An Assessment of Vegetation Cover Changes across Northern Nigeria Using Trend Line and Principal Component Analysis

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Abstract

This study is on the application of Principal Component Analysis (PCA) and trend line using time-series satellite dataset from National Oceanic and Atmospheric Administration (NOAA) Advanced Very High Resolution Radiometer (AVHRR) and Moderate Resolution Imaging Spectroradiometer (AQUA/MODIS) with the objective of characterizing vegetation cover changes across Northern Nigeria from 1981 to 2010. The dataset were both radiometically and atmospherically processed and projected on a 0.05 degree climate modelling Grid (CMD). The dataset was analysed using principal component analysis utilising the standardised principal components (SPC) and trendlines. The results from the analysis indicated that there are both negative and positive long term trends in vegetation cover changes. However, there was more greening trend of vegetation in northern part of the study area which explained 74% and 82% of the total variance in the first PCs for the NOAA-AVHRR and MODIS, dataset respectively. However, the second PC's indicated the seasonal variation of vegetation NDVI, explaining only 4.2% and 4.8% of the total variance of the AVHRR and Aqua/MODIS-NDVI datasets respectively.

Keyword: Principal Component Analysis (PCA), Vegetation cover, Seasonal variation, spectral variation, Normalized Difference Vegetation Index (NDVI), Trendlines.

1. Introduction

Time-series Normalized Difference Vegetation Index (NDVI) derived from National Oceanic Atmospheric Administration/Advanced Very

High Resolution Radiometer (NOAA/AVHRR) and Moderate Resolution Imaging Spectroradiometer (AQUA/MODIS) dataset have been used for detecting long-term land-use/cover changes and for modeling terrestrial ecosystems on the global, continental, and regional scales. For example, several studies which utilised NDVI dataset from these sensors such as IGBP, 1992; Justice *et al*., 1985; Myneni *et al*., 1997; Potter *et al*., 1993; Prince, 1991; Reed *et al*., 1994; Running and Nemani, 1988; Tucker and Sellers, 1986; Tucker *et al*., 1985 exhibited valuable results.

NDVI generally provides a measure of the amount and vigor of vegetation on the land surface. The magnitude of NDVI is related to the level of photosynthetic activity in the observed vegetation. In general, higher values of NDVI indicate greater vigor and amounts of vegetation. Other research that utilized NDVI from these type of sensors were able to obtain useful and reliable results which are closely related to percent cover, leaf area Index (LAI), and plant canopy (eg. Malingreau, 1986; Marsh *et al*. 1992; Di *et al*, 1994; John *et al*, 1998). Depending on the type of sensor utilized in acquiring the imagery, NDVI generally is calculated as a ratio of red and NIR bands of a sensor system and is represented by the following equation:

$$NDVI = \frac{NIR - R}{NIR + R} \quad (1)$$

The NDVI approach is based on the fact that healthy vegetation has a low reflectance in the visible portion of the Electromagnetic Spectrum (EMS) due to chlorophyll and other pigment absorption and has high reflectance in the NIR because of the internal reflectance by the mesophyll spongy tissue of green leaf (Campbell, 1987). Thus, NDVI values range from -1 to +1 or 0 to 255 if scaled NDVI values are utilized with the computer colour range.

Because of high reflectance in NIR portion of the EMS, healthy vegetation is represented by NDVI values between 0.1 and 1. Conversely, non-vegetated surfaces such as water bodies yield negative values of NDVI because of the electromagnetic absorption quality of water. Bare soil areas represent NDVI values which are close to 0 due to high reflectance in both visible and NIR portions of the EMS (Lillesand and Kiefer, 2005). NDVI has also been shown to be related to photosynthetically active radiation (PAR) and basically measures the capability of leaves, which is related to vegetative canopy resistance and water vapour transfer (Malo and Nicholson, 1990).

A different approach in characterising land-cover types from multitemporal data sets is through the use of principal component analysis (PCA). PCA has been successfully employed in remote sensing for image data transformation, information compression, and change detection analysis. In this study PCA was utilized as a form of image transformations and compression technique because of the amount of the dataset used in the analysis. PCA aims to identify which bands account for the largest amount of variance in a dataset and thus, can be selected for use in other analysis tasks like image classification or simply for purpose of image enhancement by combining information from various spectral bands. Unlike PCA calculated using the covariance matrix called unstandardized PCs; however, those calculated using the correlation matrix is referred to as standardized PCs. The use of standardized PCs and unstandardized PCA has been discussed by (Singh and Harrison, 1985).

The use of PCA which utilized Standardized Principal Components (SPC) in this case is to determine variance of patterns in the spectral and temporal domain covering the study area. The procedure of Standardized PCA with SPC is found to be very useful in the analysis of time series data sets where the interest is in the identification of phenomena or signals that propagate over time.

Often it is applied to single band data (vegetation index maps) which maps only one given phenomena over the land surface e.g vegetation greenness. The standardization is intended to minimize the undue influence of other extraneous factors e.g. atmospheric interference (aerosols and water vapour), changes in surface illumination conditions, etc. In this way that the different time variance patterns of the phenomena of interest (Vegetation) can be extracted from the time series measurements effectively. This multivariate statistical technique has proven to be particularly effective when applied to both short and long time-series image data to identify surface change (Byrne *et al*., 1980; Eastman, 1992; Eastman and Fulk, 1993; Fuug and LeDrew, 1987; Ingebritsen and Lyon, 1985; Singh, 1989).

The purpose of this study therefore, is to investigate the application of PCA utilizing the SPC with the objective of determining seasonal trends of vegetation cover changes from the AVHRR and Aqua/MODIS-NDVI datasets across Northern Nigeria from 1981 to 2010.

1.1 Theoretical Background

According to Steffen and Tyson, (2001) the vegetative surface cover has an important function in the earth surface because it is linked via several feedback mechanisms to hydrological and climatological processes. Identifying and quantifying these linkages delivers important insight for environmental modelling, management and informed decision making. Satellite earth observation data with high temporal repeat intervals such as AVHRR (Advanced Very High Resolution Radiometer) or MODIS (Moderate Resolution Imaging Spectroradiometer) deliver spatially dense information about the earth surface and are well-suited for monitoring continental scale surface processes.

Although component analysis was used in contemporary studies relating to land surface phenomena (eg. Singh and Harrison,1985; Ingebritsen, and Lyon1985; Fung and LeDrew, 1987; Eastman and Fulk, 1993; Eklundh and Singh 1993; Verbesselt et al, 2010), it was initially used to determine different growth curves for a single variable measured through time across a number of individuals or cases (Tucker, 1966). This type of analysis yields a set of reference curves, where each component represents a single curve that is statistically uncorrellated with the others and thus, reflects different information about the input data. Once the family of reference curves has been established, then the individuals can be associated with a characteristic curve.

However, the study conducted by Yelwa, (2008) on broadscale vegetation change assessment across Nigeria from coarse spatial and high temporal resolution AVHRR-NDVI data utilised PCA to identify spatial change patterns as a result of seasonal trends as was also shown by Eastman and Fulk, (1993) over the African continent.

Pugesek and Wood (1992) provided another good example of Tucker (1966) analysis using California Gull reproduction data. Tucker's (1966) component analysis yielded two significant growth curves, or components, that explained almost all of the data set variance.

These were interpreted as separate reproductive strategies employed by two groups within the overall gull sample. This interpretation satisfactorily explained anomalies in seagull reproduction patterns.

In most time-series analysis that utilised AVHRR imagery this satisfies the data requirements of the Tucker model. There exists a single variable (the NDVI) measured through time on a number of individuals, which are the pixels.

The components are then interpreted as statistically decorrellated NDVI trajectories over a time period. Typically, these are the seasonal patterns of greening-up or otherwise in the phenological cycle. The true magnitude of these reflectance patterns are preserved by the use of unstandardized input NDVI images. If nearby pixels are associated with the same growth curve, or component, then they exhibit similar phenology and probably will belong to a single vegetation community. If nearby pixels belong to a different reference curve, then multiple phenological patterns may be present that must be interpreted in a geographical context.

The spectral data from the sensor has generally been made available as the normalized difference vegetation index (NDVI). In the analysis of global landcover information, NDVI has frequently been utilized (e.g., Townshend, 1994). Eastman (1992), and Eastman and Fulk (1993) established the advantage of starting the solution of the eigenvalue problem with the correlation matrix instead of the variance-covariance matrix to calculate the eigenveetors in PCA for change detection. This produces a standardized PCs data set which has also been shown to have an improved signal-to-noise (SNR) ratio (Eklundh and Singh, 1993) when analyzing AVHRR, Landsat-TM, and SPOT data.

These pioneering studies utilizing NDVI identified the first two PCs as representing the accumulated greenness during the period of analysis (the first PC) and the seasonal variability of vegetation (the second PC).

The first two PCs could be identified through analysis of the structure of the eigenvectors. The elements of the first PC eigenvector were positive, higher in value, and very consistent over the period of analysis, while the elements of the second PC exhibited a cyclical pattern or seasonal variation. Therefore, in this case the first PC serves as a means of quantifying the density and photosynthetic activity of vegetation while the second PC can quantify the seasonal pattern of vegetation change.

By using the first two PCs, the time trend profile of NDVI can be converted into two values which can be easily calculated for each pixel permitting the quantitative comparison of these trends between pixels. Fung and LeDrew (1987) also analyzed the effect of changing the area under analysis when performing multitemporal land-cover change detection using PCA. They extracted four subset areas from their study area using an unsupervised classification map of 32 spectral classes. Results from the subset area did not always show clear land-cover change information. This therefore explained why the spectrally and statistically similar pixels within the subset areas were distributed in a narrower range in multidimensional space. When the PCA was applied to this distribution, none of the eigenvectors provided greater separability between landcover types present in the study area. Because the subset area consisted of only one land-cover type on a spectral basis, the eigenvectors emphasized the substructure within the subset land-cover type. Thus, applying PCA to spectrally similar areas proved to be effective in detecting more detailed information about these areas but less effective for overall land-cover change detection.

Anders *et al*. (1994), Olsson and Eklundh (1994), Azzali and Menetti (2000) used the Fourier Transformation (FT) to analyze NOAAAVHRR time series while Anders et al. (1994) applied FT to monthly-averaged Global Vegetation Index (GVI) data over Brazil. They successfully classified vegetation from the first two FT components using a minimum-distance algorithm. Azzali and Menetti (2000) however, applied a Temporal Fast Fourier Transformation (TFFT) to monthly-averaged GAC (Global Area Coverage) NDVI data to map vegetation-soil-climate complexes in Southern Africa. On the other hand, Anyamba and Eastman (1996) used PCA to study climatic trends in Africa 1986-1990 using dekadal NDVI Maximum Value Composite (MVC) data (Holben, 1986).

Young and Anyamba (1999) however, applied standardized PCA to time series of GVI and Pathfinder AVHRR Land 8 km (PAL) data for China 1982-1992. The GVI and PAL data were first aggregated to monthly MVC, and then averaged for each year. Radiometric inconsistency was related to successive changes in satellites as well as their orbital drift; these were observed in the GVI data and to a less extent in the PAL data. The PC4 derived from the PAL data showed changes associated with anthprogenic activities, whereas less significant components exhibited various climatic effects.

Lambin and Strahler (1994) used change vectors in multi-temporal space to study land-cover change based on time series of monthly MVCs NDVI. The length of the change vector correlates to the magnitude of the change, whereas the direction indicated the nature of the change. They compared their results with a PCA for two years in West Africa. In practical terms the magnitude of change vectors can be compared to simple summing up of NDVI values or to long term averages, but direction in multitemporal space is still hard to characterize in an unambiguous way.

Sunar (1998) on the other hand utilised five techniques, including: addition, subtraction, division, principle component (PCI), and post classification analysis to detect land cover changes in Aykitali, Turkey. It was identified in that study that the technique of addition and subtraction of images was the most simple among these techniques, while PCI and post classification analyses showed better results in change detection.

Tardi and Contalgon (2001) used three methods including: multi-temporal color composite, subtraction, and classification in order to examine physical development of Massachusett's urban area and the resulting land cover changes. Finally, they used post classification analysis in order to estimate total accuracy.

Rigina and Rasmussen, (2003). evaluated existing methods and techniques for analysing time series of remotely sensed vegetation index data. This was done within the framework of assessing long-term changes in the vegetation of Senegal in West Africa, and using time series of NDVI. One case study of Saqqez city was presented by Shahabi *et al*. (2012) where the detection of urban irregular development and green space destruction using three remote sensing techniques NDVI, PCA and post classification methods (PCM) were employed to detect the green space changes.

Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (ETM+) data covering the period from 1989 to 2009 were used to recognize land use changes, particularly the physical development of the area and its devastating effects on the green space. The result showed that green space has been reduced from 530 ha in 1989 to 198.3 ha in 2009. In that study, the capabilities of LANDSAT data which is oriented towards determining land use changes, via the standard methods was tested.

The result showed that NDVI and post classification analysis methods are better than principal component analysis in detecting the devastating effects of unplanned constructions and forming projects on Saqqez's green space.

2. Materials and Methods

The Global NDVI data sets utilized for this study contains 8 km resolution Monthly maximum value composite (MVC) NDVI images provided by NOAA/NASA-AVHRR (1981-2000, with the exception of September-December 1994); and AQUA-MODIS Monthly NDVI dataset at 250m resolution from 2000 to 2010. The MODIS CMG Monthly NDVI dataset were however pre-processed by NASA Goddard from the Terra sensor and projected on a 0.05 degree Climate Modeling Grid (CMG), as well as precipitation (rainfall) data, and all the dataset were in IDRISI format.

The original values were not altered. All files are provided in the latitude / longitude reference system. However, all the NDVI dataset utilised in the analysis were averaged and their standard deviations for the monthly NDVI for the twelve months were also calculated and determined. Furthermore, each of the NDVI datasets from NOAA/NASA and AQUA/MODIS-CMD were used as input in the PCA analysis using standardized principal components (SPC). For each of the component loadings derived from the SPC a trend line was generated so as to indicate the pattern of the changes and trend in the vegetation cover across the study area for the entire time-series.

2.1 Model Specification

PCA is a linear transformation of correlated variables into uncorrelated variables which does not change the number of variables (spectral or temporal bands). Because the transformed variables, which are called principal components (PCs), are uncorrelated, they can be considered to be independent.

The transformed variables are ordered in terms of variance, so that the first PC represents the largest amount of variance within the data set. On a statistical basis, the multitemporal information present in the data is reflected by the variance. Therefore, at least a portion of the variance of the multitemporal image data set can be utilized to characterize land cover. If the PCA can extract factors that can be utilized to distinguish land cover, they will be objective and mutually independent.

The process first computes the covariance matrix ρ among all input bands (in the case of time series, dates). ρ is symmetric and of dimensional $k \times k$ where k is the total number of input bands. Each element of ρ is calculated as :

$$cov k_1, k_2 = \frac{1}{nm} \sum_{i=1}^{n} \sum_{j=1}^{m} \left(P_{i,j,k_1} - \mu k_2\right)\left(P_{i,j,k_2} - \mu k_2\right) \quad (2)$$

Where

k_1, k_2 two input bands, $P_{i,j}$ brightness value of a pixel in row i and column j, n is the number of rows, m number of columns and μ is the mean of all pixel values in the subscripted input band.

α is defined as an orthogonal matrix that diagonalizes ρ, such that the diagonal elements are by descending order, fixing the order of column in α. In other words computing $\alpha^t \rho \alpha$ results in a diagonal similar to ρ, whose diagonal elements are eigenvalues (λ_i) of ρ. The columns of $\alpha(\propto_i)$are eigenvectors of ρ. The percent of total dataset variance explained by each component *i* is :

$$\%_i = \frac{100 \times \lambda_i}{\sum_{i=1}^{k} \lambda_i} \quad (3)$$

A value is calculated for each pixel to produce a series of image layers, called eigenchannels or components, by multiplying the eigenvector for that component by the vector of original pixel values in the input bands.

$$P_i = \sum_{k=1}^{n} P_k \propto_{ki} \qquad (4)$$

Where

P_i indicates a brightness value in component i;
$\propto_{ki}$ eigenvector element for component i in input band k;
P_k brightness value in band k;
n is the number of input bands.

A loading or correlation R of each component i with each input band k can be calculated

$$R_{ki} = \frac{\propto_{ki}\sqrt{\lambda_i}}{\sqrt{vark}} \qquad (5)$$

Where the $vark$ is the variance of input band k (obtained by reading the k^{th} diagonal of the covariance matrix). If the eigenvalues and eigenvectors are computed from the correlation matrix, the loadings are simply the $\propto_{ki}$ (Jakubauskas *et al;* 2002). The computation of PCA is described as an eigenvalue problem of the matrix:

$$|\rho - \lambda_i I|\alpha_i = 0 \qquad (6)$$

where ρ is a variance-covariance matrix, λ is an eigenvalue, α_j is an eigenvector corresponding to the eigenvalue λ, I is the unit matrix, and 0 is the zero vector. According to this equation, the eigenvector and eigenvalue depend upon the relative size of the variance and covariance in the matrix ρ.

If a variable has a large variance, this variable will significantly affect the result of PCA. For example, if a few contaminated pixels are included in one of the multitemporal images, the variance of this image and associated covariance will increase. This effect is undesirable if the analysis is designed to identify non-unique characteristics. Fung and LeDrew (1987),

3. Results and Discussion

Results derived from this study are presented as NDVI vegetation maps obtained through Principal Component Analysis (PCA) that utilized standardized principal component images and graph of loading scores showing trend lines.

3.1 Long Term Changes in Vegetation Productivity

Trend analysis was executed as described by Fuller (1998). For the period 1981 – 2010 the annual NDVI integrals were computed for the entire growing season. The output was a slope image and intercept image.

The slope image captures long-term trends in Northern Nigeria. From a statistical point of view the trend itself represent an actual situation because the entire data population is known. This cannot be compared with linear regression techniques used to show correlation between samples of observations. For the same reason, the regression correlation coefficient for the trend line will only give information about the variation in the data set, whether or not the trend is likely to represent a real world situation.

For this reason all trends can be considered as valid information. In order to investigate whether the trends (the slopes) capture the development in the annual integrated NDVI (rather than merely representing a data artefact, or heavy influence by outliers), areas showing the same trends were identified and compared with the original annual integrated NDVI values variation in time.

Furthermore, rainfall data were included whenever possible, as we believed at least some of the observed trends would reflect changes in rainfall.

This procedure, maps out the coefficient of determination (r^2) from a linear regression between the values of each pixel over time and a perfectly linear series. The result is a mapping of the degree to which a linear trend is present. Linear trend is measured by the coefficient of determination from regression analysis (Figure 1). Even though the R^2 value of the trends in NDVI was low, only 0.00 to 0.15+ for NOAA-AVHRR and 0.00 to 0.17+ for MODIS, correspondingly, these browning trends may serve as indicators for negative change of climate conditions in the study region. During the study period, two severe drought episodes with duration 3 years occurred in 1982-84. Besides, two years (1989 and 1990) exhibited dry conditions with rainfall mean of 119mm-128mm below the long-time mean of 159mm. In 2007 and 2008, the amount of rainfall was below the average value.

The linear trend values of most stations exhibited low coefficient of determination, R^2, and cannot be believed to be statistically significant. The results of analysis of trend in climate parameters exhibited low statistic inference of trends for the most stations and seasons. Ordinary Least Squares (OLS) Slope Analysis: This is the slope coefficient of an OLS regression between the values of each pixel over time and a perfectly linear series. The result is an expression of the rate of change per time step because the monthly data expresses the rate of change per month.

Since the results of OLS slope images of NDVI time series were a set of continuous images, with a unique value for each pixel, each image therefore showed the slope values, which represent the trend of each of the different time segments of the NDVI time series (Figure 1 and Figure 2) with different length of time series to represent different pattern level trend periods for the whole study area. To better illustrate the results, all the maps' ranges were standardized, representing the rate of change in NDVI period. In these figures, the regional pattern of pixel-level trends based on linear regressions of NOAA-AVHRR 1981 – 2000 and AQUA/MODIS dataset reflects the south to north climatic gradient, with pixels having the strongest declining trend in NDVI occurring driest region of Northern Nigeria. Thus, NDVI trends in this part of the study area suggest that they are both due to climatic and anthropogenic forces.

The Linear Modelling (LM) here, allowed an examination of the relationship between the time-series dataset. In Figure 3, for example, green colour or positive values indicate a positive trend while the red or negative values is indicative of negative trend. The analysis of variance (ANOVA) of the LM results shows that the identified trends are significant in large parts of southern part of the study area.

However, trends are weak in most of the northern part of the study area. Spatial patterns of the coefficient of variations of R^2 appear to correspond exactly with patterns of vegetation cover: variability of R^2 decreases from shrubs and desert vegetation in the north of the study area, to guinea vegetation in the south part of the study area. These results indicate a major degree of temporal variation in the relationship between NDVI and rainfall in the study area.

The strength of relationship between NDVI and rainfall, along with the use of regression statistics, provides useful information for assessment of land cover performance. In the dry regions, areas with exceptionally low NDVI-rainfall correlation identify sites where vegetation cover is damaged and land degradation is going on (Li *et al.*, 2004).

Looking into time-series of regression statistics, especially R^2, the ability of the land surface to respond to rainfall over the time period can be implied.

Thus, a decrease of R^2 over the study period would indicate a decreasing dependence of the vegetation cover on rainfall patterns and an increasing dependence on others factors such as temperature patterns or human influence. This negative trend however, indicated an area with vegetation cover being more stressed. On the other hand, an increase of R^2 over time suggests a surface with an increasingly better response of the vegetation cover to rainfall and a decreasing role of other predictive factors. There is no doubt, that any change in land cover or in land use would be reflected in a change of R^2 value. So, abandonment or expansion of cultivated areas as well as taking virgin land into agricultural use should be noticeable in the time-series of R^2.

The spatially averaged time-series of growing season NDVI exhibited a statistically significant upward trend with an increase of 0.5 % for all vegetated pixels over the period 1982 - 2010.

The determination coefficient of the trend is high enough, $R^2 = 0.17$. The growing season NDVIs also exhibited significant upward trends for each land-cover type with an exception of semi-desert region.

3.2 Principal Component Analysis (PCA)

For the PCA, standardized PCs were performed as recommended by Eastman and Fulk (1993). Each component was interpreted using a combination of loadings for month and geographic pattern. Standardized PCs were calculated based on the correlation matrix, providing an equal weight to each element within the original data series. PC1 explains most of the variation in the NDVI integrals and represents the average spatial integrated NDVI pattern.

Subsequent components explain progressively less variance but nonetheless exhibit temporal behaviour similar to the NDVI data. Since high values of each PC loading identify a specific event in the dataset (e.g. occurrence of bush fires, failed harvest etc.), the change patterns can be analyzed by plotting the integrated NDVI for areas with equally high and low PC loadings. This was done in order to identify how PCs depict changes in integrated NDVI for the period 1981 – 2010. All image processing was done using the IDRISI Selva software.

Figure 3 to Figure 6 shows the loadings for 1981 to 2010. They perform similarly with high correlation between CMP 1 and all months. High CMP1 pixel values correspond to areas with maximum integrated yearly vegetation density, grading to low values in areas of permanent no vegetated cover. As shown in Figure 4, the first component PC1 accounting for 74% for AVHRR and 81.7% for MODIS of total dataset variance, correlates strongly with all dates across all years, higher values are directly linked to the density of forest vegetation in the study area while lower values correspond to places of arid climate where the dominant vegetation is shrubland.

It illustrates a representative vegetation pattern across Northern Nigeria. The high degree of correlation of this component is demonstrated in the plot of loadings, since its variance is above 0.54 and 0.8 throughout the year for both the NOAA-AVHRR and AQUA-MODIS. This indicates that most part of the variability in NDVI is related to the spatial distribution pattern of vegetation and, consequently, to the total amount of rainfall received. Components 2 and 3 in Figure 4 which account for 7.6% and 6.14% for the AVHRR and MODIS, (PC2 and PC3) are interesting since they depict the different behaviours throughout the year of the different types of land covers. The components from 5 to 10 account for the remaining of the total variance which mostly gather noise images.

Component 2 illustrates the first change component; it represents the intensity of seasonality, thus a prevalent element of variability in NDVI. As can be seen by the loadings in Figure 4, this component shows an annual cycle indicating that this is a major element of variability of NDVI in Northern Nigeria generally which was due to the late rainy season or harmattan dust. It can also be seen from Figure 4 how the component images correlate positively with the months known to be the late rainy months (August- September) and negatively with the early rainy months (June - July). Loadings alternate between positive for August - September and negative for June - July. The crossover between positive and negative varies somewhat with the year and is associated with particular climatic conditions. The positive peaks on the other hand correspond with the peaks of rainy seasons in most part of the northern part of study area.

The third component like the second component, also shows anomalous events but this time it indicated that there is a great deal of contrast between two groups of months: all of June and July on the other hand and August-September on the other from year to year.

This occurs much of the northern most of the study area that undergo changes in the late harmattan and early parts of the raining season. PC 3, quite prominent positive and negative anomalies are seen in the northern part of the study area. These areas experience maximum vegetation peaks in the late raining seasons due to coincidence of the sun latitudinal position and the rainy season. PC4 loadings in figure 4 are highly prone to unexpected changes or erratic and the geographic pattern shows mainly latitudinal variation with no evidence of topographic or biome influence. It is interpreted as showing variance due to sun angle differences across the image.

PC5 to PC10 explains the remaining variance of dataset both exhibiting other typical seasonal cycles, both with crossovers from positive to negative loading in August and September. Although they may have potential in showing certain spatial and temporal events that my be linked socio-political or socio-economic events that may be related to vegetation changes, more environmental information or data is required to ascertain these other results.

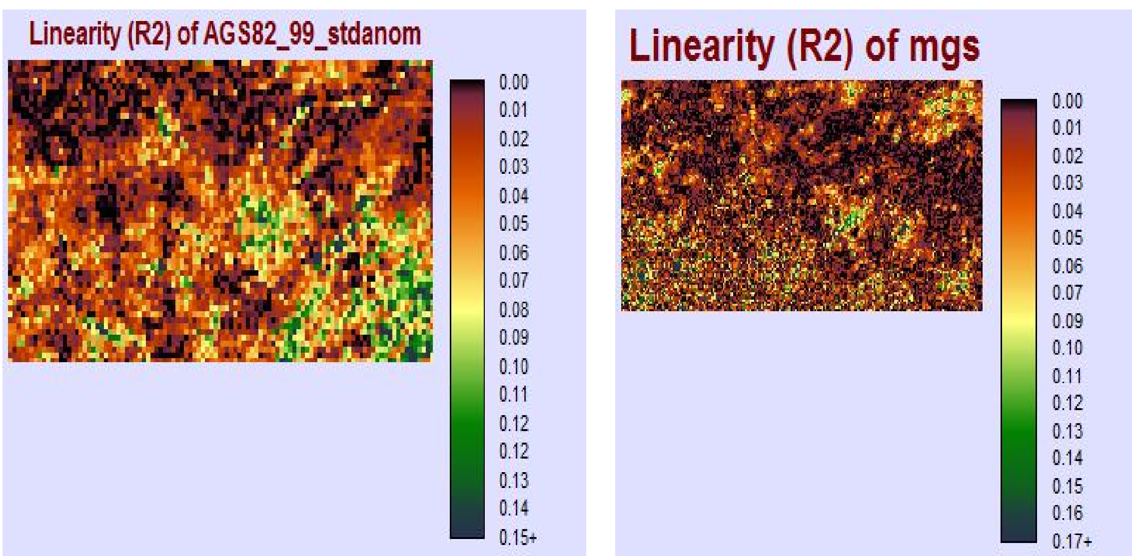
4. Conclusion

This study presented certain methodologies using linear trends and PCA that evaluated long time-series NDVI from NOAA-AVHRR and AQUA-MODIS dataset from 1981 to 2010 covering the northern part of Nigeria. The results identified some underling trends in vegetation cover change as a result of both climatic and anthprogenic factors. It has shown that long-term changes in vegetation productivity can be assessed using linear trend lines and PCA-SPC with time series of AVHRR and MODIS NDVI dataset. It further showed that there was both negative and positive trends in NDVI vegetation productivity across the northern part of Nigeria generally.

When PCA was applied to the entire study area, two of the most important factors for characterizing vegetation cover were extracted in the first two PCs. The first PC for example, which explained 74% and 82% of the total variance for both NOAA-AVHRR and MODIS, reflects the spatial variation of vegetation NDVI distribution. The second PC reflects the seasonal variation of this phenomenon. Its contribution was nevertheless small which occupied 4.2% and 4.8% in terms of the total variance. Thus, analysis of the changing climate as carried out in this study provided relevant information for policy makers who are responsible for land use planning and environmental conservation and protection.

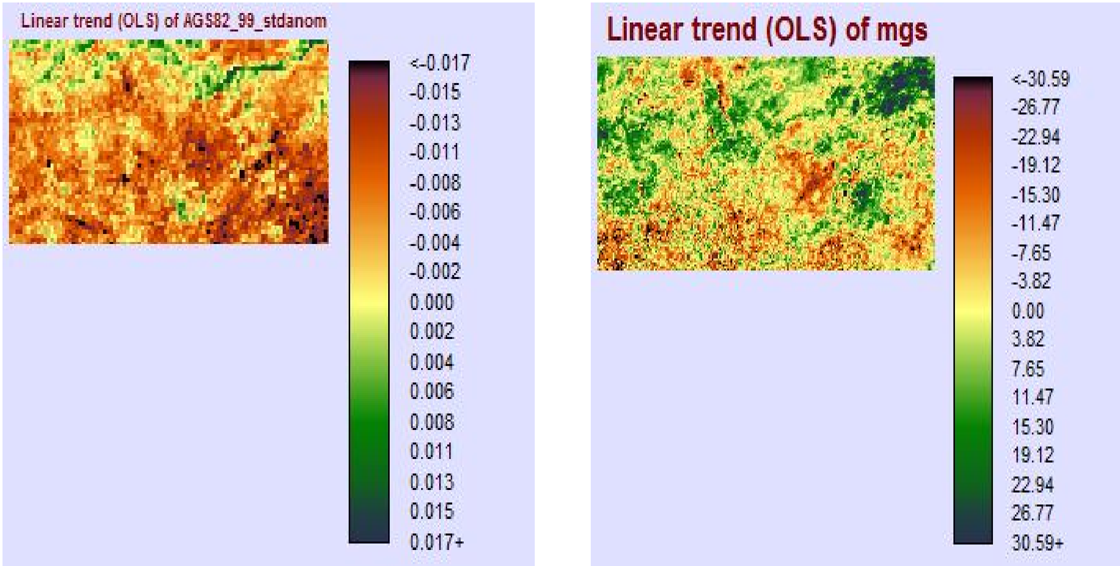
As the changing climate is more complex to unravel, a set of policy prescriptions is required to address the adverse effects of the phenomenon including the peoples' attitude on the use and misuse of environmental resource such as vegetation. It is therefore recommended that unsustainable agricultural activities at the expense of forest cover leading to lost of soil nutrients should call for agricultural intensification-related policy initiatives to discourage expansion of cultivation on fragile lands.

Such intensification strategies should address sustainable land cover management and farming techniques. The continuous call for establishment of afforestation strategies in Nigeria should involve the choice of appropriate species that are well adapted to our local environment in order to maximise general increase in biomass thereby minimising the menace of desertification. Ecological funds meant for utilisation to enhance environmental sustainability should be increased and its management monitored to ensure utilisation and productivity. Other polices already in place regarding environmental conservation and protection of forest other natural resources should further be enforced.



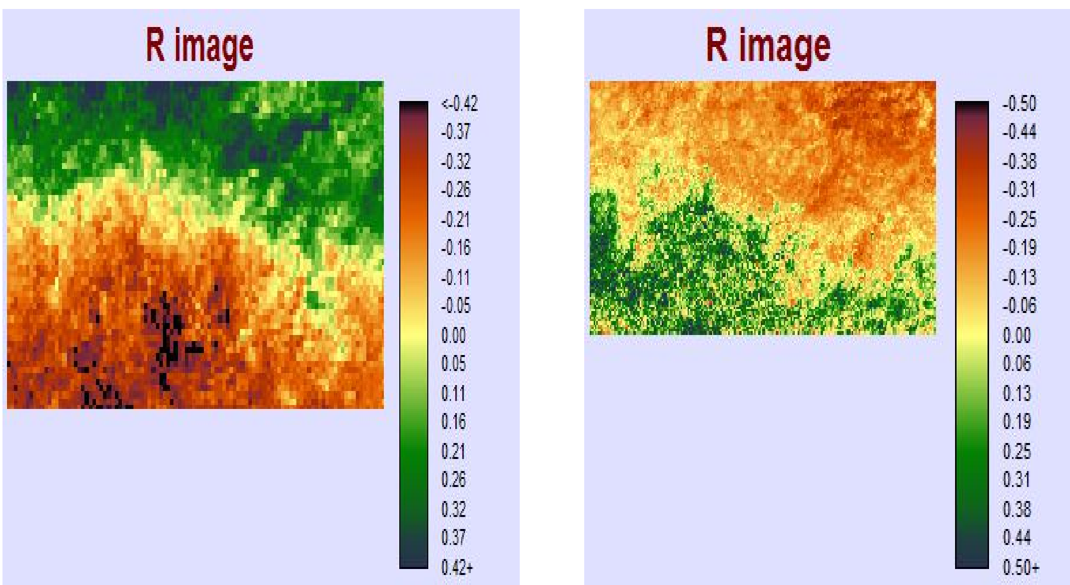
(a) NOAA-AVHRR **(b) AQUA-MODIS**

Figure 1: Linearity (R^2) of (a) NOAA-AVHRR and (b) MODIS NDVI datasets



(a) **(b)**

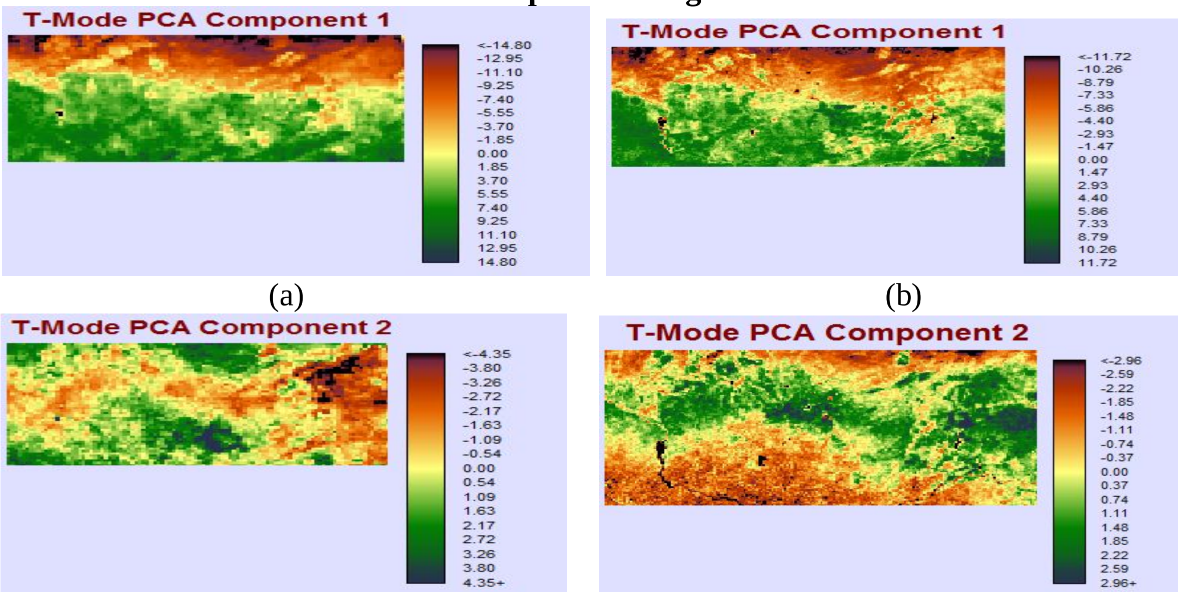
Figure 2: Linear Trend (OLS) of (a) NOAA-AVHRR and (b) MODIS NDVI datasets



(a) **(b)**

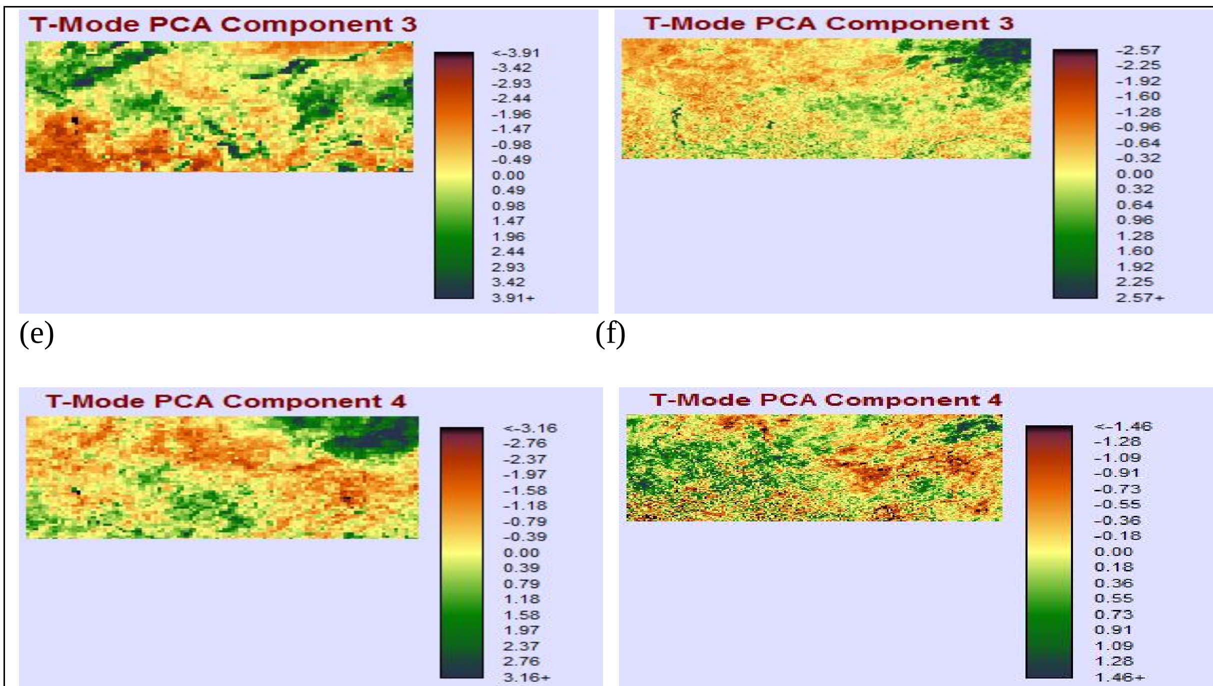
Figure 3 R – images from AVHRR and MODIS dataset. **(a)** is a Linear Model of AVHRR NDVI time series 1981 to 2000 while **(b)** is the Linear Model from AQUA/ MODIS NDVI time series 2000 – 2010.

Component Images



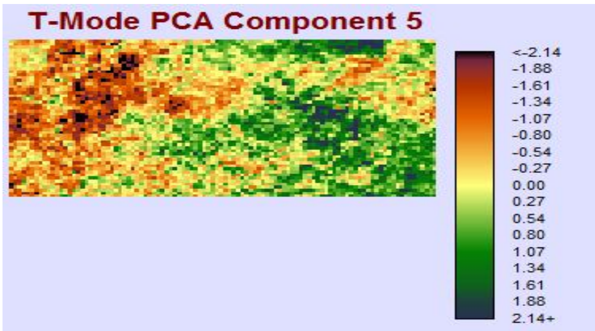
(a) (b)

(c) (d)

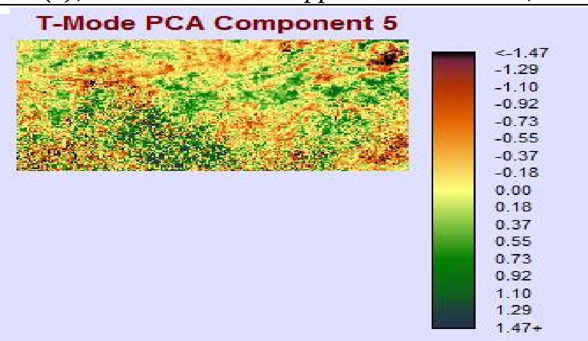


(e) (f)

(g) (h)

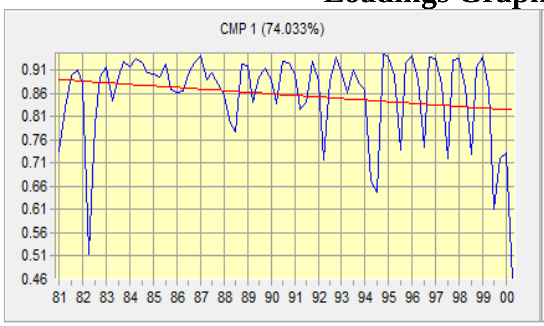


(i)

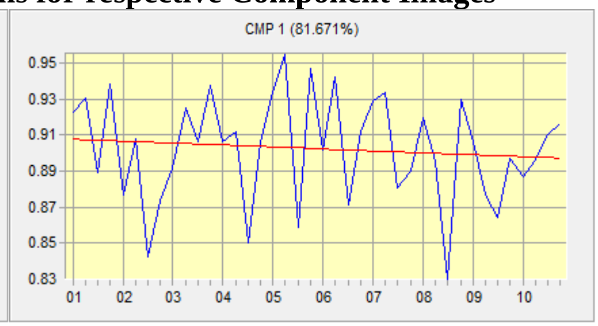


(j)

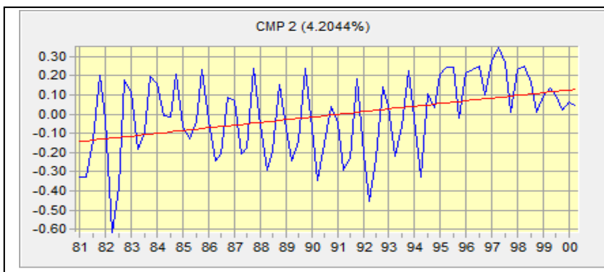
Loadings Graphs for respective Component Images



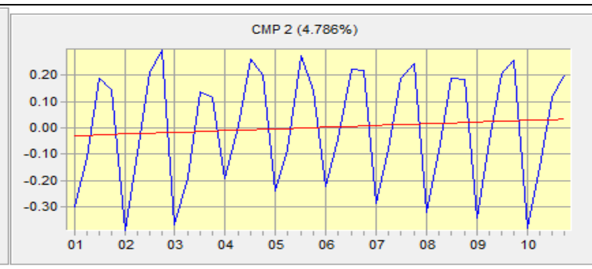
(a1)



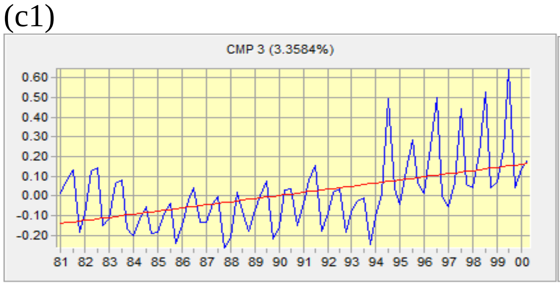
(b1)



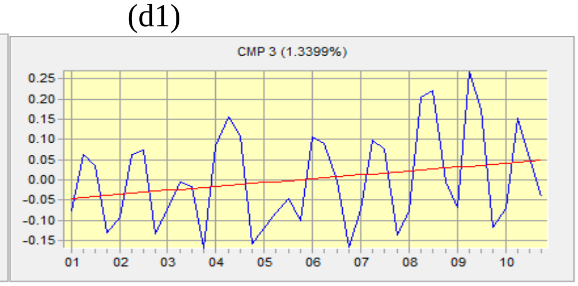
(c1)



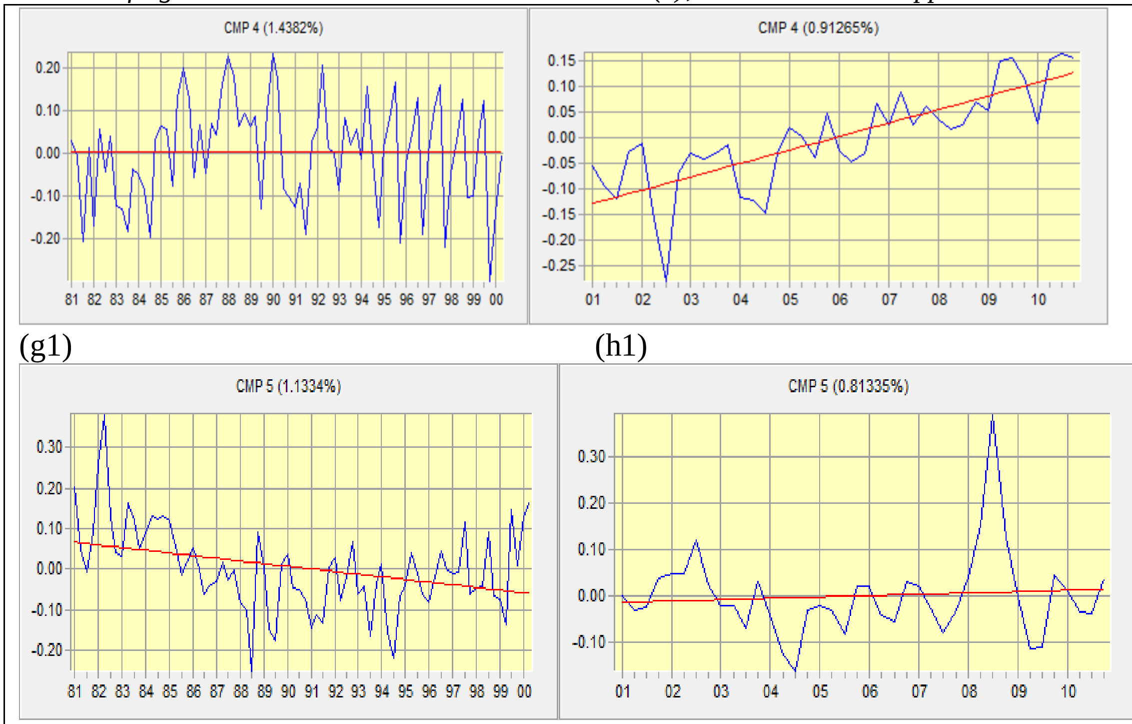
(d1)



(e1)



(f1)



(g1) (h1)

(i1) (j1)

Figure 4: Component images and their respective graphs of loading scores

(a), (c), (e), (g), (h) and (j): Principal Components of NDVI time series 1981 to 2000 from AVHRR
(b), (d), (f), (h), and (j): Principal Components of NDVI time series 2000 to 2010 from AVHRR
(a), (c), (e), (g), (h) and (j): Component Loadings of NDVI time series 1981 to 2000 from AVHRR
(b1), (d1), (f1), (h1) and (j1): Component Loadings of NDVI time series 2000 to 2010 from MODIS

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