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# Regional Assessment of Trends in Vegetation Change Dynamics using Principal Component Analysis

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## ABSTRACT

Vegetation forms the basis for the existence of animal and human. Due to changes in climate and human perturbation, most of the natural vegetation of the world has undergone some form of transformation both in composition and structure. Increased anthropogenic activities over the last decades had pose serious threat on the natural vegetation in Nigeria, many vegetated areas are either transformed to other land use such as deforestation for agricultural purpose or completely lost due to indiscriminate removal of trees for charcoal, fuelwood and timber production. This study therefore aims at examining the rate of change in vegetation cover, the degree of change and the application of Principal Component Analysis (PCA) in the dry sub-humid region of Nigeria using Normalized Difference Vegetation Index (NDVI) data spanning from 1983-2011. The method used for the analysis is the T-mode orientation approach also known as standardized PCA, while trends are examined using ordinary least square, median trend (Theil-Sen) and monotonic trend. The result of the trend analysis shows both positive and negative trend in vegetation change dynamics over the 29 years period examined. Five components were used for the Principal Component Analysis. The results of the first component explains about 98 % of the total variance of the vegetation (NDVI) while components 2-5 have lower variance percentage (< 1%). Two ancillary land use land cover data of 2000 and 2009 from European Space Agency (ESA) were used to further explain changes observed in the Normalized Difference Vegetation Index. The result of the land use data shows changes in land use pattern which can be attributed to anthropogenic activities such as cutting of trees for charcoal production, fuelwood and agricultural practices. The result of this study shows the ability of remote sensing data for monitoring vegetation change in the dry-sub humid region of Nigeria.

***Keywords:*** *Principal Component Analysis, Trend, Vegetation Change, Land cover, Nigeria*

## 1. INTRODUCTION

Long term monitoring of land cover change is important for proper understanding of climate-human induced vegetation change in the dry sub-humid regions (Garonna et al, 2016; Zhang et al, 2016; Tian et al, 2016; Fensholt and Proud, 2012). Change in vegetation (either increase or decrease in vegetation vigor) are greatly influence by natural and anthropogenic activities (Zhang et al, 2016), however, in-depth assessment of this phenomena still remains a challenge in Nigeria due to lack of up to date data. However, the availability of remotely sensed time series data such as Advanced Very High Resolution Radiometer (AVHRR) and Moderate Resolution Imaging Spectroradiometer (MODIS) has made global environmental monitoring possible because more or less the entire surface of the earth can be sensed and changes on the earth's surface can be monitored consistently and in a synoptic way (Eastman et al, 2013). Vegetation plays a significant role in maintaining the earth's climate, hydrological processes and also serves as bank for genetic diversity. But due to human interference with the ecosystem, many vegetated areas are transformed or lost completely.

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The vegetation of Nigeria being the most populous nation in Africa has experienced various forms of transformation over the last decades due to human perturbation which has led to gradual degradation of the natural vegetation in most regions (Osunmadewa et al, 2015; Akinyede et al, 2015). Several studies such as that of Usman et al, 2012; Eastman & Fulk, 1993; Fung & LeDrew 1987; Parmentier, 2014; Do et al 2014; Chamaille et al, 2006 had proved the potentials of using AVHRR NDVI data coupled with advance analytical method (PCA) for monitoring vegetation change at regional level in Africa. Multi-temporal satellite imagery from remote sensing has provided an analytical means which allows for the identification where and when changes in vegetation cover had occurred and also to better understand factors which are responsible for these changes (Fensholt et al 201). Therefore, the aim of this study is to explore the potential of Principal Component Analysis to detect vegetation trends over a long term period using Normalized Difference Vegetation Index data from Advance Very High Resolution Radiometer sensor from 1983-2011 in the dry sub-humid region of Nigeria.

## 2. MATERIALS AND METHODS

### 2.1. Description of the study area

Niger state being the second largest state in Nigeria lies between latitude 8°N and 11°N and longitude 3°E and 7°.20´E. The state bordered to the north by Zamfara state, to the northwest by Kebbi state, to the south by Kogi and Kwara state, to the east by Kaduna and Abuja and share international with Republic Benin (Fig.1). The state has a total landmass of 68,925km$^2$ and a population of 2,421,581 in 1991 and 3,954,772 in 2006 (ABS, 2010). The climate of the state is mainly tropical, and it is characterized by alternating dry and wet season. The annual rainfall is about 1500mm in the south to 1300mm in the north with a single maximal in August month. Generally, the temperature is high. The minimum temperature is about 22°C while the maximum temperature is about 37°C (ABS, 2010). The vegetation of the state falls within the Southern Guinea Savannah vegetation type and it is usually characterized by woodlands and tall grasses (Oguntoyinbo et al, 1983; Ajewole et al, 2013; Mayomi et al, 2014). Some among the economic trees species are: *Ceiba pentandra, Tamarindus indica, Adansonia digitata, Afzelia africana, Acacia albida, Khaya senegalenesis, Parkia biglobosa, Daniellia oliveri, Ficus sycomorus and Mangifera indica while some of the grasses are Panicum kerstingii, Setaria pallide-fusca and Rhynchelytrum repens* (Oguntoyinbo et al, 1983). The soil of the state is derived from Basement complex rock, it is very fertile and support cultivation of various agricultural crops. Thus, the state can be referred to as agrarian state because vast majority are into farming, fishing and rearing of livestock (Mayomi et al, 2014).

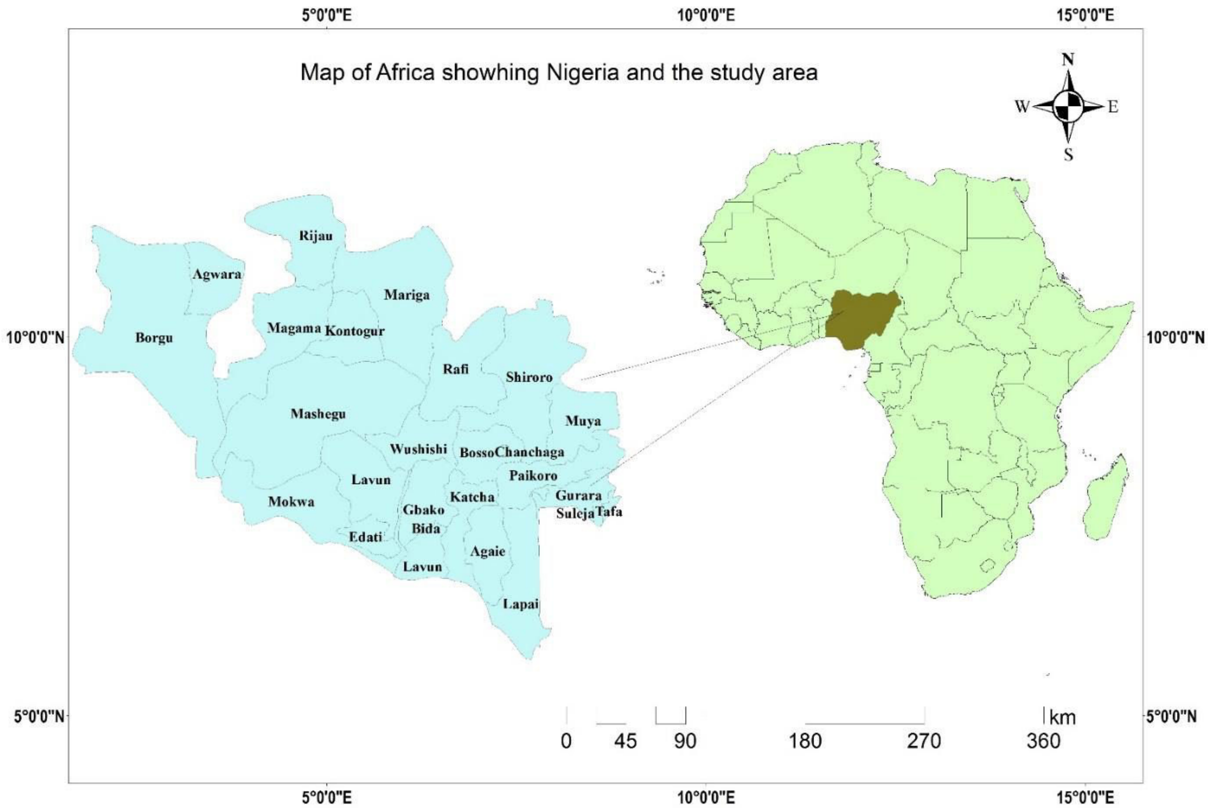


Figure 1. Map of study area
Source: GAMD database, 2016

## 2.2 Data source

The updated version of Normalized Difference Vegetation Index (NDVI3g) from Global Inventory Modeling and Mapping Studies (GIMMS) was used in this study. The GIMMS NDVI3g is the most suitable data for long term analysis of vegetation trend because it span from 1981 through 2011 (Tian et al, 2016; Eastman, 2013). The NDVI3g product is a reconstructed version of the previous NDVI, it has been processed for solar angle effect which might occur as a result of orbital drift, and/or volcanic aerosols (which might cause seasonality in the NDVI) using an adaptive empirical mode decomposition (Pinzon and Tucker, 2014; Tucker et al, 2005). GIMMS NDVI3g is a bi-monthly composite dataset with 8km spatial resolution from Advanced Very High Resolution Radiometer (AVHRR) sensors which is now available freely for (https://ecocast.arc.nasa.gov/data/pub/gimms). For this study, the NDVI dataset used starts from 1983 through 2011.

The second data used in this study was the Global land cover datasets of 2000 and 2009 from European Space Agency (ESA). As changes in vegetation dynamics is mostly associated with land cover change, therefore, the global land cover datasets of two different years (2000-2009) was used as supporting data for explaining any change which might be observe from the results of the vegetation analysis over the study period. The global land cover map of 2009 is a one year (January-December) product and has spatial resolution of 300m, the dataset is derived from MERIS sensor on ENVISAT and has 22 land cover classes (Bontemps et al., 2010; http://due.esrin.esa.int/page_globcover.php). The global land cover map of 2000 is also one year product, which was using acquired by the SPOT4 vegetation instrument and it has 1km spatial resolution.

### 2.3. Methods

Both parametric and non- parametric statistical method were used in the analysis of trend over the study area. The bi-monthly NDVI3g dataset was aggregated into monthly composites using maximum value composite in order to further reduce the influence of noise and enhance vegetation signals (Holben, 1986). Before performing the trend analysis, the NDVI monthly composite were deseasoned in order to remove serial correlation which might make the results of the trend analysis to be biased (Eastman, 2012). The study area was then clipped out of the global data using the administrative shape-file of Niger state and was then reprojected to the Universal Transverse Mercator (UTM). The global land cover (GLC) data for the two years (2000 and 2009) were also clipped out of the global data. The GLC data of 2009 was resampled to GLC 2000 using the nearest neighbor resampling algorithm resulting in spatial resolution of 1km, this was necessary for proper comparison of the GLC datasets.

The analysis of the NDVI3g dataset for the study period (1983-2011) was done following four steps: (a) Ordinary least square (OLS), (b) Theil-Sen median trend, (c) Mann Kendall test and (d) Principal Component Analysis (PCA) using the T-mode orientation approach which is also known as standardized PCA, the T-mode produces both spatial and temporal results (components and loading) which can be used for explanation of vegetation change dynamics.

#### (a) Linear Regression Model

Ordinary least square method which is a parametric method commonly used for NDVI trend estimation was used in this study where time is the independent variable and smoothed NDVI is the dependent variable. Ordinary Least Squares (OLS) is a linear regression method which can be used for modelling environmental phenomena such as vegetation and climatic datasets.

#### (b) Theil-Sen median

The result of the parametric test might be biased especially when assumptions about normality are not met in any time series analysis estimation (Faour, 2016). Therefore, a robust non-parametric estimator which is based on the median values of pairwise combinations known as Theil-Sen was also used in the analysis to buttress the result of the OLS. Thiel -Sen median trend estimator is suitable for assessing the rate of change in time series analysis, although the result is often similar to that of ordinary least square regression (OLS) when used for long time series analysis, but it is resistant to outliers unlike the OLS (Gilbert, 1987; Eastman, 2012; Parmentier, 2014). The Theil-Sen median slope was determined by calculating the slope between all pair wise combination and then assessing the median over time. The breakdown bound for the median is approximately 29%, which means that outliers do not affect the values of TS if it is not more than 29% of the length of the series (in time steps) in contrast to the OLS.

#### (c) Mann-Kendall (MK) Trend Test

Mann-Kendall (MK) test is a non-parametric trend test which is resistant to outliers. To perform this analysis, the time series dataset do not have to normally distributed, and it can also be used with missing data (Gilbert, 1987, Osunmadewa et al, 2015). The test measures the degree to which a trend in any time series is consistently increasing or decreasing and it is computed by comparing each data value with subsequent data values. If an earlier value or measurement is less in magnitude than a later one, the statistic $S$ is assigned a value of 1 and if an earlier value is greater in magnitude than the later one, it is assigned a value of -1, while two identical values (measurement) are assigned 0, the result of all increment and decrement values gives the final value of $S$ (Gilbert, 1987).

#### (d) Principal Components Analysis (PCA)

PCA is an orthogonal transformation (linear transformation) of correlated images in a time series into uncorrelated images which does not alter the numbers of images in the time series (Eastman, 2012; Parmentier, 2014). The time series dataset (images) are transformed into sets of component (principal component) which are independent of each other and are ordered in terms of variance. The largest amount of variance within the time series is contained in the first component (Eastman, 2012; Fung and LeDrew, 1987; Thiam, 1997). The method used for the analysis is the T-mode orientation approach also known as standardized PCA in order to give equal weight to each image in the NDVI time series. The T-mode produces both spatial and temporal results (components and loading), five components were used for the Principal component analysis. The PCA can be computed according to (Mackiewicz and Ratajczak, 1993; Jackson, 1991) as covariance matrix and it is presented as:

$$y\begin{bmatrix} y_{1,1} & y_{1,2} & \cdots & y_{1,n} \\ y_{2,1} & y_{2,2} & \cdots & y_{2,n} \\ \cdots & \cdots & \cdots & \cdots \\ y_{m,1} & y_{m,2} & \cdots & y_{n,m} \end{bmatrix} \quad (1)$$

where $y_{1,1}$ is the variance of the *ith* variable, $x_i$, and $y_{ij}$ is the covariance between the *ith* and *jth* variables.

## 3. RESULTS AND DISCUSSION

### *3.1. Trend analysis*

The results of the trend analysis for this study are presented graphically. Ordinary least square (OLS) modeling, Theil Sen median slope estimator and Mann-Kendall (MK) were used for the detection of vegetation trend over the study period. Positive and negative trends were observed from the results of the analysis, where positive trends indicates vegetation greening, while negative trends indicates vegetation browning.

(a) Ordinary least square (OLS) modeling

Trends in vegetation change dynamics were quantified by the slope coefficient of an ordinary least squares regression between the values of each pixel over time and a perfectly linear series. Thus, the results of the OLS is an expression of the rate of vegetation change per month because the bi-monthly NDVI3g dataset used in this study were aggregated to monthly composite as described in section 2.3. Figure 2 shows the result of the OLS for the study period.

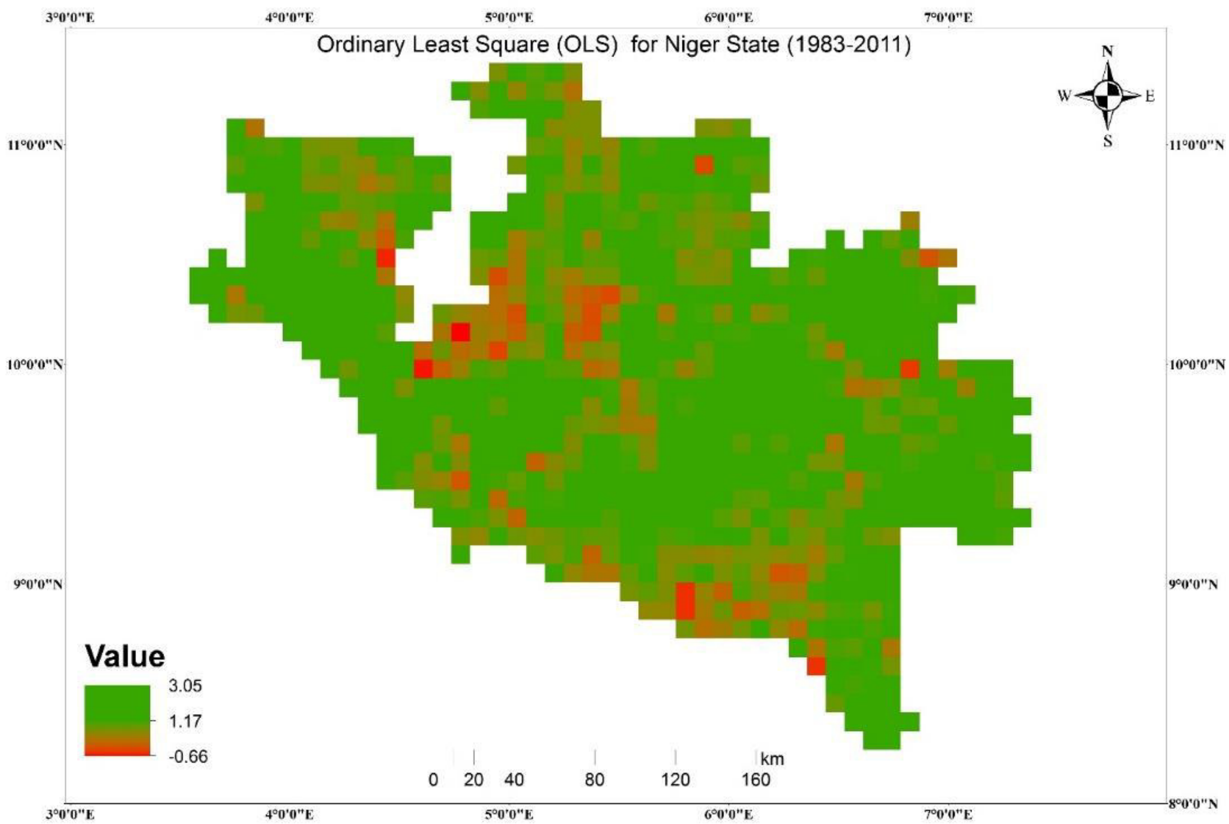


Figure 2. Slope coefficient of an ordinary least square regression model

It is obvious from the result of the OLS above that positive trends (green color) are more dominant which indicate vegetation greening over time while areas with red color indicate vegetation browning. Similar result was observed from the global study of de Jong, 2013 where vegetation greening was observed in some part of Nigeria.

About 5.72 % of the pixels used in this analysis showed negative NDVI value (negative slope coefficient value) which implies monthly loss in vegetation greenness over the study period while a monthly gain in NDVI of about 94 % was observed. This implies that the study area witnessed increase in vegetation greenness over the examined period (1983-2011).

(b) Theil Sen (TS) median trend estimator

Theil Sen was used to calculate the slope of the monthly NDVI over the study period. Figure 3 shows the result of the monthly TS for 1983-2011.

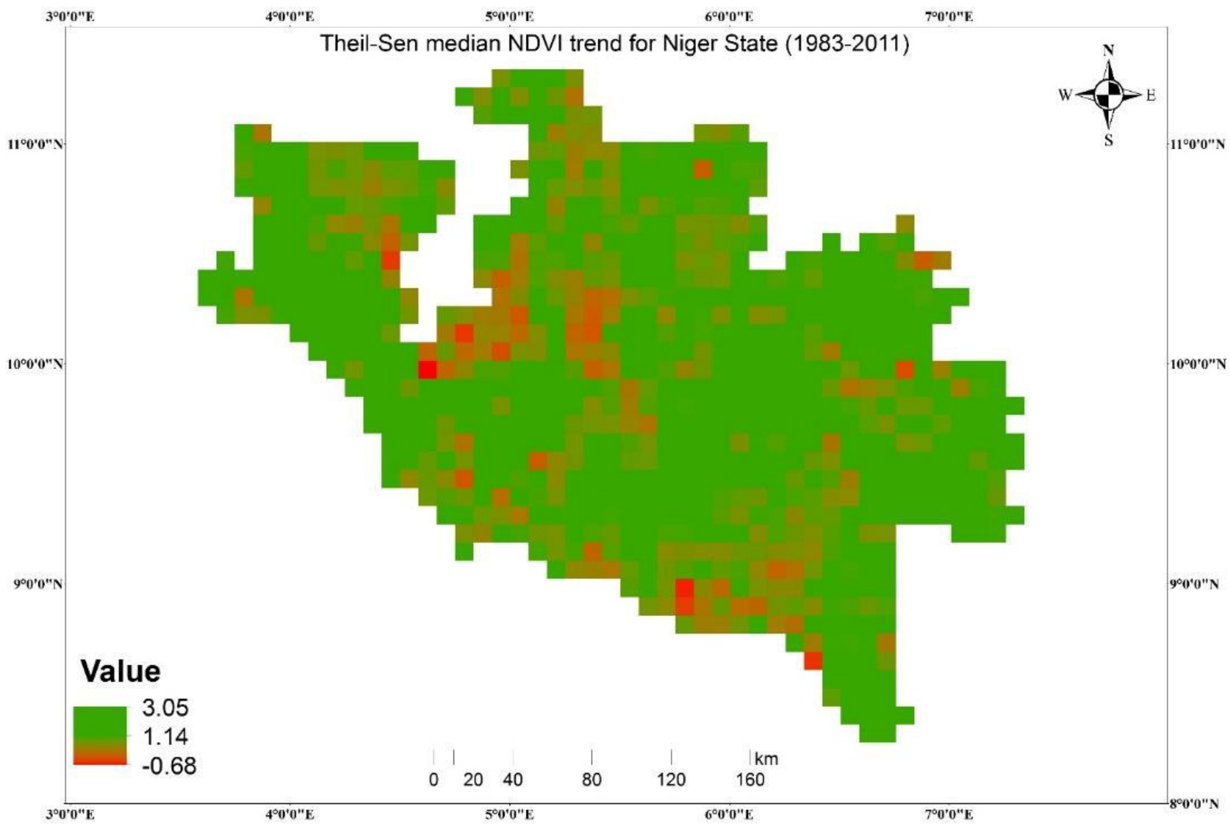


Figure 3. Theil Sen Regression model

Both increasing and decreasing trends where observed from the slope of the TS regression model. About 93 % of the pixels used in the calculation showed an increasing NDVI trend (monthly gain in vegetation greenness) while about 6 % showed decreasing trend. As stated in section 2.3, the result of the Theil Sen is similar to that of OLS, hence, where negative trend was observed in the OLS, similar negative trend was also observed in the Theil Sen which is in line with the result of Osunmadewa et al 2015 where the results of both regression model are similar.

(c) Mann-Kendall Trend Test

Mann-Kendall trend test shows the degree at which vegetation trend is consistently increasing or decreasing over time which can also be referred to as the direction of vegetation change. The result of the Mann-Kendall trend test which is also referred to as monotonic trend analysis in this study is presented in figure 4.

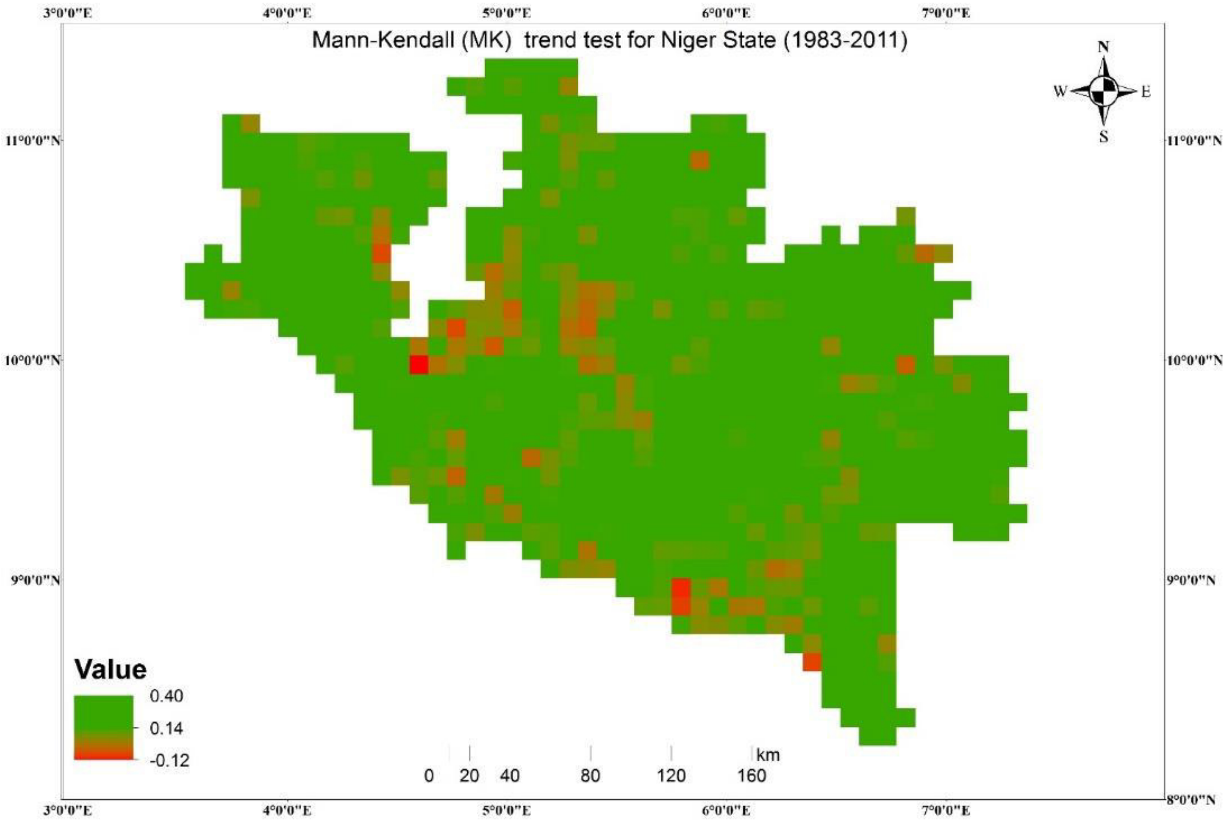


Figure 4. Mann-Kendall monotonic trend

The result of the monotonic trend analysis showed that 90 % of the study area experienced increasing trend while 10 % showed decreasing trend. Generally, the results obtained from the trend estimators used in this study showed an increase in vegetation trend (i.e vegetation greenness) over the last decades. The result is in line with that of Fensholt et al 2012, de Jong, 2013 where greening trends was observed in the semi-arid regions.

(d) Principal Component Analysis (PCA)

PCA was performed to decompose the NDVI time series dataset used in this study. Standardized PCA were calculated and all the variables (NDVI dataset) are assigned equal weight. The results of the first component (PC1) explains about 98% of the total variance of the vegetation (NDVI) while components two to five have lesser variance (< 1%) as presented in table 1. High values in the results of the component analysis correspond to area with higher concentration of vegetation density while lower values are indication of low vegetation density which depict different land use pattern in the study area.

Table 1. Principal component Eigenvalues

| | Component 1 | Component 2 | Component 3 | Component 4 | Component 5 |
|---|---|---|---|---|---|
| % Variance | 98.57 | 0.30 | 0.13 | 0.08 | 0.06 |
| Eigenvalue | 343.02 | 1.04 | 0.46 | 0.28 | 0.21 |

Figure 5 shows the result of principal component 1 for the study period, it should be noted that figures 2-5 for the other principal components are not presented in this study as they contain lesser variance value (table 1).

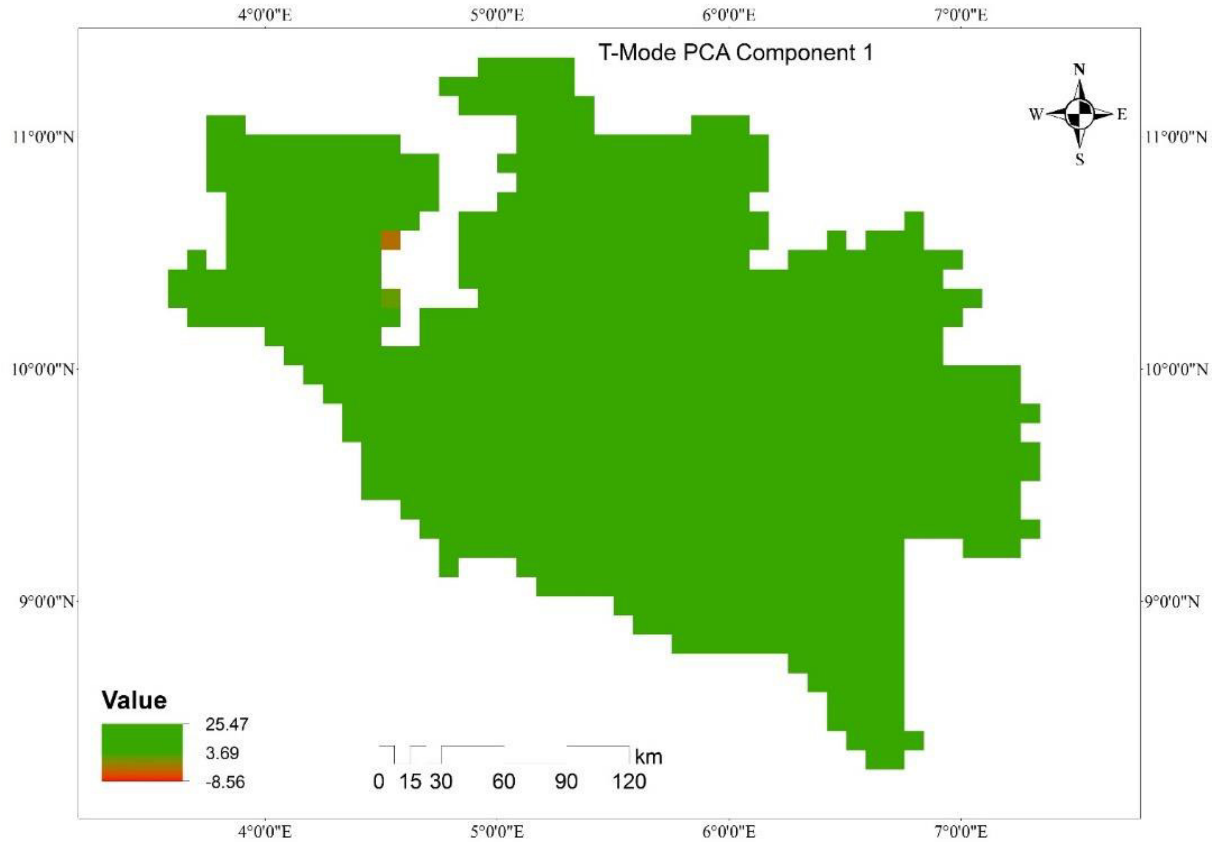


Figure 5. The first principal component of NDVI time series for 1983-2011.

As mentioned earlier, higher values were observed from the result of component 1 for the whole study area which indicate high biomass distribution across different land cover types in Niger state over the study period. Similar results was obtained in the Northern part of Nigeria (Usman et al, 2012), although the underling factor for the increasing NDVI trend has to be verified.

### 3.2 Discussion

Results obtained from the analysis of vegetation trend across the study area (Niger state) revealed that there is an increase in vegetation trend over the examined period (1983-2011). Increasing trend was observed from the results of the parametric and non-parametric trend estimator used, this result is in line with the study of Ghazaryan et al, 2016 where monotonic increase in NDVI trend was observed in Ukraine. In order to understand the dynamics of change in land cover transition, land cover data for 2000 and 2009 were used and the result was summarized in table 2.

Table 2: Land cover types for GLC 2000 and GLC 2009

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

The above table shows a clear decline in grassland/sparse vegetation, shrubland and forest while an increase in the size of cropland was observed in 2009. Although, the result of the trend analysis and PCA showed an increasing trend in vegetation dynamics, this increase is linked with human induced modification of the ecosystem as revealed by the result of the land cover for the study area. Field visit during this study shows the existence of Agricultural development project (ADP) in Niger state Nigeria where land are allocated large scale agricultural practices. Change in the land cover for the period of 2000-2009 was assessed using change matrix, the result confirmed that there is a significant shift from one land use to the other (Fig.6).

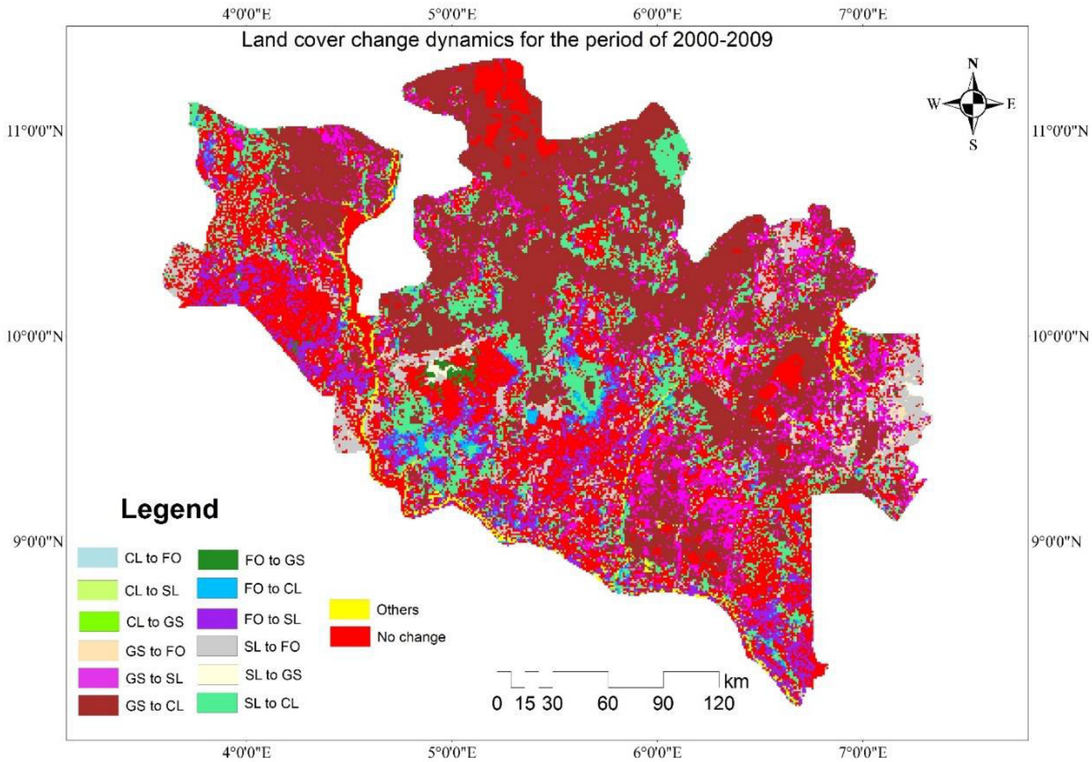


Figure 6. Change dynamics for 2000-2009 (Global land cover)

# 4. CONCLUSION

This study addressed the potentials of using AVHRR NDVI dataset for the assessment of long-term trends in vegetation dynamics in Niger state, Nigeria. The results of the study showed that increase in NDVI trends dominate the study area. The increase in vegetation trend over the study area is associated to the transition of the land cover from natural ecosystem to human dominated activities such as extensive and intensive agricultural practices. The results of the first component (PC1) explained 98% of the total variance of the vegetation (NDVI) while components two to five have lower variance percentage (< 1%). Two ancillary land use land cover data of 2000 and 2009 from European Space Agency (ESA) were further used to explain changes observed in the Normalized Difference Vegetation Index (NDVI). The result of the analysis of land use data showed changes in the land use pattern which is attributed to anthropogenic activities such as cutting of trees for charcoal production, agricultural activities, urbanization among others. The result of this study is useful for improving knowledge about vegetation change in the region, it also provides policy makers with adequate information which can be used for proper land use management. However, further research on vegetation response to climatic parameters are needed in the future for in-depth assessment of climate-vegetation productivity in the dry sub-humid region of Nigeria.

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