Evaluation of the impact of climate and human induced changes on the Nigerian forest using remote sensing

Submitted by

Ike Felix

To the university of Exeter as a thesis for the degree of Doctor of Philosophy in Geography October, 2015

I certify that all material in this thesis which is not my own work has been identified and that no material has previously been submitted and approved for the award of a degree by this or any other University.

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ABSTRACT

The majority of the impact of climate and human induced changes on forest are related to climate variability and deforestation. Similarly, changes in forest phenology due to climate variability and deforestation has been recognized as being among the most important early indicators of the impact of environmental change on forest ecosystem functioning. Comprehensive data on baseline forest cover changes including deforestation is required to provide background information needed for governments to make decision on Reducing Emissions from Deforestation and Forest Degradation (REED). Despite the fact that Nigeria ranks among the countries with highest deforestation rates based on Food and Agricultural Organization estimates, only a few studies have aimed at mapping forest cover changes at country scales. However, recent attempts to map baseline forest cover and deforestation in Nigeria has been based on global scale remote sensing techniques which do not confirm with ground based observations at country level. The aim of this study is two-fold: firstly, baseline forest cover was estimated using an 'adaptive' remote sensing model that classified forest cover with high accuracies at country level for the savanna and rainforest zones. The first part of this study also compared the potentials of different MODIS data in detecting forest cover changes at regional (cluster level) scale. The second part of this study explores the trends and response of forest phenology to rainfall across four forest clusters from 2002 to 2012 using vegetation index data from the MODIS and rainfall data obtained from the TRMM.

ACKNOWLEDGEMENTS

First, I would like to thank my parents Ike Amasike and Elizabeth Ike for their continual support and prayers throughout this PhD. I was fortunate to have a combination two great supervisors Dr. Luiz Aragão and Dr. Lina Mercado who were very patient with my progress from upgrade to PhD and transition to submission. Indeed, one thing I learnt from both of them is that research is about quality and not quantity. This notion really changed my orientation as a researcher. In fact, their patience towards my development in scientific writing is something that will never leave my memory. Despite the three of us rarely being in the same location during the past year, both Luiz and Lina have made some quality time for me, whether it is over email, phone, or video, so I remain grateful to you both.

Without the help of friend's, locals and government officials, fieldwork in Nigeria would have been almost impossible. For , this, would like to thank Idoko, Macero, Elvis, Alex, Okyor, Adex, Ignatiius, Bongi, Emeka, Ernest, Leo, Kelechi, Don Mike, Chinyere Ottah, Anthony Ogbuji, Okyor, Aron, Ogilo,Enero, Bengilo, Erima, Pastor, and other whose name I can't recall for their assistance during forest surveys. Some friends who helped during field research in Nigeria, but as of today, they are gone: Agwilo died in an automobile accident while Bossy died of injuries sustained from a bomb blast-I miss them. I was also fortunate to survive a fatal automobile road accident during fieldwork in Nigeria that saw me hospitalized for several months. Annaline too, you are still in my memory. I remain grateful to Jitoboh Moses for all the financial assistance I received during and after the period of my accident. I will also like to thank Ignatius and Chinwe Nwabueze for the encouragement and support during the period of my PhD. To Laura Yeves, your team work with Lina in the management of my registration status at Exeter University after my discharge from the hospital will remain in my memory forever-so, I thank you both.

I would like to thank the Tertiary Education Trust Fund for their part in funding this research. through studentship grant ASTD/ABSU/12/414271/. Also, I am thankful to fellow PhD students and staff in the Geography department at Exeter and Abia State University including M.A Ijioma, I.S Onwuchekwa, G N Chima, J U Ogbonna, D. S Okorigwe, Alozie M C and Nkemdirim V U, Peter Ani and Ogobonna C E for supporting me through the duration of the PhD. I specifically want to thank Simon, Felix and Colin for their social mentorship in Exeter. Finally, I thank siblings and friends who provided fun times for me when needed. They are: Celestine, Michael, John, Matin, Florence and Lucy. I also thank Nwabueze Chinenyenwa for your care and support.

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Acronyms & Abbreviations

Acronym	**Definition**
AVHRR	Advanced Very High Resolution Radiometer
CDM	Clean Development Mechanism
COY	Composite Day of the Year
CIFOR	Center for International Forestry Research
ENVI	Environment For Viewing Images
ETM	Earth Thematic Mapper
EVI	Ehanced vegetation Index
FAO	Food and Agricultural Organization
GCP	Ground Control Point
GMS	Geostationary Meteorological Satellite
GNNS	Global Navigation Satellite System
GOES	Geostationary Operational Environmental Satellite
HCD	Hybrid Change Detection
ICI	Incorrectly Classified Pixels
ITCZ	Inter Tropical Convergence Zone
LIDAR	Light Detection And Ranging
LPS	Length of the Phenology Season

Acronym	**Definition**
LRS	Length of the Rainfall Season
MODIS	Moderate Resolution Imaging Spectroradiometer
NARDSA	National Space Research Development Agency
NCRS	National Center for Remote Sensing
NEEDS	National Economic Empowerment and Development Strategy
NEST	Nigerian Environmental Study/Action Team
NGDI	National Geosptial Data Infrastructure
PCD	Phenology Cessation Date
POD	Phenology Onset date
POS	Phenology Onset Date
REDD+	Reducing Emissions from Deforestation and Forest Degradation
ROD	Rainfa Onset date
SVM	Support Vector Machine
TOA	Top of the Atmosphere
TRMM	Tropical Rainfall Measuring Mission

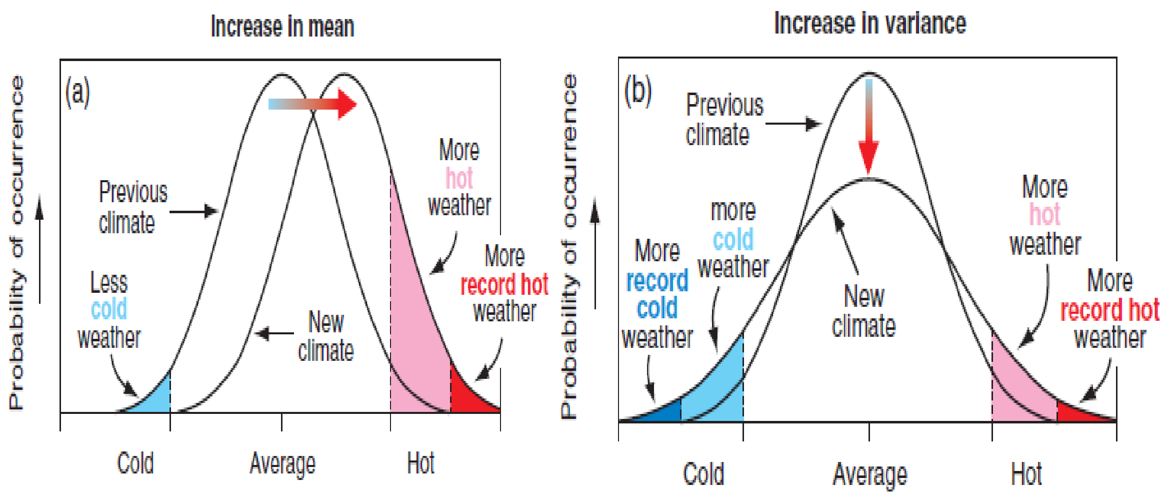
CHAPTER ONE

INTRODUCTION

1.1 Rationale for Research

It is widely accepted that our climate is changing (Stocker et al. 2013) and these changes have potential impacts on forest cover (Coe et al. 2013) in numerous ways. Human activities also physically impacts on the spatial structure of forest cover through deforestation. Climate change has the potential of initiating extreme variations in climatic elements such as rainfall. Changes in forest cover due to climate variability can be assessed using phenological matrices derived from observational data (Richardson et al. 2013).

Records have shown that the period 1995-2006 ranked among the twelve warmest years in the instrumental record of global surface temperature since 1850: The 100-year linear trend (1906-2005) of 0.74 (0.56 to 0.92) °C is larger than the corresponding trend of 0.6 (0.4 to 0.8) °C from 1901-2000 (Solomon, 2007). Indicators of climate change are observed from marked departures from an initial climate over a long (30 years or more) period (Meyer 1996). Depending on the magnitude of change, climate also varies across space and time. Climate variability is the deviations of climatic elements such as rainfall and temperature, usually from their long-term trend. Variability denotes deviations of climate threshold over a given period (such as a specific month, season or year) from the long-term climatic mean. Climate variability therefore is associated with the influence of anomalies in observed seasonal patterns of climate. As an example, increase in mean temperature may lead to record high temperature (Figure 1a) but change in mean does not imply change in variability (Figure 1b).



Source: (Folland et al. 2002)

Figure 1: Effects of increase in mean temperature (a) and variance temperature (b) on climate variability

As indicated in Figure 1a, the range between the hottest and coldest period did not change, rather it only led to a hotter weather condition. Increase in variance (Figure 1b) without a complementary rise in mean will only lead to a 'new weather'. Many studies (e.g. Bounoua et al. 2010) have shown that forest cover changes have linked to changes in climate regimes. Therefore, the effects of shifts from one climate regime to another may have far-reaching impact on the forest cover in numerous ways.

Deforestation is the second largest anthropogenic source of carbon dioxide and contributes 6–17% of global anthropogenic CO_2 emissions to the atmosphere (van der Werf et al. 2009). Emissions from deforestation increases atmospheric CO_2 and other trace gasses and affects local climate (Le Quéré et al. 2009; Spracklen et al 2012). When the amount of forest cover available in an area changes, it may affect the immediate local environment (Coe et al. 2013) or feedback to the atmosphere by modifying evapotranspiration and albedo (Brovkin 2002; Richardson et al. 2013). However, the major problem of mapping global and regional deforestation using remote sensing techniques (e.g. Achard et al. 2002; Achard et al. 2014) is their spatial and temporal disparities when compared with ground based observations at different scales. Correspondingly, most global and regional estimates of forest cover from remote sensing do not conform to regional and national ground- based estimates (Achard et al. 2002; Mayaux et al. 2013). The quantification of real-time forest cover changes from remote sensing based on country observations will no doubt provide adequate data necessary for Reducing Emissions from Deforestation and Forest Degradation (REED).

The forest covers of Nigeria occupy about 10 million ha of land representing almost 10% of the total land area of 92, 377 km^2 (FRA 2010b). The Food and Agriculture Organization of the United Nations (FAO 2006) ranked Nigeria to have the world's highest deforestation rate of primary forests between 2000-2005 and ranks 4th in countries with largest annual net loss of forest area between 1990 and 2010 (FAO 2010). In 1995, the forest area in Nigeria was 13 million ha while by 2010 it had reduced to 9 million ha (FAO 2001; FAO 2010). The forest cover in Nigeria provides habitat for many plant and animal species and plays a pivotal role in both local and regional climate systems with over 60% of the population dependent on forest energy (Akinbami et al. 2003) for domestic activities and cultivation of crops for food as means of survival.

Human activities and population expansion are also increasingly changing forest cover and increasing deforestation rates across different geographic regions on Earth and these changes are not the same for all countries. With a population of 173.6 million in Nigeria (UNDESA 2013), excessive use of forest, resources (such as firewood) due to population expansion have the tendency to increase deforestation. The forest resources of Nigeria are contained in 445-

gazetted reserves distributed over the major vegetation zones (FMEA 2006; FRA 2010b). The reserved forests occupies an area of 96043 km^2 of forest (FMEA 2006) which are found in both the natural forest and eight national parks occupying a land area of 2,238,296 ha (FRA 2010b). Nigeria is endowed with 4,600 plant species, of which 205 are endemic (Ugochukwu and Ertel 2008). Persistent deforestation driven by both natural and human induced factors threatens the rich forest biodiversity found in Nigeria.

Phenology is the seasonal plant cycle stages in vegetation such as green- up, maturity, senescence, and dormancy (Min et al. 2010). It is an important indicator for the evaluation of climate-biosphere interactions (Hwang et al. 2014). Accurate measurements vegetation phenology are required to improve models and understanding of inter-annual variability in terrestrial ecosystem carbon exchange and climate–biosphere interaction (Zhang et al. 2003). Phenology controls many feedbacks of vegetation to the climate system by influencing the seasonality of albedo, length, canopy conductance, and fluxes of water (Richardson et al. 2013). Furthermore, phenology can also be influenced by global climate change through the modification of rainfall seasonality (Hmimina et al. 2013) and the extension of rainfall deficits or excesses (Fauchereau et al. 2003) which can be used for environmental risk assessments and land-use change evaluations (Zhang et al. 2005).

The relationship between forest cover phenology and rainfall variability on ecosystem functioning and structure have been given much attention (e.g. Peñuelas et al. 2004). This relationship allows for the accurate prediction of the future response of vegetation to climate variation. In Nigeria, the degree to which spatial and temporal variation of forest phenology depends on rainfall trends has not been widely explored.

Advancements in the use of satellite technology to assess the Earth's regional and global climate relative to biogeochemical and bio geophysical processes has been given much attention by scientists from geographic, physical and biological sciences in a bid to understand the functioning of terrestrial ecosystems. Studies using both ground based field measurements and satellite-derived vegetation indices have demonstrated that global warming is influencing forest growth and phenology (Zhang et al. 2005).

Remote sensing data and techniques obtains and monitor changes in forest cover, trends in phenology and variations in climate at varying spatial and temporal scales. Remote sensing techniques for monitoring forest cover and deforestation rates at global and regional levels include-but not limited to- change detection using fine resolution satellite imagery and measuring change using coarse resolution satellite imagery (Coppin 2004). Satellite remote-sensing techniques offer the potential to detect continuous forest cover change and phenology for the parameterizing climate models. Satellite Earth observation products such as the Moderate Resolution Imaging Spectroradiometer (MODIS) (which is a continuation of the Advanced Very High Resolution Radiometer –AVHRR) and Landsat are useful for detection of the trends of both climate and human induced changes in the forest. Although the resolution of MODIS (250m, 500m, and 1km) and AVHRR composites is coarse, they are still useful for detection of the impacts of both climate and human processes in regions such as Nigeria where it is practically impossible to isolate ecosystem functioning from human activities without using a continuous data.

Spectral Vegetation Indices (VI) derived from MODIS have been widely applied in earth observation research to ascertain not only the spatial and temporal patterns of vegetation photosynthetic activity but also for the derivation of eco-sensitive parameters such as Normalized Differential Vegetative Index (NDVI) and Enhanced Vegetative Index (EVI) used in estimating phenology matrices (Sellers, et al. 1994). A rich source of continuous remotely sensed rainfall data for Nigeria is available from the Tropical Rainfall Measuring Mission (TRMM) satellite. Such data in conjunction with vegetation cover data provides platforms for the assessment of climate, deforestation and phenology trends at varying scales.

Recently, government and the scientific community of developing countries have strived to generate detailed information on the complex nature of deforestation and trends of rainfall and phenology within the forestfor planning, decision-making and mitigation. Yet, despite the massive population sprawl of Nigerians into forested ecosystems (USAID 2002), there is a limited understanding on trends in forest cover change, climate variability and forest phenology. Effective decision making and mitigation can only be carried out if government have detailed and verifiable information on the relationship between these variables

1.2 Research Background

Evaluating baseline forest cover and rainfall- phenology relationship requires continuous satellite data (Tucker and Townsend 2000; Park 2010). Evaluation of forest phenology requires both field and remote sensing data. However, it is cost and time effective to monitor phenology trends using continuous satellite data if the target output is to compare time series (Zhang et al. 2005). Rainfall retrieved from TRMM estimates rainfall trends with high accuracies (Zhang, et al. 2005) at varying scales.

Field based remote sensing methods for assessing deforestation, rainfall and forest cover phenology are adequate because they provide near accurate measurements of rates/

geographic extents, and give an insight into their spatial patterns from time series. Similarly, in Nigeria, complex uncontrolled interrelated man-environment activities abound, studying the dynamics of deforestation (human/physical), rainfall and phenology trends, requires intensive fieldwork. Bearing this in mind, this study incorporated both the impacts of localized human activities and physical factors in analyzing the remote-sensed data. Since this research provides about the first most comprehensive platforms to evaluate trends in forest cover, and rainfall-phenology relationship from remote sensing in Nigeria, this study addresses three research questions and four objectives

1.3 Research Questions

1. Most global and regional estimates of baseline forest cover from remote sensing do not conform to local and national ground based estimates. First, I examine methods to detect baseline forest cover in Nigeria using remotely sensed data that allows estimates at a scale that is in agreement with regional (country level) and local (cluster-level) observations.

2. What was the spatial and temporal variation of deforestation rates and hotspots between 2002 and 2012?

3. What is the relationship between forest phenology and rainfall?

1.4 Objectives

1. To estimate baseline forest cover for Nigeria between 2002-2006 and 2007-2012

2. To estimate and compare the rates of deforestation for selected forest areas (clusters) using different MODIS data from 2002-2006 and 2007-2012.

3. To map the spatial and temporal patterns of deforestation for the selected forest clusters

4. To evaluate the relationship and trends between rainfall and phenology in each of the forest clusters.

1.5 Nigeria: Setting the Scene

This part of the thesis briefly presented a general introduction of the location and extent of Nigeria, followed by the vegetation, climate, drainage and soil. Section 3.3 presents the geographic description of each of the forest clusters.

1.5.1 Location and Extent of Nigeria

Nigeria lies between latitude 4^0N, and 14^0 N and longitude 3^0N, and 15^0E. It is located in Western Africa on the Gulf of Guinea and has a total area of 923,768 km² (land 910,768 and water 13,000 km²) making it the world's 32nd-largest country. The distribution of forest in Nigeria is not homogeneous: Forest cover is more concentrated in the southern zones than any other region of Nigeria.

1.5.2 General Climate of Nigeria

The climate of Nigeria is in four sub-groups: The Equatorial monsoon found in the south, the wet /dry climates in the middle belt, the dry climate in the far North and the highland climates in areas with very high altitude. In southern Nigeria, two main features abound in the climate. The first is the moisture-laden wind that flow from the Atlantic Ocean as Southeasterly wind known as Tropical Maritime air mass (MT) and the second being the intensity of the sun that is usually high throughout the year. Due to the proximity of southern Nigeria to the equator, variation in temperature is usually the same throughout the year. Temperature values for most part of southern Nigeria are usually between 29^0C and 27^0C throughout the year. With favourable temperature regime and abundant moisture, the tendency for the MT air mass to rise is high and hence high rainfall exceeding 4000 mm for most part of the Niger Delta and 2000 mm in other areas (Ayoade 1983).

Rainfall in Nigeria originates from the moisture bearing South-Westerly (SW) winds that is a recurved extension of the Southeast trades from the Atlantic Ocean (Anyadike 1992; Anyadike 1993). The northward penetration of the SW in any month marks the surface location of the intertropical Convergence zone (ITCZ) (Ayoade 1983). Around January, the ITCZ is at its southernmost location of the Nigerian coast. The ITCZ progresses Northward with the invasion of the moisture bearing air from Atlantic Ocean such that by April-May each year rainfall is well established across most regions of Nigeria. Rainfall in Nigeria is associated with several disturbances of which line squall is the most predominant (Ekpoh and Nsa 2011).

Another feature in the southern part of Nigeria is the double maxima regimes that relates to the average position of the Intertropical Convergence zone (ITCZ) (Ayoade 1983; Olaniran 1983). The double rainfall maxima is characterized by two high rainfall peaks followed by a short dry season and another longer dry season falling between and after each peaks. The normal rainy season begins around March and lasts to the end of July with a peak in June; afterwards a short break occurs in August (Ayoade 1983). As the ITCZ retreats this short break is broken by the short rainy season starting round early September and lasting to Mid-October (Olaniran 1983). The distance of western and middle belt region of Nigeria from the equator creates a single peak of a slightly well defined rainy and dry season each year. Temperature is usually between 18^0C and 36^0C (Ezekwe 1988) and rainfall varies between 1200 mm to 1500 mm a year. The dry climate zones, found mostly around the Sahel zones in Maiduguri and Potiskum, are the predominant climate type in the northern part of Nigeria with rainfall of less than 500 mm per annum (Ayoade 1983). The rainy season usually starts around June and lasts for only four months. Temperature peaks around 40^0 C in some regions in the dry season due to high annual sunshine hours (Ezekwe 1988).

The Jos plateau and Mambila in central and North Eastern portions of Nigeria houses montane climate. Due to the topographic nature of these areas with altitudes usually above 1600 m, they tend to portray a mountain climate type with temperature dropping to as much as 50^0C in the dry season (Ayoade 1983). Seasonality and place are the major factors affecting temperature; the uniformity of temperature is strongest near the equator and increases in a minor extent with latitude. The major factor that affects thermal uniformity in tropical countries is elevation. Due to temperature uniformity, variations in temperature may not be the best tool for monitoring forest change because most of the forest in Nigeria are located very close to the equator and hence temperature variations are usually the same all year.

1.5.3 Vegetation and Soils of the Savanna Forest Regions of Nigeria

Forest resources in Nigeria are, distributed over the five main ecological zones of fresh water/mangrove, the rainforest, the derived savanna and the Sahel/Sudan savanna and accounting for about 2.5 % of the Gross Domestic Products (FRA 2010b). In Nigeria, there are three broad types of vegetation namely forest, montane and savanna. The forest areas predominate in the south around latitudes 3^0 to 8 ^{0}N and consist of the mangroves, fresh water swamp and rainforest zones. The savanna regions stretch from 8^0 to 15 ^{0}N and consist of the derived savanna, guinea savanna, Sahel savanna, montane vegetation and Sudan savanna (figure 2).

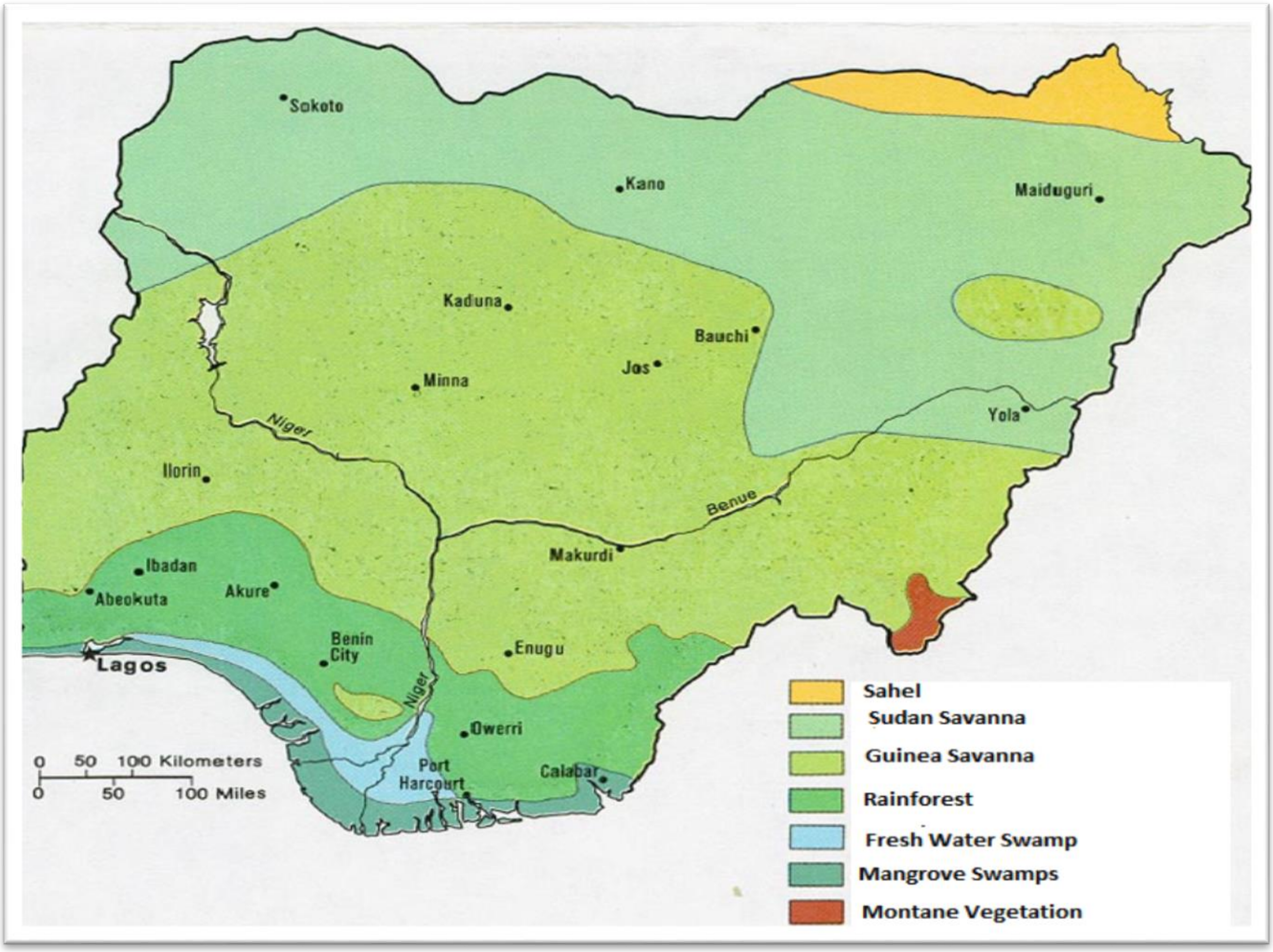


Figure 2 :Vegetation zones of Nigeria

Zone containing dense cluster of Trees

The mangrove swamp lies along the Nigerian coastline consisting of swampy ground lagoons and brackish water Mangroves in the drier outer margin along the Nigerian coastlines attain heights of 50 m and a girth of up to 2.7 m (Adekanmbi and Ogundipe 2009). After the mangroves comes the fresh water swamp inhabited by fresh water plants. Within the fresh water swamps, are slender trees of height ranging from 30-50 m and possessing silt roots (Olusola and Ogundipe 2008). Next to the fresh water swamp is the rainforest zone with an area of about 170,000 km^2 stretching west to east and embedded by rainforest perennial streams and rivers, the most important being river Niger.

The rainforest of Nigeria consist of three different layers: the first is the upper layer that consists of taller trees of height ranging between 40-50 m. This emergent is the first class of trees (Barbour 1982). They are scattered with no continuous canopy, and have wide crowns. The second layer has heights ranging between 16-40 m. The third layer ranges between 10-16 m and forms a continuous canopy of trees (Barbour 1982).

The Savannas

They are located next to the rainforest and are characterized by high rural population densities and shifting cultivation (Barbour 1982). Annual bush burning activity within these areas have, to an extent shaded the vegetation structure to the extent that fire tender vegetation is being replaced by fire tolerant species. The level of variation of vegetation within the area is high as low forest, dense woodland alternate with open tree and grass savanna (Morgan and Moss 1965). The Guinea savanna comprises both the northern and southern guinea savannas and are perhaps the largest vegetation zone in the study area. Four major subdivisions are identifiable (Barbour 1982): Savanna woodland where trees and shrubs form a closed canopy, Tree savanna where trees and shrubs are scattered, Shrub savanna where trees are absent and grass savanna where both trees and shrubs are absent (Adejuwon and Adesina 1988). The guinea savanna woodland consist of different layers but less than those of the rainforest do. Savannas the Niger-Benue trough of central Nigeria comprises mainly mixed leguminous species. Around Abuja, the Alzelia Africana covers most of the area (Keay 1949). In addition, the northern guinea savanna zones contains wooded landscapes

The Sudan zone is mainly composed of mixed woodland with series of short grasses that exist with heights of about 1-1.5 m. The grass distribution in most of these areas is less continuous and occasionally contains patches of short trees (Keay 1949). The Sahel are areas around the extreme north corner of Nigeria in Borno State, contains sparse tress, and grasses with thorny leaves (Keay 1949). Around the Jos Nigeria and Mambila Plateau montane vegetation associated with elevated topography, exist

Based on the FAO Guidelines for soil taxonomic classification, the major soil types in Nigeria are: fluviso, acrisol, ferrasols, alisol, lixisols, cambisols, luvisols, nitosols, arenosols, vertisols, regosols and glycols. The soil found in the moisture-rich humid rainforest zone differs from those found in drier savanna zone. These variations in moisture largely determine their nature, productivity and fertility. Generally, these soils are into groups made up of four (climatic) zones that are soil association. These groups are Northern zone of sandy soil, Interior zone of laterite soil, southern belt of forest soil and zone of alluvial soil (Okoth, et al. 1987).

There are five major soil major formations of in Nigeria: Ferruginous tropical soil, ferrisols, regosols and hydromorphic soils. The Ferruginous tropical soil is the most important group of soil in Nigeria because they cover the greatest proportion in the country and support most of the cash and food crops (Agboola 1979). They develop mainly on basement complexes and old sedimentary rocks. However, on the northern high plains, they develop on drift deposits covering these rocks (Kogbe 1976). Ferruginous soils exhibits marked differentiation of horizons and the abundance of free iron oxides usually deposited as red or yellow mottles or concentrations (Klinkenberg and Higgins 1970).In the drier or exposed sites; a distinct lateritic layer is present in the profile. The soil becomes increasingly brown the profile because of intense leaching and eluviations from above. The clay fraction consist mostly of Kaolin although there are small quantities of illite (Barbour 1982).

Ferrisols dominates the sandstone formations around the Guinea savanna zone of Nigeria (Gbadegesin 1995). They are transitional soils but having less well-developed profiles, a higher nutrient status, a better structure and higher biological activity (Udo 1970; Barbour 1982). The lower annual rainfall is responsible for the reduced degree of profile development and leaching while the relatively sparse population left soil protected under dense woodland vegetation is responsible for the high humus content. The soil are usually deep, red and with clay-enriched subsoil. Lateritic iron caps develop on tops of flat ridges such as those found in Bida, Northern Nigeria.

Weakly developed regosols are the major group of immature weakly developed soils in Nigeria, consisting of rocks fragments, which occur in isolated hilly areas. They are loose, excessively drained by water and intensely leached (Areola 1978). Apart from the humus rich-rich surface layer, the regosols show little evidence of pyogenesis except for the oxidation and consequent reddish or brownish colouring of sands (Gbadegesin 1995). They occur mainly on coastal sand ridge-barriers that abound in the Chad basin on desert sand rift (Gbadegesin 1995). The sparse vegetation does not provide much litter but the plant roots that often decay in the soils are responsible for the even distribution of humus in the profile. These soils usually have clay enriched B-profile suggesting some degree of eluviation. However, the degree of leaching is small; soils have a high content of weather able minerals, and of monotinorillonrite clay, that has high water and nutrient holding capacity.

Hydromorphic Soils are seasonally or permanently waterlogged soils found in the Niger Delta and Chad axis of Nigeria. The influence of poor drainage accounts for the whitish or greyish colour due to the reduction of oxides in the soils (Klinkenberg and Higgins 1970). The depth or the permanent water table limits the extent of the profile development of the seasonally waterlogged soil. Permanently waterlogged surface usually have a surface accumulation of raw organic matter, which imparts a highly acidic reaction, and a very dark colour to the soil (Moss and Morgan 1967).These soil are the organic hydromorphic soils. In contrast, the mineral hydromorphic are usually seasonally waterlogged ones where the organic matter decomposed periodically when the water level subsides (Kogbe 1976). The organic types are most common along coastal creeks, valleys, depressions and estuaries covered by mangrove swamps, while the mineral types are more characteristic of river valleys, floodplains and Chad basin. Among the mineral hydromorphic soil, there is distinction between the sandy and silty or clayey types. Most mineral hydromorphic are of sandy types; the clayey types occur in pockets within valleys and floodplains

Thesis Outline

This chapter has provided a broad overview of the issue this study aims to address. Chapter 1 also provides a general description of the geographic features found in Nigerian forest. A thorough review of literature on the major themes of this thesis is in Chapter 2. Chapter 3 describes the data and methodology used in answering all the research questions, Chapter 4 is a presentation of all the results derived from the analysis chapter. Chapter 5 is the discussion of findings, implications of the results and ways to develop the research.

CHAPTER 2

BRIDGING GAPS

2.1 Introduction

The aim of this chapter is to review climate-forest related literature relevant to this thesis. The chapter starts by assessing the relationships between deforestation, phenology and climate, from global, regional and national (Nigerian) perspectives. The second part discuses remote sensing options for acquiring and assessing deforestation, rainfall and phenology. It discusses methods and options for analyzing and estimating rainfall and phenology. The third part of this chapter assesses the methods and dimensions for monitoring deforestation. It also assessed the drivers of deforestation. The fourth part of this chapter looks at historical forest change, deforestation, and related climate impacts in Nigeria. The fifth section of this chapter addressed definitional issues on forest including management, structural and policies for in the administration of the entire forest covers in Nigeria. The sixth section of this chapter addressed change detection techniques in remote sensing.

2.2 Forest and Climate

Approximately 30% of the Earth's land surface is covered by forest which contains about 45% of terrestrial carbon (Field and Raupach 2004). Interactions between forest and climate lies in the exchange of energy balances through water, carbon and other atmospheric aerosols(Bonan 2008). Carbon uptake by forests contributed to a "residual" 2.6 Pg C year−1 terrestrial Carbon sink in the 1990s (Solomon 2007). Geographical variations, biogeochemistry and physical structure largely determine the mode of interaction between forest and the atmosphere. Similarly, aerosols released during biomass burning within the forest may influence its local climate.

Tropical forest contains about 25% of carbon (Bonan 2008) in the biosphere and accounting for over 33% of the Net Primary Productivity (Field and Raupach 2004). Tropical forest maintain high rate of evapotranspiration, low surface temperature and high rainfall when compared to other land cover types (Bonan 2008, Sheil and Murdiyarso 2009). Tropical forest also maintain high rates of carbon neutrality which servers as sinks for carbon(Stephens, Gurney et al. 2007). In Africa, Amazonia and Asia, surface warming arising from the low albedo of forest is offset by the evaporative cooling potential of the forest (Cox, et al. 2004, Bonan 2008). High carbon sequestration potentials and sensitivity tropical forests to climate are key areas that provides insights on climate-vegetation interactions.

In Boreal forest, climate model simulations reveal that the low surface albedo during the snow season, evident in and remote sensed data (Lyons et al. 2008, Boussetta, et al. 2015), warms climate compared to when there is an absence of trees(Bonan 2008). The global warming potentials of boreal forest gives it a far better biophysical effects on temperature when compared with other biomes(Snyder et al. 2004, Brovkin, et al. 2006). Boreal forest 'types' differ with tropical forest in the partitioning of radiation into latent and sensible heat fluxes. While confer forest exhibit low latent to sensible heat, deciduous broad leaves forest exhibits high sensible heat thresholds which produces strong atmospheric boundary layers(Baldocchi et al. 2000).

In contrast to tropical forest, boreal systems store most of its carbon in soil, permafrost and wetlands (Field and Raupach 2004, Launder and Thompson 2009) which serves as carbon sink. Increased albedo due to changes in the vegetation cover has the potentials of offsetting forcing from carbon emission in boreal forest. Due to sustained industrial development and expansion for agriculture, majority of the temperate forest found in most developed countries have been cleared and converted to cropland in the past decades. As a result, majority of the land(or crop land) in these countries have higher albedo than forest(Bonan 2008). During periods of high temperature and solar intensity, the lower albedo of tress will allow it to maintain temperature relative to crops land(Bonan 2008). Such relationship has the potential of regulating clouds and precipitation around the forest.

Temperate forest holds about 20% of the global plant biomass and 10% of terrestrial Carbon(Bonan 2008). The rate of carbon sequestration in matured forest is also high, but studies e.g. (Albani et al. 2006) have shown these forest may be carbon source due to sustained deforestation. Due the low albedo during winter and evapotranspiration in summer, climate-deforestation relationship in temperate forest is very complex to describe. Such complexities can be explained from two point of views first, a combination of high albedo and forest cover lost have the potential to offset the effects of deforestation-this makes temperature impacts negligible(Bonan 2008). Secondly, reduction in evapotranspiration with loss in trees could affect other biophysical factors that may trigger other climatic elements.

Forest are major actors in the hydrological cycle. They can extract deep soil water and pump it back to the atmosphere through evapotranspiration(Aragao 2012). On a global scale, water evaporates to the atmosphere and spend about 10 days before precipitating back to the surface (Eltahir and Bras 1996, Gimeno et al. 2010). However, at any point on the Earth surface, after precipitation, some of the water flows beneath or on the surface as runoff while others evaporate back to the atmosphere. Due to horizontal and frontal wind systems, the probability that the precipitation will fall on the same spot is almost zero. Conversely, the probability that water evaporates and participate at the same spot cannot be zero at non-point scale. This implies that the probability increases with scale of the region considered (Eltahir and Bras 1996). The atmospheric mechanism of transport and surface/ ground water flows brings water into and outside boundaries of a region. The process of precipitation forming from this two components (atmospheric and locally recycled water vapour molecules) defines the rate at which regions recycle precipitation(Eltahir and Bras 1996). The rate at which any region recycles precipitation is dependent on the partition water vapour molecules in the atmosphere, evaporation from the region and molecules of water that abound in the atmosphere due to atmospheric transport across the area(Van der Ent et al. 2010). The precipitation produced by the internal cycle is defined as the recycled precipitation while those produced by the external cycle is referred to as the external precipitation (Eltahir and Bras 1996). The relative contribution of recycled precipitation to the total precipitation is defined as the precipitation recycling ratio (Eltahir and Bras 1996). Forest are primary agents of precipitation recycling because they sustain evaporation from their surfaces to the atmosphere.

The surface properties of Forest plays important role regulating the precipitation produced within a region. Spatiotemporal patterns of precipitation are expected to respond to drivers of global change, such as atmospheric CO_2 and changes in land use (Meehl 2007).Despite the evaporative cooling and carbon sequestration potentials in tropical forest, very little attention has been paid on how deforestation-rainfall feedback at varying spatial scales. Hetzel and Gerold (1998) explored the impacts of land-surface changes on climate and the hydrological cycle in drainage catchments of Africa and found a strong relationship between large-scale forest clearance and rainfall. In large tropical forest tracks, precipitation is supplied by localized evaporation and horizontal flux of atmospheric water vapour (Eltahir and Bras 1996). Atmospheric circulation controls the patterns of water vapour supply while large-scale land cover change (including deforestation) has the potential of altering the patterns of evaporation in such regions. Therefore, changes in the land cover may initiate changes in the regional atmospheric circulation. Changes in precipitation that may result from any large scale modification of land cover are attributable to changes in local recycling of moisture and variations in regional circulation(Spracklen et al. 2012). In tropical ecosystems, a large amount of water proportion of rain water that comes from water vapour is recycled by the forest (Aragao 2012). However when the forest becomes deforested, water circulation is reduced which inhibits water molecule recycling. Decreasing evapotranspiration may also increase localized run-off and raise water level.

Climate ensemble analysis predicts that large-scale tropical deforestation causes reduced regional precipitation(Henderson-Sellers and Gornitz 1984, Hasler, et al. 2009) at varying spatial resolution (D'Almeida et al. 2007). At the meso- scale level, the effect of deforestation on land-atmosphere feedback are assessed at a finer scale in other resolve question or missing links associated with using coarse (macro) resolution data. Weaver and Avissar (2001) using fine resolution data reported significant spatial variability in land surface processes and fluxes of heat which macro and meso scale data could not account for. Eltahir and Bras (1994) used simulated models to evaluate the impact of deforestation on rainfall recycling for the Amazon reported a weaker decline on water cycle between macro and meso scale analysis. Spracklen et al. (2012) used satellite remote-sensing data of tropical precipitation and vegetation and simulated atmospheric transport flux, to describe the effect of forests cover on the dynamics of rainfall. Their study found that over 60% of the tropical land surface produces higher rainfall on densely vegetated surface than areas with sparse vegetation cover. This means that evaporation from forest maintains atmospheric moisture in the air that passes over it.

At the macro-scale, modelling simulations on forest-climate interaction uses General Circulation of the Atmosphere (GAC) parameters in comparing deforestation and non-deforestation scenarios based on appropriate adjustment of the parameters used in the model. Predictions at macro level of change in moisture fluxes satisfy mass balance to the extent that change in precipitation equals the sum of the change in evaporation and atmospheric moisture convergence(Eltahir and Bras 1996). This mean that changes in the land cover supports non-linear feedback that amplify the linear response of land-atmosphere systems to deforestation (Eltahir and Bras 1996, D'Almeida et al. 2007).

Changes in the spatial distribution and magnitude rainfall events in many parts of the African continent occur in conjunction with climate change and climate variability (Nicholson 2000). Rainfall trend in Nigeria showed a general decline of 81 mm between 1901 and 2005 (Odjugo 2010). However, in most of Nigeria interior, Odjugo (2006) reported a decrease of rainfall by 58% for the period 1901-2005. Consequently, the increasing trend of rainfall in the coastal regions of Calabar and Porth-harcourt may lead to sea incursion and salt-water intrusion into the fresh water and possibly destroy the mangrove forest. Increasing temperature and decreasing rainfall in the savannas, (i.e. Nigerian Interior) has been associated with frequent drought and desertification (Joos et al. 2001) which may negatively affect forest cover.

2.3 Remote Sensing of Forest and Phenology

The primary goal remote sensing of forest is to provide consistent data on their spatial and temporal trends. Such data originates from platforms flown on aircraft and other Earth orbiting satellites using different platforms. The Optical platforms (e.g. MODIS and Landsat) provide data at different spatial and temporal resolutions. However, newer technologies, such as radar and light detection and ranging (LiDAR), systems, are now becoming available.

MODIS instruments onboard the Terra (morning) and Aqua (afternoon) platforms provide daily coverage of the entire globe with 36 bands of spectral information at a Swath width of 2300 km(Justice et al. 2002). MODIS products provide continuous data that are applicable for spatial and temporal comparisons of global vegetation cover trends. Spectral bands of MODIS are processed and converted to various reflectance products such as the daily and 8-day composite Surface Reflectance (MOD09), 16 day composite Surface Reflectance and Vegetation Indices (MOD13). These datasets provide consistent spectral information at Red, NIR, Medium Infrared that can be used for the assessment of land cover changes and vegetation functioning. Vegetation Cover Conversion (VCC;MOD44A) and Vegetation Continuous Fields (VCF: MOD44B) products, provide periodic estimates of deforestation and forest cover respectively and have been used for monitoring and validation of deforestation with high degree of certainty in comparison to Landsat 7 spectral datasets.

After the launch of first Landsat satellite in 1972, more advanced multispectral imaging sensors, such as TM—Thematic Mapper, have been added ranging from Landsats 4 (1982), 5 (1984) to 7 (1999) (Enhanced Thematic Mapper Plus, ETM+) and recently Landsat 8. The Landsat TM and ETM+ imaging sensors have stored millions of images with a near-complete continuous record of global land surface data since 1972. The Landsat ETM+ imagery has a spatial resolution of 30 m for the multispectral bands and 60 m for the thermal infrared band. The revisit cycle (∼16 days) of Landsat are extended sometimes due to cloud contamination or duty cycle limitations (Roy et al. 2008). Such anomalies in the actual image acquisition date can create difficulties in detecting vegetation changes events in a timely manner is a major limitation in the tropics where the probability of acquiring complete cloud-free Landsat imagery for a given year is low.

The long history of Landsat spectral is no doubt a rich source of data for long-term vegetation cover analysis. Wall to Wall Landsat images, consisting of 143 billion pixels, were used to predict and produce high-resolution global maps of 21st-Century for forest cover change(Hansen et al. 2013). Landsat products are mainly used in vegetation mapping at regional scales (Wulder, et al. 2008). Due to the differences in spectral sensors in the Landsat image series, it is necessary to correct the spectral reflectance between images acquired by those sensors using varieties of secondary data that comes with such images. This is especially necessary in long-term vegetation cover monitoring research.

One technique for increasing the temporal frequency of high-spatial resolution satellite observations is the blending of data from sensors with complementary spatial and temporal characteristics. Such blending generates synthetic observations with both high spatial and temporal resolutions(Lunetta et al. 1998). Data-fusion models use the high-spatial resolution imagery to capture spatial details on the landscape and incorporate the high-temporal-frequency data to describe changes over time (Lunetta et al. 1998). The major limitation in data-fusion approaches is the near-lack of spatial integration of reflectance observations between different data(Pohl and Van 1998). Such limitations restricts the use of data fusion techniques in mapping sub-pixel range of changes such as aboveground biomass and disturbances- instead higher capabilities platforms such as Lidar and Radar are now gaining momentum in vegetation studies.

Lidar is a technique that utilizes lasers, usually in the near-infrared wavelengths, to actively transmit energy from a satellite or aircraft and then record the energy reflected back to the instrument at those same wavelengths(Gao et al. 2000). There are many types of LiDar systems, portraying variations in wavelength, size of the spatial 'footprint' at the surface, and sampling intensity of the returned signal (thus vertical profile resolution), among others (Gao et al. 2000). The potentials of LiDAR in monitoring of tropical forest carbon stock changes through time have been explored(e.g. Laporte et al. 2007). The measurements of vertical forest structure, is a major breakthrough technology with many vegetation applications potentials. Radar systems on the other hand uses microwave or radar signal to measure forest vertical structure. Sensors of Radar platforms send out signals that penetrate ground cover and clouds and 'see' the underlying terrain as well as the top of the canopy (Gibbs et al. 2007)

Remote sensing of forest vegetation involves the space and time measurements spectral signatures of the forest cover from sensors in order to quantify the amount of change in such parameters. Several studies (e.g. Wulder et al. 2008) have used the dynamics of reflected energy to characterize of the amount of forest cover available in an area. Generally reflected red band energy decreases with plant development due to chlorophyll absorption by the active leave cover. Conversely, NIR energy increases with vegetation improvement due to the scattering and active turgidity found in healthy leaves. Unfortunately, because the amount of energy reflected by forest canopy surface and reaching satellite sensors varies with irradiance, canopy structure and other environmental factors, one cannot use a simple measure of reflected to quantify forest cover changes on a global level.

This problem has been solved by combing two or more reflectance on each waveband into a vegetation index (VI) for the quantification of forest cover changes. The two most widely used VI are NDVI and Enhanced Vegetation Index (EVI). NDVI is derived as (Red − NIR)/ (Red + NIR). EVI is estimated by adding a soil adjustment coefficient and aerosol scattering in the blue band due to noise (Rouse et al. 1974). EVI was proposed based on a feedback-based approach that incorporates both background adjustment and atmospheric resistance concepts into the NDVI and can be seen as modified from NDVI especially in areas with high biomass concentration. The atmospheric resistance in the EVI is based on the wavelength dependency of aerosol effects, utilizing the more atmosphere-sensitive blue band to correct the red band for aerosol influences (Kaufman and Tanre 1992).

NDVI indices have been applied extensively to the evaluation of tropical forest functioning because of its distinct ability to carve out large signal proportions of signal variation arising from calibration of satellite sensors(Tucker et al. 2005)**.** The NDVI is chlorophyll sensitive, whereas EVI is more responsive to canopy structural variations,(Gao et al. 2000). Generally, the EVI perform better than NDVI in the assessment of heavy aerosol, and biomass burning in the tropics(Anaya, et al. 2009). On the other hand, NDVI is more suitable than EVI for assessing changes in forest cover over time. The major disadvantage of the NDVI in forest cover monitoring lies in the influence of additive noise effects, such as atmospheric path radiances.

The temporal profile of vegetation indices depicts seasonal and phenological dynamics, including length of the growing, peak greenness, onset of greenness and leaf dry-down periods. In studies on remote sensing of forest phenology, several equations and fitting methods are applied to describe the vegetation green up start and end dates. Amongst which are: NDVI double logistic function (Beck et al. 2006; Sobrino et al. 2011), NDVI ratio (Kogan 1995), and NDVI threshold (White et al. 1997). Other include the largest NDVI increase (Kaduk and Helmann 1996) and EVI time series (Pan et al. 2012).

One advantage of utilizing remote sensing for phenology applications is the ability to capture continuous expression of phenology patterns across the landscape and retrospectively observe it from archived satellite data sets (Reed et al. 2009). Though all the above mentioned methods have been used to effectively account for vegetation phenology at varyingly scales, it is only the NDVI double logistic function that accounts for both multiple growth cycles in the characterization and fitting of vegetation cycles in relation to the seasonal patterns of rainfall tropical regions(Vrieling et al. 2013, Turner et al. 2014).

2.4 Indices for Quantifying Rainfall Onset and Cessation

In Nigeria, the two major climatic elements that are of direct importance to biophysical processes are atmospheric precipitation and temperature (Miller 1952; Ayoade 1983). Atmospheric precipitation in Nigeria (tropical) consists almost entirely of rainfall. Varieties of methods exist to assess rainfall trends or anomalies over time. The onset/cessation date of rainfall is a key variable to which all other seasonal rainfall attributes are related (Ayoade 1983; Stewart 1991; Ati et al. 2002). Several models have been proposed for determining of Rainfall Onset Date (ROD), Rainfall Cessation Date (RCD) and Length of the Rainfall Season

(LRS) using traditional to semi-empirical and scientific techniques, with daily/ monthly rainfall and evapotranspiration thresholds. Amongst them are the Ramadan method (Olaniran 1983; Ati et al. 2002), the Siva-Kumar model, (Sivakumar 1988), method of accumulated rainfall (Walter 1967),rainfall–evapotranspiration model (Kowale and Knabe 1972; Benoit 1977) and Theta-E technique (Omotosho 2002). Other methods for evaluating ROD and RCD dates based on definition are those of Ilesanmi (1972) and (Odekunle 2004).

The Ramadan method is named after the Muslim fasting period. Through this model, ROD and RCD are determined by the first good rain after Ramadan if it is at least 7 months from the last effective rain of the previous season. If these dates are not close, a 7 months' rule is applied and planting is advised to be 7 months after the last effective rain of the previous season (Ati, et al. 2002). The Siva- Kumar model defines the ROD in the southern sahelian and sudation climate zones of West Africa, as the date after 1st May when rainfall accumulated over three consecutive days was at least 20 mm and when no dry spell within the next 30 days exceeded 7 days (Sivakumar 1988; Ati et al. 2002). The accumulated rainfall method is based on the assumption that after a particular threshold of rainfall is reached, the possibility of a dry spell that may lead to crop failure or vegetation growth is relatively small. The onset date is therefore defined by number of days in the first Month with Effective Rain (MER). The MER is the first month in which the accumulated rainfall totals equal or exceed 50.8 mm.

According to Ilesanmi (1972), ROD and RCD are obtained by calculating the percentage mean annual rainfall that occurs for each 5-day interval. Next, is the percentages are accumulated of the 5-day periods. Illesami (1972) assumptions follows the principle that the first point of maximum positive curvature of the graph during the course of the year corresponds to the time of rainfall onset while the last point of maximum negative curvature corresponds to the rainfall cessation. Finally, onset on the graph corresponds to the time when an accumulated 7–8% of the annual rainfall totals has been obtained, whereas that of rainfall cessation is 90% Ilesanmi (1972). The method by Omotosho (2002) assumes that the probability of rain on any given date can be estimated by the proportion of rainy days on that date. This means that the probability of rainfall for each day of the year is directly related to the number of rainy days as a proportion of the total number of days considered for each day of the year (Odekunle 2004).

The rainfall-evapo-transpiration model defines the onset date for Nigeria as the date when accumulated daily rainfall exceeded 0.5 of the accumulated potential evapo-transpiration for the remainder of the season, if no dry spell longer than 5 days occurs immediately after that date (Ati et al. 2002). Kowale and Knabe (1972) define the onset date, as the 10-day in which rainfall is equal to or greater than 25 mm, but where the subsequent 10-day rainfall total is greater than 0.5 of the potential evapo-transpiration. Theta-E technique, is dependent on the equivalent potential temperature, daily mean values of surface pressure, temperature, and relative humidity (Omotosho 2003).

The methods for estimating rainfall onset/cessation in have been shown (e.g. Sivakumar 1988; Ati et.al 2002; Omotosho 2003) to perform better in different geographic regions in Nigeria. For example, the rainfall–evapo-transpiration models perform well in predicting rainfall onset dates in the savanna (Ati, et al. 2002), while the rainfall accumulated model have been successfully applied for the determination of rainfall onset and retreats dates in most parts of southern Nigeria (Aweda and Adeyewa 2010).

These models have some shortcomings. The rainfall–evapotranspiration model has been found to be insufficient for three mains reasons. Firstly, studies in Nigeria have shown that temperature is not a good indicator of the available energy for potential evapotranspiration, since it lags behind solar radiation (Ojo 1977). Secondly, the model does not take into account the accumulated impact advection forcing (Ojo, 1977) and thirdly, in the tropics, temperatures are relatively uniform and seasonal variations are small (Odekunle 2004) which limits their overall significance. Studies such as Ati, et al. (2002) found that the Ramadan and Siva Kumar models performed better in arid and semi-arid regions than rainforest thus applying the models to the coastal regions might not appropriate. The accumulated rainfall method is semi-empirical because it does not satisfy all situations (Olaniran 1983). For example, it does not account for all dry spell situations in semi-arid areas. This shortcoming was discussed by Olaniran (1983) who postulated that the model could only be accepted if it is not followed by a month with less than 50.8 mm of rainfall. If it is less, the rainfall of the MER is disregarded.

Generally, rainfall totals are more widely used for ROD and RCD estimation mainly because they are more readily available. In fact, the use of rainfall data is a more direct approach rather than the use of some other related factors from which to make inferences (Odekunle 2004) for rainfall. Studies (e.g. Omotosho 2003; Odekunle 2004) have shown the rainfall probability model sufficiently reflects rainfall distribution characteristics for any given region in Nigeria.

TRMM datasets are becoming a valid alternative rainfall data source, particularly in countries such as Nigeria with sparse and non-reliable meteorological stations.It was launched November 27, 1997 carrying 5 instruments, one of which is the Microwave Imager (TMI). TMI is a multi-channel, dual polarized, conical scanning passive microwave radiometer designed to measure rain rates over a wide swath under the TRMM satellite (Kozu, et al. 2001). The performances of the various products of TRMM have been evaluated across different spatial and temporal scales in Africa with rain gauge and other datasets. Rainfall estimates from rain gauge data have their own endogenic and exogamic errors, for example Anagnostou et al. (1999) using a packed gauged area in northeast Brazil, reported distortion in the rainfall distribution caused by the rain gauge sampling error when compared with automated microwave samplers.

Although satellite data provided rainfall at very high (sometimes hourly) resolutions, adjustments in most cases are still needed to correct biases and stochastic errors in order for them to fit to insitu observations (Barrett, et al. 1994). Biases emanating from remote sensed rainfall data are caused mostly by the sampling frequency, the diurnal cycle of rainfall, the non-uniform field of view of sensors, and the uncertainties in the rain retrieval algorithms (Anagnostou et al. 1999; Aweda and Adeyewa 2010).

Haque et al. (2013) compared TRMM rainfall with the gauge data from 12 stations using neighborhood and bilinear weighted interpolation methods. Their results showed that TRMM reasonably captured both spatial and temporal rainfall pattern but failed to detect higher intensity rainfall close to the mountainous parts of the basin. Al-Dousari et al. (2008) reported a good correlation between the computed TRMM and measured rainfall data using bilinear weighted Interpolation method in Kuwait. They further recommended the usefulness of bilinear weighted interpolation method to derive precipitation information at varying spatial scales for several locations in Kuwait. Bilinear interpolation in question aggregates the functions of two variables on a regular 2D grid and uses the distance-weighted average of the four nearest pixel values to estimate a new pixel value. Bilinear interpolation is among the commonly used methods of climate grid interpolation which have been successfully used to validate daily monthly rainfall at varying spatial scales with very high accuracies (e.g. Rozante et al. 2010; Cui et al. 2015).

Adeyewa and Nakamura (2003) validated TRMM rainfall data over major climatic regions in Africa and found out that over land, all the satellite estimates showed significant seasonally and regionally dependent bias which are high in the dry seasons than rainy seasons. Bias in rainfall data are caused primarily by factors such as the sampling frequency, the diurnal cycle of rainfall, the changing field of view of satellite sensors and inherent uncertainties in the rain retrieval algorithms(Berg et al. 2002). The temporal impact of sampling error in satellite estimates is reflected in the production of a ‘‘conditional’’ bias in which the algorithm overestimates high rainfall and underestimates low rainfall. Both the temporal and regional rainfall biases of satellite-derived rainfall products are the result of systematic changes in (diurnal) rainfall systems associated with meteorological regimes(Berg, et al. 2002).Satellite rainfall retrieval algorithms are fundamentally under- constrained (Berg et al. 2006) as such number of assumptions must be made in the retrieval. Because of the time-dependent nature of these biases, it is practically impossible to apply corrections based on regionally defined characteristics,(Berg et al. 2006) . Most study on climate modelling in Africa(e.g. Nicholson et al. (2003)) that relied on ground measurement of rainfall have reported very unreliable data emanating from Nigeria. Therefore, for countries like Nigeria, with sparse and highly unreliable ground based rainfall data, TRMM is about the best alternative.

2.5 Methods for Monitoring Deforestation

Recently, a lot of institutional and policy instruments for monitoring and halting deforestation (e.g. PRODES) have been developed in response to climate change and variability. In Particular, the aspect of REDD+ scheme centered towards monitoring deforestation, is now high on environmental policy and management agendas(Parker et al. 2008). Effort at various levels and scales are made to integrate deforestation and forest degradation results into national processes in order to develop strategies for conservation of forest. Decision makers at national (country based) and international levels need real time information on forest change and extents in other prioritize interventions on areas at risk. Verifiable data on these changes and areas at risk to both internal and external factors are required to avoid, mitigation problems. Such data when transformed into information needs to be of sufficient spatial and temporal outputs.

Remote sensing technology is the best and only practical method for monitoring forest cover change at varying spatial and temporal scales (Morton et al. 2005). Though time-series products for basic properties such as NDVI and EVI exist, there are few attempts to use such information for evaluating forest changes. Land cover data updates takes every 5-10 years sometimes with different methods and sensors, which make comparison challenging and error-prone (Mayaux et al., 2005). Consequently, a pan-tropical near-real time monitoring (Terra-i) system for natural ecosystems based on machine learning algorithms which uses vegetation greenness of the land surface (and its temporal variation) as a surrogate for land-cover (Louis et al 2012) to relate the effects of changes in forest cover to other factors. The

Terra-i model functions by relating variations in the greenness of a given pixel to meteorological, climatic factors and anthropogenic factors.

In remote sensing there are different methods and strategies for monitoring deforestation. The two most common are: wall-to-wall mapping and direct sampling methods (Wertz-Kanounnikoff 2008). Wall-to-wall mapping method for monitoring deforestation involves where the entire country or forest area is monitored comprehensively using several satellite data scenes. Direct Sampling approach is monitors deforestation in a small area. Sampling procedures are cost effective method for monitoring deforestation especially in countries where forest is located in specific regions.

Deforestation rates and baseline forest cover change have been estimated by remote sensing techniques using both wall to wall (Tucker and Townsend 2000; Mayaux et al. 2013) and sampling procedures (Czaplewski 2003; Brink and Eva 2009;Zhu et al. 2014). Over the years there has been arguments as to the best approach for monitoring deforestation rates from satellite data, for example Tucker and Townsend (2000) using sampling techniques, suggested that 10% sampling is not sufficient enough to monitor deforestation on a country for individual countries in South America, and recommended wall-to-wall coverage to capture real localized land-cover dynamics. Conversely, Czaplewski (2003) showed that even with localized dynamics, a 10% sample was adequate to detect deforestation at varying geographic scale ranging from continental to local scales.

As suggested by Riitters et al. (2006) a sampling approach can estimate deforestation for a given geographic area, to any specified degree of precision, if the sample size is large enough.

A wall-to-wall map is simply a 100% sample that provides measurements for all geographic areas (Czaplewski 2003). Usually during sampling expert knowledge can also help determine deforestation (including hotspots) from both ‘systematic sampling’ (where samples are taken at a regular interval) and ‘stratified sampling’ (where samples are located by known proxy variables) (Czaplewski 2003). Hence, discussion of sampling versus wall-to-wall mapping should consider the type of information that needs to come from remote sensing by the end user (Czaplewski 2003; Riitters et al. 2006).

Whereas a focus on estimating deforestation rates leads naturally to a statistical sampling approach, a focus on managing deforestation leads to a geographical mapping approach (Riitters et al. 2006) which implies that both wall-to-wall and sampling approaches are interwoven. For example, medium-resolution data can be analyzed to identify deforestation hotspots requiring further analysis from direct field sampling in order to reduce need to analyze the entire forested region. This approach is known as nested model and has been applied (e.g. Hansen et al. 2008) with accuracy level at global and regional levels to compute rates of humid tropical forest clearings between 2000 and 2005. Considering the random distribution and nature of the Nigerian forest Nigeria, majority of this study uses the nested method for forest change evaluation Hansen et al. (2008).

The standard reference for global scale forest resource is the Forest Resource Assessment report for countries. High resolution satellite and other wall-to-wall products on forest change such as Terra-i and Google Earth Engine are becoming available. However, several discrepancies exist between FRA and other observational-derived forest area change data as indicated in Table 1. The discrepancies between FAO forest and Satellite observation for

African countries reported by Hansen et al.(2013) further exposes the lack of comprehensive systematic forest mapping capabilities for many African countries.

Table 1: Results on deforestation estimates for Nigeria from Previous Studies

Source	Coverage	Time	Total Forest Area (ha)	(Methodology
FAO 2000,2010,2015	Nigeria	2000-2010	13,137,125 (2000) 9,041,143 (2010) 6,993,632 (2015)	Projection
Hansel 2013	Nigeria	2002-2012	10,00,000 (2000) 9,956,615(2012) 9,903236(2014)	Observational

For Nigeria, several limitations are associated with the FRA reports at diminish their utility and reliability in analyzing change assessment. Firstly, the methods used in assessing forest extents are inconsistent between countries; The FAO 2010 estimates for Nigeria were developed and updated using past forest survey records(FRA 2010) while in Brazil, forest cover are estimated in connection with observational data. Secondly the definition of "forest" based on land use instead of land cover obstructs the biophysical reality of whether tree cover is present or not (Hansen et al. 2013). Finally, forest definitions used to estimate forest cover in successive reports have changed over time. This will no doubt bring about bias estimates. Hansel et al (2013) developed an observational global forest cover map using Google Earth Engine that combines data catalogs using computational facility optimized for parallel processing of geospatial data. The computation of the forest maps of Hansen et al. (2013) were validated using MODIS top of canopy (TOC) reflectance time series (Potapov et al. 2012) No doubt the Hansel (2013) is about the most up to date information on forest coverage. Detailed discussion of the methodology and applicability of both the Hansel (2013) and FAO (2010) results for Nigeria is in chapter 5 of this study.

Deforestation directly or indirectly influences both climate and human activities at varying spatial scales. However, the question of what factors drive deforestation remains largely unanswered. As suggested by Geist and Lambin (2002) the two major, mutually exclusive and still unsatisfactory explanations for the drivers of tropical deforestation are single-factor causation and irreducible complexity. The proponents of single-factor causation are of the view that the spatial and temporal trends in dimensions of forest cover change (including deforestation) is controlled by a single factor such as shifting cultivation or population growth.

The irreducible complexity school of thought are of the view that the causes deforestation are from multiple factors. Deforestation is the consequence of a variety of interrelated social, economic, and environmental factors (Fearnside 1993; Skole et al. 1994). Generally, to measure deforestation two broad dimensions are integral: they include human and physical dimensions (Skole et al. 1994). The human dimension of deforestation takes into account why deforestation occurs. It also assess human factors as they affect large scale, regional or local forest cover change (Skole, Chomentowski et al. 1994). Allen and Barnes (1985) cited population increase as the major factor that shape deforestation in developing countries.

In Nigeria (a developing country), both poverty and institutional arrangements have been identified to be the major cause of uncontrolled forest clearance (Mayaux et al. 2013). Specifically both Economic, demographic and institutional factors are also responsible for the various dimension and dimensions of forest cover lost. Studies have shown development of market economies and conditions at national and international scales influenced the explosive rates of deforestation (Skole et al. 1994; Geist and Lambin 2002). As an example in the Amazon, estimates of total deforested area derived from satellite and statistical records indicate that 90% of the deforested area in 1988 came into being after 1970 due to the establishment of Amazonian frontier development (Skole, et al. 1994). Geist and Lambin (2002) using 152 subnational cases to understand linked proximate cause of deforestation to economic factors, national policies, agricultural expansion, and infrastructure expansion.

In a bid to provide a satisfactory answer to the major cause of deforestation globally, researches has tended to study deforestation by sampling both local and environmental factors using experiences from their localities. Therefore, without gathering knowledge base on local scale dynamics as to the pattern and dynamics of deforestation, it will be practically impossible for example to generalize either statistically or otherwise the best approach to study and map deforestation.

2.6 Vegetation and Forest-in- Transition

Tropical vegetation covers an area of over 5 × 107 km^2, ca. 42% of the Earth's terrestrial vegetated surface (Walter 1975). The concept of vegetation formation in the tropics can be defined as "a community-type defined by dominance of a given growth form in the uppermost stratum of the community, or by combinations of dominant growth forms"(Torello-Raventos et al. 2013) . Within the tropics, several of vegetation structure ranging from evergreen forest, dry and wet deciduous forest, savanna (including scrub and grasslands) exists. The classification of these contrasting vegetation formations hinders comparisons and causes confusion as words such as 'forest' and 'savanna'. Both words have different meanings to different people(Torello-Raventos et al. 2013). There has been confusion as to reaching of an agreement on what exactly constitutes a 'savanna' (Eiten 1986; Ratnam et al. 2011) and 'forest' (including 'woodland'). The confusion between identifying and differentiating what constitute forest and savanna creates a further problem in identifying the boundary between them.

The boundary between two contrasting ecosystems may be an ecotone (Leopold 1934) or border (Fagan et al. 2003). Ecotones and ecoclines are associated with narrow and wide transitional ecosystems units respectively (van der Maarel 1990). Using floristic associations and stand structure of different vegetation types, Torello-Raventos et al. (2013) produced a classification scheme for tropical Vegetation types and boundaries between forest savannas. The forest -savanna boundary in the tropics has undergone wide shifts in the past and may respond more to under future climate scenarios (Hoffmann and Franco 2003). The forest – savanna boundary in West Africa is one of the world's remarkable geographical feature because of the absence of sharp contrasts along the boundary line (Morgan and Moss 1965).

The dynamics of the location of an ecotone is useful in understanding and predicting vegetation distribution following variability in climate and changes in human activities. Although most ecotones contains discontinuity in species composition, (Adejuwon and Adesina 1992), they still represent a balance between forest advance and retreat caused primarily by fire (Hopkins 1992). In Nigeria, the forest-savanna boundary stretches from the East (around the Mambila Plateau) to the west in Ilorin and Ibadan.

The factors that are responsible for the movement of an ecotone are complex to describe. For example in the Brazilian Cerrado, the savanna movement tends to respond more to physical factors (such as nutrient and water availability) than to forest fires (Hoffmann and Moreira 2002; Hoffmann and Franco 2003). Conversely, in Nigeria the forest- savanna boundary is a zone of high agricultural activity/ shifting cultivation accompanied with intensive human induced fires (Adejuwon and Adesina 1992). Forest accounts for more resource (including phonological events and nutrient cycling) to light while savannas allocate more resources to belowground resources (Hoffmann 2003).

Lehmann et al. (2011) defined savanna as the presence of a dominant C4 grass layer and a discontinuous tree cover, this definition is not only vague, it disregards the notion that within savanna ecosystems clusters of trees and woodland meeting the criteria of forest zone can be found. Walker and Gillison (1982) defined a savanna as "a formation where single-stemmed woody plants over 3 m tall occur in excess of 0.2% and less than 90% crown cover and where there is a graminoid component greater than 2% cover. While the definition of Walker and Gillison (1982) may appear useful, it lacked global application due to its reliance on structural-physiognomic configurations of the Australian woodland savanna. Torello-Raventos et al.(2013) defined the word 'savanna' as vegetation formation types where the fractional herbaceous cover is greater than 0.1. Such definitions are subject to applicability and utility. Specific taxon words such as 'forest' and 'savanna' have been used as descriptors for the vegetation(e.g. Boland et al. 2006) formation found in an area. In such cases comparison have been made between 'forest species' and 'savanna species' as investigative tool (e.g. Hoffmann et al. 2003). While classifications may lack definition of the words 'forest' and 'savanna', they may still be useful in identifying clusters of 'formations" within a broad vegetation group.

2.7 Historical Forest Change in Nigeria

Historical footprints of deforestation dates back to 1830 when Europeans near old Calabar, South-Eastern Nigeria, cultivated oil palm. But by 1890, cultivation spread into SW Nigeria, Ivory Coast, Central Ghana and Cameroon (Pugh 1969; Agboola 1979) and by 1960 over 40% of the Nigerian forest had been deforested (Iloeje 1965). Records the from British colonial forest department as reported by Akachuku (2007) in Nigeria indicated that, virtually all of the southern part of the country 'with exception of few towns' were densely covered by rainforest by the year 1500 AD. However, between 1900 and 1960 (the year of Nigerian independence from Britain) the remaining rainforest lowered into two large blocks with scattered fragments (Onuche 2010). Between 1960 and 1981, the remaining blocks tremendously degraded such that very few considerable patches of the rainforest remained in some forest reserves and national parks for protection.

The forestland of Nigeria is widely used for cultivating both cash and subsistence crops, grazing, fuel wood, gathering, building materials sourcing and lumbering. Other drivers of deforestation include but are not limited to exploitation of timber, farming, population expansion/ growth, and forest fires. As an example, the volume of timber export in 1964 stood at around 700,000 m^3 / year but declined steadily to about 290,000 m^3 in 1970. By 1960, the strain of intensive timber exploitation on the forest resources in Nigeria began to manifest negatively such that valued species of forest trees were increasingly scarce in logged areas (FMEA 2006). Consequently, logging actives were concentrated in forests outside forest reserves in order to meet the timber demand (FMEA 2006; Adekanmbi and Ogundipe 2009) due to shifting cultivation and related activities.

Shifting cultivation is a rotational system of farming whereby a farmer cultivates a plot of land for three to four years to the extent of which soil fertility is depletes and move to another plot to allow the previous plot to fallow and recuperate after 3 to four years (FMEA 2006). As of 2014, more than 30 per cent of rural dwellers in southern Nigeria practiced shifting cultivation (WorldBank 2013). During land preparation for cultivation by the farmers, most trees burns on site due to lack of work force and technology to move or transport them. In areas where shifting cultivation are practiced farmers freely encroach on forest reserves and natural forest sites where soils are relatively more fertile. Over 70% of Nigerians living in both rural and urban areas uses fuel wood for cooking and energy use (Adekanmbi and Ogundipe 2009) which exceeds the replenishment rate through various afforestation and related programs by the Nigerian government (Oyedepo 2012). Over 51% of the inhabitants are rural dwellers (WorldBank 2013) and depend directly on fuel wood as their major source of energy for domestic and related activities. More recently due to population expansion and rural-urban migration, demand for fuel wood has increased tremendously. Population expansion appears to be a major factor affecting forest depletion and deforestation in Nigeria, because the country's population will be among the top 20 most densely populated countries on Earth by 2050.

Of all the factors causing environmental degradation and depletion of resources, none has as many destructive effects as uncontrolled forest fires. Forest fire occurs mostly in the dry season and early planting season. Bush fire in the savanna region, leaves large tracts of forested land burnt within minutes, resulting in destruction of large volume of forest resources. In short, the devastation of the forest ecosystem by fire is more thorough than that of any other single factor of forest degradation.

Colonization of Nigeria came along with deforestation, massive commercialization of agriculture and population growth. Scientists have been unable to link the changes in land use to extreme climatic events: as an example and drawing from the West African experience (Nigeria inclusive), anthropogenic vegetation change led to only 0.4% increase in albedo in over 100 years and 0.5 % cumulatively, with conservative estimates of desertification (Gornitz 1985). Also, additional assumptions regarding desertification and a lower albedo value for tropical forest during most of this period (of deforestation) compensate for each other and do not significantly alter the result of the initial calculation (Fuller and Ottke 2002). During these period soil properties, anthropogenic activity or even unknown external forces (Iloeje 1965; Gornitz 1985) contributed to desert encroachment or land use changes.

A number of studies have evaluated forest dynamics in tropical Africa (e.g. Mayaux, Holmgren et al. 2005; Mayaux et al. 2013), and in Nigeria (e.g Schneider et al. 1985; Rogers et al. 1996; Salami, 1999; Salami et al. 1999). Most of these studies have focused on the change detection capability of some remotely sensed images to account for rate of deforestation and land use changes. While the results from these studies have been useful in describing local climate experience and impacts, most of them have been restricted to very small regions in Nigeria. Some others (e.g. (Njoku 2007; Capodici, et al. 2008; Nwagbara 2008) have focused on decadal or annual trends in vegetation and pertinent climatic parameters without taking into account the influence of local sampling of local factors. Studies have shown that the savanna and Sudan parts of Africa and Nigeria may be greening-up due to increasing rainfall trends (Flavio et al 2006; Habib et al 2008; and Nwagbara 2008). According to Chima and Nwagbara (2009) in the savanna, zone of Nigeria increasing rainfall appears to be the major driver of vegetation change. Nwagbara (2008) linked positive trends in vegetation cover in Northern Nigeria directly to rainfall and indirectly to temperature (Nwagbara 2008). However, as correct as the results of Nwagbara (2008) is, the use of Nigerian Sat 1 data to assess vegetation change is relatively inadequate. Nigerian Sat 1 images when compared with other sensors were shown to be very efficient in the analysis of information within the visible portion (400 nm-700 nm) of the electromagnetic spectrum, and less efficient outside the visible range (Ojo and Adesinab 2010). Vegetation, on the other hand, reflects better outside this range, suggesting a caution in the interpretation of vegetation vigour within the visible portion.

Furthermore, in marginal environments, apparent correlations between climate and satellite vegetation measurements vary from year to year indicating a persistent lag between vegetation activity and climate dynamics (Prince and Goward 1995). External factors also affect vegetation growth based on its composition for example the three major droughts in Nigeria over the past 100 years (1970s, and 1980s) manifested in the deterioration of the land cover of which the impact was more in the savanna regions than the rainforest zones (NEST 1991).

2.8 Defining Forest and Deforestation

FAO (2006) defines a forest as any land spanning more than 0.5 hectares with trees higher than 5 meters and a canopy cover of more than 10 per cent, or trees able to reach these thresholds in situ which does not include land that is predominantly under agriculture or urban land use. When a forest is under pressure due to human induced changes or climate, it manifests physically by deforesting or degrading. Deforestation is the conversion, change or permanent loss of forest cover into another land use due to human induced factors or natural perturbation.

The United Nations Framework Convention on Climate Change (UNFCCC 2001) decision defines forest as a minimum area of land of 0.05-1.0 hectares with tree crown cover (or equivalent stocking level) of more than 10-30 per cent with trees having the potential to reach a minimum height of 2-5 meters at maturity in situ. A forest may be open, closed, moist or dry. Most closed forest consist of various story and undergrowth while others remain permanently open. Deforestation means different things in different places and as a result, it almost impossible to define (Hamilton, 1987).However, logging most often falls under the category of forest degradation and thus is not included in deforestation statistics. Therefore, forest degradation rates are considerably higher than deforestation rates (Butler 2012).

The definition by UNFCC (2001) favours most tropical countries because it recognizes forestland of as low as 0.05 hectares. However, as correct as the definition of forest may be most countries, in pursuit for national development and sustainable growth came up with their own national definition of what forest is. Ghana defines a forest as "A piece of land with a minimum area of 0.1 hectares, with a minimum tree crown cover of 15% or with existing tree species having the potential of attaining more than 15% crown cover, with trees which have the potential or have reached a minimum height of 2.0 meters at maturity insitu "(CDM Ghana 2007). In India, a forest is defined as tree crown cover value between 10 and 30%:15% or equivalent stocking level Land area value between 0.05 and 1 hectare with Tree height value between 2 and 5 meters (CDM India 2007): as at the time of writing this report, there is no country-specific definition for forest in Nigeria.

The first attempt to set up forest policies and manage the forest resource in Nigeria dates back to 1887 when the British Empire published the first Sketch of forest resources of West Africa (FMEA 2006).By 1970, the Federal Department of Forestry (FDF) was created to coordinate forestry activities throughout the country. The main functions of FDF include initiate and to formulate national forest policy and land use planning, foster forestry and environmental development, promote and fund projects of national interest, co-ordinate and monitor state forestry activities (FMEA 2006; FRA 2010b).

The forest of Nigeria is a national asset that for the conservation of the natural environment, but also for the generation revenue of carbon tax through forest resource accounting. The first national forest policy in Nigeria was in 1988. The 1988 forest policy recognized forestry as the management and utilization of forests as renewable natural resources. By 2006, a new forest policy in Nigeria to address lapses of the 1988 forest policy came into being. The aim of the 2006 forest policy covers government reform agenda, of poverty reduction and good governance. The objectives of the 1988 and 2006 forest policies as summarized by (FMEA 2006) is in Table 2

Table 2: Summary of the main objectives of the 1988 and 2006 forest policies for Nigeria.

1988 forest policy objectives	**2006 forest policy objectives**
Consolidation and expansion of the forest estate, and its management for sustained yield,	Address the factors affecting the decline of the forest resources.

Forest regeneration at a greater rate than exploitation	Streamline the contribution of forests to economic development and Growth particularly the National Economic Empowerment and Development Strategy (NEEDS).
Forest conservation and protection of the environment	Mobilize the community and civil society in forestry development.
Reduction of waste in utilizing both the forest and forest products	Promote partnerships with the private sector, the Non-Governmental Organizations (NGOs) and Community Based Organizations (CBOs).
Protection of the forest from fires, poachers, trespassers and unauthorized grazers	address transparency and accountability in the tendering administration for forest concessions and to encourage long term concessions
Encouragement of private forestry	accommodate the international forest policy initiatives, the implementation of the Intergovernmental Panel in Forests (IPF) and on Intergovernmental Forum on Forests (IFF) proposals for action for a sustainable forest Management
Creation of man-made forests for specific end uses	Mainstreaming forestry activities into the national development agenda including the Millennium Development Goals
Increase of employment opportunities	
Development of national parks and game reserves	
Development of secondary forest products which are significant in the local economies, and encouragement of agro-forestry	
Cooperation with other nations in forestry development	

Source: (FMEA 2006)

The major problem of 1988 forest policy was that it was "demand-led" since its stated objective was for the development of the forestry sector to meet the increasing national demand for forest products. Demand-led policies have the tendencies to over-utilize resources and increase deforestation. The 2006-revised policy for Nigeria also lacked a defined aim because its major objectives were bogus and political. The policy did address its fundamental principles due to Illegal activities in the forest, lack of labour and capacity in forestry department such as inadequate forest patrol and outdated laws.

2.9 Change Detection Techniques in Remote Sensing For Estimating Forest Cover Change and Deforestation.

Change Detection (CD) is the process of identifying differences in the state of an object or phenomenon by observing it at different times. CD in remote sensing involves the application of multi-date remotely sensed data to analyze the time-space relationships of a target feature. Lu et al. (2004) reported ten broad areas of application of CD techniques in remote sensing; they include Land use, forest change, forest mortality, and crop monitoring. Generally, in remote sensing CD identifies the nature of the change by measuring the areal coverage and investigating their spatial patterns (Macleod and Congalton 1998).

Varieties of change detection techniques for monitoring environmental change have been developed and new ones are still evolving however, CD can be object or pixel based. Object based CD techniques assumes a pixel as an atomic analytical unit whose spectral characteristics detects and measures changes (Hussain et al. 2013). In pixel based CD techniques, the assumption is that ‘a pixel’ is not a true geographical object; rather, it is a cell representation of spectral values in a grid whose boundaries lack real-world correspondence (Fisher 1997). Object based CD techniques goes a step beyond pixel-based image analysis by incorporating spectral, spatial, temporal and geometrical aspects for comprehensive representation of change in real time. In remote sensing, four broad methods of change detection include; algebra, transformation, classification and advanced models. Algebra category for change detection are image differencing, image regression, image rationing, vegetation Index differencing, Change Vector Analysis (CVA) and background subtraction (Lu et al. 2004). A summary of their algorithms, advantages and disadvantages are summarized in table 3

Table 3 Properties of Algebra Change Detection Techniques in Remote Sensing:

Techniques	**Algorithm**	**Advantage(s)**	**Disadvantages**
Image Differencing	Subtracts the first date Image from second date Image pixel by pixel(Lu, Mausel et al. 2004)	Simple and straight forward. Ease of interpreting results.	Cannot produce detailed change matrix.(Singh 1989; Coppin 2004; Lu, Mausel et al. 2004)
Image Regression	Estimates pixels values of the second date image using regression function to subtract regressed differences from the first date image.	Reduces the impact of atmospheric, sensor and environmental factors	Requires accurate development of regression functions for selected bands (Singh 1989)
Image Rationing	Data are rationed pixel by pixel based on the band ratio of the two dates	Reduces the impact of topography and solar angle(Lu, Mausel et al. 2004)	Band outputs are usually not normally distributed
Vegetation Index differencing	Subtracts the second date vegetation index from the first	Differences in the spectral profile responses is effectively highlighted	Enhances random noise
Change Vector Analysis (CVA)	Generates the magnitude and direction of change from the first to the second image and also computes the total change magnitude per pixel	Provide detailed change detection information	Difficult to identify land cover change trajectories (Lu, Mausel et al. 2004)
Background subtraction	New image is produced through subtracting the background image from the original image (Singh 1989; Lu, Mausel et al. 2004)	Easy to implement	Very Low accuracy

All algebra methods for change detection except CVA are relatively simple and easy to implement. CVA on the hand is an extension of image differencing and has the capacity to detect both the magnitude greater than the identified threshold and change information. The major problem of adopting most algebra method for change detection is the difficulty in selecting suitable threshold for the determination of changes between remotely sensed images. However, with improvements in Satellite sensor capabilities and computer hardware/software, researchers of remote sensing have been able to develop different models and threshold for assessing deforestation. Morton et al. (2005) successfully using a threshold of mean plus 0.5, 1, or 2 standard deviations of the mean difference to map deforestation in Brazilian Amazon.

The Transformation category for change detection unlike algebra methods assumes that multi temporal data are highly correlated and change information highlighted in the new components (Lu et al. 2004). The three methods of transformation technique that have been widely used in change detection are Principal Component Analysis (PCA), tasselled cap (KT) and Gram Schmidt (Table 4).

Table 4: Transformation techniques for change detection techniques in remote sensing

Technique	Algorithms	advantage(s)	Disadvantages
Principal component Analysis	Uses two or more images to account for changes information by separating and subtracting the second date principal components	Reduces data redundancies	Change detection results between dates are often difficult to define and interpret
Tasselled cap (KT)	The difference between KT and PCA is that KT is scene independent and change detection is applied based on brightness, greenness and wetness.	Reduces data redundancy	Cannot provide detailed change matrix

Gram Schmidt (GS)	Orthogonizes spectral vectors from images and adds a change component to the brightness, wetness and greenness in the data	The association of transformed components with scene characteristics allows the extraction of information that would not be accessible using other change detection techniques (Lu, Mausel et al. 2004)	Produces only a single component related to the given type of change

Another method of change detection in remote sensing is classification. This technique classifies the image into thematic layers using the spectral profiles found within the image layer. There are six major classes of classification methods for change detection. They include post classification comparison, spectral temporal combine analysis, expectation maximization, unsupervised change detection and hybrid change detection. Table 5 describes the details 'classification' techniques

Table 5: Properties of classification techniques for change detection remote sensing

Technique	**Algorithms**	**advantage(s)**	**Disadvantages**
Post Classification comparison	Classifies multi-temporal images into thematic maps, then implements comparisons of the classified images pixel by pixel.(Lu, Mausel et al. 2004)	Reduces the influence of atmospheric noise, sensor and environmental differences between the images	Time consuming and requires extensive ground trothing. Accuracy is also dependent quality of the classified image of each date (Lu, Mausel et al. 2004)
Spectral temporal combined analysis	Assembles multi-temporal data into a single image and then classifies the combined datasets and identifies scale of change (Lu, Mausel et al. 2004)	Easy to implement and saves time	Difficulty in identifying and labelling change classes.
Expectation Maximization	Uses an Expectation maximization based classification algorithm to estimate the a priori joint class probabilities of two	Provides better change detection accuracy than other methods (Coppin 2004; Lu, Mausel et al. 2004)	singularity of the variance-covariance matrix and sensitivity of randomly selected initial values which causes computation failure and unstable

	times directly from the images.		classification results respectively (Yang, Peng et al. 2013)
Unsupervised Change Detection	Images with similar spectral properties are clustered in first and second date image. The difference between the two clusters from both images are automatically stored in a new output	Automated and easy to implement	Difficulty In labeling change trajectories (Lu, Mausel et al. 2004)
Hybrid Change Detection	Hybrid change detection refers to the use of two or more methods for CD, employing pixel or object, based techniques. HCD are categorized as: (a) procedure-based (using different detection methods in different detection phases), and (b) result-based (using different CD methods and analyzing their results) (Jianya, Haigang et al. 2008)	combine the advantages of the threshold based and classification based CD methods(Lu, Mausel et al. 2004)	Change related to specific spectral directions might not be readily identified (Coppin 2004). It is also unclear how the final change results are influenced by the different combinations of pixel-based and object-based schemes (Chen, Hay et al. 2012)

Through linear and nonlinear methods, advance models, converts physically based parameters to image reflectance values or fractions (Lu et al. 2004). The characteristics, advantages and disadvantages of advanced model is discussed in table 6

Table 6: Advanced models for change detection techniques in remote sensing

Technique	Definition	advantage(s)	Disadvantages
Spectral mixture model	Uses spectral mixture analysis to derive fraction images from end members of spectral materials either in the study site or from spectral library(Lu, Mausel et al. 2004)	The fractions have biophysical meanings and represents the areal proportion of each end member within the pixel.	Complex method Time-consuming (Hussain, Chen et al. 2013)
Fuzzy change detection	*Fuzzy* clustering are semi-supervised technique to *detect* the *changes* in remote sensing images that takes care of spatial correlation.	Objectively defines threshold by Allowing a probabilistic class membership to provide appropriate representation of change (Hussain, Chen et al. 2013)	Labeling change among a matrix of many overlapping classes may be difficult or non-informative(Hussain, Chen et al. 2013)

Before applying any of the four remote sensing change detection methods listed above, the following steps are taken into consideration: one must ensure that all the images are registered. Two, radiometric correction must be implemented to normalize the reflected value the images must have similar phenologic status, and the image spatial and temporal status should be the same (Coppin 2004; Lu et al. 2004).

The need to incorporate the spatial context and relationships into change detection mechanism cannot be overemphasized. Recent improvement in computational power and the availability of data were among the major barriers in the early stages of object-based method development have made it easier for incorporation of both pixel based and object oriented change detection capabilities . In developing countries such as Nigeria where control of forest and similar resources is hardly achievable, ordinary pixel based change detection capabilities may not be sufficient to account for uncontrolled forest fires, shifting cultivation and selective logging. Several studies such as (Johansen et al. 2010; Addink et al. 2012) have applied and compared both pixel and object-based change detection capabilities in environmental monitoring. In all this studies, recommendation have been to apply both techniques for high accuracy assessment. However, until recently, the analytical framework in RS change detection is becoming more data driven because of a rapid increase in the availability of RS data especially at very high resolution, and increased computational power with more sophisticated algorithms (Hussain et al. 2013). This has led to a change from data and computational-poor scenario to a data-rich and information-poor scenario (Zhou et al. 2010). Recent trend in remote sensing have been on the use of data mining technique to extracting non-trivial, and implicit information leading to constructing a knowledge model (Hussain et al. 2013).

This means that both object-based image analysis and spatial data mining are now more frequently used; they have great potential for answering the challenges of traditional change detection techniques on very high-resolution image (Hussain et al. 2013) or even with sufficient ground control points. Regardless of the available spatial resolution, the spectral signals collected in natural environments are invariably a mixture of the signatures of the various materials found within the spatial extent of the ground instantaneous field view of the remote sensing imaging instrument (Keshava and Mustard 2002).

CHAPTER THREE

DATA AND METHODOLOGY

3.1 Introduction

The aim of this chapter is to introduce the datasets and describe methods for answering the research questions raised. The description of the methods and analysis of the datasets is very significant in this thesis because it helps in answering the research questions raised. This study assesses trends in forest cover changes at national and cluster levels. It also evaluates the relationship between forest rainfall and phenology

The spatial and temporal dynamics of forest cover change over time manifest in different dimensions such as deforestation, degradation, selective logging, phenology, clearance, ecotone change and depletion. This study only assessed aspect of deforestation, phenology and rainfall trends in Nigeria. By using remotely sensed rainfall and forest cover data, the research develops a country-level method for detecting the spatial and temporal dynamics of deforestation and rainfall- phenology trends at cluster level. In this chapter, the datasets were first introduced, followed by the pre- fieldwork, data collection procedure and lastly the methods used for analysis

3.2 Remote Sensing Data

This section describes the raw data and details of the methodology used for analysing both the rainfall and spectral data used throughout the research. Datasets in this study are collected for the period between January 2002 and December 2012. This study uses a combination of Landsat and MODIS satellite images to estimate baseline forest cover for 2002, 2006 and 2012. This study also assessed the potentials of Four MODIS data in detecting deforestation at forest cluster level. The trends and relationship between rainfall and phenology were respectively evaluated using MODIS and TRMM data.

3.2.1 Land Cover Remote Sensed Data

Landsat 7 data for 2002, surface reflectance 8-Day global 250m (MOD09Q1), surface reflectance 8-Day Global 500m (MOD09A1) and vegetation indices 16-day global 250m (MOD13Q1) for the period 2002-2012 for Nigeria were assembled, processed and used in this study. This study uses the percent tree cover layer (MOD44B) to validate and asses the accuracy of pixels detected as forest.

The MOD09Q1 and MOD09A1 data study provides bands 1- 2 (0.6µm - 0.9µm) and bands 3-7 (0.4µm - 2.1µm) in an 8-day gridded data in the sinusoidal projection. The 250m resolution data are produced based on high-observation coverage, low-view angle, the absence of clouds or cloud shadow, and aerosol loading (Masuoka et al. 1998). Global MOD13Q1 provides data on NDVI and EVI every 16 days at 250-meter spatial resolution as a gridded product in the sinusoidal grid system. Inputs for the MOD 44B are a 16-day surface reflectance composite which includes MODIS bands 1 – 7 and brightness temperature from MODIS bands 20, 31,32;and the MODIS Global 250m land/water map (Townshend et al 2011). The percent tree cover layer describes the percent of a pixel which is covered by tree canopy and can be used to identify forested areas for a variety of applications. The Landsat 7 data used in this study is important for terrestrial remote sensing and global change research because of its relatively fine spatial resolution of 30 m for bands 1-5/7 and extensive terrestrial coverage (Teillet et al. 2001).

3.2.2 Rainfall Remote Sensed Data

The TRMM daily and monthly rainfall (Jan 2002 –Dec 2012) were used in this study to describe rainfall trends in the Nigerian forest .TRMM is a joint U.S.-Japan satellite mission to monitor tropical and subtropical precipitation and to estimate its associated latent heating. Remotely sensed TRMM version 3b42_3B42_DAILY.007 (NASA 2010) is obtained from 3-hourly over 0.25 x 0.25 degree lattitude/longitude boxes The TRMM calculates daily data by combining the 3-hourly merged estimates with GMS, GOES-E, GOES-W, Meteosat-7, Meteosat-5, and NOAA-12 data (NASA, 2010). The daily-accumulated rainfall product is derived from this 3-hourly product. The data are stored in flat binary.

3.2.3 Limitations of the Remote Sensed Data

Interpretation of scientific information from global, long-term series of remote sensing products requires the ability to discriminate between product artefacts and changes in the Earth processes being monitored (Roy et al. 2002). Therefore, the quality control tags attached to each MODIS data were assessed for quality assurance. Similarly, all the MODIS data sets used in this study were evaluated to ascertain their Quality Assurance (QA). The Land Data Operational Product Evaluation (LDOPE) QA tool (Roy et al. 2002) was used to evaluate the data quality mask attached to each of the MODIS products.For the Landsat products, Dark Subtraction (DS) was applied in ENVI software to the bands in order to enhance the image pixel quality due to atmospheric artifacts. DS uses the Digital Number (DN) to subtract from each band from either the band minimum, an average based upon a region of interest (ROI), or a specific value (Richards and Richards 1999; Pu et al. 2008). Therefore, only the best quality images for the period of study covered in this thesis were used. For the TRMM data, validation of this datasets was precisely conducted across West Africa (Zhang et al. 2005). Therefore, its use may not compromise the results of this study.

Data management was carried out using ENVI 5, Arcp Map 10, ERDAS Imagine 2013 and Weka data mining software.

3.2.4 Fieldwork, Data Collection and Image Preparation and Registration

Fieldwork was conducted between December 2012 and March 2013 in order to estimate the baseline forest cover, develop a classification model that reliably detect forest covers from 250m MODIS data and map forest changes and test different satellite data capabilities for mapping deforestation at cluster levels.

Fourty-eight (scan line error free) Landsat 7 images covering the Nigerian territorial boundary of 923,768 km² were assembled using Global Viewer (Glovis) multiple data extraction tool of the United States Geological survey (USGS). Cloud cover especially the southern and central regions made it impossible to assemble single-year satellite coverage for the target year (2002). Consequently, 51.06% of the data accounted for the images processed for 2001, while 44.68 % and 4.26% were for 2002 and 2003 respectively. The mean acquisition date of all images was 18th December 2001 while the average and maximum cloud cover for the entire period were 1.51% and 18% respectively.

Geometric correction and orthorectification procedures were applied to the Landsat data to assess the position of image pixels. Geometric correction reduces the inherent problem associated with random errors during retrieval and transmission of satellite images. To achieve this, two steps were undertaken viz: identification and collection of Ground Control Points (GCPs) and development of a rectification database and accuracy checks. GCPs were collected using Garmin 8 GPS units and other forest survey equipment during fieldwork. This study also used point data and related information from the Nigerian Geospatial infrastructure (NGDI) and the Nigerian Global Navigation Satellite Systems (GNSS) reference network (NIGNET-www.nignet.com) databases. NGDI is a platform for spatial data distribution under the National Centre for Remote Sensing (NCRS) and the National Space Research Development Agency (www.narsda.net).

Before normalizing the Digital Number (DN) values of the Landsat scenes to reflectance, each of the scenes was screened for physicaly noise. Consequently, minor line stripping (probably systematic) on Landsat row/path numbers 19151, 19051 and 18961 was ignored because the area covered by these strips are bare sand surfaces and are not of interest in this study. In addition, (Crippen 1988) cautioned that scan-line noise removal distorts useful image details, which may affect extraction of biophysical information. The normalization of the Landsat data process involves two steps: Conversion of measured DN to radiance using flight sensor parameters and calculating Top of Atmosphere (TOA) reflectance for each band (NASA 2003). Conversion DN to radiance is determined by:

$$L_{\lambda} = \left(\frac{\mathrm{LMAX}\lambda - \mathrm{LMIN}\lambda}{\mathrm{QCALMAX} - \mathrm{QCALMIN}}\right) * (\mathrm{QCAL} - \mathrm{QCALMIN}) + \mathrm{LMIN}\lambda \quad \text{......} 3.1$$

L_{λ} is the Spectral Radiance at the sensor's aperture, QCAL is the quantized calibrated pixel value in DN. LMINλ = the spectral radiance that is scaled to QCALMIN. LMAXλ= the spectral radiance that is scaled to QCALMAX .QCALMIN=the minimum quantized calibrated pixel value CALMAX=the maximum quantized calibrated pixel value (corresponding to LMAXλ) in DN = 255. Equation 3.2 is the mathematical expression of top of the atmosphere reflectance.

$$\rho_p = \frac{\pi \cdot L_\lambda . d2}{ESUN_\lambda \cdot \cos\theta s} \text{..} 3.2$$

ρ_p is the unitless planetary reflectance, L_λ is the spectral radiance at the sensor's aperture d = Earth-Sun distance in astronomical units $ESUN_\lambda$ = Mean solar exoatmospheric irradiances` θs =Solar zenith angle in degrees. A further absolute image correction was applied on each scene in other to correct the images attenuation .These procedures were carried out because conversion of Images from DN to TOA does not specifically account for atmospheric influence such as illumination of ground objects. Scattering effects to the sensor DN of very dark spots especially in lakes and dams were selected because automated dark spot removal tends to increase the reflectance values for band 5 and band 7 are actually higher than the original bands (Schowengerdt 2006).

Finally the 48 Landsat 7 scenes were mosaicked and clipped with a polygon map of Nigeria using Nearest Neighbor (NN) interpolation technique. The 2002 orthorectified Landsat 7 data was then used to identify physical features and to perform image –to image registration for all the MODIS data input used in this study. During fieldwork, in order to reduce GPS errors, 4 to 5 readings per location. GPS readings was collected for exposed soil and deforested patches and other land cover. At forest sites, mini surveys for deforested patches (where possible the total deforested area was ascertained) was undertaken. Forest guards and locals were also helpful in providing information about the duration (age) of each deforested site where possible.

For the fieldwork, 12,210 GCPs was collected for clusters of tress (or forest), deforested patches and open surfaces around forest. Other data collected randomly include, other land cover types (e.g. rock out crop, buildings and landmarks) and water bodies. Table 8 presents the distribution of data collected during field are presented. Detailed fieldwork was not carried out around the Chad region owing to security concerns.

Table 8: Details of Forest survey

Location	GPS point collected	Deforested patches surveyed	Soils in Forest surveyed	Number of GCP used for Classification and analysis	Number of GCP Reserved for accuracy
Cross River Forest Axis	2431	223	116	1215	1216
Niger-Delta Axis	3625	447	129	1813	1812
Mambila Axis	857	113	57	429*	428*
Chad Axis	0	0	0	230	230
Other regions of Nigeria	2143	NA	NA	NA	-
From NGDI	1560	NA	NA	NA	NA
From GNNS	1594	-	NA	NA	NA
Total	12210	783	302	3687	3686

*The Datasets are from NGDI and GNSS

The GCP points were stored into searchable database showing description (land cover type, GPS points, age of forest, and climate zone) of each field data. Classification accuracies and georectification was validated using Root Mean Square Error (RMSE).. *RMSE* is the square root of the sum of squares error divided by the number of predictions. It measures the difference between the computed and estimated coordinates in the original Landsat images. This means that the smaller the values of RMSE, the better the georefrencing and registration. RMSE is given by:

$$TotalRMSE = \sqrt{\frac{1}{n}(x' - x_{orig})^2 + (y' - y_{orig})^2} \quad \ldots\ldots (3.3)$$

x_{orig} and y_{orig} are the original row and column coordinates of the GCP in the image and x' and y' are the computed or estimated coordinates in the original image. The smaller the values of RMSE the better the performance

3.3 Geographic Description of the forest clusters

Chad Cluster

The Lake Chad forest cluster (figure 3) is located between longitude 12^0 14' to 14^0 28'' E and latitude 11^0 12' to 14^0 31'N. From a broader view, the region consists of the boundaries of four African countries. It is bounded to the north by Chad Republic, South by Nigeria, East by Cameroon and North West by Niger. A unique feature about this region is the large expanse of inland water formed during the cretaceous period(Lemoalle and Dupont 1973). The lake is the seventh largest lake globally and fourth in Africa (Lemoalle 2005). The Lake Chad observes varying degrees of alternating rainy and dry seasons, which are largely dependent on the continental and maritime air masses. During the raining season, winds from the south-west push the moisture marmite wind north over the country bringing moisture. Toward the middle of each year, the maritime air mass moves southwards paving way for the dry continental air mass originating from the Sahara desert. Generally based on the influence of climate, the region consist of three major climatic regions. They are Saharan, Sahelian and Soundonian regions.

The Sahara region of the Lake Chad region is located around the far- northern part of continent covering large expanse of areas in Chad and Niger. The mean daily

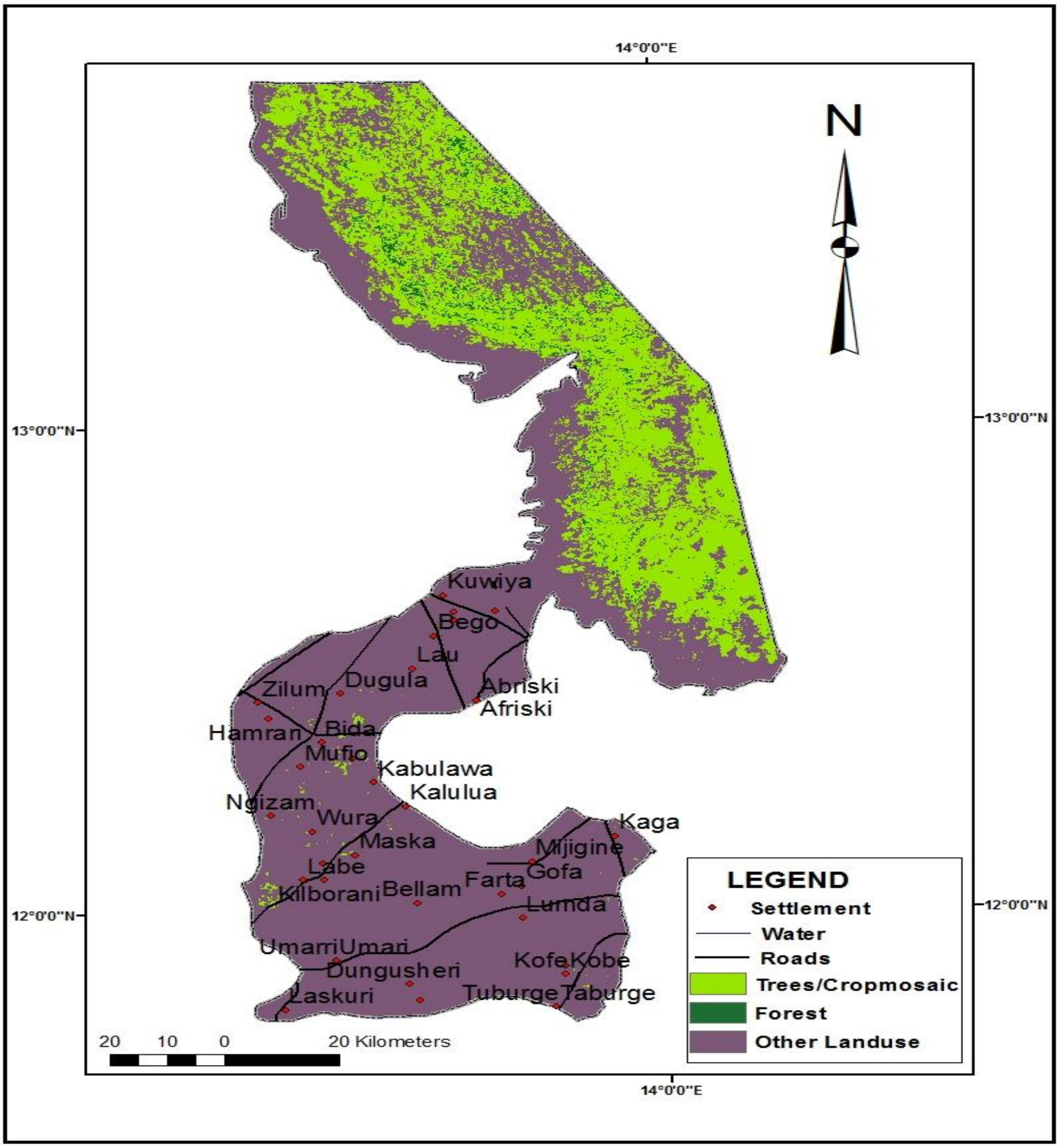


Figure 3: Location of the Chad Forest Cluster

maximum temperature is about 32^0C and 45^0C which occurs in January and May respectively. This area receives about 289 mm of rainfall between July and August each year. This region marks a transition between the desert and inland. Rainfall in these areas last from June to early September. They Lake Chad forest cluster used in this study is in the Soudonian zone. Rainfall in this region last between April and October with rainfall reaching 750 to 1000 mm each year. Temperature varies between 32^0C and $40\ ^0C$ throughout the year. The high temperature profile coupled storm winds recorded during the raining season in this region is responsible for high annual potential evapotrapitration (Ayoade 1983).

The soils of the Lake Chad forest consist mainly of ferragioinous tropical soil. Other soil types are vertisol, regosols and alluvial fangs. The Ferruginous soil types covers over 90% of the Chad Forest cluster analyzed in this study. During fieldwork (brief) in it was noticed that majority of the soil around this region swell when wet and shrink when dry. The forest vegetation in the Chad axis consist of mainly woodland specie. The high density of woodland along these edges of the Lake is sustained by the sub humid tropical wet tropical climate that provides moisture (Ayodae 1983). However as one progresses north of the Chad towards Chad and Niger, the woodland gradually declines as grasses and shrubs dominates.

The Mambila Cluster

The Mambila Forest cluster is found in a Plateau (called Mambila) in Taraba State, North-Eastern Nigeria (Figure 4). It is located between longitude 10^0 12' to 12^0 18' 4' E and latitude 6^0 12' to 9^0 11' N. It is bounded to Cameroon republic in the East, Obudu hills to the south, the Benue trough to the West.

Mambila is the highest spot in Nigeria with mean altitude of 1524 m a.sl. The Chappal Waldis hills are even above 2400 m (Chapman et al. 2001). The climate of the Mambila is relatively cold. It consists of mountain climate induced by topography The relative steepness of the southwestern escarpment of the plateau which comes into direct contact with southwestern monsoon wind from the Atlantic Ocean between December and March Produces rainfall for up to 250 days in year (Chapman et al. 2001). They winds are forced to rise in contact with the escarpment of the plateau which rises from an altitude of 200 m in plains to 1524 m at the plateau resulting to heavy rainfall of up 1780 mm annually. Daytime temperature is usually below 25^{0}C making it the coldest plateau in Nigeria.

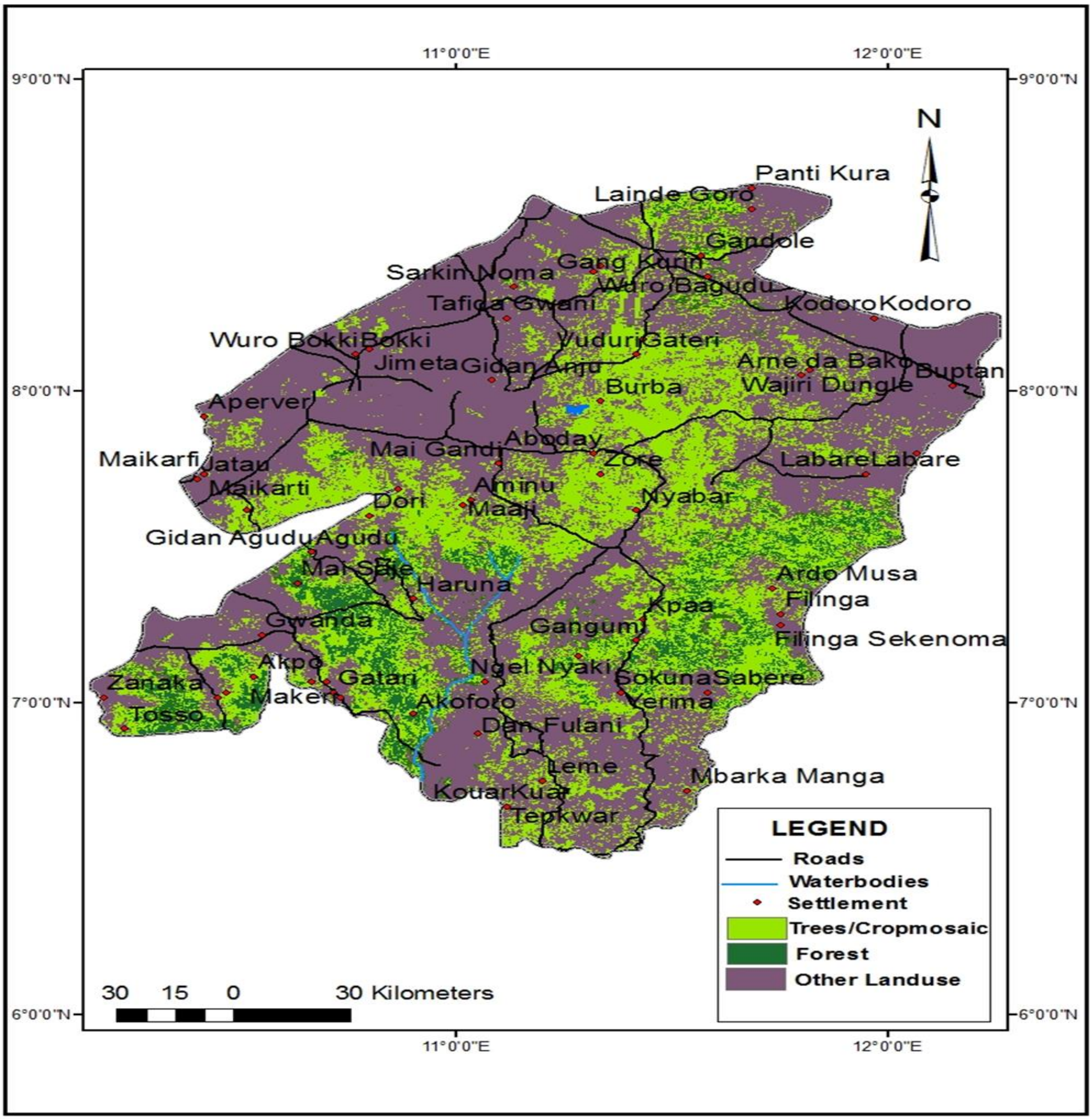


Figure 4: Location of the Mambila Forest

The soil of the Mambila forest cluster consists mainly of ferrosol that originates from the volcanic rocks. These basement complex soils are reddish brown in appearance with high

Quartz content and in most cases exhibit low capacity to hold nutrients or moisture(Mould 1960) . The vegetation on the plateau consist of low grasses, trees and man-made forest planted by German colonist. Vegetation in the Mambila contains several Afro Montane forest fringes scattered spread across the plateau and harboring of wild animals. The Eucalyptus specie is the most dominant tree in that is mainly grown in the area due to its adaptability to the harsh climatic condition. The presence of the low lush grasses on the regions has drew a large number of cattle, who advent beginning during the British rule have affected the plateaus vegetation. This has resulted into overgrazing of the region.

The Niger Delta Cluster

The Niger Delta forest cluster is located longitude 4^0 25' to 7^0 23' E and latitude 4^0 32' to 7^0 71' N (Figure 5). It is bounded to the south by the Atlantic Ocean and to the East by Calabar forest region. The area has average temperature and relative humidity, which range from 23 °C to 42°C and 65.00 to 96.80% respectively. The annual rainfall ranges from 1,500 mm to 2,000 mm. Rain falls almost throughout the year in the area. However, a defined rainy season period (April to October) and dry season (November to March) is recorded in the area(Agbagwa and Ekeke 2011).The Niger Delta forest cluster is a rich and diverse mosaic of 3 ecological types consisting of coastal mangroves, fresh water swamp forest and derived savanna. The coastal vegetation occupies the southern portions of the cluster and consist of freshwater swamp forest with occasional small salt marshes, where seawater washes over beaches (Short and Stauble 1967). Majority of the mangroves found in the southern portions of the Niger-Delta cluster consist mostly of the red mangrove. The fresh water swamp forest lies between the mangrove and derived savanna zones

The zone is characterized by intensive lumbering and contains important forest products. The most common species of tree found around this region is the raffia palm that dominates the swamps closer to the mangrove. The palm trees and big trees like

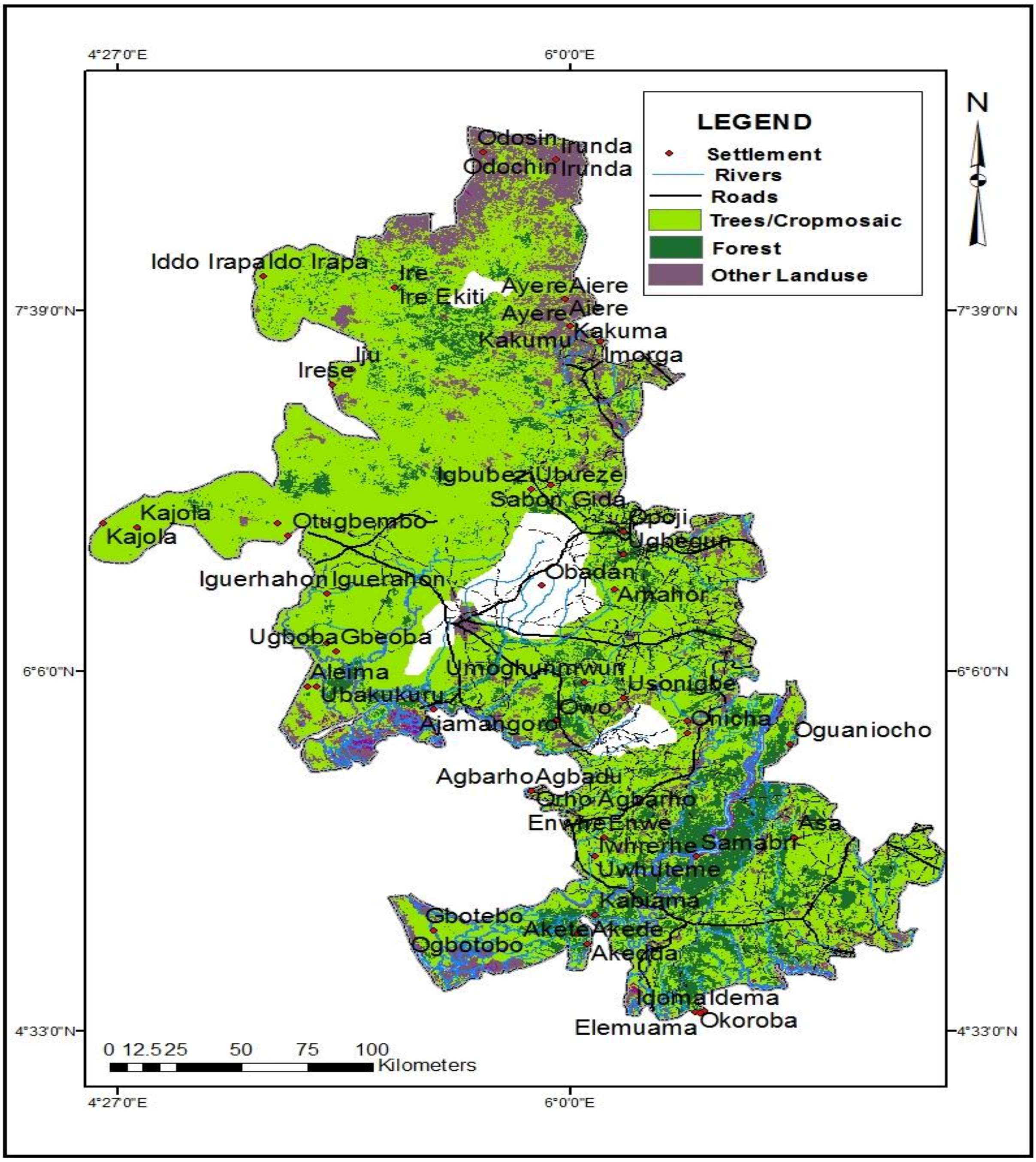


Figure 5: Location of the Niger-Delta Forest Cluster

Iroko are sparsely distributed the northern areas of this region. The derived savanna zone is found in the northern part of the of the Niger Delta forest cluster. It is a zone of transitional vegetation type consisting re-growth and scattered tree clusters. Around northern boundary of the forest cluster, Iroko tress and other fires resistant tress exist in small clusters. The soil is composed of Ultisols that encourages agricultural activities.

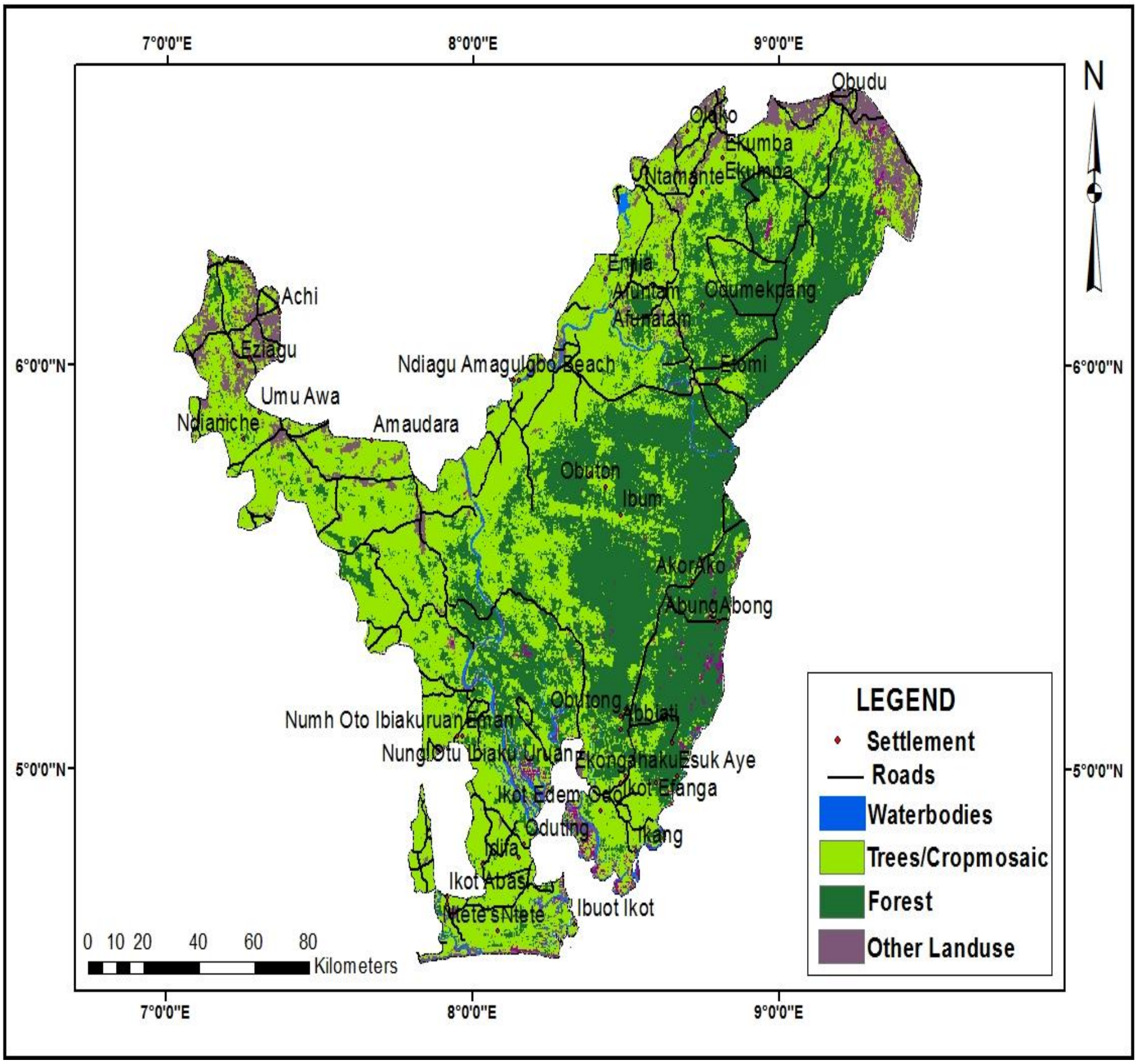


Figure 6: Location of the Calabar forest Cluster

The Calabar Cluster

The Calabar forest cluster is located between longitude 4^0 16'' to 9^0 83' E and latitude 4^0 22' to 6^0 81' N (Figure. 6). It is bounded to the North by the Mambila hills, East and South by the Cameron and west by the Niger delta forest cluster. The Calabar forest cluster consists of two ecological biomes of Montane and tropical evergreen forest. The zone is confined to the northeastern part of the forest cluster with altitude of approximately 900 to 1500 m above sea level and consisting tropical high forest trees, shrubs and grasses. The slopes of the hills favoured by southwesterly moisture-laden wind from the Atlantic are covered by dense tress.

The Tropical Evergreen Rainforest comprises of tall trees with dense undergrowth of shorter species dominated by climbing plants(Agbagwa and Ekeke 2011). This evergreen vegetation consist mainly of economic trees such as the Mahogany, Iroko, Obeche, Sapele Wood and Walnut that stretches from the western flank of the south-eastern region of Nigeria, through the river Calabar into the extensive area in the south west of Cameroon republic. The clustering of climbing plants found in this zone makes accessibility and deforestation of big trees very difficult. The soil is composed of Ultisols.

The climate of the Calabar forest cluster consists of the equatorial forest type in the southern axis to the cool montane region. The wet season is relatively long, lasting between seven and eight months of the year, from the months of March to October resulting in high annual rainfall above 2,000 mm per annum. Temperatures are generally high in the region and constant throughout the year. Average monthly maximum and minimum temperatures vary from 28^0C to 33 ^{0}C and 21 ^{0}C to 23 ^{0}C, respectively, increasing northward and westward (Inyang 1980). The warmest months are February, March and early April.

3.4 Estimation of Baseline Forest Cover

This study focuses on the operationalization of large areal forest cover change monitoring due to the moderate resolution of the satellite data used. The ability to develop a model that can accurately assess the temporal trajectory forest cover will contribute to policy applications, such as Reducing Emissions from Deforestation and Degradation (REDD+) initiative.

Deforestation in Nigeria follows is large-scale pattern. As such, MODIS data offers a temporal coverage better than most satellites and can largely provide a monitoring sense in detecting change events since there has not been any national scale study for Nigerian in the past. It is a known fact that the FAO definition of 'forest' "as all areas of at least 0.5 ha size with tree cover (canopy) density greater than 10 and tree height greater than 5 m" cannot be applied with highaccuracy using both Landsat satellite and MODIS imageries due to their pixel sizes (Achard, et al. 2014). The seventh Conference of the Parties of the UNFCCC adopted a robust definition of forest as an area of land of 0.05–1.0 ha with tree crown cover of more than 10–30%. This study uses a minimum mapping unit of 1 ha to characterize landcover of the 2002 Landsat image using unsupervised classification. The classification results of the Landsat images was then used train MODIS pixels at 6.5 ha mapping units for Forest and other land cover for 2002, 2006 and 2012. In order to compensate for the low accuracy associated with MODIS pixels in mapping forest covers, a forest in this study was regarded as clusters of tress reaching 6.5 ha or more. This study also adopted a moderated version of (Achard, et al. 2007) canopy threshold to differentiate forest from other vegetation types using the percentage tree cover data of MODIS(see section 3.2.1): (i) areas with portion of tree cover over 30% were classified as forest (ii) those tree cover below 30% including shrubs and regrowth were classified as trees and crops. (iii) all other land covers outside trees and vegetation were classified as either water or 'other 'land use '.

In order to estimate national baseline cover for the study period (2002, 2006 and 2012) several classification schemes were tested, however, this study only reports results of the adaptive remote sensing model because it classifies forest pixels better. However, the forest cluster analysis compared the potentials of different MODIS data in detecting deforestation.

Classification in this study is the process of relating pixels in a satellite image to known land cover and algorithms or image classifiers (Mather 1987).

To quantify national baseline forest change, a three-staged classification scheme was undertaken (figure 7) using Support Vector Classification (SVC) and Iterative Self-Organizing Data Analysis Technique (ISODATA) SVC function by nonlinearly projecting the training data in the input space to a feature space of higher (infinite) dimension (Anthony et al. 2007). In ISODATA, each iteration threshold recalculates means and reclassifies pixels with respect to the new means (Johansen et al. 2010). The first stage of the 'adaptive' classification involved using SVC to identify forest locations across Nigeria.

The second stage involved splitting and classifying the processed reflectance datasets into rainforest and savanna regions using either SVC or ISODATA. Classification of the rainforest and savanna vegetation zones are carried out using ISODATA and SVC respectively. Although the second classification stage performed better for forest pixel, it presented low accuracy results of forest pixels along the boundary between the rainforest and savanna regions. Hence, a third classification scheme was developed whilst retaining results of stage 2. For the third classification model, all forest pixels extents that fell within the rainforest and savanna boundary were reclassified using ISODATA. The location of the forest extents of the boundary region used for stage 3 classification were derived from polygonised forest pixels from stage 1 and 2 classifications. The adaptive model was applied to the 2002, 2006 and 2012 processed satellite data for the estimation of national baseline forest four forest clusters (see section 3.3) were selected from the national classification results for further analysis

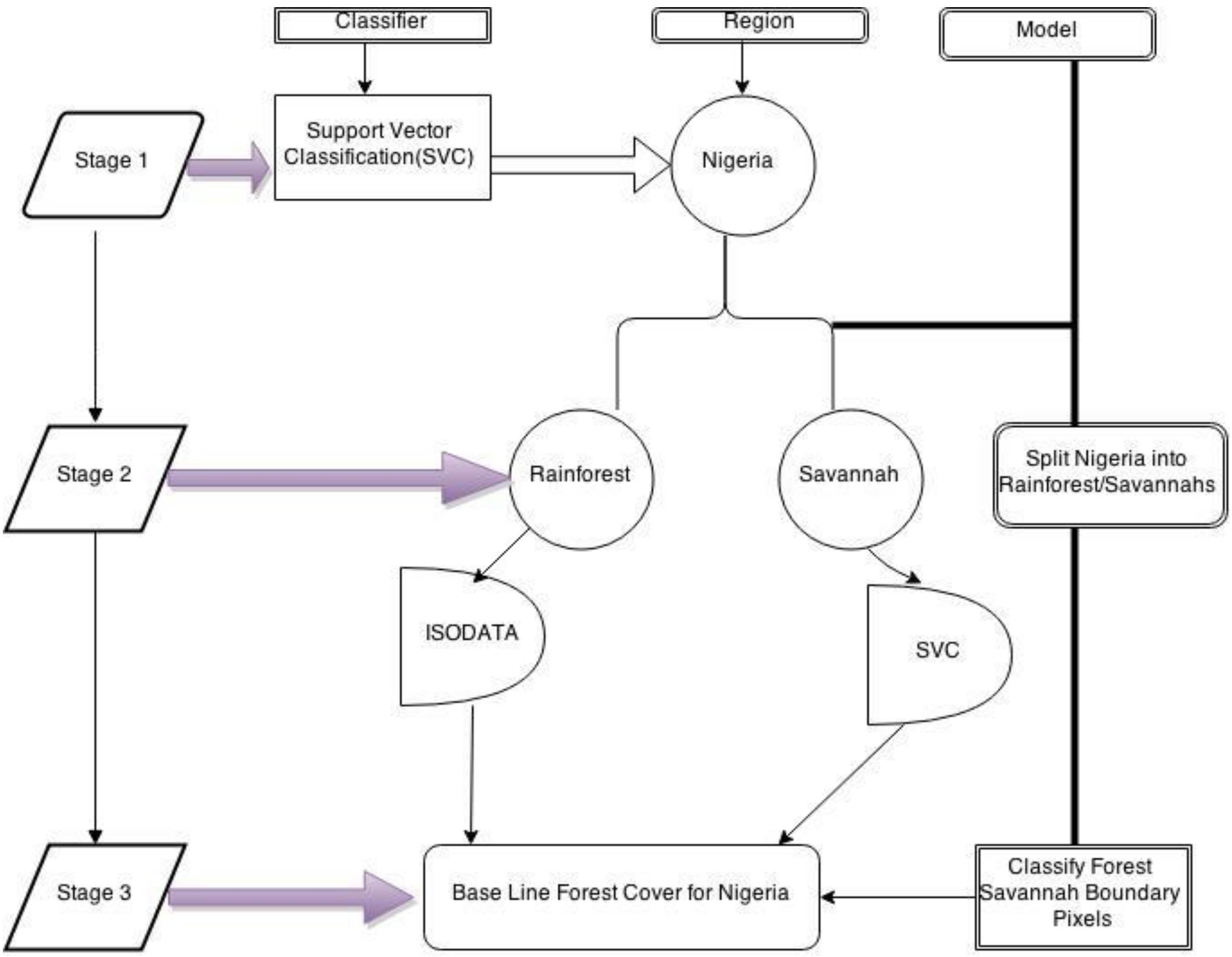


Figure 7: Flow chat model of classification for baseline forest cover Nigeria

This study uses Julian dates 361 for 2002, 2006 and 2012 as target period for the measurement of deforestation based on climatic and social factors. Under climatic factors, during that time of the year, Nigeria experiences near-cloud free periods every year (Anyadike 1993). Under social factors around December, the incidence of forest fire is at minimum due to festivities and related activities.

3.5 Mapping of Deforestation Areas and Hot Spots at Cluster level

To explore the potentials of MODIS single band (including indices) contribution in identifying deforestation across sites, this study also assessed forest dynamics at cluster level. This study applied Vegetation Index Differencing (VID), spectral unmixing, change vector analysis and

Image differencing techniques to evaluate changes in deforested patches across the forest clusters for the period between 2002-2006 and 2007-2012. The change detection techniques were tested on Red, NIR ,NDVI and soil fractions derived from and MODIS surface reflectance (MOD09Q1) and 16 day vegetation indices (MOD13Q1) for the period 2002-2012. In order to explore the potentials of MODIS single data in detecting deforestation, this study uses mean plus 0.5, 1 or 2 standard deviations of the mean difference between images based on the prototype of DeFries et al. (2002) and Morton et al. (2005) to identify deforested patches.

Vegetation Index Differencing (VID) involves the independent analysis of spectral values of vegetation indices or in combinations of two or more bands (Singh 1989). It was used in this study to obtain areas of deforested areas from the NDVI data obtained from MODIS time series .In VID, two change detection algorithms are normally applied- direct differencing and rationing. For rationing two spectral bands negates the effect of any extraneous multiplicative factors in sensor data that act equally in all wave bands of analysis (Singh 1989). The process of linear spectral unmixing involves identifying presence of materials of interest mixed with other materials and occupy less than a whole pixel in the image being analyzed (Shimabukuro and Smith 1991). The proportions of pure spectral components that related to surface constituents in a scene identifies and defines linear spectral pixels (Hussain et al. 2013). Linear unmixing model is mathematically expressed as:

$$x(i,j) = \sum_{k-1}^{p} a_k\,(i,j).e_k\, + n(i,j) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 3.4$$

The component $x(i,j)$ is spectral response vector,$a_k\,(i,j)$ is a scalar value representing fractional abundance of endmember vector e_k at pixel $x(i,j)$, $n(i,j)$ vector that denotes the spectral band error and P is the total number of endmember (Sánchez et al. 2010). Conventionally, endmembers from linear unmixing are selected directly from the image or field-spectra measures in situ or in labs (Solans and Barbosa 2010).

In this study signature derivation for soil end members were generated using the red (band 1), near-infrared (band 2) and short-wave infrared (band 6) bands at 250m spatial resolution based on the method by Shimabukuro and Smith (1991). Spectral signatures for endmembers were also generated and validated from training data sets collected during fieldwork (with exception of the Chad axis where valid historical was applied) in order to generate sub- pixel fraction of soil for each of the 4 forest clusters.

CVA describes the direction and magnitude of change from the first to the second date as a spectral change vector (Singh 1989). This study uses CVA to calculate the aerial extents of pixels (or polygons) detected as deforested. CVA calculates the magnitude of change of vectors from different time seires (Lorena et al. 2002). The derived change pixel value is a vector of spectral band of change generated by subtracting vectors for all pixels at different dates from a time series (Malilaw 1980). The direction of the CVA depicts the type of change whereas the magnitude of the change corresponds to the length of the CV (Hussain et al. 2013).

In image to Image differencing, spatially registered images of time t1, and t2, are subtracted, pixel by pixel, to produce a further image which represents the change between the two times. This study, measures differences from the converted reflectance images and not the raw radiance. Pixels with no change in radiance or reflectance are distributed around the mean (Lu et al. 2005), while pixels with change are distributed in the tails of the distribution curve (Singh, 1989). Image to Image differencing is expressed mathematically as:

$$Dxk\ ij = xk\ ij(t2) - xk\ ij\ (t1) + c \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..3.5$$

where, Xk ij = pixel value for band k and i and j are line and pixel numbers in the image, t1 = first date and t2 = second date and C = a constant to produce positive digital numbers(Ramachandra and Kumar 2004).A critical element of the image differencing method is deciding the thresholds for determining boundaries between change and no-change pixels. Finally, deforested pixels for each of the four forest clusters are disaggregated into cohorts of 6.25-10ha, 10-20ha, and 20-30ha and above 30ha in order to gain insight into their dynamics and explain their spatial patterns.

Deforestation hotspots were estimated using expert knowledge because there is no universal unit for evaluating what constitutes a 'hot spot of deforestation'.Deforestation hot spots were mapped using fieldwork data and areal dimensions of deforested pixels. First, the total area of forest was divided by the total deforested area in each of the cluster in order to derive the ratio between both variables. Secondly, due to spatial disparities in the forest-deforestation ratio for the savanna and rainforest clusters detected in stage one, the Chad /Mambila and Niger-delta /Calabar clusters were grouped into a single mapping unit of savanna and rainforest respectively. This was necessary to reduce bias in calculating deforestation concentration because the ratio of deforestation to forest area in higher in the rainforest than savanna regions. Thirdly, the average pixel areas generated for the rainforest and savanna clusters were aggregated such that any pixel area above this "value" is regarded as a deforestation hotspot. Finally, in order to spatially represent boundary conditions emanating from multi-linear collinearity (Ord and Getis 1995) in hot spots, the deforested patch must cover at least 1% of the $5km^2$ by $5km^2$ grid and the area must greater than or equal to 28.22 ha and 40.54 ha (aggregated values) for savannas and rainforest mapping units respectively.

Varieties of methods for detecting hotspots, (e.g Satscan and Getis Ord) were tested, but they provided lower accuracy when compared to the method used in this study. While these methods (e.g. Getis Ord Gi*****) are good tools in defining hotspots, they limit the spatial extent of the association such variables (Getis and Ord 1992). Limiting spatial association among variables may not be a useful tool in mapping deforested hotspots generated from remotely sensed data because what constitutes a hot spot in a given region (e.g. savanna) may not be the same as those found in other regions

3.6 Estimating Forest Phenology

Time-series of the 250m NDVI 16-Day (MOD13Q1) was used in this study for the period 2002-2012 consisting of 1012 images (253 images per forest cluster) to evaluate phenology trends of the forest pixels for deforestation and non-deforestation scenarios. The NDVI data provides one image every 16 days and a total of 23 images per year, without missing data (Alfredo 1999) which are less noisy than daily VI data (Testa et al. 2014). Although MODIS 13Q1 provides both NDVI and EVI layer composites, only the former was used in this research because it is more sensitive to changes small increases in the amount of photosynthetic vegetation (Sesnie et al., 2012) and has been widely used in phenological research (Boschetti et al. 2009). However, NDVI data also suffers from reliability due to background and path radiance effects and saturation especially over dense canopies (Huete et al., 2002).

However, the NDVI creates discontinuities generated by the compositing process such that the actual temporal distance between adjacent VI values can vary from 1 to 32 days, depending on the dates of acquisition of the reflectance used to compute the VI (Testa et al. 2014). Such uncertainty affects the shape of the fitting function used to estimate the phenological metrics of interest and this can make remote sensing results not precisely comparable with other data due to loss of precision (Testa, et al. 2014). When working with composite data of MOD13Q1, the possibility of processing internally coherent images (all VI values refers to the same date) is missing because over the 16-days period VI are chosen from different dates of the actual compositing period. Such adjacent pixel may originate from different days with different sun-pixel-sensor viewing geometries (Solano et al. 2010; Teste et al. 2014). The technique proposed by Testa, et al (2014) was applied in this research in order to generate uniform, temporally corrected dates to be used for the MOD13Q1 NDVI phenology time series.

3.7 Correcting the Compositing Problem

Testa et al. (2014) proposed a technique to recover the temporal accuracy of 250m 16-day VI from the MODIS MOD13Q1 using the dates contained in the composite day of the year layer and Pixel Reliability (PR) layers supplied with the MODIS data. The PR layer identifies and defines the overall quality of the NDVI value of each sampled pixel, giving detailed information on its status (Table 7). Similarly, the lower the weight, the less the NDVI value affects the estimation of the function fitting parameters (Jönsson and Eklundh, 2004).

To achieve this, the following procedures were undertaken: first, original NDVI layers for the forest pixels were stacked in a 253 x 4 image-long Time series (23 images/year x 11 years x 4 forest clusters) with the actual acquisition date of the raw NDVI values stored in the Composite Day of the year layer (CDOY).

Table 7: MODIS Pixel reliability flags and corresponding quality

Rank Key	Summary QA	Description	Weight assigned in TIMESAT
-1	Fill/No Data	Not Processed	n.a
0	Good Data	Use with Confidence	1.0
1	Marginal Data	Useful but look at the QA information	0.99
2	Snow/Ice		0.90
3	Cloudy		0.15

Secondly, for each of the 253 stacked images, the median values and inter-quartile range were calculated using the original acquisition date contained in the CDOY layer. Consequently, the Median was used in place of mean because the population of the acquisition dates was not expected to be normally distributed (Testa et al. 2014). Because the mean values were not symmetric, the inter-quartile range was used to represent the dispersion of the median values of the acquisition dates (Rousseeuw and Croux, 1993). Thirdly, the median date temporal patterns were aggregated by (a) 16-days compositing period; (b) month; season; and, (c) year units for the evaluation the modal day of occurrence of the VI values (Table 8).

Table 8: Aggregated temporal patterns of NDVI

(a) Composite	(b) CDOY	(c) Non Leap years	(d) Leap years
1	1	01-Jan	01-Jan
2	17	17-Jan	17-Jan
3	33	02-Feb	02-Feb
4	49	18-Feb	18-Feb
5	65	06-Mar	05-Mar
6	81	22-Mar	21-Mar

7	97	07-Apr	06-Apr
8	113	23-Apr	22-Apr
9	129	09-May	08-May
10	145	25-May	24-May
11	161	10-Jun	09-Jun
12	177	26-Jun	25-Jun
13	193	12-Jul	11-Jul
14	209	28-Jul	27-Jul
15	225	13-Aug	12-Aug
16	241	29-Aug	28-Aug
17	257	14-Sep	13-Sep
18	273	30-Sep	29-Sep
19	289	16-Oct	**15-Oct**
20	305	**01-Nov**	**31-Oct**
21	321	**17-Nov**	16-Nov
22	327	03-Dec	02-Dec
23	353	19-Dec	18-Dec

Based on the suggestion of Testa, et al. (2014) the following considerations were undertaken in order to ratify composting errors emanating for leap and non-leap yeas: to achieve this, CDOY from leap years greater than or equal to 60 was corrected by subtracting 1. Correspondingly for the yearly NDVI time series used in this study 2004, 2008 and 2012 were leap years hence 170,160,155 and 165 values were moved from the 29th of February to the 28th of February for the Niger -delta, Cross River, Mambila and Chad forest clusters (0.007% of the total number of values) respectively. Secondly, the acquisition dates in the last image of each year (the 23rd) may be greater than 365 (366 in leap years), values stepping over this threshold falls in the first days of the following year. For this, their actual value may range between 1 and 3 (2 in leap years) instead of between 366 (367 in leap years) and 368 meaning that dates from the CDOY layers must be corrected in order to avoid incorrect calculations of the median acquisition date. This problem was corrected by adding 365 (or 366) to CDOY values belonging to the last image of each year if their value was less than 353, the minimum value possible(Testa, et al. 2014). Finally, in order to generate nominal dates that are true representations of the actual position of the NDVI values, the CDOY values were rescaled as follows:

$$CDOY_{i,j,t\ CP} = CDOY_{i,j,t\ CP} - 16.(CP - 1) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 3.6$$

CP is the *CPth* compositing period of the year and *CDOYi, j,* is the value of the CDOY stack at the position *i, j, t*. As fully explained in the results section, the nominal MEAD based on modal occurrences was set to 9 in all forest clusters. This means that from the original NDVI data sets contained the CDOY dates, two NDVI were generated viz: the NDVI data that has been moved to its proper acquisition date and values interpolated using a cubic spline interpolation (Hmimina et al., 2013) and re-sampled to the modal date of occurrence in each of the forest clusters. Finally, Results of the correction procedures are found in Appendix C.

3.8 Generation of phenological metrics for Phenology Onset Date (POD), Phenology Cessation Date (PCD) and Length of the Phenology Season (LPS) for standing forest

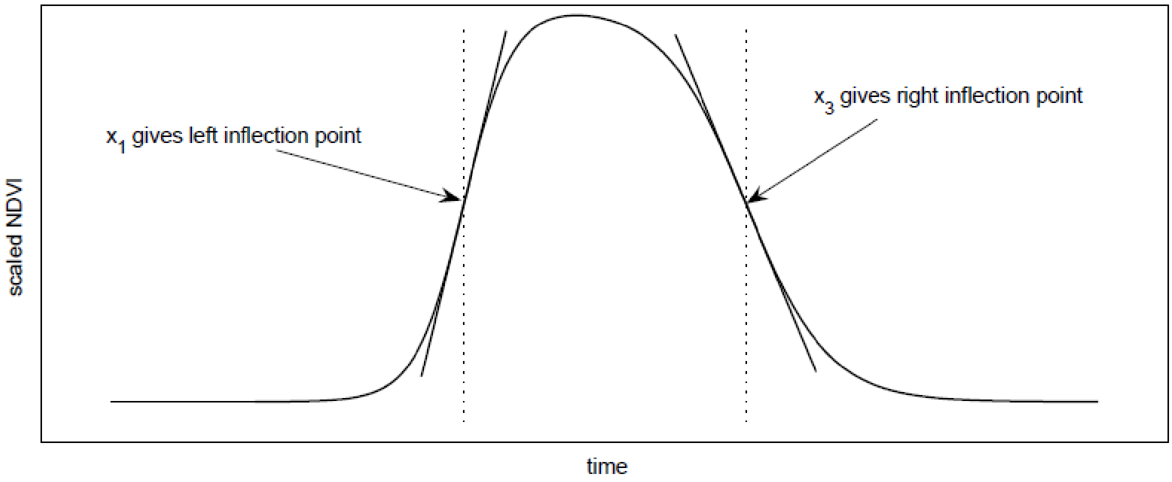
The interpolated *(*Time-series corrected NDVI data) for all the 11 years were smoothed in order to reduce noise distortions, (Hird and McDermid, 2009) and improve signal detection during onset of forest phenology (Hmimina et al., 2013). The logistic smoothening technique in TIMESAT (Jönsson and Eklundh 2004) was applied because of its near-perfect performance in terms of noise reduction and seasonality performance (Zhang, et al. 2003; Pan, et al. 2012) due to the saturation and overestimation problems of NDVI. As suggested in the TIMESAT manual, the smoothning algorithm was set to run 3 envelope iterations with low adaption strength to high values. The TIMESAT filter is a fitting technique that allows the user to set parameters such as land use change and product quality to the raw NDVI data thereby gives the user an idea as to how such changes will affect the overall phenophase of the vegetation.

It has been used extensively in Africa to monitor land use change and length of phenology season (Eklundh and Olsson 2003).

In addition, during the smoothing process in TIMESAT, the NDVI values in the stacked images were weighted using the reliability rank found in Table 3.1. The NDVI logistic fit was applied in this study using the TIMESAT–double logistic filter (Jönsson and Eklundh 2004) in order to generate phenological metrics in each of the forest clusters. The double logistic function is a fitting procedure which allows for determination of changes in the vegetation phases, which could further be used to compare with trends in other variables such as rainfall. The double logistic uses local model functions to fit data in intervals around maxima and minima in the time-series. The local model functions (equation 3.7) determines the model amplitude while the double logistic fits (equation 3.8) marks the inflection points and calculates the start and end of the seasons from the vegetation index data

$$f\ (t) \quad f\ (t;\ c, x) = \ c1\ +\ c2\ g(t;\ x),\text{-…………… ………………………}3.7$$

Where the linear parameters c = (c1, c2) determine the base level and the amplitude. The non-linear parameters x = (x1, x2. . . xp) determine the shape of the basis function g(t; x). Consequently, x1 determines the position of the left inflection point while gives the rate of change (figure 8)



Source: (Jönsson and Eklundh 2004)
Figure 8: NDVI double logistic Fits Showing Inflection for POD and PCD

Similarly, x3 determines the position of the right inflection point while x4 gives the rate of change at this point. Also for this function, the parameters are restricted in range to ensure a smooth shape.

$$g(t; x_1 \ldots \ldots .., x_4) = \frac{1}{1+\exp(\frac{x_1 - t}{x_2})} - \frac{1}{1+\exp\left(\frac{x_3 - t}{x_4}\right)} \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots .3.8$$

In order to generate uniform start and end of the forest phenological phases in each of the forest cluster, a threshold value of 0.50 was set as the value for determining start and end of the season. This implies that the start and end of the season dates are the ones where the fitting function value has increased by 0.5 respective to the closest leftward minimum rise and rightward maximum drop for the season(Jönsson and Eklundh 2004) . Based on the suggestion in TIMESAT manual 28 images per year (instead of 23) were used as the temporal window for the estimation of start and end of the season.

The 0.5 threshold used for the determination of POD is a scaled value that refers to the midpoint of the seasonal amplitude in NDVI. This scaling has both climatic and biological significance. Phenology responds to both climate behaviour (Schucknecht et al. 2013) trends in climate system(Stroppiana et al. 2014). Similarly, several studies have linked trends biogeochemical cycles to changes in phenology (Noormets, et al. 2009). Therefore, accurate estimation of phenological seasons (Start and End) becomes important when dealing with their temporal features. For example, in desert shrub lands time series NDVI shows little seasonal amplitude while for most regions tropical regions, the curve illustrates double-crop growing seasons each year(Justice et al. 1985).

There are alternatives in evaluating POS for example at USGS/EROS phenological metrics are set from time-series NDVI data using a curve derivative method, which employs a backward-looking predictive or delayed moving average . The setting of the smoothed NDVI data values are compared to a moving average of the previous number observations in order to identify departures from an established trend. The trend change is defined as the point where the smoothed NDVI values become larger than those predicted by the delayed average(Reed, Brown et al. 1994). This departure point determines the start of the growing season while the length of the growing season is assumes a similar manner, when the moving average run in reverse.

In order to make remote sensed phenological metrics reliable and qualitatively comparable with other variables (e.g. climatic), the VI,s used in evaluating phenology are required to have good temporal resolution and alignment. It is preferable to use threshold-based approaches that use either relative or pre-defined (global) reference values at which vegetative activity is assumed to begin. Seasonal midpoint NDVI is a threshold-based approach that uses relative reference values to derive metrics.

This approach delineates nnset date by using the midpoint between minimum and maximum NDVI values, thus tying the threshold to the seasonal amplitude of individual pixels and, in turn, the dynamic characteristics of each pixel(Schwartz, Reed et al. 2002). By contrast, in a pre-defined threshold, if the value is set at 0.099, start of the season is the point at which NDVI values reach this point at the beginning of the growing season(Zhang et al. 2003). This method can be effective for deriving the start of season in localized areas with relatively uniform land cover(White, et al. 1997). Nevertheless, difficulties arise when using it to determine start of the season over large areas with varying soil background characteristics (White, et al. 1997, Gu, et al. 2010). In addition, considering the nature of the data (varying soil background across sites) used in this study, it was necessary to set POD to 0.5 because the rainfall probability model used in estimating ROD is based on the rainfall probability values. ROD is a day with a probability value that is greater than or equal to 0.50. Therefore, the use of 0.5 threshold for POD creates a better platform for comparison.

3.9 Generation of Rainfall Seasonality Metrics for Rainfall Onset Date (ROD), Rainfall Cessation Date (RCD) and Length of the Rainfall Season (LRS)

In this study, only the probability/ reliability of rainfall index model (Odekunle 2004) was applied for the generation of rainfall onset, cessation and length of the season dates. This method assumes that the probability of rain on any given date can be estimated by the proportion of rainy days on that date. The probability of rainfall for each day of the year is directly related to the number of rainy days as a proportion of the total number of days considered for each day (Odekunle 2004). Similarly, the success and failure breaking even at 0.50 since probability values ranges from 0 to 1. A probability value above 0.5 is therefore an indicator for reliable rainfall. Full detail of this method is in the review of literature chapter. Appendix D presents the raw values of the rainfall matrices for onset and cessation

3.9.1Trends in Phenology and Rainfall Time Series for Forest

The Mann-Kendall trend uses the lengths rainfall and phenology time series in thisto show if between the beginning and end of all years, a monotonic increase, decrease or stability trend exist for their length of the season. The Mann-Kendall trend statistic (S) is dependent on the Confidence Factor (CF) and the Coefficient of Variation (COV). The trend is decreasing if Z is negative and the computed probability is greater than zero. If Z is positive and the probability value is greater than the level of significance, there is an increasing trend. The trend is stable or 'no trend' if the compared probability is less than the level of significance (Ike and Eludoyin 2013). The test statistic Kendall S is calculated as:

$$S = \sum_{J=1}^{n=1} \sum_{J=k+1}^{n} \mathrm{sgn}\left(x_j - x_k\right) \text{ . ... (3.9)}$$

Where x are the data values at times j and k. n = length of the dataset

$$\text{Sign } \left(x_j - x_k\right) = \begin{Bmatrix} +1 \text{ if } \left(x_j - x_k\right) > 0 \\ 0 \quad \text{if} \left(x_j - x_k\right) = 0 \\ - \text{ if } \left(x_j - x_k\right) < 0 \end{Bmatrix} \text{ .... (3.9.1)}$$

$$\text{Var (s) = } \left| n(n-1)(2n+5) - \sum t_{(t-1)(2_t+5)} \right| \Big/ 18 \text{ .... (3.9.2)}$$

The Mann-Kendall test has two parameters that are of importance for trend detection. These parameters are the significance level that indicates the test strength and the slope which indicate the direction as well as the magnitude of the trend (Ike and Eludoyin 2013). The notation t is the extent of any given tie and Σt denotes the summation over all ties. In cases where the size n > 10, the standard normal value Z is computed by using equation 3.9.3.

$$Z=\left\{\begin{array}{cc} \frac{s-1}{\sqrt{\ \mathrm{van(s)}}} & \mathrm{if}\ s>0 \\ 0 & \mathrm{if}\ s=0 \\ \frac{s+1}{\sqrt{\ \mathrm{van(s)}}} & \mathrm{if}\ s<0 \end{array}\right\} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 3.9.3$$

This study also calculates the correlation between the values of ROD/POD, RCD/PCD and LRS/LPS for each year (i.e. 12 samples a year x 11 (2002-2012) years) across the forest clusters

CHAPTER FOUR

RESULTS

4.1 Introduction

This chapter aims at presenting the results achieved in order to answer the three scientific questions proposed. In order to answer the first and second research questions, baseline forest cover for Nigeria between 2002-2006 and 2007-2012 were estimated using multiple-classification remote sensing models generated from fieldwork, Landsat and MODIS data. An 'adaptive' three-staged classification scheme to estimate baseline forest cover changes from fieldwork and satellite data. Similarly, 4 CD techniques were then applied to test the performance of Red, NIR, NDVI and Soil fractions derived from linear spectral unmixing of forest pixels in detecting deforestation at cluster level. This was necessary because it exposes the potentials of detecting forest changes from multiple data for different geographic regions.

At cluster level, matrices of onset, retreat and length of phenology and rainfall in each of the forest were calculated in order to explore trend and relationship between the former and later for the period between 2002 and 2012. Before estimating the forest phenology a compositing error correction procedure of NDVI time series, was undertaken (see chapter 3). The Mann-Kendall statistic and correlation, was applied to respectively calculate trends and bivariate relationship between rainfall and phenology in each of the forest cluster

4. 2 Accuracy Assessment of Classification Results

Table 9 is the results of national scale baseline forest cover classification accuracies for years 2002, 2006 and 2012. In 2002, for the savanna region of Nigeria, SVM classifier performed better by 20% than ISODATA classification of the forest pixels. For the rainforest region the accuracy of classifying forest cover using ISODATA were 70% and 22% higher than SVM respectively. In 2006, the accuracy of SVM for the forest pixels in the savanna regions of Nigeria was 77% when compared to the 51.2% recorded using ISODATA for the same region.

Table 9: Classification results for baseline forest cover in Nigeria for A (2002), B (2006) and C (2012). Where: CCI – Correctly Classified Instances, ICI–Incorrectly Classified Instances, RSB – Rainforest Savanna Boundary and Accuracy

	Region	CCI	IC1	Unclassified	Country Accuracy (%)	Forest Accuracy (%)	RMSE (Pixels)
A SVM	Nigeria	4333	1456	21	71.84	41.22	2.145
	Rainforest	562	231	19	69.87	70	0.087
	Savanna	456	199	18	64.61	**67.23**	0.432
	RSB	12	10	4	52.54	31.21	0.993
ISODATA	Rainforest	923	245	5	77.02	**89.12**	0.005
	Savanna	333	145	4	69.66	55.32	0.897
	RSB	31	21	4	52.61	**58.71**	0.965

	Region	CCI	ICI	Unclassified	Country Accuracy (%)	Forest Accuracy (%)	RMSE (Pixels)
B SVM	Nigeria	6143	923	36	86.13	33.52	1.0431
	Rainforest	699	545	44	53.18	71.45	0.0644
	Savanna	665	142	13	81.40	**77.13**	0.0732
	RSB	15	11	6	54.69	11.11	7.1772
ISODATA	Rainforest	1124	356	7	72.94	**83.26**	0.0914
	Savanna	134	187	6	39.74	51.23	1.2213
	RSB	44	16	3	73.15	**56.67**	0.7564

	Region	CCI	IC	Unclassified	Country Accuracy (%)	Forest Accuracy (%)	RMSE (Pixels)
C SVM	Nigeria	10544	1645	21	86.53	40.12	0.0663
	Rainforest	1294	1765	23	41.98	23.78	1.4114
	Savanna	665	42	3	93.40	**77.02**	2.8432
	RSB	34	50	23	31.77	11.11	9.1125
ISODATA	Rainforest	2311	716	1	76.32	**91.66**	0.0436
	Savanna	364	321	17	51.12	31.43	0.0877
	RSB	79	19	9	73.8	**66.67**	0.9664

Note: Bold values are the accepted forest accuracies reported in this study

For the rainforest region and RSB, ISODATA classification of forest pixels performed better than SVM classification. In 2012, the first classification covering the whole country, had an overall accuracy was 86.53%. However, subclasses classification of the forest pixels performed very badly with only 41.2% accuracy. For the rainforest split, classification accuracy using ISODATA for the forest pixel was 91% while the classification accuracy for the savanna clusters using SVC summed up to 77.02%. The second classification model showed an improvement of 51.66% and 37.2% for the sub-classification of the forest pixels. Cluster level classification accuracies generated from various MODIS data are presented in table 10.

Table 10: Cluster level classification results for NDVI, Red, and NIR and soil fraction

Data	**Chad axis**		**Mambila**		**Niger-Delta**		**Calabar**	
	Savannas				**Rainforest**			
	02-06	**07-12**	**02-06**	**07-12**	**02-06**	**07-12**	**02-06**	**07-12**
NDVI	47%	41%	47%	55%	61%	21%	54%	37%
RED	65%	77%	54%	71%	73%	73%	76%	71%
NIR	41%	54%	44%	53%	43%	57%	51%	57%
SOIL FRACTION	63%	61%	67%	86%	73%	79%	77%	71%

At cluster level, accuracy for deforestation in the savannas and rainforest regions were better from unmixing of soil fraction from forest pixels However, the rainforest regions performed better for all the data evaluated in detecting deforestation. The nature of the data used explains some of the low accuracies registered in the savanna forest clusters. Moderate resolution data provide lower forest accuracy in the savanna than rainforest because pixels in dense vegetation (such as rainforest) show better spectral contrast with soil than savanna vegetation. The second factor is the fact that the spectral differences between the savanna and forest soil is lower since deforested patches in the former are smaller hen compared to those of the later.

4.3 Quantification of Baseline Forest Cover and Deforestation Rates

In Nigeria, the forest cover decreased from 11,321,456 ha in 2002 to 9,455,599 ha in 2006 and to 7,596,310 ha in 2012 (Figure 9).

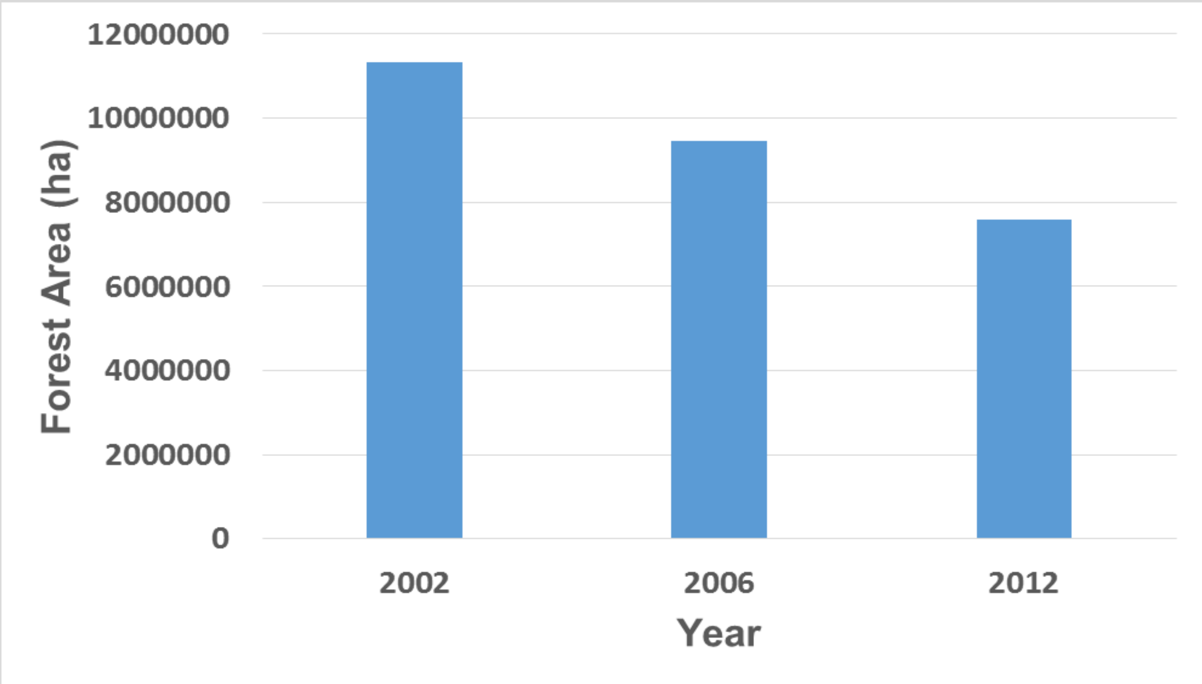


Figure 9: Baseline values of forest covers in Nigeria between 2002 and 2012. The values are derived from MOD09Q1 and MOD09A1 using ‘adaptive’ classification model for different vegetation zones

At national scale, the rate forest cover declined by 16.36 % and 19.66% for the period 2002-2006 and 2007-2012 respectively. For the period 2002-2012 the “Sparse Trees and crops Land” increased from 33,471,331 ha in 2002 to 58,455,599 ha in 2006 and to 177,487,440 ha in 2012. The land classes for “water bodies” pixels increased by 6% in 2002-2006 but reduced by 13% for the period 2007-2012. The other “Land uses class” increased by 2% and 11% for the period 2002-2006 and 2007-2012 respectively.

Cluster level patterns of pixels detected as deforested from NDVI, NIR, Red and soil fractions of MODIS for the selected clusters are presented in table 11. For the Chad axis, the total forest area as of 2002 was 15562 ha representing only 2% of the total (of the cluster) area of 969,395 ha. By 2012, the total deforested area was 974 ha. About 80% of the deforestation pixels in the Chad cluster are between 6.25 and 10 ha. Both NDVI and NIR bands of the MODIS used for the estimation of deforestation patches estimated deforestation areas range of 6.25-10 ha, 50% greater than spectral unmixing of soil from the forest pixels but still underestimated the total deforestation by 9% for the same area. In the Mambila, the total forest area as of 2002 was 31,323 ha representing only 4.3% of the total area cluster area. In 2012, the total deforested area had declined by 3,239 ha. The distribution of deforested pixel patches in the Mambila were 96.5 %(6.25- 10 ha), 2.89 %(10-20ha) and 0.61 %(20-30 ha).

For the Niger-delta forest cluster used in this study was 248,740 ha of which pixels detected as forest clusters were 9,50871 ha representing 38.2% of the total area. However, as of 2012, the total area of the forest had reduced by 21,453 ha which amounts to a decline of 22.5%. In the Calabar forest cluster, the total forest area as of 2002 was 1,073,256 ha but by 2012, it had reduced 6.2 ha to 30 ha.

Table 11Table 11: Results of Number of Pixels (NP) and deforested areas at cluster level generated from MOD09Q1, MOD09A1 and MOD13Q1 between 2002 -2006 and 2007-2012 for A, Chad B, Mambila, C River Niger-delta and D, Calabar

Data (A)`	6.25- 10(ha)NP		10- 20(ha)NP		20-30(ha)NP		>30 NP		Total ForestArea(ha) 2002	Total Deforested Area (ha) (1000) 2012
	02-06	07-12	02-06	07-12	02-06	07-12	02-06	07-12		
NDVI	14	17	25	7	0	0	0	0	18441	924
Red	14	16	22	5	0	0	0	0	16311	934
NIR	17	17	25	5	0	0	0	0	15332	971
Soil fraction	16	17	22	5	0	0	0	0	**15562**	974

Data (B)	6.25- 10(ha)NP		10- 20(ha)NP		20-30(ha)NP		>30 NP		Total ForestArea(ha) 2002	Total Deforested Area (ha) (1000) 2012
	02-06	07-12	02-06	07-12	02-06	07-12	02-06	07-12		
NDVI	24	23	39	3	4	3	0	0	49478	3112
Red	22	21	11	8	2	2	0	0	31324	3123
NIR	25	24	16	3	3	2	0	0	51221	3432
Soil fraction	22	22	11	3	2	2	0	0	**31323**	3239

Data (C)	6.25- 10(ha)NP		10- 20(ha)NP		20-30(ha)NP		>30 NP		Total Forest Area 2002	Total Deforested Area (ha) (1000) 2012
	02-06	07-12	02-06	07-12	02-06	07-12	02-06	07-12		
NDVI	123	152	17	14	16	11	2	3	95477	22134
Red	121	122	18	11	14	5	2	3	95066	23335
NIR	183	155	21	10	17	8	1	2	95634	23456
Soil fraction	125	125	17	18	11	6	2	2	**95087**	21453

Data (D)	6.25- 10(ha)NP		10- 20(ha)NP		20-30(ha)NP		>30 NP		Total Forest Area 2002	Total Deforested Area (ha) (1000) 2012
	02-06	07-12	02-06	07-12	02-06	07-12	02-06	07-12		
NDVI	81	34	7	5	2	1	2	2	1132144	13564
Red	72	33	5	3	1	1	2	2	1034738	11321
NIR	83	36	8	3	2	2	2	2	1114536	12444
Soil fraction	74	34	4	4	1	2	2	2	**1073256**	12254

Note: Bold values are the accepted forest accuracies reported in this study

Figures 10-13 present spatial and temporal extents of deforestation(for only the clusters) in each of the forest cluster for 2002-2006 and 2007-2012 respectively The maps were generated using MODIS soil fractions derived from spectral unmixing of forest pixels in all the forest clusters. The spatial pattern of deforestation across the four forest clusters is not the same. In the savanna forest clusters, (Chad and Mambila) deforestation occurs around edges of physical features such as mountain base or water bodies.

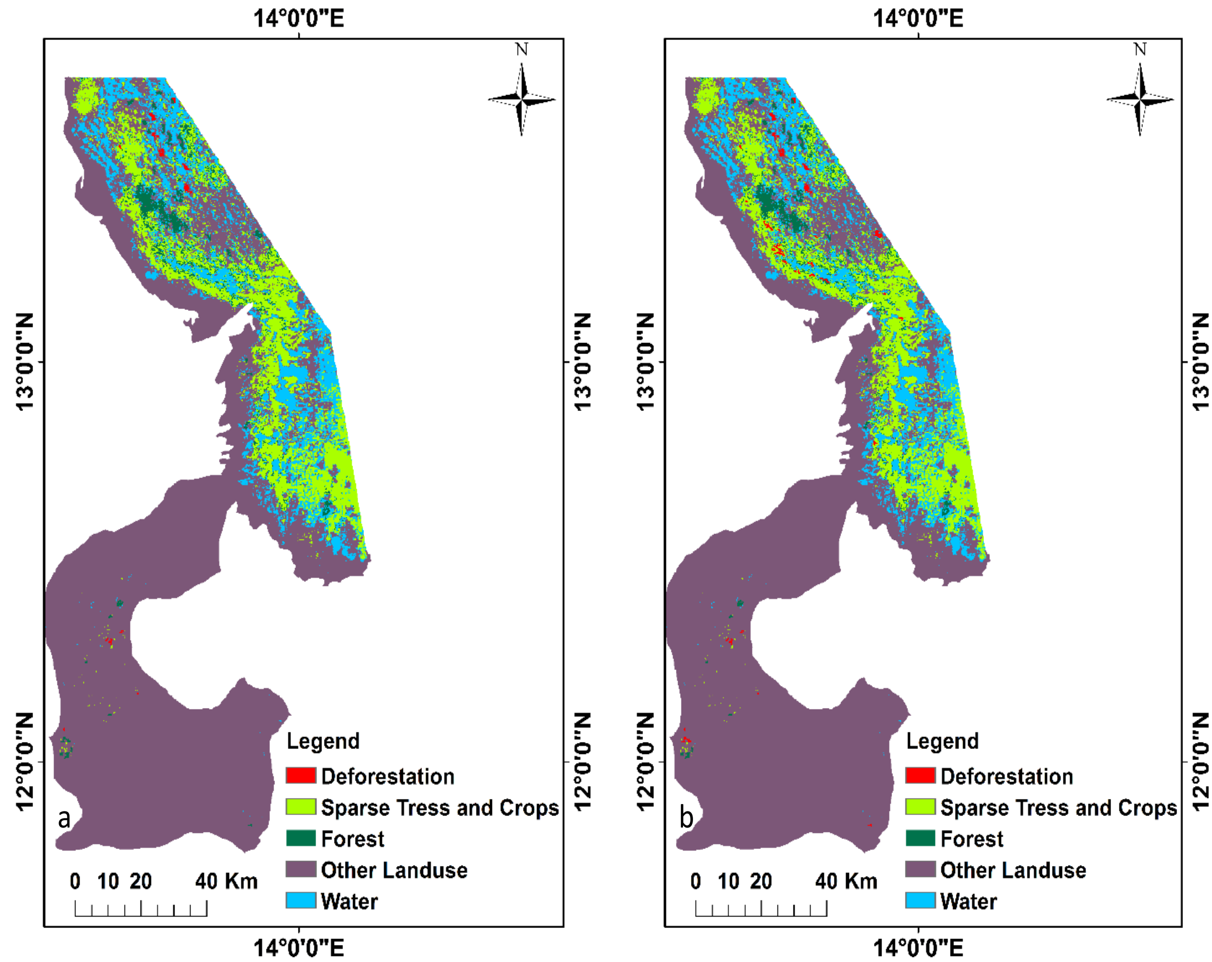


Figure 10: Spatial distribution of deforestation for the Chad forest cluster between 2002-2006(a) and 2007- 2012(b) The deforestation areas were mapped using change detection results of spectral umixing of MODIS surface reflectance data

Conversely, in the rainforest zones, the spatial distribution of deforestation is related to population densities and occurring mostly in the middle of the forest. In the Chad zone, deforestation and forest fragmentation follows a straight-line pattern stretching from a North-south direction.

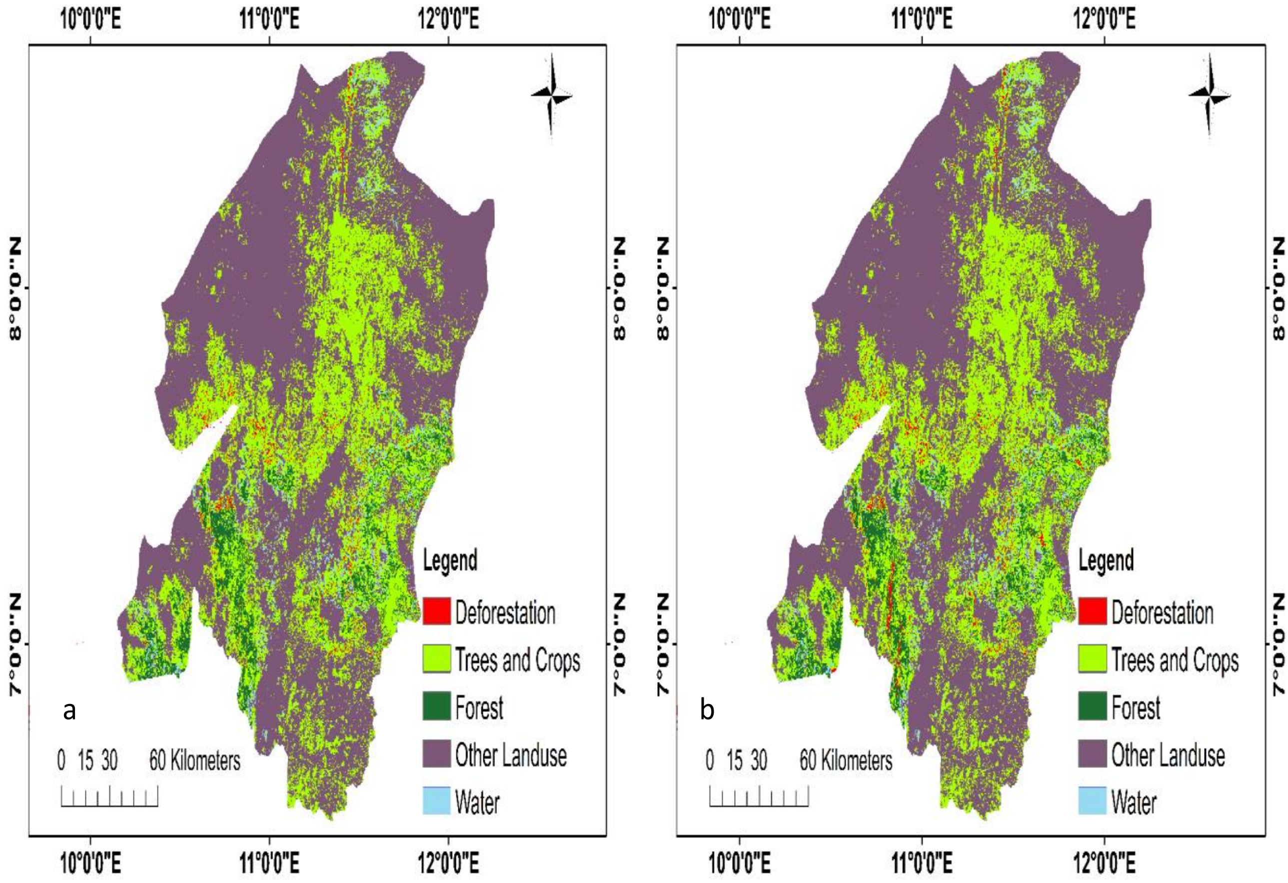


Figure 11: Spatial distribution of deforestation for the Mambila forest cluster between 2002-2006(a) and 2007- 2012(b) The deforestation areas were mapped using change detection results of spectral umixing of MODIS surface reflectance data

Within the Mambila (Figure 11) axis, deforestation occurs around the base of hills and similar landscape due to physical barriers posed by the mountainous landscape. Around the rainforest axis, due to favourable topographic features, deforestation occurs both around the forest edge and deep inside the forest.

For the Niger-Delta zone (Figure 12), deforestation is more concentrated along the banks of the River Niger East and West of Onitsha, South Eastern Nigeria. For the Calabar forest clusters (Figure 13), deforestation is more concentrated around the middle and the Nigerian-Cameroon boundary to the East. The majority of the deforested forest pixels detected along the Nigerian-Cameroonian boundary as of 2012 were above 20 ha.

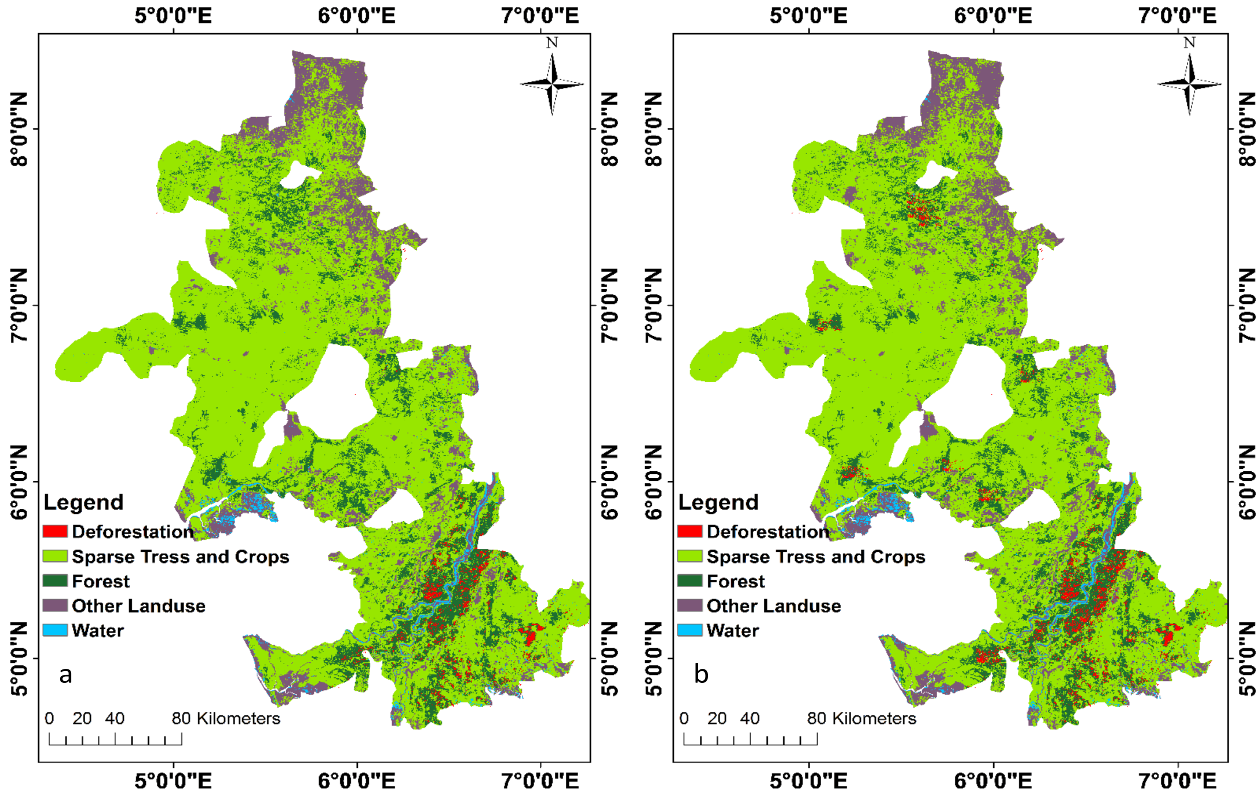


Figure 12:Spatial distribution of deforestation for the Niger-Delta forest cluster between 2002-2006(a) and 2007- 2012(b) The deforestation areas were mapped using change detection results of spectral umixing of MODIS surface reflectance data

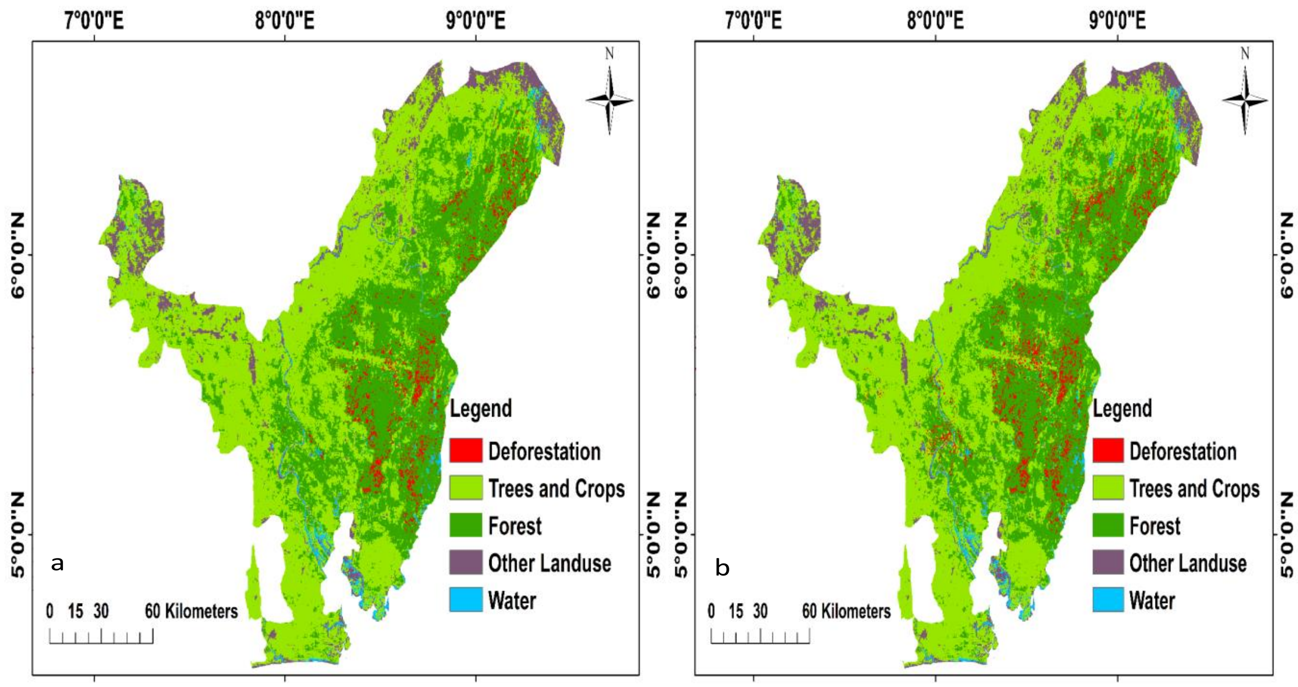


Figure 13: Spatial distribution of deforestation for the Calabar forest cluster between 2002 and 2006(a) and 2007 and 2012(b)

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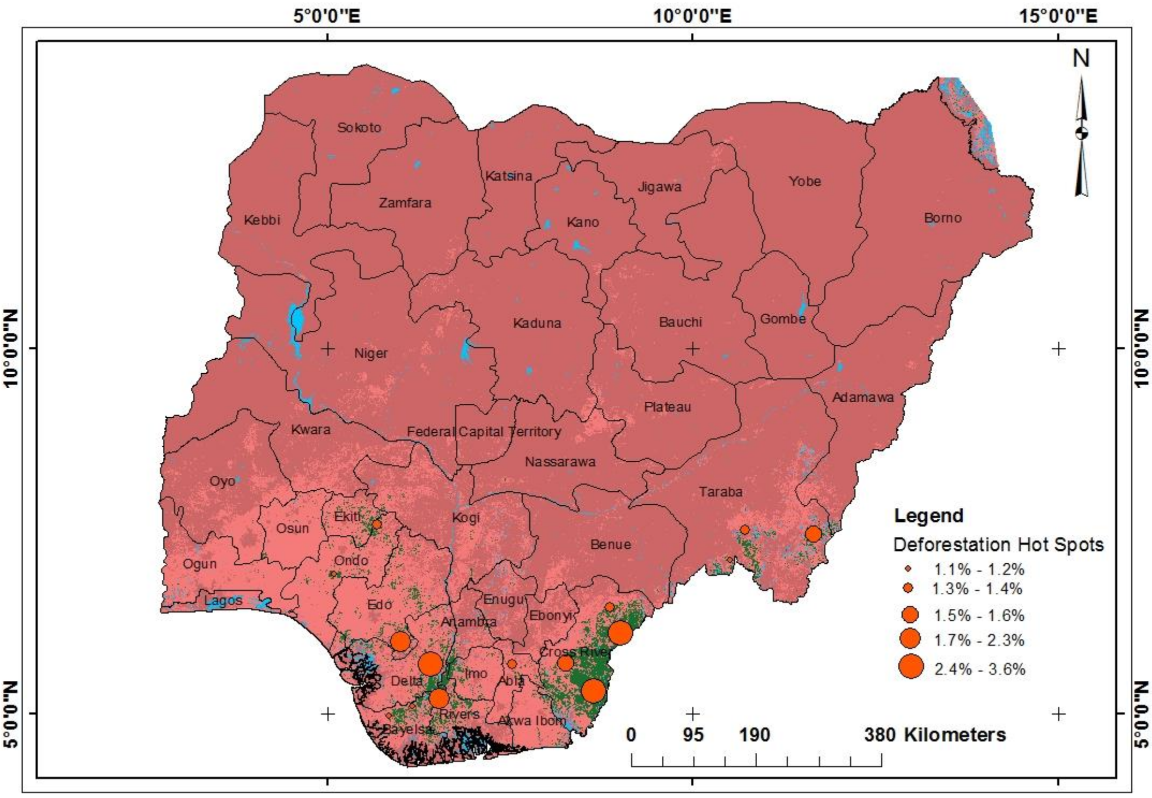


Figure 14: Cluster level deforestation hotspots in Nigeria between 2002 and 2012. The map indicates the percentage of deforestation area greater than or equal to 1% for 28.22 ha (savannas) and 40.54 ha (rainforest) at 5km X 5km grid.

The deforestation areas were mapped using change detection results of spectral umixing of MODIS surface reflectance data Figure 14 is the hot spot map of deforestation for the forest clusters. The Mambila forest accounts for 3 hot spots of deforestation. In the rainforest region, 12 areas are deforestation hot spots. Of the 12 areas identified, 6 each are in the Niger-delta and Calabar forest clusters

4.4 General Patterns of Forest Phenology and Rainfall

Figure 15 shows the temporal patterns of onset, cessation and length of the season for phenology and rainfall estimated from MODIS and TRMM data respectively. Figure 15 (a-c) clearly illustrates the distinctive patterns of forest phenology across the four clusters in

Nigeria. The phenology matrices shows considerable variation between the savanna (Chad and Mambila) and rainforest (Niger-delta and Calabar) zones of Northern and Southern Nigeria respectively. Phenology onset occurs between April and July and cessation occurs between late October and November in the savanna

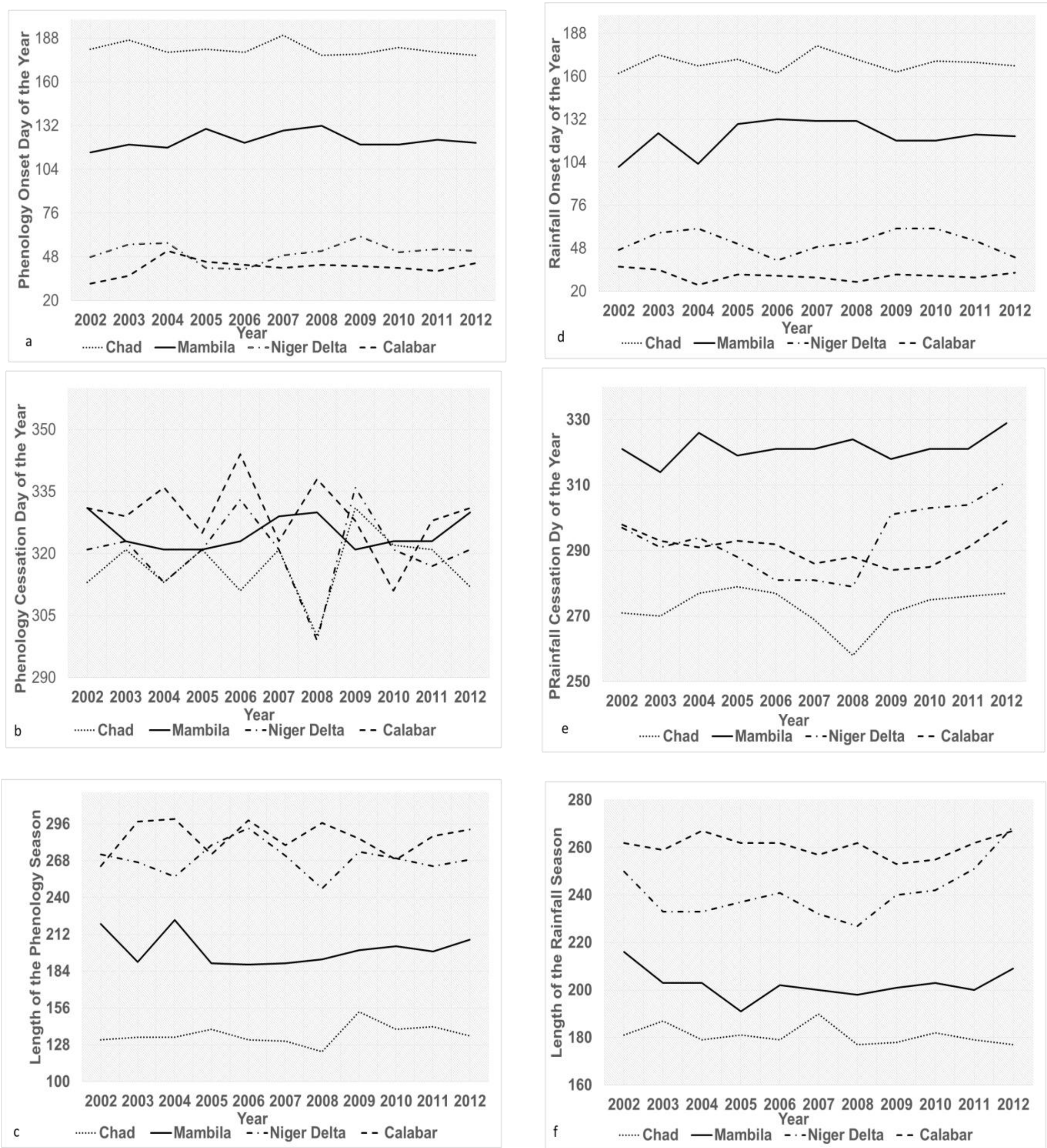


Figure 15:Patterns of Phenology (a-c) and Rainfall (d-f) across the forest clusters

In contrast, phenology onset and cessation respectively occurs in February and late November/early December for the rainforest zone. Furthermore the length of the Phenology season last between 128 to 212 in the Savannas while in the rainforest it last between 268 to 296 days as reflected in amplitude of the phenological cycle across the four sites(appendix E). The pattern of phenology cessation is more complex in both the Savanna and rainforest zones. Besides the general flux in the cessation matrices, Mambila cluster shows an increasing trend compared to the Niger delta. Details on the date retrieval matrices of phenology for the four clusters can be found in Appendix (A)

Figures 15 (d-f) presents the temporal distribution of rainfall onset cessation and season length between 2002 and 2012 based on the rainfall probability model described in chapter 3. Rainfall onset reduces gradually southwards from late May in the savanna zone to second week of February in rainforest zones. The temporal pattern of rainfall cessation across all the clusters is complex to describe. Normally, ROD should increase gradually southward; however, this is not the case for the Mambila forest. In The Mambila, rainfall cessation is higher (figure 15(b)) than those of the Niger delta and Calabar clusters. The length of the rainfall season follows a linear pattern; it increases from 180 days in the Savanna to 268 days in the rainforest regions.

4.4.1 Phenology and rainfall lags in the Savanna (Chad and Mambila Forest Cluster)

Inspection of derived phenology and rainfall indices in the Chad forest cluster indicates a regular pattern across all years in phenology and rainfall onset, cessation and length of the season. For all years, green-up onset is relatively stable and starts at an average of 46 days after rainfall onset. Rainfall cessation lags behind the same phenology trend by 28 days.

Rainfall rises steadily until onset is achieved, after this period it starts dropping steadily before rising again around July. In contrast phenology patterns are stable after green-up onset.

For the Mambila forest cluster, phenology and rainfall onset date have a lag of 4-days for the period 2002-2012. The only difference was in 2007 when POD was earlier than ROD by 12 days. Rainfall and Phenology onset occurs almost simultaneously in the Mambila forest cluster. After onset of phenology and rainfall, both variables exhibit different characteristics- while phenology trend downwards after onset, rainfall maintains a steady rise before dropping sharply from late October each year. Unlike the Chad cluster, after cessation of rainfall and phenology both variable drops in a regular pattern

4.4.2 Phenology and rainfall lags in the Rainforest Zone (Niger-Delta and Calabar Forest clusters)

In the Niger delta forest cluster, matrices for phenology and rainfall show an irregular pattern in onset date. While rainfall rises steadily before setting in March, phenology rises gradually showing no distinctive pattern. Rainfall in the Niger-delta forest cluster for the period 2002-2012 appears not to be a major factor for phenology onset because both variables shows no distinctive connections within the course of the year. Inspection of retrieved rainfall and phenology time series indicates that while the former fluctuates after onset, the later maintains a stable rising trend until cessation sets in. The Calabar and Niger delta forest clusters shows similar patterns in rainfall and phenology trends. Rainfall increases steady from late January before picking up in February. After the onset of rainfall, the trend starts fluctuating before cessation date is achieved. In the Calabar cluster time series observational data derived from MODIS indicates a gradual steady and rise and drop in phenology onset and cessation respectively.

4.5 Trends in Rainfall and Phenology Time Series

For each of the forest cluster, Mann-Kendall analysis was applied to the time series of the lengths of the phenology and rainfall seasons in order understand if between 2002 and 2012 the trends are increasing decreasing or undefined (no trend). Full details on the procedure for generating and summarizing the Mann-Kendall has been discussed in the methodology chapter.

Table 12 is a summary of the Mann Kendall analysis generated using NDVI and rainfall data derived respectively from MODIS and TRMM. In the Chad cluster, between 2002 and 2012 both rainfall and phenology seasons decreased. For the Mambila, while phenology season was decreasing, the rainfall season was increasing. The Niger delta forest cluster, LPS showed no trend while the LRS increased. For the Calabar forest cluster, between 2002 and 2012, LPS showed no trend while the LRS decreased.

Table 12: Mann-Kendall Trend for all forest clusters

Year 2002-2012	Trend LPS	Trend LRS
Chad	Decreasing	Decreasing
Mambila	Decreasing	Increasing
Niger-Delta	No Trend	Increasing
Calabar	No Trend	decreasing

Decreasing= Negative trend in the Length of the Season Mann-Kendall trend $p \leq 0.05$)
Increasing = Positive trend in the length of the season Mann-Kendall trend ($p \leq 0.05$) No trend = relatively stable trend at $p \leq 0.05$

Figure 16 displays the scatterplots showing the onset cessation and phenology season lengths between 2002 and 2012. The correlation between these variables varies across clusters. Generally, the correlation between POD and ROD (Figure 16 a, b, c d) is higher in the Savanna zone than the rainforest. The Chad forest is able to explain 54% variation between phenology and rainfall onset dates. For the Mambila forest cluster a positive correlation (R^2 =0.95, P≤ 0.05) between ROD and POD was also recorded. In the rainforest zone, insignificant relationships between phenology and rainfall onset were recorded. In other words, ROD defined in this study can be used to predict the onset of onset date for phenology in the savanna than rainforest zones of Nigeria.

Low correlation was reordered between phenology and rainfall cessation dates Figure 16 (e, f, g and h). This is an indication that other factors may be responsible for phenology cessation than rainfall. Furthermore such low correlations are not unexpected, since variability in climate often become clearer obvious with longer records. Finally, the correlation between length of the rainfall and phenology seasons (figure 16 I, j, k and l) was fairly higher for the savanna than rainfall region. This is also an indication that rainfall to an extent explains trend in forest phenology in savannas than rainforest regions.

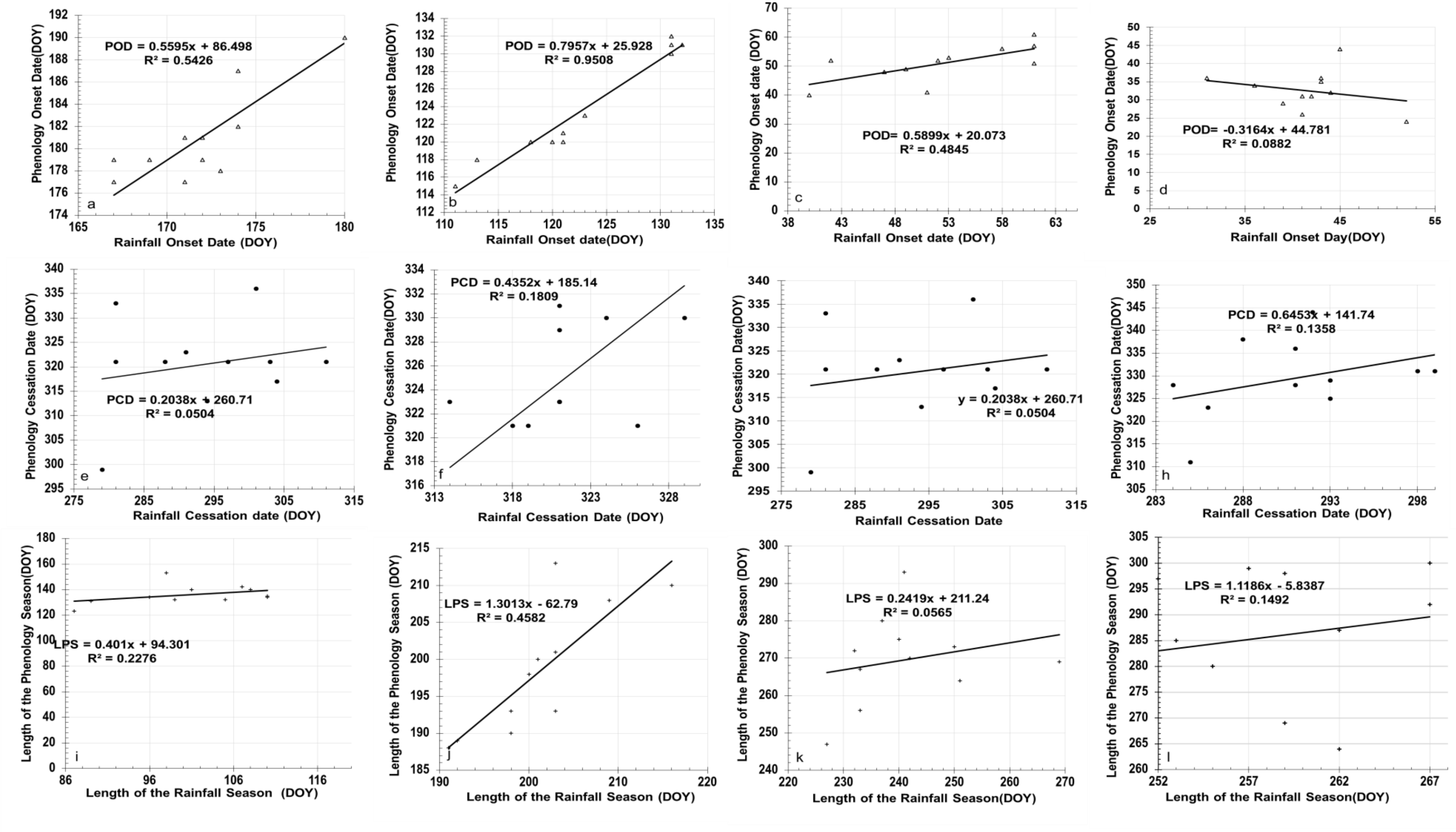


Figure 16: Comparison between POD with ROD, PCD with RCD and LPS with for Chad(a,e,i), Mambila (b,fj) , Niger-Delta(c,g,k) and Calabar (d,h l) clusters for the period 2002-2012

4.6 Summary of Results

This chapter presented results of analysis based on the research questions raised in chapter one. The rate of national (baseline) forest loss for the period 2002-2006 was 3% lower than 2007-2012. Linear spectral unmixing of forest pixels from MODIS data is better than NDVI, NIR and Red bands in detecting cluster-level deforestation. The length of the rainy season is increasing in the Mambila and Niger-delta region, but decreasing in the Chad and Calabar forest clusters. The length of the phenology seasons is decreasing in the savanna(Chad and Mambila) but stable in rainforest zone(Niger-delta and Calabar) and e) forest phenology closely follows with spatial and temporal patterns in rainfall seasonality in savanna than rainforest zones of Nigeria. Chapter five presents the discussion of findings.

CHAPTER 5

DISCUSSION OF FINDINGS AND CONCLUSION

5.1 Introduction

The aim of this chapter is to discuss and compare the results of this thesis in relation to both the research questions raised and existing literature. The results of the first research question on national baseline forest detection and cluster level deforestation are comapred with similar studies carried out in Africa and specifically in Nigeria. The second research question: compares some spatial patterns of deforestation hotspots presented from similar studies in Nigeria. The second research question also discusses in relation to the behaviour of various MODIS bands in detecting areas affected by deforestation. The third research question discuses rainfall and phenology relationship for each of the forest cluster based on trends and bivariate threshold of the derived matrices

5.2 Baseline forest cover, deforestation rates and Hotspots

This study has provided adequate information on the spatial and temporal variation in forest cover for Nigeria. It also provides relevant data on forest cover extents, cluster level deforestation and hotspots of deforestation. Results of this study will no doubt, have policy implications for Nigeria in the estimation greenhouse gas emissions as stream lined in the REED+ policy. Results from this study indicate the importance of spatial and temporal information in bringing transparency to the extent of change of not only forest cover but also other land use. The results of the land cover in this study show a gradual transformation of forest to other lands uses. This conversion of forest to “Sparse Tress and Crops” is higher than other land cover classification used in this study. The estimates of baseline forest cover in Nigeria in this study for year 2002, 2006 and 2012 (11,321,456 ha, 9,455,599 ha and 7,596,310 ha) are respectively comparable to the estimates of Hansen et al. (2013). Their study uses four 'Tree Cover' classes: '<25% TC', '26–50% TC', '51–76% TC', and '76–100% TC to describe forest change'. Hansel et.al (2013) respectively defines forest loss and gain as the sum of losses from the four classes forest cover and change from non-forest to more than 50% tree cover.

The estimates of baseline forest cover in this study are similar to the 30 % tree cover canopy of Hansen (2013). As an example, tree cover of 30% canopy density is 9% higher for 2002 but 12% and 8% lower for than the Hansen (2013) estimates for Nigeria in 2006 and 2012 respectively. However, at 20% canopy density, the results of this study are comparatively 12% 26% and 39% lower than the Hansel (2013) values for Nigeria in 2002, 2006 and 2012 respectively. At 50% canopy density, Hansel (2013) estimated the total tree cover to be lower than 5 Million ha which is not the case in Nigeria. The discrepancies between the Hansen (2013) values for Nigeria and this study relates to differences in the definition of forest and the reliance on satellite imagery acquired during growing season.

The definitional limitations Hansel et.al (2013) estimates of forest reduces its reliability for country based (specifically Nigeria) forest detection and change assessments. They major limitations include i) Definition of tress as vegetation taller than 5m (ii) Disaggregation of forest change by volume of tree cover stratum (e.g. >30% crown cover to ~0% crown cover) (iii) Use of satellite imageries captured during growing season for land cover mapping.

For Nigeria, the definition of tress as vegetation greater than 5 m will largely create discrepancies in forest change 'areal' estimation in the savanna and mangrove regions. In the savanna region, majority of the tree cover around the Sambisa, Mambila and Alantica hills are less than 5 m (Chapman et al. 2001). Therefore defining tress as vegetation taller than 5 m undermines the detection of forest cover for most regions in Northern Nigeria. There is also confusion between differentiating “trees loss” and “forest loss” in Hansen et.al (2013). Such confusion undermines the spatial coverage factors in the definition of forest. The Disaggregation of forest change by volume of tree cover stratum will no doubt present different estimates of forest cover changes. Such stratum will only lead to confusion as to the exact estimate to accept in comparative research and decision-making.

Hansel et.al (2013) depended largely on images acquired during dormant season in mapping tree cover. When satellite data used in forest mapping are acquired during the growing season, they perform better than those captured during senescence or dormant seasonal periods(Tucker et al. 2004) However, in the coastal areas of Nigeria where larges clusters of mangroves and evergreen tree covers exist, during dormant season, (march-October) clouds covers to very high. Such clouds covers reduce the reliability of the satellite data in mapping forest cover.

The estimates of FRA (2010) country reports for Nigeria are not directly comparable with this study due to variations in the estimating periods. The FAO (2010) country forest survey for Nigeria in for 2005 (11 089 432 ha) is 1.6 mha lower than the 2006 estimate of this study. The 2012 estimate of this study was also 1.8 mha lower than the 2010(9 041 088) FAO estimate. The calibration of forest change for Nigeria by FAO indicates a declining rate of forest loss. Similarly, the estimate of forest lost 2000-2005 is 12% higher than the 2006-2010 estimates b7 3% for 2002-2006 and 2007-2012..

For Nigeria, several limitations are associated with the FRA reports diminish their utility and reliability in analyzing change assessment. Firstly, the methods used in assessing forest extents are inconsistent between countries. The FAO 2010 estimates for Nigeria were developed and updated using past forest survey records(FRA 2010) while in Brazil, forest cover are estimated in connection with observational data.Secondly,the definition of “forest” based on land use instead of land cover obstructs the biophysical reality of whether tree cover is present or not (Hansen, Potapov et al. 2013). Finally, changes forest definitions used to estimate forest cover in successive reports have changed over time.

The estimates of forest cover in this study is also comparable to results from a recent continental result of forest cover (Mayuax 2013). Their study estimated baseline rainforest cover for only the rainforest zone of Nigeria and found total area of forest cover to be 3,158,000 ha in 2005 which is 51% lower than the estimate (6,612,466 ha) of this study. The discrepancies in these results is due to the approach used and biased field validation using NDVI threshold.

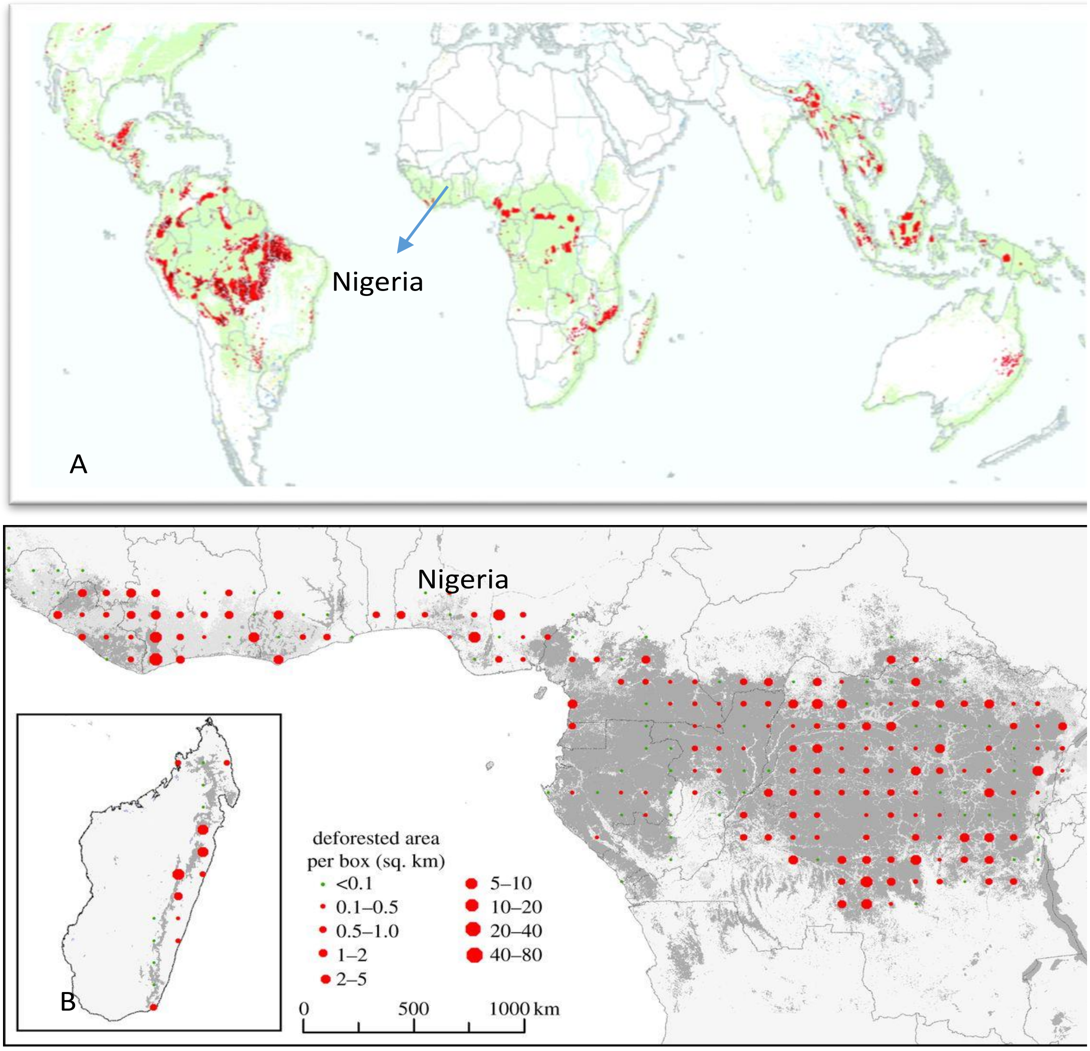
Their study-validated forest cover classifications using high spatial image without fieldwork data to back up their findings in any part of the Nigerian rainforest. The use NDVI threshold to exclude open dry forests, savannas, bare soils and water surfaces to some extent reduced the quality of the their estimate because even in the rainforest of Nigeria, some forest cover types also exhibit characteristics of savanna vegetation (Chapman et al. 2001). By implication, Mayaux (2013) excluded relevant rainforest vegetation by using NDVI threshold to exclude unwanted data from their images. For example, in the Niger-delta region of Nigeria, a very close relationship exist between mangrove vegetation and water bodies (Short and Stauble 1967). Their study might have mistaken water for mangroves during the exclusion process. While no remotely sensed dataset and analysis will ever be true reflection of on-the ground processes, this study have provided data that can play an integral role in improving our understanding about the dynamics of forest cover change.

Despite problems of poor governance, corruption and conflicts between policy makers and local authorities, Information on direct drivers and underlying causes of forest cover change is necessary. Although the Federal government of Nigeria recently implemented a deforestation-monitoring scheme through the National Space Development Agency (NARDSA), in 2010, it appears that nothing has been done to control forest cover loss. Based on the findings of baseline forest change, in this study, the government appears not be serious in reducing forest loss. The data generated from this study will no doubt provide a background to implementing and evaluating policies such as the reduction of emissions from deforestation and forest degradation.

5.3 Deforestation Hotspots

Up- to- date remote sensing research on deforestation and forest cover hotspots in Nigeria between 1980 and 1990 \(Mayaux et al. 2005) and 2000-2010 (Mayaux et al. 2013) figures 17 a and b) do not reflect their true spatial and temporal patterns as observed on ground. Figure 17 (a) is based on the deforestation hotspots in the humid tropics of tree cover based on NOAA AVHRR 8 km resolution data for the Amazon basin, and from time-series of Landsat TM data (Skole and Tucker 1993; Achard et al. 1998; DeFries et al. 2000).

Mayaux, et al (2013) analysis of forest cover was restricted to the rainforest zone of Nigeria whereas this study included the savanna areas as well. Mayaux et al. (2013) estimated surface affected by deforestation in 2010 in samples of 100 km^2 and concluded that in the Nigerian rainforest, the active deforestation patches had the following dimension: 1) two zones of deforestation area of 40-80 km^2 2). A zone of deforestation area of 20–40 km^2, 3) three zones of deforestation area of 10–20 km^2 and 4) four zones of deforestation ranging from 5–10 km^2. This study estimated deforestation rates at a much finer scale (5 km^2) for the year 2012 and mapped 15 deforestation hotspots that were above 0.3 km^2. Similarly, only four deforestation hot spots mapped by Mayaux,et al. (2013) had the same spatial location as the ones for this study.



Source:Mayaux et al 2005, Mayaux e al 2013)

Figure 17: Main tropical deforestation fronts in the 1980s and 1990s indicating the number of times each 0.1° grid identified as being affected by rapid deforestation by the different datasets b) Net deforestation between 1990 and 2000

The disparities in the spatial extent of deforestation active zones between this research and those of Mayaux, et al. (2013) is a source of concern. Specifically results of Mayaux (2010) those only two zones in the Calabar forest had areas of deforestation of 10-20 km^2 is an in reality, the area accounts for two proportions of deforestation above 40 km^2.

Figure 17 (b) is based on 250m MODIS data, (same as this study) only reported two zones of active deforestation of up to 20-40 km^2 one around the river Niger channel (close to the town of Onitsha) and the other in the Niger delta region. Conversely, there are over two areas of active deforestation greater than 40 km^2 this area.

They discrepancies between ground observational and direct remote sensing based observations in estimating deforestation estimates is attributable to approach, and definitional differences. Another major driver of the spatial pattern of deforestation is based on topographical factors. In areas where the terrain is flat, deforestation tends to be concentrated around the middle of the forest while in elevated terrain, (e.g. Mambila) deforestation is concentrated around the edges of the forest.

5.4 Deforestation Rates from Multiple MODIS Bands

Different spectral bands from remote sensed data have been used to estimate forest change and deforestation rates globally (Achard et al. 2014), in the Amazon (Morton et al. 2005; Aragao et al. 2008) and Africa (Mayaux et al. 2005; Mayaux et al. 2013). All results from these studies showed that deforestation rates detection are not the same for each spectral profile of the satellite data bands applied. This study also found similar results as those of Morton et al. (2005) in deforestation rates estimates using multiple MODIS bands and unmixing of soil pixels from the forest clusters. Spectral unmixing of soil from forest pixels showed in that both savannas (Chad and Mambila) and rainforest deforestation extent and rates can be best detected and estimated by unmixing soil from forest pixels. Morton et al. (2005) suggested use of the Vegetation Continuous Field (VCF), percent of tree-cover data as a forest mask before detecting deforested pixels from multiple MODIS bands- their suggestion were tested in this study but the accuracy of the forest pixels was very low in both the savanna and forest zones

Therefore, this study recommends the use of high-resolution data for the rectification of moderate resolution data in order to detect forest pixel and then applying adaptive remote sensing models to estimate large-scale forest cover trajectories.

The main drivers of deforestation are not the same for the savanna and rainforest regions. In the rainforest zones, the main causes of deforestation may be related to shifting cultivation and urbanization; while for the savannas, they important drivers are rural population expansion and fuel-wood extraction. Deforestation points and hotspot identified in the savanna regions in this study are in areas of low population density as opposed to those of rainfall forest zones. They low population densities around these deforestation zones in the savanna is a strong indicator that 'is not the local population that uses the logs' (of trees) rather, they are transported to other regions of high demands. For example, around the Chad and Mambila zones forest covers are more concentrated, in areas of population densities of 58 km^2 and 863 km^2 respectively..

5.5 Trends and Relationships between Rainfall and Forest Phenology

MODIS data coupled with TRMM rainfall matrices provide a veritable tool for monitoring the relationship between forest phenology and rainfall. Remote sensing provides a better opportunity to study and provide data on climate-biosphere interaction at a national scale (Nigeria) in a way that has not been previously done. This study have demonstrated that forest phenology in the savannah is largely dependent on seasonal trends of rainfall than in the rainforest zone. The pattern of forest phenology is strongly controlled by spatial variations in ROD, RCD and LRS, which are controlled by the general circulation of the atmosphere. Lags between phenology and rainfall reduces with progression from Northern to southern Nigeria. The spatial-temporal patterns of forest phenology and trends in rainfall ROD and LRS for each of the cluster were consistent for the different years considered in this study. Due to the consistency in patterns of rainfall and phenology across the forest cluster ,when coupled with other deterministic factors(e.g soil), results from this study can be used for the prediction of phenology in response to rainfall regimes across the Nigerian forest clusters.

The results of the rainfall onset, cessation and length generated in this study clearly defines the characteristics of rainfall in Nigeria as indicated in the single and double maxima of rainfall (Olaniran 1983; Anyadike 1993; Ati et al. 2010) .The general pattern of rainfall and forest phenology seasonality in Nigeria are controlled mainly by location of the moisture bearing winds from the Atlantic Ocean. On arrival of the ITCZ around the Chad region, forest phenology closely follows with spatial and temporal patterns in rainfall seasonality.

For the Mambila forest cluster, precipitation and phenology regimes are more complex to describe. Rainfall variation is primarily the result of interactions among climate and topography. The moisture bearing airstream coupled with the topography of the Mambila leads to localized torrential rains (Chapman et al 2001). These torrential rains leads to early phenology onset. The absence of significant lags between rainfall and phenology onset data in the Mambila further exposes the likely effects of topography in vegetation functioning. In the Niger delta and Calabar forest clusters, insignificant correlation between rainfall and phenology matrices, is an indication that other factors (e.g soil and proximity to the ocean) are needed to explain the relationship between phenology and rainfall.

5.6 Implications of Research

The findings from this study have both policy and scientific implications. The Nigerian forest policy is geared toward the reduction of deforestation, however, continuous expansion for agriculture; human-induced forest fires and energy demand are threatening the forest. It has been shown here that deforestation in Nigeria appears not be slowing down and if policy precaution are not taken, the entire forest coverage may be under severe threat. Although it is difficult for government to effectively monitor the drivers of deforestation, early warning systems could as well be developed for massive agricultural activities and uncontrolled forest fires.

5.7 Developing the Research

This study has improved our understanding on how baseline forest cover is changing, including the relationship rainfall and forest phenology. It has also provided data and a methodology for forest cover estimation for future studies. This research has provided an eye to the public on the identification of the major forest clusters in Nigeria. The potential role of other important factors such as forest fire, soil, water, and other socio-economic variables could be included in future studies, in order to understand the complex relationships between deforestation and the local environment. More so, specific factors such as radiant transfer process, at both cell and leaf morphology levels and canopy elements in the forest must the taken into account for more-valid assessment of forest change and other environmental variables. In addition, the use of NDVI in the estimation of forest phenology may not be 100 per cent correct for rainforest due to saturation in dense canopies (Atkinson, Dash et al. 2011). It will be also important for further studies to use ground-based measurement to confirm the authenticity of the patterns of the phenological trends presented in this study.

This is the only study that has looked at deforestation trends on the major forest clusters in Nigeria using remote sensing. Developing a more comprehensive understanding of the interactions between deforestation and local environmental variables will allow for effective evaluation of their impacts to both the local, regional and global environment. Thus, there is a need to analyze more recent satellite data such as Landsat 8 and MODIS between 2013 and 2015 to compare and develop the findings of this study. Incorporating other data not used in this study to evaluate the impacts of deforestation on rainfall and phenology will assist in creating a working model for the development of deforestation-early warning system in similar and contrasting regions.

5.8 Conclusion

This thesis has highlighted the rates of baseline forest cover lost, cluster-level deforestation estimates and spatial pattern of deforestation hot spots in Nigeria. The study also evaluated the relationship between rainfall and phenology across four forest clusters, highlighting the fact that forest phenology closely follows with spatial and temporal patterns in rainfall seasonality in savanna than rainforest zones of Nigeria. Despite the measures put by the Nigerian government in halting deforestation, the rate of forest loss for the period 2002-2006 was 3% lower than 2007-2012. Though deforestation hotspots are more concentrated in the rainforest zone, the rate of forest loss in relation to other landcover is higher in the savanna forest cluster (especially Mambila). At cluster level, the primary data that describes deforestation spatial trend have been shown to be soil spectra derived from the unmixing forest pixels, highlighting the need for more in-depth research at country scale. Despite this research providing evidence that forest cover loss in Nigeria is not decreasing as opposed FAO (2010) results, limited knowledge exists on the mode of forest transformation to other land cover types. Therefore, this research provides a starting point for future work on the dynamics of forest transition to other land cover types in Nigeria.

In conclusion, the threat posed by forest loss in Nigeria may have large-scale implications not only on climate but also on vulnerable human populations exposed to the resultant impacts. It will be good if deforestation control legislation are implemented in order to mitigate the potential of forest loss on climate and human wellbeing. However, adaptation measure must be pursued in terms of establishing regional monitoring schemes in each of the major forest cluster. These measures, together, would ensure a better planning not only for the 'health' of the forest but also mitigation needs as streamlined in REED.

Appendices

Appendix A Phenologgy indices of forest clusters

CHAD

129	151	159	174	194	208	226	243	255	272	286	303	322
	337	353	367									
0.47	0.4	0.41	0.44	0.5	0.71	0.74	0.79	0.77	0.57	0.55	0.5	0.45
	0.47	0.462	0.49									
0.46	0.4	0.409	0.437	0.5	0.707	0.74	0.77	0.75	0.568	0.54	0.48	
	0.447	0.469	0.457	0.48								

107	129	151	159	174	194	208	226	243	255	272	286	303
	322	337	353	367								
0.46	0.47	0.46	0.4	0.409	0.437	0.5	0.707	0.74	0.77	0.75	0.568	0.54
	0.48	0.447	0.469	0.48								
0.456	0.465	0.455	0.4	0.409	0.423	0.51	0.708	0.75	0.76	0.73	0.565	
	0.532	0.452	0.445	0.466	0.5							

MAM

129	151	159	174	194	208	226	243	255	272	286	303	322
	337	353	367									
0.57	0.4	0.41	0.44	0.5	0.81	0.74	0.83	0.77	0.63	0.65	0.5	0.45
	0.47	0.462	0.59									
0.51	0.4	0.409	0.4	0.5	0.707	0.694	0.79	0.75	0.568	0.54	0.48	
	0.447	0.469	0.457	0.48								

129	151	159	174	194	208	226	243	255	272	286	303	322
	337	353	367									
0.48	0.46	0.4	0.41	0.44	0.5	0.71	0.74	0.83	0.77	0.643	0.65	0.5
	0.45	0.47	0.492	0.59								
0.465	0.455	0.4	0.409	0.423	0.51	0.708	0.75	0.82	0.74	0.635	0.63	0.52
	0.445	0.466	0.5									

CROSS

129	151	159	174	194	208	226	243	255	272	286	303	322
	337	353	367									
0.67	0.742	0.79	0.87	0.89	0.91	0.88	0.89	0.891	0.77	0.71	0.62	0.61
	0.59	0.56	0.581									
0.67	0.72	0.78	0.88	0.87	0.912	0.88	0.901	0.9	0.76	0.71	0.62	0.6
	0.578	0.557	0.577									

129	151	159	174	194	208	226	243	255	272	286	303	322
	337	353	367									
0.67	0.67	0.72	0.78	0.88	0.87	0.912	0.88	0.901	0.9	0.76	0.71	0.62
	0.6	0.578	0.557	0.577								
0.67	0.68	0.74	0.79	0.89	0.88	0.923	0.89	0.911	0.9	0.77	0.73	0.64
	0.62	0.58	0.568									

NIGER DELTA

129	151	159	174	194	208	226	243	255	272	286	303	322
	337	353	367									
0.66	0.67	0.67	0.77	0.78	0.79	0.81	0.87	0.89	0.79	0.69	0.66	0.62
	0.6	0.55	0.55									
0.656	0.68	0.68	0.78	0.79	0.78	0.88	0.87	0.89	0.893	0.71	0.67	0.63
	0.63	0.55	0.56	129	151	159	174	194	208	226	243	255
	272	286	303	322	337	353	367					
0.61	0.656	0.68	0.68	0.78	0.79	0.78	0.88	0.87	0.89	0.893	0.74	
	0.7799	0.63	0.63	0.55	0.56							
0.62	0.66	0.69	0.69	0.79	0.793	0.785	0.881	0.88	0.88	0.88	0.76	0.77
	0.63	0.63	0.57									

Appendix B Rainfall Probability Indices of Forest Clusters

Chad Axis

Rainfall Probability /Day of the Year				1	2	3	4	5	6	7	8
9	10	11	12	13	14	15	16	17	18	19	20
21	22	23	24	25	26	27	28	29	30	31	32
33	34	35	36	37	38	39	40	41	42	43	44
45	46	47	48	49	50	51	52	53	54	55	56
57	58	59	60	61	62	63	64	65	66	67	68
69	70	71	72	73	74	75	76	77	78	79	80
81	82	83	84	85	86	87	88	89	90	91	92
93	94	95	96	97	98	99	100	101	102	103	104
105	106	107	108	109	110	111	112	113	114	115	116
117	118	119	120	121	122	123	124	125	126	127	128
129	130	131	132	133	134	135	136	137	138	139	140
141	142	143	144	145	146	147	148	149	150	151	152
153	154	155	156	157	158	159	160	161	162	163	164
165	166	167	168	169	170	171	172	173	174	175	176
177	178	179	180	181	182	183	184	185	186	187	188
189	190	191	192	193	194	195	196	197	198	199	200
201	202	203	204	205	206	207	208	209	210	211	212
213	214	215	216	217	218	219	220	221	222	223	224
225	226	227	228	229	230	231	232	233	234	235	236
237	238	239	240	241	242	243	244	245	246	247	248
249	250	251	252	253	254	255	256	257	258	259	260
261	262	263	264	265	266	267	268	269	270	271	272
273	274	275	276	277	278	279	280	281	282	283	284
285	286	287	288	289	290	291	292	293	294	295	296
297	298	299	300	301	302	303	304	305	306	307	308
309	310	311	312	313	314	315	316	317	318	319	320
321	322	323	324	325	326	327	328	329	330	331	332
333	334	335	336	337	338	339	340	341	342	343	344
345	346	347	348	349	350	351	352	353	354	355	356
357	358	359	360	361	362	363	364	365			
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0.087	0	0	0	0	0	0	0
0.075	0	0	0	0	0	0	0.011	0.02	0.023	0	0
0	0	0	0.03	0.04	0.05	0.05	0.05	0.05	0	0	0
0	0	0	0	0.001	0.005	0.02	0.031	0.2	0.03	0.02	0.1
0.09	0.26	0.17	0.19	0.178	0.18	0.18	0.18	0.18	0.123	0.21	0.23
0.34	0.25	0.26	0.13	0.43	0.365	0.32	0.35	0.33	0.31	0.34	0.21
0.44	0.45	0.44	0.24	0.22	0.21	0.3	0.3	0.3	0.3	0.3	0.3

0.41	0.29	0.27	0.26	0.25	0.27	0.24	0.27	0.31	0.31	0.29	0.29
0.23	0.33	0.27	0.21	0.29	0.4	0.3	0.3	0.3	0.31	0.276	0.29
0.32	0.32	0.27	0.37	0.23	0.33	0.32	0.33	0.38	0.38	0.39	0.33
0.21	0.26	0.38	0.39	0.35	0.22	0.32	0.33	0.41	0.25	0.38	0.45
0.467	0.5	0.41	0.44	0.5	0.61	0.56	0.55	0.48	0.6	0.6	0.6
0.6	0.45	0.43	0.44	0.45	0.44	0.43	0.5	0.43	0.23	0.34	0.45
0.1	0.23	0.4	0.13	0.33	0.36	0.31	0.31	0.21	0.01	0.2	0.1
0.05	0.06	0.04	0.04	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0									

Mambila

Probability /Day of the Year			1	2	3	4	5	6	7	8	9
10	11	12	13	14	15	16	17	18	19	20	21
22	23	24	25	26	27	28	29	30	31	32	33
34	35	36	37	38	39	40	41	42	43	44	45
46	47	48	49	50	51	52	53	54	55	56	57
58	59	60	61	62	63	64	65	66	67	68	69
70	71	72	73	74	75	76	77	78	79	80	81
82	83	84	85	86	87	88	89	90	91	92	93
94	95	96	97	98	99	100	101	102	103	104	105
106	107	108	109	110	111	112	113	114	115	116	117
118	119	120	121	122	123	124	125	126	127	128	129
130	131	132	133	134	135	136	137	138	139	140	141
142	143	144	145	146	147	148	149	150	151	152	153
154	155	156	157	158	159	160	161	162	163	164	165
166	167	168	169	170	171	172	173	174	175	176	177
178	179	180	181	182	183	184	185	186	187	188	189
190	191	192	193	194	195	196	197	198	199	200	201
202	203	204	205	206	207	208	209	210	211	212	213
214	215	216	217	218	219	220	221	222	223	224	225
226	227	228	229	230	231	232	233	234	235	236	237
238	239	240	241	242	243	244	245	246	247	248	249
250	251	252	253	254	255	256	257	258	259	260	261
262	263	264	265	266	267	268	269	270	271	272	273
274	275	276	277	278	279	280	281	282	283	284	285
286	287	288	289	290	291	292	293	294	295	296	297
298	299	300	301	302	303	304	305	306	307	308	309
310	311	312	313	314	315	316	317	318	319	320	321
322	323	324	325	326	327	328	329	330	331	332	333
334	335	336	337	338	339	340	341	342	343	344	345
346	347	348	349	350	351	352	353	354	355	356	357
358	359	360	361	362	363	364	365				
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0.01	0.02	0.01	0.03	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0.1	0.1	0.01	0.3	0.45
0.3	0.4	0.3	0.46	0.46	0.32	0.1	0.1	0.1	0.2	0.2	0.2
0.2	0.324	0.345	0.245	0.4	0.01	0.1	0.3	0.3	0.4	0.45	0.33
0.31	0.23	0.34	0.32	0.21	0.24	0.34	0.32	0.23	0.45	0.367	0.34
0.39	0.33	0.36	0.42	0.44	0.34	0.43	0.45	0.45	0.43	0.1	0.1
0.1	0.1	0.33	0.32	0.23	0.34	0.33	0.41	0.22	0.21	0.12	0.31

0.34	0.34	0.47	0.46	0.45	0.45	0.45	0.44	0.44	0.41	0.33	0.32
0.32	0.31	0.31	0.34	0.49	0.47	0.45	0.5	0.51	0.67	0.77	
0.838	0.81	0.83	0.84	0.76	0.76	0.67	0.56	0.4	0.2	0.2	0.43
0.54	0.32	0.44	0.44	0.34	0.33	0.31	0.32	0.33	0.35	0.45	0.44
0.41	0.3	0.3	0.3	0.2	0.34	0.24	0.33	0.45	0.23	0.55	0.67
0.66	0.79	0.81	0.81	0.65	0.56	0.56	0.45	0.44	0.43	0.31	0.45
0.61	0.7	0.7	0.5	0.5	0.43	0.3	0.323	0.44	0.33	0.37	0.71
0.77	0.76	0.65	0.64	0.68	0.69	0.43	0.55	0.44	0.45	0.43	0.34
0.44	0.44	0.44	0.34	0.33	0.34	0.45	0.44	0.33	0.45	0.65	0.65
0.81	0.82	0.34	0.45	0.22	0.43	0.42	0.43	0.41	0.43	0.4	0.32
0.4	0.2	0.4	0.3	0.41	0.22	0.41	0.32	0.42	0.43	0.51	0.2
0.4	0.5	0.5	0.5	0.51	0.44	0.31	0.32	0.43	0.44	0.42	0.41
0.44	0.43	0.42	0.41	0.42	0.43	0.45	0.44	0.43	0.32	0.33	0.21
0.45	0.53	0.53	0.33	0.32	0.42	0.44	0.45	0.65	0.35	0.5	0.3
0.2	0.1	0.01	0.2	0.1	0.0034	0.1	0.1	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0						
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0.2	0	0.11
0.17	0.12	0.21	0.22	0.3	0	0	0.21	0.2	0.31	0.39	0.29
0.21	0.19	0.11	0.21	0.13	0.14	0.27	0.31	0.22	0.32	0.35	0.34
0.26	0.32	0.21	0.34	0.36	0.31	0.29	0.42	0.41	0.41	0	0.06
0	0	0.25	0.21	0.17	0.31	0.21	0.34	0.312	0.2	0.2	0.2
0.2	0.1	0.1	0.37	0.34	0.32	0.33	0.45	0.34	0.43	0.32	0.34
0.21	0.1	0.1	0.21	0.34	0.47	0.5	0.44	0.42	0.66	0.6	0.76
0.8	0.84	0.78	0.72	0.62	0.61	0.44	0.37	0.2	0.18	0.33	0.45
0.29	0.41	0.38	0.23	0.32	0.3	0.29	0.31	0.31	0.38	0.39	0.38
0.21	0.27	0.29	0.18	0.33	0.18	0.31	0.44	0.123	0.43	0.6	0.48
0.6	0.67	0.77	0.59	0.45	0.44	0.45	0.43	0.33	0.3	0.42	0.45
0.65	0.69	0.48	0.45	0.32	0.28	0.33	0.37	0.24	0.33	0.55	0.69
0.6	0.56	0.61	0.52	0.65	0.33	0.51	0.34	0.44	0.41	0.31	0.21
0.44	0.44	0.23	0.21	0.31	0.45	0.43	0.23	0.38	0.64	0.68	0.79
0.71	0.31	0.39	0.19	0.41	0.41	0.44	0.4	0.37	0.34	0.23	0.38
0.19	0.34	0.27	0.27	0.21	0.33	0.31	0.35	0.4	0.43	0.17	0.33
0.45	0.49	0.44	0.44	0.23	0.21	0.33	0.34	0.38	0.39	0.4	0.33
0.41	0.33	0.38	0.4	0.41	0.41	0.41	0.34	0.27	0.21	0.15	0.44
46	0.49	0.28	0.31	0.35	0.42	0.37	0.45	0.41	0.5	0.176	0.01
0	0.02	0.16	0	0	0.03	0	0	0	0	0	0
0	0	0	0								

Calabar

Rainfall Probability /Day of the Year				1	2	3	4	5	6	7	8
9	10	11	12	13	14	15	16	17	18	19	20
21	22	23	24	25	26	27	28	29	30	31	32
33	34	35	36	37	38	39	40	41	42	43	44
45	46	47	48	49	50	51	52	53	54	55	56

57	58	59	60	61	62	63	64	65	66	67	68
69	70	71	72	73	74	75	76	77	78	79	80
81	82	83	84	85	86	87	88	89	90	91	92
93	94	95	96	97	98	99	100	101	102	103	104
105	106	107	108	109	110	111	112	113	114	115	116
117	118	119	120	121	122	123	124	125	126	127	128
129	130	131	132	133	134	135	136	137	138	139	140
141	142	143	144	145	146	147	148	149	150	151	152
153	154	155	156	157	158	159	160	161	162	163	164
165	166	167	168	169	170	171	172	173	174	175	176
177	178	179	180	181	182	183	184	185	186	187	188
189	190	191	192	193	194	195	196	197	198	199	200
201	202	203	204	205	206	207	208	209	210	211	212
213	214	215	216	217	218	219	220	221	222	223	224
225	226	227	228	229	230	231	232	233	234	235	236
237	238	239	240	241	242	243	244	245	246	247	248
249	250	251	252	253	254	255	256	257	258	259	260
261	262	263	264	265	266	267	268	269	270	271	272
273	274	275	276	277	278	279	280	281	282	283	284
285	286	287	288	289	290	291	292	293	294	295	296
297	298	299	300	301	302	303	304	305	306	307	308
309	310	311	312	313	314	315	316	317	318	319	320
321	322	323	324	325	326	327	328	329	330	331	332
333	334	335	336	337	338	339	340	341	342	343	344
345	346	347	348	349	350	351	352	353	354	355	356
357	358	359	360	361	362	363	364	365			
0.03	0.05	0.04	0.03	0.021	0.03	0.03	0.03	0.01	0.09	0.1	0.03
0.02	0.03	0.02	0.01	0.11	0.01	0.1	0.2	0.21	0.3	0.32	0.21
0.33	0.33	0.2	0.2	0.1	0.4	0.43	0.32	0.2	0.22	0.22	0.33
0.23	0.2	0.3	0.21	0.32	0.31	0.1	0.315	0.155	0.15	0.35	
0.319	0.12	0.17	0	0.318	0.41	0.315	0.1	0.1	0.312	0.25	0.28
0.287	0.23	0.38	0.39	0.22	0.23	0.32	0.31	0.32	0.33	0.31	
0.308	0.36	0.32	0.25	0.21	0.22	0.23	0.39	0.35	0.386	0.35	0.21
0.22	0.222	0.1	0.3	0.3	0.3	0.13	0.38	0.35	0.3	0.3	0.13
0.35	0.37	0.33	0.37	0.33	0.33	0.33	0.33	0.45	0.36	0.34	0.39
0.23	0.36	0.42	0.51	0.34	0.43	0.45	0.45	0.43	0.53	0.54	0.55
0.51	0.57	0.45	0.45	0.75	0.55	0.75	0.57	0.77	0.77	0.77	0.77
0.54	0.51	0.57	0.55	0.7	0.75	0.78	0.57	0.51	0.55	0.2	0.2
0.2	0.2	0.23	0.32	0.8	0.7	0.7	0.47	0.45	0.44	0.43	0.41
0.32	0.34	0.37	0.54	0.45	0.44	0.45	0.43	0.42	0.41	0.34	0.39
0.45	0.47	0.4	0.43	0.45	0.7	0.47	0.45	0.75	0.8	0.55	0.51
0.57	0.45	0.45	0.75	0.55	0.75	0.57	0.77	0.43	0.33	0.33	0.54
0.51	0.57	0.55	0.7	0.75	0.78	0.57	0.51	0.44	0.51	0.3	0.2
0.34	0.45	0.56	0.35	0.44	0.51	0.52	0.55	0.31	0.33	0.33	0.43
0.41	0.44	0.42	0.41	0.44	0.47	0.4	0.5	0.4	0.43	0.56	0.67
0.55	0.33	0.33	0.421	0.34	0.42	0.31	0.344	0.247	0.24	0.35	0.44
0.243	0.71	0.78	0.77	0.54	0.71	0.12	0.3	0.3	0.3	0.3	0.34
0.43	0.8	0.7	0.7	0.47	0.12	0.44	0.44	0.41	0.43	0.44	0.47
0.54	0.12	0.44	0.12	0.44	0.43	0.41	0.44	0.49	0.12	0.47	0.4
0.44	0.12	0.7	0.47	0.12	0.75	0.8	0.5	0.4	0.5	0.7	0.64
0.43	0.34	0.42	0.51	0.55	0.7	0.7	0.7	0.7	0.7	0.65	0.54
0.34	0.14	0.23	0.34	0.45	0.44	0.34	0.45	0.34	0.44	0.43	0.46
0.44	0.55	0.46	0.52	0.51	0.5	0.47	0.49	0.44	0.45	0.43	0.45
0.43	0.45	0.45	0.37	0.43	0.44	0.37	0.38	0.42	0.44	0.45	0.43
0.43	0.34	0.34	0.12	0.49	0.12	0.12	0.44	0.12	0.4	0.4	0.4
0.49	0.4	0.44	0.33	0.3	0.33	0.3	0.03	0.3	0.3	0.3	0.3
0.4	0.33	0.34	0.05	0.04	0.04	0.05					

0	0	0	0	0	0.012	0	0.02	0	0.02	0	0
0	0.011	0	0	0.1	0.01	0	0.09	0.08	0.21	0.21	0.13
0.28	0.31	0.18	0.11	0.03	0.32	0.32	0.18	0.14	0.11	0.16	0.27
0.13		0.13	0.28	0.16	0.31	0.318	0.317	0.18	0.314	0.455	0.31
0.31	0	0.157	0.4	0.317	0.15	0.312	0.31				

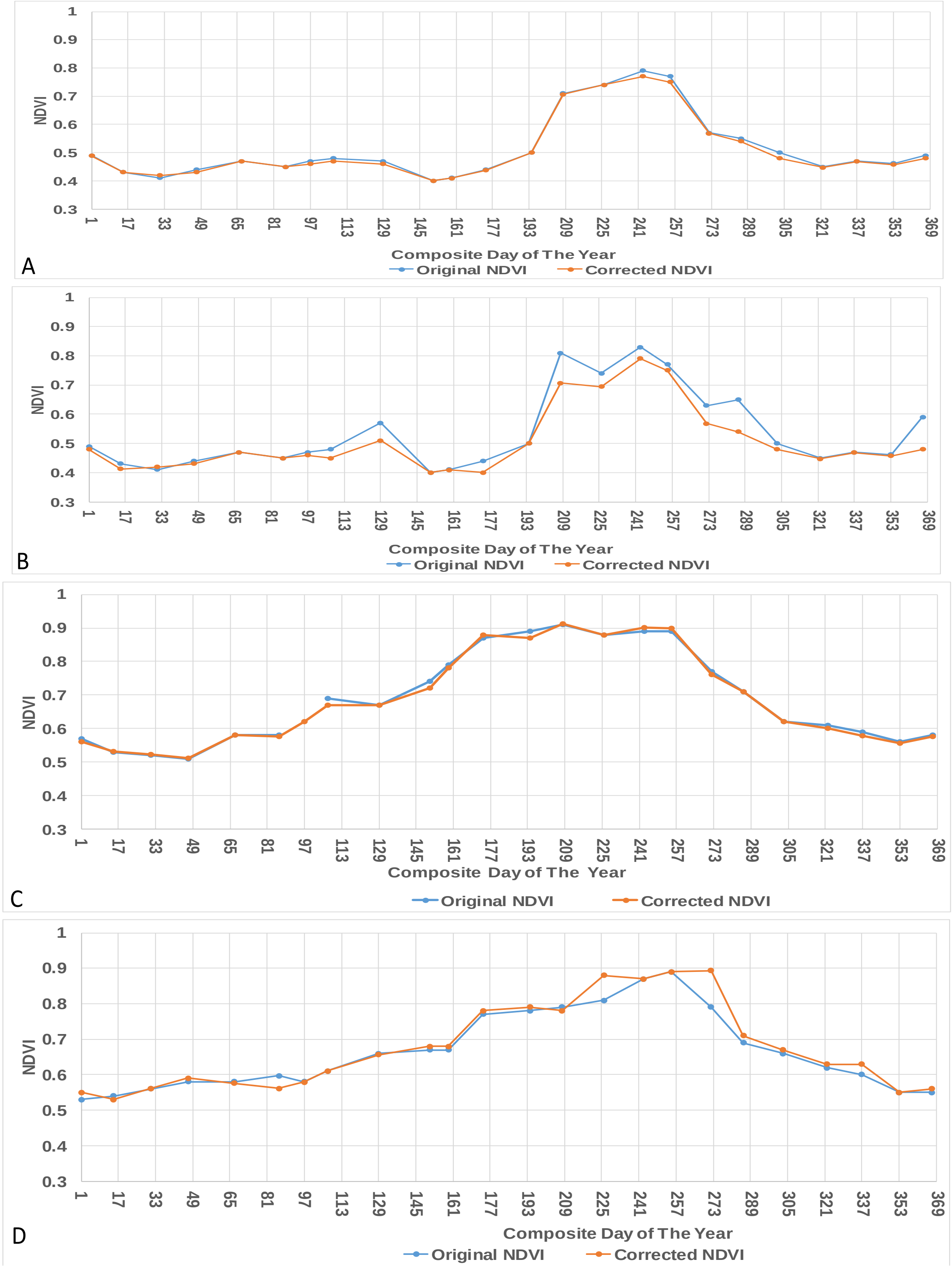
Niger Delta

Rainfall Probability /Day of the Year				1	2	3	4	5	6	7	8
9	10	11	12	13	14	15	16	17	18	19	20
21	22	23	24	25	26	27	28	29	30	31	32
33	34	35	36	37	38	39	40	41	42	43	44
45	46	47	48	49	50	51	52	53	54	55	56
57	58	59	60	61	62	63	64	65	66	67	68
69	70	71	72	73	74	75	76	77	78	79	80
81	82	83	84	85	86	87	88	89	90	91	92
93	94	95	96	97	98	99	100	101	102	103	104
105	106	107	108	109	110	111	112	113	114	115	116
117	118	119	120	121	122	123	124	125	126	127	128
129	130	131	132	133	134	135	136	137	138	139	140
141	142	143	144	145	146	147	148	149	150	151	152
153	154	155	156	157	158	159	160	161	162	163	164
165	166	167	168	169	170	171	172	173	174	175	176
177	178	179	180	181	182	183	184	185	186	187	188
189	190	191	192	193	194	195	196	197	198	199	200
201	202	203	204	205	206	207	208	209	210	211	212
213	214	215	216	217	218	219	220	221	222	223	224
225	226	227	228	229	230	231	232	233	234	235	236
237	238	239	240	241	242	243	244	245	246	247	248
249	250	251	252	253	254	255	256	257	258	259	260
261	262	263	264	265	266	267	268	269	270	271	272
273	274	275	276	277	278	279	280	281	282	283	284
285	286	287	288	289	290	291	292	293	294	295	296
297	298	299	300	301	302	303	304	305	306	307	308
309	310	311	312	313	314	315	316	317	318	319	320
321	322	323	324	325	326	327	328	329	330	331	332
333	334	335	336	337	338	339	340	341	342	343	344
345	346	347	348	349	350	351	352	353	354	355	356
357	358	359	360	361	362	363	364	365			
0.05	0.01	0.05	0.04	0.05	0.04	0.04	0.03	0.05	0.04	0.03	0.04
0.04	0.04	0.04	0.04	0.1	0.2	0.3	0.3	0.3	0.13	0.48	0.45
0.3	0.4	0.13	0.45	0.37	0.44	0.47	0.33	0.43	0.44	0.33	0.45
0.48	0.487	0.43	0.38	0.39	0.44	0.43	0.34	0.31	0.32	0.33	0.31
0.308	0.36	0.32	0.45	0.41	0.44	0.43	0.39	0.35	0.386	0.35	0.41
0.44	0.424	0.5	0.7	0.84	0.81	0.83	0.77	0.76	0.72	0.73	0.74
0.77	0.71	0.76	0.45	0.45	0.65	0.77	0.67	0.56	0.66	0.66	0.66
0.66	0.74	0.71	0.56	0.77	0.6	0.67	0.68	0.56	0.71	0.77	0.65
0.61	0.65	0.68	0.66	0.54	0.61	0.45	0.2	0.2	0.2	0.2	0.23
0.32	0.8	0.6	0.6	0.46	0.47	0.44	0.43	0.41	0.32	0.34	0.36
0.54	0.45	0.44	0.45	0.43	0.42	0.41	0.34	0.39	0.47	0.46	0.4
0.43	0.45	0.6	0.46	0.45	0.67	0.8	0.7	0.4	0.5	0.6	0.5
0.7	0.4	0.3	0.4	0.6	0.7	0.6	0.6	0.6	0.5	0.5	0.56
0.7	0.76	0.71	0.77	0.66	0.5	0.6	0.45	0.54	0.76	0.56	0.54

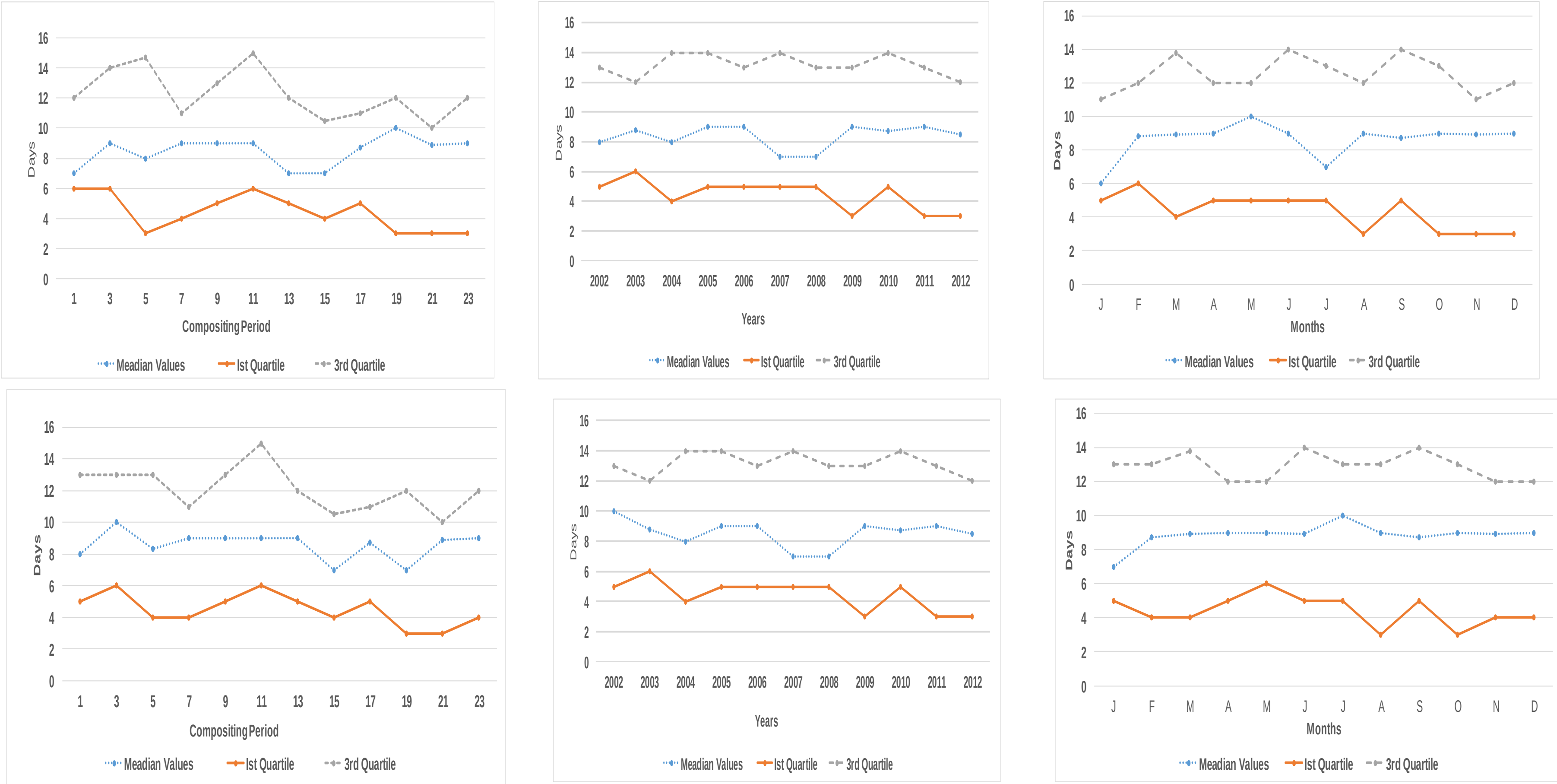
0.7	0.51	0.4	0.21	0.21	0.32	0.31	0.33	0.3	0.21	0.1	0.1
0.1	0.1	0.54	0.57	0.61	0.52	0.53	0.51	0.5	0.53	0.43	0.49
0.44	0.53	0.57	0.56	0.44	0.56	0.5	0.45	0.56	0.55	0.55	0.56
0.53	0.54	0.4	0.51	0.45	0.5	0.65	0.66	0.61	0.62	0.65	0.62
0.56	0.53	0.22	0.54	0.31	0.33	0.33	0.22	0.34	0.81	0.55	0.41
0.43	0.33	0.42	0.41	0.44	0.41	0.44	0.42	0.41	0.31	0.33	0.45
0.67	0.66	0.66	0.66	0.66	0.62	0.71	0.77	0.71	0.45	0.45	0.39
0.36	0.38	0.37	0.34	0.5	0.55	0.51	0.55	0.51	0.34	0.44	0.45
0.43	0.45	0.67	0.8	0.8	0.81	0.83	0.81	0.82	0.82	0.81	0.67
0.32	0.45	0.32	0.34	0.56	0.56	0.44	0.26	0.3	0.329	0.33	0.5
0.64	0.44	0.39	0.31	0.43	0.45	0.43	0.45	0.34	0.46	0.389	0.44
0.41	0.42	0.43	0.405	0.44	0.43	0.39	0.321	0.33	0.34	0.45	0.43
0.32	0.39	0.389	0.34	0.45	0.32	0.36	0.43	0.37	0.37	0.31	0.21
0.29	0.234	0.33	0.56	0.34	0.55	0.54	0.5	0.49	0.45	0.49	0.49
0.49	0.35	0.39	0.35	0.35	0.33	0.35	0.3	0.3	0.3	0.39	0.3
0.33	0.22	0.2	0.22	0.2	0.02	0.2	0.2	0.2	0.2	0.3	0.22
0.23	0.05	0.03	0.03	0.05							

Appendix C Corrections for the satellite data

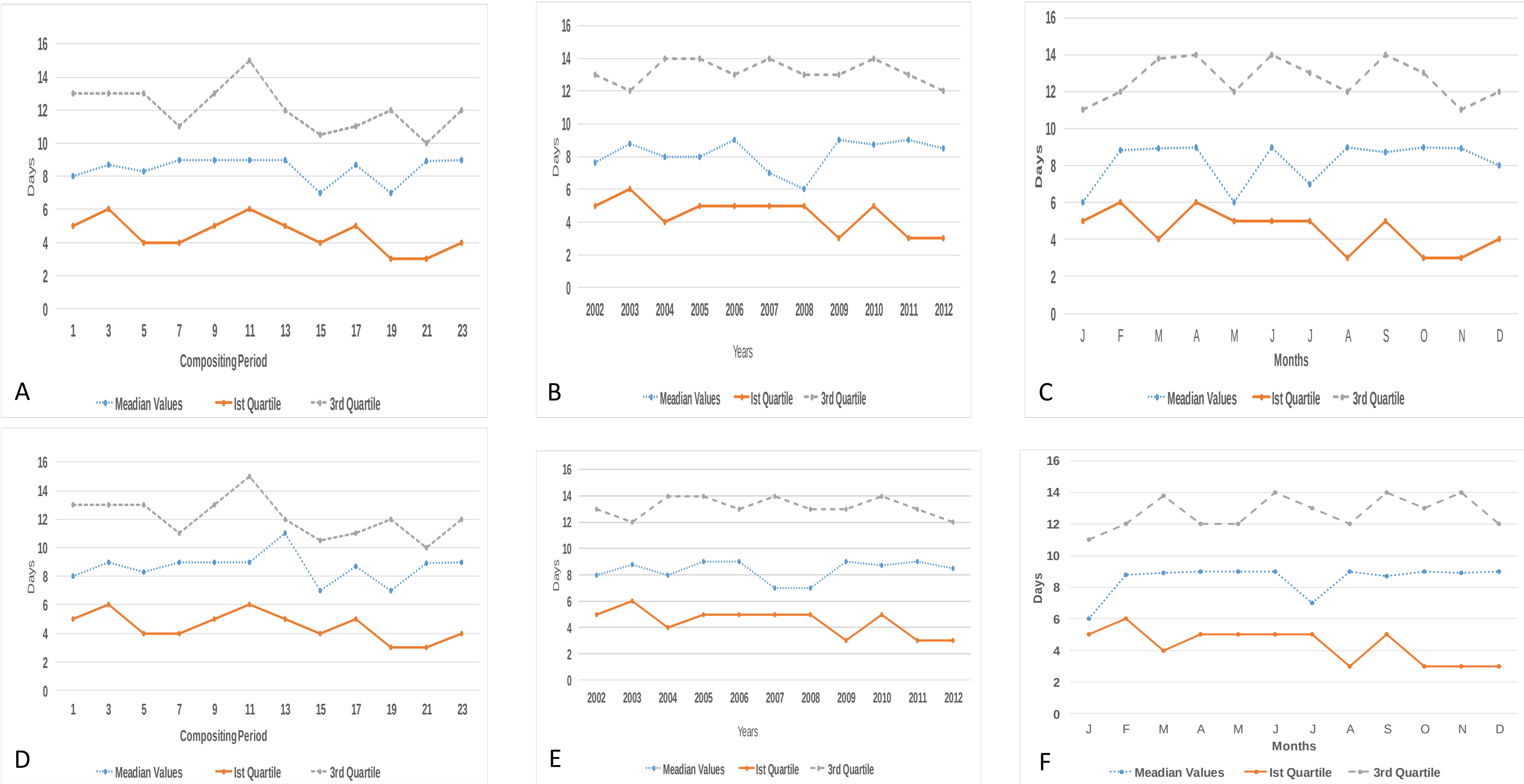
Results of correction of the NDVI nominal equidistant values based CDOY adjustments are presented. For each forest cluster, the original NDVI data were moved to its proper acquisition date CDOY, thereby generating a new 'corrected NDVI', Furthermore, Median Values of the Acquisition Dates (MEAD) were generated for each of the forest clusters because one nominal date is required to generate the corrected time series data from the interpolated NDVI (Testa, Mondino et al. 2014). As evident in figures, the MEAD values were close to the 9th day of the 16-day period during most of the years, months and compositing periods in all the forest clusters.



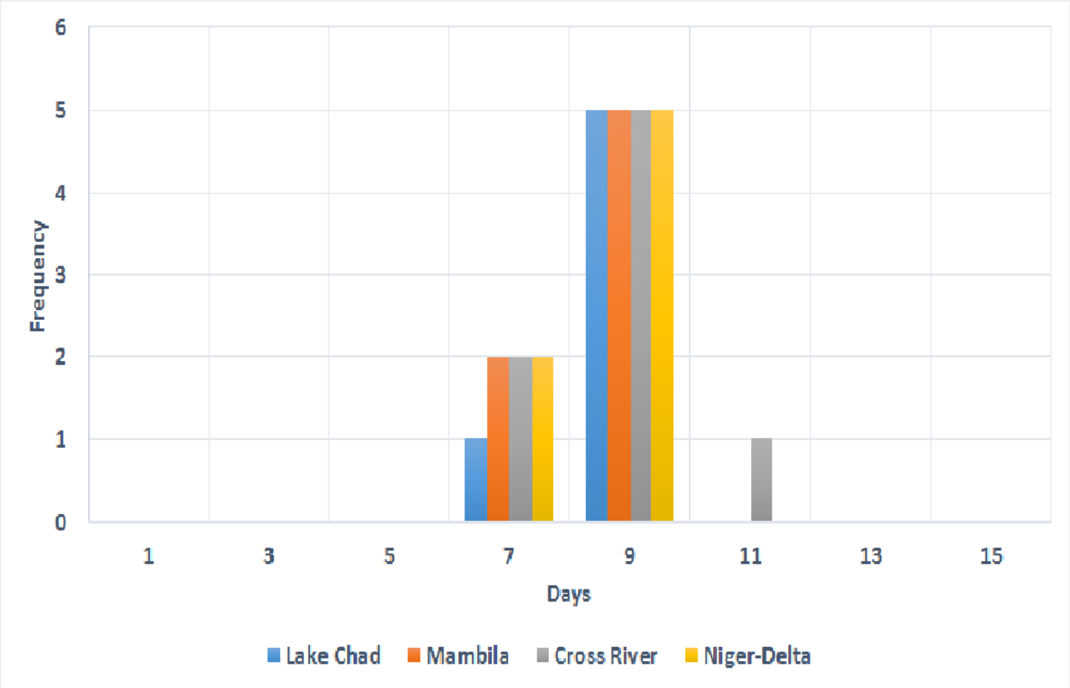
Comparison between Original NDVI (Based on 16-Day equidistant composite) and Corrected NDVI Time Series (Based actual composition Day) for the central forest pixel in A, Chad, B, Mambila, C, Niger-delta and D, Calabar forest clusters



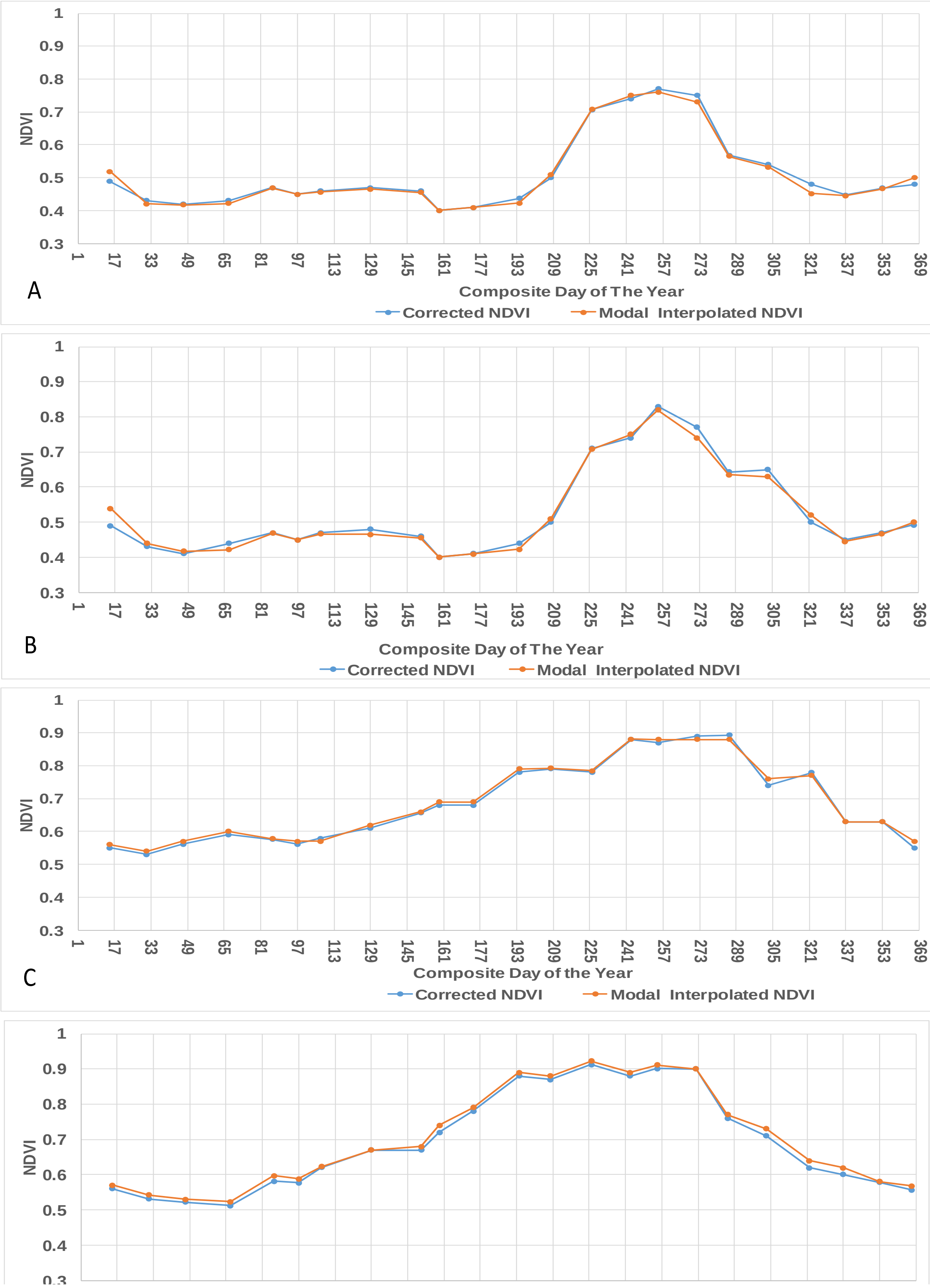
MEADs averaged over (a), Compositing period Months (b) Years (C) Months for Chad (A-C) and Mambila (D-F) forest clusters



: MEAD’s averaged over compositing period, years and months for Niger-delta (A-C) and Calabar (D-F) forest clusters

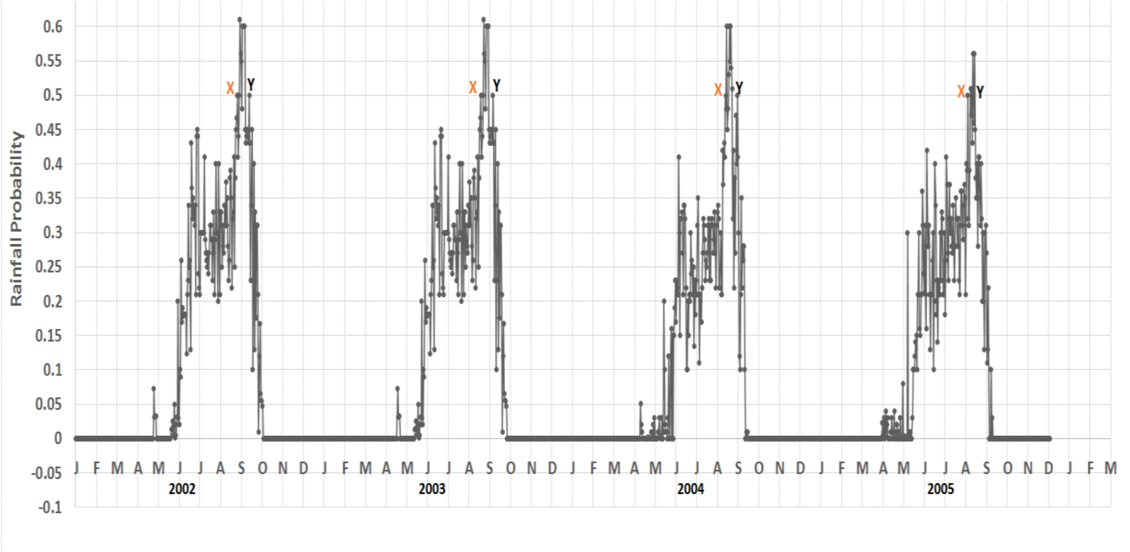


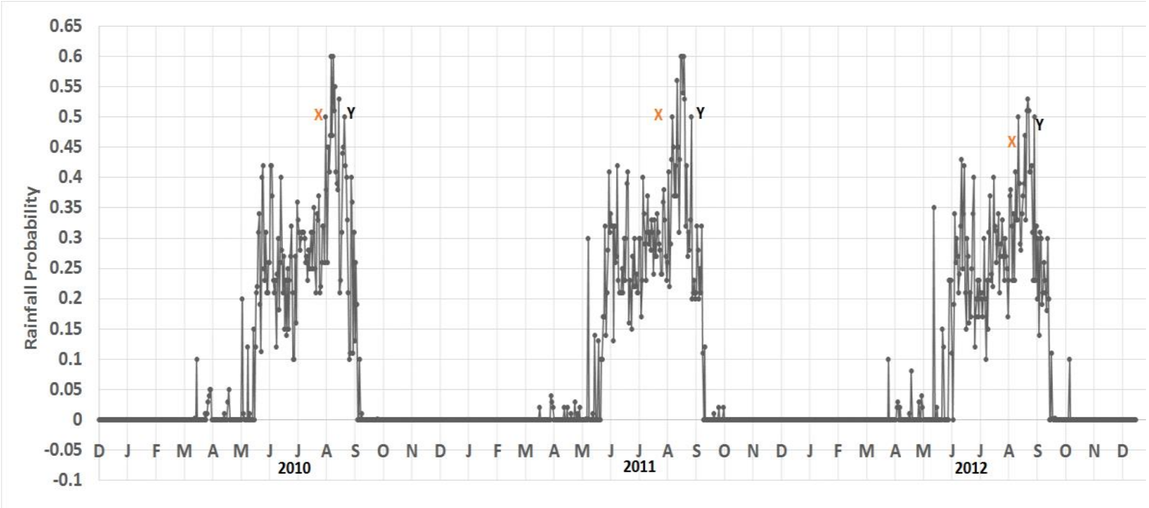
Frequency histogram of the MEAD series for the compositing period for all the forest clusters

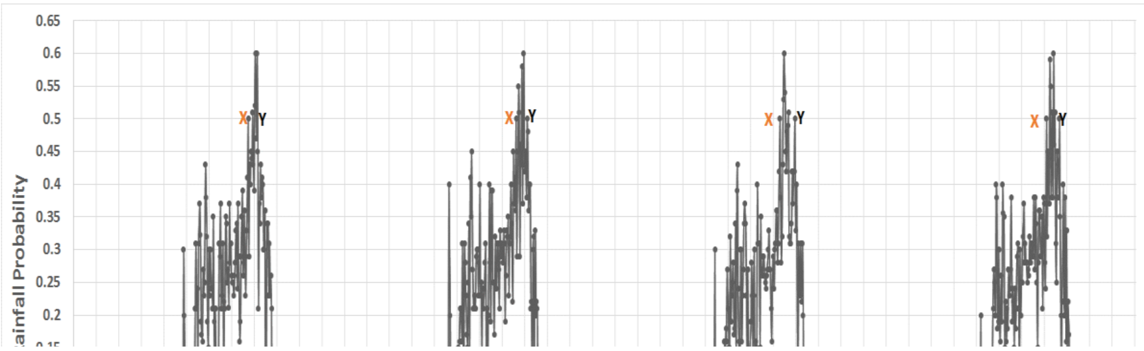


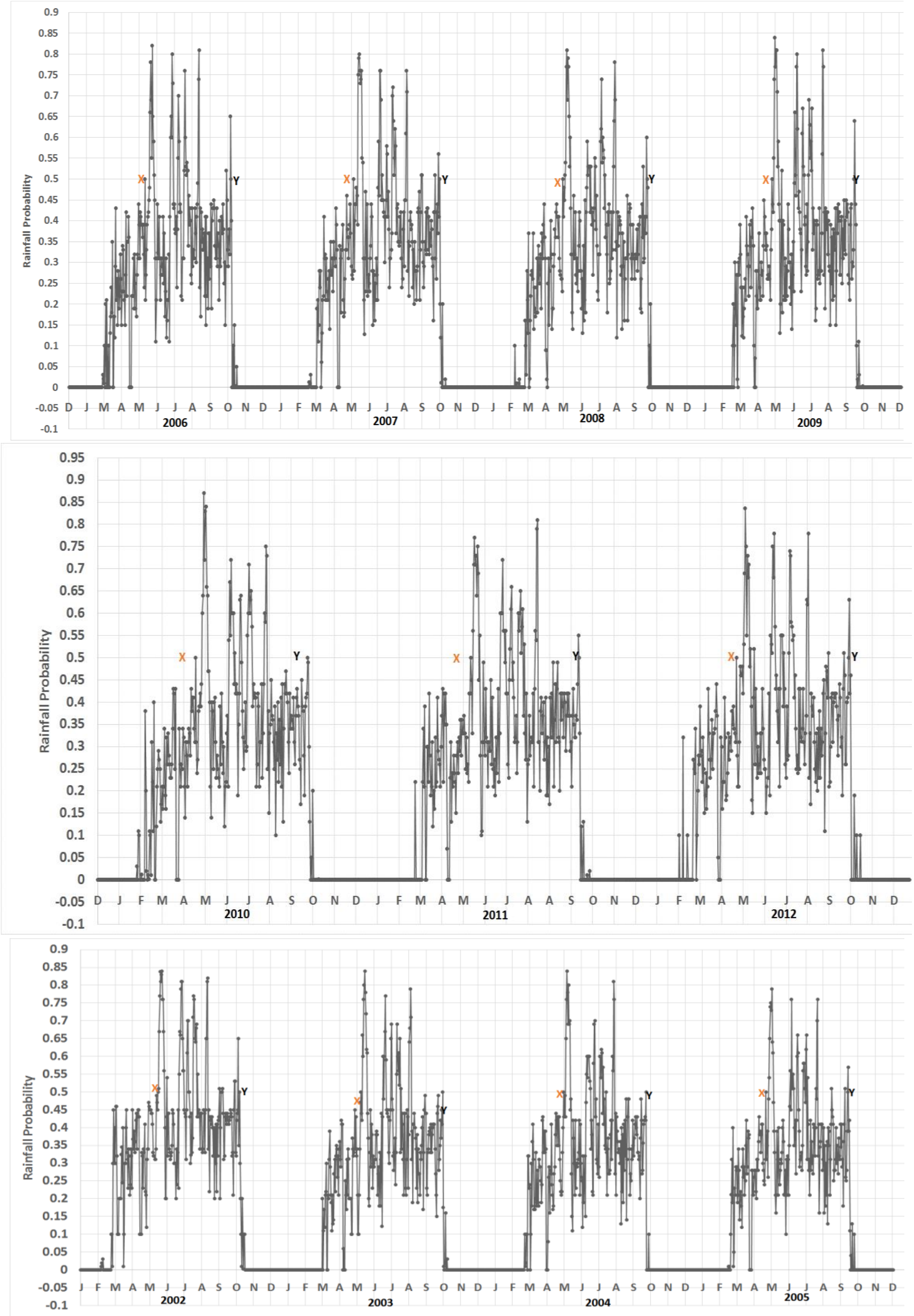
Comparison between corrected NDVI and modal Interpolated NDVI (modal occurrence of NDVI) for the central forest pixel in A, Chad, B, Mambila, C, Niger-delta and D, Calabar forest clusters

Appendix D Matrices for ROD, RCD and LRS

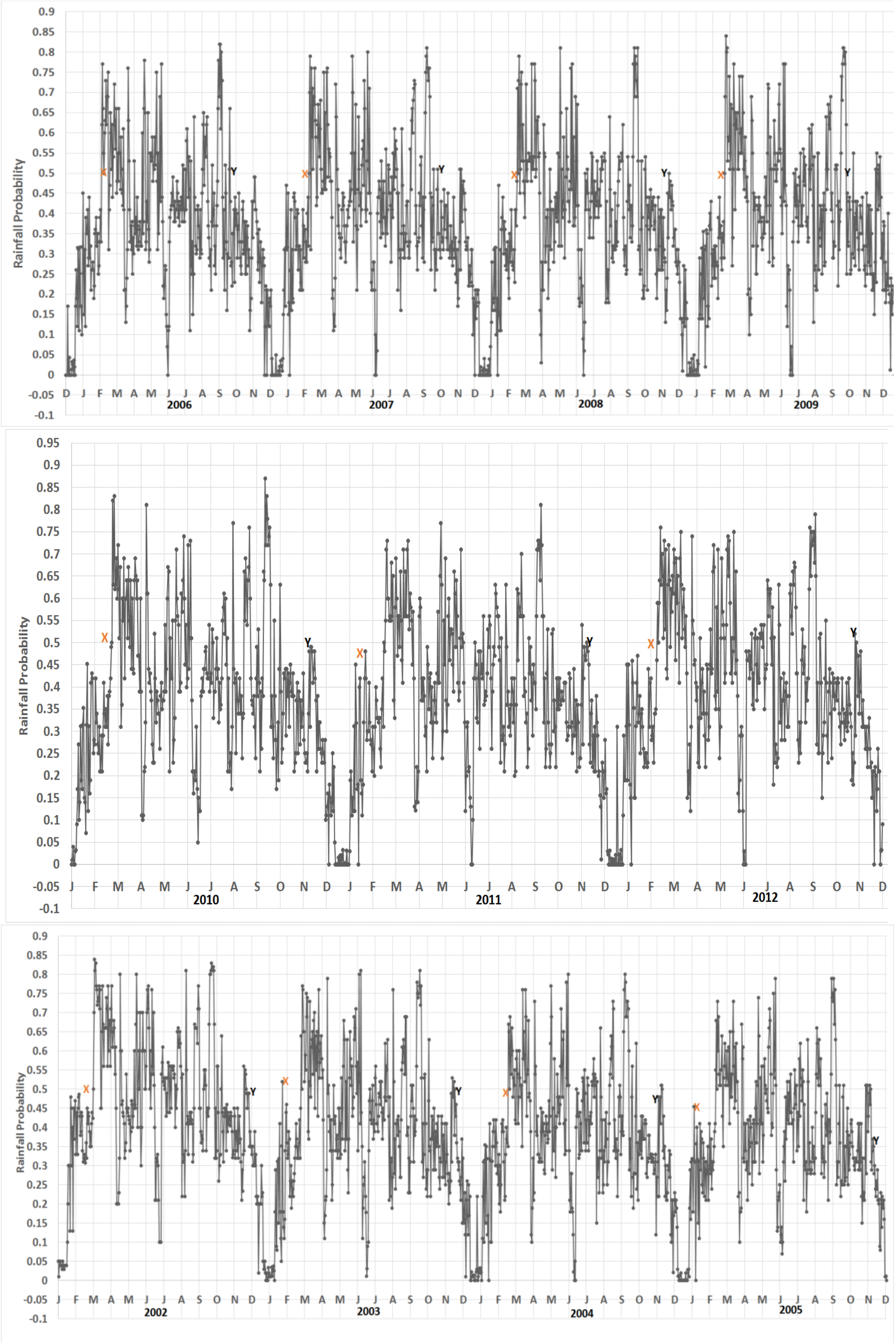




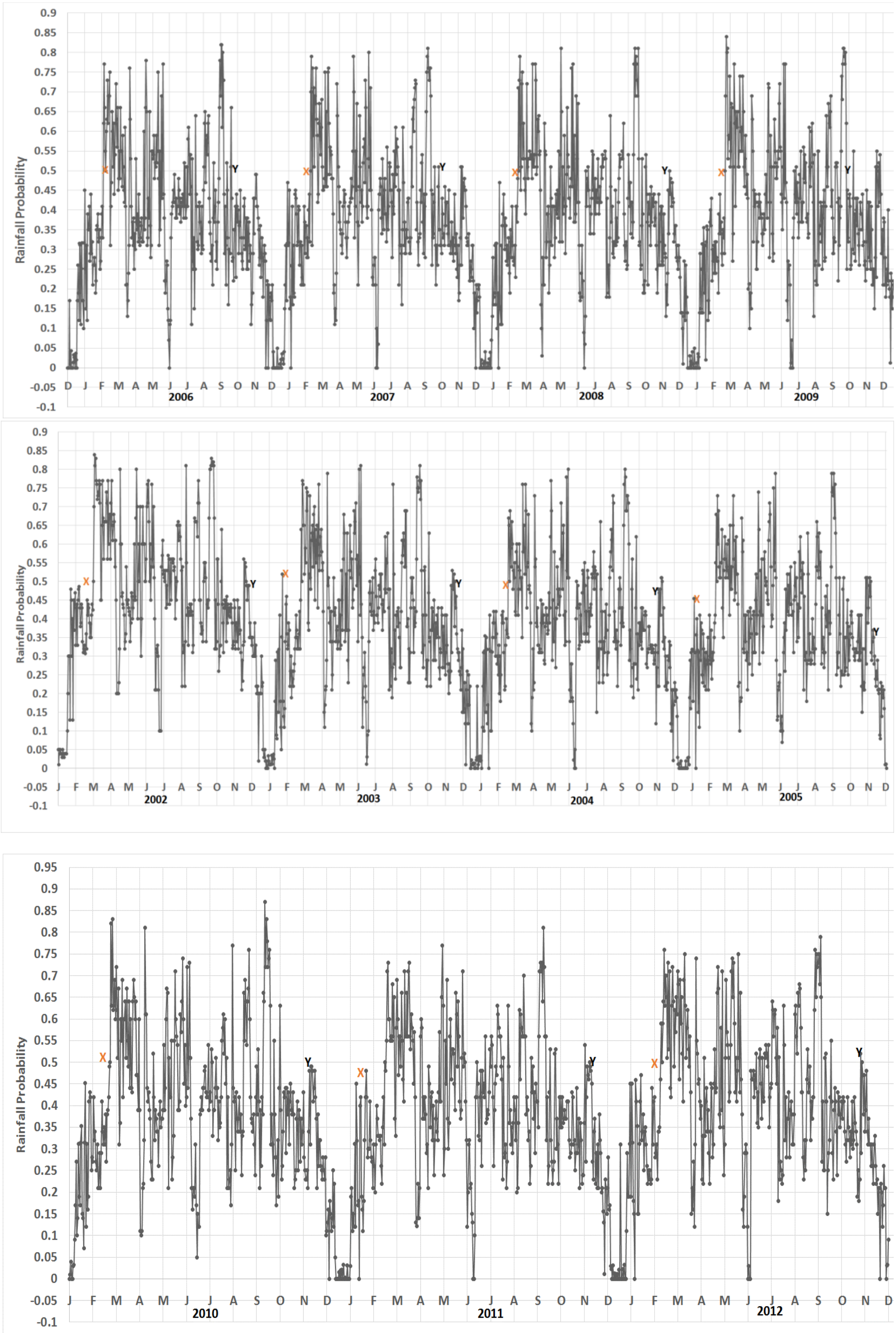




TRMM based rainfall onset (x) and retreat (y) for the Mambila forest cluster

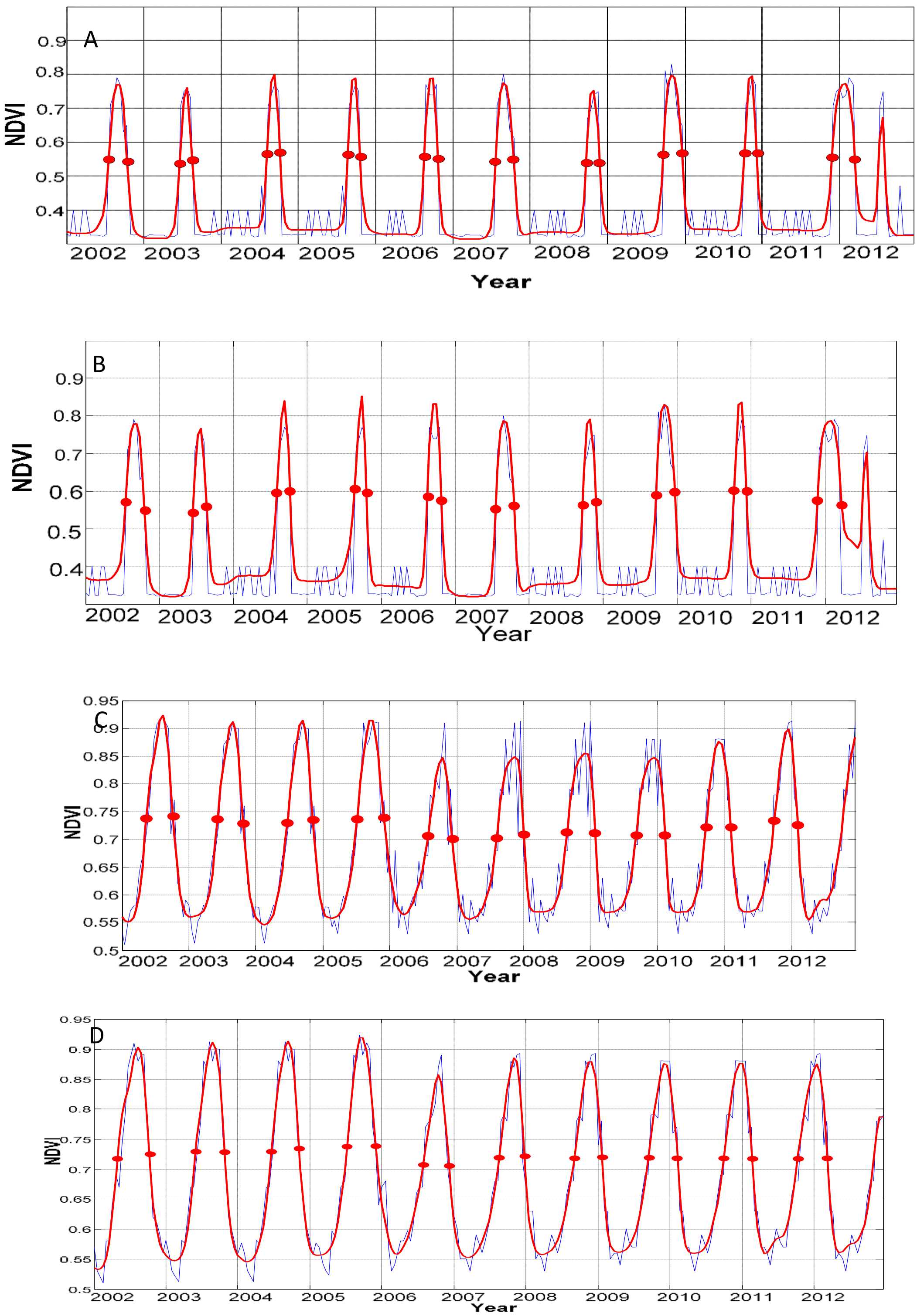


TRMM based rainfall onset (x) and retreat (y) for the Niger-delta forest cluster



TRMM based rainfall onset (x) and retreat (y) for the Calaba forest cluster

Appendix E: NDVI logistic fits across the forest clusters



NDVI-Double logistic fit for phenology between 2002 and 2012 in for A, Chad, B, Mambila, C Niger-delta and D, Calabar forest clusters. The red dots marks the beginning and end of the season for each year.

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