal for averaged monthly precipitation. However, a slight tendency for the onset of the rainy season to come earlier than March as anticipated in the previous years though due to limited data availability, it’s hard to ascertain if these changes constitute a long term trend or merely a short term variability pattern (Fig. 4.2).

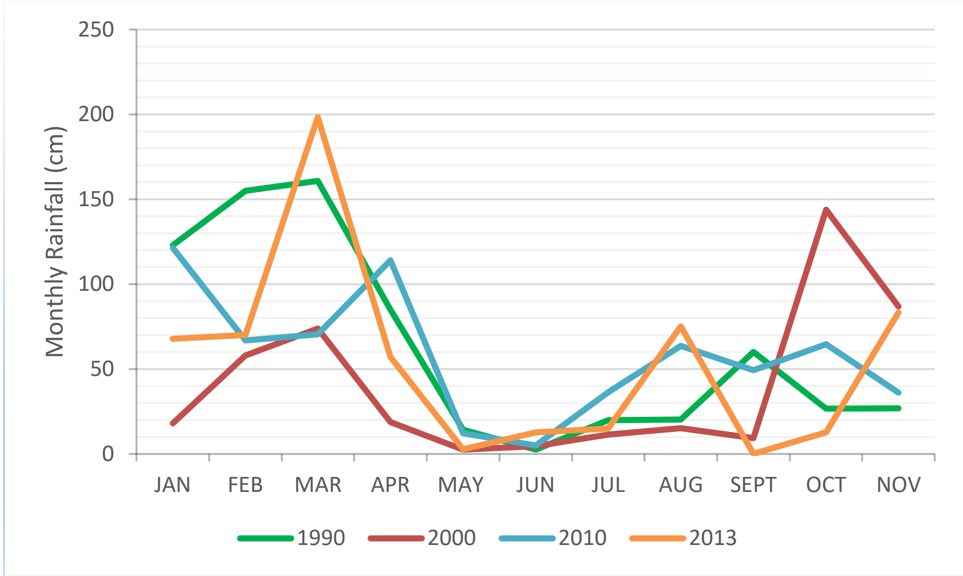


Fig. 4.2: The trends of monthly rainfall variability from 1990 – 2013

For instance, in the year 1990, the onset of rainy season was in January. It then increased to a peak of 1700 mm in March and declined to 140 mm in May. The year 2000 had a similar trend but with a very wider variation in the volumes received. The variation in the peak rainfall was 1000 mm in March. In the year 2010, onset of rainy season was in February with a peak precipitation of 1140 mm in April while in 2013, the onset was in February with a peak precipitation of 2000 mm in March. During the short rainy season in (Oct – Dec), a similar variation in rainfall trends were observed in timings of precipitation onset and the volumes received. These abnormalities in average monthly rainfall oscillation caused uncertainties in seasonal precipitation circles which culminate in flash floods or severe drought events. The average monthly rainfall significantly reduced during the drier months (June – August) by 1050mm (86.1%) drop in rainfall. Total monthly maximum and minimum precipitation portrayed an erratic trend with some abrupt heavy downpours causing flash floods.

Trends in the distribution of mean annual rainfall variability from 1990 – 2016 indicated an overall decline throughout the years with computed Mann Kendall value T0.0142 (P < 0.05) (Fig. 4.6). Comparatively, the area experienced high precipitation in 1990, 1993 – 1994, 1997 – 1998, 2002, 2006 and 2010 while low precipitation (driest years) occurred in 1992, 1995, 2000, 2008 – 2009 and 2013. However, the gap between maximum mean annual precipitation and minimum mean annual precipitation widened. For instance, the gap between 1990 and 1992 was 280 mm, 1992 and 1993 was 280 mm, 1995 and 1997 was 270 mm, 1997 and 2000 was 440 mm, and 2005 and 2006 was 540 mm. This resulted to the variation in the height of the crests observed with time indicating that precipitation variability is increasing while overall precipitation trend is reducing with time.

4.2 Trends in Observed Temperature

The mean monthly temperature indicated that the warmest months were Feb – March with the highest mean monthly maximum temperature of 27.4℃ in March. The months of June – September were observed to have the lowest average mean monthly temperature with September recording the lowest mean monthly minimum temperature of 9.3℃ (Fig. 4.3). The rainy season (long rains in March – April and short rains in Oct. – Dec.) were coincidentally the warmest months recording the highest mean monthly maximum temperatures while the driest months (June – Sept. and Dec. – Feb.) recoded the lowest mean monthly minimum temperatures (Figs. 4.1 and 4.3).

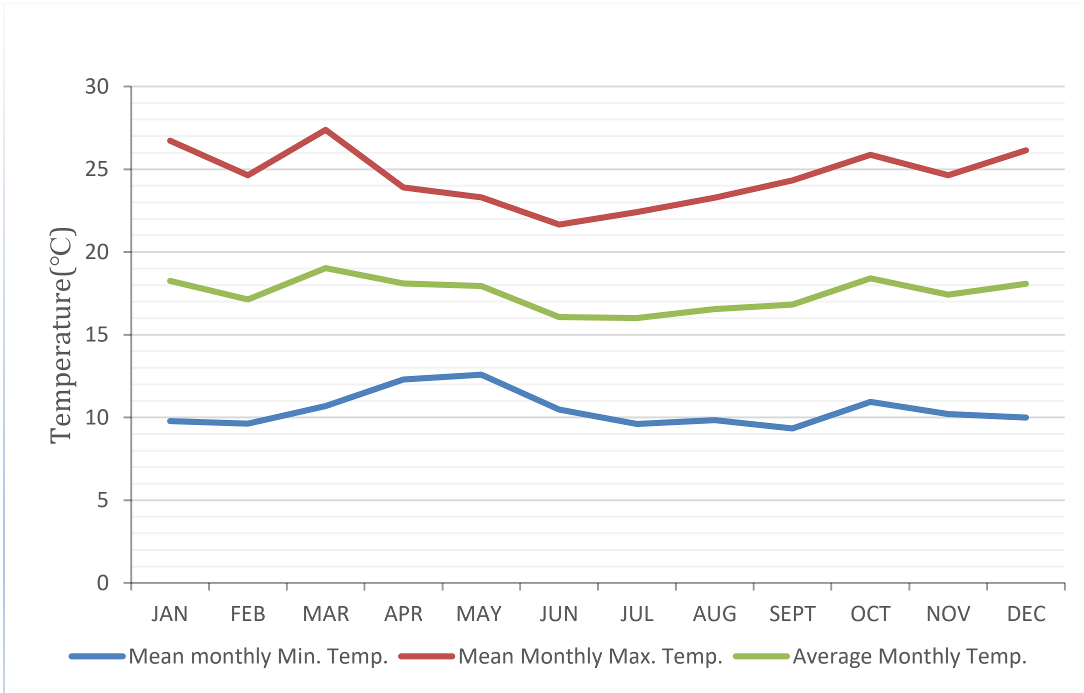


Fig. 4.3: The trends of mean monthly minimum, average and maximum temperature.

However, the warm spells recorded extreme mean daily maximum temperature of 37.8℃ and 32.8℃ in March of 2009 and 2010 respectively (Fig. 4.4). This was a record warmest month (March, 2009) during the study period, which occurred when the country experience one of the worst drought in 2008 – 2009 leading to loss of animals, livestock and people. The coldest spell recorded extreme mean daily minimum temperature of 7.4℃ in June, 1999 (Fig. 4.5). These extreme temperature variability trends demonstrated scenarios when above or below normal temperatures were observed indicating warming tendencies during the study period. Extreme temperature events constitute climate change and variability. Temperature greater than 35℃ is above normal and is described as an extreme event (Lasco *et al.*, 2010).

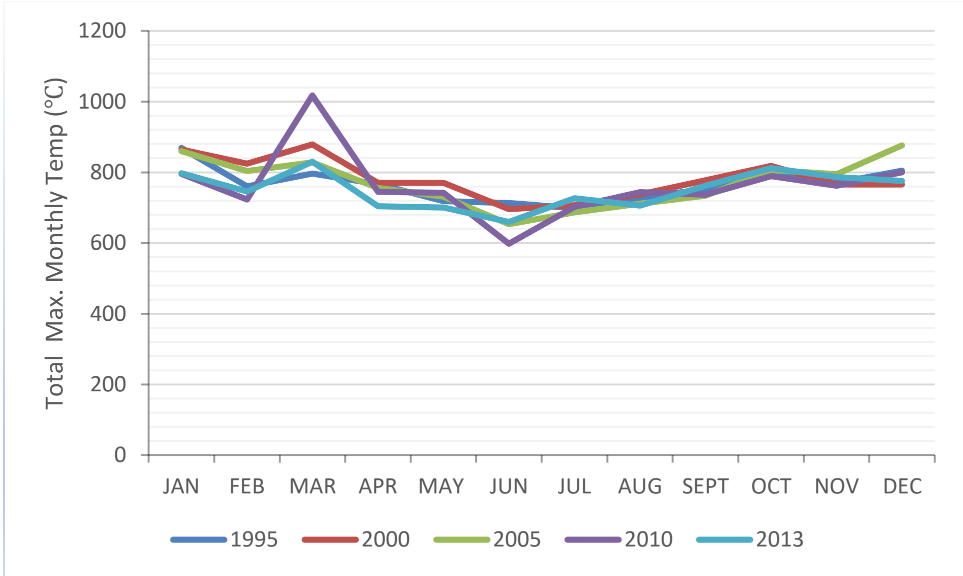


Fig. 4.4: The trends of monthly maximum temperature

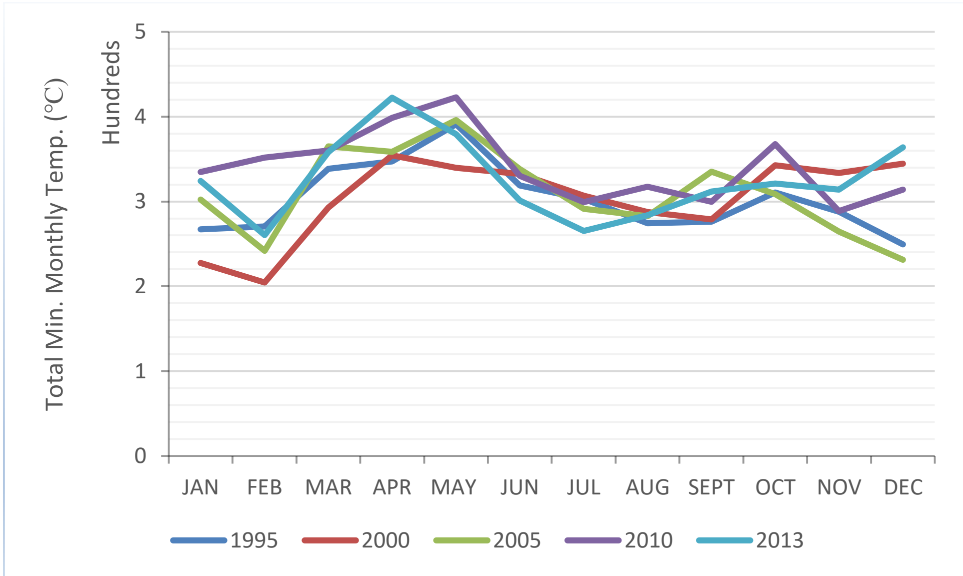


Fig. 4.5: The trends of monthly minimum temperature

Maximum monthly temperature did not show significant variability with time except in the year 2010, which experienced extreme temperature events between the months of February to April and May to July as shown in (Fig. 4.4). Analysis of minimum monthly temperature indicated temporal variation with the greatest temporal variability occurring during the first and the last quarter of the year as shown in (Fig. 4.5).

The mean annual temperature increased by 1.8°C during the 26 years study period. Analysis of time series of temperature records for the study area indicated evidence of climate variability with increasing trends of mean annual temperature with computed Mann Kendall value T0.0351 (P < 0.05). The increasing trend of mean annual temperature and the declining trend of mean annual precipitation are shown by the trend lines in (Fig. 4.6).

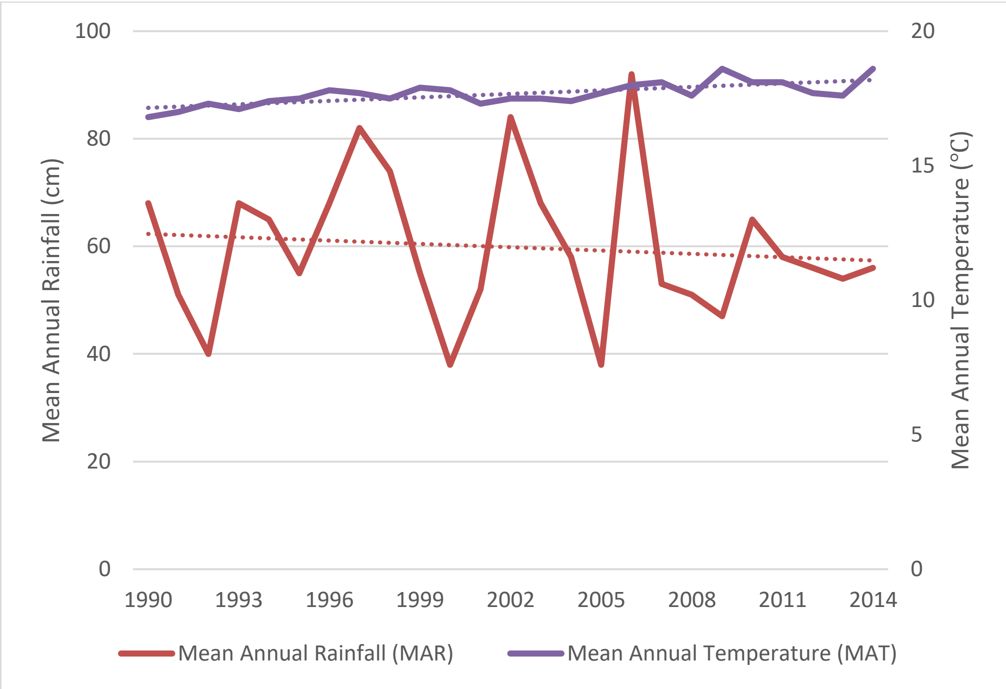


Fig. 4.6: The trends of mean annual rainfall and temperature variation

4.3 Characterization of Land Cover / Use Changes in MFC using Remote Sensing Techniques

4.3.1 Images Classification

Based on the baseline information, knowledge of the study area, visual interpretation of the original images, expected classes identified during ground truthing and familiarity of the study area, 5 land cover classes were identified as defined in (Table 4.1).

Table 4.1: Land cover/use classes in the study area and their descriptions.

Land Cover Classes	Descriptions
1. Agricultural land	Cropland, Cultivated fields and Fallow land
2. Bare grounds	Roads, Residential areas, Open grounds and Rocky surfaces
3. Degraded forest	Destroyed forest areas – Bushed forest, thickets, forest glades etc.
4. Forest	Dense forest canopy
5. Tea Plantation	Tea growing areas

During the images classification process for the study area, the land cover classes thematic maps were generated for the years 1990, 2000, 2010 and 2016 showing 5 major land cover classes that were identified as Agricultural land, Bare grounds, Degraded forest, Forest and Tea plantation (Figs. 4.7 – 4.10).

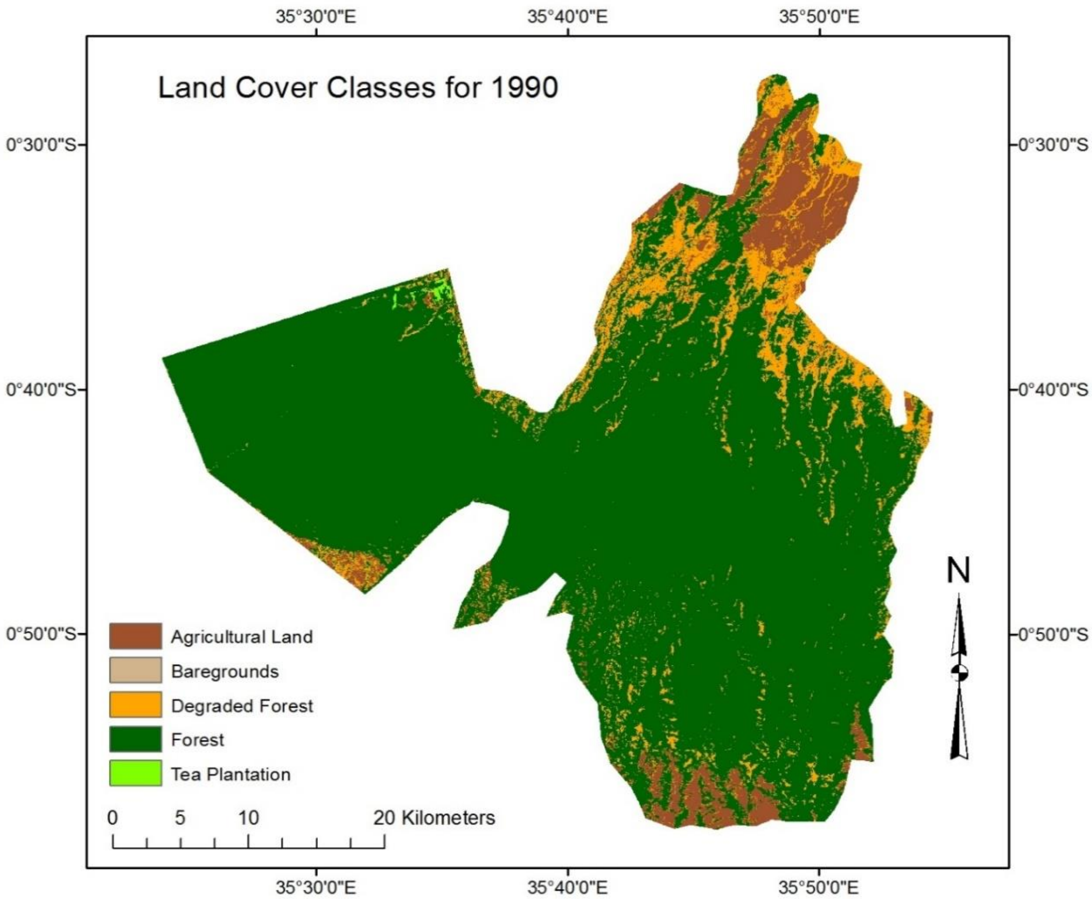


Fig. 4.7: Land cover/use thematic map of the study area for the year 1990

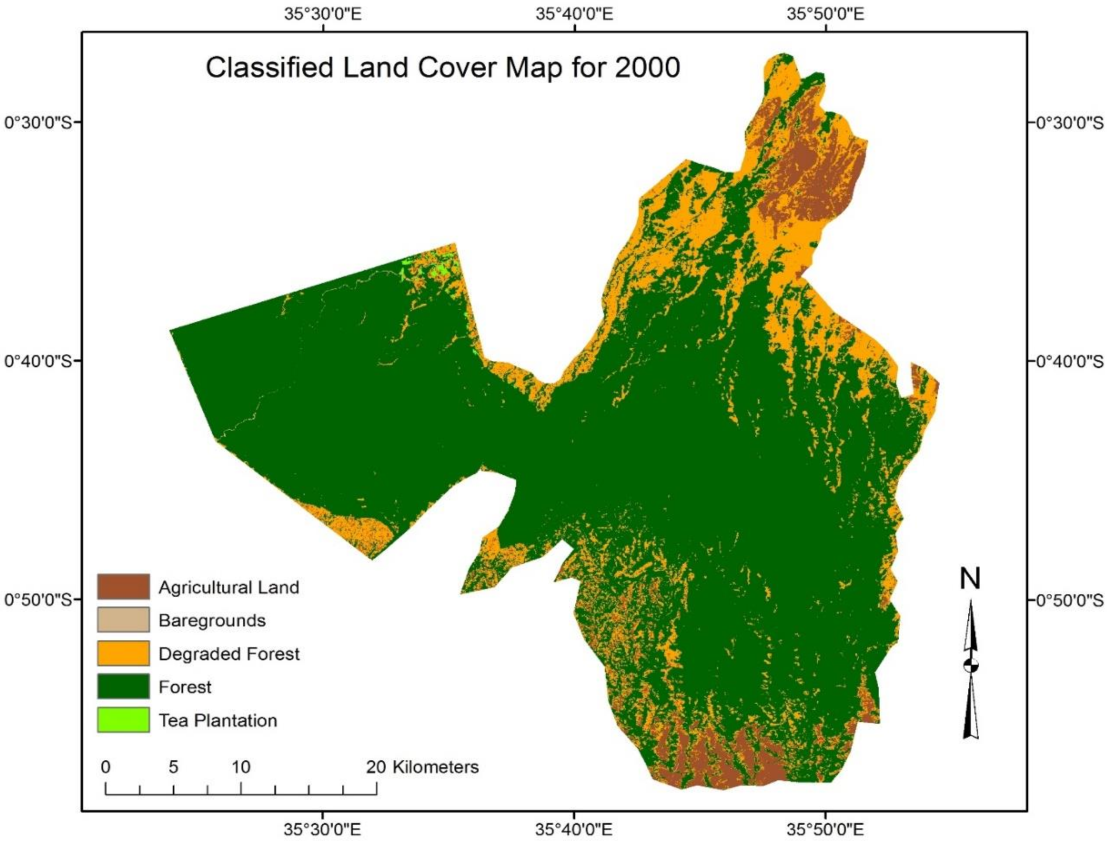


Fig. 4.8: Land cover/use thematic map of the study area for the year 2000

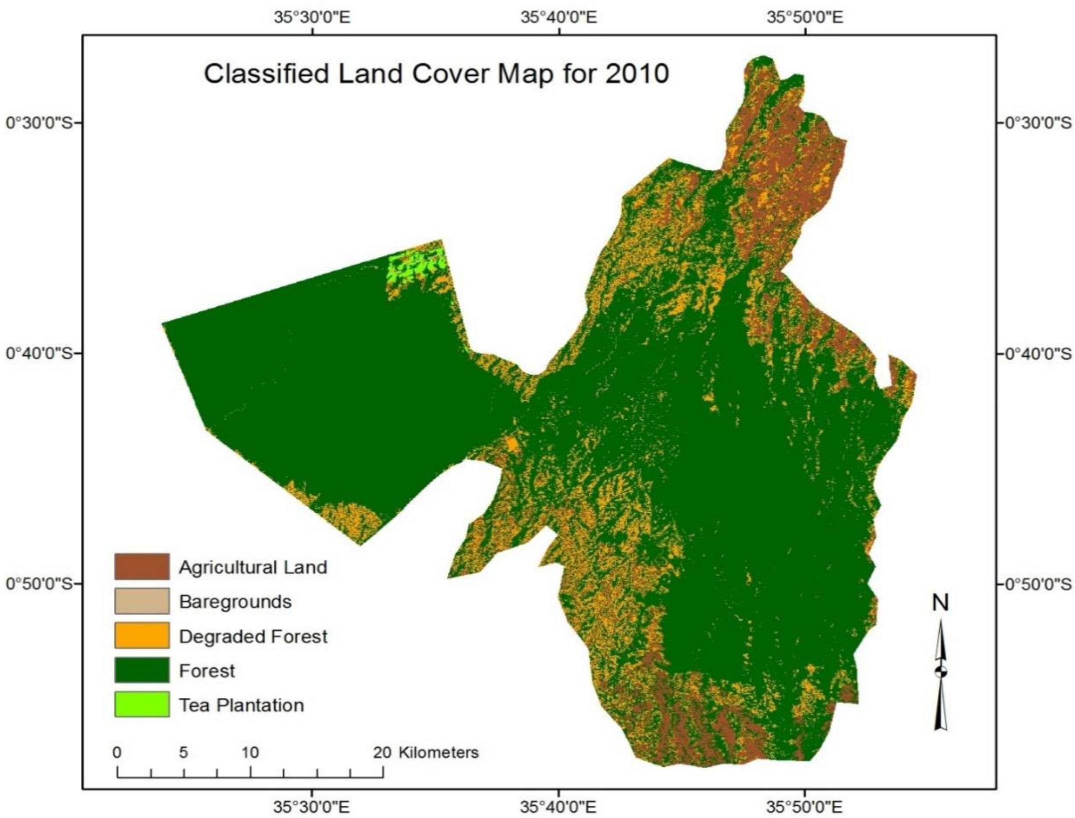


Fig. 4.9: Land cover/use thematic map of the study area for the year 2010

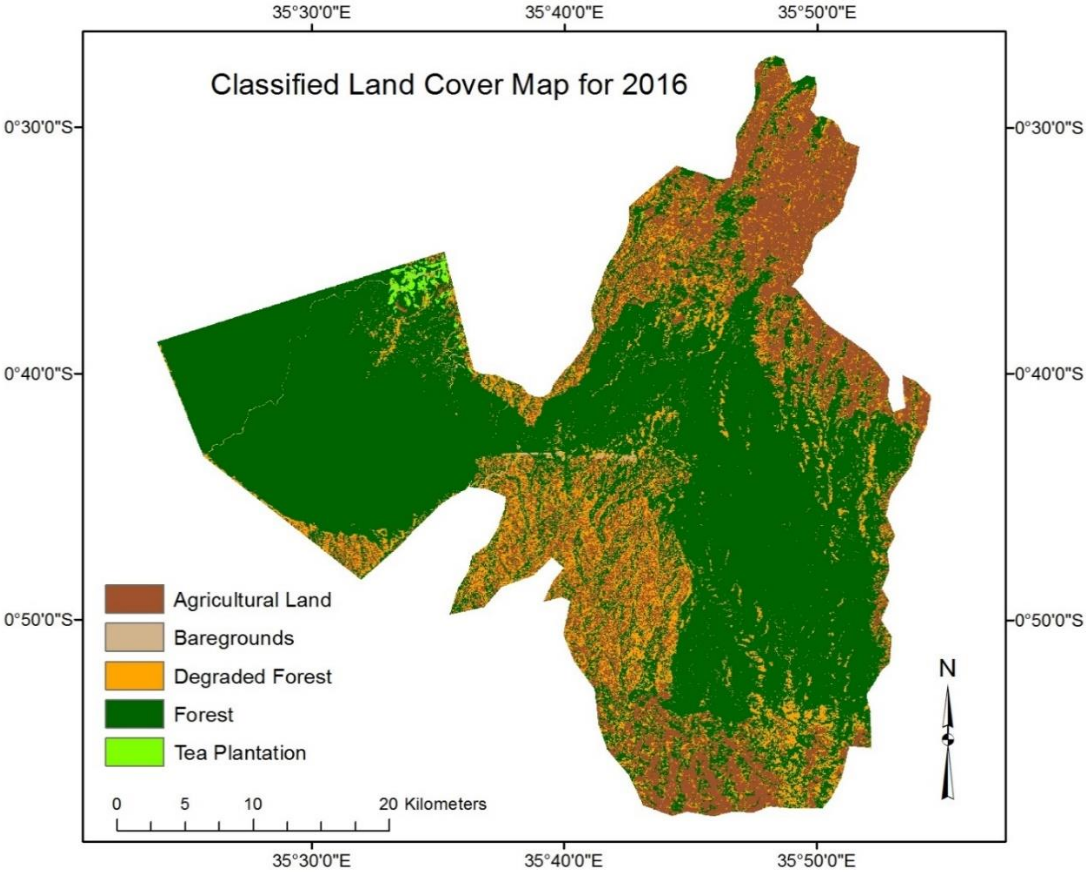


Fig. 4.10: Land cover/use thematic map of the study area for the year 2016

The Landsat TM, ETM+, and OLI/TIRS data classified generated different land cover/ land use types with their respective time series trends. Dense forest vegetation with upper canopy had the highest percentage coverage of (83.2%, 77.7% , 78.1% and 66.5% for the years 1990, 2000, 2010 and 2016 respectively) the total study area. Dense forest cover reduced by 6.8% between the years 1990 – 2000 but did not significantly change between the years 2000 – 2010, and merely remained constant with a slight increment of 0.4%. Dense forest cover changed remarkable between the year 2010 – 2016; in a span of only 6 years, the dense forest cover reduced by 15% of the total dense forest area (Fig. 4.11 and Table 4.2)

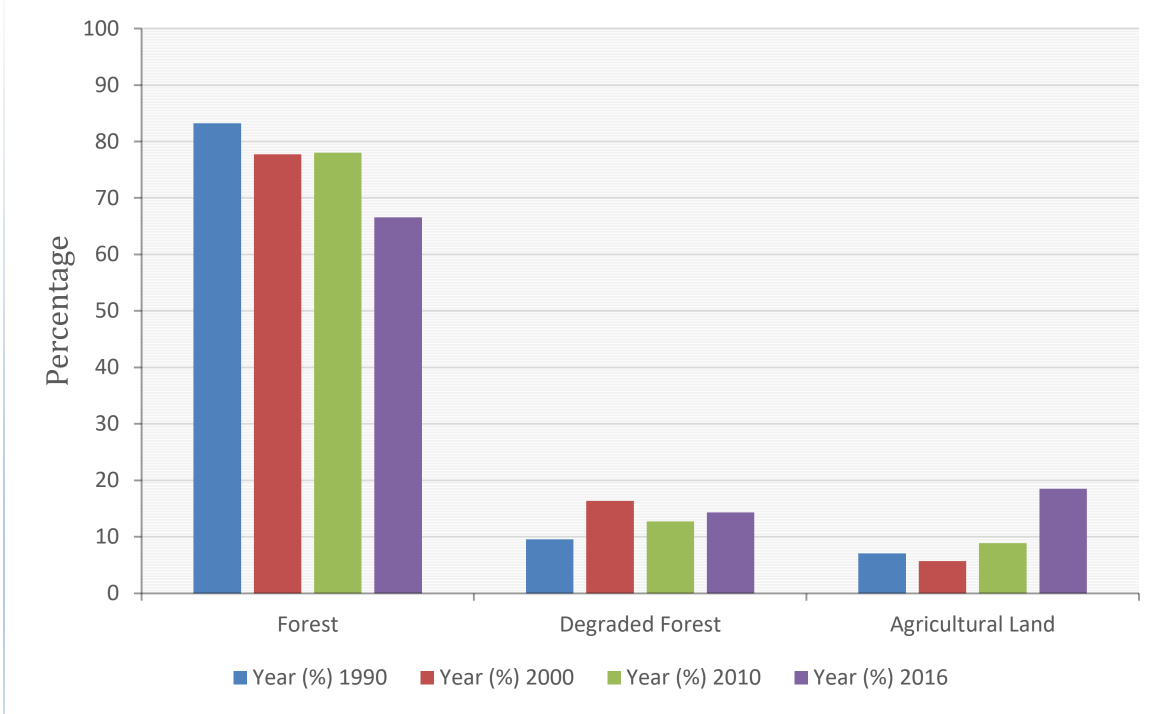


Fig. 4.11: Land Cover Classes Trends from 1990 – 2016 (%)

The dense forest cover changes that occurred between the years 1990 – 2000 were due to forest excision notices issued in late 1990s and early 2000s, severe encroachment and settlement, and unabated forest destruction and degradation in 1990s and early 2000s (Baldyga *et al*., 2007; Kinyanjui, 2009). This resulted to the higher percentage change of 70.9% in degraded forest between the years 1990 – 2000 as shown in (Fig. 4.8). However, this changed in the mid and late 2000s due to change of governance in the year 2002, injecting in stringent forest conservation policies which culminated in the formation of MFC restoration task force in the year 2008. These efforts yielded results as there was a gain in dense forest cover of 0.4% and a reduction of 22% in degraded forest which are believed somehow to have been restored back to dense forest but partly converted to agricultural land which increased by 55.2% between the years 2000 - 2010. Land use conversion to agricultural land was highest (109%) between the years 2010 – 2016 as was the reduction of the dense forest cover (15%). The degraded forest gradually increased by 13% between the years 2010 – 2016 as shown in (Table 4.2).

Agricultural land showed an increasing trend since 1990 with a slight decrease between the years 1990 – 2000 and thereafter, a gradually constant increment towards 2016. A similar trend was observed in degraded forest though with a slightly narrower margins. Evidently, tea plantation has shown an increasing trend as a form of land use in the study area since 1990 with 0.1%, 0.13%, 0.33% and 0.39% for the years 1990, 2000, 2010 and

2016 respectively. The highest increment margin of 151% and 17% occurred between the years 2000 -2010 and 2010 – 2016 respectively (Fig. 4.12). Tea plantations have been on the rise since the initiation and subsequent expansion of Kiptagich tea plantation on the north-western tip of the Trans-Mara forest block in 1980s exacerbated by the excision notice of 2001.

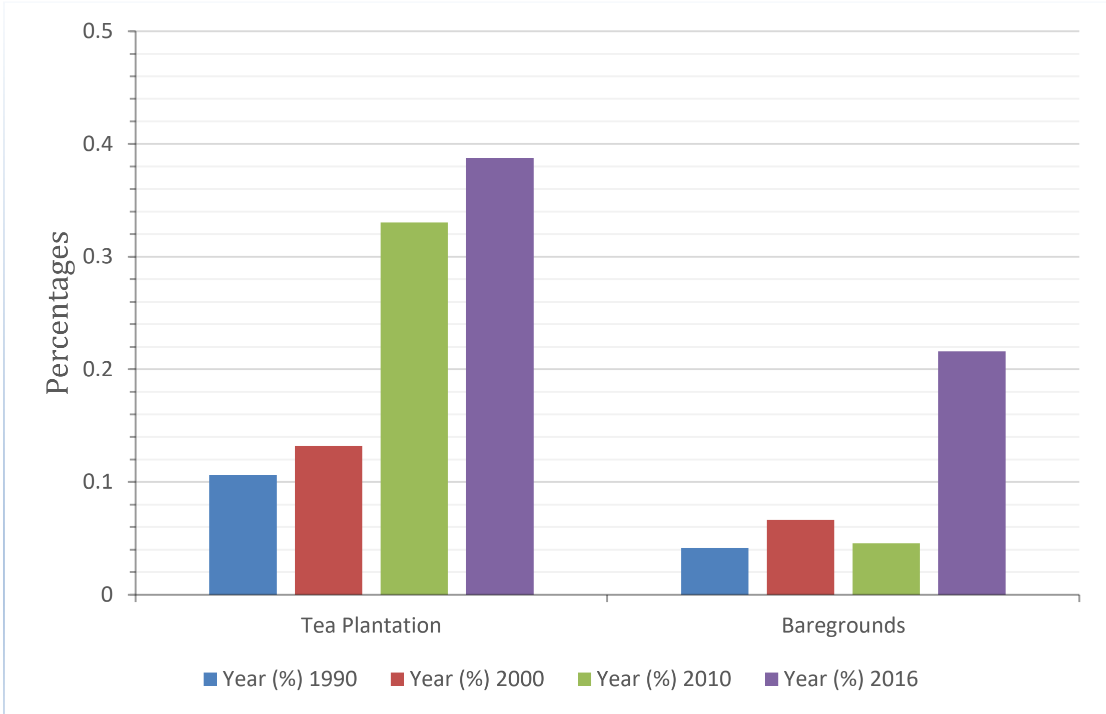


Fig. 4.12: Land Cover Classes Trend from 1990 – 2016 (%)

The land cover change analysis revealed that bare grounds increased by 60.1%, -31% and 374% between 1990 – 2000, 2000 – 2010 and 2010 – 2016 respectively. The highest percentage increment in bare grounds occurred between the years 2010 – 2016. Bare grounds percentage coverage of the study area was highest in the years 2016 and 2000 with 0.22% and 0.07% respectively. These were also the years when highest reduction rate occurred in dense forest cover and increment rate in degraded forest hence creation of many bare grounds.

Comparatively, visual interpretation of the images for the year 2000 and 2016 revealed that road surfaces were more visible compared to those of the year 1990 and 2010 when the dense forest canopy cover was higher and thicker impairing the visibility of the bare surfaces. Encroachment and contested settlement in the opened up forest areas and formation of centres such as Sierra Leone, Arorwet and Nyamira Ndogo also contributed to the increment of bare ground areas. Land cover changes were mainly characterized by a decline in the dense forest area, an increase in agricultural land, tea plantation, bare grounds and degraded forest, and inter-conversions between degraded forest, agricultural land and bare ground classes (Fig. 4.7 – 4.10).

Table 4.2: Land Cover Classes Area (in Ha) and their Respective Percentages

Land Cover Classes Area (in Ha) and their Respective Percentages																
Land Cover	**Area of Land Cover Classes for Respective Years**								**Relative Changes**							
Classes	**1990**		**2000**		**2010**		**2016**		**1990 - 2000**		**2000 - 2010**		**2010 - 2016**		**1990 - 2016**	
	Area	**%**	**Area**	**%**	**Area**	**%**	**Area**	**%**	**Area**	**%**	**Area**	**%**	**Area**	**%**	**Area**	**%**
Forest	123906	83.4	115470	77.7	115879	78	98852.9	67	-8436	-6.8	409	0.35	-17026	-15	-25053	-20
Degraded Forest	14211.5	9.56	24286.7	16.3	18880.1	12.7	21273.7	14	10075	70.9	-5407	-22	2393.6	13	7062.2	49.7
Tea Plantation	157.7	0.11	195.7	0.13	490.46	0.33	575.56	0.4	38	24.1	294.8	151	85.1	17	417.86	265
Agricultural Land	10544.1	7.1	8477.08	5.7	13159.9	8.86	27517.1	19	-2067	-20	4683	55.2	14357	109	16973	161
Baregrounds	61.38	0.04	98.27	0.07	67.62	0.05	320.597	0.2	36.89	60.1	-30.7	-31	252.98	374	259.22	422
Totals	**148607**	**100**	**148607**	**100**	**148607**	**100**	**148607**	**100**								

There were consistent trends observed between these periods with some insignificant deviations. The forest initially reduced by 6.8% (8,436 ha) from 1990 – 2000, then followed by a slight increment of 0.34% (409 ha) from 2000 – 2010 and finally declining by 15% (17,026 ha) from 2010 -2016, contributing significantly to the overall reduction of 20% (25,053 ha) observed in forest cover from 1990 – 2016. The degraded forest land cover class increased by 70.9% (10,075 ha) from 1990 – 2000, before reducing by 22% (5,407 ha) from 2000 – 2010 and exhibiting an increment of 13% (2,393.6 ha) from 2010 – 2016. An overall increment in degraded forest cover of 49.7% (7,062.2 ha) was observed in the 26 years study period (Table 4.2 and Fig. 4.13).

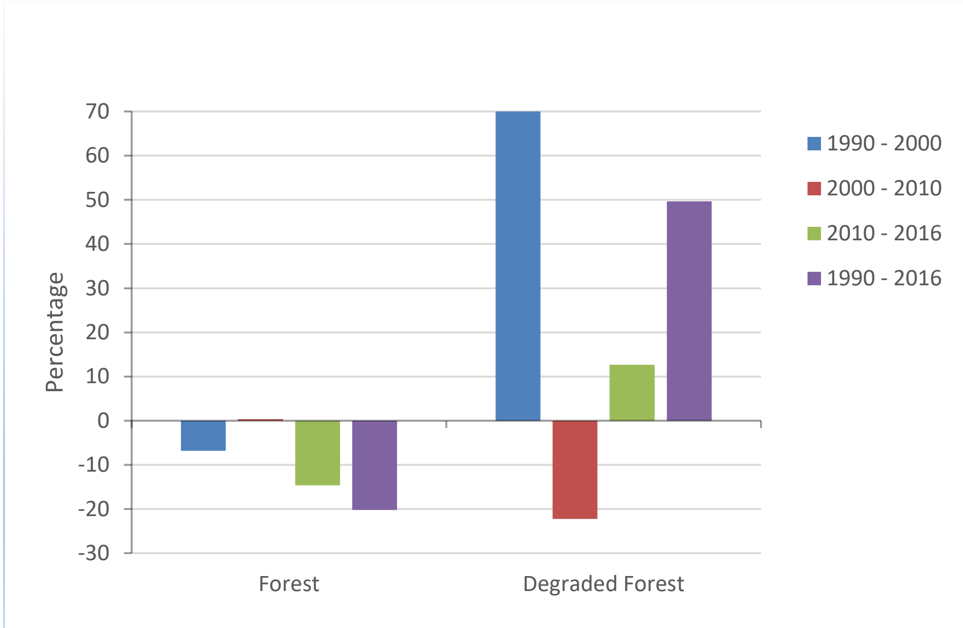


Fig. 4.13: Percentage Land Cover Changes (1990 – 2016)

Agricultural land use initially reduced by 20% (2,067 ha) from 1990 – 2000 and subsequently increasing by 55.2% (4,683 ha) and 109% (14,357 ha) between the years 2000 – 2010 and 2010 – 2016 respectively. This land use class had an overall increment trend of 161% (16,973 ha) during the 26 years study period. Tea plantation had an all-time gradual increment of 24.1% (38 ha), 151% (294.8 ha) and 17% (85.1 ha) between the years 1990 – 2000, 2000 – 2010 and 2010 – 2016 respectively, with an overall change of 265% (417.9 ha) from 1990 – 2016. Finally, bare grounds had an increment of 60.1% (36.89 ha) from 1990 – 2000, a reduction of 31% (30.7 ha) in 2000 – 2010 and a subsequent increment of 374% (252.98 ha) in 2010 – 2016 exhibiting relatively the highest overall percentage change of 422% (259.22 ha) during the 26 years study period (Table 4.2 and Fig. 4.14).

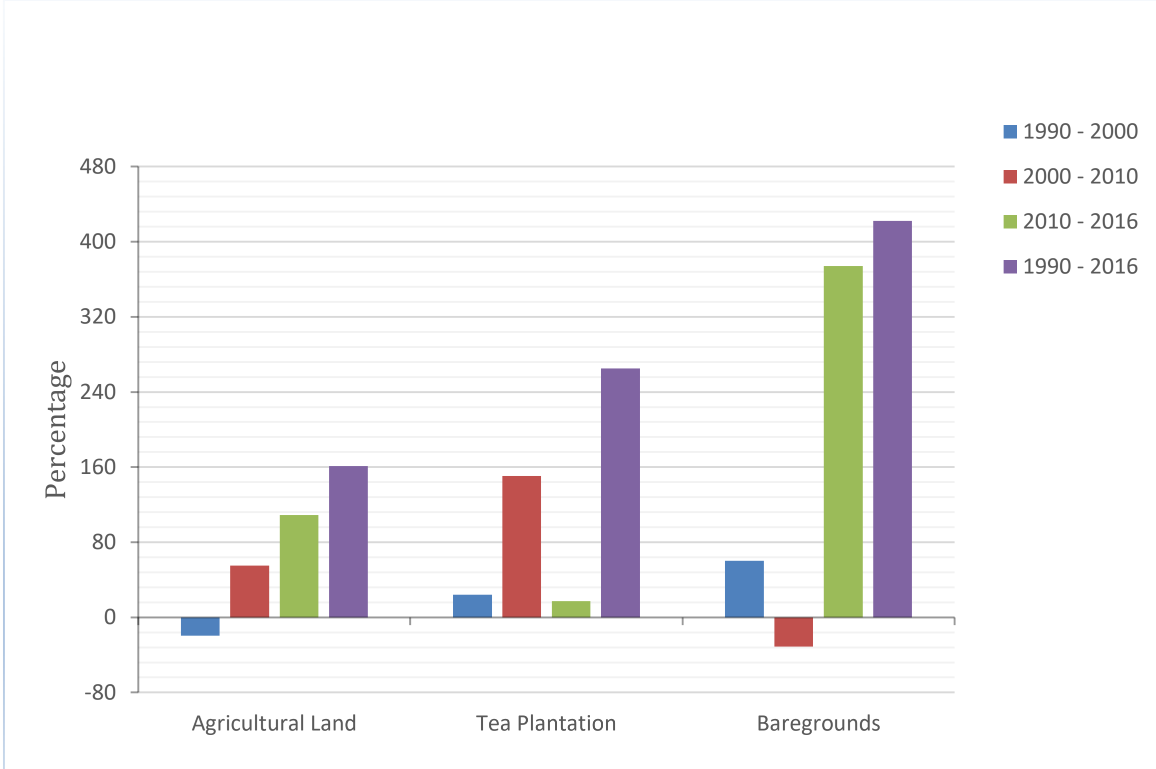


Fig. 4.14: Percentage Land Cover Changes from 1990 – 2016 (%)

Generally, forest land cover has significantly shrunk unabated as degraded forest land cover, agricultural land use, tea plantation and bare grounds both exhibiting an increasing trend during the study period. Observations during the 26 years period from 1990 – 2016 showed that the forest land cover reduced by 25,053 ha (20 %) whereas degraded forest coverage increased by 7,062.2 ha (49.7%), tea plantation increased by 417.86 ha (265%), agricultural land increased by 16,973 (161%) and bare grounds increased by 259.22 ha (422%).

The results indicated that the forested area increased from 92.9% (138,117.5 ha) in 1990 to 94.04% (139,756.7 ha) in 2000 thereafter reducing to 90.68% (134,759.1 ha) in 2010 and gradually reducing to 80.84% (120,126.6 ha) in 2016; an indication that the forested area had significantly shrunk (Fig. 4.15).

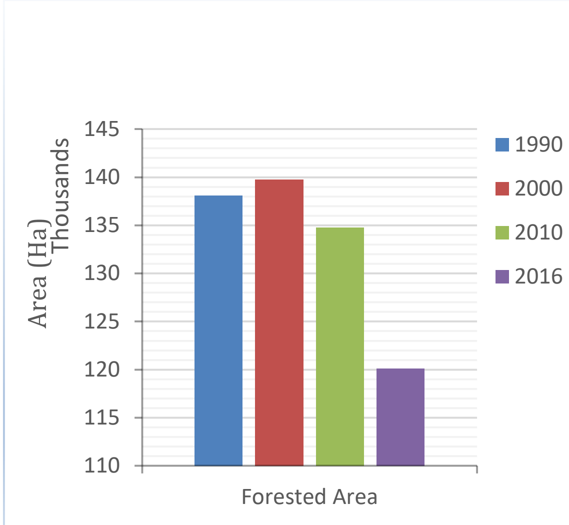


Fig. 4.15: Overall changes in forested land cover areas

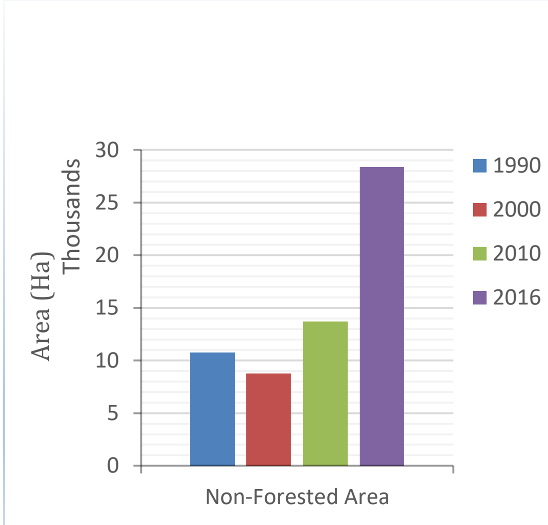


Fig. 4.16: Overall changes in non-forested land use areas

Overall, 13.03% (17,990.9 ha) of the forested area had been lost from 1990 – 2016. The non-forested area (agricultural land, tea plantation and bare grounds) showed an increasing trend with a combined area of 7.24% (10,763.2 ha) in 1990, reducing to 5.9% (8,771.05 ha) in 2000, and subsequently increasing to 9.23% (13,717.98 ha) and 19.12% (28,413.26 ha) in 2010 and 2016 respectively (Fig. 4.16). The non-forested land use areas gained 164% (17,650.08 ha) during the study period (1990 – 2016).

4.3.2 Classification Accuracy Assessment

The outputs were represented in error matrix tables as shown in (Tables 4.3 – 4.6).

Table 4.3: Accuracy Assessment Error Matrix for 1990

Error Matrix for 1990	**Reference Data**					
Classified Data	Forest	Tea Plantation	Degraded Forest	Agricultural Land	Bare Grounds	Row Totals
Forest	**48**	0	1	0	0	49
Tea Plantation	0	**7**	3	0	0	10
Degraded Forest	1	0	**14**	1	0	16
Agricultural Land	0	0	1	**10**	0	11
Bare Grounds	0	0	3	0	**7**	10
Column Totals	**49**	**7**	**22**	**11**	**7**	**96**

Table 4.4: Accuracy Assessment Error Matrix for 2000

Error Matrix for 2000			Reference Data			
Classified Data	Forest	Tea Plantation	Degraded Forest	Agricultural Land	Bare Grounds	Row Totals
Forest	**52**	0	3	0	0	55
Tea Plantation	1	**8**	1	0	0	10
Degraded Forest	1	0	**17**	1	0	19
Agricultural Land	0	0	2	**8**	0	10
Bare Grounds	1	0	1	0	**8**	10
Column Totals	**55**	**8**	**24**	**9**	**8**	**104**

Table 4.5: Accuracy Assessment Error Matrix for 2010

Error Matrix for 2010			Reference Data			
Classified Data	Forest	Tea Plantation	Degraded Forest	Agricultural Land	Bare Grounds	Row Totals
Forest	**16**	0	2	0	0	18
Tea Plantation	1	**17**	0	0	0	18
Degraded Forest	5	0	**13**	0	0	18
Agricultural Land	1	0	4	**13**	0	18
Bare Grounds	0	4	0	0	**14**	18
Column Totals	**23**	**21**	**19**	**13**	**14**	**90**

Table 4.6: Accuracy Assessment Error Matrix for 2016

Error Matrix for 2016			Reference Data			
Classified Data	Forest	Tea Plantation	Degraded Forest	Agricultural Land	Bare Grounds	Row Totals
Forest	**19**	0	1	0	0	20
Tea Plantation	1	**19**	0	0	0	20
Degraded Forest	3	0	**16**	1	0	20
Agricultural Land	0	0	3	**17**	0	20
Bare Grounds	2	0	1	0	**17**	20
Column Totals	**25**	**19**	**21**	**18**	**17**	**100**

The column of row totals on the right hand edge of the error matrix gives the sum of pixels in each class on the map while the row of sums at the bottom shows total pixels in each class in the classified image. The main diagonal or the trace (the sequence of values extending from the upper left corner to the lower right corner) shows the number of correctly classified pixels; forest classified as forest, tea plantation classified as tea plantation, degraded forest classified as degraded forest and so on. For instance, the error matrix for 1990 (Table 4.3), forest – 48; tea plantation – 7; degraded forest – 14; agricultural land – 10; and bare grounds – 7 pixels were correctly classified as forest, tea plantation, degraded forest, agricultural land and bare grounds respectively.

Non-diagonal values in each column gives error of omission as indicated in the third column (Table 4.3), 1 of 22 reference data in degraded forest was mapped as forest, that is, the image analyst omitted 1 pixel of degraded forest from the interpreted image. Similarly, 3 pixels in degraded forest was misclassified as tea plantation, 1 pixel in degraded forest was wrongly classified as agricultural land and 3 pixels in degraded forest was incorrectly classified as bare grounds. This was an indication that border pixels at the edge of degraded forest were most likely misclassified as either forest, tea plantation, agricultural land or bare grounds in the classified image. This was consistent in all the classified images for both the years (1990, 2000, 2010 and 2016) as shown in (Tables 4.3 – 4.6).

In contrast, errors of commission (mis-assignment of classes) are given by non-diagonal values along the rows, for example, in second row (Table 4.3), 3 pixels of tea plantation were incorrectly assigned to degraded forest class. Errors of commission are found by reading the incorrectly assigned pixels across the rows. For instance, error of commission is committed by assigning an area of degraded forest on the ground to tea plantation on the map (assigning a category on map which is not present on the ground). These values, forest, 0; degraded forest, 3; agricultural land, 0; bare grounds, 0; across the second row (Table 4.3) indicated that classification of tea plantation was most often confused with degraded forest. Similarly, there were 10 pixels for bare grounds (last row, Table 4.3) of which 7 were correctly classified, 3 pixels were incorrectly classified as degraded forest while none was neither classified as forest, tea plantation nor agricultural land. Row totals in the matrix give the total number of pixels in each class as recorded on the reference point, whereas the column totals shows the number of pixels assigned to each class as depicted on the image evaluated.

The map user gains insight about the varied reliabilities of the classes on the map by examining these two kinds of errors while analyst learn about the performance of the process that generated the map. Producer’s accuracy informed the analyst who did the classification that, of the actual degraded forest area, 63.64% was correctly classified.

This was calculated by dividing the number correct (14) by the reference totals (22) for the degraded forest of the accuracy totals in (Table 1xb), which is, 14/22 = 0.6364*100 = 63.64%. Whereas for the same class, user accuracy revealed the reliability of the map as a predictive device. For instance, user accuracy of 87.5% indicated that this proportion of degraded forest in the map actually corresponded to degraded forest on the ground. This proportion was calculated by diving the number correct (14) by the classified total (16) for the degraded forest class in the accuracy totals for year 1990 image (Table 4.7), which is, 14/16 = 0.875*100 = 87.5%. The user's accuracy (consumer's accuracy) guides the user of the map that a certain percentage of the category on the map actually corresponds to that category on the ground. For instance, in 1990, of the forest area, 97.96% actually corresponded to forest on the ground; of the tea plantation area, 70% actually corresponded to tea plantation on the ground while of the agricultural land area, 90.91% actually corresponded to agricultural land on the ground and so on (Table 4.7).

Overall accuracy being one of the most widely used measure of accuracy was used to report the overall proportion of correctly classified pixels in the image or sample used to construct the matrix. It was calculated by dividing the sum of the correctly classified values in the main diagonal (the trace) entries by the total number of pixels examined. Therefore, the overall accuracy for the year 1990 image classification (Table 4.3) was given by:

$$48 + 7 + 14 + 10 + 7 = 86/96*100 = 89.58\%$$

Similarly, overall accuracy for the classified images for the years 2000, 2010 and 2016 was 89.42%, 81.11% and 88% as shown in (Tables 4.8, 4.9 and 4.10). Overall accuracy suggests the relative effectiveness of classification when used without the error matrix but provides a convincing evidence of the classification's accuracy when examined together with the error matrix. It indicated that image classification for the year 1990 was the closest to the true value (overall accuracy of 89.58%) followed closely by that of the year 2000 (89.42%), and the year 2016 (88%). Image classification for the year 2010 achieved overall accuracy of 81.11% which was fairly a drop from the rest. This could be attributed to lack of imagery with no or low cloud cover percentage. However, the information from image metadata file indicated that the scene had 0.00% cloud cover, but the actual downloaded image (which was the best image at or near that time period) had some traces of cloud cover which interfered with the spectral resolution of the image during processing and classification.

Table 4.7: Accuracy Assessment Totals for 1990

Class Name	Accuracy Totals for 1990					
	Reference Totals	Classified Totals	Number Correct	Producers Accuracy (%)	Users Accuracy (%)	Kappa for each Category
Forest	49	49	48	97.96	97.96	0.9583
Tea Plantation	7	10	7	100	70	0.6764
Degraded Forest	22	16	14	63.64	87.50	0.8378
Agricultural Land	11	11	10	90.91	90.91	0.8973
Bare Grounds	7	10	7	100	70	0.6764
Totals	**96**	**96**	**86**			
Overall Classification Accuracy = 89.58%					**Overall Kappa Statistics = 0.8452**	

Table 4.8: Accuracy Assessment Totals for 2000

Class Name	Accuracy Totals for 2000					
	Reference Totals	Classified Totals	Number Correct	Producers Accuracy (%)	Users Accuracy (%)	Kappa for each Category
Forest	55	55	52	94.55	94.55	0.8842
Tea Plantation	8	10	8	100	80	0.7833
Degraded Forest	24	19	17	70.83	89.47	0.8632
Agricultural Land	9	10	8	88.89	80	0.7811
Bare Grounds	8	10	8	100	80	0.7833
Totals	**104**	**104**	**93**			
Overall Classification Accuracy = 89.42%					**Overall Kappa Statistics = 0.8385**	

Table 4.9: Accuracy Assessment Totals for 2010

Class Name	Accuracy Totals for 2010					
	Reference Totals	Classified Totals	Number Correct	Producers Accuracy (%)	Users Accuracy (%)	Kappa for each Category
Forest	23	18	16	69.57	88.89	0.8507
Tea Plantation	21	18	17	80.95	94.44	0.9275
Degraded Forest	19	18	13	68.42	72.22	0.6479
Agricultural Land	13	18	13	100	72.22	0.6753
Bare Grounds	14	18	14	100	77.78	0.7368
Totals	**90**	**90**	**73**			
Overall Classification Accuracy = 81.11%					**Overall Kappa Statistics = 0.7639**	

Table 4.10: Accuracy Assessment Totals for 2016

Class Name	Accuracy Totals for 2016					
	Reference Totals	Classified Totals	Number Correct	Producers Accuracy (%)	Users Accuracy (%)	Kappa for each Category
Forest	25	20	19	76	95	0.9333
Tea Plantation	19	20	19	100	95	0.9383
Degraded Forest	21	20	16	76.19	80	0.7468
Agricultural Land	18	20	17	94.44	85	0.8171
Bare Grounds	17	20	17	100	85	0.8193
Totals	**100**	**100**	**88**			
Overall Classification Accuracy = 88.00%					**Overall Kappa Statistics = 0.85**	

Another measure which was examined was κ (kappa) which attempted to provide a measure of agreement that is adjusted for chance agreement. It's the difference between the observed agreement between two maps (as reported by the diagonal values in the error matrix) and the agreement that might be attained solely by chance matching of the two maps (Campbell and Wynne, 2011). κ is estimated by ḱ ("k hat"):

$$\acute{k} = \frac{\text{Observed} - \text{Expected}}{1 - \text{Expected}}$$

Observed is the value for overall accuracy, while expected is the estimate of the contribution of chance agreement to the observed overall accuracy. Expected values was calculated using product of row and column totals in the error matrix, for instance, accuracy assessment totals for the year 1990 (Table 4.7), gave overall κ (kappa) statistics of 0.8452. κ (kappa) in effect adjusts the overall accuracy measure by subtracting the estimated contribution of chance agreement. Overall κ (kappa) statistics of 0.8452 meant that the classification achieved an accuracy that is 84.52% better than would be expected from chance assignment of pixels to categories in the year 1990 image. Likewise, overall κ (kappa) statistics of 83.85%, 76.39% and 85% for the years 2000, 2010 and 2016 respectively. As the overall accuracy approaches 100, and as the contribution of chance agreement approaches 0, the value of κ approaches positive 1.0 (100%), indicating the effectiveness of the classification. Classification effectiveness was better for the year 2016 image followed by 1990, 2000 and 2010 images in that order.

4.3.3 Normalized Difference Vegetation Index (NDVI)

The NDVI images generated for 1990 had a minimum value of -0.85 and the maximum value of 0.98, whereas the NDVI image for the year 2000 had a minimum value of -0.65 and a maximum value of 0.90, and that of the year 2010 ranged from -0.45 to 0.95 while the NDVI for the year 2016 ranged from -0.38 to 0.92. NDVI images showed that the dense forest cover had the highest pixel values ranging from 0.58 to 0.98, whereas bare grounds corresponded to NDVI values between -0.15 and 0.18, areas with sparse vegetation (degraded forest) had NDVI values ranging from 0.19 to 0.28. The NDVI values corresponding to tea plantation pixels ranged between 0.34 and 0.45. Majority of the agricultural land use areas had lower NDVI value almost similar to the bare grounds range of 0.09 to 0.22. This indicated that the images were taken during tillage period when most of the farms were cultivated. Some of the few remaining fallow or uncultivated land produced NDVI values corresponding to areas with sparse vegetation. The NDVI values for the generated NDVI images are represented in the NDVI maps as shown in (Fig. 4.17 – 4.20).

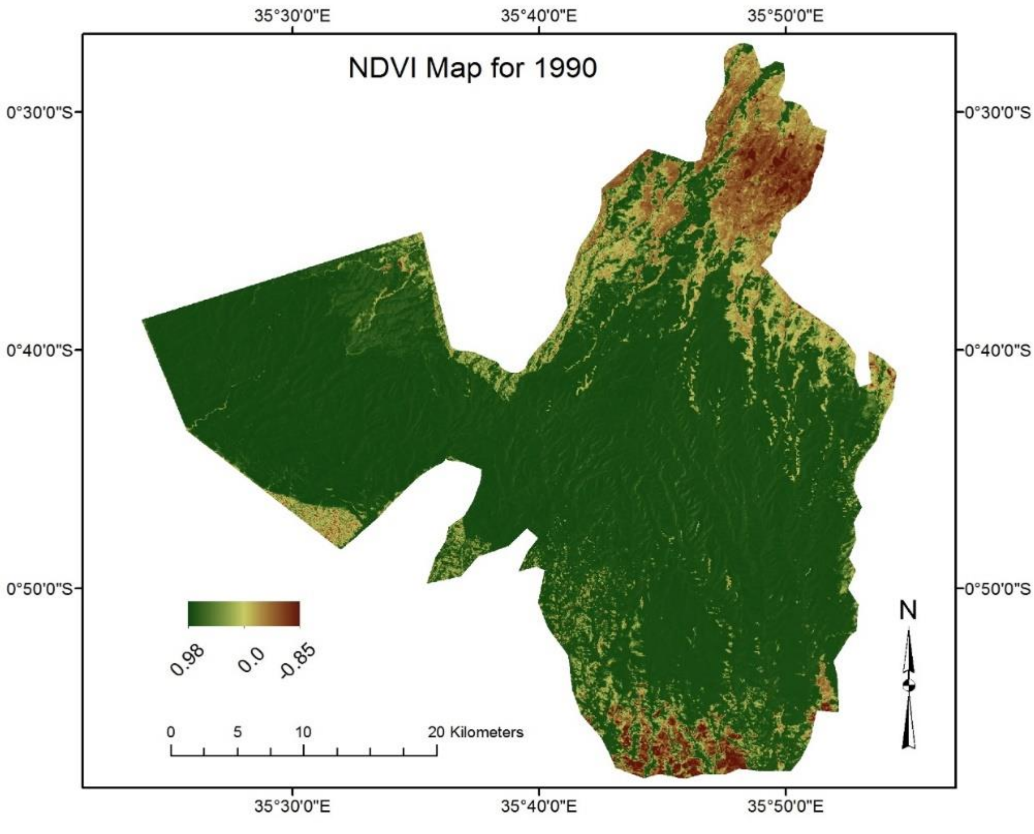


Fig. 4.17: The study area NDVI thematic map for the year 1990

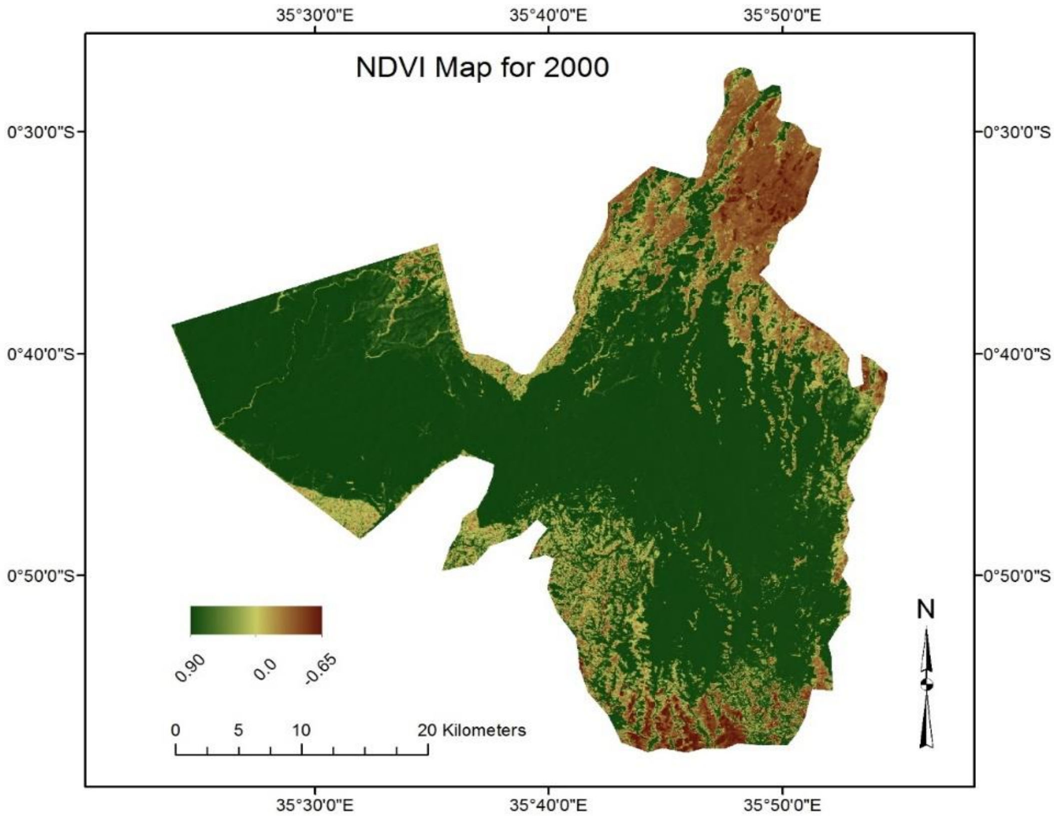


Fig. 4.18: The study area NDVI thematic map for the year 2000

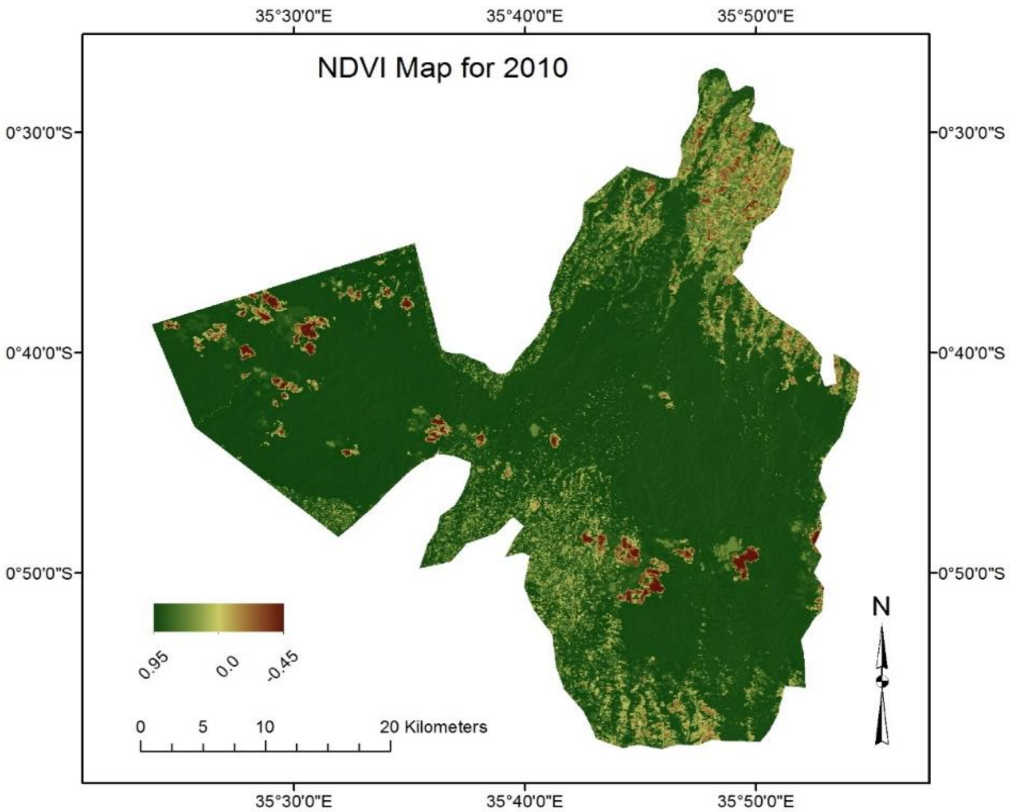


Fig. 4.19: The study area NDVI thematic map for the year 2010

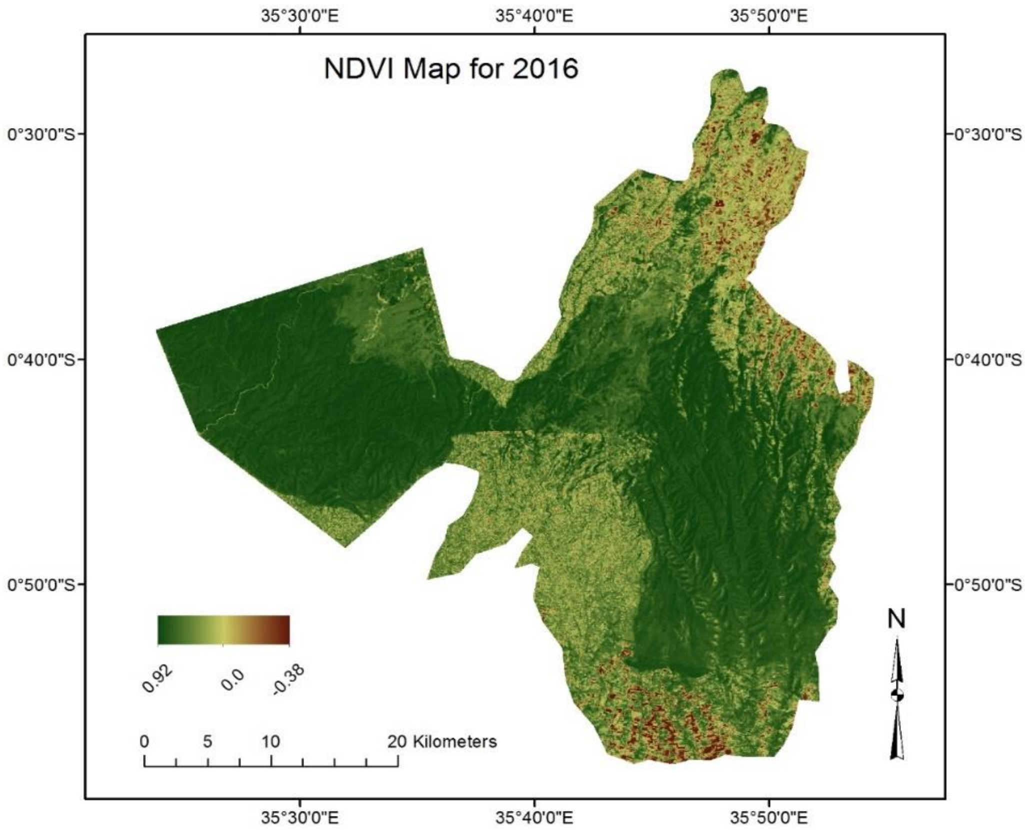


Fig. 4.20: The study area NDVI thematic map for the year 2016

4.3.4 Change Detection

4.3.4.1 NDVI Change Detection

Image differencing was performed by subtracting the NDVI of the previous images from the NDVI of the corresponding subsequent time-series images. Positive changes (increase in vegetation density) were assigned violet colour whilst negative changes (decrease in vegetation density) were assigned red colour. The areas with no significant changes remain black. The generated NDVI difference images are shown in (Figs. 4.21 – 4.24).

Further analyses of the NDVI images differencing, NDVI changes highlight image between 1990 and 2000 revealed significant negative changes (decrease in vegetation density or vigour) as depicted by the areas with reddish and golden shades. These were the changes which resulted to the higher percentage change realized in degraded forest for the classified image in the year 2000. The negative changes observed evidently indicate forest cover reduction in the area as a result of deforestation and conversion to farmlands. Most of the decrease in NDVI values occurred in Maasai Mau and Olpusimoru forest blocks. Trans-Mara forest block experienced reduction in NDVI values on the Olenguruone border and areas around Kiptagich tea plantation which could have occurred as a result of excision of the forest for the expansion of tea plantation and agricultural land. Area that experienced increase in NDVI values was around tea plantation at Kiptagich tea farm indicating expansion of the tea plantation area (Fig. 4.21).

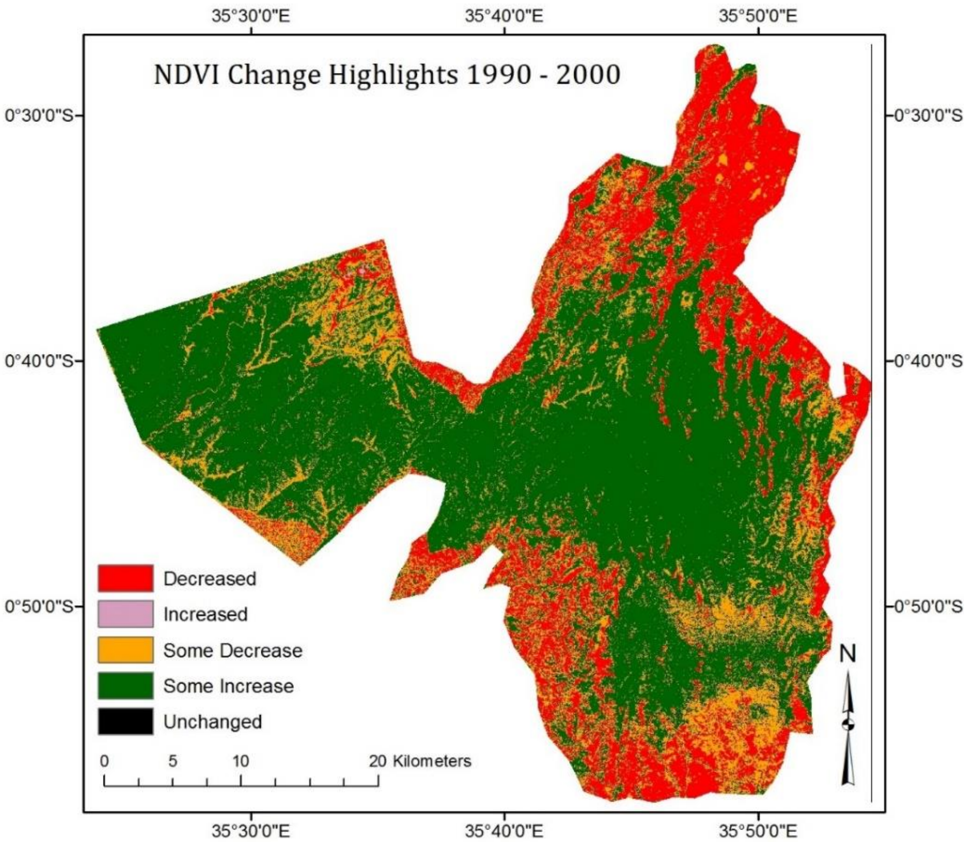


Fig. 4.21: NDVI changes highlight map of the study area for 1990 – 2000

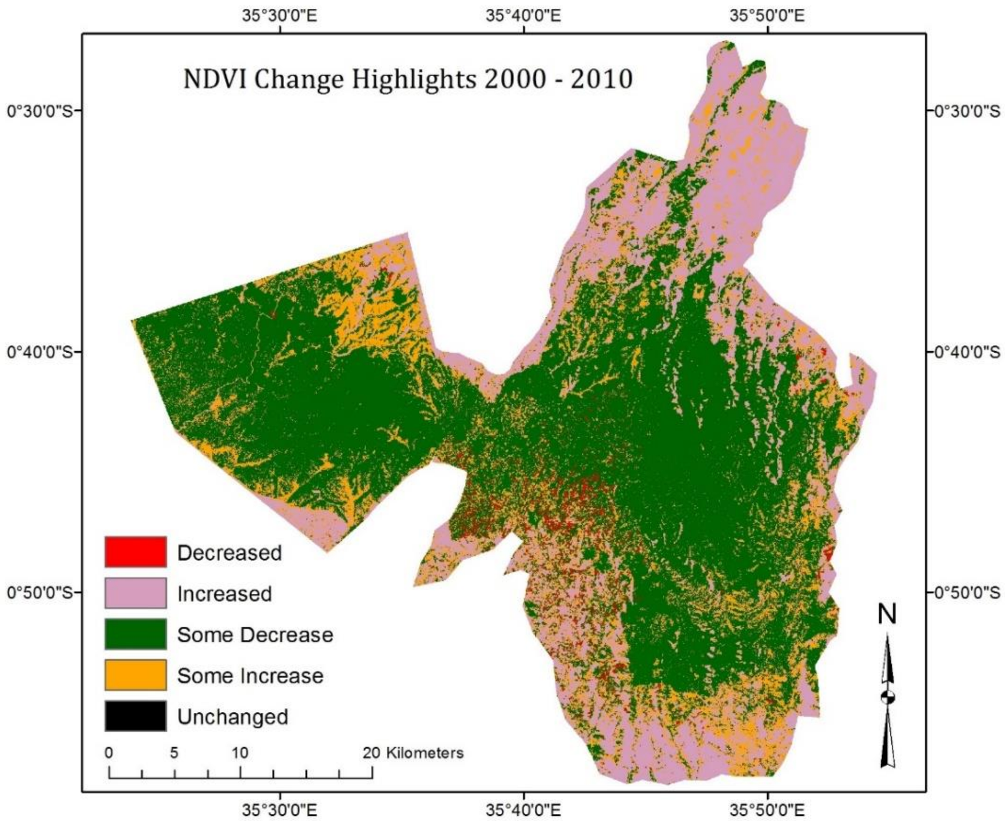


Fig. 4.22: NDVI changes highlight map of the study area for 2000 – 2010

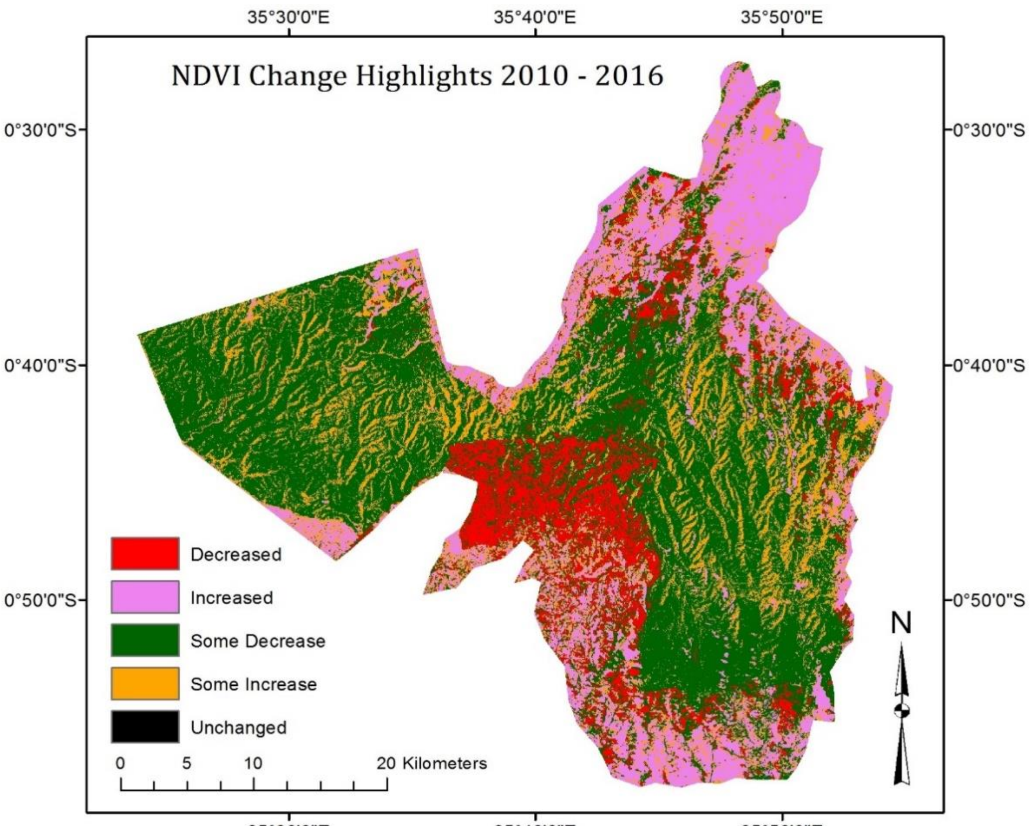


Fig. 4.23: NDVI changes highlight map of the study area for 2010 – 2016

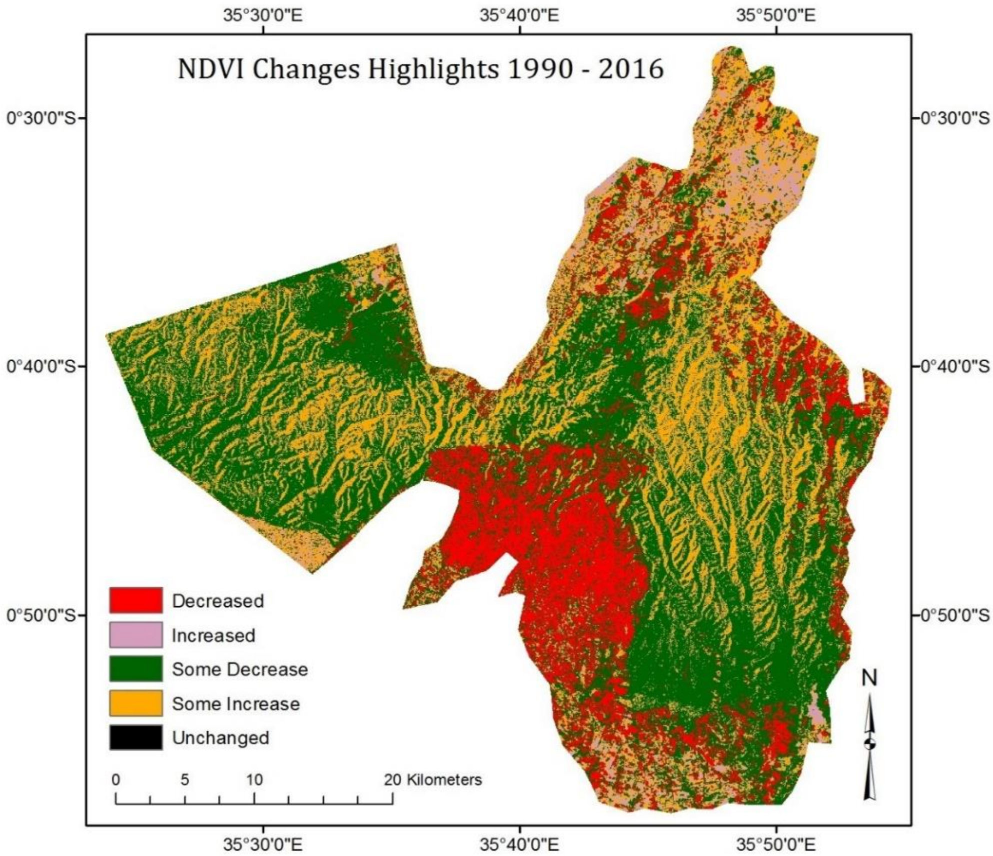


Fig. 4.24: NDVI changes highlight map of the study area for 1990 – 2016

The NDVI difference image for the year 2000 – 2010 had the highest positive changes (gain in vegetative vigour) and very minimal negative changes (decrease in vegetative vigour). The deviations from and to normalcy NDVI values was an indication of forest resilience to degradation and disturbance. The results gave a preliminary indication of vegetation response to destruction at short intervals and effects of short term climatic variations. Despite degradation and disturbances, the resilience of the forest was further confirmed as the forest retained the characteristic of a well-stocked healthy forest. Most of the previously degraded forest areas recovered showing the increase in NDVI values observed between the year 2000 and 2010 as shown in (Fig. 4.22).

The NDVI difference image between the year 2010 and 2016 indicated both positive and negative changes in the NDVI values. There were increase in vegetation vigour in areas that had been degraded previously which could be attributed to either regeneration or conversion to tea plantation and farmlands. Nevertheless, the Maasai Mau forest block further experienced decrease in vegetation density with negative changes occurring mostly around upper sections of Melelo, Nkoben, Ereteti, Nkareta, Sogoo, Enkaroni and lower sections of Olpusimoru (Kamurar and Ol Mariko) and Olokurto locations (Fig.

4.23). The NDVI changes highlight image between the year 1990 and 2016 was analysed to depict the overall changes in NDVI values during the study period. The NDVI difference image for 26 years study period revealed major negative changes (decrease in vegetation vigour) within Maasai Mau forest block (Fig. 4.24). The degradation and reduction of dense forest cover mostly occurred within this forest block compared to the other two forest blocks. This could be attributed to the fact that both the two forest blocks (Olpusimoru and Trans-Mara) are already gazetted forest reserves while Maasai Mau is still under communal jurisdiction. The management style compounds the effects of CCV, hence exerts a lot of pressure on the trees and forestry resources. As the temperature increases and rainfall decreases, the adaptive capacity and resilience of the forest also reduces exacerbated by the pressure from the anthropogenic activities such as encroachment and settlement, charcoal burning, logging, overgrazing, and conversion to agricultural land.

4.4 Assessment of Vulnerability of the Forest Resources and People to CCV

4.4.1 Socio-Demographic Characteristics and Education

A total of 405 respondents were interviewed from the sampled HHs at all the selected sub-locations, with 57.1% comprising males and the rest were females. The results showed that this gender proportion was significantly different (χ^2 = 8.18, df = 1, P = 0.004). The larger proportion of the respondents belonged to the younger age bracket of 25 – 34 years, with 23.2% and 32.1% being male and female respondents respectively. The difference in age categories of the respondents were statistically significant (χ^2 = 14.57, df = 7, P = 0.042) as shown in (Table 4.11).

Table 4.11: Gender proportions by age categories of the respondents.

Age Categories	Males		Females		Total
	n	%	n	%	n
18 – 24	49	21.9	25	14.9	**74**
25 – 34	52	23.2	54	32.1	**106**
35 – 44	47	21	36	21.4	**83**
45 – 54	28	12.5	27	16.1	**55**
55 – 64	19	8.5	9	5.4	**28**
65 – 74	24	10.7	8	4.8	**32**
75 – 84	4	1.8	6	3.6	**10**
85 or Over	1	0.8	3	1.8	**4**
Total	**224**	**57.1**	**168**	**42.9**	**392**

It was revealed that the highest level of education attained by most of the respondents was secondary (O – level) education (29.5%), with 17 % attaining primary education. The highest level of education attained by many respondents was significantly different ($P <$ 0.001). Most of the respondents (70.2%) had basic and elementary education. There was no statistically significant difference ($P = 0.52$) in the levels of education between male and female respondents despite the fact that more males had attained some form of education than the females.

There was a higher unemployment rate ($P < 0.001$) where 41.4% of the respondents were jobless and were not looking for employment while 33.8% were unemployed but looking for employment. Only 16.2% of the respondents had part-time jobs while 8.6% had full time engagements. The level of education significantly influenced the employment status of the respondents ($P = 0.001$). 34.6% of those with no formal education were neither employed nor looking for employment even though none had part-time or full-time engagements. Alternately, majority of those with degree or postgraduate qualifications were either partly or fully engaged (Table 4.12).

Table 4.12: Cross tabulation of education levels and employment status of the respondents

	Occupation and Employment of Respondents (%)					
Highest Level of Education Qualification	No (not looking)	No (looking)	Yes (part-time)	Yes (part-time, looking)	Yes (full time)	**Total (%)**
No formal qualification	53 (34.6)	6 (4.8)	1 (2.4)	0 (0)	0 (0)	**60 (16.2)**
Primary	33 (21.6)	22 (17.6)	3 (7.3)	2 (10.5)	3 (9.4)	**63 (17.0)**
Informal schooling only	13 (8.5)	13 (10.4)	2 (4.9)	6 (31.6)	0 (0)	**34 (9.2)**
Some primary schooling only	6 (3.9)	6 (4.8)	2 (4.9)	0 (0)	1 (3.1)	**15 (4.1)**
Some secondary school	13 (8.5)	19 (15.2)	4 (9.8)	2 (10.5)	1 (3.1)	**39 (10.5)**
Secondary (O - level)	29 (19.0)	51 (40.8)	16 (39.0)	2 (10.5)	11 (34.4)	**109 (29.5)**
Higher (A- level)	2 (1.3)	3 (2.4)	0 (0)	1 (5.3)	5 (15.6)	**11 (2.0)**
Post-secondary school	1 (0.7)	2 (1.6)	1 (2.4)	0 (0)	2 (6.3)	**6 (1.6)**
Vocational	1 (0.7)	1 (0.8)	2 (4.9)	2 (10.5)	0 (0)	**6 (1.6)**
Degree or equivalent	0 (0)	2 (1.6)	5 (12.2)	3 (15.8)	7 (21.9)	**17 (4.6)**
Postgraduate qualification	2 (1.3)	0 (0)	5 (12.2)	1 (5.3)	2 (6.3)	**10 (2.7)**
Total (%)	**153 (41.4)**	**125 (33.8)**	**41 (11.1)**	**19 (5.1)**	**32 (8.6)**	**370**

4.4.2 CCV awareness

The study revealed that 84% of the respondents had knowledge of CCV ($P < 0.001$) which they associated to a particular climatic event they normally experienced in the area(s) where they lived. Respondents observed "changes in rainfall patterns" (31.4%) and "in temperature regimes" (15.7%). CCV was also perceived as "low food production". Others (2.8 %) attributed the term to "human diseases and deaths" and "drought and changes in planting seasons" (10%).

Awareness of CCV was examined against gender, age, level of education and years of residence. More male respondents (86.6 %) were found to be aware of CCV than female (80.8 %) but the gender differences did not significantly influence awareness of CCV ($\chi^2 = 2.27$, df = 1, $P = 0.132$) (Fig. 4.25), except the intergenerational differences that had a significant influence on awareness of the respondents ($P = 0.041$) (Table 4.13). Kimani *et al*. (2014) also found out that gender does not influence respondent's awareness of CCV.

Table 4.13: Awareness of CCV in different age categories of the respondents

Awareness of CCV (%)	**Age bracket of the respondents (%)**								**Total n (%)**
	18 - 24	25 - 34	35 - 44	45 - 54	55 - 64	65 - 74	75 - 84	85 or Over	
Yes	60	84	60	47	24	26	4	2	**307 (84.6)**
No	12	14	12	8	4	1	5	0	**56 (15.4)**
Total (%)	**72 (19.8)**	**98 (27.0)**	**72 (19.8)**	**55 (15.2)**	**28 (7.7)**	**27 (7.4)**	**9 (2.5)**	**2 (0.6)**	**363**

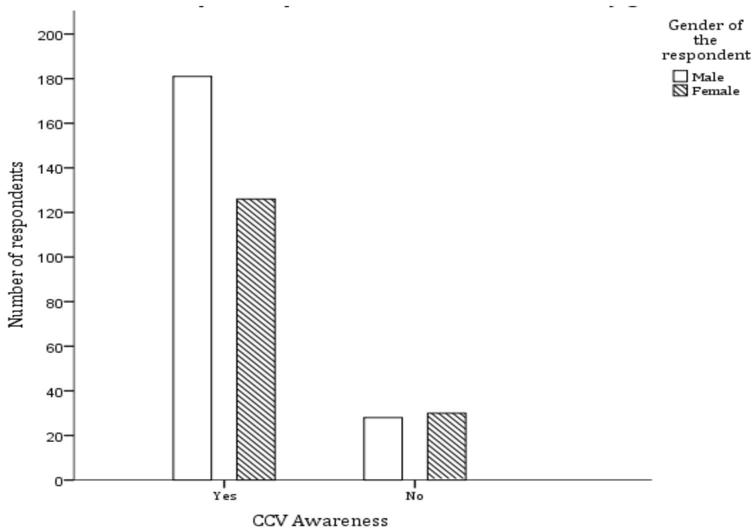


Fig. 4.25: Awareness of CCV by gender of the respondents

The younger generation with age categories between 18 – 24, 25 – 34 and 35 – 44 were more aware of CCV (19.5%, 27.4% and 19.5% respectively) compared to the older generation between 65 – 74, 75 – 84 and 85 and over (8.5%, 1.3% and 0.7% respectively)

(Fig.4.26). The level of education of the respondents was not important in determining awareness of CCV (P = 0.156), but those who had attained secondary education were more aware (Fig. 4.27).

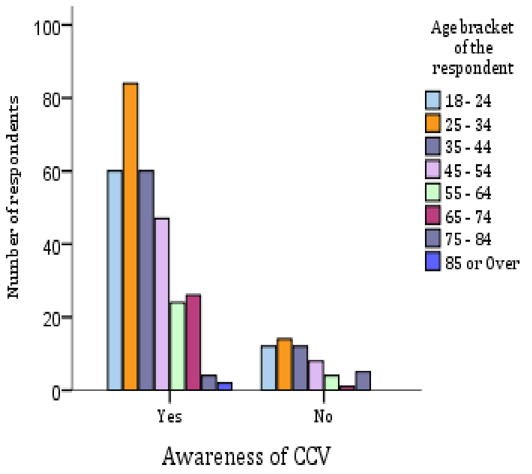


Fig. 4.26: Awareness of CCV by age

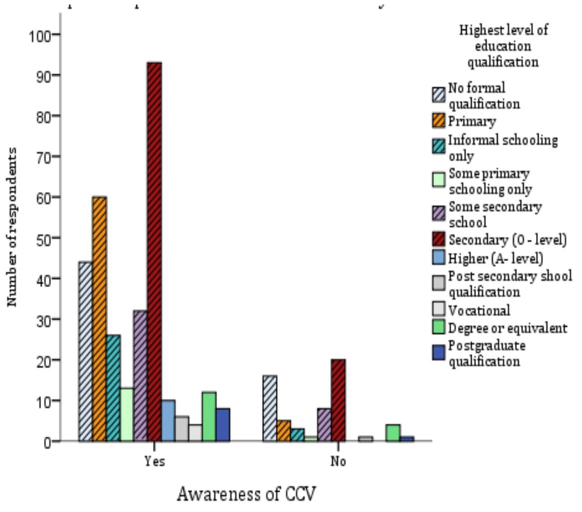


Fig. 4.27: Awareness of CCV by level of education

Similarly, the respondent's years of residence in a certain area did not significantly influence the awareness (P = 0.098) of CCV (Table 4.14), and neither did the occupation and employment status of the respondents (P = 0.071).

Table 4.14: Awareness of CCV by years of residence of the respondents

Awareness of CCV (%)	**Years of residence (%)**						**Total n (%)**
	< 5	6 – 10	11 – 15	16 – 20	21 – 30	> 30	
Yes	19	29	35	66	87	65	**301 (84.1)**
No	6	4	11	18	10	8	**57 (15.9)**
Total n (%)	**25 (7.0)**	**33 (9.2)**	**46 (12.8)**	**84 (23.5)**	**97 (27.1)**	**73 (20.4)**	**358**

On the contrary, unemployed respondents were more aware of CCV than the employed, because the unemployed were potentially vulnerable to the effects of CCV than the employed as shown in (Table 4.15).

Table 4.15: Awareness of CCV against the respondent's occupation and employment status

Awareness of CCV (%)	Occupation and employment status (%)					Total n (%)
	No (not looking)	No (looking)	Yes (part - time)	Yes (part - time) searching 2nd job	Yes (full)	
Yes	110	102	30	17	24	**283 (84.0)**
No	31	13	3	1	6	**54 (16.0)**
Total n (%)	**141 (41.8)**	**115 (34.1)**	**33 (9.8)**	**18 (5.3)**	**30 (8.9)**	**337**

A generalized linear regression model to determine whether the risks from exposure to CCV influenced the respondent's awareness showed that the increasing occurrence of risks related to CCV significantly influenced the awareness on CCV. Respondents who experienced rising risk of human diseases, deaths or infection were more aware of CCV (P = 0.007) compared to those who felt that such risks were constant or reducing. Similarly, those who encountered rampant incidences of livestock diseases, deaths and infections were more aware of CCV (P = 0.002) than those who thought such cases were reducing or none existent. However, those who felt that the incidence of food insecurity was on the rise (P = 0.082) insignificantly linked it to CCV.

4.4.3 Perception of the Study Population on CCV

Using a five-point Likert scale (*1 = Agree strongly to 5 = Disagree strongly*), respondents were to state the extent to which they either agree or disagree with some statements about CCV.

4.4.3.1 Perception on Causes of CCV

The respondents neither agreed (47.3%) nor disagree (42.1%) that CCV is just natural fluctuations in the earth's temperatures (Fig. 4.28), but 75.4% indicated that human activities have significant impact on global temperature (Fig. 4.29). Similarly, 89% of the KIIs indicated that human activities caused CCV.

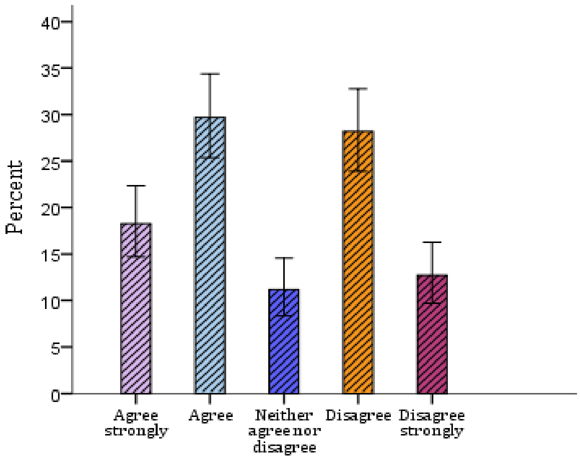


Fig: 4.28: CCV is natural fluctuation in earth's temp.

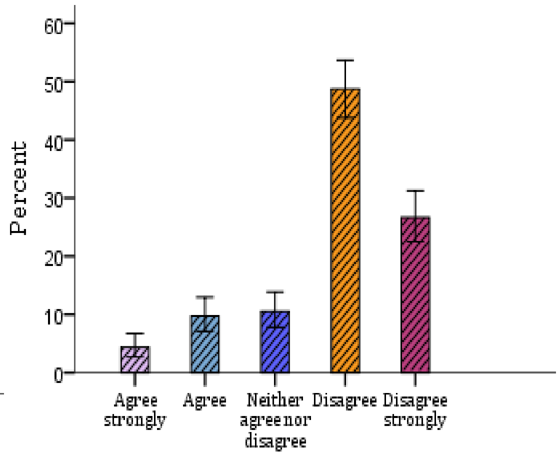


Fig. 4.29: Human activities have no impacts on temp.

Pollution from industries and emission from different sources including vehicles and industries were also ranked high by the respondents (77.8 % and 62 % respectively) as the main causes of CCV (Fig. 4.30). Respondents (42.8%) indicated that whatever they do on a daily basis contributed to the problem of CCV. However, 63.8% of the respondents disagreed that leaving the lights on in their houses adds to CCV. It was worth noting that 71.9 % felt that developing countries should take the blame for CCV contrary to the notion that it's the developed countries that should take responsibility (Fig. 4.31).

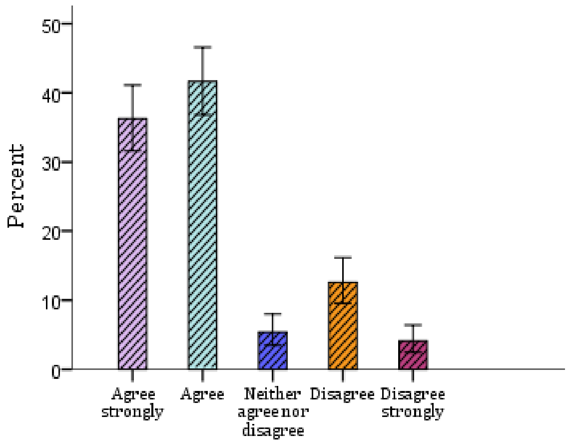


Fig. 4.30: Pollution is the main cause of CCV

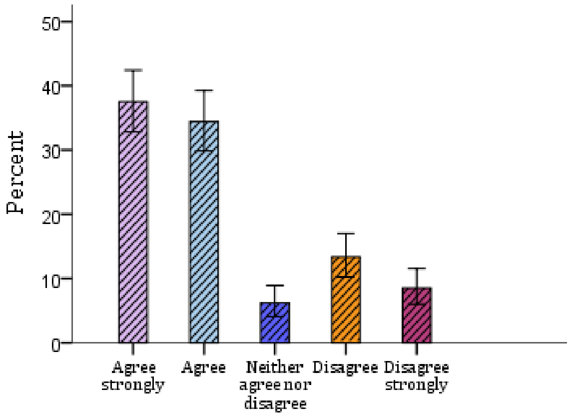
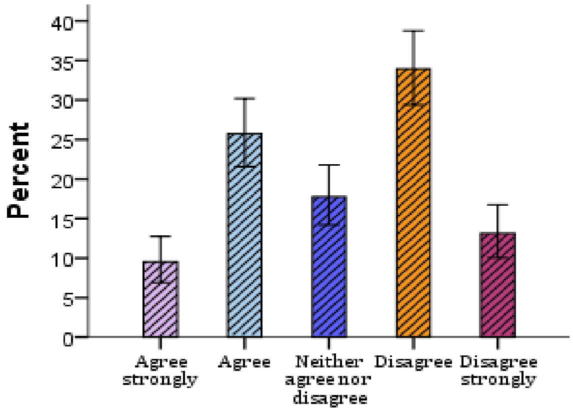


Fig. 4.31: Developing countries to blame for CCV

4.4.3.2 Perception on the Evidence for CCV

It was found out that evidence on CCV generated by the scientific community was not perceived very reliably and permissible to the respondents. 25.7% perceived it as neither reliable nor permissible, whereas 33.9% considered the evidence reliable while 17.7% were impartial (Fig. 4.32). As a result of experiencing the effects of CCV with limited knowledge about it, many did not believe in their science. However, 81.2% of the respondents believed experts, that CCV is a problem which can still be tackled (Fig. 4.33).



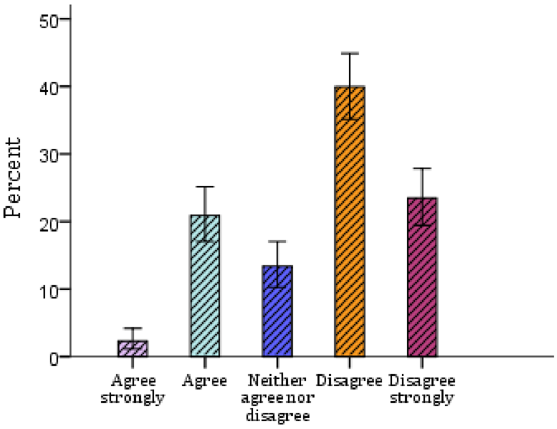
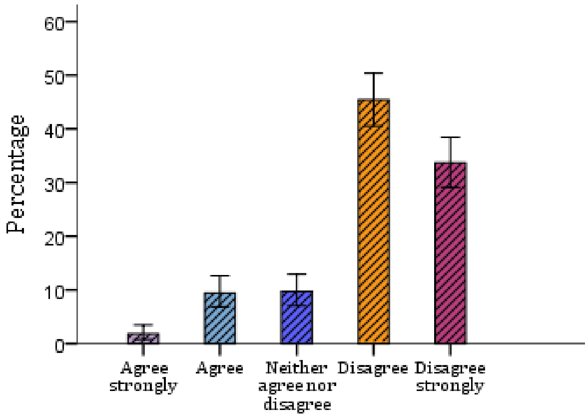


Fig. 4.32: The evidence for CCV is unreliable Fig. 4.33: It is too early to say CCV is a problem

4.4.3.3 Perception on Adaptation and Mitigation of CCV

Respondents indicated that it was still not too late ($P < 0.001$) for CCV adaptation and mitigation measures to be pursued, and that desirable adaptation and mitigation strategies can be achieved (Fig. 4.34). 77.7% agreed that industries should be doing more to tackle CCV. It was also believed that the government is not doing enough to tackle CCV and said (65.5 % of the respondents) that more is still desired from the government to help tackle CCV (Fig. 4.35).



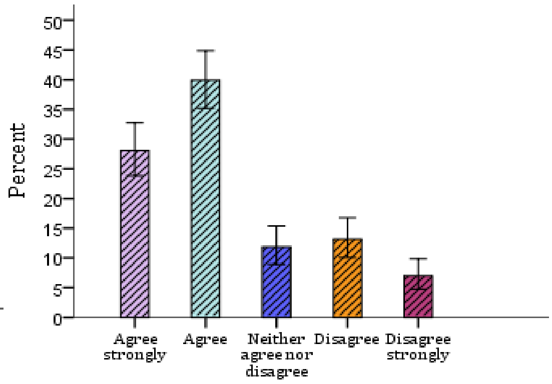


Fig. 4.34: It is already too late to do anything about CCV Fig. 4.35: The gov't is not doing enough

4.4.3.4 Perception on CCV Impacts and Vulnerability

It was found out that 77.6% of the respondents believed that not only was the reporting by the media of the severity and incidences of floods and drought are on the rise ($P < 0.001$) but that they had increased (Fig. 4.36) and the effects of CCV were likely to be catastrophic (49.7% of the respondents), indicating that the vulnerable communities and biophysical systems would be at risk and highly exposed to the impacts of natural disasters and calamities (Fig. 4.37).

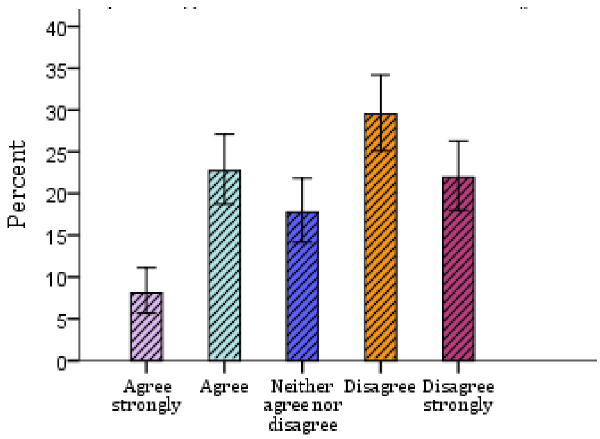


Fig. 4.36: Flooding not increasing but its reporting

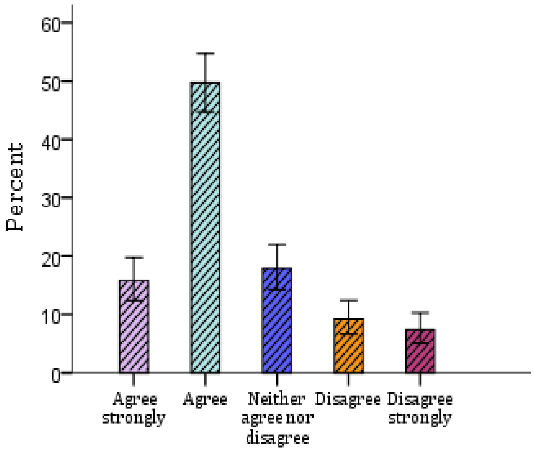


Fig. 4.37: The effects is catastrophic

4.4.4 Assessment of CCV Vulnerability

4.4.4.1 Exposure

Results on exposure showed that a significant percentage of the respondents (90.5%) had experienced natural disasters (EWEs) in the last 25 years where floods (heavy/extreme precipitation), droughts, landslides/mudslides, windstorms and extreme temperatures were the most common EWEs experienced. An increasing trend in both incidence (34.2%) and severity (31.8%) of floods, and incidence (48.2%) and severity (45.3%) in drought were registered as shown in (Table 4.16). The survey revealed that more vulnerable biophysical and socio-economic systems (P < 0.001) are continually being exposed to the impacts of floods, droughts, landslides/mudslides, windstorms and extreme temperatures. It was also revealed that the total amount of rainfall experienced by the respondents in the area had significantly reduced (P < 0.001) in the last 25 years. Occurrence of late rainfall was reported (39.2% of the respondents) and had shown a significant rise (P < 0.01) over the years. Respondents felt that extreme hot or warm spells (53.6%) and extreme cold events (47.7%) were also significantly on the rise lately (P < 0.001).

Table 4.16: Respondents opinion about occurrence of natural disasters (EWEs)

Variables	Respondent's opinion frequency (%)					Total (n)
	Increased a lot	Increased	Same	Decreased	Decreased a lot	
Total rainfall per year	35 (8.8)	26 (6.5)	16 (4.0)	238 (59.8)	83 (20.9)	**398**
Incidence of floods	49 (12.7)	132 (34.2)	75 (19.4)	106 (27.5)	24 (6.2)	**386**
Severity of floods	71 (19.0)	119 (31.8)	66 (17.6)	88 (23.5)	30 (8.0)	**374**
Incidence of drought	86 (22.3)	186 (48.2)	44 (11.4)	58 (15.0)	12 (3.1)	**386**
Severity of drought	83 (21.8)	172 (45.3)	58 (15.3)	46 (12.1)	21 (5.5)	**380**
Early rainfall	60 (15.4)	132 (33.8)	50 (12.8)	139 (35.5)	9 (2.3)	**390**
Late rainfall	66 (16.9)	153 (39.2)	59 (15.1)	105 (26.9)	7 (1.8)	**390**
Extreme warm spells	77 (20.1)	206 (53.6)	43 (11.2)	41 (10.7)	17 (4.4)	**384**
Extreme cold spells	100 (25.9)	184 (47.7)	31 (8.0)	64 (16.6)	7 (1.8)	**386**

Majority of the respondents (62.8%) believed that weather prediction became significantly inaccurate ($P < 0.001$) with time (Fig. 4.38) and that rainfall (68.6% of the respondents) became significantly inconsistent ($P < 0.01$) compared to 25 years ago (Fig. 4.39).

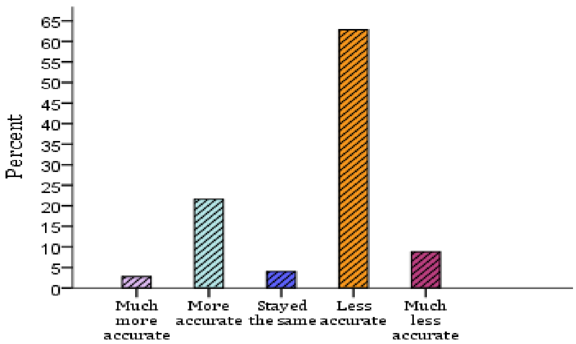


Fig. 4.38: The ability to make accurate weather predictions

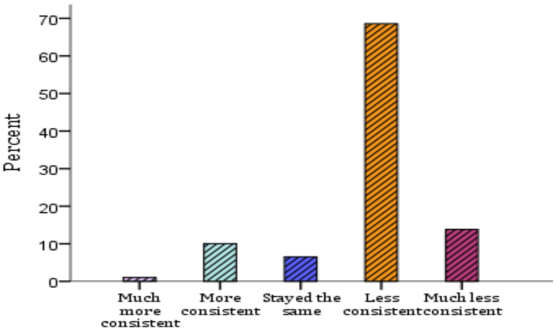
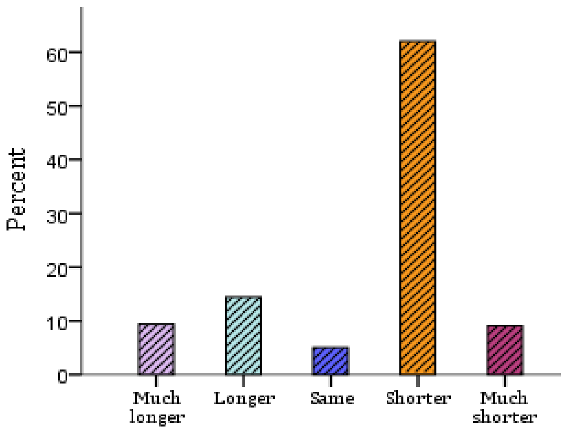


Fig. 4.39: Rainfall consistency

The length of growing period (seasonality) had also become shorter ($P < 0.001$) as stated by 62% of the respondents (Fig. 4.40) and the floristic composition of vegetation (factored in as an indicator of habitat quality) was reported (64.3% of the respondents) to have exhibited a declining trend ($P < 0.001$) (Fig. 4.41).



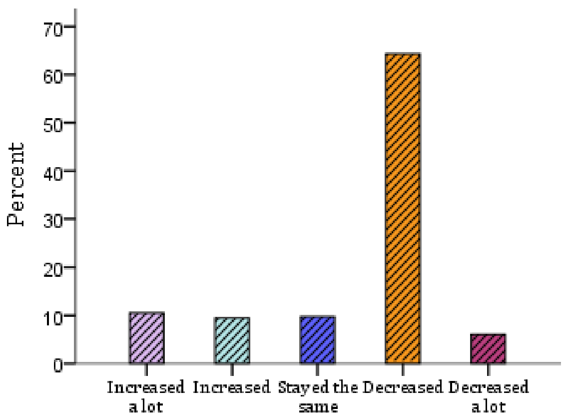


Fig. 4.40: Length of growing season Fig. 4.41: Floristic composition of vegetation

4.4.4.2 Sensitivity

4.4.4.2.1 Forestry and Forest Resources

Forests composition was observed by 97% of the respondents to have undergone significant changes over the past 25 years ($P < 0.001$). Forest components reported to have reduced considerably included water resources (rivers, springs, swamps, marshes and wells), forest cover (number of trees, pasture, flowering plants, wild fruits and medicinal plants), wildlife, birds, beehives and fuel wood. About 51.9% of the respondents reported a significant reduction in water resources in the area (Fig. 4.46).

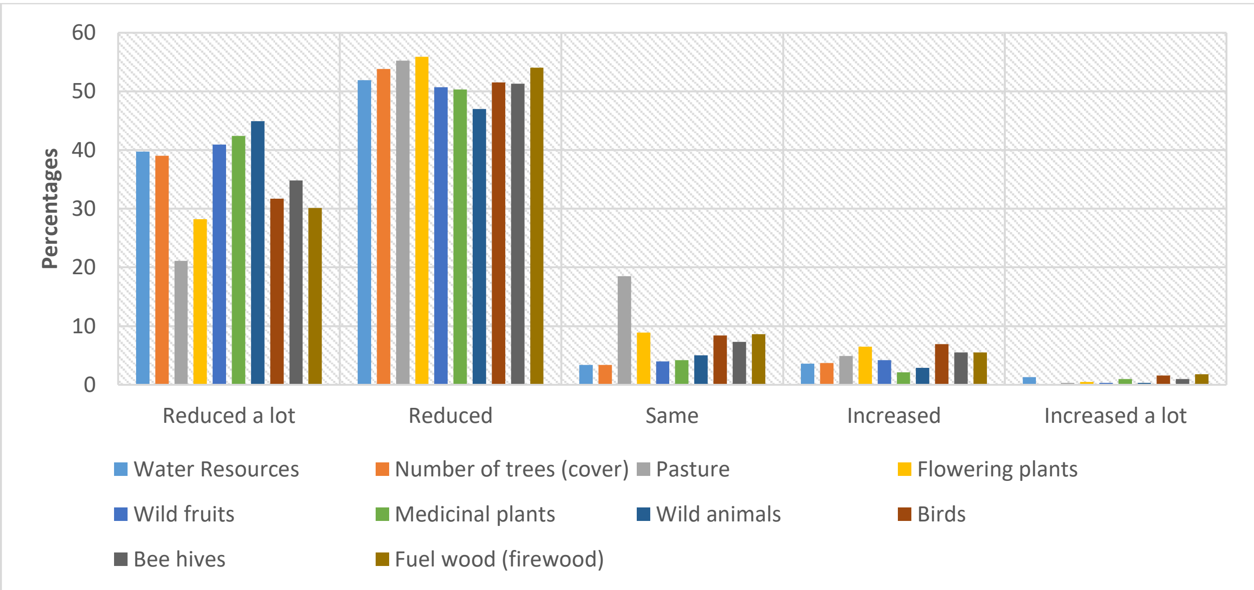


Fig. 4.42: Percentages of respondents on changes in forestry and forest resources

Apart from the reduction in forest components, remarkable changes in forest coverage over the same time period were observed (98.2 % of the respondents). These changes were gradually increasing with time as stated by 44.3% of the respondents, with more of the forest area being converted into other land use types especially agriculture and settlements. As a result, the continued exposure of forestry and forest resources to the impacts of CCV would greatly affect the livelihoods of 72.4% of the respondents (Fig. 4.43) because most of their livelihoods (54.8%) directly or indirectly relied on forestry and forest resources (Fig. 4.44).

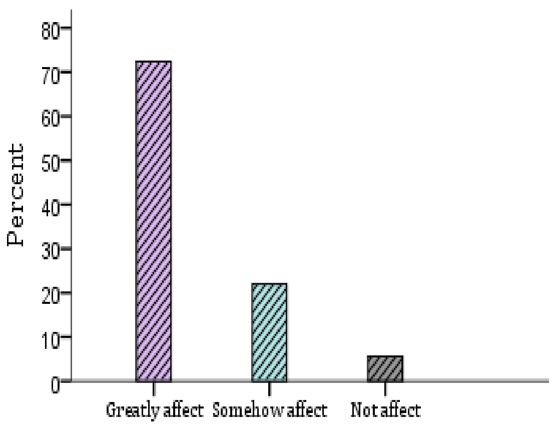


Fig. 4.43: Effects on livelihoods if exposure on forestry continued

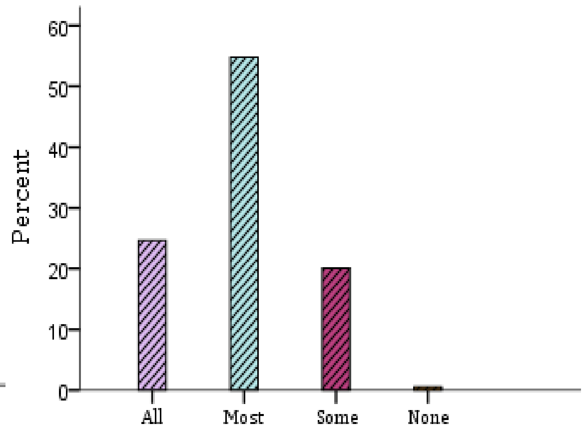


Fig. 4.44: Livelihoods that rely on forestry

4.4.4.2.2 Food security

Farm produce (vegetable, cereals and fruits) which constituted a larger percentage of food requirements for the study population was reported to be significantly scarce ($P < 0.001$). 68.3% of the respondents showed that the farm produce they primarily relied on for food were increasingly becoming scarce compared to 26 years ago. Similarly, livestock products (milk, meat and blood) were also reported (54.2% of the respondents) to have become scarce. Other products such as wild fruits and honey which supplemented the food sources had also become scarce as reported by 79.3% and 82.4% of the respondents respectively (Fig. 4.45). Access to farm produce and livestock products had become difficult as reported by 37.6% and 54.7% of the respondents respectively unlike in the past ($P < 0.001$). 89.3% of the respondents found it difficult to access wild fruits now than in the past and 87.3% showed that it has become very difficult to access honey (Fig. 4.46).

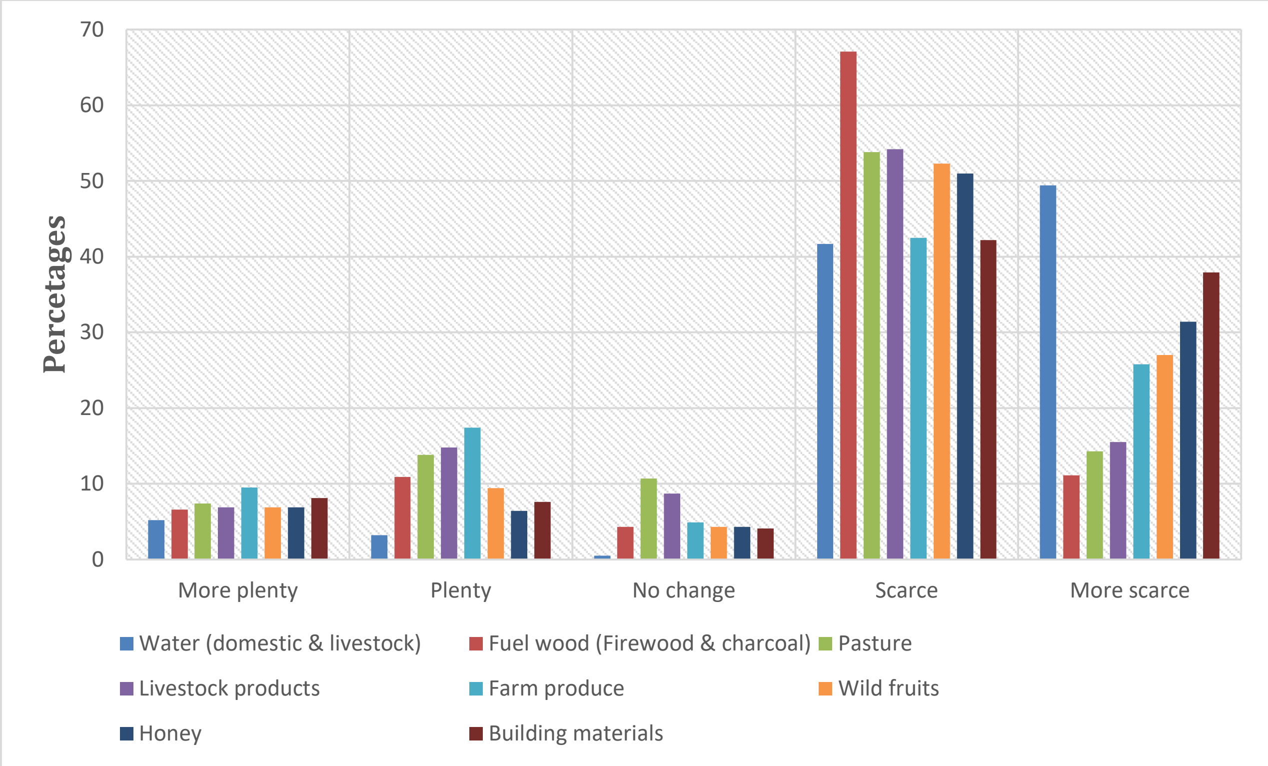


Fig. 4.45: Percentages of respondent's rating on livelihood resources availability

In addition, it was revealed (58.3% of the respondents) that they had become more food insecure ($P < 0.001$) than in the past. The availability and accessibility of food supplies considerably reduced resulting to more vulnerable communities facing food shortage. About 62% of the respondents stated that the length of the growing season had changed significantly ($P < 0.001$) resulting to either total crop failure or poor harvest from the farms (Fig. 4.46). This exacerbated the food insecurity situation among the respondents. Most of the respondents (41.6%) believed that poverty levels were rising making them more exposed to the impacts of CCV.

Spearman's bivariate correlation analysis showed a statistically significant relationship between incidences of food insecurity and rainfall inconsistency (r = 0.263, $P < 0.01$). However, a similar correlation statistics showed that there was no significant relationship between the total amount of rainfall and incidences of food insecurity (r = 0.029, P = 0.565). On the other hand, correlation analysis also revealed a relationship between late rainfall and incidence of food insecurity (r = -0.103, P = 0.04).

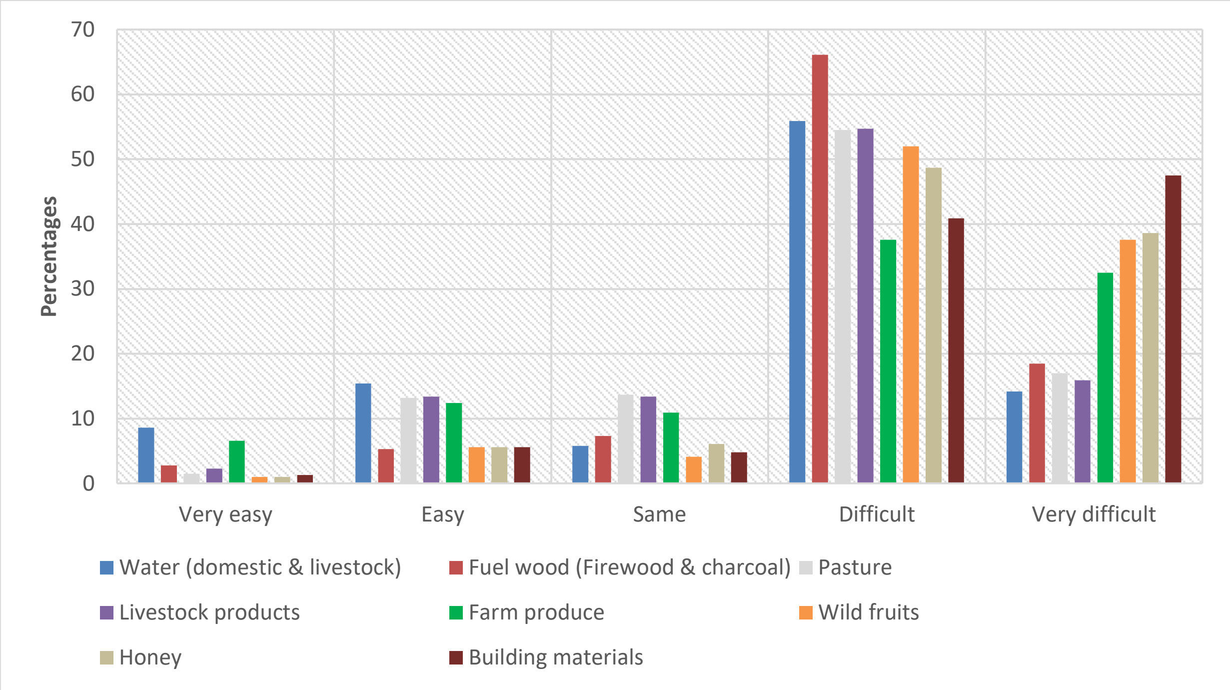


Fig. 4.46: Percentages of respondent's rating on livelihood resources accessibility

4.4.4.2.3 Health

The study revealed that HHs took on average five hours to access medical facilities in the study area. However, some HHs took longer (6 - 8 hours) and some shorter (1 hour). The only means through which medical facilities could be accessed during the occurrence of EWEs in the area was on foot as indicated 51.9% of the respondents, while 30.5% believed that it was possible to access medical facilities by motor cycles (Table 4.17). This was an indication of how vulnerable these communities were to the impacts of CCV, especially the women, children, elderly, sick and marginalized groups. Gender differences in terms of accessibility of medical facilities during natural disaster periods was statistically significant ($P < 0.05$).

Table 4.17: Accessibility of medical facilities by gender during occurrence of EWEs

Gender (%)	**Access to Medical Facilities (%)**						**Total n (%)**
	Ambulance	Car Hire	Motor Cycle	On foot	Impossible	No Means	
Males	13	6	67	125	5	11	**227 (57.2)**
Females	13	16	54	81	2	4	**170 (42.8)**
Total n (%)	**26 (6.5)**	**22 (5.5)**	**121 (30.5)**	**206 (51.9)**	**7 (1.8)**	**15 (3.8)**	**397**

Among the common waterborne and climate related diseases of cholera, malaria, diarrhoea, common cold, typhoid, and dysentery; exposure to malaria and common cold was more prevalent as 44.7% and 28.1% of the respondents respectively reported such cases. Cholera, typhoid and diarrhoea were reported by 8.6%, 6.1% and 3.2% of the respondents respectively. Exposure to such diseases was mostly felt among females (58.7%) compared to males (41.3%) and according to 38.4% and 35.3% of the respondents, children and the elderly respectively experienced higher cases of ailments during EWEs ($P < 0.001$). 66.4% of the respondents observed a significant increase in incidences of crop diseases and infections ($P < 0.001$) (Fig. 4.47), while 50.8% of the respondents observed that human diseases, deaths and infections were significantly on the rise with the occurrences of natural disaster events ($P < 0.05$) (Fig. 4.48). Similar tendencies were also reported with incidences of livestock diseases, deaths and infections where 57.8% of the respondents showed that there was a significant rise ($P < 0.01$) as shown in (Figs. 4.49).

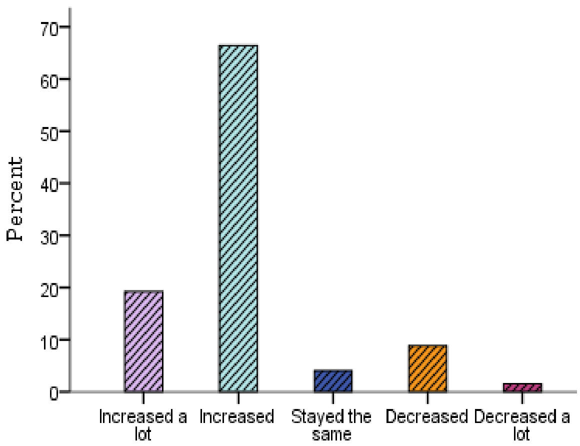


Fig. 4.47: Incidences of crops diseases and infections

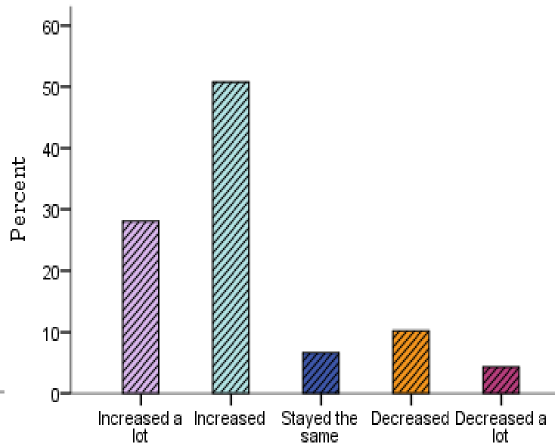


Fig. 4.48: Human diseases and infections

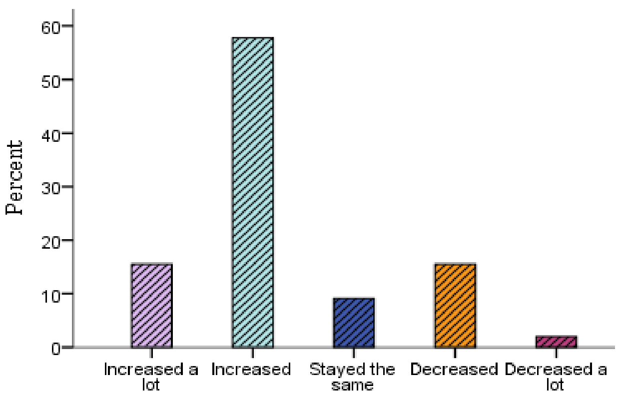


Fig. 4.49: Incidences of livestock diseases and deaths

Using Spearman's correlation test, a statistically significant relationship between emergence of some of the diseases and prevailing weather events was established. The test showed that extreme cold events (chilly spells) and incidences of human diseases, deaths and infections were significantly correlated ($r = 0.391$, $P < 0.001$) and that severity of floods was correlated with incidences of human diseases, deaths and infections ($r = 0.273$, $P < 0.01$). A correlation matrix for EWEs with climate/weather related exposure and risks are shown in (Table 4.18).

Table 4.18: Correlation matrix on relationship between occurrence of EWEs and diseases/infections

	IF	SF	ID	SD	EP (R)	LP (R)	EHW	EC	HDDI	ILDD	ICDI
IF	1.000										
SF	.778**	1.000									
ID	.153**	.216**	1.000								
SD	.096	.105*	.638**	1.000							
EP (R)	.288**	.330**	.132*	.232**	1.000						
LP (R)	.229**	.279**	.204**	.176**	.481**	1.000					
EHW	.206**	.250**	.398**	.374**	.160**	.260**	1.000				
EC	.314**	.295**	.264**	.145**	.269**	.331**	.238**	1.000			
HDDI	.274**	.245**	.144**	.069	.122*	.161**	.220**	.391**	1.000		
ILDD	.253**	.276**	.192**	.176**	.147**	.113*	.279**	.287**	.363**	1.000	
ICDI	.296**	.253**	.242**	.238**	.119*	.077	.189**	.235**	.284**	.588**	1.000

**. Correlation is significant at the 0.01 level (2-tailed) *. Correlation is significant at the 0.05 level (2-tailed).

IF = Incidence of floods
SF = Severity of floods
ID = Incidence of droughts
SD = Severity of droughts
EP (R) = Early Precipitation (rainfall)
LP (R) = Late Precipitation (rainfall)
EC = Extreme cold (chilly spells)
EHW = Extreme heat waves (hot/warm spells)
ICDI = Incidences of crop diseases and infections
ILDD = Incidences of livestock diseases and deaths
HDDI = Human diseases, deaths and infections
ILDD = Incidences of livestock diseases and deaths

4.4.4.2.4 Livelihoods of the Study Population

The study revealed that 86.5% of the respondents are agro-pastoralist where 43.9% were dependent on livestock keeping and 42.6% were dependent on crop farming as their primary sources of livelihood ($P < 0.001$) (Fig. 4.50). Further examination, revealed that 99.2% of the respondents were involved in livelihoods that were directly or indirectly sensitive to CCV (Fig. 4.51). Low precipitation (drought) and failed rains were the major climatic aspects that posed the greatest problems to livelihoods of 44.9% and 19.3% of the respondents respectively (Fig. 4.52).

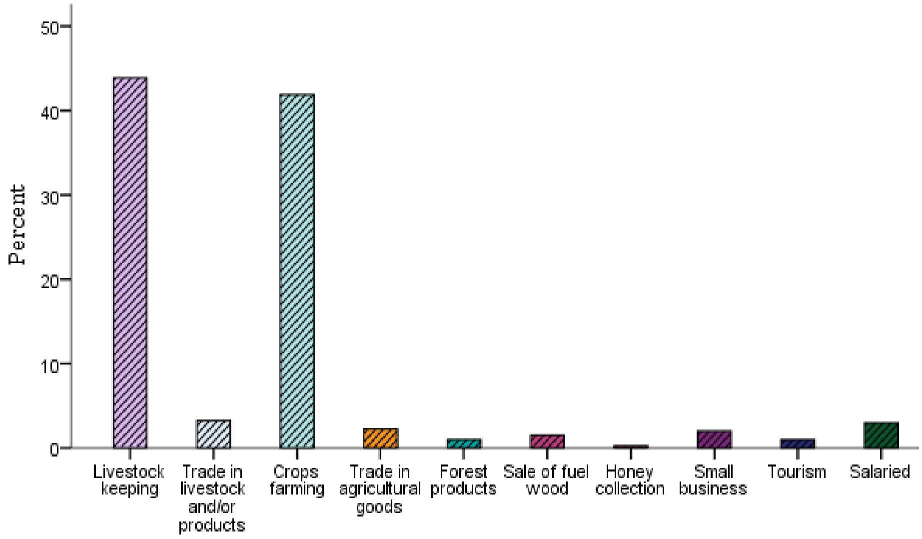


Fig. 4.50: Activities primarily depended upon for livelihood

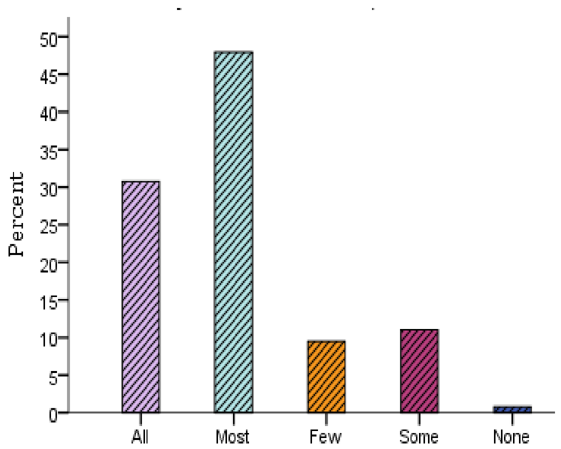


Fig. 4.51: Proportion of primary livelihood activities that are directly reliant on climate/weather

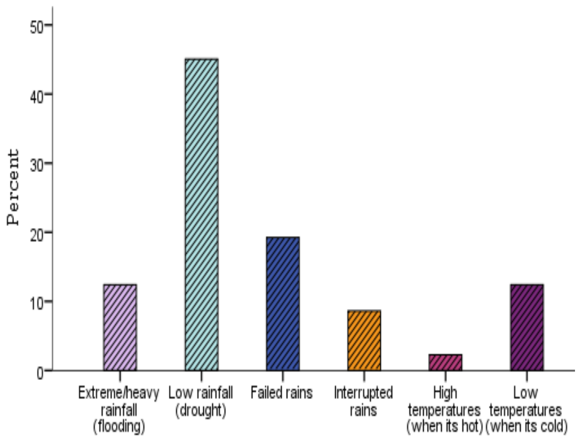


Fig. 4.52: Aspect of climate that poses the greatest livelihood problems

While low precipitation (drought) and failed rains had significant effects on crop farming and livestock keeping ($P < 0.001$); the two were the major means of livelihoods of the respondents. Extreme precipitation (flooding), low temperatures, and interrupted rains influenced the main livelihoods activities for the respondents in that order (Table 4.19).

Tables 4.19: Primary livelihood activities and climate aspects with greatest impacts.

Activity primarily relied upon for livelihoods (%)	**Aspect of climate that poses the greatest livelihood problems (%)**						**Total n (%)**
	Extreme Precip. (Flooding)	Low Precip. (Drought)	Failed Rains	Interrupted Rains	High temp. (Hot/warm)	Low temp. (Cold)	
Livestock keeping	21	62	51	19	5	15	**173 (43.9)**
Livestock products	1	6	4	0	0	1	**12 (3.0)**
Crops farming	21	91	19	11	3	23	**168 (42.6)**
Agricultural products	0	5	2	2	0	0	**9 (2.3)**
Forest products	0	2	0	2	0	0	**4 (1.0)**
Fuel wood/charcoal	2	2	0	0	0	0	**4 (1.0)**
Honey collection	0	1	0	0	0	0	**1 (0.3)**
Small business	0	3	0	0	0	5	**8 (2.0)**
Tourism	1	2	0	0	1	0	**4 (1.0)**
Salaried or waged	3	3	0	0	0	5	**11 (2.8)**
Total n (%)	**49 (12.4)**	**177 (44.9)**	**76 (19.3)**	**34 (8.6)**	**9 (2.3)**	**49 (12.4)**	**394**

Liquid fuel (paraffin) was the most preferred primary source of energy for lighting by 45.3% of the respondents, followed by home solar system (HSS) at 37.6%, while only 6.2% of the respondents used electricity from the grid as their primary source of energy (Fig. 4.53). Firewood and charcoal were the most preferred primary source of energy for cooking (65.9% and 28.1% respectively) and heating (74.8% and 21.5% respectively) by the respondents (Fig. 4.54 and 4.55).

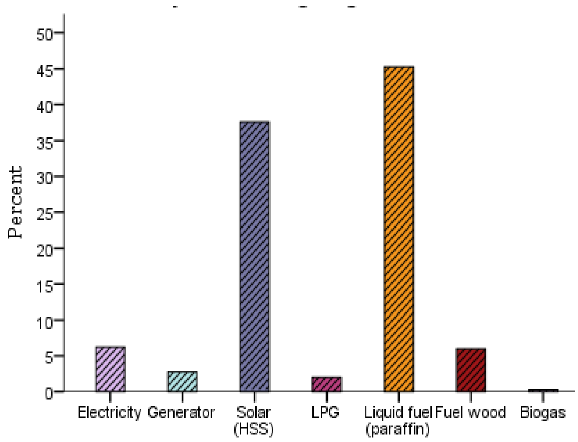


Fig. 4.53: Primary source of lighting to the home

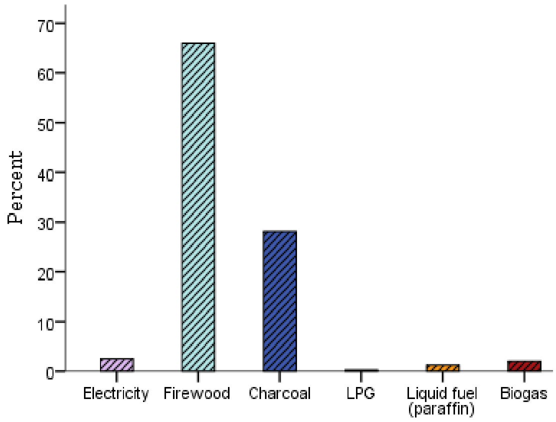


Fig. 4.54: Primary source of energy for cooking

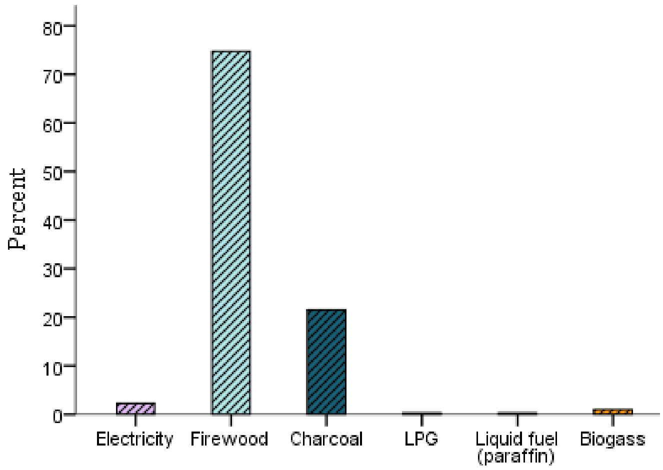


Fig. 4.55: Primary source of energy for heating

4.4.4.2.5 Water sources

The major source of water for domestic and livestock use was obtained from the streams (64.6% of the respondents) while 20.3% of the respondents obtained their water from springs, wells and boreholes. 11% obtain water from water pans. Water harvesting was not a common practice among the respondents as reported by a mere 4.1%. Water resources (rivers, springs, marshes, swamps and wells) were reported by 51.9% of the respondents to have decreased in the study area. Majority (81.2%) of the respondents obtained water for drinking from springs, wells and boreholes (Fig. 4.56).

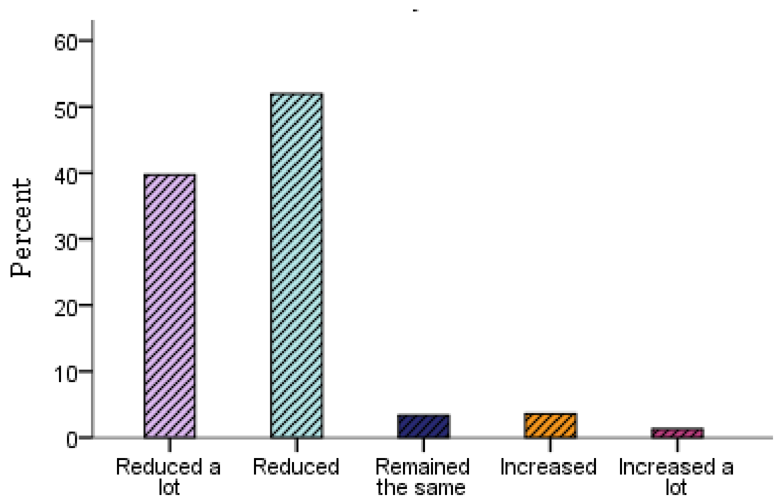


Fig. 4.56: Water resources (rivers, springs, swamps, marshes and wells)

A simple generalized linear model (GzLM) regression analysis was performed to examine the influence of the trend of total amount of rainfall per year on water resources status. The results showed that the reducing trend of total amount of rainfall received per year has significant effect on water resources status ($P < 0.001$) in the area. The reduction of water resources (rivers, springs, marshes, wells and swamps) observed by the respondents in the area is greatly influenced by the total amount of rainfall received per year. GzLM regression results also revealed that rainfall consistency had a significant influence on the status of water resources in the area ($P = 0.004$). The reduction of water resources in the area is associated with less consistent rainfall pattern.

To ascertain the results from GzLM and further determine the type and strength of relationship between water resources (rivers, springs, marshes, wells and swamps) status, total amount of rainfall per year trends and rainfall consistency, a correlation analysis was performed. The results from correlation analysis clearly indicated that water resources status had a significantly weak negative association with total amount of rainfall received per year ($r = - 0.132$, $P = 0.01$); and similarly, a significantly weak negative association was revealed between water resources status and rainfall consistency ($r = - 0.160$, $P = 0.002$).

4.4.4.3 Adaptive Capacity of the Households

The respondents indicated that there it was possible to tackle (adapting to or mitigating) CCV. A majority of the respondents (99.7%) showed that they embraced the responsibility to enhance the household's adaptive capacity. The measures that had been taken by the respondents to tackle (adapt or mitigate) CCV are shown in (Table 4.20).

Table 4.20: Respondent's CCV adaptation and mitigation strategies

How to tackle CCV (%)	Possibility of tackling CCV (%)		Total
	Yes	No	
Afforestation & reforestation	141	0	**141 (43)**
Avoid deforestation & forest degradation	29	1	**30 (9.1)**
GHGs emission reduction	21	0	**21 (6.4)**
Forest rehabilitation and restoration	9	0	**9 (2.7)**
Agroforestry	9	0	**9 (2.7)**
Climate policies	13	0	**13 (4.0)**
Environmental conservation awareness	56	0	**56 (17.1)**
Conservation agriculture (e.g. mulching or proper tillage)	8	0	**8 (2.4)**
Reduce pollution	11	0	**11 (3.4)**
Changing mix of livestock (interbreeding or tolerant breed)	1	0	**1 (0.3)**
Supplementary feeding	2	0	**2 (0.6)**
Drip irrigation	3	0	**3 (0.9)**
Use renewable/green energy sources	13	0	**13 (4.0)**
Life style change(e.g. production and consumption patterns)	2	0	**2 (0.6)**
Adopt drought tolerant breeds	1	0	**1 (0.3)**
Use sustainable charcoal kilns (production)	5	0	**5 (1.5)**
Conservation of water and their catchment areas	2	0	**2 (0.6)**
Proper waste disposal and management	1	0	**1 (0.3)**
Total	**327 (99.7)**	**1 (0.3)**	**328**

Respondents indicated that they had taken some actions out of concern for CCV which included tree planting (46.4%), community environmental conservation awareness and sensitization campaigns (11.3%) and proper waste management (9.2%). The responsibility to adopt strategies that would be vital to deal with issues of adaptive capacity and resilience relied directly on individuals as indicated by 45.1% of the respondents. It was noted that respondents (21%) also felt that the national government should take charge to tackle the impacts of CCV with the help of environmental organizations/lobby groups (14.1%).

4.4.5 Household Survey Discussion

The study interacted with 57.1% males who were regarded as HH heads and responded to HH issues unless otherwise. The males were more involved in the decision making processes concerning the HHs; a contextual and typical African societal arrangement in which the males are automatically regarded as the HH heads. This portrayed a scenario in which women are discriminated and are not adequately involved in such processes and consequently an indication of gender disparity. Studies (Kimani *et al.*, 2014; Prince *et al*., 2015 and Kabir *et al*., 2016) have found that integrating gender into short, medium and long-term adaptation and mitigation strategies can help to ensure that adaptive capacity and resilience of the people and resources is enhanced. Integrating gender is also expected to help ensure that the implementation of adaptation activities will bridge socio-economic, employment, exposure, responsiveness and sensitivity disparities and other vulnerabilities (UNFCC, 2013).

During this study, in understanding the vulnerability to the effects of CCV, gender of the respondents was considered as one of the key pillars. In this study, 23.2% and 32.1% of the male and female respondents respectively were at an economically active age group between 25 – 55 years. The children and elderly were greatly exposed and sensitive to the impacts of CCV due to circumstantial discrimination from vulnerability decision making processes and subsequently not adequately informed about issues on adaptive capacity and resilience. Elsewhere, RSPN (2012) in a study showed that age categories of the respondents were predominantly between 25 – 55 years. Their results indicated that illiteracy was most prevalent among the older generation above 55 years. Most of the elderly respondents above 55 years had either no formal education qualification or only attained primary education level. The results also revealed that unemployment is quite rampant among the respondents as 75.2% of the respondents were unemployed. Conventionally, people with higher education level and socio-economic status are considered to be more likely informed about the climatic phenomena. The unemployment rate among the respondents is an indication of their exposure to the impacts of CCV and further exacerbates their vulnerability. The high level of unemployment rates was associated with illiteracy levels in the area.

This study found that 57% of the respondents had relatively no or little formal education. For those who had formal education, 29.5% attained secondary (O-level) as the highest level of education. 86.5% of the participants had basic education giving an impression that illiteracy level among the respondents was not very high. It was also revealed that there existed a little difference in education levels among male and female indicating that the female were no longer educationally segregated in the area and therefore were able to express their views intellectually.

Eighty four percent (84%) of the respondents indicated that they were aware and knowledgeable of CCV. In this study, it appeared that the respondents believed that CCV was actually the manifestation of the impacts experienced at their localities. From the results, it was found that exposure to natural climatic events influenced awareness of the respondents to CCV as prior experience of exposure to risk increased awareness. Based on this perception and knowledge, the respondents generally had a clear perception and knowledge of CCV except on its causes (whether CCV is caused by natural fluctuations in earth's temperature and leaving lights on in the room) and who should bear the responsibility. Kabir *et al*. (2016) found that the respondents perceived CCV well when exposed to natural climatic events. In essence, the respondents in this study perceived the real causes of CCV, the evidence laid forth, the impacts and their vulnerability, as well as the need for adaptation and mitigation strategies. This indicated that CCV is a reality and its effects are consequently experienced by the biophysical and socio-economic systems as clearly stated in IPCC reports (IPCC, 2007; IPCC, 2013).

Socio-demographic factors of the respondents such as gender, age, education and year of residence in this study, did not have any significant influence on CCV awareness. However, the length of time the respondent stayed in a particular place, remarkably had a gradual increment of respondents' awareness. Only 6.3 % of the respondents had stayed in the study area for less than 5 years while those who had stayed between 16 and 20 years were 22 % and those who had stayed between 21 and 30 years were 29 %. Similarly, socio-economic factors such as occupation and employment status did not have any influence on respondent's awareness of CCV. Conversely, age of the respondents significantly influenced their awareness of CCV. Older respondents had lived longer in the study area, hence had greater awareness of CCV.

Several studies have linked demographic factors such as gender, age, education and socio-economic factors to differences in awareness and perception of CCV (Street *et al.,* 2009; UNFCCC, 2013; Gallina and Williams, 2014). In addressing the CCV concerns and influencing behavioural as well as attitude change world-wide, education has been considered as the single most essential tool to enlighten humanity about the environmental issues and improve their intellectual capabilities (Getachew *et al.*, 2014; UNESCO, 2014). In other studies, it was found that education insignificantly influenced awareness of CCV (EAC, 2011; Mandleni & Anim, 2011; Kimani *et al*., 2014). However, Tazeze *et al*. (2012) found that age of the respondents significantly influenced the awareness of CCV. This study found out that age of the respondents was a factor in CCV awareness and therefore believes that as one ages, they tend to acquire more experience in weather forecasting.

Severity and incidences of EWEs (floods, drought, extreme temperatures, landslides/mudslides and windstorms in this study were reported to have tremendously increased over time by 90.5% of the respondents. In addition, the study also revealed that the total amount and consistency of rainfall had reduced substantially over the years. The increasing trends in the occurrence of late rainfall tended to shorten the growing seasons as reported by 56.1% of the respondents. A report by FAO (2010) showed that the frequency of drought and floods had increased and indicated that the increment in trends of natural disasters was the main cause of food insecurity, climate related diseases, infections, loss of human life and livestock.

A key informant during this survey observed that rainfall had become much more unpredictable and unreliable that farmers were uncertain on when to start land preparation for planting. Further, that even when it rains, they never knew the intensity and duration. This has significantly hampered crop production, and about 71% of the farmers were recording increasing trends in crop failure and/or poor harvest. Kashaigili *et al*. (2014) revealed that indicators of CCV include decreasing rainfall, increasing incidences of drought and unpredictable rainfall patterns. Changes in rainfall pattern, particularly drought have considerably affected agricultural production due to soil moisture stress (IPCC, 2007; FAO, 2010; Sara *et al*., 2012; IPCC, 2013; Kashaigili *et al*., 2014). As a result of increasing variability in rainfall, agricultural dependent HHs had experienced livelihood challenges such as food insecurity, water scarcity and diseases and infections.

Sensitivity analysis revealed that 96.7% of the respondents had observed changes in forestry and forest resources composition and coverage, while 51.9% of the respondents believed that water resources had reduced. As 54.8% of the respondent's livelihoods directly or indirectly depended on forestry and forest resources and 99.2% of the respondents who relied on climate sensitive activities, their livelihoods have been greatly affected. The vulnerable communities were more food insecure with rising poverty levels and were greatly exposed to rising climate related diseases and infections. The situation was exacerbated by inaccessibility of medical facilities during episodes of climatic events as 82.4% of the respondents indicated that the most common means of accessing medical facilities at such times was on foot and by motor cycles. Women, elderly and children were the most sensitive and were greatly exposed. These views have been reported elsewhere (IPCC, 2007, 2013; Lasco *et al*., 2010). The studies found out that in addition to the impact on the ecosystem, CCV is expected to have serious consequences on human and environmental health: conflicts over access to food or water, spreading of disease (in human, crops and livestock) and an increase in human migration. This is expected to further cause negative effects in food availability, crop production, livelihood, health and water supply to the residents in the watershed (Lasco *et al*., 2010; Sara *et al*., 2012; Prince *et al*. 2015).

Streams, swamps, marshes, springs, wells, boreholes and water pans were the main sources of water supply for both domestic and livestock use to the community. The uncertainty surrounding these water resources due to CCV is enormous hence the community was vulnerably faced with greater challenges of water supply in terms of quality and quantity. This study found that waterborne and climate related diseases and infections had affected 72.8% of the respondents as the exposure was greatly felt by 58.7% of the female respondents. Water conservation and management was a rare strategy practiced only by 4.1% of the respondents. The total amount of rainfall received per year and rainfall consistency was significantly associated with water resources status as both showed reducing trends.

The study population was primarily agro-pastoralist relying on crop farming and livestock keeping. Almost all (99.2%) of their livelihoods were directly or indirectly sensitive to

CCV. 64.2% of the respondents stated that low rainfall (drought) and failed rains were the major climatic aspects that posed the greatest problems to their livelihoods. Vulnerable communities and resources were greatly exposed and sensitive to the impacts of CCV. However, they still primarily relied on unclean and unsustainable household energy sources of liquid fuel (paraffin) and fuel wood (firewood and charcoal) which further aggravates CCV.

The respondents were keen about adaptation and mitigation strategies to enhance their adaptive capacity and resilience to CCV. 99.7% of the respondents believed that CCV can be tackled and have been involved in different activities to adapt and mitigate its effects. They preferred afforestation and reforestation and community environmental conservation awareness as the best strategies to improve the adaptive capacity and resilience. This could be due to the observed unabated reduction of forest coverage and ensued negative effects realized as a result of anthropogenic activities. They indicated that individuals bear the sole responsibility to build adequate adaptive capacity and resilience followed by the national government and environmental organization/lobby groups as supported by results from a research done by Yaro (2013).

CHAPTER 5: CONCLUSION AND RECOMMENDATION

5.1 Summary of the Key Findings

The summary of the key research findings are presented as follows based on the research specific objectives.

5.1.1 Spatio-temporal variability in the state of climate variables in the study area

The extreme temperature variability observed indicated warming tendencies with mean annual temperature increasing by 1.8℃ and an overall increasing mean annual temperature trend over the last 26 years. The spatial and temporal precipitation variation was an indication of low rainfall reliability and inconsistency. Erratic and abrupt rainfall trends led to flash floods and landslides. Climate variables, spatio-temporal and household survey analyses both demonstrated an increasing frequency and incidences of extreme temperature events in the area over the years due to occurrence of above and below normal maximum and minimum temperatures respectively. The abnormalities observed in precipitation cycles in terms of unreliability, inconsistency and unpredictability has caused a lot of uncertainties in seasonal precipitation resulting to flash floods, land/mudslides and severe drought events. The increasing trend of mean annual temperature and the declining trend of mean annual precipitation are indication of CCV in the area.

5.1.2 Characterization of the land cover/use changes in the study area

The comparative land cover/use changes analysis demonstrated that there was overall reduction in forest cover caused by deforestation, degradation and conversion to other land uses especially agriculture. Land cover/use changes were mainly characterized by decline in the dense forest area and increases in both agricultural land, tea plantation, bare grounds and degraded forest; and inter-conversions between degraded forest, agricultural land and bare ground areas. Generally, forest land cover has significantly shrunk unabated as degraded forest land cover, agricultural land use, tea plantation and bare grounds both exhibiting an increasing trend during the study period.

5.1.3 Impacts of climate variability and land cover/use changes in the study area

The changes observed in mean annual temperature and precipitation trends have escalated climate related events and impacts resulting to shorter growing seasons, late onset and early offset of rainfall, crops yield failure, rising prices of farm produce, drought livestock loss, human and livestock diseases prevalence, destruction of infrastructure, human displacements and deaths, abject poverty, political instability, resources use conflicts and food insecurity. Increased frequency and severity of droughts has made the people, forestry and forest resources more vulnerable to the impacts of CCV. Prolonged droughts often lead to famine, lack of food and increased malnutrition, disrupting livelihoods and adversely affecting mainly the elderly, children and women.

The post classification and NDVI image differencing results both depicted the ramification of CCV on the biophysical and socio-economic systems by weakening the adaptive capacity and resilience of the communities, forestry and forest resources. The reduction in vegetation vigour (greenness) depicted by the generated NDVI vegetation maps through the study period is an indication of declining vegetation health as a result of increasing incidences and severity of drought and anthropogenic activities in the area. The NDVI graphics, represented a rough measure of declining vegetation health which were used to detect differences in the lag between decline in rainfall and its effect on vegetation.

The effects of CCV are systemic processes in which the resulting flash floods, land/mudslides, severe droughts and extreme temperature events lead to reduction or loss of livelihoods, destruction of properties, human displacement and/or death. The impoverished and displaced population further exacerbate the degradation and destruction of the environment by engaging in unsustainable livelihood activities such as conversion of the forest to agricultural land to boost food production, encroachment and illegal settlements, illegal logging, charcoal production, overgrazing and overharvesting of the resources to compensate their lost livelihoods. WCED (1987) iterated that many parts of the world are caught in a vicious downwards spiral and poor people are forced to overuse environmental resources to survive from day to day, and the impoverishment of their environment further impoverishes them, making their survival ever more difficult and uncertain. The intensified anthropogenic activities in the forested areas render them incapable to offer their provisioning, regulating, supporting and cultural roles which further impoverishes the population.

5.1.4 Vulnerability of the people and forest resources to the impacts of CCV

The HH survey revealed that majority (84%) of the respondents were aware of CCV and are consequently vulnerable and experiencing its effects at varying magnitude. Forestry and water resources, women, elderly, children and the sick are the worst hit. Several livelihoods are critically affected and uncertain. Agricultural and livestock production in the study area are unfavourably threatened and progressively confronted with gradual decline. Being agro-pastoralist communities, they were greatly vulnerable to the impacts of CCV and forced to resort to unsustainable resources use such as deforestation and forests degradation through encroachment and settlement, logging, expansion of agricultural land, intensive use of fertilizers, poor tillage, charcoal burning, overharvesting and resources use conflicts in order to survive; which further exacerbated and intensified the impacts of CCV by weakening the resources and communities' adaptive capacities and resilience. Sustainability and resilience of food systems are a matter of survival, for those who earn their living in food production and value chains, but also for humanity as a whole. The COVID-19 crisis impressively demonstrated how vulnerable our current societies, forestry and forest resources and food systems are to disruptions. Climate change, though on a longer time-scale, poses an even bigger and deeper challenge for our food systems. Agro-ecology could be one of the most promising approaches to achieve the mitigation and adaptation potentials of agricultural systems to climate change and to strengthen their resilience. The survey also revealed that people are still of the opinion that it's not too late and that adaptive and mitigation strategies can be put in place to tackle CCV, and that the government, industries and businesses should devote most of their commitments and resources towards this noble course, spearheaded by individual concerns for the environmental restoration, conservation and management.

Therefore, CCV adaptation and mitigation policies formulation must gravitate around potential programmes and projects to boost food production practises with minimum impacts on the biophysical systems, focused on poverty eradication, employment creation, intensified conservation agriculture, use of climatic adversities tolerant breeds, and cheap, affordable and energy effective technological advancements. Activities adopted to help cope with the changing climate included afforestation and reforestation, cultivating different crop varieties, changing planting dates, use of soil and water conservation techniques, conservation agricultural practises, adopting drought and diseases tolerant breeds, observing climate early warning systems, supplementary feeding, using improved cook stoves and home solar systems, investing in social capital, build savings, adopting traditional knowledge indicators, construction of holding barriers and tarmac/serviced roads, soil erosion measures, agroforestry, sustainable charcoal production and engaging in non-farm income activities/alternative income sources.

5.2 Recommendations

The Narok County government and the national government must devote their resources in educating and informing the communities about all CCV's aspects in all sectors through tailor made educational programmes, awareness and sensitization campaigns, incentive environmental conservation programmes, strengthening adaptive capacity and mitigation strategies, formulation and implementation of adequate adaptation and mitigation policies such as afforestation and reforestation, relocating people from the encroached and areas with contested settlement, enhance sustainable charcoal production, boost food production with minimum impacts, agroforestry, enhance the use of traditional knowledge, poverty alleviation and livelihoods improvement strategies, invest in social capital systems and adopt measures to curb soil erosion; and investing in climate smart technologies and resilient projects such as conservation agriculture, adopting climate tolerant breeds, growing crop varieties and inter-cropping, soil and water conservation – drip irrigation, climate early warning system, supplementary feeding, improve cook stoves, home solar systems and cheap affordable clean energy. In addition, all adaptation, mitigation and resilience strategies must be inclusive regardless of gender, age, disabilities, health, employment status, poverty, religion and ethnic affiliations.

5.2.1 Suggestions for further research

There is a need for an in-depth study:-

1. To evaluate the current status of climate change adaptation and mitigation strategies on the ground and their feasibility for building adequate adaptive capacity (process indicators), delivering adaptation outcomes and delivering adaptation action (outcome indicators).

REFERENCES

Akotsi, E., Gachanja, M., & Ndirangu, J. (2006). *Changes in the Forest Cover in Kenya's Five "Water Towers" (2003-2005).* Department of Resource Surveys and Remote Sensing, Nairobi, Kenya Forests Working Group.

Alireza S., Tayeb R. & Peyman D. A. (2014). On The Effects of Climate Change and Global Warming on Water Resources in Iran. *International Bulletin in Water Resources & Development*, 2 (04)

Almutairi A. & Warner T. A. (2010). Change detection accuracy and image properties: a study using simulated data. *Remote Sensing*, 2, 1508 - 1529.

Alphan H., Doygun H. & Unlukaplan Y. I. (2009). Post-classification comparison of land cover using multi - temporal Landsat and ASTER imagery: the case of Kahramanmaras, Turkey. *Environmental Monitoring Assessment,* 151, 327 - 336.

Anyamba A. & Eastman J. R. (1996). Inter-annual variability of NDVI over Africa and its relation to El Nino/Southern Oscillation. *International Journal of Remote Sensing.* 17(13), 2533-2548.

Arieira, J., Karssenberg, D., de Jong, S. M., Addink, E. A., Couto, E. G., Nunes da Cunha, C. & Skoien, J. O. (2011). Integrating field sampling, geostatistics and remote sensing to map wetland vegetation in the Pantanal, Brazil. *Biogeosciences*, 8, 667 - 686.

Baker, L., Gemmill-Herren, B. & Leippert, F. (2019). Beacons of Hope: Accelerating Transformations to Sustainable Food Systems. *Global Alliance for the Future of F*ood. https://foodsystemstransformations.org

Baldyga T. J., Scott N. M., Driese K. N. L. & Gichaba C. M. (2007). Assessing Land Cover Change in Kenya's Mau Forest Region Using Remotely Sensed Data. *African Journal of Ecology,* 46, 46-54.

Baral B. (2012). Climate change and global warming: an ultimate havoc and a great threat to our existing biodiversity. Nepal Academy of Science and Technology (NAST). Khumaltar, Lalitpur, Nepal. *Sonsik Journal*, 4,20-23

Boitt M. K. (2016). Impacts of Mau Forest Catchment on the Great Rift Valley Lakes in Kenya. *Journal of Geoscience and Environment Protection,* 4, 137-145.

Boivin T., Coates D., Werle D. & Baird J. (2003). *Remote Sensing Applications for Information Generation and Monitoring of Large River Fisheries*. Abstract submitted to the Second International Symposium on the Management of Large

Rivers for Fisheries. Phnom Penh, Mekong River Commission. www.ibcperu.org/doc/isis.pdf.

Boko M. I., Niang A., Nyong C., Vogel A., Githeko M., Medany B., & Yanda P. (2007). *Africa climate change 2007: Impacts, adaptation and vulnerability.* UK: Cambridge University Press.

Bontemps S. (2011). Revisiting land cover observations to address the needs of the climate modelling community. *Biogeoscience Discussion*, 8, 7713–7740.

Botkin, B. D., Estes, E. J., MacDonald, M. R. & Wilson, V. M. (1984). Studying the Earth's Vegetation from Space. *Bio-Science*, 34, 508 - 514.

Bours D., McGinn C., & Pringle P. (2014). *Selecting indicators for climate change adaptation programming.* SEA Change CoP, Phnom Penh and UKCIP, Oxford.

Burrough P. A. & R. A. McDonnell (1998). *Principles of Geographical Information Systems.* New York: Oxford, (333).

Bwangoy, J. B., Hansen, M. C., Roy, D. P., De Grandi, G. & Justice, C. O. (2010). Wetland mapping in the Congo Basin using optical and radar remotely sensed data and derived topographical indices. *Remote Sensing of Environment,* 114, 73 - 86.

Campbell J. B. (2008). Origins of Aerial Photographic Interpretation. U.S. Army, 1916–1918. *Photogrammetric Engineering and Remote Sensing*, 74, 77–93.

Campbell J. B. & V. V. Salomonson (2010). Remote Sensing - A Look to the Future. Chapter 25 in Manual of Geospatial Science and Technology, (2nd ed.). London: *Taylor & Francis*, 487–510.

Campbell J. B. & Wynne R. F. (2011). *Introduction to remote sensing.* 5th ed. New York. London, The Guilford Press.

Campbell J. B., T. Hardy & R. C. Barnard (2010). Emerging Markets for Satellite and Aerial Imagery. Chapter 22 in Manual of Geospatial Science and Technology (2nd ed.). London: *Taylor & Francis,* 423–437.

Cannell M., Tommy B., Tim S., Terry M., Terry P. & Glen G. (2003). *Review of U.K. Climate Change Indicators.* Department for Environment Food and Rural Affairs. Accessed July 22, 2015 at http://www.ecn.ac.uk/iccuk

Cavaliere C. (2009). The effects of climate change on medicinal and aromatic plants. *Herbal Gram,* 81, 44-57.

Chander G., Meyer D. J., & Helder D. L. (2004). Cross-calibration of the Landsat-7 ETM+ and EO-1 ALI sensors. *IEEE Transactions on Geoscience and Remote Sensing,* 42(12), 2821−2831.

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

Chen, S., Xiao, X., Liu, J., & Zhuang, D. (2003). *Observations of land use cover change or the Xitin river Basin, Inner Mongolia, using multi - temporal landsat images.* Proceedings of SPIE, ecosystems dynamics, ecosystem society interactions and remote sensing applications for semi-arid and arid land, (4890).

Chrisphine O. M., Mary O. A., & Mark B. K. (2016). Assessment of Hydrological Impacts of Mau Forest, Kenya. *Hydrol Current Res,* 7, 223.

Chukwu, G. U. (2008). Poverty-driven causes and effects of Environmental degradation in Nigeria. *Pacific Journal of Science and Technology,* 9(2), 599-602.

Chukwu, G. U. & Asiegbu, A. D. (2011). Global warming and climate change: Impacts and implications in Nigeria. *International Journal of Current Research,* 33(6), 112-115.

Cohen, W.B., & Goward, S.H. (2004). Landsat's role in ecological application of remote sensing. *Bioscience*, 54, 535 - 545.

Congalton, R. G. & Green K. (2009). *Assessing the Accuracy of Remotely Sensed Data:*

Congalton, R. G. & Green, K., (1999). *Assessing the Accuracy of Remotely Sensed Data: Principles and Practice*. Boca Raton: Lewis Publishers.

Cubasch U., D. Wuebbles, D. Chen, M. C. Facchini, D. Frame, N. Mahowald, & J. G. Winther (2013). *Introduction. In: Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the 5th Assessment Report of the Intergovernmental Panel on Climate Change* [Stocker, T.F., D. Qin, and G. K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.)]. Cambridge, United Kingdom and New York, NY, USA, Cambridge University Press.

Dahdouh - Guebas, F. (2002). The use of Remote Sensing and GIS in the sustainable management of tropical coastal ecosystems. *Environment, Development and Sustainability*, 4, 93 - 112.

Dahdouh - Guebas, F., Hiel1, V. E., Jonathan, C. W., Chan., Jayatissa, P. L. & Koedam1, N. (2004). Qualitative distinction of congeneric and intro-gressive mangrove species in mixed patchy forest assemblages using high spatial resolution remotely sensed imagery (IKONOS). *Systematics and Biodiversity*, 2, 113 - 119.

Dangermond J. & Baker J. (2010). *GIS for Climate Change*: GIS best practices. ESRI.

Dangermond J. & Matt A. (2010). Climate Change Is a Geographic Problem That Requires a Geographic Solution. *Climate Action*.

De Roeck, E. R., Verhoest, N. E. C., Miya, M. H., Lievens, H. Batelaan,O., Thomas, A. & Brendonck, L. (2008). Remote Sensing and Wetland Ecology: a South African Case Study. *Sensors,* 8, 3542 - 3556.

Dolinets, J. & Mozgovoy, D. (2009). Training of specialists in the field of Earth remote sensing. *Acta Astronautica,* 64, 75 - 80.

Du, P., Luo, Y., Cao, W. & Zhang (2008). A comparison and evaluation of four vegetation analysis approaches based on remote sensing imagery. *Institute of Electrical and Electronics Engineers,* 1, 1 - 5.

Dyurgerov, M. B., & Meier, M. F. (2005). *Glaciers and Changing Earth System*: A 2004 Snapshot, Boulder (Colorado): Institute of Arctic and Alpine Research, University of Colorado, Occasional Paper 58.

EAC (2011). *East African Community climate change master plan 2011-2031*.

EEA (2012). Climate change, impacts and vulnerability in Europe 2012: An indicator-based report. *European Environmental Agency*, Copenhagen. Accessed online at http://www.eea.europa.eu/publications/climate

ERDAS (2009). *ERDAS Field Guide.* ERDAS Inc. (850).

Erhard M., Jelle M., & Thomas V. (2002). *Proposed Set of Climate Change State and Impact Indicators in Europe*. Technical Report. European Topic Centre on Air and Climate Change. Accessed at http://acm.eionet.europa.eu/reports

Everitt J. H., Yang, C., Escobar, D. E., Lonard R. I. & Davis, M. R. (2002). Reflectance characteristics and remote sensing of a riparian zone in south Texas. *The South Western Naturalist,* 47, 433 - 439.

FAO (2010). Analysis of Climate and Variability Risks in the Smallholder Sector: A case study of the Laikipia and Narok districts representing major agro-ecological zones in Kenya. *Environmental and Natural Resources Management working paper.* Food and Agricultural Organization (FAO) of the United Nations. Rome. Italy, Viale delle Terme di Caracalla, 00153.

FAO (2019a). *The State of the World's Biodiversity for Food and Agriculture*. J. Bélanger & D. Pillingt, eds. FAO Commission on Genetic Resources for Food and Agriculture Assessments. Rome. (572). http://www.fao.org

Foody G. M. (2009). Sample size determination for image classification accuracy assessment and comparison. *International Journal of Remote Sensing*, 30, 5273–5291.

Foody G. M., T. A. Warner & M. D. Nellis (2009). *A Look to the Future.* Chapter 34 in the Sage Handbook of Remote Sensing (T. A. Warner, M. D. Nellis and G. M. Foody, eds.). Washington, DC: Sage, 475–481.

Foody, G. M. (2002). Status of land cover classification accuracy assessment. *Remote Sensing of Environment*, 80, 185 - 201.

Fotheringham, A. S. & P. A. Rogerson (1993). "GIS and spatial analytical problems". *International Journal of Geographical Information Systems*, 7, 3–19.

Fotheringham, A. S., C. Brunsdon & M. Charlton (2000). *Quantitative Geography:* Perspectives on Spatial Data Analysis. Sage.

Franklin S. E. (2001). *Remote sensing for sustainable forest management.* Boca Raton, Florida: CRC Press.

Fraser R. H., Olthof I., Carriere M., Deschamps A. & Pouliot D. (2011). Detecting long - term changes to vegetation in northern Canada using the Landsat satellite image archive. *Environmental Research Letters,* 6, 1 - 9.

Fredolin T. T., Liew J., Ester S., Kwan M. S., Loh J. & Halimatun M. (2012). Climate Change and Variability over Malaysia: Gaps in Science and Research Information. *Sains Malaysiana*, 41(11) (2012), 1355–1366

Gallina M. & Williams A. (2014). Perception of air quality and sense of place among women in northeast Hamilton, Ontario Canada. *International journal of Social Science Studies,* 2, (3).

Getachew S., Tilahun T. & Teshager M. (2014). *Determinants of agro-pastoralist climate change adaptation strategies*: Case of Rayitu Woredas, Oromiya Region, Ethiopia. Science Alert.

Ghent D., Kaduk J., Remedios J. & Balzter, H. (2011). Data assimilation into land surface models: The implications for climate feedbacks. *International Journal for Remote Sensing,* 32, 617–632.

GoK (2008). *Mau Complex and Marmanet forests: Environmental and economic contributions.* Current status and trend reconnaissance survey. Government printers.

GoK (2009). *Ministry of Environment and Mineral Resources*. National Climate Change Response Strategy.

GoK (2009). *Rehabilitation of the Mau Forest Ecosystem*. A project concept of the interim coordinating secretariat. Office of the Prime Minister. Kenya.

GoK (2010). *National Climate Change Response Strategy*. Nairobi, Kenya. Government Press.

GoK (2013). *National Climate Change Action Plan (NCCAP).* Ministry of Environment and Mineral Resources (MEMR). Government printer.

Gong P. (2013). Finer resolution observation and monitoring of global land cover: first mapping results with Landsat TM and ETM+ data. *International Journal for Remote Sensing,* 34, 2607–2654.

Goodchild, M. F. (1987). "A spatial analytical perspective on geographical information systems". *International Journal of Geographical Information Systems,* 1, 327 – 44.

Greegor, H. D. (1986). Ecology from Space. *Bio-science,* 36, 429 - 432.

Green, R.E., Buchanan, G. & Almond, R. (2011). *What do conservation practitioners want from remote sensing?* Cambridge, UK. Cambridge Conservation Initiative Report, (27). http://www.conservation.cam.ac.uk/ resource/working.

Hayman, G., Clark, D., Blyth, E., Bartsch, A., Paulik, C., Schlaffer, S., Reschke, J., Prigent, C., Aires, F., Buchwitz, M., Schneising, O., Burrows, J., O'Connor, F., & Gedney, N. (2012). Using novel Earth observation products to characterize wetland extend and methand dynamics in the Jules Land surface model: the ESA ALANIS - Methane Project. *European Geosciences Union General Assembly 2012‖, Geophysical Research Abstracts*, 14, 2012 - 5755, (1).

Holme A.Mc R., Burnside D.G. & Mitchell A.A. (1987). The development of a system for monitoring trend in range condition in the arid shrub lands of Western Australia. *Australian Rangeland Journal,* 9, 14-20.

Homewood, K., Coast, E., Kiruswa, S., Serneels, S., Thompson, M. & Trench, P. (2006). *Maasai Pastoralists: Diversification and Poverty*. London: LSE Research Online. Available at: http://www.ilri.cgiar.org/

Hulme M., Doherty R., Ngara T., New M., & Lister D. (2001). African Climate Change*:* 1900 – 2100. *Climate Res,* 17, 145 -168.

IPCC (1996). *Climate change 1995. The science of climate change. Contribution of the Working Group I to the Second Assessment Report (SAR) of the Intergovernmental Panel on Climate Change.* World Meteorological Organization, Geneva, Switzerland and United Nations Environment Programme, Nairobi, Kenya

IPCC (2001). *Climate change 2001: Impacts, Adaptation and Vulnerability.* Contribution of Working Group II to the Third Assessment Report (TAR) of the Intergovernmental Panel on Climate Change. , UK. Cambridge: Cambridge University Press.

IPCC (2007). *Climate Change 2007: Working Group II: Impacts, Adaptation and Vulnerability*. Parry M. L, Canziani O. F, Palutikof J. P, van der Linden P. J and Hansen C. E [Edn], , Cambridge, UK. Cambridge University Press.

IPCC (2013). *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* [Stocker T. F., D. Qin, G. K. Plattner, M. Tignor, S. K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P. M. Midgley (eds.)]. Cambridge, United Kingdom and New York, NY, USA, (1535). Cambridge University Press.

IPCC (2014). *Climate Change 2014: Synthesis Report*. *Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* [Core Writing Team, R.K. Pachauri and L.A. Meyer (eds.)]. IPCC, Geneva, Switzerland, (151).

IPCC (2018). *Summary for Policymakers. In: Global Warming of 1.5°C.* An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty [Masson-Delmotte, V., P. Zhai, H.-O. Pörtner, D. Roberts, J. Skea, P.R. Shukla, A. Pirani, W. Moufouma-Okia, C. Péan, R. Pidcock, S. Connors, J.B.R. Matthews, Y. Chen, X. Zhou, M.I. Gomis, E. Lonnoy, T. Maycock, M. Tignor, and T. Waterfield (eds.)]. In Press.

IPCC (2019). *Summary for Policymakers. In: Climate Change and Land*: an IPCC special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems. [P.R. Shukla, J. Skea, E. Calvo Buendia, V. Masson-Delmotte, H.- O. Pörtner, D. C. Roberts, P. Zhai, R. Slade, S. Connors, R. van Diemen, M. Ferrat, E. Haughey, S. Luz, S. Neogi, M. Pathak, J. Petzold, J. Portugal Pereira, P. Vyas, E. Huntley, K. Kissick, M. Belkacemi, J. Malley, (eds.)]. In press.

Jennifer E. (2014). *Climate Resilience Indicator Literature Review:* "Using Columbia Basin State of the Basin Indicators to Measure Climate Adaptation". Natural resources Canada. Columbia Basin Trust.

Jensen J. R. (2007). *Remote Sensing of the Environment: An Earth Resource Perspective.* Upper Saddle River, NJ: Prentice-Hall, (608).

Jensen J. R., (2007). *Remote Sensing of the Environment*: *An Earth Resource Perspective*. 2nd eds. Pearson Education Inc., Prentice Hall.

Johnson R. B., Onwuegbuzie A. J. & Turner L. A. (2007). Toward a Definition of Mixed Methods Research. *Journal of Mixed Methods Research*, 112(1).

Jun Y., Peng G., Rong F., Minghua Z., Jingming C., Shunlin L., Bing X., Jiancheng S. & Robert D. (2013). The role of satellite remote sensing in climate change studies. *Nature Climate Change.* Review Article. Macmillan Publishers Limited. DOI: 10.1038/NCLIMATE1908.

Kabir M. D., Bayzidur R., Wayne S., Mirza A.F. L., Syed A. & Abul H. M. (2016). *Knowledge and perception about climate change and human health: findings from a baseline survey among vulnerable communities in Bangladesh.* BMC Public Health 16, 266.

Kalton G. (2009). *Methods for oversampling rare subpopulations in social surveys.* Survey Methodology, 35(2), 125–141.

Kashaigili J. J, Levira P., Liwenga E., & Mdemu M. V. (2014). *Analysis of Climate Variability, Perceptions and Coping Strategies of Tanzanian Coastal Forest Dependent Communities.* American Journal of Climate Change, 2014, 212-222. Published Online June 2014 in SciRes. http://www.scirp.org/journal, http://dx.doi.org/10.4236/ajcc.2014.32020

KIFCON (1992). *The Utilization of honey in South West Mau and Trans-Mara Forest reserves*. Management issues.

KIFCON (1994). *Forest Inventory report for South West Mau & Trans Mara*.

Kimani E. W., Ogendi G. M., & MakenziP. M. (2014). Perceptions of climate change. *European Journal of Applies Science*, 7(2). Ozean Publication. ISSN 1943-2429.

Kinyanjui J. M. (2009). *The Effect of Human Encroachment on Forest Cover, Structure and Composition in the Western Blocks of the Mau Forest Complex.* Ph.D. Thesis, Egerton University, Njoro.

Kinyanjui M. J, Petri L. K., Prasad S. B., Kariuki P, Gichu A, & Wamichwe K (2014). An Inventory of the Above Ground Biomass in the Mau Forest Ecosystem, Kenya. *Journal of Ecology*, 4, 619-627. http://dx.doi.org/10.4236/oje.2014.41052

Kinyanjui M. J. (2010). NDVI-based vegetation monitoring in Mau forest complex, Kenya. Department of Resource Surveys and Remote Sensing (DRSRS). *African Journal of Ecology*. Blackwell Publishing Ltd, Afr. J. Ecol., 49, 165–174.

Klemas, V. (2001). Remote Sensing of Landscape - Level Coastal Environmental Indicators. *Environmental Management*, 27, 47 - 57.

KNBS (2009). *The 2009 Kenya Population and Housing Census*. Counting our people for the implementation of vision 2030. Population distribution by administrative units. (1)

Lasco R. D., Cruz R. V. O., Pulhin J. M & Pulhin F. B. (2010). *Assessing climate change impacts, adaptation and vulnerability:* The case of the Pantabangan-Carranglan Watershed. World Agroforestry Centre and College of Forestry and Natural Resources, Los Baños, University of the Philippines (95).

Lauer D. T., S. A. Morain, & V. V. Salomonson (1997). The Landsat Program: Its Origins, Evolution, and Impacts. *Photogrammetric Engineering and Remote Sensing,* 63, 831–838.

Leippert, F., Darmaun, M., Bernoux, M. & Mpheshea, M. (2020). *The potential of agroecology to build climate-resilient livelihoods and food systems.* Rome. FAO and Biovision. https://doi.org/10.4060/cb0438en

Li G., Lu D., Moran E. & Hetrick S. (2011). Land - cover classification in a moist tropical region of Brazil with Landsat TM imagery. *International Journal of Remote Sensing*, 32, 8207 - 8230.

Li J., Wang M. H. & Ho Y. S. (2011). Trends in research on global climate change: A Science Citation Index Expanded-based analysis. *Glob. Planet. Change*, 77, 13–20.

Li R. (1998). Potential of High-Resolution Satellite Imagery for National Mapping Products. *Photogrammetric Engineering and Remote Sensing*, 64, 1165–1169.

Li Z. & Kafatos M. (2000). Inter-annual variability of vegetation in the United States and its relation to El Nino/Southern Oscillation. *Remote Sensing of Environment,* 71(3), 239-247.

Lillesand T. M., R. W. Kiefer, & J. W. Chipman (2008). *Remote Sensing and Image Interpretation.* New York: Wiley, (756).

Lillesand, M. T. & Kiefer, W. R. (2004). *Remote Sensing and Image Interpretation*, 4th Edn. New York, John Wiley and Sons Inc.

Lorenzen, B. & Jensen, A. (1988). Reflectance of blue, green, red and near infrared radiation from wetland vegetation used in a model discriminating live and dead above ground biomass. *New Phytot.,* 108, 345 - 355.

Lu D., Mausel P., Brondizio E. & Moran E. (2004). Change detection techniques. *International Journal of Remote Sensing*, 25, 2365 - 2407.

Lynn P. (2009). *Methodology of Longitudinal Surveys*: John Wiley and Sons, Ltd.

Mabwoga S. O. (2013). *Ecological Characterisation of Harike Wetland, a Ramsar Site, using Remote Sensing.* A PhD thesis, Department of Botanical & Environmental Sciences Guru Nanak Dev University. Amritsar - 143 005, India.

Madden M. (2009). Manual of Geographic Information Systems. Bethesda, MD: *American Society for Photogrammetry and Remote Sensing*, (1352).

Mandleni B. & Anim F. (2011). Perceptions of cattle and sheep farmers on climate change and adaptation in the Eastern Cape province of South A. J. *Hum. Ecol.*, 34, 107-112.

Markham B. L. (2004). Landsat Sensor Performance: History and Current Status. *IEEE Transactions on Geoscience and Remote Sensing*, 42, 2691–2694.

Mas, J. F., (1999). Monitoring Landcover Changes: A Comparison of Change Detection Techniques. *International Journal of Remote Sensing*, 20, 139 - 152.

Mayer, A. L. & Lopez, R. D. (2012). Use of Remote Sensing to Support Forest and Wetlands Policies in the USA. *Remote Sensing*, 3, 1211 - 1233.

Melesse, A. M., Weng, Q., Thenkabail, P., & Senas, G. (2007). Remote sensing sensors and application in environmental resources mapping and modeling. *Sensors*, 7, 3209-3241.

MEMR (1994). *Kenya Forestry Master Plan: Development Programmes*. Ministry of Environment and Natural Resources: Nairobi, Kenya.

MEMR (2009). *Narok District Environment Action Plan 2009 – 2013*. National Environmental Management Authority (NEMA).

Mendelson R. & Williams L., (2004). “Comparing Forecasts of the Global Impacts of Climate Change”. *Mitigation and Adaptation Strategies for Global Change*, 9, 315-333.

Mertes, L. A. K., (2002). Remote Sensing of Riverine Landscapes. *Freshwater Biology*, 47, 799 - 816.

Ministry of Forestry and Wildlife (2009). *Kenya Forest Service Strategic plan 2009 – 2013.*

Ministry of Forestry and Wildlife (2010). *Maasai Mau Strategic Management Plan 2010 – 2020*. A report produced by KFS, KWS, WARMA, KFWG and Narok C. Council.

Mngumi, J.W. (2016). *Perceptions of climate change, environmental variability and agricultural adaptation strategies by small-scale farmers in Africa: The case of Mwanga District in Northern Tanzania.* D.Phil. thesis, University of Glasgow, School of Geographical and Earth Sciences, Glasgow, UK.

Mundia N. C. & Murayama Y. (2009). *Analysis of Land Use/Cover Changes and Animal Population Dynamics in a Wildlife Sanctuary in East Africa.* Division of Spatial Information Science, Graduate School of Life and Environmental Sciences, University of Tsukuba, 305-8572, Japan.

Munyati, C. (2004). Use of Principal Component Analysis (PCA) of Remote Sensing Images in Wetland Change Detection on the Kafue Flats, Zambia. *Geocarto International*, 19, 11 - 22.

Muoghalu I. J. (2014). *Vulnerability of biophysical and socioeconomic systems in moist tropical forests in west and central Africa to climate change*. African Forest Forum. Working Paper Series, 2 (13), 45.

Murck, B., B. Skinner, & S. Porter (1999). *Environmental Geology*. New York: John Wiley & Sons, Inc.

Nabutola W (2010). *The Mau Forest in the Rift Valley: Kenya's Largest Water Tower:* a Perfect Model for the Challenges and Opportunities of a Sustainable Development Project? FIG Congress 2010: Facing the Challenges – Building the Capacity; Sydney, Australia.

NASA (2007). Landsat 7 Science Data Users Handbook. Landsat Project Science Office at NASA's Goddard Space Flight Centre in Greenbelt, Maryland, in press *Remote Sensing of the Environment*.

Nasr A. H., El Leithy B. M., & Badr H. S. (2012). Estimation of radiometric calibration coefficients of egyptsat-1 sensor. National Authority for Remote Sensing and Space Sciences. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XXXIX-B1, XXII ISPRS Congress, Melbourne, Australia.

NEMA (2013). *Effects of climate change in Kenya*. A publication of the National Environment Management Authority. Kenya.

NMK & KIFCON (1993a). *West Mau, South West Mau, Trans-Mara Forest reserves.* Biodiversity review. Report by Center for Biodiversity: NMK & KIFCON.

NMK & KIFCON (1993b). *West Mau, South West Mau, Trans-Mara Forest reserves Mammal Survey*. Report by Center for Biodiversity: NMK & KIFCON.

OEHHA (2013). *Indicators of Climate Change in California*. Office of Environmental Health Hazard Assessment, California Environmental Protection Agency.

Ongoma V. & Onyango O. A. (2014). A Review of the Future of Tourism in Coastal Kenya: The Challenges and Opportunities Posed by Climate Change. *J Earth Sci Clim Change*, 5, 210

Pearce D. (1996). *"The Social Costs of Climate Change: Greenhouse Damage and Benefits of Control" in Climate Change 1995:* Economic and Social Dimensions of Climate Change J. Bruce H. Lee E. Haites (Eds). Cambridge UK, 179-224, Cambridge Univ. Press.

Peng L., Luguang J. & Zhiming F. (2013). *Cross-Comparison of Vegetation Indices Derived from Landsat-7 Enhanced Thematic Mapper Plus (ETM+) and Landsat-8 Operational Land Imager (OLI) Sensors.* Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China.

Phiri M., G. Ibrahim & Saka R A. (2005). *The impact of changing environmental conditions on vulnerable communities of the Shire valley*. Southern Malawi. Lilongwe, Malawi.

Prince T. B., Samuel O. K., & Oppong D. (2015). Assessment of People's Knowledge and Perception on Climate Change: a Case Study of Asunafo North District, Ghana. *International Journal of Innovative Research in Science, Engineering and Technology,* 4 (1). *Principles and Practices* (eds). Boca Raton, FL: CRC Press, 183.

Reddy, M. A., (2001). A Textbook of Remote Sensing and Geographical Information Systems. BSP Publications. *Hyderabad, A.P.*

Richard Y. M. K., Claude G. M., Agnes G.M, Elikana K. & Pius Z.Y (2016). Climate change and variability impacts on agricultural production and livelihood systems in Western Tanzania. *Climate and development Journa.* Available at http://dx.doi.org/10.1080/17565529.2016.1146119

Rocchini, D. (2010). Ecological Status and Change by Remote Sensing. *Remote Sensing,* 2, 2424 - 2425.

Rogan J. & Miller J. (2006). *Integrating GIS and Remotely Sensed Data for Mapping Forest Disturbance and Change,* 133.

RSPN (2012). *Assessment of Climate Change Vulnerabilities in Kangpara Gewog, Trashigang*. Royal Society for Protection of Nature. Gross National Happiness Commission, Thimphu.

Russell B. H. (2006). *Research methods in anthropology*: qualitative and quantitative approaches, 4th ed.

Ryerson B. & S. Aronoff (2010). Why "Where" Matters: Understanding and Profiting from GPS, GIS and Remote Sensing. Manotick, ON: *Kim Geomatics,* 378.

Sanchez - Azofeifa, G. A., Castro, K. L., Rivard, B. & Kalascka, M. R. (2003). Remote Sensing Research Priorities in Tropical Dry Forest Environments. *Bio-tropica,* 35, 134 - 142.

Sarah A. O., Christian R. V., Josef E. & Michael H. (2012). Local Perceptions and Responses to Climate Change and Variability: The Case of Laikipia District, Kenya. *Sustainability,* 4, 3302-3325.

Satyanarayana, B., Mohamad, K. A., Idris, I. F., Husain, M. & Dahdouh - Guebas, F. (2011). Assessment of mangrove vegetation based on remote sensing and ground - truth measurements at Tumpat, Kelantan Delta, East Coast of Peninsular Malaysia. *International Journal of Remote Sensing,* 32, 1635 - 1650.

Schönthaler K., Stefan A. W., Daria N., Sonja P., Jenny T., Helmut K. & Stephanie R. (2011). *Entwicklung eines Indikatoren systems für die Deutsche Anpassungsstrategie an den Klimawandel* (DAS): English Summary.

SEI (2009). *The Economics of Climate Change in Kenya.* Stockholm. Environment Institute. Oxford.

Sheffield, J. & Wood, E. R. (2008). Projected changes in drought occurrence under future global warming from multimodel, multi-scenario, IPCC AR4 simulations. *Climate dynamics,* 31(1), 79-105.

Shoshany, M. (2000). Satellite remote sensing of natural Mediterranean vegetation: a review within an ecological context. *Progress in Physical Geography,* 24, 153 - 178.

Sinclair, F., Wezel, A., Mbow, C., Chomba, S., Robiglio, V., & Harrison, R. (2019). *The Contribution of Agroecological Approaches to Realizing Climate-Resilient Agriculture* [online]. Rotterdam and Washington, DC. https://cdn.gca.org/assets/2019-09/

Singh, A., (1989). Digital Change Detection Techniques using Remotely Sensed Data. *International Journal of Remote Sensing,* 10, 989 - 1003.

Song C., Woodcock C. E., Seto K. C., Lenney M. P. & Macomber S. A. (2001). Classification and change detection using Landsat TM data: When and how to correct atmospheric effects? *Remote Sensing of Environment*, 75, 230-244.

Stein, A. F., Van der Meer, & B. Gorte (2002). *Spatial Statistics for remote sensing.* (eds).

Stephen M. & Rachel W. (2013). *Towards a Coherent and Cost Effective Policy Response to Climate Change in Kenya: Country Report*. Heinrich Böll Stiftung. Camco Advisory Services (K) Limited.

Street J., Culley M., Carton A. & Ogley-Oliver E. (2009). *Demographic factors and perceived barriers to climate change*. New Jersey Montclair State University.

Surazakov A. & V. Aizen (2010). Positional Accuracy Evaluation of Declassified Hexagon KH-9 Mapping Camera Imagery. *Photogrammetric Engineering and Remote Sensing*, 76, 603–608.

Takao G., Priyadi H. & Ikbal N. W. (2010). *The operational role of remote sensing in forest and landscape management:* Focus group discussion proceedings. CIFOR, Bogor, Indonesia.

Tao F., Yokozawa M., Hayashi Y. & Lin E. (2003). Future climate change: The agricultural water cycle and agricultural production in China. *Agriculture Ecosystems and Environment*, 95(1), 203-215.

Tazeze A., Haji J. & Ketema M. (2012). Climate change adaptation strategies of smallholder farmers: The case of Babilie District, East Harerghe zone of Oromia regional state of Ethiopia. *J. Econ. Sustainable Dev.*, 3, 1-12.

Tiner, R. W. (2004). Remotely sensed indicators for monitoring the general condition of natural habitat in watersheds: an application for Delaware’s Nanticoke River watershed. *Ecological Indicators*, 4, 227 - 243.

Tol R. (2002). “Estimates of the damage costs of climate change. Part 1: benchmark estimates”. *Environmental and Resource Economics*, 21, 47-73.

Tuxen, K., Schile, L., Stralberg, D., Siegel, S., Parker, T., Kelly, M., Callaway, J. & Vasey, M. (2011). Mapping changes in tidal wetland vegetation composition and pattern across a salinity gradient using high spatial resolution imagery. *Wetlands Ecology and Management*, 19, 141 - 157.

UN (2005). *Household Sample Surveys in Developing and Transition Countries.* Department of Economic and Social Affairs Statistics Division. Studies in Methods. United Nations Publication. New York. Series F No. 96

UNEP (2009). *Vulnerability and Impact Assessments for Adaptation to Climate Change* (VIA Module). IEA Training Manual, 2. DEW/1251/NA.

UNEP/GoK (2005). *Climate change vulnerability in Kenya*: Response and strategies.

UNEP/GoK (2008). *Kenya Atlas of our changing environment*.

UNESCO (2014). *Climate change education for sustainable development*. UNESCO.

UNFCCC (2013). *Gender and climate change*. United Nations Framework Convention on Climate Change.

UNFCCC Secretariat (2010). *Synthesis report on efforts undertaken to monitor and evaluate the implementation of adaptation projects, policies and programmes* *and the costs and effectiveness of completed projects, policies and programmes, and views on lessons learned, good practices, gaps and needs.* UNFCCC, Bonn. Accessed online on July 20, 2015 at http://www.gsdrc.org/go/display&type=Document&id=3947

USEPA (2016). *Climate change indicators in the United States.* 4th edn. EPA 430-R-16-004. www.epa.gov/climate-indicators.

USGS (2015). *Landsat 8 (L8) data users' handbook*. Department of the Interior U.S. Geological Survey, Landsat Project Science Office at the Earth Resources Observation and Science (EROS) Centre Sioux Falls, South Dakota and the NASA Landsat Project Science Office at NASA's Goddard Space Flight Centre in Greenbelt, Maryland. LSDS-1574 Version 1.0.

USGS (2016). *Landsat 8 (L8) data users' handbook*. Department of the Interior U.S. Geological Survey, Landsat Project Science Office at the Earth Resources Observation and Science (EROS) Centre Sioux Falls, South Dakota and the NASA Landsat Project Science Office at NASA's Goddard Space Flight Centre in Greenbelt, Maryland. LSDS-1574 Version 2.0.

WCED (1987). *Our common future:* From one Earth to one World. An overview by the World Commission on Environment and Development.

Williams D. L., S. N. Goward & T. L. Arvidson (2006). Landsat: Yesterday, Today, and Tomorrow. *Photogrammetric Engineering and Remote Sensing*, 72, 1171–1178.

Wondimagegn T. & Lemma S. (2016). "Climate change perception and choice of adaptation strategies: Empirical evidence from smallholder farmers in east Ethiopia". *International Journal of Climate Change Strategies and Management*, 8 (2), 253 – 270. http://dx.doi.org/10.1108/IJCCSM-01-2014-0017

Wulder M. A., J. C. White, S. N. Goward, J. G. Masek, J. R. Irons, M. Herold, W. B. Cohen, T. R. Loveland & C. E. Woodcock (2008). Landsat Continuity: Issues and Opportunities for Land Cover Monitoring. *Remote Sensing of Environment*, 112, 955–969.

Wulder M. & S. Franklin (2003). *Remote sensing of forest environments: Concepts and case studies.* Dordrecht, Boston, London: Kluwer Academic Publishers.

Yaro J. A. (2013). The perception of and adaptation to climate change variability/change in Ghana by smallscale and commercial farmers. *Regional Environmental Change*, 13(6), 2059-1272.

Yates H. W. (1977). Measurement of the Earth radiation balance as an instrument design problem. *Appl. Opt.* 16, 297–299.

Zhang, Y., Lu, D., Yang, B., Sun, C. & Sun, M. (2011). Coastal wetland vegetation classification with a Landsat Thematic Mapper image. *International Journal of Remote Sensing*, 32, 545 - 561.

APPENDICES

Annexure Table 1.1: Narok County Climate Change Indicators (NCCCI) suite model used in the study

Climate Change Indicators	**Climate Impacts Indicators**	
Changes in the Climate System	***Climate Impacts on Biophysical (Environmental) Systems***	***Climate Impacts on Socio-economic Systems and Health***
Temperature • Mean annual temperature • Mean monthly temperature • Mean min. and max. temperature • Extreme temperature events • Length of warm and cold spells • Variability of temperatures *Precipitation* • Mean annual precipitation • Mean monthly precipitation • Extreme precipitation events (flash floods, landslides, mudslides, hailstorms) • Prolonged drought (frequency and severity) • Seasonality of precipitation • Changes in precipitation gradient • Consistency of precipitation	*Terrestrial ecosystems and Biodiversity* • Changes in ecosystems composition and biodiversity • Changes in forest coverage (vigour) • Changes in forest density • Shifts in vegetation/tree lines • Forest growth stages (Disturbances) • Forest fires (frequency and severity) • Forest encroachments (settlements and croplands) • Changes in species behavioural patterns • Reduction or disappearance of certain species (plants and animals) • Plants development • Soil erosion and/or landslides *Freshwater quantity and quality* • Water sources status • Rivers seasonality • Water availability and accessibility • Water shortage (scarcity)	*Agriculture* • Changes in growing season (Length of growing seasons) • Water-limited productivity (Drought tolerant species) • Adoption of irrigation agriculture (water requirement for irrigation) • Plants phenology • Failed rain fed agriculture • Changes in crop varieties • Changes in quantity and quality of farm produce (Failure and/or poor yields) • Changes in prices of farm produce • Crop suitability • Pests and diseases *Human health and Livelihoods* • Floods and health • Vector-borne diseases and pathogens • Extreme temperatures and health (heat related mortality) • Air pollution and health • Accessibility to healthcare • Food insecurity

		• Changes in livelihood sources • Reliance and over-dependence on unsustainable resource use *Community and society* • Changes in livelihood sources • Traditional ways of life *Transport services and infrastructure* • Transport services and infrastructure status • Damage cost (climate related damages) • Direct loss from weather disasters *Tourism* • Tourist numbers • Sales of seasonal products *Energy consumption* • Heating and cooling requirements • Use of unsustainable sources • Overreliance on non-renewable energy sources • Adoption of renewable and clean energy sources – (Clean Mechanism Development – CMD) • Energy sources sustainability

Appendix 1: Landsat Missions, Sensors onboard and Images Characteristics.

Satellite	Sensor	Bandwidths	Resolution
LANDSATs 1-2	RBV	(1) 0.48 to 0.57	80
		(2) 0.58 to 0.68	80
		(3) 0.70 to 0.83	80
	MSS	(4) 0.5 to 0.6	79
		(5) 0.6 to 0.7	79
		(6) 0.7 to 0.8	79
		(7) 0.8 to 1.1	79
LANDSAT 3	RBV	(1) 0.505 to 0.75	40
	MSS	(4) 0.5 to 0.6	79
		(5) 0.6 to 0.7	79
		(6) 0.7 to 0.8	79
		(7) 0.8 to 1.1	79
		(8) 10.4 to 12.6	240

Satellite	Sensor	Bandwidths	Resolution
LANDSATs 4-5	MSS	(4) 0.5 to 0.6	82
		(5) 0.6 to 0.7	82
		(6) 0.7 to 0.8	82
		(7) 0.8 to 1.1	82
	TM	(1) 0.45 to 0.52	30
		(2) 0.52 to 0.60	30
		(3) 0.63 to 0.69	30
		(4) 0.76 to 0.90	30
		(5) 1.55 to 1.75	30
		(6) 10.4 to 12.5	120
		(7) 2.08 to 2.35	30
LANDSAT 7	ETM^+	(1) 0.45 to 0.52	30
		(2) 0.52 to 0.60	30
		(3) 0.63 to 0.69	30
		(4) 0.76 to 0.90	30
		(5) 1.55 to 1.75	30
		(6) 10.4 to 12.5	60
		(7) 2.08 to 2.35	30
		PAN 0.50 to 0.90	15

Satellite	Sensor	Wavelength (μm)	Resolution (m)
Landsat 8	OLI/	(1) 0.43 – 0.45	30
	TIRS	(2) 0.45 – 0.52	30
		(3) 0.53 – 0.60	30
		(4) 0.63 – 0.68	30
		(5) 0.85 – 0.89	30
		(6) 1.56 – 1.66	60
		(7) 2.10 – 2.30	30
		(8) 0.50 – 0.68	15
		(9) 1.36 – 1.39	30
		(10) 10.6 – 11.2	100
		(11) 11.5 – 12.5	100

Appendix 2.1: Scaling factor for conversion of TM DN values to at-sensor Radiance and Reflectance

TM Sensor (Q_{calmin} = 1, Q_{calmax} = 255)

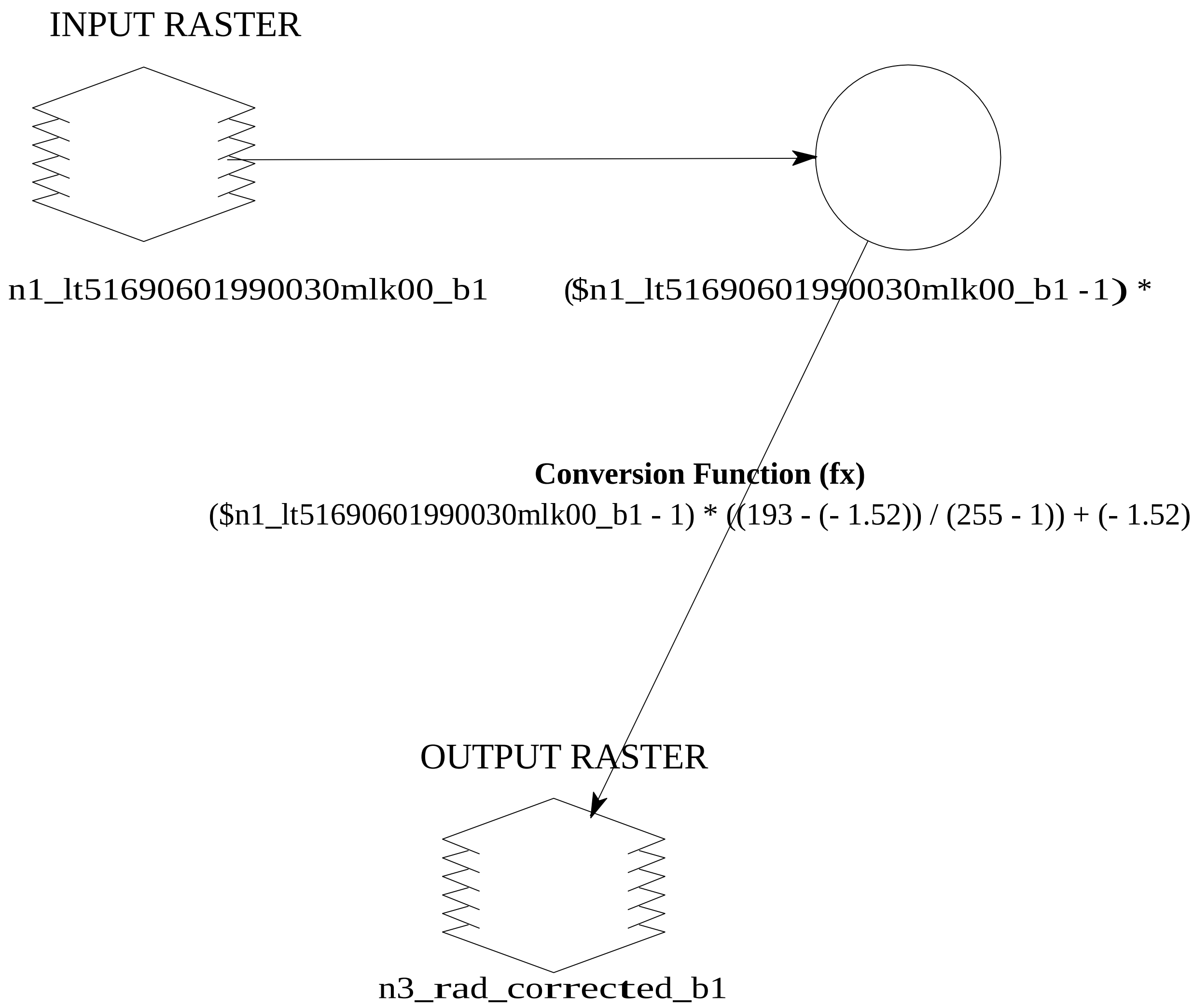
Bands	**Spectral Range**	**Mid Bandwidth**	**$LMIN_\lambda$**	**$LMAX_\lambda$**	**$ESUN_\lambda$**
Units	**(µm)**		**W/(m^2 * sr * µm)**		**W/(m^2*m)**
L5 TM (LPGS)					
1	0.452 – 0.518	0.485	- 1.52	193	1983
2	0.528 – 0.609	0.569	-2.84	365	1796
3	0.626 – 0.693	0.660	-1.17	264	1536
4	0.776 – 0.904	0.840	-1.51	221	1031
5	1.567 – 1.784	1.676	-0.37	30.2	220
6	10.45 – 12.42	11.435	1.2378	15.303	N/A
7	2.097 – 2.349	2.223	-0.15	16.5	83.44

Appendix 2.2: Scaling factor for conversion of ETM+ DN values to at-sensor Radiance and Reflectance

ETM+ Sensor (Q_{calmin} = 1, Q_{calmax} = 255)

Bands	**Spectral Range**	**Mid Bandwidth**	**$LMIN_\lambda$**	**$LMAX_\lambda$**	**$ESUN_\lambda$**
Units	**(µm)**		**$W/(m^2 * sr * \mu m)$**		**$W/(m^2 * m)$**
Landsat 7 ETM+ (LPGS)					
1	0.452 – 0.514	0.483	- 6.2	191.6	1997
2	0.519 – 0.601	0.560	-6.4	196.5	1812
3	0.631 – 0.692	0.662	-5.0	152.9	1533
4	0.772 – 0.898	0.835	-5.1	241.1	1039
5	1.547 – 1.748	1.648	-1.0	31.06	230.80
6_1	10.31 – 12.36	11.335	0.0	17.04	N/A
6_2	10.31 – 12.36	11.335	3.2	12.65	N/A
7	2.065 – 2.346	2.206	-0.35	10.80	84.90
PAN	0.515 – 0.896	0.706	-4.7	243.10	1362

Appendix 3: Graphical Model for Converting DN to Radiance - TM and ETM+ (e.g for 1990 image, band 1)



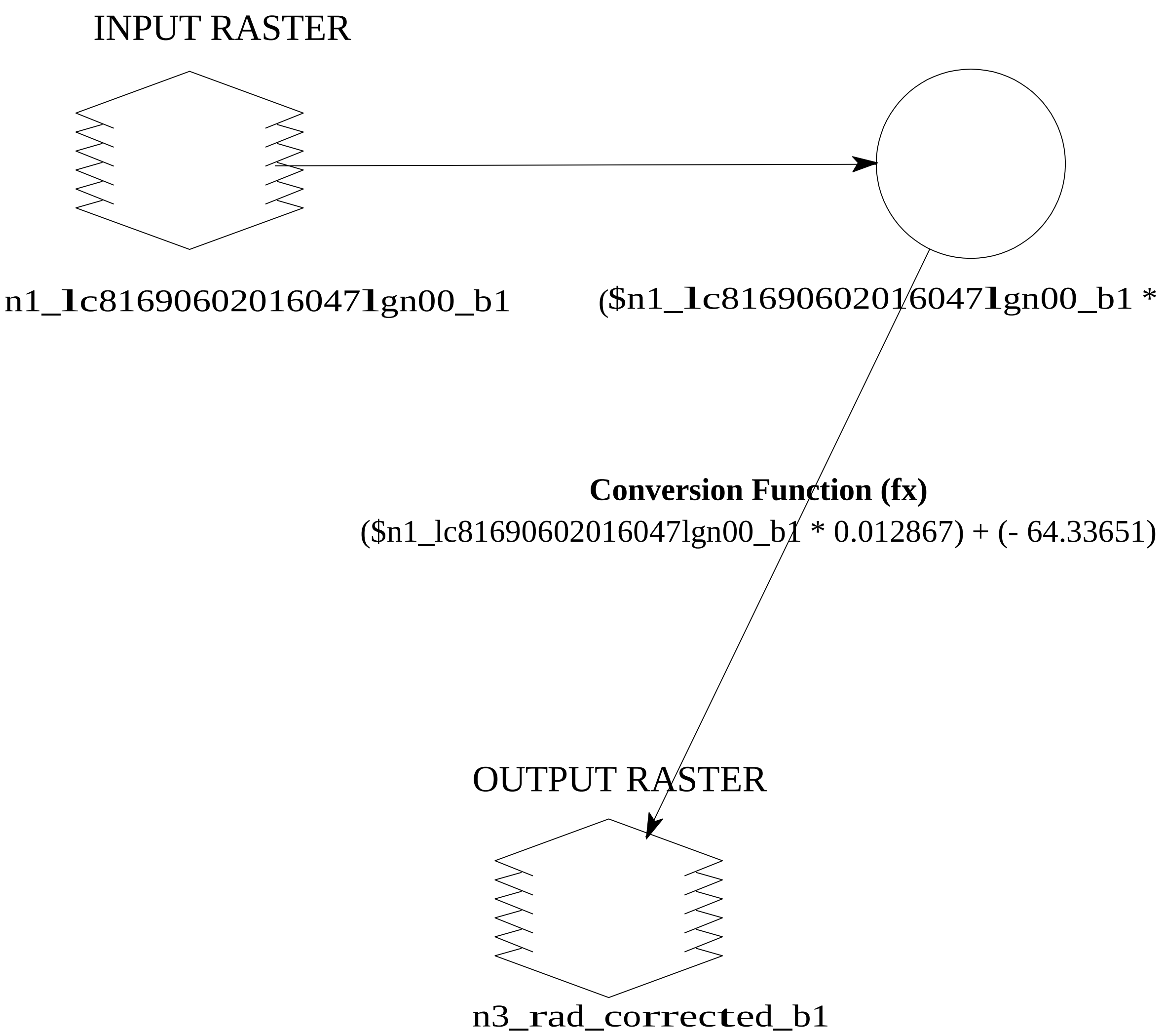
Appendix 4: Scaling factor for conversion of OLI/TIRS DN values to at-sensor Radiance and Reflectance

OLI_TIRS Sensors (Q_{calmin} = 1, Q_{calmax} = 65535)

Bands	Spectral Range	Mid Bandwidth	M_L	A_L	Mρ	Aρ
Units	**(µm)**		**W/(m² * sr * µm)/DN**		**DN⁻¹**	
LC8 OLI_TIRS (LPGS)						
1	0.433 – 0.453	0.443	0.012867	- 64.33651		
2	0.450 – 0.515	0.483	0.013176	- 65.88137		
3	0.525 – 0.600	0.563	0.012142	- 60.70912		
4	0.630 – 0.680	0.655	0.010239	- 51.19335		
5	0.845 – 0.885	0.865	0.0062656	- 31.32778	0.00002	- 0.10000
6	1.560 – 1.660	1.610	0.0015582	- 7.79093		
7	2.100 – 2.300	2.200	0.00052519	- 2.62596		
8	0.500 – 0.680	0.590	0.011587	- 57.93678		
9	1.360 – 1.390	1.375	0.0024487	- 12.24361		
10	10.6 – 11.2	10.90	0.00000	0.10000	0.0000	0.0000
11	11.5 – 12.5	12.00	0.00000	0.10000	0.0000	0.0000

M_L = Radiance Multiplicative scaling factor for the band (RADIANCE_MULT_BAND_n)
A_L = Radiance Additive scaling factor for the band (RADIANCE_ADD_BAND_n)
Mρ = Reflectance Multiplicative scaling factor (REFLECTANCE MULT BAND_n)
Aρ = Reflectance Additive scaling factor (REFLECTANCE ADD BAND_n)

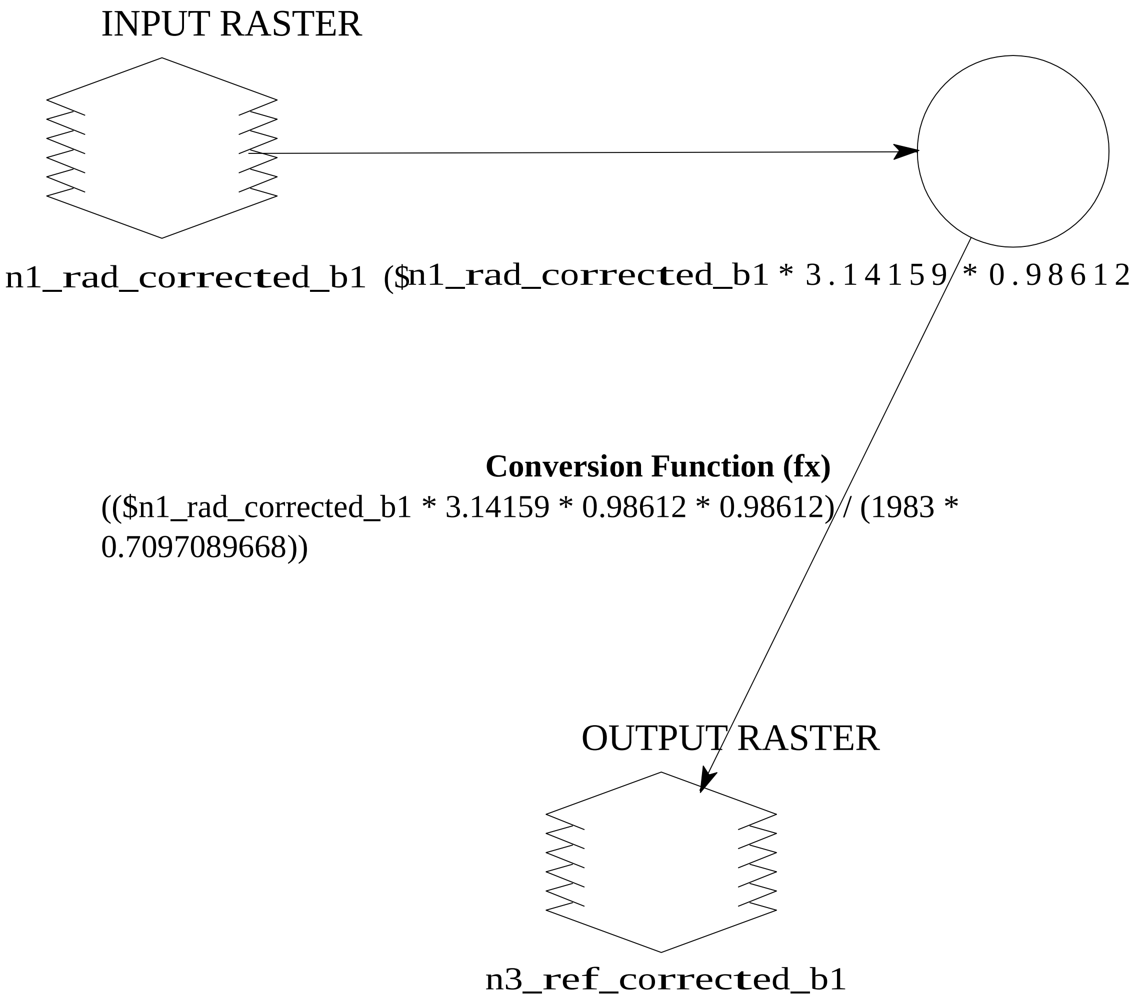
Appendix 5: Graphical Model for Converting DN to Radiance - OLI/TIRS (e.g for 2016 image, band 1)



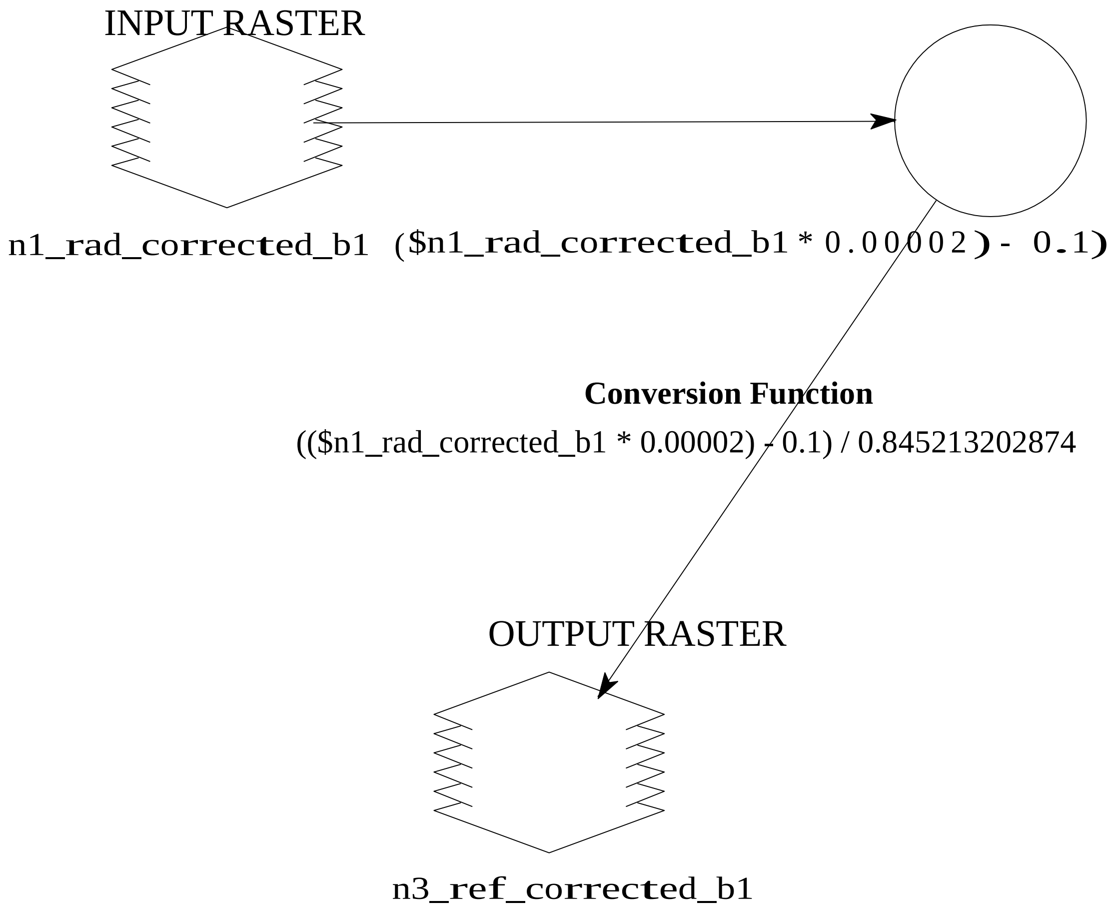
Appendix 6: Earth – Sun distance in astronomical units and solar elevation angle for the Landsat imageries used in the study

Spacecraft	Sensor	Acquisition Date	Day of the Year (Julian)	Sun Azimuth		Sun Elevation		Earth – Sun Distance (Astronomical units)
				Scene 1 (Path 169; Row 060)	Scene 2 (Path 169; Row 061)	Scene 1 (Path 169; Row 060)	Scene 2 (Path 169; Row 061)	
Landsat 5	TM	06 – Feb – 1990	037	112.633712	111.193077	45.211241	45.562071	0.98612
	TM	30 – Jan – 2010	030	120.632649	118.778284	53.457595	53.995808	0.98509
Landsat 7	ETM+	12 – Feb – 2000	043	114.809023	112.778326	55.123900	55.518252	0.98717
Landsat 8	OLI_TIRS	16 – Feb – 2016	047	113.615235	111.394810	57.332486	57.694786	0.98782

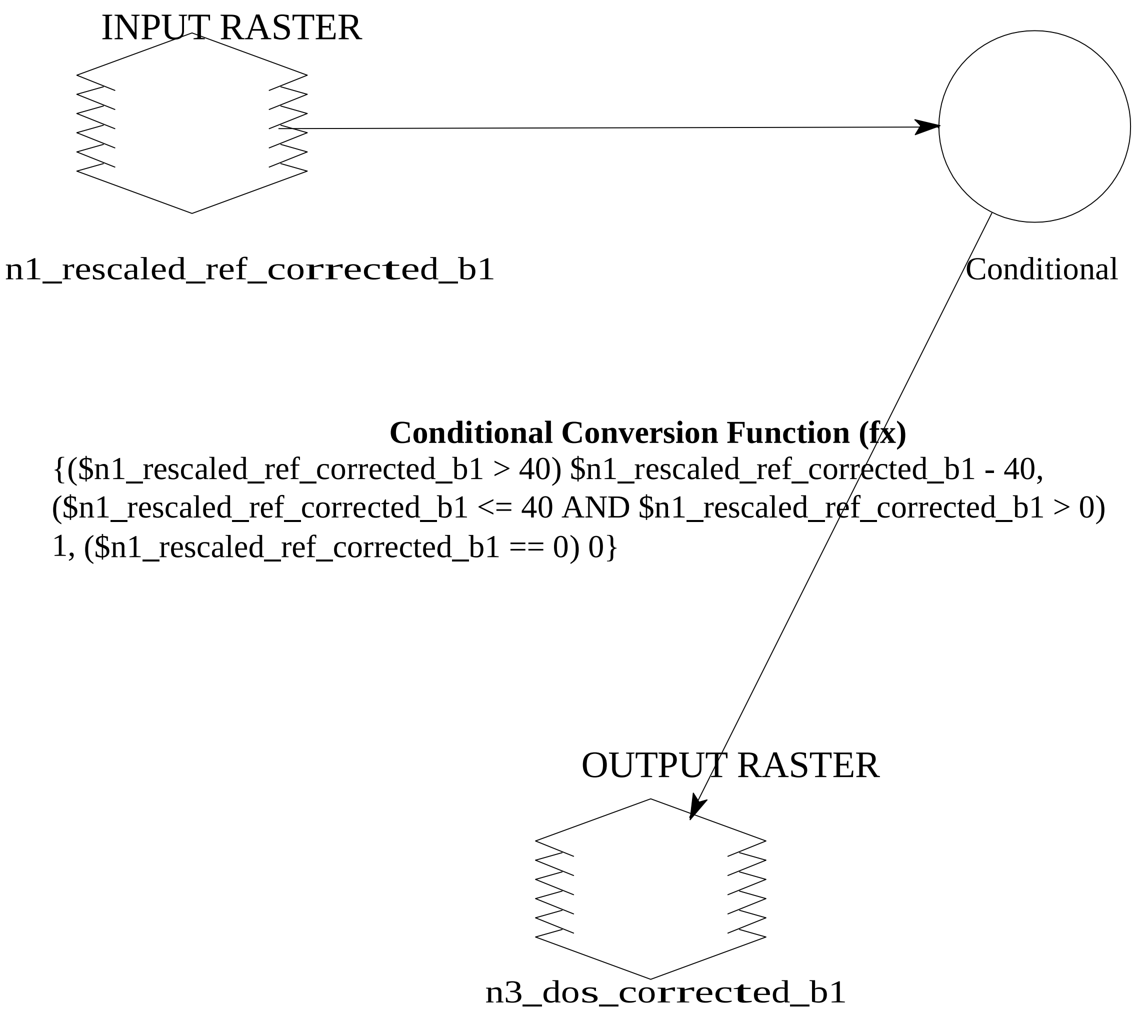
Appendix 7: Graphical Model for Converting Radiance to Reflectance - TM and ETM+ (e.g for 1990 image, band 1)



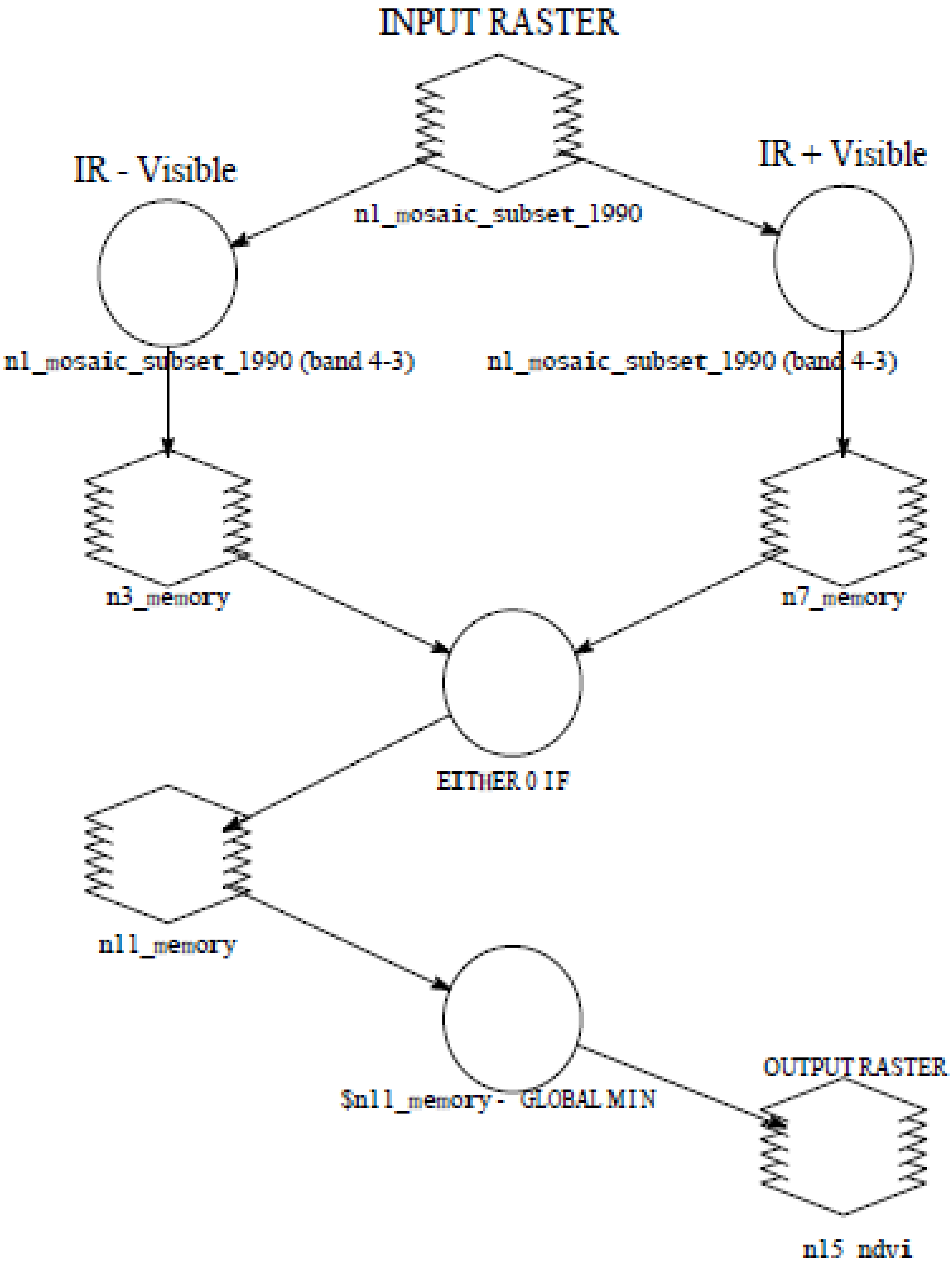
Appendix 8: Graphical Model for Converting Radiance to Reflectance - OLI/TIRS



Appendix 9: Graphical model for Atmospheric Correction - Dark Object Subtraction (DOS)



Appendix 10: Graphical model for Normalized Difference Vegetation Index (NDVI)



Appendix 11: Number of respondents (Households) sampled in every Sub-location

S/No.	Division	Location	Sub-location	Total Population	No. of HHs	HHs S. Size	No. of R. Assist.	Area (Sq. Km)	Density
1	Central	Lower Melili	Naisoya	4,840	927	16	1	147.0	33
2		Nkareta	Nkareta	6,856	1,194	21	1	216.7	32
3	Olokurto	Olokurto	Olokurto	6,305	1,171	21	1	292.9	22
4		Naituyupaki	Naituyupaki	5,310	959	16	1	133.1	40
5		Enabelibel	Enengetia	7,604	1,508	26	1	75.1	101
6			Kisiriri	4,764	1,018	16	1	48.0	99
7		Ol Pusimoru	Ol Pusimoru	2,557	519	11	1	25.2	101
8			Ol Mariko	2,703	523	11	1	26.4	102
9			Kamurar	3,637	668	11	1	107.4	34
10	Ololulunga	Melelo	Oloshapan	24,845	4,529	70	1	111.2	223
11		Endonyo Ngiro	Ereteti	6,526	1,481	26	1	74.1	88
12			Nkoben	2,219	430	6	1	37.0	60
13	Mulot	Sogoo	Sogoo	15,505	2,781	45	1	34.4	450
14			Nkaroni	13,238	2,478	41	1	49.7	266
15		Sagamian	Sagamian	10,168	1,891	31	1	21.8	466
16			Mogoiwet	5,141	916	16	1	14.1	364
17			Tendewet	5,748	1,079	21	1	379.5	15
TOTALS				**127,966**	**24,072**	**405**	**17**	**1,793.6**	

Source: Numbers obtained from (KNBS, 2009)

Appendix 12: Research Questionnaire

SECTION 1: GENERAL ENVIRONMENT AND CLIMATE CONCERNS

1. Please look at the following list of environmental issues, and **tick** the **three** issues that **concern** you the most. *Please only tick* ***three*** *issues from the list:*

   - Air pollution ☐
   - Water Pollution ☐
   - Flooding ☐
   - Litter ☐
   - Poor waste management ☐
   - Traffic/ congestion ☐
   - Greenhouse gas emission ☐
   - Climate change ☐
   - The ozone layer depletion ☐
   - Deforestation and environmental degradation ☐
   - Biodiversity loss/extinction of species ☐
   - Electronic waste ☐
   - Overpopulation (of the earth by humans) ☐
   - Drought ☐

2. In your view, has any of the above ever affected your health or that of your family or friends?

   ☐ Yes
   ☐ No
   ☐ Don't know

3. **Apart from effects on people's health**, are you aware of any other effects of the above mentioned in (Q1)?

   ☐ Yes (Go to Q4)
   ☐ No (Go to Q5)
   ☐ Don't know (Go to Q5)

4. If yes, what other effects are you aware of? ____________________________________

5. In your opinion, do you think that the weather and/or seasonal patterns have changed since approximately 25 years ago?

A lot	A little	Not changed	Not sure	Don't Know
☐	☐	☐	☐	☐

6. If yes, why do you think this might be? ________________________________

____

7. How do you get information about weather or climate change and variability? (*Tick as many as you feel apply)*

Television	☐	Meteorological department	☐
Radio	☐	Public libraries	☐
Friends/ family	☐	Newspaper	☐
Internet	☐	Energy suppliers	☐
Barazas	☐	Group (Chamas) meetings/Social media	☐
Demos (how to use/do)	☐	Posters and Billboards	☐
Bulk SMS	☐	Opinion leaders (Local leaders/talks)	☐
Drama, Songs, Kits	☐	Astrological indicators	☐
Specialist publications/academic journals	☐	Local county	☐
Environmental groups (e.g. WWF)	☐	Vegetation condition (Phenology)	☐
School/ college/university	☐	Other (Please specify) ______________	☐
Traditional Knowledge (e.g. animal's behavoural changes etc.)	☐		

8. By **ticking one box on each row** please indicate **how much you would <u>trust</u> information about weather or climate change and variability** if you heard it from...

	A lot	A little	Not very much	Not at all	Can't choose
A family member or a friend	☐	☐	☐	☐	☐
A scientist	☐	☐	☐	☐	☐
The government	☐	☐	☐	☐	☐
An energy supplier	☐	☐	☐	☐	☐
Environmental organizations (e.g. WWF)	☐	☐	☐	☐	☐
The media (e.g. Television, radio, newspapers)	☐	☐	☐	☐	☐
Traditional Knowledge	☐	☐	☐	☐	☐
Opinion leaders (Local leaders/talks)	☐	☐	☐	☐	☐
Barazas	☐	☐	☐	☐	☐
Group (Chamas)/Social media	☐	☐	☐	☐	☐

9. **<u>Currently</u>,** why do you choose to have **confidence in/trust** these specific way(s) of predicting **climate or weather changes** above *(Tick all that apply)***?**

I trust it based on my own experience ☐
It is what other people use to make decisions ☐
It provides specific information that I need to make decisions ☐
I participated in the production of the information ☐
I feel like the information was open and fair ☐
Don’t know ☐

10. Have you heard of “Climate Change and Variability”?
☐ Yes (Go to Q11)
☐ No (Go to Q12)
☐ Don't know

11. What do you know about it? ____
____
____

12. How important is the issue of climate change and variability to you personally?
☐ Very important (Go to Q13)
☐ Quite important (Go to Q13)
☐ Not very important
☐ Not important (Go to Q14)

13. Why is it important to you? ---

----

14. Do you think climate change and variability is something that is affecting or is going to affect you, personally?
☐ Yes (Go to Q15)
☐ No (Go to Q16)
☐ Don’t know

15. If yes, in what way(s) is it affecting you, or is it going to affect you? ----------------------------
----
----

16. What do you think are the driving forces/pressure **causing** climate change and variability? Rank the major five (5) driving forces and pressure behind climate change and variability *(1 = major driving force/pressure ……………. 5 = minor driving force/pressure)*

		Rank
Natural fluctuation (Radiative forcing, Volcanic activities, Ocean circulation)	☐	
Human activities (Transportation, Industrialization, Urbanization etc)	☐	

Population growth	☐	
Use of fossil fuel (Petroleum products e.g. diesel, paraffin, coal, petrol etc)	☐	
Greenhouse Gases (Water vapour, CO_2, Methane, NOx, SOx, CFC etc)	☐	
Air Pollution (Industrial, Motor vehicles etc)	☐	
Agricultural practices (Fertilizers, Herbicides, Pesticides, Insecticides etc)	☐	
Deforestation and forest degradation	☐	
Poor waste management	☐	
Production and Consumption patterns (wasteful and insensitive)	☐	
Unsustainable practices(e.g. charcoal burning, encroachment etc)	☐	
Livestock husbandry	☐	
Any other (Specify)……………..	☐	

17. Do you think anything can be done to tackle climate change and variability?
    - ☐ Yes (Go to Q18)
    - ☐ No (Go to Q19)
    - ☐ Don't know

18. If yes, what do you think can be done to tackle climate change and variability? -----------------
    ----
    ----

19. Who do you think should have the **main** responsibility for tackling climate change and variability? (***Please tick one box only)***
In the blank column on the right, please rank from (1 = most responsible……. 6 = least responsible)

☐	International organizations (e.g. the UN)	
☐	The national government	
☐	Local government	
☐	Business and industry	
☐	Environmental organizations/lobby groups (e.g. WWF)	
☐	Individuals	
☐	Other (*please write in*: _______________)	

20. Please indicate how much you agree or disagree with the following statements about **climate change and variability** by **ticking one box on each row**:

	Agree strongly	Agree	Neither agree nor disagree	Disagree	Disagree strongly
Climate change is just a natural fluctuation in earth's temperatures	☐	☐	☐	☐	☐
It is already too late to do anything about climate change	☐	☐	☐	☐	☐
Human activities have no significant impact on global temperatures	☐	☐	☐	☐	☐

Developing countries should take most of the blame for climate change	☐	☐	☐	☐	☐
The evidence for climate change is unreliable	☐	☐	☐	☐	☐
Leaving the lights on in my home adds to climate change	☐	☐	☐	☐	☐
Pollution from industry is the main cause of climate change	☐	☐	☐	☐	☐
It is too early to say whether climate change is really a problem	☐	☐	☐	☐	☐
Flooding is not increasing, there is just more reporting of it in the media these days	☐	☐	☐	☐	☐
Experts are agreed that climate change is a real problem	☐	☐	☐	☐	☐
Industry and business should be doing more to tackle climate change	☐	☐	☐	☐	☐
Nothing I do on a daily basis contributes to the problem of climate change	☐	☐	☐	☐	☐
The effects of climate change are likely to be catastrophic	☐	☐	☐	☐	☐
The government is not doing enough to tackle climate change	☐	☐	☐	☐	☐

21. What action(s) have you ever taken, or do you regularly take, out of concern for the climate change and variability? --
----

SECTION 5: PERSONAL INFORMATION

Finally, just so that I can compare the views of different people, please could you tell me about yourself:

22. What is your gender?

- Male ☐
- Female ☐
- Prefer not to say ☐

23. What is your current marital status?

- Single, unmarried ☐
- Married ☐
- Married (separated) ☐
- Married (multiple wives) ☐
- Divorced ☐
- Widowed ☐
- Don't know ☐

24. How long have you lived here *(in year)*?

< 5	☐	16 – 20	☐
6 – 10	☐	21 -30	☐
11 - 15	☐	> 30	☐

25. Please indicate your age bracket?

18 - 24	☐	65 – 74	☐
25 - 34	☐	75 – 84	☐
35 - 44	☐	85 or Over	☐
45 – 54	☐	Prefer not to say	☐
55 - 64	☐		

26. How many children (under age 18 or 25 and also unemployed) live in this household?
……………………………………………………………………………………………..

27. What is your highest education level/qualification?

- No formal qualifications ☐
- Primary ☐
- Informal schooling only ☐
- Some primary schooling only ☐
- Some secondary school ☐
- Secondary (O – level) ☐

Higher (A – level) ☐
Post-secondary school qualification ☐
Vocational ☐
Degree or Equivalent ☐
Postgraduate Qualification ☐

28. What is your highest education level/qualification in a **science – related subject**?

No formal qualifications ☐
Primary ☐
Secondary (O – level) ☐
Higher (A – level) ☐
Vocational ☐
Degree or Equivalent ☐
Postgraduate Qualification ☐
Others (specify) …………… ☐

29. Do you own (or regularly drive) a car/ van? If yes, approximately how many km per year?

Yes ☐ Km/yr ---------
No ☐

30. Do you have a job where you earn cash income? If yes, is it full-time or part- time? If no, are you presently looking for a job? *[Interviewer: press for clarification on matter of searching for work].*

No (not looking) ☐
No (looking) ☐
Yes, part time ☐
Yes, part time (looking for a second job) ☐
Yes, full time ☐
Refused to answer *[DNR]* ☐
Don’t know or cannot say *[DNR]* ☐

31. What is the status of your cash income employment? *[Interviewer, if no job above, fill N/A].*

Self-employed ☐
Employed by immediate family ☐
Employed by government (county or national) ☐

Employed by private company ☐

Not Applicable ☐

Refused to answer *[DNR]* ☐

Don't know or cannot say *[DNR]* ☐

32. Please indicate your approximate gross income per month (*before tax*)?

Up to Ksh 9,000	☐	Ksh 50,000 – 59,000	☐
Ksh 10,000 – 19,000	☐	Ksh 60,000 – 69,000	☐
Ksh 20,000 – 29,000	☐	Ksh 70,000 – 79,000	☐
Ksh 30,000 – 39,000	☐	Ksh 80,000 0r Over	☐
Ksh 40,000 – 49,000	☐	Prefer not to say	☐

33. Are you a member of any environmental organizations (e.g. Friends of the Earth, Nature Kenya, WWF, CFA etc)?

Yes ☐

No ☐

34. If you have anything to add about the issues raised in this questionnaire or any comments about the questionnaire itself, please write them here: