UNIVERSITY OF NAIROBI

DEPARTMENT OF PHYSICS

MONITORING LAND COVER CHANGES AND THE IMPACTS OF THE RECLAMATION INITIATIVE - CASE OF MAU FOREST COMPLEX

By

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I56/80233/2012

This thesis is submitted in partial fulfillment of the requirements for the award of the degree of Master of Science in Physics of the University of Nairobi.

April, 2015

Declaration

This thesis is my original work and has not been presented for examination in any other university.

Signature………….. ……..

Date………………………..

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The undersigned supervisors certify that they have read and hereby recommend for acceptance by the University of Nairobi a thesis entitled **Monitoring Land Cover Changes and The Impacts of The Reclamation Initiative - Case of Mau Forest Complex**, in fulfillment of the requirements for the degree of Master of Science (Physics).

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Dedication

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1996-2011

Abstract

The Mau Forest Complex is the largest closed canopy forest in Eastern Africa, covering about 400,000 hectares. It is of great value to Kenya and its neighbors as it supports hydroelectric-power generation, the tourism industry and agriculture in this region. Despite this, over 100,000 hectares of the forest has been destroyed over the past few decades largely due to human encroachment. Using satellite based measurements, this study sort to establish whether the current restoration and conservation policies are producing any noticeable improvement in the condition of the forest. There was also an attempt to determine how vegetation in the forest relates to rainfall and Land Surface Temperature (LST). By understanding how the forest is responding to current restoration and conservation initiative, and the influence of climatological variables, better restoration and conservation strategies can be developed. To achieve these objectives, the Moderate Resolution Imaging Spectroradiometer (MODIS) MOD13Q1 and MOD11C3 products were used to estimate vegetation density/vigor and LST variation respectively. Tropical Rainfall Measuring Mission (TRMM) 3B43 rainfall data was used to estimate the rainfall received by the forest over the period of interest.

The Normalized Difference Vegetation Index (NDVI) time series, extracted from MOD13Q1 data, were divided into two groups; one covering 2001-2007 and the other 2008-2013. Ordinary Least Square (OLS) slopes were then used to estimate the changes in the trend of the NDVI time series during the two periods. The result show that there was a general increase in NDVI values within the forest in 2008-2013, with over 26% of the Mau Forest Complex recording positive NDVI slopes during this period, up from only 7% in 2001-2007. The regression analysis results show that there is a weak correlation between NDVI and Rainfall R^2 values less than 0.5. It was also observed that vegetation in the Mau Forest Complex takes between one and two months to respond to changes in precipitation. On the other hand, there is a strong LST-NDVI relationship, with some blocks recording R^2 values greater than 0.7. Generally, this study showed that the restoration and conservation initiative is producing positive results, hence more resources should be allocated to it. Higher spatial resolution sensors should also be used to determine how the forest is changing at a finer spatial scale.

Acknowledgements

First and foremost, I would like to acknowledge the invaluable contributions of my supervisors; Dr. Collins O. Mito of University of Nairobi and Prof. Giovanni Laneve of University of Rome, “La Sapieza”. This study would not have been possible without their diligence and commitment. I highly appreciate their supervision, constructive comments, encouragement and guidance.

I would also like to thank my parents for the financial and moral support they offered me. I am especially grateful to my dad for not only assisting me financially but also for being patient with me during the entire period it took to complete this research. I am also thankful to my mother for providing moral support. Her encouragement provided the boost I needed to complete this work.

I would also like to thank Koinonia community for providing financial support for my study. I highly appreciate the fact that the Koinonia community paid my tuition fees in time thus enabling me focus on my study. I am eternally indebted to this community for their unwavering generosity.

I would also like to extend many thanks to Dr. Kinyanjui of DRSRS for availing the Mau Forest shape files and for offering technical support. I would also like to recognize the contribution of Dr. Khamala of LocateIT for assisting me with the high resolution 2001 - 2009 cover map of Mau Forest Complex. I am also very grateful to prof. Christopher Conrad of University of Wuerzburg, Germany for assisting me with TiSeG software package that was used to carry out quality analysis of MODIS NDVI images.

I would like to thank all the academic and nonacademic staffs of the University of Nairobi for working together to create an atmosphere that encourages learning. Finally I would like to thank all my colleagues for offering academic and moral support.

List of Acronyms

AFRI	Aerosol Free Vegetation Index
AGPI	Adjusted Geostationary Observation Environment Satellite (GOES) Precipitate Index
ARVI	Atmospheric Resistant Vegetation Index
AVHRR	Advanced Very High Resolution Radiometer
BISE	Best Index Slope Extraction
CERES	Clouds and the Earth's Radiant Energy System
CMORPH	Climate Prediction Center Morphing method
CVMVC	Constrained View Maximum Value Compositing method
DIAEE	Dipartimento di Ingegneria Astronautica, Elettrica e Energetica
EMR	ElectroMagnetic Radiation
ENSO	El Niño Southern Oscillation
ENVI	ENvironment for Visualizing Images
ETM	Earth Trends Modeler
ETM+	Enhanced Thematic Mapper Plus
EVI	Enhanced Vegetation Index
FAO	Food and Agriculture Organization
GOES	Geostationary Observation Environment Satellite
GPCP	Global Precipitation Climatology Project
GV	Ground Validation
LIS	Light Imaging Sensor
LST	Land Surface Temperature
MODIS	Moderate Resolution Imaging Spectroradiometer
MRT	MODIS Re-projection Tool
MSAVI	Modified Soil Adjusted Vegetation Index
MSS	Multispectral Scanner
NASA	National Aeronautics and Space Administration
NASDA	National Space Development Agency
NDVI	Normalized Difference Vegetation Index
NetCDF	Network Common Data Form

NIR	Near Infrared
NOAA	National Oceanic and Atmospheric Administration
OLI	Operational Land Imager
OLS	Ordinary Least Square
OSAVI	Optimized Soil Adjusted Vegetation Index
PERSIANN	Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks
PR	Precipitate Radar
QA	Quality Assurance
QA-SDS	Quality Assurance Science Data Sets
SARVI	Soil Adjusted and Atmospheric Resistant Vegetation Index
SAVI	Soil-Adjusted Vegetation Index
SWIR	ShortWave InfraRed
RFE	Rainfall Estimator
TAMSAT	Tropical Applications of Meteorology using SATellite
TIR	Thermal Infrared
TiSeG	Time Series Generator
TM	Thematic Mapper
TMPA	Tropical Rainfall Measuring Mission Multisatellite Precipitation Analysis
TMI	TRMM Microwave Imager
TRMM	Tropical Rainfall Measuring Mission
TSAVI	Transformed Soil Adjusted Vegetation Index
UNEP	United Nations Environment Programme
USGS	U.S. Geological Survey
VIS	VISible band
VIRS	Visible Infrared Scanner
VI	Vegetation Index
VIs	Vegetation Indices

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1. INTRODUCTION

1.1. Background

Land-Cover Change detection is one of the most important applications of remote sensing in Earth Science. Land-cover change detection entails determination of how land-cover of a given region is changing with time. Duadze (2004) define land-cover as the physical characteristics of the surface of the earth, captured in the distribution of water, soil, vegetation, and other physical features. Human activities, such as farming, deforestation, and mining, also have a profound effect on the land-cover of a region. According to FAO (2001), human activities especially agriculture have degraded the world’s forests to extents never witnessed before. This has made forest monitoring an international concern as the world strives to keep tabs on the rate at which the forests are undergoing degradation (Desclée *et al.,* 2006).

Land cover change has a profound effect on a region’s local climate, biogeochemistry, hydrology, radiation balance, and biodiversity of terrestrial species (Fichera *et al.*, 2012; Hong *et al.*, 2007). As such, keeping tabs on land-cover change is an important endeavor. Land-cover change detection provides means through which this can be achieved. In this study, the land-cover changes of Mau Forest Complex from 2001 to 2013 were studied using Moderate Resolution Imaging Spectroradiometer (MODIS). To investigate how Vegetation health and density vary with changes in rainfall and temperature, Tropical Rainfall Measuring Mission (TRMM) data and MODIS Land Surface Temperature (LST) images were used. Whereas this information can be obtained from meteorological stations, Satellite measurements are preferred due to their superior spatial distribution of measured values (Dinku *et al.,* 2010; Immerzeel *et al.*, 2009).

Change detection entails determination of how the state of an object or phenomenon has changed in the course of time. With change detection, it is possible to determine the nature as well as the amount of change an object or an area has undergone in the course of time. Vegetation land cover change detection involves determination of how vegetation cover of an area is changing with time. Remote sensing based change detection of land cover involves use of sensors mounted on airborne platforms or space borne (mostly satellites) platform to study the land surface.

Satellite sensors are used in such an endeavor due to their ability to collect data over a large area and regularly (Mas, 1999). Different change detection techniques have been developed over the years to facilitate remote sensing based land cover change detection.

In this study, Normalized Difference Vegetation Index (NDVI) time series data is used to estimate the temporal variation of vegetation in the Mau Forest Complex. NDVI was developed by Rouse et al. (1974) to study temporal and spatial variation of vegetation. It exploits the unique interaction of green vegetation with the electromagnetic radiation (The theory of NDVI is presented in section 3.2.1 of this document). Generally the NDVI values reflect the density of green vegetation in a given region. The NDVI values of densely vegetated areas will be close to 1, while that of sparsely vegetated area will be close to 0. As such, NDVI can be used to estimate the temporal changes of vegetation density of a given point with time. A continuous increase in NDVI with time suggests an improvement in the vegetation condition of the area, while the reverse suggests degradation of vegetation. It is therefore possible to detect change in vegetation cover using NDVI time series.

1.2. Study area

The Mau Forest Complex is the largest closed canopy forest in eastern Africa and is located to the south of the Rift Valley region in Kenya. The geographical coordinates of the Mau Forest Complex is approximately 0.0^{o}S to 0.9^{o}S (latitude) and 35.30^{o}E to 36.0^{o} E (longitude). It covers an area of about 400,000 hectares (Wass, 1995). It is one of the five ‘Water Towers’ in Kenya, and by far the most important (Crafford *et al.*, 2012). Areas like Mau Forest Complex that are usually located in highland and mountainous regions and which supplies water to the lowland areas are referred to as “Water Towers” (Viviroli and Weingartner, 2008). Such areas are very important as they control supply of water to the lowlands and therefore sustain life in these regions. For example, the Maasai Mara National Park relies on the Mara River that originates from the Transmara forest block. It should also be noted that River Nile drains from Lake Victoria which is replenished by rivers that originate from the Mau Forest Complex (UNEP, 2011).

Mau Forest Complex is a source of twelve major rivers that supply water to millions of people and also feed six major lakes: Lake Nakuru, Naivasha, Baringo, Victoria, Turkana, and Natron in

Tanzania (Kundu *et al.,* 2007). From an economical point of view, the significance of Mau Forest Complex is immense (Crafford *et al.*, 2012). According to UNEP report of 2008, the Mau Forest Complex is worth well over Kenya shillings 20 billion per year. According to this report, Kenya earns around 286 million US dollars every year through agriculture (especially tea farming), tourism and generation of hydroelectric power, all courtesy of the Mau Forest Complex (Sayagie, 2014; UNEP, 2008).

Despite its obvious importance to Kenya and the region as a whole, the prime minister's task force on the conservation of the Mau Forest Complex found out that Mau Forest Complex has been destroyed to disturbing extent (Prime Minister's Task Force, 2009). According to this task force, Mau has witnessed serious degradation in the past few decades, with over 107,000 ha of land having been lost due to irregular and ill-planned settlement in the past 15 years. Illegal and uncontrolled extraction of forest resources from the Forest Complex, such as uncontrolled timber harvesting, has made the situation even worse (Crafford *et al.*, 2012). One of the recommendations of the Mau Forest Task Force was that all land that had been encroached or illegally/irregularly acquired be repossessed, a recommendation that the Government of Kenya has so far implemented.

Mau Forest Complex exhibits tropical rainforest climate. Regions of such climatic conditions experience frequent clouds cover, making data acquisition by satellite very difficult (Lu, 2006). Also the rain pattern is very important since the abundance of green vegetation in any given area will follow the seasonal variation of the rainfall. Obviously, vegetation density will be high during the rainy season and low during the dry season. Olang and Kundu (2011) note that generally, the forest receives an average annual rainfall of about 1300mm in years devoid of extreme climatic events such as the El Niño Southern Oscillation (ENSO). The temperature ranges from 10^{o} C to 22 ^{o} C, with July being the coldest month. The Mau Forest Complex has two rainy seasons in a year with the "Long rains" being experienced in march-June and the "short rains" in October-December (Kinyanjui, 2011; Muti and Kibe, 2009).

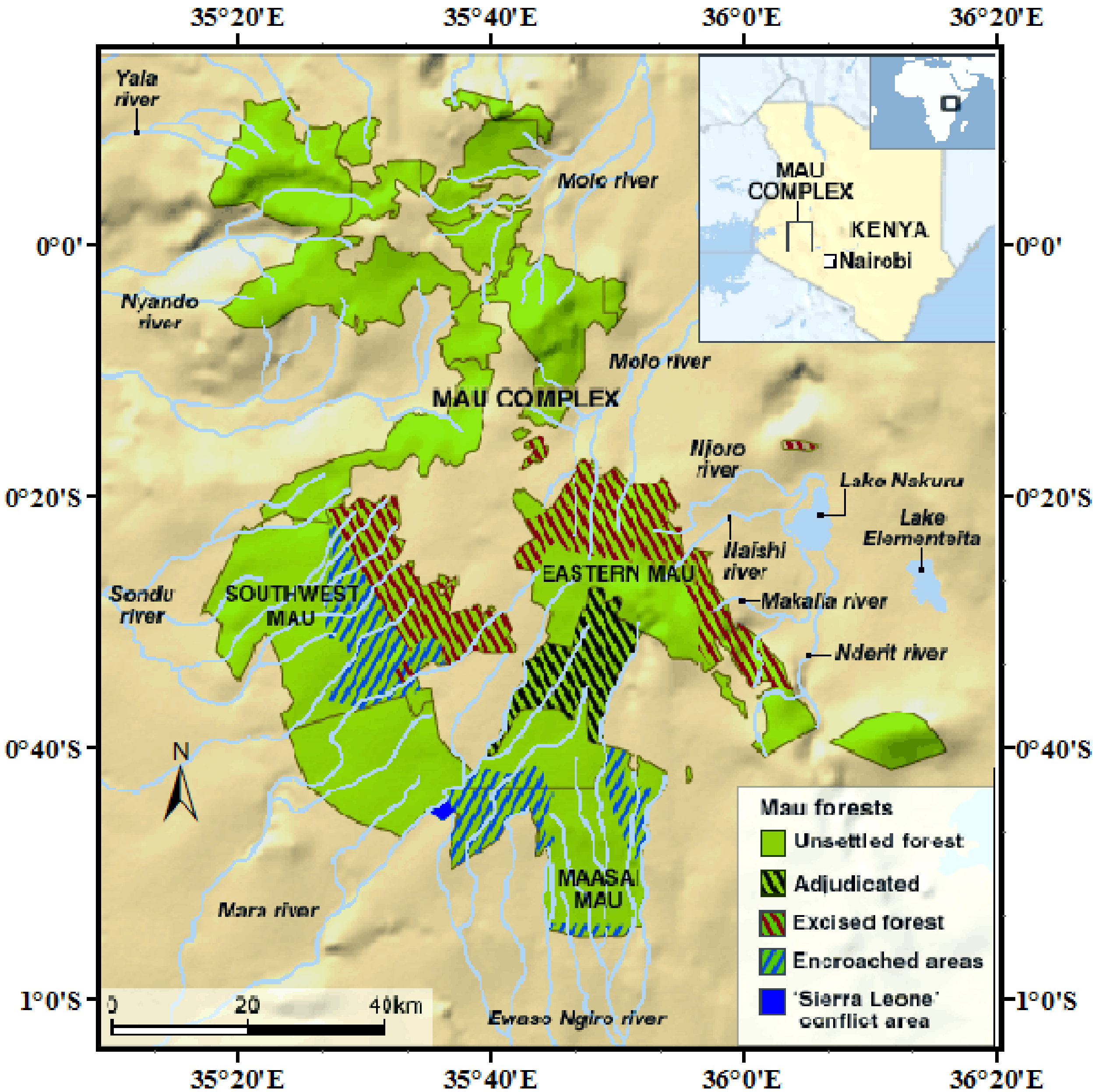

Figure 1-1 Areas of Mau that have experienced high levels of degradation (Modified from Morgan, 2009)

It is worth noting that this study is partly motivated by the report produced by the Prime Minister’s task force on Mau Forest conservation that recommended repossession and restoration of land considered to be part of the Mau Forest Complex (Prime Minister’s Task Force, 2009). The land that was recovered had been lost as a result of the 2001 excision and illegal ocupation of forest land that had largely affected Southwest Mau, Eastern Mau, Molo and Maasai Mau (see

Figure 1-1). This study focussed on these four forest blocks and their neighbouring blocks; Transmara, Western Mau, Mount-Londiani,Tinderet and Eburu (Figure 1-2). In otherwords, these study focused on these nine blocks of the Mau Forest Complex (Figure 1-2).

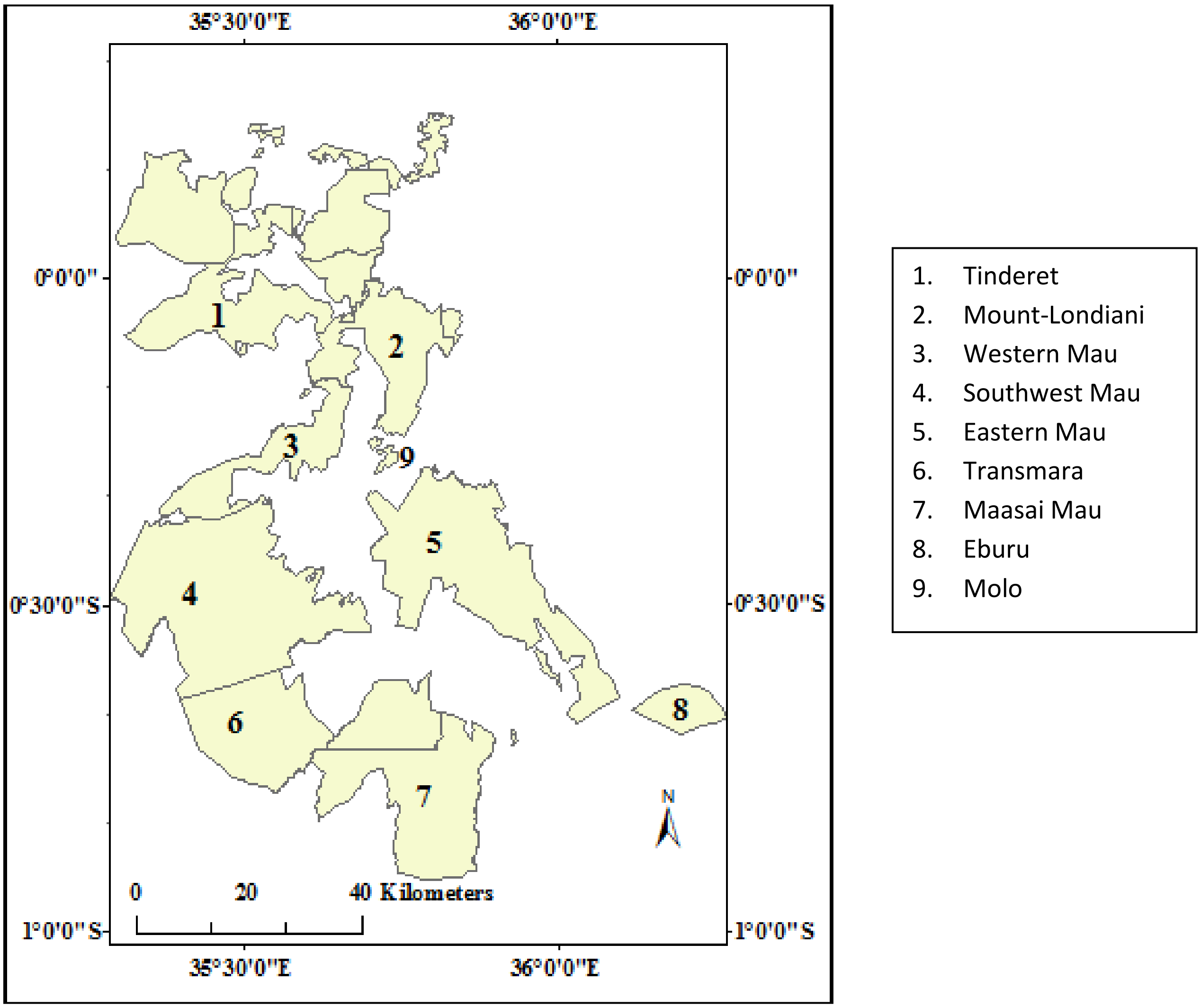

Figure 1-2 The Mau Forest Complex blocks that this study focused on (Developed using Mau Forest Complex shape files)

It is worth noting that by 2013, the Government of Kenya had already implemented some of the recommedation of the Mau Forest Task Force. Phase I and phase II of the recommedations of the Mau Forest Task Force were implemented before the end of 2010. Phase I involved repossession of land excised from Eastern Mau by the Government of Kenya in 2001 (Mau Forest Complex Interim Coordinating Secretariat, 2010). This part of the forest had not yet been occupied by their pontential owner hence repossession was swift. Phase II led to repossession of about 19,000 hectares of land in South Western Mau Forest Reserve. This part of the forest had been occupied by illegal squatters. In total, phase I and II led to repossesion of about 21,000ha (Interim Coordinating Secretariat Mau Forests Complex, 2010). The third phase concerned the repossession of titled forestland in the Maasai Mau Trust Land .

1.3. Remote sensing

Remote sensing is defined as a technique that utilizes remotely-located sensors to identify, classify and obtain data about the physical characteristic of objects without involving any physical contact between the sensor and the objects (Gupta, 2013; Weng, 2009; Okamoto, 2001). Using various dataset processing and analysis techniques, information can then be extracted from the datasets so acquired. The main advantage of using remote sensing in environmental studies is the fact that one can acquire and analyze data from a large area within a short time and at regular interval. Mas (1999) note that remote sensing enables one to acquire data rapidly and frequently at lower cost compared to other alternative methods of data acquisition. Using specialized software, such as ENvironment for Visualizing Images (ENVI) and ArcGIS, the process of information extraction from the datasets is equally rapid and economical.

However, remote sensing systems do possess some limitations, such as poor performance of optical sensors during cloudy days, interference of the signal by atmospheric aerosols, geometric distortion of the images especially those taken by sensors with wide swath, among others (Mas, 1999). However, some techniques have been developed to deal with these problems, especially to minimize the effects that the clouds and other atmospheric components have on the integrity of data collected via remote sensing systems (Wagenseil and Samimi, 2006; Viovy *et al.*, 1992). Another limitation is the resolutions of the images used. For example, there exists a trade off in satellite image between spatial (area represented by a pixel) and temporal resolution (revisit time).

Higher spatial resolution enables one to see finer details of an image and therefore extract more accurate information from such an image. Higher temporal resolution increases the chances of acquisition of high quality images as well as change detection of land surface at a finer time step. Ability to acquire images at high frequency is particularly important in the study of plant phonological changes. Spectral and radiometric resolutions of a sensor are also important as they enable a sensor differentiate between different objects better. In this study, MODIS 16-days composite images of 250m spatial resolution were used to study vegetation variation in the Mau Forest Complex within the period of interest.

1.4. Statement of the problem

It has been shown that human encroachment on the Mau Forest Complex has so far affected negatively the forest stocking, composition of species and the hydrology of the forest (Kinyanjui, 2011). The situation is made even worse by unsustainable extraction of the natural resources from the forest. This implies that the restoration and conservation of the forest will only succeed if the Government monitors the forest in addition to evicting the settlers and planting millions of trees. Monitoring of the forest will ensure that people do not continue to destroy the forest through agricultural activities or uncontrolled extraction of other forest resources. In addition to this, monitoring of the forest will enable the Government evaluate the success of its restoration and conservation policies and therefore modify them appropriately.

The problem with monitoring Mau Forest Complex is the vast area involved coupled with small budget allocated to the whole restoration and conservation process. This makes traditional monitoring methods, such as survey of the forest by teams of Forest Rangers, unreliable and uneconomical. This project will attempt to use Remote Sensing, which is reliable and economical, to investigate the effects that the Government restoration and conservation initiative has had on the recovery of the Mau Forest Complex. By understanding how the Mau Forest Complex is responding to the current restoration and conservation initiative, the Government can prioritize its conservation activities so as to allocate more resources to areas that need them most. By comparing the conservation policies with the outcome, the Government can determine which policies are working best and how to improve on them.

1.5. Objectives / Goal

The main goal of this study was to investigate the impacts of the changes in forest cover of Mau Forest Complex from 2001 to 2013 using satellite images. The major questions that this study attempted to answer is: What impacts has the Government’s effort to restore and conserve Mau

Forest Complex had on its rate of degradation? In other words, is the forest showing any signs of recovery from the degradation it has experienced over the past years? The study also attempted to establish how Rainfall and Land Surface Temperature (LST) relate with variation in vegetation. Such information can be used to determine the role the variation in climatic condition play in degradation and recovery of the forest. Information obtained here can be fed in other prediction models to obtain more information on the dynamics of the forest.

1.5.1. Specific objectives

i. To obtain NDVI, Rainfall and LST time series for the Mau Forest between 2001 and 2013

ii. To determine the variation of NDVI with principal climatic elements (Temperature and Rainfall) in Mau Forest Complex.

iii. To Determine the overall change in vegetation distribution of the Mau Forest Complex from 2001-2013, and by extension assess the possible impacts of the restoration and conservation initiative.

1.6. Hypothesis

Remote sensing techniques provide a unique way of studying large and remote areas in an economical and effective manner. Remote sensing based vegetation cover change detection can be implemented using Normalized Difference Vegetation Index (NDVI). In general, NDVI is a measure of density of green vegetation and will therefore increase with improvement in vegetation condition and decrease with vegetation degradation. Since the Mau Forest was excised in 2001 and little was done between 2001 and 2007 to curb destruction of the forest, it is expected that the NDVI time series trend of most parts of the forest will be negative during this period.

After the kickoff of the restoration and conservation initiative in 2008, one would expect that the slope of the NDVI time series to increase as the vegetation starts to recover. If the conservation initiative is succeeding, then the NDVI time series for the period covering 2008-2013 should have positive slopes (showing that vegetation is recovering) or slopes close to zero (Indicating the destruction of the forest has slowed down). It is also expected that rainfall will have a positive influence on the NDVI. Since growth and decay of vegetation is not instantaneous, it is expected that NDVI will take time to respond to variation in rainfall. The process of water absorption and loss by soil is not rapid due to the structure of soil and shading of the surface by the tree canopy.

Since Mau Forest Complex is a tropical rainfall forest, it is expected that there will be a negative correlation between NDVI and LST. NDVI-LST relationship tends to be positive in regions where vegetation growth is energy limited (for example, in the Arctic) and negative in regions where growth is water/moisture limited, as is the case for tropical climatic regions. This negative relationship has been used as an indicator of vegetation water stress and the rate of evapotranspiration (Karnieli *et al.*, 2010; Prihodko and Goward, 1997; Kogan, 2000).

1.7. Report outline

Chapter one of the thesis introduces the problem that this study intend to solve. It gives a brief description of the study area which is important as far remote sensing is concerned as the size and climate of the region being studied via satellite sensors is important. The objectives of the study and the statement of the problems are also introduced here. This chapter is followed by literature review (Chapter 2) which gives a brief outlook of other studies that have been done on this area and their findings.

Chapter three gives the theoretical background of the remote sensing concepts used in this study. The spectral characteristics of Vegetation and the concept of Vegetation Indices are introduced here. This chapter describes how vegetation interacts with the Electromagnetic Radiation (EMR) and how satellite sensors can thus be used to detect changes in vegetation cover. Chapter 4 presents the methodology used to achieve the objectives of this study while Chapter five reports the findings. The NDVI time series, the correlation graphs of NDVI with rainfall and LST, and the NDVI Ordinary Least Square (OLS) slopes are presented in chapter five. This chapter also gives a detailed analysis and discussions of the results. The conclusions and recommendations that follow from these results analysis and discussions are presented in chapter six. Chapter seven presents a list of the books, journal and other academic works referred in this work.

2. LITERATURE REVIEW

2.1. Destruction of Mau Forest Complex

Over the past three decades, the Mau Forest Complex has suffered serious degradation mainly due to human encroachment as the ever growing human population demands more and more land for settlement and agriculture (Kundu *et al.*, 2007). Several researchers have documented these destruction (Olang and Kundu, 2011; Raini, 2009; Kundu *et al.*, 2007; Akotsi and Gachanja, 2004).This encroachment has led to destruction of headwater catchment areas and wetlands that have caused reduction in discharge rate of rivers as well as the water quality (Baldyga *et al.*, 2008). Raini (2009), pointing to the 2001 excision, argues that excision is probably the greatest threat that the Mau Forest Complex faces.

During the colonial era the Mau Forest Complex was covered by dense natural vegetation, thanks to the protection of the forest by the colonial Government. The colonial government recognized very fast the value of the Mau Forest Complex and placed measures to protect it (Raini, 2009). The destruction of Mau Forest started between 1970 and 1986 when more than 82,410 ha of southwest Mau were declared adjudicated areas erroneously (Raini, 2009). This was followed by an establishment of a major settlement scheme in Olenguruone. A further 40% of the Mau Forest land was lost following this unfortunate incident. In 1994 the Government of Kenya de-gazetted over 20,099 ha in southern and southwest Mau, an action that Akotsi, and Gachanja (2004) blames on demand for more farmland to feed the ever growing human population. This action, on itself, took away about 30% of the Mau Forest Complex.

The settlement of people in part of Mau Forest Complex did not only rob the Mau Forest Complex of land, but also exposed the remaining forest land to other forms of human induced land degradation. For example, parts of the remaining forest experienced heavy exploitation of the forest resources such as wood for timbers and charcoal. The clearing of the forest either for agricultural purpose or through cutting down trees for timbers and other purposes have also caused soil erosion. The introduction of roads, rooftops, sidewalks and other impervious surfaces to the forest ecosystem has also led to interference of the processes that are based on infiltration, therefore interfering with groundwater systems recharge (Raini, 2009). Expansion of subsistence agricultural land at the expense of forest land has also led to accelerated rate of sediment deposits into the lakes that are replenished by rivers from Mau Forest ((Raini, 2009); Hesslerová and Pokorný (2011),).

The sediments contain nutrients that have potential to interfere with the normal growth and development of algae and other aquatic vegetation thus affecting the biodiversity of the lakes. A good example would be the interference of the growth of blue-green algae in Lake Nakuru that forms the main source of food for flamingoes. Flamingoes are the main source of tourist attraction in Lake Nakuru implying that changes in the Mau are capable of affecting the ecotourism of the Nakuru area thus interfering with the source of the income for the Nakuru County. The deforestation of the Mau Forest Complex has also led to increase in evaporation rate and runoff process thus affected the hydrological cycle of rivers that run from the forest to the surrounding areas and lakes Olang and Kundu (2011).

According to Olang and Kundu (2011), the dominant land cover types in the Mau Forest Complex area before 1986 were forest at 75%, woodland at 12% and farm land at 13%. However by 1989 the land cover had changed to the extent that the forest area and woodland areas covered only 60% and the other land cover was agricultural land and built up areas. The forest land to the south of Kipkelion and Londiani was about 254,100 ha in 1973, 249,400ha in 1986 and 179,000 ha in 2009 implying that the highest rate of forest destruction was witnessed between 2000 and 2009. Raini (2009) argues that excision of forest land is the greatest threat to the existence of the Mau Forest Complex. He notes that the 2001 excision affected about 15% of the forest especially in Southwest and Eastern Mau.

A study by Were *et al*. (2013) showed that there has been an increase in croplands and built up areas at the expense of forest-shrublands from 1973 to 2011. They reported that croplands had expanded by 660km^2 while the built up areas had expanded by 24km^2 within this period. The forest-shrublands had decreased from 1067km^2 in 1973 to about 639km^2 in 2011. They therefore recommended that restoration and conservation policies be accompanied by agricultural production enhancement programs so as to reduce the demand for more agricultural land. These land cover conversions from natural vegetation to farmland were also reported by Baldyga *et al*. (2008). Baldyga *et al*. (2008) showed that there has been a conversion of forest land to small scale farm land within the Mau Forest. The study of impacts of such land cover changes have been reported by Hesslerová and Pokorný (2011), who showed that the deforestation of the Mau Forest have caused a decline in the level of precipitation of the affected regions. They did also observe that heavy forest degradation have reduced levels of water in lakes that depend on such deforested catchments.

Recent studies have however shown that the Mau Forest Complex has the potential to recover and with proper management, the forest can be restored to its previous state. By dividing the forest cover into heavily disturbed, undisturbed, and moderately disturbed areas, Kinjanjui *et al*. (2013) showed that disturbed areas can regenerate naturally into undisturbed areas. This implies that if the destruction of the Mau Forest Complex is brought to a halt, the forest can regenerate naturally. However, this study focused only on Western Mau and Southwestern Mau implying that the potential of the other forest block to recover was not evaluated.

This study aims at using NDVI time series to determine how vegetation cover within the Mau Forest Complex has changed over the period extending from 2001 to 2013. MODIS NDVI images are used due to their relatively high spatial and temporal resolution. The variation of NDVI with rainfall and land surface temperature is also evaluated to determine how they relate to vegetation change. Use of NDVI to analyze changes in vegetation health and density in the Mau Forest Complex has been carried out by Kinyanjui (2011) using SPOT images with spatial resolution of 1 km and temporal resolution of 10 days. He did also evaluate the trend of rainfall (measured by rain gauge) with that of NDVI for Eastern Mau, but not for the other Mau Forest blocks. In this study, the relationships between NDVI and satellite based rainfall and Land Surface Temperature (LST) for nine blocks of the Mau Forest are evaluated. The study also attempts to establish possible impacts of the reclamation initiative that started in 2008

2.2. Land Cover Change detection

According to Macleod and Congalton (1998), change in land cover should be analyzed qualitatively and quantitatively. That is, it should be possible to determine where change has taken place, the nature of such a change, as well as the extent of the change. Macleod and Congalton (1998) also emphasize that change detection should be able to reveal the spatial pattern of the change. It is these aspects of change that change detection techniques attempt to address. Over the years, many change detection techniques have been developed to enable land cover change detection (Sader *et al.*, 2001; Lyon *et al.*, 1998; Coppin and Bauer, 1996; Singh, 1989). In this study, IDRISI 17.0 software package is used to calculate the per-pixel NDVI Ordinary Least Square (OLS) slope for the whole of Mau Forest Complex during the two periods: 2001-2007, which represent the period before the initiative began, and 2008-2013, which represent the period after the initiative began.

2.3. Use of Satellites to Estimate Vegetation Cover, Land Surface Temperature and Rainfall

2.3.1. Vegetation Cover

Use of satellite sensors to study vegetation started in the 1970s following the launch of the first Landsat satellite (Landsat 1) in 1972. The most important sensors onboard Landsat satellites as far as the study of vegetation is concerned have been Multispectral Scanner (MSS), Thematic Mapper (TM), Enhanced Thematic Mapper plus (ETM+) and Operational Land Imager (OLI) (USGS, 2014). The MSS sensor was introduced in Landsat 1 and was included in subsequent Landsat satellites (2-5). The TM sensor was carried onboard Landsat 4 and 5 and was succeeded by Enhanced Thematic Mapper plus (ETM+) sensor onboard Landsat 7 satellite launched in 1999 (USGS, 2014).The latest addition to the Landsat satellite series sensors is the OLI sensor launched onboard Landsat 8 satellite on February 2013.

Researchers like Macdonald and Hall (1980) and Badhwar *et al*. (1982) have successfully used Landsat satellite data to study various aspects of vegetation variations. To date, Landsat satellite images have remained very useful tools for studying land cover changes mainly due to their relatively high spatial resolutions and long period of coverage (since 1972) However, they are not suitable for use in studying plant phonological changes due to their low temporal resolution which is about 16 days. This low temporal resolution is more pronounced in regions that are prone to frequent cloud cover such as the tropical regions (Xiao *et al.*, 2002). This is in fact the main reason why Landsat images were deemed unsuitable for use in this study since Mau Forest Complex exhibits tropical rainforest climate.

Another satellite sensor that has proven to be very valuable in the study of vegetation dynamics is the National Oceanic and Atmospheric Administration’s (NOAA) Advanced Very High Resolution Radiometer (AVHRR) launched into space in 1978. This satellite sensor has been used by various researchers to study various aspects of land cover conversion. For example, Norwine and Greegor (1983) used multi date NDVI to classify vegetation across Texas State. AVHRR has a ground resolution at nadir of about 1.1km for local area coverage (and 5km for Global Area Coverage) and a revisit time of one day (Lillesand *et al.*, 2007). In December 1999, National Aeronautics and Space Administration NASA launched another new and more advanced sensor, known as Moderate Resolution Imaging Spectroradiometer (MODIS) onboard Terra satellite. This was followed by the launched of another MODIS sensor onboard Aqua satellite in May 2002, thus bringing the number of MODIS sensors operating currently to two (Parkinson, 2003). Some products of MODIS sensors are comparable to those of the extensive AVHRR in terms of spectral and spatial resolution thus ensuring that the products started by AVHRR can be continued through the use of MODIS sensors (Huete *et al.*, 1999).

However, the MODIS sensor has some advantages over AVHRR which include higher spatial resolution of some MODIS products and narrower bandwidth of the spectral bands. The narrowing of the spectral bandwidth reduced the water absorption problems experienced in the AVHRR (Huete *et al.*, 1999). Huete *et al*. (2002) also note that reflection correction, atmospheric correction coupled with the Bidirectional Reflectance Distribution Function (BRDF) corrections performed on vegetation products produced by MODIS sensors improve the performance of the MODIS products available to public. This effectiveness and efficiency of MODIS data is boosted even further by continued monitoring and validation of the MODIS products by various teams of users and specialists (Huete *et al.*, 1999). It is these factors and the fact that MODIS vegetation products are free of charges that have made MODIS popular among the remote sensing community.

2.3.1.1. Vegetation Indices (VIs)

Various vegetation indices (VIs) have been developed by different researchers over the years to monitor temporal and spatial variation of vegetation. VIs exploits the unique spectral characteristics of vegetation that distinguishes vegetation from other objects. Some, like NDVI, exploits the interaction of vegetation with the Visible and the Infrared part of the electromagnetic spectrum. Others, like Aerosol Free (AFRI) vegetation Index, exploit the relationship that exists between the Short Wave Infrared (SWIR) and the NIR part of the electromagnetic spectrum (Pettorelli *et al.*, 2005; Karnieli *et al.*, 2001; Myneni *et al.*, 1995; Huete, 1988). However, of all

VIs, NDVI is the most widely used in the world especially in the study of vegetation phonology (Pettorelli *et al.*, 2005; Myneni *et al.*, 1995). Myneni *et al*. (1995) attributes this success to its ease of use, its good correlation with photosynthetic activity and the long standing tradition of its use.

Although VIs are widely used in the study of vegetation changes in remote sensing, it should be noted that they are affected by noise, thus limits their use and the accuracy of the results obtained via their use. Some of the factors that introduce noise in VIs include atmospheric effects, aerosols, clouds, variation in angle of the sun and the sensor view angle at the surface, co-registration errors and sensor calibration errors (Kang *et al.*, 2005; Sakamoto *et al.*, 2005; Roerink *et al.*, 2000; Huete *et al.*, 1999; Cihlar *et al.*, 1997; Viovy *et al.*, 1992; Goward *et al.*, 1991). All these factors have the potential to affect the signals captured by the satellite sensors and lead one to make misleading conclusions. It is therefore important that this noise is eliminated or compensated for before VIs products can be used to evaluate land cover changes.

Most of the new satellite data products are corrected to some degree for these noises before they are made available to the public (Huete *et al.*, 1999). However, it should be noted that complete removal of noise from the satellite data is not practical due to the large size of modern satellite data and lack of sufficient ancillary data necessary for such an endeavor (Cihlar *et al.*, 1997). To reduce noise in remote sensing data and make them more useful for time series analysis, temporal compositing algorithms have been developed. Temporal compositing algorithms are mathematical models that take several satellite images captured over a given period, discard all but the best pixels thus producing a single image. The results of such operations are composite images made up of pixels taken at different times but of much better quality than either of the original single day images. Temporal compositing have proved to be an economical and effective method of reducing noise especially those produced by clouds (Chen *et al.*, 2003; Holben, 1986).

Carreiras *et al.* (2003) noted that compositing does not eliminate noise completely. Still there are some remnant noise signals present in the composite images that require further processing. To deal with this remnant noise, several researchers have come up with various algorithms. Viovy *et al.* (1992) investigated the use of BISE (Best Index Slope Extraction), Wagenseil and Samimi, (2006), Moody and Johnson (2001), Sellers *et al.* (1994) and Menenti *et al.* (1993) have suggested the use of Fourier transform model. In this study, Savitzky-Golay filter is used in the Timesat environment (Chen *et al.*, 2004; Jönsson and Eklundh, 2004; Jönsson and Eklundh, 2002; Savitzky and Golay, 1964). Savitzky-Golay filter is used in this study since it was observed that it was able to fit the NDVI time series data used in this study better than the other filters available in the Timesat software package.

Although NDVI has been used by various researchers to study various aspect of vegetation change, especially phonological variation, some researchers have reported some of its limitations. According to Huete *et al*. (1997) and Holben and Fraser (1984), NDVI tend to saturate in areas with very high vegetation density. Holben and Fraser (1984) found that due to NDVI saturation, they were having difficulty in distinguishing between regions with high density green leaves and those with low density green leaves due to NDVI saturation problem. The other problem associated with NDVI is soil background reflection and scattering problem. While studying vegetation cover across the Sahara desert, Holben (1986) noted that the satellite derived land cover so produced did not match very well with the actual situation on the ground. He concluded that the disparities in the results obtained were most likely caused by soil background interference due to the low vegetation density of the sites.

To deal with these problems, new and more advanced vegetation indices have been developed. They include Soil-Adjusted Vegetation Index (SAVI) and Enhanced Vegetation Index (EVI) (Huete, 1988). However, these indices introduce other problems that NDVI is known to be resistance to, such as sensitivity to topographic and atmosphere effects. The problems introduced by new VIs are actually more difficult to correct for than those presented by NDVI (Huete *et al.*, 2002). For this and other reasons, NDVI is still the most preferred Vegetation Index. In this research, MODIS13Q1 products are used to assess variation of vegetation with time and climatic variables of the Mau Forest Complex.

2.3.1.2. MODIS Normalized Difference Vegetation Index (NDVI) Product (MD13Q1)

The MODIS sensor has 36 bands with 250m, 500m and 1000m spatial resolutions and covers the whole globe in one to two days. This implies that one can get at least one image in two days for regions along the equator and at least one image per day for regions far away from the equator such as Europe. Using the data acquired by the two MODIS sensors, three categories of products; atmospheric, oceanic and terrestrial, are produced by the MODIS Science Teams (Justice *et al.*, 2002). This study will utilize MOD13Q1, which is one of the products that belong to the level 3 VI data sets. Like all the other Level 3 VI products, MOD13Q1 comes in gridded 1200 by 1200 km tile, and sinusoidal projection (Huete *et al.*, 1999). All MOD13 products are generated from the level 2 MOD09 surface reflectance data which are in turn generated from calibrated Level 1B data. The advantage of using Level 2 MOD09 products to generate the Level 3 MOD13 product is the fact that level 2 MOD09 products have already been corrected for atmospheric errors, such as aerosols interference, molecular scattering and ozone absorption (Vermote *et al.*, 2002). Huete *et al.* (2002) note that the primary objective in the production of MOD13 products is to remove as much external noise as possible through use of improved calibration, atmospheric correction, cloud and cloud shadow removal techniques. The MODIS science teams responsible for the production of MOD13 product also correct for geometrical distortions produced by the wide swath of the MODIS sensor (Huete *et al.*, 2002). As a result of these processing, each of the pixels in Level three products is precisely geo-located and atmospherically corrected thus providing high quality product.

The compositing algorithm used to generate MODIS NDVI products takes data observed by the MODIS sensors over a period of 16-days, which increases the chance of getting high quality pixels in every region on the earth's surface (Huete *et al.*, 1999). Within this period, between zero and 64 observation may be made in each location due to the wide sensor swath of the MODIS sensor that leads to overlap of observations in some areas and multiple observation in a day for some regions (Huete *et al.*, 2002). This implies each region on the earth's surface will have multiple observations of varying quality. The compositing algorithm selects the highest quality pixels and uses them to create the final images. The result of this operation is an image with pixels that were taken in different days and/or time. This method of compositing produces images that are of better quality than either of the images used. In addition to this, the MOD13 data comes with quality assurance (QA) information that gives quality information of each pixel (Huete *et al.*, 2002).

Morisette *et al*. (2002) note that NASA has been conducting validation of all MODIS Land Products using airborne sensors and other space-borne sensors as well as in situ measurement. For these reasons, MODIS products provide high quality data for use in evaluation of spatial and temporal variation of land cover. So the choice of MOD13Q1was informed by the fact that MOD13Q1 are atmospherically corrected, geo-corrected, have QA-SDS that can be used to improve the quality of the images even further and the fact that these images are at 250m resolution which matches the scale at which human driven degradation occur at (Townshend and Justice, 1988).

2.3.2. Land Surface Temperature (LST) and MODIS Product (MOD11C3)

Land Surface Temperature is an important parameter that plays a major part in energy and water exchange cycles. LST has found practical application in evapotranspiration monitoring, vegetation monitoring, hydrological cycle and many other environmental areas (Li *et al.*, 2013). Whereas there are many LST products from various satellite sensors, MODIS Products provide a good compromise between the temporal and spatial resolution. For example, the Meteosat Second Generation/ Spinning-Enhanced Visible and Infrared Imager MSG/SEVIRI LST products are taken at relatively higher temporal resolution (of about 15min) but the spatial resolution is 3km at nadir (Göttsche *et al.*, 2013).

In this study, MOD11C3 products are used to investigate the correlation between NDVI and temperature. LST is used instead of air temperature, due to the fact that LST taken by satellite sensors offer better spatial distribution of temperature than weather stations which are generally few in number, even if we have to consider that LST could be strictly correlated to NDVI through the emissivity that changes with the surface coverage. According to Mostovoy *et al.* (2006), LST can be used successfully to estimate air temperature at local scale. Mostovoy *et al.* (2006) found that there is a linear correlation between maximum and minimum air temperature implying that LST can be used to estimate air temperature of a region. This is important since air temperature has been shown to affect the climate of a region (Garratt, 1994; Oke, 1987).

Other researchers who have used LST to estimate air temperature include Kawashima *et al.* (2000) and Garratt (1994). Just like Mostovoy *et al.* (2006), Kawashima *et al.* (2000) used linear regression to estimate air temperature from LST and concluded that air temperature could explain 80% of the variation in LST observed. In terms of relationship between NDVI and temperature (LST/Air temperature), Kawashima *et al.* (2000) argue that vegetation density, which can be inferred from NDVI, has an influence on the thermal properties of the ground. In their study, they found that NDVI had influence on the LST and in fact the accuracy of estimation of air temperature from LST got improved when NDVI was introduced into the model. Other authors who have investigated the relationship between vegetation cover and LST include Nemani and Running (1989) and Smith and Choudhury (1990). Validation studies of MODIS LST products in East Africa suggest that there is an underestimation of minimum air temperatures by nighttime LSTs of 3.3°–4.2°C (Vancutsem *et al.*, 2010).

2.3.3. Rainfall Estimation and the Tropical Rainfall Measuring Mission (TRMM) Data

In this study, the rainfall data was extracted from the Tropical Rainfall Measuring Mission (TRMM) Multisatellite Precipitation Analysis (TMPA) 3B43 product (Herrmann and Mohr, 2011). The TMPA 3B43 products are generated by the 3B43 algorithm which generates the "best" monthly rainfall estimates using TRMM instruments, Rain gauges and other satellite measurements. According to Adler *et al*. (2003) and Bolvin *et al*. (2009), satellite based rainfall estimation are based on the connection between emissive and radiative properties of cloud hydrometers and the rainfall at microwave, infrared and visible wavelengths. The Tropical Rainfall Measuring Mission (TRMM) satellite is a tropical rainfall measuring satellite launched in 1997 in a joint mission between the Japanese National Space Development Agency (NASDA) and the American National Aeronautics and Space Administration (NASA). TRMM satellite carries five instruments namely: Precipitate Radar (PR), TRMM Microwave Imager (TMI), Visible Infrared Scanner (VIRS), Clouds and the Earth's Radiant Energy System (CERES), and Light Imaging Sensor (LIS) (Kummerow *et al.*, 1998).

PR was the first rain radar designed for use in space and is used to quantitatively measure rainfall, improve TMI measurements accuracy, and provide a three dimensional structure of rain. TMI is multi-channel / dual-polarized microwave radiometer that provide accurate measurements of rain rate in ocean. TMI in combination with PR provide the primary tools for estimation of precipitate. VIRS is a five band passive radiometer that operates in the visible and infrared region of the EMR and is primarily used to measure cloud distribution. LIS acquires data about lightening in the earth atmosphere while CERES collects data on atmospheric radiation energy distribution. With these tools, TRMM collects data on the spatial and temporal distribution of rainfall globally evenly and regularly (Sivakumar *et al.*, 2004; Kummerow *et al.*, 1998). This is particularly important in Africa and other third world countries where the ground based weather stations are sparsely distributed. TRMM also offer a relatively higher spatial resolution compared to other satellite sensors, with TMI and VIRS having the possibility of capturing data at resolutions of 5km and 2.2km (Kummerow *et al.*, 1998).

However, satellite data need validation so that any existing biases in the measurements can be dealt with effectively. So far most of the validation of the TRMM data in Africa has been done in western region Nicholson *et al*. (2003a) and eastern Africa, especially in Ethiopia Dinku *et al*. (2007). Nicholson *et al*. (2003) found that PR and TMI performed poorly in western Africa. However, when TRMM-adjusted Geostationary Observation Environment Satellite (GOES) precipitate index (AGPI) was used, better results were achieved (Nicholson *et al.*, 2003b). Dinku *et al*. (2007) found that satellite based rainfall estimates performed well in low lying areas of the Ethiopia, but they underestimated rainfall rate in high and mountainous regions. In Uganda, Asadullah *et al*. (2008) showed that TRMM 3B42 product and TAMSAT products have better resemblance to rainfall gauge than CMORPH, PERSIANN and RFE 2.0 products.

Other studies that have sort to investigate performance of TRMM products in Africa include Roca *et al*. (2009) in West Africa, Dinku *et al*. (2010) in east Africa and Adeyewa and Nakamura (2003) in the whole of Africa. In general, TMPA have been found to correlate well with rain gauges and are therefore deemed suitable for use in this study. In Kenya, Ouma *et al*. (2012) showed that TRMM-3B42 data correlate well with rainfall gauge data ($R^2 > 0.9$) but with a slight overestimation in wet season and underestimation during dry season. TRMM 3B43 data have also been used successfully in Kenya by Ember *et al.* (2012) to investigate the link between livestock raids and variability in rainfall. TRMM data and other satellite based rainfall measurement products provide a means through which spatial and temporal distribution of rainfall data can be estimated to reasonable degree of accuracy. Rain gauges measurement may be continuous and accurate, at a point, but they give insufficient information about spatial distribution of the rainfall. They are also subject to calibration errors and their measurements can be affected by wind and uncertainty in sampling (Van de Beek *et al.*, 2011); Bowman, 2005; Pardo-Igúzquiza, 1998).

3. THEORETICAL BACKGROUND

3.1. Objects Detection and Discrimination.

In remote sensing, different objects are discriminated against each other through detection and analysis of the radiation energy reflected or emitted by the objects (Sivakumar *et al.*, 2004). Radiation energy reflected or emitted by a given object is unique to that object. Figure 3.1 shows the reflectance characteristics of vegetation, water and soil (Lillesand *et al.*, 2007). Vegetation absorbs strongly in the visible part of the electromagnetic radiation (EMR), particularly in the blue and the red portion. This part of the electromagnetic energy is used by the plant in the process of photosynthesis (Elachi, 2006). Another important characteristic of plants is that they reflect strongly in the Near-Infrared (NIR) part of the EMR. The combination of these two plant characteristics makes it possible to distinguish plants from other objects, and forms the basis of most Vegetation indices, like NDVI.

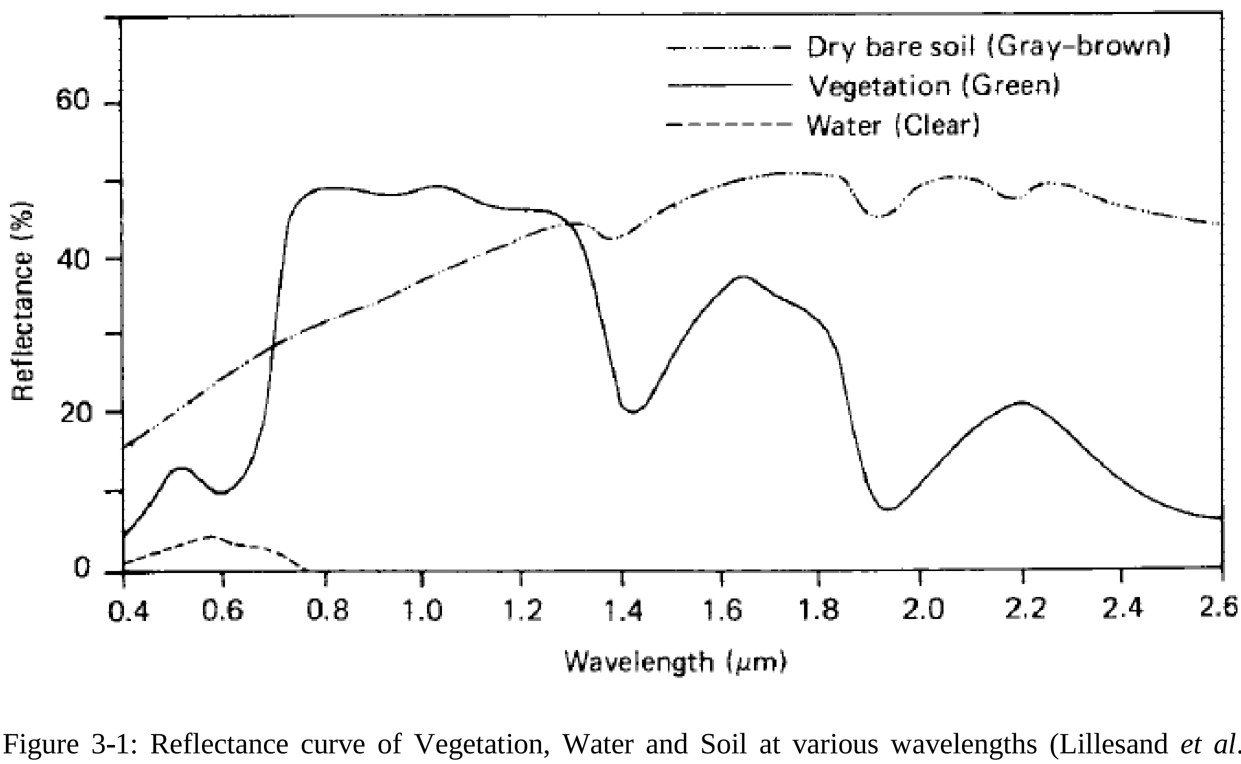

Figure 3-1: Reflectance curve of Vegetation, Water and Soil at various wavelengths (Lillesand *et al.*, 2007)

However, Vegetation indices are not suitable for studying temporal and spatial evolution of non-vegetation objects. Vegetation indices are most effective when the main interest is studying the spatial and temporal variation of vegetation density. Vegetation indices lack the ability to determine which types of vegetation are in different location at different times, since they measure greenness. To get a better understanding of spatial and temporal variation of different end members (objects), image classification techniques are used (Lillesand *et al.*, 2007). Image classification technique involves the use of spectral features of different end members to classify images taken at different periods of time (Lillesand *et al.*, 2007). By quantifying the area that different end members are occupying at different periods of time, one can determine the evolution of the land surface with time. There are two major types of classification techniques used in land cover change detection namely: unsupervised and supervised classification.

3.1.1. Unsupervised classification

In this classification technique, the classifying algorithm automatically recognizes and organizes different features into different classes (Lillesand *et al.*, 2007; Hay *et al.*, 2000). The software uses statistical method to determine the natural clustering of the pixels in the image (Murayama and Thapa, 2011). Those pixels that are closely related in terms of spectral features are placed into the same groups while those that are different are placed in different groups. The assumption here is that pixels belonging to the same class will have similar spectral characteristics while those belonging to different classes will not. The main advantage of this technique is the fact that prior knowledge of the area under study is not required. It is therefore the most appropriate classification technique for use in cases where ground truth data is not available and cannot be easily acquired. This would, for example, be the case when studying areas that are not easily accessible. The disadvantage of this technique is the fact that the analyst has to relate the classes generated by the classifying algorithm to real land cover types in order to make sense of data. This is a potential problem of these techniques since the classes generated automatically would not necessarily match the land cover classes present in the area of interest.

3.1.2. Supervised classification

On the other hand, supervised classification, involves use of auxiliary data to assist the classifying algorithm classify the images. The classifying model is “trained” to recognize different end members (objects) in an image and then instructed to classify the whole image using this information. A combination of fieldwork, aerial photograph interpretation, personal experiences and map analysis, can be used to obtain the "training" information required to training the classifying model (Murayama and Thapa, 2011; Jensen, 2007; Lillesand *et al.*, 2007; Jensen, 1986). In this case the analyst needs to provide the spectral characteristic of each class.

Generally, supervised classification involves three stages (Hay *et al.*, 2000). The first stage involves training of the model, where pixels representing different end members are identified and their spectral statistics extracted. The second stage involves use of the training statistics so obtained together with classifying algorithms to allocate each pixel in the image to the appropriate class. The final stage involves classification accuracy assessment where the accuracy of classification achieved in stage two is quantified. The main advantage of supervised classification is the fact that the map so generated matches well with existing land cover types. The potential problem with supervised classification is the fact that "training" data is not always available. Some areas have no land cover maps and the processed of collecting data from the field may proof to be very expensive especially when dealing with very remote areas.

3.2. Spectral Response of Vegetation and the Concept of Vegetation Indices

Chlorophyll in the leaves of plants absorbs highly in the visible (VIS) part of the electromagnetic radiation. This means that the reflectance of the leaves in the visible region of the electromagnetic radiation is very low. At the same time, leaves reflect highly in the near infrared (NIR) portion of the electromagnetic radiation. According to (Jensen, 2007), healthy vegetation has reflectance of about 46% in the Near Infrared (700 to 1000nm) portion of the electromagnetic spectrum. This is largely due to the plant mesophyll layer present in the internal structure of plant leaves. This plants spectral response is referred to as 'red edge' and is the basis of some vegetation indices like NDVI (Huete *et al.*, 2002; Myneni *et al.*, 1995).

Although leaf reflectance is dependent on its pigment concentration, it is worth noting that other factors do affect the way the leaves interact with electromagnetic radiation in the forest canopy. At the canopy, other factors apart from the leaves' pigment concentration, affect the reflectance of the canopy in general. Such factors include size and shape of the leaves, ground cover, shadows as well as the reflectance of soil surface (Blackburn, 2007; Sellers, 1985). According to Running *et al*. (1989), the water quantity in the leaves and the internal structure of the leaves do affect the reflectance, absorption and transmittances of radiation. Also leaves below the canopy surface suffer from shadowing from the leaves above them. These factors interfere with the actual relationship that exists between the spectral reflectance of leaves and the concentration of chlorophyll. Consequently, the spectral characteristics of plants observed in laboratory experiment do not match exactly with what is observed in the field.

3.2.1. The Normalized Difference Vegetation Index (NDVI)

Normalized Difference Vegetation Index (NDVI) has been used widely in forestry, rangeland, agriculture, and environmental studies (Karnieli *et al.*, 2001). Various researchers have shown that NDVI is highly correlated with canopy closure, leaf area index (LAI) and most importantly green biomass (Sellers, 1985; Tucker, 1979). Since NDVI is normalized, it minimizes the effects of differential solar illumination of slopes while at the same time normalizing the brightness values differences between multi-temporal images (Lillesand *et al.*, 2007; Lyon *et al.*, 1998). NDVI can be expressed as follows:

$$NDVI = \frac{\rho NIR - \rho VIS}{\rho NIR + \rho VIS} \qquad 3.1$$

Where: ρNIR is the reflectance in the Near Infrared channel, and ρVIS is the reflectance in the visible Red channel.

The Values of NDVI range from -1 to +1 where the negative values indicate absence of vegetation and values higher than 0.8 indicate regions with very dense vegetation (Huete *et al.*, 1999; Myneni *et al.*, 1995). However, as noted earlier, NDVI has several shortcomings which include saturation and sensitivity to aerosols. These limitations have prompted development of other vegetation indices that are relatively resistant to aerosols and saturation. Such vegetation indices include Soil Adjusted Vegetation Index, Enhanced Vegetation Index (EVI), Atmospheric Resistant Vegetation Index (ARVI), Soil Adjusted and Atmospheric Resistant Vegetation Index (SARVI) and Aerosol Free Vegetation Index (AFRI) (Ben-Ze'ev *et al.*, 2006; Karnieli *et al.*, 2001; Kaufman and Tanre, 1992; Huete, 1988). Two of these Vegetation indices (SAVI and EVI) are discussed in section 3.2.2 and 3.2.3 due to their widespread use by various researchers in vegetation studies especially in areas characterized by sparse vegetation (Jiang *et al.*, 2008; Huete, 1988).

3.2.2. Soil Adjusted Vegetatoion Index (SAVI)

Soil Adjusted Vegetation Index (SAVI) was developed to deal with problems associated with NDVI. According to Huete (1988), SAVI is aimed at eliminating the influence of soil background to the measured vegetation index. SAVI is generally similar to NDVI with the exception of an addition of soil adjustment factor "L" which correct for the variation in soil background condition. Although L can take different values depending on the area being studied, Huete (1988) recommend a value of 0.5. SAVI has been shown to be more resistant to temporal and spatial variation of soil wetness than NDVI. SAVI is given by:

$$SAVI = \frac{\rho NIR - \rho VIS}{\rho NIR + \rho VIS + L}(1 + L) \qquad 3.2$$

Where ρNIR and ρVIS are the reflectance in the near infrared and Red bands respectively and L is the soil adjustment factor. The main weakness of SAVI is its susceptibility to variation in the atmospheric condition (Qi *et al.*, 1993). To deal with this and other problems associated with SAVI, some researchers have developed different variations of SAVI that are resistance to the influence of atmosphere in addition to being resistance to the effects of soil background. These indices include Modified Soil Adjusted Vegetation Index (MSAVI), Transformed Soil Adjusted Vegetation Index (TSAVI) and Optimized Soil Adjusted Vegetation Index (OSAVI) (Gilabert *et al.*, 2002; Steven, 1998; Rondeaux *et al.*, 1996; Baret *et al.*, 1989).

3.2.3. Ehanced Vegetation Index (EVI)

Enhanced Vegetation Index (EVI) was developed specifically for use with MODIS data (Jiang *et al.*, 2008). EVI is generally resistance to soil and atmospheric effect and does not saturate as easily as NDVI in regions of High biomass. EVI is defined by:

$$EVI = G\frac{N - R}{N + C_1 R - C_2 B + L} \qquad 3.3$$

Where, N, R and B , are surface reflectances in red, near infrared, and blue bands respectively. G is the gain factor, while C_1 and C_2 are aerosols correction coefficients used in combination with the blue band to correct for aerosols effects in the red bands using the blue band (Matsushita *et al.*, 2007). L is the soil adjustment factor used to correct for soil background effect (Jiang *et al.*, 2008). In general, L = 1, C_1 = 6, C_2 = 7.5, and G = 2.5. EVI is therefore corrected for both soil and atmospheric effects. EVI has been used successfully to study regions that have very high vegetation density, like the Amazon forest (Huete *et al.*, 2006) due to its ability to resist saturation in densely vegetated areas. It should however be noted that EVI uses the blue band which limit its use as majority of earlier satellite sensors, such as AVHRR, did not have this band (Jiang *et al.*, 2008). EVI has also been shown to be more sensitive to topographic effects than NDVI due to the soil adjustment factor "*L*" (Matsushita *et al.*, 2007)

3.3. Satellite Based Land Surface Temperature (LST) Estimates

MODIS LST is another product produced by the MODIS science team that was used in this study. MODIS LST products are generated from bands 31 and 32 using Split Window Technique described by (Wan and Dozier, 1996). The Split Window Technique is used under the assumption that the differences in surface emitted radiance in the two bands are caused by atmospheric interference (Guo *et al.*, 2012). The spectral radiance of the two bands (band 31 and 32) are calculated using the Planck's function, B(λ, Ts). Planck's function on itself gives an estimate of the Energy that a blackbody (a body whose emissivity is one) would emit at a given temperature. To estimate the same for real objects, the Planck's function is multiplied by the emissivity of the body (Dash *et al.*, 2002). In other words, the energy emitted $L(\lambda, T)$ at wavelength λ by a body with emissivity $\varepsilon(\lambda)$ that is at temperature T_s is given by equation 3.4 (Dash *et al.*, 2002).

$$L(\lambda, T_s) = \varepsilon(\lambda)B(\lambda, T_s) = \varepsilon(\lambda)\frac{c_1\lambda^{-5}}{\pi(exp\left({}^{c_2}/_{\lambda T_s}\right)-1)} \qquad 3.4$$

Where $B(\lambda, T_s)$ is the Planck's function ($Wm^{-2}\ \mu m^{-1}\ sr^{-1}$); $L(\lambda, T_s)$ spectral radiance of the body ($Wm^{-1}\mu m^{-1}sr^{-1}$); λ wavelength of the emitted radiation (µm); $\varepsilon(\lambda)$ the emissivity of the body at wavelength (λ); T_s the temperature (K); c_1 and c_2 are universal constants. By making T_s the subject of the formula, the above equation can be used to estimate the Temperature of an emitting body.

$$T_s = \frac{c_2}{ln[\frac{\varepsilon(\lambda)c_1}{\pi\lambda^5 L(\lambda, T_s)}]} \qquad 3.5$$

4. METHODOLOGY

To achieve the objectives of this study, satellite based measurements were used. The NDVI datasets were extracted from level 3 MODIS 250m spatial resolution NDVI products (MOD13Q1). The Land Surface Temperature (LST) datasets were extracted from MOD11C3 products and the precipitate estimates were extracted from the TRMM-3B43 products. These datasets were processed using several software that included ENVI 5.0, Erdas Imagine 11.0, Idrisi 17.0, ArcGIS 10.0, TiSeG, Matlab 7.12 and Timesat 3.2.

4.1. Image Data Requisition and Processing

4.1.1. MODIS NDVI product (MOD13Q1)

MOD13Q1 images were acquired from the NASA website (http://ladsweb.nascom.nasa.gov/). Two tiles (h21v08 and h21v09) were required to cover the whole of the Mau Forest Complex. Images downloaded covered the period extending from February 2000 to February 2014, which totaled to 644 images, with a size of about 142 GB. Only MODIS images taken by the Terra satellite were used in this project due to the fact that they are relatively cloud free. Images taken by Aqua tend to be contaminated by cloud due to the fact that clouds tend to be dense in the early afternoon (The overpass local time for Aqua). The equatorial overpass local time for Aqua is 1.30 pm while that of the Terra satellite is about 10.30 am. After acquiring all the necessary images, they were preprocessed to prepare them for further processing. Using MRT (MODIS Re-projection Tool), the MOD13Q1 images were re-projected from sinusoidal projection to UTM zone 37S projection and Datum WGS-84.

4.1.2. Quality Analysis of NDVI data

Although the *Constrained View Maximum Value Compositing Method* (CVMVC) used to compose the MOD13 NDVI products from the 16 days data can reduce the number of poor quality pixels, it is worth noting that sometimes there are fewer than five pixels (Huete *et al.*, 2002). In the Mau Forest Complex, which is a tropical rainforest, it is expected that some area may record zero cloud free pixels during the 16 days. In other words, despite the effort that is applied towards removal of noise from MODIS images by the compositing method, some noise will still persist. To enable users establish the quality of each pixel in an image, MOD13Q1 products come with additional per pixel quality information dataset known as *Quality Assurance Science Data Sets* (QA-SDS) (Huete *et al.*, 2002). QA-SDS provide quality information of each pixel in an image and can therefore be used to flag out and subsequently eliminate poor quality pixels. In this study, Time Series Generator (TiSeG) software package (Colditz *et al.*, 2008; Colditz, 2007) was used to carry out quality analysis and interpolation of the low quality pixels.

TiSeG generates two critical indices that give information on the quality of the pixels in the images being analyzed (Colditz *et al.*, 2008; Colditz, 2007). The first index is the "invalid pixels" which give a general idea of how many pixels are valid at a given point over the entire period of interest. The more valid pixel (less invalid pixels) there are at a given point in the image, the easier it would be to generate a time series that depicts the actual state of vegetation on the ground. The second index is the "maximum gap length" which is the highest number of consecutive poor quality pixels at a given point. This value indicates the feasibility of using interpolation technique to fill the pixels that have low quality data. Balance between data quality and data quantity can be achieved by modifying the quality of pixels that are acceptable. TiSeG classifies all pixels using the vegetation usefulness index that accompanies MODIS data. The Vegetation usefulness index ranges from 0 to 15, where 0 marks pixels with the highest quality (labeled "perfect"), and 15 marks pixel with the lowest quality (labeled "Not useful"). In this study, it was determined that a good balance between data quality and data quantity was achieved when only pixels with NDVI usefulness index between 0 ("Perfect") and 5 ("intermediate") were used. The low quality pixel values were interpolated using linear interpolation technique, which assumes that NDVI values vary steadily with time.

The images for 2000 and those for 2014 were merely used here as "shoulder" data (Colditz *et al.*, 2008) for interpolating any invalid pixels that could have been present at the start and/or the end of the time series. After the quality analysis and interpolation was completed, these "shoulder" data were removed from the series so that only those images acquired between January 2001 and December 2013 were left. These images were stacked together into one image that had 322 bands using ERDAS IMAGINE 11.0 software. ERDAS IMAGINE was used here because the ENVI software had problems processing the output of the TiSeG software.

Using Mau Forest Complex Legal boundaries shape files acquired from Department of Resource Survey and Remote Sensing (DRSRS), the average NDVI values of the nine blocks of Mau were extracted in the ENVI 5.0 software environment. The results of this operation were exported to the Microsoft excel for further analysis. Among the operations executed in excel include extraction of NDVI time series at 16 days, monthly and annual intervals. The annual mean NDVI images were generated by averaging the 16 days images present in each year.

Although MODIS NDVI data is corrected for atmospheric effects and geometric errors, there are still some residual errors that are left behind (Eklundh *et al.*, 2007). To correct for this remnant errors, NDVI dataset were smoothened using Adaptive Savitzky-Golay filter present in the TIMESAT program (Jönsson and Eklundh, 2004). Several authors have successfully used this software package to smoothen NDVI time series data (Eklundh *et al.*, 2009; Gao *et al.*, 2008; Olofsson *et al.*, 2008; Heumann *et al.*, 2007). According to Hird and McDermid (2009) atmospheric related noise causes a negative bias in NDVI time series. This is because atmospheric aerosols, low sun zenith and off-nadir viewing angles reduces the amount of near infrared radiation reflected from the land surface and therefore reduce the value of NDVI (Goward *et al.*, 1991; Gutman, 1991; Holben, 1986). Generally, Savitzky-Golay filter is able to correct for this negatively biased noise while at the same time preserving the higher values. Also according to (Jönsson and Eklundh, 2002), Savitzky-Golay is very effective at filtering time series data that has low level of noise, which is the case for data enhanced by TiSeG software package.

4.1.3. Land Surface Temperature Data (MOD11C3)

MODIS Land Surface Temperature (LST) (MOD11C3) data for the years 2001-2013 for the areas of interest were downloaded from the same website as the MOD13Q1 and re-projected to the same projection as MOD13Q1. The MOD11C3 images were also resampled to 1 by 1 km. The MOD11C3 product has a temporal resolution of one month and spatial resolution of about 0.05 by 0.05 degrees, which is approximately 5.6×5.6 km^2 (Wan *et al.*, 2004; Wan and Li, 1997). This implies that about 156 MOD11C3 images were used in this analysis. In this study, only Terra daytime LST images were used due to the fact that they are statistically less likely to be contaminated by clouds. In addition to this, only the Thermal Infrared (TIR) bands are operational in the MODIS sensor during the night, thus limiting cloud cover evaluation and correction (Neteler, 2010). Using ENVI software, Mau Forest Complex shape files and Microsoft excel, mean monthly LST and mean annual LST were extracted for each of the nine forest blocks. These average monthly LST values together with average annual LST were used to determine the variation of vegetation density and health with variation in LST. The LST values were stepped up by 0 to 3 months ahead of NDVI to determine when the relationship is strongest.

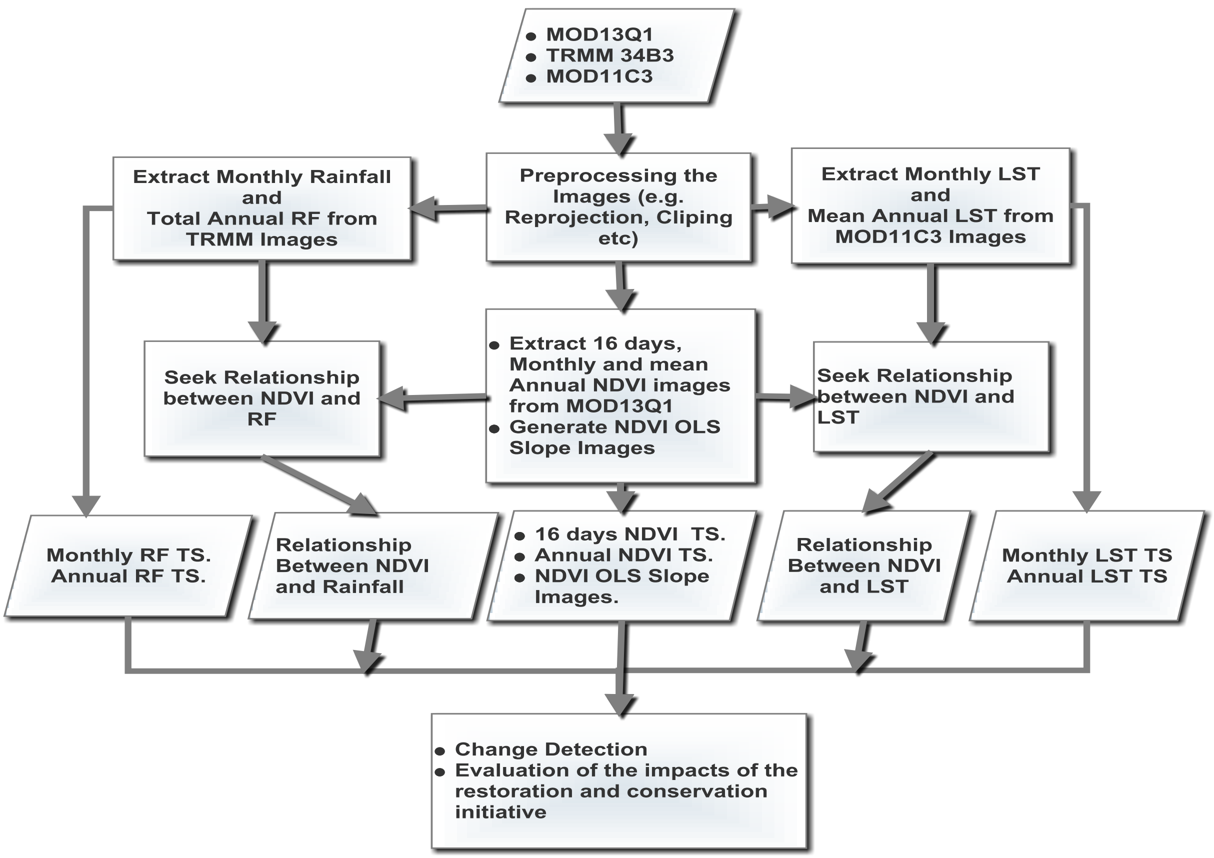

Figure 4-1: Flow Chart showing summary of the Methodology. In the Figure, RF stands for “Rainfall”, TS stands for “Time Series” and RF TS stands for “Rainfall Time Series"

4.1.4. Rainfall Data (TRMM 3B43)

TRMM 3B43 images were downloaded from Mirador website (http://mirador.gsfc.nasa.gov/) in the Network Common Data Form (NetCDF) file format. Using ArcGIS, these images were re-projected to the same projection as the MODIS datasets and stacked together. The resultant image was a 156 multiband image containing monthly rainfall data from January 2001 to

December 2013. Using ENVI software and the Mau Forest Complex shape files, the monthly rainfall in mm/hr. were extracted from the nine block of Mau Forest Complex. This monthly rainfall data were converted from mm/hr. to mm/month by multiplying the average hourly rainfall data for each month by the number of hours in the month. The monthly rainfall estimates for each year were in turn summed up to obtain the total annual rainfall for each year. TRMM 3B43 data sets were selected for use in this study due to their relatively higher spatial resolution as compared to those of other satellite based rainfall estimation satellites products like the Global Precipitation Climatology Project (GPCP) (Huffman *et al.*, 2007; Immerzeel *et al.*, 2009; Huffman *et al.*, 2009). The mean monthly and total annual rainfall estimates were then used to investigate how vegetation in the different blocks of the Mau Forest Complex relate to changes in seasonal and annual precipitate.

4.2. NDVI Ordinary Least Square (OLS) Slope Images

Using ENVI 5.0 software package, the 16 days NDVI images from 2001 to 2013 were aggregated into mean annual NDVI images so that all the 322 images reduced to just thirteen images (one image per year). This was achieved by calculating the mean annual NDVI image from the 23 images captured in each year. By doing this, the influence of seasonal variation within a year was minimized. The thirteen images were then separated into two groups; one containing all images extending from 2001 to 2007 (The period before the reclamation initiative began) and 2008-2013 (period after the reclamation initiative began).The images covering the period 2001-2007 were stack together and labeled “2001-2007_image” while those that covering 2008-2013 were stack together and labeled “2008-2013_image”. The Ordinary Least Square (OLS) slopes for each pixel in these two images were obtained using IDRISI 17.0 (Idrisi Selva) Earth Trends Modeler (ETM). According to Jamali *et al.* (2012), OLS performs better than non-parametric methods such as Theil-Sen method and the Mann-Kendall test when dealing with annual NDVI data. The resulting OLS slopes images were then threshold using the standard deviation method, which is frequently used threshold technique in NDVI based change detection (Yacouba *et al.*, 2009).

5. RESULTS, ANALYSIS AND DISCUSSION

5.1. NDVI Time Series of Mau Forest complex (2001-2013)

5.1.1. Eastern Mau Time Series

Eastern Mau, which is actually the forest blocks that experienced the worst form of land degradation in the period leading to 2007 (Olang and Kundu, 2011), recorded the second highest change in slope of the NDVI trend line. The slope of the NDVI trend for Eastern Mau increased from -0.07 (R^2= 0.01) during the 2001-2007 period to +0.31 (R^2=0.09) during the 2008-2013 period, which is an increase in slope of the NDVI trend of about 0.38. Between 2001 and 2007, the NDVI values were decreasing despite the fact that the rainfall was fairly constant (Figure 5-2). The temperature was also decreasing meaning that the change in NDVI values was not caused by temperature dependent processes like evapotranspiration (Figure 5-3). It is therefore reasonable to conclude that this decrease in the NDVI values was caused by other factors other than rainfall and temperature. It is during this period that the Mau Forest Complex experienced the highest excision and therefore high rate of forest degradation (Olang and Kundu, 2011; Raini, 2009). Eastern Mau is one of the Forest blocks that was targeted by the 2001 excision.

However, this forest block does show some improvement in vegetation density between 2008 and 2013. During this period, the NDVI time series trend line slope is positive and is higher in magnitude than that for 2001-2007. This period also witnessed an increase in rainfall and a substantial decrease in temperature. In other words the environmental conditions were conducive for vegetation growth and development. The forest block responded positively to the existing environmental conditions during this period unlike in 2001-2007 suggesting that the pressure that was inhibiting growth and development of the forest was eliminated. This could be a response of the forest to the restoration and conservation initiative that saw eviction of settlers from the forest and plantation of new trees during this period.

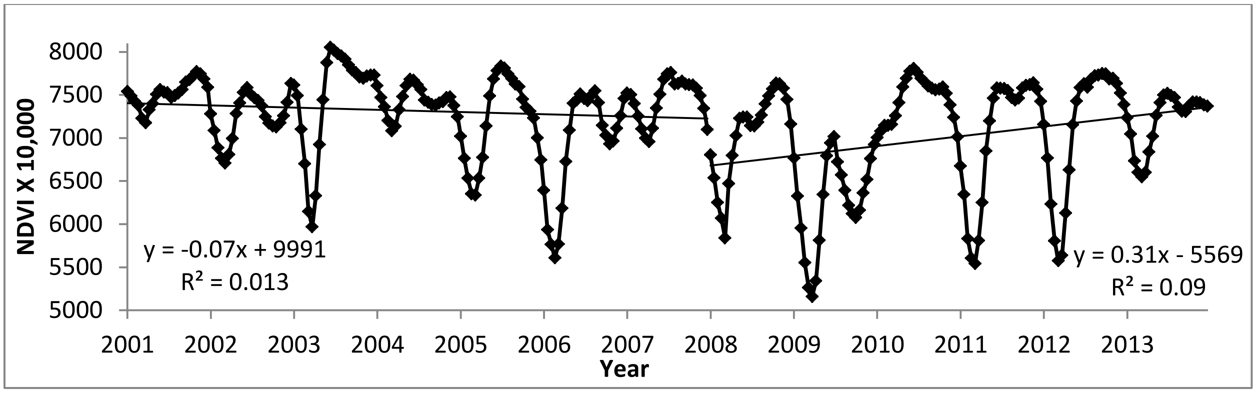

Figure 5-1 NDVI Time series at 16 days interval for Eastern Mau (2001-2013)

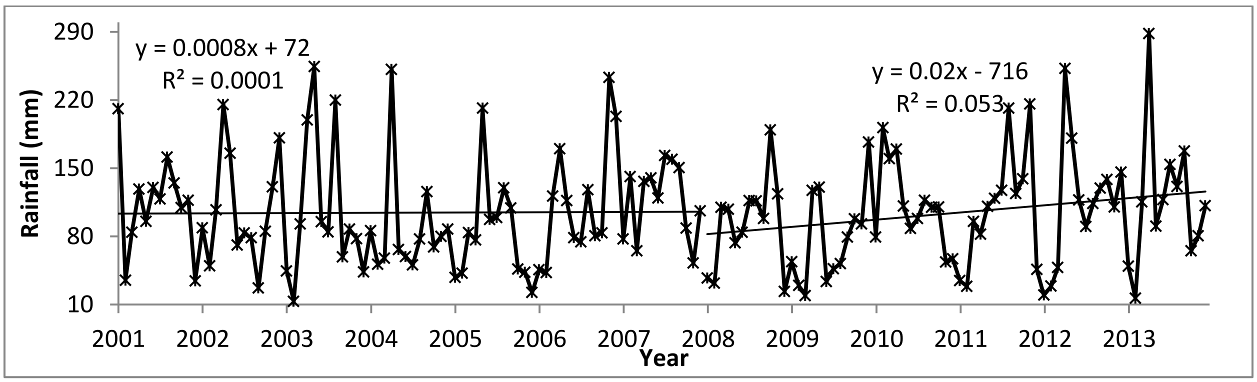

Figure 5-2 Rainfall at one month interval for Eastern Mau (2001-2013)

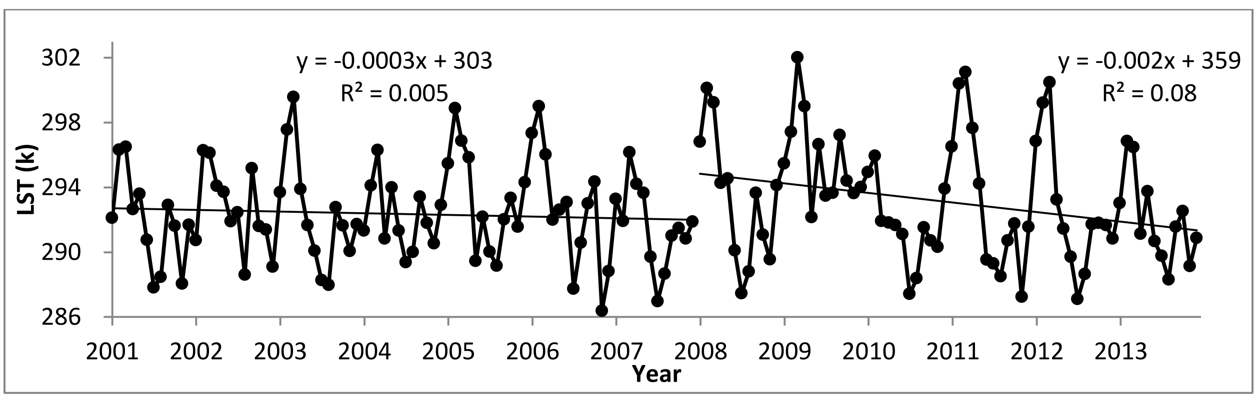

Figure 5-3 LST at one month interval for Eastern Mau (2001-2013)

5.1.2. Tinderet Time Series

Tinderet recorded positive values of the NDVI time series slopes in the two periods suggesting that this forest block has remained relatively stable over the thirteen years (Figure 5-4). In 2001-2007, the NDVI slope was +0.069 while that of rain was +0.008. In 2008-2013 the NDVI slope was about +0.05 and that of Rainfall +0.02 (Figure 5-4 and Figure 5-5). The slope of temperature time series did not change much during these two periods (Figure 5-6). These results suggest that rainfall may have been responsible for the increase in NDVI in the two periods. However, the increase in NDVI with rainfall was not linear since the 2008-2013 received higher rainfall than 2001-2007 periods yet the NDVI slope for 2001-2007 was higher than that for 2008-2013. It is also possible that this was caused by variation in rainfall pattern, especially the 2009 and 2012 droughts that exerted huge negative pressure on the vegetation.

The minimum bimonthly NDVI for this forest was actually recorded in 2012, a year characterized by a long period of less than average rainfall. This implies that prolonged periods of drought will affect the forest despite its being very dense. In general, Tinderet shows characteristics of a very dense and healthy forest with a minimum NDVI of 0.7. In fact the NDVI time series of Tinderet has a positive slope during the two periods, although the coefficient of determination (R^2) is very low. This implies that Tinderet is one of the most stable forest blocks of the Mau Forest Complex. However, it should be noted that it is possible that there are changes in the forest that are occurring at much smaller scale (less than the 250m, the spatial resolution of the MODIS sensor).

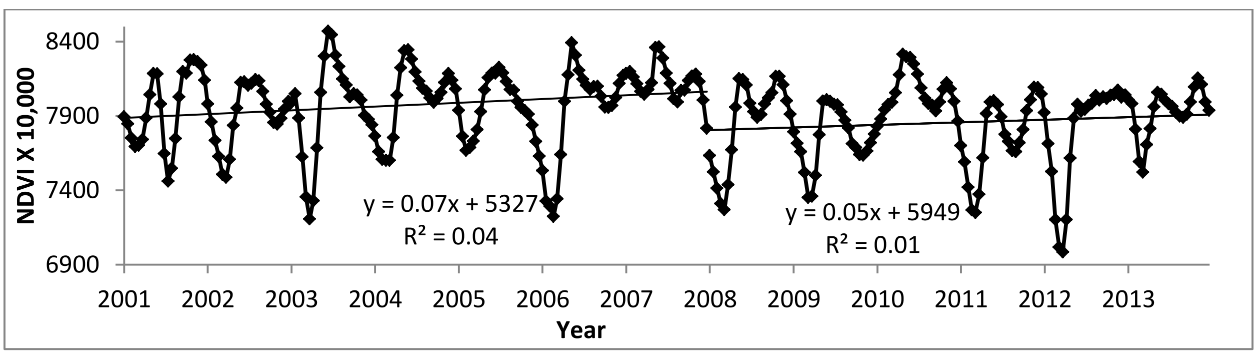

Figure 5-4 NDVI Time series at 16 days interval for Tinderet (2001-2013)

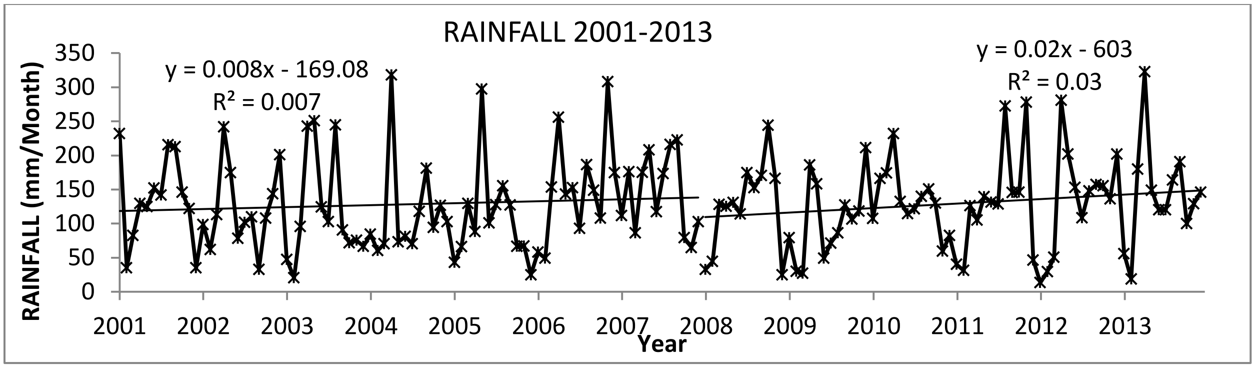

Figure 5-5 Rainfall at one month interval for Tinderet (2001-2013)

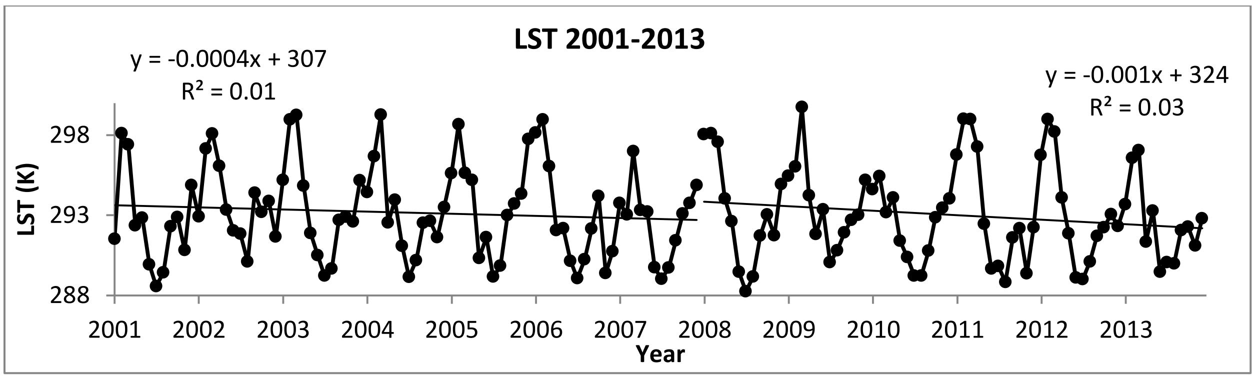

Figure 5-6 LST at one month interval for Tinderet (2001-2013)

5.1.3. Mount-Londiani Time Series

Mount Londiani recorded NDVI slope of +0.07 in 2001-2007 and +0.22 in 2008-2013 (Figure 5-7). The rainfall slope was +0.006 in 2001-2007 and +0.023 in 2008-2013 (Figure 5-8). The temperature had a slope of less than -0.001 throughout the thirteen year period (Figure 5-9). This implies that the increase in NDVI time series slope was most likely caused by the increase in precipitate. This fact also supports the fact that growth and development of vegetation in the Mau Forest Complex depend on the amount of rainfall present. A detailed analysis of how NDVI vary with precipitate is carried out in section 5-3. Mount-Londiani recorded the minimum bimonthly NDVI value of 0.63 in February 2006 (Figure 5-9). In fact Mount-Londiani is the only block that recorded Minimum bimonthly NDVI value in 2006. The maximum NDVI value of 0.84 was achieved in July 2003. The average bimonthly NDVI value for Mount-Londiani is 0.75 implying that it is a dense forest.

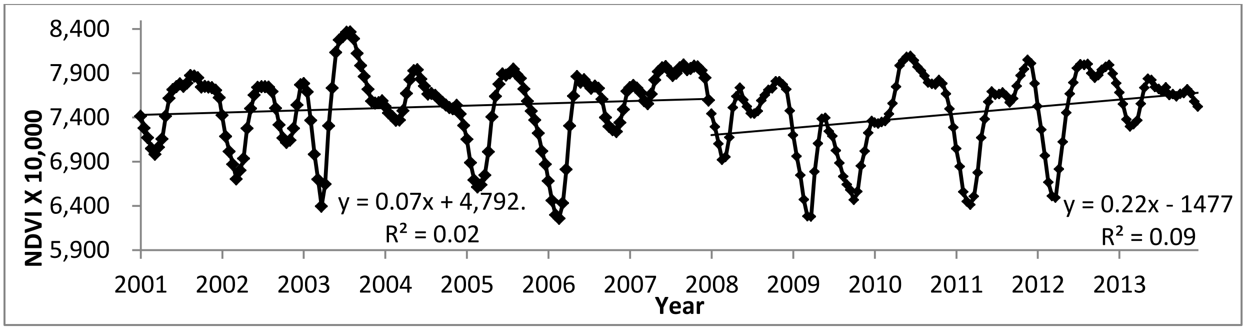

Figure 5-7 NDVI Time series at 16 days interval for Mount-Londiani (2001-2013)

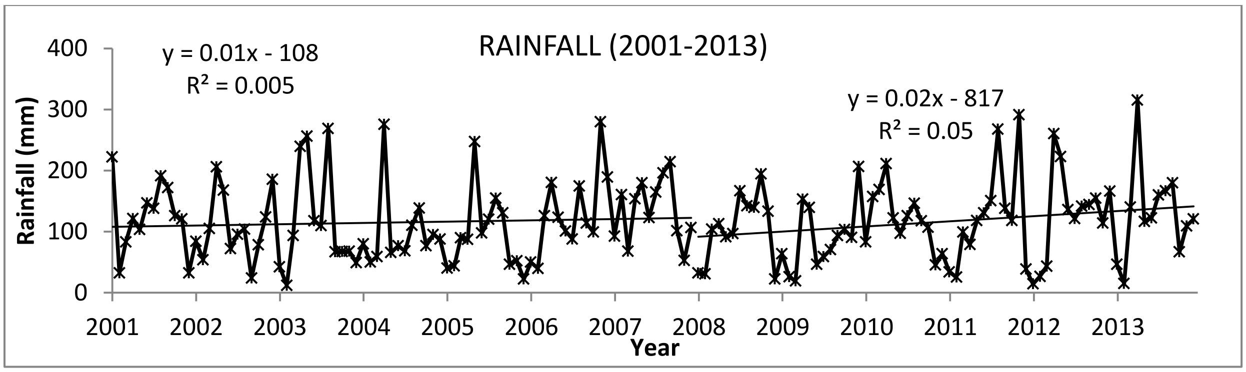

Figure 5-8 Rainfall at one month interval for Mount-Londiani (2001-2013)

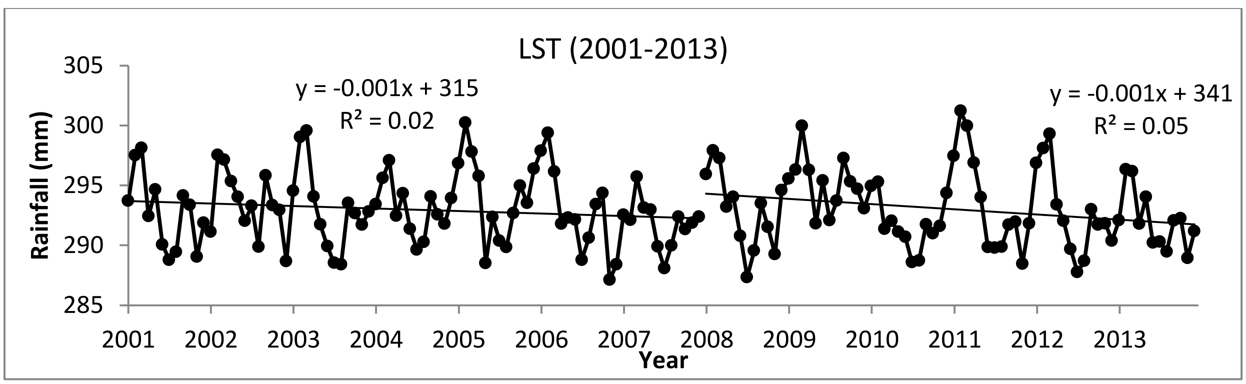

Figure 5-9 Temperature at one month interval for Mount-Londiani (2001-2013)

5.1.4. Western Mau Time Series

Western Mau NDVI time series shows that the slope of the NDVI trend line prior to 2008 was actually close to zero (slope = -0.0009), which implies that the forest block was not undergoing major degradation (Figure 5-10). From 2008 to 2013, the forest block shows a positive slope of the NDVI trend, indicating some form of improvement in biomass. The slope of monthly rainfall also increased from 0.008 to about 0.018 suggesting that the rainfall could have been the cause of this improvement in vegetation condition within the forest over the period of study (Figure 5-11). The lowest value of bimonthly NDVI of about 0.68 was recorded in March 2012, while the maximum value of about 0.80 was recorded in October 2001. The cause of the low NDVI in March 2012 seems to be the low rainfall recorded between December 2011 and March 2012. During this period, the monthly rainfall was maintained below 51mm, with the rainfall falling to 15.9 mm in January 2012 (Figure 5-11).

In fact the combined rainfall for January, February and March 2012 was about 98.8mm, which is very low compared to the mean monthly rainfall of the area, which is about 126mm per month. The only other time that the rainfall dropped to such a low value was in February 2003, and was followed by a drop in NDVI in March 2003. It should however be noted that the drop in NDVI values in March 2003 was lower than that of 2012 due to the fact that although the rainfall recorded in 2003 was low, it did not remain so for a long time. The average bimonthly NDVI is 0.79, implying that Western Mau is one of the densest forest blocks of the nine forest blocks considered here. The maximum NDVI value, of about 0.85, was recorded in October 2001 despite the fact that the highest rainfall was recorded in April 2013. On the other hand, the highest temperature recorded in Western Mau was 302K in March 2009 while the lowest was 289K in July 2008 (Figure 5-12). The average LST for Western Mau was about 294K over the period of study.

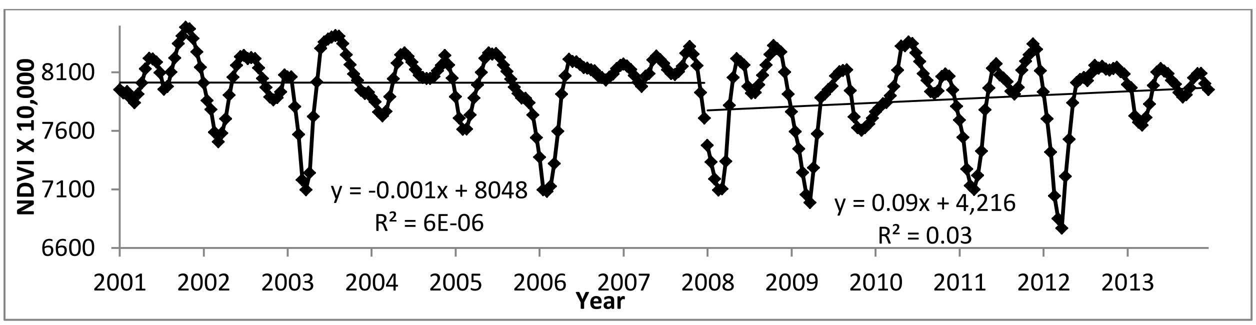

Figure 5-10 NDVI Time series at 16 days interval for Western-Mau (2001-2013)

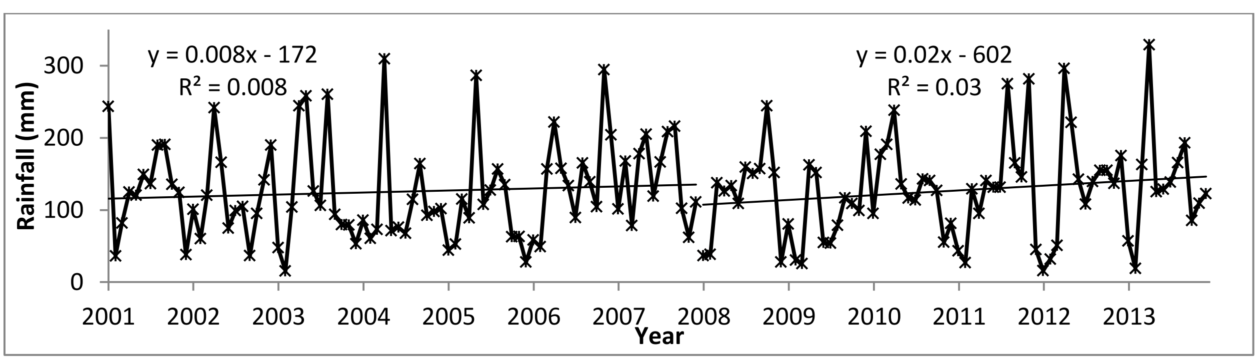

Figure 5-11 Rainfall at one month interval for Western Mau (2001-2013)

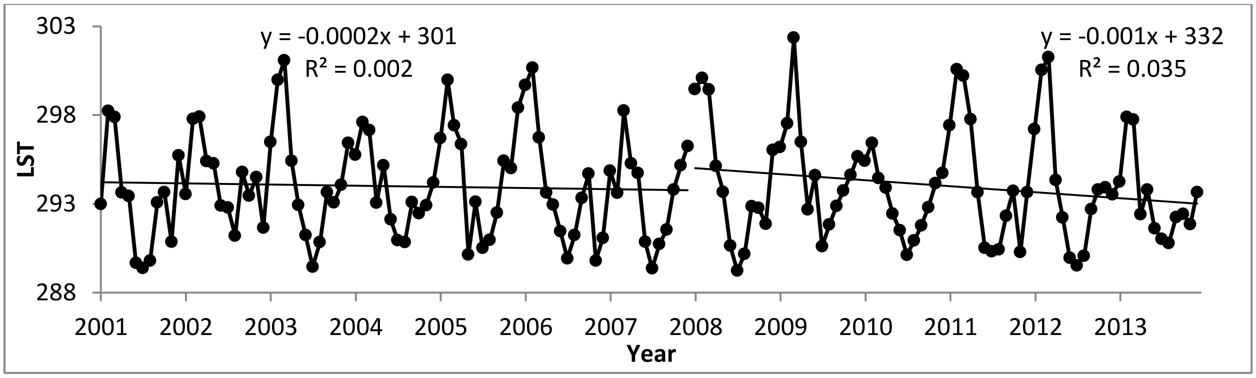

Figure 5-12 LST at one month interval for Western Mau (2001-2013)

5.1.5. Southwest Mau time series

Southwest Mau is one of the forest blocks that were targeted for excision in 2001. It is therefore expected that the NDVI will have a negative slope from 2001 to 2007 depicting the impacts of this unfortunate event. A look at the NDVI time series for this block reveals that the NDVI times series trend line had a slope of about -0.02 (R^2 = 0.004) during the 2001-2007 period and +0.12 (R^2 = 0.038) in the 2008-2013 period (Figure 5-13). The rainfall time series slope for the two periods was about +0.01 implying that on average, the rainfall did not change much during the period of study (Figure 5-14). The shift in the direction of the NDVI slope is therefore likely to be as a result of the restoration and conservation initiative. It is reasonable to expect this given that about 19,000ha of this forest block were recovered during phase 2 of the restoration and conservation initiative (Mau Forest Complex Interim Coordinating Secretariat, 2010).

The minimum bimonthly NDVI of about 0.64 was recorded in March 2012. The total rainfall for January to march was 127mm which is low compared to monthly average rainfall of 133mm. The maximum NDVI of 0.82 was recorded in December 2004. The average bimonthly NDVI value for the area over the period of study was 0.78. The maximum temperature of about 300K (27^{o}C) was recorded in February 2012 while the minimum of about 288K (15^{o}C) was recorded in June 2001 (Figure 5-15). Generally, the highest temperatures are recorded between February and March while the lowest temperatures are recorded between June and July. The other forest blocks show similar LST patterns.

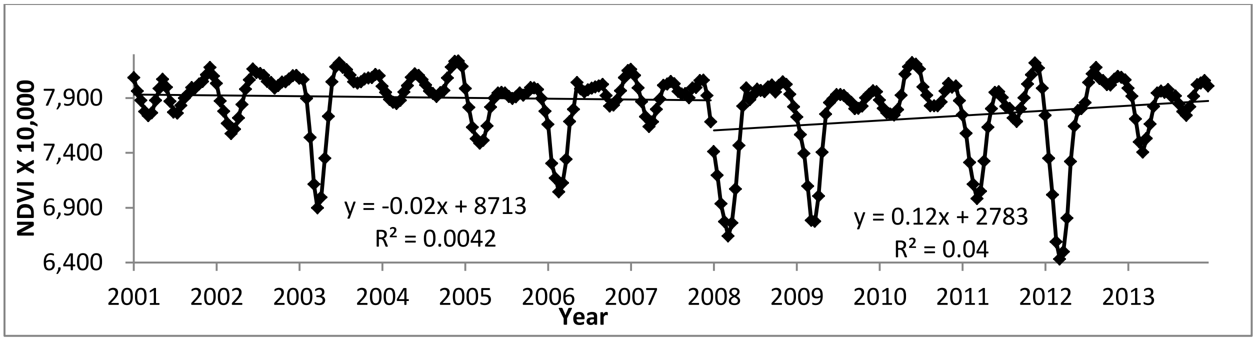

Figure 5-13 NDVI Time series at 16 days interval for Southwest Mau (2001-2013)

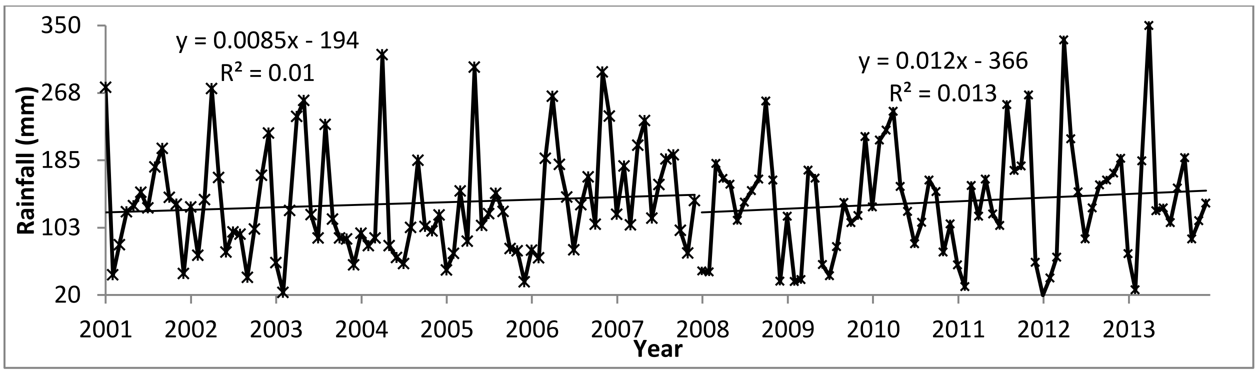

Figure 5-14 Rainfall at one month interval for Southwest Mau (2001-2013)

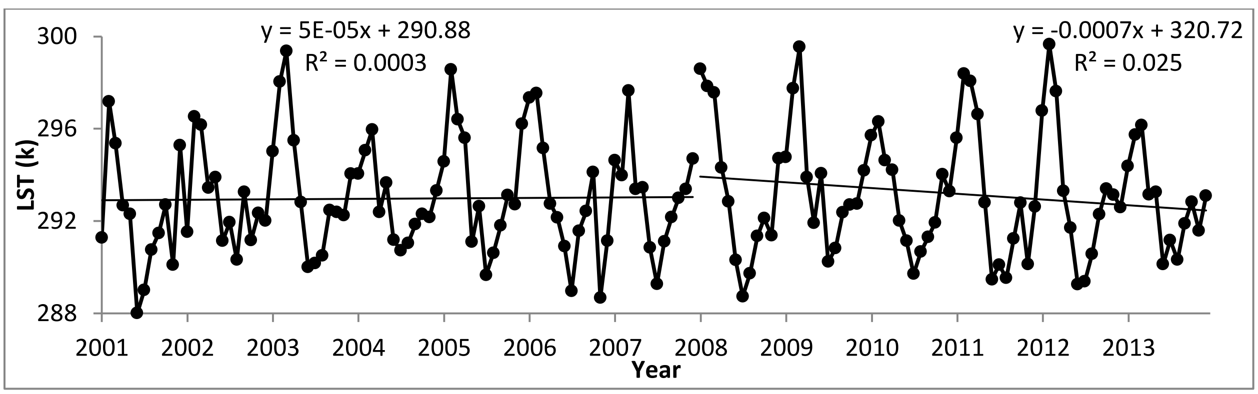

Figure 5-15 LST at one month interval for Southwest Mau (2001-2013)

5.1.6. Transmara Time Series

Transmara is the only forest block that recorded negative slopes for the NDVI trend in both periods. The NDVI slope values were -0.06 in 2001-2007 and -0.03 in 2008-2013 (Figure 5-16). During the whole period the rainfall rate did not change much, implying rainfall was not the cause of this degradation (Figure 5-17). It should also be noted that this forest block receives some of the highest rainfall in the area. Transmara forest block is located close to three major forest blocks of Mau Forest Complex (Maasai Mau, Eastern Mau and Southwest Mau) that have suffered serious human induced degradation especially due to the 2001 excision. This forest block may have suffered some human driven forest degradation due to its proximity to these forest blocks. Being close to these forests and being poorly protected meant that people were highly likely to enter the forest and destroy it especially through extraction of forest resources. However, it should be noted that this forest block recorded the highest bimonthly NDVI values of about 0.86, which implies that the forest still has very high density of vegetation. More effort should be applied to stop further degradation of the forest and ensure that any destruction that has been done is reversed. A look at the NDVI time series of this forest block reveals that it recorded the lowest bimonthly NDVI of about 0.80 in March 2012 and a Maximum bimonthly NDVI of 0.895 in June 2003 (Figure 5-16). The highest LST was recorded in January 2006 while the minimum was recorded in November the same year (Figure 5-18).

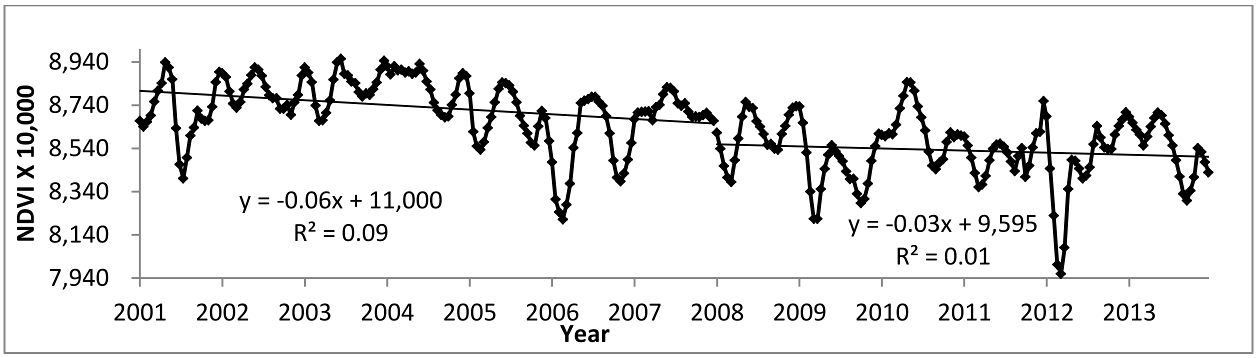

Figure 5-16 NDVI Time series at 16 days interval for Transmara (2001-2013)

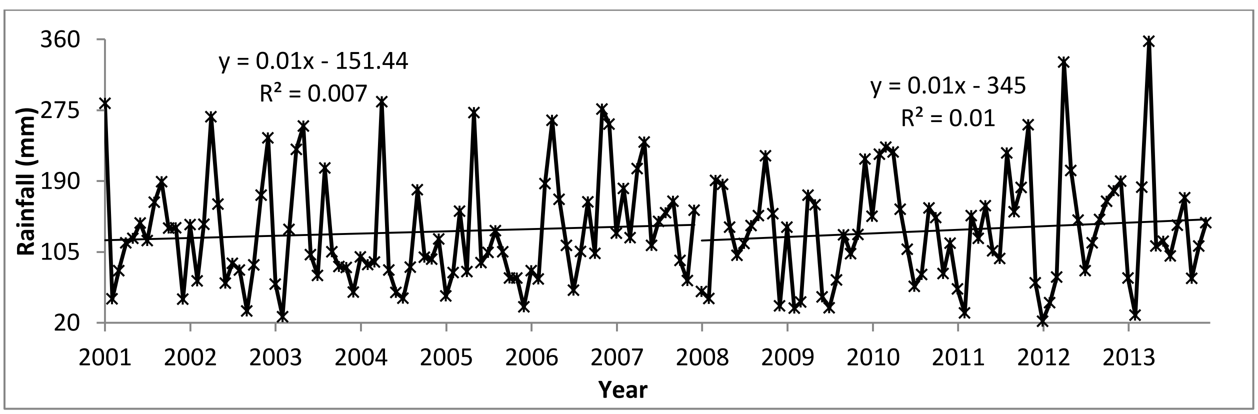

Figure 5-17 Rainfall at one month interval for Transmara (2001-2013)

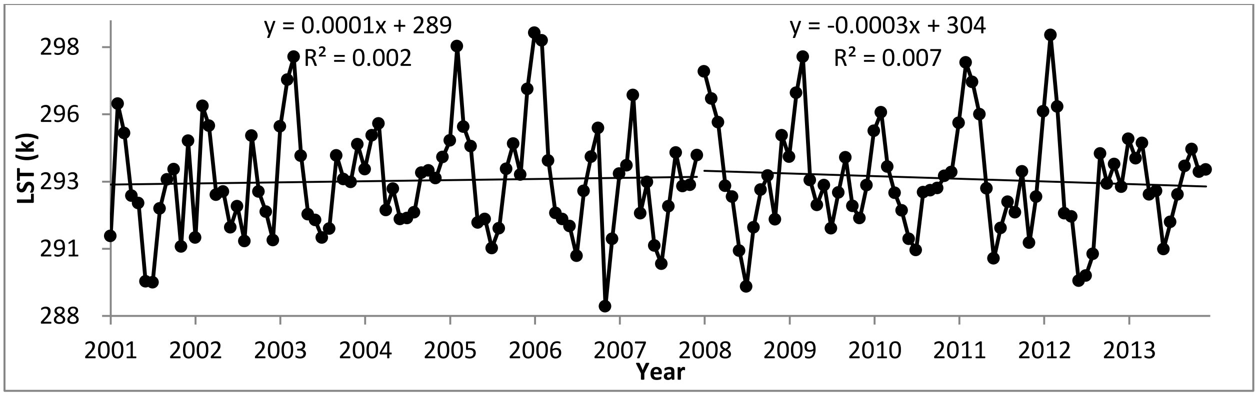

Figure 5-18 LST at one month interval for Transmara (2001-2013)

5.1.7. Maasai Mau Time Series

Maasai Mau is another forest block that has experienced high land cover conversion from forest cover to agricultural land. Figure 5-19 shows that there was an obvious decline in NDVI values for Maasai Mau from 2001-2007 (slope = -0.144, R^2 = 0.26), which indicate a continuous destruction of the forest during this period. Maasai Mau experienced high level of destruction between 2001 and 2007 especially the western part of the forest, mainly due to human encroachment (Olang and Kundu, 2011). During the 2008-2013 period, the NDVI trend leveled off, which may be an indication of success of the initiative. It is worth to note that the NDVI trend for the period covering 2008-2013 is almost flat, suggesting that, the overall density of vegetation in the forest did not necessary increase, but the destruction of the forests was brought to a halt.

Figure 5-20 indicates that the amount of rainfall received by the forest between 2001 and 2007 was mostly stable, hence it unlikely that it caused the obvious decline in vegetation witnessed during this period. However, during the second period (2008-2013), the rainfall did actually record an increase in trend. The positive response of vegetation to this increase in rainfall could be an indication that the factors that were inhibiting vegetation growth and development between 2001 and 2007 have been eliminated. On the other hand, the influence of rainfall on vegetation in this forest cannot be ignored. Between December 2008 and march 2009 this forest block received rainfall below 71.20 mm per month, and this was followed by the deepest drop in NDVI (about 0.69) over the period of study. In general, the rainfall received by the forest block between January 2007 and 2009 was below 157.7mm. The temperature trend remained relatively stable over the period of study, with the highest LST being recorded in June 2001 and highest in March 2009 (Figure 5-21).

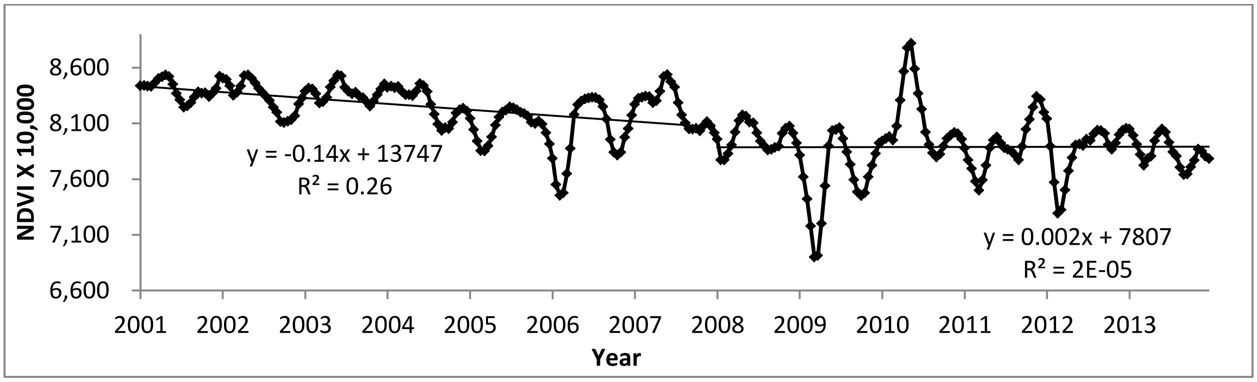

Figure 5-19 NDVI Time series at 16 days interval for Maasai Mau (2001-2013)

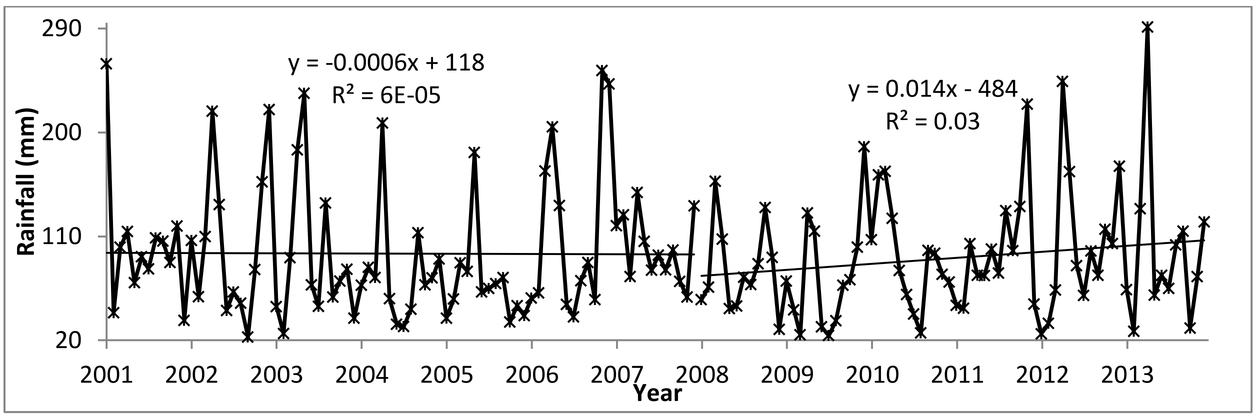

Figure 5-20 Rainfall at one month interval for Maasai Mau (2001-2013)

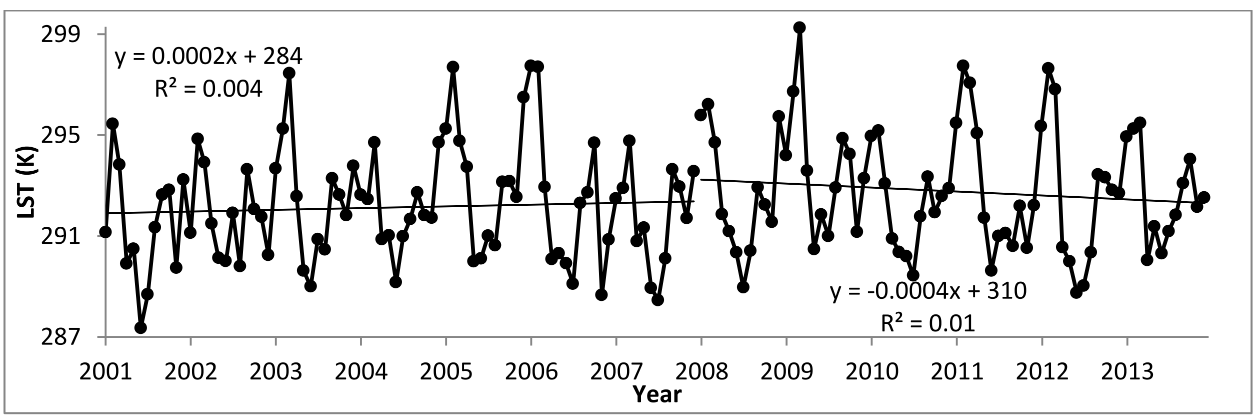

Figure 5-21 LST at one month interval for Maasai Mau (2001-2013)

5.1.8. Eburu Time Series

Eburu is one of the smallest blocks of the Mau Forest Complex and covers an area of approximately 81,400 ha. According to Kamondo (2008) and Rhinoark (2012), this forest block has experienced serious human induced degradation. However, several measures have been put in place to restore and conserve the forest. The fencing project that saw the forest block fenced using electric fence is one of many measures that have been taken to protect the forest (Rhinoark, 2012). This forest block recorded minimum 16-days NDVI value of about 0.64 in March and September 2009 and a maximum of about 0.86 in April 2010. The Low NDVI values in 2009 were most probably caused by low rainfall and very high temperatures witnessed in this year (Figures 5-22 and 5-23). In addition to this, Eburu Mau was among the forest blocks that were affected by fire during this year (Obwocha and Gitonga, 2009; UNEP, 2009). The average 16-days NDVI value was 0.79, which implies that this forest block has much inferior vegetation compared to blocks like Transmara and Western Mau. The NDVI time series slope show that this forest is recovering from the destruction it has suffered in the past.

The NDVI slope increased from -0.09 in 2001-2007 to +0.18 in 2008-2013. This negative slope of 2001-2007 confirms that the forest was undergoing degradation while the positive in 2008 to 2013 period values indicate that the forest is recovering. The rainfall slope also increased from -0.003 in 2001-2007 to 0.02 in 2008-2013 period. The temperatures were on average higher in the 2001 to 2007 period than in the period covering 2008-2013. The increase in NDVI could therefore be due to conservation initiative or improvement in climate. A check at the dependence of NDVI on rainfall in Eburu Mau reveals that the forest has a fair dependency on rainfall (R = 0.47). The regression analysis reveal that in 2001-2007 variation in rainfall could explain about 25% (R^2=0.25) variation in NDVI, while in 2008-2013 it could explain 20% (R^2=0.20). This implies that, although rainfall did contribute to the improvement of vegetation in Eburu, there were also other factors. This could be the effects of restoration and conservation initiative. Figure 5-24 shows that the maximum LST value was recorded in March 2009 while the minimum was recorded in June 2012. There is also an obvious negative trend of LST between 2009 and 2013 corresponding to a positive trend in NDVI and rainfall in the same period.

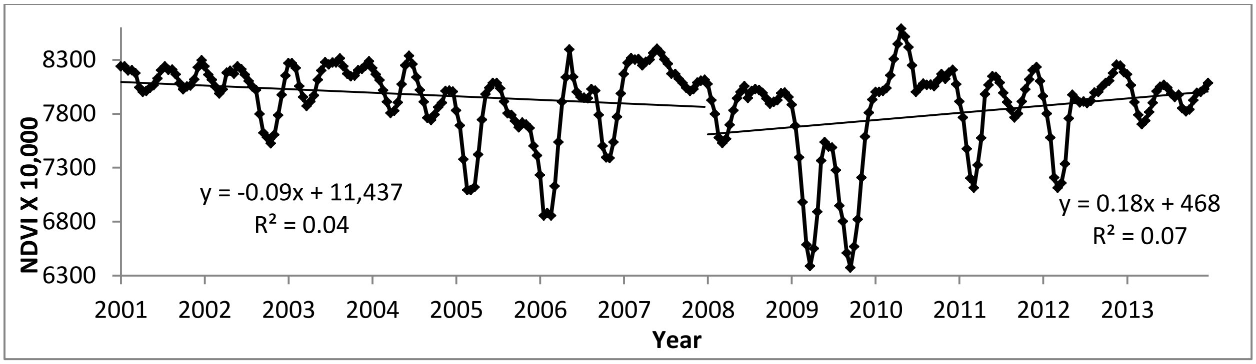

Figure 5-22 NDVI Time series at 16 days interval for Eburu (2001-2013)

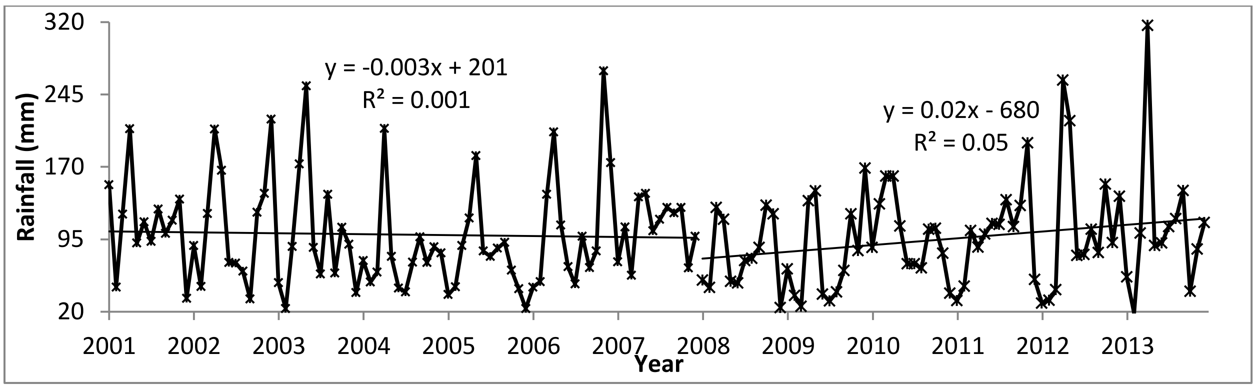

Figure 5-23 Rainfall at one month interval for Eburu (2001-2013)

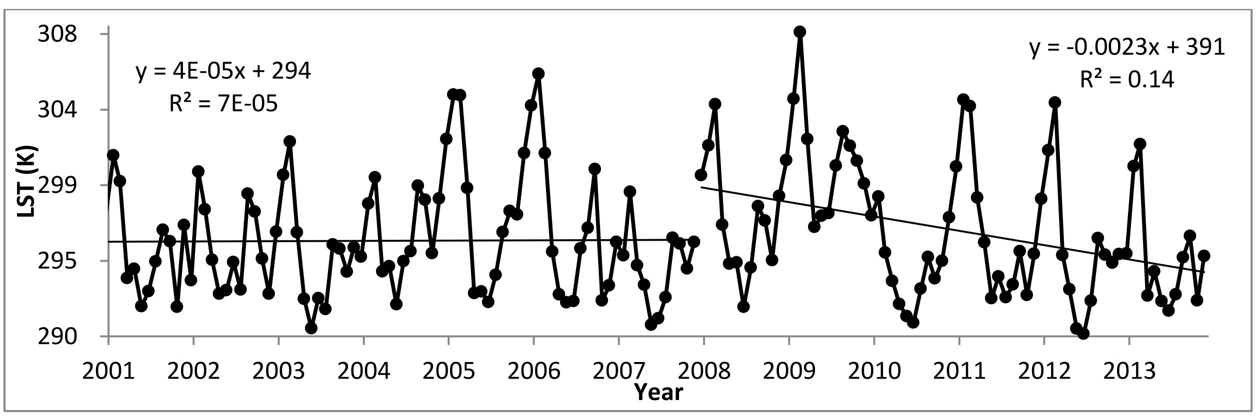

Figure 5-24 LST at one month interval for Eburu (2001-2013)

5.1.9. Molo Time Series

Molo on the other hand shows some improvement on the overall health and vigor of the forest from 2001 all the way to 2013. The NDVI time series slope increases from +0.14 (R^2 = 0.01) in 2001-2007 to +0.54 (R^2 = 0.1) in 2008-2013 (Figure 5-25). The minimum bimonthly NDVI value of about 0.38 was recorded in March 2009, while the maximum NDVI value of about 0.80 was recorded in July 2003. This forest block recorded the lowest minimum NDVI values, implying that of the nine blocks, it has the most inferior vegetation. However, this forest block is showing signs of recovery. However, the improvement seems to be a product of environmental factors rather than the restoration and conservation effort. The rainfall slope increased from +0.01 to +0.02 suggesting that rainfall could be the cause of the increase in NDVI over the period (Figure 5-26). The maximum LST of 399.9 was recorded in March 2009 while the minimum of 387.8 was recorded in November 2006 (Figure 5-27).

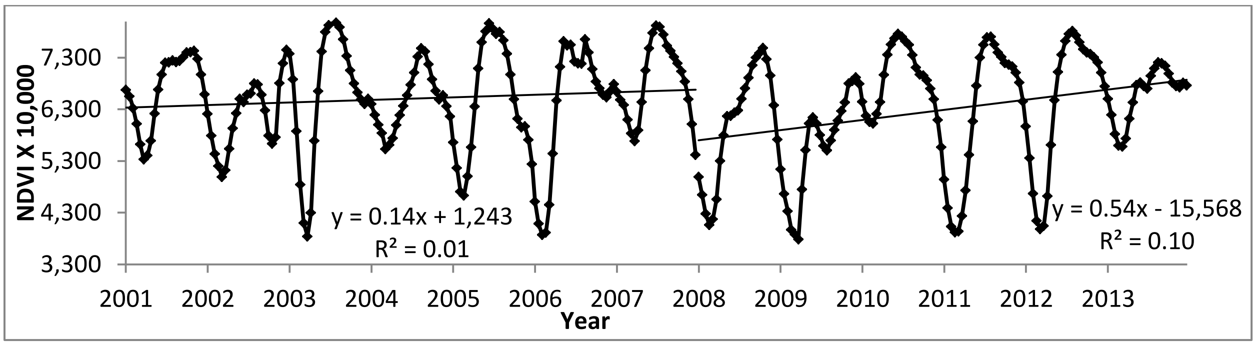

Figure 5-25 NDVI Time series at 16 days interval for Molo (2001-2013)

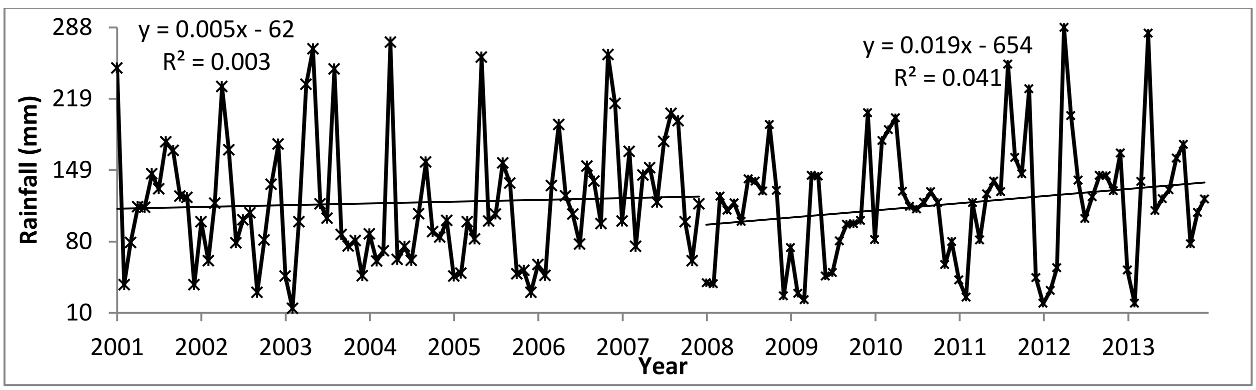

Figure 5-26 Rainfall at one month interval for Molo (2001-2013)

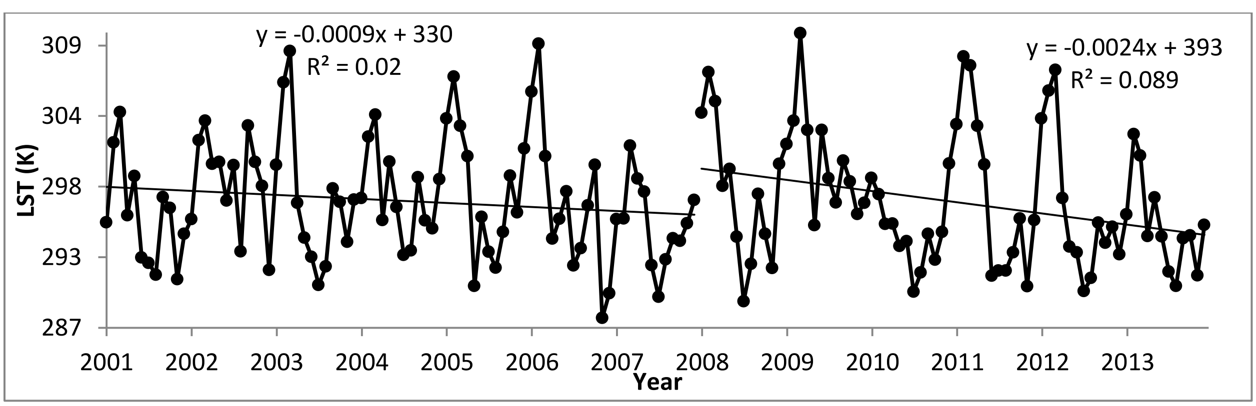

Figure 5-27 LST at one month interval for Molo (2001-2013)

5.2. An overview of NDVI Time Series of the Forest Blocks

The year 2006 is peculiar in that the entire Mau Forest Complex received very high rainfall yet all the forest blocks recorded very low NDVI values. In fact the Mau Forest blocks received maximum rainfall either in 2006 or 2007 during the period of study (2000-2013), yet all the NDVI time series show dips in the NDVI values. These dips cannot be explained by variation in the total annual rainfall since 2006 received generally higher rainfall than 2005. However, a check on the distribution of rainfall in 2005 and 2006 shows that the short rains expected in October to December 2005 failed. This meant that the forest was exposed to a long period (over five months) of abnormally low rainfall thus affecting the vegetation growth and development cycle. It can therefore be argued that the performance of the vegetation within the forest does not depend only of the total annual rainfall but also on the pattern of the rainfall. This idea is supported by the fact that Eburu, unlike the other forest blocks, recorded lower NDVI values in 2005 than in 2006. Most of the Mau Forest Complex show similar dips in 2003, 2009, 2011 and 2012.

Further analysis of NDVI time series graphs show that Eburu Mau, Eastern Mau, Maasai Mau and Molo recorded the lowest NDVI values in 2009, a year that was characterized by very low rainfall. This implies that these forest blocks are highly dependent on the amount of rainfall present within a given period than the other forest blocks. In fact the minimum values of NDVI recorded in these blocks are lower than those recorded in most of the other blocks. The minimum values of NDVI recorded for these forest blocks were 0.38 for Molo, 0.52 for Eastern, 0.64 for Eburu and 0.69 for Maasai Mau. This is an indication of the fact that these forest blocks have relatively inferior vegetation compared to the other forest blocks. Molo is the only forest block that records an NDVI value that is lower than 0.5.

The other four blocks recorded the lowest NDVI values in March 2012, most probably due to poor performance of rainfall. Southwest Mau recorded a minimum NDVI value of 0.64, Tinderet 0.70, Transmara 0.80 and Western Mau 0.68. This implies that Transmara has much more superior vegetation than all the other Mau Forest blocks. However, the NDVI time series trend, as noted earlier, has a negative slope which means the forest block is undergoing some sort of degradation. This could be due to its proximity to Southwest Mau, Maasai and Eastern Mau, all of which have experienced phenomenon human induced forest destruction over the past few decays. In fact the magnitude of bimonthly NDVI slope of Transmara seems to decrease in the period covering 2008-2013. This suggests that eviction of the settlers from the other major blocks of Mau may have reduced pressure that was causing degradation of the forest. On the other hand, Southwest Mau, which borders Transmara to the north, has inferior vegetation compared to Transmara. This is mainly due to human encroachment that affected mainly the eastern part of this forest block. The western part of southwest Mau is much denser than the eastern part.

With exception of Maasai Mau and Eburu, all the Mau Forest Complex blocks recorded the maximum NDVI before 2007. Both Maasai Mau and Eburu recorded the maximum NDVI values in 2010 a fact that can be an indication of success of the rehabilitation of the forest blocks. Eburu is a much smaller block and has attracted the attention of major conservation bodies like RhinoArk (Rhinoark, 2012), which have worked tirelessly to conserve the forest. The small size of Eburu makes restoration and conservation initiative more efficient and effective as the amount of area to monitor and conserve is small. Rhinoark have actually started a project aimed at fencing the entire Eburu Mau, a venture that would be almost impossible to carry out on a larger forest blocks like Southwest Mau. Maasai Mau NDVI time series shows an obvious negative trend from 2001-2007 and then the time series levels off. The leveling off of the Time series slope during the period covering 2008-2013 suggests that the degradation of forest has slowed down, a fact that can be attributed to the conservation and restoration initiative.

According to the NDVI time series graphs obtained, Southwest Mau, Eastern Mau, Maasai Mau and Eburu Mau show a shift in the direction of the NDVI trend. These blocks recorded a negative slope in the period prior to the start of the restoration and conservation initiative and then recorded a positive trend in NDVI over the period after the initiative began. This can be taken as an indicator of success of the initiative in these forest blocks. Tinderet, Mount Londiani and Molo recorded positive trend in the two periods indicating that these forest blocks are generally stable or improving and have not undergone major land cover change over the thirteen year period (2001-2013). Any land degradation that may have occurred in these forest blocks are likely to have occurred at very small scale so that the overall state of the forest was not affected.

On the other hand, Western Mau recorded almost zero slope of the NDVI time series trend line in the first period and then a positive slope in the second period therefore suggesting improvement in land cover. The following sections will focus on the NDVI time series of each of these nine Mau Forest blocks.

5.3. Variation of NDVI with Climatological Parameters

Many climatic factors affect the growth and development of vegetation, but of all climatic factors, temperature and rainfall are the most important (Bachelet *et al.*, 2001; Kawabata *et al.*, 2001). This is due to the fact that both temperature and rainfall have a direct effect on the hydrological cycle through influence of soil moisture and the evapotranspiration process, both of which affect the growth and development of vegetation (Chang *et al.*, 2014). It is through this understanding that this study sort to establish the influence of these two climatic factors on the vegetation dynamics of the Mau Forest Complex.

5.3.1. Rainfall

According to Figure 5-28, Southwest Mau, Transmara and Tinderet receive on average higher rainfall than the other forest blocks, with each of these forest blocks receiving average annual rainfall of about 1500mm. In 2006, each of these three forest blocks received over 1800mm of rain. On the other hand, Maasai Mau, Eburu and Eastern Mau receive the lowest average rainfall which is well below 1300mm per annum. Southwest Mau receives very high rainfall hence the low mean NDVI values recorded are most likely due to degradation. The high Rainfall recorded in Southwest Mau suggest that if the restoration and the conservation initiative is driven in an aggressive manner, the forest can easily recover from the many years of degradation it has experienced. This is due to the fact that rainfall has a strong impact on the growth and development of vegetation in the forest.

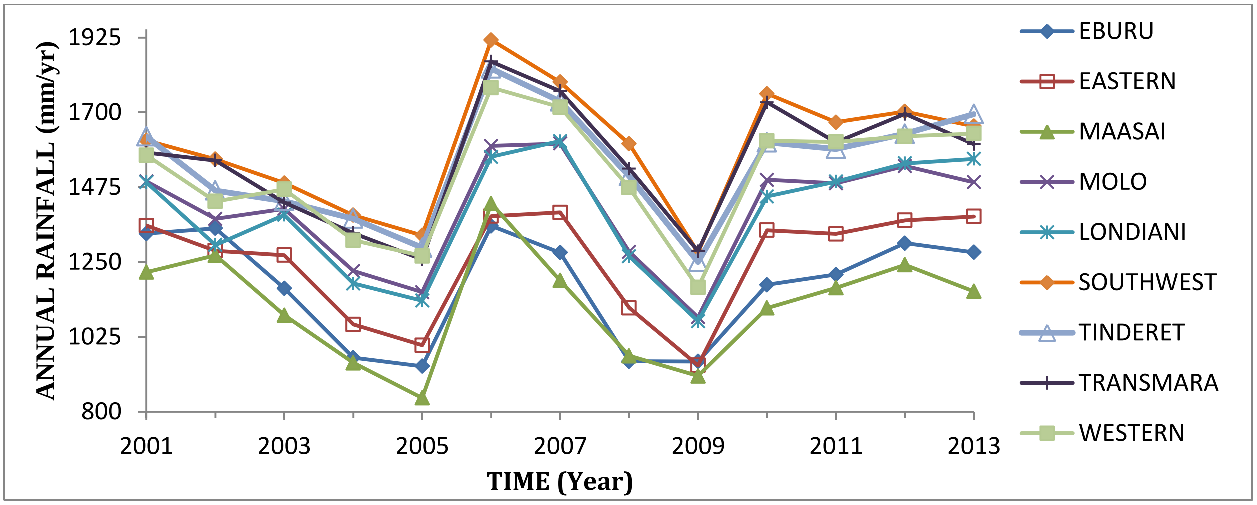

Figure 5-28 Total annual rainfall for various blocks of the Mau Forest Complex obtained from TRMM satellite datasets (2001-2013)

The mean annual NDVI time series trend confirms that Transmara is the densest forest with mean annual average NDVI value of 0.86. In fact the mean annual NDVI of Transmara is maintained at mean annual value of at least 0.85 for all the years except in 2009 when the NDVI was about 0.84. This fact confirms that Transmara possesses more superior vegetation than the other eight blocks of the Mau Forest Complex. The annual NDVI time series (Figure 5-29) also confirms that the forest is actually undergoing some sort of degradation, though at a relatively low rate. When a linear trend line is plotted for Transmara in Figure 5-29, a slope of about -0.0027 with coefficient of determination (R^2) = 0.60 is obtained. Transmara recorded the lowest NDVI values in 2009 (0.84), 2012 (0.85), 2011 (0.85) and 2006 (0.85). This implies that most of the lowest NDVI values were recorded in the years following the reclamation initiative. Transmara shows a steady decline in the NDVI values from 2001 to 2013, and the initiative has not done much to curb this destruction. There is therefore need for the Government of Kenya to focus on this important forest block before the damage becomes worse.

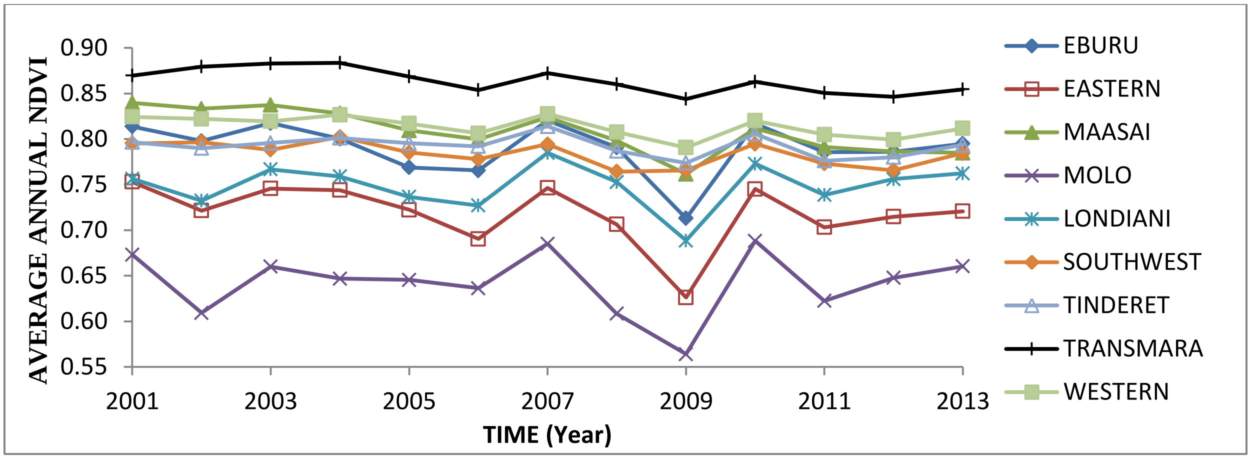

Figure 5-29 Mean annual NDVI for the Mau Forest Complex blocks obtained from MODIS datasets.

All the Mau Forest blocks recorded the lowest mean annual NDVI values in 2009 with exception of Southwest Mau, which recorded the minimum mean annual NDVI value of about 0.76 in 2008. This decline in NDVI values in most of the Mau Forest Complex was most likely caused by the low rainfall recorded in 2009. It is also worth noting that Molo is the only forest block that recorded the maximum annual mean NDVI value after 2008. All the other forest blocks recorded the highest mean annual NDVI before 2008. Eastern Mau and Maasai Mau had the highest mean NDVI values in 2001, Southwest Mau and Transmara in 2004, Eburu, Mount Londiani, Tinderet, and Western Mau in 2007. This means that although the initiative is showing some improvement in vegetation condition of the forest, the effects of the destruction experienced during the 2001 to 2007 period have not been completely reversed. This is consistent with the fact that restoration of a tree canopy takes a long period of time.

To determine how vegetation relates to variation in precipitate, regression analysis between NDVI and rainfall was performed. First regression analysis was carried out between NDVI and rainfall without lagging or stepping up any of these two variables. Then regression analysis was carried out with NDVI being lagged by one, then two, and finally three month behind rainfall. The results of this analysis are presented in Figures 5-30 to 5-39.

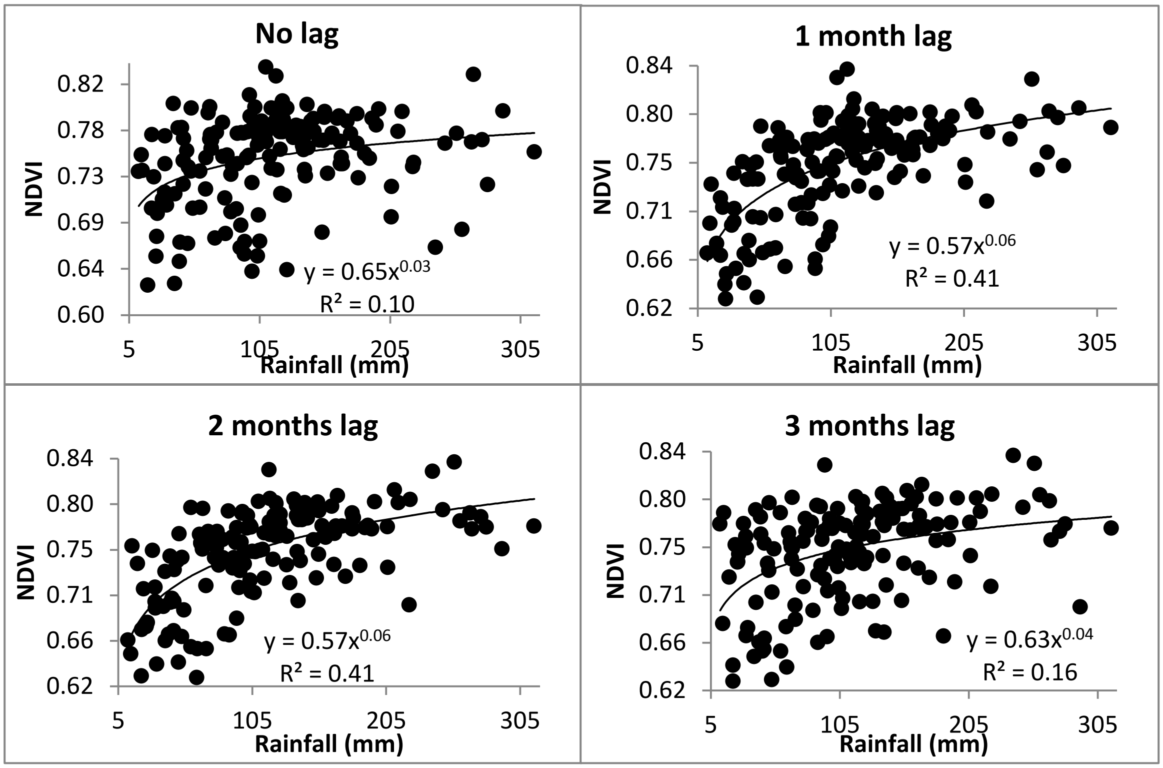

Figure 5-30 Correlation between NDVI and rainfall in Mount Londiani for various delay periods

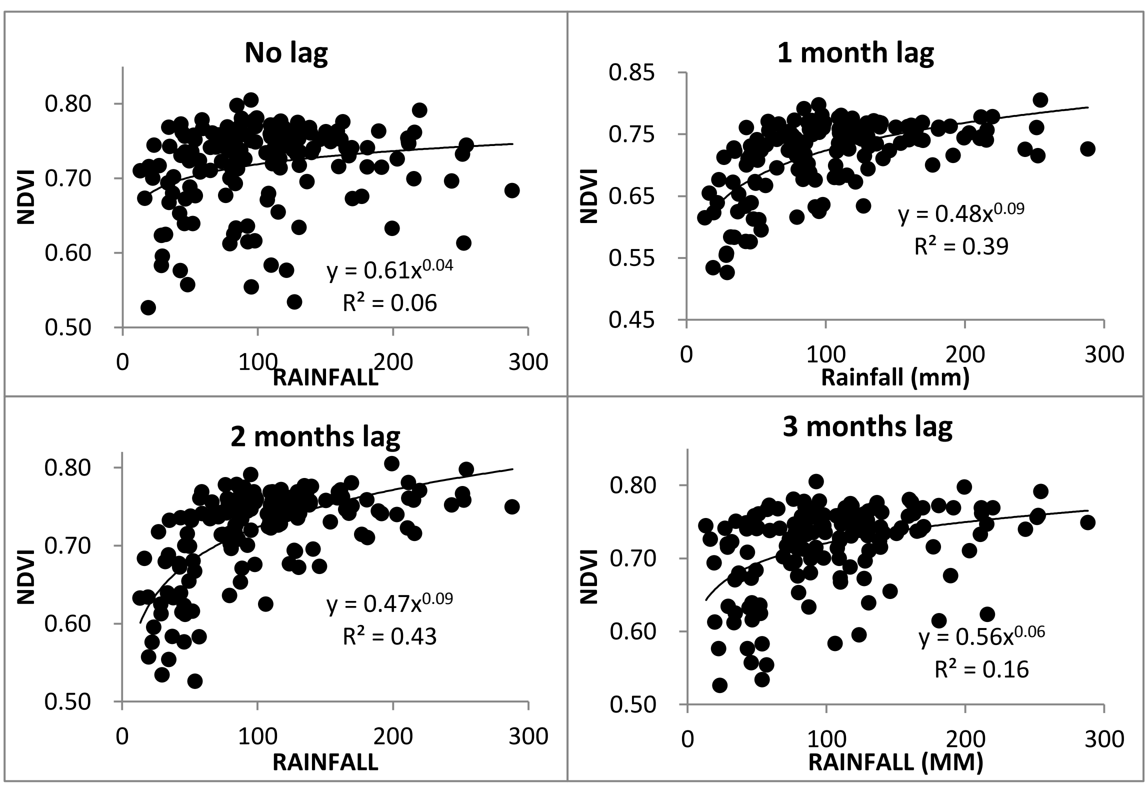

Figure 5-31 Correlation between NDVI and rainfall in Eastern Mau for various delay periods

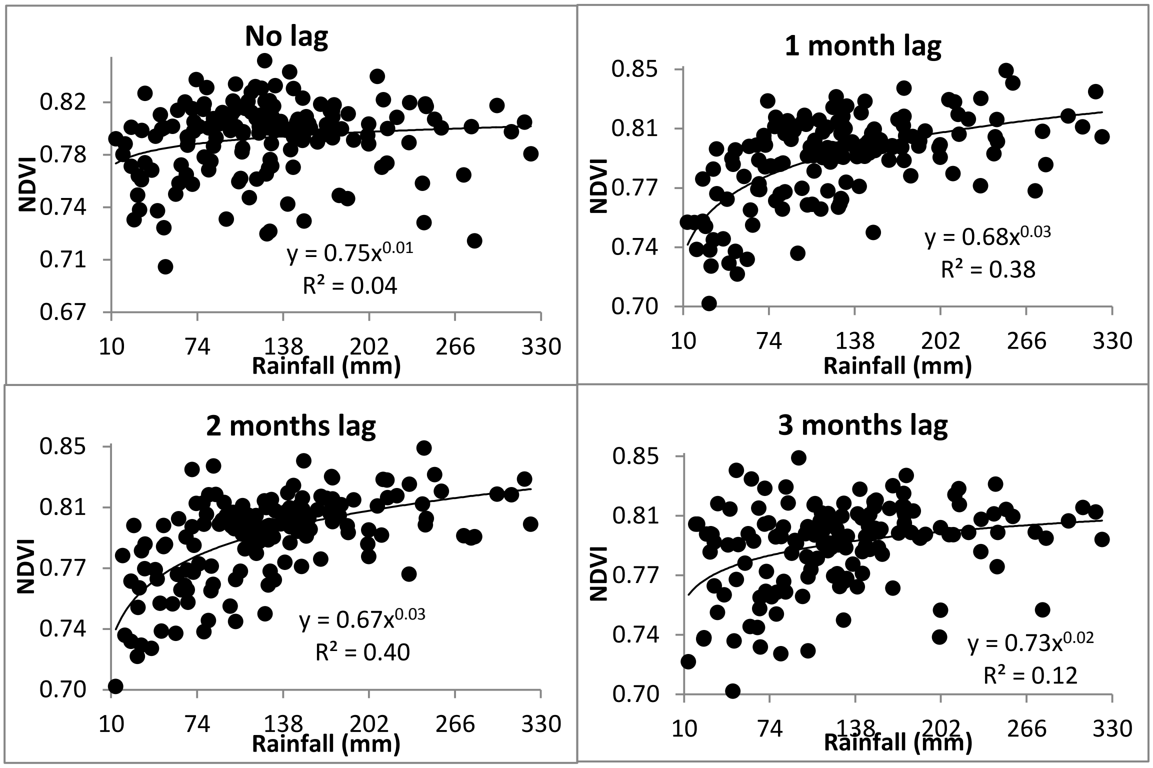

Figure 5-32 Correlation between NDVI and rainfall in Tinderet Mau for various delay periods

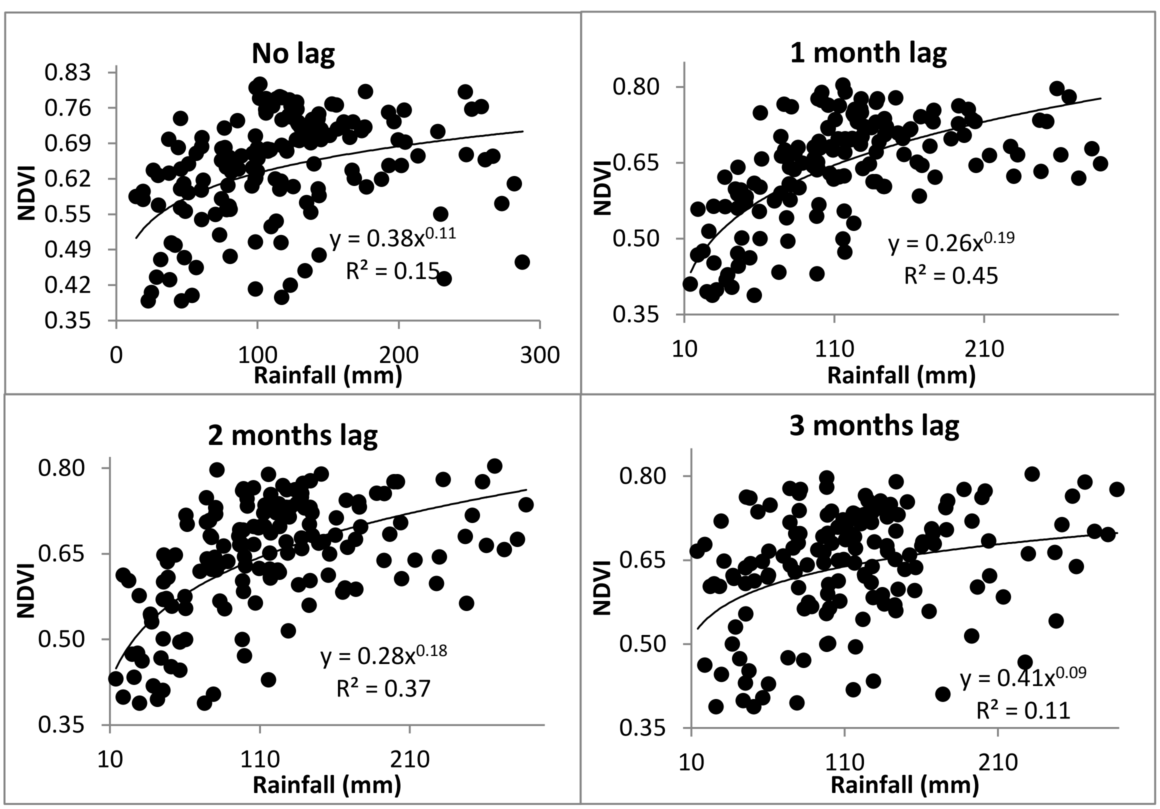

Figure 5-33 Correlation between NDVI and rainfall in Molo Mau for various delay periods

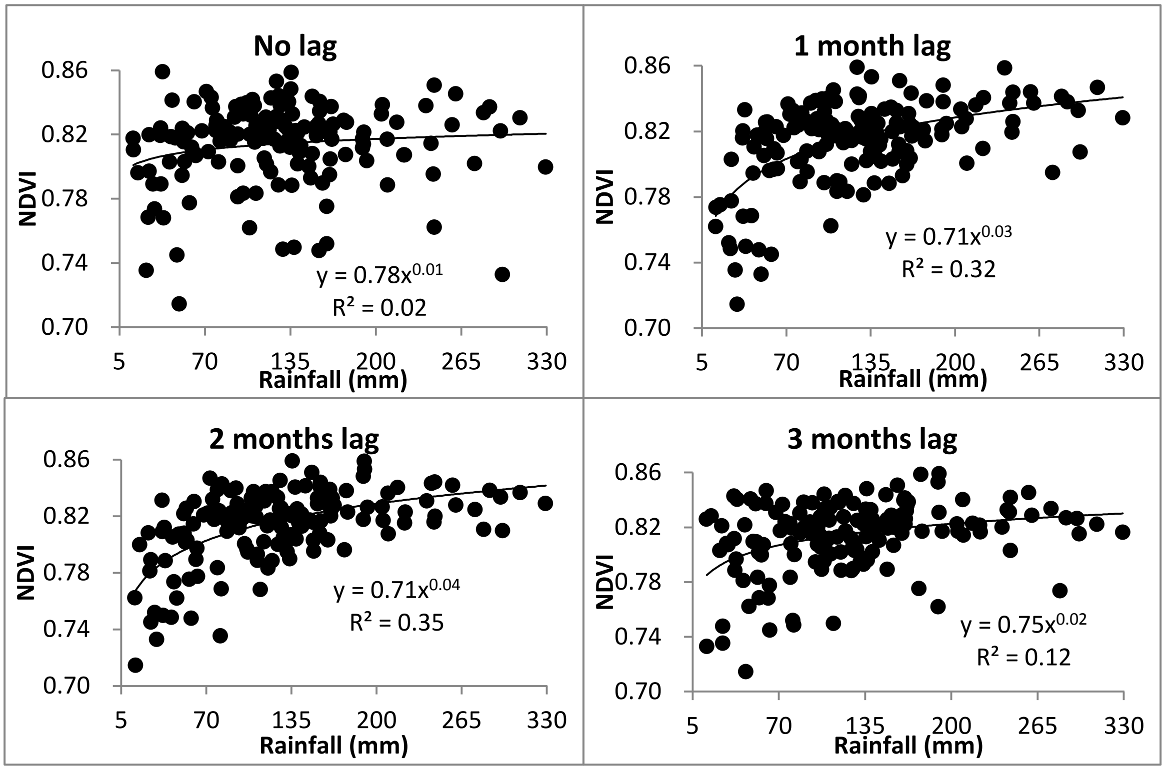

Figure 5-34 Correlation between NDVI and rainfall in Western Mau for various delay periods

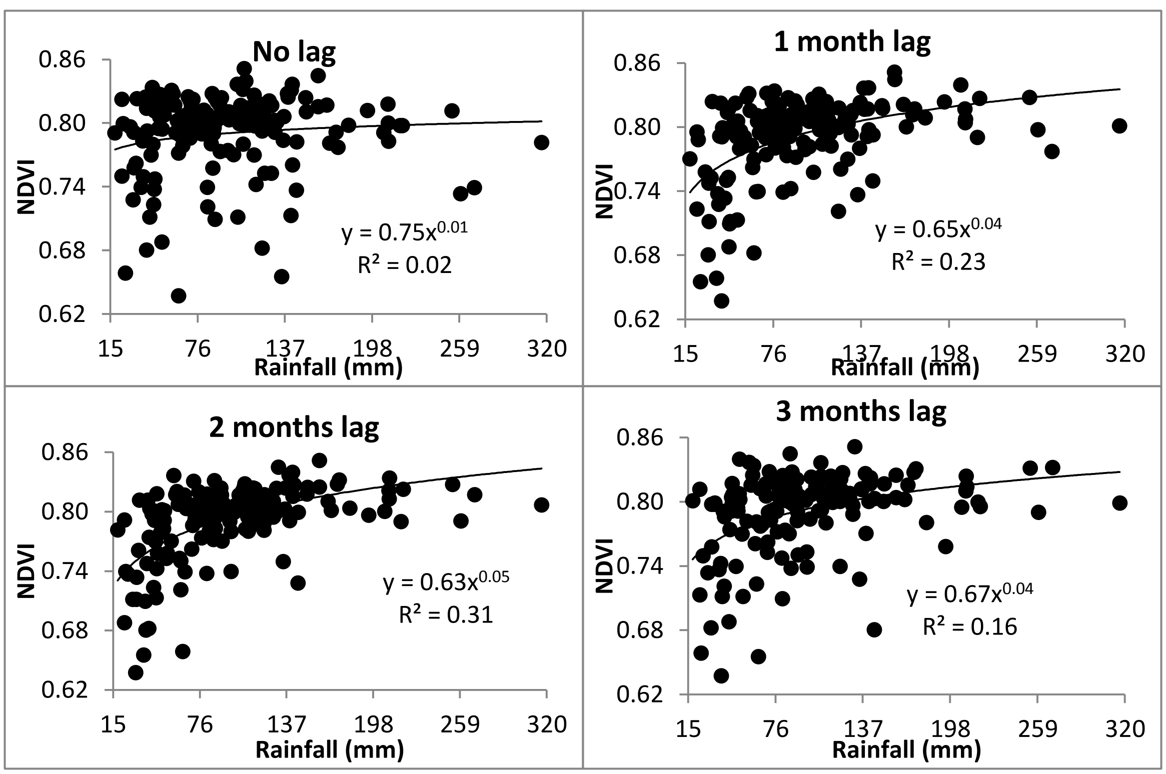

Figure 5-35 Correlation between NDVI and Rainfall in Eburu Mau for Various Delay periods

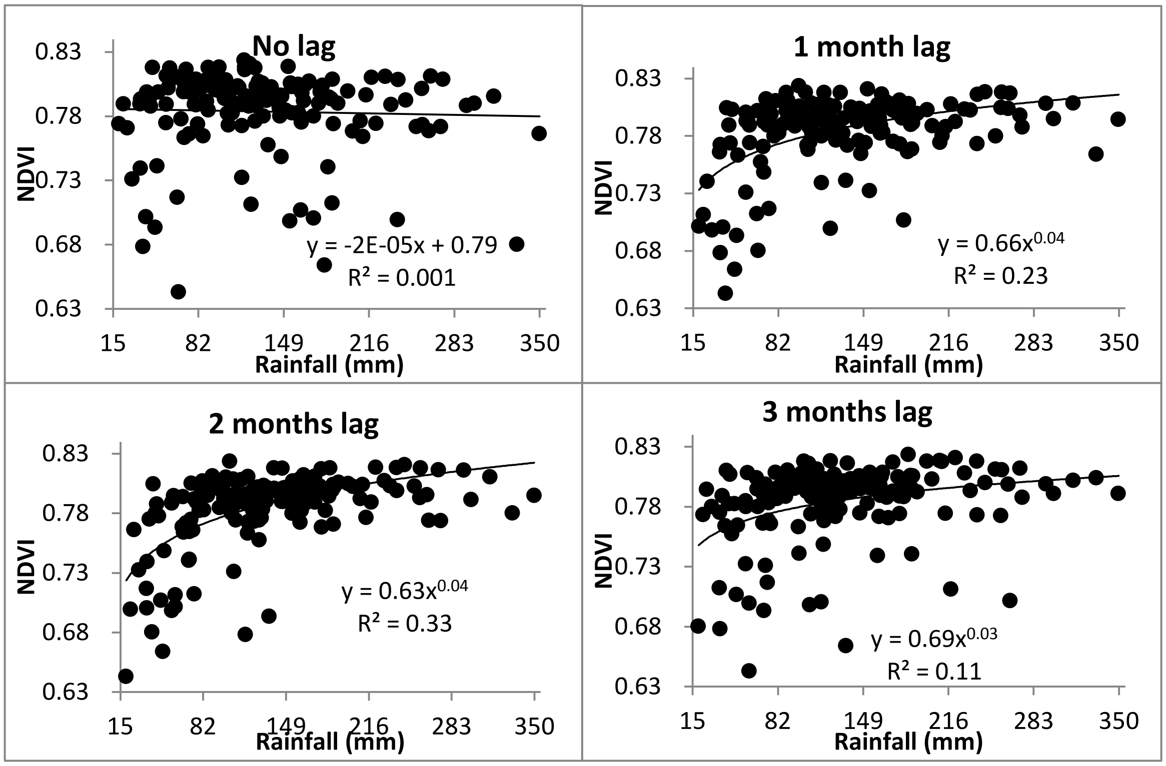

Figure 5-37 Correlation between NDVI and rainfall in Southwest Mau for various delay periods

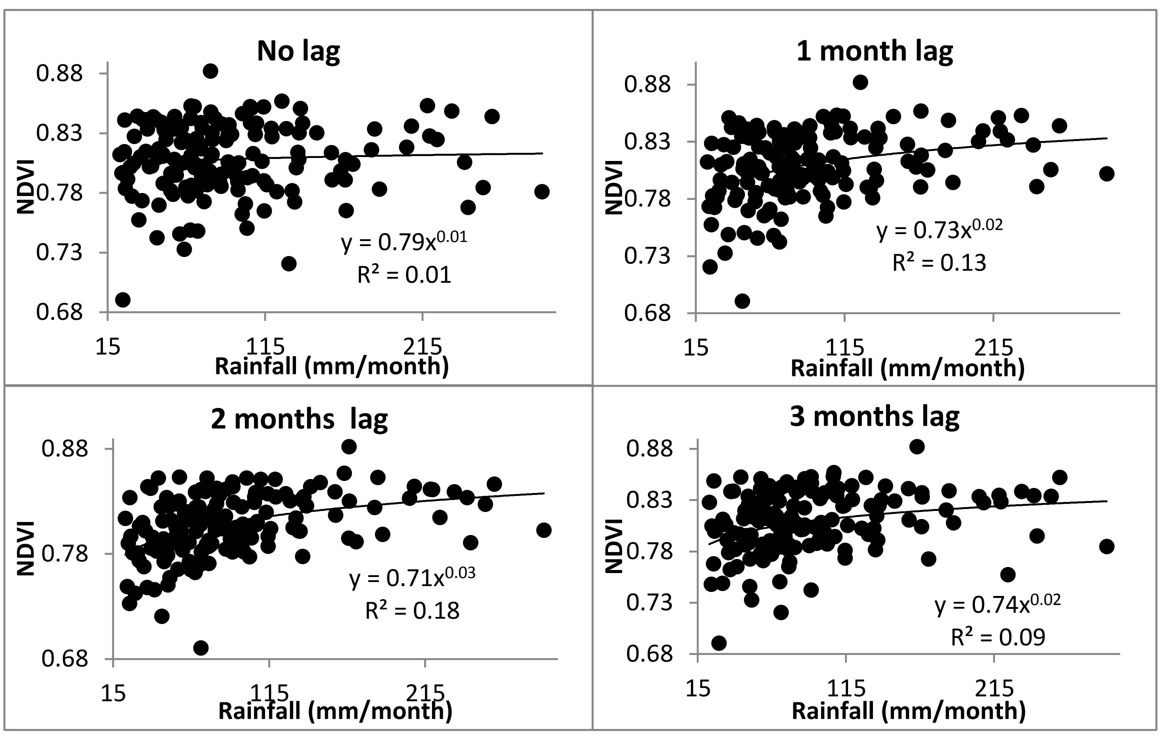

Figure 5-38 Correlation between NDVI and rainfall in Maasai Mau for various delay periods

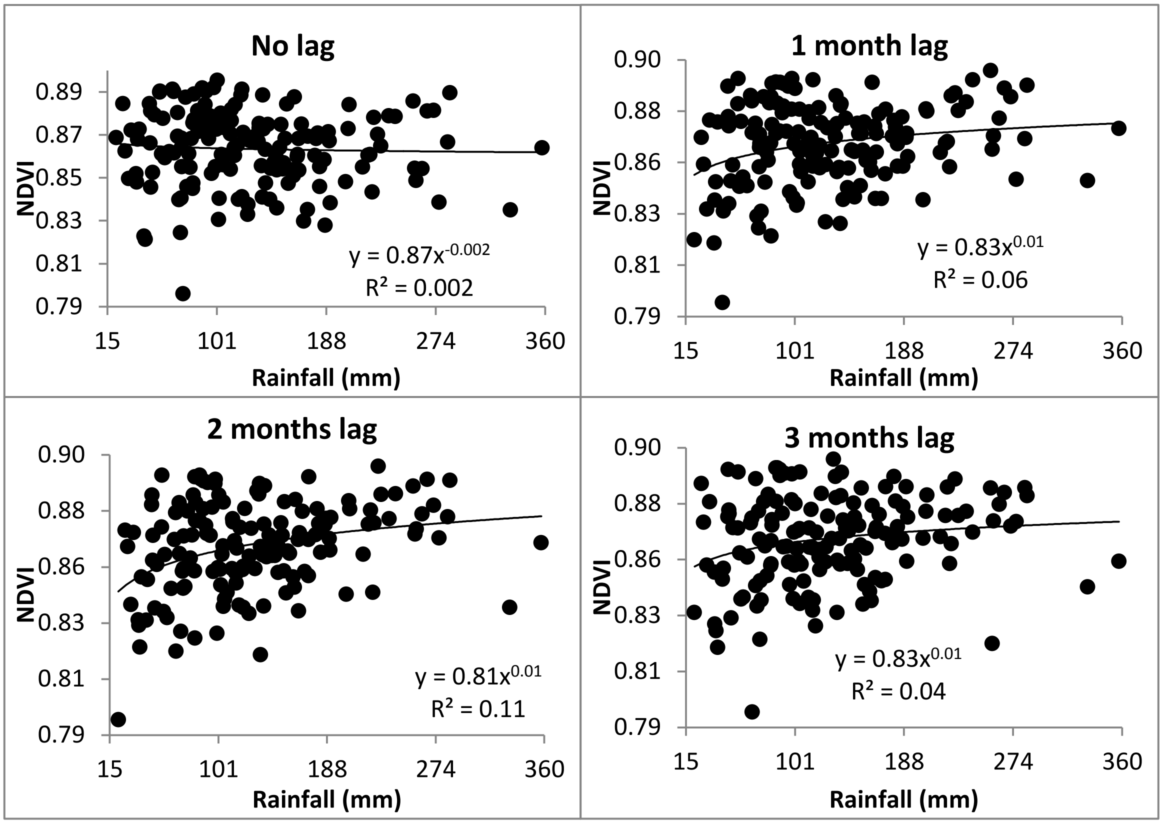

Figure 5-39 Correlation between NDVI and Rainfall in Transmara for Various Delay periods

It was observed that the highest coefficient of determination (R^2) was obtained when NDVI was lagged by one month (for Molo) and two months (for all the other forest blocks). Figure 5-40, shows a summary of the lag test of the nine blocks of the Mau Forest Complex. Although R^2 values were highest when NDVI was lagged by one to two months for all the Mau Forest blocks, it was observed that the dependence of the NDVI values on Rainfall varied from one block to the other. Molo recorded the highest maximum R^2 of about 0.45 when of about 0.43 when NDVI was lagged by two months. Also the other forest blocks recorded R^2 value less than 0.43, with Transmara recording the lowest maximum value of about (0.11). Transmara and Maasai Mau recorded the lowest maximum R^2 of about 0.11 and 0.18 respectively, at two months lag period.

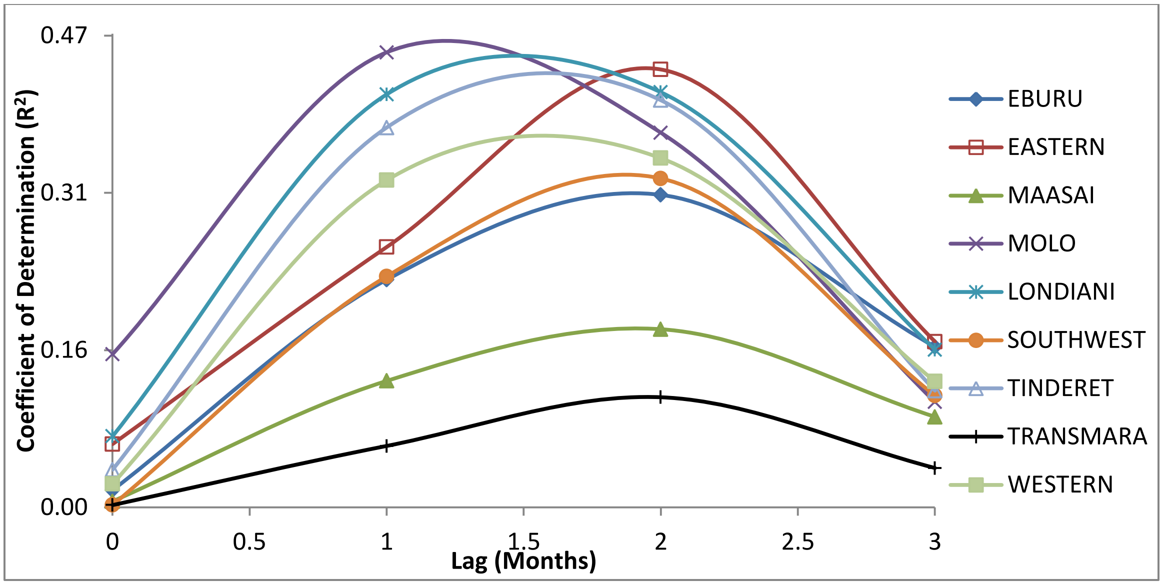

Figure 5-40: Coefficient of determination (R^2) against NDVI lag for the various blocks of the Mau Forest.

This implies that these two forest blocks are more resistant to variation in precipitate than the other forest blocks, while Eastern Mau and Molo are more affected by rainfall than the other blocks. It should also be noted that, although regression analysis showed that the relationship between NDVI and Rainfall is positive, that is, increase in rainfall leads to improvement of vegetation, the relationship is nonlinear. A plot of two months lagged NDVI values against rainfall for all the blocks revealed that the best fit line equation is actually an exponential function defined by equation 5.1 (see Figure 5-41). In the equation 5.1, y is the NDVI, x the average rainfall in mm/month, a, b, and c are constants that vary from one block to the next.

$$\boldsymbol{y = a + b\, e^{-cx}} \qquad 5.1$$

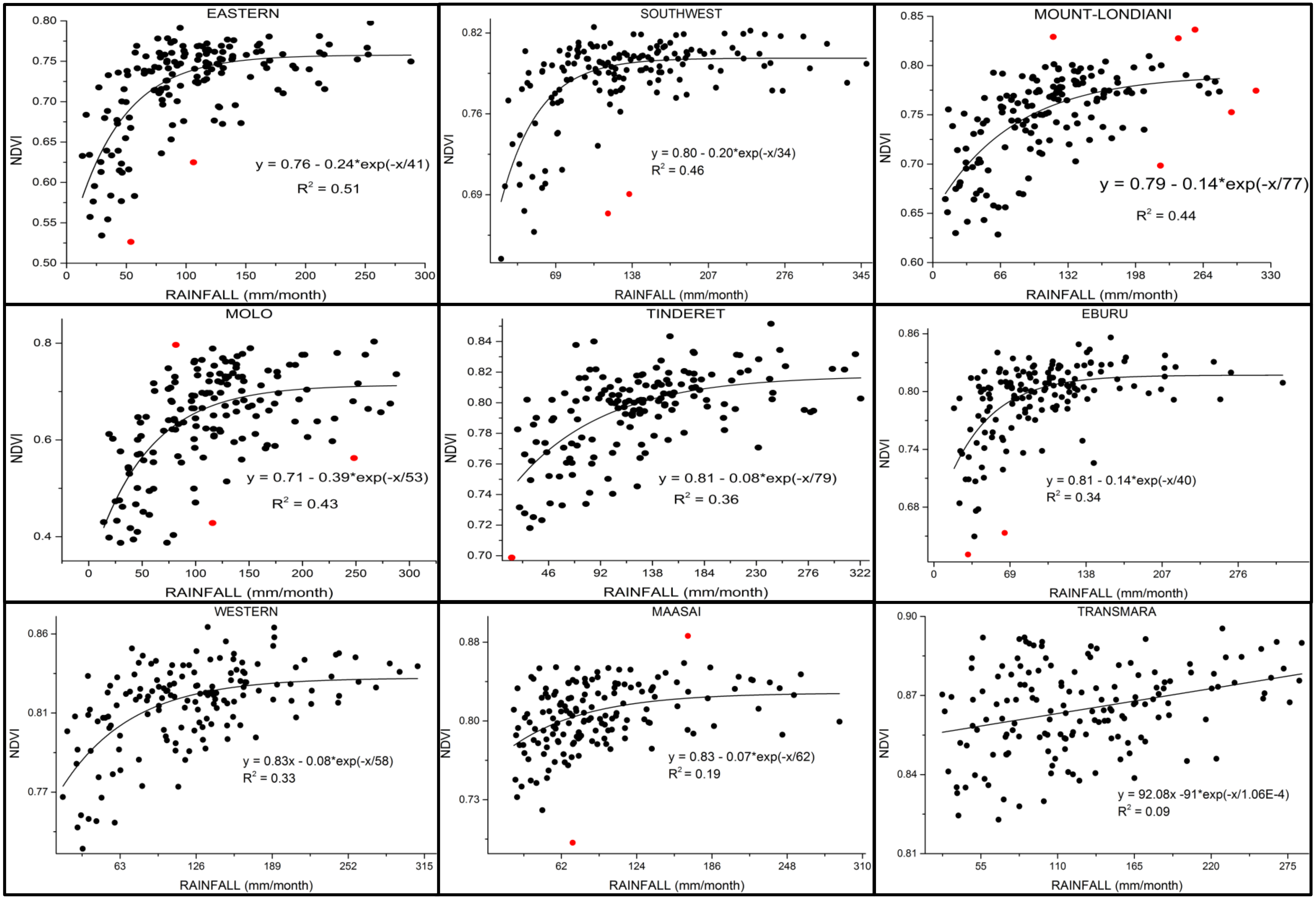

Figure 5-41 Correlation between two months lagged NDVI and Rainfall

Molo and Mount Londiani show the highest correlation between mean annual NDVI and total annual rainfall while Western Mau, Southwest Mau and Transmara show very low correlation (Figure 5-42). This implies that these forest blocks are more resistance to variation in total annual rainfall than the other forest blocks. This in turn means that these forests are more dense and healthier than the other forests, a fact that is evident from the high values of NDVI recorded for these forest blocks.

A comparison of the R values for the correlation between NDVI and monthly rainfall to that of NDVI and total annual rainfall reveal that NDVI is more dependent on monthly rainfall than on total annual rainfall. This implies that biomass tend to be more dependent on the rainfall pattern than on total annual rainfall. This explains the low NDVI observed in 2006 despite the presence of high rainfall. It should however be noted that Molo seems to be an exception to this rule as the NDVI depends more on the total annual rainfall (R=0.63) than on monthly rainfall (R=0.51). This information is important in that, by understanding which forest are more susceptible to changes in rainfall, the Government of Kenya together with the other stake holders can make strategic decisions on which blocks to focus on at different times. This is important due to the fact that Kenya is a third world country, which means that there is shortage of resources for use in the restoration and conservation initiative.

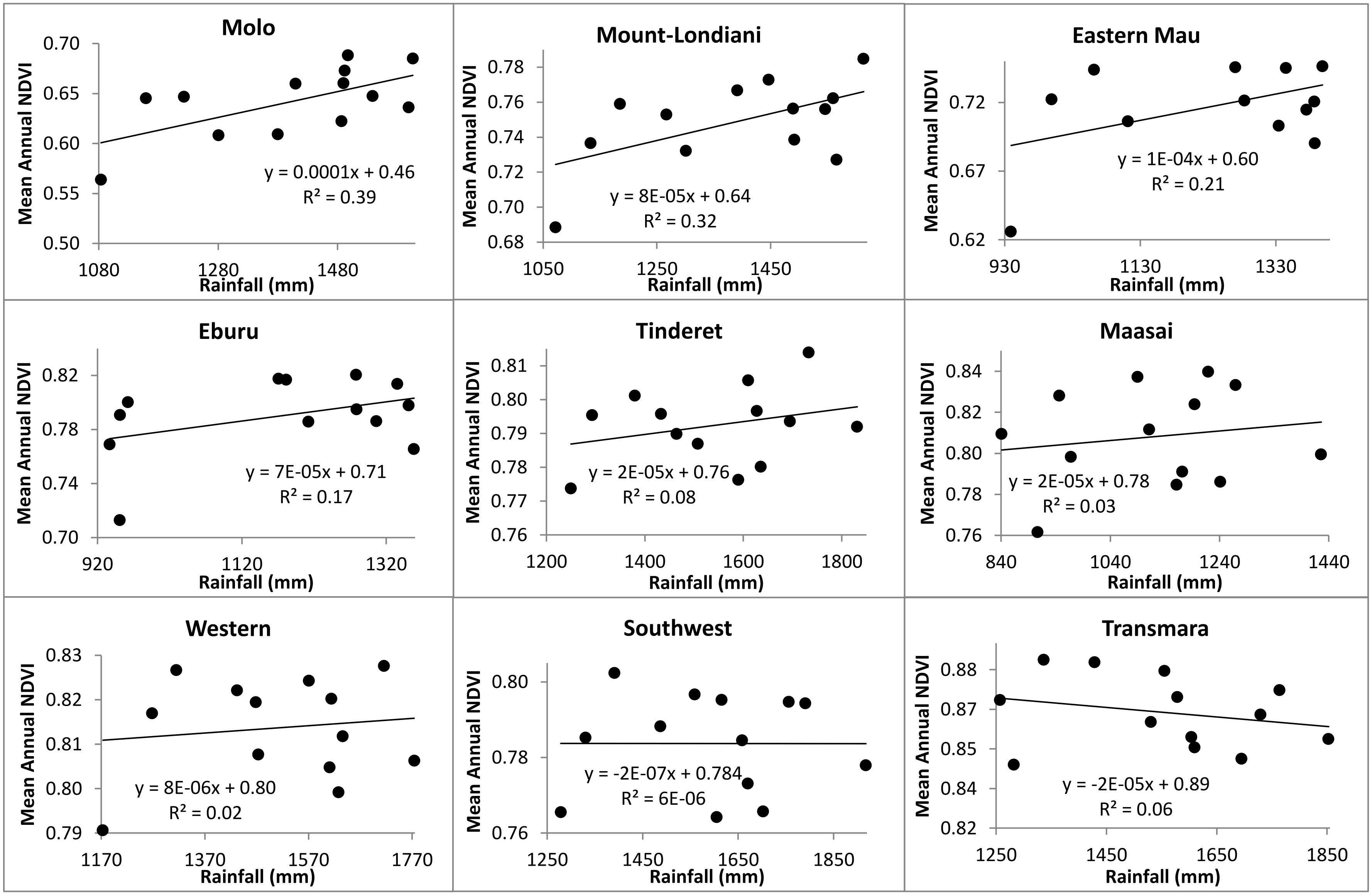

Figure 5-42 Correlation between mean annual NDVI and total annual rainfall for the Mau Forest Complex

5.3.2. Temperature

Molo and Eburu recorded the highest mean annual Land Surface Temperature (LST) of above 296K (23 ^{o}C), followed by Western Mau with about 294K (21 ^{o}C) during the period of study (Figure 5-43). Eastern Mau and Maasai Mau recorded the lowest LST compared to the other Mau Forest blocks. The entire Mau Forest Complex recorded the highest LST in 2009, which implies that the year 2009 did not only record very low rainfalls, but also very high temperatures. This had tremendous impact on the health and vigor of vegetation as is evident from the dip in the overall mean annual NDVI values of the forest. Eastern Mau and Eburu recorded the greatest decrease in mean annual NDVI from 2008-2009 emphasizing their dependence on rainfall and temperature. Southwest, Tinderet, Transmara and Western Mau recorded relatively low decrease in NDVI in response to the decrease in the amount of annual rainfall, while Southwest Mau actually remained almost unaffected (NDVI trend slope = +0.001) by this drought. This increase in mean annual NDVI value for Southwest Mau was definitely not caused by the rainfall or the Temperature and could have been caused by the restoration and conservation initiative.

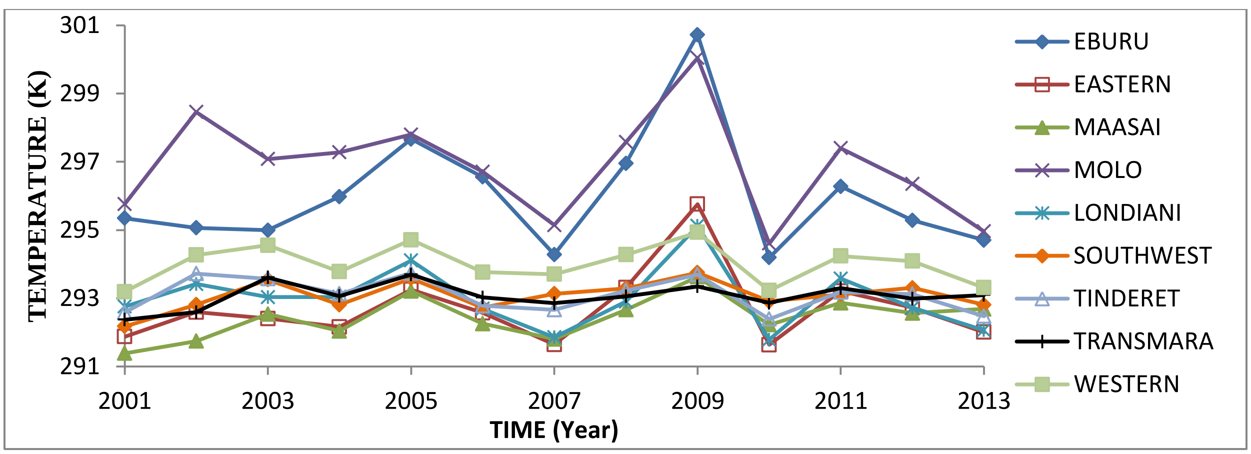

Figure 5-43 Mean annual temperature for the Mau Forest Complex extracted from MODIS LST images (2001-2013)

The relationship between LST and density of healthy vegetation is complex as these two variables have potential to affect each other. The LST-NDVI relationship is mainly governed by the process of evapotranspiration. High temperature causes increase in evapotranspiration, which causes a decrease in soil moisture, which in turn causes a deterioration of vegetation density and health (Boegh *et al.*, 1999; Price, 1990). On the other hand, high vegetation density provides large surface area for evapotranspiration which lowers the LST (Boegh *et al.*, 1999; Price, 1990).

This implies that LST has the potential to affect vegetation growth therefore influencing the values of NDVI. Likewise dense vegetation can lower temperature by consuming latent heat of vaporization.

However, if there is enough moisture in the soil, then the process of evapotranspiration will not cause a lot of stress on vegetation, as soil moisture will replenish lost water. This implies that if the soil contains sufficient moisture, it is the vegetation that will affect the LST by absorbing latent heat of vaporization. It is due to this relationship between LST and evapotranspiration that researchers like Gutman (1990) have used LST to evaluate changes in soil moisture content. Furthermore, Nemani and Running (1989) argue that in tall tree canopies, it is the Vapor Pressure Deficit (VPD) of air passing over the canopy surface that control the rate of evapotranspiration, and not the net radiation received on the land surface

The results of regression analysis between monthly NDVI and LST revealed that the coefficient of determination (R^2) is highest when NDVI is lagged by between 0 and 1 month behind LST as demonstrated by Figures 5-44 to 5-52. Similar results were obtained by Cuba *et al.* (2013) when studying the variation of EVI with MODIS derived LST. Cuba *et al*. (2013) observed that the correlation between EVI and LST was strongest when the LST was not lagged. The strong correlation between LST and NDVI when NDVI is not lagged confirms the dependence of LST on NDVI. LST has been shown to be dependent on both soil moisture and vegetation fraction (Nemani *et al.*, 1993; Gutman, 1990). The result of the regression analysis also revealed that NDVI and LST have a strong inverse relationship. These results are consistent with observation made by several other researchers (Nemani *et al.*, 1993; Nemani and Running, 1989). Karnieli *et al*. (2010) argue that this relationship is caused by the cooling effect produced by the forest canopy. In other words, increase in vegetation density increases the rate of evapotranspiration, which in turn lowers the LST.

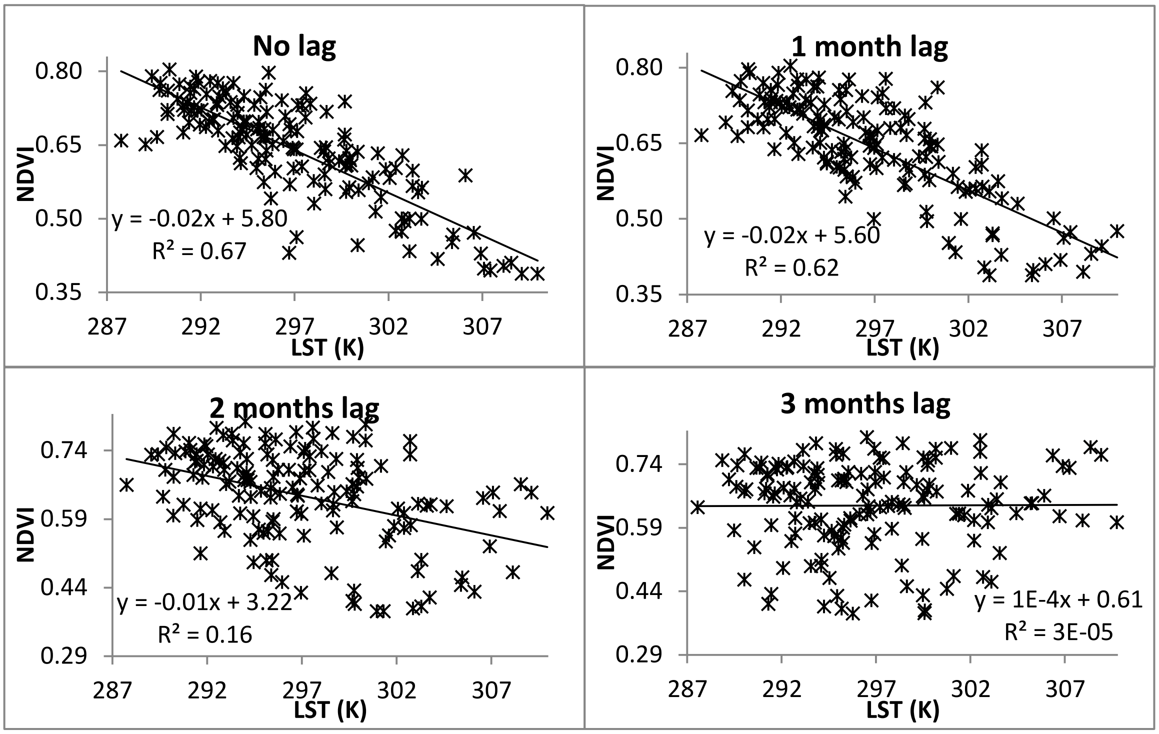

Figure 5-44 Correlation between NDVI and LST in Molo for various delay periods

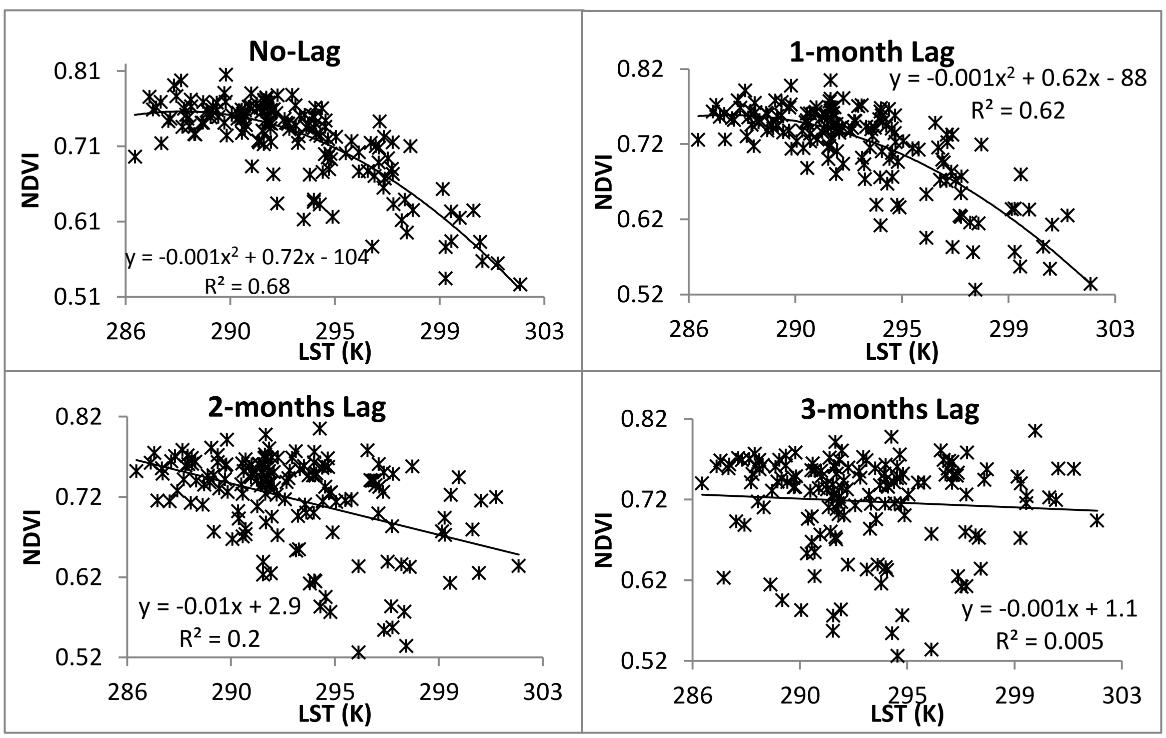

Figure 5-45 Correlation between NDVI and LST in Eastern Mau for various delay periods

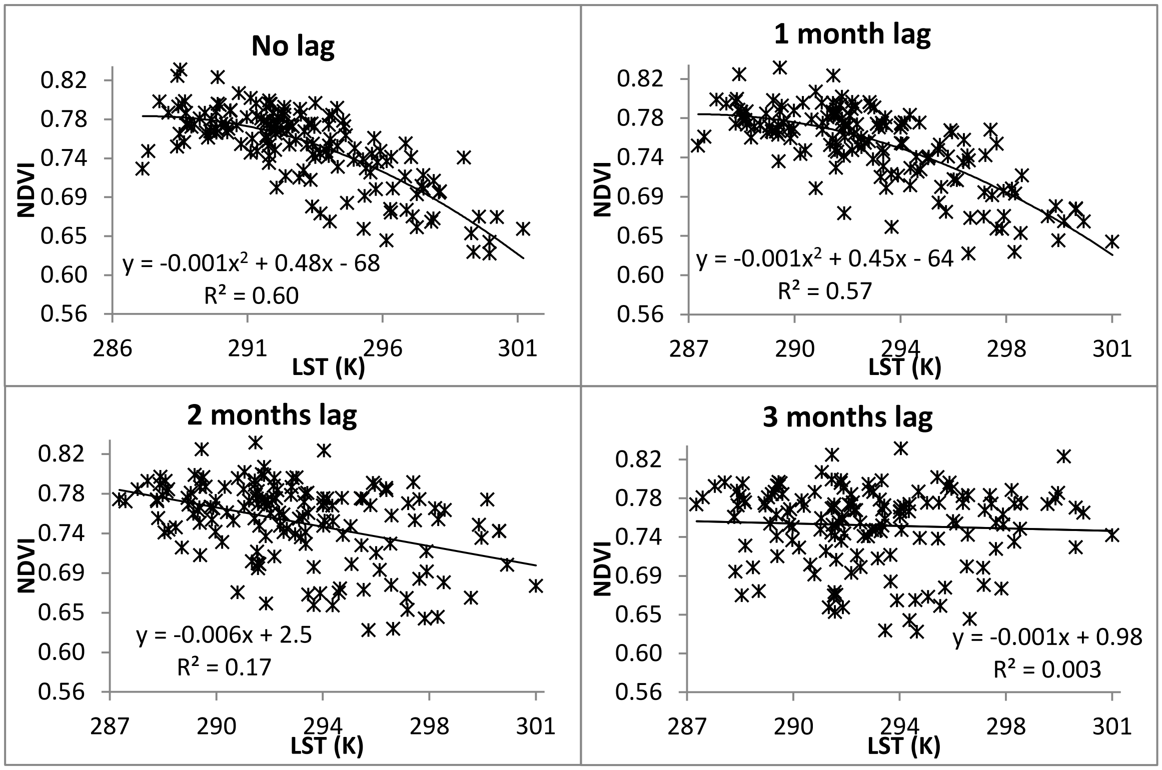

Figure 5-46 Correlation between NDVI and LST in Mount Londiani for various delay periods

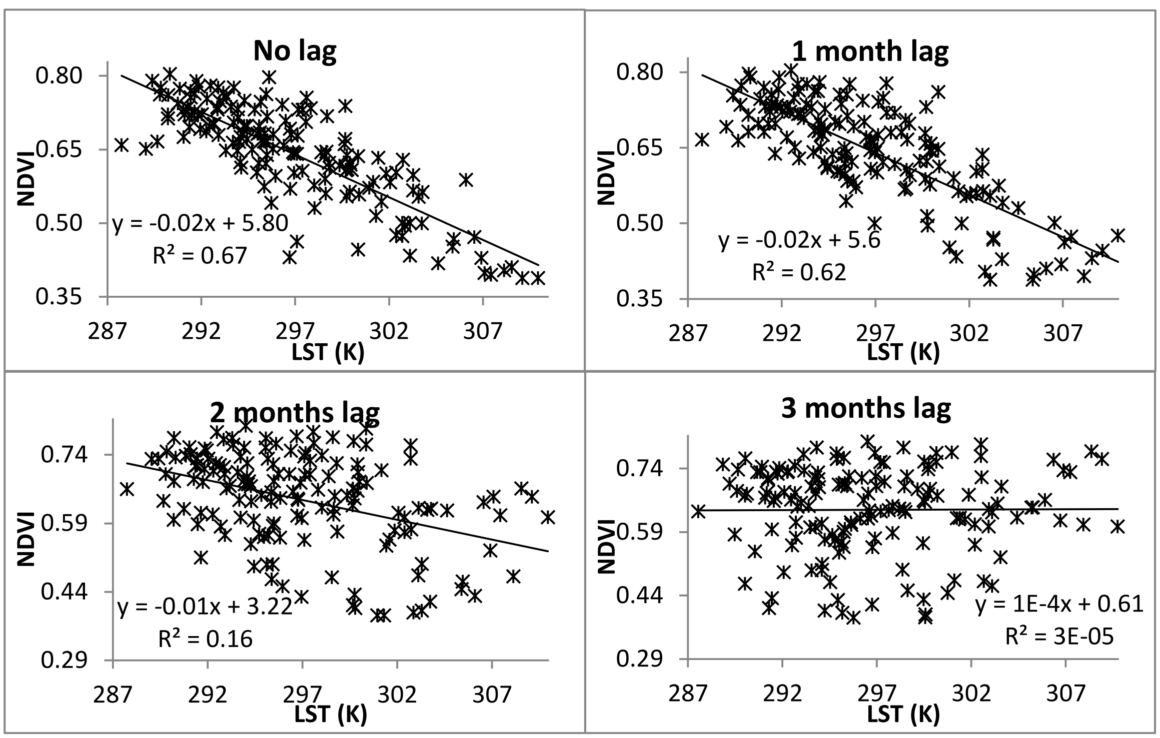

Figure 5-47 Correlation between NDVI and LST in Eburu for various delay periods

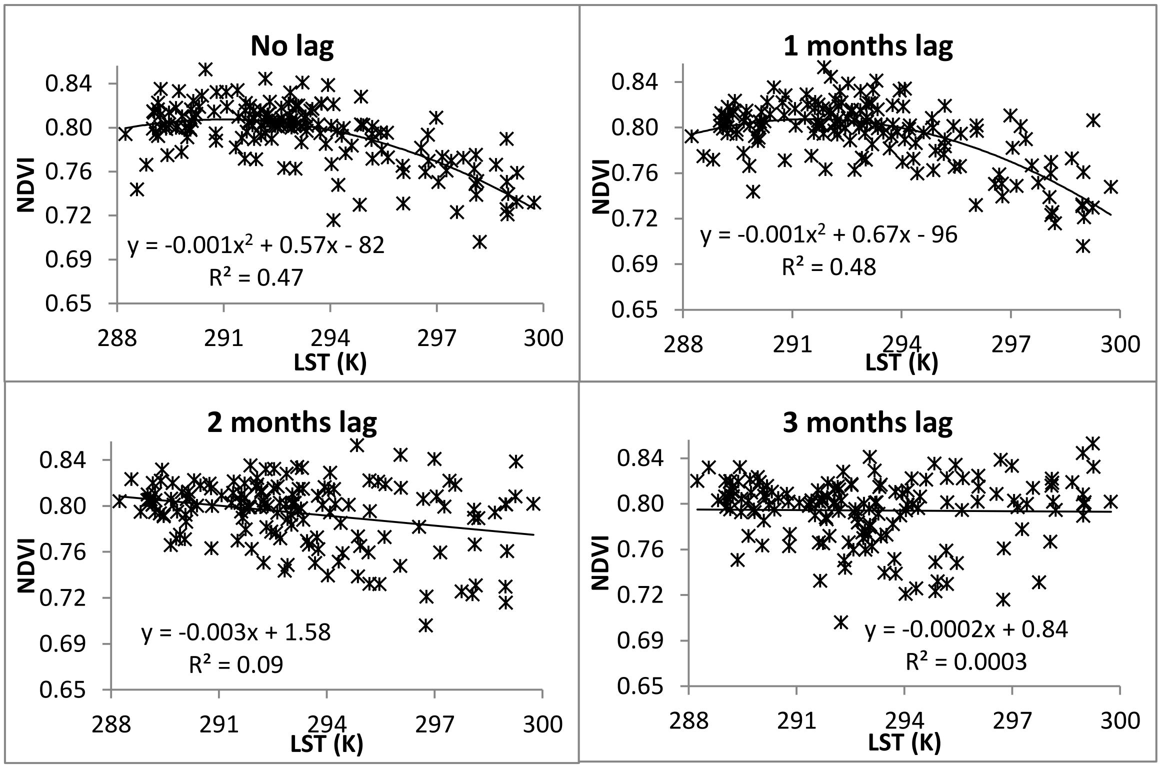

Figure 5-48 Correlation between NDVI and LST in Tinderet for various delay periods

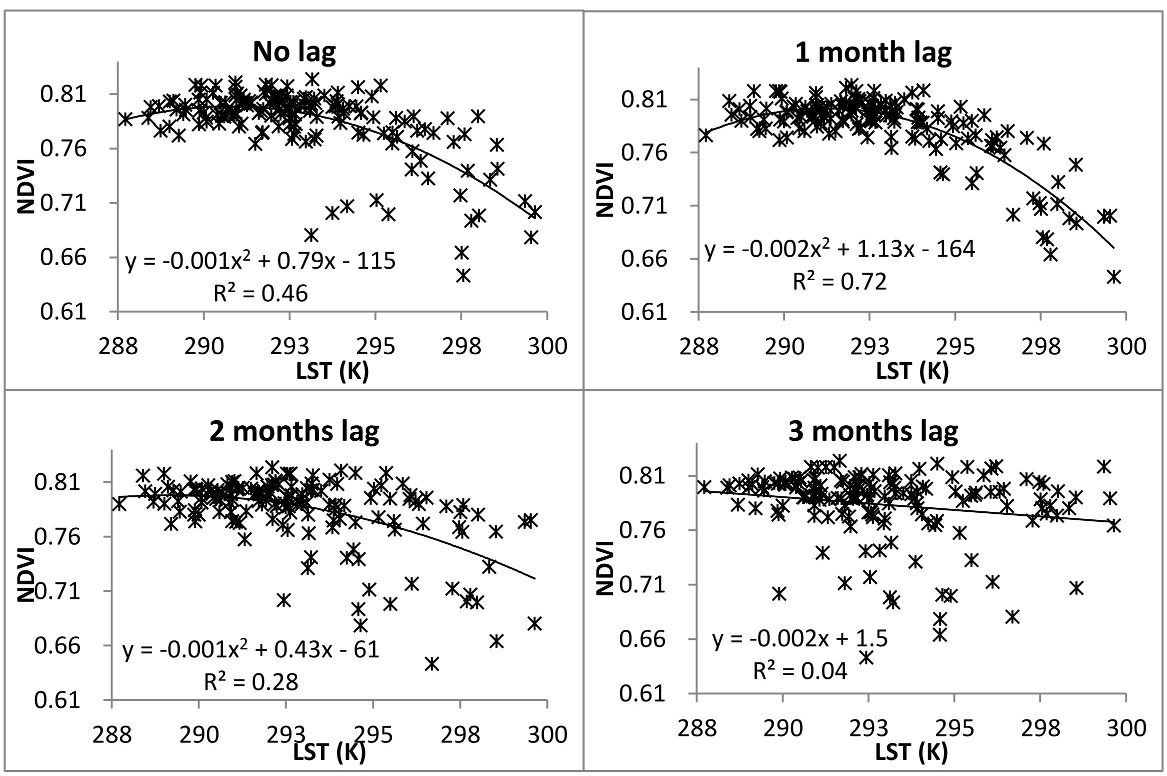

Figure 5-49 Correlation between NDVI and LST in Southwest Mau for various delay periods

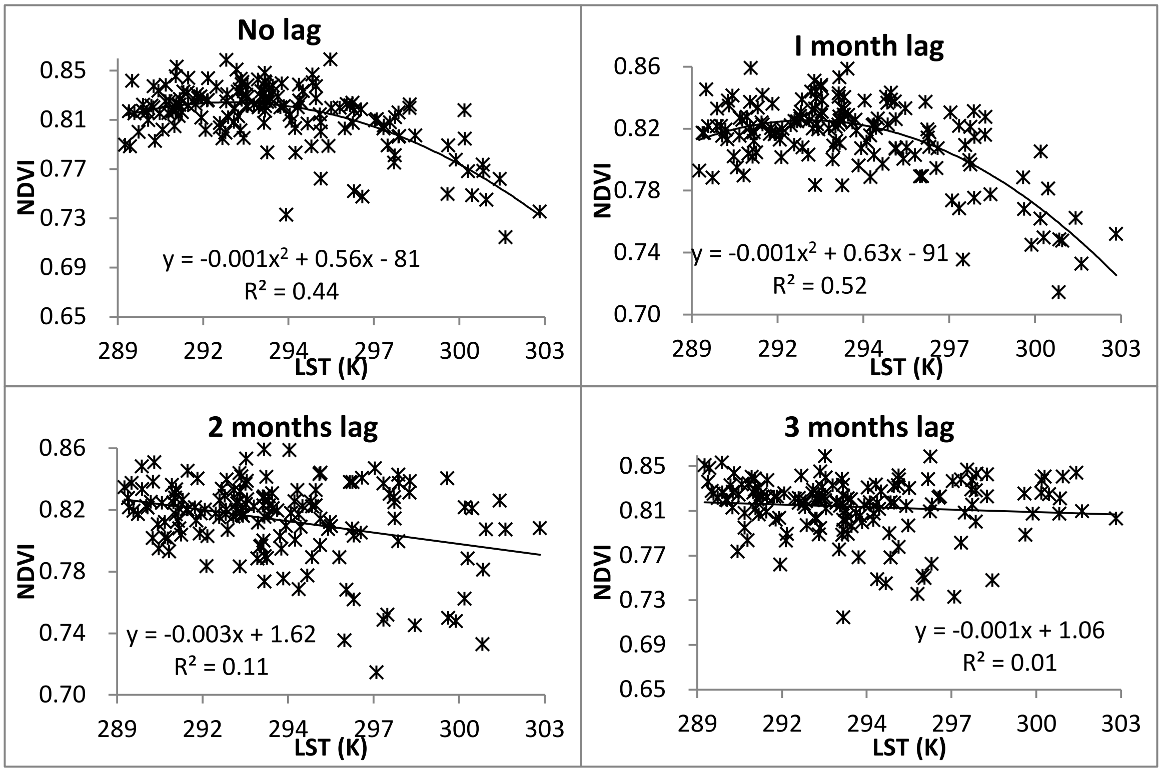

Figure 5-50 Correlation between NDVI and LST in Western Mau for various delay periods

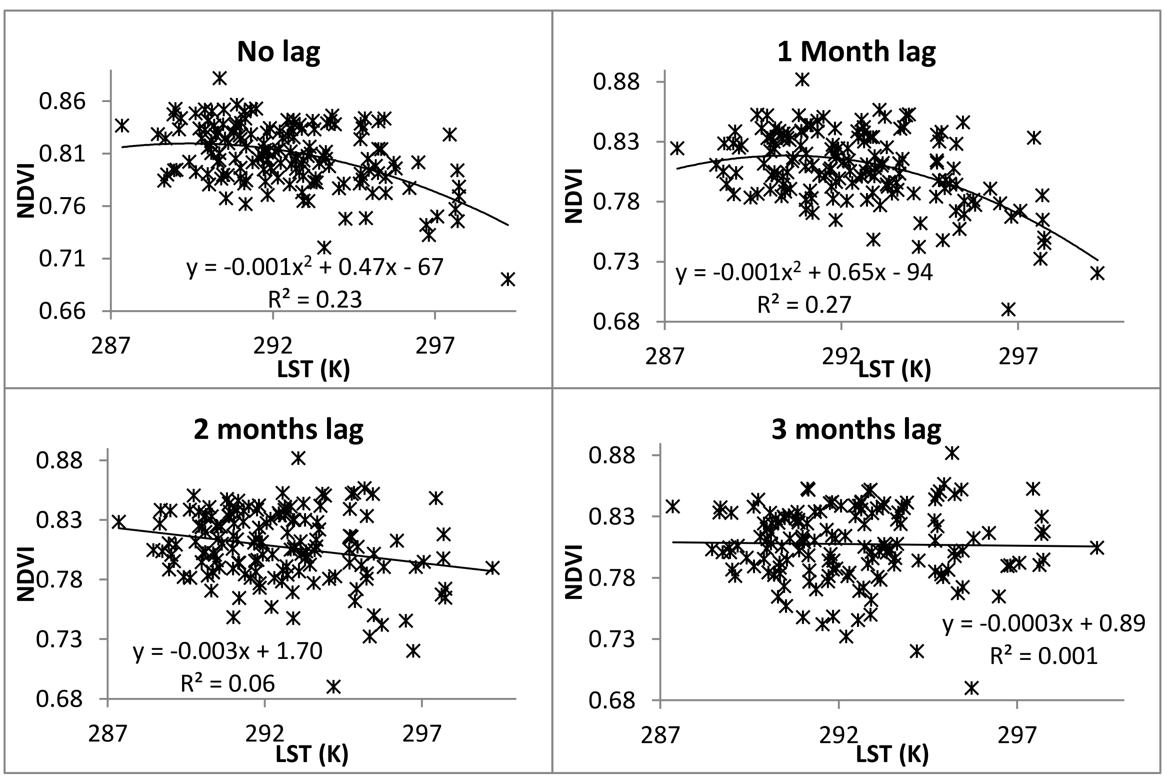

Figure 5-51 Correlation between NDVI and LST in Maasai Mau for various delay periods

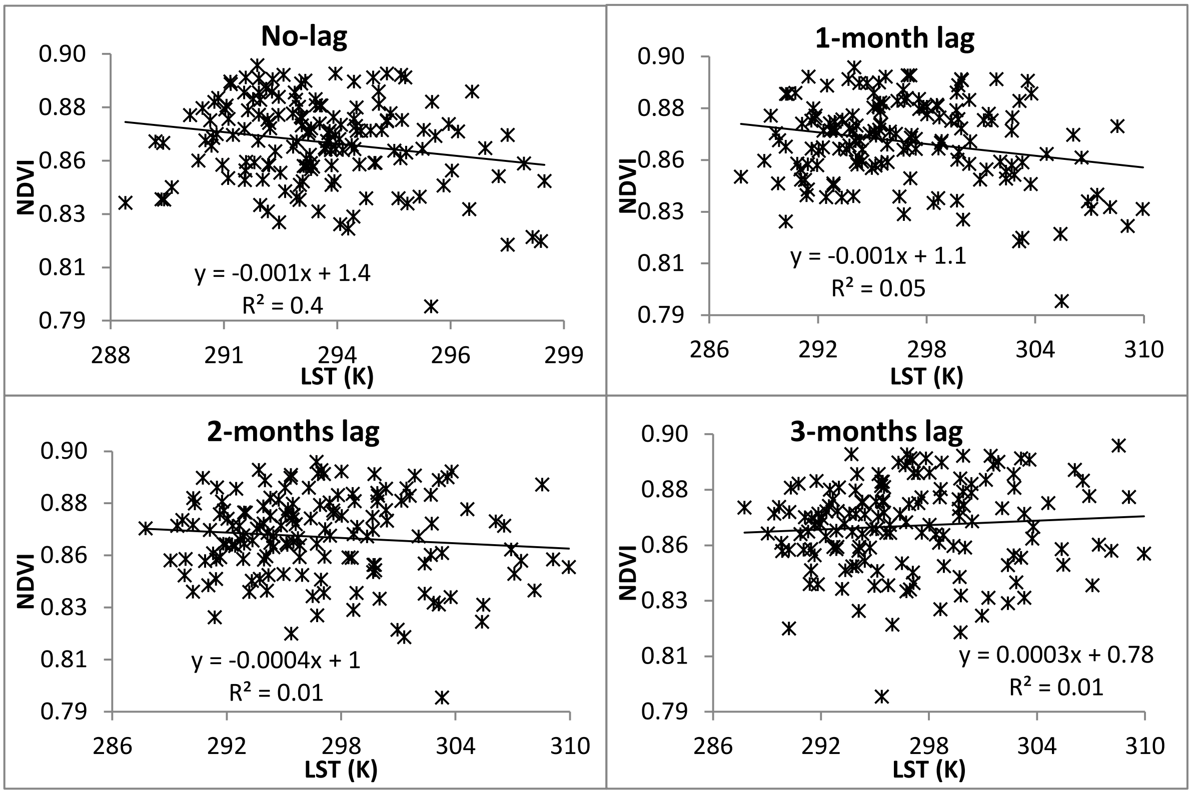

Figure 5-52 Correlation between NDVI and LST in Transmara for various delay periods

Figure 5-53 shows a summary of the LST-NDVI relationship for the nine blocks of the Mau Forest Complex considered in this study. From the Figure, it is clear that Southwest Mau has the strongest LST-NDVI relation ($R^2 = 0.72$) that is observed when the NDVI is lagged by 1 month. Eastern Mau, Mount Londiani, and Molo show stronger LST-NDVI relationship ($R^2 > 0.5$) while Transmara, the densest forest blocks, show relatively weaker relationship ($R^2 < 0.2$).

These results echo those of Hong *et al*. (2007) who observed that the LST-NDVI relationship is generally stronger in areas with sparse vegetation than in those with dense vegetation. It was also observed that the LST-NDVI relationship is relatively strong when NDVI is lagged by up to one month behind the LST. Since LST can be used as a proxy for estimating soil moisture and vegetation water stress (Karnieli *et al.*, 2010; Hong *et al.*, 2007), then this could be an indication of how long it takes for the Mau Forest Complex to respond to variation in soil moisture. According to Hong *et al*. (2007), LST provide an important link between evapotranspiration and quantity of soil moisture present.

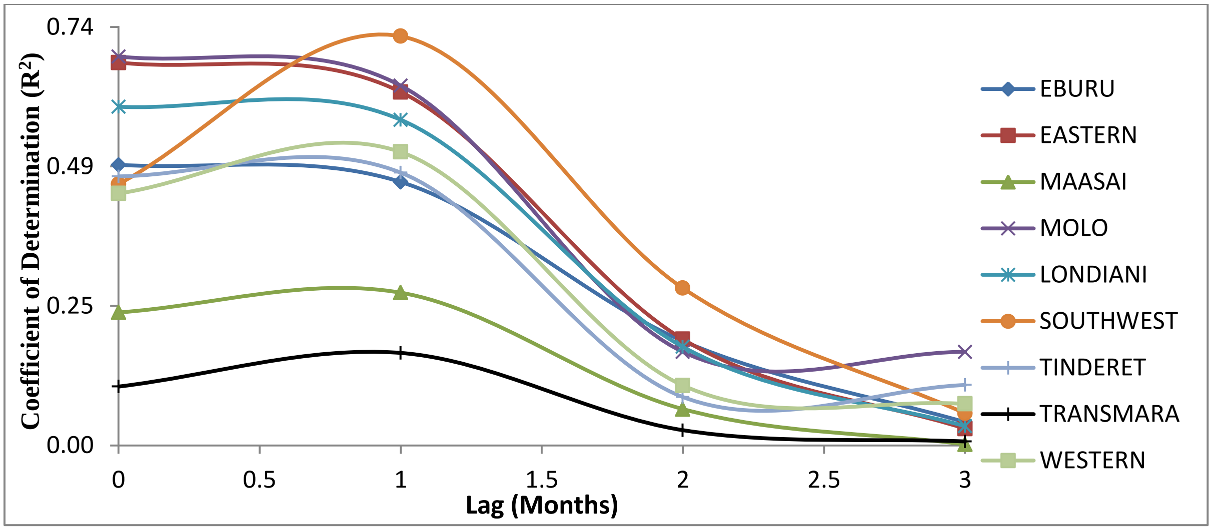

Figure 5-53 Coefficient of Determination (R^2) of monthly NDVI and LST against NDVI lag

The results for regression analysis between mean annual NDVI and mean annual LST are presented in Figure 5-54. Eburu, Eastern Mau and Molo show very strong negative linear correlation between LST and NDVI at annual interval. These forest blocks have R values of magnitude greater than 0.9. On the other hand, Transmara and Western Mau show insignificant LST-NDVI relationship, with Transmara recording an R value of about -0.11. As shown earlier, Transmara has an average mean annual NDVI of 0.86, Western Mau 0.81, while Eburu has an average NDVI of 0.79 and Eastern Mau. This implies that the relationship between NDVI and mean annual LST is, to some degree, dependent on the health and vigor of vegetation in the forest. In general, the relationship between mean annual NDVI and LST is linear and much stronger than that of mean monthly NDVI and LST. It therefore follow that a predictive model based on Mean annual NDVI and LST will produce better results than one based on mean monthly NDVI and LST.

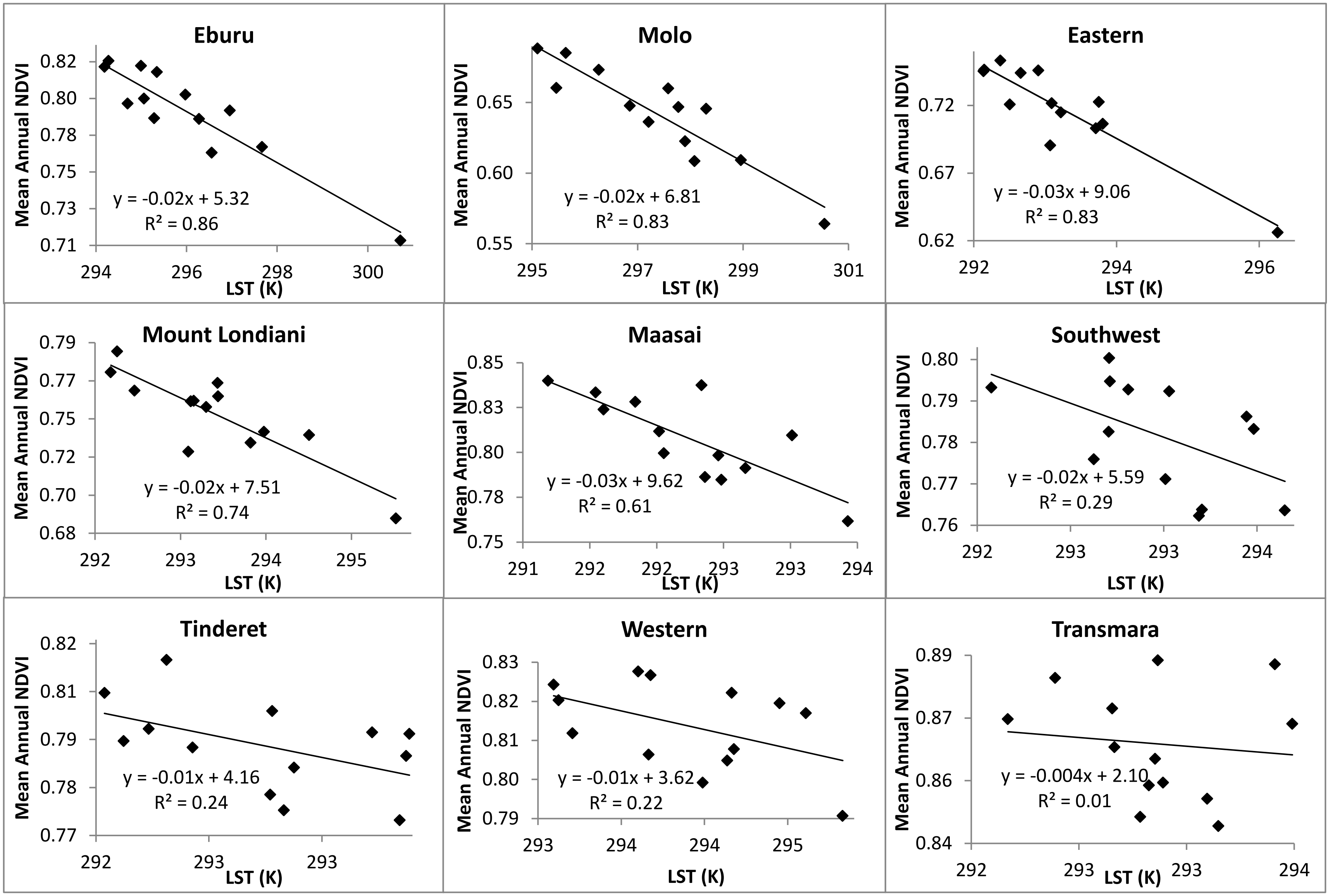

Figure 5-54 Correlation between mean annual NDVI and mean annual LST for Mau Forest Complex

5.4. Inter-Annual NDVI Ordinary Least Square (OLS) Slope

Figure 5-55 shows the NDVI slopes of the Mau Forest Complex before and after the restoration and conservation initiative started. The NDVI slope is an indication of annual changes in vegetation in the Mau Forest Complex. The NDVI slope indicates the rate at which the NDVI values are increasing or decreasing on average per year. Areas that are undergoing degradation will have negative OLS slope values while the areas that are stable or improving will have positive values. Figure 5-55 shows that Southwest Mau, Eastern Mau and Maasai Mau were undergoing land cover degradation between 2001 and 2007. In these forest blocks, very few pixels recorded positive OLS slopes during this period. In fact areas that had been encroached on, recorded NDVI slopes of between -0.025 and -0.005. This implies that the NDVI values of these areas were reducing continually from 2001 to 2007. This was most likely caused by the 2001 excision, reported by Olang and Kundu (2011), coupled with illegal encroachment of the forest blocks especially the northwest part of Maasai Mau. A look at these same areas in 2008-2013 shows that they are actually improving. Most areas in Eastern Mau recorded NDVI slope values of over + 0.006 in 2008-2013, up from values as low as -0.025 during 2008-2013.

The NDVI Slope values of Southwest Mau increased in 2008-2013, with some areas recording NDVI slopes of over + 0.006. The fact that the NDVI slopes increased in the areas that had been encroached on means that this increase was most likely caused by the restoration and conservation initiative. The central part of Southwest Mau recorded NDVI slope values of over +0.006. These are the areas that had scattered illegal settlers (UNEP, 2008) which meant that they were not heavily degraded during the 2001 to 2007 period. This could be the reason they show quicker recovery than the other parts of Southwest Mau. The areas of Southwest Mau that are on the eastern part of the forest block also show some signs of improvement. Most areas of the Maasai Mau show signs of recovery with some of the areas that had recorded NDVI slopes less than -0.025 in 2001-2007 recording values higher than -0.004, and some regions even recording over +0.006.

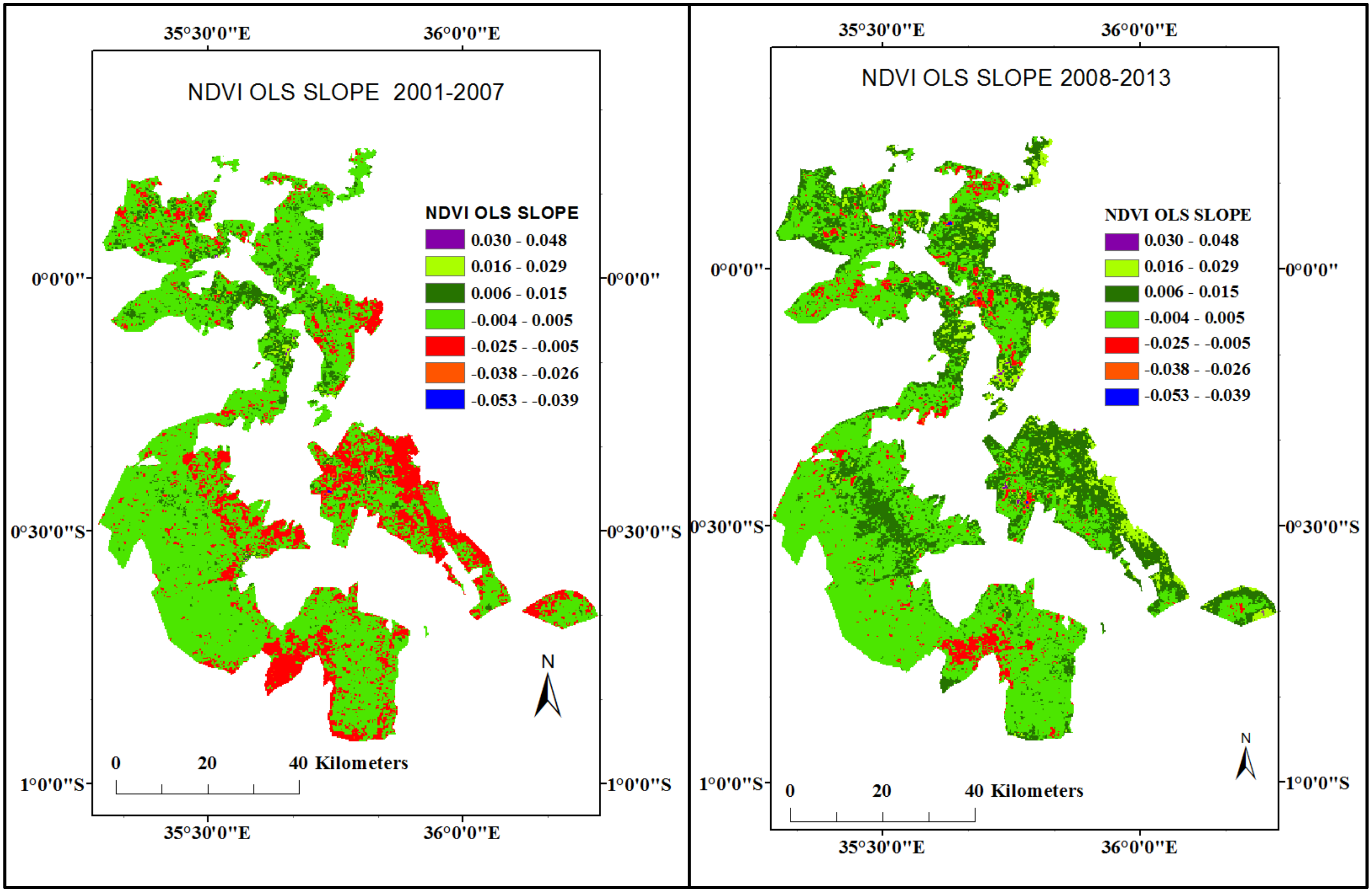

Figure 5-55 NDVI OLS Slopes images for the Mau Forest Complex

However, it is clear that there are some areas especially in the Western part of the Maasai Mau that are still undergoing degradation. According to Olang and Kundu (2011), these are the areas that were destroyed between 2001 and 2009. It is possible that the delay in recover of these areas is a reflection of the fact that restoration started later in Maasai Mau than in Southwest Mau and Eastern Mau (Mau Forest Complex Interim Coordinating Secretariat, 2010). This implies that Southwest and Eastern Mau have had longer recovery time than Maasai Mau and hence the impressive recovery rate witnessed in these two forest blocks. This also supports the claim that the recovery witnessed in Eastern Mau and Southwest was as a result of the restoration and conservation initiative that started in 2008. However, further study need to be carried out on Maasai Mau to ensure that the slow recovery is not caused by continued occupation of the forest by illegal settlers or any other inhibiting factors.

Most of the positive NDVI OLS values in 2001-2007 were recorded in the northern blocks, especially in Mount Londiani and Tinderet. This implies that the northern blocks of the Mau Forest Complex did not suffer as much damage as the Lower blocks during this period. However the areas that show positive NDVI OLS values recorded some of the lowest NDVI values during the period of study and showed high variability of NDVI with rainfall, suggesting that they have inferior vegetation. In fact some of this areas suffered degradation between 1986 and 2000, especially parts of Western Mau (Olang & Kundu, 2011). Also there are some areas in the northern blocks of the Mau Forest Complex that recorded NDVI OLS slopes below -0.025, like eastern part of Mount Londiani.

To estimate the total area that showing significant trend during the two periods, a threshold of one standard deviation was applied to the two images. Standard deviation has been used by several researchers to set threshold in NDVI based change detection (Mancino *et al.*, 2014; Sarp, 2012; Yacouba *et al.*, 2009; Sepehry and Liu, 2006). Based on this threshold, the whole of Mau Forest complex was classified into three classes: Significant negative trend (labeled Negative), Insignificant trend (labeled Insignificant) and the Significant Positive trend (labeled Positive) (Figure 5-56). According to Figure 5-56, about 19% (75,119 hectares) of the Mau Forest Complex show signs of degradation, while only 7% (27,056 hectares) show signs of greening during the 2001 to 2007 period. This is consistent with the fact that the Mau forest was undergoing degradation during this period.

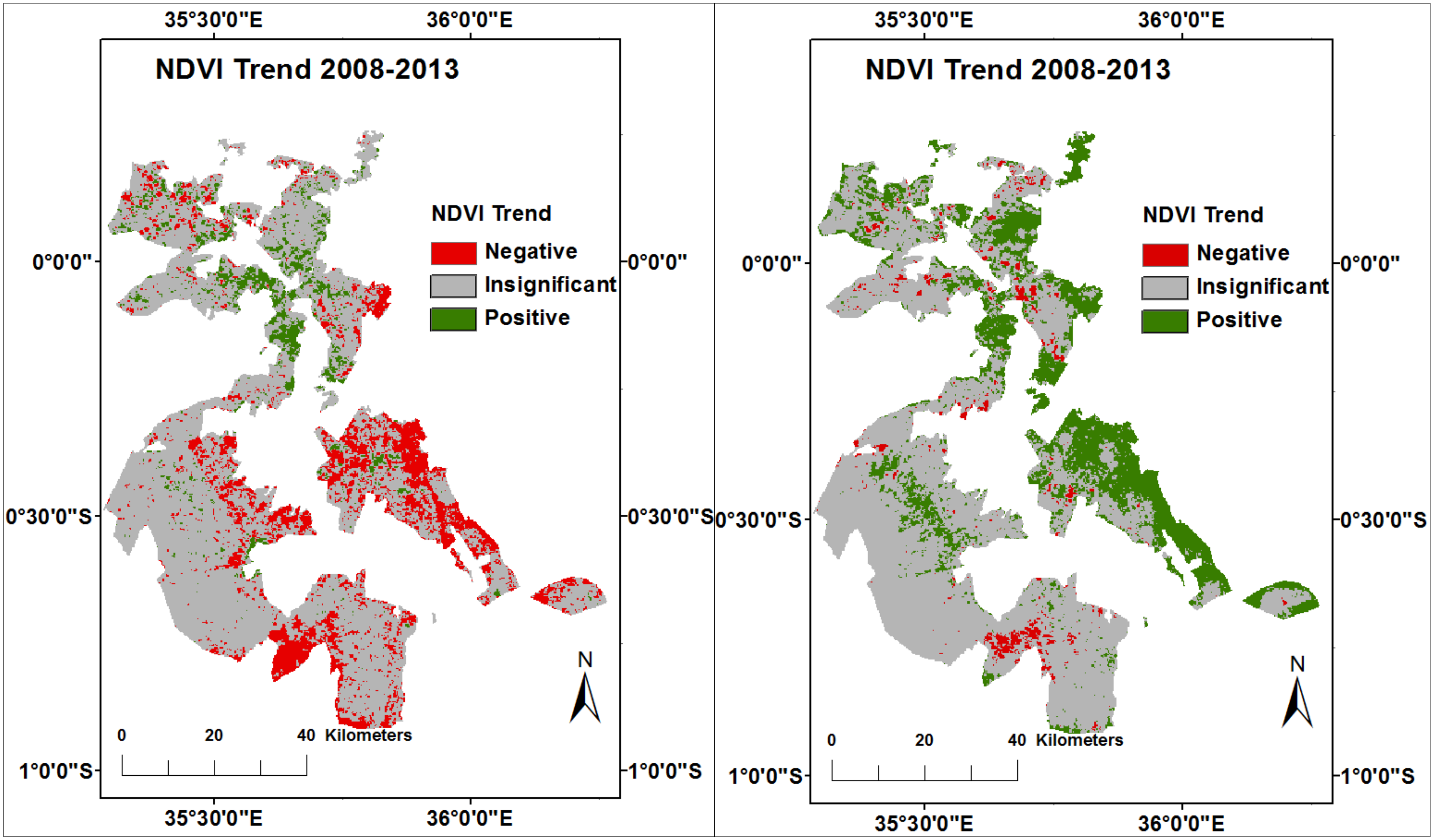

Figure 5-56 Significant NDVI slope for Mau Forest Complex during the two periods (2001-2007 and 2008-2013)

During the 2008 to 2013 period, there is an increase in the area showing signs of improvement in vegetation by about 19%. During this period, about 26% of the forest recorded a positive NDVI trend while only 3% recorded a negative NDVI trend (Table 5-1). These results imply that areas that are undergoing degradation have reduced by 15%, and those greening have increased by 19%. Areas that could be considered relatively unchanging (areas with insignificant NDVI trend) reduced by 5.27% in 2008-2013. This implies that some of the areas that were undergoing degradation as well as some that were relatively unchanging are now experiencing positive increase in NDVI. The sum total of all these changes is an increase in the total area of the forest that is greening. Overall, the Mau Forest Complex is greening up, a fact that may point to the success of the restoration and conservation initiative.

Eastern Mau experienced the highest level of improvement in vegetation, with majority of the area experiencing a shift in the NDVI trend from negative in 2001-2007 to positive in 2008-2013. Areas that were affected by the 2001 excision in Southwest Mau recorded a shift in NDVI trend, from negative (areas with significant negative trend) to areas of insignificant change. Some areas in Southwest Mau recorded a shift from unchanging to positive trend suggesting an improvement in vegetation in areas that were initially unchanging. Most areas of Maasai Mau that recorded a negative trend in 2001-2007 recorded an insignificant trend in 2008-2013 implying that degradation was brought to a halt, but more need to be done to increase vegetation density of the forest. Eburu Mau also shows some impressive change in NDVI trend suggesting improvement in vegetation. Mount Londiani shows signs of vegetation regeneration especially on the eastern side, while most of the other upper blocks, like Tinderet, show no significant change in the NDVI trend over the two periods.

Table 5-1 NDVI Trend Statistics

	2001-2007		**2008-2013**		**Change**	
NDVI Trend	Area (ha)	% Area	Area (ha)	% Area	Area (ha)	% Area
Negative	75,118.75	18.76	14,000.00	3.45	-61,118.75	-15.31
Insignificant	298,250.00	74.48	280,856.25	69.21	-17,393.75	-5.27
Positive	27,056.25	6.76	105,568.75	26.01	78,512.50	19.26
TOTAL	400,425		400,425			

6. CONCLUSIONS AND RECOMMENDATIONS

6.1. Conclusions

The analysis of NDVI time series and the NDVI OLS slopes show that the Mau Forest Complex is recovering from the destruction it has been experiencing over the past few decades. There is an increase in the slope of the time series trend from 2008 to 2013 for most of the Mau Forest Complex. Areas that were excised in 2001 are showing signs of recovery since the restoration and conservation initiative began. The NDVI time series show that most blocks recorded the maximum NDVI values during the period extending from 2001 to 2007. This implies that although the forest is recovering, it has not yet been restored back to the state it was before the 2001 excision. More resources will have to be channeled to the conservation and restoration initiative to ensure complete recovery of the forest. It takes a long time, to the tune of over ten years, for the seedlings to mature into large trees that can form a forest canopy.

With a mean annual NDVI value of 0.86, Transmara is the densest forest blocks among the nine forest blocks. However, the NDVI time series show that this forest block is undergoing some form of land cover degradation, though at a small rate (-0.06 during 2001-2007 and -0.03 during 2008-2013). It is important that the cause of this degradation is determined and dealt with before this forest block suffers serious degradation. The analysis of variation of biomass in this forest with climatic parameters (rainfall and temperature) showed that this forest is highly resistant to variation in these variables. It is therefore unlikely that these climatic variables are responsible for this degradation. It is therefore probable that human activities are responsible for this destruction. The gradual decrease in the negative NDVI trend slope of the forest block in the period covering 2008-2013 could be an indication that the decrease in the NDVI values experienced in the 2001-2007 period was caused by human induced degradation.

Molo, on the other hand, has the lowest mean annual NDVI value of about 0.64 followed by Eastern Mau with a mean annual NDVI value 0.72. Western Mau, Maasai Mau and Transmara have mean annual NDVI values that are above 0.8, while all the other forest blocks have NDVI values higher than 0.7 but less than 0.8. It is therefore clear that more attention should be focused on Molo and Eastern Mau to stop further destruction. The fact that these two forest blocks have lower mean annual NDVI values than the other forest blocks implies that they are more inferior in terms of vegetation density and vigor than the other forest blocks and would therefore require more resources to rehabilitate. However, these forest blocks show signs of recovery as depicted by the 2008-2013 NDVI OLS slope values.

Analysis of the variation of NDVI with rainfall revealed that some of the forest blocks are highly dependent on it. This is critical because the forest blocks that recorded low NDVI values (for example Molo and Eastern Mau) showed high dependence on rainfall and also showed very strong negative LST-NDVI correlation. This implies that recovery of this forest will depend on climate changes. Decrease in rainfall will definitely slow down recovery of the forest. The relationship between NDVI and both monthly LST and rainfall is nonlinear whereas the relationships between mean annual NDVI and both total annual rainfall and average annual temperature are linear. This study also shown that the NDVI does not only depend on the total annual rainfall, but also on the monthly variation of rainfall. It takes between one and two months for the forest blocks to respond to variation in rainfall (precipitate). There is also a strong negative NDVI-LST relationship attesting to the fact that the forest has an influence on the surface temperature of the region.

6.2. Recommendations

Using MODIS images, this study has shown that the vegetation density within Mau Forest Complex has been improving since the restoration and conservation initiative began back in 2008. However, more information about the nature and magnitude of change in the forest can be obtained using higher spatial resolution satellite sensors. Using such sensors will provide more information about the changes in land cover within the forest. For example, the rate of increase/decrease in biomass can be linked to the type of vegetation and therefore provide more information about the land cover change that the restoration and conservation stakeholders can use to restore and conserve the forest more effectively. The 250m MODIS images can be used as a device for obtaining preliminary results while the high spectral resolution sensors can be used to carry out a detailed analysis of the land cover changes.

There is also need to establish relationship between resources allocated and rate of forest cover recovery achieved. That way the Government can determine how much money it needs to achieve certain levels of improvement in the different forest blocks. By getting this information, the Government will be able to determine any progress that is made by the restoration and conservation initiative and pinpoint areas of the forest that are suffering degradation despite allocation of huge amount of resources. Any inhibiting factors can then be identified and eliminated thus ensuring optimum use of the conservation resources available. There is also need for continued monitoring of the forest block to ensure that gains made so far are not lost and that more positive results are achieved.

More resources should be channeled to the restoration and conservation initiative to enable further improvement of the forest. It is also important that the performance of TRMM and MODIS LST as tools for measuring rainfall and temperature be determined. Various researchers have shown that these tools correlate well with ground based measurements. However, their performance in Mau Forest Complex has not been determined, and effort should be made to ensure that this is done. That way any biases in these satellite based measurements can be corrected or accounted for in data analysis.

There is also need for long term monitoring of the forest to understand how temperature and rainfall affect the growth and development of vegetation in the forest. This is due to the fact that in addition to the normal seasonal variation of rainfall there is also El Niño southern Oscillation that is said to occur after every ten years (Albert *et al.*, 2003). This coupled with global warming is bound to affect the recovery of the forest in the long run.

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