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TESTING SPECTRAL VARIATION HYPOTHESIS ON THE AFROMONTANE FOREST ECOSYSTEM OF NGELNYAKI, NORTH EASTERN NIGERIA WITH LANDSAT 8(OLI) AND MACRO-ECOLOGICAL DATA

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ABSTRACT

Afromontane forest ecosystems are highly diverse in both flora and fauna species. Information on species composition and distribution are necessary for adequate conservation strategy. Extensive survey which is often time consuming and labor intensive is required for the assessment of such ecosystem. Remote sensing platform is an inexpensive tool for assessing both quantitative and qualitative information on ecosystem biodiversity. This research examines the application of Spectral Variation Hypothesis (SVA) in an Afromontane forest ecosystem using features derived from medium resolution satellite image combined with macro ecological data to predict tree species distribution. The result revealed that Elevation (r=0.75), slope (r=0.56) and aspects (r=0.34) were the determinant of tree species distribution in the study area. Spectral and textural features significantly contributed to the enhancement of the alpha diversity model in Landsat image. Landsat8spectral and textural heterogeneity showed a significant correlation with species richness (r=0.87) and (r=0.53) 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.

Keywords: Afromontane, Spectral Variation Hypothesis, Macro ecology, OBIA, Random Forest Algorithm.

INTRODUCTION

Montane forests situated in the afro tropical region (henceforth referred to as “Afromontane forests”) are high on the list of the worlds most threatened ecosystem. 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. Ecologists have relied on the traditional method of field surveys to quantify biodiversity of large area, which often is time consuming, costly and dependent on expert knowledge. This has led to the conclusion that field measurements represent estimates rather than absolutes, especially when applied at a landscape scale (Palmer *et al.,* 2002). While it is impracticable to measure diversity at all level and in all places, information on landscape biodiversity can be optimized through use of ecological proxies. Plant species richness is widely adopted as an ecological proxies for the determination of biodiversity and is often correlated with diversity at other levels of organization, such as genetic diversity and ecosystem functioning. Plant species constitutes the primary components of terrestrial ecosystem and can be used as a surrogate for ecosystem biological diversity. Thus, plant/tree species richness defines ecosystem structures and functions, and is therefore a central component of biodiversity assessment (Rochinni *et al*., 2004)

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 and spatial scale Warren *et al.,* 2014).Ecologist have subscribed to the theory of the existence of a linear relationship between diversity and environmental gradients. Afromontane forests are located across broad range of landscapes with various abiotic factors influencing plant diversities and productivities For instance, macro-ecological factors such as slope, elevation, aspects and solar radiation are known to affect the distribution of insolation in the terrain. Theses also have effects on the ecosystem microclimate (sunlight, 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(Jennifer *et al.,* 2001).A new frontier of obtaining information on biological diversity at spatial scale is the application of the Spectral Variation Hypothesis (SVH) proposed by Palmer. SVH infers that the spectral heterogeneity of a remotely sensed image can be correlated with habitat heterogeneity (that is, complex macro-ecological structures).Therefore SVH represents a potential tool for predicting plant species diversities at local and spatial scale with satellite remotes sensing(Rocchini *et al.,* 2007).

Optical satellite images provide the bulk of satellite images used in the application of 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 potentials 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 increase in pixel variability. This is often the case in mountainous region, where a pixel may cover 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 (Rochchini *et al.,* 2007, Nagendra and Rocchini 2008, Immitzerr *et al.,* 2012 and Warren *et al.,* 2014).

The medium resolution images such as Landsat have greater number of bands and are able to 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 (Rocchini *et al.,* 2010).The major limitation of the medium resolution sensors has been that of insufficient spatial resolution. A single pixel of the medium sensor may cover a number of plant of different species, thus each pixel often correspond to mixed signature of different objects, leading to difficulties in species identifications. Despite these limitations, studies using the medium resolution sensors has been moderately successful for both temperate and tropical ecosystem .

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 . 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 Spectral Variation Hypothesis is now been focused in the use of textural variables and vegetation indices computed with the object based image analysis technique .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, 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. The object features often related with SVA is the second order statistics after Haralick (1979). The second-order statistics 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 .

There are arrays of literatures suggesting the advantages of the object based image analysis over the pixel based analysis in land cover classifications; biomass estimations; and species diversity/ecological modellings. Satellite remote sensing has been used for mapping and modelling species distribution in arrays of ecosystems ranging from temperate and tropical, but none of the studies has focus on the subtropical Afromontane ecosystem. This research is aimed at modelling the structural diversity of the Afromontane forest ecosystem medium resolution Landsat 8 satellite image combined with macro-ecological data. The objectives of this study are to: Determine the effects of sensor spatial and spectral resolution on species diversity prediction using medium resolution Landsat-8 image, determine the relationship between spectral, textural and alpha diversity and determine the effects of macro-ecological features on the Afromontane tree species diversities.

METHODOLOGY

Study area

The study was carried out at the Montane forest of NgelNyaki (Longitude 07^{o} 20$^{'}$ N and Latitude 11^{o} 43$^{'}$ E),along the Nigerian/Cameroon border in Nigeria (Fig 1). Situated at an altitude of over 1650 meters above sea level, the forest is classified as a sub-montane moist broadleaf (Terrestrial Ecoregion, WWF) and is highly diverse in both fauna and flora. Afromontane endemic tree species, Cameroon highland endemics and possible local endemics are found in the study area. NgelNyaki Montane forest is 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 .

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 with mean annual rainfall of 1780 mm in the NgelNyaki.The temperature of the study area rarely exceeds 30°C .

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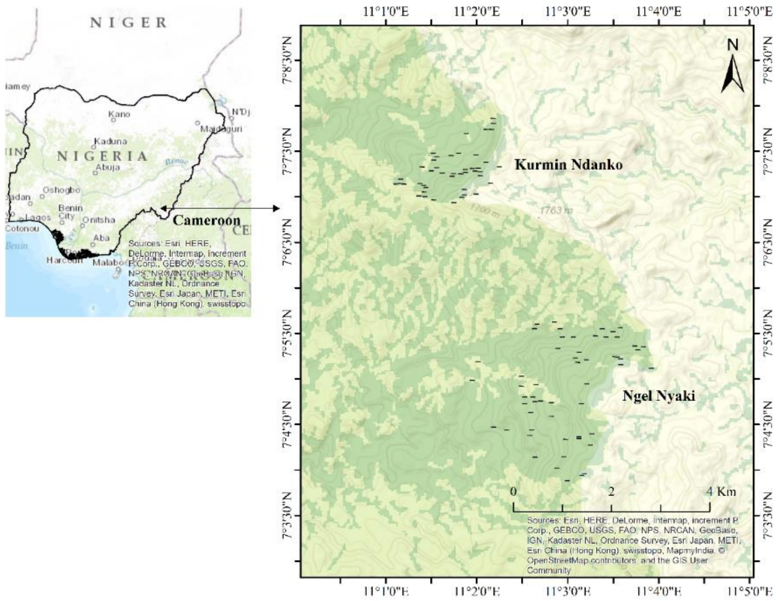

Figure 1: Plot layout along macro-ecological gradients in NgelNyaki and KurmiNdanko forest

Plot inventory/ alpha diversity study

Afromontane tree species inventory data were collected using the modified Gentry plots. 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 diameter at breast height (dbh) ≥ 10 cm were identified and recorded using Trees of Nigeria, An Ecological Accounts and Species Checklist and local knowledge of the trees. A total of sixty plots were randomly established at NgelNyaki forest. Tree species diversity by plot were assessed with the Dominance Simpson index and the Alpha(α) diversity index.

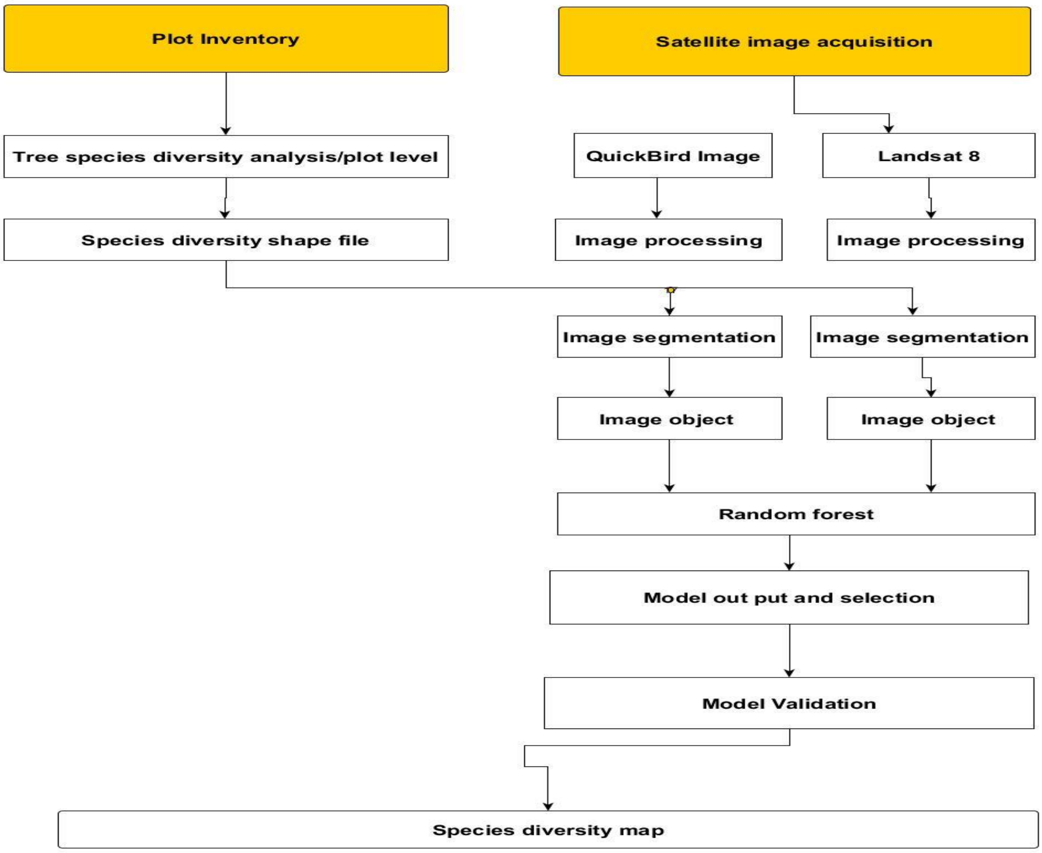

Figure 2: Diagrammatic scheme of methods and process for species diversity study

Satellite images and macro-ecological data acquisition and processing

Landsat 8 (OLI) satellite image of the study area was acquired at the onset of the field survey in March 2014. The image was atmospherically corrected and geo-referenced to Universal Transverse Mercator Projection (WGS 84). Elevation, slope, aspect and solar radiation were extracted from the 30m ASTER Global Digital Elevation Model (GDEM) of the study area using the Spatial Analyst and Topography toolbox in ArcGIS 10.3. The details of image Landsat-8 characteristics are in Table 1.

Table 1: characteristics of Lansat-8 satellite images

Image	Band	Spectral range (µm)	Spatial resolution (meters)
Landsat- 8 (OLI)	1-Coastal aerosol	0.43-0.45	30
	2-Blue	0.45-0.51	30
	3-Green	0.53-0.59	30
	4-Red	0.64-0.67	30
	5- NIR	0.85-0.88	30
	6- SWIR 1	1.57-1.65	30
	7-SWIR 2	2.11-2.29	30

Spectral, textural and macro-ecological metrics

Within each of the 60 plots, the alpha diversity (species richness),the mean standard deviation of Landsat 8 spectral bands, slope-based vegetation indices, textural features consisting of the Gray Level Co-occurrence matrix (GLCM) and macro-ecological features (slope, Aspects, Elevation and Mean Solar radiation/annum) were extracted using the chessboard segmentation algorithm in the Trimble Developer software (eCognition 9.0.3). The Gray Level Co-occurrence matrix (GLCM) is a second order texture features after Haralick (1979). 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 for the five different directions; namely 0^o, 45 ^{o}, 90 ^{o}, 135 ^{o}, and all directions (Table 2). The afore-mentioned features and thematic layers with information containing alpha density were exported as a shape file from the eCognition environment and used in the random forest algorithm to model Afromontane tree species diversities. A total of 69578 variables were used in the random forest algorithm for modelling and predicting tree species diversities for the Afromontane forests.

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Table 2: All feature inputs for modelling Afromontane tree species distribution

Spectral values (mean)	Texture features	Vegetation indices
Blue	GLCM Homogeneity	Difference Vegetation Index(DVI)
Green	GLCM Contrast	Green Vegetation Index (GDVI)
Red	GLCM Dissimilarity	Green Normalised Vegetation Index (GNDVI)
NIR	GLCM entropy	Normalised Vegetation Index (NDVI)
Shortwave Infra Red1	GLCM 2 Angular moment	Normal Green (NG)
Thermal Infra-Red	GLCM mean	Normalised Near Infra-Red (NNIR)
Shortwave Infra Red2	GLCM Std.	Ratio Vegetation Index (RVI)
	GLCM Correlation	Green Ratio Vegetation Index (GRVI)

Data 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 analysis 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 and. Pearson correlation coefficient were computed as a measure of relationship. The closer the coefficient is closer to one, the stronger the relationship. Cluster analysis was used to determine the relation between alpha diversity and macro-ecological parameters.

RESULTS AND DISCUSSIONS

Landsat 8 image heterogeneity showed a statistically significant correlation with species richness ($r=0.8$) (Figure 3). The species density maps showed pattern of tree distributions in the study area with the lowest density range of 0, belonging to the grass and ≥1 to ≥10 belonging to ecosystem ranging from savanna to high forest ecosystem (Figures4 and 5). Lansat-8 satellite images correlated with alpha species richness of the NgelNyaki forest reserve.

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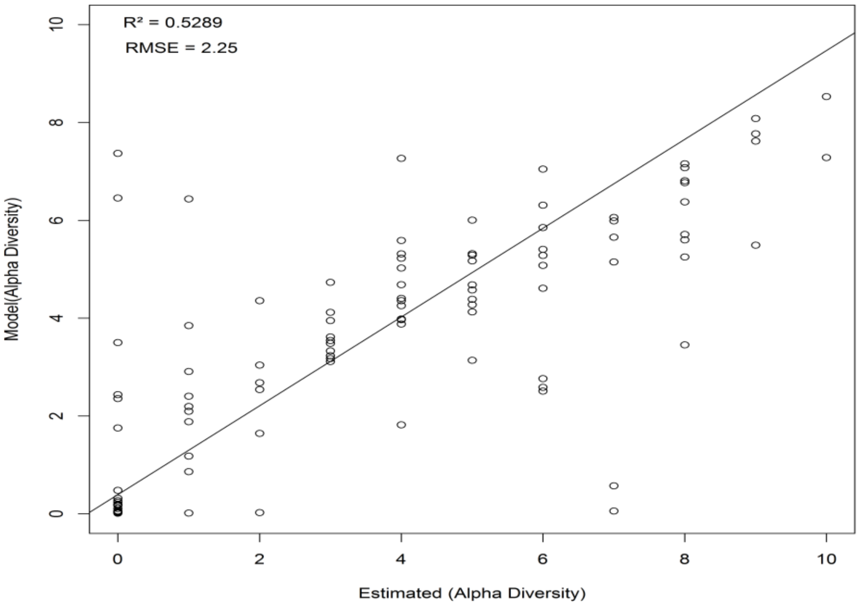

Figure 3: Validated species distribution model with Landsat-8

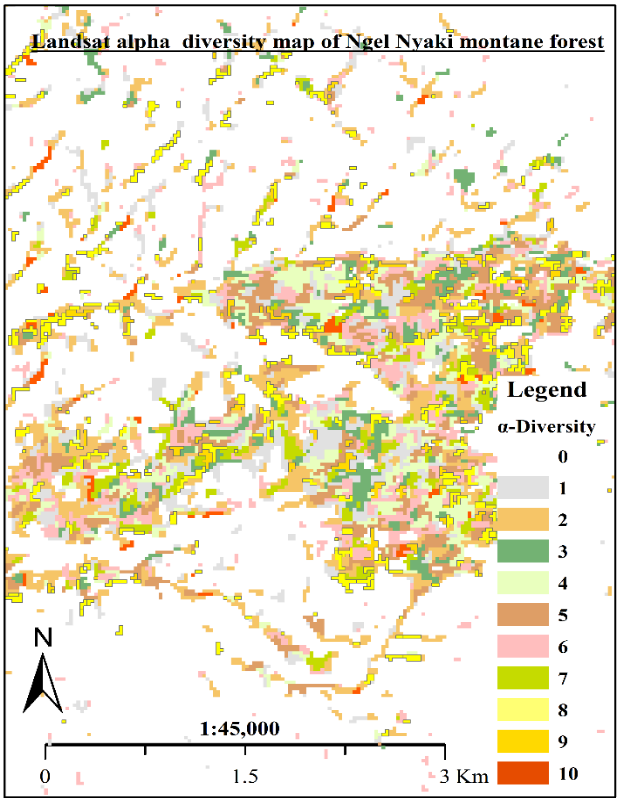

Figure 4: Tree species density map of NgelNyaki Montane forest from Landsat 8

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Influence of spectral, textural and vegetation indices on tree species diversity prediction

The relationship between the GLCM, spectral, macro-ecological features and alpha density (≥ 10 cm diameter at breast height) were explored using regression analysis in the random forest algorithm to select a set of candidate models. Based on the variable of importance, model-averaged parameters and linear regression between number of species and the variable of importance (VI) were calculated. Results of the variable of importance model from the random forest algorithm indicated that alpha diversity positively correlation with the near spectral the (Near Infra-red band), textural (GLCM) and vegetation indices (NDVI) of both images (Table 3).

The Near Infra-red band (NIR) is generally known to correlates with vegetation and is adjudged to be the most important of the spectral band for mapping and modelling vegetation properties. It was however observed that the combination of textural and spectral features enhanced the predictive ability band Landsat- 8 image.

Table 3: Linear regression between tree species and Satellite images variables

Spectral	**r**	**rmse**
NIR Red Green	0.22	2.4
Texture GLCM)	0.19	2.9
Vegetation indices (NDVI)	0.22	2.6

Environmental heterogeneity on tree species distribution

The determinants of tree species distribution obtained from random forest algorithm are in table 4. Three of the four macro ecological factors had a strong linear relationship with tree species distribution (slope, aspect and altitude). The study area is a mountainous region with steep slope and escarpments and altitudes ranging from 1250 to 1750 meters above sea level. Slope of the terrain and the direction which it faces (aspect) has been observed to have multiple effects on montane species diversities .These factors have been found to have linear relationship with vegetation attributes such as species richness and diversities . Species distributions and richness pattern are also known to be regulated by altitude, slope and aspects .

A Similar study concluded that tree diversity, canopy openness and basal area increase along slope gradient from ridges to valley. Field survey confirmed that area with high escarpment in and around the forest core were rich in tree species. Similar to that was the observation of decrease in tree species richness from the along altitudinal gradients. Plant species diversities have been observed to decreases with increasing elevation in tropical montaneforests .

Table 4: Linear regression between tree species and macro ecological variables

Macro-ecological features	R^2
Elevation	0.75
Slope	0.56
Aspect	0.34
Mean solar radiation	0.12

Ecological implication of Afromontane tree species modelling

Heterogeneous landscape such as the study area are reservoir of genetic diversities due to the complex interaction of the various micro and the macro ecological 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 slope and escarpment. 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 restricted 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 the pixel segmentation combined with satellite image spectral features and vegetation indices in object-based image analysis is being deduced herein this paper. In mountainous vegetation, the possibility of hill side shadow covering a forest area is well known and documented. Image segmentation algorithm played a significant role in canopy cover mapping, discrimination of forest covered by shadow by adjourning hills from other Eco zones.

Remote sensing has the potential of shaping the next generation of species distribution model when fully exploited with biotic and abiotic variables. The inclusion of macro ecological parameter with satellite remote sensing for modeling Afromontane tree species diversity is an indication of the importance of the macro ecological variables in the species distribution of the study area. The theoretical approach of this model is that species richness can be spatially represented in biodiversity hotspots. Also, species distribution modelling can be use as habitat mapping for endemic species such as the Nigerian-Cameroon Chimpanzee (*Pan troglodyteselliotì)* and other species

Known to be present in the two study sites.However, it 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.

CONCLUSION

Landsat-8 images positively correlated with tree species diversity. However, detailed object features were not captured Landsat 8 satellite image.this is purely due to the resolution. The medium resolution images has mixed pixel effects and hence was less sensitive to spatial the complexity. The combination of textural and spectral features of both satellite images improved the ability of Landsat 8 image 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 density in the Afromontane forest of Nigeria and the adjourning Cameron highland.

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