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Spatio-Temporal Modeling of Vegetation Change Dynamics in the Guinea Savannah Region of Nigeria using Remote Sensing and GIS Techniques.

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Dedication

This work is dedicated to my parents (Engr A.O Osunmadewa & Mrs E.O Osunmadewa), Adebomi Oluwaseun Sojirin and Ayomide Osunmadewa.

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Acronyms and Abbreviations

ABS= Annual Abstract of Statistics

ACF= Autocorrelation Function

AOI= Area of Interest

AutoMCU= Automated Monte Carlo Unmixing

AVHRR= Advanced Very High Resolution Radiometer

AVI= Ashburn Vegetation Index

BGS= Beginning of Growing Season

BOKU= University of Natural Resources and Life Sciences

BS= Bare Substrate

CC= Cross-Correlation

CIS= Carnegie Institution for Science

CLASlite= Carnegie Landsat Analysis System-lite

CMK= Contextual Mann-Kendall

CO^2 = Carbon Dioxide

CRU= Climatic Research Unit

CTVI= Corrected Transformed Vegetation Index

cT = Continental Tropical

DVI= Difference Vegetation Index

EGS= End of the growing season

EMD= Empirical Mode Decomposition

ENVI= ENvironment for Visualizing Images

EOS= End of Season

ESA= European Space Agency

ETM= Enhanced thematic mapper

FAO= Food and Agricultural Organization

FC= Fractional Cover

FORMECU= Forestry Monitoring and Evaluation Coordinating Unit

GCOS= Global Climate Observation System

GIMMS= Global Inventory Modeling and Mapping Studies

GLC= Global Land Cover

GloVis= Global Visualization Viewer

GSR= Guinea Savannah Region

GTS= Global Telecommunication System

GVI= Global Vegetation Index

IITA= International Institute of Tropical Agriculture

ITCZ= Inter-Tropical Convergence Zone

ITD= Inter-Tropical Discontinuity

KRC= Kendall’s Rank Correlation

LULC= Land Use Land Cover

LULCC= Land Use Land Cover Change

MERIS= MEdium Resolution Imaging Spectrometer

MODIS= Moderate Resolution Imaging Spectroradiometer

MK= Mann-Kendall

MSAVI= Modified Soil-Adjusted Vegetation Index

NDVI= Normalized Difference Vegetation Index

$NDVI_{max}$ = Maximum Normalized Differenced Vegetation Index

NIR= Near Infrared

NOAA= National Oceanic and Atmospheric Administration

NPV= Non-Photosynthetic Vegetation

NRVI= Normalized Ratio Vegetation Index

OLI= Operational Land Imager

OLS= Ordinary Least-Square

PACF= Partial Autocorrelation Function

POES= Polar Operational Environmental Satellite

PPMC= Pearson Product Moment Correlation

PVI= Perpendicular Vegetation Index

PV= Photosynthetic vegetation

QQ= Quantile-quantile

RVI= Ratio Vegetation Index

SAVI= Soil-Adjusted Vegetation Index

SOS= Start of Season

SPOT= Satellite Pour l'Observation de la Terre

STA= Seasonal Trend Analysis

TAMSAT= Tropical Applications of Meteorology using Satellite data

T_m= Tropical maritime

TM= Thematic Mapper

TIR=Thermal Infrared

TIRS= Thermal Infrared Sensor

TVI= Transformed Vegetation Index

TSAVI= Transformed Soil-Adjusted Vegetation Index

TS= Theil-Sen

USGS= United States Geological Survey

VIs=Vegetation Indices

WA= West Africa

WMO = World Meteorological Organization

°C= Degree Celsius

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Abstract

The use of Normalized Difference Vegetation Index (NDVI) time series over the last decades has increased our understanding of vegetation change dynamics from global to regional scale through quantitative analysis of inter-annual trends in NDVI and climatological parameters (rainfall and temperature). Change in land cover induced by human activities such as livestock grazing and deforestation for large-scale farming (subsistence and mechanized) has influenced the ecological pattern of the Guinea savannah region (GSR) of Nigeria, thereby resulting in loss of biodiversity and changes in vegetation cover. In the context of the GSR of Nigeria where agriculture still plays a major role in people's economy, it is important to identify the relationship between climatic variables, vegetation productivity and human activities which can be used to understand the on-going transition processes.

This study, therefore, examines the spatial and temporal relationship between NDVI and climate parameters, land use land cover change (LULCC) and the perspective of local people on vegetation change dynamics in the study region. In order to do this, bi-monthly NDVI3g time series datasets from Global Inventory Modeling and Mapping Studies (GIMMS), monthly rainfall datasets from Tropical Applications of Meteorology Satellite (TAMSAT), monthly temperature datasets from Climate Research Unit (CRU), national land use land cover (LULC) data of Nigeria from Forestry Management Evaluation & Coordination Unit (FORMECU), global land cover datasets from European Space Agency, Landsat imagery and socio-economic field data collection were used in order to understand vegetation change dynamics across the Guinea savannah regions of Nigeria.

Time series analysis (TSA) was applied to both NDVI and climate data used in order to examine the temporal dynamics of vegetation cover change and to detect NDVI-climate relationship during the period from 1983 through 2011. Both parametric and non-parametric statistical models were employed for the assessment of long-term inter-annual trend on the decomposed time series datasets for the whole region (Guinea savannah region) and selected locations. In addition to the TSA, harmonic regression analysis was performed on NDVI and rainfall datasets in order to examine change in seasonality and phyto-phenological characteristics of vegetation. Detection of change in land use and land cover was done by extracting information from existing land cover datasets (ancillary datasets). CLASlite was used for the assessment of the extent of deforestation, while linkage between remotely sensed data and social science was carried out via field surveys based on questionnaires in order to understand the drivers of vegetation change.

The study reveals that about 90 % of the Guinea savannah region show positive NDVI trends which indicate greening over time, while about 10 % of the region shows negative trends. This greening trends are closely related to regions where intensive agriculture is being practiced (also along inland valleys) while regions with negative trends show significant loss in woodlands (forest and shrublands) as well as herbaceous vegetation cover due to over-grazing by agro-pastoralism. The result confirms that there is a good relationship (statistically significant positive correlation) between rainfall and NDVI both on intra-annual and inter annual time scale for some selected locations in the study region (> 65 %), while negative statistical correlation exists between NDVI and temperature in the selected locations. This implies that vegetation growth (productivity) in the region is highly dependent on rainfall. The result of the harmonic regression analysis reveals a shift in the seasonal NDVI pattern, indicating an earlier start and a more prolonged growing season in 2011 than in 1983. This study proves significant change in LULC with evidence of an increase in the spatial extent of agricultural land (+ 30 %) and loss of woodlands (- 55 %) between 2000 and 2009 for Kogi State. The results of the socio-economic analysis (people's perception) highlight that vegetation change dynamics in the study region are the resultant effects of increased anthropogenic activities rather than climatic variability. This study couples data from remote sensing and ground survey (socio-economics) for a better understanding of greening trend phenomena across the Guinea savannah region of Nigeria, thus filling the gap of inadequate information on environmental condition and human perturbation which is essential for proper land use management and vegetation monitoring.

Zusammenfassung

Die Anwendung von Zeitreihen des "normalisierten differenzierten Vegetationsindexes (NDVI)" hat in den vergangenen Jahrzehnten zu einem umfassenderen Verständnis von Vegetationveränderungsdynamiken vom globalen zum regionalen Maßstab geführt, vor allem durch die quantitative Analyse von NDVI-Trends und von den Klimaparametern Jahresniederschlag und -temperatur. Der Wandel der Landoberflächen, hervorgerufen durch menschliche Einflüsse wie Viehweidetrieb und die Abholzung des Waldes für großflächige Subsistenz- als auch mechanisierte Landwirtschaft hat die ökologische Struktur der Guinea Savannah Region (GSR) in Nigeria stark beeinträchtigt, was zu einem Verlust der Biodiversität und zu Veränderungen der Vegetationsbedeckung führte. In einer Region, in der Landwirtschaft die wichtigste Einnahmequelle der Menschen darstellt, ist es wichtig, die Beziehung zwischen Klimavariablen, Leistungsfähigkeit der Vegetation und menschlichen Aktivitäten zu bestimmen. Diese Beziehung kann herangezogen werden für ein besseres Verständnis der andauernden Transitionsprozesse.

Die vorliegende Arbeit untersucht daher die räumliche und zeitliche Beziehung zwischen dem NDVI und Klimaparametern, Landnutzungs- und Landoberflächenwandel (LULCC) sowie der Perspektive der lokalen Bevölkerung auf Vegetationsveränderungsdynamiken in der Untersuchungsregion. Um die Dynamiken der Vegetationsveränderung in der gesamten Guinea Savannah Region in Nigeria besser verstehen zu können, wurden folgende Daten genutzt: zweimonatige NDVI3g Zeitreihen-Datensätze von Global Inventory Modeling and Mapping Studies (GIMMS), Datensätze des Monatsniederschlages der Tropical Applications of Meteorology Satellite (TAMSAT), Datensätze der Monatsmitteltemperatur des Climate Research Unit (CRU), nationale Landnutzungs- und Landoberflächendaten (LULC) von Forestry Management Evaluation & Coordination Unit (FORMECU), globale Daten der Landoberfläche der Europäischen Weltraumorganisation, Landsat Bilder und eine Sammlung von empirischen sozio-ökonomischen Feldforschungsdaten.

Eine Zeitreihenanalyse (Time series analysis – TSA) des NDVI und der Klimadaten wurde durchgeführt, um die zeitlichen Dynamiken der Veränderung der Vegetationsbedeckungen zu untersuchen und um eine NDVI-Klima-Beziehung zwischen den Jahren 1983 und 2011 herzustellen. Sowohl parametrische als auch nicht-parametrische statistische Modelle wurden

herangezogen für die Bewertung des Langzeittrends innerhalb eines Jahres anhand zersetzter Zeitreihen-Datensätze für die gesamte Region und ausgewählte Hotspots. Ergänzend zu den TSA wurde eine harmonische Regressionsanalyse des NDVI und der Niederschlagsdaten durchgeführt, um den Wandel der Saisonabhängigkeit und phyto-phänologischen Eigenschaften der Vegetation genauer zu untersuchen. Der Wandel der Landnutzung und damit der Landoberfläche wurde anhand von Informationen aus Landoberflächendaten (ergänzende Datensätze) festgestellt. CLASlite wurde für die Bewertung des Ausmaßes der Abholzung verwendet, während eine Verknüpfung von Fernerkundungsdaten und Sozialwissenschaften anhand von empirischen Feldforschungen mit Hilfe von qualitativen Fragebögen hergestellt wird um auch die (menschlichen) Einflussfaktoren auf die Vegetationsveränderung zu verstehen.

Die vorliegende Untersuchung zeigt, dass etwa 90 % der Guinea Savannah Region positive NDVI Trends aufzeigen, welche auf ein dauerhaftes Wachstum hinweisen, während etwa 10 % der Region negative Trends aufweisen. Die Positive Trends sind in Gebieten mit intensiver Landwirtschaft zu finden (auch entlang der Inland-Täler), während Gebiete mit negativen Trends eine signifikante Abnahme von Gehölzflächen (Wald und Buschland) und ebenso von krautartiger Vegetationsbedeckung aufgrund von Überweidung zeigen. Das Ergebnis bestätigt eine gute Beziehung (statistisch signifikante positive Korrelation) zwischen Niederschlag und NDVI sowohl innerhalb eines Jahres als auch zwischen den jährlichen Zeitskalen für ausgewählte Standorte innerhalb der Untersuchungsregion (> 65 %), während negative statistische Korrelationen zwischen NDVI und Temperatur in ausgewählten Standorten bestehen.

Das bedeutet, dass die Zunahme der Vegetation (Produktivität) in der Region mehr vom Niederschlag als von der Temperatur abhängt. Das Ergebnis der harmonischen Regressionsanalyse verdeutlicht eine Verschiebung der saisonalen NDVI Muster, indem sie eine früher einsetzende und länger andauernde Vegetationsperiode im Jahr 2011 als 1983 aufzeigt.

Diese Arbeit belegt einen signifikanten Wandel von Landnutzung und –oberfläche mit dem Hinweis auf einen Anstieg der landwirtschaftlichen Nutzfläche (+ 30 %) und einer Abnahme von Waldgebieten (- 55 %) zwischen 2000 und 2009 im Bundesstaat Kogi. Das Ergebnis der sozio-ökonomischen Analyse (Wahrnehmung der Menschen) hebt hervor, dass die Vegetationsveränderungsdynamiken in der Untersuchungsregion stärker als Effekte von gestiegenen menschlichen Aktivitäten als von Klimavariabilitäten zu verstehen sind. Diese Arbeit verbindet Fernerkundungsdaten und qualitative empirische Feldforschungen zugunsten eines besseren Verständnisses von Vegetationstrends-Phänomenen über die gesamte Guinea Savannah Region in Nigeria. Die neu gewonnenen Erkenntnisse schließen die Lücke von inadequater Information über Umweltbedingungen und menschliche Einflüsse, die essenziell sind für ein angemessen Landnutzungsmanagement und Vegetations-Monitoring.

1. Background

1.1. Introduction

Vegetation which is one of the most important assets on earth plays a significant role in global in terrestrial ecosystem and climate change research (De Jong et al., 2013). However, change in the global vegetation cover over the last decades has caused shifts in vegetation physiognomic characteristics which is attributed to both natural and anthropogenic factors especially in the arid and semi-arid region of Africa where both factors (i.e anthropogenic and natural) play a key role (Wu et al., 2016). The structure and composition of vegetation across different land use shows that anthropogenic activities can have long-term effects in influencing habitat loss and vegetation cover transition while variability in annual precipitation in some parts of the world such as the Sahel might cause change in vegetation distribution and pattern over time. However, the association between climate and vegetation is not easy to decouple owing to the fact that change in climate may have significant impact on vegetation dynamics (Pearson and Dawson, 2003). Several factors such as climate, grazing activities, CO^2 concentration in the atmosphere, agricultural activities and fire regime are responsible for global vegetation change dynamics (Andela et al., 2013; De Jong et al., 2013; Herrmann et al., 2005) and this change has direct impact on the ecosystem. Assessment of vegetation condition as well as its change are major components of global studies which are topics of considerable societal relevance today because of its potentials for monitoring environmental change (Salami, 1998). Human induced climate change may cause changes to the structure and composition of natural vegetation cover especially in the savannah region where variability in rainfall pattern has influence on vegetation productivity (Wu et al., 2016). Changes in land use land cover induced by human activities due to excessive grazing, large scale agricultural practices, population growth and lack of awareness among the people about the importance of forests has led to deforestation, loss of biodiversity and change in vegetation which have intense implications on climate (Dickinson et al., 1990; Dickinson and Henderson-Sellers, 1988; Lean and Warrilow, 1989). Spectral vegetation indices are among the most widely used satellite data products which provide key measurements for climate, hydrological, biogeochemical, phenological studies, land cover mapping and change detection for natural resource management and sustainable development. The availability of Normalized Difference Vegetation Index products from different sensors such as Advanced Very High Resolution Radiometer (AVHRR) and Moderate Resolution Imaging Spectroradiometer (MODIS) makes long-term spatio-temporal monitoring and modeling of environmental change both at regional and global scale possible (Huete et al., 2011). Vegetation as important component of the ecosystem processes form the base for humans and other living organisms of the environment (Hansen et al., 2000). Loss of vegetation and other alterations of biological assemblage, structure and function result from various factors, including climatic variations and human activities (Glenn et al., 1998; Hansen et al., 2000; Riva-Murray et al., 2010). Fuhlendorf and Engle, (2004) contend that pressures from population, cultivation, grazing and bush burning are some of the main factors that shape arid, semi-arid and dry sub-humid landscapes. These pressures cause disturbances leading to degradation of vegetation characteristics. Human activities have impacts on vegetative land cover which can cause changes in habitat. Changes in habitat can alter ecosystems thereby causing reduction in the quality and quantity of resources. For instance, total loss or degradation in vegetation as well as average changes in regional weather conditions can cause disturbances and changes in composition of species. These disruptions commonly reduce vegetation quality (Loram et al., 2007). It was revealed by Richards and Flint, (1994) that about 560 million hectares of land covered by grass and pasture have declined in the last three centuries while cropland areas has increased for about 1200 million hectares. The current state of global vegetation has made classification of land cover to be done according to their structural characteristics and land use land cover change pattern (Chown, 2010; Goldewijk et al., 2004; Running Steven W et al., 1995). The state of global vegetation therefore makes monitoring vegetation change dynamics important. In order to address this issue (i.e monitoring vegetation change dynamics), new techniques, datasets, and tools to quantify and provide holistic explanation about the changes in vegetation cover are needed (Eastman et al., 2013; Zhang et al., 2015). Similar changes in vegetation composition and structure are evident in Nigeria, most especially in the Guinea savannah region where most of the forest cover is lost due to anthropogenic activities thereby causing a shift in seasonal vegetation phenology and modulation of regional climate pattern (Igbawua et al., 2016; Osunmadewa et al., 2015; Wu et al., 2016). The dynamics of change in West Africa was revealed by the assessment of United Nations Food and Agricultural Organization (FAO) where loss of forest area from 1990 - 2010 accounted for about 44 % i.e from 91589000 hectares in 1990 to 73234000 hectares in 2010 (Berkat and Tazi, 2006; FAO, 2011). An annual net loss in forested area of about -3.7 % was recorded in Nigeria between 2000 -2010 (Lindquist et al., 2005). This shows that most of the ecological zones of Nigeria have been experiencing noticeable transition due to large scale transformation of land cover. Several studies on land use land cover change have been done in Nigeria using remote sensing data, for example the assessment of land use land cover by Opeyemi, (2006) in Ilorin, Kwara State, using time series of Landsat imagery of 1972, 1986 and 2001 to calculate land consumption rate and forecast future change using Markov chain and cellular automata analysis. However, an in-depth assessment of vegetation using NDVI is lacking. Adeofun et al., (2011) used land use land cover data of 1995 from Forestry Monitoring, Evaluation and Coordinating Unit (FORMECU) of Nigeria to carry out change assessment in Nigeria between 1976 – 1995 (Osunmadewa and Wessollek, 2014). The result of the study shows that several physiognomic characteristics of the vegetation cover have significantly changed from its original form to another. The study further revealed dense population rate (i.e habitat index of 3.94) which has consequential impact on the services rendered by the ecosystem to nature. Increasing human footprints (perturbation) on the ecosystem are revealed in form of increase in fuelwood and timber consumption, increase in the numbers of enclaves within forest areas, fragmentation of forest for road projects. The FORMECU land use land cover classification project adopted by Adeofun et al., (2011) provides information at the national level thereby proving the impact of human induced land use pattern and its influence on the biogeochemical cycle, hydrological cycle and physical climatic system. Although the study of Adeofun et al., (2011) is an eye opener regarding the importance of vegetation monitoring in Nigeria, however, the national FORMECU land cover map used in the study has limitations due to its small-scale of 1:250,000 (Ademiluyi et al., 2008; Adeoye, 2012). An annual rate of deforestation of about 400,000 hectare was reported by Adesina, (2005) due to mineral exploitation, growing demand for tropical hard wood among other anthropogenic activities. All the aforementioned facts make assessment of vegetation change dynamics very important in Nigeria for suggesting the development of proper management plans.

1.2. Problem statement

There have been significant variations in the physiognomic characteristics of Nigeria's vegetation over the last decades owing to climatic variability and anthropogenic activities in all the agro-ecological zones of the country. Knowledge about the structure, function and seasonality of the terrestrial ecosystem in Nigeria is inexact due to the fact that adequate assessment, monitoring and mapping of vegetation cover had not been carried out thoroughly and properly archived. The forest estates from which wood and non-wood products are obtained have been subjected to severe encroachments, vegetation degradation for agriculture, urbanization and industrial development. Regular acquisition of up to date data on vegetation productivity is a major challenge in Nigeria till date as most of the inventories performed and documented in the late 1990's on land use land cover change are mere indicative but do not truly reflect the actual vegetation change dynamics over a long period of time. Although the natural resources of the country do not grow similarly, some of the vegetated areas (forested area) which are assumed to have limited disturbance are currently experiencing substantial biodiversity loss due to increased anthropogenic activities which has led to the existence of gullies, desertification and forest degradation amongst other environmental issues. This makes information on the spatial heterogeneity of vegetation cover a focal issue for setting up a proper ecosystem management strategy. The above mentioned problems show that conventional assessment of vegetation trend at the regional scale is insufficient. Adequate knowledge about ecosystem response (vegetation) to environmental change (climate parameters) has become necessarily important for monitoring vegetation trend and assessment of the impact of land-use change on the ecosystem. It is therefore fundamental to assess the biomass accumulation of some agro-ecological zones in Nigeria. Though studies on environmental monitoring using NigeriaSat-1 and NigeriaSat-2 have been carried out (Akinyede et al., 2015), research on long-term monitoring of vegetation change dynamics is still missing. In order to bridge the gap created by previous studies, research on reliable means of monitoring and modeling vegetation change dynamics and land use land cover change over a longer period of time is imperative.

1.3. Justification

In the light of continuous increase in human population, it is important to have a comprehensive spatial and temporal information on vegetation change dynamics with appropriate resolution in order to effectively manage biological resources (Bino et al., 2008). In the past 30 years, population in the study region has increased with severe consequences on the landscape. The green-belts and wetlands have depleted and vegetation surrounding the cities has degraded due to continuous overuse of the resources of the ecosystems by man. The need for proper assessment of vegetation change dynamics is crucial as this will serve as an important starting point for environmental management since little or nothing has been documented on vegetation trend over a long-term period in the study area. Thus, the study aims at providing detailed information on long term trends in vegetation change at the regional scale which will provide adequate answers to some questions related to land use because the existing information such as that of FORMECU is relatively old. As the landscape of the study area has been profoundly altered, a reliable and fast methodology for detecting change is vital. This study will also show the relevance of land-use land cover assessment, which supports some of the observed trends in vegetation dynamics for proper understanding of ecosystem properties and the role which remote sensing plays in analyzing regional vegetation change dynamics. The outcome of this research is expected to provide benefit not only to research institutes or scientists, but also to policy makers, regional planners as well as educational institutions in the study area and Nigeria as a whole on issues related to climate change and environmental monitoring.

1.4. Research question

Several studies at the global level have established the fact that the last decades have experienced an increase in plant growth (De Jong et al., 2013) which is true for some parts of the world. However, more research on other parameters associated to this fact has to be examined. Nigeria being the most densely populated country in Africa has experienced several years of vegetation change coupled with change in land cover and climatic variation. Hence, the question of debate is: Is the global increase in plant growth a positive signal for at the local or regional scale as well? In order to answer this main question, other detailed questions have been generated which this research will intend to answer

1. Can vegetation change dynamics be explained by climatic parameters? Or is there any relationship between vegetation productivity and climatic drivers?
2. Can a seasonal vegetation trend be detected by remote sensing data?
3. What is the impact of land use land cover change on vegetation trend or can change in vegetation dynamics be influenced by land use pattern?
4. What is the impact of socio-economic activities on vegetation change dynamics?

1.5. Objectives

The main objective of this study is to detect long-term trends in vegetation dynamics over the transition zones of Nigeria, their association (relationship) with climatic factors and land cover change using remote sensing data.

1. To examine inter-annual trends in vegetation activity and their inter-relationship with variability in climate
2. To detect seasonal change dynamics in vegetation activity and their phenological pattern
3. To examine the impact of land use change on vegetation dynamics
4. To assess the inter-relationship between the observed trends in vegetation dynamics by qualitative measures (socio-economic data).

1.6. Thesis organization

A brief introduction of the relevant problems affecting the Guinea savannah region of Nigeria is discussed in **chapter 1**.

Chapter 2 deals with the remote sensing approach for investigating vegetation and land use land cover change.

Chapter 3 comprises the geographical location, climate and vegetation of the study area.

Chapter 4 deals with the datasets used and the methodological approaches.

Chapter 5 deals with the results of the inter-annual trend analysis.

Chapter 6 deals with the results of the seasonal trend analysis.

Chapter 7 focuses on land use land cover assessment.

Chapter 8 deals with socio-economic analysis through the use of questionnaires.

Chapter 9 deals with results synthesis, limitations and recommendations for future works.

2. Remote sensing and its applications for monitoring vegetation and land use change.

2.1. The concept of the ecosystem

The use of remotely sensed data in ecosystem monitoring and modeling of environmental processes is very important for understanding, interpretation and comprehension of the complex ecosystem. Generally, an ecosystem represents a whole community of organisms and its environment as a unit. It consists of the community of organisms (biotic factors) and the physical environment (abiotic factors) that occurs in an area (Whitman et al., 1998). However, the geographical distribution of the ecosystem is largely influenced by climate. This form the base for major vegetation types around the world (Cote and Darling, 2010; Malik and Husain, 2006).

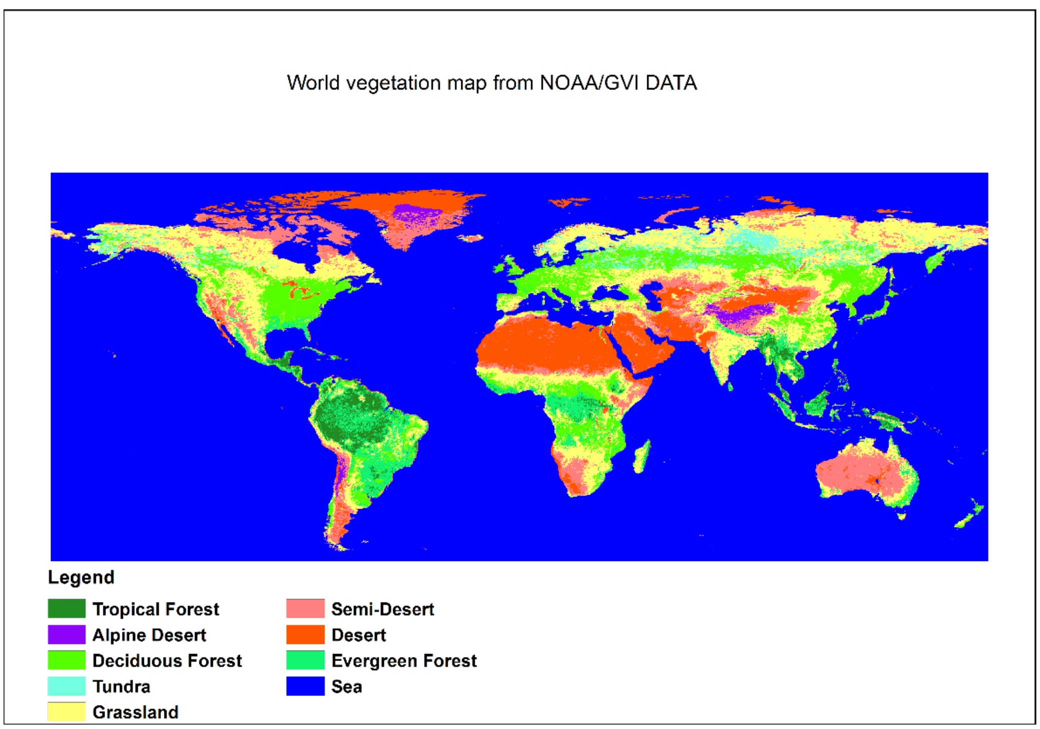


Figure 1. World Vegetation Map (Derived from National Oceanic and Atmospheric Administration (NOAA)/ Global Vegetation Index (GVI) from 1985 to 1987 with a spatial resolution of 12.7km)

Source: (http://www.grid.unep.ch/data/).

The vegetation cover of Nigeria is governed by the interaction of climate (i.e rainfall, temperature) and soil types. Hence, the agro-ecological zones of Nigeria are classified into:

(i) The Mangrove forest and coastal vegetation
(ii) The Freshwater swamp forest
(iii) The Tropical high forest
(iv) The Guinea savannah zone
(v) The Sudan savannah
(vi) The Sahel savannah
(vii) Montane vegetation

The mangroves are found in the coastal region under the influence of brackish water. The main types of mangroves are Rhizophora (commonly known as red mangroves), Avicennia (black mangroves) and Laguncularia (white mangroves) (Jackson, 2000; Kinako, 1977). The fresh water swamp forests are found within the lowlands. The zone is characterized by mixture of trees, palm and fiber plants such as Raphia spp, *Raphia vinifera*, *Raphia hookeri*, *Eleais guineenais* (oil palm), *Chlorophora exceisa*. The tropical high forest zone is of high importance in Nigeria because it supports food and timber production. This area is characterized by prolonged rainfall. Both economic cash crops and tree species are found in this zone, including *Theobroma cacao* (Cocoa), *Hevea brasiliensis* (Rubber), *Cola nitida* (Cola nut), *Chlorophora excels* (Iroko). The Guinea savannah which is the focal zone of this study is the most extensive ecological zone in Nigeria. This zone is divided into two (i.e the northern and the southern guinea savannah). It is characterized by tall grasses, mixed deciduous and semi-deciduous woodlands. The Sudan savannah is found in the north and is dominated by grasses, some shrubs and trees such as *Butyrospermum parkii* (Shea butter), *Mangifera indica* (Mango) while the Sahel savannah is characterized by short grasses. The montane zone is characterized by grasses on the top of some hills while forest cover are found along the slope. However, due to climate change, ecosystem alteration and direct human intrusion on the vegetative cover, the need for a novel algorithm for ecosystem modeling and quantitative analysis of vegetation change dynamics across the different agro-ecological zones of Nigeria through the use of remote sensing datasets is essential (Ahmad et al., 2015; Gitelson et al., 2002; Liang et al., 2012; Magurran and Henderson, 2010).

2.2. Application of remote sensing for monitoring vegetation and land use land cover

Remote sensing and GIS techniques have been widely used for global management, ecosystem modeling and environmental monitoring. Because of the ability of remote sensing techniques to obtain near-real time environmental data over an extensive area with short repetitive cycle over time, its use for vegetation and land cover assessment has become imperative (Akinyede et al., 2015; Atzberger et al., 2013; Liang et al., 2012). In addition, the relevance of earth observation techniques (i.e remote sensing satellites) in ecosystem assessment cannot be controverted because it provides adequate information to decision makers which can be used for vegetation mapping, climate modeling, land use land cover assessment and change detection analysis (Akinyede et al., 2015; C. et al., 2013; Xie et al., 2008).

The most commonly used remote sensing satellites in the field of vegetation mapping and monitoring of global land use change include Landsat, Moderate Resolution Imaging Spectroradiometer (MODIS), Satellite Pour l'Observation de la Terre (SPOT), IKONOS, National Oceanic and Atmospheric Administration (NOAA) Advanced Very High Resolution Radiometer (AVHRR), MEdium Resolution Imaging Spectrometer (MERIS) and QuickBird among other sensors. Most of these sensors have long record dated back to the 1970s. For example first Landsat (i.e Landsat 1) was launched in 1972, while the latest Landsat (Landsat 8) became operational in 2012 (Loveland and Dwyer, 2012). AVHRR as well has a long archived record dating back to 1979 till date (https://lta.cr.usgs.gov/products_overview, assessed 2016; Xie et al., (2008). The availability of these sensors makes earth observation monitoring at different spatial and temporal resolution possible. The main characteristics and applications of some of the satellite sensors are presented in table 1.

Table 1: Products and properties of different satellite sensors

Satellite (sensors)	Properties/features	Applications
AVHRR	Coarse resolution of 1km or 8km on NOAA satellite (available from 1981-2015). The 8km dataset has a temporal resolution of 15 days (https://ecocast.arc.nasa.gov/data/pub/gimms/)	The dataset is a global product and it can be used for monitoring vegetation phenology, mapping of land cover types
MODIS	Low resolution multi-spectral datasets (250, 500 and 1000 m) on board of Terra and Aqua satellite. Available from 2000 (i.e Terra) and 2002 (Aqua). It has a temporal resolution of 8 to 16 days.	For deriving leaf area index, vegetation mapping and hydrological modeling.
SPOT	Medium spatial resolution (2.5 m, 5 m, 10 m, and 20 m). SPOT 1,2,3,4 and 5 were launched in 1986, 1990, 1993, 1998 and 2002 respectively.	For mapping vegetation at regional scale and also mapping of land cover types.
Landsat TM	Medium resolution multi-spectral datasets (30 m for the visible to middle infrared channels and 120 m for the thermal band). Landsat 4 and 5 has a temporal resolution of 16 days and is available till present (i.e from 1982 till present). Each Landsat scene covers an area of 185*185 km. Landsat 4 and 5	Monitoring land use land cover change at regional scale.
Landsat ETM+ (Enhanced Thematic Mapper plus)	Medium resolution multi-spectral dataset. (It has 60 m thermal band, 30 m for multi-spectral bands, 15 m for panchromatic band). Landsat ETM+ (Landsat 7) was launched in 1999. It has a temporal resolution of 16 days, each scene covers an area of 185*185 km.	For mapping vegetation and discriminating dominant tree species at regional scale.
Landsat 8	Landsat 8 has two sensors, the Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS). It is launched tentatively in 2012. The multi spectral bands of OLI is 30 m and 15 m for panchromatic band while TIRS collects imagery with 100 m resolution. It has a temporal resolution of 16 days.	For monitoring land use land cover change at regional scale and also in coastal and aerosol studies

Notes: All the remote sensing sensors presented in table 1 can be used for NDVI calculation at the visible and near-infrared region.

2.2.1. Remote sensing and vegetation analysis

Vegetation cover forms an intrinsic part of the ecosystem and provides the basic foundation for all living organism (Hansen et al., 2000; Osunmadewa et al., 2015). Analysis of vegetation cover and its dynamics of change both in space and time is important for assessment of natural resource and land use management. However, remote sensing techniques have been widely used for quantitative assessment of vegetation vigor and detection of change for proper decision making and environmental management (Fensholt et al., 2012; Mao et al., 2012; Notaro et al., 2010).

Vegetation indices (VIs) are commonly used in remote sensing for extracting quantitative information on the amount of greenness for each pixel in an image. VIs are used in remote sensing for classification such as land use land cover change, vegetation quality, crop discrimination, sand detection and waterbodies (Lu et al., 2005). Because of the ability of VIs to discriminate between spectral features at different wavelengths (spectral signatures), its use in remote sensing for long-term monitoring of vegetation change dynamics, crop yield prediction, desertification and land degradation, and ecosystem monitoring at global and regional scale is indispensable (Fensholt et al., 2015; Higginbottom and Symeonakis, 2014; Ju and Masek, 2016; Panda et al., 2010; Tripathy et al., 1996). However, a broad band of VIs has been developed for assessing green biomass such as NDVI (Huete and Tucker, 2007; Tucker et al., 2005) and soil background (Soil-Adjusted Vegetation Index) Huete, (1988) based on the different interaction between vegetation and electromagnetic energy in the red and near infrared region (Silleos et al., 2006) . Some of the commonly used VIs are summarized in table 2

Table 2: List of some vegetation indices (VIs)

Vegetation Index	Abbreviation
Ratio Vegetation Index	RVI
Normalized Difference Vegetation Index	NDVI
Normalized Ratio Vegetation Index	NRVI
Transformed Vegetation Index	TVI
Corrected Transformed Vegetation Index	CTVI
Perpendicular Vegetation Index	PVI
Difference Vegetation Index	DVI
Ashburn Vegetation Index	AVI
Soil-Adjusted Vegetation Index	SAVI
Transformed Soil-Adjusted Vegetation Index	TSAVI
Modified Soil-Adjusted Vegetation Index	MSAVI

The most commonly used method for transformation and enhancement of vegetation information as well as vegetation change detection is the Normalized Difference Vegetation Index (NDVI) (Riaño et al., 2002). NDVI is a quantitative measure that correlates with the quantity of living matter (biomass) and greenness on land surface (Boone et al., 2000; Hess et al., 1996; Tucker et al., 2005). It is an indicator of the photosynthetic active radiation (PAR) intercepted by crops or natural vegetation (Gamon et al., 2016). The pigment in plant leaves such as chlorophyll, strongly absorbs visible light (from 0.4 to 0.7 µm) for use in photosynthesis. The cell structure of the leaves, on the other hand, strongly reflects near-infrared light (from 0.7 to 1.1 µm). Thus, if there is much more reflected radiation in near-infrared wavelengths than in visible wavelengths, then the vegetation in that pixel is likely to be dense (dense forest/woodland). If there is very little difference in the intensity of visible and near-infrared wavelengths reflected, then the vegetation is probably sparse and may consist of grassland, tundra, or desert.

Calculations of NDVI for a given pixel always result in a number that ranges from minus one (-1) to plus one (+1). A zero means no vegetation and close to +1 (0.8 - 0.9) indicates the highest possible density of green leaves (Viña et al., 2011).

In addition to biomass productivity and desertification, NDVI can be used for land degradation assessment (Xia et al., 2014). For this study, NDVI was used as an indicator for monitoring land use land cover change in the study region.

2.3. Time series analysis

Time series analysis of multi spectral remote sensing datasets has been used for assessing seasonal and inter-annual trend in vegetation cover, climate change, hydrological processes and biophysical parameter estimation in the arid and semi-arid region (Bounoua et al., 2015; Fernández-Manso et al., 2012; Tucker et al., 1990).

The extraction of the values (*x,y*) at a particular pixel *k* on the satellite image for consecutive time *t* produces a time series data *q1, q2, q3, q4,…..qn* as illustrated in figure 2.

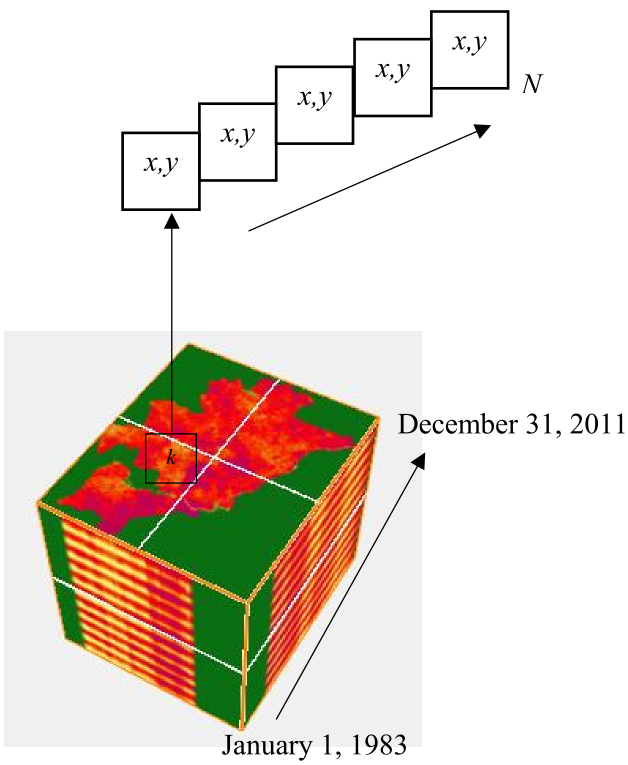


Figure 2. Time series of NDVI from 1983 through 2011for Niger State, Nigeria
Source: (Author’s work)

Time series analysis has been widely used to study the relationship between climatological parameters and NDVI in order to understand land cover change both in space and time (Detsch et al., 2016).

2.4. Combined Application of Remote Sensing and Social Science

Bridging the gap between remote sensing and social science is essential for better understanding of the processes of land use land cover change, vegetation change dynamic, climate change and issues pertaining to human-environment interactions (Hellegers et al., 2010; Herrmann et al., 2014; Rindfuss and Stern, 1998). Social science information such as demography, gender, urbanization can be used to compliment the results of remotely sensed data analysis regarding the rate of deforestation, expansion of agricultural land among other. In Nigeria where increase in population and high level of poverty have led to large scale exploitation of the natural ecosystem for various purposes, studies on linking social science and remote sensing are essential.

2.5. Review of some studies on vegetation and land use land cover change in Nigeria

Continuous monitoring of vegetation and land use land cover change dynamics has become an important topic in Nigeria due to increased anthropogenic activities (Osunmadewa et al., 2016). Though several research on this topic has been done in the past, however, some short comings have been identified. Some out of the studies are mentioned in this section.

Yelwa and Isah, (2010) used NDVI data from AVHRR sensor to monitor vegetation productivity in Sokoto State, Nigeria. Though the result of the study show high variability in irrigated and rain-fed cropland, but the dataset used is too old and covers a too narrow time period of five years (1982-1986) which makes it not suitable for monitoring vegetation change dynamics in the arid and semi-arid region of Nigeria. Also, the study fails to use climatic datasets in the analysis.

It is evidenced from the result of the study of Jibrin, (2013) that the structural composition of the vegetation the Guinea savannah region of Nigeria has changed over time. Though the study used medium resolution satellite imagery (NigeriaSat-1 with a spatial resolution of 32 m) and stratified random sampling, the study fails to compare the results with historical data such as Landsat imagery. Furthermore, life span of NigeriaSat-1 has expired in orbit which makes validation of the result difficult.

Similarly, Salami, (1998) monitored vegetation modification in the southwestern part of Nigeria using plot sampling method (i.e a plot of 10 km * 10 km). The results of the study showed degradation in the structural composition of the vegetation cover as a result of increased farming activities, however, the study lacks the application of remote sensing technique.

From the few studies that have been reviewed, it is evident that the use of up to date remotely sensed datasets is needed for proper monitoring of vegetation dynamics and land use land cover change in Nigeria. Adequate socio-economic data analysis is also important for proper understanding of the drivers of ecosystem change.

3. Study area

This section provides a description of the geographical characteristics of Nigeria as a whole and of the study area in particular.

3.1. Description of the study area

The study region is located in Nigeria, West Africa. It lies between latitude 4^o– 14^o north of the Equator and longitude 3^o– 14^o East of the Greenwich Meridian Time (GMT). The country shares borders in the northern, southern, eastern and western parts with Niger Republic, Equatorial Guinea, Chad and Cameroon, and Benin Republic respectively (National Bureau of Statistics, 2010; Suleiman, 2014)**.**The total land area of Nigeria is about 923 769 km^2 (National Bureau of Statistics, 2010; Suleiman, 2014), the vast land mass gives room for vegetation diversity in different climatic zones. Nigeria is the most populous country in Africa (The world fact book 2011, www.mapsofworld.com) with a population of about 140,431,790 people in 2006. The projected population in 2009 is 154,349,250 (National Bureau of Statistics, 2010; Suleiman, 2014), while the current population is about 184, 635, 279 (http://countrymeters.info/en/Nigeria). The specific locations where this research was carried out are Kogi, Kwara and Niger state. The amount of population and the area extent of each state vary considerably which is described in subsequent section. The three study areas were selected based on similar climatic conditions and agro-ecological zone. The study area is categorized as the Guinea savannah region. The regions are geographically located in the North central which is known as the middle-belt. The study region (Kogi, Kwara and Niger) lies within 2°00 E to 8°20 E and 11°50 N to 7°40 N of the Greenwich meridian.

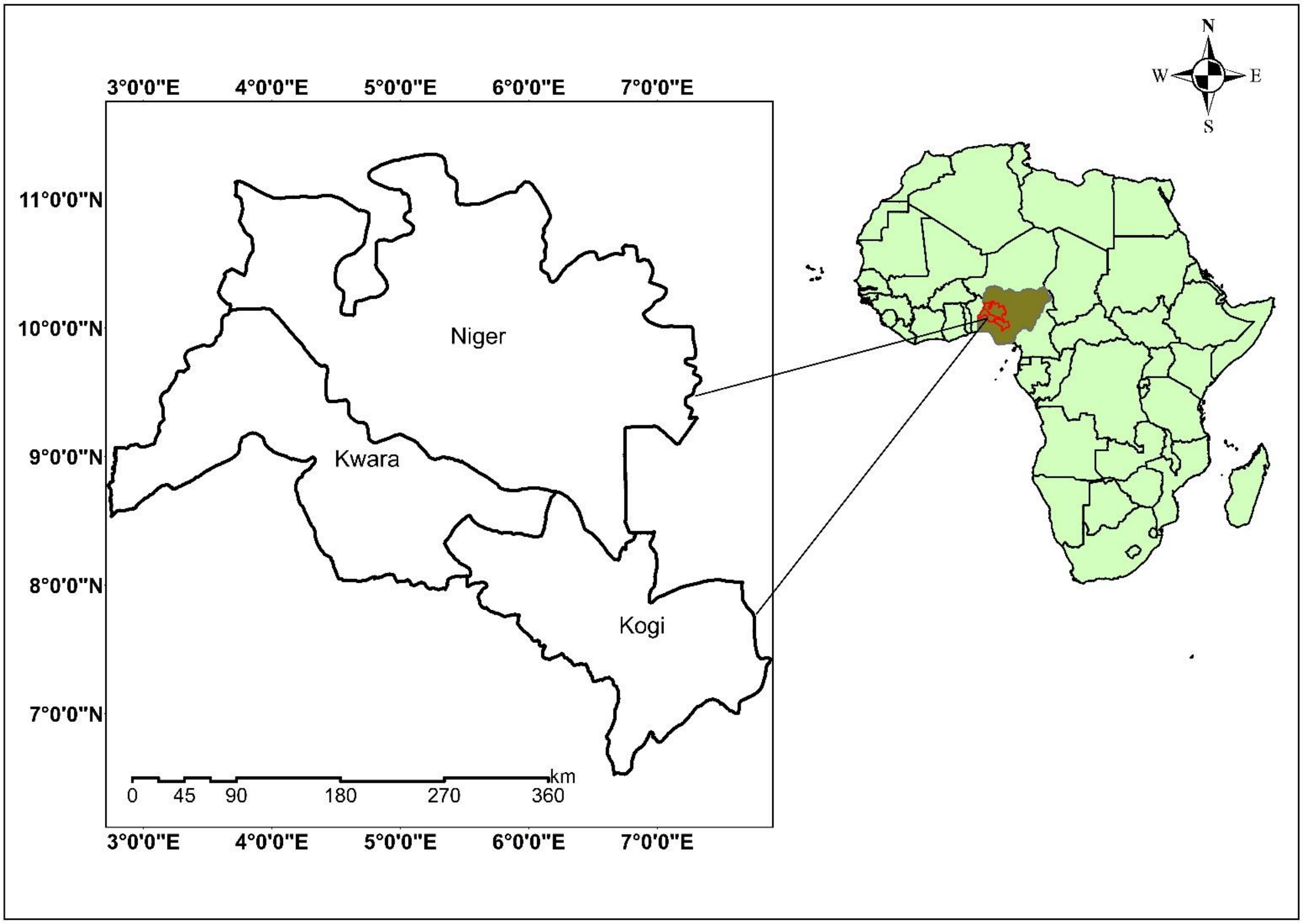


Figure 3. Map of Africa showing Nigeria and the study area

3.2. Climate

The climate of Nigeria can be described as microcosm of the other West African countries because of its size, shape and latitudinal location within the Tropics (Ogungbenro and Morakinyo, 2014). The temperature in Nigeria is relatively high throughout the year. It is characterized by dry and wet condition which is associated with the movement of Inter-Tropical Discontinuity (ITD) or Inter-Tropical Convergence Zone (ITCZ) north and south of the equator (Omogbai, 2010). Notably, the length of the dry and wet season varies in the upper north (for example Yobe, Maiduguri, Sokoto States) to the south (for example Rivers, Akwa Ibom States). There is considerable variation in the mean maximum and minimum temperature across the country. The mean maximum temperature in the coastal region is about 32.2° C, it is about 40.6° C in the extreme north while the mean minimum temperature is about 21.1°C at the coast and 12.8°C in the north (Oguntoyinbo et al., 1978). The eastern part of the country receives over 4000 mm rainfall annually, the southeast receives about 2000 - 3000 mm of rain per year, in the southwest total rainfall is between 1250 and 2500 mm while rainfall decreases to about 500-1000 mm in the central and northern part of Nigeria. These variations are directly linked to the influence or movement of ITCZ northward and southward of the equator (Omogbai, 2010). The climate of Nigeria is largely influenced by three air masses namely: the tropical maritime (Tm) air mass, the continental tropical (cT) air mass and the equatorial easterlies (Adejuwon and Odekunle, 2006). The Tm air mass originates from the southern high pressure belt which is located off the coast of Namibia and its trajectory. Tm picks up moisture over the Atlantic Ocean, moves inland towards the equatorial zone thus entering Nigeria. The dew point of Tm exceeds 14°C (Oguntoyinbo et al., 1978). The cT air mass originates from the high-pressure belt which is centered on the Tropics of Cancer and Capricorn in the Northern Hemisphere and forms over the Sahara desert, thus cT is dry in nature (Oguntoyinbo et al., 1978). The convergence of the two air masses (Tm and cT) is at the ITCZ. The third air mass known as the equatorial easterlies is erratically cool, it comes from the east and flows in the upper atmosphere along the ITCZ. The movement of the ITCZ either to the north or south of the equator brings about the two distinct seasons in Nigeria (rainfall and dryness). When there is movement of the two air masses (Tm and cT) to the south of the equator, the north-east winds brings dry season, while on the other hand, movement of the air masses towards the north of the equator where the south-westlies prevail brings rainfall (Oguntoyinbo et al., 1983). Owing to the seasonal pattern of climatic condition over Nigeria, the study region (Kogi, Kwara and Niger state) enjoys both wet and dry season which vary on annual basis.

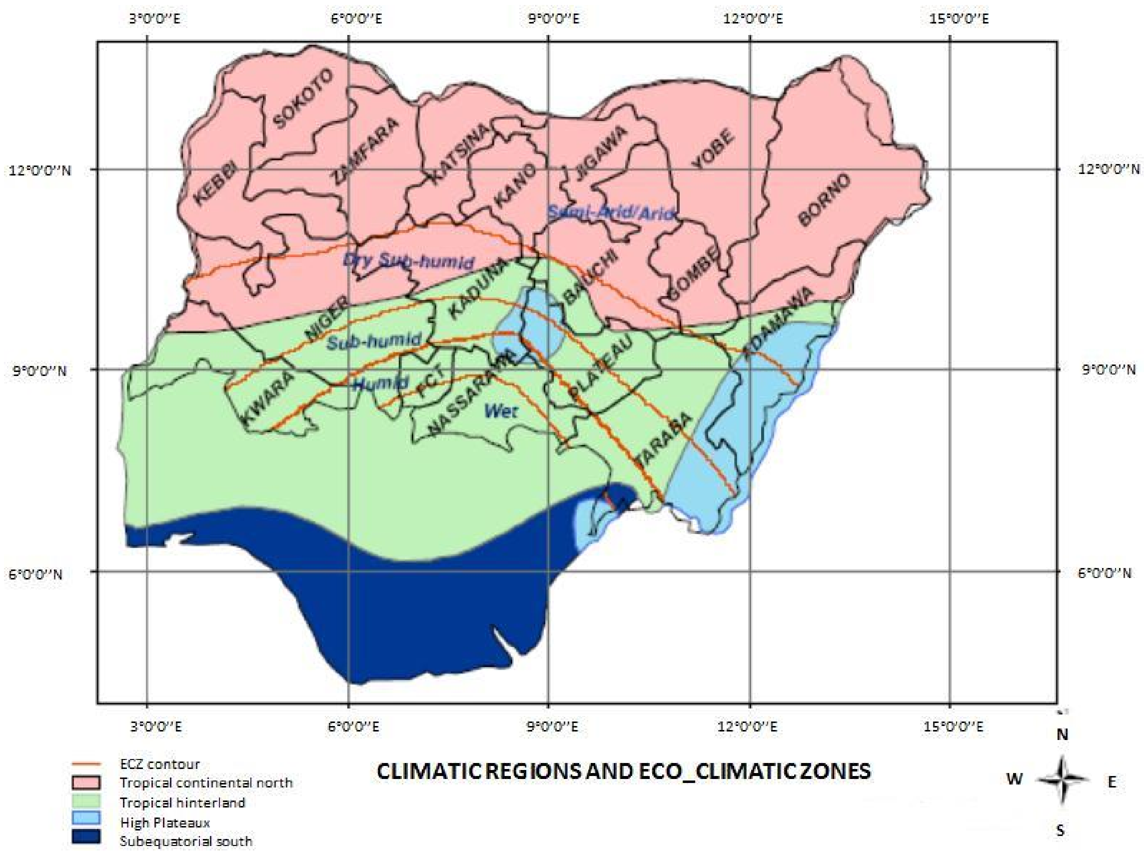


Figure 4. The eco-climatic zones of Nigeria according to Iloeje 1976 cited by AbdulKadir et al. (2015)

3.3. Rainfall

As described earlier (section 3.2), rainfall pattern in Nigeria (the tropics) is often the only input that varies significantly from year to year. The amount and duration of rainfall decreases from the coast to the extreme north except for some areas like the plateau where there is higher amount of rainfall due to the effect of altitude. This makes variability in vegetation vigor or water balance subjective to rainfall variability in some parts of Nigeria (Olusola and Israel, 2015). According to (National Bureau of Statistics, 2010), rainfall distribution over the study area varies from about 1422 mm along the northern boundary (Niger) to about 1631mm along the southern boundary (Kogi and Kwara). The southern part of the study area namely Kogi and Kwara is characterized by double rainfall maxima (bimodal) usually in June/July and September while the Northern part (Niger) is characterized by single maxima rainfall regime usually in the month of August. Rainfall begins in Kogi towards the end of March and lasts till October (Forest, 2013; Osunmadewa et al., 2014), similar rainfall pattern is observed in Kwara while there is a slight difference in the rainfall pattern in Niger (rainfall begins in April till October). Generally, the expected duration of wet season in the sub humid region ranges from 5 months in the north to about 8 months in the south. The precipitation figures for each location shows on how many days per month when certain precipitation amounts are reached between 1985 -2015. The climatic information in figures 5 are from meteoblue and it is derived from NOAA Environmental Modeling System (NEMS). The data has a resolution of 30 km (https://www.meteoblue.com).

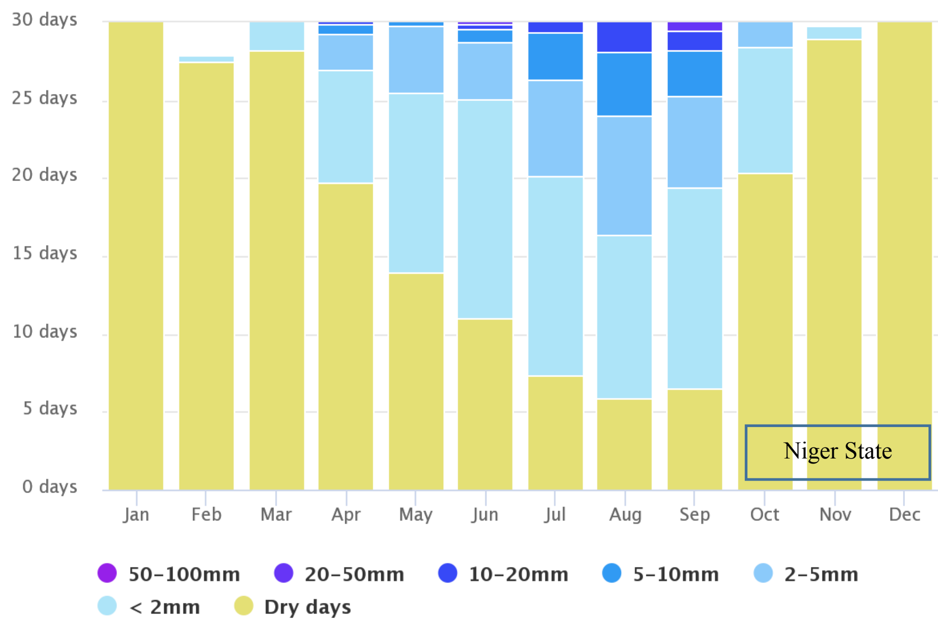


Figure 5. Number of days versus intervals of precipitation per month for Niger State [mm]

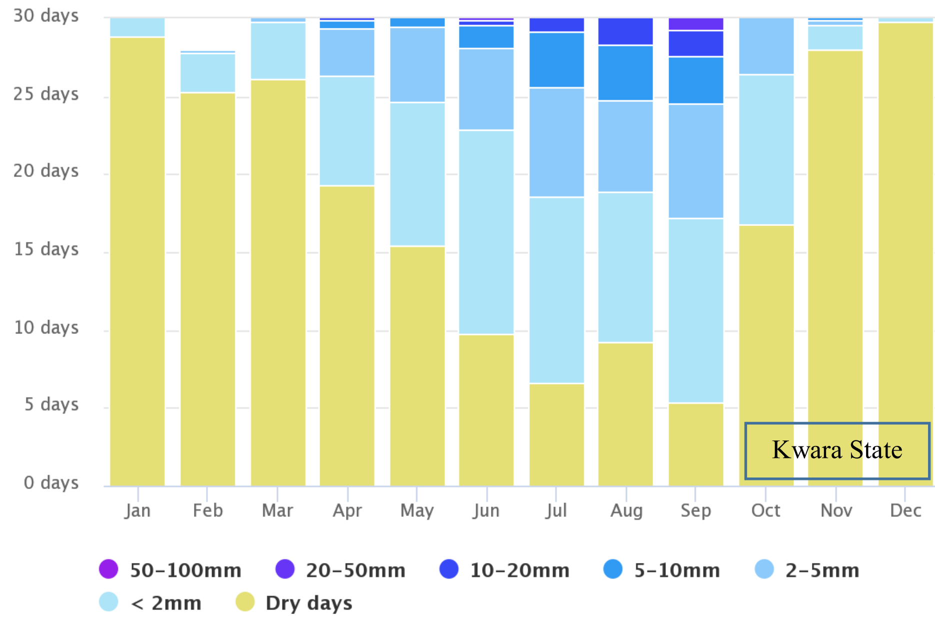


Figure 6. Number of days versus intervals of precipitation per month for Kwara State [mm]

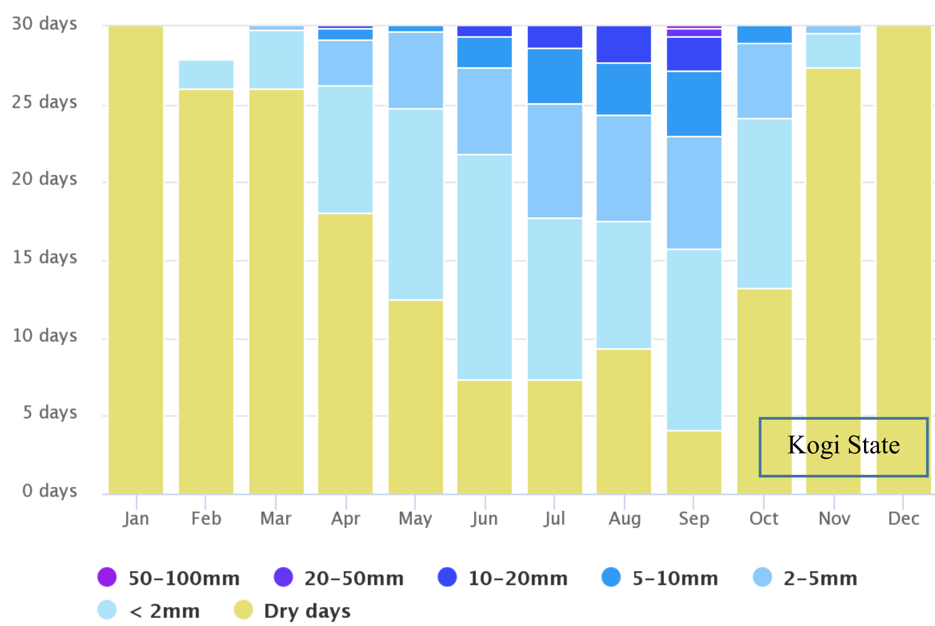


Figure 7. Number of days versus intervals of precipitation per month for Kogi State [mm]

Source: https://www.meteoblue.com

3.4. Temperature

The temperature of Nigeria vary considerably depending on the regions of the country. In some parts of the country, the mean annual temperature is about 27°C (Oguntoyinbo et al., 1983) due to altitudinal effects (for example Plateau and Adamawa State). The mean annual temperature varies between 21°C to 40°C as compared to that of lowlands of > 27°C (Oguntoyinbo et al., 1983). Generally, the temperature of the study regions (i.e Kogi, Kwara and Niger states) range between 22°C to 34°C (ABS, 2010). In such regions where diurnal variations are more pronounced than seasonal variation, differences in the performance of plants which are sensitive to photoperiodism might occur.

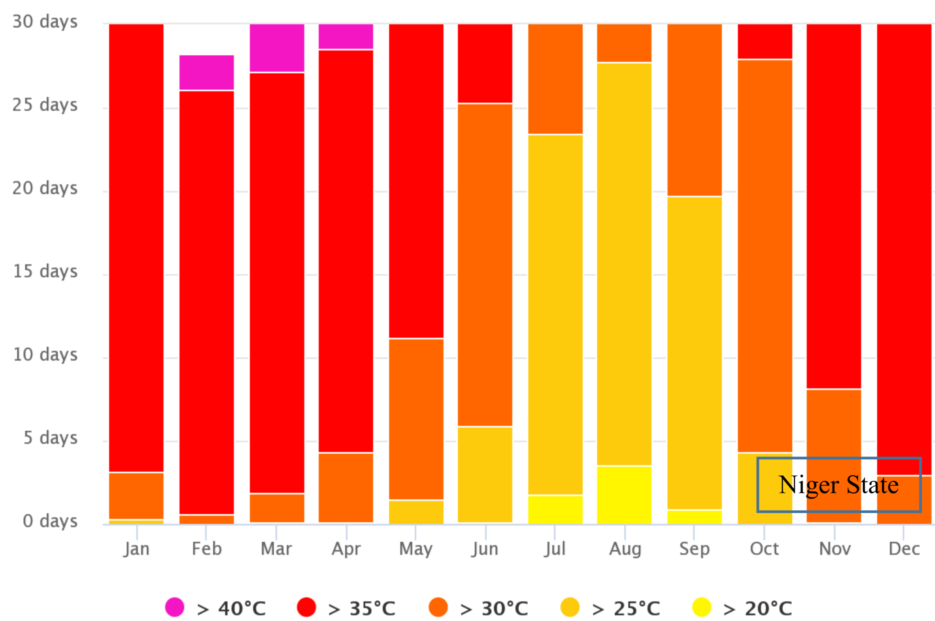


Figure 8. Number of days versus maximum temperature for Niger State

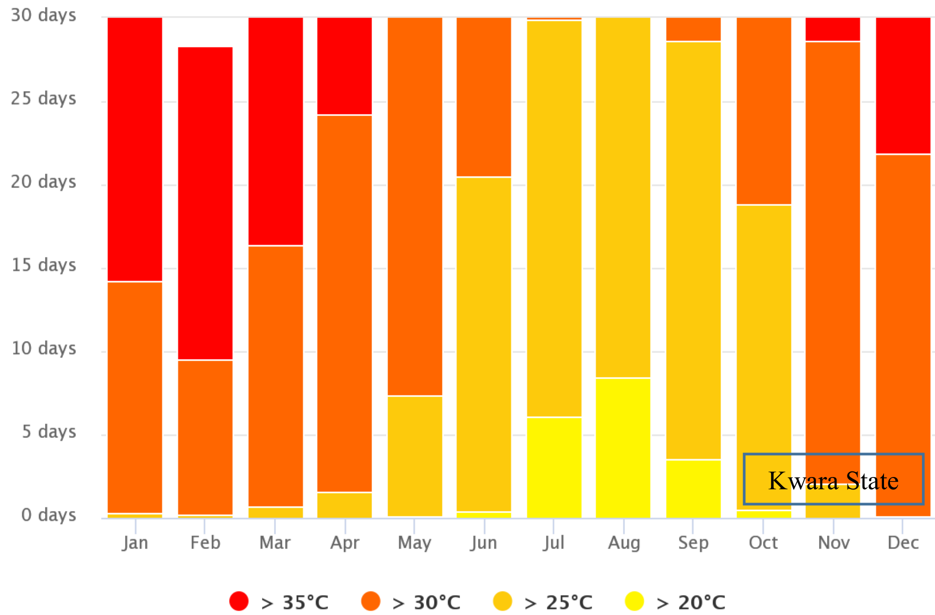


Figure 9. Number of days versus maximum temperature (Kwara State)

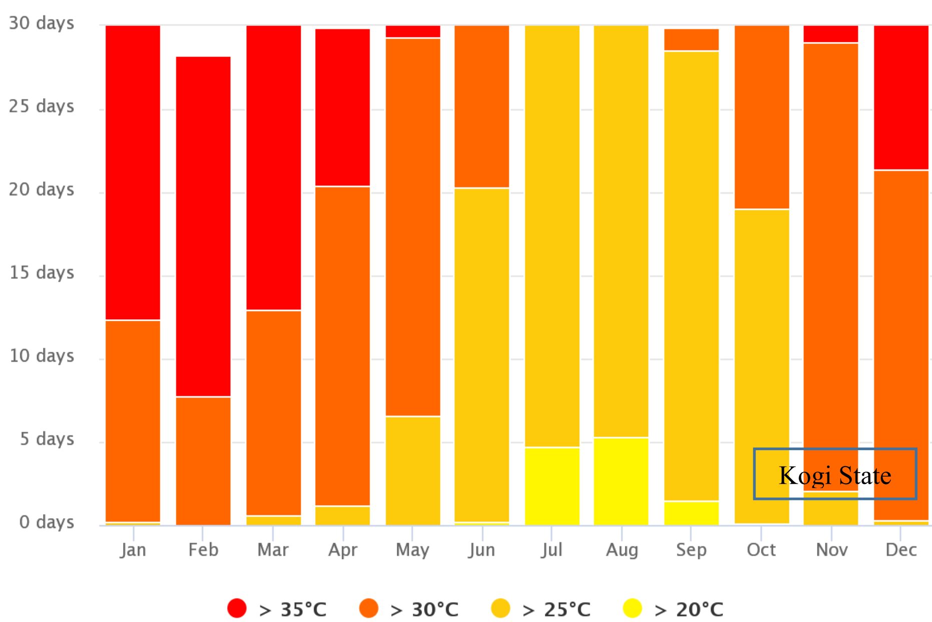


Figure 10. Number of days versus maximum temperature (Kogi State)

Source: https://www.meteoblue.com (assessed on 26th January 2016)

3.5. Relief

The relief of Nigeria is characterized by a gradual rise from the coastal region to the northern region where the elevation is above 600 meters above sea level (Oguntoyinbo et al., 1978). As mentioned in previous sections, altitudes of more than 1200m are found around the Jos Plateau and some parts of the eastern highlands which borders Cameroon (National Bureau of Statistics, 2010; Oguntoyinbo et al., 1978). The inselberg landscape which occurs within Abeokuta and Ibadan rises to 300m to 600m above sea level (asl) with a similar stretch in elevation from Kontagora (Niger) to Gombe. The low areas within the Chad basin stretches from Gumel, Ngur, and Maiduguri (northeast) are below 300m asl(Oguntoyinbo et al., 1978). The relief of Kogi is generally undulating with high hills, the elevation ranges between 300-600m asl (Ajaokuta, Okene, Kabba). The elevation of Kwara state ranges between 273 meter to 333 meter in the West and 200 meter to 364 meter in the East (http://elevationmap.net/kwara-nigeria), which this indicates that the topography is plain. The topography of Niger state is undulating and it is characterized by inselbergs. The average elevation of Niger state is about 350m asl.

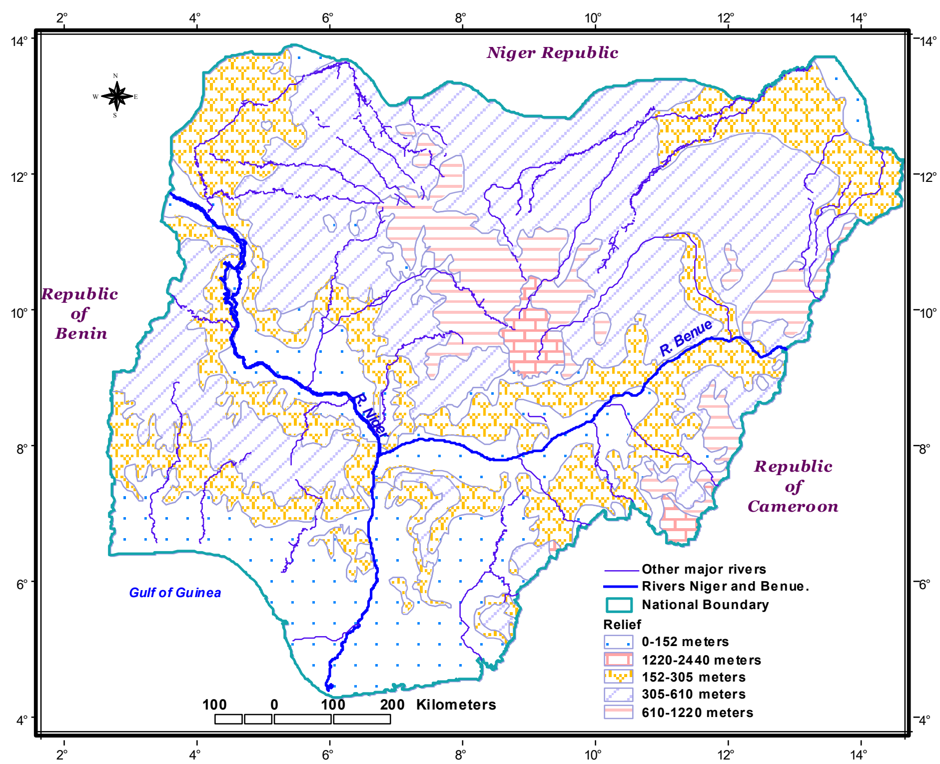


Figure 11. Relief (Adapted after Oguntoyinbo et al., 1978)

3.6. Drainage system

Nigeria is one of the nations in West Africa which is endowed with abundance of water resources. The country is well drained with a close network of rivers and streams (Oguntoyinbo et al., 1978). Nigeria has two major rivers namely: the Benue which enters into Nigeria from the border of Cameroon and river Niger which rises from the mountains to the eastern part of Sierra Leone (Bello et al., 2014). Both rivers meet at Lokoja and flow into the Atlantic Ocean (National Bureau of Statistics, 2010). Nigeria has three drainage sytems namely: short swift flowing coastal rivers, the inland drainage system of the Chad basin and the long plateau rivers as well as eight catchments namely: Niger North, Upper Niger, Upper Benue, Lower Benue, Niger south, Western Littorial, Eastern Littorial and Lake Chad (Bello et al., 2014). The coastal rivers include the Ogun, Osun, Benin and the Osse to the west of Niger while the Imo, Cross and Anambra rivers are to the east of river Niger. Katsina-Ala and Gongola rivers are in the lower basin of Benue. The main inland drainage system runs from the central of Jos Plateau into Yobe and flows into Lake Chad, Danaga and Taraba and their tributaries leads into the Benue.

Kogi State: The state is also known as the confluence state because both river Niger and Benue meet at its capital called Lokoja (Osunmadewa et al., 2014). The state is drained by both rivers (Niger and Benue) and their tributaries.

Kwara state: The state has seven major rivers (Wuruma, Moshi, Awan, Oshin, Oyun, Asa and Ero) which are mainly drained into River Niger (Olabode et al., 2014).

Niger: The state is well drained by many drainage channels, with the main courses as river Chanchaga which takes its source from the north central highlands, river Kaduna at the south west of Minna and other tributaries such as Gbako, Gurara, and Kampe rivers drains in river Niger (T. Olabode et al., 2012).

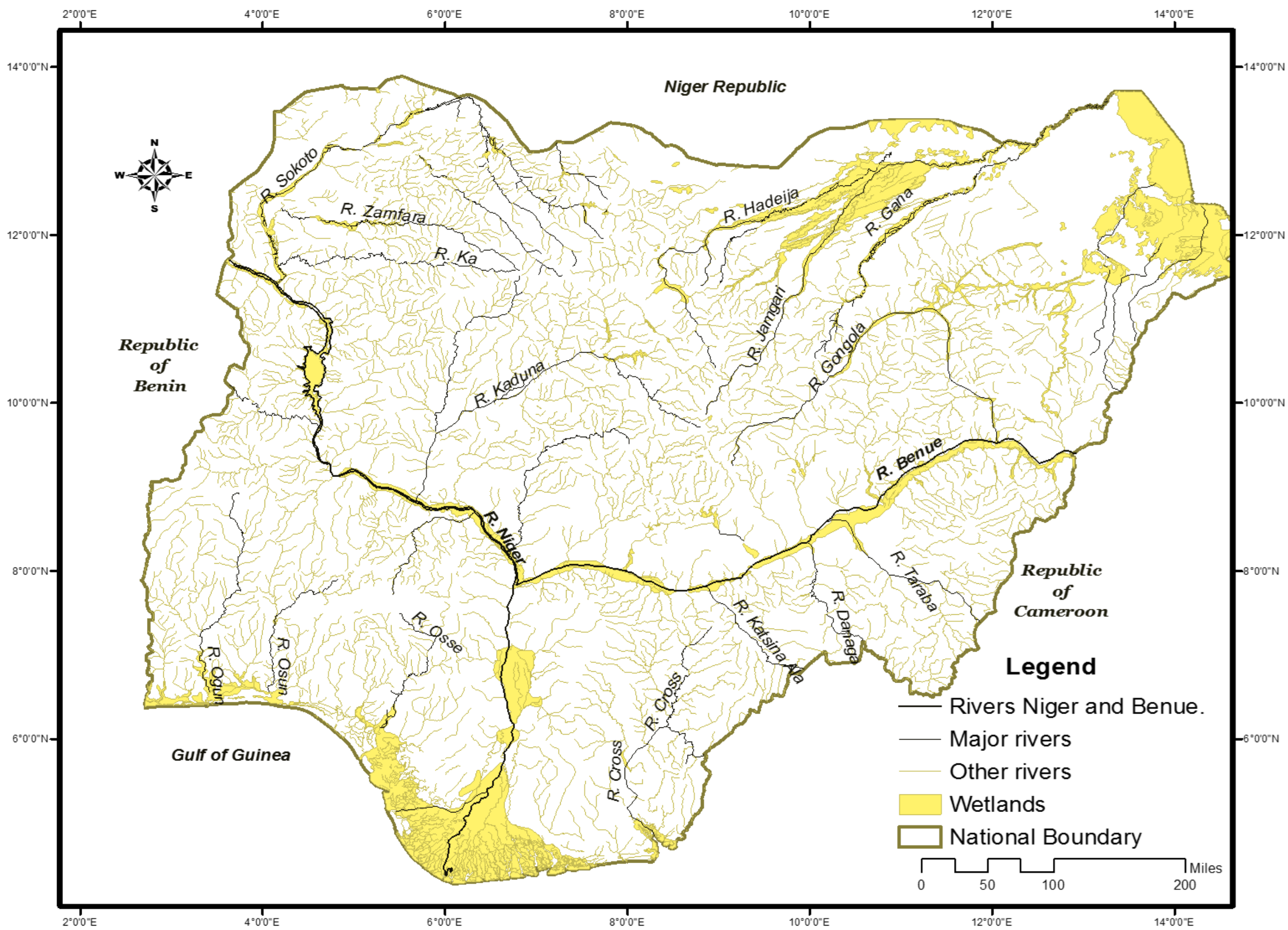


Figure 12. Hydrology and drainage network of Nigeria (adapted from ADS, 2005) (https://www.loc.gov/resource)

3.7. Geology of Nigeria

Nigeria is underlain by a basement complex and sedimentary rocks, each of which are equally dispersed over the country (Ajibade and Wright, 1989). The basement complex is most extensive in Nigeria, it extends from the western part into the Rebulic of Benin, Togo, Ghana, on the eastern part to Cameroon and northward to the republic of Niger. The sedimentary rocks are found in the southern part of Nigeria, Sokoto (northwest), Borno and also extend to the Chad basin in the north-east (Ajibade and Wright, 1989).

Geology of Kogi: Kogi state is made up of both the basement complex and sedimentary rock. The basement complex rock (the Precambrian) in the southwest extends to the lower Niger valley eastward, while the sedimentary rocks extend along the banks of River Niger and Benue (Imasuen et al., 2010)**.**

Geology of Kwara: Generally, the geology of Kwara consists of the basement complex rock (Precambrian) which comprises of biotite-granite, granite-gneiss and meta-sediments (mainly quartz-mica schist and quartzite) (Alagbe, 2000).

Geology of Niger: Like the other two study areas mentioned above, Niger state is underlain by the basement complex and sedimentary rocks (Mayomi et al., 2014). As a matter of fact, the geology of the study areas provides a unique source of mineral wealth which gives immense opportunities for rapid economic development.

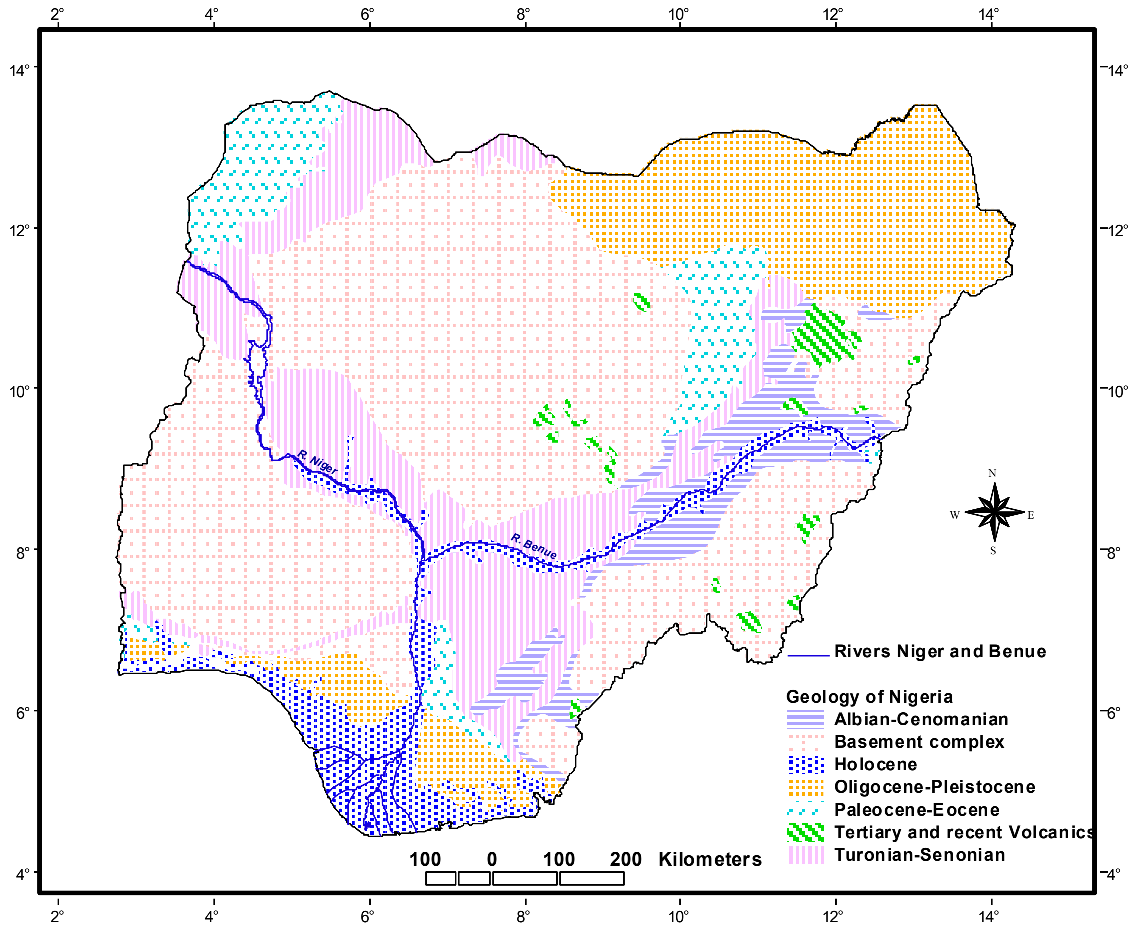


Figure 13. Generalized geology map of Nigeria (Federal Survey, 1967) (https://www.loc.gov/resource)

3.8. Overview of soil types in Nigeria and the study area

The soil types of Nigeria vary according to the climate and vegetation structure of each agro-ecological zone. According to FAO, the soils of Nigeria are classified under four major groups namely: the hydromorphic soils, regosols, ferralsols and the ferruginous tropical soils. The soil of the study area is similar in nature thus enabling diverse vegetation types (Salako, 2003) The soil type of Kogi state is hydromorphic in nature, this soil type is developed on alluvial (Adeoye, 2012). Ferruginous tropical soil which is derived mainly from the basement complex and sedimentary rock is the major soil in Kwara state, the soil is fertile in nature and supports vast food export and cash crops (Oriola and Bamidele, 2012). Three unique soil types are found in Niger state i.e (ferruginous tropical soils, hydromorphic soils and ferrosols). Ferruginous tropical soils are the most dominant and are derive from the basement complex and sedimentary rock like in Kwara state. The soil types coupled with favorable climatic condition support agricultural activities throughout the year (Mayomi et al., 2014). Further information about Nigerian soil types can be seen in fig 14.

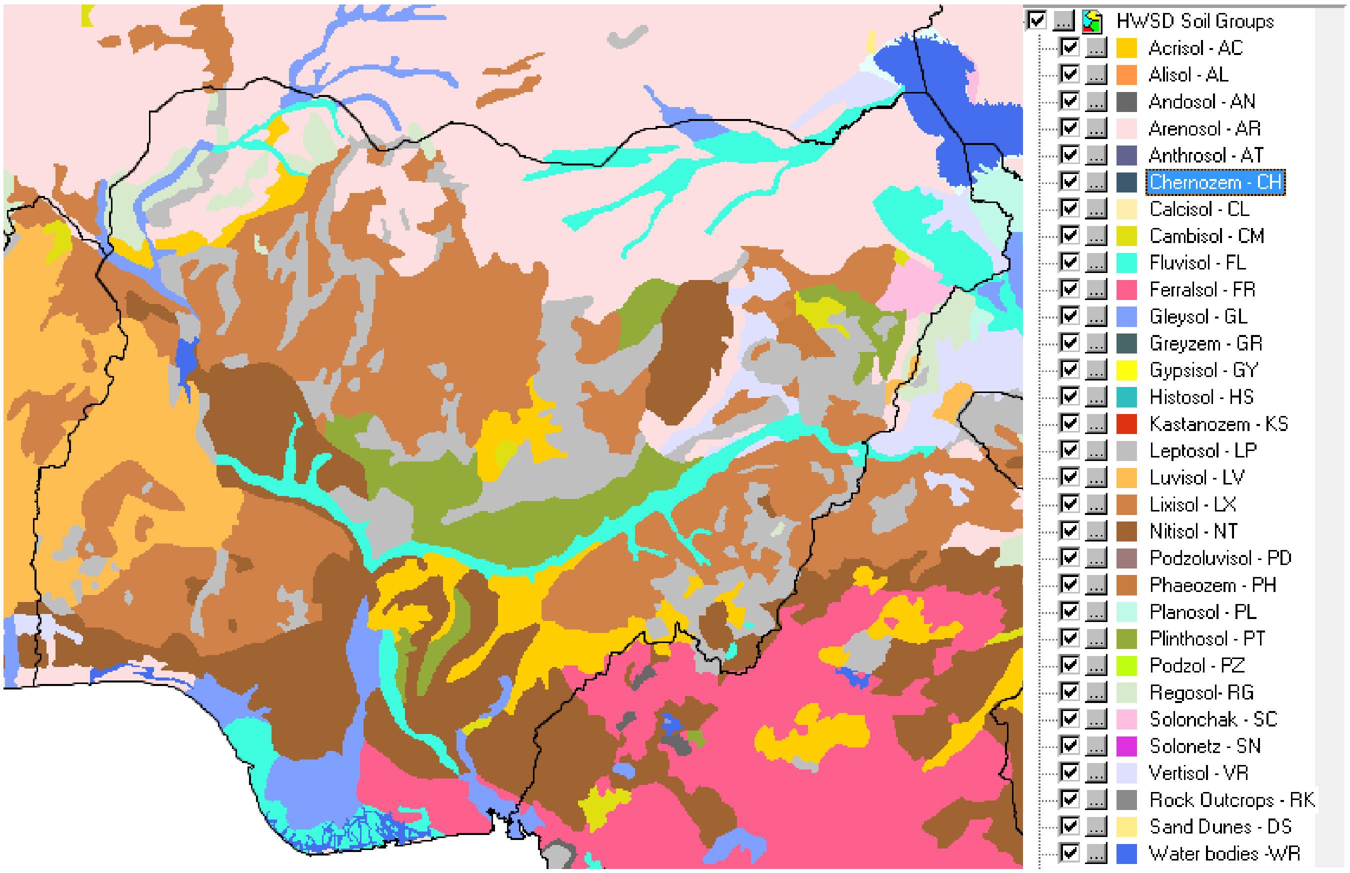


Figure 14. Soil Map of Nigeria (FAO, 2009 Harmonized World Soil Database)

3.9. Overview of vegetation types in Nigeria and in the study areas

Nigeria is Africa's most populous nation with over 140 million people and a land area of 909.890 km^2 (National Bureau of Statistics, 2010). Nigeria has a considerable diversity of ecosystems, and falls within the climax of west and central Africa. Two broad types of vegetation are found in Nigeria forest and savannah communities. The vegetation types are further described according to their structure, composition and zone in relation to climate, topography and soil types (Oguntoyinbo et al., 1983). Each vegetation type extends from west to east across the country as a result of rainfall gradient from the wet coastal zone fringing the Gulf of Guinea to the arid Sahel in the north (ABS, 2010). Coastal mangrove swamp and the tropical rain forest in the south gives way to savannah grasslands further north until they reach the arid Sahelian ecosystems bordering the Sahara desert. Montane vegetation is found on the Jos, Mambilla and in Obudu Plateaus. The largest remaining areas of closed-canopy rain forest are in the south-east and Cross River State, these forest are contiguous with the forests of south-west Cameroon (Oguntoyinbo et al., 1983; National Bureau of Statistics, 2010).

Broadly speaking, the study areas fall within the savannah communities known as the Guinea savannah (Oguntoyinbo et al., 1983; Osunmadewa et al., 2016, 2014). The vegetation of Kogi state is mainly of Guinea savannah type, it comprises trees which grow up to about six meters tall and grasses of about three meters tall (Adeoye, 2012). The vegetation composes of gallery forests in the riverine areas, mixed leguminous wooded savannah, weeds and shrubs. Some of the tree species found in the study area include: *Pentaclethra macrophylla Benth (Oil bean tree), Daniella oliveri, Isoberlinia spp (Legume), Parkia biglobosa (locust bean tree), Afzelia africana, Mitragyna inermis and Terminalia spp.* Grasses include: *Andropogon gayanus, Bekeropsis uniseta, Imperata cylindrical (weed).* The vegetation of Kwara state lies at the belt of semi-rain forest and derived savannah because it falls within the transition zone between the high forest in the south and woodlands in the north (Alagbe, 2000; Olaoye and Oloruntoyin, 2014; Oriola and Bamidele, 2012; Suleiman, 2014). Some of the economic wood species found in this region are: *Milicia excelsa (Iroko tree), Butyrospermum parkii (Shea butter tree), Parkia biglobosa (locust bean tree), Acacia trees, Baobab trees,* elephant grasses, shrubs and weeds. The vegetation type of Niger state is Southern Guinea savannah. It is characterized by woodland vegetation with relics of rain forest and tall grasses. Some of the tree species found in this region are: *Mangifera indica (Mango), Ceiba pentandra (obeche), Parkia biglobosa, Daniellia oliveri* and grasses such as *Panicum kerstingii* and *Setaria pallide-fusca*, (Ajewole et al., 2013; Jibrin, 2013; Mayomi et al., 2014). It should be noted that the vegetation of the study area is not in its natural state due to indiscriminate disturbance of the ecosystem by human impact.

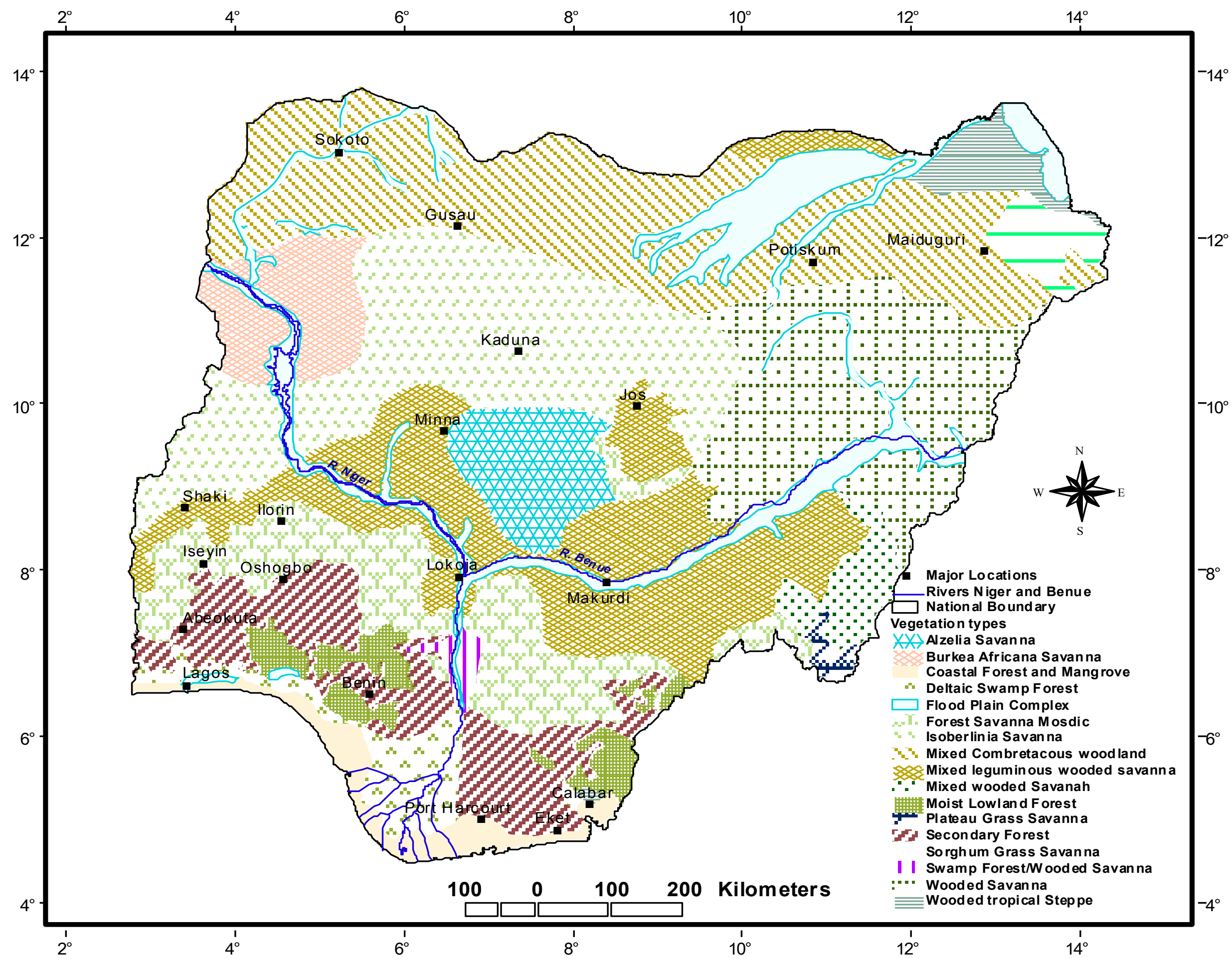


Figure 15. Major vegetation types in Nigeria (Oguntoyinbo et al., 1983)

4. Methodology

Detailed description of the datasets and methodologies used in this study are presented in this section. Several methodological approaches were used to achieve the objectives of the study. These approaches are duly explained in the sub-sections.

4.1. Description of data collection/acquisition

Both primary and secondary datasets were used in this study. The source of the primary data includes field observation for ground check (ground truthing), interview with key informants and administration of questionnaires. The ground truthing was carried out in Niger, Kogi and Kwara states.

The secondary data sources include satellite-derived vegetation index data generated by Global Inventory Modeling and Mapping Studies (GIMMS), rainfall data for Africa (Tropical Applications of Meteorology using SATellite and ground-based observations (TAMSAT) African Rainfall Climatology And Time series) (www.tamsat.org.uk), temperature data from the Climatic Research Unit (CRU) global climate dataset (www.cru.uea.ac.uk), demographic data from Nigerian Population Commission (NPC), national land cover data from Forestry Monitoring and Evaluation Coordinating Unit (FORMECU), Nigeria, and global land cover data from European Space Agency (ESA).

4.1.1. Primary data collection

Field studies were executed in cooperation with environmental experts of the College of Environmental Resources Management, Federal University of Agriculture, Abeokuta. Initial identification of sites for the selected states and hotspots was guided by analyzing FORMECU land cover data along with Google Earth imagery. The study sites cut across three different geopolitical and agro-ecological zones (Kogi State, Kwara State and Niger State) thereby representing a wide variety of vegetation distribution patterns.

4.1.2. Secondary data collection

Both Advanced Very High Resolution Radiometer (AVHRR) and Moderate Resolution Imaging Spectroradiometer (MODIS Terra) vegetation index datasets were used in this study for profound assessment of vegetation trend dynamics across the Guinea savannah region of Nigeria. The AVHRR data used span from 1983-2011 and MODIS data from 2001- 2011. Other data used include TAMSAT rainfall data, CRU temperature data, national land cover classification map from

Forestry Management Evaluation and Coordinating Unit and global land cover data of 2000, 2005 and 2009 from the European Space Agency (ESA). The climatological datasets were used for climate modelling while the land cover datasets were used for land use land cover change assessment.

4.2. Description of datasets

4.2.1. Normalized Difference Vegetation Index (NDVI) dataset

The growing usefulness of time series of vegetation indices (VI) data for environmental and ecological studies has increased tremendously over the last decades. AVHRR provides long-term data and has been used by many researchers both at the global and regional scale for monitoring vegetation dynamics, desertification and has supported ecosystem management (Anyamba et al., 2001).

4.2.1.1. GIMMS NDVI3g

The updated version of NDVI3g datasets with a spatial resolution of 8km was used in this study (https://ecocast.arc.nasa.gov/data/pub/gimms). The GIMMS NDVI3g is however the reconstructed extension of the previous NDVI version and it comprises of NDVI measurements derived from the seven NOAA instruments (Anyamba et al., 2014). It is one of the longest NDVI time series imagery available and is developed by the Global Inventory Modelling and Mapping Studies (GIMMS) group at NASA's Goddard Space Flight Centre from the Advanced Very High Resolution Radiometer (AVHRR) instruments on the National Oceanic and Atmospheric Administration (NOAA) Polar Operational Environmental Satellite (POES) series (Eastman et al., 2013). This data set has been processed using an adaptive Empirical Mode Decomposition (EMD) (Eastman et al., 2013; Pinzon and Tucker, 2014; Tucker et al., 2005; Zeng et al., 2013). The reason for using this processing method is to ensure that the NDVI time series data are free from the influence of externalities such as orbital drifts, and/or volcanic aerosols which might affect the results of the analysis (Eastman et al., 2013).The general equation for NDVI according to Tucker (1979) and other referenced authors (McCloy, 2010; Tucker and Sellers, 2007) is given thus:

$$NDVI = \frac{\mathrm{NIR-RED}}{\mathrm{NIR+RED}} \qquad (1)$$

It is referred to as the normalized difference ratio of red and NIR bands.

NDVI is based on the principle that actively growing plants absorb radiation in the visible region (580-680 nm) (blue and red spectral bands) of the electromagnetic spectrum due to chlorophyll (leaf pigment) absorption and reflect radiation at the NIR region (725-1100 nm) (Tucker, 1979; Usman, 2012).

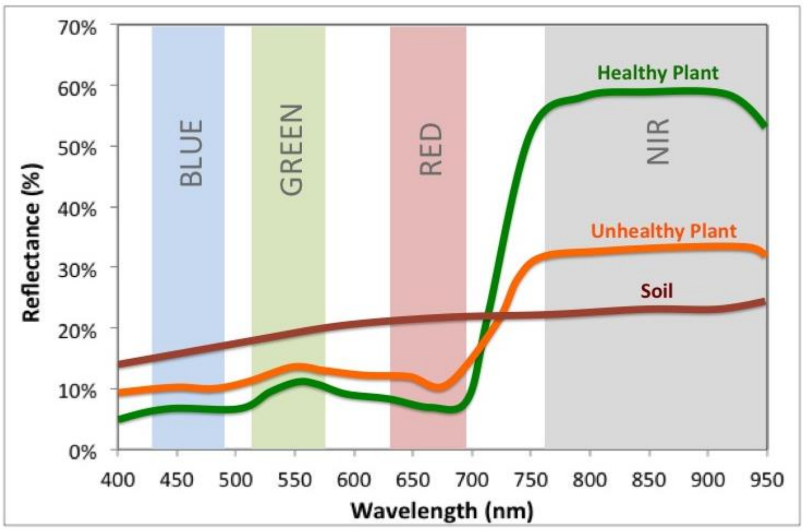


Figure 16. Spectral signatures of vegetation

Source: (Yu et al., 2010)

It should therefore be noted that a negative NDVI value represents a non- vegetated area such as water, ice or snow while a significant positive NDVI value indicates vegetated surfaces and increasing NDVI values are indication of increase in green vegetation.

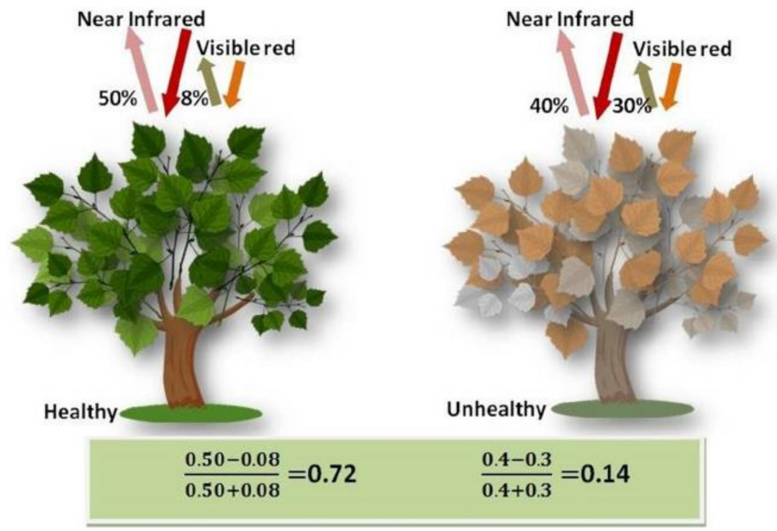


Figure 17. Vegetation vigor

Source: (Wu et al., 2014)

NDVI3g was used in this study for the spatio-temporal detection of seasonal variation and long-term trends in vegetation dynamics across the Guinea savannah region of Nigeria. The NDVI3g is a bi-monthly dataset and is available from 1982 through 2012 with 8km spatial resolution. The NDVI3g is a 15 days composite dataset which is derived from NOAA sensor with two additional channels so as to improve its quality and period (1982-2012). This makes the dataset suitable for long-term monitoring of vegetation trends (Pinzon and Tucker, 2014). The NDVI data used in this study cover the period from 1983 through 2011.

4.2.1.2. Moderate Resolution Imaging Spectroradiometer (MODIS)

The MODIS NDVI product used in this study is MOD13Q1. It is a 16-days composite data with a spatial resolution of 250m. The MODIS NDVI dataset is a complement of AVHRR NDVI product and is on board of the Terra and Aqua satellite. MODIS NDVI provides continuity of time series for monitoring vegetation productivity (Tucker and Yager, 2011). The MODIS NDVI data was obtained through an online data pool at the University of Natural Resources and Life Sciences, Vienna (BOKU) (http://ivflinfo.boku.ac.at/) covering the period from January 2001 to December 2011. The MODIS data has seven bands (620-670 nm, 841-876 nm, 459-479nm, 545-565 nm, 1230-1250 nm, 1628-1652 nm and 2105-2155 nm). The most commonly used bands are the blue (469nm), red (645nm) and near-infrared (858nm) reflectance's for determining daily vegetation indices (Huete et al., 2002; Solano et al., 2010). MODIS NDVI is used for monitoring land condition and phenological dynamics over time (Verbesselt et al., 2010b). Smoothed MODIS NDVI was used in this study for assessing vegetation trend over a ten years period. Whittaker's filtering algorithm method implemented in Matlab has been used to gap-fill and smoothen the MODIS NDVI time series datasets. Hence, filtering and gap-filling is not needed. Further pre-processing such as aggregation to monthly composite and maximum value composite were done to further reduce the effect of atmospheric artefacts and noise (Huete et al., 2002).

Other datasets used in this study are: Tropical Applications of Meteorology using SATellite (TAMSAT) rainfall data and Climate Research Unit (CRU) temperature data of the same period (1983-2011). The TAMSAT rainfall data used in this study have been locally calibrated using historical rain gauge records which are produced monthly (Maidment et al., 2015). The TAMSAT dataset provides both historical and real-time rainfall estimates for drought monitoring over the African continent (Maidment et al, 2015). TAMSAT is derived from Meteosat Thermal Infrared (TIR) channels and it is calibrated against ground observations for estimating rainfall over Africa with a spatial resolution of 4km (http://www.met.reading.ac.uk). TAMSAT rainfall datasets span over a period of more than 30 years (January 1983-December 2015). This makes it suitable for monitoring long-term trends in rainfall. Although several other satellite rainfall products exists, these products provides global or near-global coverage, few are tailored for estimating rainfall distribution in Africa. Jobard et al., (2011) pointed out that this Tropical Applications of Meteorology using SATellite (TAMSAT) data perform better in Africa, this makes it suitable for this study. This dataset was used for detecting long-term rainfall trend from 1983 through 2011 and also for assessing the degree of association with the NDVI time series dataset for same period.

The CRU temperature data is a global dataset which provides gridded temperature anomalies across the world (Morice et al., 2012). The dataset is available as land and sea component which are obtained from national meteorological station/services such as World Meteorological Organization (WMO) and Global Climate Observation System (GCOS). The CRU dataset is usually updated by using data received via the Global Telecommunication System (GTS), (Morice et al., 2012). The CRU dataset consists of monthly composites in a 0.5° by 0.5° grid (50km spatial resolution). Change in temperature across the study region was examined using monthly averaged temperature from1983 -2011 so as to have the same span as the TAMSAT rainfall and NDVI time series datasets.

4.2.2. Data pre-processing

As described in section 4.2.1.1, the GIMMS NDVI3g data used in this study has already been pre-processed for the effect of aerosols, solar zenith angle and orbital drifts. However, application of methods of noise removal in time series datasets are still needed. Hence, all the satellite based data used in this study is corrected for the effect of noise prior to data analysis using IDRISI Selva software. As a first step before image pre-processing, the global GIMMS NDVI dataset was imported into the ENvironment for Visualizing Images (ENVI) software in order to stack the 696 bi-monthly NDVI composites. A similar process was performed for MODIS NDVI, TAMSAT rainfall and temperature datasets used in this study. Because the GIMMS NDVI dataset is provided in global projection, it is therefore necessary to re-project it to Universal Transverse Mercator (UTM) and subset imagery of the study area was clipped out of the datasets based on Kogi, Kwara and Niger state provincial boundaries. All other datasets were also re-projected. Prior to the intra-annual and seasonal trend analysis, two major pre-processing steps were carried out in IDRISI and R-programming. The pre-processing steps performed via IDRISI are related to the whole study areas i.e the satellite imagery covering Kogi, Kwara and Niger states. The clipped GIMMS NDVI and MODIS datasets for each region were aggregated into monthly composites by using maximum value composite (MVC) technique. This is necessary so as to reduce noise or any biasness which might be caused by atmospheric effects (Holben, 1986). The time series datasets (NDVI, rainfall and temperature) were de-seasoned before carrying out the inter-annual trend assessment. This step is necessary in order to remove seasonality from the original time series (Neeti et al., 2012). Temporal profiling for delineating regions of interest, trend estimation (ordinary least square, monotonic trend and significant test), seasonal trend analysis and extraction of phenological metrics were done in IDRISI while map creation was done with ArcMap 10.

4.3. Inter-annual trend analysis for selected locations

For the temporal analysis of inter-annual trends in the selected locations, GIMMS NDVI3g, MODIS, TAMSAT and CRU datasets were used. The main part of the analysis was done for each dataset separately. This includes determination of seasonality frequency, decomposition of the time series and trend analysis using different methods. Cross correlation and correlation coefficient was done in the last step to describe the relationship between NDVI versus rainfall and NDVI versus temperature over time (Fig 18). All the aforementioned steps was done by applying R open source software to the time series.

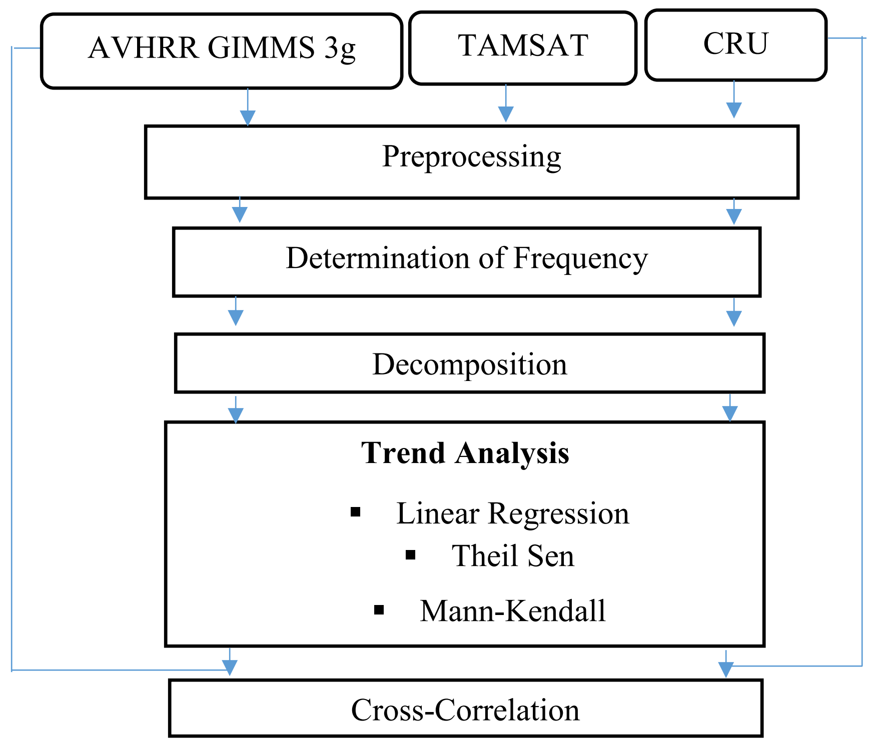


Figure 18. Flowchart of trend analysis

4.3.1. Determination of seasonality frequency time series

Some of the main problems in any time series analysis is the existence of seasonality, serial correlation and outliers. Serial correlation thus makes the results of trend detection and statistical inferences of time series analysis to be biased (Hong, 2006; Osunmadewa et al., 2015). It is therefore necessary to check for serial correlation in the time series dataset used in this study before further statistical methods are performed. Autocorrelation (ACF) and Partial Autocorrelation (PACF) function were used to check for the presence of serial correlation in the time series (Venables and Ripley, 2002). Autocorrelation simply means correlating a time series with itself i.e correlation with past and present values. Partial autocorrelation was calculated as a further step to determine the existence of periodicity in the data sets. Thus, PACF gives consideration to intermediate values that are comparably found as an echo in the values of ACF. This effect can be avoided with the partial autocorrelation function (PACF). Partial autocorrelation is similar to autocorrerlation, except that it partials out the effect of other elements such as autocorrelation to get a unique contribution of each time lag. PACF takes into account the effect of intermediate values which is not considered in ACF. For instance, the third partial autocorrelation coefficient measures the correlation between x_t and x_{t-3} taking into account the effects of x_{t-1} and x_{t-2}.

4.3.2. Decomposition method

Time-series analysis of remotely sensed data has gained considerable attention in earth observation today. However, models which are capable of detecting changes over time while taking the influence of seasonality into account are important especially in environmental monitoring studies. Decomposition of the time series into its different components is very important in order to monitor inter-annual fluctuations which might occur as a result of change in seasonal vegetation cycle or climatic variability across the year. As a first approach, the time series were separated into the seasonal, trend and random components. The relationship between the three components (seasonal, trend and random) can be described by an additive or multiplicative model as shown in equation 2 and 3.

Equation for additive model:

$$Y[t] = T[t] + S[t] + e[t] \qquad (2)$$

The multiplicative model is represented as:

$$Y[t] = T[t] * S[t] * e[t] \qquad (3)$$

where t is time, T is trend, S is seasonal and e is the error or irregular component.

The seasonal and trend component contain vital information about changes in any time series analysis. The seasonal component depicts changes in the phenological pattern of vegetation which might be a result of land-use change while the trend component depicts long-term change such as deforestation or fire incidents (Verbesselt et al., 2010a). A centered moving average method was used to determine the trend and after removing trend from the original series the seasonal figure was computed by averaging for each time unit over the whole period.

4.3.3. Normality test

In order to choose the most appropriate statistical method for analyzing trends in time series of remotely sensed data, it is important to carry out a normal distribution test. For this study, a normal distribution test was carried out using Shapiro-Wilks and Anderson-Darling test. Both tests either accept or reject the hypothesis of normal distribution. The Shapiro- Wilks test can be used to detect deviation from normality due to skewness or kurtosis (Osunmadewa et al., 2015; Rahman and Govindarajulu, 1997). The Shapiro-Wilks test uses variance (i.e the W statistic is the ratio between the variance of an assumed normal distribution and the variance of the real distribution of measurements). If the W value is near to 1, this indicates that the time series data are normally distributed$(0 < W \leq 1)$, (Shapiro and Wilk, 1965). Anderson-Darling on the other hand is used to test how well a data follows a particular distribution.

4.4. Trend analysis

Several statistical methods was applied to the time series dataset used in this study in order to observe long-term trends over the study period.

4.4.1. Linear regression model

Ordinary least-square (OLS) regression model was used to test the linear relationship between the variables used in this study. At first, each variable (NDVI, rainfall, temperature) was regressed against time, where time (x) is referred to as independent variable and NDVI (y) as dependent variable. OLS trends were quantified by the slope of the regression line, and their significance was tested at 0.05 significant level (α). The OLS model is illustrated in equation 4.

$$y = \alpha + \beta * x + \varepsilon \tag{4}$$

where y = dependent variable (NDVI, rainfall, temperature)

x = Independent variable (time)

α = is the intercept

β = slope coefficient for independent variable (relationship between x and y variable)

ε = random error

4.4.2. Theil-Sen median slope

A robust and non-parametric alternative (known as Theil-Sen trend estimator) to OLS (parametric) which is capable of modeling how the median of a time series changes linearly with time was applied to the datasets used in this study. Theil-Sen trend estimator is suitable for assessing the rate of change in time series because of its ability to estimate trend slope even when data are missing. The Theil-Sen (TS) median slope is determined by calculating the slope between all pair wise combinations and then estimating the median over time. The TS trend estimator is resistant against the effect of outliers, it has a breakdown bound of 29% (Dubovyk et al., 2015; Eastman et al., 2009; Parmentier, 2014; Parmentier and Eastman, 2014). This implies that the values of the TS slope are not affected by outliers when they do not exceed 29% of the observations used in the time series. The rate of change can be calculated if a significant trend is observed in the time series as described in the Sen estimator equation (Gilbert, 1988):

$$m_{ij} = \frac{Z_j - Z_i}{j - i} \tag{5}$$

where *Zj* and *Zi* are considered as data values at time *j* and *i* (for all *j* > *i* and *i* = 1, 2,…., (*n*-1) and *j* =2, 3… n) respectively. The median of these N values of m_{ij} is represented as Sen's estimator of slope (α_1). Thus, the estimate of the slope is given as:

$$\beta = m\lfloor (N+1)/2 \rfloor \quad if\ N\ is\ odd \tag{6}$$

$$\beta = \frac{1}{2}(m\lfloor N/2 \rfloor) + \ (m\ \lfloor (N+2)/2 \rfloor) \quad if\ N\ is\ even \tag{7}$$

However, positive β indicates an increasing trend while the opposite indicates a decreasing trend in the time series.

4.4.3. Mann-Kendall trend analysis

Mann-Kendall (MK) test is a non-parametric test for assessing monotonic trend in time series. MK trend test is less sensitive to outliers, and it can be used with missing data without taking into consideration if the dataset used follows a specific distribution (normal distribution) or not (Tabari and Talaee, 2011). This trend test was first introduced by Stuart and Ord, (1987) and has been widely used for hydrological and environmental monitoring (Gilbert, 1988). MK was applied by Alcaraz-Segura et al., (2010) and de Jong et al., (2012) for testing the significance of change in NDVI. The test measures the extent at which a trend is consistently increasing (+1) or decreasing (-1). A value of +1 indicates an increasing trend, value of -1 indicates a decreasing trend while a value of 0 indicates no trend. The null hypothesis (H_0) assumes that there is no trend while the alternative hypothesis (H_A) assumes that there is both increasing and decreasing trend in the time series (Gilbert, 1987). However, if the p-value is < 0.01 this shows that there is trend in the time series over time. The computational procedure for the Mann Kendall test considers the time series of n data points and X_j and X_i as two subsets of data where j = 1,2,3,…, n-1 and i = i+1, i+2, i+3, …, n. The data values are evaluated as an ordered time series and each data value is compared with all subsequent data values (pairwise combination). The result of the increasing and decreasing monotonic trend values gives the final value of S. Both Kendall score and its variance (Var *S*) are computed separately(Gilbert, 1988).

The Mann-Kendall *S* Statistic is computed as follows:

$$sign(x_j - x_i) = \begin{cases} 1 \; if \; (x_j - x_i) > 0 \\ 0 \; if \; (x_j - x_i) = 0 \\ -1 \; if \; (x_j - x_i) < 0 \end{cases} \qquad (8)$$

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sgn\,(x_j - x_i) \qquad (9)$$

where Xj and Xi are the annual values in years j and i, $j > i$, respectively

When n is greater than 40, the variance S is calculated because it is assumed that many tie data might exist. The variance statistic is computed as:

$$Var(S) = \frac{n(n-1)(2n+5) - \sum_{q=1}^{p} t_q(t_q-1)(2t_q+5)}{18} \quad (10)$$

where t_q is considered as the number of ties up to sample q.

In this study, the MK was used for assessing long term trends both in NDVI and climate variables using their trend components.

4.5. Correlation coefficient between NDVI and climate parameters

The strength and direction of linear relationship between two variables can be statistically proven by performing correlation analysis between them. The strength of linear relationship between NDVI and the climatic data used in this study was examined using Pearson Product Moment Correlation (PPMC) and Kendall's rank correlation. Better understanding of vegetation productivity and land condition becomes more understandable when the spatial and temporal relationship between NDVI and climate parameters are duly assessed (Fensholt and Proud, 2012; Higginbottom and Symeonakis, 2014). However, if positive correlation exist between the variables (for example NDVI and temperature), this indicates a relationship between both variables (i.e as NDVI increases, temperature also increases). But if a negative correlation exist between the two variables, this shows that as variable *x* is increasing, variable *y* is decreasing (opposite direction). The Pearson correlation coefficient is computed as follow:

$$r = \frac{n \sum xy - (\sum x)(\sum y)}{\sqrt{n(\sum x^2) - (\sum x)^2}\ \sqrt{n(\sum y^2) - (\sum y)^2}} \quad (11)$$

where x represents NDVI and y either rainfall or temperature. It should be noted that both rainfall and temperature are the climatic dataset used for this analysis and the results were computed in R programming.

4.6. Comparison between GIMMS and MODIS dataset

One of the main conditions of combining NDVI data from different sensors is to examine similarities in signals over time. To do this, the MODIS datasets was re-sampled to the spatial resolution of GIMMS datasets (i.e 8 km) by applying a bilinear method. Temporal trends in the monthly NDVI values of the datasets (GIMMS and MODIS) was examined using Ordinary Linear Regression model and Mann-Kendall trend test.

4.7. Seasonal Trend Analysis (STA)

4.7.1. Data and method

The datasets used for this analysis are GIMMS NDVI3g and TAMSAT rainfall data. Prior to the STA, the bi-monthly GIMMS NDVI3g dataset was aggregated to monthly composites and the study areas were clipped out (see section 4.2.2). The three approaches used for this analysis are as follows: (a) application of harmonic regression to the monthly NDVI and rainfall composites (b) significance test using Contextual Mann–Kendall (CMK) approach and (c) visual observation of NDVI phenological curves for the selected locations.

4.7.1.1. Harmonic regression for seasonal trend analysis

Changes in the seasonal NDVI trend pattern (greenness) was analyzed using the harmonic regression approach as described by Eastman et al., (2009). This method was selected because of its ability to detect seasonality in any time series sequence, to reject noise and resilience to short-term variability. It is similar to Fourier analysis, but the methodology is different. STA uses two stages of time series analysis for detecting trends in NDVI, which is preceded by visualization of the produced image (amplitude and phase image) at the final stage (Eastman et al., 2009). STA performs harmonic regression of annual (yearly) imagery in the time series as described in equation 12. In the first stage of STA however, each annual imagery in the time series (1983-2011) was subjected to harmonic regression in order to approximate the seasonal curve (Dubovyk et al., 2015; Eastman et al., 2009; Neeti et al., 2012). Thus, amplitude 0, amplitude 1 and phase 1 were computed using harmonic regression procedure. The overall greenness of NDVI for each year is described as Amplitude 0, the magnitude of peak of annual greenness as amplitude 1, while the timing of annual peak of greenness is referred to as phase 1. An increase or decrease in Phase 1 symbolizes a shift in the timing of the annual peak of greenness to an earlier or later time of the year. The generalized equation for the harmonic regression is presented as follows:

$$y = \alpha_0 + \sum_n \{ a_n \; sin\left(\frac{2\pi nt}{T}\right) + b_n \cos\left(\frac{2\pi nt}{T}\right) \} + e \qquad 12$$

where t is referred to as time, y is the series value, T is the length of the time series, n is a harmonic integer multiplier, e is error term, α_0 is the mean of the time series while a_n and b_n are regression parameters.

The harmonic regression curve can also be expressed as:

$$y = \alpha_o + \sum_n \alpha_n \sin\left(\frac{2\pi nt}{T}\right) + \varphi_n \qquad 13$$

after the term of equation (12) has been rearranged and the error term has been omitted or ignored. Hence, α_n and φ_n are referred to as amplitude and phases (Eastman et al., 2009).

In the second stage of the analysis, trends (i.e slope) in the annual greenness parameters were computed (Eastman et al., 2009). This stage involves calculation of yearly trends in the greenness parameters (i.e amplitude 0, amplitude 1 and phase 1) using a non-parametric trend detection technique known as Theil Sen estimator (see section 4.4.2).

4.7.1.2. Contextual Mann-Kendall test

Trends in vegetation dynamics for each pixel in the NDVI time series was statistically tested in order to identify areas undergoing similar trends (Neeti et al., 2012). In order to evaluate the significance of trends observed in the greenness parameters during the Theil-Sen slope calculation as mentioned in the above section, a non-parametric statistic test known as Contextual Mann-Kendall (CMK) was applied (Eastman et al., 2009; Neeti and Eastman, 2011). CMK test is resistant to outliers and uses a similar approach like that of Mann-Kendall by incorporating geographical information. To perform CMK test, three stepwise approaches are involved. The first step accounts for the elimination of serial correlation in the NDVI time series which might influence the trend test using a method known as prewhitening (Neeti and Eastman, 2011; Yue and Wang, 2002). In the 2nd stage, trend in a 3*3 neighborhood around each pixel is evaluated at a regional scale and in the last stage (3rd stage), the calculated 3*3 neighborhood result of the 2nd stage is used for calculating spatial autocorrelation (Neeti et al., 2012). The results obtained from the CMK trend test are in image forms (i.e statistical *p-value* and *Z* score). Each of the results describes statistical significant trend (positive and negative trend) as observed in the greenness parameters. It should be noted that a positive *Z* score is an indication of upwards trend where a negative value indicates a downwards trend (Neeti and Eastman, 2011).

4.7.1.3. Visual interpretation of phenological curve

An interactive approach as described by Eastman et al., (2009) was used to further examine change in NDVI over the 29 years examined. This was done by selecting the regions of interest in the produced amplitude image. In order to achieve this aim, temporal profiles showing monthly NDVI of the first and last period (1983 and 2011) of the data set were compared for selected locations across different land cover types and the seasonal NDVI curves were produced. The examined locations were sampled based on a single pixel (i.e. 64 km2). The differences between the two curves indicate resultant changes which can be used to describe seasonal trends in the observed vegetation phenological pattern (Eastman et al., 2013; Neeti et al., 2012).

4.7.2. Phenological metrics extraction

The timing of a specific biological phase such as flowering, leaf growth, leaf fall (growth and senescence) and their causes can be described as phenology (Bradley et al., 2007; Chen and Pan, 2002; Reed et al., 1994). Vegetation phenology has a close relationship with climatic variability which has influence on the timing of plant growth and development in the dry sub-humid region of Africa. Remotely sensed vegetation indices data provide means of measuring phenological events over a longer period of time. Several methods have been used in the past to extract phenological metrics such as that of Eastman, (2002) where a dynamic threshold is used (He et al., 2015). This study follows the approach of Reed et al., (1994) for extracting phenological information from the GIMMS NDVI3g time series dataset from 1983 – 2011. Eleven (11) seasonal metrics are defined from the GIMMS NDVI data and were categorized into three types:

(1) Temporal (timing of an event),

(2) NDVI-based (the value of NDVI during specific events), and

(3) Metrics derived from time-series characteristics as shown in Table 3.

Table 3: Phenological interpretation of seasonal NDVI metrics

Metrics	Phenological interpretations
Temporal NDVI metrics	
Time of green up	Beginning of measurable photosynthesis
Time of green down	Cessation of measurable photosynthesis
Duration of greenness	Duration of photosynthetic activity
Time of peak NDVI	Time of maximum measurable photosynthesis
NDVI Value metrics	
Value of time green up	Level of photosynthetic activities at the beginning of growing season
Value of time green down	Level of photosynthetic activities at the end of growing season
Value of peak of NDVI	Maximum measurable level of photosynthetic activity
Range of NDVI	Range of measurable level of photosynthetic activity
Derived metrics	
Time integrated NDVI	Net primary production
Rate of green up	Acceleration of photosynthesis
Rate of green senescence	Deceleration of photosynthesis

4.7.3. Temporal Metrics of NDVI and their Values

Temporal NDVI metrics may not correspond to the conventional (ground-based) phenological events but provide indicators on vegetation dynamics. However, certain events such as increase in NDVI can be observed from satellite imagery for detecting changes in vegetation phenology (Reed et al., 1994).

The method used in this study is to identify the point when an increase in NDVI signal is reached. This point indicates the start of significant photosynthetic activity, noticeably when about 40% of the vegetation cover in a specific location shows significant photosynthetic activities. This process is referred to as onset of green-up or beginning of growing season (BGS) (Eastman et al., 2009; Yu et al., 2010). This analysis was performed in IDRISI software (Eastman, 2002).

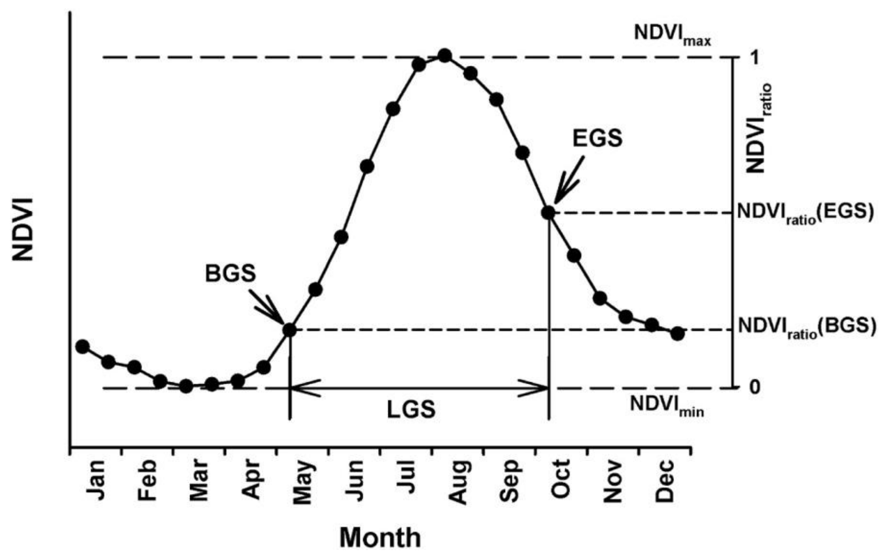


Figure 19. Derivation of phenological metric (BGS= Beginning of growing season, EGS= End of growing season)
Source: Yu et al, 2010

When the beginning of growing season (BGS) and end of the growing season (EGS) has been identified (start of significant photosynthetic activity), the remaining phenological metrics can be easily computed. The length of growing season can be derived by finding the difference between the start of growing season and the end of growing season as shown in figure (Fig 19). After the metrics for the maximum NDVI value ($NDVI_{max}$) had been identified, the range of NDVI can then be computed by subtracting the NDVI value of either the BGS or EGS (which ever was lower) from the maximum NDVI value. The rates of green-up and senescence were computed as straight line slopes from onset to the maximum and from the maximum to the end of the growing season, respectively. Modality can be determined in conjunction with the identification of the end of season (Reed et al., 1994).

4.7.4. Methodology for Qualitative Analysis

Qualitative analysis of the socio-economic characteristics for the people living in the rural and semi-urban communities is performed in order to be able to explain factors responsible for long-term vegetation change dynamics. The methods used in this study are summarized below.

4.7.5. Survey Method

Field survey (field visit) of the study areas and selected locations was carried out from February to April 2013. This was done in order to examine human impacts on vegetation change dynamics across the Guinea savannah region of Nigeria. The field visit was necessary in order to identify areas going through serious land use land cover change (LULCC) and also to identify key informants (indigenous inhabitants) who have knowledge about the study locations. After the key informants had been identified, qualitative data such as questionnaire, interviews and group discussions were carried out.

4.7.6. Questionnaire

The primary data used in the study was obtained through the use of structured questionnaires and interviews with respondents (farm and non-farm household). The questionnaire was design based on the background knowledge of the study area, previous research work and discussion with key informants. In order to collect relevant information from the respondents, a scheduled interview was prepared considering the objectives in view. Personal interview was conducted with the respondents using an interview schedule (see plate 6).

4.7.7. Key Informants Interview

Information about historical changes in vegetation dynamics was obtained through interviews held with elderly people (head of village) in the respective study areas. These interview covers a vast range of topics regarding land-use, vegetation change, livestock and human perception on the drivers of change. These interviews were very important as they provide information about the perception of local people on human impacts on vegetation change dynamics dated back to the 1980's to the mid-20^{th} century.

4.7.8. Sample Size and Selection of Respondents

The cross-sectional study was carried out in twelve different Local Government Areas (LGA), with four LGA's selected for each state. The sampled locations are Igalamela odolu, Ankpa, Koton-karfe and Kabba-bunu LGA in Kogi, Kaiama, Edu, Ekiti, Baruten in Kwara and Rijau, Mashegu, Lapai and Muya in Niger state. A total of 300 respondents was selected using stratified random sampling method. 25 respondents were selected for each LGA according to Hinton, (2014) who argued that 25% of respondents successfully represent the population in social studies (Israel, 2013; Sandelowski, 1995). However, 283 questionnaires were retrieved.

4.7.9. Data Analysis

The analysis was performed using simple descriptive statistics like percentage. The collected data were analyzed using Statistical Package for Social Science (SPSS) version 18.00 and the results are presented in the form of tables and graphs.

4.8. Land use land cover (LULC)

Land is the bedrock which supports all living organisms including human existence and various activities (Olaleye et al., 2012). Land use/land cover are interlocked in which change in one affects the other (Rawat and Kumar, 2015). Land cover change both in time and space is associated with human activities such as charcoal production, farming, and excessive logging among others. Thus, assessment of land use land cover change dynamics in a periodical way is needed due to change in the distribution and physiognomic characteristics of tropical forests (Adeoye, 2012). The national land use map of 1976 and 1995 by the Forestry Management Evaluation and Coordination Unit (FORMECU) was used as baseline data for monitoring land use land cover change in the study region. The FORMECU land cover datasets have a scale of 1:250,000. In addition, three global land cover datasets (2000, 2005 and 2009) by the European Space Agency (ESA) were used for land use land cover change assessment. The global land cover data of 2000 has a spatial resolution of 1km while the global land cover of 2005 and 2009 have a spatial resolution of 300m. The global land cover map of 2009 was resampled to 1km resolution so as to merge with the same spatial resolution of the 2000 global land cover using the nearest neighbor resampling algorithm. The land cover classes for both maps (2000 and 2009) were aggregated to six major classes for comparison. In order to corroborate the results obtained from the time series analysis, further assessment using Landsat imagery of three different time steps was used. Landsat imagery was used to examine the extent of deforestation in specific locations (region of interest). The analysis was performed using Carnegie Landsat Analysis System-lite (CLASlite) software developed by Carnegie Institution for Science (CIS). This analysis (LULC) is imperative because of large scale anthropogenic activities going on in the study area as observed during the field survey. For this analysis cloud free (0%) Landsat imagery of three epochs (1986, 2000 and 2014) was downloaded free of charge via the United States Geological Survey (USGS) Global Visualization Viewer (GloVis) (http://glovis.usgs.gov/). The spatial resolution and acquisition dates are presented in table 4.

Table 4: Data source

Year	Location	Path/Row	Image Acquisition Date	Satellite	Sensor/Scale	Cloud Cover
1986	Niger	189/53	08-01-1986	Landsat 5	30m ^{TM}	0.00%
2001	Niger	189/53	25-01-2001	Landsat 7	30m ^{ETM}	0.00%
2014	Niger	189/53	06-02-2014	Landsat 8	30m $^{OLI\text{-}TIRS}$	0.00%
1987	Kogi	189/55	21-12-1987	Landsat 4	30m ^{TM}	0.00%
2001	Kogi	189/55	09-01-2001	Landsat 7	30m ^{ETM}	0.00%
2014	Kogi	189/55	23-12-2014	Landsat 8	30m $^{OLI\text{-}TIRS}$	0.77%
1986	Kwara	190/54	17-12-1986	Landsat 5	30m ^{TM}	0.00%
2000	Kwara	190/54	15-02-2000	Landsat 7	30m ^{ETM}	0.00%
2014	Kwara	190/54	15-01-2014	Landsat 8	30m $^{OLI\text{-}TIRS}$	0.05%

CLASlite is largely automated and requires four analytical steps as described below.

Step 1: Image calibration and atmospheric correction

The Landsat scenes to be analyzed are imported into the software (CLASlite) with associated information and are calibrated from units of digital number (DN) to top-of-atmosphere radiance imagery using the conversion factor (gain and offset values) provided by the satellite sensor source (i.e GLOVIS). Image calibration is expressed in equation 14.

$$\rho_{\lambda} = \frac{\pi L_{\lambda} * d^2}{ESUN_{\lambda} \sin\theta} \quad (14)$$

where:

L_{λ} = Radiance in units of W/(m^2 * sr * μm)

d = Earth-sun distance, in astronomical units.

$ESUN_{\lambda}$ =Solar irradiance in units of W/(m^2 * μm)

θ = Sun elevation in degrees

The reflectance gains and offsets have been scaled by the sine of the sun elevation in Landsat 8. Atmospheric correction is then performed with the 6S model after image calibration has been done (Asner et al., 2009; Reimer et al., 2015). Haze removal is also implemented in the CLASlite 3.2 version especially for Landsat imagery. Masking of water bodies and cloud cover is performed in this step as well, although total masking of cloud is carried out in subsequent steps.

Step 2: Fractional cover generation

The major step in CLASlite is the generation of fractional cover of photosynthetic vegetation (PV), a Non-photosynthetic vegetation (NPV) and bare substrate (S). PV is referred to as live vegetation, NPV as senescent vegetation/deforestation residues (slash) while BS is referred to as mineral soil, rock, roads or urban surfaces. Step 2 is performed by applying the Automated Monte Carlo Unmixing (AutoMCU) algorithm to the image (i.e the reflectance image in step 1). The AutoMCU is based on a probabilistic algorithm which uses spectral endmember libraries for each of the PV, NPV and S surface types that are derived from satellite imagery (Asner et al., 2009; Reimer et al., 2015) . Each image pixel is then decomposed by the spectral libraries using a linear equation as expressed hereafter.

$$\rho(\lambda)\,pixel = \sum[C_e * \rho(\lambda)e] + \varepsilon = \left[C_{pv} * \rho(\lambda)\mathrm{pv} + C_{npv} * \rho(\lambda)npv + C_{substrate} * \rho(\lambda)substrate\right] + \varepsilon \quad (15)$$

where $\rho(\lambda)_e$ is the reflectance of each land-cover endmember (e) at wavelength λ and ε is an error term, while *Ce* is the sub-pixel cover fraction of each land-cover endmembers (see CLASlite user guide, 2014 for more details (Asner, 2014).

Step 3: Classification of forest cover

At this stage, a decision tree is applied to the output of step 1 and 2 in order to estimate forest cover per single image (Reimer et al, 2015). Thus, the image is classified into three classes which are defined as:

0 = Masked pixels

1 = Forest: PV ≥ 80 AND S < 20

2 = Non-forest: PV < 80 OR S ≥ 20

PV is referred to as photosynthetic vegetation while S is included in order to eliminate non-forest regrowth.

Step 4: Forest change detection

Change detection between multi-temporal images is done at this stage to determine deforestation and forest disturbance over different time steps. This step is done in CLASlite by applying decision trees to the imagery thereby producing both deforestation and disturbance maps (Asner et al., 2009; Haruna et al., 2014; Lui and Coomes, 2015). Figure 20 illustrates the processing steps of CLASlite 3.2 version, the major processes are in red color. Further analysis was performed in ENVI and ArcGIS in order to determine the extent of deforestation in the selected study locations. For more information, see CLASlite user guide (Asner, 2014).

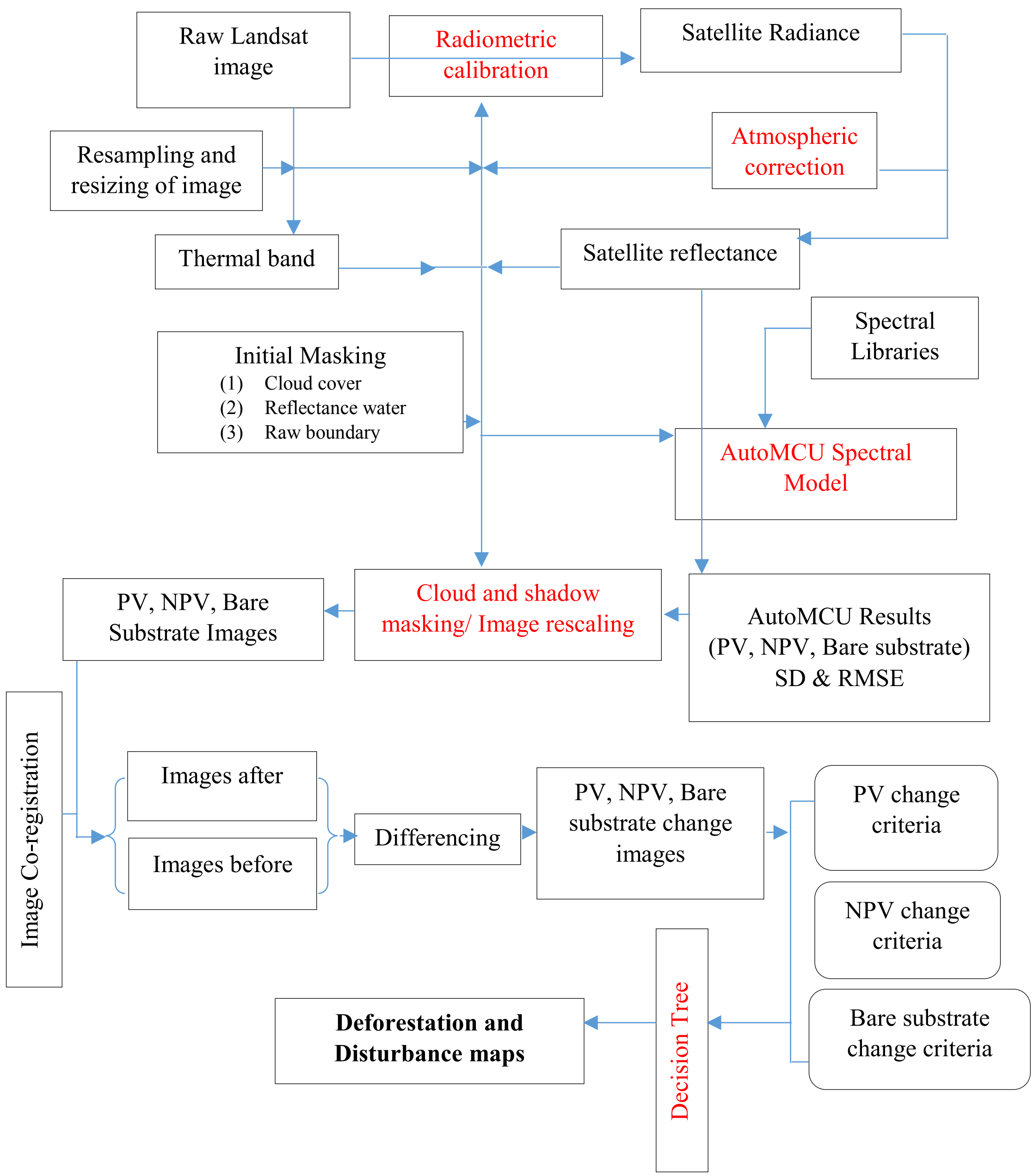


Figure 20. CLASlite processing steps
Source: adopted from Asner et al., (2009)

Visual interpretation of the results obtained from the fractional image and deforestation map for the study area was used in this study.

5. Results and discussion

5.1. Inter-annual trend analysis

5.1.1. Abstract

The use of Normalized Difference Vegetation Index (NDVI) product from Advanced Very High Resolution Radiometer (AVHRR) over the last decades has increased our understanding about vegetation change dynamics from global to regional scale through quantitative analysis of inter-annual trends in NDVI time series and climatological parameters (rainfall and temperature) which is can be influenced by land use land cover change especially in the Guinea savannah region of Nigeria where increased anthropogenic activities have led to vegetation cover transition. This study therefore aims at examining the relationship between NDVI and climatic variability using remotely sensed data. In order to do this, bi-monthly NDVI3g time series data from Global Inventory Modeling and Mapping Studies (GIMMS), monthly rainfall dataset from Tropical Applications of Meteorology Satellite (TAMSAT) and monthly temperature data from Climate Research Unit (CRU) for the period of 1983 to 2011 were used. Long-term inter-annual trends in NDVI and climatic variable were examined using Ordinary Least Square (OLS), Theil-Sen (TS) median slope trend and Mann Kendall (MK) monotonic trend test. The result of the linear regression model is statistically positive significant ($p < 0.01$) which indicates increase in vegetation trend over time (i.e greening trend). The significance of the result was tested using Kendall's tau rank correlation coefficient and the results are significant at p-value <0.01. Positive correlation was observed by the result of the correlation between NDVI and rainfall, in contrast negative correlation exists between NDVI and temperature. Although, increase in rainfall over the last decades enhances biomass productivity, other factors such as land use land cover change needed to be examined so as to better explain human induced vegetation change in the study region.

5.2. Inter-annual trends in vegetation and climatic parameters

Up to date assessment of the rate and direction of vegetation change dynamics over a long period using NDVI time series is very important for proper ecosystem and environmental monitoring most especially in Nigeria where human transformation of the land cover and climate variability is inherent. Spatio-temporal trend analysis across the Guinea savannah region of Nigeria was carried using the flowchart as described in section 4.3- 4.5 of this study. Positive trends were observed in the NDVI and climatic time series datasets for the period of study (1983-2011). Variation in the results of the applied trend estimators for the study region are presented in table 5. About 90-97 % of the pixels used in the analysis show positive vegetation trend over time which can be referred to as vegetation greening (De Jong et al., 2012; De Jong et al., 2013).

Table 5: Trend analysis results for the entire transition zones for monthly NDVI time series of GIMMS (1983-2011) OLS= Ordinary Least Square, TS= Theil-Sen, MK= Mann-Kendall.

Location	Trend estimator	Area with negative trend value (%)	Area with positive trend value (%)
Niger State	OLS	10.18	89.82
	TS slope	12.04	87.96
	MK tau	10.85	89.15
Kwara State	OLS	5.04	94.96
	TS slope	6.50	93.50
	MK tau	6.50	93.50
Kogi State			
	OLS	2.94	97.06
	TS slope	4.63	95.37
	MK tau	4.98	95.02

About 10 % of the pixels used in the assessment of vegetation trend in the study area showed significant negative NDVI trend which is referred to as vegetation browning (De Jong et al., 2013). Similarly, an increasing trend was observed from the result of both rainfall and temperature datasets for the same period.

5.3. Linear NDVI trends

Fig 21. show the results of the per-pixel linear trend analysis (monthly rate of change) in NDVI time series in the study regions over a period of 29 years period. A positive trend was observed which indicates an increase of vegetation greenness over time.

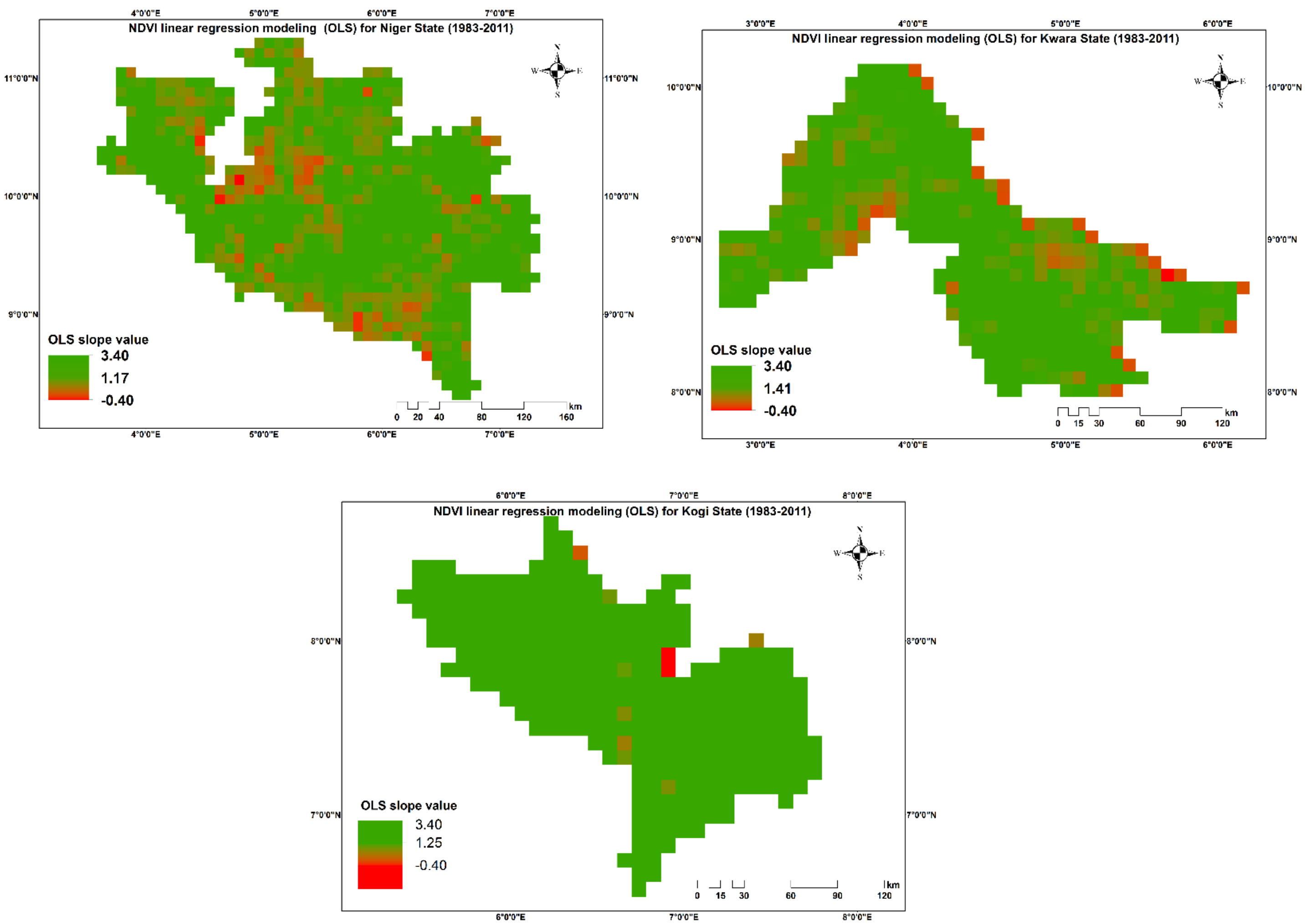


Figure 21. Ordinary Least Square (OLS) regression model for NDVI

During the examined period (1983-2011), about 10% of the land cover in Niger state show a negative trend (slope coefficient value) which implies a loss in vegetation cover over time. Kwara state which is known as the transition zone between the northern and southern part of Nigeria exhibits about 5% negative vegetation trend while about 3% of the land cover in Kogi state show negative NDVI trend (green and red color indicate positive and negative trend respectively). A more robust trend estimator (i.e Theil-Sen) was used to check if the trends observed from the OLS analysis are in the same direction with that obtained from TS. The results of the TS analysis for the whole study area is presented in Fig 22.

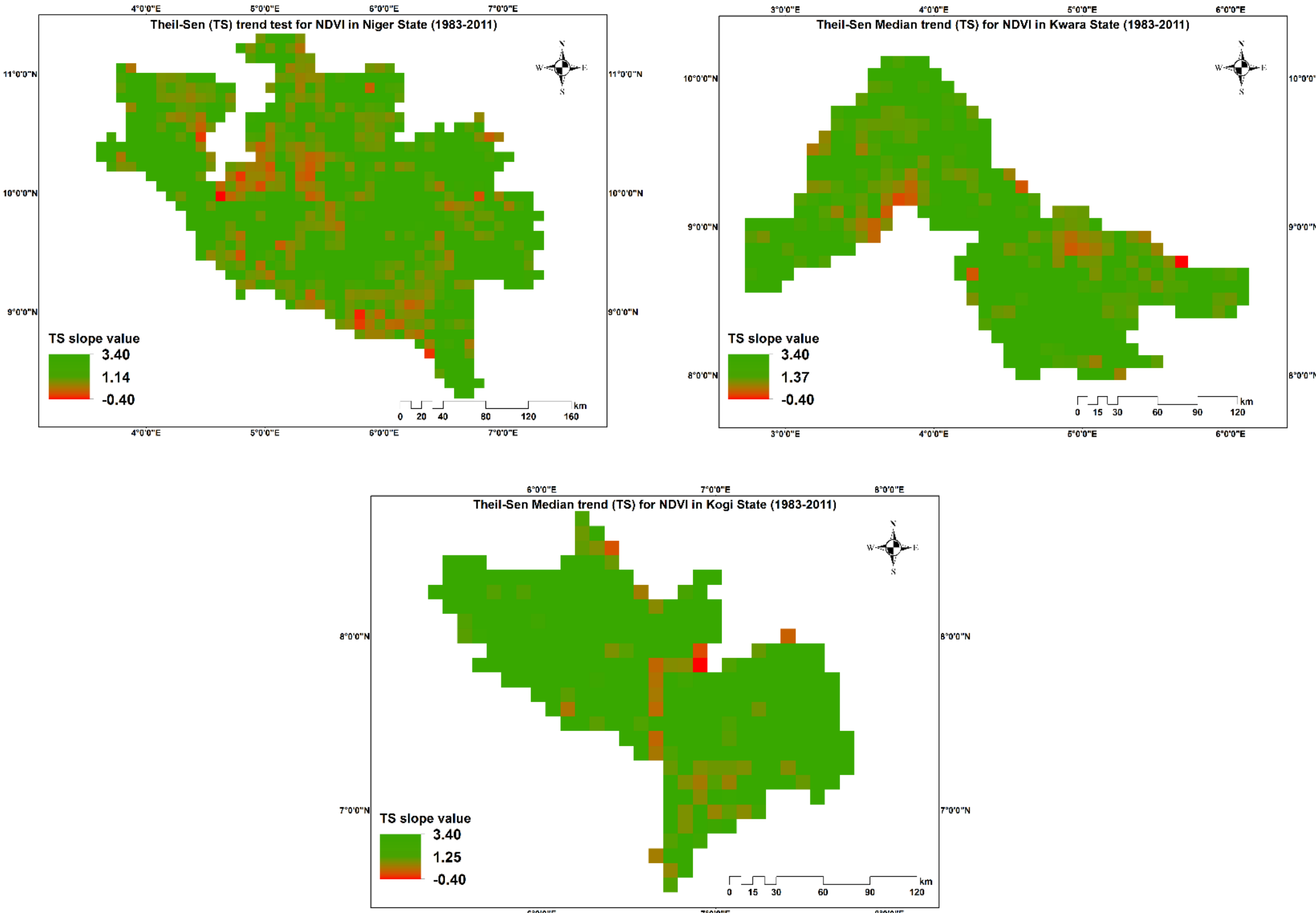


Figure 22. Theil-Sen (TS) regression model for NDVI

Similar direction of slope was observed from the results of both regression analysis, although it is assumed that outliers might affect the result of OLS, hence, variation in both results is less than 2% (table 5). It should be noted that the results of the Theil-Sen has resistance to outliers if not more than 29% of the observation in the time series data as observed in result of OLS and MK.

5.4. Monotonic trends in NDVI

The degree at which trend in vegetation dynamics is increasing and decreasing is a very important aspect of trend analysis. Monotonic trend analysis has been used in various studies to illustrate vegetation greening and browning both at the global and regional scale. However, a value of +1 indicates vegetation greening, value of -1 indicates browning while a value of 0 indicates no trend (see section 4.4.3). Figure 23 shows the result of the monotonic trend test for the study regions. Generally, greening trend predominates in all the study regions which indicates increase in vegetation trend over time. The results of this analysis are in line with that of global and regional studies (De Jong et al., 2012; Fensholt et al., 2012; Herrmann et al., 2005; Ibrahim et al., 2015) where a greening trend was observed in some parts of the semi-arid regions of Africa and also in the northern part of Nigeria.

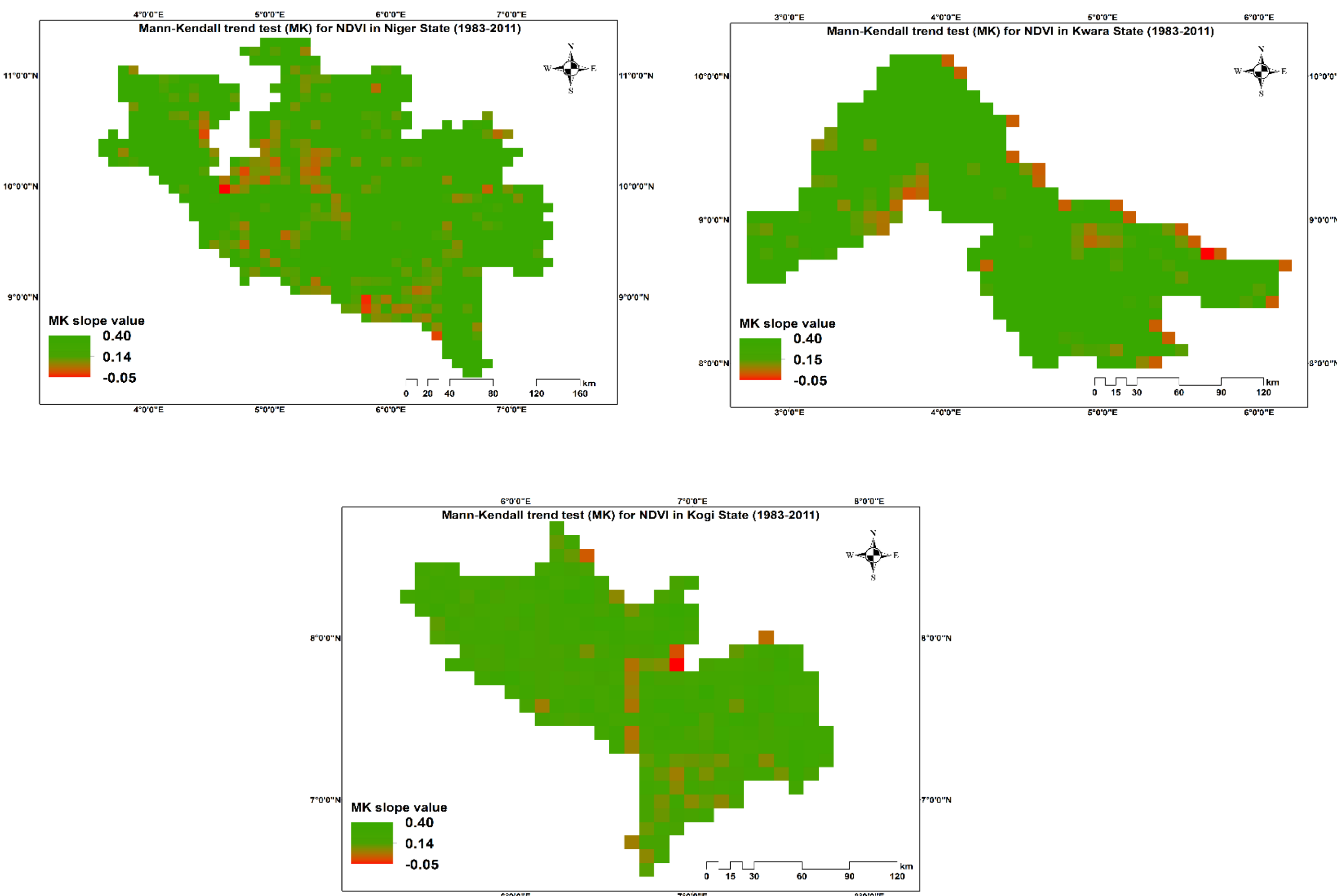


Figure 23. Mann-Kendall trend test for NDVI

5.5. Spatio-temporal analysis of trends in NDVI and climatic time series datasets for selected locations

5.5.1. NDVI

Both parametric and non- parametric statistical methods were used for the assessment of vegetation trends in the selected locations as shown in figure 24. The analysis was performed as described in section 4.4 of this thesis. Thus, the time series analysis was carried out across different land cover types using a single pixel. The study locations were selected based on the agro-ecological zones of the region and on local knowledge.

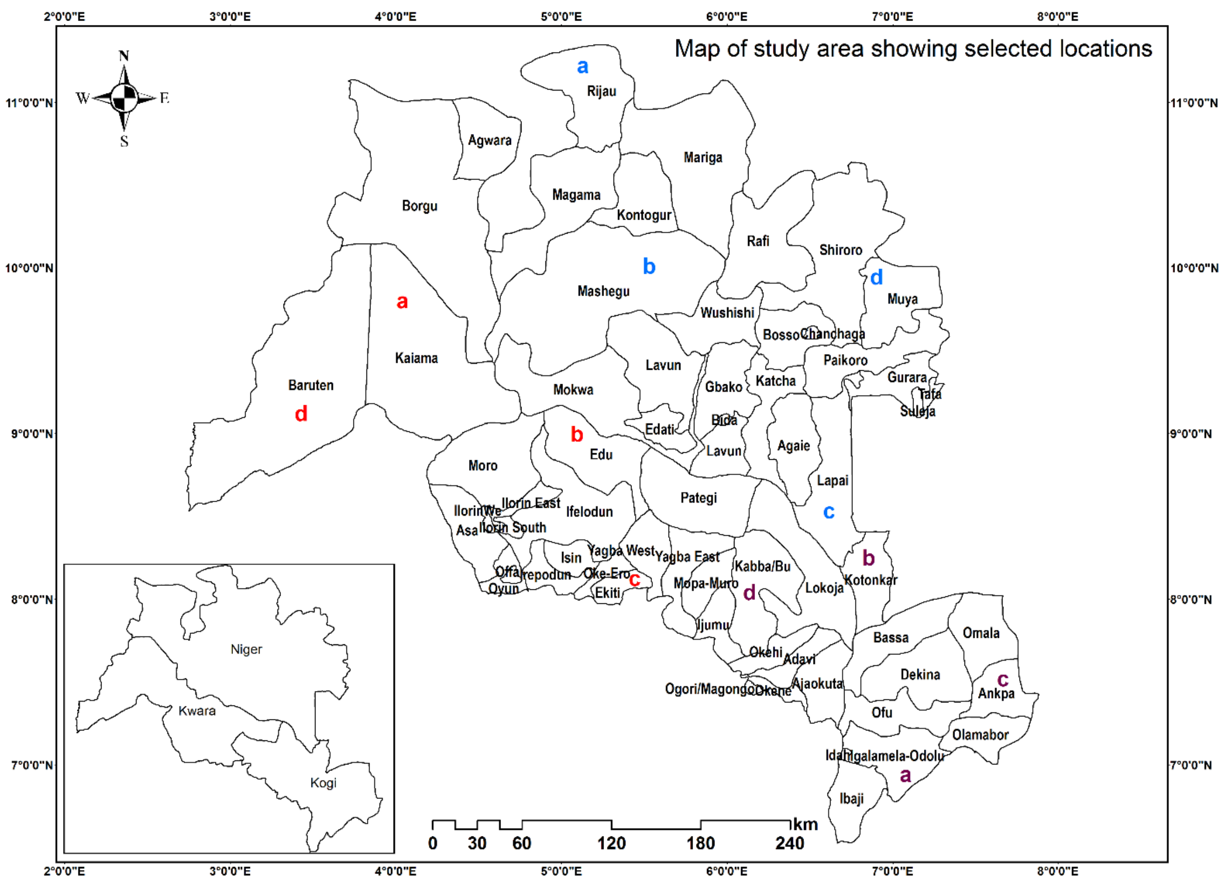


Figure 24. Map of study area showing selected locations

Figure 25 shows the results of the raw NDVI time series (1983-2011) for selected locations in Niger state before decomposition. It is observed from the visual observation (fig 25) that the NVDI time series for the study locations are dominated by components of seasonal signals which are as a result of periodic change (fluctuation in rainfall, temperature and/or start of growing season) over time. As a general phenomenon, long-term seasonal signals in any time series can influence the statistical inference of the trend analysis results. Therefore, it is imperative to remove the seasonal signals by disintegrating the time series datasets used in this study into their components. This can be done in the best way by using an additive model because the random fluctuation varies over a long period.

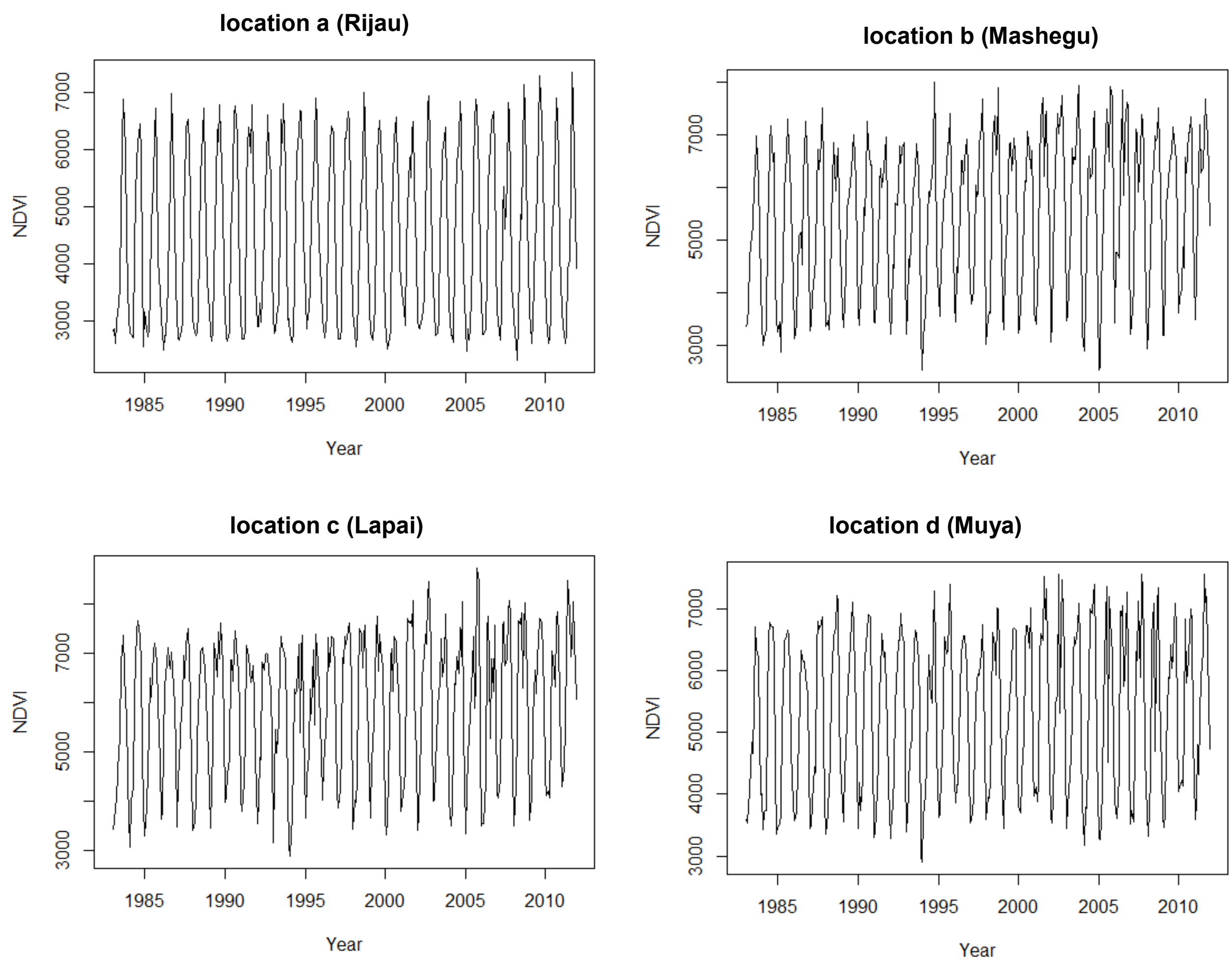


Figure 25. Original NDVI3g time series data for selected locations in Niger State

5.5.2. Rainfall analysis for Niger state

Several studies have revealed that vegetation productivity (increase) in some regions of Africa is mostly influenced by rainfall (Herrmann, 2007; Herrmann et al., 2005; Ibrahim et al., 2015) or soil moisture content as a result of soil-water availability over time. In this regards, trend analysis was carried out for the rainfall time series datasets in order to examine if the observed trends in NDVI can be explained by rainfall. Figure 26 show the raw rainfall data (TAMSAT) used in this study.

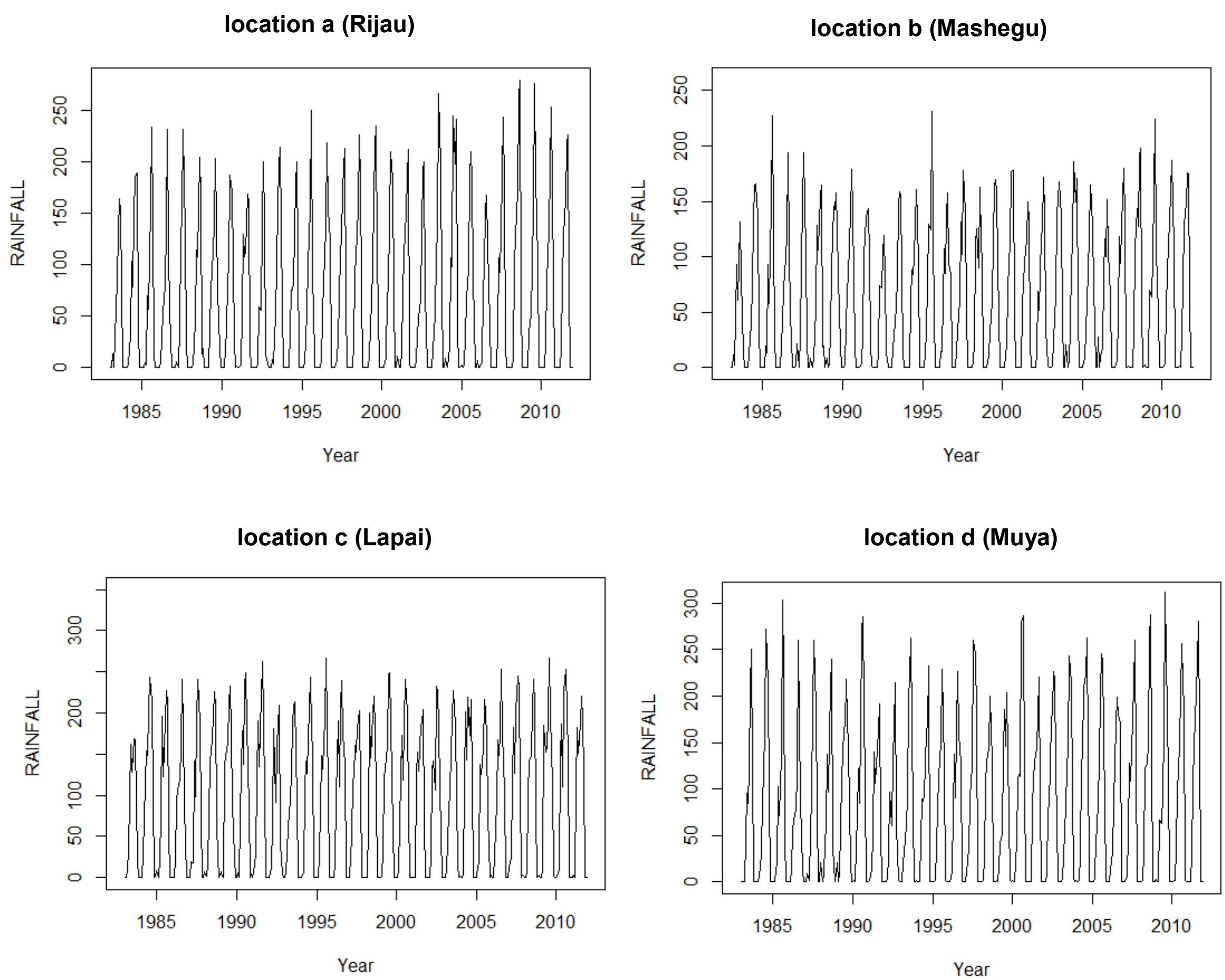


Figure 26. Original TAMSAT time series data of selected locations in Niger State from 1983-2011

Variation in the seasonal signal of rainfall (TAMSAT) was observed for the whole study period. Fluctuation in the seasonal signal might be due to variation in the length (start and end of rainfall) and/or intensity of annual precipitation. It should however be noted that the fluctuation might be marked by the period where there is no rain (dry season).

5.5.3. Temperature analysis for Niger state

Solar energy is one of the important climatic drivers for photosynthetic activities in plants (vegetation). Studies have revealed that increase in temperature has positive influence on vegetation net primary production (Gao et al., 2017; Olusegun and Adeyewa, 2013; Wang et al., 2011). In order to ascertain this fact, an analysis of trends in temperature and its association with NDVI for the study region was performed.

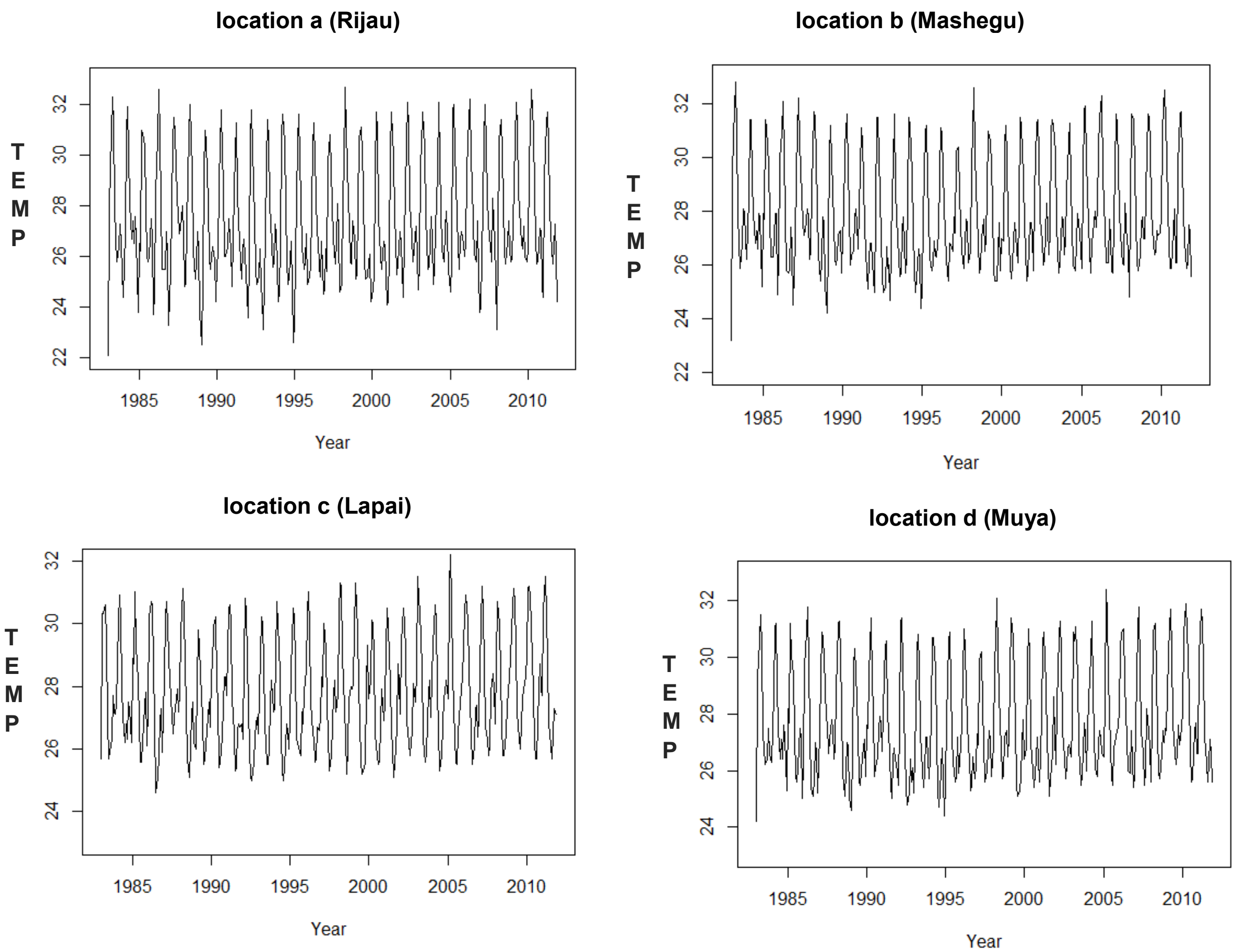


Figure 27. Original temperature time series data of selected locations in Niger State from 1983-2011

Seasonal signal as observed in the results of NDVI and rainfall (TAMSAT) datasets was also observed in the results of the temperature time series. The same seasonal signal was observed for Kogi and Kwara state. Hence, further analysis in order to determine the frequency of the observed seasonal signals was carried out (see appendix for the results of other locations).

5.6. Frequency of seasonality

5.6.1. Determination of seasonal frequency in NDVI

Seasonality in time series datasets is referred to as regular pattern of change which repeats itself in systematic interval over time (periodic fluctuation). However, the presence of serial correlation often leads to the violation of model assumptions. It is therefore necessary to know the frequency of the seasonal signal before other modeling methods can be applied to the NDVI time series data used in this study. Hence, the NDVI dataset of Niger state was subjected to auto-correlation analysis.

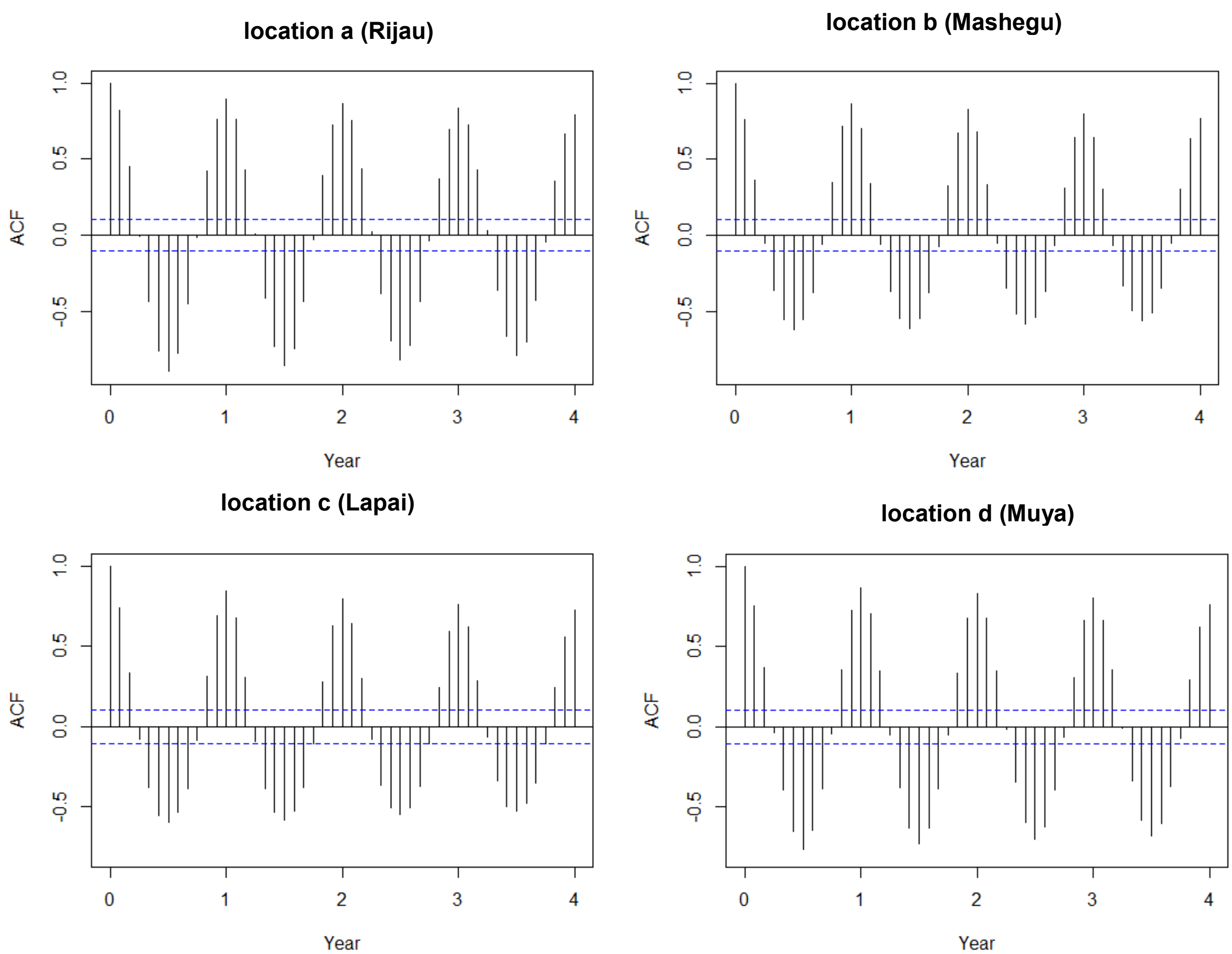


Figure 28. NDVI auto-correlation function (ACF) for selected locations in Niger State with annual lags (lag 96= 4 years). The lag was set to 4 years to examine long-term effect of auto-correlation on the bi-monthly NDVI dataset. The dotted lines indicate the significant confidence interval (95%) of zero auto-correlation.

It is observed from the correlogram that there is variation in the result of the autocorrelation which confirms the assumption of the presence of serial correlation in the study locations. Strong correlations were observed by shifts in annual integer periods. This implies that the statistical inference can be biased if a method that addresses the problem of serial correlation in time series analysis is not applied. Partial autocorrelation was calculated as a further step of determining if the periodicity will partial out (i.e to eliminate or remove the influence of a factor or variable during statistical analysis). The result of the partial correlogram shows that some of the partial autocorrelation at lag 0 – lag 1 exceed the significance bounds and are slowly decreasing in magnitude with increasing lag as compared to the simple autocorrelation function.

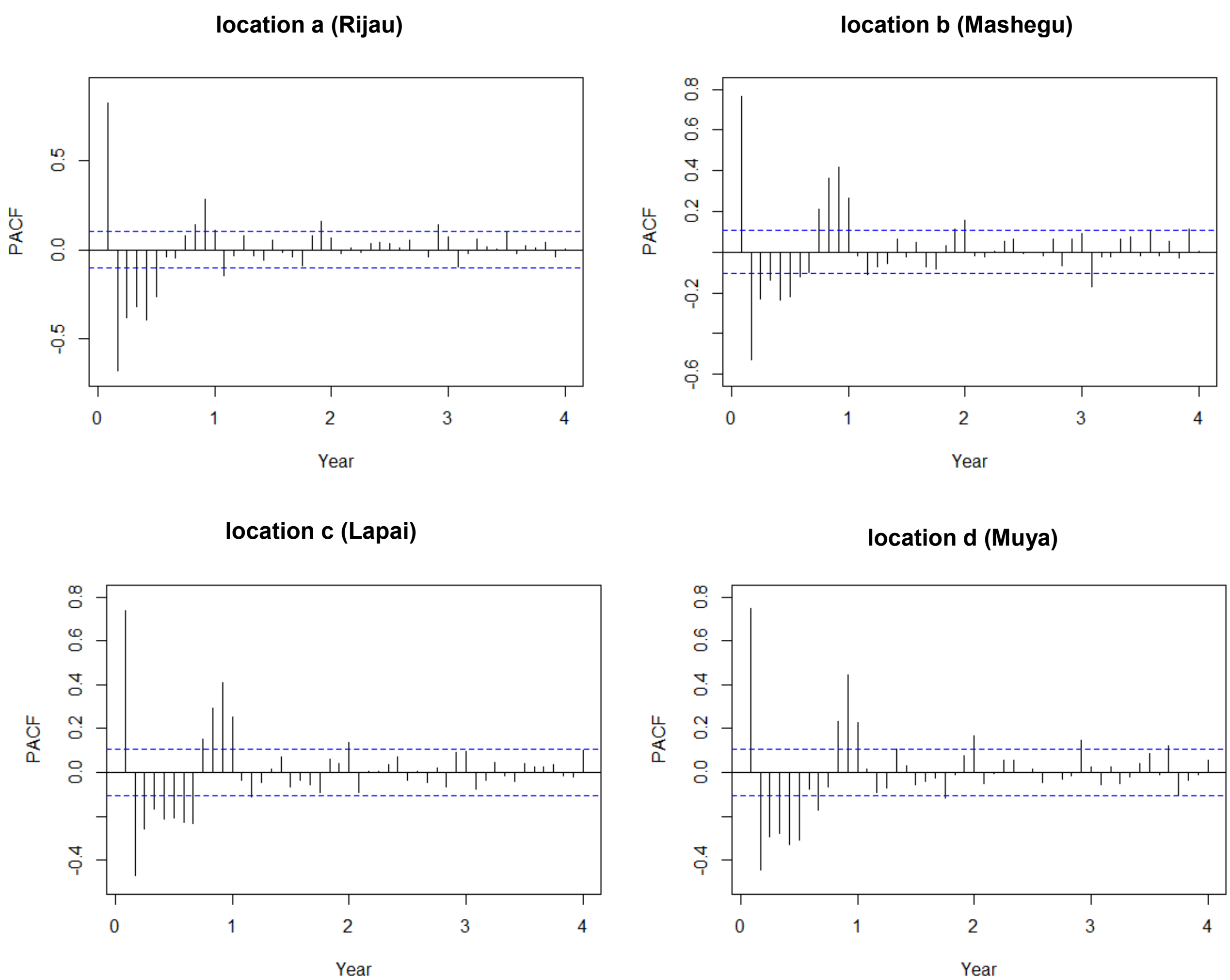


Figure 29. Partial autocorrelation function (PACF) for the time series of NDVI for the selected locations in Niger

It is therefore evident from the results of the seasonal frequency determination that annual seasonality is dominant (one year) in the NDVI time series dataset as observed in both ACF and PACF. Owing to this fact, the frequency (seasonality) was set to 24 because the NDVI dataset is bi-monthly (1 year). Apart from the NDVI3g dataset, TAMSAT rainfall and temperature datasets from CRU were also checked for the presence of serial correlation using the ACF and PACF (see appendix for results). A dominant period of one year was revealed by the result of both functions (AC and PAC). Hence, the frequency was set to 12 (1 year). It should be noted that both datasets are monthly. For this reason, the time series datasets need to go through further analytical step.

5.6.2. Decomposition of NDVI time series dataset for Niger state

Figure 30 shows the results of the decomposition of the NDVI time series dataset into its trend, seasonal and random component (noise) as described in section 4.3.2. These results show that vegetation change dynamics within time series are influenced by the signal of the ratio of noise (random) present in the time series.

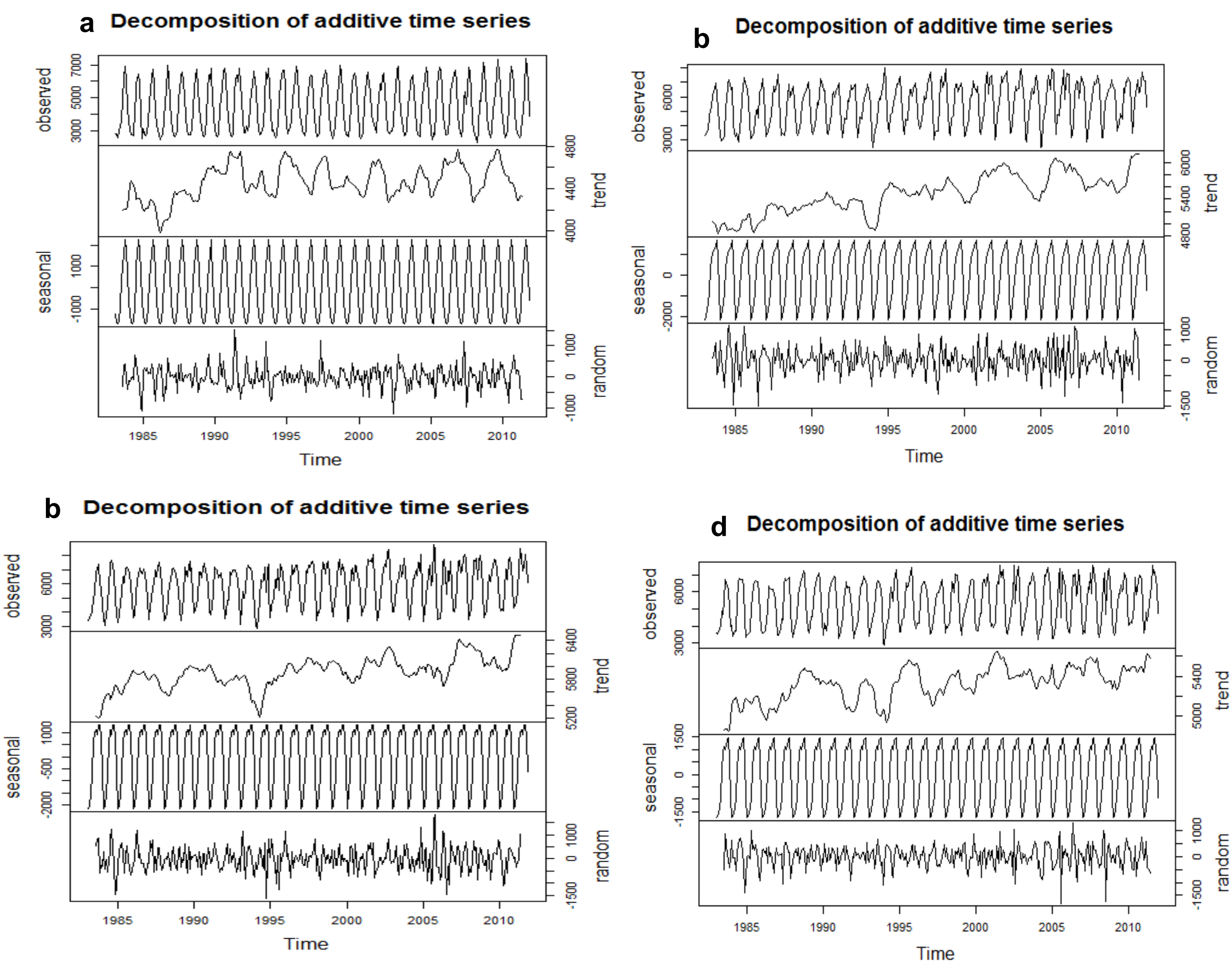


Figure 30. NDVI time series decomposition for the selected locations in Niger State (NDVI*10,000)

The above plot shows the original time series (top), the estimated trend component (second from the top), the estimated seasonal component (third from the top) and the estimated random component i.e noise (bottom). From the visual interpretation of the time series analysis of the four study locations, it can be concluded that there is a positive trend in NDVI (Fig. 30). It is also obvious that the characteristics of the annual seasonality varies considerably in the study locations.

It is observed from the result of the NDVI decomposition that the estimated trend component shows a decrease between 1987, 1993 and 1995 respectively. Visual analysis of the random component shows that no other systematic (trend, seasonality) are in this part of the original signal.

5.6.3. Decomposition of rainfall time series for Niger state

Figure 31 shows the results of the decomposition of the rainfall time series dataset. The frequency was set to 12 indicating one year seasonal frequency. The units of the rainfall dataset is in millimeter (mm).

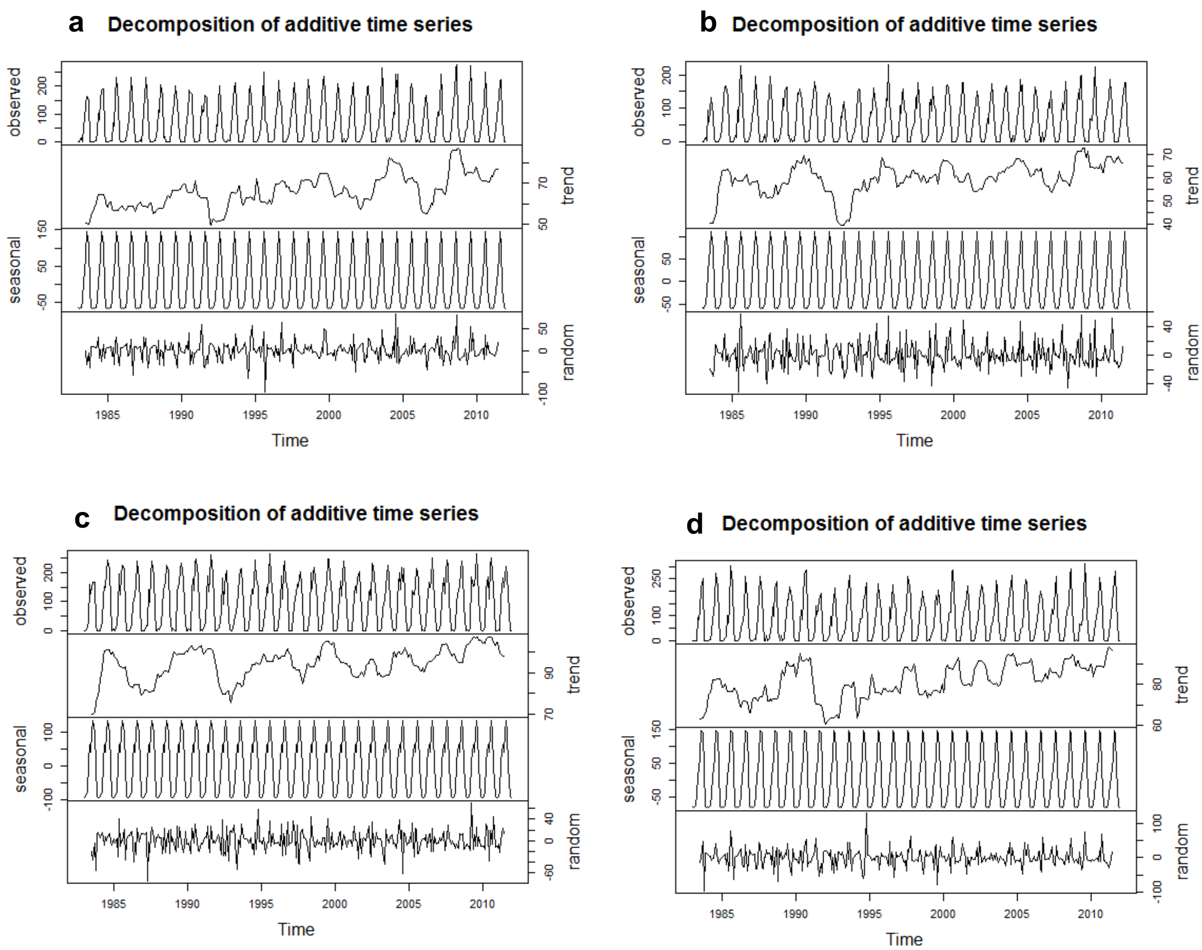


Figure 31. Decomposition of the rainfall (mm) dataset for the selected locations in Niger State

Both increasing and decreasing rainfall trend was observed based on the result of the analysis, though an increasing trend is more obvious which indicates water availability over time. However, the decrease in rainfall trend as observed in 1991-1993 might be a result of the severe drought across West Africa in this period (Masih et al., 2014).

5.6.4. Decomposition of temperature time series dataset for Niger state

Similar to the results obtained from the decomposition of NDVI and rainfall datasets for the selected locations, both increasing and decreasing trend was observed from the decomposition of the temperature time series dataset used in this study (fig 32). The temperature data are in degree Celsius.

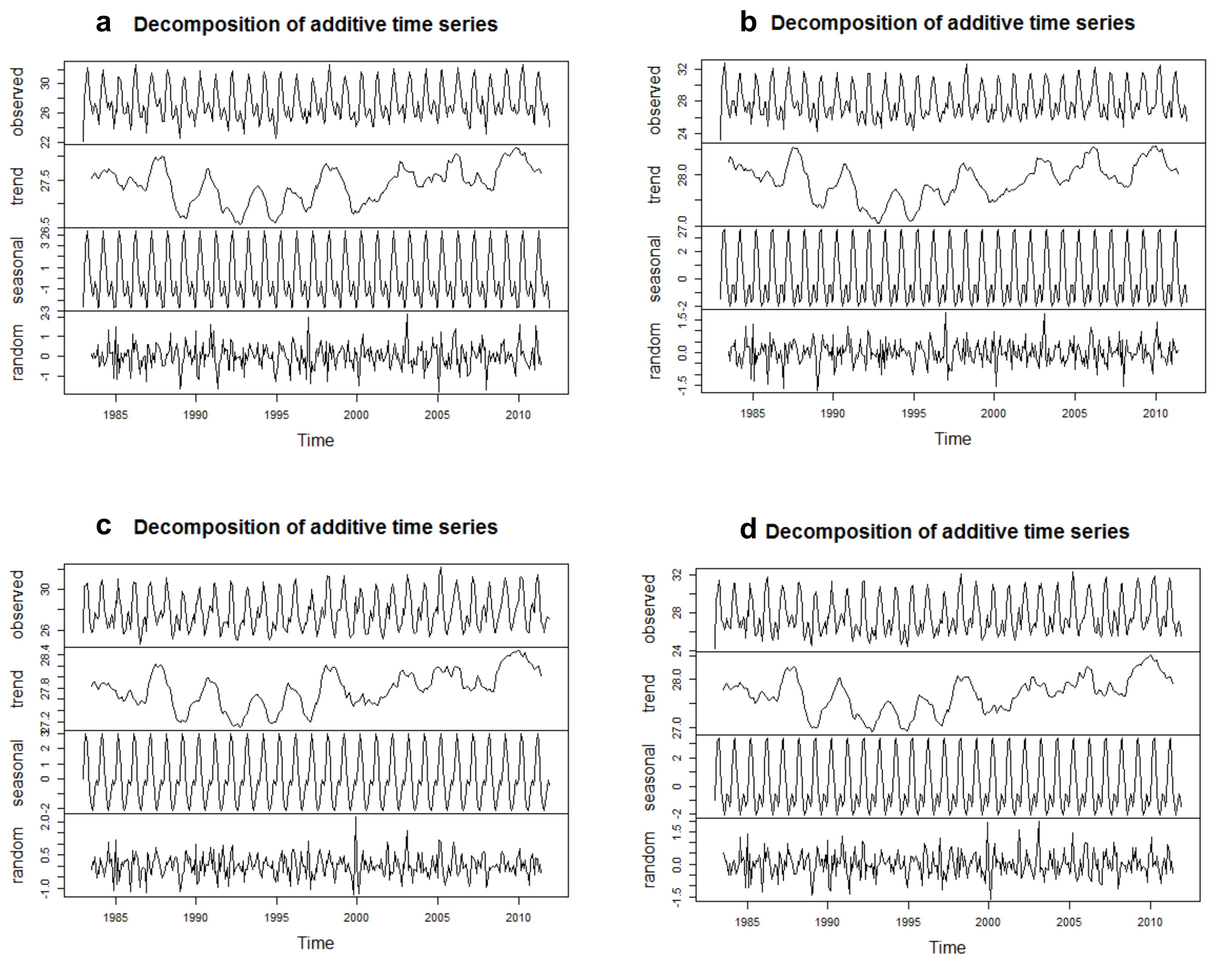


Figure 32. Decomposition of temperature time series dataset for the selected locations in Niger State

It can be emphasized from the result of the analysis (decomposition of the time series datasets into its components) that there is an overall positive trend (increasing trend) over the study period (1983-2011) with some decrease in 1987-1993 and 1995-1997. Annual seasonality varies considerably in the study locations which might be associated to the effect of climate change. However, the results obtained from the decomposition of the climate datasets will assist in understanding climate-vegetation change patterns across the study region.

5.7. Trend analysis

5.7.1. NDVI trend analysis in Niger state

Linear modeling method which is also referred to as Ordinary least square (OLS) was the first approach used in this study to analyze NDVI trends. The results of the linear regression model of NDVI against time are shown in Fig. 33. Slight variations were observed from the regression analysis of the selected locations.

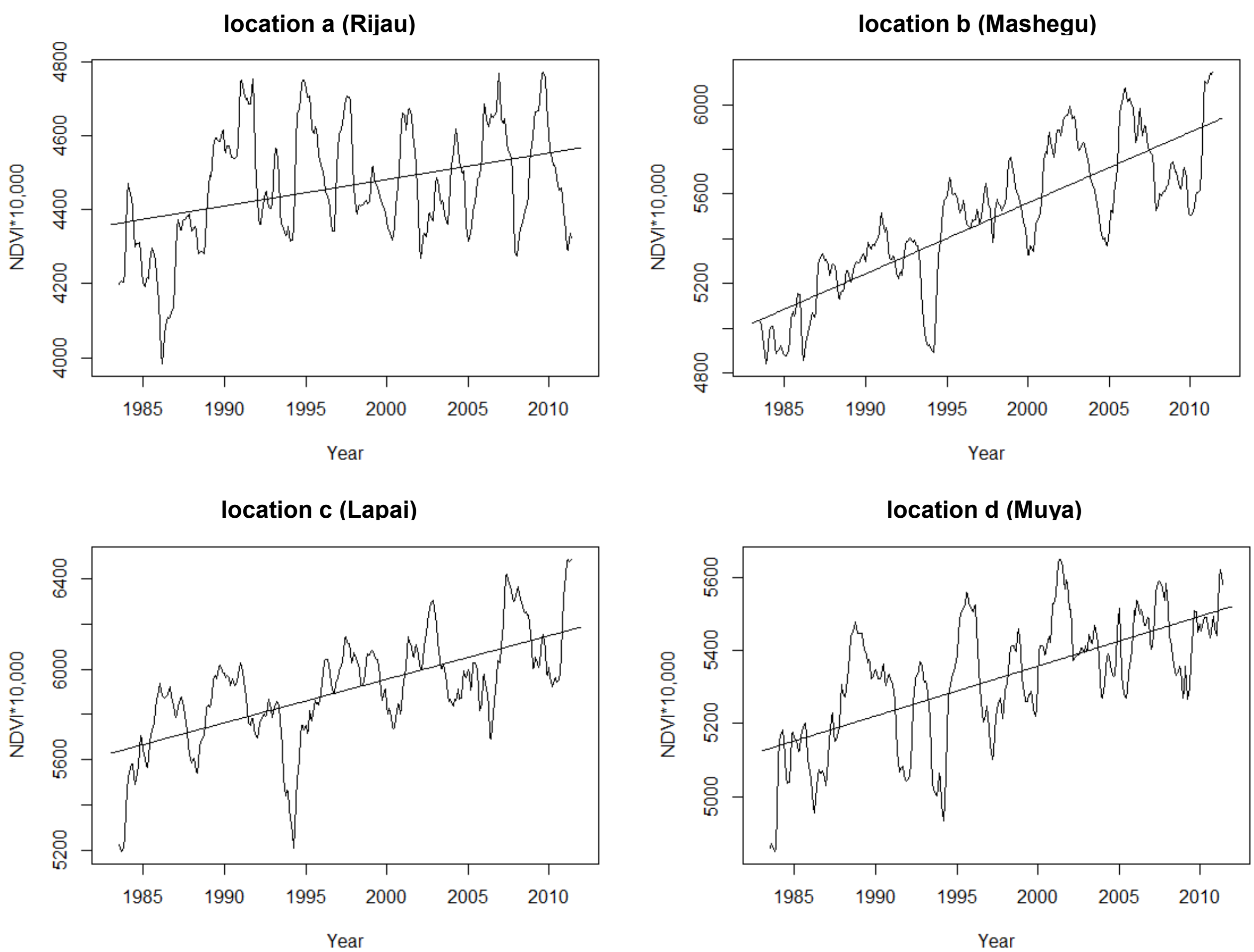


Figure 33. Linear regression of NDVI against time for the selected locations in Niger State

All the results of the selected locations show consistent increase in NDVI signals for the study period (1983-2011). Although the existence of outliers influences the result of parametric analysis (OLS) when more than 29% (see section 4.4.2), it can thus be inferred that rainfall variation and other anthropogenic factors such as land use land cover change might be responsible for the decline in NDVI as observed in the early 90's (location b, c and d). Generally, an increase in NDVI can be seen from the regression line. Table 6 show the results of the linear regression including information about the statistical parameters (i.e F-statistic, R^2, and P-value). All regression coefficients were significant at $p > 0.001$.

Table 6: NDVI linear regression model for the selected locations in Niger State

Location	Slope	Residual Standard Error	F-Statistic	R^2	p-value
a	15.28	125.2	653.8	0.49	< 2.2e-16
b	23.91	126.9	155.7	0.70	< 2.2e-16
c	11.51	162.2	220.9	0.25	< 2.2e-16
d	11.58	193.2	157.9	0.19	< 2.2e-16

Results of the coefficient of determination (R^2) show that about 19 – 70 % of NDVI can be explained with time. The OLS results for the selected locations are significant and thus indicate a positive NDVI trend over time in Niger state. Similar increase in NDVI trend was observed for the selected locations in Kogi and Kwara state. The results of the OLS for both locations (Kogi and Kwara) are presented in table 7 and 8 respectively.

Table 7: NDVI linear regression model for the selected locations in Kogi State

Location	Slope	Residual Standard Error	F-Statistic	R^2	p-value
a	11.97	181.1	191.9	0.22	< 2.2e-16
b	19.05	163.8	593.7	0.47	< 2.2e-16
c	24.75	149.5	1204.0	0.64	< 2.2e-16
d	18.05	212.5	316.6	0.32	< 2.2e-16

Table 8: NDVI linear regression model for the selected locations in Kwara State

Location	Slope	Residual Standard Error	F-Statistic	R^2	p-value
a	14.98	153.4	418.5	0.39	< 2.2e-16
b	5.61	174.5	45.33	0.06	3.582e-11
c	3.49	156.7	21.8	0.03	3.663e-06
d	18.32	148.9	664.5	0.50	< 2.2e-16

The results of OLS for the selected locations in Kogi and Kwara across the different land cover types vary considerably. About 22-64 % of NDVI can be explained with time for the selected locations in Kogi while about 1-50 % of NDVI can be explained with time in Kwara. Variability in the results makes generalization of change in vegetation greenness over time in the study area (Niger, Kogi and Kwara state) difficult. Due to the suspicion of outliers in the results of the OLS, a non-parametric and more robust trend estimator (i.e Theil Sen) was used. The results of Theil Sen trend estimator for all the study locations are presented in table 9-11.

Table 9: Results of the Theil-Sen Estimator NDVI for the selected locations in Niger State

Location	Slope	Residual Standard Error	p-value
a	16.08	140.7	< 2e-16
b	22.40	127.5	< 2e-16
c	9.67	187.9	< 2e-16
d	9.19	195.4	< 2e-16

Table 10: Results of the Theil-Sen Estimator for the selected locations in Kogi State

Location	Slope	Residual Standard Error	p-value
a	13.80	187.6	< 2e-16
b	20.33	168.7	< 2e-16
c	23.48	154.0	< 2e-16
d	17.20	214.4	< 2e-16

Table 11: Results of Theil-Sen Estimator for NDVI for the selected locations in Kwara State

Location	Slope	Residual Standard Error	p-value
a	14.64	176.4	< 2e-16
b	3.49	183.2	< 2e-16
c	4.43	156.9	< 2e-16
d	18.88	164.3	< 2e-16

When compared with the result of the OLS, slight variation in the slope and residual standard error can be observed from the results of the Theil-Sen trend estimator. As discussed earlier in section 4.4.2, one of the major aims of performing both tests is to determine a suitable representation for the trend signals. As a next step, the standardized residual data values for all the study locations were analyzed for the effect of outliers. Figure 34 show the result of the standardized residual analysis for the study locations in Niger state (see appendix for the results of Kogi and Kwara).

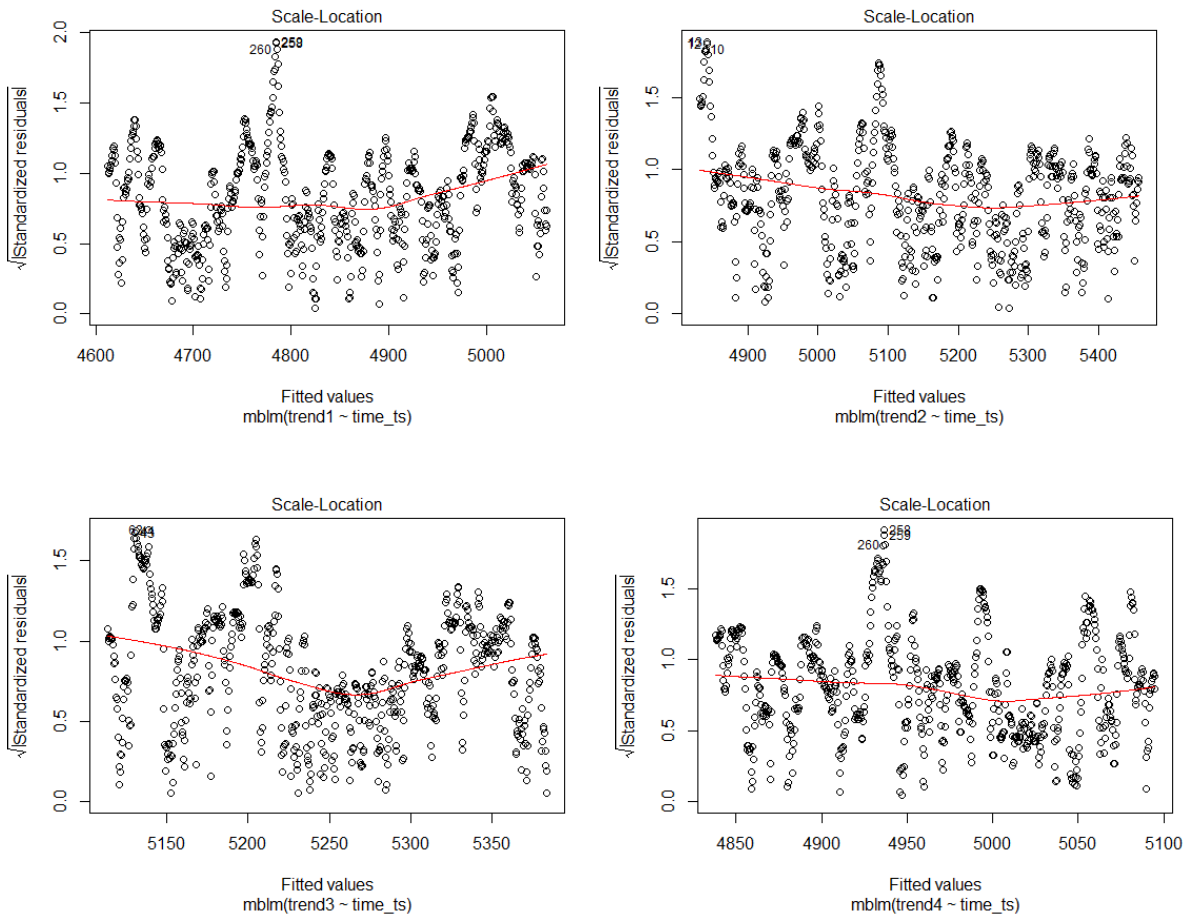


Figure 34: Standardized residuals for Theil-Sen estimation of NDVI trend signals for the selected locations in Niger state

The result obtained from the statistical analysis (Fig.34) show the existence of outliers in the time series (the numbers inside the figure represents outliers). Thus, further analysis using Cook distance and leverage effect revealed that these outliers have no significant influence on the parameters of the regression (Chatterjee and Hadi, 2015).

Assessment of Gaussian distribution (normal distribution) for the NDVI time series used in this study is very important before further calculation such as correlation coefficient can be carried out. Owing to this fact, some test was performed to find out if the datasets occur as a Gaussian distribution. The results of the normal distribution test are presented in figure 35.

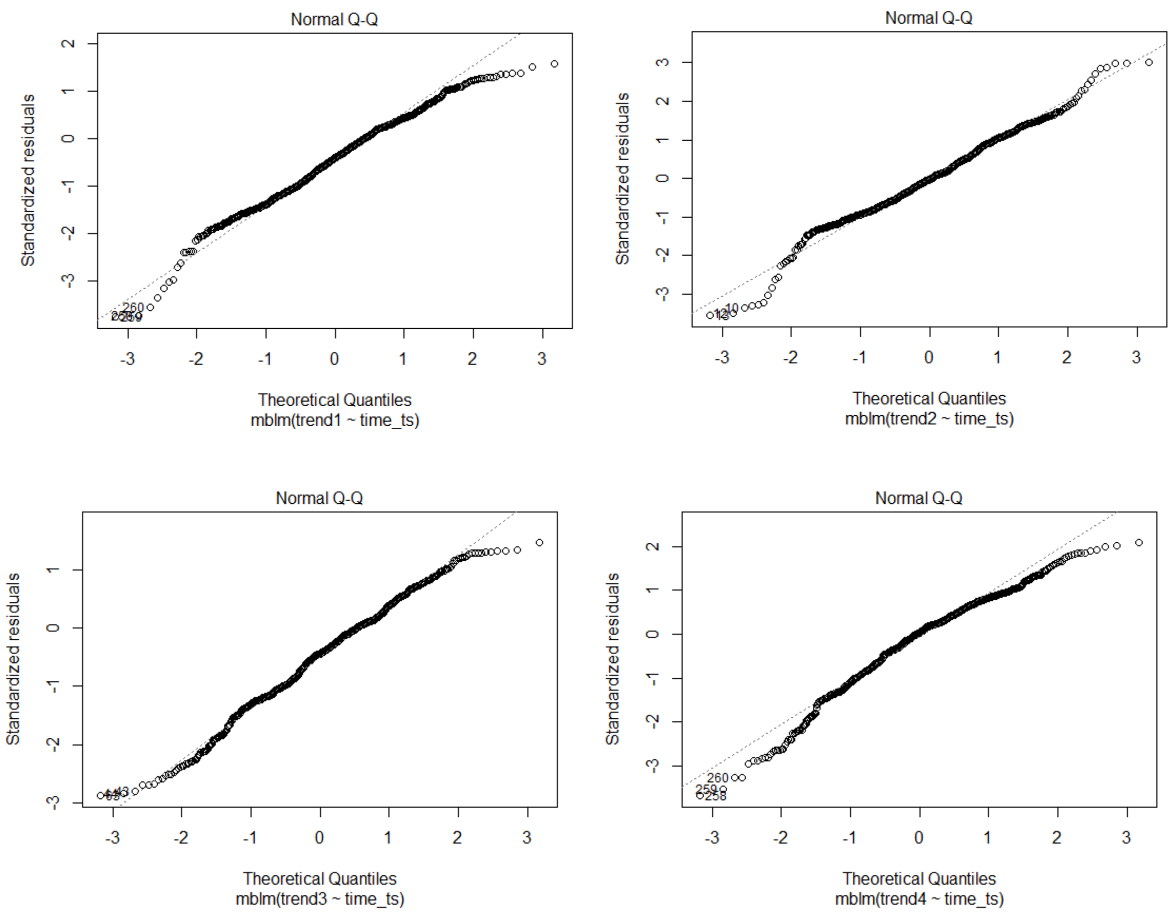


Figure 35: Theil-Sen QQ-Plot for the trend signal of NDVI for the selected locations in Niger State

The result of the Theil Sen standardized residual estimation of the QQ plot show that the assumption of a normal distribution does not longer holds (i.e some of the points fall outside the QQ line as can be seen in the QQ plot)**.** To establish this fact, two tests of normal distribution namely Shapiro Wilks and Anderson Darling were carried out.

Table 12: Results of Shapiro-Wilks and Anderson-Darling Normality Test for alpha=0.05 for the selected locations in Niger State (Critical Values: $W_{critical} = 0.996$ / $A_{critical} = 0.787$)

location	**Shapiro-Wilks**		**Anderson-Darling**	
	W	**p-value**	**A**	**p-value**
a	0.9764	5.958e-09	5.3206	3.84e-13
b	0.9550	1.825e-13	9.0974	< 2.2e-16
c	0.9646	1.176e-11	6.7084	< 2.2e-16
d	0.9629	5.276e-12	10.49	< 2.2e-16

Table 13: Results of Shapiro-Wilks and Anderson-Darling Normality Test for alpha=0.05 for the selected locations in Kogi State (Critical Values: $W_{critical}$=0.996 / $A_{critical}$=0.787)

location	Shapiro-Wilks		Anderson-Darling	
	W	p-value	A	p-value
a	0.9547	1.635e-13	10.3497	< 2.2e-16
b	0.9929	0.00292	0.9972	0.01244
c	0.9855	3.29e-06	4.0906	3.498e-10
d	0.9875	1.708e-05	3.1219	7.794e-08

Table 14: Results of Shapiro-Wilks and Anderson-Darling Normality Test for alpha=0.05 for the selected locations in Kwara State (Critical Values: $W_{critical}$=0.996 / $A_{critical}$=0.787)

location	Shapiro-Wilks		Anderson-Darling	
	W	p-value	A	p-value
a	0.9728	7.484e-10	5.1051	1.262e-12
b	0.9945	0.01636	0.8295	0.03225
c	0.9775	1.22e-08	3.3839	1.8e-08
d	0.9728	7.578e-10	4.5923	2.157e-11

The critical values of both tests explains the existence of a normal distribution in time series dataset. The critical Values W (Shapiro Wilks: $W < 0.996$) and A (Anderson-Darling: $A > 0.787$) indicate that the null hypothesis has to be rejected (there is normal distribution). Since the value is smaller than the chosen significance level (alpha=0.05), the null hypothesis was rejected (Rahman and Govindarajulu, 1997). For this reason, the use of correlation coefficients such as the Pearson correlation coefficient might be limited. Therefore, Mann-Kendall correlation coefficient was used for the analysis of monotonic trend in NDVI.

Table 15: Mann-Kendall correlation test for decomposed NDVI

Location (Niger)	Mann Kendall	
	tau	p-value
a	0.49	< 2.22e-16
b	0.65	< 2.22e-16
c	0.31	< 2.22e-16
d	0.45	< 2.22e-16

Table 16: Mann-Kendall correlation test for decomposed NDVI

Location (Kogi)	Mann Kendall (MK)	
	tau	**p-value**
a	0.35	< 2.22e-16
b	0.51	< 2.22e-16
c	0.62	< 2.22e-16
d	0.40	< 2.22e-16

Table 17: Mann-Kendall correlation test for decomposed NDVI

Location (Kwara)	Mann Kendall	
	tau	p-value
a	0.41	< 2.22e-16
b	0.15	< 2.22e-16
c	0.11	4.9829e-05
d	0.50	< 2.22e-16

The result of the Mann Kendall (MK) tau trend test obtained from the decomposition of the NDVI time series show that about 31 -65 % of NDVI can be determined by time for the selected locations in Niger state while about 35-62 % and 10-50 % of NDVI can be determined by time for the selected locations in Kogi and Kwara state respectively. The p-values for the MK test show that the relationship between NDVI and time is significant at α=0.05 level. Hence, the null hypothesis cannot be rejected as false.

5.7.2. Inter-annual trend analysis for climatic datasets for selected locations in Niger state

The same procedure used for the analysis of NDVI trend was also adopted for the analysis of the climatic (rainfall and temperature) time series datasets for the selected locations. Figures 36 and 37 show the results of linear regression analysis for both climatic datasets against time. The findings reveal that there is positive trend in the TAMSAT (i.e rainfall) and CRU (temperature) time series datasets for the study period (1983-2011).

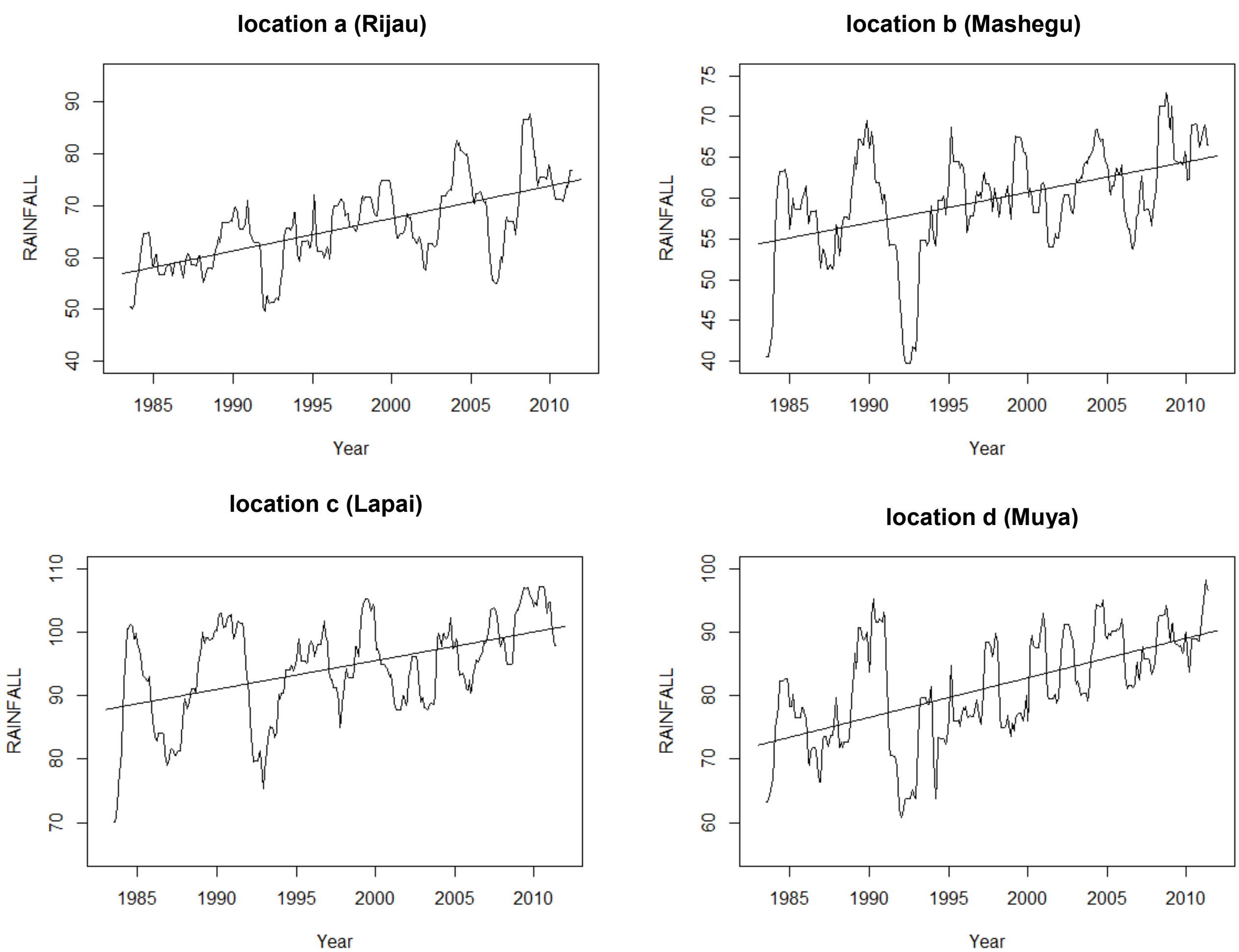


Figure 36: Linear regression model for rainfall for the selected locations in Niger State

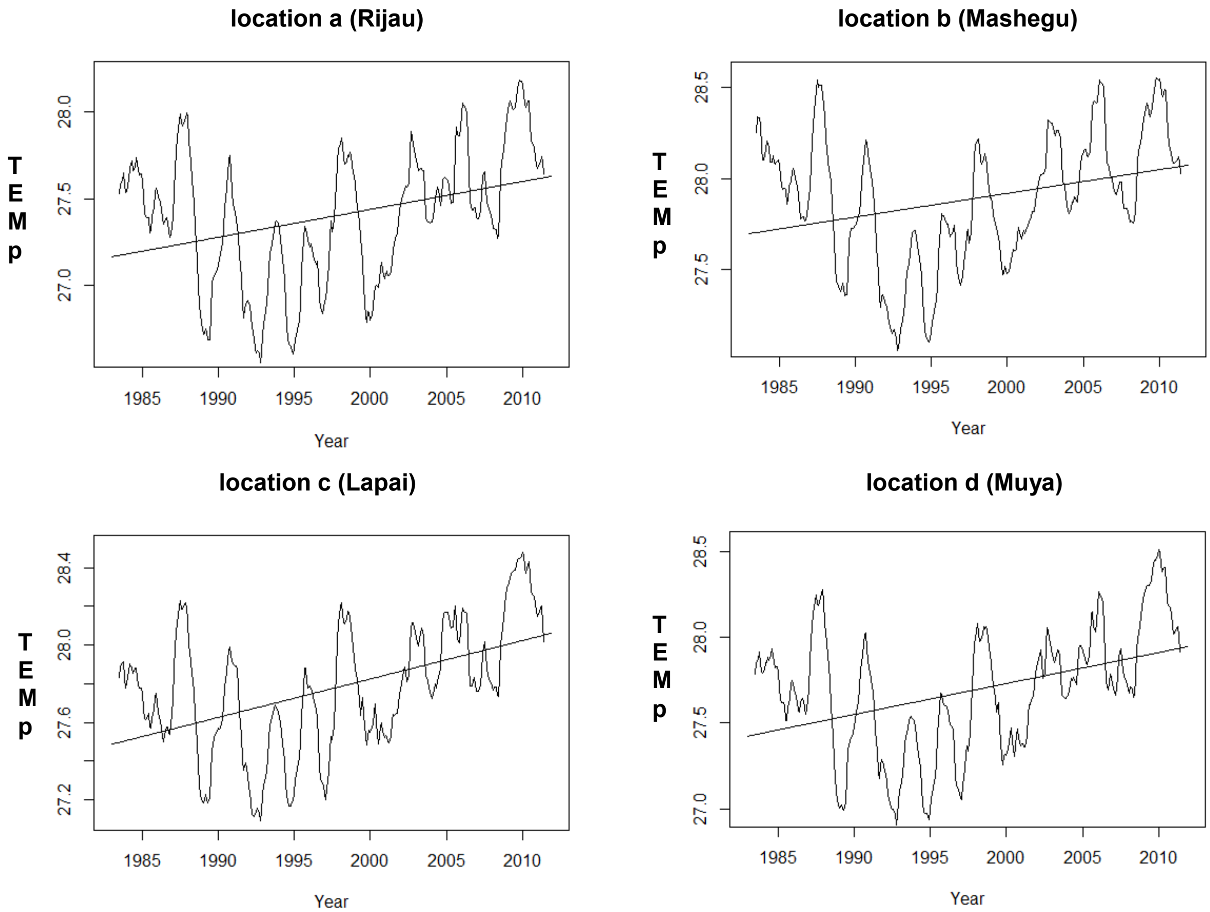


Figure 37: Linear regression model for temperature (for selected locations in Niger state)

Variations in the regression line of rainfall for the study locations this indicate variation in the geographic distribution of rainfall in the study region. The summary of the results of the application of the estimators (OLS, TS, MK) used for calculating trends in the climatic datasets for the study locations in Niger state are presented in table 18-23 (see appendix for the results of the other study locations).

Table 18: Results of linear regression model for rainfall for the selected locations in Niger State

Location (Niger)	Slope	Residual Standard Error	F-Statistic	R^2	p-value
a	0.712	6.310	279.2	0.455	< 2.2e-16
b	0.485	5.243	188.1	0.360	< 2.2e-16
c	0.451	6.645	101.2	0.233	< 2.2e-16
d	0.531	6.484	146.9	0.306	< 2.2e-16

Table 19: Results of the Theil-Sen Estimator for rainfall for the selected locations in Niger State

Location (Niger)	Slope	Residual Standard Error	p-value
a	0.609	6.371	< 2e-16
b	0.531	5.267	< 2e-16
c	0.391	6.907	< 2e-16
d	0.537	7.182	< 2e-16

Table 20: Mann Kendall correlation Test for rainfall data for the selected locations in Niger State

Location (Niger)	Mann Kendall	
	tau	p-value
a	0.50	< 2.22e-16
b	0.43	< 2.22e-16
c	0.31	< 2.22e-16
d	0.37	< 2.22e-16

Table 21: Results of linear regression model for temperature for the selected locations in Niger State

Location (Niger)	Slope	Residual Standard Error	F-Statistic	R²	p-value
a	0.016	0.364	42.47	0.113	2.648e-10
b	0.013	0.347	31.19	0.085	4.86e-08
c	0.019	0.287	105.7	0.241	< 2.2e-16
d	0.018	0.157	62.34	0.157	4.196e-14

Table 22: Results of the Theil-Sen Estimator temperature for the selected locations in Niger State

Location (Niger)	Slope	Residual Standard Error	p-value
a	0.024	0.395	< 2e-16
b	0.024	0.372	< 2e-16
c	0.023	0.349	< 2e-16
d	0.027	0.371	< 2e-16

Table 23: Mann Kendall correlation Test for temperature data for the selected locations in Niger State

Location (Niger)	Mann Kendall	
	tau	p-value
a	0.224	< 2.22e-16
b	0.203	< 2.22e-16
c	0.326	< 2.22e-16
d	0.273	< 2.22e-16

Results of the OLS between rainfall and time for all locations vary though they are statistically significant (P-value). The R^2 for all the locations in Kogi state (see appendix) reveal that about 12-24 % of rainfall can be determined by time. About 14-31 % (R^2) of rainfall can be explain with time in Kwara, while about 23-45 % of rainfall can be determined by time in Niger state. Although there is similarity in the results of OLS and Theil-Sen, decrease in the slope value of Theil-Sen was observed for all the selected locations in Kogi state when compared with the TS slope values of the selected locations in Niger and Kwara state. After the normality test (rainfall normality test) for each location has been performed, Mann-Kendall test was used for the rainfall trend because the datasets are not normally distributed. As can be expected, the result of the Mann-Kendall trend test are positive which implies that there is an increase in rainfall trend over the study period.

The results of the trend estimators for temperature time series datasets for the study locations in Kogi and Kwara are summarized in the appendix. Lower slope values were observed for both OLS and TS of all the study locations which is in contrast to that of rainfall. Though, the results are statistically significant which indicates an increase in temperature trend over time. Based on the assumption of normal distribution as observed in the NDVI and rainfall time series, normality test shows that the temperature time series datasets for all the study locations are not normally distributed. Hence, Mk trend test was used for further analysis. The results of the MK trend analysis for all the locations are positive which means an increase in temperature trend over time (see appendix). In summary, the results of the study show that there is an increasing trend in NDVI, rainfall and temperature over time. As one of the major objectives of this study is to examine the relationship between NDVI and climatic data, hence, further analysis was performed in the next step in order to justify this objective.

5.7.3. Correlation analysis between NDVI and climatic data

Since vegetation productivity (or dynamics) has a high degree of association with weather parameters such as rainfall and temperature as confirmed by previous studies (Fensholt et al., 2012). Cross-correlation between NDVI and climate parameters was calculated out with different lags (-2 to +2 years). The results are presented in figure 38.

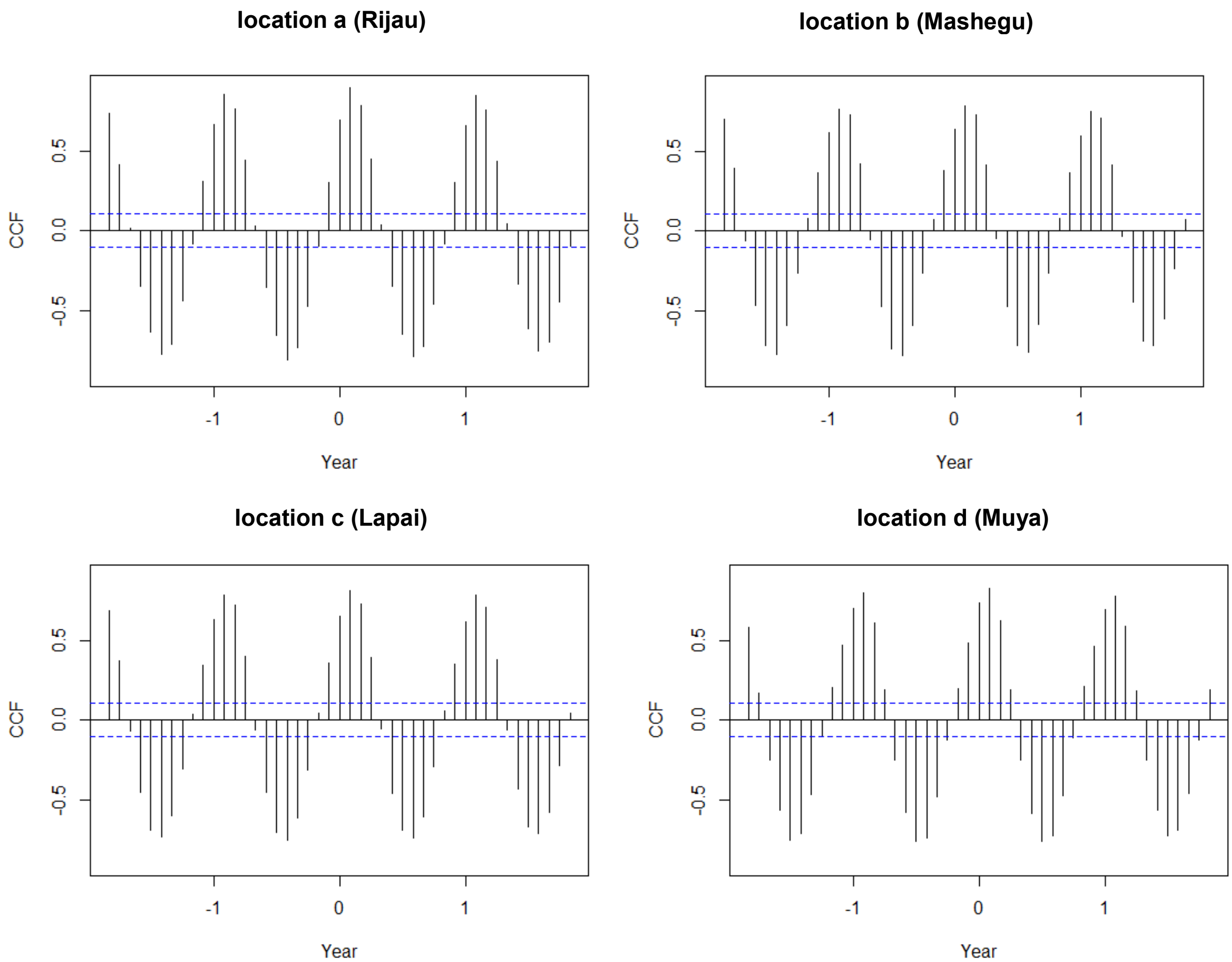


Figure 38: Results of cross correlation analysis between NDVI and rainfall data for lags between -2 and +2 years for the selected locations in Niger State

A maximum shift of one month was observed from the result of the cross-correlation between NDVI and rainfall for all the study locations (Niger, Kogi and Kwara) which indicates a gradual response of vegetation growth to the available water content in the soil at the start of the growing season. In contrast, a negative shift of month was observed from the result of the cross-correlation between NDVI and temperature which implies that rainfall has more influence on vegetation growth than temperature. The result of the cross-correlation between NDVI and temperature is presented in figure 39.

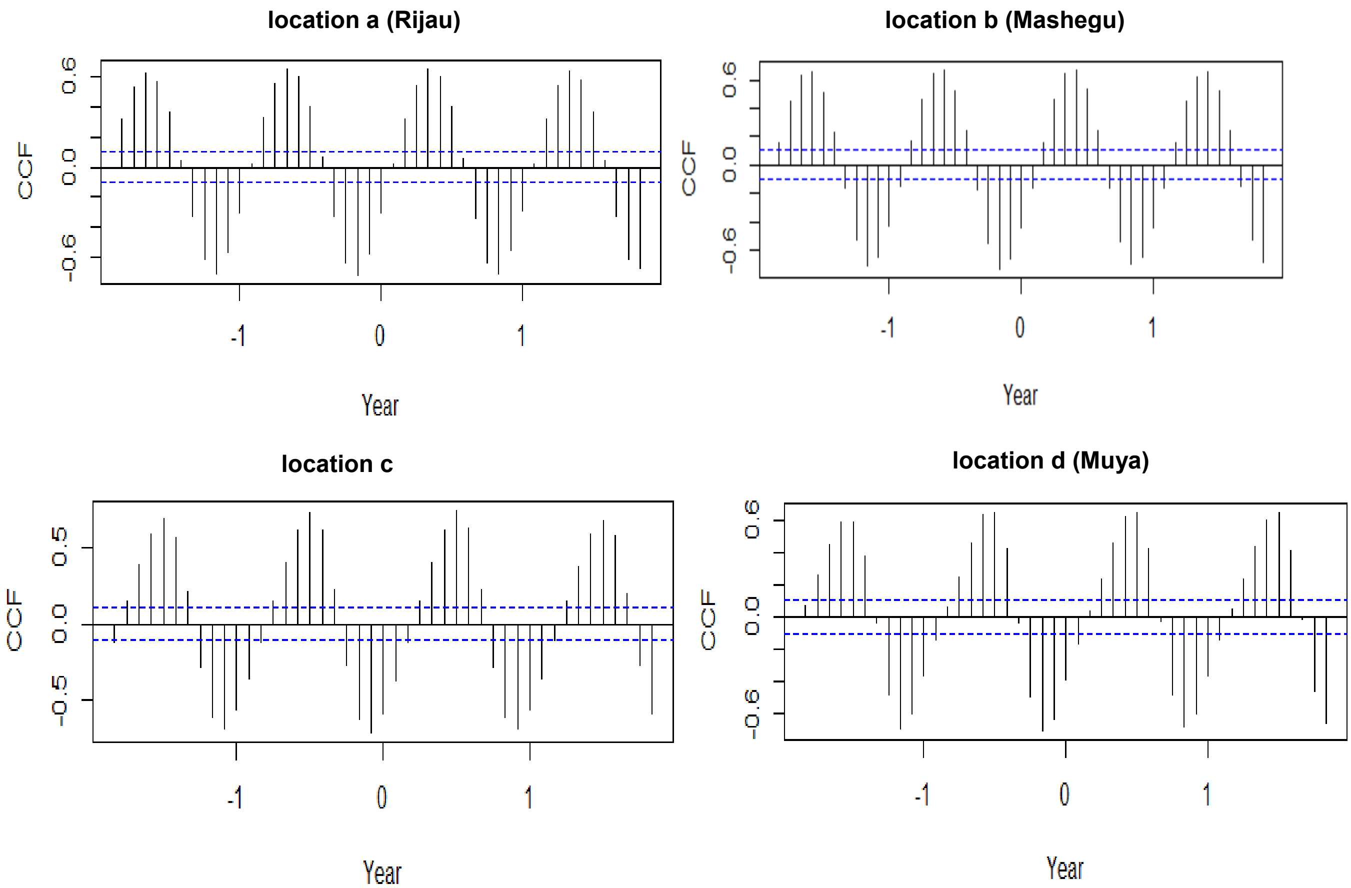


Figure 39: Results of cross correlation analyses between NDVI and temperature for lags between -2 and +2 years (for the selected locations in Niger State)

The strength of association (correlation) between NDVI, rainfall and temperature for the study locations was further examined using Pearson product moment correlation coefficient and Kendall's rank correlation tau and the results are presented in the table 24-36.

Table 24: Pearson product moment correlation and Kendall's rank correlation result for NDVI and climatic parameters (Niger) (95% confidence interval)

Location	Pearson product moment correlation				Kendall's rank correlation			
	NDVI/RAIN	P-value	NDVI/TEMP	P-value	NDVI/RAIN	P-value	NDVI/TEMP	P-value
a	0.70	< 2.2e-16	-0.30	7.89e-09	0.46	< 2.2e-16	-0.16	1.499e-05
b	0.64	< 2.2e-16	-0.44	< 2.2e-16	0.46	< 2.2e-16	-0.28	5.373e-15
c	0.65	< 2.2e-16	- 0.58	< 2.2e-16	0.44	< 2.2e-16	-0.38	< 2.2e-16
d	0.74	< 2.2e-16	-0.39	8.036e-14	0.56	< 2.2e-16	-0.22	2.027e-09

Table 25: Pearson product moment correlation and Kendall's rank correlation result for NDVI and climatic parameters (Kogi) (95% confidence interval)

Location	Pearson product moment correlation				Kendall's rank correlation			
	NDVI/RAIN	P-value	NDVI/TEMP	P-value	NDVI/RAIN	P-value	NDVI/TEMP	P-value
a	0.75	< 2.2e-16	-0.59	< 2.2e-16	0.51	< 2.2e-16	-0.41	< 2.2e-16
b	0.72	< 2.2e-16	-0.66	< 2.2e-16	0.49	< 2.2e-16	-0.46	< 2.2e-16
c	0.64	< 2.2e-16	-0.35	1.285e-10	0.42	< 2.2e-16	-0.17	4.27e-06
d	0.62	< 2.2e-16	-0.43	< 2.2e-16	0.41	< 2.2e-16	-0.28	4.288e-15

Table 26: Pearson product moment correlation and Kendall's rank correlation result for NDVI and climatic parameters (Kwara) (95% confidence interval)

Location	Pearson product moment correlation				Kendall's rank correlation			
	NDVI/RAIN	P-value	NDVI/TEMP	P-value	NDVI/RAIN	P-value	NDVI/TEMP	P-value
a	0.75	< 2.2e-16	-0.44	< 2.2e-16	0.56	< 2.2e-16	-0.29	< 2.2e-16
b	0.70	< 2.2e-16	-0.62	< 2.2e-16	0.50	< 2.2e-16	-0.44	< 2.2e-16
c	0.71	< 2.2e-16	-0.47	1.285e-10	0.50	< 2.2e-16	-0.30	3.359e-16
d	0.72	< 2.2e-16	-0.56	< 2.2e-16	0.54	< 2.2e-16	-0.38	< 2.2e-16

The results of the correlation analysis between NDVI and rainfall for all the study locations are positive while negative correlation exists between NDVI and temperature. This implies that rainfall has a stronger influence on biomass productivity rather than temperature as observed in all the selected locations. However, care must be taken because other factors such as land use change might be responsible for some decline in vegetation productivity as observed in the early 1990.

5.8. Comparison of GIMMS and MODIS datasets

The result of the per pixel linear regression (OLS) analysis and Mann-Kendall trend test between GIMMS and MODIS NDVI (2001 – 2011) data in Niger State are shown in Fig 31.

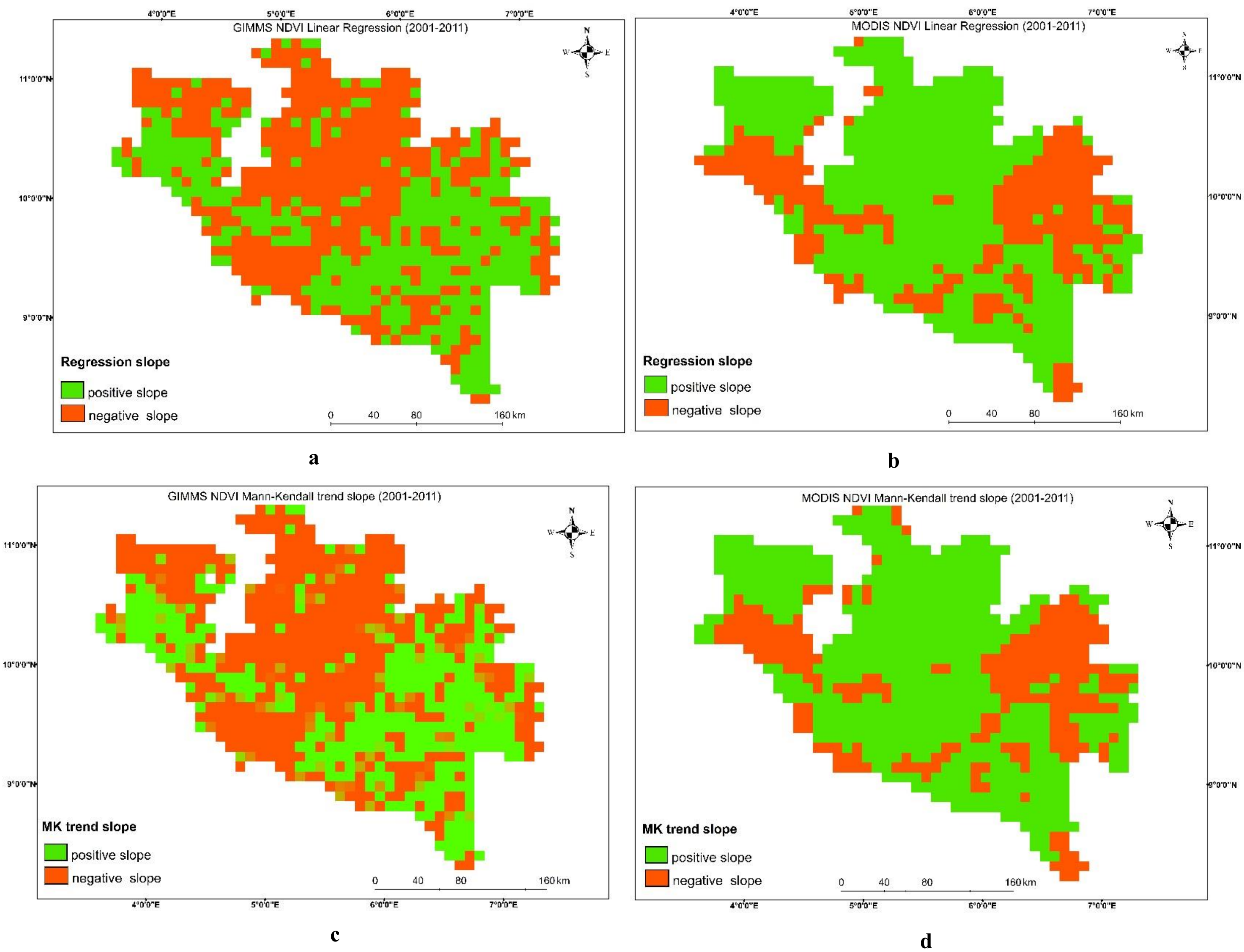


Figure 40: (a) GIMMS NDVI linear regression slope. (b) MODIS NDVI linear regression slope. (c) GIMMS NDVI Mann-Kendall trend test. (d) MODIS NDVI Mann-Kendall trend test

Both datasets show a mixed pattern of increasing and decreasing trends in vegetation cover, positive trend of about 9 % was observed at the regional scale for MODIS NDVI and a negative trend of about 4 % while on the contrary, positive trend of about 4 % was observed in the magnitude (slope direction) of GIMMS NDVI and a negative slope direction of about 7 %.. Similar variation in NDVI trend was also observed from the result of Mann-Kendall trend test for both datasets (more greening trend in MODIS NDVI dataset). The result of the comparison between MODIS and GIMMS NDVI corresponds for example with that of the global study of Fensholt and Proud, (2012) and regional a study of Schucknecht et al., (2013) where positive NDVI values were observed for MODIS data. Hence, MODIS data can be used for validating the results of AVHRR data. However, care must be taken in the interpretation of the results as different vegetation types coupled with land use types might impact on the temporal correlation between both datasets.

5.9. Discussion

Time series analysis of vegetation change dynamics and climate parameters across the Guinea savannah region of Nigeria over 29 years was assessed using various statistical approaches as explained in the result section.

5.9.1. Overall trends in NDVI and climatic data

The NDVI and climate datasets used for the trend assessment across the study region were estimated separately using both parametric (ordinary least square) and non-parametric (Theil-Sen) regression modelling. Both positive and negative NDVI trends were observed from the result of the regression models. Generally, positive trends dominates representing about 80-90% of the pixels used in the trend analysis while about 10% of the pixels shows negative trend. The results of the trend analysis for both rainfall and temperature time series datasets for the period of 1983-2011 also show positive trend which indicates that the climatic parameters follow a similar pattern like NDVI over time. The results of both regression models (OLS and TS) are similar and show increase in NDVI trend over time. This implies that both models can be used to quantify trends in vegetation and climate parameters. Additionally, Mann-Kendall (MK) tau-correlation coefficient was used to test the degree at which trends in NDVI and climate parameters are consistently increasing or decreasing (monotonic trend) because this trends cannot be determined by OLS or TS. However, both positive and negative monotonic trend was revealed by the results of the MK trend test for NDVI while consistent increasing trend was observed for rainfall and temperature although the slope direction varies (see appendix for results). The results of the trend estimators used for monitoring vegetation trend are similar which by interpretation implies vegetation greening over time.

Monitoring vegetation dynamics across the Guinea savannah region of Nigeria is very important because most of the agro-ecological zones of Nigeria have witnessed population increase in the past few decades. Therefore, an in-depth study on the relationship between NDVI and climate drivers was carried out in specific locations (i.e regions of interest) across different land cover types using the methods described in section 4.3. The rate of change in NDVI time series for the study locations was calculated using linear regression models in order to estimate the coefficient of determination (R^2) over time. Positive trend was observed from the results of linear modelling of NDVI against time. Though the linear trend for the study locations varies, however the results are statistically significant (see table 6, 7 & 8 above). This can be interpreted as “greening” trend across the selected land cover types. The results of the OLS regression modelling was compared with that of a more robust non-parametric trend estimator (Theil Sen) in order to verify if the statistical inferences are not influenced by outliers. The results of both regression models are similar which confirms the assumption of greening over time in all the study locations. Considerable variation in the results of the R^2 for rainfall and temperature were observed for each location in the study areas. This variation is typical in the semi-arid regions of Nigeria. Positive increase in vegetation productivity was revealed by the result of the Mann-Kendall tau correlation for all study locations. When Mann-Kendall tau is greater than zero and the accompanying p-value is low at the significant level of $\alpha = 0.05$ (i.e, tau > 0, p<0.1), the null hypothesis of no trend should be rejected. This hypothesis is true for all the study locations. The results therefore show that there is monotonic greening (i.e positive vegetation trend) in all the study locations. Comparatively, both monotonic greening and browning was observed for the whole study region. The results of this research agree with those of previous studies on greening and re-greening of vegetation trend at the global and regional scale (Anyamba et al., 2014; de Jong et al., 2011; Dubovyk et al., 2016).

5.9.2. Correlation between NDVI and Climatic drivers

Positive correlation between NDVI and climatic drivers has been established by previous studies (Boschetti et al., 2013; Gao et al., 2013). For this study, the relationship between NDVI and TAMSAT rainfall time series were firstly analyzed followed by the analysis of NDVI and CRU temperature time series using cross-correlation (CC), Pearson product moment correlation (PPMC) and Kendall’s rank correlation (KRC). The results of the NDVI-rainfall analysis indicate an increase in vegetation productivity during the growing season which means that NDVI has increased in response to high rainfall over time (Wessollek et al., 2015). Although, shifts in the signals were observed in the growing months, vegetation tends to respond better to rainfall as revealed by the result of the cross-correlation analysis. This is in line with the findings of Herrmann et al., (2005). The results of the PPMC and KRC analysis show positive and high correlation between NDVI and rainfall (Table 34-36) which is in line with the results of Anyamba et al., (2014); Boschetti et al., (2013) and Wang et al., (2011). In contrast, the correlation between NDVI and temperature for all the study locations is negative which is in line with the result of Wang et al., (2011) where negative correlation exists between temperature and net primary productivity (see appendix for the CC results for Kogi and Kwara). However, increase in biomass productivity (positive trend) as observed from the results of the trend analysis (section 5.5) might not be a result of rainfall only, but also a result of anthropogenic activities such as land use land cover change. It should be noted that "greening" is purely quantitative without any relation to vegetation quality as NDVI is a proxy for vegetation biomass measurement. Therefore LULC classification is essential for proper understanding of the greening trend across the study region.

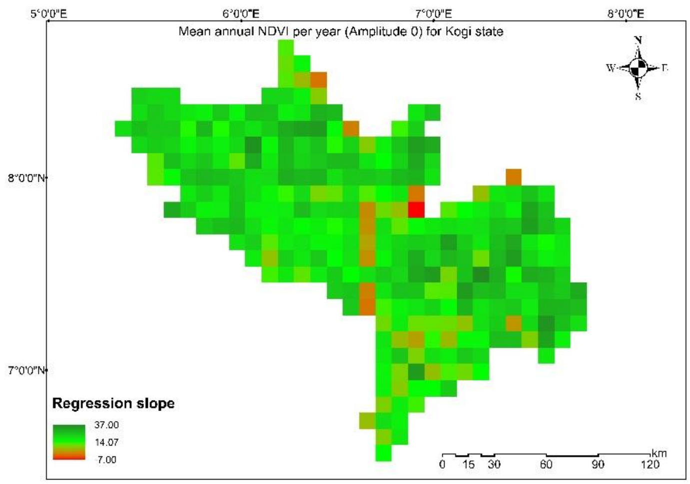
6. Assessment of seasonal trends and variation in vegetation cover through phytophenological characteristics

6.1. Abstract

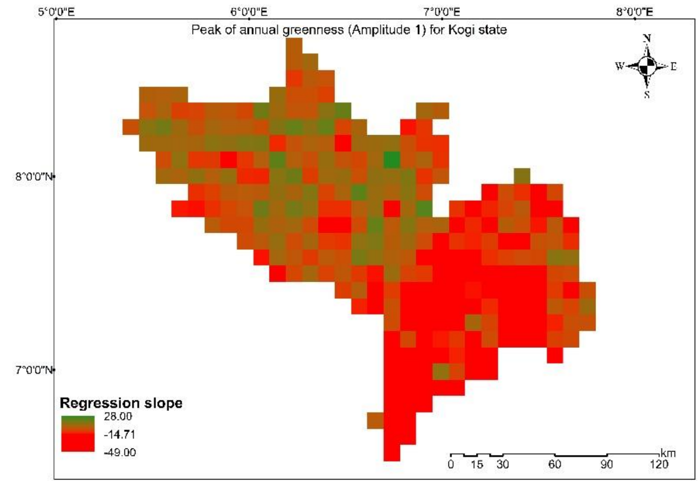
Long-term monitoring of vegetation phenology is very important for monitoring and detection of change in seasonal plant cycle (greening-up, maturity or senescence) which may occur as a result of climate change and/or anthropogenic activities. Spatio-temporal analysis of the beginning and end of growing season can provide better information on the effect of climate change, biodiversity reduction and land degradation at global and regional scale. However, as human population continues to increase, information on vegetation that is both spatially comprehensive and of appropriate resolution is becoming more vital for reliable assessment of biological resources. In this study, time series of Normalized Difference Vegetation Index (NDVI3g) was used to provide information on the phenological characteristics of vegetation in the Guinea savannah region of Nigeria from 1983 through 2011, while TAMSAT rainfall data was used to provide information on vegetation response to climate change. Slope direction was used to explain the results of the harmonic regression analysis.

6.2. Seasonal Trend Analysis for the study areas

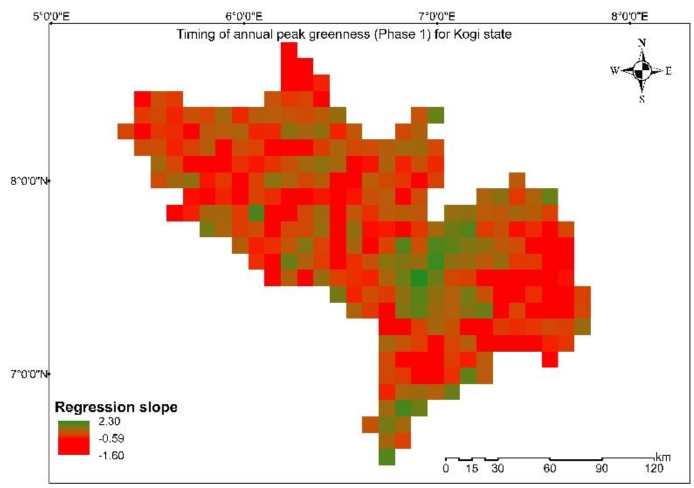
The results of the significant spatial patterns in the slopes of NDVI as derived from the harmonic regression analysis are presented in figures 41-43 for the period of 1983-2011. This analysis was performed in order to examine trends in the seasonal cycle of vegetation in relation to rainfall data across the study region. Increase in the spatial pattern of mean annual NDVI (amplitude 0) was observed across Kogi state (Fig 41a). However, positive and negative slope values which indicates increase and decrease in the mean annual NDVI trend was observed for the study period. Areas within dark to light green color indicates regions with positive NDVI trend while areas with darker red can be described to have degraded over time. Figure 41 b shows the spatial pattern in the slopes of peak of annual greenness (amplitude 1). About 70% of the study area are dominated by negative NDVI trend, which is specifically obvious in the south-eastern part of the study area. A shift to a later time was observed from the result of the spatial pattern of the timing of greening events (Fig 41 c). The negative trend as observed from the result indicates later green-up, while the positive trend as observed in southeast indicates earlier green-up.



a



b



c

Figure 41: Theil–Sen trends from 1983 to 2011 for each 64 km^2 pixel in the study region for (a) annual mean NDVI (amplitude 0), (b) peak of annual greenness (amplitude 1) and (c) timing of greening events (phase 1)

The significant spatial patterns in the slopes of NDVI for Kwara and Niger region are shown in figure 42 and 43. Generally, overall increase in the mean annual NDVI (overall greenness) trend was observed from the spatial pattern of both regions, which is similar to the observed trend in Kogi region. Both positive and negative NDVI trend was observed regarding peak of annual greenness and timing of annual greenness for Kwara and Niger (Fig 42 *b-c* and 43 *b-c*).

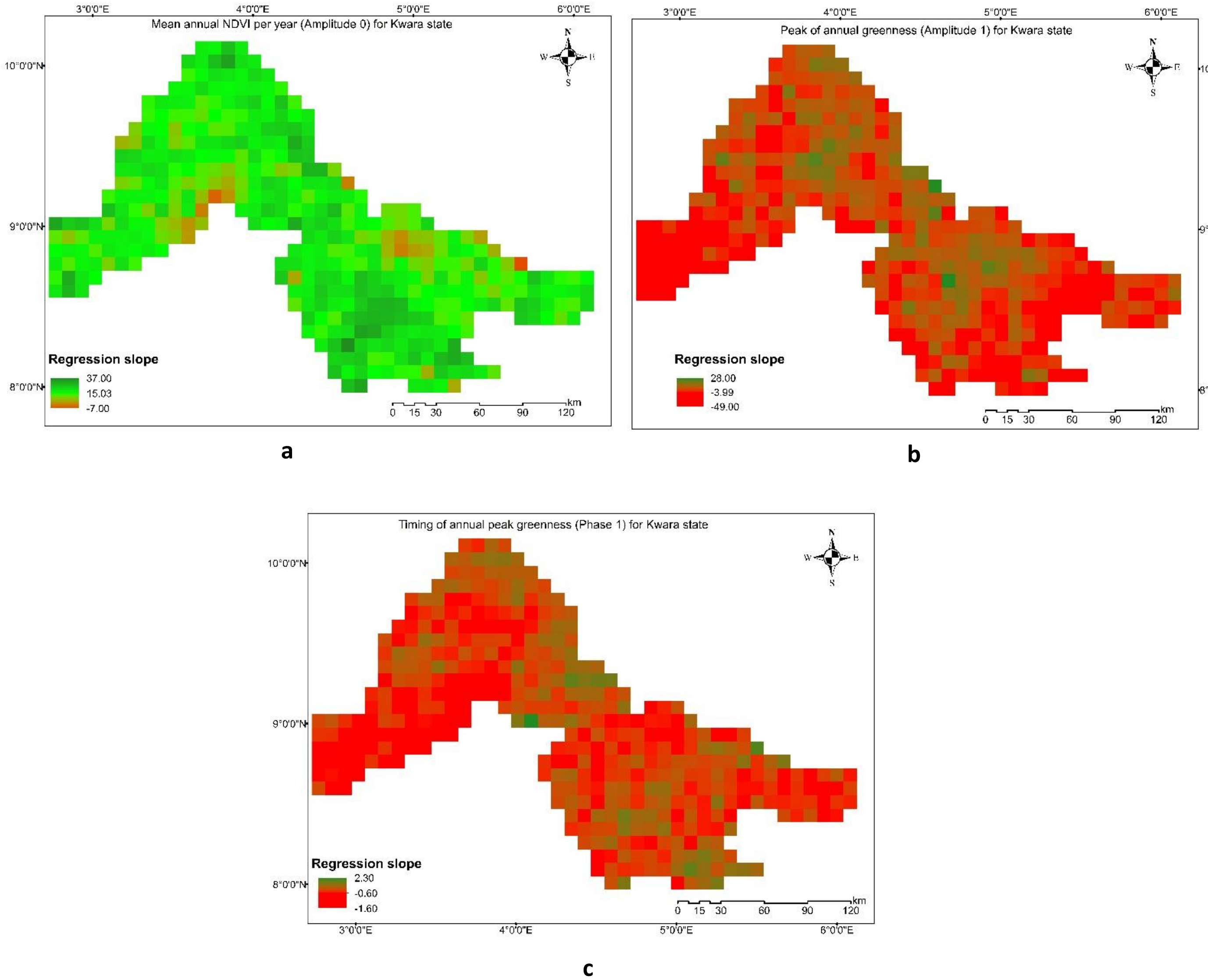
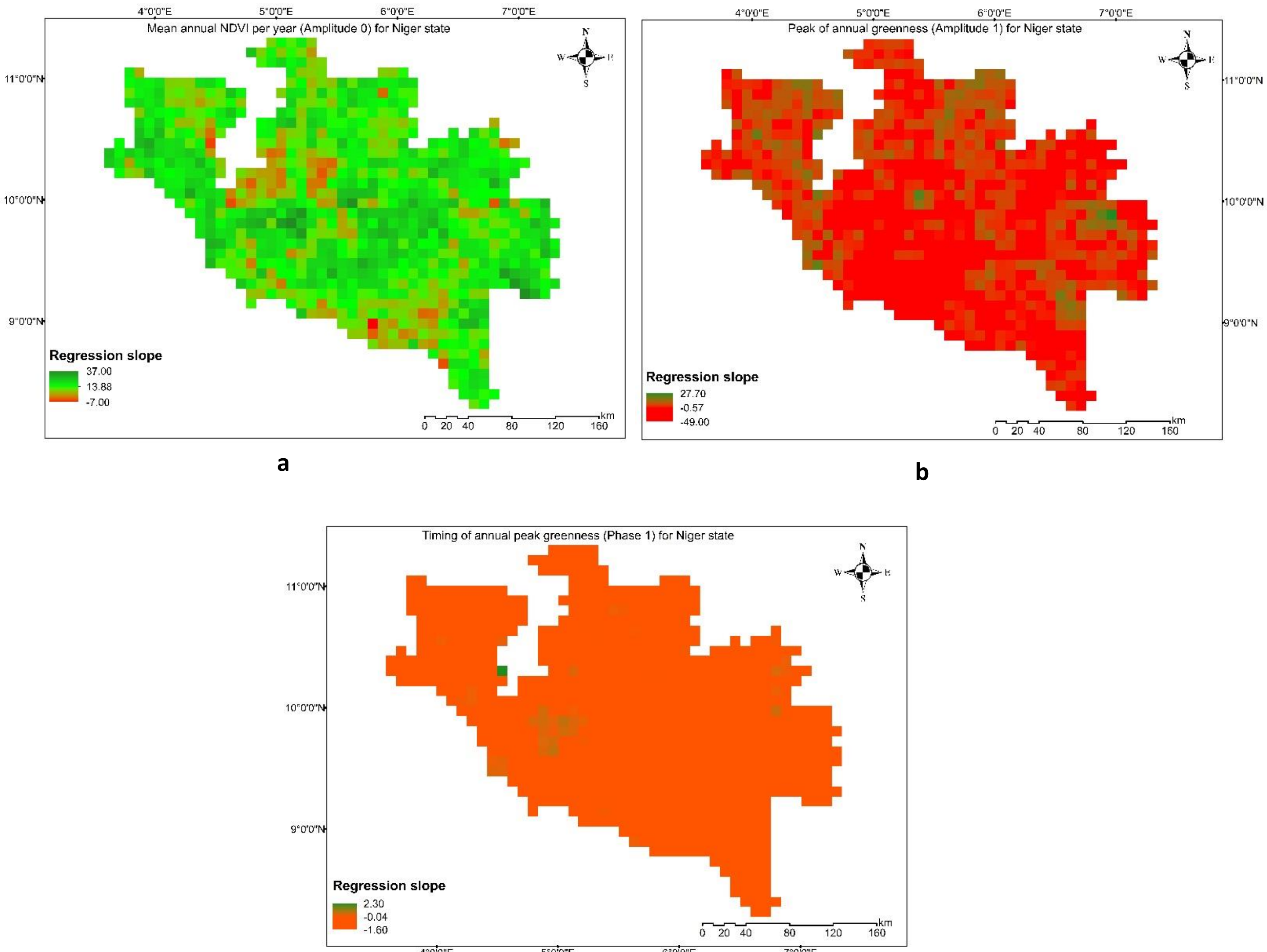


Figure 42: Theil–Sen trends for Kwara state from 1983 to 2011 for each 64 km^2 pixel in the study region for (a) annual mean NDVI (amplitude 0), (b) peak of annual greenness (amplitude 1) and (c) timing of greening events (phase 1)



a

b

c

Figure 43: Theil–Sen trends for Niger state from 1983 to 2011 for each 64 km2 pixel in the study region for (a) annual mean NDVI (amplitude 0), (b) annual seasonal NDVI magnitude (amplitude 1) and (c) annual seasonal NDVI timing (phase 1)

A positive trend was detected in the results of the analysis of mean annual rainfall for the three study regions (Fig. 44). However, negative trend in the peak of annual rainfall was observed in the southern part of Kogi state while positive trend was observed in Kwara and Niger state (see appendix). The results of the timing of annual rainfall (phase 1) show similar trend pattern (i.e both positive and negative slope) as observed in the NDVI trend of Niger and Kwara (Fig 44). In contrast, positive trends of about 70% was observed in Kogi which indicates a shift in rainfall pattern to an earlier time

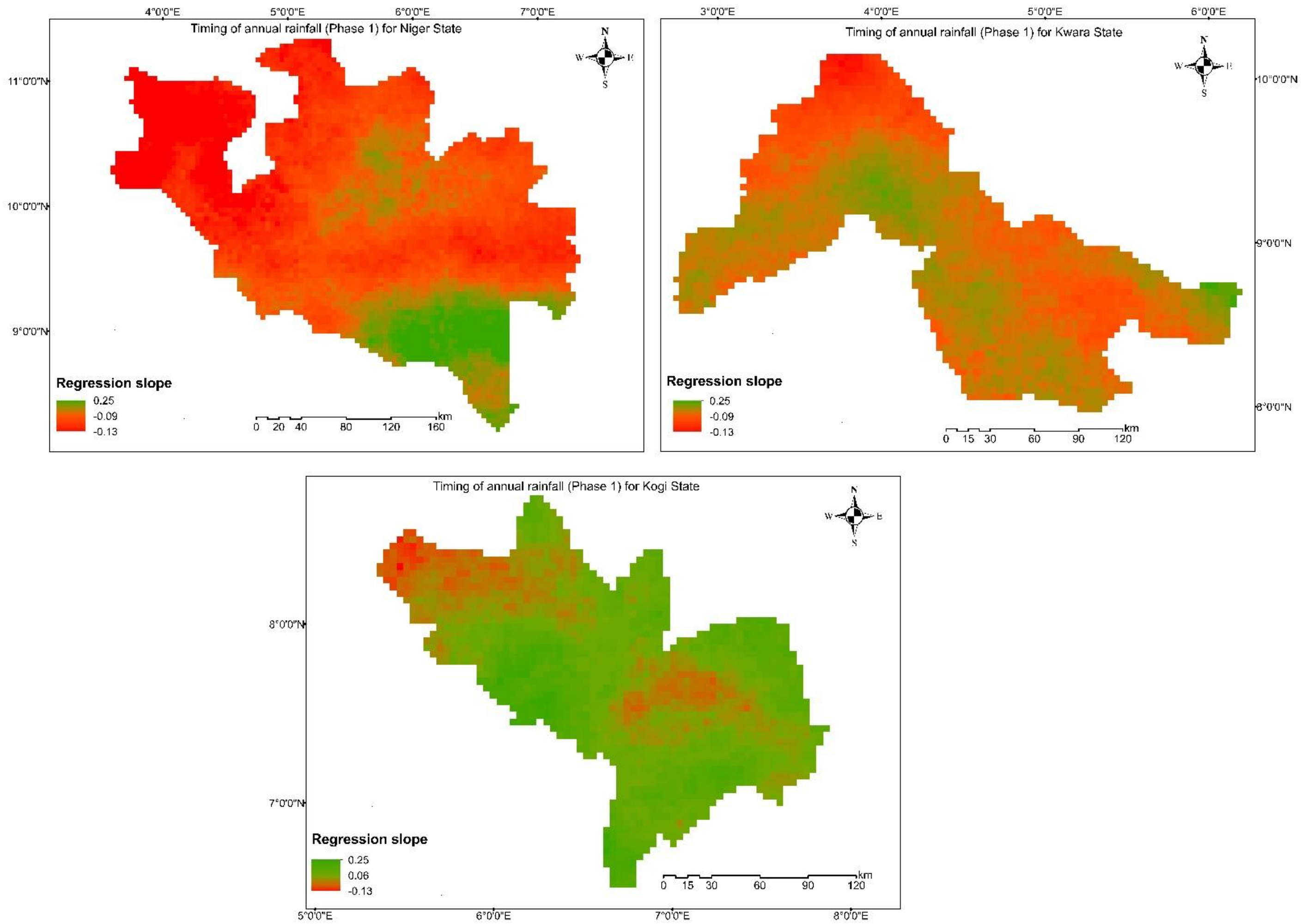


Figure 44: Timing of annual rainfall (phase 1) for the study regions (1983-2011)

The results of this analysis show that the observed NDVI trend follows similar trend patterns like that of rainfall, which implies that rainfall is one of the drivers of change in vegetation productivity. The results of this study (i.e, seasonal trend in vegetation dynamics) are in line with other studies where both positive and negative NDVI trends are observed from the seasonal trend analysis results at regional scale (Dubovyk et al., 2015; Eastman et al., 2009; Panday and Ghimire, 2012).

6.3. Interpretation of seasonal NDVI curves for the study regions

The use of fitted seasonal curves plotted against time makes the detection of inter-annual phenological pattern of NDVI time series possible. However, because of the difficulty in interpreting the produced seasonal image, i.e the amplitude and phase imagery, an interactive interpretational aid was developed following the approach of Eastman et al., (2009). In order to do this, areas of interest (the selected locations) were temporally profiled from the produced amplitude image because it provides the greatest amount of information about vegetation phenology (Eastman, 2012). This analysis (NDVI phenological trend detection) was performed based on a green-up and green down approach. Green-up refers to the start of growing season (SOS) while green-down refers to the end of growing season (EOS). Graphs of observed values and fitted values plotted against time of the year were used to generate the NDVI seasonal curves of the fitted (smoothed) trend. The graph shows the year from January through December on the x-axis and NDVI on the y-axis. The two lines in the fitted NDVI curve are like fitted regression lines which indicate the start and the end of the series, i.e 1983 and 2011. The fitted curves are derived mathematically from the entire series and represents the first (i.e, green color) and the last (i.e, red color) year of the series. For this study, graphs of the fitted curves were used to describe seasonal NDVI trend pattern. Four locations each were selected from the three study regions to visualize the monthly mean NDVI profile curves for the first and last years of the time series (1983-2011) across different land cover types. The seasonal curves for the examined year were compared for (a) cropland (b) open broad leave deciduous forest/woodland (c) mosaic grassland and (d) closed to open shrubland. However, the differences between the two curves (1983 and 2011) indicate changes in seasonal NDVI trend pattern.

6.3.1. Seasonal NDVI curve for Kogi state

Variations in the pattern of seasonal NDVI curves were observed for all the selected locations which might probably be an effect of land use land cover change. Two distinctive seasonal NDVI peaks were observed in 2011 for the selected locations in Kogi state, this can be attributed to the bi-modal pattern of rainfall in this region which influences biomass productivity.

Location a of the study area is composed of 5 land cover types namely: crop land, open broad leaved deciduous forest, mosaic shurbland/grassland, mosaic grassland and closed to open shrubland. The most dominant land cover type in this location is grassland. Therefore, it was used for the phenological trend assessment. Two peaks are noticeable in the seasonal NDVI curve of 2011 when compared with that of 1983. This can be attributed to land cover change as grassland is sometimes used for agricultural practices during raining season and for grazing. The STA (Contextual Mann-Kendall significance test) map of this location shows that there is significant increase in overall greenness while there is significant decrease in the peak annual greenness and timing of annual peak of greenness (Fig. 41 a-c) for the study location. The maximum difference between the curves occurs between February through June. Break in the seasonal NDVI curve was observed in 2011. This break symbolizes the end of first growing season in which there is no rainfall for almost 2 weeks. Although the soil moisture content is sufficient for second planting. This rainfall pattern is typical in the arid and semi-arid region. Minimum difference occurs in July/September which is towards the end of the first growing season and the beginning of the second growing season. Hence, one can infer that there is increase in biomass productivity in this location throughout 2011.

Location b: Significant increase in overall greenness (Amplitude 0) was revealed by the seasonal trend analysis (STA) of this location (41a-c). The seasonal curve from the land cover type (Closed to open shrubland) shows an increase in vegetation productivity in 2011. The maximum differences between the curves occurs in June and July (the wettest months) while the minimum difference occurs in March/April as a result of the response of vegetation to the on-set of rainfall season.

Location c: The land cover type is dominated by cropland. Significant increase in overall greenness (amplitude 0) is depicted by the results of the spatial slope map of this region, while decrease in the other two greenness parameters (Amplitude 1 and Phase 1) was observed in more than half of the region (41a-c). The maximum difference in the curves occurs at the peak of agricultural growing season in June/July, also in December and January (farming along river banks) while minimum difference occurs in April. Decline in NDVI was observed in September 2011, which might be due to fallow period or delayed growth after the August break.

Location (d): This location represents an example of both open woodland and shrubland. This land cover class exhibits a significant increase in overall greenness and magnitude of peak of annual greenness for the study period (41a-c). Maximum difference between trend at the beginning of the time series (1983) and end of the time series (2011) occurs during the wet months (June, July and October) while minimum difference occurs in Feb and April.

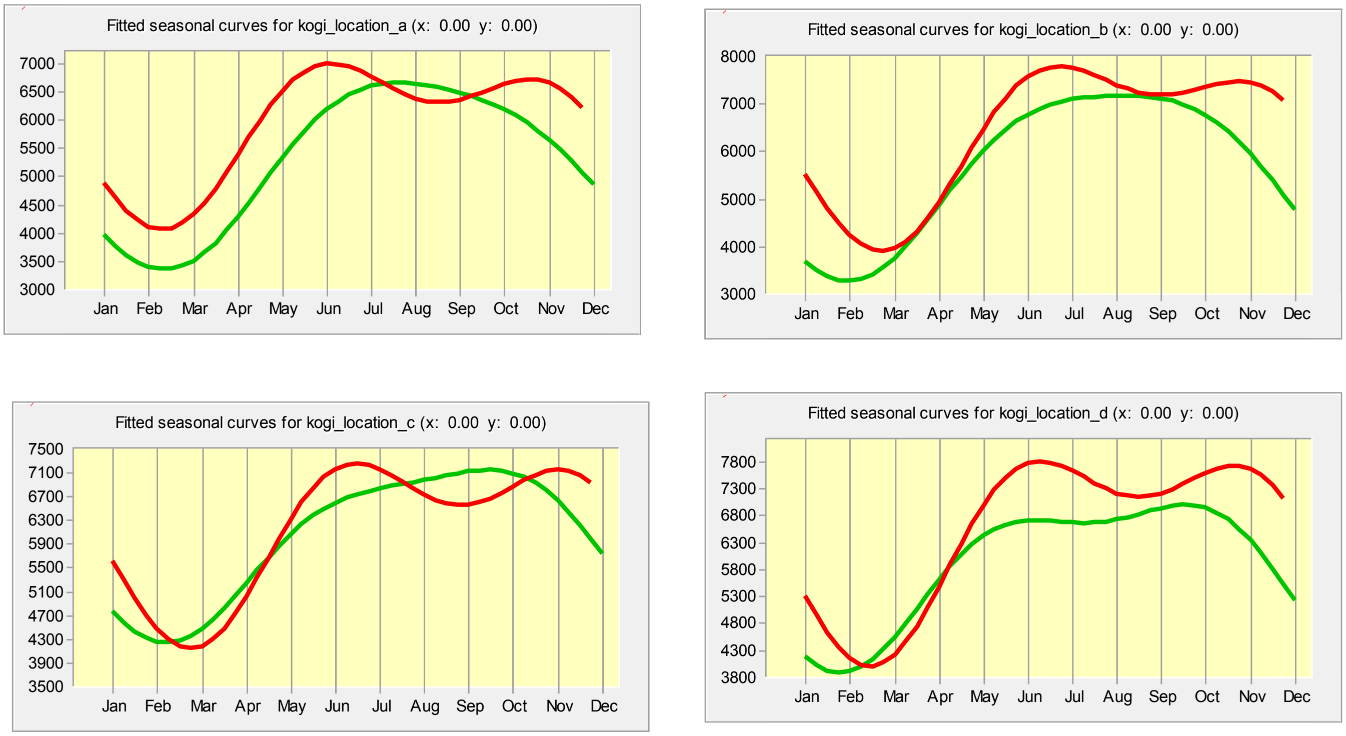


Figure 45: Seasonal NDVI curves of the land cover types for the selected locations in Kogi state: (a) Grassland (Igalamela-odolu); (b) Shrubland (Koton-karfe); (c) Cropland (Ankpa); (d) Forest/woodland (Kabba-bunu). 1983 in green and 2011 in red

Generally, increase in overall greenness was observed across the land cover types in the study locations. However, as human being interferes with the ecosystem, land use land cover transformation is bound to occur. This is revealed by the result of the phenological change pattern in the study locations during the period of study (1983-2011).

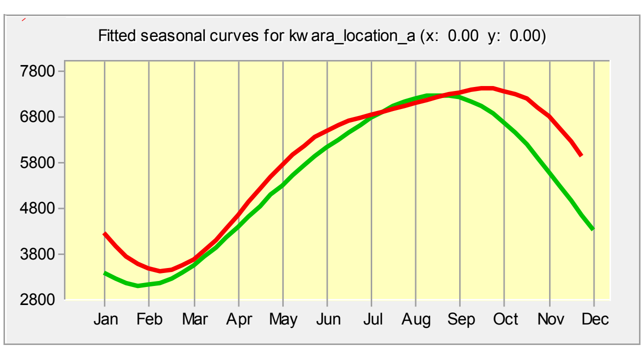
6.3.2. Seasonal NDVI curve for Kwara state

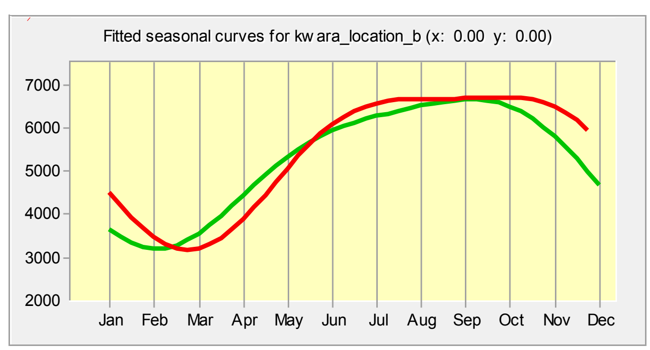
The seasonal NDVI curve patterns as observed in the different land cover types for Kwara are presented in figure 46.

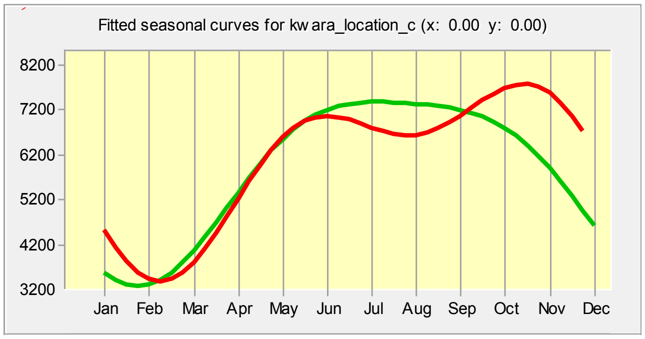
Increase in overall greenness (Amplitude 0) was observed in location a (Kaiama) while decrease in other greenness parameters (Amplitude 1 and Phase 1) predominates about 80% of the pixels used in the harmonic regression (STA) analysis (Fig. 42). Increase in vegetation productivity across the land cover type deciduous forest/woodland was revealed by the seasonal NDVI curve of 2011. The maximum difference between the two curves occurs in the month of January months, October, November and December months while minimum difference occurs in March, July, August and September.

Location b (Edu) exhibits significant increase in overall greenness and peak of annual greenness while a significant decrease was observed for the timing of annual peak of greenness for this location (Fig. 42). The land cover type in this region is associated with cropland. Both intensive and extensive agricultural activities are practiced all year round coupled with irrigation system. Minimum difference occurs between the two curves in May and September while maximum difference occurs between the two curves in April, July and November.

Location c & d (Ekiti and Baruten) exhibit significant increase in overall greenness (Amplitude 0) and decrease in other greenness parameters (Amplitude 1 and Phase 1) over the study period (1983-2011) (Fig. 42). Location *c* (Ekiti) of the study area is associated with shrubland while location *d* is associated with grassland. Minimum difference between the two seasonal NDVI curves for location c occurs in February/April while maximum difference occurs in July and October. In location *d*, minimum difference occurs between the two curves in April while maximum difference occur between the two curves in November.







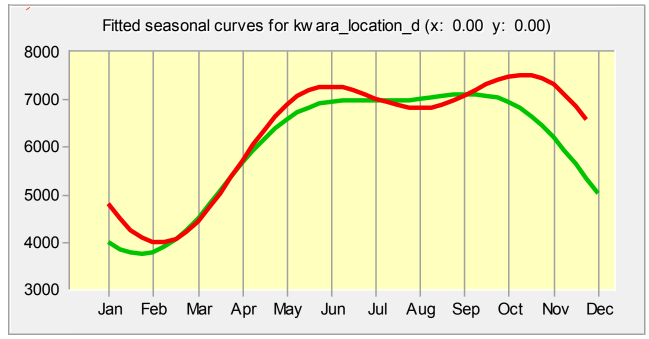


Figure 46: Seasonal NDVI curves of the land cover types for the selected locations in kwara state: (a) Forest/woodland (Kaiama); (b) Cropland (Edu); (c) Shrubland (Ekiti); (d) Grassland (Baruten). 1983 in green and 2011 in red

6.3.3. Seasonal NDVI curve for Niger state

Location *a* (Riaju) registers a significant increase in overall greenness (Amplitude 0) and magnitude of peak of greenness (Amplitude 1) for all months while shift to a later time (decrease) can be observed for the timing of peak of greenness (Phase 1) for this location (Fig 43). Minimum difference occurs between the two seasonal curves at the beginning of raining season (March – May) which is the start of growing season, while maximum difference between the two curves occurs in October, November and December. The land cover type of this location is classified as cropland (Global land cover classification, 2009). Generally, both NDVI curves (1983 and 2011) exhibit a similar pattern. A decline in vegetation productivity occurs earlier in 1983 as compared to 2011.

Location *b* (Mashegu): Increase in the seasonal NDVI curve pattern was observed for the seasonal NDVI curve of 2011. The dominant land cover type in this location is mosaic grassland. Significant increase in overall greenness (Amplitude 0) and timing of annual peak greenness (Phase 1) was observed by the result of the STA while there is decrease in peak of annual greenness (Amplitude 1) in this study location (Fig 43). Difference in the two seasonal NDVI curves for this location is obvious. Vegetation green-up (start of growing season) starts early in 2011 when compared with 1983. Maximum difference between the two curves occurs during the wet months (April to July) while decline in vegetation activity was observed in the month of August (2011).

Similar pattern of seasonal trend was observed for location *c and d* (Lapai and Muya). Both locations register significant increase in overall greenness (Amplitude 0) and magnitude of peak of greenness (Amplitude 1) for all months with decrease in timing of peak of greenness (Phase 1). These locations are characterized by woody land cover (woodland and shrubland respectively). Minimum difference in both locations (Lapai and Muya) occur in April while maximum difference occurred in June, October, November and December. In general, an increase in vegetation productivity for 2011was revealed by the pattern of seasonal curve for these locations.

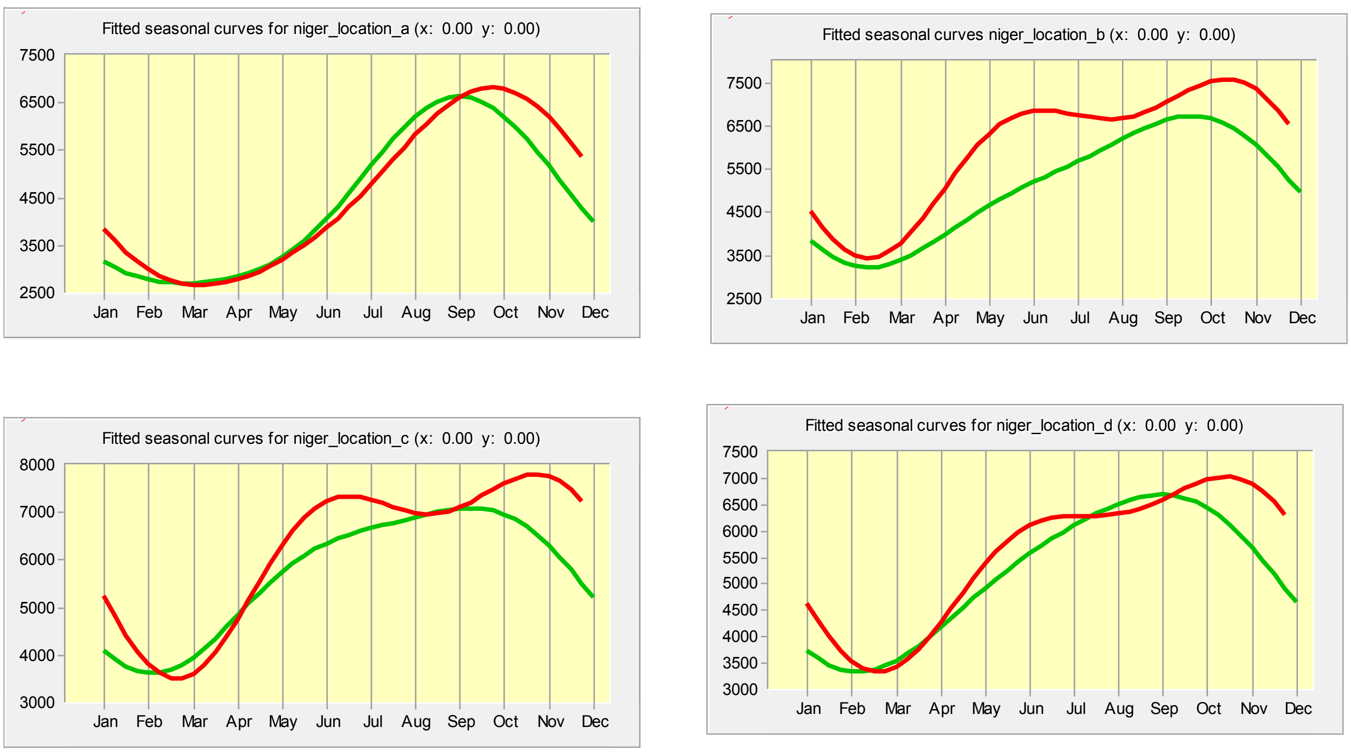


Figure 47: Seasonal NDVI curves of the land cover types for the selected locations in Niger state state: (a) Cropland (Rijau); (b) Grassland (Mashegu); (c) Forest/woodland (Lapai); (d) Shrubland (Muya). 1983 in green and 2011 in red

The results obtained from the seasonal trend analysis (STA) show an increase in vegetation greenness over the examined period (29 years). About 94 % of the pixels used for this analysis shows positive NDVI trend (i.e. p-value <0.05) as observed from the image of mean annual greenness i.e (Amplitude 0) for the three study regions (Kogi, Kwara and Niger). Both increasing and decreasing trend was observed for the other greenness parameters (Amplitude 1 and Phase 1) across the different land cover types as revealed from the results of the seasonal NDVI curves. The results of the Seasonal Trend Analysis are in line with the studies of Dubovyk et al., (2015); Eastman et al., (2013) and Panday and Ghimire, (2012) where increasing trend in vegetation productivity was observed for some selected land cover types. Though increase in NDVI trend was revealed by the results of this study, an assessment of land use pattern is necessary in order to understand the drivers of land cover change across the study region as land use land cover change might have influence on vegetation change dynamics over time.

6.4. Phenological metrics

The analysis was performed on NDVI datasets and the key seasonal metrics used in this study were defined as: Onset of growing season, End of growing season, Duration of growing season, Peak NDVI value, Onset NDVI value, End NDVI value, Range of NDVI, Peak value of NDVI, Time-integrated NDVI value, Rate of green-up, Rate of senescence and Seasonal modality (Fig. 19) based on the approach of Reed et al., (1994).Four examples were selected to represent the different land cover types in the study region: cropland, grassland, shrublands and forest/woodland. The results presented in this segment of the study focus on the examination of seasonal trends in ecosystem dynamics through evaluation of phenological characteristics of land cover types in the study locations as derived from the seasonal trend analysis. Valuable information on the seasonal characteristics of vegetation, such as emergence and senescence, peak of greenness and length of growing season and other phenological metrics were derived from the seasonality curves. In order to determine the beginning and end of growing season, the approach used in this study was to identify the point in time when 40% of vegetation exhibits an increase in NDVI which signals the onset of significant photosynthetic activity (Eastman, 2012). Once the onset of the greening metrics and the end of the greening period (onset value of NDVI and onset time) has been identified using similar method, the other phenological metrics can be computed relatively easily. The resulting phenological parameters can therefore be used for making decision on land use land cover change in order to fully understand shift in vegetation phenological pattern.

Table 27: Median Phenological metrics for 1983 and 2011 in selected locations of Kogi State, Nigeria

Land cover type	Year	Onset	End	Duration	Peak date	Onset value	End value	Range of NDVI	Peak value	Rate of green up	Rate of Senescence
Cropland	1983	4/8	12/11	247	9/23	0.52	0.57	0.19	0.71	0.02	0.02
	2011	4/11	1/6	271	6/22	0.50	0.68	0.23	0.73	0.06	0.01
Grassland	1983	4/13	12/7	239	7/12	0.43	0.48	0.23	0.66	0.04	0.02
	2011	3/14	1/6	300	6/7	0.43	0.60	0.27	0.70	0.04	0.01
Shrubland	1983	4/1	11/30	244	8/1	0.49	0.48	0.24	0.72	0.03	0.04
	2011	3/31	1/15	291	6/16	0.40	0.68	0.38	0.78	0.06	0.01
Forest/woodland	1983	3/19	12/3	260	9/22	0.45	0.52	0.25	0.70	0.02	0.03
	2011	3/26	1/4	285	6/15	0.42	0.68	0.36	0.78	0.06	0.01

Table 28: Median Phenological metrics for 1983 and 2011 in selected locations of Kwara State, Nigeria

Land cover type	Year	Onset	End	Duration	Peak date	Onset value	End value	Range of NDVI	Peak value	Rate of green up	Rate of Senescence
Cropland	1983	4/7	12/4	242	9/7	0.44	0.47	0.22	0.66	0.02	0.03
	2011	4/20	12/30	255	9/30	0.39	0.57	0.28	0.67	0.03	0.02
Grassland	1983	3/18	11/29	257	9/6	0.45	0.53	0.26	0.71	0.02	0.05
	2011	3/19	12/25	288	10/14	0.44	0.62	0.31	0.75	0.02	0.03
Shrubland	1983	3/23	11/24	247	7/3	0.40	0.53	0.34	0.74	0.04	0.03
	2011	3/27	12/24	281	10/22	0.38	0.63	0.40	0.78	0.03	0.04
Forest/woodland	1983	4/14	11/20	221	8/24	0.44	0.46	0.29	0.73	0.04	0.05
	2011	4/5	12/19	259	9/23	0.46	0.56	0.28	0.74	0.03	0.03

Table 29: Median Phenological metrics for 1983 and 2011 in selected locations of Niger State, Nigeria

Land cover type	Year	Onset	End	Duration	Peak date	Onset value	End value	Range of NDVI	Peak value	Rate of green up	Rate of Senescence
Cropland	1983	6/8	11/24	170	9/5	0.40	0.43	0.26	0.66	0.04	0.06
	2011	6/16	12/20	188	9/27	0.39	0.50	0.29	0.68	0.05	0.03
Grassland	1983	5/1	12/9	223	9/23	0.47	0.49	0.20	0.67	0.03	0.03
	2011	3/24	12/29	281	10/15	0.38	0.61	0.38	0.76	0.03	0.03
Shrubland	1983	4/24	11/29	220	9/1	0.42	0.49	0.2	0.67	0.03	0.05
	2011	4/14	12/30	261	10/22	0.43	0.60	0.27	0.70	0.02	0.03
Forest/woodland	1983	4/7	12/6	244	9/15	0.48	0.52	0.23	0.71	0.02	0.03
	2011	4/7	1/5	274	10/29	0.47	0.52	0.31	0.78	0.03	0.04

Tables 27-29 show the phenological metrics for four different land cover types in the Guinea savannah region of Nigeria using the composite period as the unit of measurement to derive the metrics which are then translated to commonly used units for easy presentation. The rates of green-up and senescence are given in NDVI units per composite period. The time period metrics are calendar dates, while the NDVI value metrics are given in NDVI units, which range from – 1.0 to 1.0.

It is evident from the above table that most of the land cover types in the study locations exhibit similar level of consistency in the onset and end of the growing season with few exceptions. The land cover type for the three study locations was compared for ease of interpretation.

Croplands

The median onset of greenness in Kogi and Kwara state is quite similar for the two years (April 8 and April 11 for Kogi, April 7 & April 20 for Kwara in 1983 and 2011 respectively) while a considerable difference in the onset of greenness was observed for Niger state (June 8 and June 16 in 1983 and 2011). The difference observed in the onset period is possibly due to the time when rainy season begins. It should be noted that Niger state falls within the central northern part of Nigeria where changes in climate is pronounced. The median rate of greening for the selected locations in Kogi State in 2011 was more rapid than in 1983 (0.06 and 0.02 NDVI per composite period). An increasing rate of green-up was also observed for Kwara (0.03 and 0.02) and Niger state (0.05 and 0.04) respectively. Increase in the duration of growing season was observed in all the three study regions (Kogi, Kwara and Niger) for 2011 while there is an increase in the maximum NDVI ($NDVI_{max}$) value for 2011 which indicates positive NDVI trend over time.

Grassland

Variation in dates of the onset of green-up was revealed in the selected region of interest across the Guinea savannah region of Nigeria. Vegetation greening begins earlier in the selected location in Niger state (May 1 and March 24 in 1983 and 2011)as compared with that of Kogi and Kwara. A difference of about 29 days in the on-set of vegetation greening was observed in Kogi (April 13 and March 14 in 1983 and 2011 respectively) while there is no significant difference in the onset of green-up for Kwara state (see tables 27 and 28). The rate of green-up for the 2 years (1983 and 2011) in all the three locations is constant. An increase in maximum NDVI ($NDVI_{max}$) value for the study locations was observed between the 2 periods (1983 and 2011).

Shrubland

Variation in the start of growing season (SOS) was observed in shrubland vegetation for the three study regions. The onset of greenness i.e the start of growing season for the selected location in Kogi state is April 1 and March 31 in 1983 and 2011. The difference between the start of growing season in the selected location for Kwara state is about 3 days which indicates that SOS was earlier in 1983 as compared to 2011 (March 23 and March 27). Greening-up i.e SOS starts earlier in1983 as compared to 2011 for the selected location in Niger state (April 24 and April 14) respectively. In 2011, the median rate of green-up in Kogi was more rapid (0.06 vs 0.03 NDVI per composite period) whereas for both Kwara and Niger, the median rate of green-up was rapid in 1983 (tables 28 and 29). The results of the phenological metric analysis show an increase in the duration of the growing period in 2011. An increasing trend in maximum NDVI value ($NDVI_{max}$) was observed in 2011 across the study regions.

Forest

Consistent phenological metrics for the onset of green-up for the 3 regions were observed for the two periods. These characteristics are distinct when compared with other land cover types. However, this consistency may assist in the classification of land cover types. The rate of green-up was high in 2011 for Kogi and Niger state while a low rate of green-up was observed for Kwara state (Table 28).

The phenological metrics presented in tables 27-29 were derived from the seasonal NDVI curves. In order to determine the beginning and end of growing season, both the observed and fitted vegetation index values are plotted against time. Generally, the onset of growing season is the point where there is a sharp departure of the fitted curve from the observed curve. For this study, the onset and end of active growing seasons were determined as the point where 40% of the vegetation has turned green and the same for end of growing season, i.e the point where only 40 percent of vegetation are still green (Eastman, 2012). These results can be used for ecosystem monitoring at the regional and local level. Analysis of change in phenological pattern of vegetation cover can also be used in monitoring variation in climate and their influence in vegetation greening. The results of this study are of immense importance as they provide researchers with information about the timing and progression of plant development which can be used to make inferences on vegetation vigor in different ecological zones in Nigeria.

6.5. Discussion

The results of the seasonal trend analysis (STA) over the Guinea savannah region of Nigeria from 1983-2011 show significant positive trend in Amplitude 0 (i.e., the mean annual NDVI) while both positive and negative trends were observed for the peak of annual greenness (Amplitude 1) and timing of peak of greenness (Phase 1) (Fig. 41-43). A large area of significant positive trends in overall greenness (Amplitude 0) was observed within the land cover types in the study locations. For example, some of the areas where increase in Amplitude 0 were observed in Niger State are within the floodplain area where increased subsistence agriculture is practiced. Positive increase in vegetation productivity are associated to anthropogenic activities such as extended growing season in Nigeria as revealed by the studies of Igbawua et al., (2016) and Olusegun and Adeyewa, (2013). The significant greening trend observed throughout the Guinea savannah region of Nigeria is similar to that reported by Anyamba and Tucker in the Sahel region of Africa (Anyamba et al., 2001; Herrmann et al., 2005). Although tremendous positive NDVI trend was observed in these regions, the results of the timing of peak of greenness show shift to a later time during the monitoring period while more positive trend in the slope of the timing of greenness was found only in the southeastern part of Niger state. A similar trend was observed from the result of the rainfall analysis. This implies that increase in vegetation productivity has strong relationship with rainfall as revealed by other studies in the Sahelian region (Gentine et al., 2012; Herrmann et al., 2005; Kariyeva et al., 2012). The study of Eastman et al., (2013) also confirms that increase in vegetation productivity can be attributed to climate change. The phenological metrics analysis across the different land cover types in the study locations are in line with that of Reed et al., (1994). However, variation in onset and end of greenness were observed in all the locations. It can be proffered that increasing greenness in the grassland ecotones is linked to recovering from bush fire after the first month of rainy season and/or conversion for crop production. It should be noted that the study area enjoys favorable soil and climatic condition which supports crop production and extensive grazing at the expense of forest degradation. However, the observed trends in overall greenness (Amplitude 0) signify long-term changes in vegetation productivity which can be used as an indicator for monitoring vegetation degradation or improvement as well as land degradation in these agro-ecological zones. It should be noted that this approach (i.e STA) is intended for the detection of seasonal trends across different land cover types in the Guinea savannah region of Nigeria and its relationship with phenological metrics. However, adequate knowledge of the timing of growing season (or biological event) is useful for proper land use land cover management planning and can also be used for monitoring vegetation change dynamics in the future. Although rainfall is one of the driving factors for change in vegetation phenology, further assessment on land use land cover change is needed in order to have an in-depth understanding of phenological change in the regions where significant increase in vegetation trends are observed.

7. Assessment of land use land-cover change using ancillary data and Landsat imagery

7.1. Abstract

Increased anthropogenic activities over the last decades have led to significant land cover change in the Guinea savannah region (GSR) of Nigeria, this is due to population growth and high level of poverty. Much of the human activities have resulted into large scale change in the ecosystem function and in most cases loss of biodiversity. Change in land use/land cover can be monitored through the use of multi-temporal remotely sensed data. In order to examine the impact of land cover change on vegetation dynamics (biomass productivity), this study employs a quantitative approach of combining the national land use land cover (LULC) data of Nigeria (1976 and 1995) from Forestry Management Evaluation & Coordination Unit (FORMECU), remote sensing data (Global Land Cover data of 2000, 2005 and 2009 from European Space Agency) and Landsat imagery of 1986, 2000 and 2014 for profound assessment of land use land cover change and deforestation. A significant change in LULC was revealed by the results of this analysis over the examined period. Loss in the spatial extent of forest cover was observed by the results of CLASlite analysis for the selected regions of interest. This assessment (i.e land use land cover change) show that change in vegetation dynamics across the Guinea savannah region of Nigeria is a resultant effects of different anthropogenic activities. Hence, continuous monitoring of land use land cover change in these regions is imperative.

7.2. Assessment of land cover change in the study areas (Kogi, Kwara and Niger state)

Five land use land cover ancillary datasets were used to assess the drivers of vegetation change dynamics over the last decades in the study regions. The results of this assessment are presented in the form of maps and statistical table respectively. The spatial analysis of land use land cover for Kogi state shows the extent at which the vegetation cover has changed over time. It is evident (from the maps) that vegetation in Kogi state have undergone tremendous change due to human-induced conversion of the semi-natural vegetation to other land use types such as agricultural land. These change were further examined in the selected locations used for the time series analysis in chapter 5. Results were verified during field research in 2013. The extent of human interference with the ecosystems in Kogi state are presented in figures 48-52.

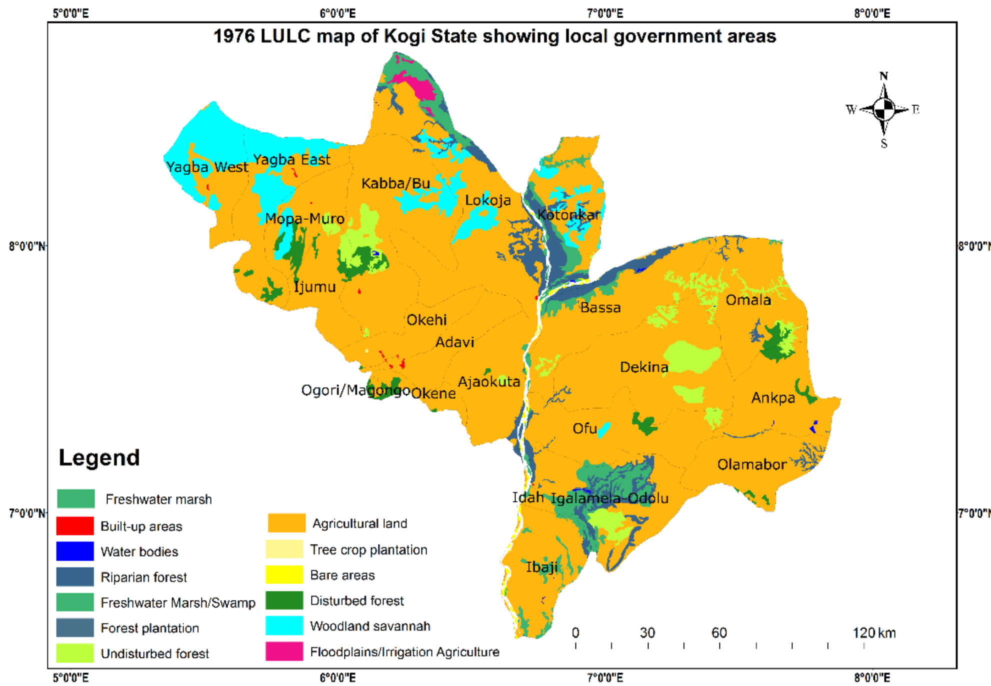


Figure 48: Land use land cover map of Kogi State (1976)
Source: FORMECU (scale: 1:250,000)

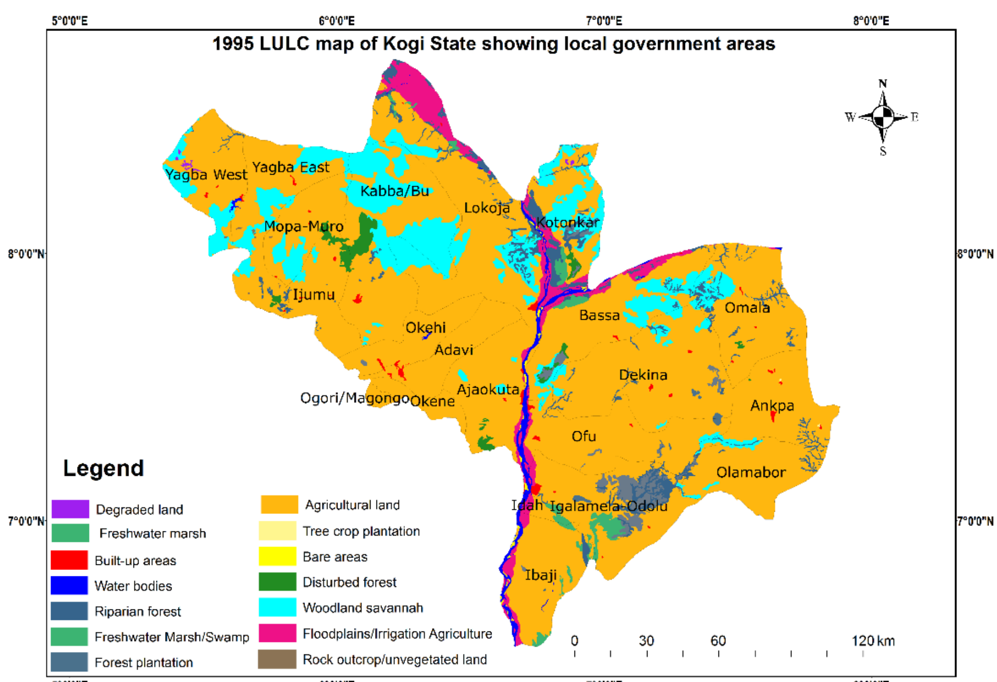


Figure 49: Land use land cover map of Kogi State (1995)
Source: FORMECU (scale: 1:250,000)

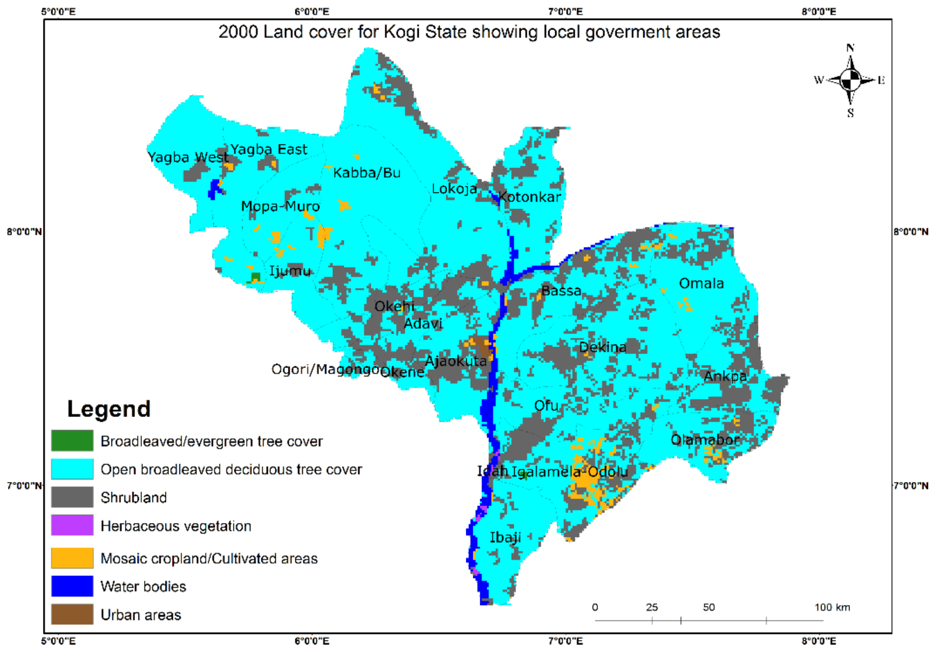


Figure 50: Land use land cover map of Kogi State (2000)
Source: European Space Agency (ESA) with spatial resolution of 1km

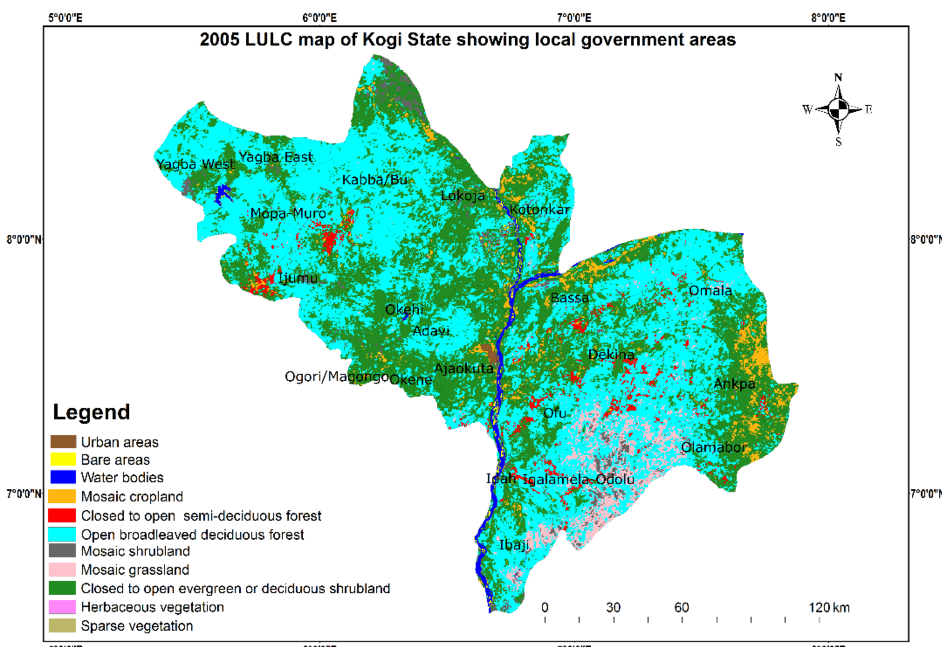


Figure 51: Land use land cover map of Kogi State (2005)
Source: European Space Agency (ESA) with spatial resolution of 300m

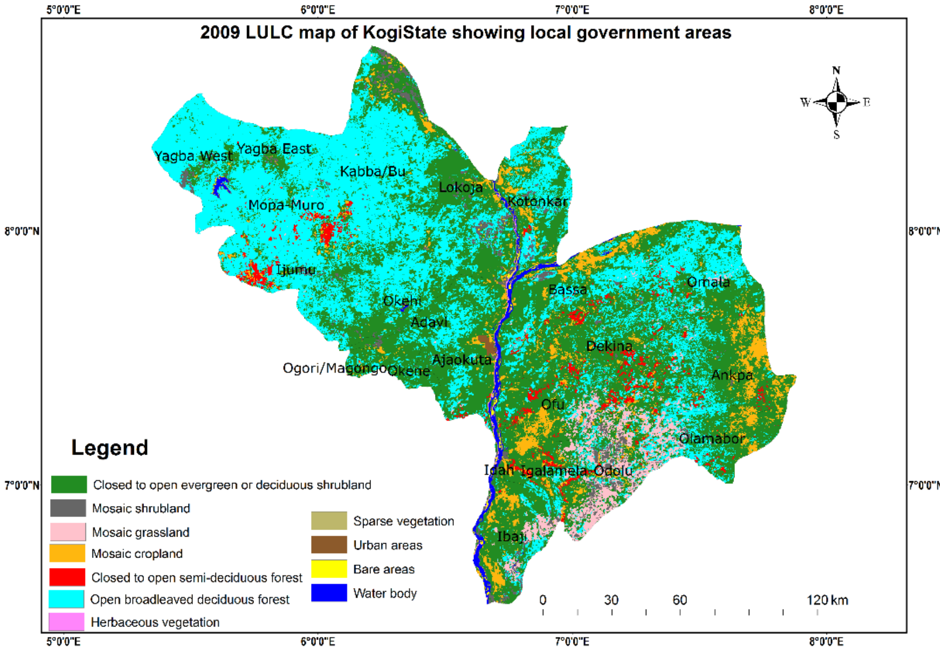


Figure 52: Land use land cover map of Kogi State (2009)
Source: European Space Agency (ESA) with spatial resolution of 300m

Table 30 show the distribution of land use land cover types for selected locations across the Guinea savannah region of Nigeria. Results of the analysis reveals that about 61 % of the areas covered by woodland was lost to other land use types between 1976 and 2009 in Igalamela-odolu (*location a*) due to human disturbance of the ecosystem. Significant change in LULC was also observed in Koton karfe (*location b*) between 2000, 2005 and 2009. Total area covered by woodland accounted for 88 % in 2000, while a tremendous decline in woodland of about 33 % and 11 % was observed in 2005 and 2011 respectively. Similar decline in woodland (forest cover) was observed in Ankpa (*location c*) between 2005 and 2009. About 21 % of woodland was transformed to other land use types, most especially agriculture.

7.3. Land use land cover assessment in Kwara state

Agriculture is one of the major sources of income of the people living in the rural and semi-urban area of Kwara state. Due to high rate of poverty coupled with increase in population, more and more land is needed for farming activities. Figures 53-57 shows the spatial extent of changes over the last decades.

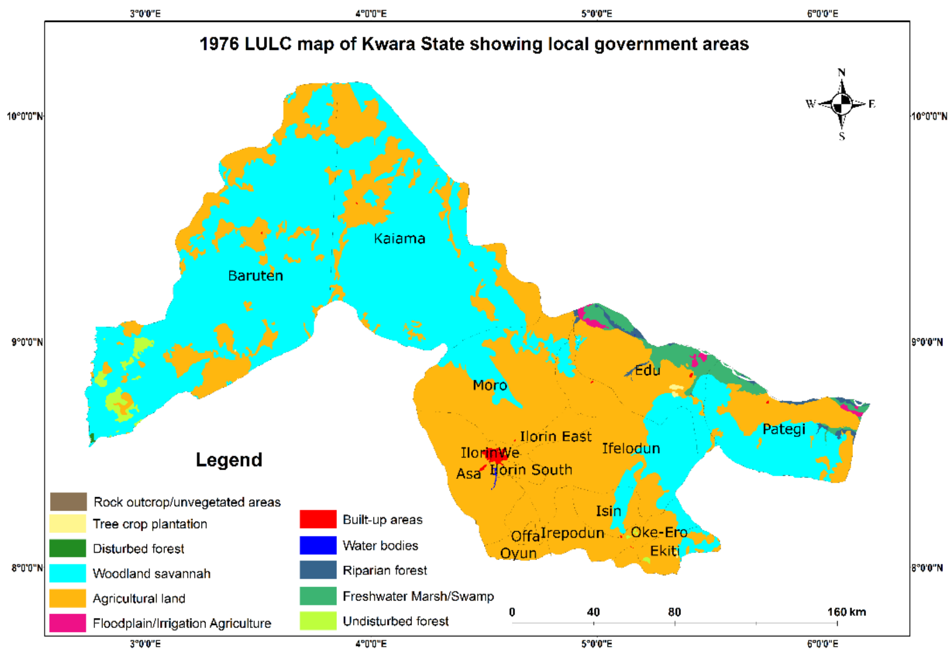


Figure 53: Land use land cover map of Kwara State (1976)
Source: FORMECU (scale: 1:250,000)

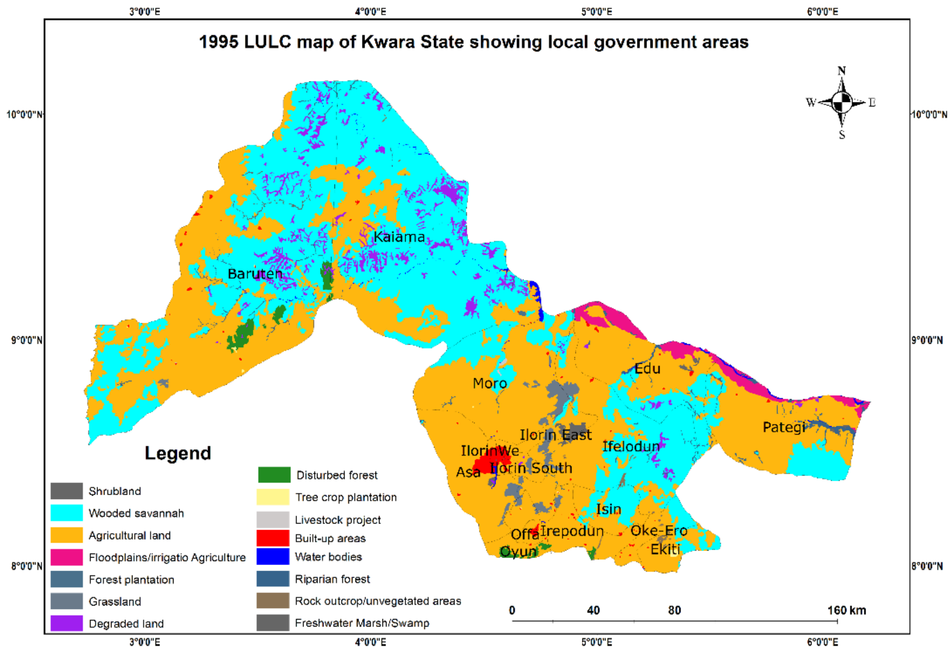


Figure 54: Land use land cover map of Kwara (1995)
Source: FORMECU (scale: 1:250,000)

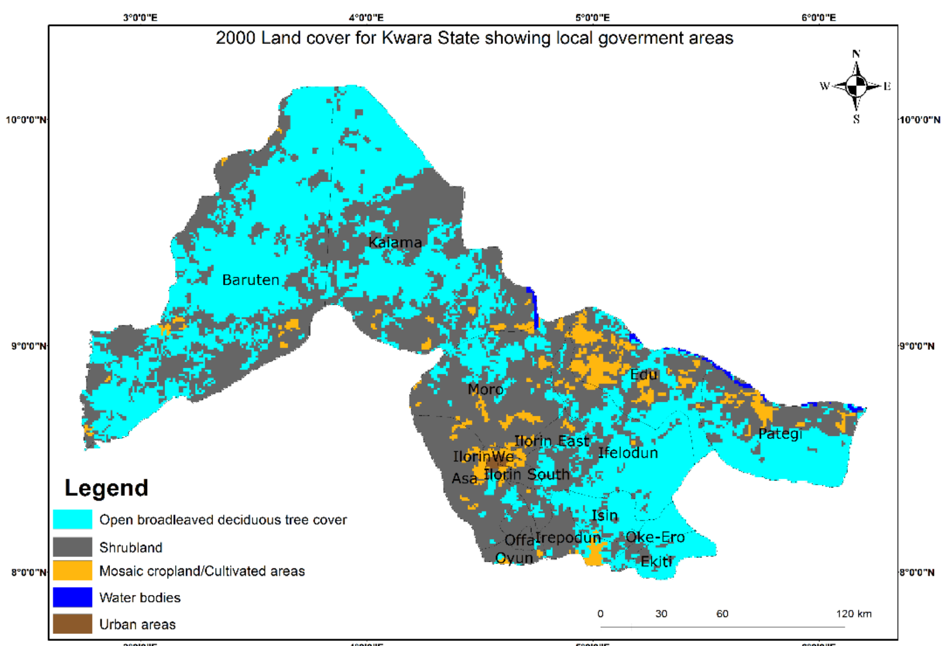


Figure 55: Land use land cover map of Kwara State (2000)
Source: European Space Agency (ESA) with spatial resolution of 1km

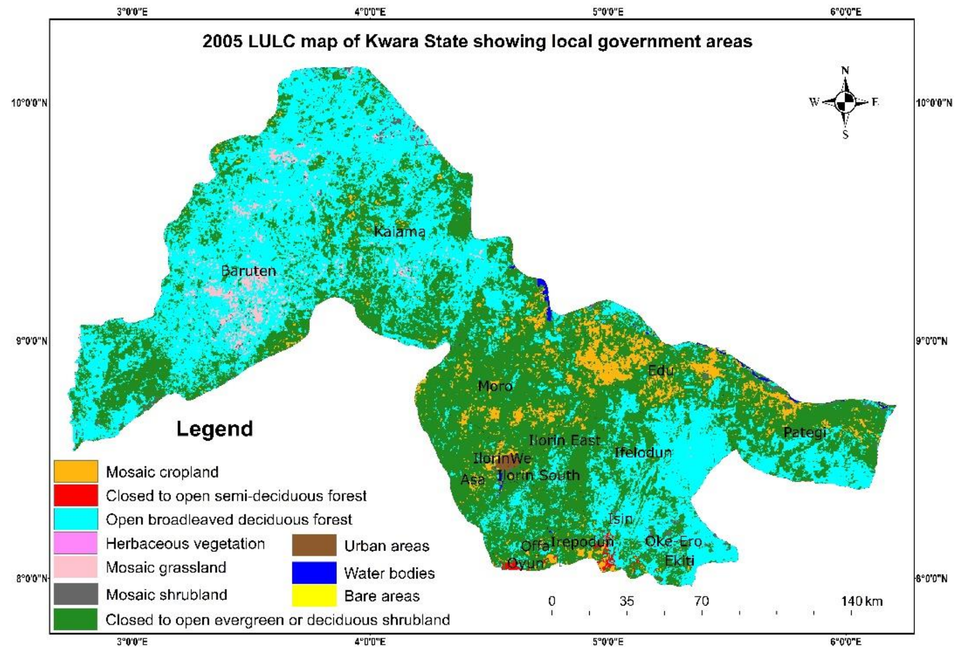


Figure 56: Land use land cover map of Kwara (2005)
Source: European Space Agency (ESA) with spatial resolution of 300m

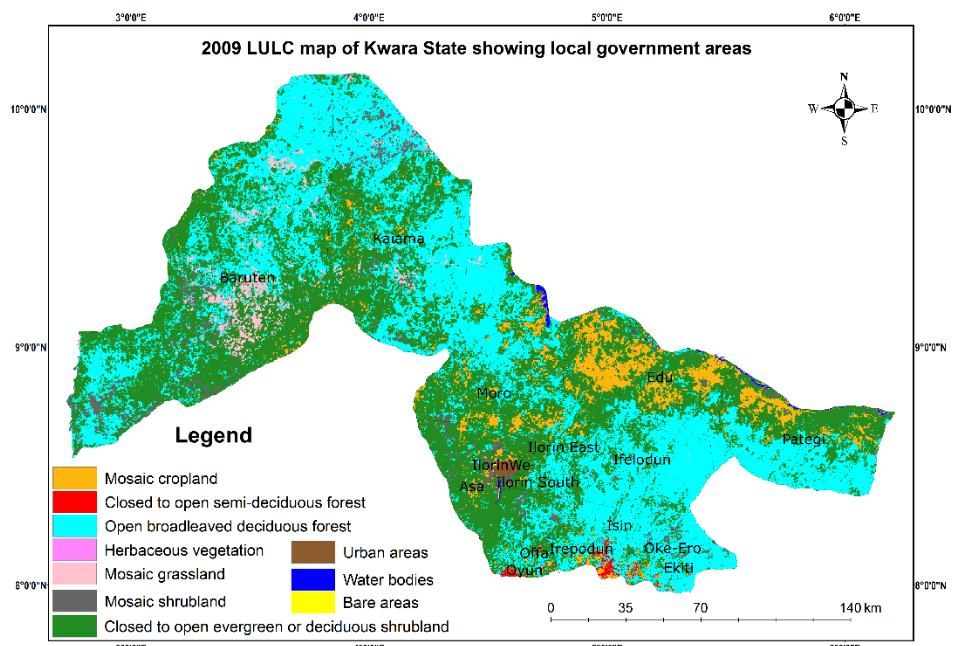


Figure 57: Land use land cover map of Kwara (2009)
Source: European Space Agency (ESA) with spatial resolution of 300m

It is obvious from the visual observation of the LULC maps of Kwara state that changes have occurred over the study periods. By visualizing the LULC classes of 1976 and 1995, it can be deduced that the vegetation/land cover types have not remain the same due to anthropogenic activities. Areas which were classified as undisturbed forest (natural forest) in 1976 have been replaced by other land use types (agricultural land) in 1995. Increase in the extent of shrub and cropland is noticeable in the LULC map of 2009 as compared with that of 2005. This indicates loss of forest cover to other LU types. Change in LULC was also observed for the selected locations used in this study. About 15 % of shrubland was lost to cropland in Edu (*location b*) between 2000 and 2009. Noticeable land cover change was observed in Ekiti (*location c*) between 2005 and 2009 where open broadleaved deciduous forest/woodland accounted for 51.26 % in 2005 and 1.84 % in 2009, which shows a loss of about 49% of forest cover to other LULC between the two years (2005 and 2009). It is obvious in this location that as woodland is decreasing, an increase of about 48 % was observed for shrubland while an increase of about 2 % was observed for areas covered by grassland. Similar change was also observe in Baruten location d where open broadleaved deciduous forest/woodland accounted for about 36 % in 2005 and 19 % in 2009 respectively.

Figures 58-62 show the spatial extent of LULC in Niger state. It is no doubt that increase in one LULC type (agricultural land) is directly proportional to decrease in other land cover types (woodland, shrubland or rangeland), this is evidenced by the results of the spatial extent of LULC in Niger state (Fig 58-62).

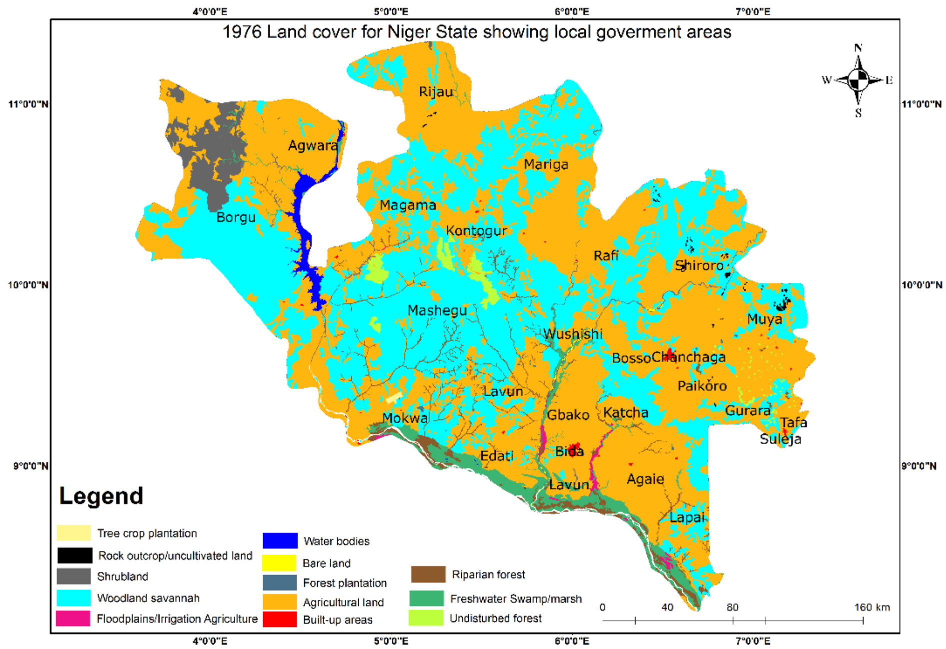


Figure 58: Land use land cover map of Niger (1976)
Source: FORMECU (scale: 1:250,000)

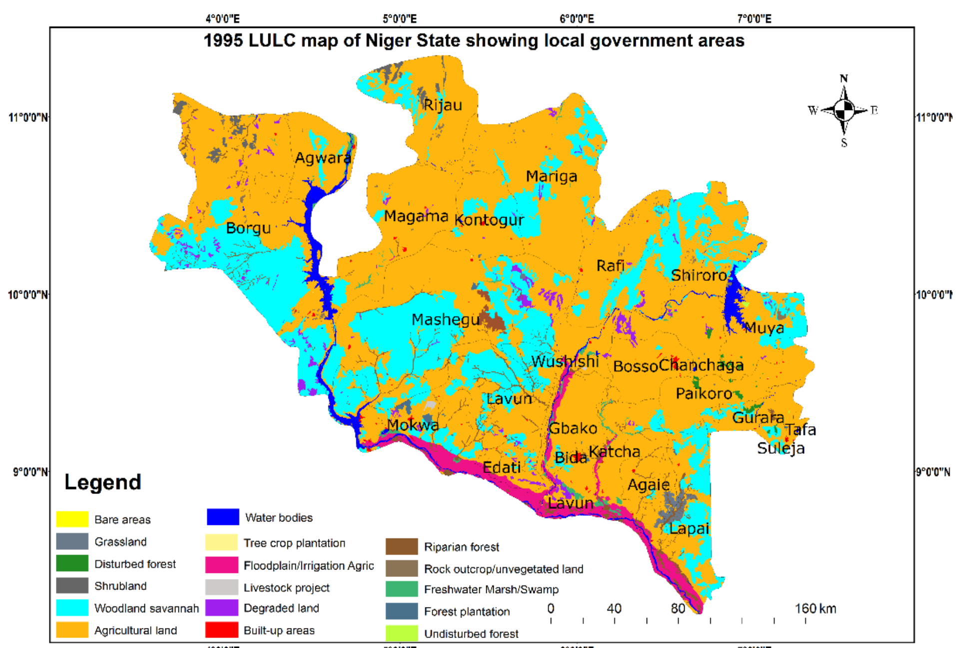


Figure 59: Land use land cover map of Niger (1995)
Source: FORMECU (scale: 1:250,000)

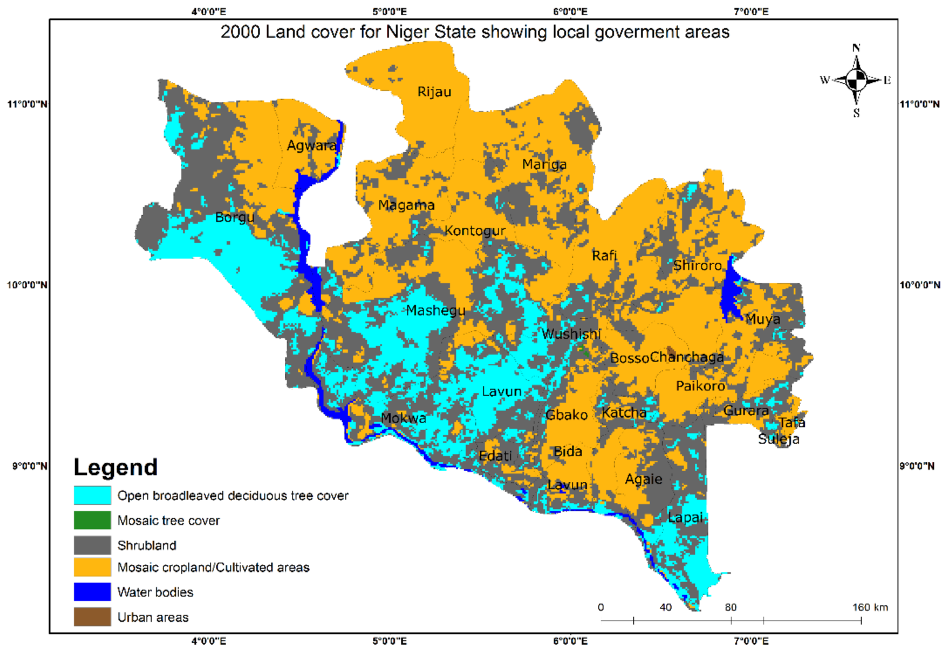


Figure 60: Land use land cover map of Niger (2000)
Source: European Space Agency (ESA) with spatial resolution of 1km

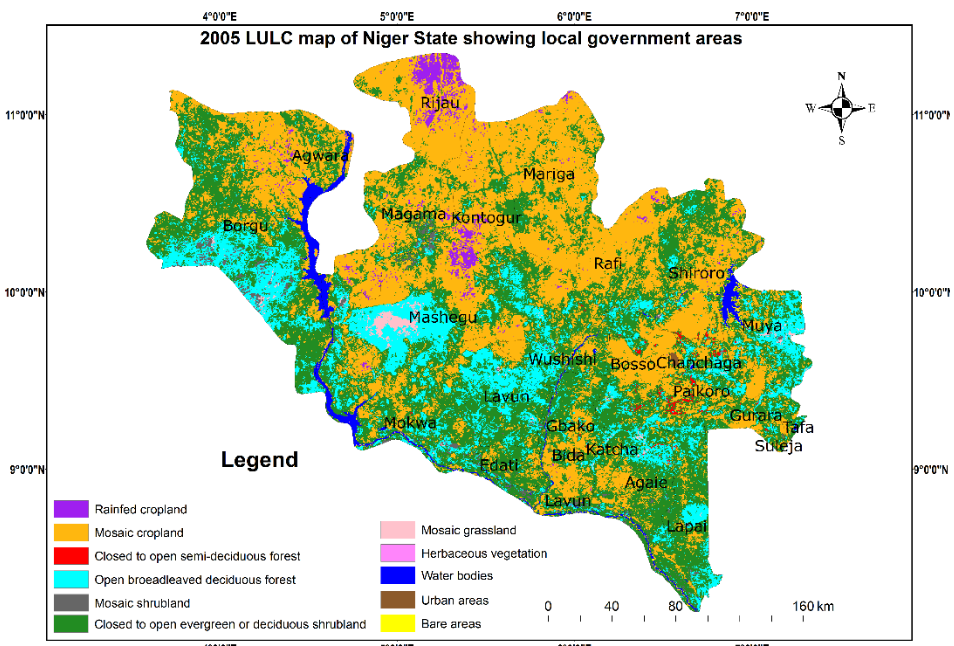


Figure 61: Land use land cover map of Niger (2005)
Source: European Space Agency (ESA) with spatial resolution of 300m

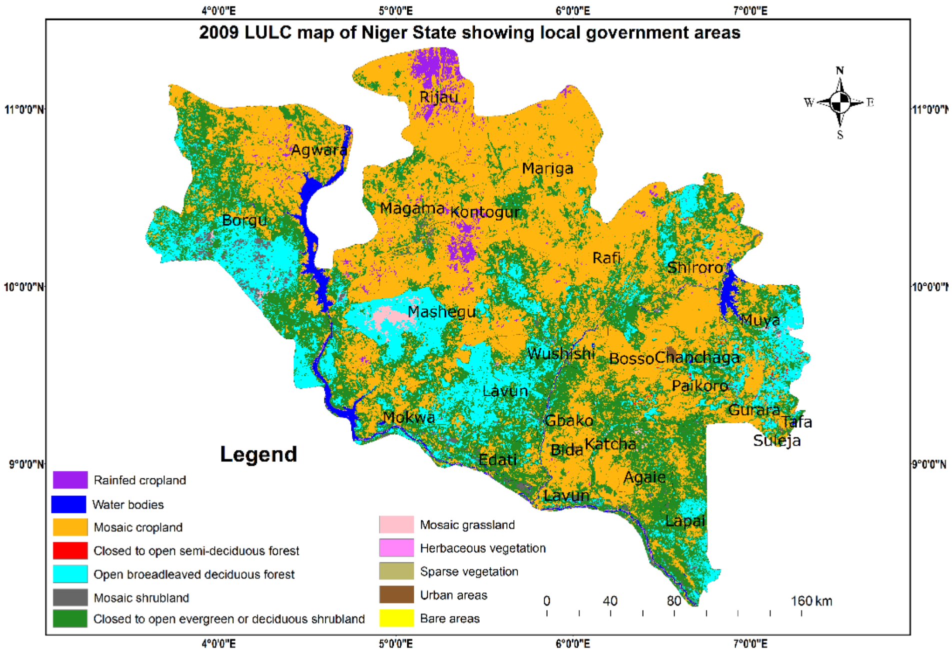


Figure 62: Land use land cover map of Niger (2009)
Source: European Space Agency (ESA) with spatial resolution of 300m

Results of the LULC assessment show that there is decrease in the area covered by riparian forest in 1995 as compared to 1976. The land cover type which were classified as undisturbed forest in 1976 were lost to other land use type such as agricultural land in 1995 (Fig. 58 and 59). Decrease in the extent of fresh water swamp and forest plantation was observed in fig. 49 (LULC of 1995). Agriculture is one of the dominant land use type as revealed by the results of the five land cover types used in this study. Change in LULC is also evidenced in the selected locations. Indiscriminate felling of trees and/or overgrazing cause change in vegetation structure and composition which is true for location b (Mashegu). Forest cover loss of about 68 % was accounted for between the period of 2000 and 2009 while increase of about 67 % of shrubland was observed in 2005 and 2009. In Muya (location d), increase in cropland accounted for about 20 % of the total land use while decrease of about 17 % was observed in woodland between 2005 and 2009.

Table 30: The assessment of land use change in the selected locations for 1976, 1995, 2000, 2005 and 2009

Source: FORMECU land use land cover map (1976 & 1995) and Global land cover 2000, 2005 and 2009 from European Space Agency

Locations (Kogi State)	LULC 1976	LULC 1996	LC 2000	LC 2005	LC 2009
a-Igalamela- odolu	(39.62 %) Undisturbed forest (35.85 %) Intensive (row crops, minor grazing) small holder rainfed agriculture (24.53 %) Riparian forest	(1.89%) Grassland (1.89%) Riparian forest (1.89%) Shrub/sedge graminoid fresh water marsh/swamp (94.33 %) Intensive (row crops, minor-grazing) small holder rainfed agriculture	(60%) Open deciduous, broadleaved tree cover (26.67) Closed –open deciduous shrub cover (13.33%) Mosaic: Cropland/Tree cover/other natural vegetation	(66.97 %) Mosaic grassland/forest or shrubland (16.96 %) Open broadleaved deciduous forest/woodland (16.07 %) Mosaic forest/shrubland/ grassland)	(66.78%) Mosaic grassland/forest or shrubland (16.08%) Mosaic forest or shrub/grassland (14.49%) Closed to open (broadleaved or needleleaved, evergreen or deciduous) shrubland (2.47 %) Open broadleaved deciduous forest/woodland (0.18 %) Mosaic cropland/vegetation (grassland/shrubland/forest)
b-Koton- karfe	(70 %) Intensive (row crops, minor grazing) small Holder rainfed agriculture (20%) Dominantly trees/woodlands/ shrubs with a Subdominant grass component (10%) Shrub/sedge graminoid fresh water marsh/swamp	(70 %) Intensive (row crops, minor grazing) small Holder rainfed agriculture (15 %) Dominantly trees/woodlands/ shrubs with a subdominant grass component (7.5 %) Riparian forest (5 %) Disturbed forest (2.5 %) Grassland	(88.46%) Open deciduous, broadleaved tree cover (11.54%) Closed –open deciduous shrub cover	(66.29 %) Closed to open (broadleaved or needleleaved, evergreen or deciduous) shrubland (33.26 %) Open broadleaved deciduous forest/woodland (0.45 %) Mosaic grassland/forest or shrubland	(87.78%) Closed to open (broadleaved or needleleaved, evergreen or deciduous) shrubland (11.76%) Open broadleaved deciduous forest/woodland (0.46 %) Mosaic grassland/forest or shrubland

c-Ankpa	(100 %) Intensive (row crops, minor grazing) small holder rainfed agriculture	(100 %) Intensive (row crops, minor grazing) small holder rainfed agriculture	(100%) Closed –open deciduous shrub cover	(76.73 %) Closed to open (broadleaved or needleleaved, evergreen or deciduous) shrubland (22.24 %) Open broadleaved deciduous forest/woodland (1.03 %) Closed to open broadleaved evergreen or semi-deciduous forest	(76 .21%) Mosaic cropland/vegetation (grassland/shrubland/forest) (22.59%) Closed to open (broadleaved or needleleaved, evergreen or deciduous) shrubland (0.69%) Closed to open broadleaved evergreen or semi-deciduous forest (0.34%) Mosaic vegetation (grassland/shrubland/forest)/ cropland (0.17) Mosaic forest or shrubland/grassland
d-Kabba-Bunu	(100 %) Extensive (grazing, minor row crops) small holder rainfed agriculture	(78 %) Dominantly trees/woodlands/ shrubs with a subdominant grass component (22 %) Extensive (grazing, minor row crops) small holder rainfed agriculture	(98%) Open deciduous, broadleaved tree cover (1.72%) Mosaic:Cropland/ Tree cover/other natural vegetation	(98.52 %) Open broadleaved deciduous forest/ woodland (1.48 %) Closed to open (broadleaved or needleleaved, evergreen or deciduous) shrubland	(98.70%) Open broadleaved deciduous forest/woodland (1.30%) Closed to open (broadleaved or needleleaved, evergreen or deciduous) shrubland

Locations **(Kwara State)**	LULC 1976	LULC 1996	LC 2000	2005	2009
a-Kaiama	(63.64) Dominantly trees/woodlands/ shrubs with a subdominant grass component (36.36%) Extensive (grazing, minor row crops) small holder rainfed agriculture	(100%) Dominantly trees/woodlands/ shrubs with a subdominant grass component	(100%) Open deciduous, broadleaved tree cover	(93.75 %) Open broadleaved deciduous forest/woodland (6.25 %) Closed to open (broadleaved or needleleaved, evergreen or deciduous) shrubland	(95.83 %) Open broadleaved deciduous forest/woodland (4.17 %) Closed to open (broadleaved or needleleaved, evergreen or deciduous) shrubland
b-Edu	(98.15%) Extensive (grazing, minor row crops) small holder rainfed agriculture (1.85%) Intensive (row crops, minor grazing) small holder rainfed agriculture	(100%) Intensive (row crops, minor grazing) small holder rainfed agriculture	(52.46%) Closed-open deciduous shrub cover (47.54%) Mosaic: cropland/ shrub and or grass cover	(53.94 %) Mosaic cropland/vegetation (grassland/shrubland/ forest) (46.06 %) Closed to open (broadleaved or needleleaved, evergreen or deciduous) shrubland	(62.87%) Mosaic cropland/vegetation (grassland/shrubland/ forest) (37.13%) Closed to open (broadleaved or needleleaved, evergreen or deciduous) shrubland
c- Ekiti	(63.41) Intensive (row crops, minor grazing) small Holder rainfed agriculture (34.15%) Dominantly trees/woodlands/ shrubs with a subdominant grass component (2.44%) Extensive (grazing, minor row crops) small holder rainfed agriculture	(65%) Extensive (grazing, minor row crops) small holder rainfed agriculture (27.5 %) Intensive (row crops, minor grazing) small holder rainfed agriculture (2.5 %) Agricultural tree crop plantation (2.5 %) Disturbed forest (2.5 %) Minor urban	(91.49 %) Closed-open deciduous shrub cover (8.51 %) Open deciduous broadleaved tree cover	(51.26 %) Open broadleaved deciduous forest/woodland (40 %) Closed to open (broadleaved or needleleaved, evergreen or deciduous) shrubland (6.90 %) Mosaic forest or shrubland/grassland (1.84 %) Mosaic grassland/forest or shrubland	(88.27 %) Closed to open (broadleaved or needleleaved, evergreen or deciduous) shrubland (8.05 %) Mosaic forest or shrubland/grassland (1.84 %) Mosaic grassland/forest or shrubland (1.84 %) Open broadleaved deciduous forest/woodland

d- Baruten	(100 %) Dominantly trees/woodlands/ shrubs with asubdominant grass component	(55.56 %) Dominantly trees/woodlands/ shrubs with a subdominant grass component (44.44%) Gullies	(100 %) Open deciduous broadleaved tree cover	(64.29 %) Mosaic grassland/ forest or shrubland (35.71 %) Open broadleaved deciduous forest/woodland	(64.29 %) Mosaic grassland/forest or shrubland (19.38 %) Open broadleaved deciduous forest/woodland (16.33 %) Closed to open (broadleaved or needleleaved, evergreen or deciduous) shrubland

Locations **(Niger State)**	LULC 1976	LULC 1996	LC 2000	LC 2005	LC 2009
a- Rijau	(78.72 %) Extensive (grazing, minor row crops) small holder rainfed agriculture (21.28 %) Intensive (row crops, minor grazing) small holder rainfed agriculture	(95. 74 %)Extensive (grazing, minor row crops) small holder rainfed agriculture (4.26 %) Intensive (row crops, minor grazing) small holder rainfed agriculture	(69.81 %) Cultivated and managed area (30.19 %) Mosaic: Cropland / shrub and/or grass cover	(31.67 %)Rainfed croplands (68.33 %) Mosaic cropland/ vegetation (grassland/ shrubland/forest)	(68.33 %) Mosaic cropland/ vegetation (grassland/ shrubland/forest) (31.67 %) Rainfed croplands
b- Mashegu	(66.67 %) Dominantly trees/woodlands/ shrubs with a subdominant grass component (33.33 %) Intensive (row crops, minor grazing) small Holder rainfed agriculture	(93.94 %) Dominantly trees/woodlands/ shrubs with a subdominant grass component (6.06 %) Riparian forest	(97.83 %) Open deciduous broadleaved tree cover (2.17 %) Closed-open deciduous shrub cover	(70.90 %) Mosaic grassland/ forest or shrubland (29.10 %) Open broadleaved deciduous forest/woodland	(70.90 %) Mosaic grassland/ forest or shrubland (29.10 %) Open broadleaved deciduous forest/woodland

c- Lapai	(81.13 %) Extensive (grazing, minor row crops) small holder rainfed agriculture (9.43 %) Dominantly trees/woodlands/ shrubs with a subdominant grass component (9.43 %) Riparian forest	(83.02 %) Dominantly trees/ woodlands/shrubs witha subdominant grass component (16.98 %) Intensive (row crops, minor grazing) small holder rainfed agriculture	(66.04 %) Open deciduous broadleaved tree cover (33.96 %) Closed-open, deciduous shrub cover	(57.87 %) Closed to open (broadleaved or needleleaved, evergreen or deciduous) shrubland (28.50 %) Open broadleaved deciduous forest/woodland (13.63 %) Mosaic cropland/ Vegetation (grassland/ shrubland/forest)	(46.90 %) Open broadleaved deciduous forest/woodland (39.47 %) Closed to open (broadleaved or needleleaved, evergreen or deciduous) shrubland (13.63 %) Mosaic cropland/ vegetation (grassland/ shrubland/forest)
d- Muya	(65.31 %) Dominantly trees/woodlands/ shrubs with a subdominant grass component (30.61 %) Extensive (grazing, minor row crops) small holder rainfed agriculture (4.08 %) Rock outcrop	(39.58 %) Dominantly trees/woodlands/ shrubs with a subdominant grass component (29. 17 %) Intensive (row crops, minor grazing) small holder rainfed agriculture (22.92 %) Extensive (grazing, minor row crops) small holder rainfed agriculture (4.17 %) Gullies (4.17 %) Rock outcrop	(38.46 %) Closed-open, deciduous shrub cover, (61.54 %) Mosaic: Cropland/ shrub and/or grass cover	(54.97 %) Closed to open (broadleaved or needleleaved, evergreen or deciduous) shrubland (22.81 %) Open broadleaved deciduous forest/ woodland (19. 28 %) Mosaic cropland/ vegetation (grassland/ shrubland/forest (1.36%) Mosaic forest or shrubland/grassland (0.98 %) Mosaic grassland/forest or shrubland	(52.44 %) Closed to open (broadleaved or needleleaved, evergreen or deciduous)shrubland (39.77 %) Mosaic cropland/ vegetation (grassland/ shrubland/forest (5.46 %) Open broadleaved deciduous forest/woodland (1.36%) Mosaic forest or shrubland/grassland (0.97%) Mosaic grassland/forest or shrubland

7.4. Discussion

Significant LULCC was revealed across the Guinea savannah region of Nigeria by this study. However, due to different spatial resolution in the LC datasets, assessment of the land use dynamics was done using global land cover data of 2000 and 2009 as described in section 4.8 (page 51). The distribution and size of the land cover classes in year 2000 and 2009 are summarized in table 31-33.

Table 31: Land cover types for GLC 2000 and GLC 2009 (Niger State)

Land use type	2000(%)	2009(%)
Grassland/pasture	43.22	0.80
Shrubland	35.58	32.34
Forest	16.74	14.89
Cropland	2.37	49.78
Built up	0.04	0.32
Waterbody	2.05	1.87

Table 32: Land cover types for GLC 2000 and GLC 2009 (Kwara State)

Land use type	2000(%)	2009(%)
Grassland/pasture	4.18	2.12
Shrubland	45.12	47.91
Forest	49.60	44.34
Cropland	0.54	5.20
Built up	0.16	0.19
Waterbody	0.40	0.24

Table 33: Land cover types for GLC 2000 and GLC 2009 (Kogi State)

Land use type	2000(%)	2009(%)
Grassland/pasture	0.33	6.43
Shrubland	22.49	46.06
Forest	73.21	40.49
Cropland	1.83	5.50
Built up	0.12	0.39
Waterbody	2.02	1.13

It is clear from the assessment that the most dominant land use type is cropland. Decline in the extent of grassland/pasture, shrubland and tremendous increase in the extent of cropland was observed in Niger state. Noticeabe is the decline in forest cover of about 30 % in Kogi state while there is an increase of about 23 % in shrubland. This results clearly indicate that land use transformation is occurring with the influence of anthropogenic activities. This comparative LULC study gives an insight to the extent of damage which human interference with the ecosystem have caused. Hence, further analysis on the extent of deforestation is imperative. The in-situ photographs presented below summarize the extent of damage through various anthropogenic activities as observe during field data collection.

Plate 1: Logging of wood
Source: Author’s field work, 2013

Plate 2: Uncontrolled livestock grazing
Source: Author's field work, 2013

Plate 3: Conversion of forest areas into agricultural land/bush burning
Source: Author’s field work, 2013

Plate 4: Irrigation system
Source: Author's field work, 2013

Plate 5: Extensive charcoal production and fuelwood collection
Source: Author's field work, 2013

7.5. Assessment of land use land cover change (LULCC) using Landsat imagery

Analysis of LULCC for specific areas of interest across the study region (Kogi, Kwara and Niger states) was performed using CLASlite as described in section 4.8. The aim of this analysis is to examine if the positive trends observed from the results of the trend analysis in section 5 and 6 can be described as increase in forest/woodlands or an increase in agricultural land (croplands). In order to understand the spatial pattern of this trend (i.e positive NDVI trend), analysis of LULCC in selected region of interest was performed using Landsat imagery of 1986/87, 2000/2001 and 2014 respectively.

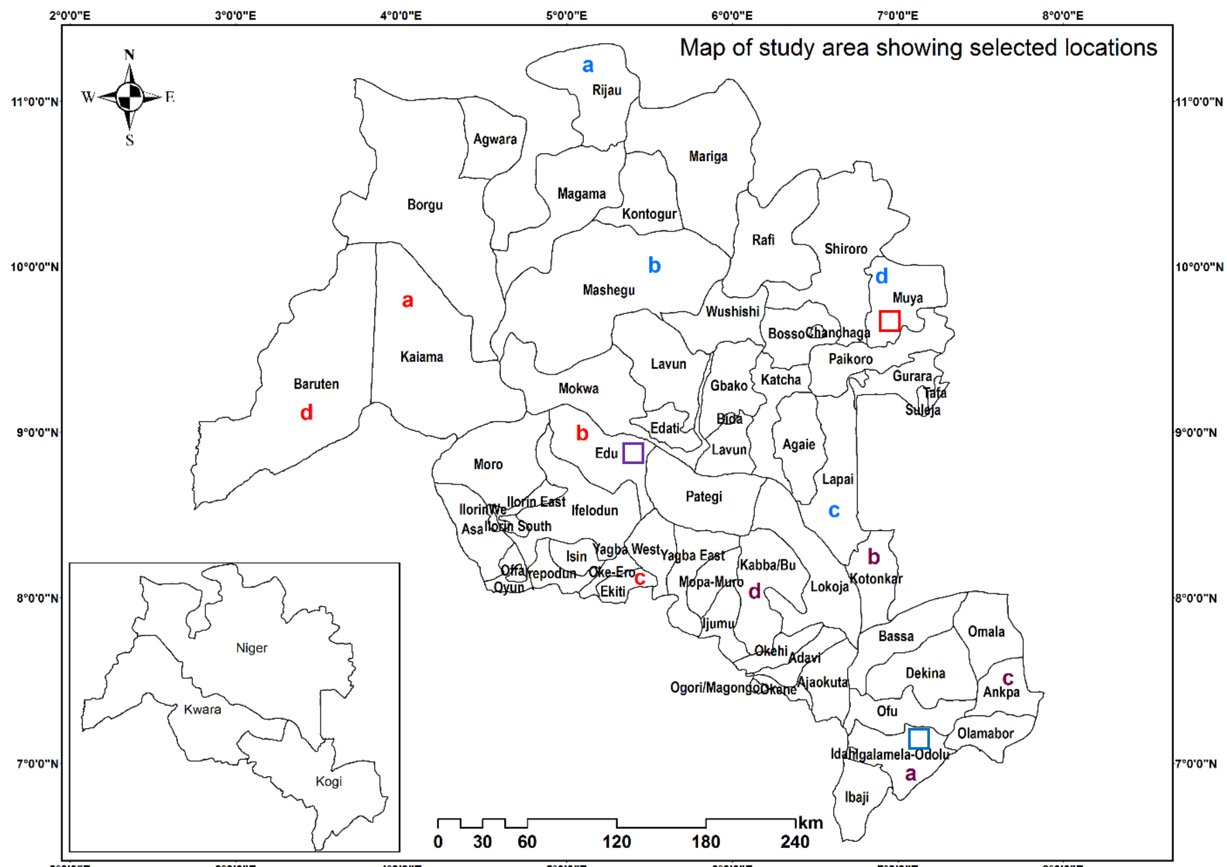


Figure 63. Areas in the study regions where the subsets of satellite imagery are taken (i.e the rectangle shape).

It should be noted that only one Landsat scene covering the area of interest was used in this analysis. After the analysis, subsets of area of interest (AOI) were used for discussion of the results as presented in figures 64-69.

Figure 64 shows the fractional cover image of Muya (Niger state) between 1986, 2001 and 2014.

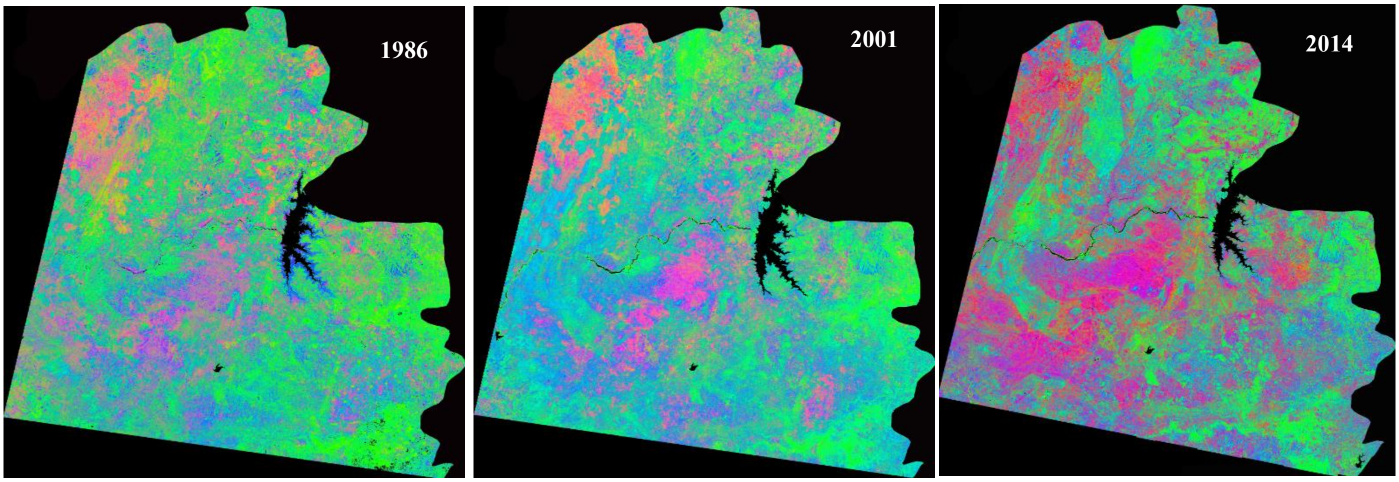
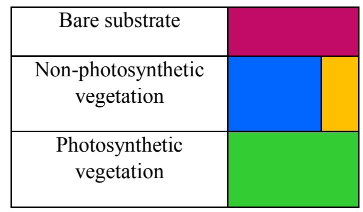


Figure 64: Fractional cover (FC) imagery of region of interest (Muya) in Niger state for three different years.



It is obvious from the analysis of the fractional cover data that there is tremendous land use land cover change over the three periods. Areas displayed as green are forest, reddish/pink color is referred to as bare surface while areas covered with blue/yellowish color are referred to as dried grassland, pasture/agricultural land. Visual observation of Fig 64 shows expansion of non-photosynthetic vegetation and bare substrate in 2001 and 2014 respectively. This change was verified during the field survey where majority of the forest cover was converted either to agricultural land or pasture (see section 8). The result of change detection between the Landsat imagery (1986, 2001, 2014) shows large scale deforestation which is a result of uncontrolled anthropogenic activities going on in the study area coupled with poor land use policy.

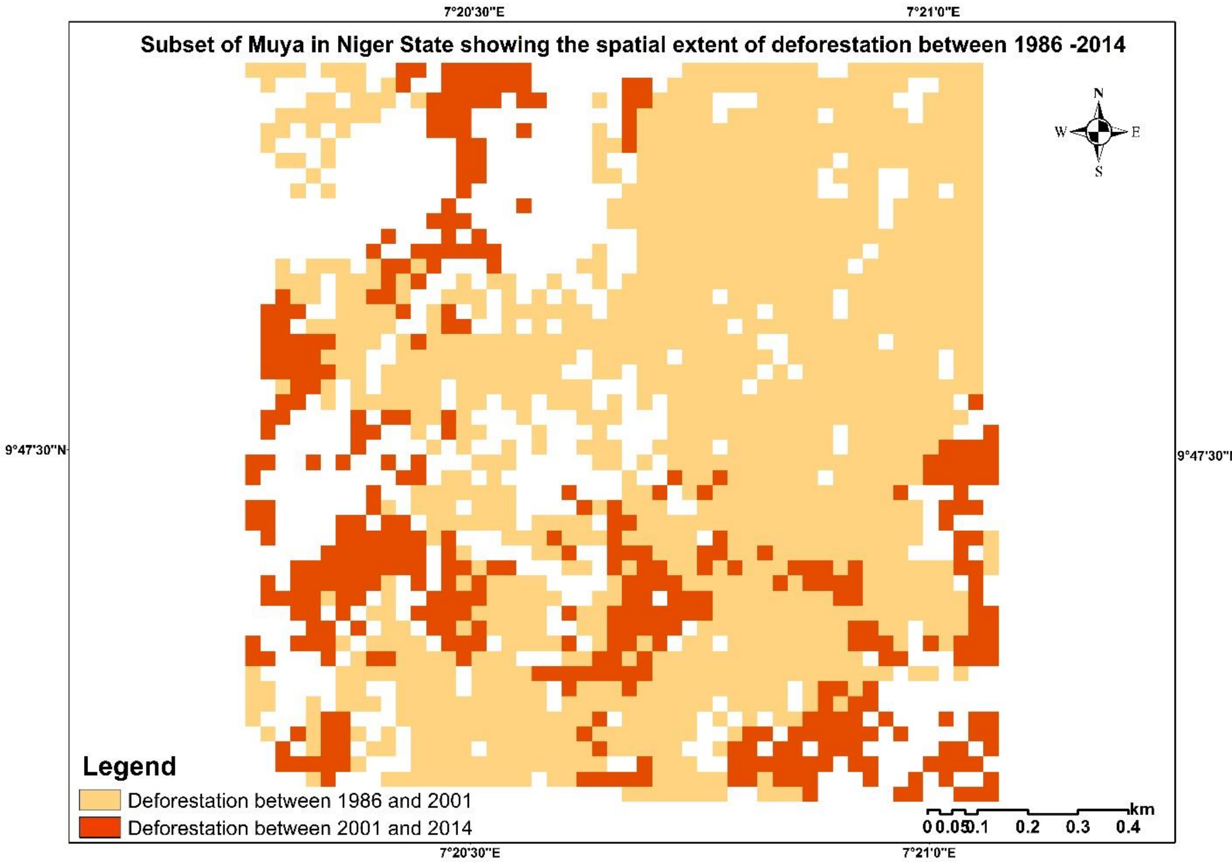


Figure 65: Subset of Muya showing the spatial extent of deforestation between 1986 -2014 (areas in white represent no change in forest cover while colored areas are deforested).

It can be seen from the result of the forest change detection that there has been removal of forest cover for other purpose. The total deforested area (forest cover loss) between 1986 and 2001 is 1.15 km^2 (area coverage) while an area of about 0.36 km^2 of forest cover loss was recorded between 2001 and 2014. The results of both fractional cover and forest change detection for the Landsat scene covering Igalamela and Edu in Kogi and Kwara state respectively are presented graphically in figures 66- 69. Subsets of the Landsat scenes were used for forest change detection analysis.

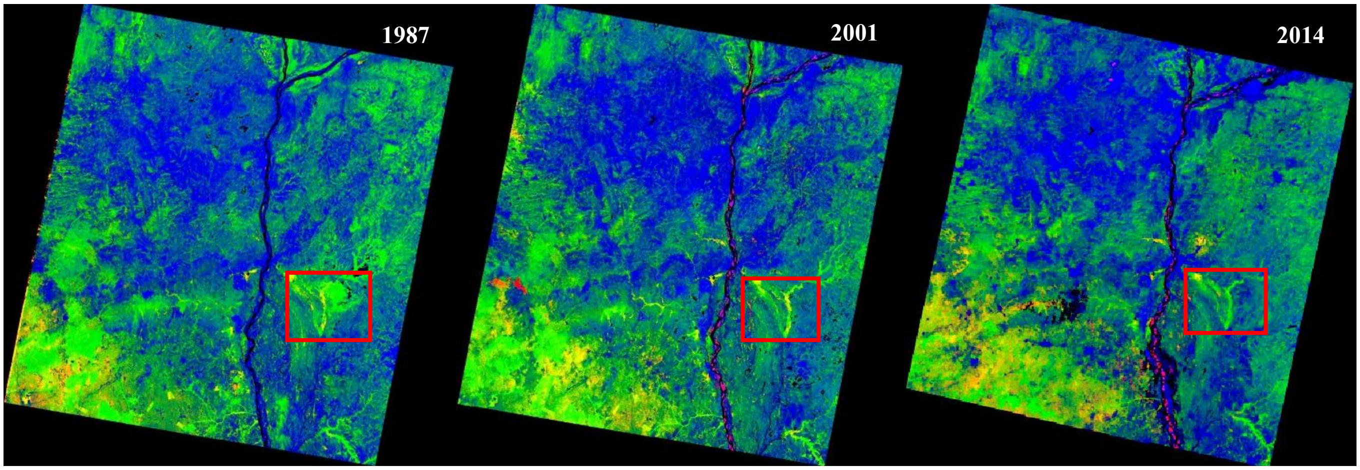


Figure 66: Fractional cover (FC) based on Landsat data covering Igalamela, Kogi State (red rectangle = aoi)

BS	
NPV	
PV	

Transition of forest cover to other land use types can be seen visually from the results of the three satellite imagery used in this analysis. Areas which are in black color are masked out (shadow, cloud and water bodies). Expansion in the extent of agricultural land (orange-yellow color) can be seen from the fractional cover of 2014 image when compared with that of 1987. This shows an increasing rate in the loss of woodlands (PV) to agricultural land (NPV) over the study period. The loss in woodland (forest cover) was further examined using subset from Igalamela to perform forest change detection as presented in figure 67. The red rectangle in figure 66 delineate the area where the subset used for the forest change detection was taken.

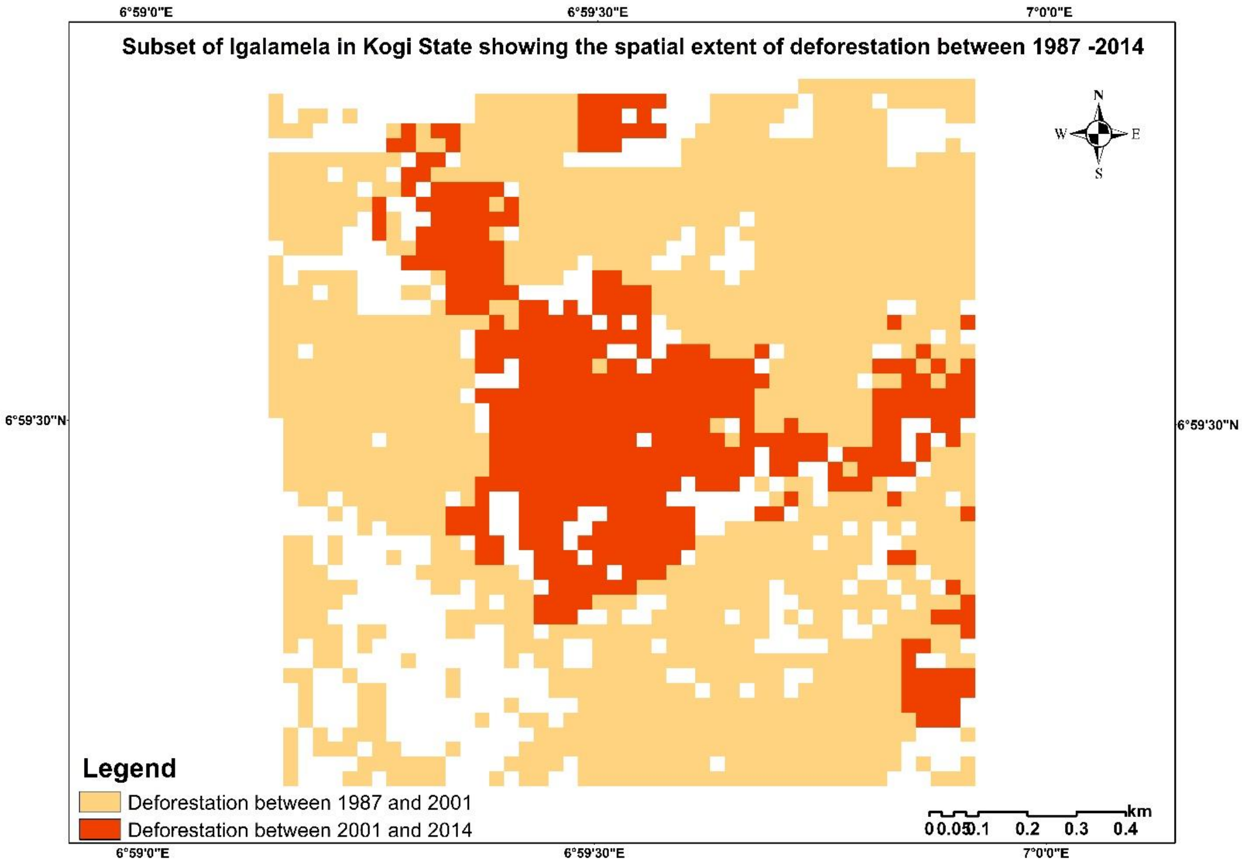


Figure 67: Subset of Igbalamela showing spatial extent of deforestation between 1986 -2014

Most of the forest cover loss (deforestation) occurred between 1987 and 2001 with an area extent of 1.17 km^2, while the total area deforested between 2001 and 2014 is about 0.41 km^2. Similarly, decrease in forest cover was observed in the subset of Edu (Kwara State) between 1986 and 2014.

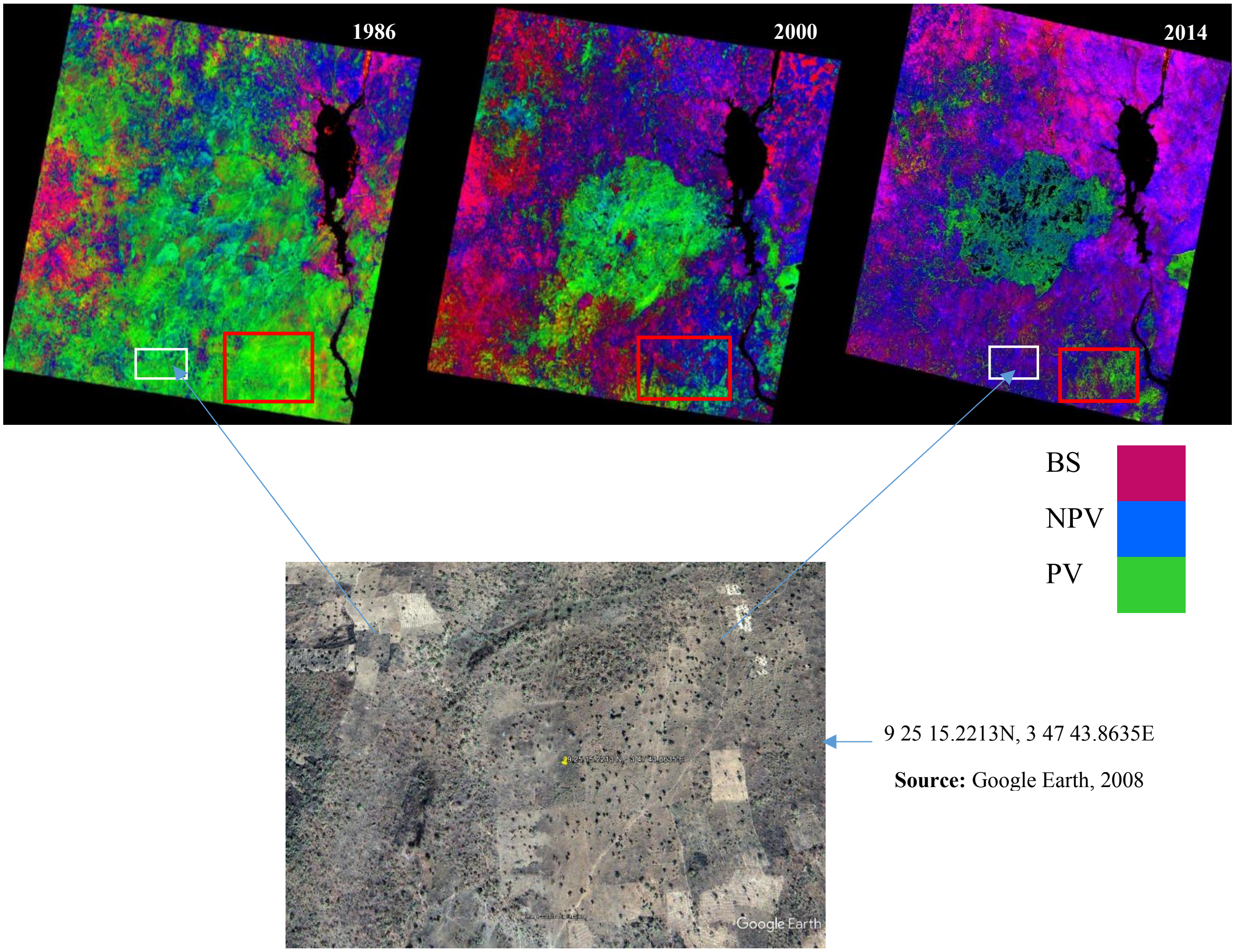


Figure 68: Fractional cover (FC) based on Landsat data covering Edu, Kwara State (red and white rectangle = aoi)

Change in land cover types was observed from the Landsat scene used for the fractional cover assessment in Kwara State. An increase in NPV and BS was observed between 2000 and 2014 which is closely associated to ongoing anthropogenic activities such as deforestation for agricultural practices over the study period. It can be clearly seen from the Google earth image of 2008 (the white rectangle in the fractional image) that most of the forest areas are converted into agricultural land with traces of bare surfaces. This is due to easy accessibility by the local people within forest zones as they move from one area to the other in order to search for fertile land for crop production. The result of the deforestation map (red rectangle) for the study area was presented in figure 69.

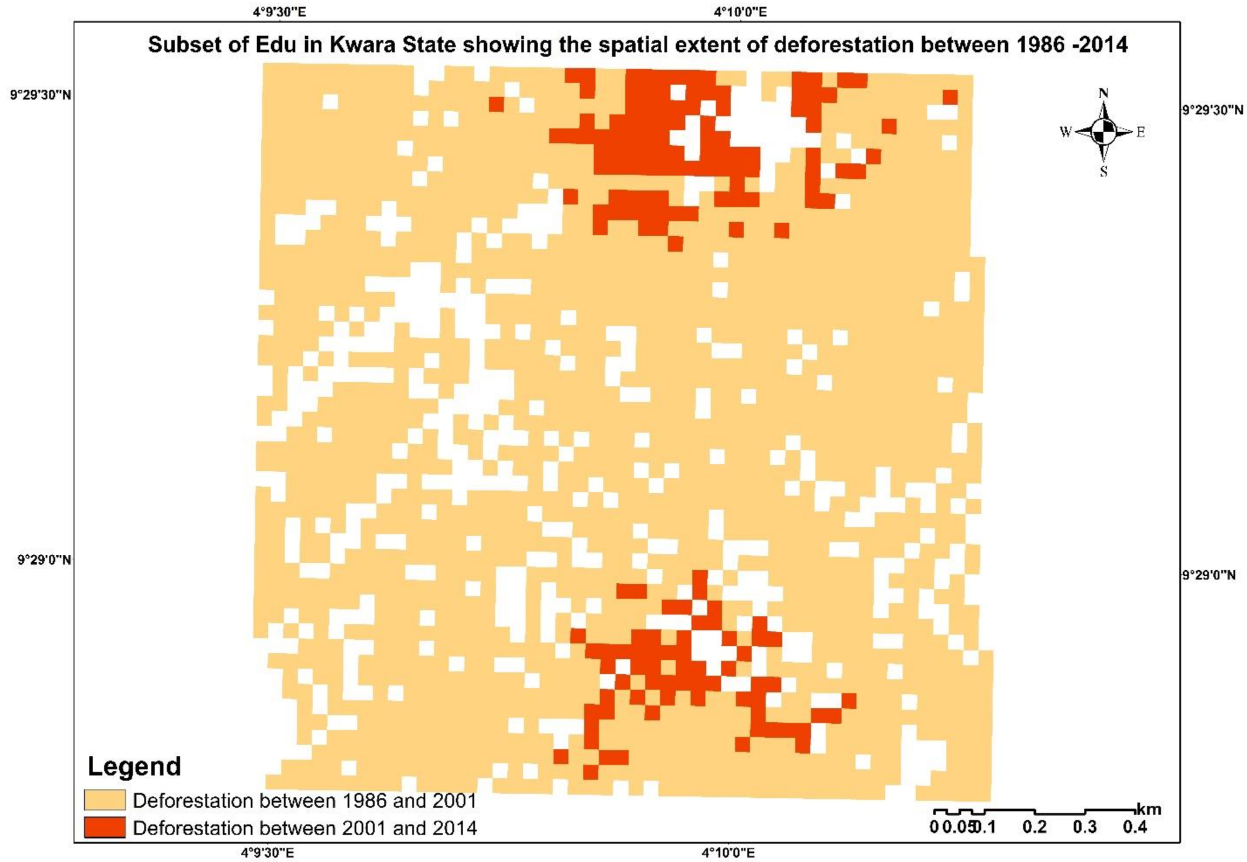


Figure 69: Subset of Edu showing spatial extent of deforestation between 1986 -2014

Total deforested area for the selected location in Edu (Kwara State) accounted for 1.52 km^2 between 1986—2001 and 0.15 km^2 in 2001 -2014 respectively. Visual interpretation of the results of the fractional cover and deforestation map of the three study areas shows the extent at which human-induced conversion of the land cover has impacted vegetal cover change over the last decades. The result of the analysis is in line with that of Haruna et al., (2014) where human activities such as farming led to deforestation across river Nanyuki catchment in Kenya.

8. Assessment of explanatory variables influencing vegetal-cover transition in the study area

8.1. Socio economics/demographic characteristics of respondents

This chapter is designed in order to determine drivers of vegetation change dynamics in the study region. Explanatory variables were obtained through the use of structured questionnaires and interviews to address issues related to the livelihood (socio-economic) of the rural people, land use mechanisms and drivers of vegetation change in order to get a better understanding of the results obtained from the analysis of remotely sensed imagery used in this research. For this analysis, the most important variables are used as it relates to both land use land cover change and vegetation change dynamics. For all the results, dash (-) represents no response from the respondents.

Table 34 show the frequencies and percentages of the socio-economic characteristics of the respondents in the study area. Result indicates that, the majority of the respondents in the study area are male (in Kogi state, male = 83 %, female = 17 %, in Kwara, male = 67 %, female = 25 % and in Niger state, male = 83 % and female = 17 %) with age range of 41-60 years. The family size in each study region (i.e Kogi, Kwara and Niger states) ranges between 6-11 persons. Increase in family size especially in the rural communities simply result to high dependency on the available natural resources for survival (i.e means of livelihood).

Plate 6: Discussion with key informants
Source: Author’s field work, 2013

Table 34: Age of respondents in the three states

Kogi State	Frequency	Percent
21-30	6	6.0
31-40	16	16.0
41-50	28	28.0
51-60	32	32.0
61-70	15	15.0
71-80	3	3.0
	100	**100**
Kwara	Frequency	Percent
21-30	6	6.5
31-40	5	16.3
41-50	32	34.8
51-60	29	31.5
61-70	9	9.8
71-80	1	1.1
	92	**100**
Niger	Frequency	Percent
21-30	4	4.0
31-40	13	13.0
41-50	39	39.0
51-60	31	31.0
61-70	13	13.0
	100	**100**

8.2. Respondents sources of Livelihood

Table 45 shows the respondent's means of livelihood. Farming (agricultural activities) constitute the highest percentage. This indicates that, the majority of the households is engaged in various forms of agricultural practices (see template 3 and 4 in page 128 & 129). Some of the respondents are also engaged in both farming and trading. This is peculiar to the lifestyle of the rural people as some of their agricultural products are sold locally in order to support their children's basic education. Some also engage in fishing activities and petty trading (cigarette, biscuits among others).

Table 35: Occupation of respondents

States	Occupation of respondents					
	Farming	Trading	Civil service	Artisanship	Others	Total
Kogi	71	8	10	2	9	100
Kwara	54	5	11	10	12	92
Niger	68	5	9	5	13	100

About 10-12% of the respondents work in the civil service. Apart from farming, some of the respondents are artisans (tailors, carpenters and cobblers) who do this job alongside their farming activities.

8.3. Land-use pattern

Table 36 shows the land use pattern in the study regions according to the respondents. It is evidenced from the result that the regions is experiencing continuous change in land use dynamics. This change is tremendous due to various contributing factors such as expansion of grazing land, increase in built-up areas and cultivation.

Table 36: Respondents view on land use change between 1976 till 2013

States	Is there changes in land use between 1976 till 2013?			Total
	-	Yes	No	
Kogi	-	96	4	100
Kwara	1	80	11	92
Niger	1	92	7	100

Noticeable change in land use pattern over the last 3 decades was confirmed by about 80-96 % of the respondents in the study regions. These change are described below.

Table 37: Changes in land use pattern by respondents

States	Description of change				Total
	-	Agriculture	Infrastructure	Agriculture/Infrastructure	
Kogi	4	58	13	25	100
Kwara	10	45	6	31	92
Niger	4	55	18	23	100

Table 37 above shows that agriculture is the major land use type in the 3 study region. Personal interviews with key informants during the field study revealed the conversion of forested/vegetated areas into roads and infrastructure by the government. A typical example of land use land cover change as described by one of the key informant in Lapai, (Niger state) is the large scale conversion of hectares of woodlands by Ibrahim Badamasi Babangida (former president of Nigeria) to university (Ibrahim Badamasi Babangida University). The key informant explained that the conversion lead to loss of endemic flora and disappearance of some wildlife in the region. It is no doubt that as population increases, more land are needed for crop production at the expense of woodlands in order to meet the demands of the growing population.

8.4. Effect of land use on soil

Soil erosion either by water or wind is a serious environmental problem affecting large areas of arable land in Nigeria. Human actions such as expansion of agricultural lands at the cost of forested areas, indiscriminate logging of wood, urbanization, climate change, drought, desertification and general misuse of land tend to exacerbate the impact of soil erosion on the environment (Okwu-Delunzu et al., 2015). Information obtained from the respondents shows that there is erosion problem in some parts of the study regions (table 38).

Table 38: Erosion types as reported by respondents

States	Type of Erosion				Total
	-	Wind erosion	Water erosion	Both	
Kogi	14	9	44	33	100
Kwara	26	2	39	25	92
Niger	17	6	33	44	100

In Niger state 33 % of the respondents mentioned that soil erosion is caused by water (run-off) during rainy season while 6 % reported that soil erosion is caused by wind, and 44 % of the respondent reported that soil erosion is caused by both factors and 17 % did not give any response. In Kogi state, 44 % of the respondents argued that soil erosion are cause by run-off, this is evident in the flooding that occurred in 2012, 9 % of the respondent reported that soil erosion are caused by wind, 33 % said erosion are caused by both wind and water, while 14 % of the respondent did provide any response. Similar results was recorded for Kwara state, 39 % of the respondent reported that soil erosion are caused by run-off, 2 % said it is caused by wind, 25 % reported that erosion are caused by both factors, while 26 % give no information about erosion.

8.5.Impact of land use on vegetation change dynamics

The existence of vegetation (forest, woodland, shrubland and grassland) was revealed by the information provided from respondents. About 90 % of the respondents in Kogi said there is presence of vegetation in the study locations, 83 % in Kwara and 89 % in Niger state respectively. However, 80 % of the respondents in Kogi reported that there is change in vegetation composition, 70 % of the respondents in Niger and 75 % of the respondents in Kwara State. These changes are said to be attributed to factors such as deforestation, grazing activities by nomads, cutting of trees for charcoal production and felling of trees for fuelwood and timber production.

Table 39: Change in vegetation composition

States	Change in vegetation composition?			Total
	-	Yes	No	
Kogi		80	20	100
Kwara	7	75	10	92
Niger	2	70	28	100

8.6. Agricultural production

Agriculture being the main source of income before the discovery of crude oil in Nigeria is widely practiced in the Guinea savannah region where this research was conducted. Osunmadewa et al., (2015 & 2016) pointed out in their studies that extensive agricultural activities are carried out across the Guinea savannah region of Nigeria. This was confirmed during the field observation. Two types of agricultural activities namely subsistence and commercial agriculture are carried out in the study region depending on the availability and fertility of the land. Farming activities sometimes extend throughout the year especially, irrigated agriculture. The information obtained from the respondents shows that the majority of the rural inhabitants are solely engaged in subsistence agriculture while the percentage of commercial agriculture is low.

Table 40: Type agricultural practices

States	What type of agriculture do you practice?			Total
	-	Subsistence agriculture	Commercial agriculture	
Kogi	0	82	18	100
Kwara	2	75	15	92
Niger	1	73	26	100

However, it should be noted that the type of agricultural practice depends solely on the existing land tenure system in the locality and the size of holdings which each individual owns. This is also depicted by the findings of this research.

Table 41: Method of land acquisition

States	How did you get the land?						Total
	-	Communal	Family	Free	Loan	Family/communal	
Kogi	0	20	57	3	1	19	100
Kwara	2	13	53	1	0	23	92
Niger	1	23	57	1	1	17	100

Most of the respondents acquired their land through family/inheritance while others through family/communal. About 85 % of the respondents in Niger state use the normal traditional way of slash and burn to prepare their lands before planting while 14 % uses mechanical method of land preparation. Figure 70 illustrates the size of land holdings as indicated by the respondents in the study region. 52 % of the respondents in Niger State own less than 5 acres, 38 % respondents own up to 10 acres while the remaining 10 % own more than 10 acres of land.

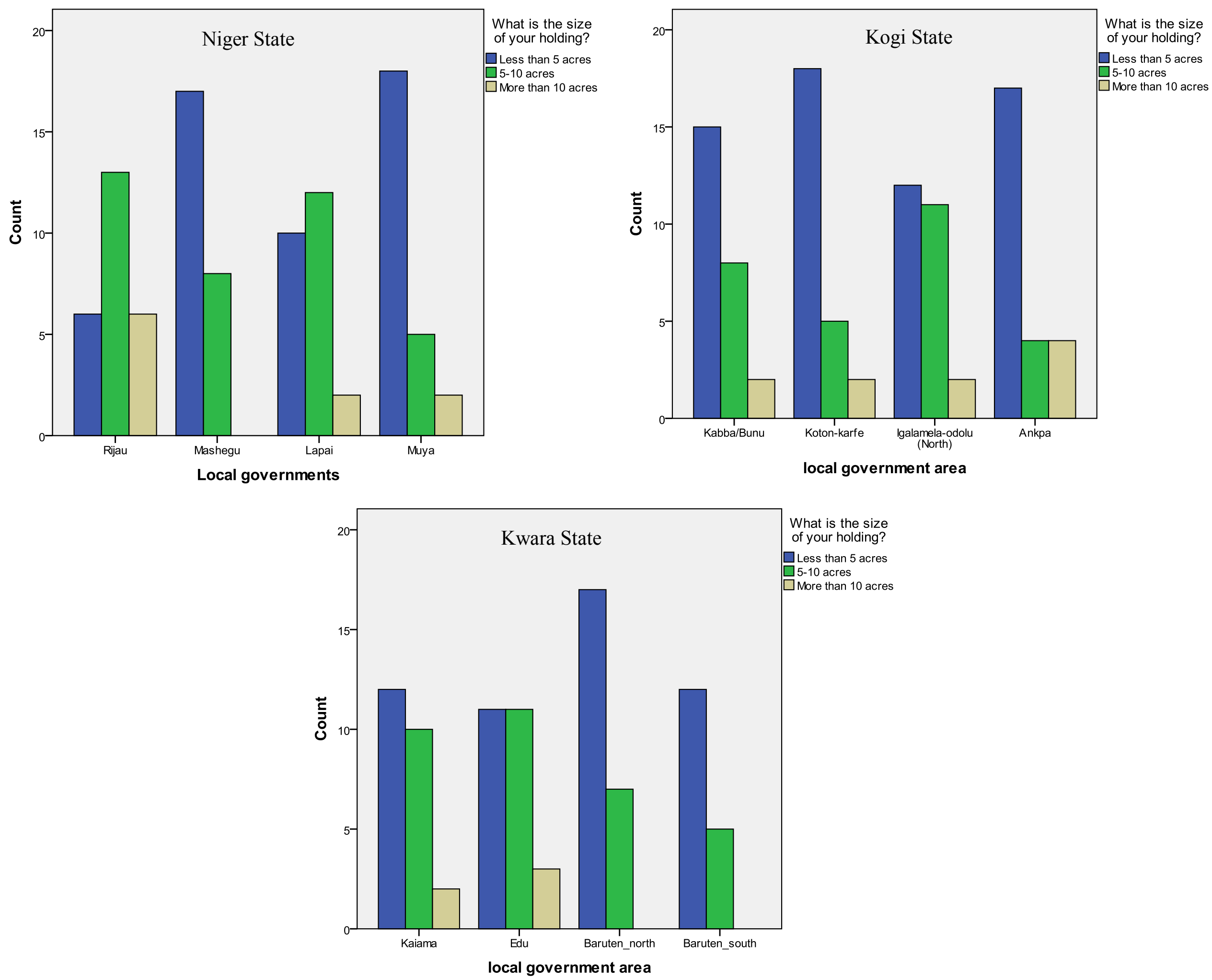


Figure 70. Size of holdings for each respondent in the study area

62 % of the respondents in Kogi State own less than 5 acres of land, 28 % have 5-10 acres of land while 10 % has more than 10 acres of land. The same was true for Kwara State where 52 % of the respondents own less than 5 acres of land, 33 % own between 5-10acres of land while 5 % own more than 10 acres of land. Several agricultural crops are being planted on these lands in order to meet household and market demand. Some of the agricultural crops include maize, rice, cassava, yam, legumes, millet, sorghum and in some areas, sugarcane. In order to improve agricultural productivity, some of the respondents use in-organic fertilizer which is purchased by established agricultural co-operative society which was set up by locals. 61 % of the interviewed persons use fertilizer in Niger, 63 % in Kogi and 74 % in Kwara State respectively. The respondents explained that they use fertilizer due to decline in soil fertility and lack of capital (money) to purchase genetically modified seeds. Majority of the respondents sells some of their products to earn living

and send their children to school while the vast majority observes little or no fallow period. Information obtained during the field work shows that some of the respondents have small scale irrigation farms. About 70 % of the respondents in Niger own irrigation plots, this is evidenced in Chancanga where some of the people grow maize and vegetables such as okro, green leaves (for example spinach (*Spinancia oleracea*), bitter leaf (*Vernonia amygdalina*) and tomatoes throughout the year. In Kogi state, 63 % of the respondents have small irrigated farms, this was observed in Lokoja and Kabba bunu area while in Kwara state 43 % of the respondents have irrigation farms. However, the word "fadama" is used in the study area meaning seasonally floodplains along major savannah rivers or depression on the adjacent low terrace. The results of this analysis is in line with that of Ohikere and Ejeh, (2012) where it is also highlighted that irrigation farming contributes immensely to the livelihood of the rural people in this region.

8.7. Livestock production

Livestock farming is one of the important sectors which contribute to the rural economy in the study regions. Many of the respondents sell their livestock including milk products to neighboring regions. Different types of animals are kept by the locals. Examples of the animals (livestock) identified during the field study include cattle, sheep, goats and poultry. Each household raises a number of about 1-20 livestock's. The majority of the respondents mentioned that they depend solely on the vegetation and natural pasture around the village for feeding their animal (livestock) both in dry and wet season.

8.8. Discussion

The results obtained from the field data collection was used in this study as explanatory variable for the greening trends which were observed across the Guinea savannah region of Nigeria between 1983 through 2011. Tremendous change in vegetation cover (vegetation physiognomy) was revealed by the information obtained from the people's perception during data collection. Some of these changes are result of human conversion of the land cover for various use such as illegal felling of tree for timber, unregulated grazing system, charcoal production and expansion of croplands. The rate of deforestation as observed by this study is between moderate and high. The rate of deforestation in Niger State is between 38 % (moderate) and 46 % (high), it ranges between 30% and 61 % in Kogi, while it is between 29 % and 47 % in Kwara State respectively. The results on deforestation can also be linked to charcoal production in the study area. 76 % of the respondents in Niger state confirm the disappearance of the tree species used for charcoal production in the state and that the disappearance is at a faster rate. Similar results were also obtained in Kogi and Kwara state (58 % and 74 %) respectively. It should be noted that increasing livestock population has negative impact on vegetation index, as increase in grazing area is directly proportional to the increase in large ruminant animals. This is also true for charcoal production and cutting down of trees for various purposes such as illegal logging activities by sawmills and for fuelwood. It is no gain saying that as population increases, struggle for better livelihood increases as well. This was confirmed by the result of the factors responsible for decline in vegetation in the study area. Table 42 shows the results of factors responsible for vegetation change dynamics in the study area as mentioned by the respondents.

Table 42: Indicators of vegetation decline

States	**Indicators of decline in vegetation**									
	-	OC/U	OC/OG & CT	OC/ SLM	OG & CT/SLM	OC	U	OG & CT	SLM	Total
Kogi	4	23	17	4	0	33	9	7	3	100
Kwara	4	15	31	6	2	18	10	0	6	92
Niger	2	30	13	2	1	35	8	7	2	100

OC = Over cultivation/Urbanization; OC/OG & CT = Over cultivation/Over-grazing and cutting of trees; OC/SLM = Over cultivation/Shift in livelihood Mechanism; OG & CT/SLM = Over-grazing and cutting of tree/Shift in livelihood mechanism; OC = Over cultivation; U = Urbanization; OG & CT = Over grazing and cutting of trees; SLM = Shift in livelihood mechanism.

Table 42 describes factors responsible for vegetation loss in the study area. Some of these factors have negative impact on biomass productivity, for example urbanization and cutting of trees while expansion of agricultural areas has influence on vegetation greenness as observed from the result of the trend analysis (NDVI). Vegetation greenness has a strong correlation with moisture content availability in the soil which is true for some part of the study area where irrigated agriculture is practiced (Osunmadewa et al., 2015). The results obtained from the qualitative analysis (i.e socio-economic data) confirm the observed trends in the analysis of NDVI data where both positive and negative trends are detected. It should be noted that areas with negative NDVI trend are totally degraded due to mining activities as shown in plate 7. It is no doubt that there is vegetation cover transition as mentioned by some of the key informants, but due to the conversion of land cover to other land use, most of the endemic tree species are either lost or replaced by shrubs, grass or cropland. Though, scientists around the world have noticed increase in biomass productivity (both at global and regional scale) which is termed *"greening trend",* however, by combining the results from remotely sensed data and socio-science (through questionnaires and interviews with farmers and local inhabitants), this study confirm that increase in vegetation (biomass) productivity *"greening trend"* across the Guinea savannah region of Nigeria is a result of land use land cover change as more and more woodlands are lost to other land use types. Although, the study regions enjoy favorable weather condition (rainfall), other anthropogenic factors play a significant role in the greening phenomenon. However, a more detailed research on population growth and its impact on vegetation productivity is necessary in the future.

Plate 7: Illegal mining activities in Lapai, Niger State

Source: Author’s field work, 2013

9. Result Synthesis

Long term monitoring of vegetation change dynamics using time series of Normalized Difference Vegetation Index (NDVI) from medium (Moderate Resolution Imaging Spectroradiometer) to coarse (Advance Very High Resolution Radiometer) spatial resolution satellite sensors provides an opportunity for quantitative analysis and modeling of environmental parameter/ecosystem functioning both on global and regional scale. Therefore, monitoring vegetation inconstancy in the Guinea savannah region of Nigeria is imperative in order to understand vegetation-climate-human induced change over the last decades. For this reason, four research questions were used and the results are summarized below.

1. *Can vegetation change dynamics be explained by climatic parameters? Is there any relationship between vegetation productivity and climatic drivers?*

Spatial and temporal monitoring of vegetation change dynamics and their inter-relationship with climatic parameters (rainfall and temperature) are very important for better understanding of human-climate induced vegetation change over a long period of time. In order to monitor vegetation change and its relation to climatic variability in the Guinea savannah region of Nigeria quantitatively, time series data of NDVI3g, rainfall and temperature were used (section 4.4-4.5). It can be stated that increase in vegetation trend across the study area (Niger, Kwara and Kogi State) correlates positively with rainfall while negative correlation exist between NDVI and temperature (section 5, table 24-55).The spatial regression between NDVI and rainfall across Niger state shows higher coefficient of determination (R^2) (Fig. 71), which indicates that increase in vegetation trend in the study area as described in section 5 is associated with favorable climatic driver (i.e rainfall). Similar results were observed for Kogi and Kwara states respectively. The results of this research are comparable to those of other studies where strong correlation between NDVI and rainfall was detected (Anyamba et al., 2014; Dardel et al., 2014; Fensholt et al., 2012).Some studies also revealed that greening trend is a result of increase in rainfall after the severe drought of the 1980’s and 1990’s (Herrmann et al., 2014; Lebel and Ali, 2009). However, change in land use land cover due to anthropogenic activities might also contribute to increase in biomass productivity as mentioned by Osunmadewa et al., (2015).

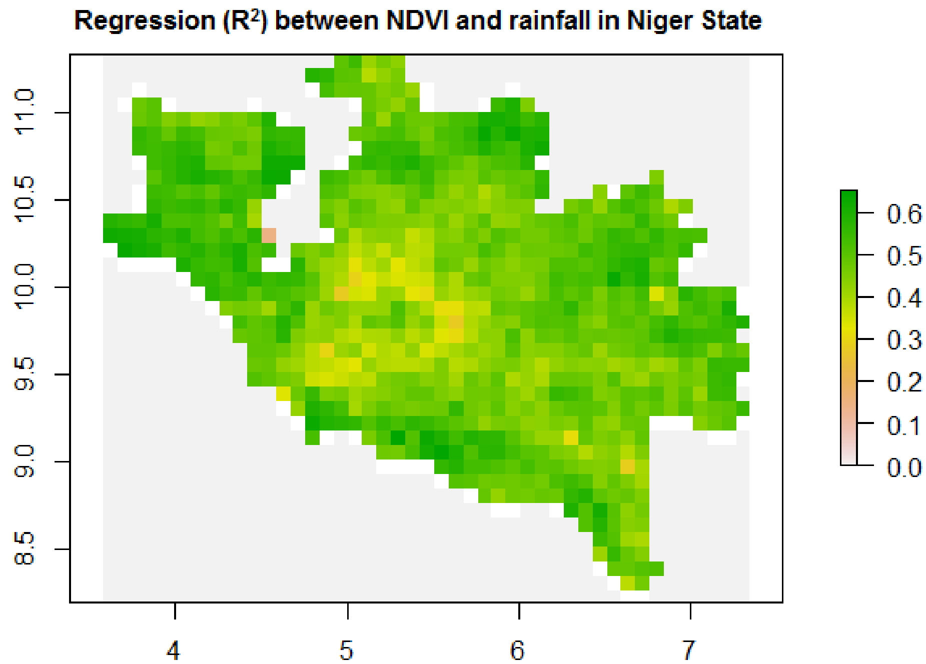


Figure 71. Regression (R2) between NDVI and rainfall over Niger state (see appendix for the graphical representation of Kogi and Kwara States)

2. *Can a seasonal vegetation trend be detected by remote sensing data?*

To address this question, seasonal trend analysis was performed on the monthly NDVI3g datasets (1983-2011) for the three study areas (Niger, Kogi and Kwara) using harmonic regression method. Assessment of phenological trend according to Reed et al (1999) was used to determine the start of season (onset), end of season (EOS) as presented in tables 27-29. Analysis of the seasonal NDVI curves for the different land cover types shows a consistent shift in the timing of annual peak of vegetation greenness to the latter period (2011). Phenological shift in the length of growing season (LGS) was observed. An increase of about 2 weeks in the selected locations was confirmed by the results, thus the LGS is later in 2011 as compared to 1983. In order to detect the phenological change, the SOS was adjusted to 40% as described in section 4.7.3. Positive trend was also revealed by the result of the harmonic regression (amplitude 0) which is attributed to the spatial pattern of rainfall in the study area.

3. *What is the impact of land use land cover change on vegetation trend/Can change in vegetation dynamics be influenced by land use pattern?*

In order to identify the extent of human influence on vegetation change dynamics over the study area, an assessment of land use land cover change was done. Land use and land cover are distinct and closely linked. The typical land use categories to which land is transformed is mainly agriculture or grazing land while land cover classes are forest, cropland, pasture or grassland. For this study, land use land cover change is used as indicator for the observed trends as derived from the results of the NDVI time series analysis. Most of the natural forest has been lost to farming activities or logging as presented in figure 72 (i.e the area in red rectangle). Similar land use land cover transition was observe in Kogi and Kwara states.

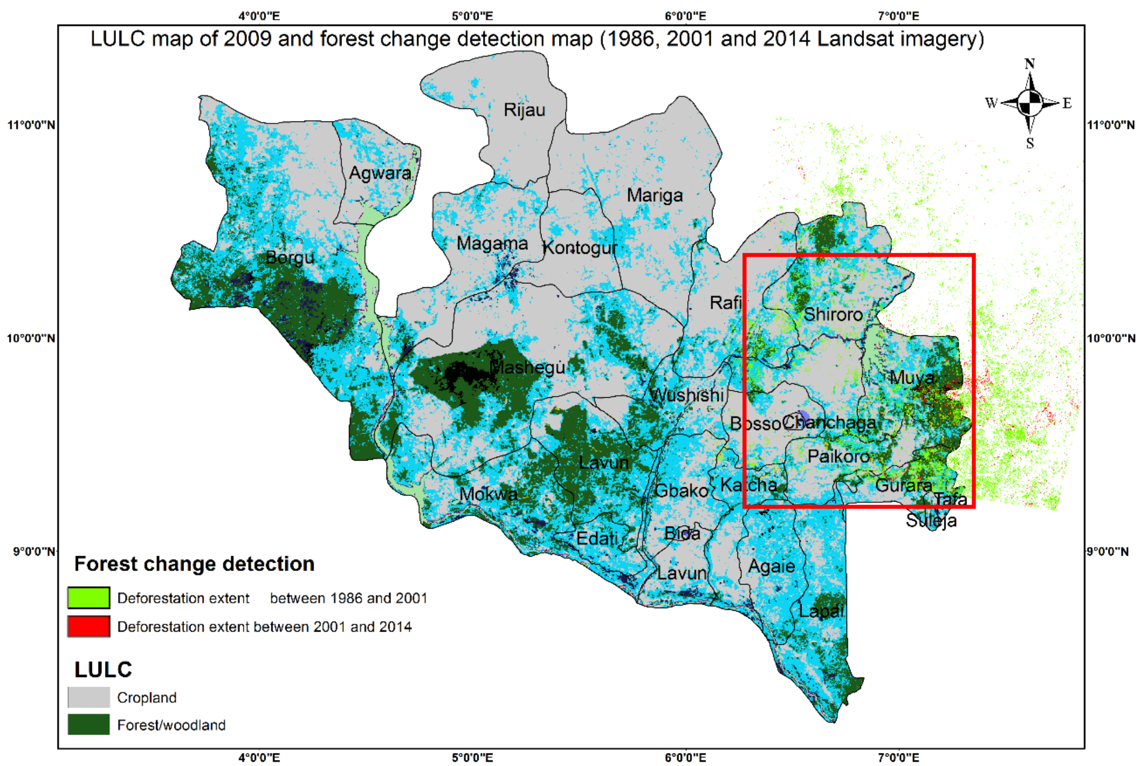


Figure 72. Overlay of land cover data derived from MERIS sensor (300m spatial resolution) and landsat imagery (30m spatial resolution) for selected region of interest in Niger state (the blue and black colors are shrub and grassland). It should be noted that the forest change detection was performed with one Landsat scene which falls within the red rectangle in figure 72 above.

However, greening trends in the Guinea savannah region of Nigeria must be handled with care as some areas with NDVI value between 0.28-0.52 are associated with agricultural land as presented in figure 73. Visual observation (comparison) of figure 73 and 74 show that there is expansion of agricultural zones (cropland) to forest/woodland zone which can be referred to as deforestation.

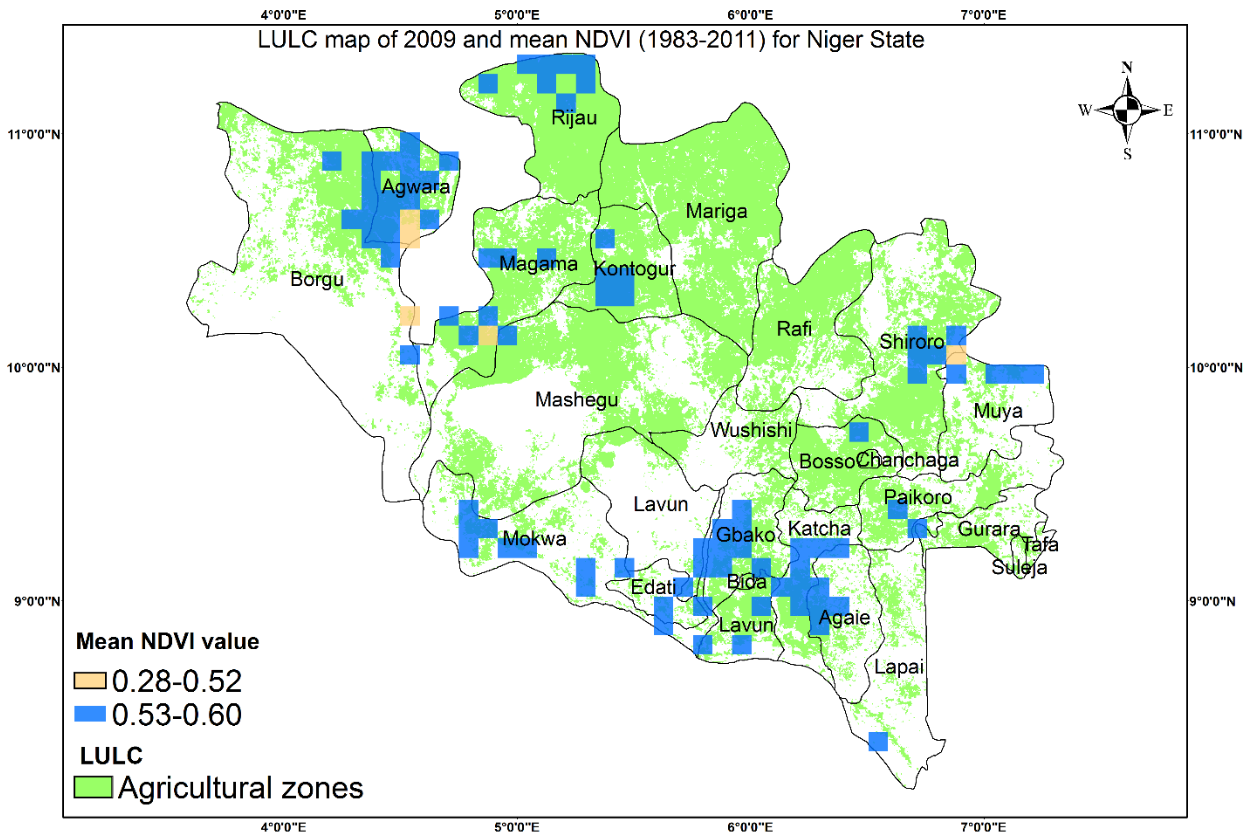


Figure 73. Overlay of land cover data derived from MERIS sensor (300m spatial resolution) and NDVI data (8km spatial resolution) for agricultural zones

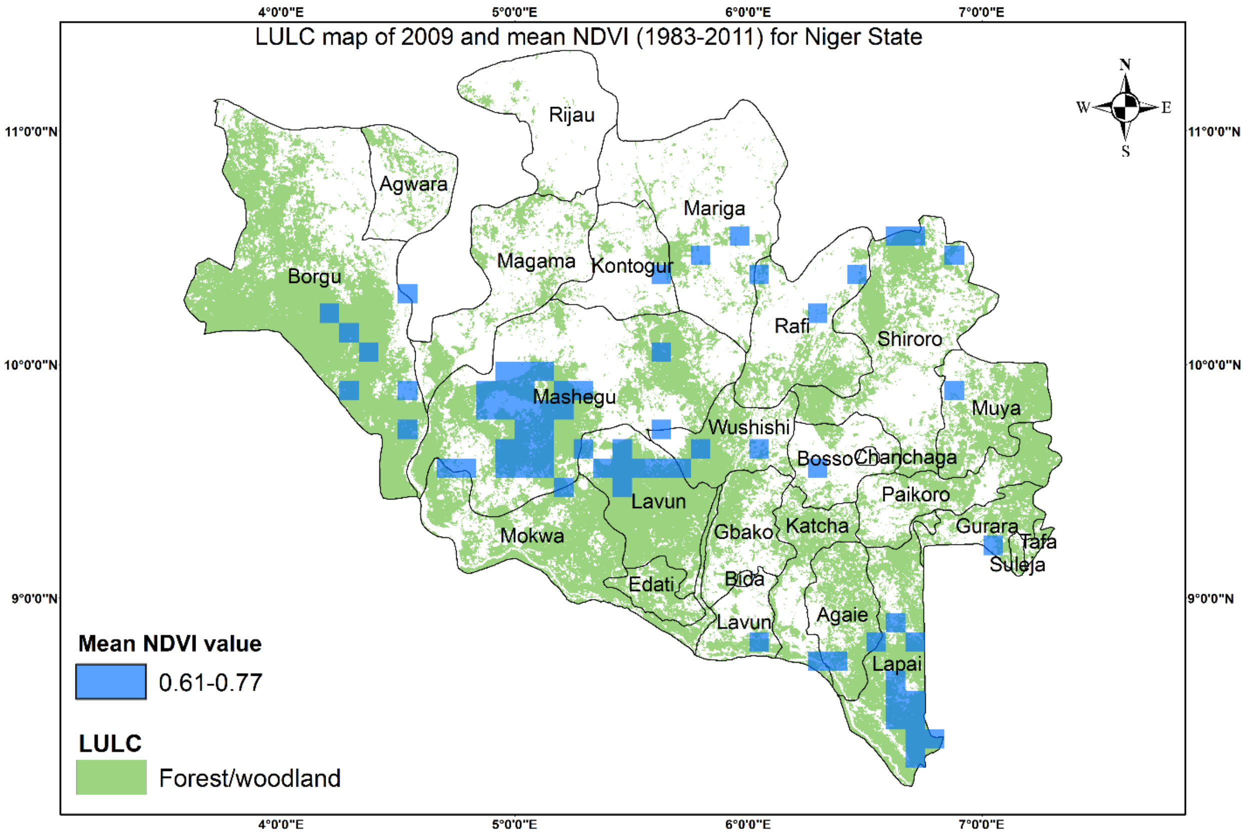


Figure 74. Overlay of land cover data derived from MERIS sensor (300m spatial resolution) and NDVI data (8km spatial resolution) for woodland (forest and shrublands are merged as woodland)

4. What is the impact of socio-economic activities on vegetation change dynamics?

One of the objectives of this study is to examine the linkage between remotely sensed data and social science which is sometimes referred to as socializing the pixel (Herrmann et al., 2014; Rindfuss and Stern, 1998). In order to understand the underlining factors and/or drivers of land use land cover change, deforestation, vegetation productivity (greening), urban development and agricultural expansion from remote sensing data, social science information (for example: demography and livelihood) in the form of questionnaires and personal interviews (qualitative analysis) are imperative. Increased anthropogenic activities, especially the conversion of semi-natural ecosystems (forest) into agricultural land has greatly influenced vegetation physiognomics in the study area. In order to elicit the greening trends as observed from NDVI and the perception of the respondents in the study area, important questions were analyzed (section 8). Demographically, population growth in the study area is exponential in nature (ABS, 2010), it increased from 2,421,581 in 1991 to 3,954,772 in 2006 (Niger state), 2,147,756 in 1991 to 3,314,043 in 2006 (Kogi state) and 1,548,412 in 1991 to 2,365,353 in 2006 (Kwara state) which simply means increase in the number of households. The means of sustenance (livelihood) for the vast majority in the sampled area is farming (subsistence and commercial). Many of the respondents reported that "they move from one location to the other" in search of fertile land for cultivation. Increase in the numbers of livestock (cattle, sheep and goat) is perceived by the respondents as one of the contributing factors to vegetation change. Cattle can browse on trees and cause damage due to their body mass while other small ruminants feed on regenerated tree species, shrubs and grass thereby causing vegetation degradation. In order to corroborate the results of Landsat analysis (remotely sensed data) on deforestation, the respondent's perception on the rate of deforestation was reviewed. Cutting of trees for fuelwood, charcoal production and timber logging are among some of the factors which exacerbate loss of endemic tree species in the study area. Some of the economic tree species of high preference for charcoal production are: Igi Emi (Shear butter) *Butyrospermum parkii,* Igi Asapa (*Burkea africana*), Igi igba (locust bean) *Parkia biglobosa,* Igi ayin (*Anogeissus leiocarpus*), Igi cassia (*Cassia spp*), Igi Iya (*Daniella oliveria*), Iga iyeye (*Spondia monbin*), Igi Bomubomu (*Calotropis procera*), Igi Ameran babo (*Hippocratea palleus*), Igi Idofun (*Parinari curatellifolia*), Igi idi (*Terminalia spp*). The respondents mentioned that these tree species have decreased in number while some are lost completely due to lack of regeneration. Shift in land use land cover over Niger state was observed between 2000 and 2009 (Osunmadewa et al., 2016). Change in land use land cover is true for the Guinea savannah region where most of the woodlands are being replaced by shrubs, grasses and agricultural land. Hence, change in vegetation dynamics as observed in the study areas can be linked to the socio-economic conditions of the respondents as most of the woodlands are being converted into agricultural and grazing land. This shows that there is strong interaction between human-vegetation changes in the study regions.

9.1. Conclusion

Long-term monitoring of vegetation change dynamics across the Guinea savannah region of Nigeria over the period of 29 years (1983-2011) was done using NDVI3g data from Advanced Very High Resolution Radiometer (AVHRR) sensor and Moderate Resolution Imaging Spectroradiometer (MODIS), TAMSAT rainfall and CRU temperature, global land cover data from European Space Agency (ESA), national land cover data from FORMECU, Landsat imagery and socio-economic data. Significant change in the spatiotemporal trend pattern of NDVI and climate variables (rainfall and temperature) was revealed by this research. The magnitude and direction of trend in NDVI, rainfall and temperature were examined separately, while the association (correlation) between NDVI and climate variables was analyzed subsequently in order to examine the degree of correlation. An increase in NDVI trend and climate variables over time was observe for the whole study area. In-depth analysis of selected locations using different trend estimators (Linear modelling, Theil-Sen trend estimator and non-parametric Mann Kendall test) shows increase in NDVI trend which means greening trend over time. The Pearson correlation coefficient between NDVI and rainfall at regional scale (Guinea Savannah Region) shows positive correlation (62-75%) for the selected locations while significant negative correlation exists between NDVI and temperature. The spatial regression between NDVI and rainfall also reveal that increase in rainfall quantity has positive influence on vegetation productivity, which is true for all the study areas. The research also provides information on vegetation phenology using harmonic regression analysis. Increase in the magnitude of mean annual NDVI for each year and length of growing season was observed in 2011 compared to 1983, while variation in the start of growing season (SOS) and end of growing season (EOS) was observed in all the study locations, following similar patterns of rainfall. In order to understand the underlying driver responsible for vegetation change phenomenon in the Guinea savannah region of Nigeria, the national land cover map coupled with global land cover map and land use land cover classification based on Landsat imagery were used. It is evident from this assessment that the vegetation cover of the study region has not remained unchanged. Areas classified as wooded savannah (woodland) have been transformed to agricultural land. This has caused significant decline in the spatial distribution of woodland over the last decades. Shift in land use classes was also revealed by this study which is attributed to the expansion of agricultural land at the expense of woodland. As observed from the correlation analysis between NDVI and rainfall, vegetation change dynamics can be attributed to human perturbation. This was revealed by the analysis of the inter-linkage between socioeconomic data and remotely sensed data. It is evident that as population increases, an increasing dependency on the resources of the environment in order to meet the demands of the ever growing population occurs. Some of the changes observed in the LULC can also be attributed to migration (Babalola, 2016). This study shows that there is a link between socioeconomic variables and land use land cover change (LULCC). Some of the areas with high photosynthetic vegetation (forest) in 1986 are lost in 2014 (deforestation) (section 7.4) due to various purposes such as indiscriminate and illegal logging of wood for timber, charcoal production, fuelwood, expansion of agricultural land, uncontrolled grazing system (over grazing) among other drivers (government project such as road construction) of land cover/vegetation degradation in the study region.

9.2. Limitation of the study

Several challenges were faced during the course of this study thus bringing about some limitations as listed below:

1. Acquisition of Landsat imagery covering the whole study area was difficult due to cloud cover and data availability. Scan Line Corrector (SLC) failure is also a limiting factor. Although gap-filling was performed, further preprocessing of the Landsat imagery (for example Landsat imagery of 2013) shows that some vital information is missing.

2. Land use land cover classification with high spatial resolution imagery such as IKONOS, Worldview or Quickbird would assist in identification of areas where increased anthropogenic activities have led to large scale deforestation.

3. Break points in the seasonal and trend component of vegetation time series are not analyzed in this study. However, application of linear and segmented linear trend detection for vegetation cover using GIMMS Normalized Difference Vegetation Index data in semiarid regions of Nigeria allows for the extraction of respective information (Osunmadewa et al., 2015).

9.3. Recommendation

1. Incorporation of breakpoints detection in NDVI with land use land cover change analysis is necessary in order to know when and where abrupt vegetation change has occurred over the year as vegetation change might also be attributed to natural phenomena such as fire or diseases.

2. Since the most recent national land cover map dates from 1976 to 1995, there is urgent need for accurate and up to date land-cover mapping of the entire country.

3. As deforestation is continuing in alarming rate, there is an urgent need for the development of effective agricultural policies which will help in ecosystem management not only in the Guinea savannah region, but in the entire country.

4. As desertification is believed to be moving southward in Nigeria, there is an urgent need for early warning on the danger associated with desertification especially where more and more forested area is exposed to wind erosion.

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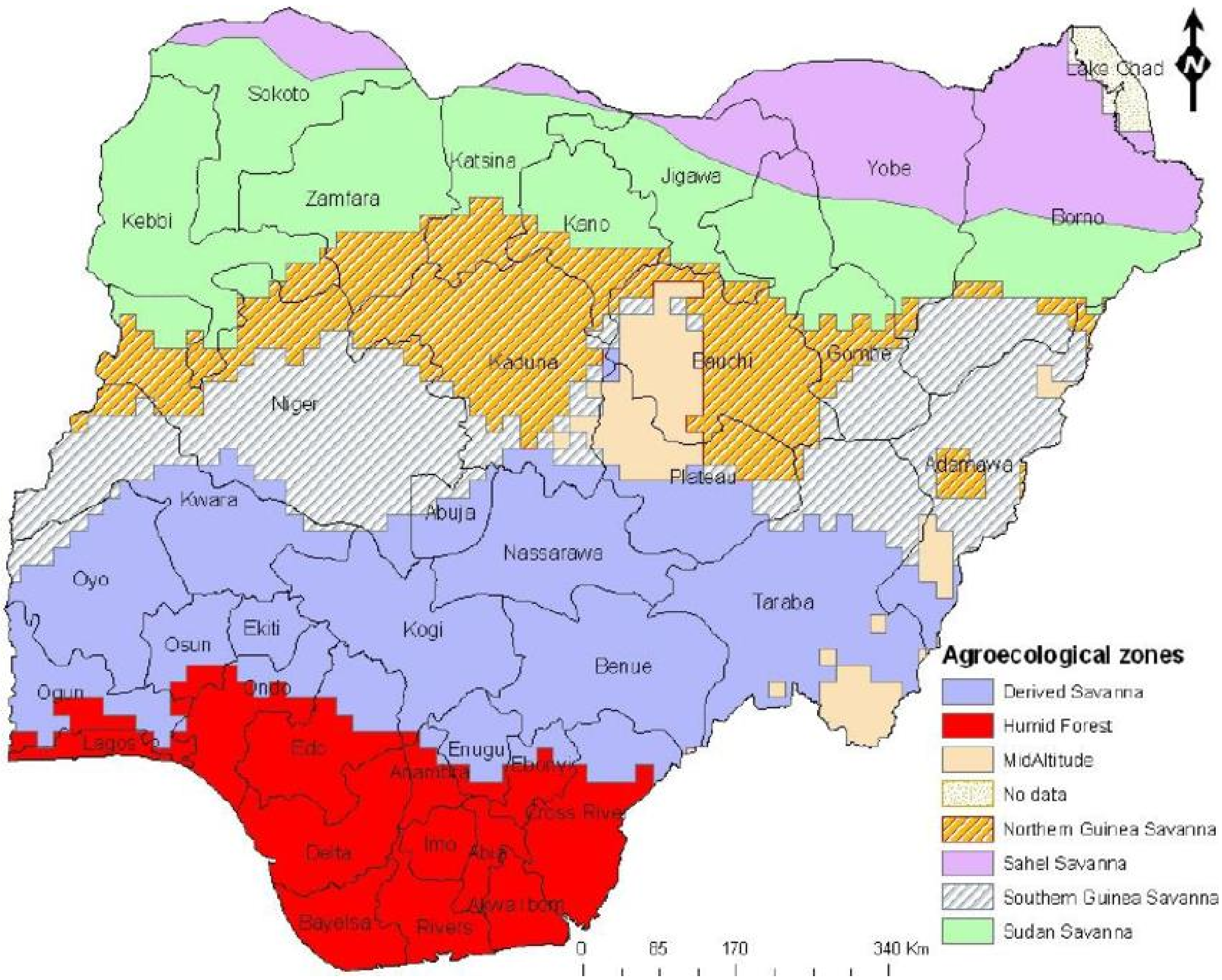
Appendixes

Chapter 3: Agro-ecological map of Nigeria

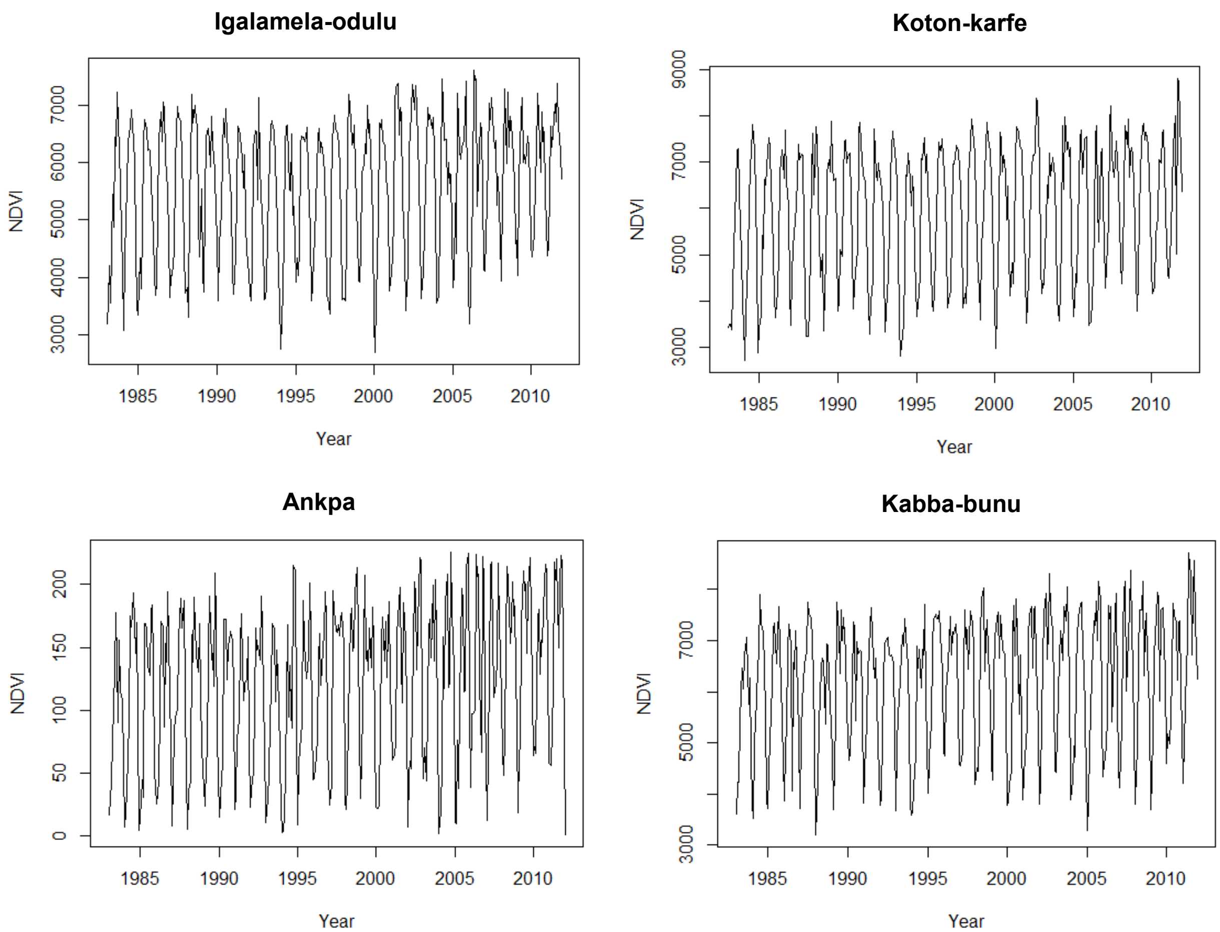


Source: International Institute of Tropical Agriculture (IITA)

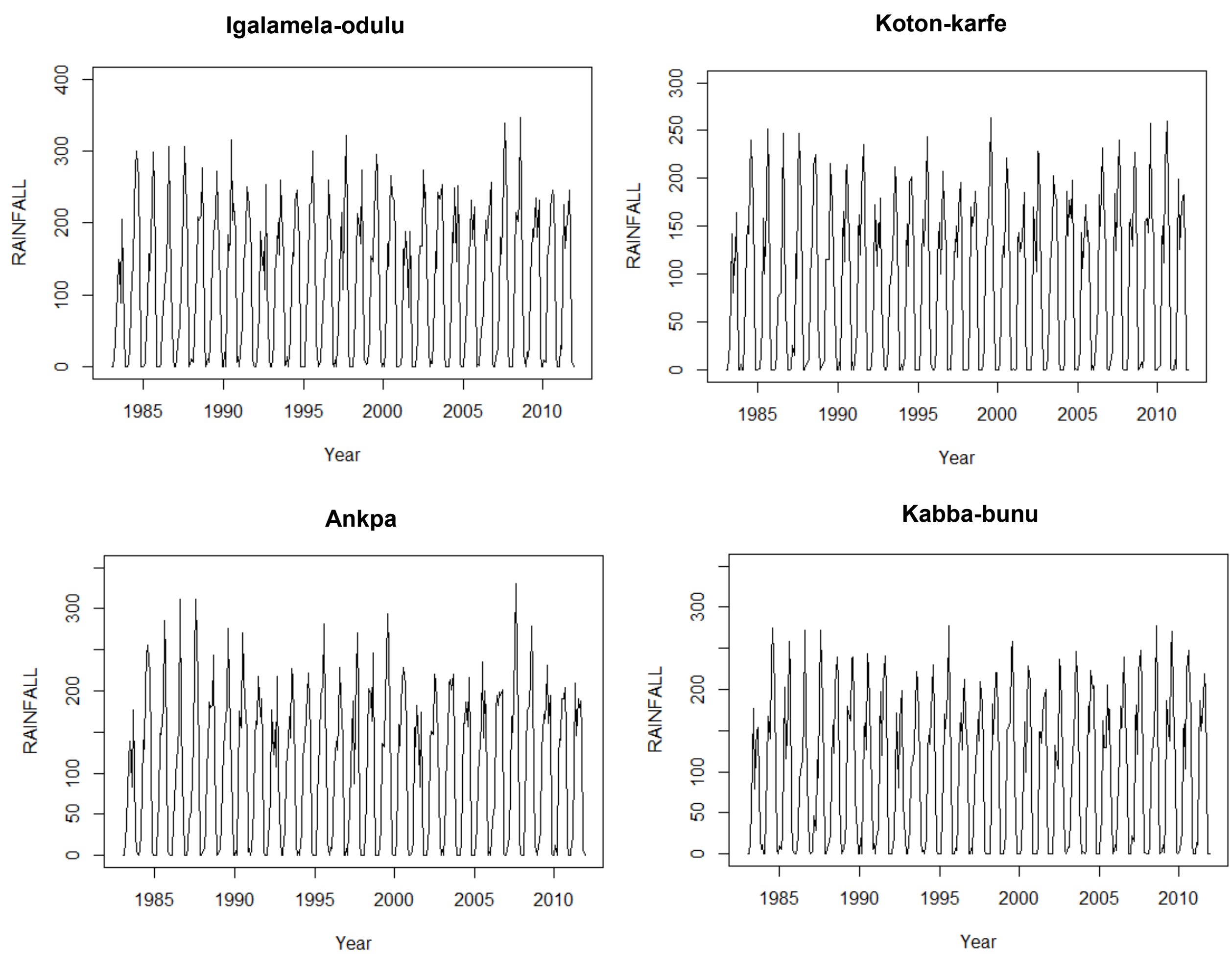
Appendix 5: Inter-annual trend analysis

Spatio-temporal analysis of trends in NDVI and climatic time series datasets for selected locations

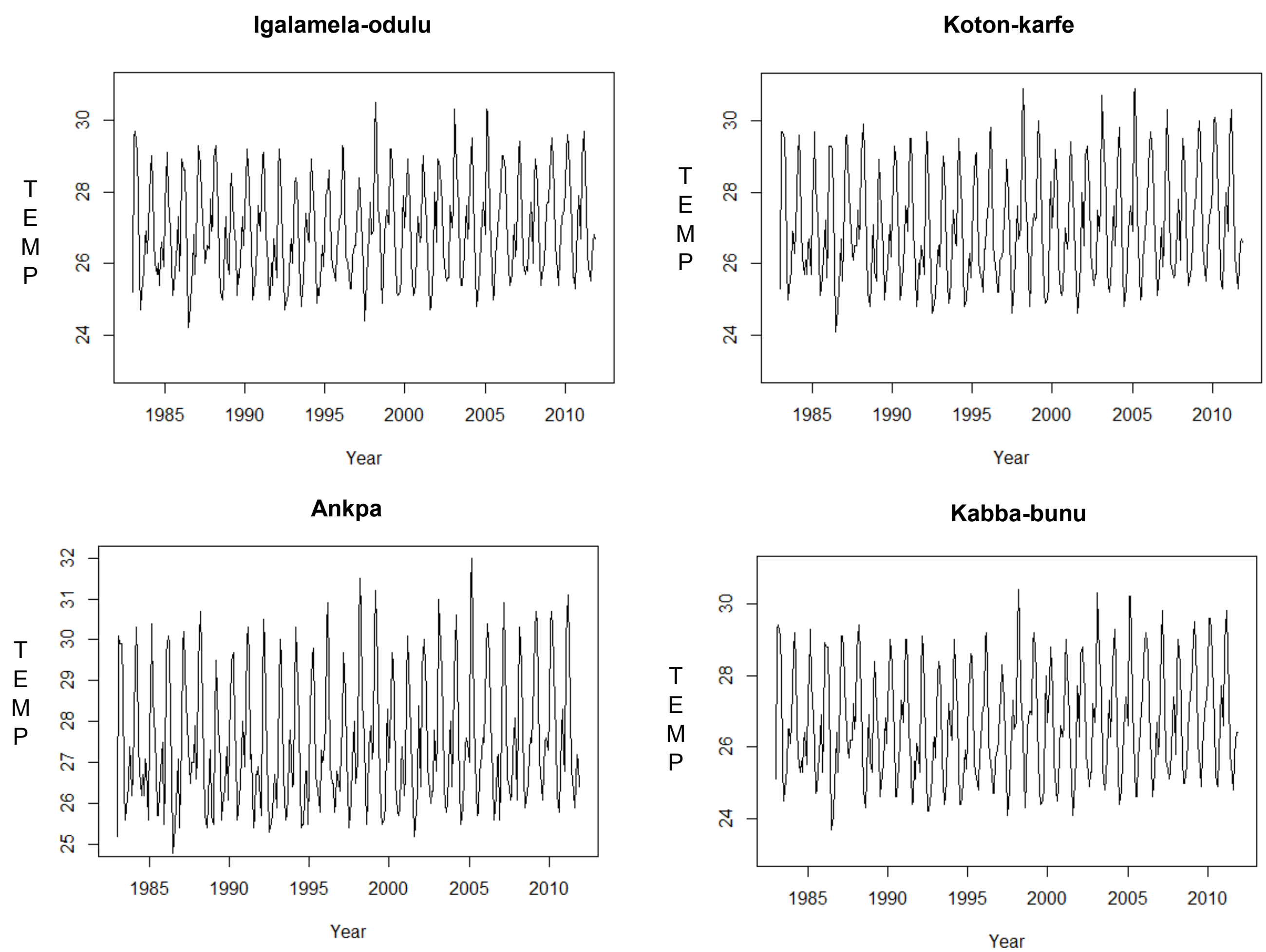
Results of NDVI and climatic datasets for selected locations in Kogi State



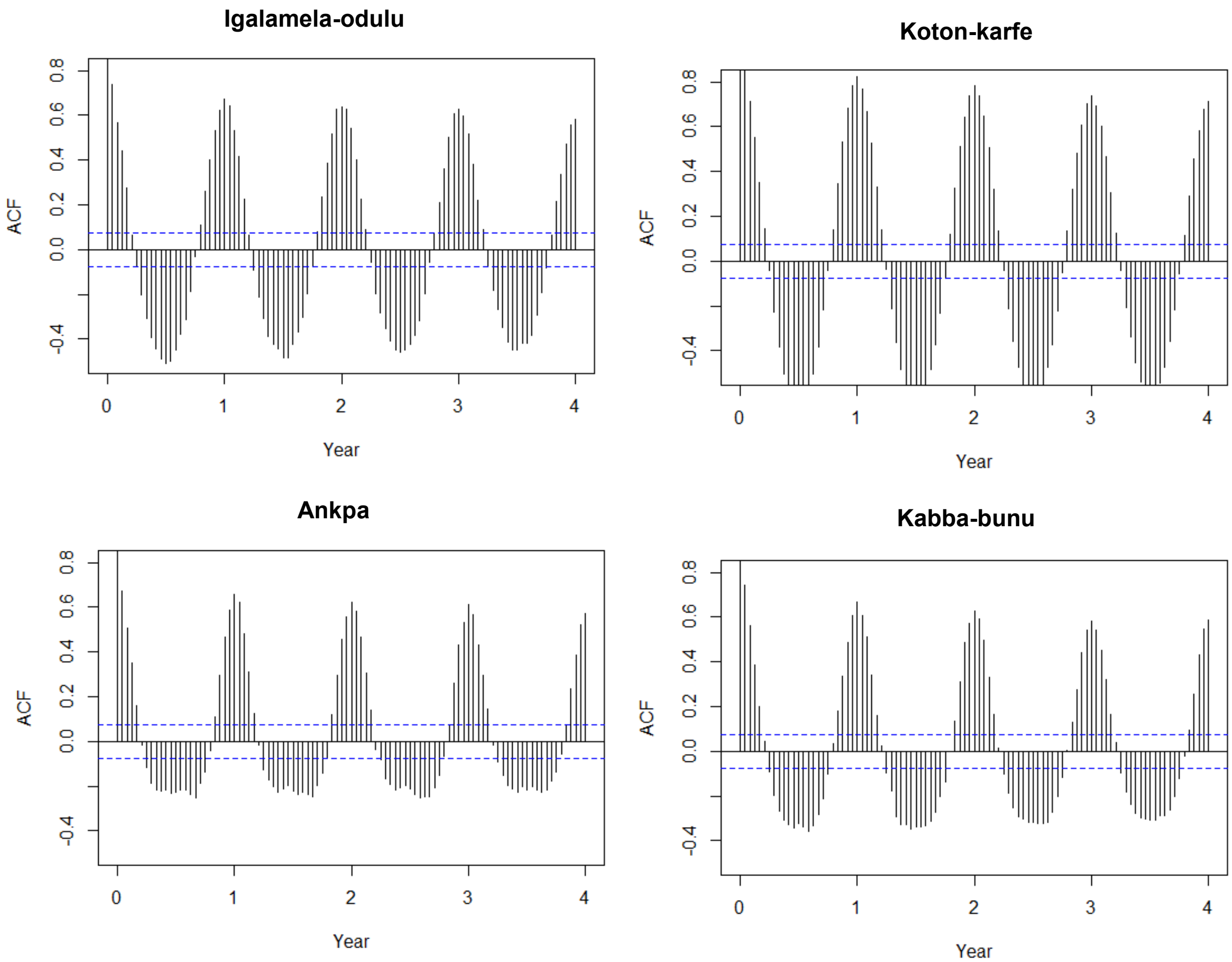
Appendix 5.1 showing original (i.e raw NDVI) datasets for the selected locations in Kogi



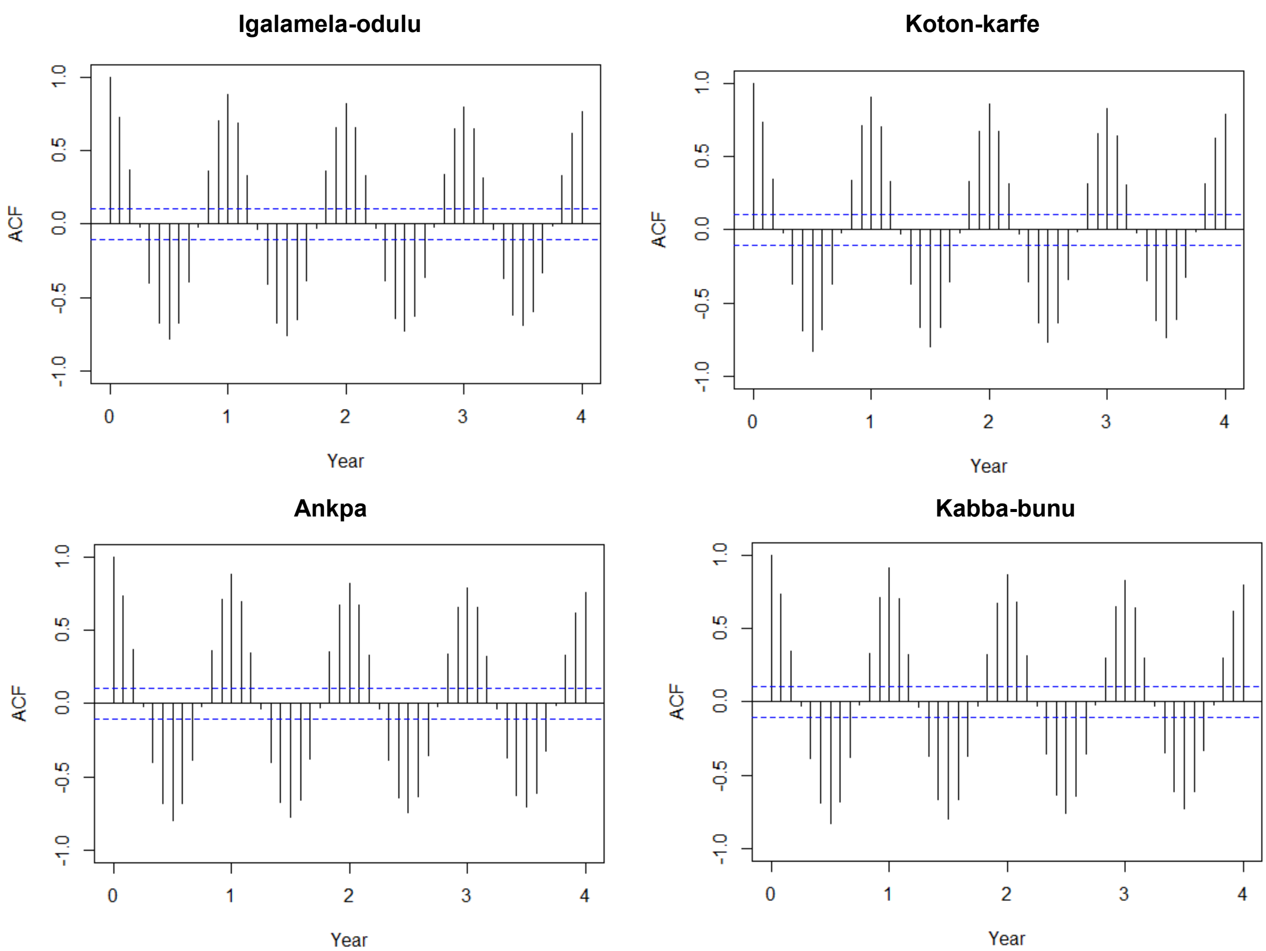
Appendix 5.2 showing original (i.e raw TAMSAT) rainfall datasets for the selected locations in Kogi



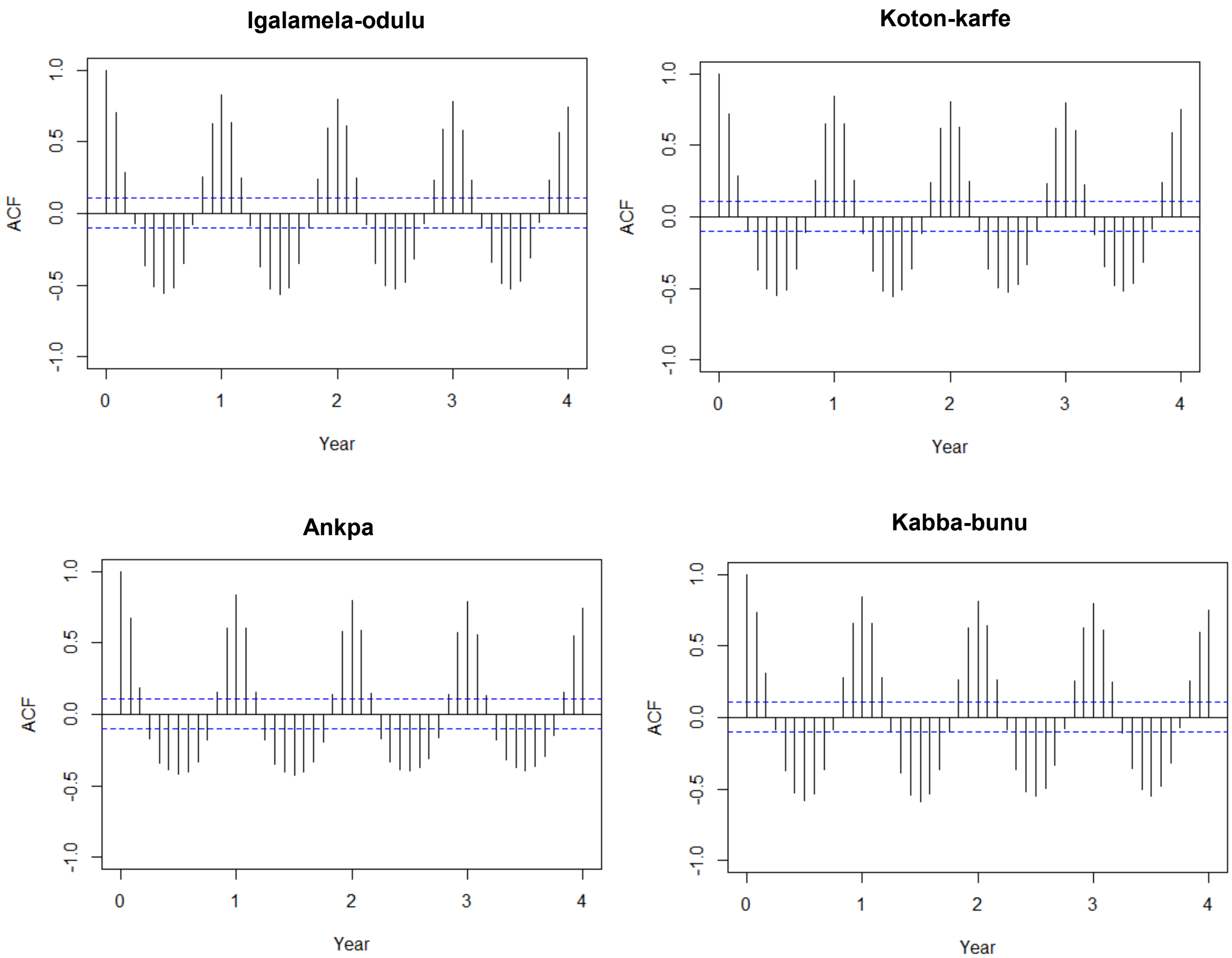
Appendix 5.3 showing original (i.e raw) temperature datasets for the selected locations in Kogi



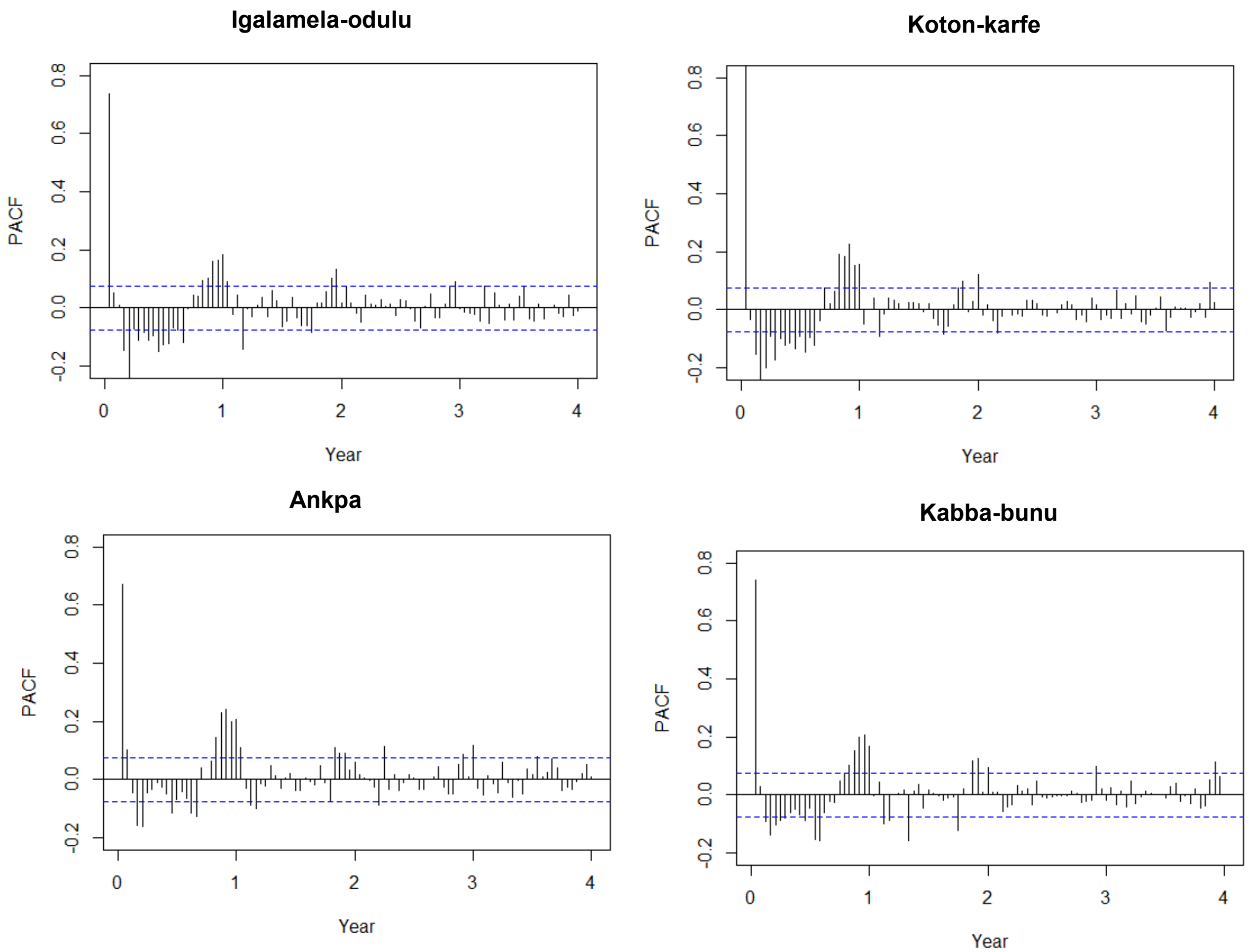
Appendix 5.4 showing NDVI auto-correlation function for the selected locations in Kogi



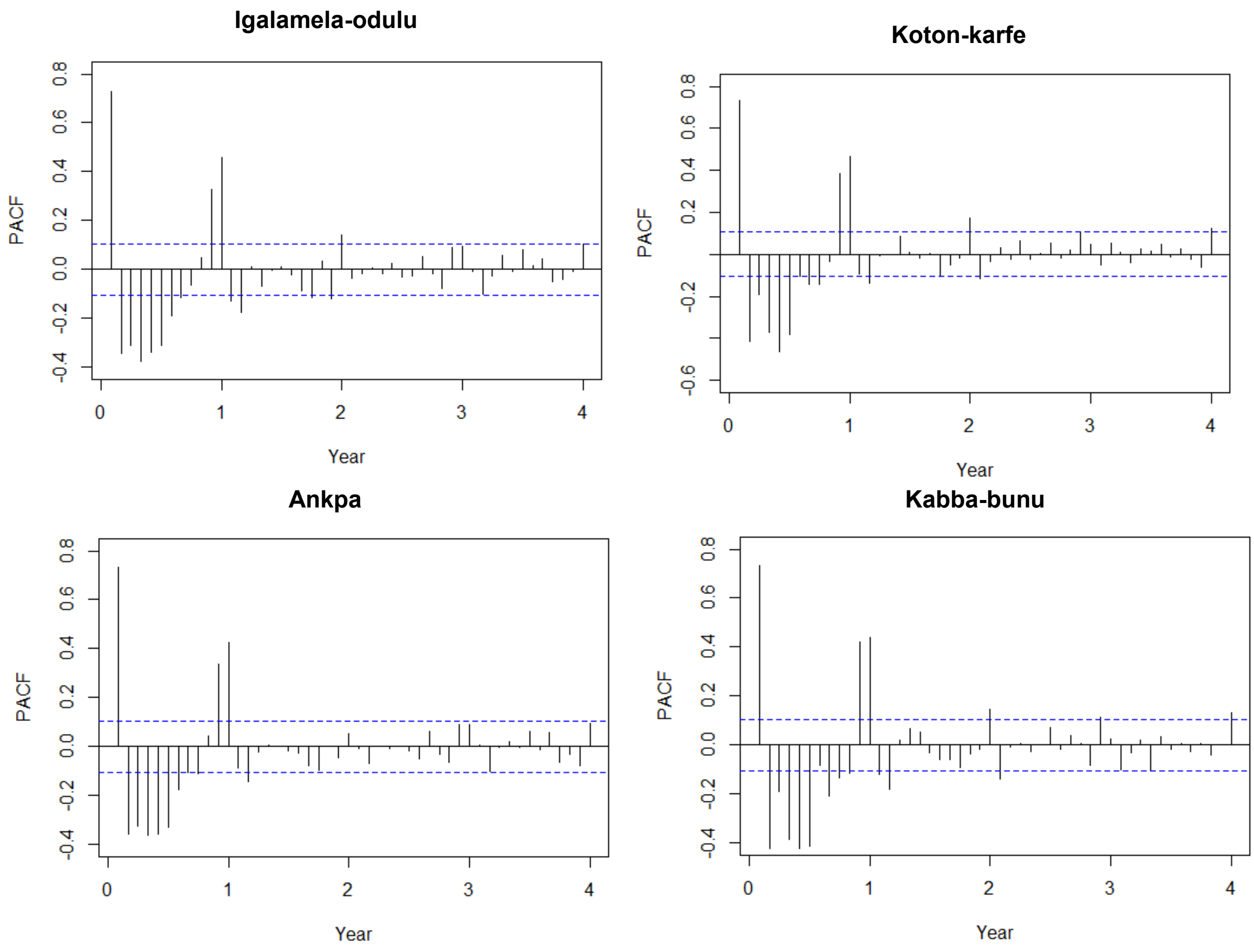
Appendix 5.5 showing rainfall auto-correlation function for the selected locations in Kogi



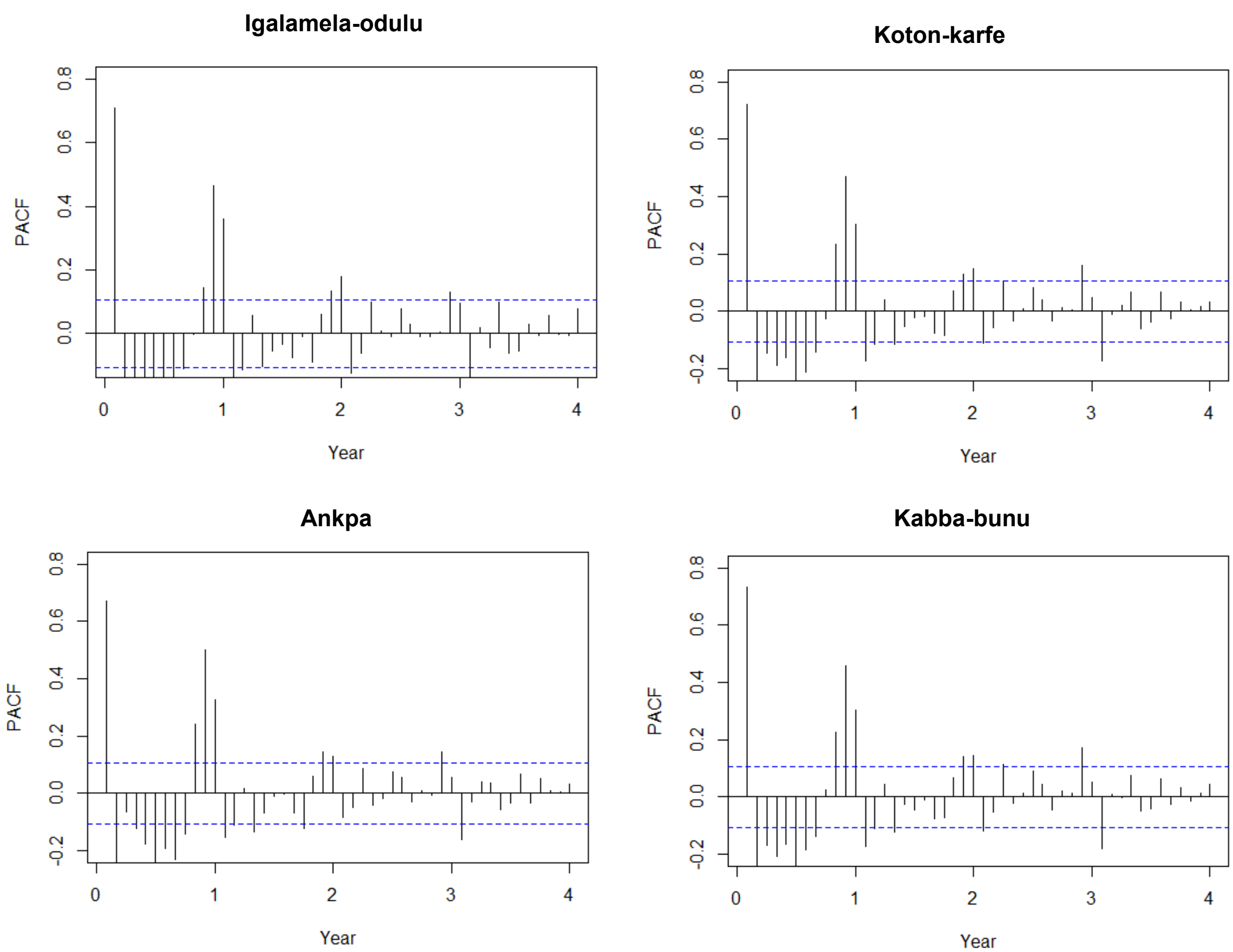
Appendix 5.6 showing temperature auto-correlation function for the selected locations in Kogi



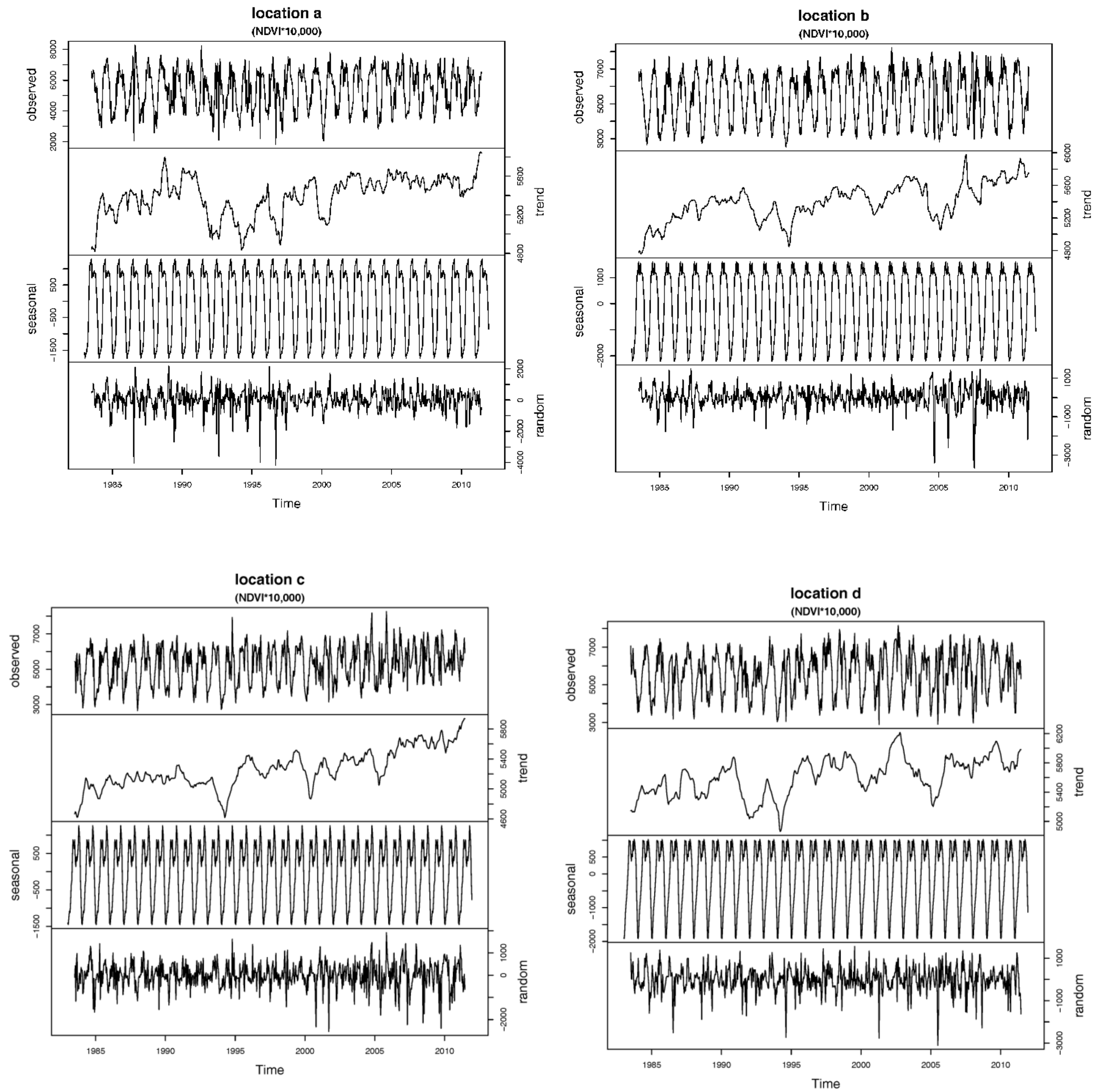
Appendix 5.7 showing NDVI partial auto-correlation function for the selected locations in Kogi



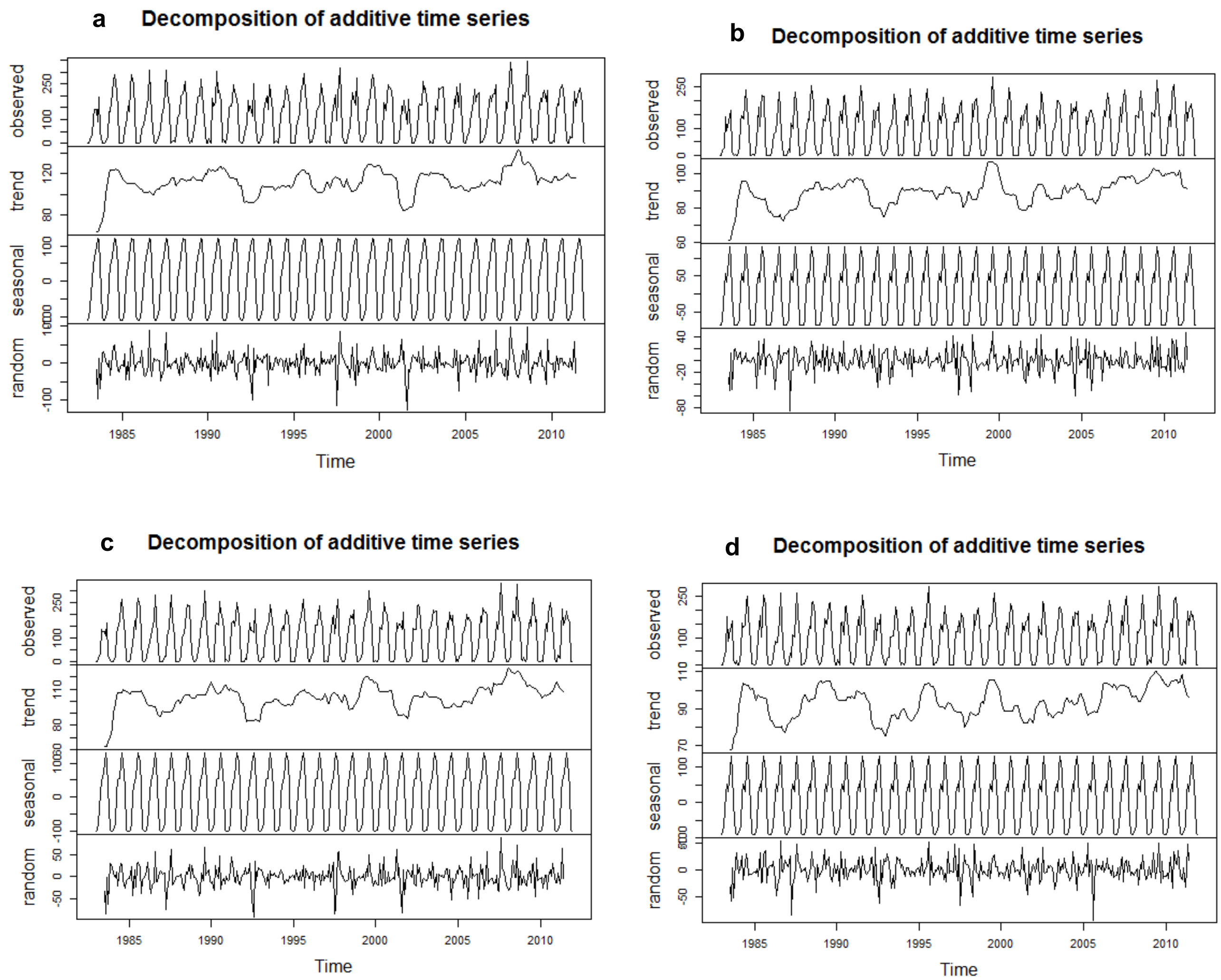
Appendix 5.8 showing rainfall partial auto-correlation function for the selected locations in Kogi



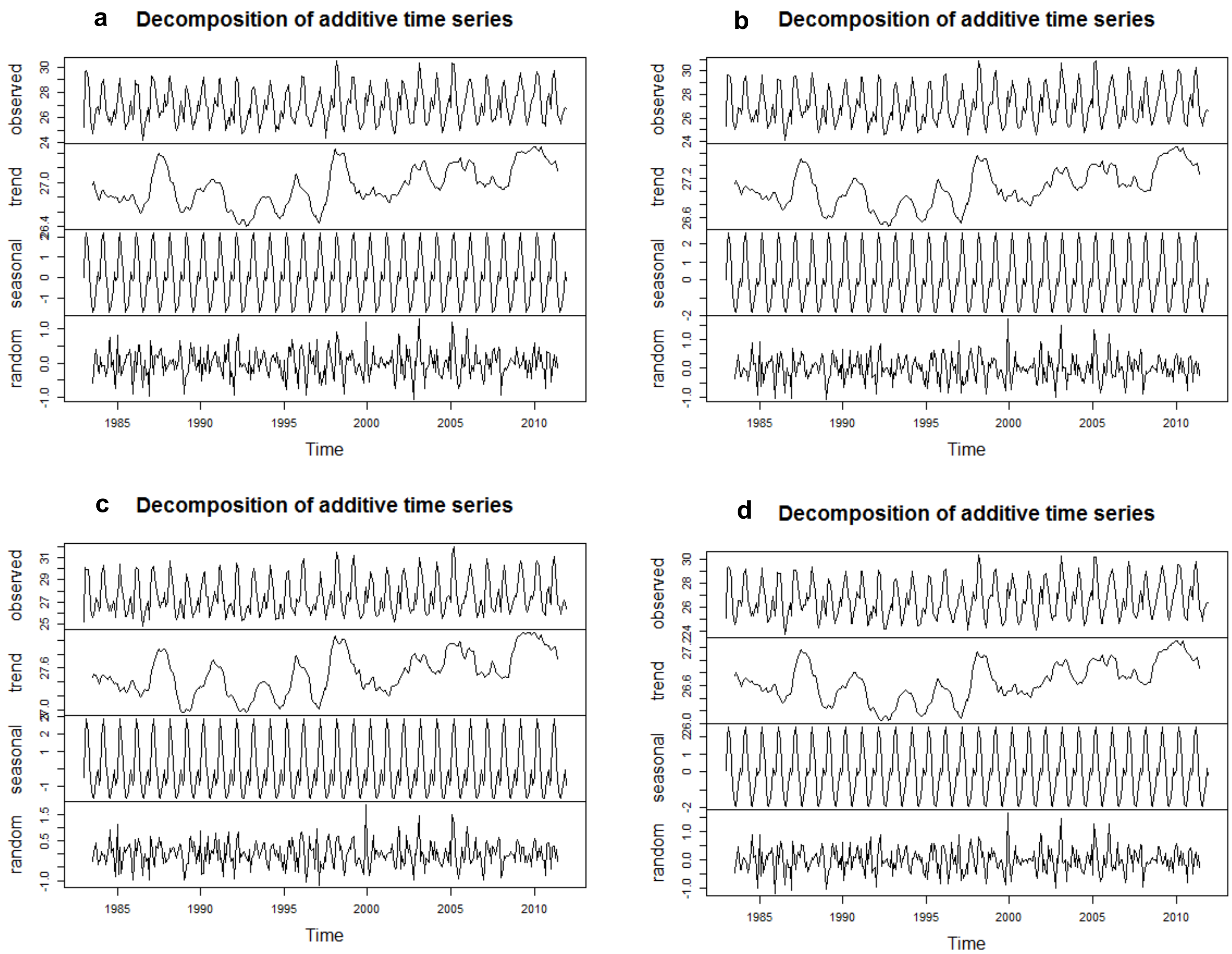
Appendix 5.9 showing temperature partial auto-correlation function for the selected locations in Kogi



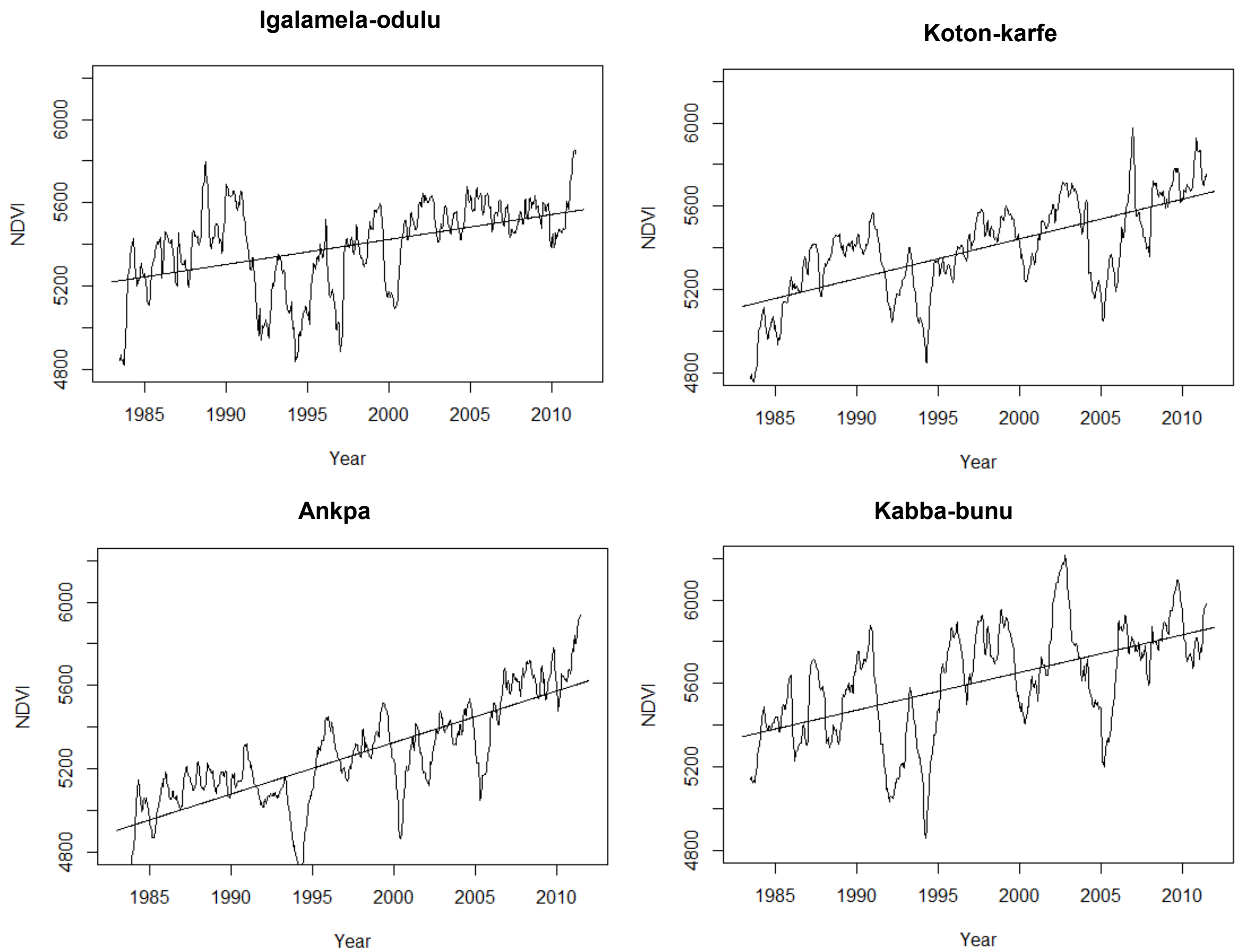
Appendix 5.10 showing decomposition of NDVI time series for the selected locations in Kogi



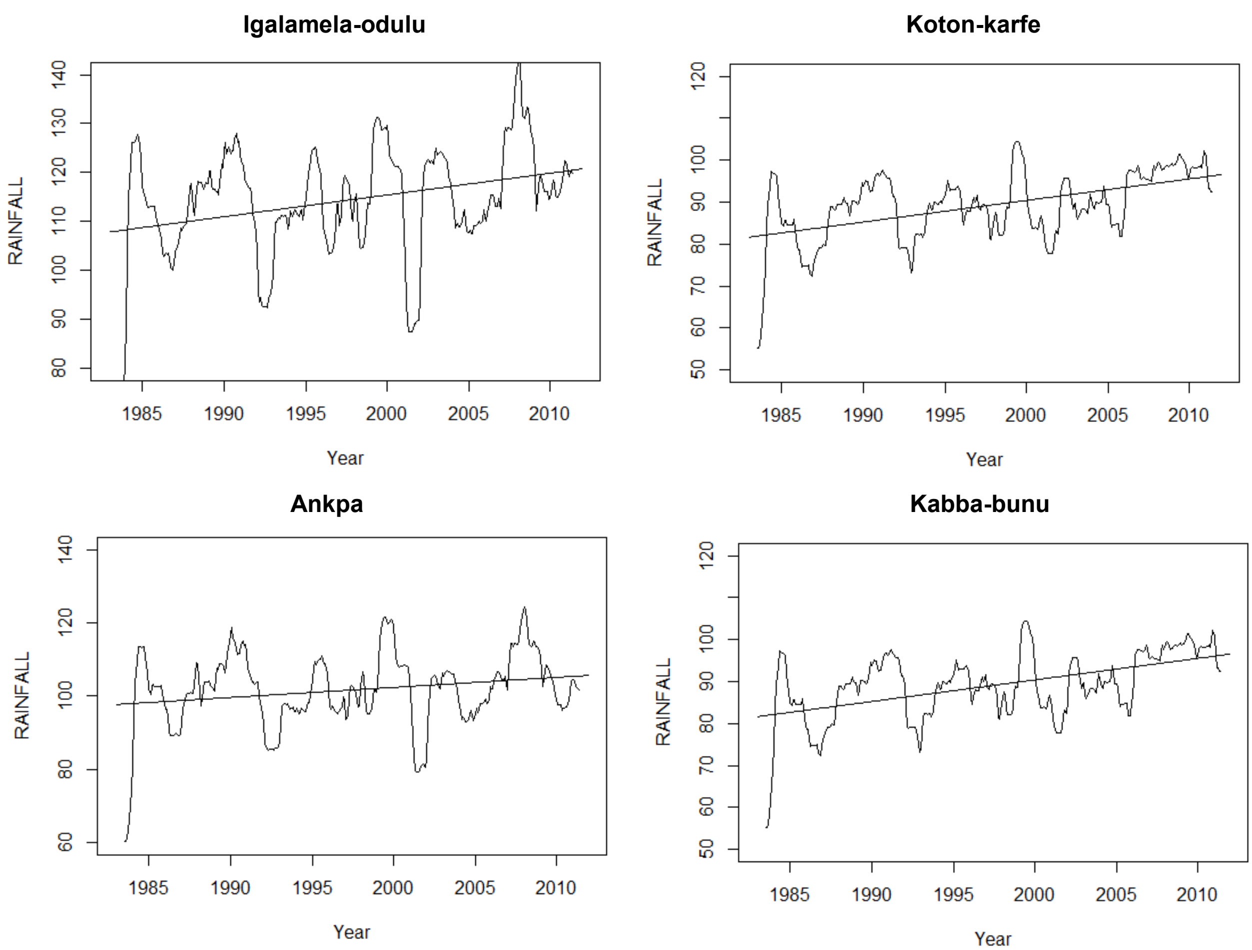
Appendix 5.11 showing decomposition of rainfall time series for the selected locations in Kogi



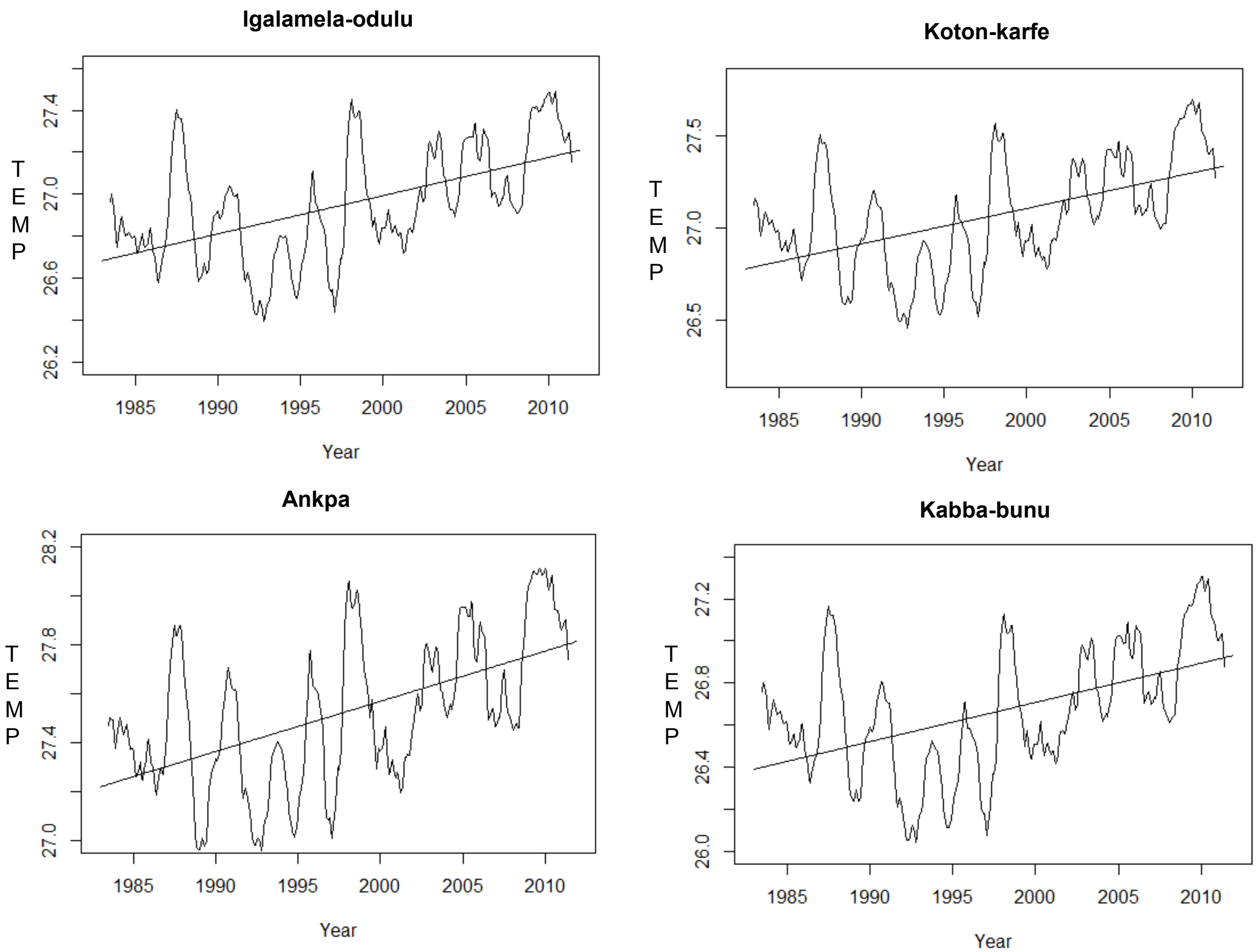
Appendix 5.12 showing decomposition of temperature time series for the selected locations in Kogi



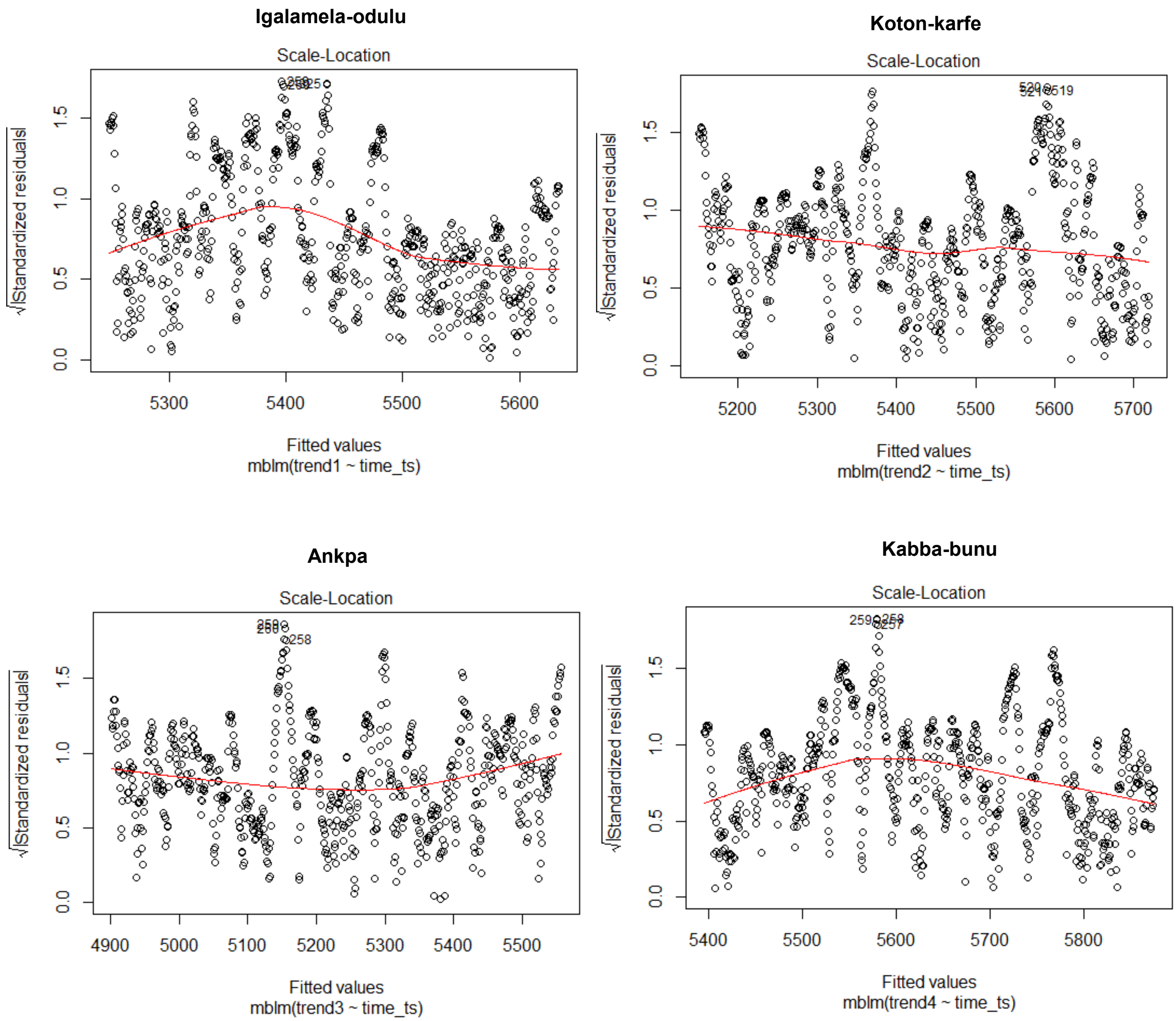
Appendix 5.13 showing NDVI linear regression model for the selected locations in Kogi



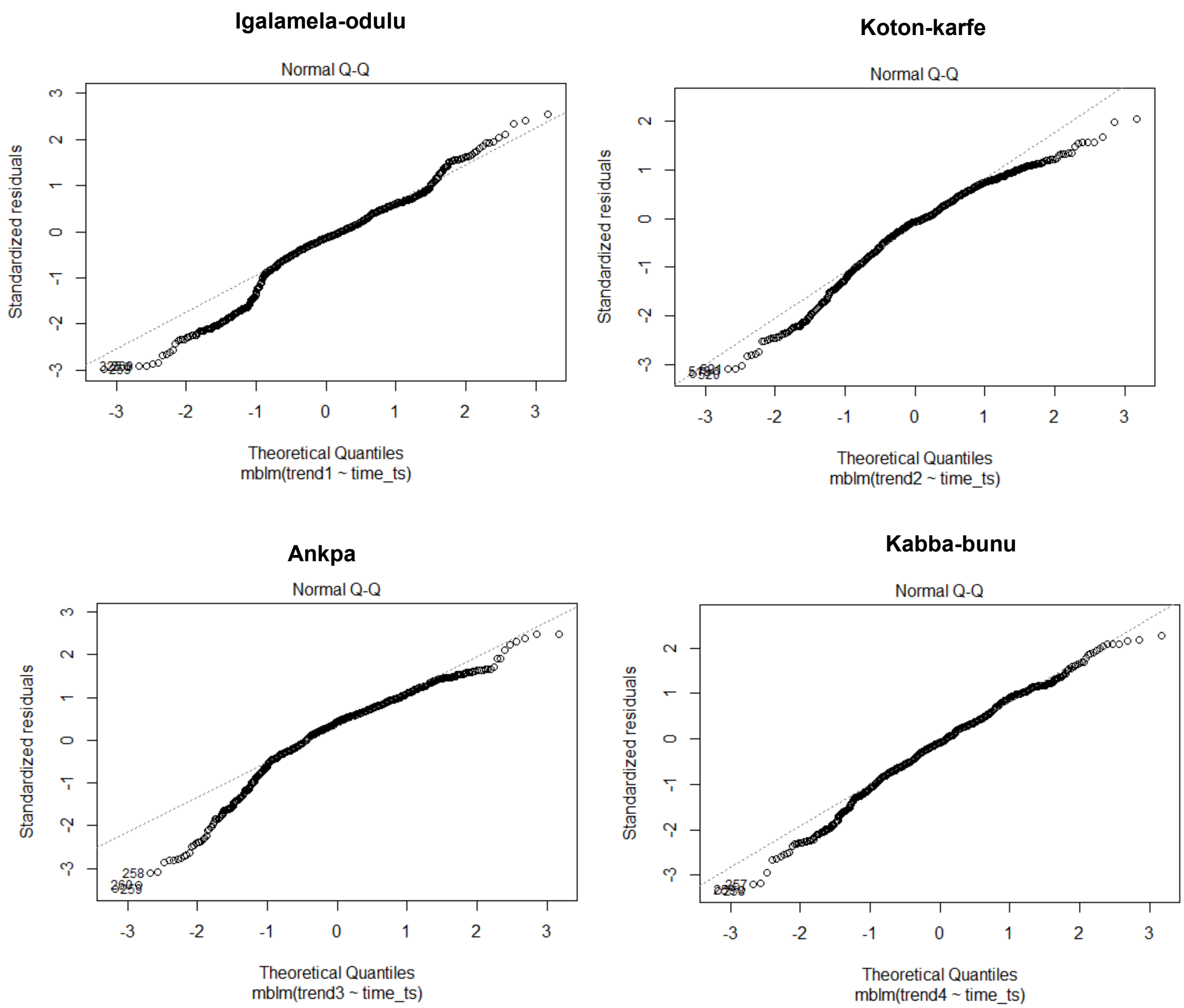
Appendix 5.14 showing rainfall linear regression model for the selected locations in Kogi



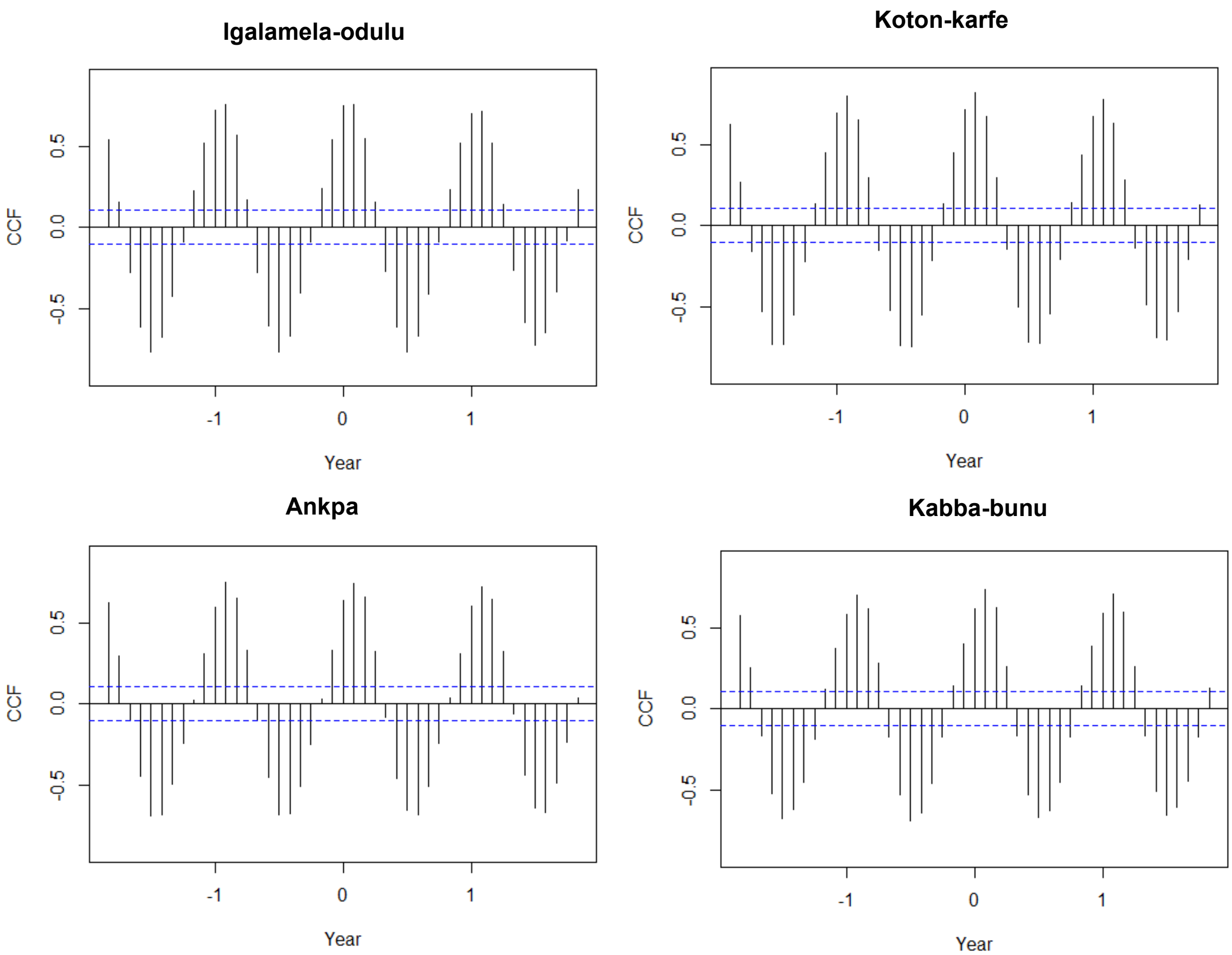
Appendix 5.15 showing temperature linear regression model for the selected locations in Kogi



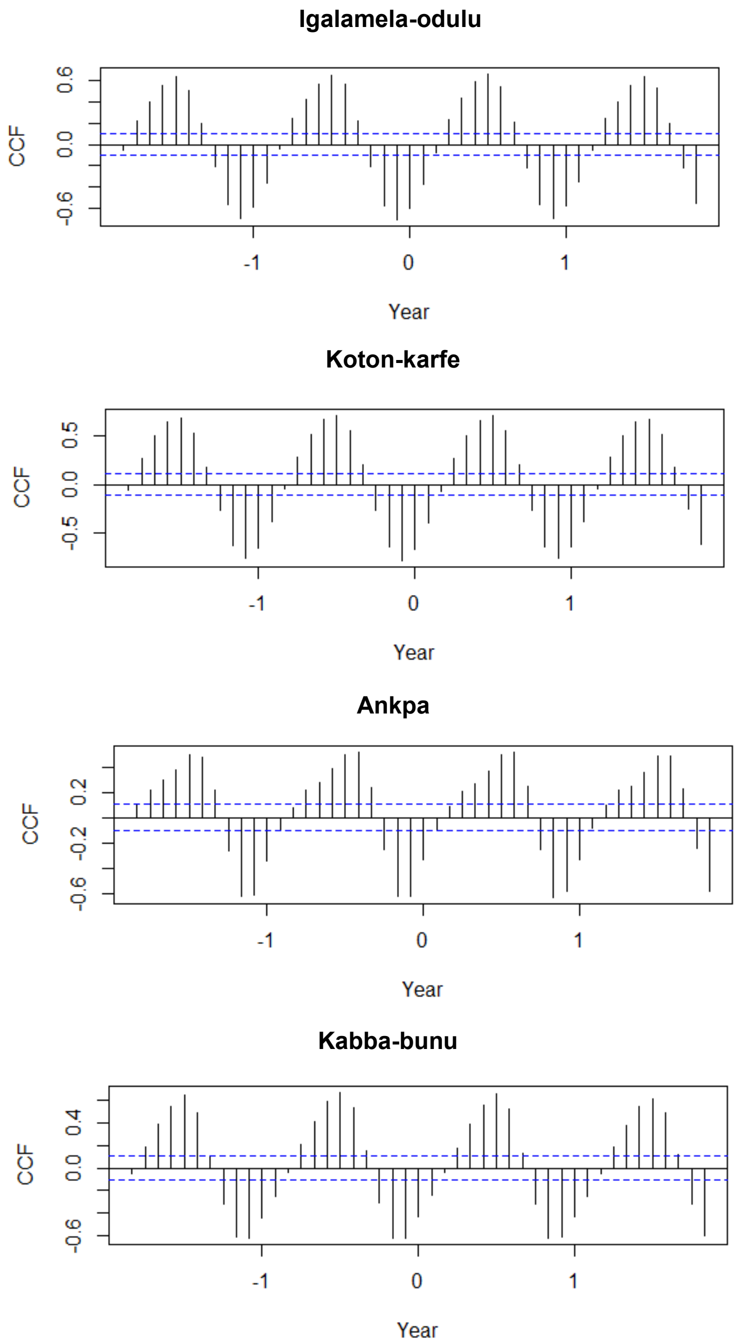
Appendix 5.16 showing standardized residuals for the Theil-Sen Estimation of NDVI trend signal for the selected locations in Kogi



Appendix 5.17 showing QQ-Plot of the Theil-Sen Estimation for the NDVI trend signal for the selected locations in Kogi State

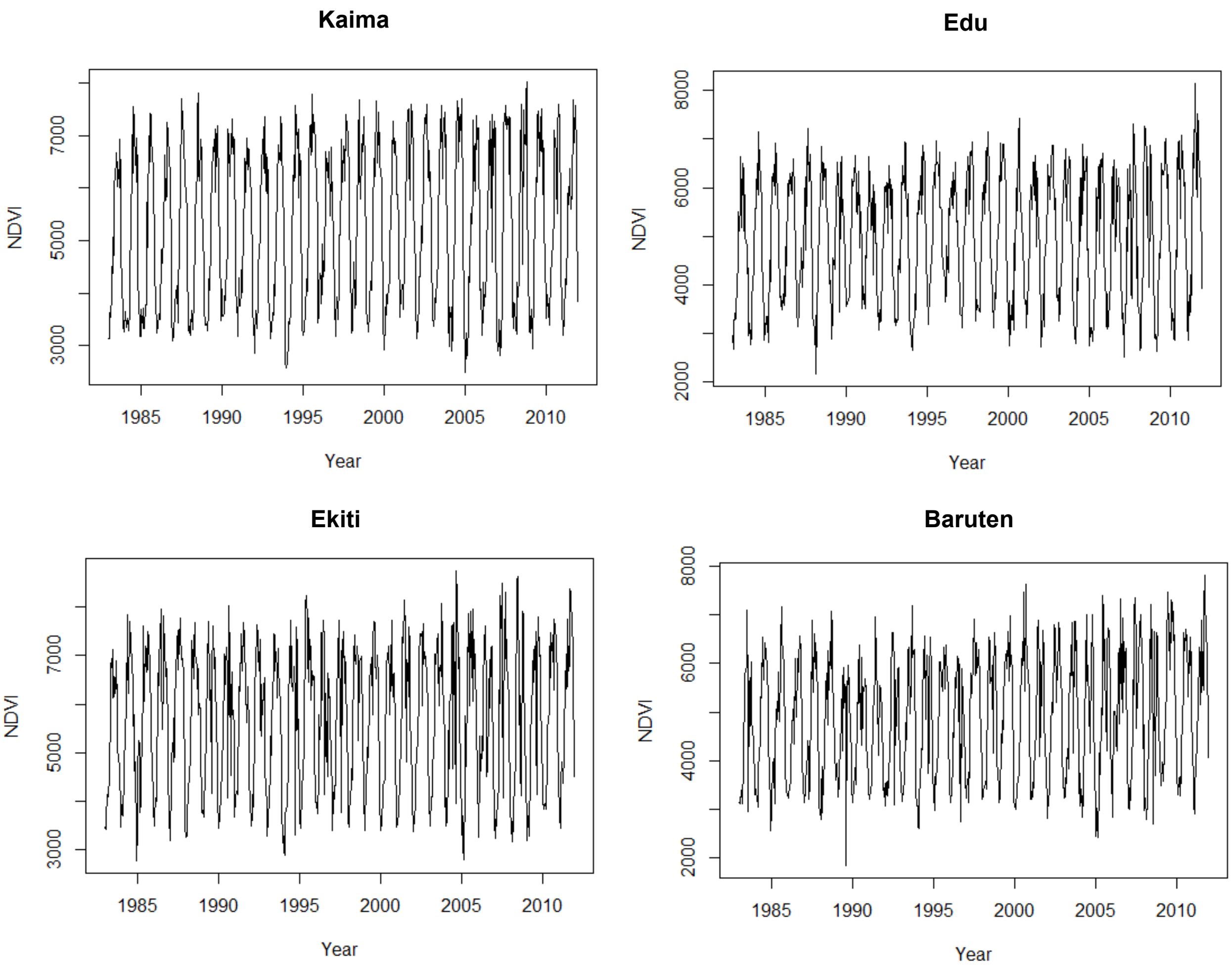


Appendix 5.18 showing cross correlation analysis between NDVI and rainfall for the selected locations in Kogi State

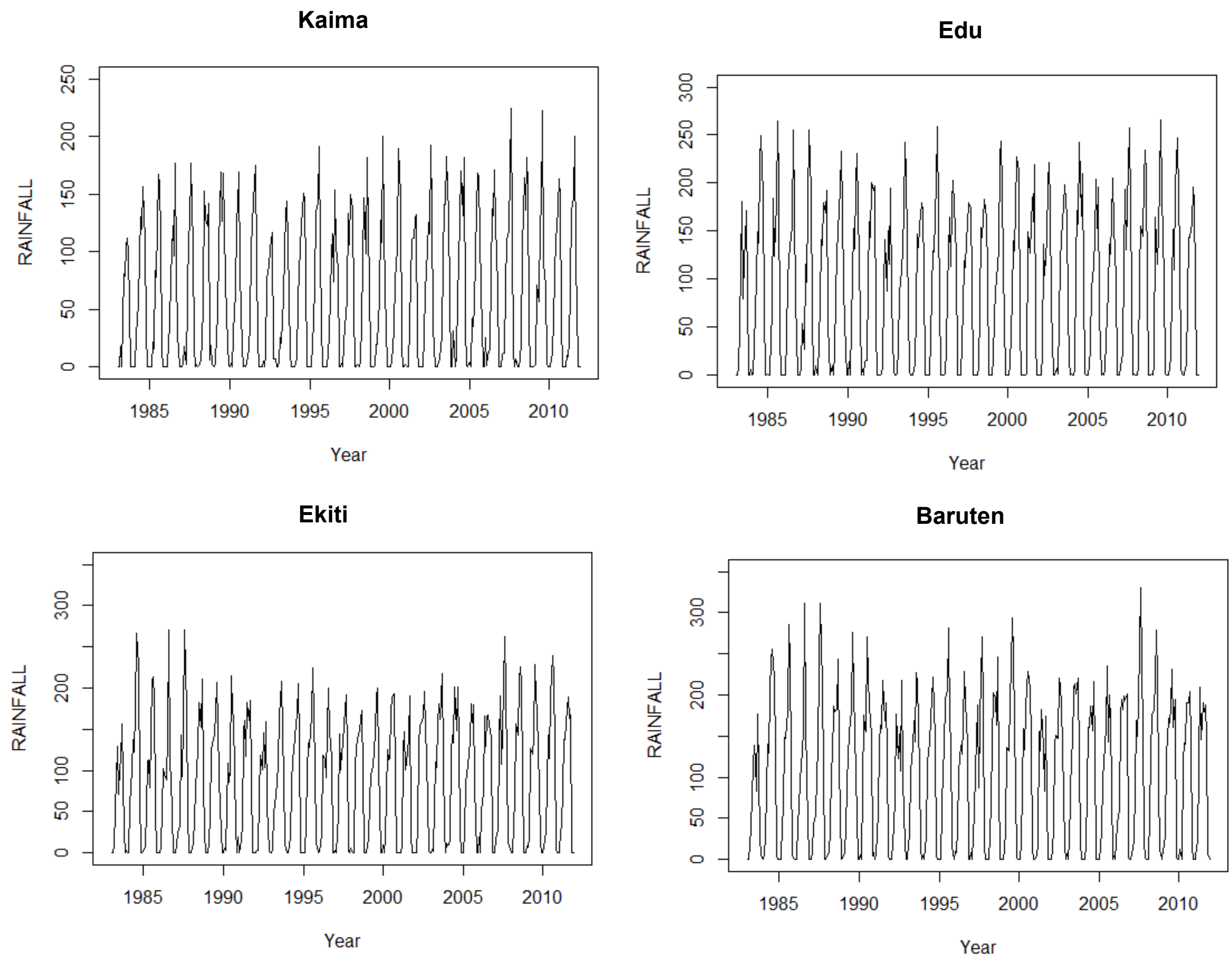


Appendix 5.19 showing cross correlation analysis between NDVI and temperature for the selected locations in Kogi State

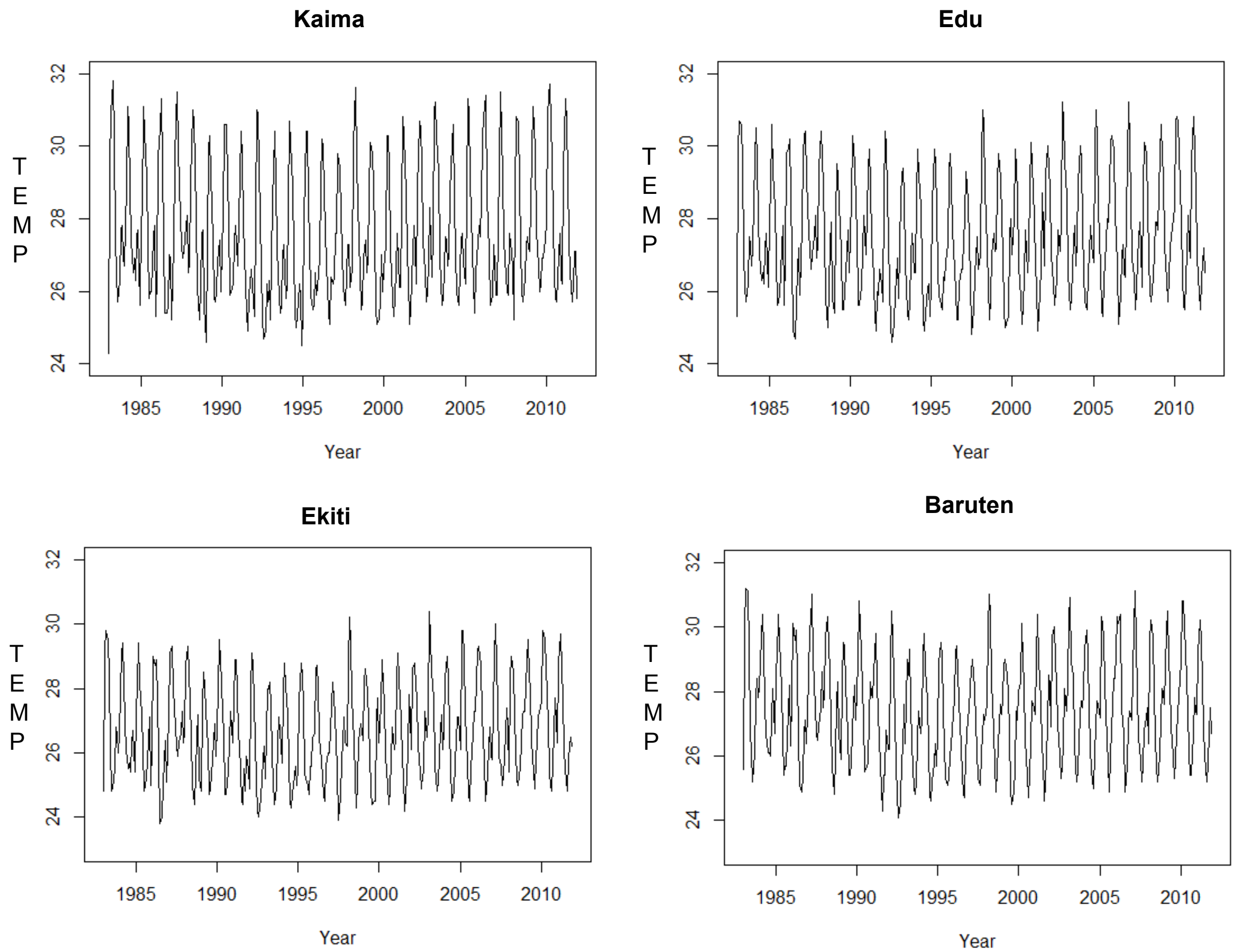
Results of NDVI and climatic datasets for selected locations in Kwara State



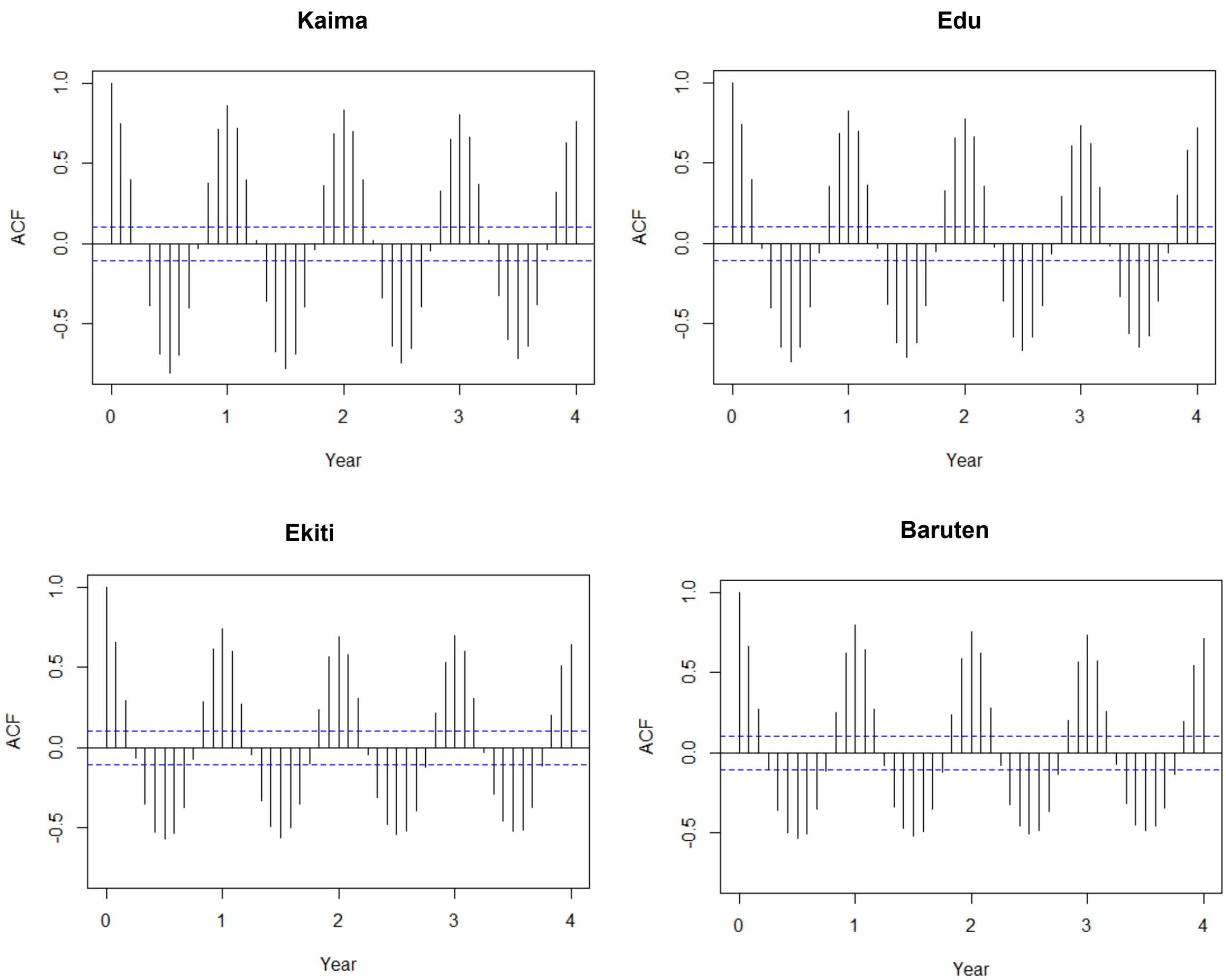
Appendix 5.20 showing original (i.e raw NDVI) datasets for the selected locations in Kwara State



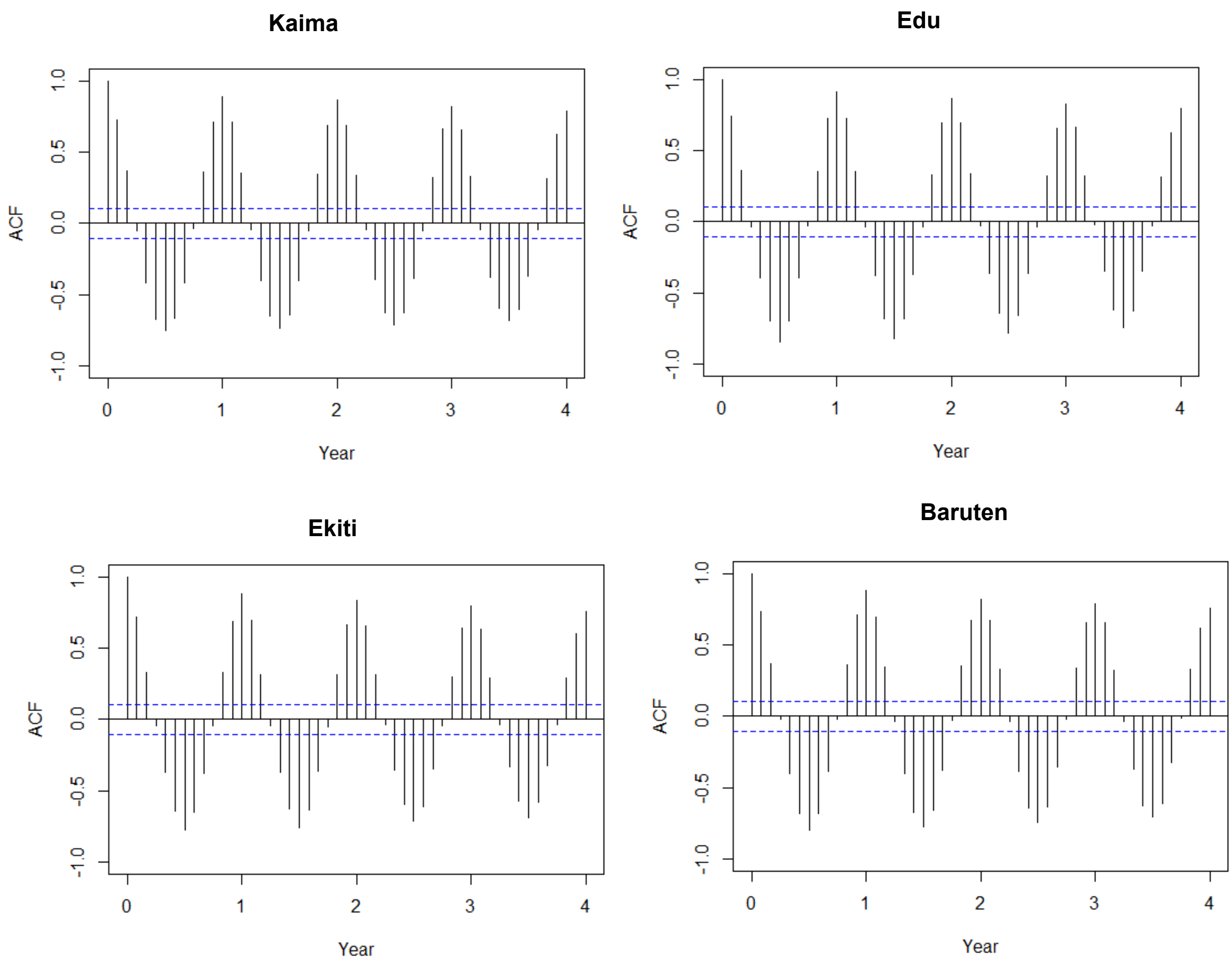
Appendix 5.21 showing original (i.e raw rainfall) datasets for the selected locations in Kwara State



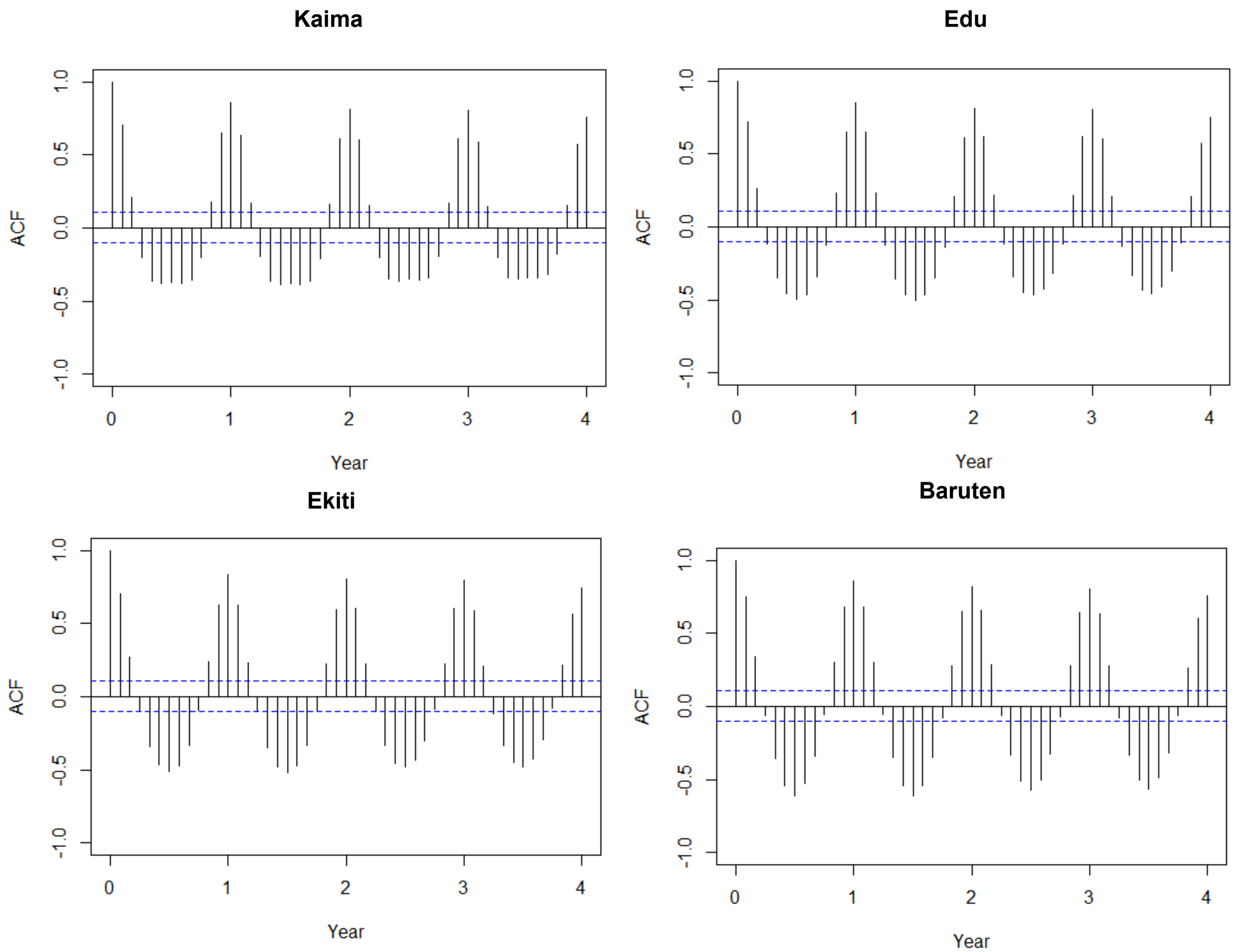
Appendix 5.22 showing original (i.e raw temperature) datasets for the selected locations in Kwara State



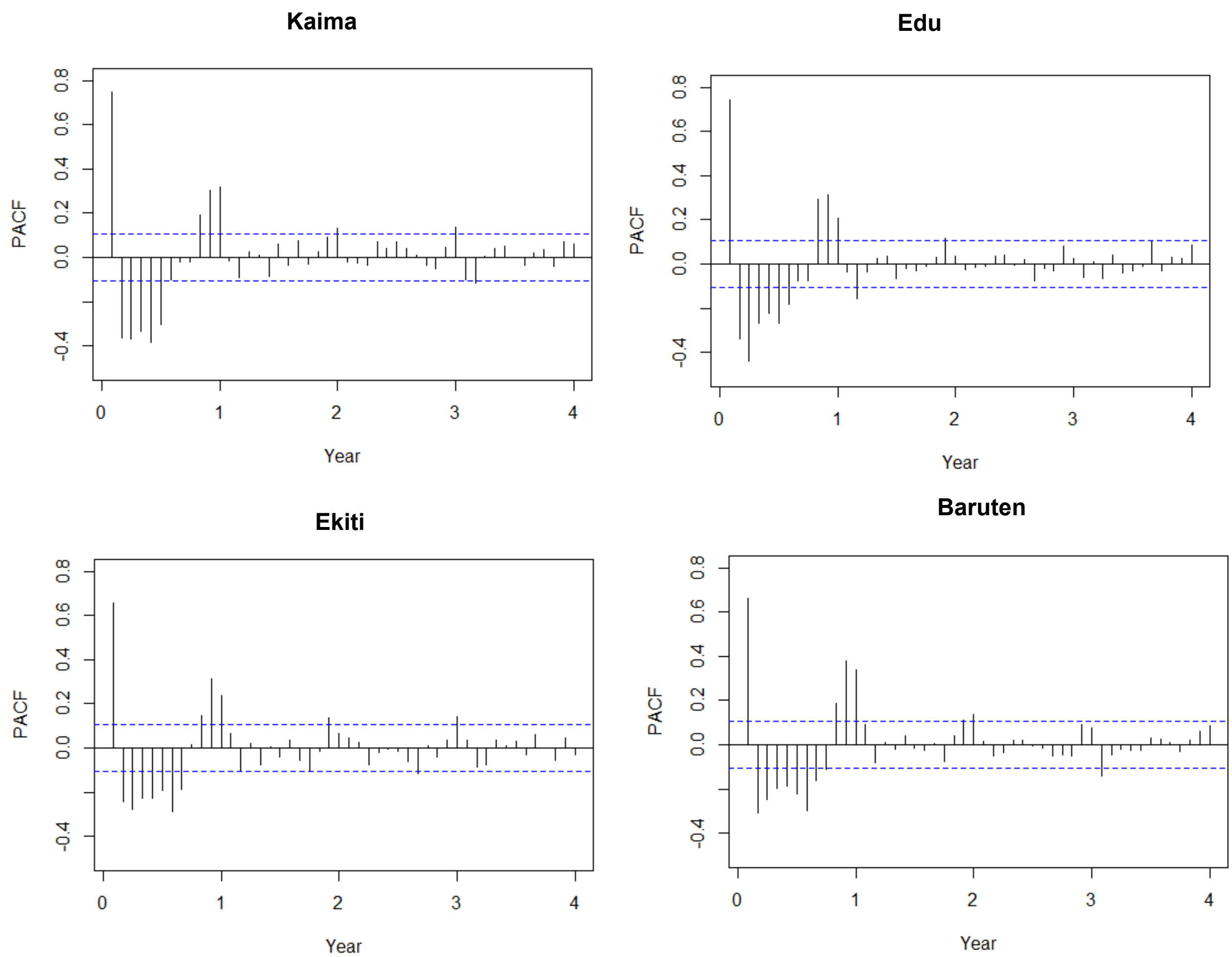
Appendix 5.23 showing NDVI auto-correlation function for the selected locations in Kwara



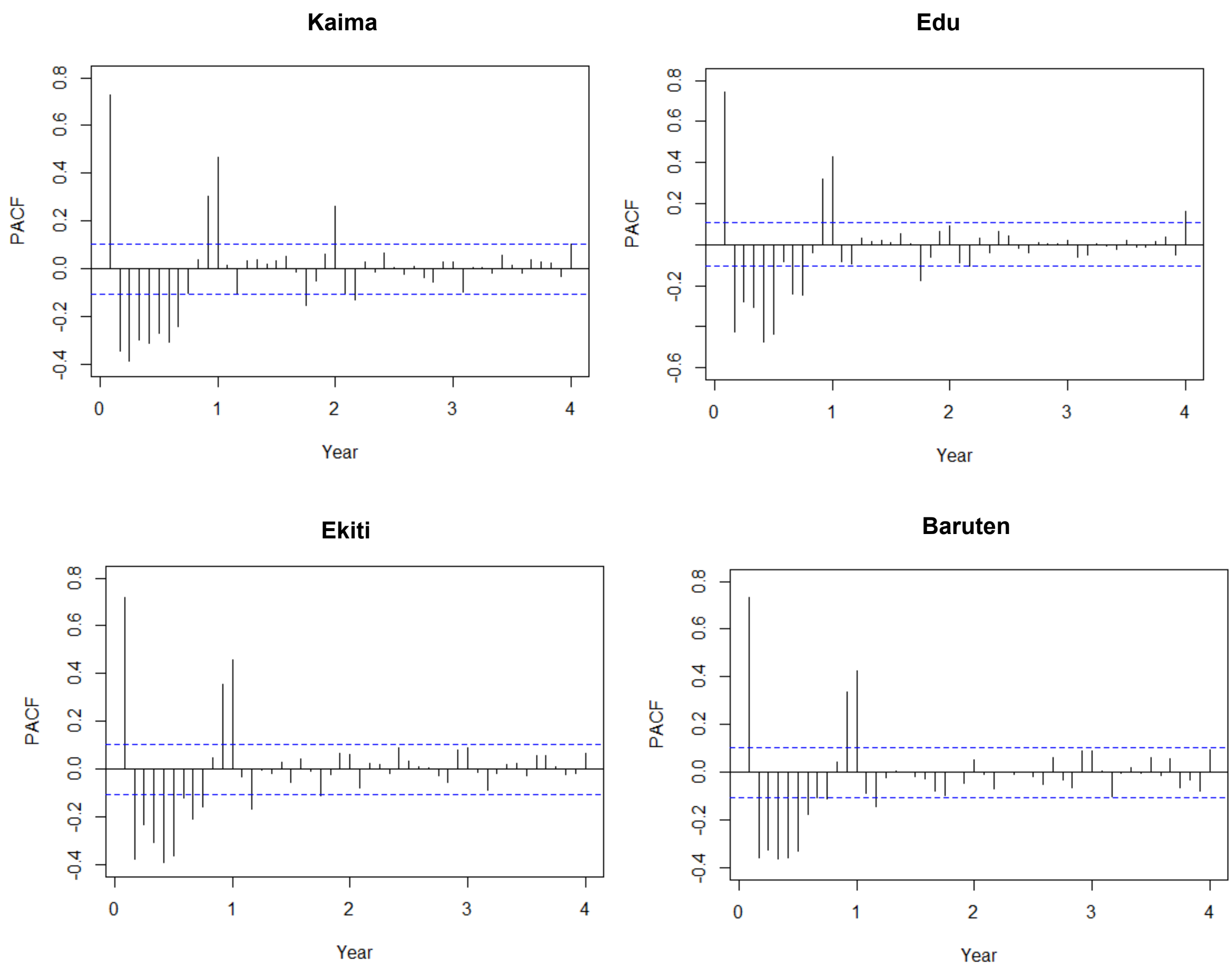
Appendix 5.24 showing TAMSAT rainfall auto-correlation function for the selected locations in Kwara



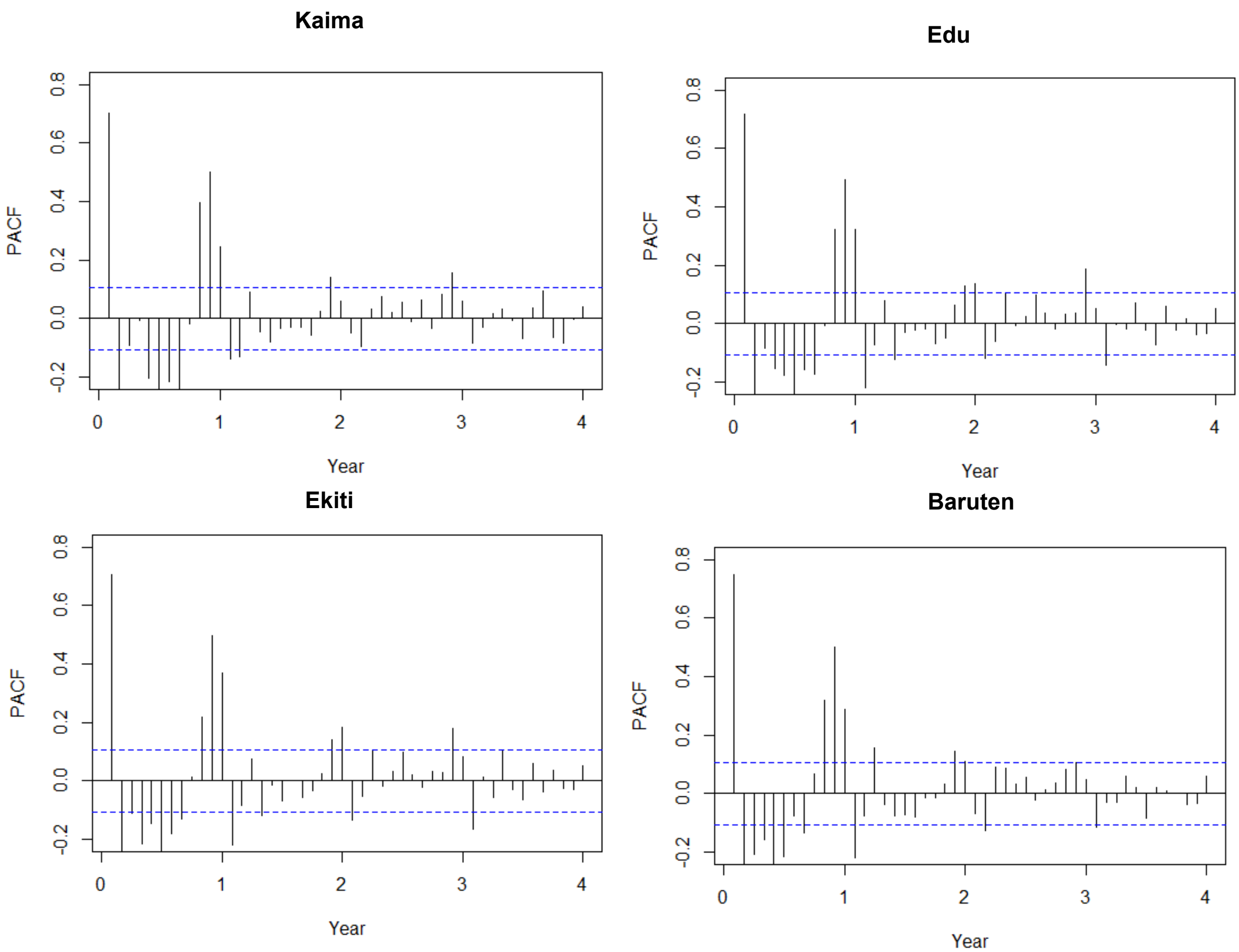
Appendix 5.25 showing temperature auto-correlation function for the selected locations in Kwara



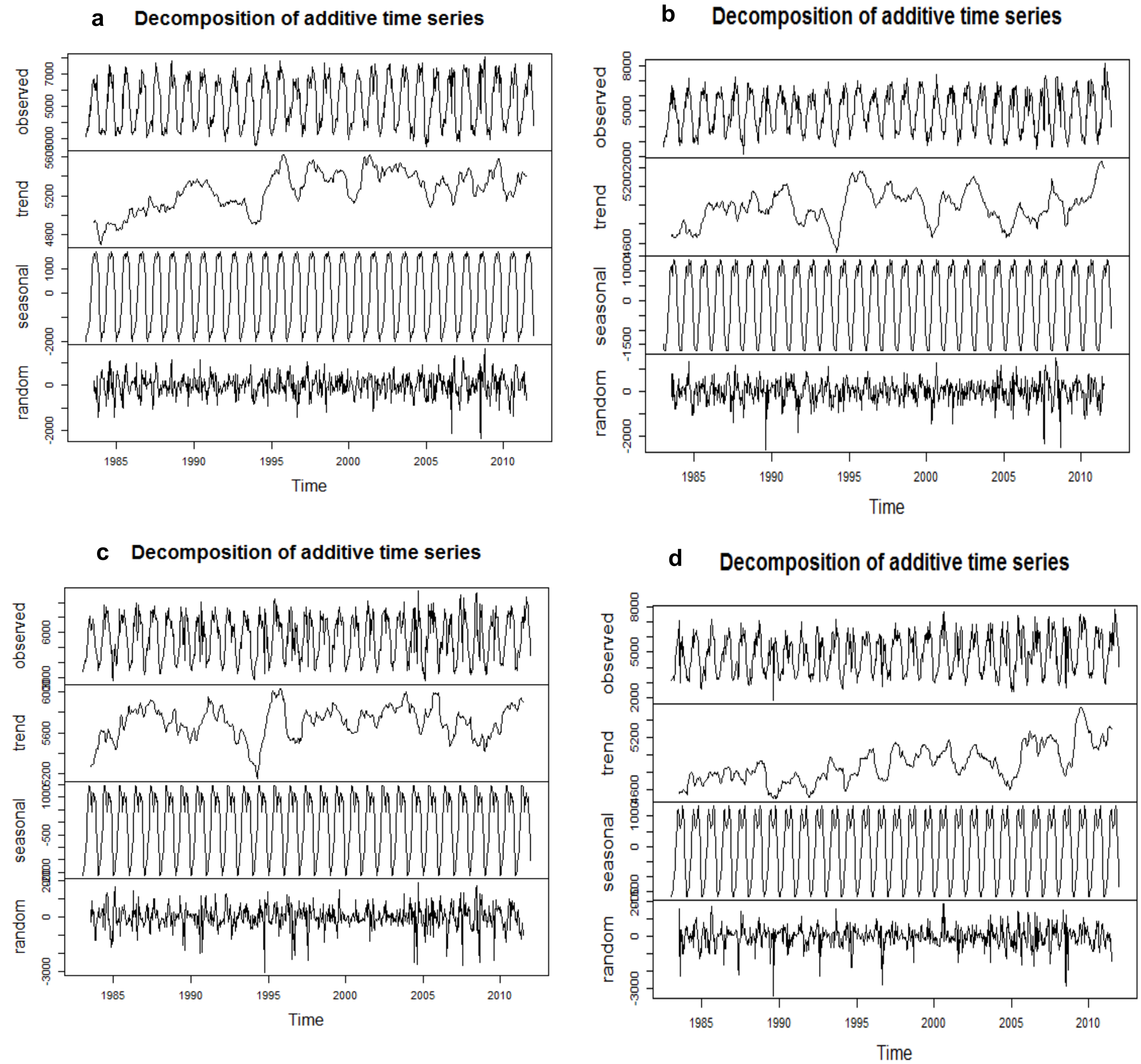
Appendix 5.26 showing NDVI partial auto-correlation function for the selected locations in Kwara State



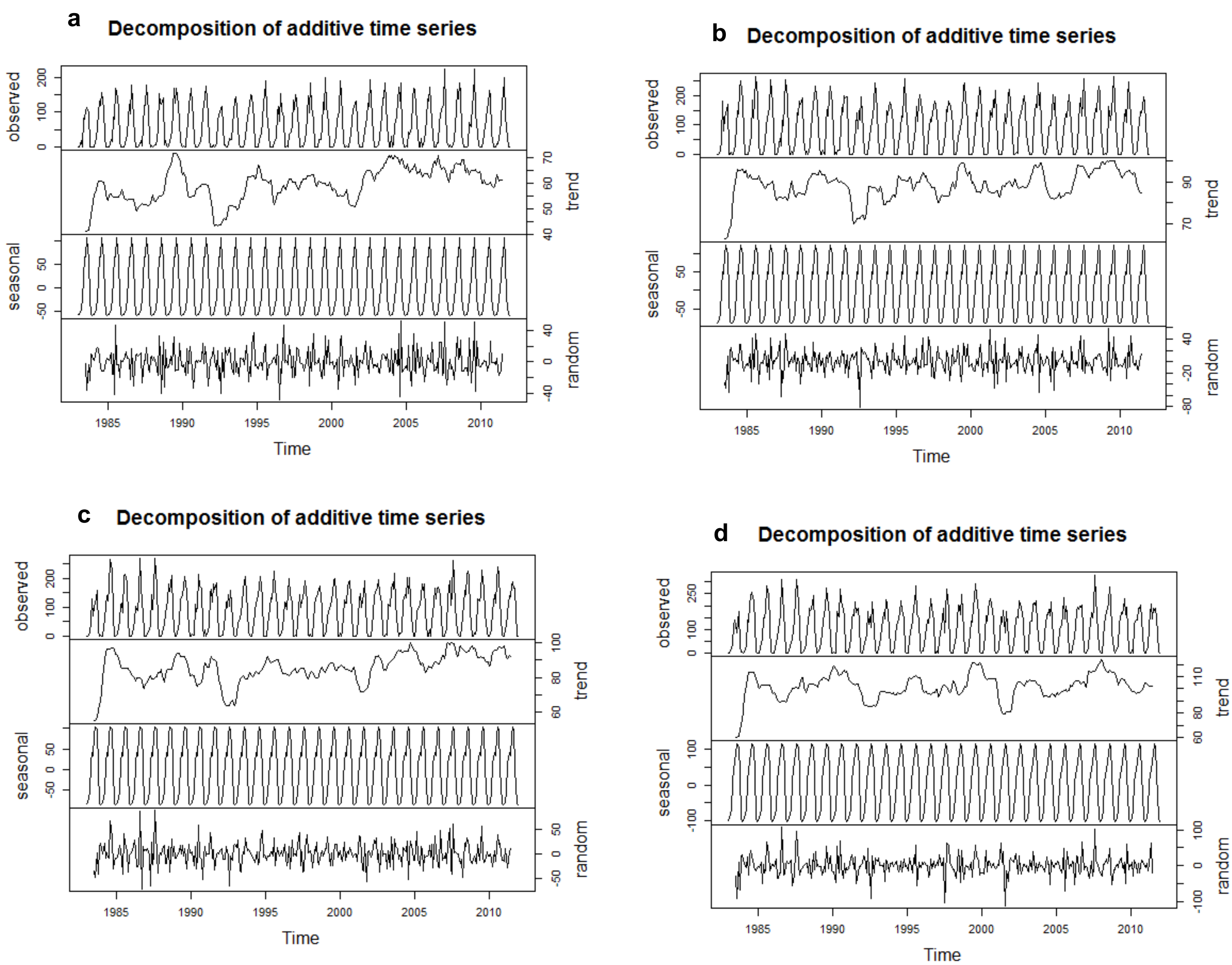
Appendix 5.27 showing rainfall partial auto-correlation function for the selected locations in Kwara State



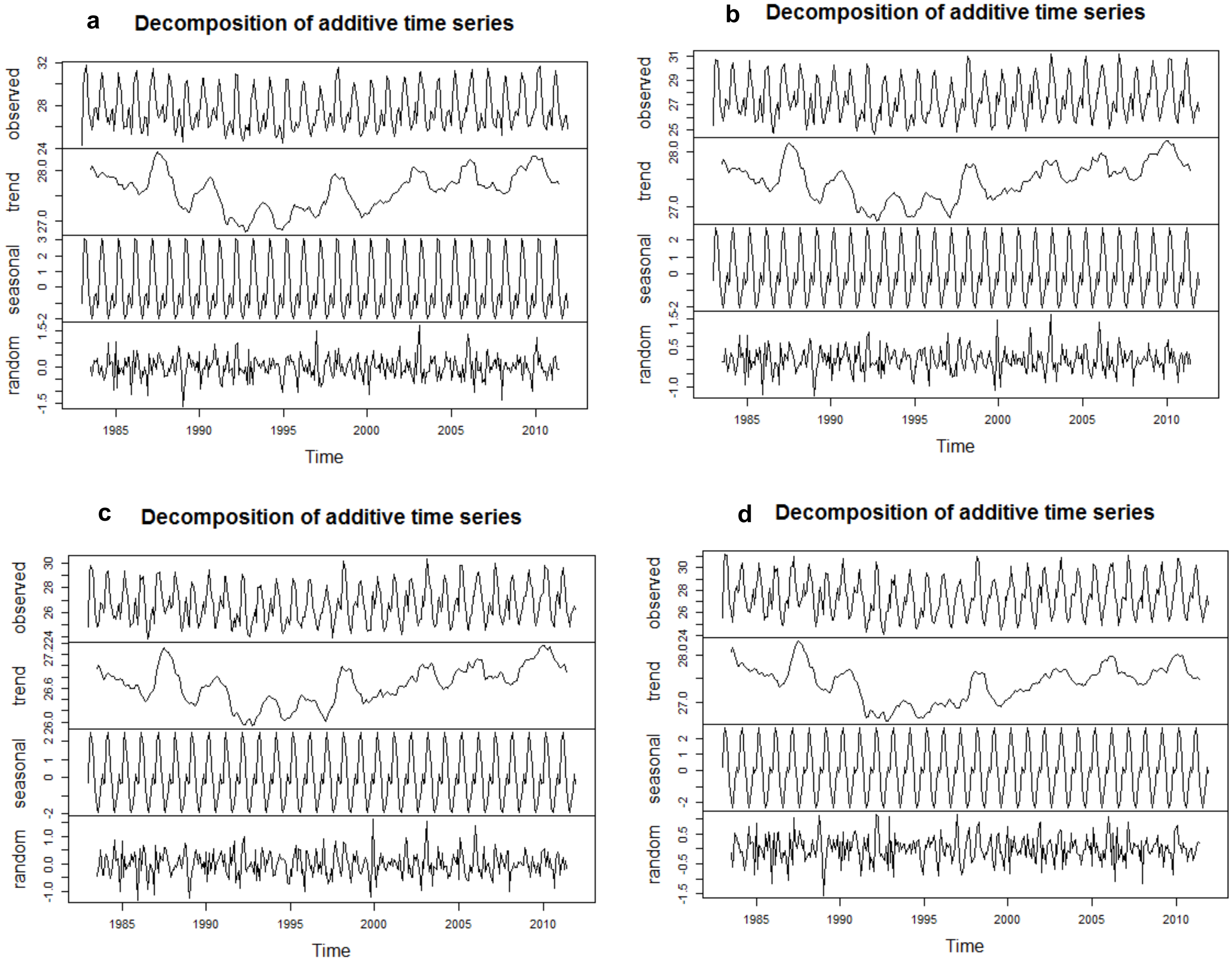
Appendix 5.28 showing temperature partial auto-correlation function for the selected locations in Kwara State



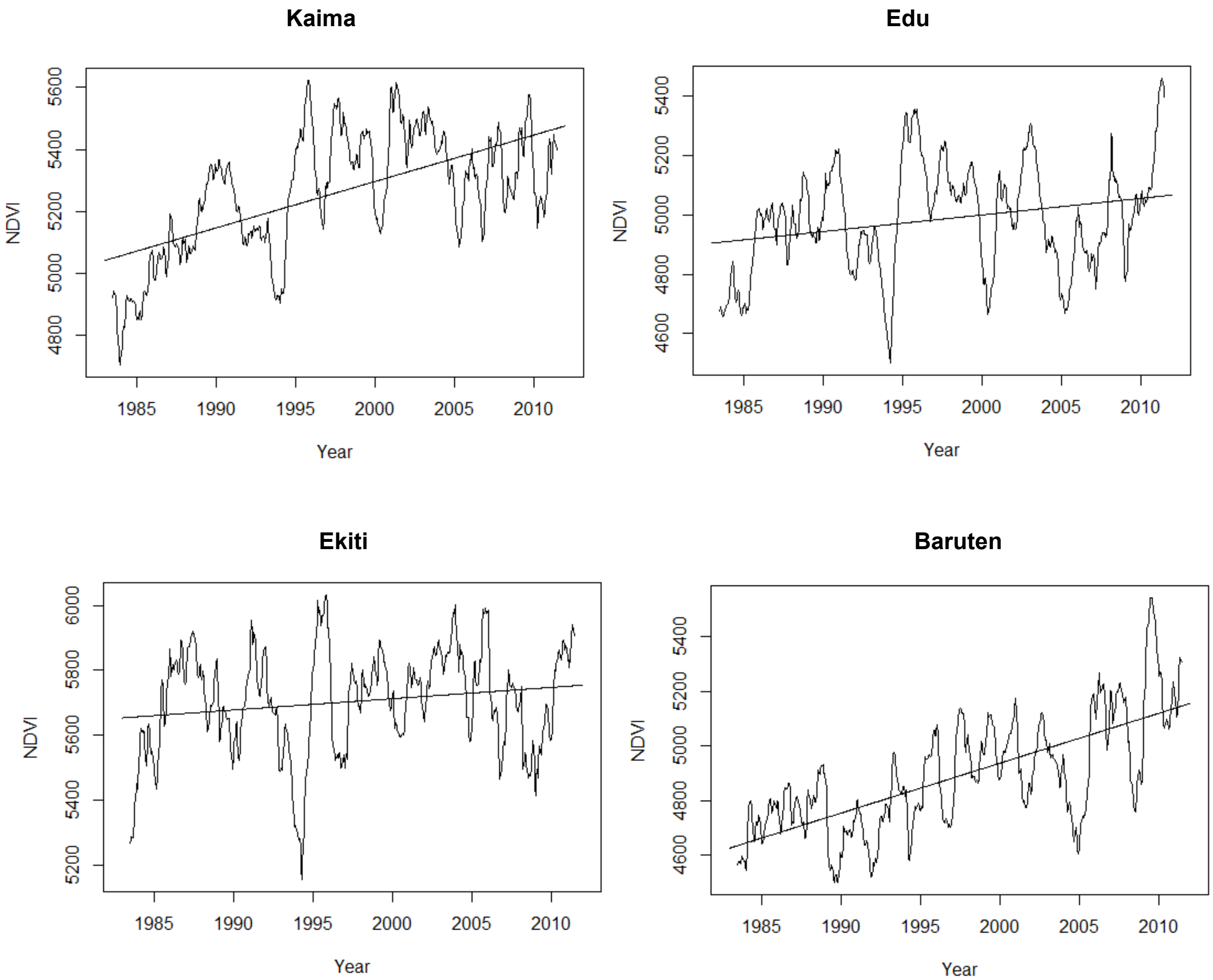
Appendix 5.29 showing decomposition of NDVI time series for the selected locations in Kwara



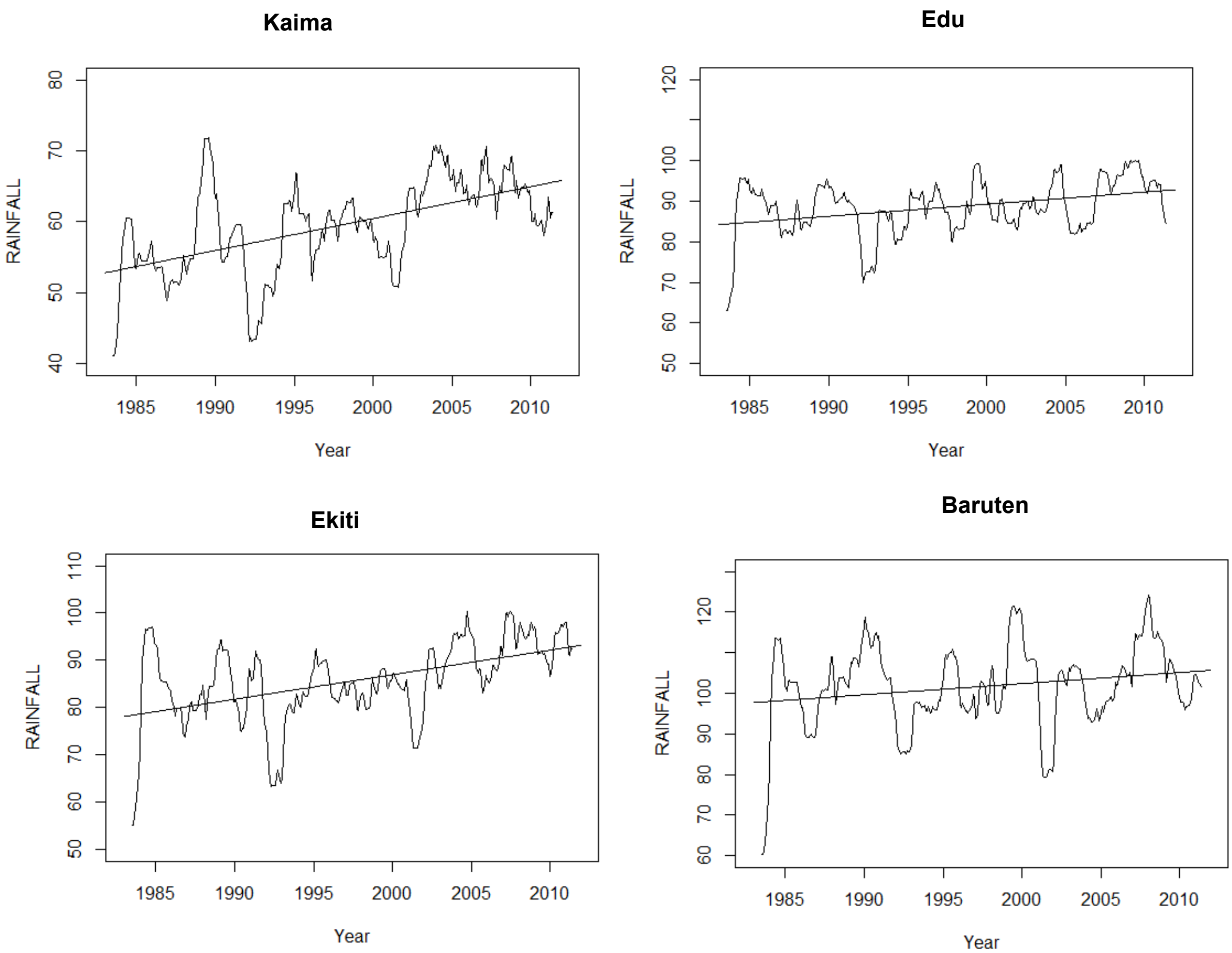
Appendix 5.30 showing decomposition of TAMSAT rainfall time series for the selected locations in Kwara



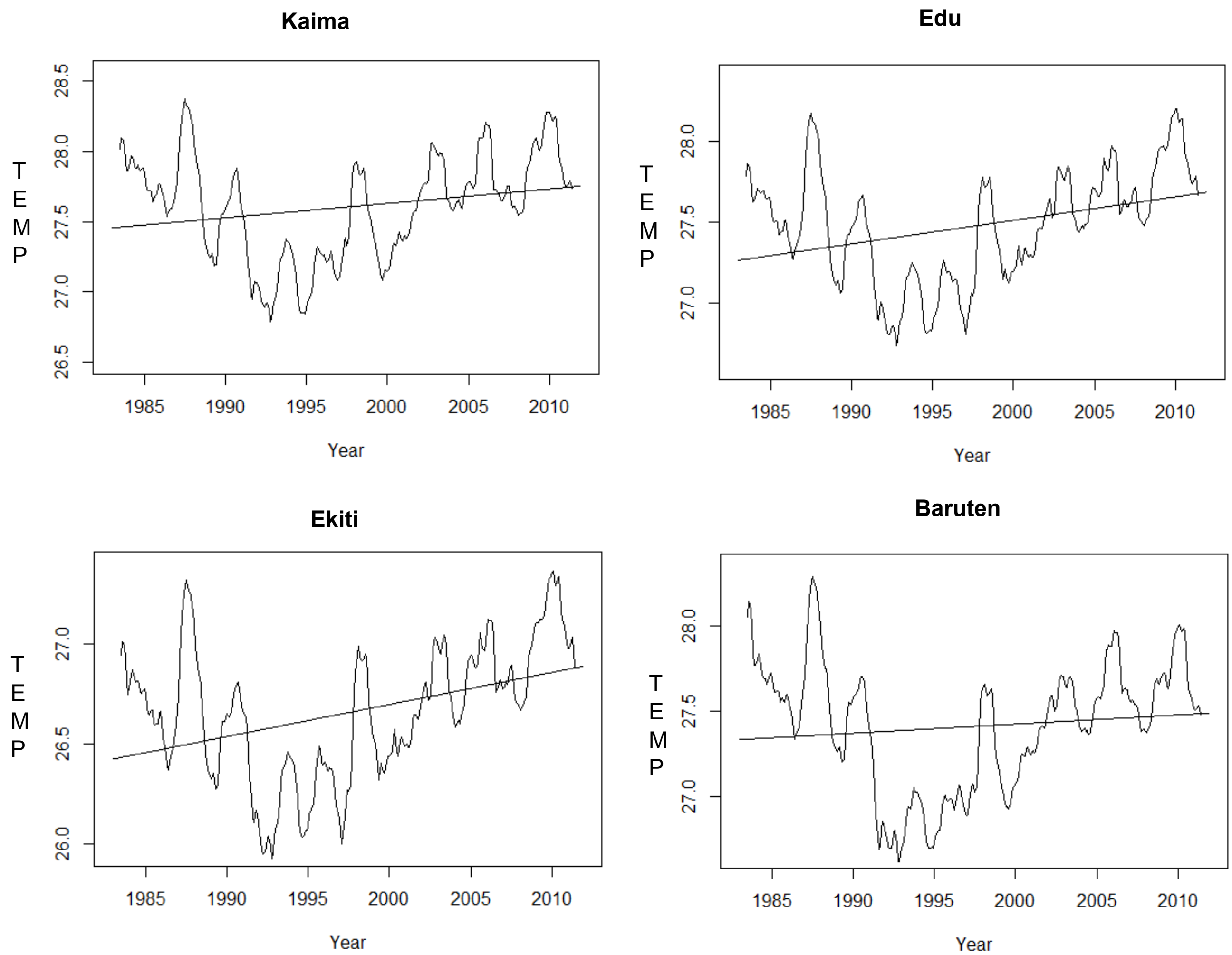
Appendix 5.31 showing decomposition of temperature time series for the selected locations in Kwara



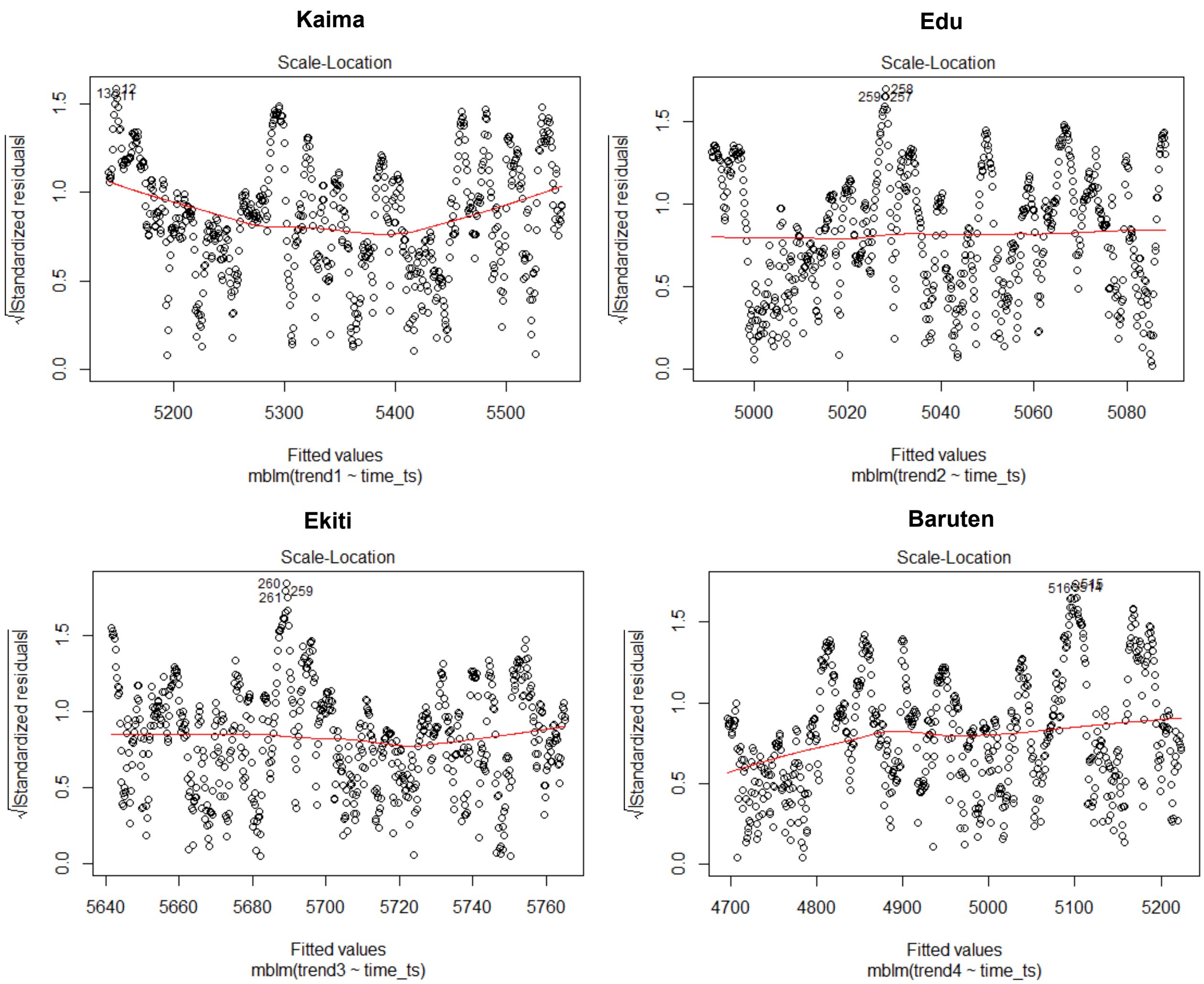
Appendix 5.32 showing NDVI linear regression model for the selected locations in Kwara



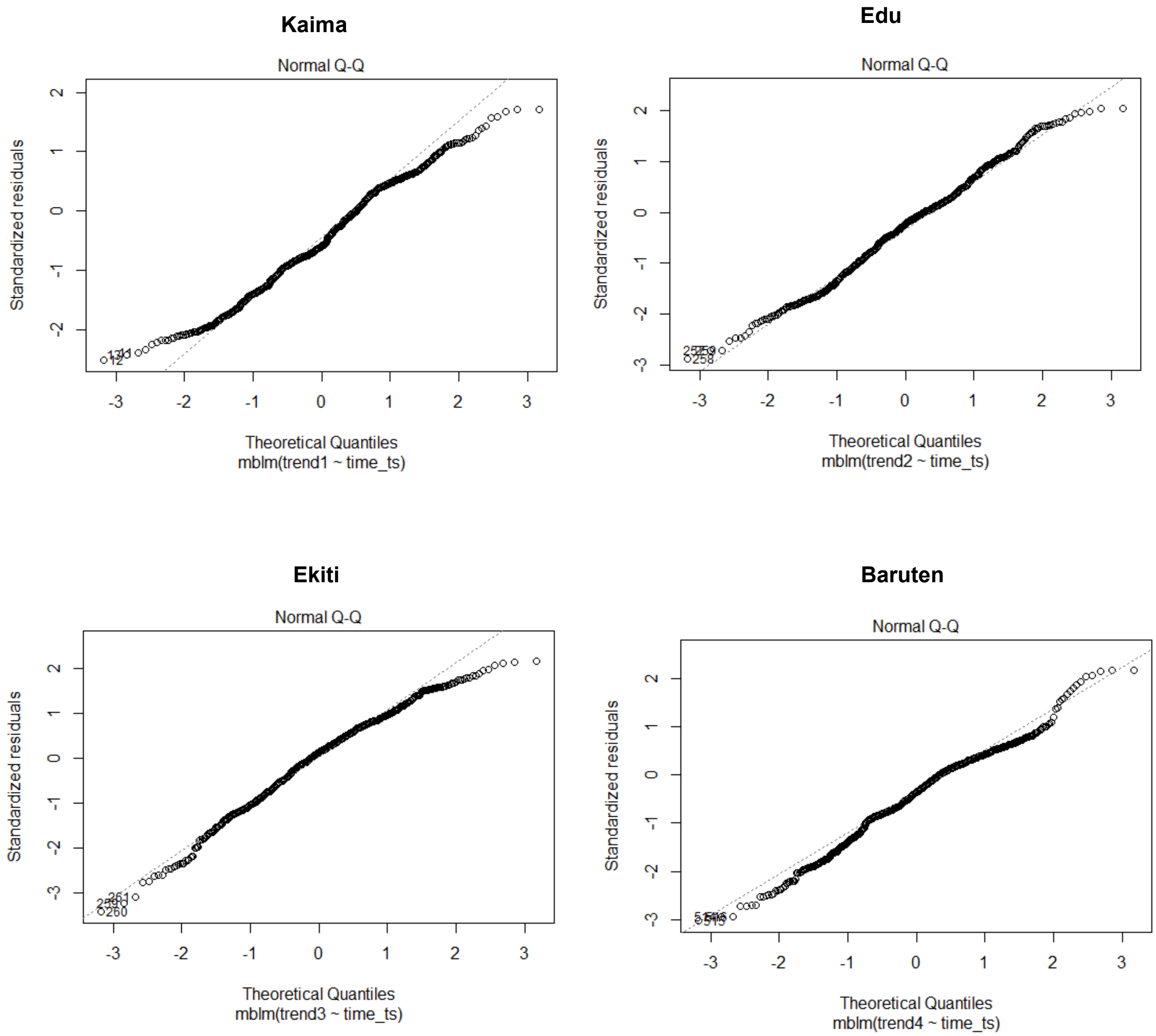
Appendix 5.33 showing rainfall linear regression model for the selected locations in Kwara



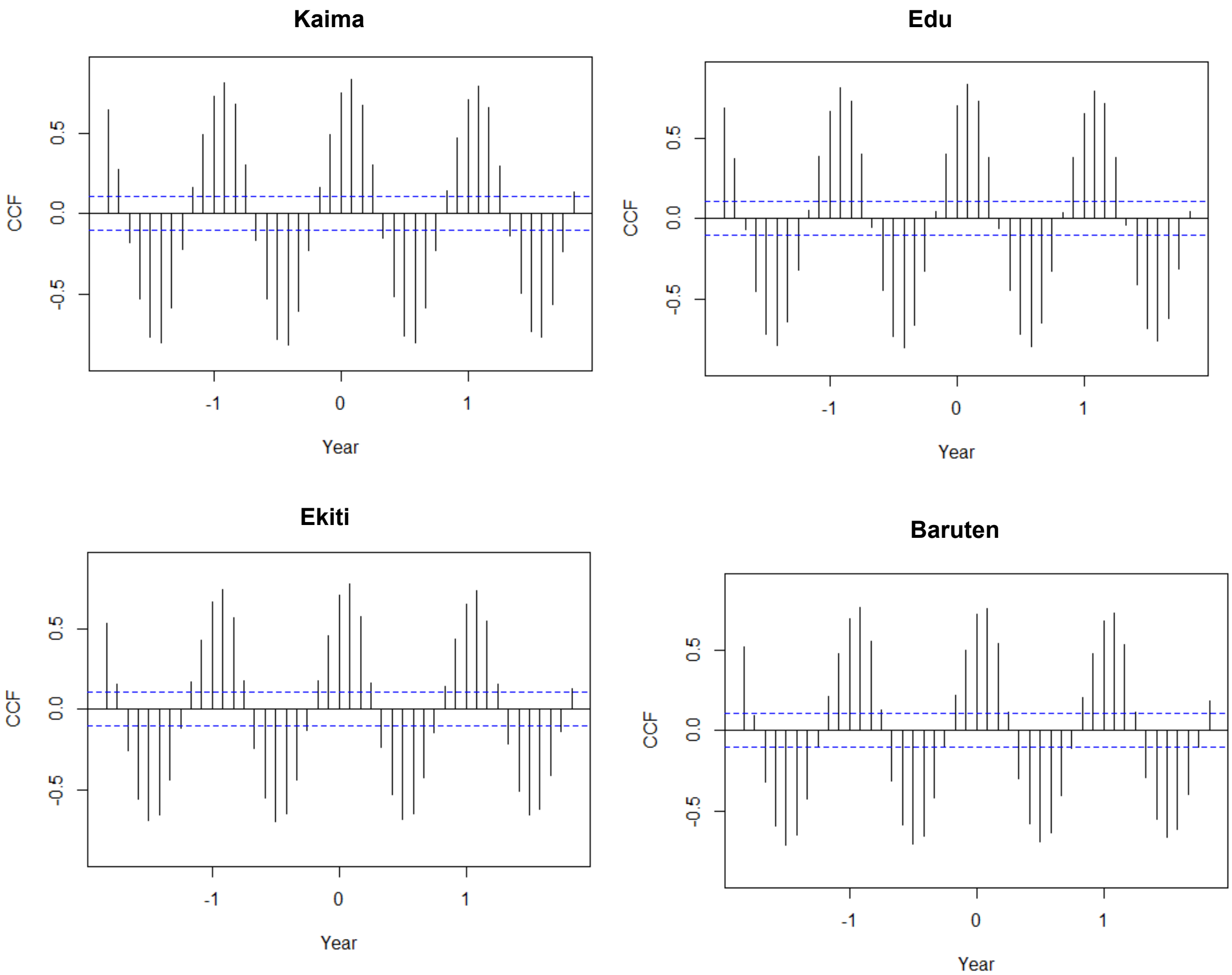
Appendix 5.34 showing temperature linear regression model for the selected locations in Kwara



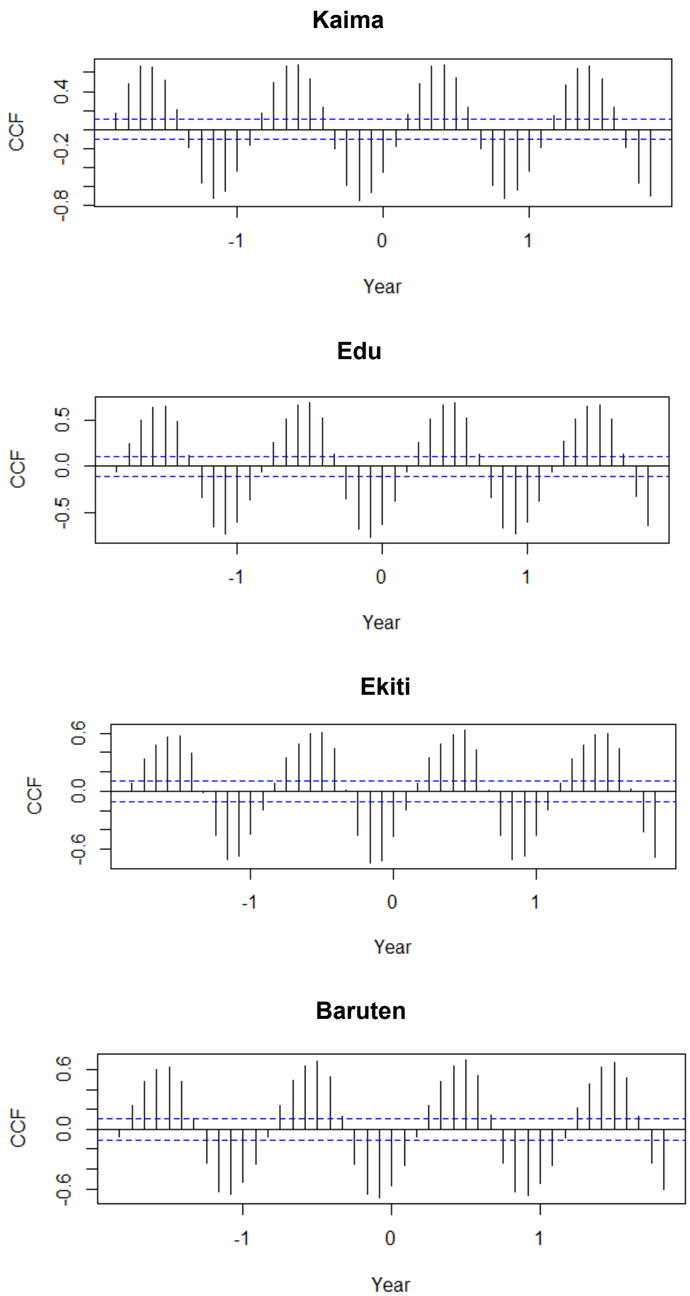
Appendix 5.35 showing standardized residuals for the Theil-Sen Estimation of NDVI trend signal for the selected locations in Kwara



Appendix 5.36 showing QQ-Plot of the Theil-Sen Estimation for the NDVI trend signal for the selected locations in Kwara State



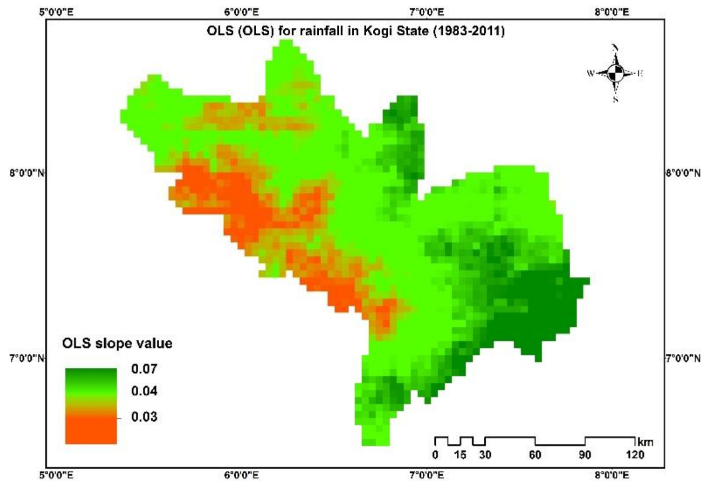
Appendix 5.37 showing cross correlation analysis between NDVI and rainfall for the selected locations in Kwara State

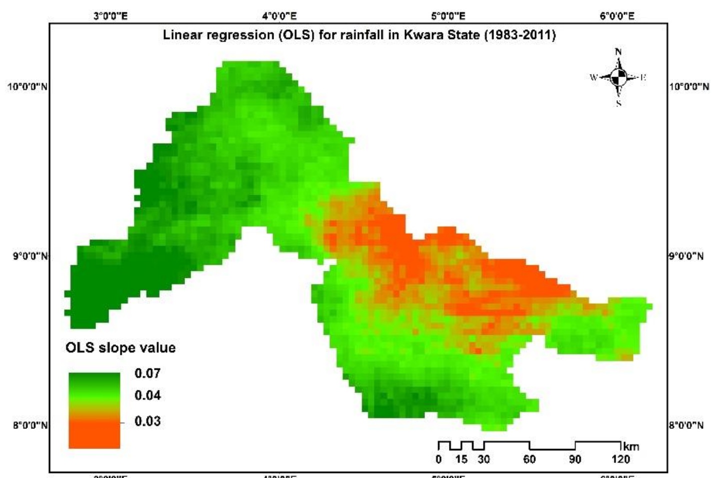


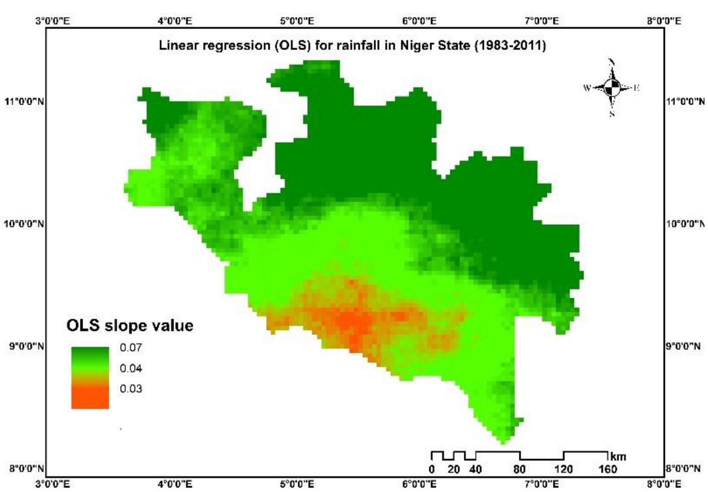
Appendix 5.38 showing cross correlation analysis between NDVI and temperature for the selected locations in Kwara State

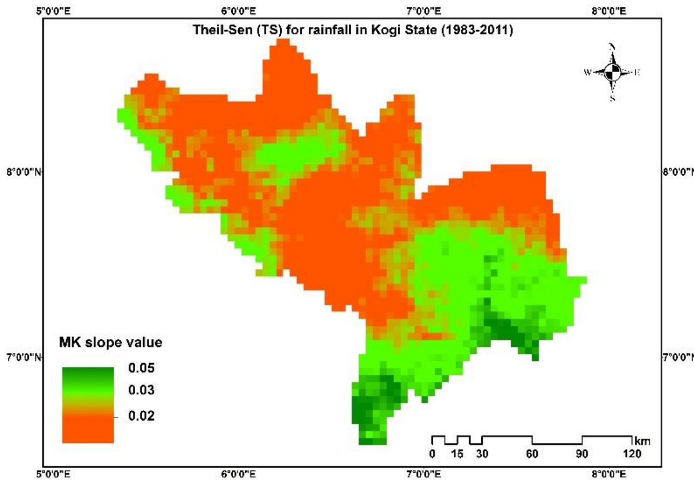
Chapter 5: Inter-annual trend analysis

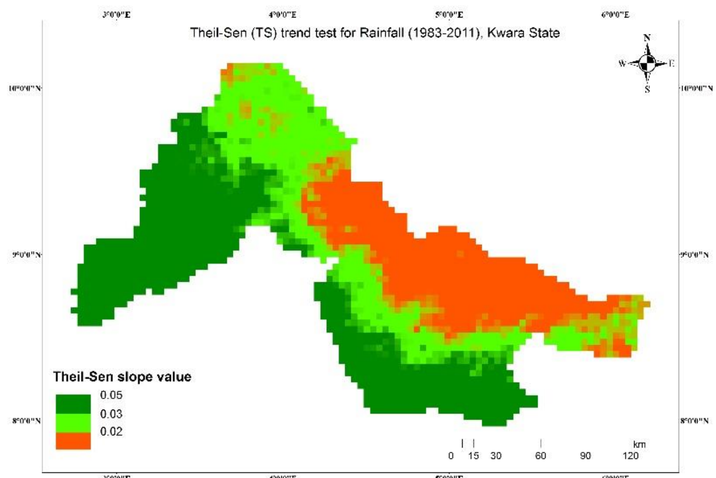
5.1 Results of OLS, TS, and MK trend test for rainfall and temperature

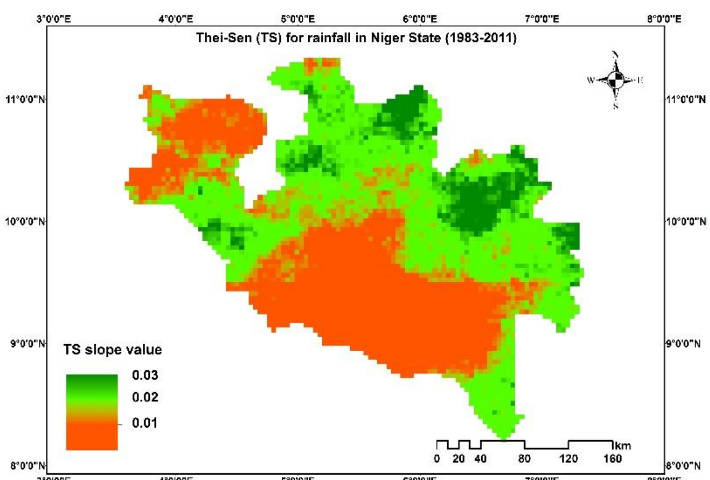


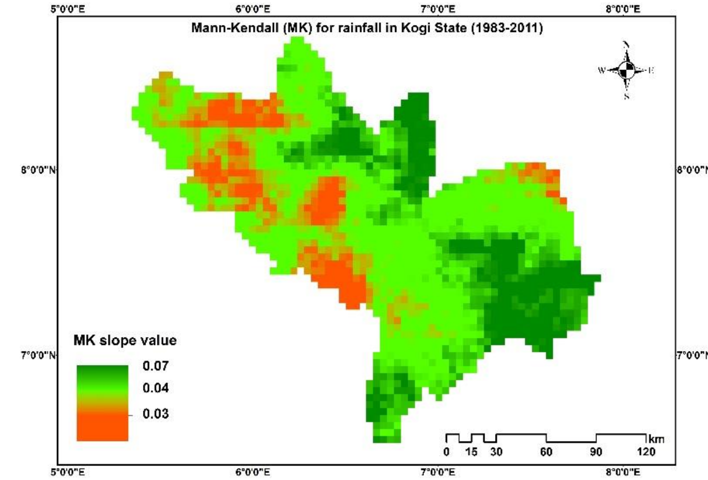


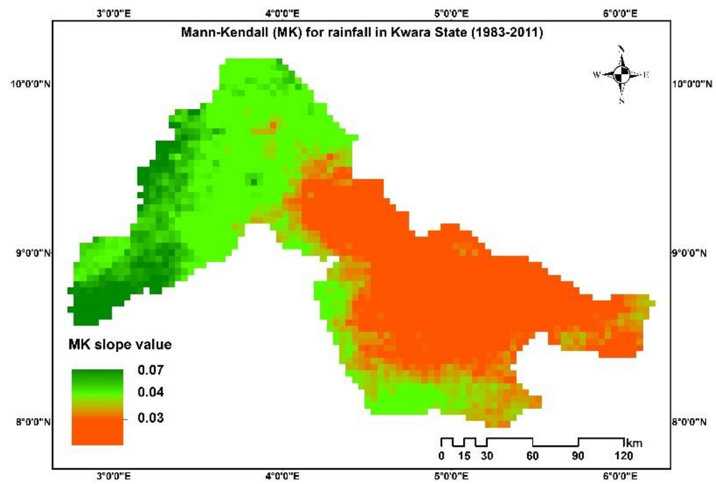


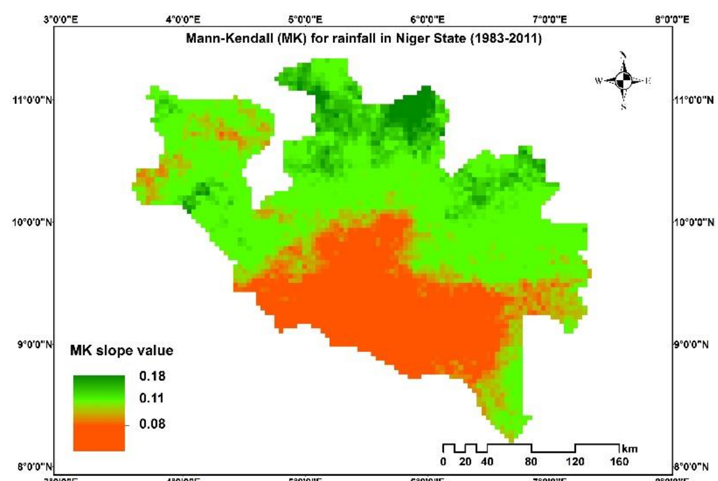

Theil-Sen (TS) for rainfall in Kogi State (1983-2011)
MK slope value
0.05
0.03
0.02
km
0 15 30 60 90 120
5°0'0"E
6°0'0"E
7°0'0"E
8°0'0"E
8°0'0"N
7°0'0"N


Theil-Sen (TS) trend test for Rainfall (1983-2011), Kwara State
Theil-Sen slope value
0.05
0.03
0.02
km
0 15 30 60 90 120


Thei-Sen (TS) for rainfall in Niger State (1983-2011)
TS slope value
0.03
0.02
0.01
km
0 20 40 80 120 160
3°0'0"E
4°0'0"E
5°0'0"E
6°0'0"E
7°0'0"E
8°0'0"E
11°0'0"N
10°0'0"N
9°0'0"N
8°0'0"N


Mann-Kendall (MK) for rainfall in Kogi State (1983-2011)
5°0'0"E
6°0'0"E
7°0'0"E
8°0'0"E
8°0'0"N
7°0'0"N
MK slope value
0.07
0.04
0.03
0 15 30 60 90 120 km


Mann-Kendall (MK) for rainfall in Kwara State (1983-2011)
3°0'0"E
4°0'0"E
5°0'0"E
6°0'0"E
10°0'0"N
9°0'0"N
8°0'0"N
MK slope value
0.07
0.04
0.03
0 15 30 60 90 120 km


Mann-Kendall (MK) for rainfall in Niger State (1983-2011)
3°0'0"E
4°0'0"E
5°0'0"E
6°0'0"E
7°0'0"E
8°0'0"E
11°0'0"N
10°0'0"N
9°0'0"N
8°0'0"N
MK slope value
0.18
0.11
0.08
0 20 40 80 120 160 km

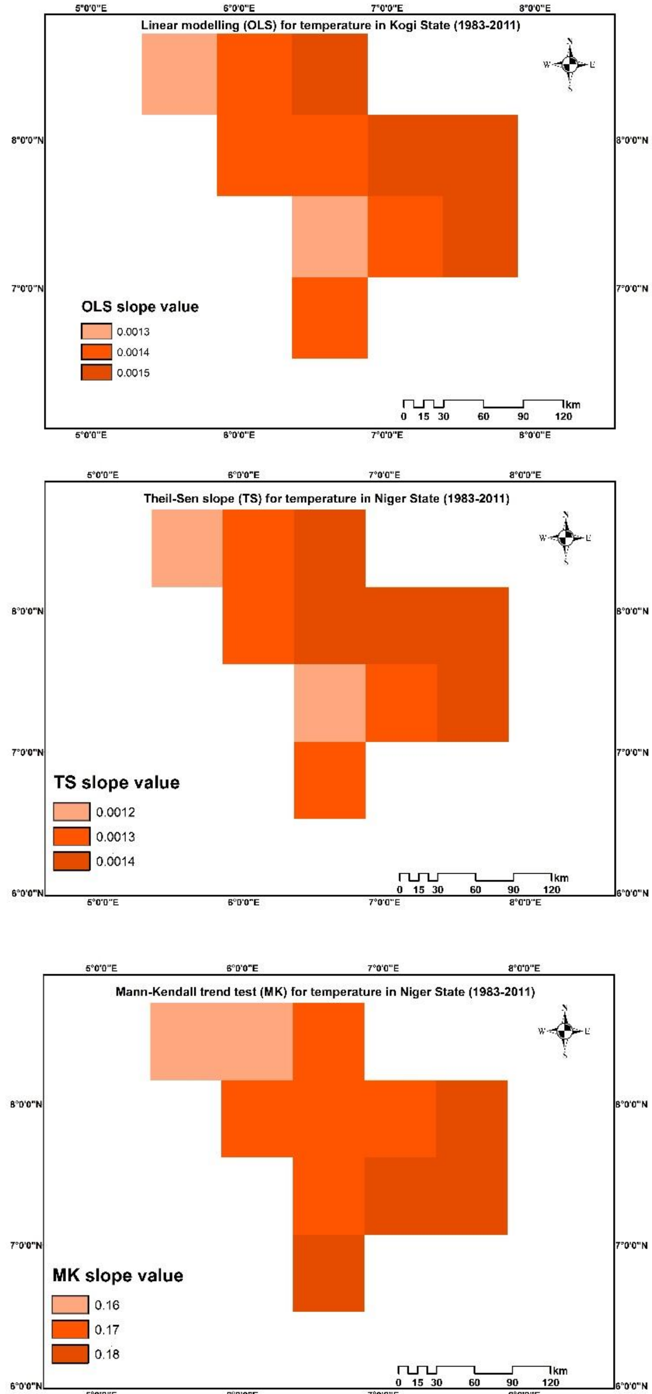


Figure showing the result of the trend analysis for temperature in Kogi state. However, similar trend was observed for Kwara and Niger.

Tables showing the results of the climatic trend estimators for the selected study locations in Kogi and Kwara State

Table 43: Results of linear regression model for rainfall (Kogi)

Location	Slope	Residual Standard Error	F-Statistic	R²	p-value
a	0.416	11.01	31.4	0.086	4.407e-08
b	0.467	6.74	120.2	0.240	< 2.2e-16
c	0.517	9.26	68.33	0.170	3.31e-15
d	0.380	8.02	49.35	0.123	1.207e-11

Table 44: Parameters of a linear regression (Theil-Sen Estimation) for TAMSAT rainfall data (Kogi)

Location	Slope	Residual Standard Error	p-value
a	0.275	11.12	< 2e-16
b	0.365	6.79	<2e-16
c	0.322	9.55	<2e-16
d	0.389	8.19	<2e-16

Table 45: Mann Kendall correlation Test for TAMSAT rainfall data (Kogi)

location	Mann Kendall	
	tau	p-value
a	0.175	1.7881e-06
b	0.319	< 2.22e-16
c	0.240	< 2.22e-16
d	0.231	< 2.22e-16

Table 46: Results of linear regression model for rainfall (Kwara)

Location	Slope	Residual Standard Error	F-Statistic	R^2	p-value
a	0.45	5.388	152.6	0.314	< 2.2e-16
b	0.31	6.13	56.61	0.145	4.974e-13
c	0.48	7.165	98.79	0.228	< 2.2e-16
d	0.41	8.432	52.46	0.136	3.055e-12

Table 47: Parameters of a linear regression (Theil-Sen Estimation) for TAMSAT rainfall data (Kwara)

Location	Slope	Residual Standard Error	p-value
a	0.48	5.458	< 2e-16
b	0.23	6.407	<2e-16
c	0.51	7.19	< 2e-16
d	0.41	8.63	<2e-16

Table 48: Mann Kendall correlation Test for TAMSAT rainfall data for Kwara State

location	Mann Kendall	
	tau	p-value
a	0.392	< 2.22e-16
b	0.216	< 2.22e-16
c	0.350	< 2.22e-16
d	0.235	< 2.22e-16

Table 49: Results of linear regression model for temperature (Kogi)

Location	Slope	Residual Standard Error	F-Statistic	R^2	p-value
a	0.018	0.227	141.4	0.297	< 2.2e-16
b	0.019	0.256	124.6	0.272	< 2.2e-16
c	0.020	0.252	144.6	0.302	< 2.2e-16
d	0.019	0.264	109.4	0.247	< 2.2e-16

Table 50: Parameters of a linear regression (Theil-Sen Estimation) for CRU temperature data (Kogi)

Location	Slope	Residual Standard Error	p-value
a	0.018	0.253	< 2e-16
b	0.021	0.265	<2e-16
c	0.021	0.254	< 2e-16
d	0.022	0.291	<2e-16

Table 51: Mann Kendall correlation Test for CRU temperature data (Kogi)

location	Mann Kendall	
	tau	p-value
a	0.383	< 2.22e-16
b	0.350	< 2.22e-16
c	0.364	< 2.22e-16
d	0.337	< 2.22e-16

Table 52: Results of linear regression model for temperature (Kwara)

Location	Slope	Residual Standard Error	F-Statistic	R^2	p-value
a	0.01	0.3638	17.35	0.049	3.966e-05
b	0.01	0.3295	42.95	0.114	2.133e-10
c	0.02	0.3108	58.16	0.148	2.541e-13
d	0.01	0.375	4.47	0.013	0.03519

Table 53: Parameters of a linear regression (Theil-Sen Estimation) for Temperature data (Kwara)

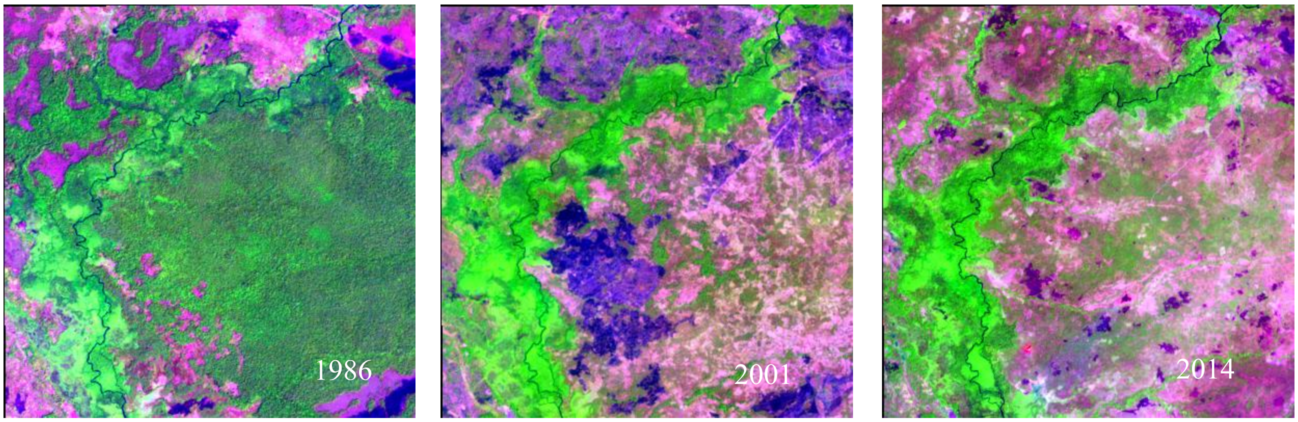
Location	Slope	Residual Standard Error	p-value
a	0.027	0.4102	< 2e-16
b	0.029	0.3544	<2e-16
c	0.028	0.3514	< 2e-16
d	0.025	0.4123	<2e-16

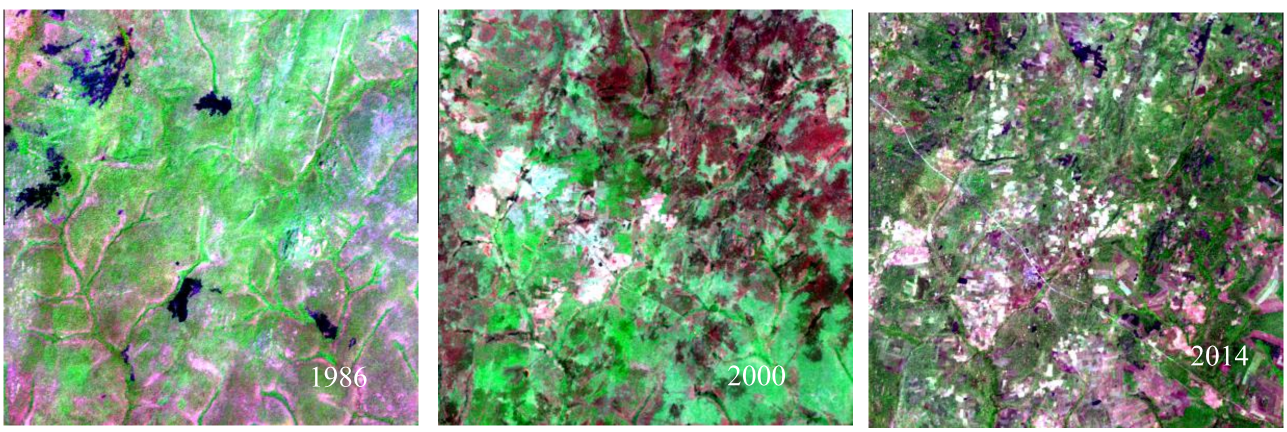
Table 54: Mann Kendall correlation Test for temperature data for Kwara State

location	Mann Kendall	
	tau	p-value
a	0.164	7.391e-06
b	0.254	< 2.22e-16
c	0.286	< 2.22e-16
d	0.118	0.0012733

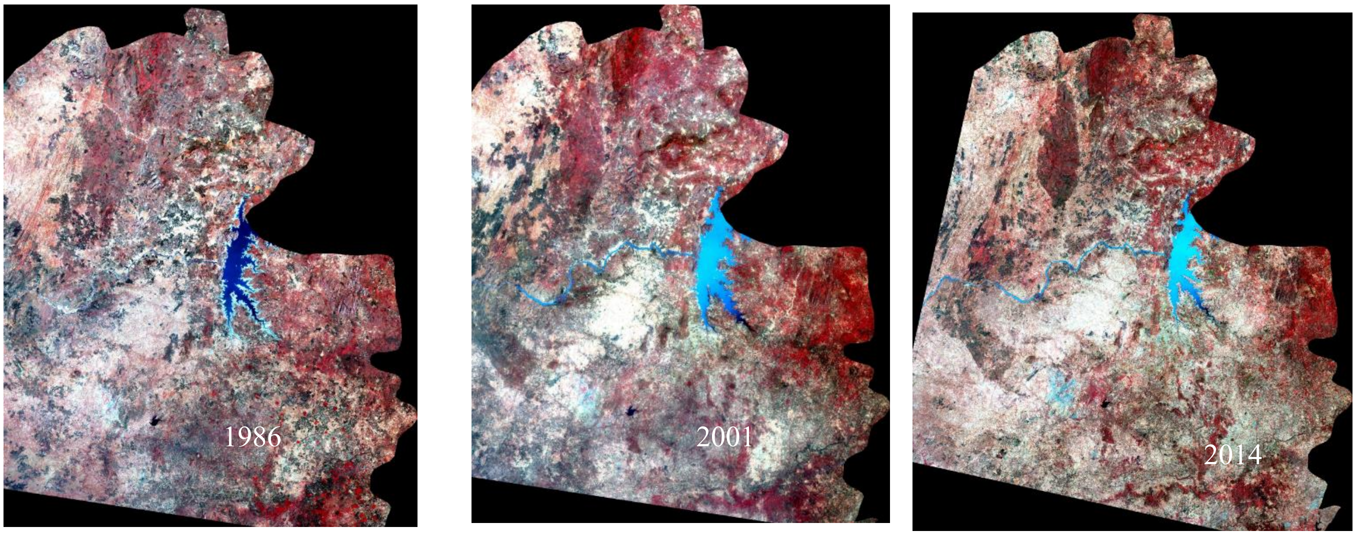
7 Land use land cover

Subsets of Landsat imagery used for the land use land cover (PV, NPV, BS) and deforestation change detection in Kogi State. Band combination = 5,4,3





Subsets of Landsat imagery used for the land use land cover (PV, NPV, BS) and deforestation change detection in Kwara State (Band combination= 5,4,3)

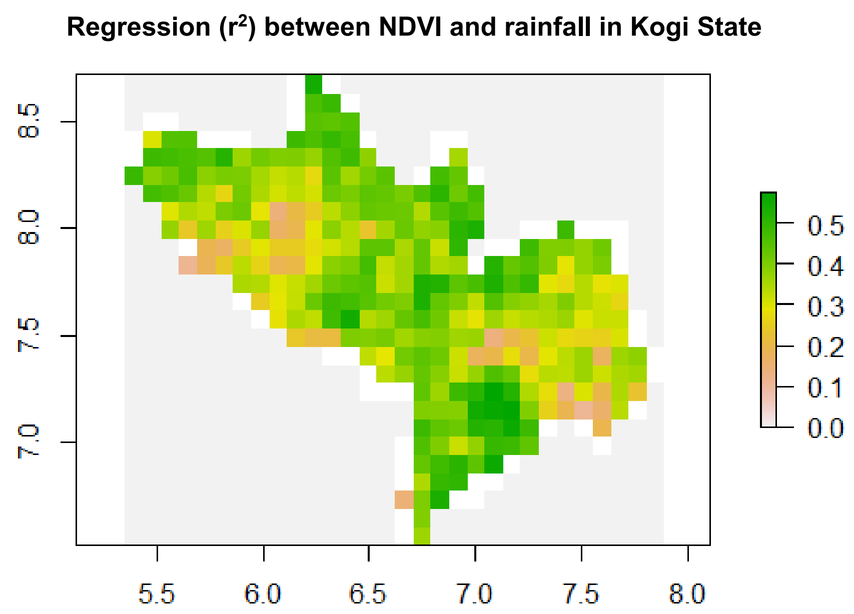


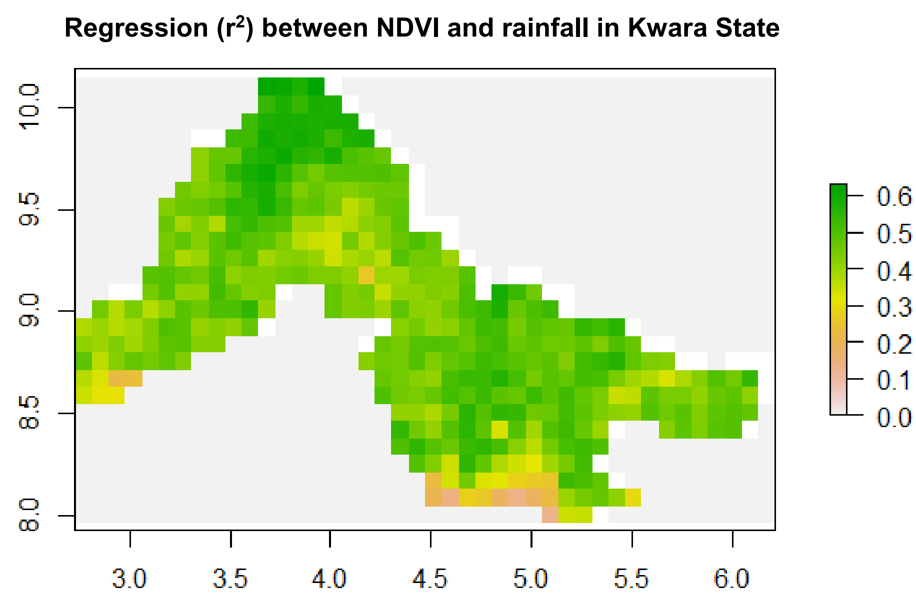
Subsets of Landsat imagery used for the land use land cover (PV, NPV, BS) and deforestation change detection in Niger State (Band combination= 4,3,2)

See table 4 for data source. It should be noted that the dataset were acquired in dry season.

Chapter 9: Result synthesis

Regression between NDVI and rainfall





Questionnaire for household survey for the assessment of vegetation and land in the study region

General

Questionnaire No.: ……..   Date:……/……/ 2013

Site of interview: ………………………………   Enumerator:

A. Socio- economic characteristics of Respondent/Demography

1. Name of Settlement: ....
2. Age of respondent: ....
3. Sex: (a) Male (b) Female
4. Marital Status: (a)Single (b) Married (c) Divorced (d) Widowed
5. If married, how many wives? (a) 1 (b) 2 (c) 3 (d) More than 3
6. No. of children/Dependants living with you….
7. Are you from this village ? a) Yes b) No
8. If no, since when are you in this village?..........
9. Level of Education:

   (a) Primary School ☐ (b) Secondary School ☐ Tertiary Institution ☐

   (d) Others, Specify☐ (e) No formal education

10. What is your major source of livelihood?

    (a) Farming ☐ (b) Trading ☐ (c) Civil Service ☐ (d) Artisanship ☐

    (e) Others, Specify ☐

B. Land Use Information

1. How do you prepare the land?

   (a) Slash and burn ☐ (b) Clearing with machines ☐

2. How did you get the land? (a) Communal (b) Family (c) Free (d) Loan

3. Who is responsible for land ownership? (a) Government (b) Local administration

   (c) Other (specify)

4. Is there any change in land use patterns in the area between the periods 1979 till 2012?

(a) Yes (b) No

5. If yes, describe….. (a) Overgrazing (b) Cutting of trees (c) Over cultivation of marginal lands (d) Shift in livelihood mechanism

6. Are there any signs of soil erosion in the area? (a) Yes (b) No

7. If yes what type? (a) Wind erosion (b) Water erosion (c) Both

8. Is there nomadic movement in the area? (a) Yes (b) No

9. If yes, what type of grazing system do you practice? (a) Set stocking system (b) Paddock or rotational system (c) Strip grazing system

B. Vegetation Information

1. Is there any change in vegetation composition? (a) Yes (b) No

2. If yes, what are the dominant species now?

Currently: a. (…………………..) b. (…………………….) c. (………………….……) d. (…………..…………….) e. (……………..……) f. (………….…………..)

Previously: a. (……………………..) b. (…………………….) c. (……………….………) d.(…………..…………….) e. (………………..……) f. (…………….………….)

3. Are there forest, woodland, shrub land and grassland in the area? (a) Yes (b) No

4. If yes, what is the rate of deforestation? (a) Fast (b) Moderate (c) Slow

5. Is making charcoal practiced in the area? (a) Yes (b) No

6. If yes, which are the best trees for charcoal production?..

……………………………………………………………………………………………………

……………………………………………………………………………………………………

7. Are the trees used for charcoal production disappearing? (a) Yes (b) No

8. If yes, at what rate? (a) Fast (b) Moderate (c) Slow

9. What are the indicators for decline in vegetation in your area-------------------------------?
(a) Over cultivation (b) Urbanization (c) Over-grazing (d) Poaching (e) Others…………

10. How would you rate the vegetation loss in this area today?

Less severe ( ) Moderately sever ( ) Very severe ( )

11. Will the rate of vegetation loss increase if no combating measure is implemented in this area? Yes ( ), No ( )

12. What are the rates of vegetation regeneration during normal raining period?

(a) Fast (b) Moderate (c) Slow (d) No regeneration

C. Climatic Information

(a) Has any change occur in the following over the past 30 year?

Total amount of rainfall Yes ( ) Increase Yes ( ) decrease No ( )	Time of rainfall Yes ( ) Increase Yes ( ) decrease No ( )
Intensity of rainfall Yes ( ) Increase Yes ( ) decrease No ( )	Frequency of rainfall Yes ( ) Increase Yes ( ) decrease No ( )
End of rainfall Yes ( ) Increase Yes ( ) Increase No ( )	Ground water level Yes ( ) Increase Yes ( ) decrease No ( )
Stream flow level Yes ( ) Increase Yes ( ) decrease No ( )	Frequency of flood into the stream Yes ( ) Increase Yes ( ) decrease No ( )
Intensity of Temperature Yes ( ) Increase Yes ( ) decrease No ( )	Effect of evapotranspiration Yes ( ) Increase Yes ( ) decrease No ( )

(b) Rank the following in order of priority as it affect you (assign 1 if it affects you more)
1, 2, 3, 4, 5

Issues	Rank
Soil erosion	
Biodiversity loss	
Deforestation	
Decline in soil fertility	
Desertification	

Other (specify)------------------------

Agricultural production

1. What type of agriculture do you practice?

   (a) Subsistence agriculture (b) commercial agriculture

2. What is size of your holding? (a) Less than 5acres (b) 5-10 acres (c) More than 10 acres

3. What are the major crops grown? (a) Cereal (b)Sorghum (c) Millet (d) Rice (e) Legumes (f) vegetables ....

4. Do you use any fertilizer? (a) Yes (b) No

5. If yes, what are in your opinion the main causes of reduction in crop yields? (a) Decline in soil fertility (b) Decrease rainfall (c) Lack of capital

6. What are the harvests now compared with that of 10 years ago?

   (a) Very good (b) good (c) not good

7. Do you sell part of your crop products? (a) Yes (b) No

8. Do you leave your land to fallow? (a) Yes (b) No

9. If yes, what is the age of the fallow period now compared to 30 yrs ago? (a) no fallow (b) 3 yrs (c) 5 yrs (d) 7 yrs (e) 10 …..yrs

10. Do you have small-scale irrigation farm? (a) Yes (b) No

11. If yes, what are the crops grown? (a) sorghum (b) millet (c) Others specify

12. Are you abandoning your land due to land degradation? (a) Yes (b) No

13. If yes, what are your livelihood options? (a) Cultivate other land (b) trading (NTFPs collection (others)..............................

14. What is the rate of migration due to land degradation in your opinion?

15. (a) High (b) moderate (c) low

Livestock production

1. Do you have livestock? (a) yes (b) no

2. What are the types and numbers of livestock that you own? (a) Cow………(b) Sheep….. (c) Goat…… (d) Camel……. (e) others……

3. Where do herds take their animals to during rainy season for grazing? (a) Around the village (b) outside the village (c) far away from the village

4. Where do herds take their animals to during dry season for grazing? (a) Around the village (b) outside the village (c) far away from the village

5. Is there movement of herders outside to the area? (a) yes (b) no

6. If yes, in what number do they come? (a) large number (b) small number

7. Does this movement affect water resources, pasture, agriculture, vegetation/forest?

   (a) Yes (b) no

8. Do herders sell milk and milk product? (a) Yes (b) no

9. How are these products affected by drought and land use change?

   (a) Severely affected (b) moderately affected (c) not affected

D. Management

i. What is (are) in your opinion the most effective measure in dealing with vegetation loss and/or to maintain and restore the forests?

   a. Afforestation and reforestation ( ) b. Awareness programs ( ) c. Job opportunities ( ) d. land management ( ) e. Other ( )

ii. What is in your opinion the best land management system?

   a. Governmental ( ) b. Community ( ) c. participatory approach ( ) d. private ( )