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Spatio-temporal monitoring of vegetation phenology in the dry sub-humid region of Nigeria using time series of AVHRR NDVI and TAMSAT datasets

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Abstract: Time series data are of great importance for monitoring vegetation phenology in the dry sub-humid regions where change in land cover has influence on biomass productivity. However few studies have inquired into examining the impact of rainfall and land cover change on vegetation phenology. This study explores Seasonal Trend Analysis (STA) approach in order to investigate overall greenness, peak of annual greenness and timing of annual greenness in the seasonal NDVI cycle. Phenological pattern for the start of season (SOS) and end of season (EOS) was also examined across different land cover types in four selected locations. A significant increase in overall greenness (amplitude 0) and a significant decrease in other greenness trend maps (amplitude 1 and phase 1) was observed over the study period. Moreover significant positive trends in overall annual rainfall (amplitude 0) was found which follows similar pattern with vegetation trend. Variation in the timing of peak of greenness (phase 1) was seen in the four selected locations, this indicate a change in phenological trend. Additionally, strong relationship was revealed by the result of the pixel-wise regression between NDVI and rainfall. Change in vegetation phenology in the study area is attributed to climatic variability than anthropogenic activities.

Keywords: Vegetation Phenology, Seasonal Trend Analysis, AVHRR NDVI3g, TAMSAT, Nigeria, Dry sub-humid Region

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1 Introduction

The timing of a specific biological phase such as flowering, leaf growth, leaf fall (growth and senescence) and their causes can be described as phenology [1–4]. Vegetation phenology has a close relationship with climatic variability [5] which has influence on the timing of plant growth and development especially in the dry sub-humid region of Africa [4] Abrupt or seasonal change in vegetation phenology may have effect on water, carbon and energy cycle which might in-turn influence global climate change and net primary production [4, 5]. However, human activities such as indiscriminate felling of trees, extensive agricultural practices, overgrazing and climate variability are some of the factors which might cause change or shift in vegetation phenology [1, 6–8].

As human population increases, spatio-temporal information on phenological change dynamics through the use of earth observation datasets is important [9, 10] most especially in Nigeria where obtaining up to date datasets is a challenge. The dry sub-humid region of Nigeria have experience noticeable vegetation cover transition due to large scale land use and land cover transformation over the last few decades [11, 12]. It is evidenced from the report of Global Forest Resource Assessment that the total forested area in West Africa as of 1990 was 91,589,000 hectares while it reduces to 81 979,000 hectares and 73 234,000 hectares in year 2000 and 2010 respectively [13]. This indicates an annual rate of change of −1.10 % in 1990–2000 and −1.12 % in 2000–2010 [13]. Similarly, the report of Forestry Outlook Studies in Africa [14] show that Nigeria forest are being depleted at an annual rate of 3.5 % due to encroachments and other form of land use such

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as cropland expansion, grazing and urbanization. Change in land use land cover across Nigeria was revealed by the study of Adeofun et al. [8] using national land-use/land-cover classification data of 1995. It is reported in this study that several physiognomic units of Nigerian's vegetation have assume identities different from the descriptions of the past [8]. Increase perturbation of natural forest cover such as forest fragmentation by government road projects, increase in fuel-wood and timber consumption, population increase, and livestock production and climatic variability have been quite instructive in the new vegetation cover characterization observed throughout the country. Osunmadewa et al. [15] pointed out that there is a significant shift in land use land cover across Niger state. In order to proficiently understand climate-human induced phenological change, the use of remote sensing datasets which can provide long-term information on vegetation productivity at global and regional scale is needed [16–18]. In this context, a commonly used index for monitoring vegetation productivity is the Normalized Difference Vegetation Index (NDVI) which provides information on the amount and vigor of vegetation from the near infrared (NIR) and visible red bands of the electromagnetic spectrum [19, 20]. Several studies revealed that time series of NDVI have been used for monitoring interrelationship between NDVI and rainfall in the semi-arid and Sahelian zone [21–23]. Strong dependency of NDVI on rainfall was revealed by the study of Wessollek et al. [24] in the semi-arid region of Nigeria. High correlation between NDVI and rainfall was also revealed by the study of Schmidt and Gitelson [25]. Although many studies have used NDVI to monitor vegetation phenology at global and regional scale [4, 26, 27] few or no study on vegetation phenology used long term NDVI time series, its relationship with climate variable (rainfall) and land use land cover change has been carried out in this ecological zone. Thus, the use of remotely sensed dataset such as Advanced Very High Resolution Radiometer (AVHRR) i.e NDVI3g can be used to analyze change in vegetation phenology in the dry sub-humid region of Nigeria where this method have not been fully utilized. The aims of this study are to examine the spatio-temporal pattern of vegetation phenology, its relation with rainfall from 1983–2011 and the impact of land use change on the shift in vegetation pattern. This study provides in-depth knowledge of climate-human induced vegetation change over a long period as this enhances understanding of vegetation dynamics in the dry sub-humid region of Nigeria for better use of policy options for environmental monitoring.

2 Materials and Methods

2.1 Study area

This study focused on Kwara state in the middle belt region of Nigeria where significant environmental changes are visible. The state geographically shares boundary with Niger state to the North, Oyo, Osun and Ekiti to the south and Kogi state to the east and lies between latitudes 8°–10°N and longitude 3°–6°E. Kwara state is bounded by River Niger from the east to the North and it is often referred to as savannah ecotone because it forms the transition zone between forest and savannah region of Nigeria [28, 29]. The state covers an area of about 36,825 square kilometer with population of 1548412 (in 1991), 2365353 (in 2006) [30] and population density ranging from 20-120 people per km^2 as shown in Fig. 1.

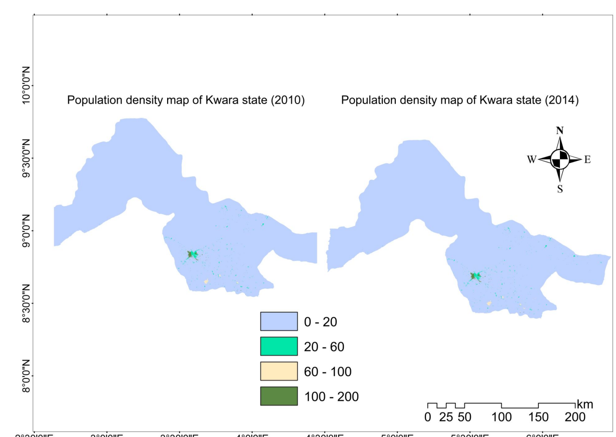

Figure 1: Population density of the study area for 2010 and 2014 (Data is 100 × 100 m)
Source: www.world population.org.UK [31]

The annual rainfall of Kwara state is between 1000 mm to 1500 mm with double rainfall peaks in June and September [28, 32]. The region is characterized by two season's namely dry and wet season, the raining season begins in March and ends in October while the dry season begins in November and ends in February. The temperature is between 25°C–30°C in wet season and 33°C0-34°C in dry season. The soil is mainly classified as ferruginous tropical soils and support crop production [33]. The vegetation is mainly forest and savanna and it constitutes about 47.78% and 35.04% respectively [29]. The common tree species found in this region includes *Vitellaria paradoxa* (shea butter), *Acacia spp, Parkia spp, Afzelia Africana, Terminalia* spp. Kwara state enjoys favorable climatic condition which supports the growth of tall grasses such as *Andropogon gayanus, Ageratum conyzoides* (goat weed grass), *Pennisetum purpureum* (elephant grass) and *Heteropogon contortus* (Spear grass) [34]. Due to the increasing rate of anthropogenic activities in this region, assessment of change in vegetation phenology is very important. Figure 2 shows the mean monthly NDVI pattern of the study area from 1983-2011 as derived from the

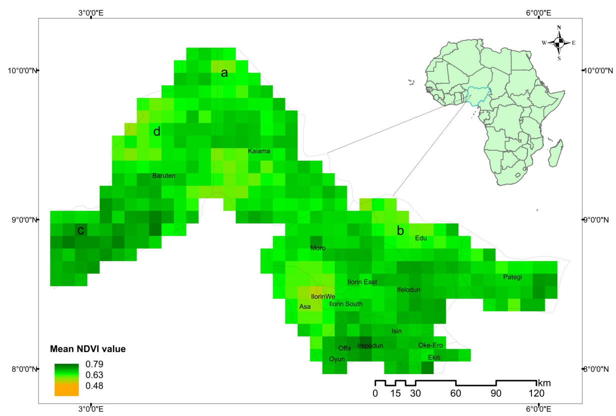

Figure 2: Location of the study area showing selected areas across different land cover types in Kwara state, Nigeria (a) open broadleaved deciduous forest/woodland, (b) Cropland, (c) shrubland and (d) grassland.
Source. www.GADM.org [35]

2.2 Datasets

Bi-weekly NDVI 3g datasets (15 days composite) from Global Inventory Modeling and Mapping Studies with spatial resolution of 8 km was used in this study (https://ecocast.arc.nasa.gov/data/pub/gimms) for the annual phenological assessment from 1983-2011. The decomposition and reconstruction of the NDVI datasets had already been done in order to correct solar zenith angle, orbital drifts or artifacts such as volcanic aerosols which might cause systematic trends in the datasets using a technique known as Empirical Mode Decomposition (EMD), this makes it different from the older version of NDVI product [27, 36–38]. The longer span of the new NDVI3g datasets (more than 30 years) makes it suitable for monitoring seasonal vegetation trends in the dry sub-humid region of Nigeria where technical resources and adequate information about change in vegetation phenology is limited. The second data used in this study is the Tropical Applications of Meteorology SATellite (TAMSAT) which is basically for Africa (https://met.reading.ac.uk/tamsat/data). The monthly rainfall datasets had been calibrated using historic rain gauge records, and it has a spatial resolution of 4 km [39]. GlobCover 2000 and 2009 datasets from the European Space Agency (http://www.esa-landcover-cci.org) was used in this study in order to have in-depth understanding of vegetation change dynamics across different land cover types. The global land cover map for 2009 has a spatial resolution of 300 m and it is derived from MERIS sensor on ENVISAT while the 2000 global land cover has a spatial resolution of 1km and is derived from SPOT-Vegetation [40].

2.3 Methods of image pre-processing

All the datasets used in this study were reprojected to the Universal Transverse Mercator (UTM) and subsets of the satellite imagery were created using the administrative boundary of Kwara State. Prior to the Seasonal Trend Analysis (STA), the bi-weekly NDVI composite data were aggregated to a monthly composite using Maximum Value Composite (MVC) method which further reduces noise in the time series [41]. The rainfall data was resampled to 8 km spatial resolution in order to match with the spatial resolution of using bilinear interpolation resampling method. The global land cover map of 2009 was resampled to 1km resolution so as to merge with the same spatial resolution of the 2000 global land cover. The land cover class for both maps was aggregated to six major classes, an overlay analysis was applied to identify the change matrices for the time period of 2000 to 2009. Assessment (STA) was performed using three approaches as described below.

2.3.1 Analysis of seasonal trend

Change in NDVI trend across the dry sub-humid region of Nigeria was analyzed using STA approach as described by Eastman et al., 2009. This method was selected based on its ability to detect seasonal signals in any time series datasets whilst rejecting noise and inter-annual variability [42, 43]. STA uses two stages of time series analysis to detect NDVI trend. This stage is then preceded by visualization of the produced image (amplitude and phase image) at the final stage [42]. STA performs harmonic regression of annual (yearly) images in the time series as described in equation 1. In the first stage of analysis, each annual imagery in the time series (1983-2011) are subjected to harmonic regression in order to approximate the seasonal curve thereby producing five greening parameters, amplitude 0 (annual mean image), amplitude 1 and phase 1 (annual cycle), amplitude 2 and phase 2 (the semi-annual cycle) [42, 44, 45]. The overall greenness (mean annual NDVI for each year) is described as Amplitude 0, the magnitude of peak of annual greenness as amplitude 1, while the timing of annual peak of greenness is referred to as phase 1 [44]. An increase or decrease in phase 1 indicates shift in the timing of greening event to an earlier or later time of the year respectively. The generalized equation for the harmonic regression is presented as follows:

$$y = \alpha_0 + \sum_n \left\{ a_n \sin\left(\frac{2\pi n t}{T}\right) + b_n \cos\left(\frac{2\pi n t}{T}\right) \right\} + e \quad (1)$$

where t is referred to as time, y is the series value, T is the length of the time series, n is a harmonic integer multiplier, e is error term, α_0 is the mean of the time series while a_n and b_n are regression parameters. The harmonic regression curve can also be expressed as:

$$y = \alpha + 0 + \sum_n \alpha_n \sin\left(\frac{2\pi n t}{T} + \varphi_n\right) \quad (2)$$

after the term of equation (1) had been rearranged and error term had been omitted or ignored. Hence, α_n and φ_n are referred to as amplitude and phases [42].

In the second stage of the analysis, annual trends in the greenness parameters are calculated [42]. This stage involves the calculation of annual trends in the greenness parameters (amplitude 0, amplitude 1 and phase 1) using Theil Sen trend detection estimator. Theil-Sen (TS) trend estimator is a robust non-parametric technique which calculates all pairwise combination of images in time, it takes the median of all slopes to generate trend images for each of the greenness parameters [46–48]. The TS trend estimator is insensitive to outliers and it has a breakdown bound of 29% [42, 43, 49, 50]. This simply implies that the values of the TS slope tolerate outliers up to 29% of the observations used in the time series without degradation of its accuracy [44, 51]. STA was also applied to the rainfall (TAMSAT) data for better comparison with NDVI.

2.3.2 Significance test of STA using Contextual Mann-Kendall (CMK)

Trends in vegetation dynamics for each pixels (NDVI time series) was statistically examined in order to identify areas undergoing similar trends [44]. In order to evaluate the significance of trends during the Theil-Sen slope calculation (*see section 2.3.1*), a non-parametric statistic test known as Contextual Mann-Kendall (CMK) was applied [52]. CMK test is resistant to outliers and uses similar approach like that of Mann-Kendall [52]. To perform CMK test, three stepwise approach are involved. The first step account for the elimination of serial correlation in the NDVI and rainfall time series which might have influence on the trend test using a method known as prewhitening [44, 53]. Prewhitening removes serial correlation from the residuals of both NDVI and rainfall while maintaining the trends in the dataset [55,56]. The trend in the prewhitened series is similar to the original data while having no serial correlation [53]. In the 2^{nd} stage, trend consisting of 3×3 neighborhood around each pixel are evaluated, while in the 3^{rd} stage, the calculated 3×3 neighborhood result which is produced in the 2^{nd} stage was used for calculating spatial autocorrelation [44]. The result of the CMK trend test are in the form of image i.e statistical p-value and z score each describing statistical significant trend (positive and negative trend) in the greenness parameters (amplitude 0, amplitude 1 and phase 1). Generally, a positive z score indicates upwards trend where as a negative z score represents a downwards trend [52].

2.3.3 Interpretation of phenological curve

An interpretational approach as described by Eastman et al, 2009 was used to describe variation in the start and end of the series based on the slope and the intercept of the five harmonic parameters (amplitude 0, amplitude 1, phase 1, amplitude 2 and phase 2) across different land cove types for selected locations. The selected locations were sampled on a single pixel base (64 km^2), seasonal curve for the beginning and the end of the series were produced by using temporal profile [Eastman, 2012]. The differences between the two curves indicate resultant changes which can be used to describe trends in the observed phenological pattern of vegetation which are useful for environmental studies and ecosystem monitoring [27, 44]. The term green-up and green-down are used inter-changeably to represent the starts of season (SOS) and end of season (EOS) respectively.

3 Results and discussion

3.1 Spatial analysis of vegetation trend pattern

Time series of (NDVI) from 1983-2011 was used to provide information on vegetation dynamics in the dry sub-humid

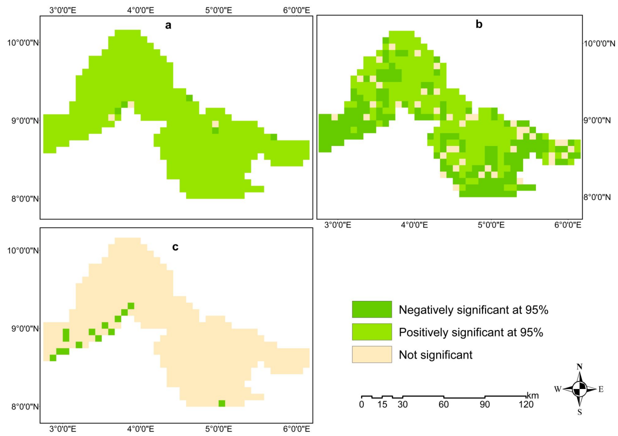

Figure 3: Spatial map of Kwara State showing the result of the Contextual Mann-Kendall statistical significance (p-value) calculated from GIMMS NDVI3g data for 1983–2011: (a) overall greenness, (b) peak of annual greenness and (c) timing of annual peak greenness

region of Nigeria. The results of the spatial pattern of statistical significant trends in overall greenness (amplitude 0), peak of annual greenness (amplitude 1) and timing of annual peak greenness (phase1) over the study area as shown in Figures 3a-c. Both positive and negative trends were observed from the results of the greenness parameters. Positive pixels in the spatial image (significant image) indicates an increasing trends while negative pixels indicate decreasing trends in vegetation dynamics over the observed period. Significant positive trends in overall greenness were observed in Fig. 3a while negative and non-significant trend pattern are observed for fewer pixels ($p< 0.05$).

Figure 3b shows significant pattern in peak of annual greenness. Positive trends are observed particularly in the northern part while negative trend were observed in the western and southeastern part. Pixels with non-significant trend in the peak of annual greenness are distributed across the study area. Figure 3c shows the significant trend pattern in timing of annual peak of greenness, more than 90% of the pixels used in this analysis showed a negative trend, this indicates a shift in the pattern of timing of annual peak of greenness to a later time, while the fewer pixels which shows a positive trend indicates earlier green-up.

Although large clusters of positive NDVI trends in overall greenness (amplitude 0) were observed in the study area during the examined period (1983–2011) as shown in Fig. 4, areas with negative NDVI trends for example the black circle (Fig. 4a) can be attributed to land degradation due to anthropogenic activities.

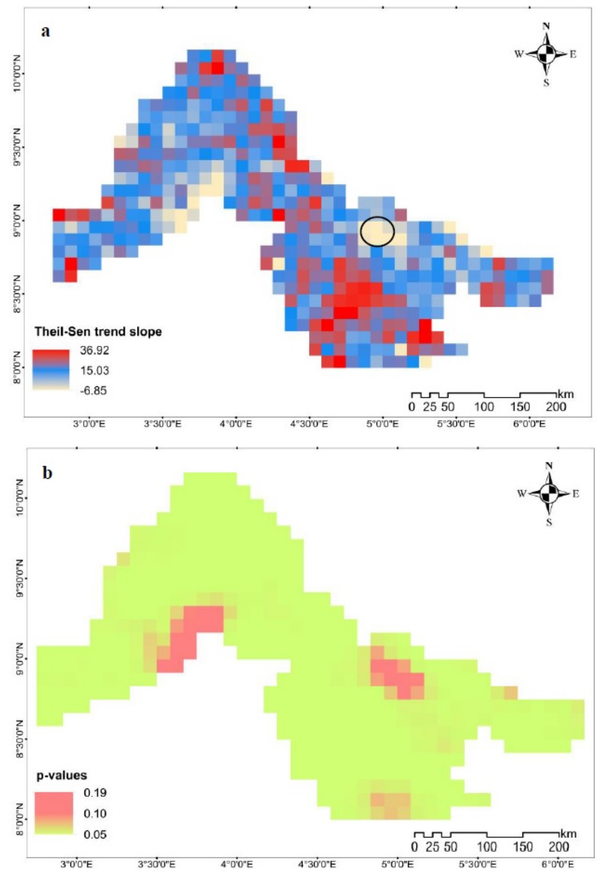

Figure 4: Spatial pattern of linear trend of mean annual NDVI for the period of 1983-2011 (NDVI/month): (a) Annual mean NDVI trends (amplitude0), (b) p-value

The results of the mean rainfall time series analysis (amplitude 0) show significant positive trends with variations in the slope direction (Fig. 5). This variations however has impact on vegetation phenology.

The result of the spatial regression between rainfall data and NDVI over the study region is presented in Figure 6. The result shows a high relationship (coefficient or determination, R^2) between NDVI and rainfall which indicates that rainfall is the main driving force for vegetation growth in sub-Sahara and tropical regions like Nigeria [5, 56, 57]. Other studies also showed that incoming short-wave radiation and air temperature are not constraints of NDVI trends compared to rainfall distribution [54].

Figure 7 shows the result of timing of annual rainfall (phase 1). Shift to a later time was observe from the result. This implies that the early months of the year received less rainfall than the later months of the year. An increasing or decreasing phase angle depicts a shift to earlier or later time of the year.

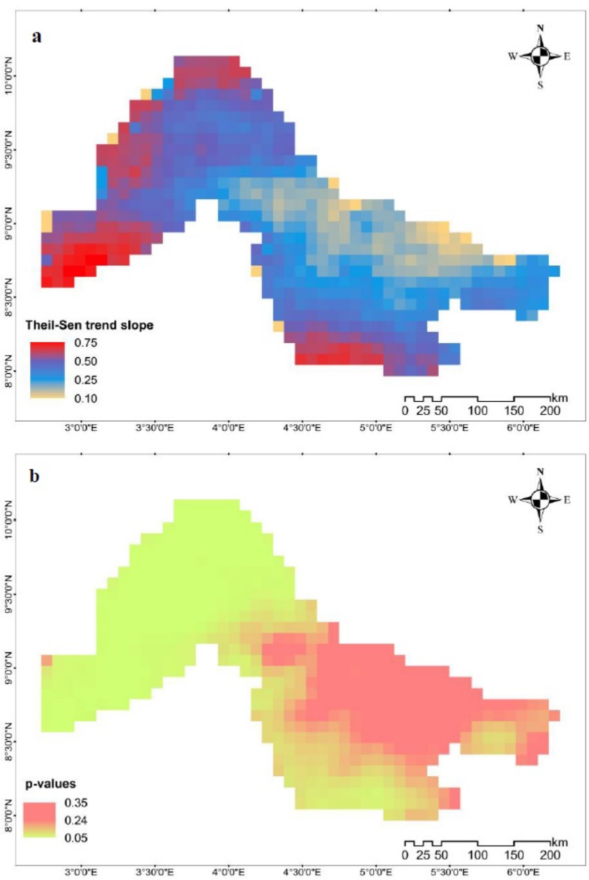

Figure 5: Spatial pattern of linear trends of mean annual rainfall calculated from monthly TAMSAT for the period of 1983-2011 (mm/month): (a) Annual mean rainfall trends (amplitude0), (b) p-value

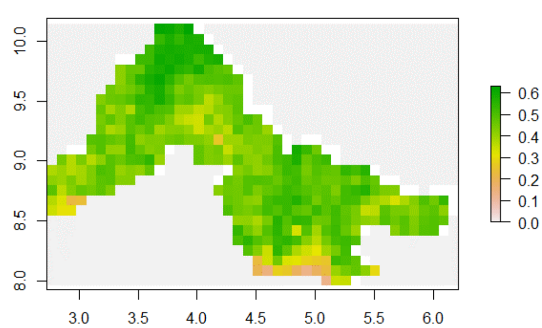

Figure 6: Spatial regression of NDVI and rainfall over the study region for the period 1983-2011, the values indicate pixel-wise R^2 of NDVI vs rainfall

3.2 Visual interpretation of phenological curves

Four locations were selected to visualize the monthly mean NDVI profile curves for the beginning and end of the time series (1983-2011) across different land cover types in

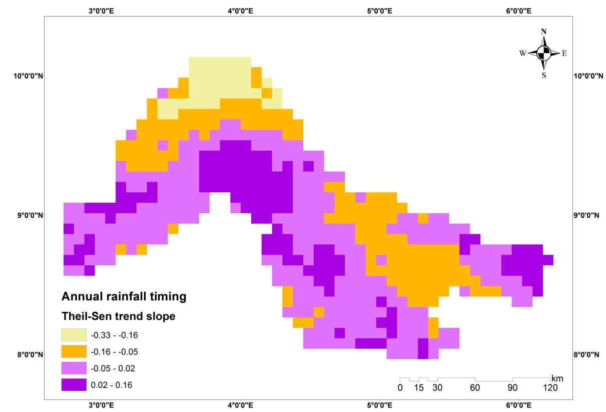

Figure 7: Spatial pattern of Timing of annual rainfall (phase1) calculated from monthly TAMSAT for the period 1983-2011 (mm/month)

the study region (Fig. 8). The seasonal curves for the examined years were compared for (a) open broad leave deciduous forest/woodland (b) cropland (c) mosaic grassland and (d) closed to open shrubland as shown in figure 8. Seasonal variation in vegetation cover was observed from the results of the NDVI curves (phenology) for the selected locations. The differences between the two curves (1983 and 2011) however indicates changes in trend pattern.

An increase in overall greenness (NDVI) for all months (except August, as there is a decline in 2011 in this month) was observed for the land cover type (Open broadleaved deciduous forest/woodland) in location *a* with an increase in vegetation productivity in 2011 while decreasing trend was observed in the other greenness parameter (peak of annual greenness and timing of annual peak of greenness). The maximum difference between the two curves occurred in the January months, October, November and December while minimum difference occurs in March, July, August and September (Fig. 8a). This location is within the Borgu game reserve where agricultural activities is not allowed, although some locals still do some illegal cultivation in the buffer zone of the game reserve.

Location *b* shows significant increase in overall greenness and peak of annual greenness, while a significant decrease was observed in the timing of annual peak of greenness for this region. The land cover type in this location is associated with cropland where intensive agriculture is being practiced almost throughout the year. The minimum difference between the two curves occurred in June and September while the maximum difference occurred in November and December (Fig. 8b).

Location *c* & *d* exhibits significant increase in overall greenness and significant decrease in other greenness parameters for the study period. Two peak of greenness was observed from the seasonal curve of both locations (Fig. 8c and d). The land cover types in these location are shrub and grassland respectively, an increase in NDVI productivity was observed during the growing season, it reaches its peak in the month of June and gradually decline in August i.e a short pause in the raining season lasting for two to three weeks which is known as August break. Minimum difference between the two curves (1983 and 2011) occurred at the start of the growing season (start of season) in February while maximum difference occurred in July, August, October, November and December months for location *c* (Fig. 8c). For location *d* however, minimum difference occurs in March, April, July and September while Maximum difference occurred in January, June, and October (Fig. 8d).

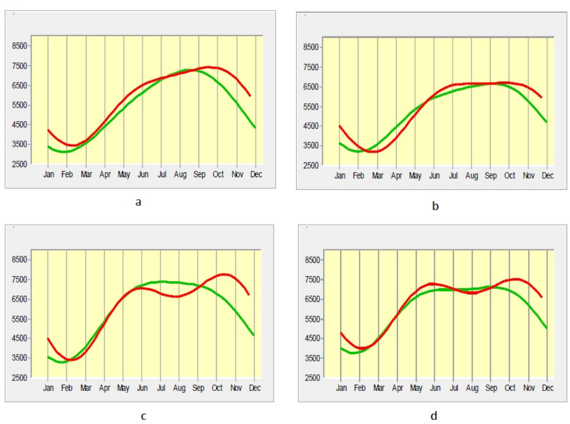

Figure 8: Seasonal curves of NDVI for four selected locations in kwara state (1983 in green and 2011 in red). The graph shows the year from January through December on the x-axis, and NDVI × 10000 on the y-axis.

Vegetation greenness in the dry sub-humid region of Nigeria generally increased over the period of study (1983–2011), this can be seen from the result of amplitude 0 (significance image of overall NDVI greenness) in Figure 3a. Variation in the phenological trend pattern was confirmed by the result of the NDVI seasonal curve across different land cover types in the selected locations.

Change in land use land cover was revealed by the result of the GlobCover between 2000 and 2009.

Table 1 summarizes the distribution and size of land cover classes in the year 2000 and 2009. It indicates a decline in sizes of forest and grassland while an increment in the size of cropland and shrubland was observed. This clearly indicates land use transformation is dominantly occurring with the influence of anthropogenic activities.

An assessment on the land use dynamics using change matrices for the year 2000–2009 (Fig. 9) also confirmed significant shifts in vegetation dynamics. Accordingly, there is a substantial transition from the natural ecosystem (Forest/Shrubland) to human dominated activities, dominantly cropland.

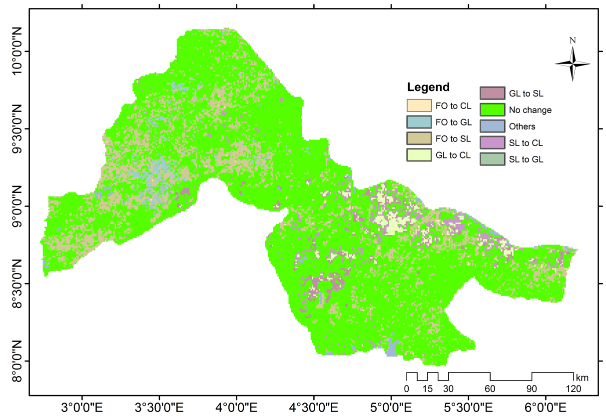

Figure 9: Change dynamics for the period 2000–2009 (FO-Forest, CL-cropland, GL-Grassland, SL-shrubland)

4 Discussion

Spatial analysis of vegetation change dynamics is crucial for monitoring biodiversity reduction, land degradation and the effects of climate change on vegetation trends. As human population continue to increase in the study area, information on vegetation that is spatially comprehensive and of appropriate resolution is vital for effective monitoring and management of biological resources especially in Nigeria where conversion of vegetative land use to other land use is common and reliable information on change in vegetation trend pattern (phenology) using long-term time series dataset (AVHRR NDVI3g) is little or non-existing.

The results of this study revealed that there has been significant increase (positive trends) in overall greenness during the study period (Fig. 3a) which is in line with the results of other studies [58, 59] where positive trends are observed in the sahelian region. Strong correlation was exhibited between the GIMMS NDVI3g and TAMSAT rainfall datasets across the study region which indicates that vegetation phenological dynamics is closely associated with the rainfall pattern on the region. Variation in the seasonal NDVI curve (phenological pattern) for the selected land cover types are revealed by the results of this study.

The differences observed in the timing of maximum NDVI peak are determined by the intensity and timing of rainfall during the period of study. Generally, the duration

Table 1: Land cover sizes in 2000 and 2009 (GLC2000 and GLC2009)

Land use type	2000 (%)	2009 (%)
Forest	49.60	44.34
Shrubland	45.12	47.91
Grassland	4.18	2.12
Cropland	0.54	5.20
Water	0.40	0.24
Built up	0.16	0.19

of the raining season in this region is about seven months (from March to October). Variation at the start and end of raining season were observed for the selected locations of this study, which is assumed to have significant effect on the phenological pattern of vegetation.

Location a of the study area is closely associated with natural and semi-natural terrestrial vegetation (woody/shrub), the two classes of vegetation types found in these location are open broadleaved deciduous woodland which accounts for 95.38 %, and broadleaved shrubland (closed to open) accounting for 4.17 % of the land cover area. The location falls within Borgu game reserve which was established in 1975 in Baruten local government area, this game reserve and its surrounding buffer zone are protected from illegal logging and encroachment from farmers. The result revealed an increase in vegetation productivity (NDVI) throughout the study period. The length of growing season (LGS) in 2011 is about 255days (April-December) and starts earlier as compared with that of 1983. Similar trend was observed for rainfall where rainfall lasted for 233 days (March-November) in 2011. Slight variation in $NDVI_{max}$ was observed for this location ($NDVI_{max}$ 0.74 in 2011 and 0.71 in 1983) as it is protected from encroachment. Increased productivity in forested land cover are reported by other studies [27] which was attributed to various factors such as decrease in the rate of tree harvesting. However, much research is needed in this location. As human population increases, demand for food and other means of livelihood sustenance increase too. This was ascertained by the result of location *b* of the study area where conversion of shrublands to agricultural land took place. This location is situated in Edu local government area under zone B of the Kwara state Agricultural Development Project (ADP). Vegetation green-up (SOS) starts earlier in 1983 (12^{th} April – 4^{th} December) as compared to that of 2011 (21^{th} April – 27^{th} December), although the length of growing season (LGS) is more prolonged in 2011 (236 and 252 days respectively), this follow similar rainfall pattern (Fig. 7). Report by Isah and Adeoye [28] showed that this region had an increase in some agricultural crops such as maize, sorghum in 2008. Two peak of $NDVI_{max}$ was observed in the seasonal curve of 2011 (in July with $NDVI_{max}$ of 0.66 and October with $NDVI_{max}$ of 0.67), indicating the existence of two growing season. The land cover type in location *b* is composed of cultivated and managed terrestrial area accounting for 62.87 % of the total land cover and shrubland accounting for 37.13 %. Vegetation green-up (SOS) starts earlier in location *c* with a difference of about 3days (March 25 and March 28 for 1983 and 2011 respectively). A difference of about 33 days was observed for the end of season (EOS) between both years which indicate prolonged greening in 2011 (248 days in 1983 and 281 days in 2011), this can be likened to availability of water content in soil at the end of the raining season. In location *d* however, difference of 1 day was observed between the start of season (green-up) in both years, the length of growing season (LGS) was 259 days in 1983 and 289 days in 2011, while the length of rainfall is 270 days in 1983 and 277 days in 2011. Location *c* of the study area is associated with shrubland while location *d* is associated with grassland. Two peak of NDVI*max* were observed in these locations (*c* and *d*) one in June and the other in October, although such peak was not observed in the seasonal rainfall curve, this may be attributed to other factors such as conversion of the existing vegetation for agricultural activities during the growing season. The results of this study showed that NDVI trends varied considerably among the selected locations and has a strong relationship with rainfall as revealed by other studies [25, 60].

Anthropogenic activities (such as land use land cover change) also have impact on the shift in phenological change pattern due to conversion of forestlands into agricultural land (Table 1 and Fig. 9). However, more research on the land use land cover change is needed for proper monitoring of the observed change in vegetation phenology using high resolution Remote Sensing dataset such as Sentinel in the future. This study therefore provides an insight on spatio-temporal analysis of seasonal trends in vegetation change dynamics in the dry sub-humid region of Nigeria using NDVI 3g data. The results of this study will serve as a baseline for providing adequate information on the urgent need for monitoring changes in vegetation phenological pattern which may be used by policy makers for proper land use management plan and ecosystem monitoring in the future.

5 Conclusion

AVHRR NDVI3g dataset from 1983-2011 was used to monitor change in vegetation phenology over the dry sub-humid region of Nigeria (Kwara state) and its relation to climate variable i.e. rainfall. Monitoring change in vegetation dynamics is very important in order to understand terrestrial ecosystem, their response to climatic variability and the impact of human perturbation. The approach used in this study was based on previous works by Eastman et al. [42], Neeti et al. [44], Dubovyk et al. [43], Pandy and Ghimire [26] where STA was used to detect trends in vegetation dynamics at global and regional scale. In this study, seasonal trends was derived using greenness parameters (annual greenness, peak of annual greenness and timing of annual greenness). Increase in vegetation greenness was observed during the growing season, although, variation in minimum and maximum NVDI are observed in the selected locations. Such variations was also revealed by the study of Heumman [61]. Significant positive trends in overall greenness was observed in the study region while negative trends are also present in some parts (Fig. 4a). This result is in line with the analysis of Pandy and Ghimire [26]. Significant negative trends in peak of annual greenness was observed for some areas with few pixels showing significant positive trends while the timing of peak of annual greenness was observed to occur at the later months of the year (Fig. 3b and c), similar trend was also observed in the rainfall pattern (phase 1). Positive trends in peak of annual greenness (amplitude 1) was revealed by the result of this study for location b, this is as a result of intensive agricultural activities (rainfed and irrigated agricultural system) so as to meet the demand of the ever increasing population over the last three decades in this region. The traditional method of land preparation (bush burning) prior to cultivation on the other hand also give room to the growth of herbaceous layer which have invariably led to change in vegetation phenology. Conclusively, the study show the ability of using NDVI and TAMSAT data, and STA approach for monitoring change in vegetation phenology over a long period across different land cover types in the dry sub-humid region of Nigeria. The spatial pattern of the regression analysis between NDVI and TAMSAT rainfall data provided a better understanding of climate variability on vegetation phenology which shows that the observed phenological trends are attributed to climate variability. However, further research on the linkages between vegetation change dynamics and human-induced conversion of the landscape for various purposes using high resolution data such as quick-bird, worldview, sentinel and demographic data is needed in the future for proper modeling of land-cover transformation in this ecological sensitive region.

Conflict of interest:
The authors of this manuscript declare no conflict of interest.

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