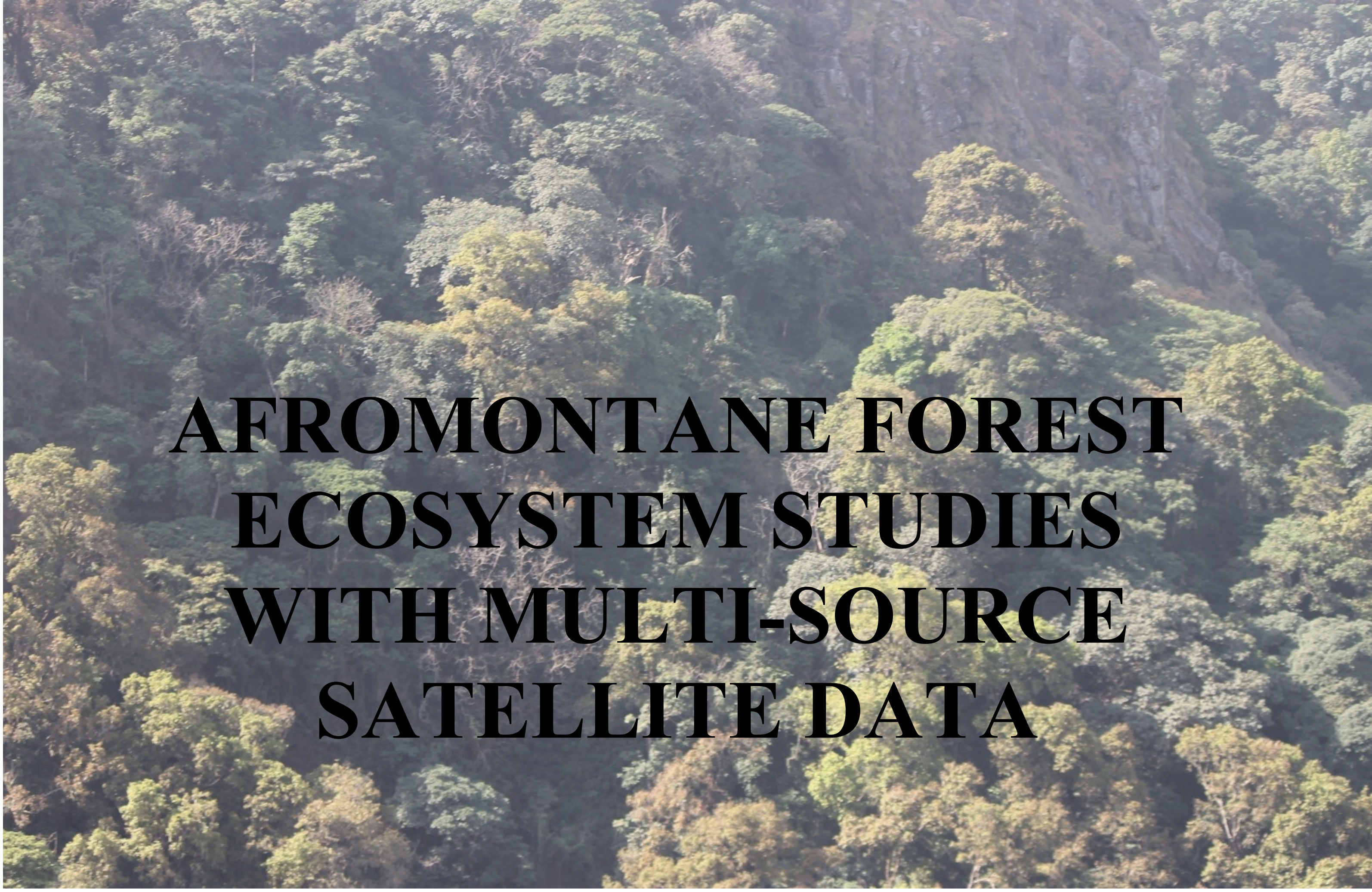

AFROMONTANE FOREST ECOSYSTEM STUDIES WITH MULTI-SOURCE SATELLITE DATA

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von Ralph Adewoye (BSc. MSc. Forest Resources Management).

I, **Ralph Adeyinka Adewoye**, hereby declare that the thesis submitted for the degree of Remote Sensing at Friedrich Schiller University is my own original work and has not been submitted for any other degree or professional qualification. I confirm that all sources used have been properly referenced and that I have not knowingly plagiarized any work.

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Abstract

The Afromontane Forest of north Eastern Nigeria is an important ecological ecosystem endowed with flora and fauna species. The Afromontane forests also uniquely have the water trapping capacity through which the forest canopy intercept water-filled cloud which drips into the forest floor forming streams. Thus, the Afromontane Forest supplies water all year round to its inhabitants. Information on structural diversity is necessary for adequate conservation and management strategy. An extensive survey which is often time-consuming and labour-intensive is required for the assessment of such ecosystem. A remote sensing platform is an inexpensive tool for assessing both quantitative and qualitative information on ecosystem biodiversity.

The main goal of this thesis was to explore the potential of multi-source satellite remote sensing for the assessment of the biodiversity-rich Afromontane Forest ecosystem. The research theme of this thesis was divided into two phases using different methods and algorithms to retrieve two major remote sensing- -essential biodiversity variables (RS-EBV). The two RS-EBV are interrelated and are also the major determinants of biological and ecosystem stability. These are the aboveground biomass and tree species distribution. The aboveground component of two Afromontane Forest sites was estimated using high-resolution QuickBird imagery with forest inventory data. The study further examines the influence of QuickBird image features (spectral and textural) in the estimation of the forest AGB. Furthermore, environmental variables (precipitation, temperature, and slope and elevation data) were used as a determinant of AGB distribution. The estimated mean value of aboveground biomass from sampled field plots was 400t/ha. The predicted aboveground biomass using feature groups, in situ, data and environmental variables was 300.10 t/ha with relative (RMSE) = 44.75%. Spectral and textural parameters, elevation and slope correlated with modelled aboveground biomass. Findings therefore imply that very high-resolution

spectral, textural and slope parameters are critical for biomass modelling of the Afromontane forests of Mambila Plateau.

The second research component of the first phase was on the species distribution modelling of the Afromontane Forest ecosystem. The research examines the application of the Spectral Variation Hypothesis (SVA) in an Afromontane Forest ecosystem using features derived from high and medium-resolution images combined with macro ecological data to predict tree species distribution. Alpha diversity (α) of tree species was calculated from in situ data obtained from the survey of two study sites. Object-Based Image Analysis (OBIA) was adopted for the tree species distribution modelling. Spectral and textural metrics from both QuickBird and Landsat images were computed with the segmentation algorithm. While the macro ecological parameters (temperature, humidity, elevation and slope) were derived from 30 m ASTER DEM and CHELSA high-resolution climatic data.

The relationships between diversity and spectral, textural features derived from the two images and the macro-ecological parameters were assessed with a random forest algorithm. Elevation (r=0.55), and slope (r=0.46) were the determinant of tree species distribution in the study area. While spectral and textural features significantly contributed to the enhancement of the alpha diversity model in both QuickBird and Landsat images. QuickBird and Landsat ETM-8 spectral and textural heterogeneity showed a significant correlation with species richness (r=0.78) and (r=0.47) respectively. The empirical models developed can be used to predict landscape-level species density in the Afromontane forests of Nigeria and the adjourning Cameron highlands.

The second phase of the research focussed on the analysis of the forest cover changes and the effects of habitat fragmentation on the Afromontane biological diversity. The study explores the use of multisource satellite data to determine the rate of degradation of the Afromontane Forest ecosystem using decadal Landsat and MODIS satellite images. The study also determined the inter-annual time series changes in the study area using MODIS Satellite images with the BFAST algorithm. Trajectory change detection analyses of Landsat images (c.1988, c. 2001, and c.2014) indicated a decrease in forest cover by 18% between 1988 and 2001 and 26% between 2001 and 2014. The overall accuracy of the change map derived from the error matrix was 93% (c. 1988-2001 change map) and 97% (c. 2001-2014 change map). The results of the phenology matrix from the MODIS time series reveal significant forest degradation through anthropogenic activities between 2000 and 2014. The overall accuracy of disturbance mapping was 93% and 74% for clear-cut deforestation and deforestation through fire. This study highlights the advantages of using multi-source satellite images with hybrid change detection techniques for the characterization of the highly diversified Afromontane ecosystem.

The last chapter was focused on forest fragmentation analysis and its effects on forest diversity. The study examined the spatial pattern changes of the study area using the forest cover map of 1988, 2001 and 2014. The spatial pattern of the landscape changed remarkably with the decrease in forest cover at 21%, 17.5% and 8.1% for the three test sites. The study also indicated an increase in fragmentation with the number of patches (NumP), mean patch size (MPS) and Mean patch (MPAR) area showing an increase with decreasing forest cover. The study also analysed the effects of fragmentation on species diversity. Species accumulation curve (r^2=0.96) indicated that tree species diversity increases with fragment size and Sorensen's similarity index (beta diversity) showered between study sites.

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Chapter 1. Thesis motivation

1.1 Research motivation

Tropical montane forests occur in mountainous altitudinal bands characterised by orographic clouds [1,2]. These forests are found between an altitude of 500 and 3500 meters above sea level and are best described as tropical montane or sub-montane forests characterised by persistent clouds, often with an abundance of mosses, ferns, lichen and flowering plants [3]. Montane forests are also found in locations with cooler climates and a stronger influence of mists and clouds. In terms of global distribution, tropical montane forests are found in tropical America, South east Asia and Africa. Tropical montane forests are about 11% of the tropical forest and cover over 50 million hectares [3].

The montane forest ecosystems exhibit characteristics related to their natural uniqueness and one such characteristic is the cloud-stripping function [4]. Trees of the montane forest intercept wind-driving clouds through the leaves and branches thereby stripping water from the cloud which moisturises the forest floor and often forms streams that flow out of the forest[4]. Through this phenomenon, the montane forest can supply water all through the dry season and increase the supply of water during the raining season by 10% [1,4]. Thus, the forest supports the local communities owing to the ability to capture water from the cloud, thereby providing water through streams and rivers all year round.

The tropical montane forests have a very high level of endemism and are home to many threatened species of both flora and fauna [4,5]. For instance, Birdlife International research on the distribution of endemic birds indicated that 10% of the world's restricted-range birds are confined to or found mainly within the montane forests[1]. Similarly, more than three-quarters of the 4,000 vascular plant species resident in the African montane forests are endemic or near-endemic [5]. The mountain Gorilla classified by the international Union for Conservation of Nature (IUCN) as critically endangered is restricted to the montane forest of

Central African Republic and Uganda. These and other range of endemic species places the tropical montane forest as hotspots of global biodiversity.

'Tropical montane forests therefore represent a rare and fragile ecosystem that is under threat in many parts of the world and urgent action is needed to conserve these rich mountain forests, not only because they harbour concentrations of endemic and threatened species but to maintain their vital role in the provision of freshwater'[4]. The ecology of the montane forest and their location along mountain slopes make them particularly susceptible to habitat fragmentation [4]. Fragmentation is known to have deleterious effects on natural resources and ecosystem structures owing to its biodiversity loss [6].

The effects of such loss have both local and global implications on the climate. Efforts at combating such loss of forests and their implications led to the formation of the Essential Biodiversity Variables (EBV) by the United Nations Convention for Biological Diversity (CBD). EBV was established to monitor the progress made by signatories to the CBD on forest ecosystem diversity. Monitoring EBV such as forest biomass, tree species diversity, forest phenology, and temporal and multi-temporal change detection (Land use, land cover) are important in determining the progress towards the Convention on Biological Diversity's 2020 Aichi targets [7].

The EBV indicators can also provide the foundation for developing scenarios of the future of biodiversity under different policy and management options. For instance, local and regional biomass information is essential for assessing the status and monitoring the dynamics of ecosystem structure. Phenology is also an important EBV which indicates trends, shifts, and structural changes of species traits within an ecosystem. Land use and land cover mapping (LULCC) and biomass information are relevant for the CBD targets 5, 11, 14, and 15. Information on plant phenology is relevant to the CBD targets 10 and 15.

Satellite Remote Sensing (SRS) offers the possibility of achieving the above targets more accurately and efficiently than the usual extensive ground field campaign often employed by ecologists. Implementation of the essential biodiversity Variables using field assessments or in situ, data gathering methods in the rugged Afromontane forest terrain is costly and time demanding. SRS data has the capability of constant, repetitive, and cost-effective monitoring of large areas and its application in biodiversity monitoring studies has been increasing [4,23-25]. Therefore, SRS data can provide precious information nearly impossible to acquire solely by field assessment [26].

Despite the availability of satellite data of various spectra and resolutions, there is still a research gap on the application of SR-EBV for retrieving Afromontane biodiversity indicators. Therefore, the identification of high-performing RS-EBV approaches and the establishment of a link to a common set of indicators widely adopted by the user community would be highly beneficial for their extraction and the minimization of this knowledge gap. The major goal of this dissertation is to bridge the gap by exploring the potential of a multi-sensor remote sensing data base for mapping and modelling the major biodiversity indicators of the rich Afromontane forest ecosystem.

1.2 Research Questions

The following research questions have been developed and will be investigated in this dissertation:

1 What are the major determinants of aboveground biomass accumulations in the ecosystem?

2 What are the major determinants of tree species distribution in the study area?

3 How can a hybrid change detection method be used to determine deforestation and fragmentation rates in the Afromontane forest ecosystem?

4 What are the effects of deforestation and forest fragmentation on biomass accumulation and tree species distribution?

5 How has remote sensing improved biodiversity monitoring in the Afromontane forest ecosystem?

1.3 Thesis structure

The structure of the dissertation is as follows: Chapter one gives a general background, introduction, and problem description and it presents the research questions of the dissertation. A state of the art of literature review was the subject of chapter two. Chapter three was on the aboveground biomass modelling of the Afromontane forest. Chapter four focussed on the modelling tree species diversity of the study area. Chapters five and six presented the hybrid change detection of the Afromontane forest ecosystem and habitat fragmentation and its effects on beta diversity. The last chapter (seven) presents the synopsis of the thesis.

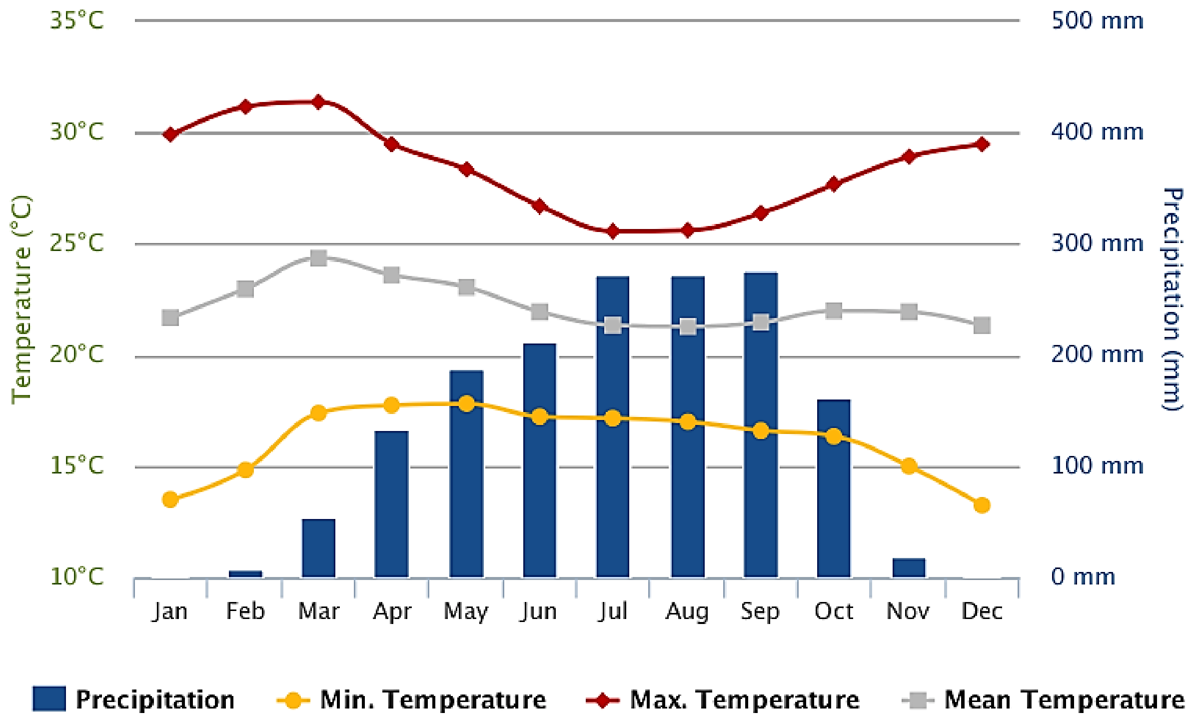
1.4 The study area

The study presented in this dissertation covers the Afromontane forests of north eastern Nigeria and its escarpments. The study area encompasses three contiguous montane forest areas with altitudes ranging from 600 m to 2400 m above sea level. The montane forest areas are as follows: The Mambilla Plateau (≥ 1750 m), the Gotel Mountains (≤ 2400 m) and the escarpment forest of Akwaizantar (≥ 600m ≤ 1170 m). The spatial area coverage of the study area is estimated at 9,267 km^2.

1.4.1 Climate and Geology

There are two distinct seasons, a dry season when there is little or no rain for approximately 6 months and a wet season when it can rain almost every day. The rainy season usually commences from early April until late October with mean annual rainfall of 1780 mm on the Mambilla Plateau but higher in the Gotel mountains. The temperature in the study area rarely exceeds 30°C in the dry season but has lower temperatures of 9-12 °C in late November to early January (Figure 1-1).

Figure 1-1. Climatic data of the study area courtesy of Digital Observatory For Protected Areas



The soils are derived from volcanic rocks and are characterised as brown soils with the presence of gravel or stone or a combination of both with pH 5.6 – 6.0 (Hilderbrand, 1966). Four types of soils have been identified in the study area and these are; Leptisols, Acrisols, Luvisols, and Ferrisols with one or a combination found within a study site[8,9].

1.5 Data.

Due to the peculiarity of the study area and the research objectives, multi-satellite data were employed to achieve the outlined objectives. The satellite images used included QuickBird, Landsat Tm, Landsat ETM, Landsat (OLI), MODIS, 30 m Digital Elevation Model DEM and precipitation and temperature data from the climatologies at high resolution for earth's land surface area (30 arc second CHELSA). The QuickBird satellite image with a resolution of 2.3 m was used with forest inventory and environmental variables (consisting of slope and elevation from the 30 m DEM and temperature and precipitation from 30 arc second high resolution global climatic data) to estimate the aboveground biomass of selected Afromontane forest.

Also, the QuickBird and Landsat 8 satellite images were used for tree species distribution modelling with environmental variables. The Landsat data (Tm, ETM and OLI) were used in trajectory change detection and forest fragmentation analysis of the Afromontane forests and their escapements, while MODIS images (from 2000-2014) were used for the phenological mapping of the same site.

Chapter 2.

Tropical forest Biodiversity monitoring with Satellite Remote Sensing

2.0 Introduction

Tropical forests cover approximately 15% of the world's land mass and are global epicentres of biodiversity with 96% of the world's tree species found within the ecosystem [10,11]. The extent and diversity of tropical forest ecosystems have largely made them an important carbon sink as their plants and soils hold approximately 460-575 billion metric tons of carbon, which is about 25% of the global terrestrial carbon [12,13]. The tropical forest ecosystem is a veritable source of carbon sinks through the process of carbon dioxide sequestration [14].

Contrasting to the value of the tropical forest ecosystem as a source of carbon sink is the gradual deforestation of the ecosystem. This has negative effects on the environment through the release of carbon stored in woods and soil. Deforestation contributes about 70% of total emissions to the atmosphere in Africa and 15-25% of the annual global greenhouse gas emissions. [15,16,17,18]. Approximately 1.6 billion metric tonnes of CO_2 are released into the atmosphere per annum through deforestation resulting in an increase in the greenhouse effect and subsequent rise in global temperature [19].

The key to understanding the importance and dynamics of the forest ecosystem is that forests interact with the environment at various spatial and temporal scales. Implications of deforestation at the ecosystem level include reduction of forest cover, loss of biodiversity and change in landscape structure (habitat fragmentation). The effects of deforestation at the ecosystem level include erosion, siltation, flooding, increase in evapotranspiration which often leads to the drying off of streams and rivers. Forest cover losses and their subsequent fragmentation are the immediate consequences of anthropogenic-induced factors.

The United Nations Framework Convention on Climate Change (UNFCCC), the Intergovernmental Panel on Climate Change (IPCC) and the Convention on Biological Diversity (CBD) recognise the importance of forests in climate change ameliorating and protecting biological diversity. These organisations have set up policies such as Reducing Emissions from Deforestation and Degradation (REDD++) and Aichi Biodiversity Targets to redress the decline of tropical forest ecosystems[7,20,21,22]. REDD aim to reduce forest loss through the provision of incentives in the form of monetary compensation[19]. The CBD mainstream policies are focused on addressing the underlying causes of biodiversity loss reducing the direct pressures on biodiversity and promoting sustainable use[21].

Most of the tropical forest ecosystems are located in remote areas with impassable road networks, thereby restricting easy access to evaluation and monitoring of the ecosystem. Also, political instabilities and lack of or limited infrastructures are hindrances to scientific research [23]. Satellite Remote Sensing (SRS) offers repeatable, standardised and veritable information on earth surfaces, hence a potential tool for monitoring biodiversity changes in tropical forests [24]. It's potential also includes identifying areas of significance to biodiversity, species distribution prediction and modelling the influence of environmental and anthropogenic factors on ecosystem biodiversity.

2.1 Monitoring tropical forest with Satellite Remote Sensing-Essential Biodiversity Variables (SRS-EBV)

Since 1992 when the Earth summit was held in Rio de Janeiro (Brazil), there have been concerted efforts to redress the continuous decline of biodiversity at both local and global levels. Biodiversity indicators have been proposed as a means to monitor the status and study the trends of biodiversity losses. Prominent among the CBD policies is the Aichi targets 2020 which is aimed at reducing the rate of biodiversity loss and averting dangerous biodiversity changes [7]. Ninety-eight biodiversity indicators were proposed by CBD for monitoring and reporting of the Aichi biodiversity targets, which was later reduced to Fifty-five indicators. However, many of the indicators used were problematic due to a lack of data standardisation [25]. The Essential Biodiversity Variables (EBVs) were developed in support of UN-CBD's

Aichi target 2020 by the Group of Earth Observation Network (GEO BON) to enhance data standardisation and reporting by the scientific and policy community.

'EBVs are measurements required for studying, reporting and management of biodiversity change and it provides concise information to the scientific and policy communities on the status and biodiversity trends, related characteristics such as ecosystem/habitat conditions, species distributions and abundance' [7,22]. GEO BON classified EBV into six major classes, namely: Genetic composition, species populations, species traits, community composition, ecosystem functioning and ecosystem structure. EBV's characteristics as summarised by Pereira et al [7] are as follows: A) EBVs must be sensitive to change over time; B) EBVs are focused on state variables; C) EBVs must be of relevance to biodiversity community; and D) EBVs must be feasible in terms of monitoring with SRS technology.

In other to enhance and broaden biodiversity monitoring in time and space with the EBV classes. The remote sensing-essential biodiversity variables (SRS-EBVs) were introduced by GEO-BON as a subset of EBVs and its application relies largely on the use of satellite-based data [26]. SRS-EBV include variables whose monitoring relies on the integration of satellite-based data with in situ data. SRS-EBVs can therefore be used as proxies for indicating defined targets for biodiversity conservation such as habitat degradation and fragmentation (table 2-1).

SRS application has been used in monitoring tropical forest components such as the aboveground biomass(AGB), species distribution, change detection, habitat fragmentation and its effects on ecosystem structure, et cetera [27]. The following literature review is based on current trends of SRS application to tropical ecosystem research. The review has been divided into four sections namely: (1) aboveground biomass retrieval (2) species distribution modelling and (3) change detection, (4) and habitat fragmentation.

Table 2-0-1. SRS-EBV variables

	Examples of SRS-EBV measurable variables		
EBV class	**EBV examples**	**variables meeting SRS-EBV**	**Relevance fore CBD targets**
Genetic composition	Habitat structure	Specific plant genotype	5, 11, 14,15
Species population	Abundance and distribution	Specie occurrence	4,5,6,7,8,9,10,11,12,14,15
Species traits	Phenology	Specie leaf area	10,15
Community composition	Taxonomic diversity	Taxonomic diversity	Targets 10, 15
Ecosystem structure	Remote sensing of cover (Biomass inclusive) regionally or globally	Vegetation height Aboveground biomass	8,10,14
	Fractional cover	Aboveground biomass	
	Forest cover		
	Land cover		
	Fraction of absorb		
	Leaf area index		
Ecosystem function	Vegetation Phenology		5,8,14

2.2 Aboveground biomass retrieval methods

Monitoring terrestrial biomass is one of the essential climate variables outlined by the Global Climate Observation System and it's also one of the target candidate variables of the essential biodiversity variables. Biomass is an essential indicator of ecosystem health and its decline has a critical impact on the greenhouse balance and macro ecological processes [27]. There is a general assumption that 75% of the overall biomass of living trees is largely stored within the aboveground biomass component of trees [27,28]. The aboveground biomass of tropical forests can be estimated using in situ/field-based inventory techniques, satellite remote sensing and a combination of both.

The *in situ* biomass estimation method is further classified into destructive and non-destructive techniques. The destructive method is the most accurate method of biomass estimation and is used in developing specie specific allometric models using measured dendrometric attributes such as diameter at breast height (DBH), tree height, and wood density [23]. The aboveground biomass of the tree is expressed as a function of DBH, tree height and wood density. Several allometric models have been developed based on the combination of tree dendrometric parameters (DBH, tree height and wood density) through linear and nonlinear regression models [23,29,30]. Although this is the most accurate method of determining the aboveground biomass, the method involves destroying trees and is limited by time, labour cost and sampling restriction to small areas.

Allometric models developed from the destructive method of AGB estimation can be used for non-destructive biomass estimations. The non-destructive techniques relate the aboveground biomass of the forest with densitometric parameters such as tree height and diameter at breast height (DBH). Most of the developed allometric equations for AGB estimations do have ecological bias and the improper use of these models may lead to large uncertainties in AGB estimations. Allometric models developed for AGB measurements are developed for specific ecological niches. Therefore, when allometric models are to be used for obtaining AGB reference data, the ecological niche for which the equation was developed must be considered. Examples of allometric equations for tropical forests and the ecological niches are in table 2-2.

2.2.1 SRS and AGB estimations

Remote sensing offers the possibility of measuring forest carbon stocks using instruments mounted on satellites or airborne platforms [48]. Optical remote sensing data, radar (microwave) data and LiDAR data are the three main types of remotely sensed data that are used to extract information for biomass and stand parameters. The passive optical and

Table 2-0-2. Allometric equations for the tropical forest ecosystem.

Equations	Forest types	DBH range	Independent Variables	Reference
$Y = \exp\{-2.134+2.530*\ln(DBH)$ $R^2 = 0.97$	moist, (1500<rainfall<4000mm)	no range	DBH	[31]
$Y = \exp\{-3.1141+ 0.9719*\ln[(DBH^2)H]\}$ $R^2 =0.97$	moist rainfall	DBH > 5 cm	DBH, H	[32]
$Y = \exp\{-2.4090+ 0.9522*\ln[(DBH^2)HS]\}$ $R^2 =0.97$	moist, (1500<rainfall<4000mm)	DBH > 5 cm	DBH, H, S	[33]
$Y = (0.0899\ ((DBH^2)0.9522)\ *(H0.9522)\ *(S0.9522))$	not specified	not specified	DBH and H	[31]
$W = p.\exp(\beta_0+ \beta_1.\ln(D) + \beta_2.\ln(D)^2 + \beta_3.\ln(D)3)$	moist	DBH ≤ 10cm	DBH, H, specific gravity $\beta_0 = -1.499$ $\beta_1 = 2.148$ $\beta_2 = 0.207$ $\beta_3 = 0.0281$	[34]
$B=rpD^{2+2c}$	moist, (1500<rainfall<4000mm)	DBH ≤ 10cm	DBH, H, S	[35]

hyperspectral provides information on tree canopy attributes, leaf area and tree species types. Optical remote sensing data are mostly used in tropical forest aboveground biomass studies because of the availability in a wide range of spatial and spectral resolutions, affordability(cost) and easy access [36].

Aboveground biomass estimations using optical remote sensing relate the ground truth measurement with spectral signals such as vegetation indices using the Red and Near Infrared wavelengths [37]. Vegetation indices, principal components analysis, minimum noise fractions, tassel cap transformation, spectral mixture analysis and texture measures are a few of the techniques that are used to produce variables for estimating AGB from optical data [23]. There are limitations on the use of optical satellite remote sensing for aboveground biomass modelling in tropical forests. The limiting factors include vegetation heterogeneity, canopy shadows and undulated landscapes that characterised most tropical forest ecosystems [49,51]. Similarly, the probabilities of data saturations in forests with high biomass levels have been observed while using optical remote satellite images for aboveground biomass modelling in tropical forest [50,52,53].

The active sensors such as Light Detection and Ranging (LiDAR) and Radar are independent of the sun and the time of the day [11]. LiDAR is known to provide accurate information on the vertical distribution of canopy/ height structure and is useful for three- dimensional (3D) characterization of forest attributes such as the aboveground biomass [54]. LiDAR data was used in mapping forest biomass in French Guiana with an error of 14% and estimates of 340 Mg/ ha [55]. LiDAR use for tropical forest biomass estimations is limited by coverage and the economic cost of procuring the images [54]. Radar data are also independent of the time of the day, and weather and can provide a multi-faceted source of information such as frequency, incidence angle range, polarization, and interferometric baseline. It's advantages also include sensitivity to surface roughness, and imaging possibility from different types of polarised energy (HH, VV, HV and VH). Aboveground biomass retrieval using radar satellites in tropical forests has risen significantly in the last few years. The Advanced Land Phased Array Synthetic Aperture Radar (ALOS-PALSAR) data was used in the estimation of the aboveground biomass of the Guinea-Bissau forest. The result obtained from the study (65.17 mg/ha^{-1}) was concurrent with the regional estimate of AGB.

2.2.2 Machine learning methods for aboveground biomass retrieval

In satellite remote sensing applications, the use of retrieval algorithms or machine learning methods has become an essential component of biomass modelling or estimation. Retrieval algorithms are crucial to remote sensing-based aboveground biomass modelling and can be grouped into two broad categories: parametric and nonparametric algorithms. In the parametric algorithm, it is assumed that the relationship between the dependent variables(AGB) and the independent variables (features derived from SR data) can be explicitly specified[23]. Simple or multiple linear regression models are examples of parametric algorithms. Most often, the AGB relationship with satellite remote sensing variables is nonlinear because the relationship between AGB and remote sensing variables is too complex to be captured by parametric algorithms.

Therefore, nonparametric algorithms are flexible and easy to adapt to complicated no linear biomass models[23]. Examples of nonparametrics include artificial (ANN), K-nearest neighbour (K-NN), support vector machine (SVM), maximum entropy (MaxEnt) and random forest algorithm. Regression-based models are the most common approach to biomass retrieval using SR data[23]. A review of retrieval algorithms and their performance by [27] showed a wide range of excellent performance with various satellite images (Table 2-3).

Table 2--0-3. Examples of machine learning algorithms for aboveground biomass retrievals using remote.

Sensor	Parameter(s)	Algorithm	Performance (r)	Reference
QuickBird	Height, Biomass, Volume	Support vector regression	0.72	[38]
World view	Biomass	Random forest	0.75	[39]
Landsat	Aboveground biomass	Random forest	0.943	[37]
Spot	Aboveground biomass	Random forest	0.84	[40]
Landsat-7	Aboveground biomass	Support vector regression	0.75	[41]
MODIS	Aboveground biomass	Random forest	0.82	[42]
GlAS	Aboveground biomass	Random forest	0.82	[43]

2.3 Monitoring species diversity with SRS

Global studies on biodiversity decline indicated more than 7,000 plant species are lost annually. The immediate effects of such lost are; (1) an ecosystem imbalance, leading to the loss of other species, the loss of seed dispersal mechanisms and 3) the decline of pollinators leading to reduced food production a few of the effects of biodiversity loss to human health and economy. As the biodiversity of an ecosystem declines, the health status of the inhabitants is negatively regressing. Ecosystem health is therefore a function of its biodiversity.

The importance of measuring species diversity as an indicator of ecosystem health has been recognized by major initiatives worldwide such as the International Geosphere Biosphere Program (IGBP), the Group on Earth Observation (GEO BON), World Climate Research Program (WCRP) and the Committee on Earth Observation Systems (CEOS) [44]. Biodiversity assessment at local and regional scales by ecologists has traditionally relied on the assessment of both local diversity (alpha diversity) and species turnover (beta diversity)[44]. Several indices have been used for estimating both local diversity (alpha diversity) and species turnover (beta diversity). Such indices included; species richness, Simpson, Berger–Parker, Shannon–Wiener, etc. However, sampling intensity over a larger area and the cost associated with field sampling is a major limitation to the use of field inventory for species diversity monitoring.

SRS application to ecological research is on the increase because of the capacity to deliver information on habitat quantity and quality. The importance of satellite remote sensing (SRS) to provide information on the state of biodiversity at landscape, regional and ecosystem levels has been highlighted through numerous scientific researches. Research studies dealing with satellite remote sensing-based species diversity estimates have majorly focused on mapping or modelling biodiversity hotspots based on spectral variation hypothesis [44].

The spectral variation hypothesis (SVA) states that spectral heterogeneity of remotely sensed data can be related to the spatial heterogeneity of the environment and could therefore be used as a proxy for species diversity [44,45,46]. It is expected that in measuring species diversity with remote sensing images, a relationship between the remote sensed spectral heterogeneity and locally measured diversity be established. Remotely sensed spectral heterogeneity information therefore provides a crucial baseline for rapid estimation or prediction of biodiversity attributes and hotspots in space and time [46]. Several modelling techniques have been used to determine the relationship between remote sensing spectral heterogeneity and species diversity. The modelling techniques include a random forest algorithm, support vector machine and maximum entropy.

Table 2-0-4. Examples of machine learning applications for Species modelling using remote sensing data

Indices	Modelling algorithm	Satellite image	Location	Reference
Alpha diversity	Univariate regression	QuickBird and Landsat ETM +	Uganda	[47]
	Univariate regression	Hyperspectral	Namibia	[48]
	Local smoothing surfaces(LOWES)	Landsat ETM and IKONOS	India	[49]
	Regression models	NOAA-AVHRR	Kenya	[50]
	Multivariate regression model	Aster	Central Asia	[51]
	Neural Network	Landsat TM	Borneo	[52]
Beta diversity	correlation coefficient	Landsat TM	Ecuadorian Amazonia	[53]
	Quantile regression	Landsat TM	India	[54]
	correlation coefficient	MODIS	Worldwide	[55]

2.4 Change detection studies and habitat fragmentation.

Change detection studies of tropical forests have become increasingly necessary because of the contributions of tropical forests to climate change. Tropical deforestation is known to account for more than 20% of global CO_2 emissions [56]. Article 3 of the United Nations Framework Convention on Climate Change (UNFCCC) stipulates change detection studies for tropical forests through Land Use Land Cover and Forestry (LULCF) studies. LULCF allows for net changes in greenhouse gas emissions by source and sinks to be accounted for through reforestation and deforestation. Change detection studies can be classified into three broad categories; pixel, object and hybrid-based change detection techniques [57].

The pixel change detection methods are based on per-pixel classifiers and change information contained in the spectral-radiometric domain of the satellite images, and they exclude textural and topological information [57,58]. Pixel-based image classification utilizes spectral information numbers stored in the image and images are classified by considering the spectral similarities with the pre-defined land cover classes. The classification methods use spectral information contained in individual pixels to generate land cover classes.

Several change detection techniques based on pixel-based analysis have been developed which include; image differencing, image rationing, regression analysis, vegetation index differencing, change vector analysis, principal component analysis and tassel cap transformation. Also, machine-learning (such as artificial neural networks, support vector machines, and decision trees) and GIS-based methods have been used for change studies. Algorithms/methods used in the pixel-based detection method include machine learning algorithms: decision tree (DT), random forest (RF), and the support vector machine (SVM). This method has been known to perform accurately for the classification of land use/cover classes [59,60,61,62,63,64]. Comprehensive reviews of pixel-based change detection methods have been published, including Coppin et al, Lu et al and Desclée et al [58,65,66]. The major disadvantages of the pixel-based method are the "salt and pepper effects"[67]. The salt and pepper effects are due to the intrinsic characteristics of the land cover elements (spectral heterogeneity) and the random variation of the sensor's response which often lead to misclassifications [67].

Object-based analysis (OBIA) is a robust method suitable for the classification of medium to high-resolution satellite imagery. An object is a group of pixels, and object characteristics such as mean value, standard deviation, ratio, etc. can be calculated; besides, there are shapes and texture features of the objects available which can be used to differentiate land cover classes with similar spectral information. In object-based techniques, contextual information such as texture, geometry and compactness are combined with spectral information of the satellite image for change detection analysis [68,69]. The main objective of the OBIA is to improve image classification through full exploitation of salient information within the satellite image for change detection analysis. The salient information includes texture, shape, and their spatial relations with neighbouring objects [57]. The OBIA technique uses objects produced by image segmentation and it combines visual interpretations with the quantitative aspect of the pixel-based approach.

OBIA interprets images using characteristics such as spectra, texture, as well as spatial and topological characteristics [66]. These extra types of information give OBIA the potential to produce land cover thematic maps with higher accuracies than those produced by traditional pixel-based methods. Object-based image analysis comprises two parts: 1) image segmentation and 2) classification based on objects' features in spectral and spatial domains. Image segmentation is a kind of rationalization, which delineates objects according to certain homogeneity criteria and at the same time requires spatial contingency [66]. Although OBIA's application was initially focused on high-resolution satellite images, there has been success in the application of OBIA in medium-resolution images. OBIA application in forest ecosystems includes forest cover mapping, canopy modelling, change detection studies, aboveground biomass estimations, species distribution modelling and habitat mapping.[64,69,70,71,72,73]. For example, OBIA was used in the change detection optimisation of the mountainous forest of Mexico with a medium-resolution Landsat image [68]. An accuracy assessment of 0.77 was obtained using the object-based classification algorithm.

The hybrid change detection technique is the integration of change detection methods and it uses two or more change detection techniques for analysis [57,70]. The major advantage of this technique is the potential of two or more appropriate change detection algorithms to solve research problems within a particular study area. Hussain et al [57], classified the hybrid change detection method into two distinct categories, namely: a) procedure-based and b) results-based.

For tropical forests with multiple ecological niches, the hybrid change detection method offers an advantage because it can be used to efficiently monitor the changing landscape.

2.5 Habitat fragmentation

The prolong effects of forest cover loss often lead to habitat fragmentation. Habitat fragmentation is defined as the process during which a large expanse of forest is transformed into a smaller, geometrically isolated number of forest islands or patches[6,74]. The definition of fragmentation as a ‘‘process’’ is an indication of the inclusion of the time frame during which fragmentation occurs. Several methods of quantifying forest fragmentation have been suggested by landscape ecologists using satellite remote sensing and geographic information systems (GIS). A review by Fahrig[74] summaries forest fragmentation approaches into six categories based on spatial pattern indices(PI). The PI is mostly used by scientists in the field of ecology and spatial science to quantify fragmentation and its effects on biodiversity. The categorized PI are 1) the reduction in forest cover, 2) the increase in the number of patches, 3) the decrease in sizes of forest patches and 4) the increase in isolation of patches. These are the major PI for interpreting forest or habitat fragmentation processes.

‘’The use of fragmentation pattern indices and its interpretation requires an acute awareness of the landscape context and the openness of the landscape relative to the biodiversity phenomenon under consideration’’[75]. For instance, % forest cover, mean patch size, edge density, and patch density were the PI used in the analysis of the fragmentation processes of Gran Chaco forest, Argentina[6]. In a related study, % forest cover, edge density and patch size were used as a fragmentation index in the Indian forest of Uttara Kannada district [76]. In both analyses, the reduction of forest cover was associated with an increase in patch areas and the transition of patch areas to non-forest areas.

The use of pattern indices can further be extended to the analysis of the effects indices of forest fragmentation on species diversity. For example, PI was used to assess the effects of fragmentation on species diversity in the Vindhyan highlands of Indian and the eastern mountain arc of Tanzania. In both studies, results showed that patch sizes can be related to tree species diversity [77,78]. Similarly, PI has been used to determine the effects of forest fragmentation on other biological diversity such as birds, mammals, reptiles, pollinators, etc. The conclusion of most research studies on the effects of fragmentation on biodiversity includes loss of species, and isolation of species thereby leading to extinction. Isolation reduces movements among fragments, thus reducing recolonization. Reducing fragment area and increasing fragment isolation generally reduce the abundance of birds, mammals, insects and plants.

Chapter 3. Estimating Aboveground Biomass of the Afromontane forests of Mambilla Plateau using QuickBird and forest Inventory data

3.0 Introduction

Tropical forest ecosystems have large reservoirs of carbon stored as above and below-ground biomass. These are majorly stored as biomass in tree stems, roots, woody debris, soil organic matter and forest litter. Among these different forest components, the aboveground biomass (AGB) of living trees contains the largest carbon pool and is the most directly affected by deforestation and degradation activities [79]. There is a general assumption that 75% of the overall biomass of living trees is stored within the aboveground biomass components of trees [27,28]. Consequently, measurements of the carbon stored within the AGB of living trees provide the best estimate of the forest carbon stocks for the United Nations Program on Reducing Emissions from Deforestation and Forest Degradation (UN-REDD).

Aboveground biomass of tropical forests has been estimated using several techniques such as field-based inventory, satellite remote sensing and a combination of both. The field inventory method has been adjudged to give the best accuracy for AGB. However, the method is known to be time-consuming, labour-intensive, and expensive, and sampling could be biased towards areas with trees with large diameters at breast height[80]. Remote sensing offers the possibility of measuring forest carbon stocks using instruments mounted on satellites or airborne platforms [81]. However, remote sensing instruments cannot measure forest carbon stocks directly but require additional ground-based data collection [82]. Several types of remote sensing data have been employed for tropical biomass mapping. These remote sensing data include LiDAR, Radar and optical data.

Optical remote sensing data are preferably used in tropical forest aboveground biomass studies because of the availability in a wide range of spatial and spectral resolutions, affordability (cost) and easy access[83]. Aboveground biomass estimations using optical remote sensing often relate the ground truth measurement with spectral signals such as vegetation indices using the red and near infra-red wavelengths [37]. There are limitations on the use of optical satellite remote sensing for aboveground biomass modelling in tropical forests. The limiting factors include vegetation heterogeneity, canopy shadows and undulated landscapes that characterised most tropical forest ecosystems [36,84]. Similarly, the probabilities of data saturations in forests with high biomass levels have been observed while using optical remote satellite images for aboveground biomass modelling in tropical forest [84,85].

The necessity to overcome the limitations of the indices-based biomass estimation method has led to the emergence of the use of feature groups or object features derived from optical satellites using Object-Based Image Analysis [86,87]. Object Based Image Analysis (OBIA) is the technique of partitioning image-objects, and assessing their characteristics through spatial, spectral and temporal scales[87,88]. OBIA is efficient in using automated image segmentation procedures to extract meaningful ground features from imagery. Image segmentation is the partitioning of an image into a set of non-overlapping or semantically interpretable regions [89]. Features derived from satellite image segmentation algorithms include textural, geometrical and spectral features [87,90]. Thus, the techniques combine both spectral and object characteristics, thus object features which are "salient or dormant" in pixel-based analysis are efficiently utilised to model biomass.

Global efforts at improving optical data efficiency, through the use of object features for accurate estimation of forest aboveground biomass have gained prominence in recent years. Literature reviews have shown consistent improvement in aboveground biomass estimations using this method. Texture derived from moderate resolution Landsat data has been used in modelling aboveground biomass of several forest sites [64,91]. Similarly, textural features from high-resolution data, such as Worldview-2, IKONOS and QuickBird have been used in modelling and estimating forest aboveground biomass [92,93,94].

Applications of object features used for aboveground biomass modelling vary across geographical regions. However, most AGB maps for African forests are usually derived from in-situ data which are not country-specific. It has been suggested that an aboveground biomass map produced and validated with locally sourced in-situ forest inventory and integrated with the site's environmental variables may be more accurate than generalised maps. The montane forests of the Mambilla Plateau can best be described as heterogeneous forests with complicated biophysical factors. The main objective of this study is therefore to estimate the aboveground biomass of the Afromontane forest using a combination of satellite data, field inventory and environmental variables. This study will answer the following research questions:

A). What is the relationship between AGB and the satellite image spectral and object features?

B). Do environmental variables influence AGB distribution in the Afromontane forest ecosystem?

3.2 The Study Area

The Mambilla Plateau is in the Eastern part of Central Nigeria, adjacent to the Cameroun border. Mambilla Plateau is home to montane forest relicts surrounded by grasslands. The study sites are Ngel Nyaki (Longitude 07^{o} $20^{'}$ N and Latitude 11^{o} $43^{'}$ E) and Kurmi Ndanko (Longitude 07^{o} $03^{'}$ N and Latitude 11^{o} $70^{'}$ E) forest. Both forests are adjacent to each other separated by undulating hills. The two forests can best be described as fragmented forests on the Mambilla Plateau and the altitude of the study sites varies from 1250 m to 1750 m above sea level.

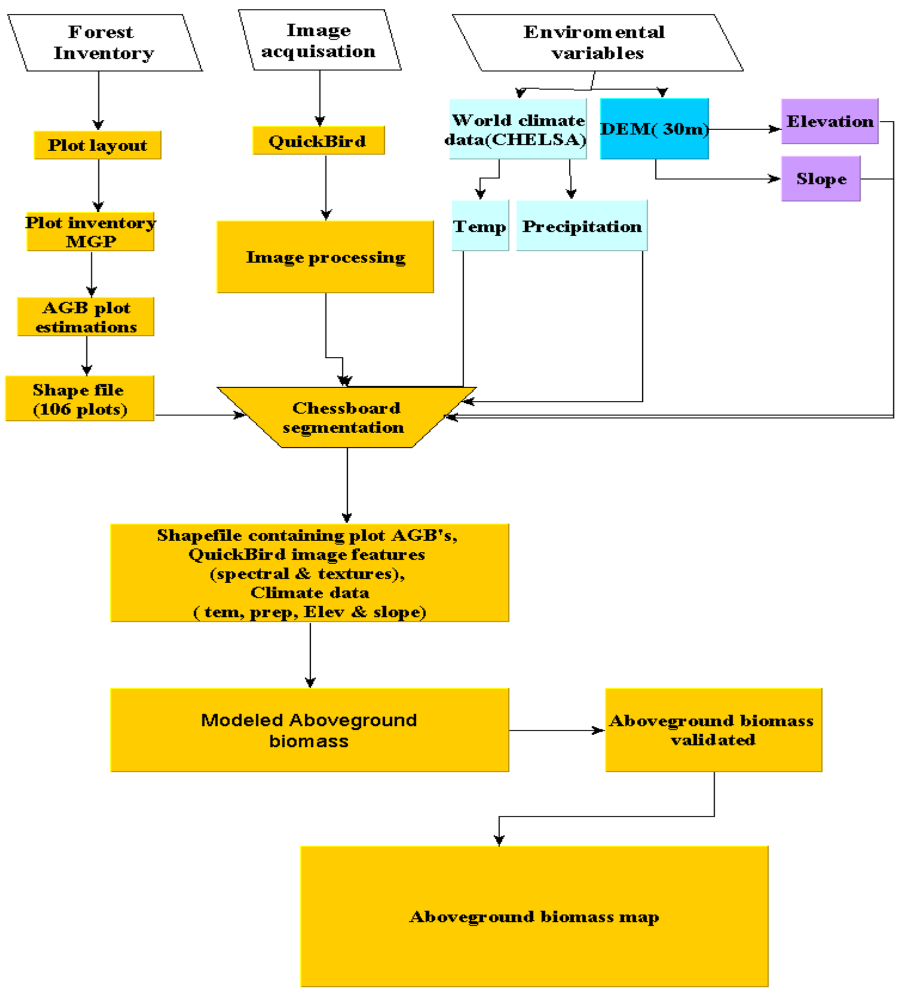
Figure 3-1. View of Ngel Nyaki forest from a high escapement

Figure 3-2. View of the forest from the grass land. Note the burnt grasses by nomadic grazers close to the forest edge

3.3 Materials and Methods

This research follows a bottom-up approach, namely: forest inventory data collections from two study sites, image acquisition and processing, image segmentation and aboveground modelling with the random forest algorithm. Detailed descriptions of the workflow (Fig. 3-3).

Figure 3-3. Model workflow



3.3.1 In-situ Forest Inventory

Forest inventory data were collected in the dry season for seasons of 2012 to 2014. Seasonal data collection commenced at the end of the raining season in late October/ November and lasted until the middle of the dry season in late January/early February. The Modified Gentry Plot

(MGP) was adopted for forest inventory data collection. The MGP is a 10 x 50m (0.05 ha) plot and has been found excellent for estimating AGB in tropical forests [25]. 106 MGP Plots were established using randomized coordinates stratified along elevation with the distance between plots to be ≥ 500m. Within the established plots, the diameter at breast height (DBH) of all trees with DBH ≥ 10 cm was enumerated and all plots' GPS positions were recorded.

3.3.2 In-situ Aboveground Biomass Estimations

Live aboveground biomass was estimated for each stem/plot for the two study sites with a site-specific pantropic equation by Brown [26] for the Afromontane forests.

$$Y = exp\{-2.134 + 2.530 * In\ (D)$$

where: D= diameter at breast height (DBH).

3.3.3 Image Acquisition and Processing

Cloud-free QuickBird imagery of the study area was acquired in January 2011. The image consists of four-band multispectral imagery with a spatial resolution of 2.4 x 2.4m divided into four spectral bands: blue (450 – 520nm), green (520 – 600 nm), red (630 – 690 nm) and NIR (760 – 900 nm) and a panchromatic band (450-900 nm) with a spatial resolution of 0.61 x 0.61 m. Image pre-processing procedures included, re-projection to a common reference system (UTM, WGS 84, Minna Datum) and sub-setting of the imagery to the geographic extent of the two forests of Ngel Nyaki and kurmi Ndanko.

3.3.4 Object-Based Image Analysis

The Object-based Image Analysis (OBIA) technique was adopted for the biomass assessment of the study areas. OBIA combines pixels with objects based on defined segmentation criteria instead of the conventional pixel classification[95] and was used in computing spectral, texture and geometric features after Haralick [96]. QuickBird image of the study area, a shape file containing 106 plots of biomass estimates and environmental variables, was imported into eCognition Developer for the image segmentation procedures.

The developed segmentation includes features such as spectral, texture and geometry features (Table 1). The texture here refers to properties such as smoothness and coarseness and is statistically computed as classified into first-order, second-order and high- order statistics[90,94]. The second-order statistic is the Gray Level Concurrence Matrix (GLCM). GLCM features provide information on the structural and geometric properties of forest canopies and can be used to discriminate textures between tree species[94]. The GLCM properties used are as follows: homogeneity, contrast, dissimilarity, entropy, angular second moment, mean, standard deviation, and correlation. Each of the textures measured is computed for each layer and the five different directions; namely 0^o, 45^o, 90^o, 135^o, and all directions (table 3-1). Only features located in the inventory plot shape files are extracted and used as reference data for the analysis.

3.3.5 Random forest modelling

The results of the image segmentation and the forest inventory data are exported as a polygon and used as training data sets for the random forest algorithm processes in R studio. Random forest is an algorithm developed by Bremen [95] for building a predictor ensemble with a set of decision trees that grow in randomly selected subspaces of data. The algorithm creates an ensemble of decor-related classification trees using bagging [95,97]. For each bootstrap sample, a classification or regression tree is grown which chooses the best splits among predictors. The predicted biomass was validated with 30% of the inventory data and evaluated with the coefficient of determination (R^2) and root mean square error (RMSE). The correlation coefficient and coefficient of determination were used to determine the effects of spectral, textural and environmental variables on the aboveground biomass of the study areas.

Table 3-0-1. Spectral and textural properties developed from image segmentation algorithm in eCognition Developer. The environmental variables are used as predictors in the modelling of AGB with random forests.

Spectral	Textural	Environmental variables
Green	GLCM homogeneity	Precipitation
blue	GLCM contrast	Temperature
red	GLCM entropy	Elevation
near-infrared	GLCM mean	Slope
	GLCM standard deviation	
	GLDV correlation	
	GLDV angular	
	GLDV entropy	

3.4 Results

The mean aboveground biomass estimated from the forest inventory was 403.7 t /ha. Cross-validation with thirty per cent of the inventory data gave a coefficient of determination (R^2=0.7484) and root mean square error (RMSE) of 179 t/ha or 44.75%. Detail results in table 3-2 show the estimated aboveground biomass from inventory plots and the predicted AGB. Correlation coefficients were explored to determine the relationship between aboveground biomass and QuickBird spectral and texture features. The texture features correlated significantly with AGB. Also, the NIR and Red bands significantly correlated with AGB.

Table 3-0-2. Aboveground biomass showing mean field estimated and the predicted for combined study sites.

Aboveground biomass	Minimum	Mean	Maximum
Estimated values	110.5	403.7	994.6
Predicted values	101.2	310.3	800.0
RMSE		179	
RMSE%		44.75	
R^2		0.7484	

Note. showing mean field estimated and the predicted for combined study sites, AGB estimates in t/ha

Figure 3-4. Aboveground biomass model validation

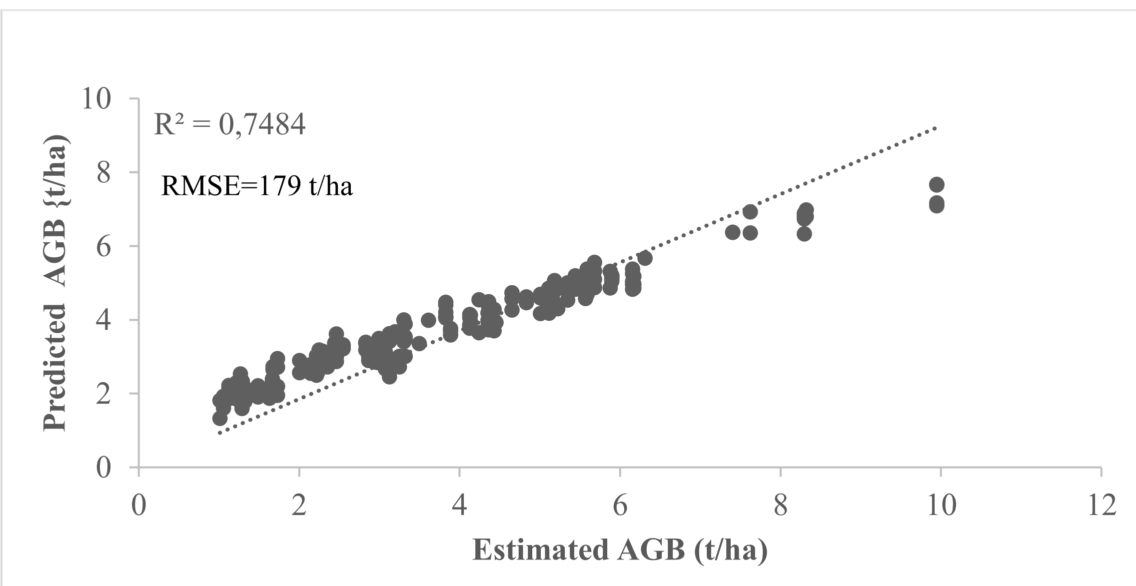


Table 3-0-3. Correlation coefficients of metrics derived from QuickBird image

		r	R^2
Textural values	GLCM homogeneity	0.56	0.31
	GLCM contrast	0.64	0.41
	GLCM entropy	0.75	0.56
	GLCM mean	0.45	0.21
	GLCM standard deviation	0.32	0.10
	GLDV correlation	0.62	0.38
	GLDV angular	0.69	0.48
	GLDV entropy	0.46	0.21
Spectral values	blue	0.10	0.01
	green	0.15	0.02
	red	0.62	0.34
	near-infrared	0.65	0.43
Environmental variables	precipitation	0.20	0.04
	temperature	0.43	0.19
	elevation	0.78	0.61
	slope	0.66	0.44

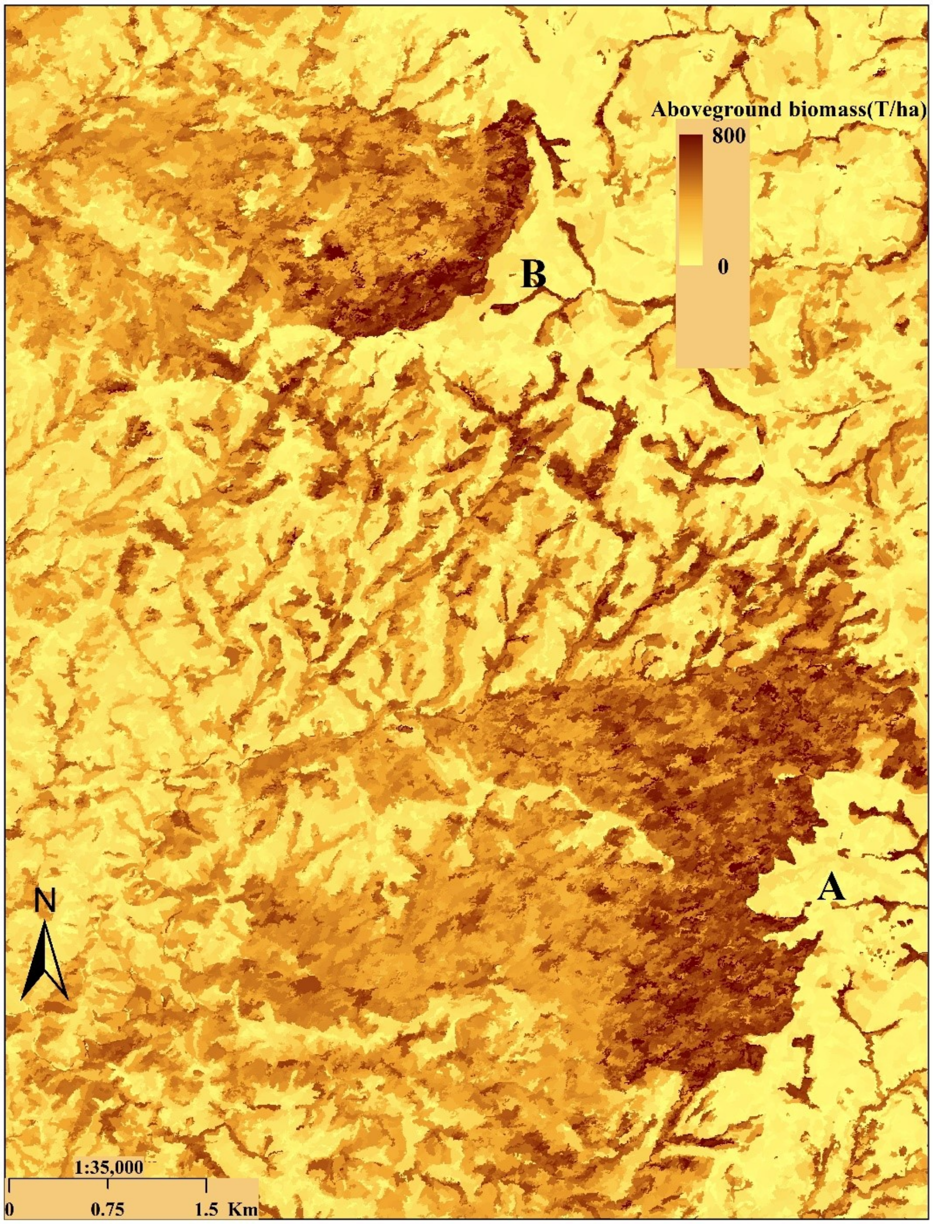
3.5 Discussions

The major objective of this study was to model the aboveground biomass of the Afromontane forest using a combination of satellite data, field inventory and environmental variables. Model-based on spectral, textural features and environmental variables was developed to estimate the aboveground biomass of two Afromontane forest sites. The textural features from QuickBird correlated with aboveground biomass. Texture features from high-resolution images are known to capture and provide information on the structural and geometric properties of forest canopies and can be used to discriminate textures between tree species thereby enhancing aboveground biomass estimate [92,98].

When the aboveground biomass correlates with forest canopy structure, it also correlates with the spectral parameters [92]. Both red and near-infrared bands correlated with the biomass of the study area. Also, elevation and slope had a significant effect on the aboveground biomass distribution. The elevation of the study areas ranges between 1250 to 1750 meters above sea level, while the recorded slope was between 4 to 35 degrees. Marshal et al[99] reported a high AGB turnover with a decreasing elevation and a high AGB with shallow slopes. The forest vegetation of the area is restricted to the south-west facing slope with frequent mist on the forest crown almost year round. The restriction of the forests to the south west escapement enables the tree canopies to intercept highly humid wind thereby acting as a water catchment. Modelling AGB with *in situ* forest inventory data and group features derived from QuickBird produced a high-resolution aboveground biomass map of the study areas (Fig. 3-5).

This result was compared with other biomass data from the region and was found to be higher than previously reported values by Baccini et al. and IPCC[13,100]. Above ground, biomass estimated by Baccini et al. and IPCC[13,100] were regionally based, and the data used were not site-specific.

Figure 3-5. Aboveground biomass map of Ngel Nyaki (A) and Kurmi Ndanko (B)



While the data used by IPCC [13,100] cannot be verified, the aboveground biomass estimation by Baccini et al [24] was based on diameter at breast height (DBH) and MODIS satellite data.

The mean aboveground biomass estimated from forest inventory reported by IPCC[13] was 435 t/ha, which was slightly higher than the 410 t/ha estimated from the field inventory of this study. This study implies that the Afromontane forest of Nigeria has a larger pool of forest biomass than previously indicated by data from regional studies.

3.6 Conclusion

The main goal of this research was to produce a high-resolution biomass map of the Afromontane forests of the Mambilla Plateau with QuickBird and forest inventory. The map produced was a local scale map with aboveground biomass values consistent with the area of study. The predicted AGB for the study area was found to be within the range of similar studies for the region. The study also demonstrated the importance of textural features in enhancing biomass estimation of an Afromontane forest ecosystem. GLCM features provided structural information which improved the accuracies of predicted biomass. Modelling with spectra texture and topographical features with *in situ* forest data and slope derived from DEM was found effective in modelling the aboveground biomass of the Afromontane forests of Mambilla. This model is transferable to other montane forest with similar biophysical factors.

Chapter 4.

Modelling tree species diversities of the Afromontane forest ecosystem with satellite remote sensing and macro-ecological data.

4.1 Introduction

Montane forests situated in the afro tropical region (henceforth referred to as "Afromontane forests") are on the list of the world's most threatened ecosystems. These ecosystems are highly diverse and adjudged as repositories of genetic diversities. Information on the biodiversity of such an important area is a prerequisite for effective conservation and management strategy [101]. Ecologists have relied on the traditional method of field survey to quantify the biodiversity of large areas, which often is time-consuming, costly and dependent on expert knowledge [101,102]. This has led to the conclusion that field measurements represent estimates rather than absolutes. Information on landscape biodiversity can be optimized through the use of ecological proxies[102]. Plant species richness is widely adopted as an ecological proxy for the determination of biodiversity and is often correlated with diversity at other levels of organization, such as genetic diversity and ecosystem functioning [44]. Plant species constitute the primary components of terrestrial ecosystems and can be used as a surrogate for ecosystem biological diversity. Thus, plant/ species richness defines ecosystem structures and functions, and is, therefore, a central component of biodiversity assessment [45].

Species diversities do not occur in isolation, rather diversities can be directly linked with their environment heterogeneity. Habitat heterogeneity is a determinant of species diversities both at local, regional and global scales [103]. Ecologists have subscribed to the theory of the existence of a linear relationship between diversity and environmental gradients. Afromontane forests are located across a broad range of landscapes with various abiotic factors influencing plant diversities and productivity [104]. For instance, macro-ecological factors such as slope, elevation, aspects and solar radiation are known to affect the distribution of insolation in the terrain[105]. Theses also have effects on the ecosystem microclimate (soil moisture and nutrients), thereby impacting resource gradients for plants.

Understanding the relationship between species richness and habitat heterogeneity is therefore crucial to habitat conservation [106]. A new frontier of obtaining information on biological diversity using remote sensing is the application of the Spectral Variation Hypothesis (SVH) proposed by Palmer [102]. SVH infers that the spectral heterogeneity of a remotely sensed image can be correlated with habitat heterogeneity[48]. Therefore SVH represents a potential tool for predicting plant species diversities at local, regional and global scales with satellite remote sensing [107].

Optical satellite images provide the bulk of satellite images used in the application of the Spectral Variation Hypothesis for modelling species diversities. The debate on the efficiency of high and medium-resolution images for modelling species diversities has been ongoing for a sometimes. High-resolution sensors have greater potential for mapping vegetation diversity and distributions owing to the pixel sizes which correspond with individual tree crowns. The major demerit of high-resolution data sets for tree species mapping is the potential for an increase in pixel variability. This is often the case in mountainous regions, where a pixel may cover the crown area with sunshine and shadow at the same time. The Spectral Variation Hypothesis has been fully tested on vascular plants using high-resolution images such as Ikonos and QuickBird [103,107,108,109,110].

The medium resolution images such as Landsat have a greater number of bands and can record additional information in the middle infra-red range of critical plant properties including leaf pigments, water content and chemical composition and can be useful for discriminating tree species [49]. The major limitation of the medium-resolution sensors has been that of insufficient spatial resolution. A single pixel of the medium sensor may cover several plants of different species, thus each pixel often corresponds to a mixed signature of different objects, leading to difficulties in species identification [49]. Despite these limitations, studies using medium-resolution sensors have been moderately successful for both temperate and tropical ecosystems [101,111].

The majority of research on species/ spectral diversity modelling with satellite remote sensing has been dedicated to the relationship between spectral entropy and local species diversity [112]. Analysis of habitat and spectral heterogeneity for species diversity studies requires an analytical technique with information beyond the spectral variability of both the high and medium-resolution images. A recent approach to the Spectral Variation Hypothesis is now focused on the use of textural variables and vegetation indices computed with the object-based image analysis technique [113]. This method has the dual advantages of the use of both spectral and textural features to discriminate and determine species diversity. Also in object-based image analysis, the field plot is linked to an object rather than a pixel hence the geometric inaccuracies in both field and image data are of less importance[114]. The object features often related to SVA are the second-order statistics after Haralick[96,115]. The second-order statistics is the Gray Level Concurrence Matrix (GLCM). The Gray Level Co-occurrence Matrix (GLCM) is the second-order texture feature after Haralick [96]. GLCM features provide information on the structural and geometric properties of forest canopies and can be used to discriminate textures between tree species [94].

There are arrays of literature suggesting the advantages of object-based image analysis over pixel-based analysis in land cover classifications [66,71,116,117]; biomass estimations [91,93,118]; and species diversity/ecological modelling [110,119,120]. Satellite remote sensing has been used for mapping and modelling species distribution in arrays of ecosystems ranging from temperate [45,102,107,108] and tropical [101,121], but none of the studies has focused on the subtropical Afromontane ecosystem. This research is aimed at modelling the structural diversity of the Afromontane forest ecosystem using high-resolution QuickBird and medium-resolution Landsat 8 satellite images combined with macro-ecological data. The objectives of this study are to: 1) Determine the relationship between sensor spatial/spectral resolution and species diversity using high-resolution QuickBird and medium-resolution Landsat 8 images. 2) Determine the relationship between species richness and satellite image spectral, textural and vegetation indices, and, 3) determine the effects of macro-ecological parameters on the Afromontane tree species diversity.

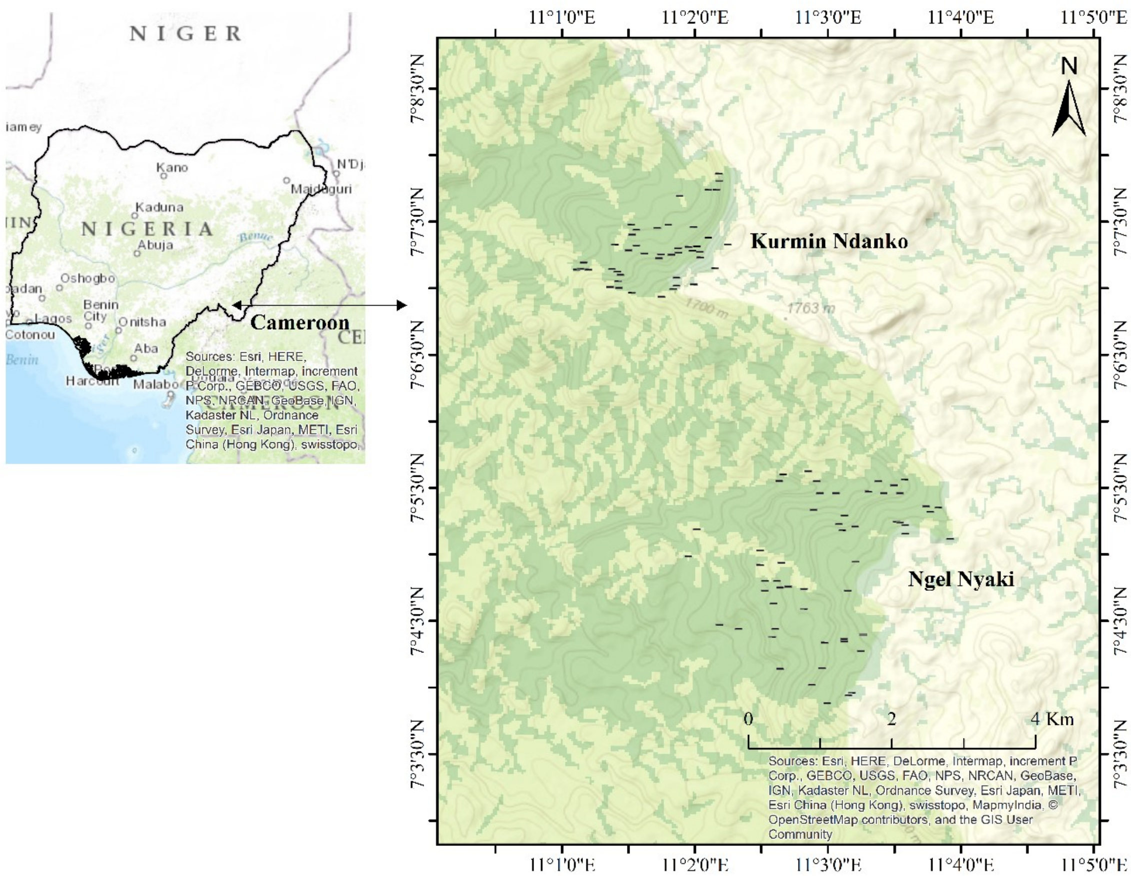
4.2 Study area

The study was carried out in the highlands of North East Nigeria, along the Nigerian/Cameroon border (Fig 1). These highlands are part of the Cameroon volcanic chain of mountains ranging from mount Oku in the north of Cameroon to Bioko in the south. These highlands are primarily grassland with patches of forest restricted to slopes where they are protected from fire and grazing or along stream sides where there is moisture and again some protection from fire [122,123]. The study concentrated on two main areas, the Ngel Nyaki forest (Longitude 07° 20' N and Latitude 11° 43' E) and the Kurmin Ndanko (Longitude 07° 03' N and Latitude 11° 70' E). The altitude of the study sites varied from 1250 m to 1750 m above sea level.

The forests are representative of sub-montane moist broadleaf (Terrestrial Ecoregion, WWF) and are highly diverse in both fauna and flora [124]. Afromontane endemic tree species [5], Cameroon highland endemics and possible local endemics are found in the forests of the study area. The forests are also rich in mammal species, especially primates including the Nigerian-

Cameroon Chimpanzee (*Pan troglodytes ellioti),* noted as the most endangered subspecies of chimpanzee in Africa [125]. There are two distinct seasons, a dry season when there is little or no rain of approximately 6 months and a wet season when it can rain almost every day. The rainy season usually commences from early April until late October[126] with a mean annual rainfall of 1780 mm in the Ngel Nyaki and Kurmin Ndanko. The temperature of the study area rarely exceeds 30°C [126].

Figure 4-1. Showing plot layout along macro-ecological gradients in Ngel Nyaki and Kurmi Ndanko forest.



4.3 Materials and methods

The approach described below aims to determine tree species richness using features from QuickBird and Landsat 8 satellite images (textural, spectral and vegetation indices). Also included as explanatory variables were slope, elevation, annual solar irradiance, temperature and annual precipitation). All the procedures are described in detail in Figure 4-8.

4.3.1 Plot inventory/ alpha diversity study

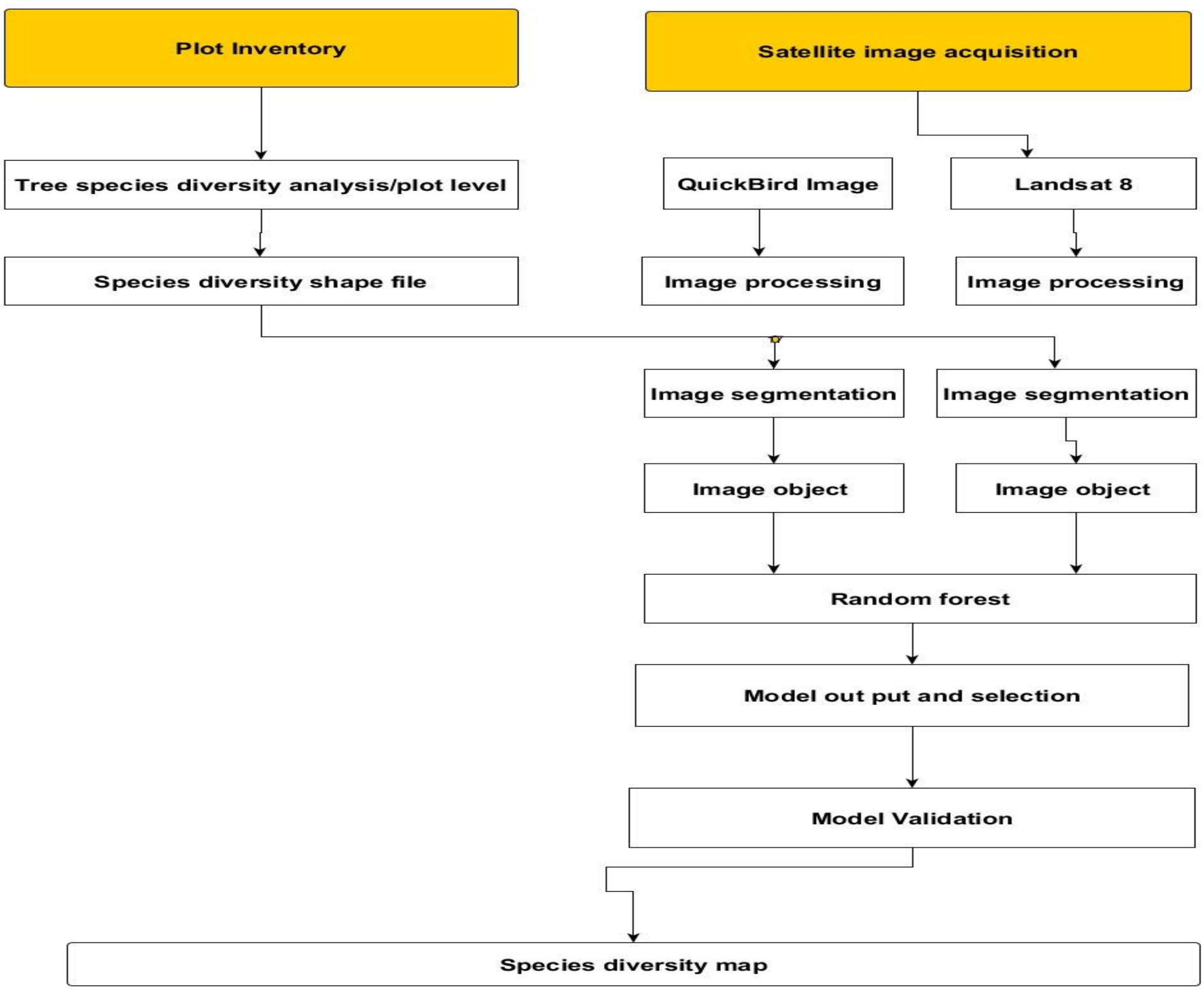
Afromontane tree species inventory data were collected using the modified Gentry plots [127]. Plots were established using randomized co-ordinates stratified by elevation (1250 m– 1750 m above sea level). Within the modified Gentry plots, all living trees with a diameter at breast height (dbh) $\geq$ 10 cm were identified and recorded using Trees of Nigeria [128], The Forests of Taraba and Adamawa States, Nigeria-An Ecological Accounts and Species Checklist [123] and local knowledge of the trees. A total of One hundred and six plots were established in the two sites. Tree species richness by plot was assessed with the Simpson's diversity indices as a measure of alpha(α) diversity index[129,130].

4.3.2 Satellite images and macro-ecological data acquisition and processing

QuickBird satellite image of the study area was acquired at the onset of the field campaign in January 2011, while Landsat 8 (OLI) satellite images were acquired in March 2014. Both images were atmospherically corrected and geo-referenced to the Universal Transverse Mercator Projection (WGS 84). Elevation, slope and solar radiation study area were extracted from the 30m ASTER Global Digital Elevation Model using the Spatial Analyst and Topography toolbox in ArcGIS 10.2.2. Precipitation and temperature data were obtained from the CHELSA- World Data Centre for Climate [131].

Within each of the 106 plots, the alpha diversity (species richness), the mean spectral bands of QuickBird and Landsat 8, slope-based vegetation indices, textural features consisting of the Gray Level Co-occurrence matrix (GLCM) and macro-ecological features (Elevation, slope, Mean Solar radiation/annum, temperature and precipitation) were extracted using the chessboard segmentation algorithm in the Trimble Developer software (eCognition 9.0.3).

Figure 4-2. Diagrammatic scheme of methods and process for species diversity study



The GLCM properties used are as follows; homogeneity, contrast, dissimilarity, entropy, angular second moment, mean, standard deviation, and correlation. All of the textures measured were computed for each layer and the five different directions; namely 0º, 45 º, 90 º, 135 º, and all directions. The afore-mentioned features and thematic layers with information containing specie richness were exported as a shape file from the eCognition environment and used in the random forest algorithm to model Afromontane tree species richness.

4.3.3 Statistical analysis

The relationship between spectral, textural and vegetation indices of Quick Bird and Landsat 8 satellite images and species diversity (≥10 cm diameter at breast height) were explored using multiple regressing analyses with the random forest algorithm. An independent data set was used to test the predicted model using linear regression. In other to explore the relationship between tree species diversity and spectral, textural and vegetation indices. Pearson correlation coefficient was computed as a measure of the relationship. The closer the coefficient is to one, the stronger the relationship.

4.4 Results

The model output from the random forest algorithm was validated and evaluated with the coefficient of determination. The coefficient of determination derived from validating modelled species heterogeneity and field-based species richness was statistically significant for QuickBird, r^2=0.77 and Landsat 8, r^2=0.47. (Figure 4-3,4-4). The correlation coefficient for the relationship between species diversity image features (spectral, textural and vegetation indices) and macro-ecological features ranged between 0.1 and 0.8 (Table 4-1A, and 4-1B).

Table 4-1. correlation coefficient between tree species diversity and macro ecological variables

Macro-ecological features	R
elevation	0.55
slope	0.46
temperature	0.12
precipitation	0.13

Figure 4-3. Landsat 8 species distribution model

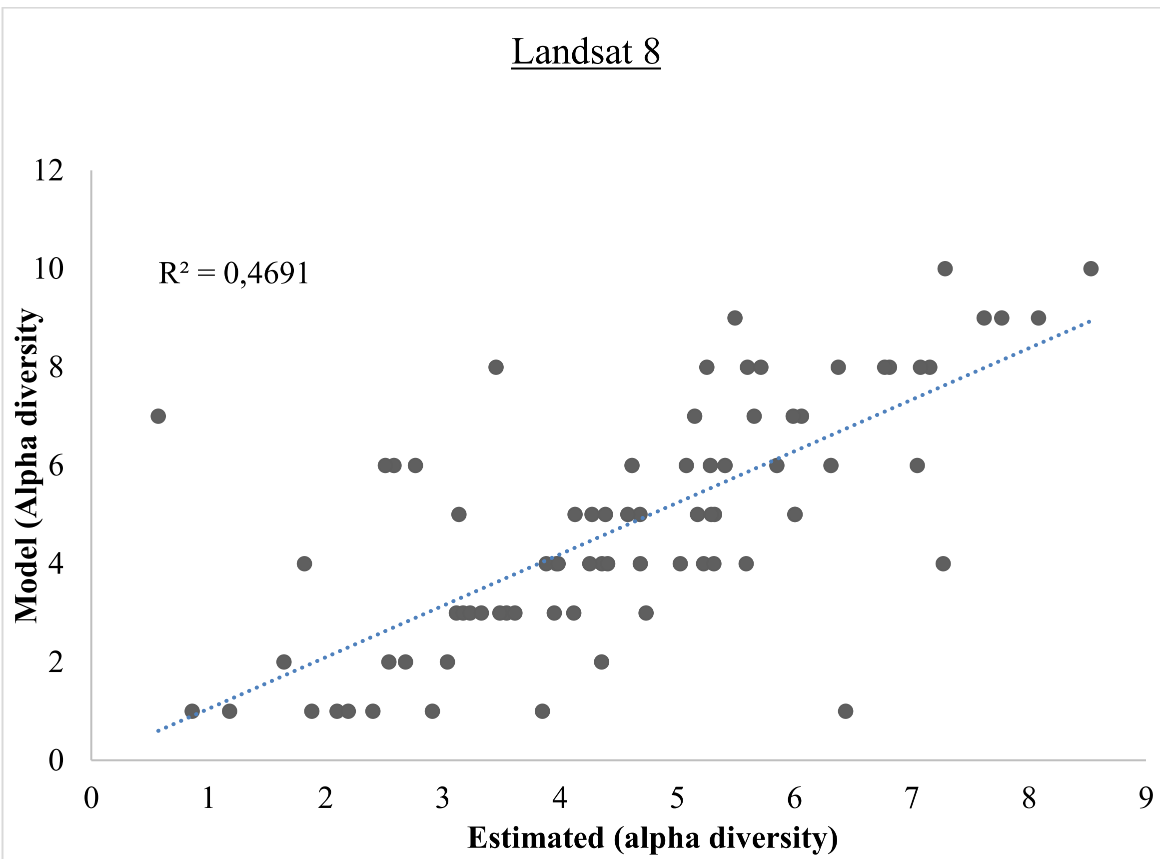


Figure 4-4. QuickBird species distribution model

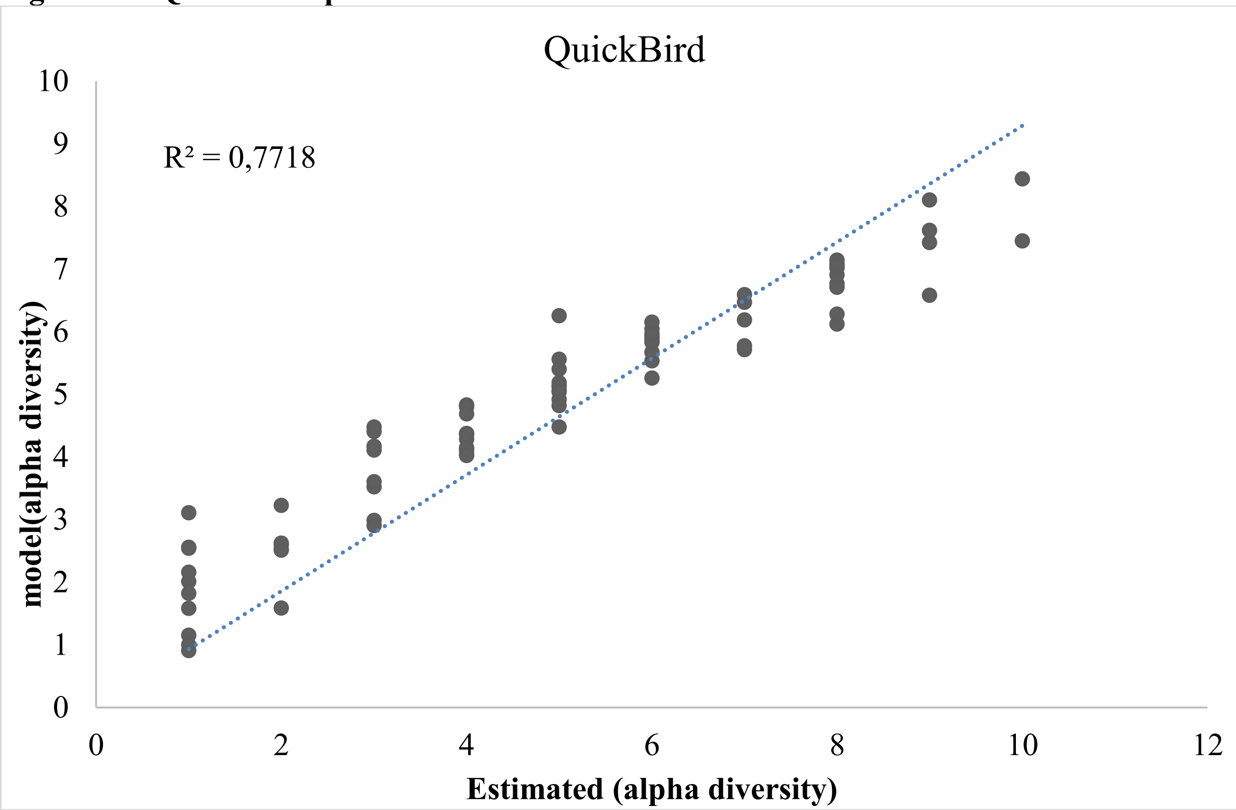


Table 4-2. Correlation coefficient between spectral bands, vegetation indices, texture and species richness

	Landsat	QuickBird
Spectral Bands		
Blue	0.3	0.5
Green	0.2	0.1
Red	0.5	0.3
NIR	0.41	0.52
Vegetation Indices		
DVI	0.04	0.13
GDVI	0.32	0.11
GNDVI	0.3	0.20
NDVI	0.1	0.30
NG	0.31	0.13
NNIR	0.04	0.23
RVI	0.1	0.25
GRVI	0.28	0.16
NR	0.20	0.31
Texture		
GLCM	0.3	0.45

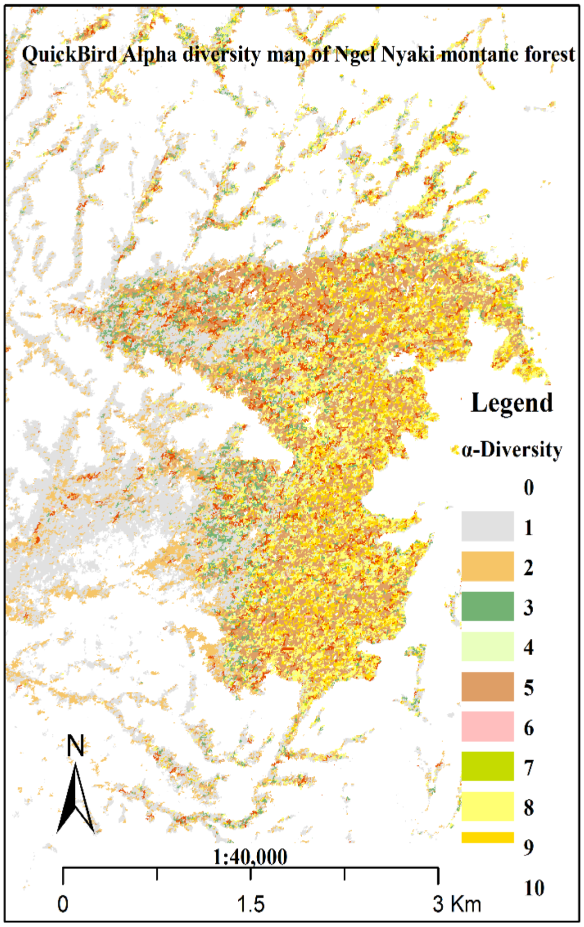
4.5 Discussions

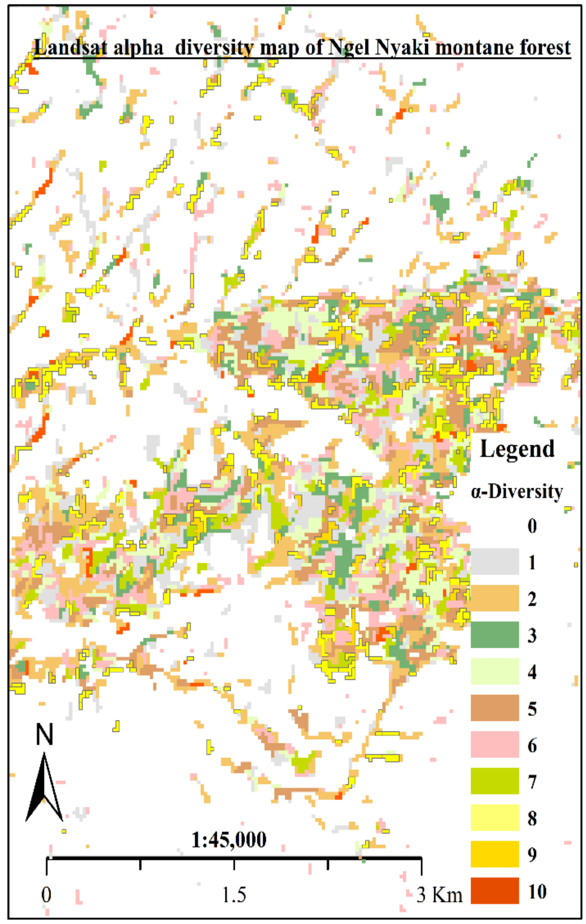
Both QuickBird and Landsat 8 satellite images correlate with the species richness of the Afromontane forest ecosystem. The species heterogeneity maps showed a pattern of tree distributions in the study area with the lowest heterogeneity range of 0, belonging to the grass and ≥1 to ≥10 belonging to the ecosystem ranging from savanna to high forest ecosystem (Figure 4-5 and Figure 4-6). The QuickBird satellite image (with a spatial resolution of 2.4 m) showed a propensity for distinctive mapping of individual objects due to its high spatial resolution as opposed to Landsat 8 which had a medium (30 meter) spatial resolution. High-resolution images such as those used in this study are potentially suited for tree species diversity mapping owing to the suitability of the pixel size corresponding to tree individual tree crowns[107].

The NIR band of the two satellite images correlated with species diversity. The Near Infra-red band (NIR) is generally known to correlate with vegetation and is adjudged to be the most important spectral band for mapping and modelling vegetation properties [46]. Similar studies on the use of spectral heterogeneity to determine species diversity corroborated these findings. For instance, a study using QuickBird spectral heterogeneity found that the NIR band was linearly related to species richness ($r=0.48$) [107]. The slope-based vegetation indices are widely used as an indicator of green vegetation and biomass abundance[132]. The NDVI of both satellite images strongly correlated with species diversity.

It has been observed that using spectral and texture information as a proxy for estimating species diversity without including additional multiscale drivers such as climate, topography and other abiotic interactions may lead to inaccuracy [44]. Two of the three macro ecological factors strongly correlated with tree species diversity (slope, and altitude). The slope of the terrain and the

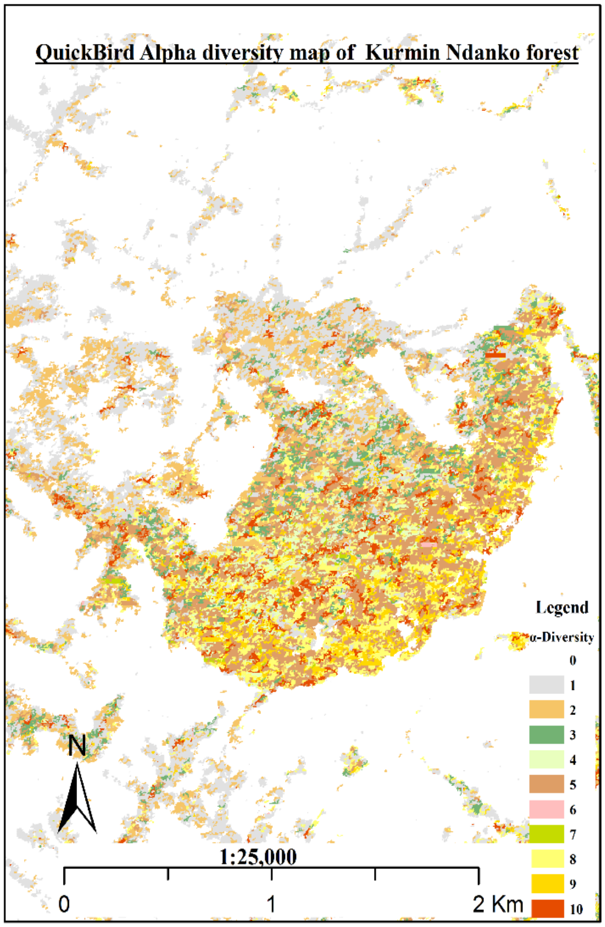
Figure 4-4. Alpha diversity map of Ngel Nyaki montane forest from QuickBird(left) and Landsat 8(right).

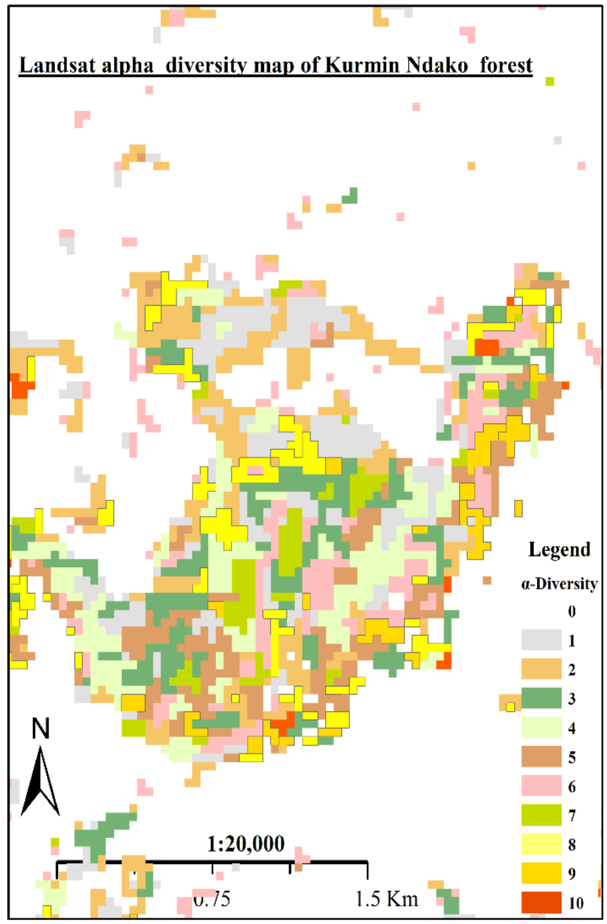




the direction which it faces has been observed to have multiple effects on montane species diversities [99,133]. These factors have been found to have a linear relationship with vegetation attributes such as species richness and diversities [134]. Species distributions and richness patterns are also known to be regulated by altitude, slope and aspects [135]. A similar field survey confirmed that areas with high escarpment in and around the forest core were rich in tree species. Similar to that was the observation of a decrease in tree species richness along altitudinal gradients. Plant species diversities have been observed to decrease with increasing elevation in tropical montane forests [113,136,137].

Figure 4-5. Alpha diversity map of Kurmi Ndanko montane forest from QuickBird (left) and Landsat 8 (right)





Heterogeneous landscapes such as the study area are reservoirs of genetic diversities due to the complex interaction of the various micro and macroecological factors. Aspects and slope are relevant to the existence of high tree diversity in the study area. Dense canopy and high tree species diversities were restricted to areas with high slopes and escarpments. While Savannah and grassland of the study areas are in locations with low escarpments as shown in the map. This is an indication of current anthropogenic activities in the area. Anthropogenic activities occasioned by forest fires are limited to flat land and drier land surfaces, while the steep slope occasioned by wet soils and close canopies restricts the entry of fire into the forest.

The importance of remote sensing in tropical species diversity mapping has been emphasized through numerous research and has often been limited to the use of the spectral band and vegetation indices for tree species discrimination and mapping. However, the advantages of tree species mapping through pixel segmentation combined with satellite image spectral features and vegetation indices in object-based image analysis are being deduced herein. In mountainous vegetation, the possibility of hill side shadow covering a forest area is well-known and documented. The image segmentation algorithm played a significant role in canopy cover mapping and discrimination of forests covered by a shadow by adjourning hills from other Ecozones.

Remote sensing has the potential to shape the next generation of species distribution models when fully exploited with biotic and abiotic variables[112]. The theoretical approach of this model is that species richness can be spatially represented in biodiversity hotspots. The inclusion of macro ecological parameters with satellite remote sensing for modelling Afromontane tree species diversity is an indication of the importance of the macro ecological variables in the species distribution of the study area. Species distribution modelling can be used as habitat mapping for endemic species such as the Nigerian-Cameroon Chimpanzee (*Pan troglodytes ellioti)* and other species known to be present in the two study sites. However, it is worth noting that remote sensing still has the limitation of mapping individual tree species, especially in a tropical ecosystem with layers of species within a few meters.

4.5 Conclusion.

Plant species richness is often used as an indicator of ecosystem diversity and health [103]. The study has demonstrated the use of remote sensing spectral and textural heterogeneity for the spatial modelling of Afromontane hotspots. Both QuickBird and Landsat 8 images positively correlated with tree species diversity. However, detailed object features were captured by the higher resolution image than the medium resolution. The medium-resolution image had mixed pixel effects and hence was less sensitive to spatial complexity[108] of the Afromontane forest ecosystem. The combination of textural and spectral features of both satellite images improved the ability of the images to discriminate and predict tree species richness. The study also revealed the influence of macro-ecological data on the Afromontane tree species distribution. The empirical models developed can be used to predict landscape-level species heterogeneity in the Afromontane forest of Nigeria and the adjourning Cameron highland.

Chapter 5.

A multi-source change detection approach for the Afromontane and escarpments of north eastern Nigeria with Landsat and MODIS satellite

5.1 Introduction

The Afromontane forests of Nigeria belong to the ecoregion referred to as the Biafran forests and highlands (BFH), which is part of the West African forest biodiversity hotspot. The ecoregion is recognised for its unique biological and ecological diversity [138,139] and thus acts as a reservoir of genetic diversities. The BFH ecoregion has the highest mean annual rainfall and is known to contain the largest block of contiguous forest in West Africa. The Afromontane ecosystems in Nigeria are situated on a chain of volcanic highlands extending from the North West of Cameroon to the Gulf of Guinea [138] with altitudes ranging from 600-2430 m above sea level.

The ecosystem exhibits a high level of species richness and endemism that transverse many taxa such as vascular Plants, Primates, Amphibians, and Birds. The forests are also rich in mammal species, especially primates, including the Nigerian-Cameroon chimpanzee *Pan troglodytes elliοti,* noted as the most endangered subspecies of chimpanzee in Africa [125,140]. Several Afro-Palearctic bird species and IUCN-listed endemic bird species have been sighted in the study areas, resulting in them being designated as important bird areas (IBA) by BirdLife International. This highly rich ecosystem has been undergoing severe anthropogenic deforestation [122,123] and requires urgent mitigations.

Mitigating the effects of deforestation requires an understanding of the causes of deforestation and its location. Satellite remote sensing provides an efficient and cost-effective source of conducting, evaluating and monitoring deforestation through change detection studies [141]. Change detection studies can be classified into three broad categories; pixel, object and hybrid-based change detection techniques [57]. The pixel change detection methods are based on per-pixel classifiers and change information contained in the spectral-radiometric domain of the satellite images, and they exclude textural and topological information [57,58].

Pixel-based classification methods use spectral information contained in individual pixels to generate land cover classes. This method has been known to perform accurately for the classification of certain land use/cover classes [59,60,61,62,63,64]. The major disadvantages of the pixel-based method are the "salt and pepper effects"[67]. The salt and pepper effects are due to the intrinsic characteristics of the land cover elements (spectral heterogeneity) and the random variation of the sensor's response which often lead to misclassifications [67].

Object-based analysis (OBIA) is a robust method suitable for the classification of medium to high-resolution satellite imagery. In object-based techniques, contextual information such as texture, geometry and compactness are combined with spectral information of the satellite image for change detection analysis [68,69]. The main objective of the OBIA is to improve image classification through full exploitation of salient information within the satellite image for change detection analysis. The salient information includes texture, shape, and their spatial relations with neighbouring objects [57]. Object-based change detection has been largely successful and more promising in improving change detection studies [70]. Recent studies have shown improved performance and accuracy of the object-based change detection techniques over the contemporary pixel-based techniques [64,69,71,72,73].

The hybrid change detection technique is the integration of change detection methods [70]. It uses two or more techniques for analysis. The major advantage of this technique is the potential of two or more appropriate change detection algorithms to solve research problems within a particular study area. There is numerous example of hybrid change detection methods. For example, Aguirre-Gutierrez *et al* [68] improved the change detection accuracies in a mountainous area of Mexico using the hybrid change detection approach.

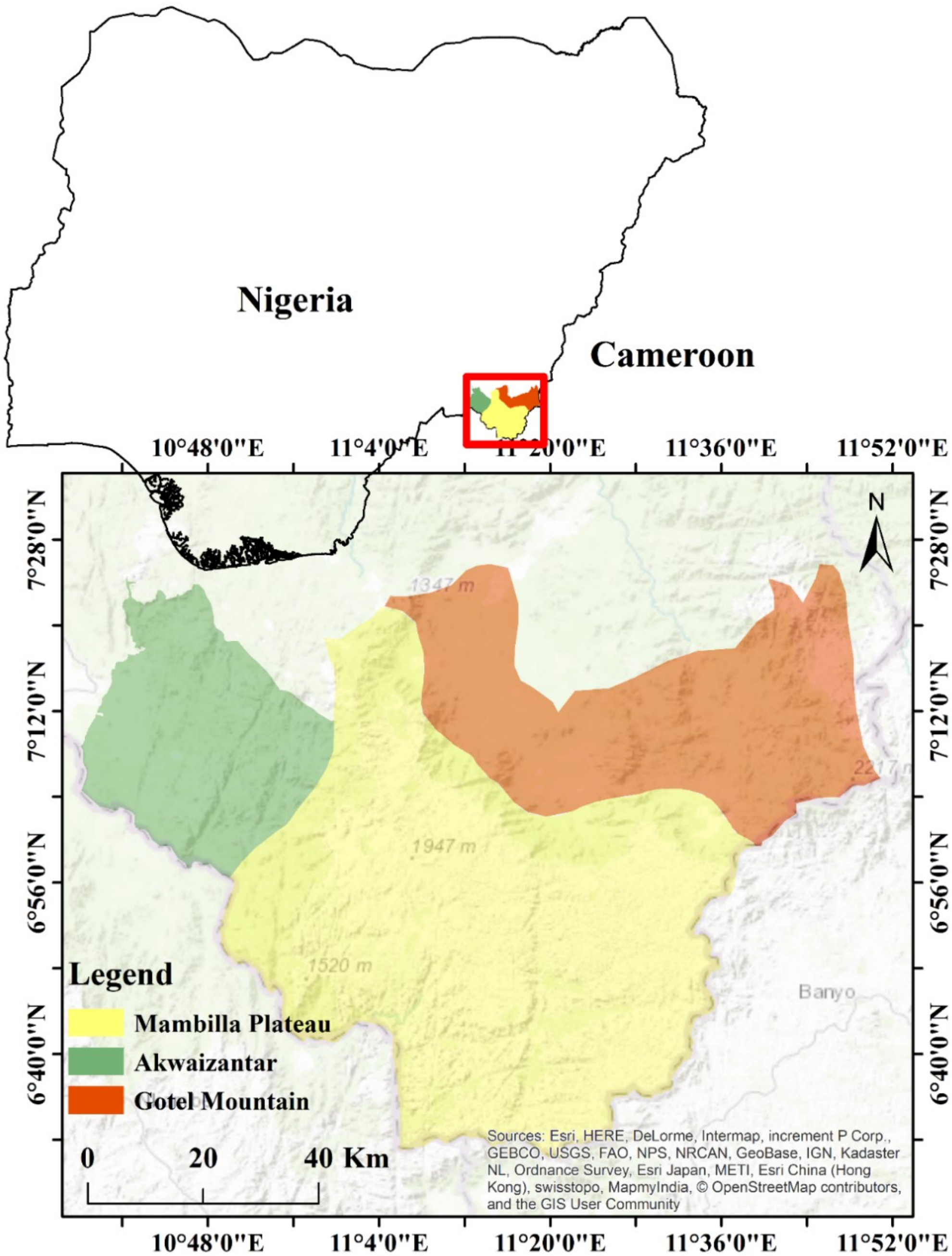
It has been suggested that no single change detection technique can be applied with equal success across different ecosystems [70]. Successful land cover change analysis is dependent on the study objectives and the nature of the landscape chosen for change detection analysis. The Afromontane forest is a heterogeneous ecosystem with a rugged and complicated biophysical landscape which requires a synergy of change detection methods and the use of a multi-source change detection approach for the change detection analysis of the ecosystem. This chapter therefore presents a hybrid change detection assessment of the Afromontane Forest ecosystem with the object-based image Analysis (OBIA) and the Breaks for Additive Seasonal and Trend (BFAST) algorithm. The study aimed to quantify the deforestation rates between the years 1988 and 2014 using decadal Landsat images. The study also evaluated the effectiveness of using MODIS Enhanced Vegetation indices (EVI) to determine the inter-annual time series changes in the study area.

5.2 Study area

The study was conducted in the highlands of North East of Nigeria, along the Nigerian-Cameroon border (Longitude 07^{o} $20^{'}$ N and Latitude 11^{o} $43^{'}$ E). These highlands are part of the Cameroon volcanic chain of mountains ranging from Mount Oku in the north of Cameroon to Bioko in the south. The study area encompasses three contiguous montane forest areas with altitudes ranging from 600 m to 2400 m above sea level. The montane forest areas are as follows: The Mambilla Plateau ($\geq$ 1750 m), the Gotel Mountains ($\leq$ 2400 m) and the escarpment forest of Akwaizantar ($\geq$ 600m $\leq$ 1170 m).

There are two distinct seasons, a dry season when there is little or no rain for approximately 6 months and a wet season when it can rain almost every day. The rainy season usually commences from early April until late October with mean annual rainfall of 1780 mm on the Mambilla Plateau but higher in the Gotel mountains. The temperature in the study area rarely exceeds 30°C in the dry season but has lower temperatures of 9-12 °C in late November to early January [142].

Figure 5-1. Map of the study area


Nigeria
Cameroon
10°48'0"E
11°4'0"E
11°20'0"E
11°36'0"E
11°52'0"E
7°28'0"N
7°12'0"N
6°56'0"N
6°40'0"N
N
1347 m
1947 m
1520 m
2217 m
Banyo
Legend
Mambilla Plateau
Akwaizantar
Gotel Mountain
0 20 40 Km
Sources: Esri, HERE, DeLorme, Intermap, increment P Corp., GEBCO, USGS, FAO, NPS, NRCAN, GeoBase, IGN, Kadaster NL, Ordnance Survey, Esri Japan, METI, Esri China (Hong Kong), swisstopo, MapmyIndia, © OpenStreetMap contributors, and the GIS User Community

5.3 Material and Methods

The hybrid change detection method was adopted for this study. The method proposed here for the Afromontane deforestation mapping is as follows: A) the object-based change detection with Landsat Images and B) the pixel-based BFAST algorithm with MODIS images.

5.3.1 Image acquisition and pre-processing

Three cloud-free multispectral Landsat images were acquired from the archive sites of the United States Geological Services. The acquisition dates coincide with the dry season and relatively cloud-free period in the area. The images acquired included, the Landsat Thematic mapper scene of February 2nd, 1988, Landsat Enhanced Thematic Mapper of November 6th, 2001 and February 16th, 2014 (Table 5-1). Each acquired scene was georeferenced, atmospherically corrected and spatially subset to the study area.

Table 5-1. Landsat data for the study area

Path /row scene	data	date	cloud cover
186/55	Landsat ETM	02-02-88	0 %
186/55	Landsat TM	06-11-01	0 %
186/55	Landsat-8	16-02-14	0 %

5.3.2 Forest change detection with the object-based image analysis

Object-based image analysis (OBIA) was adopted for the Afromontane forest change detection. The first step in OBIA is the segmentation of the image into image object primitives. The Definiens developer software (eCognition 9.03) was used for the image segmentation procedure. The segmentation algorithm is controlled by user-defined parameters such as scale, shape and compactness [71]. Image segmentation was performed using the multiresolution algorithm with three parameters (compactness, spectral and scale). Values assigned to the segmentation parameters are as follows: scale 5, shape 0.2 and compactness 0.2; a weight of 2 for the infrared layer, while the visible layers weighted 1.

The segmentation provided image primitives which serve as information carriers and building blocks for the classification processes. An automated object-based classification was developed to separate the forest from non-forest areas with the use of additional slope-based vegetation indices: the simple ratio index [143]. The simple ratio index (SRI) is a combination of reflectance measurements that are sensitive to chlorophyll concentration and canopy architecture. The SRI describes the vigour and health of green vegetation and is measured as the ratio of light that is scattered in the near infra-red (NIR) range to that which is absorbed in the red range [143,144].

$$SRI = NIR/RED \quad (1)$$

5.3.3 Accuracy assessment and deforestation statistics.

Accuracy assessment for the classified maps was determined using protocols proposed by Olofsson et al and Card[145,146,147]. A stratified random sampling method was used for reference data collection across the study area. The sampling framework consists of apportioning random sampling points based on the area proportion of the classified map. For the change map c. 1988-2001, random sampling points were apportioned as follows: 135 for the forest class, 401 for the non-forest class, 180 for the forest loss (deforestation) class and 50 for the forest increase class. Random sampling points were distributed for the change detection map c 2001-2014 as follows; 135 for the forest class, 401 for the non-forest class, 180 for the forest loss (deforestation) class and 50 for the forest increase class. The accuracy assessment samples for the change detection statistics were derived from visual interpretation of Landsat images high-resolution images from Google Earth and GPS positions obtained from field surveys.

The change detection statistics included accuracy assessment (producer's and user's accuracies), the proportion of the mapped area of each class, deforestation rates and error matrix, adjustment of the original map areas and 95% confidence intervals of each map category and scene were also calculated. The annual deforestation rates were determined using the Food Agriculture Organisation's deforestation rate formula [148]. The annual deforestation rate (q) was calculated based on two change intervals of 13 years each, (c. 1988–c. 2001) and (c. 2001–c.2014).

$$\left[q = \left(\left(\frac{A_2}{A_1}\right)^{1/(t2-t1)} - 1)\right)\right] \qquad (2)$$

Where $\mathbf{A_1}$ and $\mathbf{A_2}$ are the forest cover at times and $\mathbf{t_2}$

5.3.4 Temporal change detection with MODIS EVI in Earth Observation Monitor toolset.

Phenology change detection using time series MODIS data from 2000 to 2014 was carried out with the Earth Observation Monitor toolset. The Earth Observation Monitor (http://www.earth-observation-monitor.net/map.php) is a web-based service for vegetation monitoring using spatial time series data based on TERRA/AQUA MODIS imagery. The EOM toolset in an integration of the Breaks For Additive Seasonal and Trend (BFAST) algorithm. The BFAST package provides analytical tools for breakpoint detection and derivation of phenology metrics

(Phenometrics) for vegetation characterization and classification through satellite time-series. The algorithm integrates the decomposition of the time series into trend and season and provides the time and number of changes in the time-series. It was developed to identify abrupt and long-term changes in time series. Thus, it enables vegetation cover studies through the detection of phenology changes in inter-annual time series using the Enhanced Vegetation Index [149].

The area of interest (AO) to be analysed for change detection was selected by drawing a polygon on the AO. MODIS data from the 2nd of July 2000 to the 31st of March 2014 were retrieved for quality checks and analysis. Products from MODIS sensors are always delivered with quality flags so that users can decide which data are good enough for their specific application. For this study, the MODIS Terra EVI 16-daily (MOD13Q1) data were chosen with the quality flag set at good data use with confidence. All selected MODIS Terra EVI data were automatically clipped to the drawn polygon and extracted for analysis.

Before the analysis commenced, the BFAST parameter in the EOM toolset was set to harmonic with a minimum segment size of 0.15, breaks of 0, maximum iteration and maximum p-value of 1.0 each. The minimum segment size is the potential detected breaks in the trend model and is given as the fraction of the relative sample size (i.e. the minimum number of observations in each segment divided by the total number of time series). The 'break' threshold determines the minimum number of phenology breaks or phenometrics expected from each analysis. The maximum iteration is the amount of breakpoints in the seasonal and trend components.

The resulting MODIS phenometrics was exported as a GeoTIFF. The phenometrics was validated using validated Landsat maps of 1988, 2001, 2014 and Google Earth images. Also, two sites in the study area were selected for validation. An area of deforestation by fire and logging was selected for validation The validation of the selected test sites for logging and forest fire was performed by selecting 120 reference points each for two test sites. Accuracy assessment and % agreement between the MODIS EVI derived phenometrics and Landsat change map of 2014 were analysed in ArcGIS 10.2.2 using the multiple resolutions method by Pontius Jr. and Suedmeyer [150].

5.4 Results

The annual deforestation rate for the study period of 1988– 2001 was estimated at 18% per annum and 26% per annum for the period of 2001-2014. The classes of the change maps for the study area included Forest; Non-forest; Forest loss; and Forest increase. Forest here is defined as vegetation with at least 0.5 ha or with canopy density greater than 10% and tree height greater than 5 meters [151,152]. The total forest area was 2421 Km^2 in the first 13 years-time step of 1988/2001, but was reduced to 1904 by the second 13 years-time step of 2001/2014. The estimated forest increase arising from afforestation and natural successions or recovery was 307 km^2 and 253 km^2 for the 1988/2001 and 2001/2014 change maps (Table 5-2 and 5-3).

Table 5-2. Map area and adjusted map area for change of 1988-2011.

Class	mapped area	mapped area adjusted	Margin of Errors (95% CI)
Forest	2224.00	2421.35	±41
Non-Forest	4705.66	4341.62	±291
Forest loss	947.10	1194.03	±149
Forest Increase	307.50	227.19	±193
Total	8184.16	8184.20	

Note. Area in km²

The error matrix in Table 5-1 and 5-2 gave overall accuracies of 93% and 97% for the change map of 1998/2001 and 2001/2014 respectively. The producers and users' accuracies derived for the 1988/2001 and 2001/2014 change maps ranges from 40% to 97%.

Table 5-3. Map area and adjusted map area for change of 2001-2014.

Class	mapped area	mapped area adjusted	Margin of Errors (95% CI)
Forest	1699.20	1904.54	±34
Non-Forest	5148.28	5031.10	±18
Forest loss	1126.00	1115.00	±2.1
Forest Increase	210.58	253.11	±20
Total	8184.06	8303.75	

Table 5-4. Error matrix for the 2001-2014 change map

Class	Forest	Non-forest	Forest loss	Forest increase	Total	Producers accuracies	Users accuracies	Overall accuracies
Forest	0.202	0	0.0059	0	0.2076	0.86	0.97	0.97
Non-forest	0	0.613	0	0.016	0.6293	0.98	0.95	
Forest loss	0.00859	0	0.12891	0	0.1375	0.94	0.93	
Forest increase	0.0005	0	0.002	0.024	0.0257	0.76	0.92	
Total	0.21	0.613	0.136	0.04	1			

Figure 5-2. 1998/2001 change map of the Afromontane region of North Eastern Nigeria

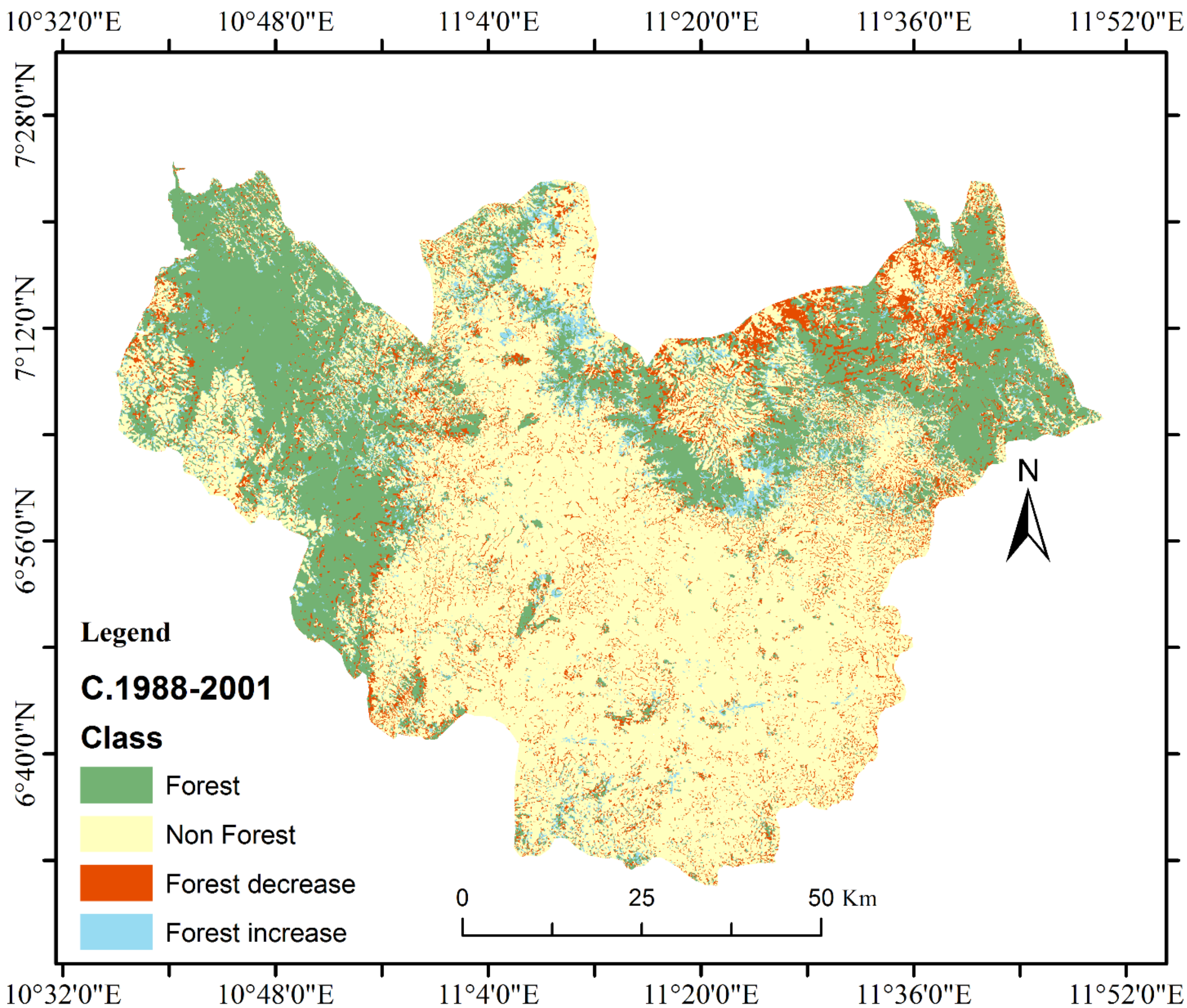
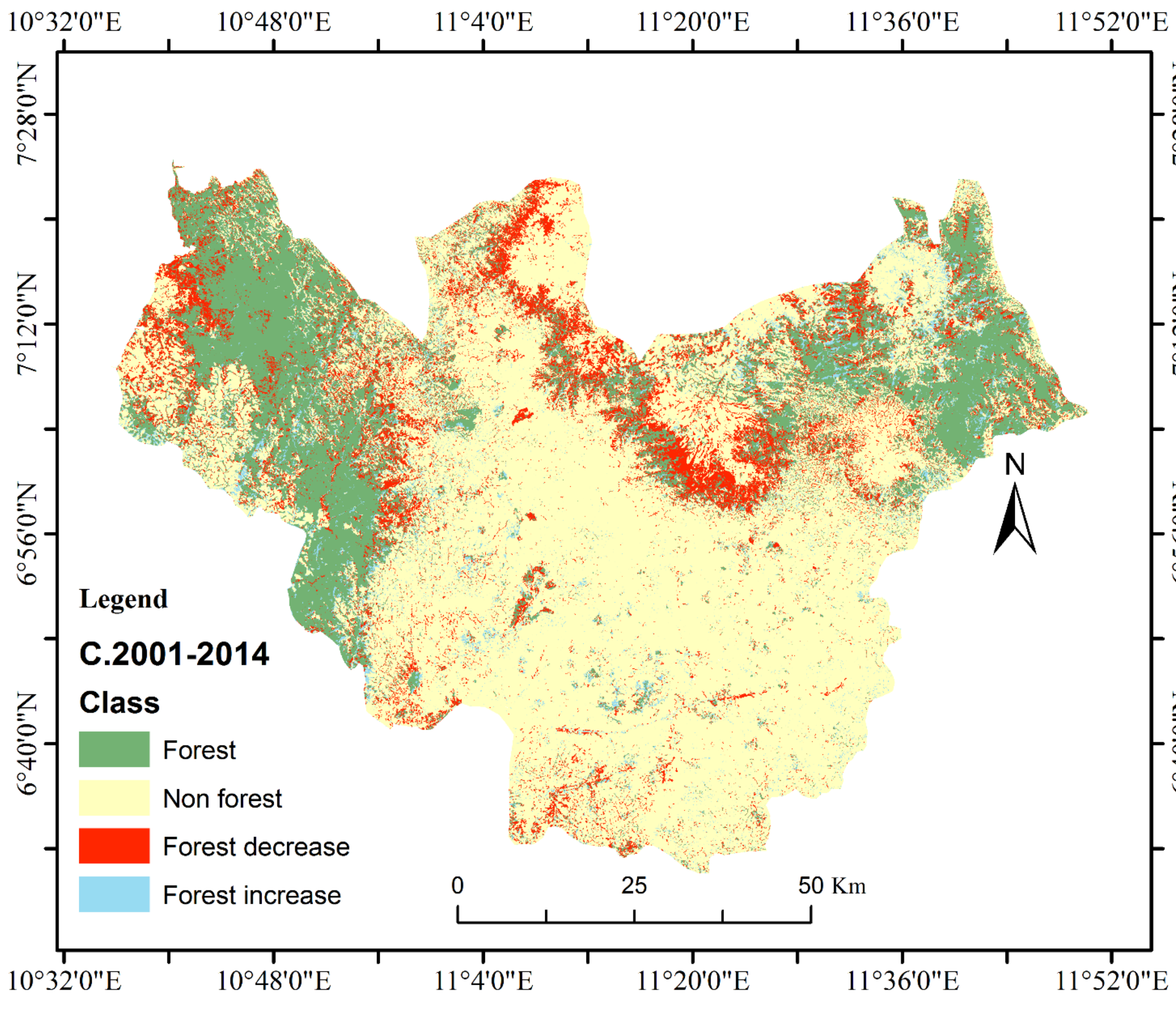


Figure 5-3. 2001/2014 change map of the Afromontane forest of North Eastern Nigeria



5.4.1 Temporal pattern change detection with MODIS data

Temporal pattern change detection was conducted using the BFAST phenology matrix-derived land-cover changes implemented in the EOM toolset. The phenology matrix is an indication of inter-annual forest disturbances. The areas observed as forest change had breakpoints within the time series components of 2000 to 2014. Examples of the break points in Figure 5-3, show phenology disturbances through forest logging of a forest site on the Mambilla Plateau. The major causes of deforestation are forest fires and logging. Forest fires are caused by seasonal bush burning by herdsmen seeking fresh grasses for their livestock [35]. Two spots observed for logging and forest fire were further analysed with the EOM toolset to determine the dates and pattern of deforestation.

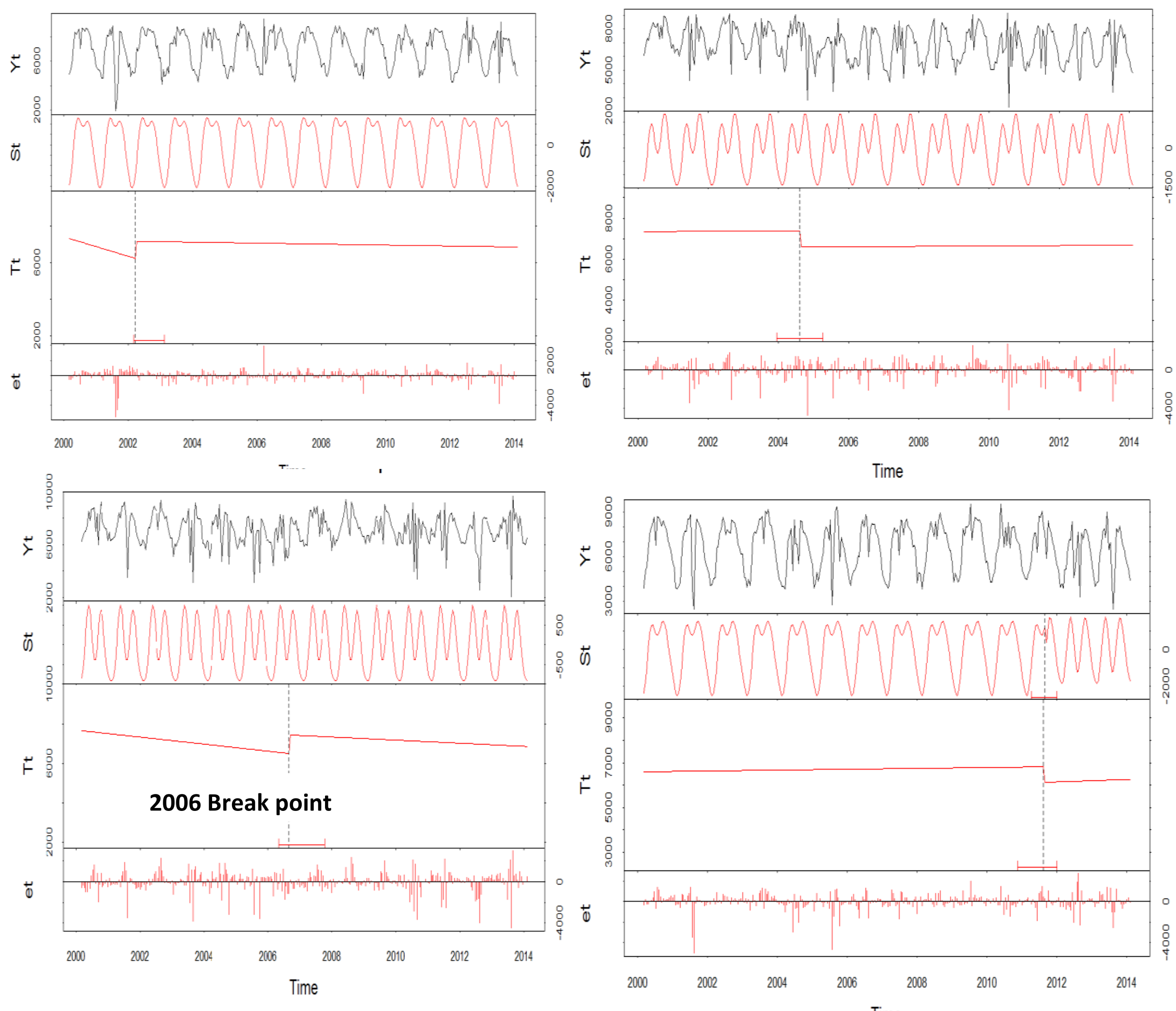
Figure 5-4. Graphical display of phenology breaks point detection for 2002, 2004, 2006 and 2012 seasons.

2002 Break point

2004 Break point

2012 Break point

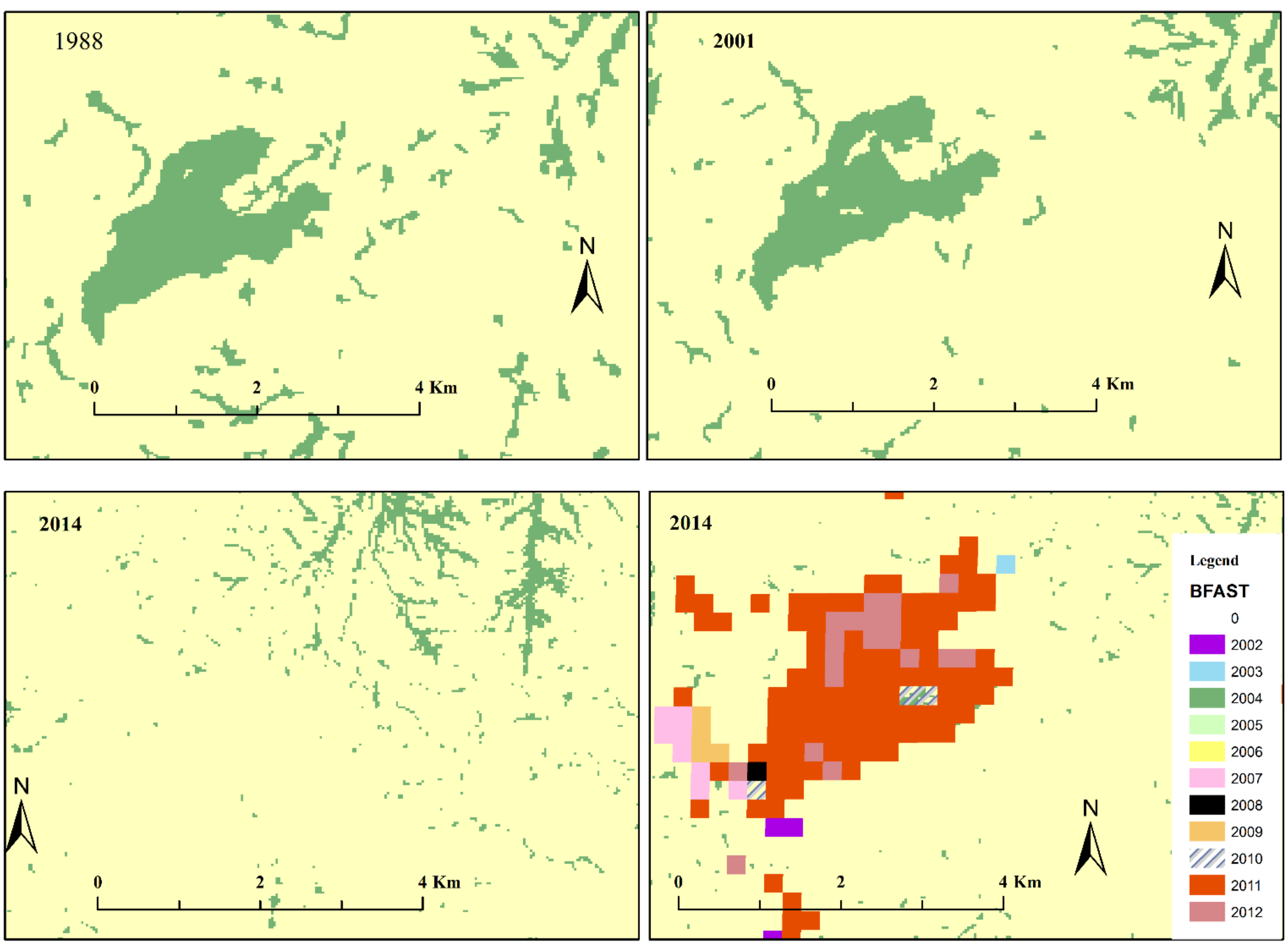
5.4.2 Validation of MODIS- EVI Phenometrics with Landsat-based Map.



Accuracy

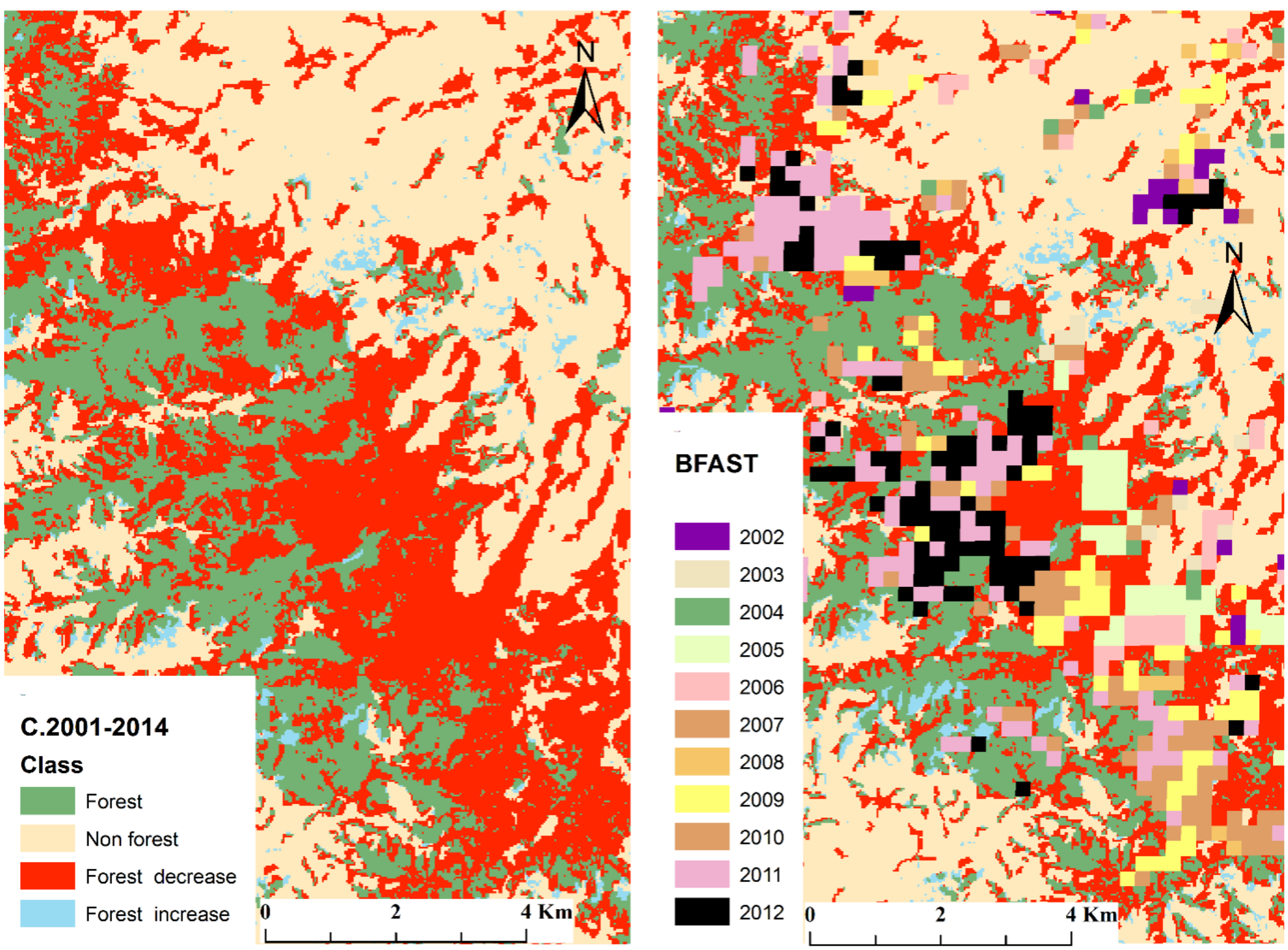
assessment between the object-based 2001/2014 change map (reference map) and the MODIS-derived phenometrics (comparison map) indicated a good agreement between the reference and the comparison map. Two sites (Figures 5-8 and 5-9) were used in testing the agreement between the reference and comparison map. There was good agreement between MODIS and reference local-scale forest disturbances. The site in Figure 5-8 was a forest site degraded through logging activities. The legend in Figure 5-8 (left) showed the commencement of deforestation in the test site between the year 2002 to 2012 when a large contiguous part of the forest was clear felled. Figure 5-9 also shows the deforestation pattern by forest fire within Gashaka Gumpti National Park. The spatial and temporal patterns of forest loss detected by MODIS time series-based breakpoint detection showed acceptable matching with locally derived reference data. The overall accuracy of disturbance mapping was 93% and 74% for clear-cut deforestation and deforestation through fire.

Figure 2-6. Change detection map showing the sequence of clear felling of a forest site from 1988 to 2014. Phenometrics derived from MODIS EVI overlaid on the changed map showing patterns and years of deforestation (bottom right).



Note: Landsat images of 1988, and 2001(top right and left) of a forest site in Mambilla Plateau and Landsat image of 2014 showing the degradation of the same site (bottom right). MODIS EVI phenology metrics (chemometrics) overlaid on the Landsat image of 2014 showing Patterns and years of deforestation in the forest (Bottom left).

Figure 5-7. Result of MODIS-based BFAST chemometrics overlaid on Landsat change map of 2001-2014 showing the pattern and years of deforestation through seasonal fire



5.5 Discussion

Monitoring heterogeneous ecosystems in the tropics requires a synergy or integration change detection methods to achieve the best possible results. The use of the hybrid technique in this study was critical to the improvement of the derived forest cover change maps, estimated areas of deforestation and the derivation of deforestation types. The object-based change detection method was fully implemented for the change detection of the study area using decadal Landsat time series for trajectory study.

Results from this study were compared with a contemporary study by Hansen *et al*[153] and FAO [151,152,153]. Results of the deforestation map were partly consistent with Hansen *et al'*smap [153] with an agreement of 73% between the two maps. Apart from the general agreement, the sites observed for deforestation in (figure 5-6 and 5-7) had 93% and 74% agreement with the compared map". However, Hansen *et al*[153] map was biased in detecting forest increase and forest loses at a finer scale. This biasedness can be attributed to mapping regional or country-wide forest cover changes without adequate in situ data for training and validating change maps. Secondly, the use of object-based classification techniques which combines contextual information within the image domain to discriminate landscape features such as trees and tree canopy features has been found effective for change detection analysis than the pixel-based approach used by the Hansen *et al*'s [32] map. Several studies have demonstrated OBIA's advantages and ability to maximize the aggregation of pixels to objects in the segmentation algorithm. This has enabled object characterization through sub-objects thereby allowing discrimination of heterogeneous landscapes such as forest canopy and gaps, vegetation patchiness or landscape complexity [154]. The advantages of the object-based approach ware maximally exploited for the change detection of the Afromontane forest areas.

The change detection mapping revealed evidence of a decreasing trend in forest cover in the study area. Deforestation rates increased from 18% (c. 1988 to 2001) to 26% (2001 – 2014). The increase in the deforestation rate from 18% or (1.3% per annum) between the 1988 and 2001 change map and 26% or (2.0% per annum) in the 2001 and 2014 change map can be attributed to the influx of nomadic herdsmen and farmers from conflicts areas in the North East and North central Nigeria to the study areas. The estimated deforestation rate of 2.0 % per annum is lower than the FAO [151] estimates of 3.7% per annum for Nigeria.

Efforts to reduce the deforestation rate require understanding the drivers and the patterns of deforestation. The Earth observation monitoring software was integrated to detect the deforestation sequence through the phenology studies of the forest ecosystem. Analysis of the web-based MODIS EVI revealed patterns and drivers of deforestation through the phenometrics generated from the studies. The MODIS satellite became operational in the year 2000, therefore limiting the applications of the EOM toolset to images available from the year 2000 and beyond. For this study, analysis using the MODIS data set was limited to the years 2000 to 2014, which coincides with the second date of deforestation rates of 2.0% per annum. The phenometrics revealed the spatio-temporal pattern of the Afromontane ecosystem dynamics with the medium-scale MODIS EVI. The interactions between human and the environment often results in modifications to land surfaces (referred to as land use, and land cover changes).

The Moderate Resolution Imaging Spectroradiometer (MODIS) data with the Break For Additive BFSAT algorithm allows for repetitive and continuous mapping of the earth surfaces using the EVI-derived phenology matrix. The phenometrics from 2001 to 2014 revealed the temporal pattern of deforestation. Thus, it indicated and subdivided the pattern of deforestation into years using the EVI phenometrics (figure 5-5 and figure 5-6). The phenology matrix derived from the web-based EOM complemented the change detection maps from the Landsat data. Results from this study are consistent with the object-based change map of 2001/2014 and the published high-resolution digital maps by Hansen el al [153]. However, the nature and types of change were inferred from the Landsat-based map and field observations. The accuracies of phenometrics prediction of disturbances within the study sites in an indication of the efficiency of the web-based EOM.

The consequences of deforestation at the local level include the loss of biological diversity (both flora and fauna), erosion, siltation, drying off of streams etc. The Afromontane forests of north eastern Nigeria are in gradual decline, with large patches of fragmented "forest islands" found in the study area. These fragmented "forest islands" lack corridors for genetic flow or interaction between species especially wild animals.

Reducing the rate of biodiversity losses and averting dangerous biodiversity changes are the international goals of the United Nations Convention on Biological Diversities (UN-BD) and the Aichi Targets for 2020. The Global Earth Observation Network (GEO BON), a partner to the Aichi targets has proposed the Essential Biodiversity Variables (EBV) as a framework for achieving the Aichi 2020 goals. One of the key mandates of EBV is the inclusion of Remote Sensing (RS)/ Earth Observation platforms for monitoring habitat loss, fragmentation and degradation. The Earth observation monitoring (EOM) toolset can be used to monitor Essential Biodiversity Variables such as deforestation at closer intervals or near real time using the MODIS-BFAST-based phenometrics. Since the EOM is web-based and is updated regularly with MODIS satellite images from the National Aeronautics Space Administration- Earth Observation Data Base. The potential for monitoring rugged and isolated landscapes in near real-time with the EOM toolset used in this study is a paradigm shift in biodiversity monitoring both for conservation scientists and decision-makers.

5.6 Conclusion

The last 26 years have witnessed an unprecedented degradation of the Afromontane forest of Nigeria, mainly driven by anthropogenic factors. The decrease in natural vegetation is not only leading to the loss of habitat, biodiversity and stored carbon but also erosion, flooding, landslide and siltation of rivers, thereby leading to the drying out of valuable water sources. The sustainability of present-day forest ecosystem management requires change detection information with adequate and accurate data that can be updated continuously. Near real-time ecosystem monitoring is important for rapid assessment to address the impacts of deforestation on carbon dynamics, biodiversity, and socio-ecological processes [155].

Abrupt changes caused by seasonal forest fire, logging and agricultural expansion can be effectively monitored in near real-time using the EOM toolset. The web-based EOM clearly showed the pattern of deforestation through the derived phenometrics. The application of the EOM toolset for change detection studies has also been proven to be an effective form of monitoring changes within the Afromontane ecosystem using phenometrics signatures derived from the 250m MODIS. The EOM toolset can provide near real-time ecosystem monitoring for disturbances. It is user-friendly, easy to use and at no cost to the end user.

This study highlights the advantages of using multi-source satellite images with hybrid change detection techniques for the characterization of the highly diversified Afromontane ecosystem. The hybrid change detection used in this study was efficient in conducting change detection in the Afromontane forest ecosystem. The proposed approach can therefore be used for achieving the Aichi targets 2020, which is aimed at measuring essential biodiversity variables with remote sensing and also redressing negative biodiversity trends.

Chapter 6.

Afromontane forest fragmentation analysis-effects on beta diversity.

6.1 Introduction

The decline in global biodiversity has been directly linked to the consistent destruction and degradation of forest ecosystems [156]. Deforestation especially in the tropics has led to the loss of more than one-third of its forest cover. The causal agents of forest degradation in the tropics are usually anthropogenic and the resultant effects of such activities are the fragmentation of the forest ecosystem. Fragmentation is a landscape process involving habitat loss and the breaking apart of habitat [74]. It is also defined as the transformation of a large expanse of habitat into isolated smaller patches or islands[157].

The intensity of forest fragmentation is dependent on three major factors, namely land use dynamics, varying patch size and structural complexity of the habitat (). The forest landscape consists of heterogeneous and complex ecological attributes and the disturbances or alterations of such landscape could negatively impact the entire ecosystem [6]. The patch corridor matrix model posits that forest fragmentation is a landscape in which a large intact area of a single forest type is progressively altered into smaller and isolated patches [6].

Forest fragmentation has negative effects on ecosystem stability and functionality through the change of landscape structures. Forest loss and changes in spatial pattern are therefore drivers of fragmentation and also the most important drivers of species extinction globally. The immediate effects of forest fragmentation are a decrease in productivity, an increase in forest isolation and a change in forest composition [158]. Forest fragmentation also has a negative impact on ecosystem services, which also affects the livelihood of forest-dependent communities[158].

The Afromontane forest of North Eastern Nigeria is one of the few remaining montane forest ecosystems in West Africa. The forest ecosystem of the region is known to be rich in biological diversities and are habitat to endemic fauna (Chimpanzee (*Pan troglodytes elliots),* Blue-bellied

Roller (*Coracias cyanogaster)*) and flora species. The Afromontane forest also provides non-timber forest products (NTFP) as a means of livelihood to the inhabitants. The last decades have witnessed consistent degradation of the ecosystem leading to fragmentation of the habitats and loss of biological diversity. The research is based on the analysis of the multi-temporal land cover maps (1978, 2001 and 2014) and examines the interdependence between forest loss and spatial pattern changes and the effects on species diversity in the study area.

6.2 Study area

The study area encompasses three contiguous montane forest areas with altitudes ranging from 600 m to 2400 m above sea level (ASL). The montane forest areas are as follows: The Mambilla Plateau (≥ 1750 m), the Gotel Mountains (≤ 2400 m) and the escarpment forest of Akwaizantar (≥ 600m ≤ 1170 m). There are two distinct seasons, a dry season when there is little or no rain for approximately 6 months and a wet season when it can rain almost every day. The rainy season usually commences from early April until late October with mean annual rainfall of 1780 mm on the Mambilla Plateau but higher in the Gotel mountains. The temperature in the study area rarely exceeds 30°C in the dry season but has lower temperatures of 9-12 °C in late November to early January [142].

6.3 Materials and Methods

6.3.1 Fragmentation analysis

The classified Landsat data for 1988, 2001 and 2014 (chapter 5) with forest and Non-forest classes were used for the fragmentation analysis in this study. Four fragmentation pattern indices(PI) accounting for interdependence between landscape composition and configuration changes were selected. The following spatial pattern metrics were used in the analysis of the Afromontane forest fragmentation using patch analyst extension in Arc GIS 10.2 and these are Percentage forest cover (%Forest), Number of Patches, and Mean parch size(MPS).

6.3.2 Tree species inventory and analysis

Tree species inventory data were collected using the modified Gentry plots[127]. Plots were established using randomized randomly in five fragmented forest ecosystems. The selected fragmented forests are: Ngel Nyaki (1750 m), Kurmi Ndanko (1450 m), Leindi fadalli (1650 m) in Mambilla Plateau; Chappal Waddi (1870 m asl) and Gangirwal (2340 m) representing Gotel mountain. Twenty-four plots were established in each of the four fragmented forests. Data obtained from the established plots included tree species composition and their diameter at breast height and density of tree species per hectare.

Sorenson's coefficient was used as a measure of beta diversity between the five fragmented forest ecosystems. The similarity coefficient is expressed as follows

RI= $100 * \frac{2a}{a+b+c+d+e}$

Where;

a number of species common to all the sites under consideration
b= number of species present in unique to site 'b'
c= number of species unique to site 'c'
d= number of species unique to site 'd'
e= number of species unique to site 'e'.

6.4 Results and discussions.

Forest fragmentation is characterised by five discrete phenomena which are reduction of total habitat area (forest cover), decrease in interior (edge ratio), isolation of forest from another, breaking up of habitat patch into smaller patches and decrease in size of habitat patch. The trend in forest cover loss in the study area (Table 6-1) shows a gradual reduction of forest cover from 1988 to 2014 in all three test sites. The forest of Akwazantar which is a montane transitional forest with an altitude rising from 600 m above sea level to 1170 m above sea level lost 21% of its forest cover between 1988 to 2014. Mambilla and Gotel mountain had their forest cover reduced by 17.5% and 8.1% respectively during the same period. The increase in the deforestation rates in the area has fragmented the Akwazantar forest escarpment from the Mambilla Plateau. The forest was once linked to the Mambilla Plateau through the Ngel Nyaki forest in 1988 (Figure 6-1). The rapid decline of vegetation covers from 67 to 47% in Akwazantar between 2001 and 2014 was occasioned by pressure from the farmers whose population have more than doubled during the same period.

The number of patches (NumP) increased along with the decrease in forest cover between 1988 to 2014 in the three test sits. The forests of Akwazantar, Gotel and Mambilla Plateau have been undergoing fragmentation processes for over four decades. The montane forests of Mambilla and Gotel were described as fragmented forests richly diverse in both flora and fauna in the early 1970's by chapman and Chapman[123] and Chapman et al[122]. Forest cover loss and increase in the rate of fragmentation seem to have intensified since the study carried out by both authors.

Table 6-0-1. Fragmentation pattern indices (PI) for 1988, 2001 and 2014

		Fragmentation pattern indices (PI)		
Site	**year**	**% forest cover**	**NP**	**MPS(acre)**
	1988	68	1113	26.3
	2001	67	2136	19.1
Akwazantar	2014	47	11710	12.8
	1988	57.5	1964	13.9
	2001	49	1877	12.0
Gotel mountain	2014	40	3098	10.5
	1988	20.2	8908	21.0
	2001	17.6	6342	17.0
Mambilla	2014	12.1	9826	12.4

6.5 Impact of fragmentation on species diversities

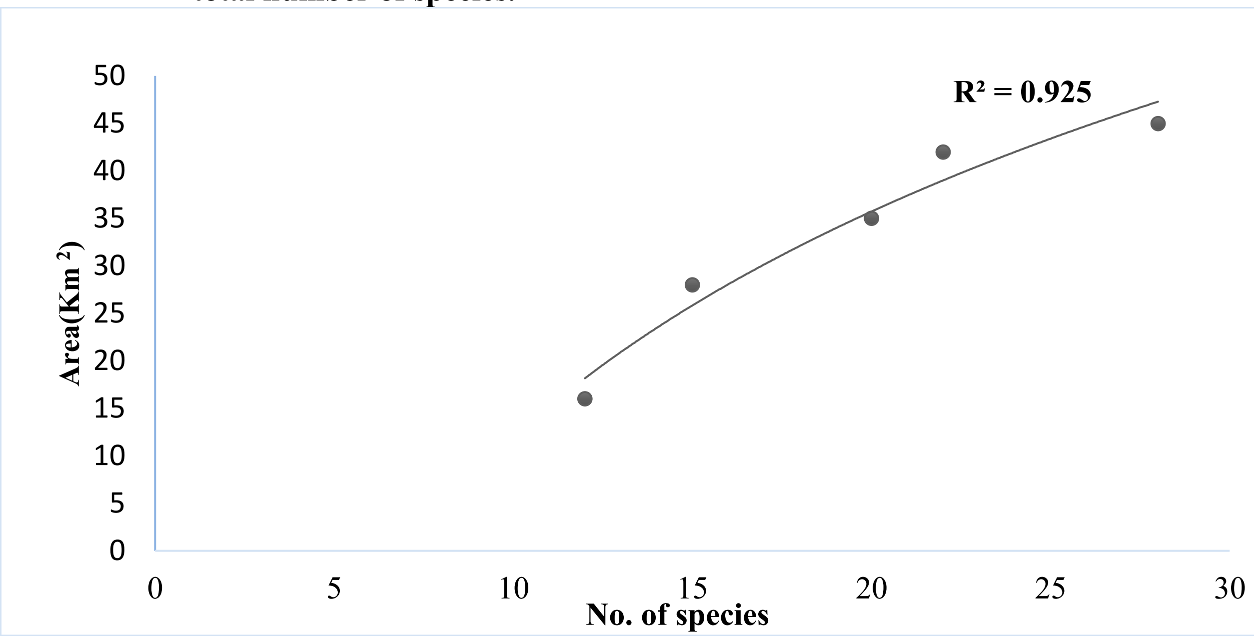
The coefficient of similarity in species composition between study sites shown in areas (Table 6-2) ranges from 50% to 88%. The most dissimilar sites were Kurmin Ndanko (1550 m asl) and Gangirwal (2430 m asl) with a 50% similarity coefficient. Also, the high coefficient recorded in Sorenson's similarity index especially between forests with little variation in attitude is an indication of the effects of land use on species diversity in the study area. Land use pressure can be adduced for the percentage of dissimilarity between the study sites. For instance, the change forest cover map for Ngel Nyaki shows the regeneration and increase in forest cover, while Kurmi Ndanko has been on a downward trend. Similar studies by MacDougall et al[159] and Onoyi et al [77] concluded that anthropogenic pressure through various land uses often leads to species dissimilarity within habitats with similar biotic and abiotic features.

Table 6-0-2. Sorensen's similarity coefficient for the different sites.

	Ngel Nyaki	**Kurmin Ndank**	**Leindi Fadalli**	**Chappal waddi**	**Gangirwal**
Ngel Nyaki	*	65.2	54.4	68.7	52.5
Kunmi Ndanko	65.2	*	84.1	61.3	50
Leindi Fadalli	54.4	65.2	*	52.3	87.5
Chappal Waddi	68.7	61.3	52.3	*	88.1
Gangirwal	52.5	50	87.5	88.1	*

The species area curve is one of the major corner stone of modern ecological studies. It is expressed as the relationship between a number of species present and the area of the habitat and can be used to predict species extinction based on habitat reduction. Ecologists have for a long time positioned that the reduction in habitat size will lead to a reduction in species diversity. Results of the species-area relation indicated the effects of habitat size on species number (figure 6-3). In this scenario, the reduction of forest cover equals a reduction in a number of tree species. Results obtained in the test sites are in line with similar observations in which tree species diversity was found to reduce with decreasing forest cover and patch area in the eastern arc mountains of Tanzania[77]. Also, while using fragmentation indices to evaluate habitat and landscape processes in Costa Rica national parks, Kramer[160] observed that a decrease in forest cover and patch size also reduces the number of species encountered.

Figure 6-1 Specie area curve showing fragments holding different proportions of the total number of species.



Forests generally become fragmented through anthropogenic (human-induced) activities, thereby leading to the loss of species. The major causes of deforestation as revealed by this study are logging, forest fires resulting from grazing and shifting cultivation. These anthropogenic activities are on the increase and causing fragmentation of the once luxuriant forest landscape. The predominant driver of fragmentation was forest fire caused by grazing. The Afromontane forest of north eastern Nigeria is gradually being turned into grazing land. The majority of the study sites are far from human habitation, but the presence of herds of cattle is abundant in all the study areas (figure 6-4).

Three of the study areas are under the management of the Gashsaka Gumpti National Park, while Ngel Nyaki and Kurmin Ndanko are protected forests by the Government of Taraba state.

However, Ngel Nyaki is the only forest that is fully protected because it is currently been administered as a research station of the University of Canterbury, New Zealand. Thus the presence of research scientists, field staff, and patrol teams has drastically reduced grazing pressure on the forest.

Figure 3. Grazing herds at the edge of the forest encountered during field survey (above). Illegal cattle ranch at the edge of a forest fragment in Gashaka Gumpti National Park(below)

6.6 Conclusion

The analysis of Afromontane landscape patterns using spatial indices has enabled the monitoring of the trends and quantification of the landscape dynamics of the Afromontane forest ecosystems. The study also has highlighted the effects of forest fragmentation on species diversity using satellite remote sensing and in situ data. Forest loss and changes in spatial pattern are both the major components of forest fragmentation and are the most important drivers of species extinction globally.

Chapter 7. synopsis

6.1 Conclusions and main findings

The Afromontane forest of North Eastern Nigeria is an important ecological ecosystem, rich in biological diversity and a source of livelihood for its communities. Most tropical forest is under threat of decimation and the Afromontane forest is much more under threat and has been decimated at an alarming rate. The Afromontane forest ecosystems have undergone significant changes in the last three decades. Most of the negative changes are anthropogenic induced and most significant of the induced negative changes were caused by incessant bush burning by grazing herdsmen and agricultural expansion.

The main goal of this thesis was to explore the potential of multi-source satellite remote sensing for the assessment of the biodiversity-rich Afromontane forest ecosystem. The research theme of this thesis was divided into two. The first segment of the research focussed on two major forest attributes (aboveground biomass and tree species distribution) that are interrelated and are the major determinants of biological diversity in any forest ecosystem. The second research theme of this thesis focussed on the analysis of the forest cover changes and the effects of habitat fragmentation on the Afromontane biological diversity. The summary of the research questions and findings are as follows;

What are the major determinants of aboveground biomass accumulations in the ecosystem?

A high-resolution map of the study area was produced using QuickBird satellite data and in situ forest inventory. The map produced was a local scale map with aboveground biomass values consistent with the area of study. The predicted AGB for the study area was found to be within the range of similar studies for the region. The study also demonstrated the importance of textural features in enhancing biomass estimation of an Afromontane forest ecosystem. GLCM features provided structural information which improved the accuracies of predicted biomass. Also, AGB distribution in the study area was found to be a function of topographic variables, (slope and elevation).

What are the major determinants of tree species distribution in the study area?

The study has demonstrated the use of remote sensing spectral and textural heterogeneity for the spatial modelling of Afromontane hotspots. Both QuickBird and Landsat 8 images positively correlated with tree species diversity. However, detailed object features were captured by the higher resolution image than the medium resolution. The medium-resolution image had mixed pixel effects and hence was less sensitive to spatial the complexity of the Afromontane forest ecosystem. The combination of textural and spectral features of both satellite images improved the ability of the images to discriminate and predict tree species richness. The study also revealed the influence of macro-ecological data on the Afromontane tree species distribution. The empirical models developed can be used to predict landscape-level species heterogeneity in the Afromontane forest of Nigeria and the adjourning Cameron highland.

How can a hybrid change detection method be used to determine deforestation rates in the Afromontane forest ecosystem?

The last three decades have witnessed an unprecedented degradation of the Afromontane forest of Nigeria, mainly driven by anthropogenic factors. The decrease in natural vegetation is not only leading to the loss of habitat, biodiversity and stored carbon but also erosion, flooding, landslide and siltation of rivers, thereby leading to the drying out of valuable water sources. The sustainability of present-day forest ecosystem management requires change detection information with adequate and accurate data that can be updated continuously. Near real-time ecosystem monitoring is important for rapid assessment to address the impacts of deforestation on carbon dynamics, biodiversity, and socio-ecological processes.

Abrupt changes caused by seasonal forest fire, logging and agricultural expansion can be effectively monitored in near real-time using the EOM toolset. The web-based EOM clearly showed the pattern of deforestation through the derived phenometrics. The application of the EOM toolset for change detection studies has also been proven to be an effective form of monitoring changes within the Afromontane ecosystem using phenometrics signatures derived from the 250m MODIS. The EOM toolset can provide near real-time ecosystem monitoring for disturbances. It is user-friendly, easy to use and at no cost to the end user.

This study highlights the advantages of using multi-source satellite images with hybrid change detection techniques for the characterization of the highly diversified Afromontane ecosystem. The hybrid change detection used in this study was efficient in conducting change detection in the Afromontane forest ecosystem. The proposed approach can therefore be used for achieving the Aichi targets 2020, which is aimed at measuring essential biodiversity variables with remote sensing and also redressing negative biodiversity trends.

What are the effects of deforestation and forest fragmentation on tree species distribution?

The degradation of tree species diversity was found to be related to the reduction of fragmentation of forest cover.

How has remote sensing improved biodiversity monitoring in the Afromontane forest ecosystem?

Identifying biodiversity hotspots and studying their ecosystem dynamics in space and time are labour-intensive, expensive and often restricted or limited to small areas. Information derived from restricted ecological research is inadequate for policy and management decisions on conservation. The studies in this thesis have shown that earth observation data can be integrated with field data to produce a large and explicit ecological map for conservation monitoring especially in inaccessible area like the Afromontane forest ecosystem.

Satellite-based variables have long been expected to be a definitive component for unified global biodiversity monitoring. The research studies in this thesis have proven that satellite remote sensing can be an integrated component for biodiversity monitoring. Specie population, community composition, ecosystem function and ecosystem structures were the EBV classes covered in this thesis using multi-source satellite data and open source algorithms such as BFAST and random forest. The retrieval of aboveground biomass of two Afromontane forests was achieved using high-resolution satellite images and a random forest algorithm. Also, the tree species diversity of the study area was modelled using a random forest algorithm with high-resolution QuickBird satellite image. In both aboveground biomass retrieval and tree species diversity modelling, in situ data was integrated with remote satellite data to achieve the outline objectives.

6.2 Research needs

The studies carried out in this thesis were limited to the montane forest of north eastern Nigeria which is less than 5% of the country's total land mass. Results from the studies carried out in this thesis have shown that despite the rich biological diversities in the study area, large-scale deforestation is ongoing. The deforestation and degradation of biological diversity is not limited to the study area but is extensive to all the regions of the country. The Aichi Targets 2020 is undoubtedly unrealistic with the current trend of deforestation and erosion of biological diversities. To redress this anomaly, the following research needs are listed below.

National or regional land use land cover map

There is a need to update the vegetation cover map of Nigeria. Signatories to both UNFCC and CBD's essential climate variables and essential biodiversity variables are required to have a base line land use land cover map and vegetation cover map. The land use land cover map and vegetation map of Nigeria was produced in 1978, therefore the maps are long overdue to ascertain the extent of the country's forest and biological resources.

Development of an integrated approach towards monitoring local and regional biodiversity.

There is also the need to have an integrated biodiversity map of the country as proposed by GEO BON. The inclusion of high-quality local biodiversity measurements will foster the generation of integrated satellite-based monitoring for both local and regional biodiversity. This will increase the visibility of remotely sensed biomass and forest structure maps for local stakeholders and policy.

Upscaling the results from this thesis

The determinants of biomass and tree species distribution were found to be elevation and slope in the both Ngel Nyaki and Kurmin Ndanko forests. The two forest are adjacent to each other and are within the same environmental niche. It is therefore necessary to apply the same environmental variables on a large scale by mapping and modelling AGB and species diversity across the mountain landscape of Nigeria and Cameroon

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Tabulated CV

Education	
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2011	PhD Enrolment @ the University of Canterbury, New Zealand
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Publications	Ralph Adewoye, Christian Huttich, Christian Schmullius and Hazel Chapman (2015). Estimating above ground Biomass of the Afromontane forest ecosystems uising QuickBird and Insitu forest inventory data. Journal of Remote sensing Technology.Volume 3, Issue 1, page 1-8. Ralph Adewoye, Christian Huettich, Jonas Eberle, Christiane Schmullius and Hazel Chapman. (Under review) A multi-source change detection approach for the Afromontane and escarpments of north eastern Nigeria with Landsat and Modis satellite. African Journal of Ecology-WILEY. Ralph Adewoye, Christian Huettich, Christiane Schmullius and Hazel Chapman (Under review). Modelling tree species diversities of the Afromontane forest ecosystem with satellite remote sensing and macro-ecological data. AIMS Geosciences. Gajere E N, Hyelpamduwa Y, and **Adewoye A .R.** (2013). Habitat Mapping of Palaearctic and afro Palaearctic waterfowl of Dogona waterfowl sanctuary of North eastern Nigeria. Journal of Ecological society of Nigeria. Gejere E N, **Adewoye A R** ,Hyelpaduwa Y (2009) Habitat Mapping of Palaearctic and afro Palaearctic waterfowl sanctuary of Dogona , North eastern Nigeria Presented at the 2nd conference of the Ecological Society of Nigeria (EcSN) held at Calabar , Cross river State October, 2009. Adewoye A Ralph and Chapman Hazel (2008) Afromontane Forest Fragments of Mambilla Plateau, Ecological implication of near extinction. Proceedings of

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Selbstständigkeitserklärung

Ich erkläre, dass ich die vorliegende Arbeit selbstständig und unter Verwendung der angegebenen Hilfsmittel, persönlichen Mitteilungen und Quellen angefertigt habe.

Jena, Oktober 2016 Ralph Adewoye