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A REMOTE SENSING ANALYSIS OF VEGETATION DYNAMICS IN THE DRYLAND ECOSYSTEM OF SOKOTO CLOSE-SETTLED ZONE, NORTH-WESTERN NIGERIA

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ABSTRACT

Understanding the vegetation dynamics is very essential for the protection and management of ecological environment especially in the dryland areas. In this paper, remote sensing satellite data and GIS analyses were used to monitor and assessed vegetation dynamics in the Sokoto Close-settled Zone, North-western Nigeria from 2001 to 2016. The objectives of the paper are threefold viz: to measure the extent and the trend of vegetation change; to determine the role of different drivers responsible for vegetation change and to discuss the implications of the observed changes on the ecosystem and the livelihoods of people in the area. The result revealed a gradual but persistent decline in the spatial distribution of vegetation cover from 66% in 2001 to 51% in 2016. Vegetation productivity also declined from 0.71 in 2001 to 0.42 in 2016. Correlation analysis shows that rainfall has a positive while population a negative relationship with the vegetation change. Therefore, deceasing rainfall and increasing population are the major factors of vegetation decline in the area. This has drastically affects the capacity of the ecosystem to provide essential goods and services such as food, water supply and pasture for livestock, with varied socio-economic consequences to the inhabitants of the area.

Keywords: *Remote Sensing; Vegetation Change; Dryland; Ecosystem.*

INTRODUCTION

The importance of vegetation in any ecosystem cannot be overemphasized. Vegetation is one of the important components that influences the structure and functions of any terrestrial ecosystem. This is because, vegetation represents a natural link, connecting the land, water and the atmosphere. It also plays important roles in primary productivity, soil conservation and maintaining atmospheric balance, in addition to its influences on micro, local, regional and global climate system (Guo *et al*., 2005; Jiang *et al*., 2015; Shen, Li & Guo 2014; Zheng, & Moskal 2009). Vegetation is however, characterised by both spatial as well as inter-annual and seasonal dynamics, which to a very large extent influences the balance, structure and functions of the ecosystem (Brandt *et al*., 2016; Ma *et al*., 2013; Ochege, & Okpala-Okaka 2017; Yang, Weisberg & Bristow 2012). Understanding the vegetation dynamics is therefore, of paramount importance for the protection, conservation and management of the ecological environment (Fang, Bai & Wu 2015; Jiang *et al*., 2015).

Periodic monitoring and assessment of vegetation condition is therefore necessary for understanding the effects of different drivers of change on spatio-temporal dynamics of vegetation. This is particularly important in the dryland environment of Sokoto Close-settled zone due to the fragile nature of the ecosystem in the region and the peoples' over dependence on it for their livelihoods. Furthermore, over the last decades, vegetation of the area has been experiencing major disturbances mainly due to anthropogenic drivers coupled with other natural processes, posing serious consequences on the natural vegetation, biodiversity, food security as well as socio-economic development of the area (Marian *et al*., 2014). Urban and agricultural expansions caused by the rapid population growth in the area, are among the major drivers of vegetation change in the area (Pooter *et al*., 2004). Other sources of vegetation disturbances in the area includes, overgrazing, fuel wood extraction, bush burning and desert encroachment all of which poses serious ecological, social and economic consequences (Mohammed, 2015; Olgunju 2015). Climate change and associated challenges further aggravates these challenges (IPCC, 2013; MEA, 2005).

One of the central and basic indicator of vegetation condition in a wide variety of physiological, climatological and biogeochemical studies is the Leaf Area Index (LAI) (Asner, Scurlock & Hicke 2003; Jonckheere et al., 2004; Shen et al., 2014; Zheng, & Moskal 2009). Although, variously defined by different authors, all the definition point to the fact that, LAI is an estimate of the amount of photosynthetic leaf area per unit ground area, and is an important vegetation biophysical parameter used to represent the spatio-temporal distributions of vegetation in an ecosystem (Fang *et al*., 2015; Jiang *et al*., 2015; Shen *et al*., 2014; Zheng, & Moskal 2009). It is a critical parameter that can be used to quantitatively measure the abundance and structure of vegetation thereby aiding the understanding of the entire biophysical processes in an ecosystem. It can also serve as an indicator of vegetation stress, which can alter the balance, structure and functions of the entire ecosystem (Asner *et al*., 2003; Shen *et al*., 2014; Vintrou *et al*., 2014; Walker *et al*., 2012). Long-term monitoring of LAI can therefore, enhance our understanding of dynamic changes in the spatial distribution and functions of vegetation as well as the impacts of climate change and variability on the terrestrial ecosystem. It will also facilitate our understanding of gas-vegetation exchange phenomenon at different spatial scales ranging from leaf to landscape level (Asner *et al*., 2003; Shen *et al*., 2014; Zheng, & Moskal 2009). Furthermore, for an area characterised by a mixed grassland ecosystem like that of our study area, LAI can be a good indicator of the variations in grassland ecosystem dynamics at the landscape level (Shen *et al*., 2014).

Another important parameter for assessing vegetation dynamics is the Above-ground Net primary productivity (ANPP). Generally considered as the amount of organic matter produced by the vegetative component of the ecosystem per unit are and unit time, ANPP is one of the most important indicators of ecosystem condition, functions and resource utilisation efficiency (Field, Randerson & Malmstrom 1995; Goroshi *et al*., 2014; José M Paruelo *et al*., 2013; Rossini *et al*., 2012; Turner *et al*., 2005; Yuan *et al*., 2013; L. Zhu, & Southworth 2013). ANPP plays an important role in global carbon cycle at various spatial and temporal scales. In the same way with LAI, periodic monitoring and assessment of ANPP is also necessary as it enhances our ability to evaluate the trends in biospheric behaviour, increase our understanding of the role of biosphere in global carbon cycle and enable us to investigate and monitor the patterns in the supply of ecosystem goods and services, all of which constitutes vital information for the management of natural resources (Goroshi *et al*., 2014; José M Paruelo *et al*., 2013; Rossini *et al*., 2012; Turner *et al*., 2005).

Both ANPP and LAI can be effectively monitored and assess with the high degree of accuracy using remote sensing data and techniques. Within the last couple of decade, remote sensing satellites provided cost and time effective global monitoring necessary for improving our understanding of the ecosystem dynamics. Following the revolutions in the field geoinformation science, particularly remote sensing within the last few decades, repeated observations of the earth surface from the space is now possible at different spatial and temporal scales. Multi-temporal satellite images such as Landsat, Advanced Very High-Resolution Radiometer (AVHRR) and Moderate Resolution Imaging Spectroradiometer (MODIS) of the same area can now be used to study the susceptibility of ecosystems to natural and other human induced changes and its associated consequences. One major advantage of remote sensing data is that, the data is collected using a consistent measurement over the entire area of interest and is free from the variations in data collection techniques in different locations which increases its usability for determining the extent, conditions and changes in ecosystems at different spatial and temporal dimensions (MEA, 2005). Earlier applications of remote sensing on ecological and environmental studies however, focused on such areas as assessment of land cover and land use changes (Ali & Bayoumi, 2004; Kerr & Ostrovsky, 2003; Rogan *et al*., 2003; Stefanov & Netzband, 2005; Turner, Ollinger, & Kimball, 2004). With the passage of time more tool, techniques and system are developed and today, remote sensing provides key data in ecological research worldwide, offering repeatable, standardized and verifiable information on the key ecosystem indicators such as productivity, disturbances, response to different natural and anthropogenic stressors as well measuring changes on different spatial and temporal scales (Pettorelli *et al*., 2014).

Different techniques and indices for integrated ecosystem measurement are being developed and used to measure different properties of ecosystem such as productivity, stresses and responses to different biophysical and human induced disturbances. The Normalised Difference Vegetation Index (NDVI) is one of the most commonly used indices for measuring different properties of the ecosystem at different spatial scales (Kerr, & Ostrovsky 2003; Pettorelli *et al.*, 2014). NDVI for example, has been extensively used to study the ecosystem’s net primary productivity (NPP) and spatial distributions of vegetation due to its strong positive correlation with vegetation photosynthesis which facilitates it common use as an excellent estimator of above ground net primary productivity and leaf area index (Chauvenet *et al*., 2015; Fraser, Kerr & Sawada 2005; Shen *et al*., 2014; Xu, & Guo 2015). In the same way with the NPP and LAI, NDVI values also changes in response to the fluctuations of climatic variables particularly temperature and precipitation thus, making it useful for the study of the impacts of climate change on ecosystem (Li *et al*., 2014; Xu & Guo 2015). When combine with land use data, NDVI is also useful in differentiating between natural and human induced changes in the structure and functions of an ecosystem (Fung, & Siu 2010; Li, Xu & Guo 2014; Paruelo, Burke & Lauenroth 2001; Paruelo *et al*., 2013; Xu, & Guo 2015; Zhu *et al*., 2017). In this research MODIS-NDVI remote sensing data was used to monitor the spatio-temporal trends in vegetation dynamics, in Sokoto Close-Settled Zone, Northwestern Nigeria, in order to understand the trend and extent of vegetation change, determine the role of different drivers in shaping the vegetation of the area and discuss the implication of the observed changes on the ecosystem and livelihood of the people in the area.

The Study Area

The study area is Sokoto Close-settled Zone located in the dryland ecosystem Northwestern Nigeria. Sokoto Close-Settled Zone is an area characterized mainly by high population density exceeding 300 persons per square kilometre and intensively cultivated, with over 80% of the land under rain-fed crop cultivation (Goddard 1972; Mamman 1989). It covers a total land area of 6000 kilometres square, extending to some 120 kilometres North to South and 50 kilometres East to West of Sokoto town (Mamman, 1989). It forms an integral part of Sokoto State, located in the Northwestern part of Nigeria, between latitudes 11^{o} 30” to 13^{o} 50”N and longitudes 4^{o} 00” to 6^{o}E (Figure 1). The state shares common boundaries with the republic of Niger to the North and West, Zamfara State to the East and Kebbi State to the South.

The area is under the influence of tropical continental climate with a very fragile ecosystems. Temperatures are high throughout the year while rainfall are low, variable and unreliable, lasting for less than five months in duration. Average annual rainfall is about 630 mm while temperatures could reach as high as 40°C in the month of April which usually records the highest of temperature in the year. The area is also a typical of Sudan Savannah type of vegetation dominated by short grasses interspaced by shrubs and short woody trees. Grasses looks green and luxuriant during the rainy season, but eventually withered and die during the dry season, leaving vast expense of bare soil (Davis, 1982). Crop cultivation, animal husbandry and artisanal fishing along the rivers, streams and pools provides the major sources of livelihoods to the people of the area. However, the dwindling income from these activities during the recent decades has compelled almost everybody in the area is to be engaged in one form of non-farming activity or the other both during the wet and dry seasons as a supplementary source of income (Illiya 1999).

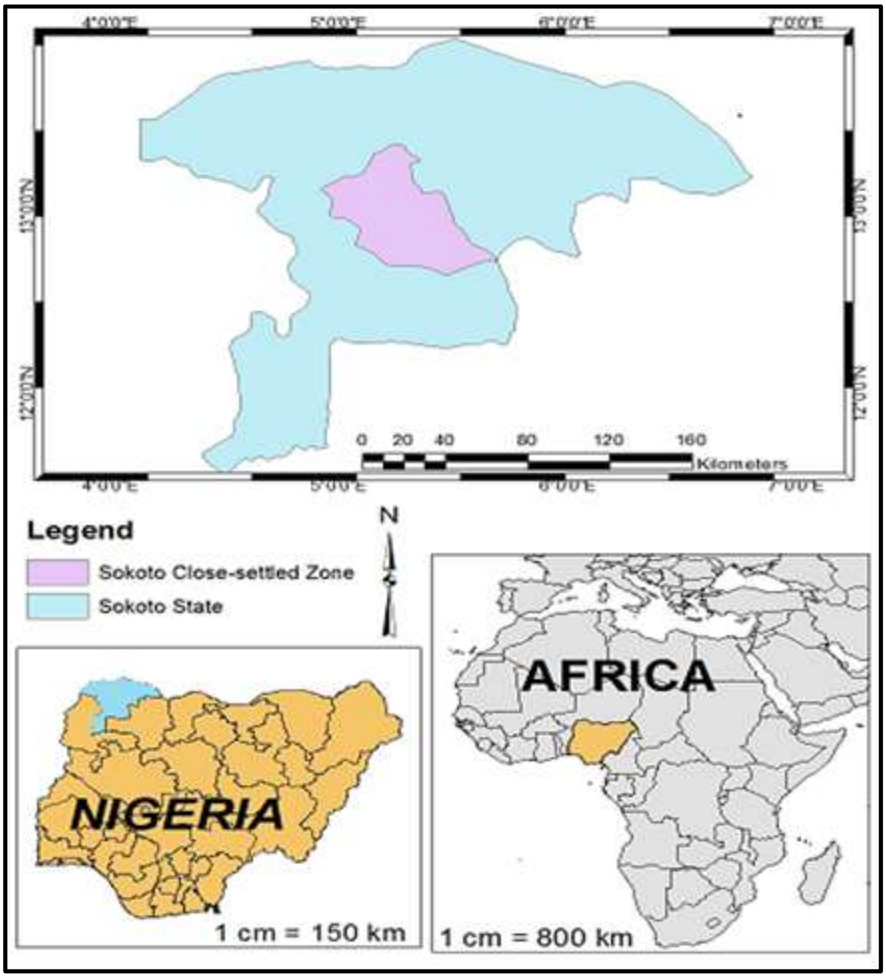

Fig. 1: The Study Area.

DATA AND METHODS

The main data for this study is the MODI-NDVI (MOD13Q1.V6), acquired by the Moderate-resolution Imaging Spectroradiometer (MODIS), on-board NASA's Terra (EOS AM). MODIS Normalised Difference Vegetation Index (NDVI) is one of the products of the of MODIS that is designed to provide consistent spatial and temporal comparisons of vegetation condition using blue, red and near-infrared reflectance centred at 469 nanometres, 645 nanometres and 858 nanometres respectively (Didan 2015). The data is computed from the atmospherically corrected bi-directional surface reflectance that have been masked for water, clouds, heavy aerosols and cloud shadows. MOD13Q1.V6 data are provided every 16 days at 250 meter spatial resolution and is widely used for global monitoring of vegetation conditions and land cover changes at various spatial and temporal scales. The data can also be used for modelling global biogeochemical and hydrologic processes, global and regional climate as well as characterizing land surface biophysical properties and processes such as primary production and land cover conversion (Didan 2015).

Spatio-temporal dynamics of vegetation in the area was obtained through the reclassification the original NDVI images, by assigning the values from -1 to 0 to represent non-vegetation areas while values from 0.1 to 1 represents vegetation areas. NDVI is derived from the ratio of red and near infrared reflectance and is based theoretically on the fact that, vegetation chlorophyll absorbs red rays of the electromagnetic spectrum (EMS), while mesophyll leaf structure scatters near infrared rays of EMS, leading to low reflectance in red and high reflectance in the near infrared regions of the EMS, the ratio of which is used to discriminate vegetation from other types of land cover. Theoretically, NDVI values are represented as a ratio ranging from -1 to +1, but in practice, values from 0 to -1 represents different types of non-vegetation land cover surfaces such as water (extreme negative values), built up areas and bare soil, while values from 0.1 to 1, represents different shade of vegetation cover (Cao *et al*., 2010; Li *et al*., 2014; Rose *et al*., 2015; Vogelmann *et al*., 2012; Zhou *et al*., 2001).

To assess the trends and changes in vegetation productivity, annual mean NDVI integral (NDVI-I) was computed and used as a surrogate of ANPP. This was based on theoretical understanding that, higher NDVI values represent both high photosynthetic activities and high net primary production of the vegetative component of the ecosystem, which in turn signifies a healthy ecosystem with a high degree of vigour. It therefore follows that, the higher the NDVI values, the more healthy and productive the vegetation is. On the other hand, the lower the NDVI values the more stressed and less productive the vegetation component of the ecosystem. Here, annual mean NDVI integral was used rather than maximum or minimum NDVI values. This is because maximum or minimum NDVI values may represent just a single pixel value in an image which will in turn represent a single location in the study area which again, might not represent the true condition of the ecosystem in the entire study area. On the other hand, mean NDVI integral (NDVI-I) is computed by summing up all the pixel values in the image and taking their average which give a more realistic representation of the vegetation productivity in the entire study area.

To determine the role of different drivers of change on the vegetation dynamics, correlation analysis was used to measure the relationships between the trends in vegetation dynamics, rainfall and population distributions of the area. Finally, annual millet production was used to statistically validates the relationship between NDVI-I and vegetation productivity. Figure 2, show the flowchart of the methodology.

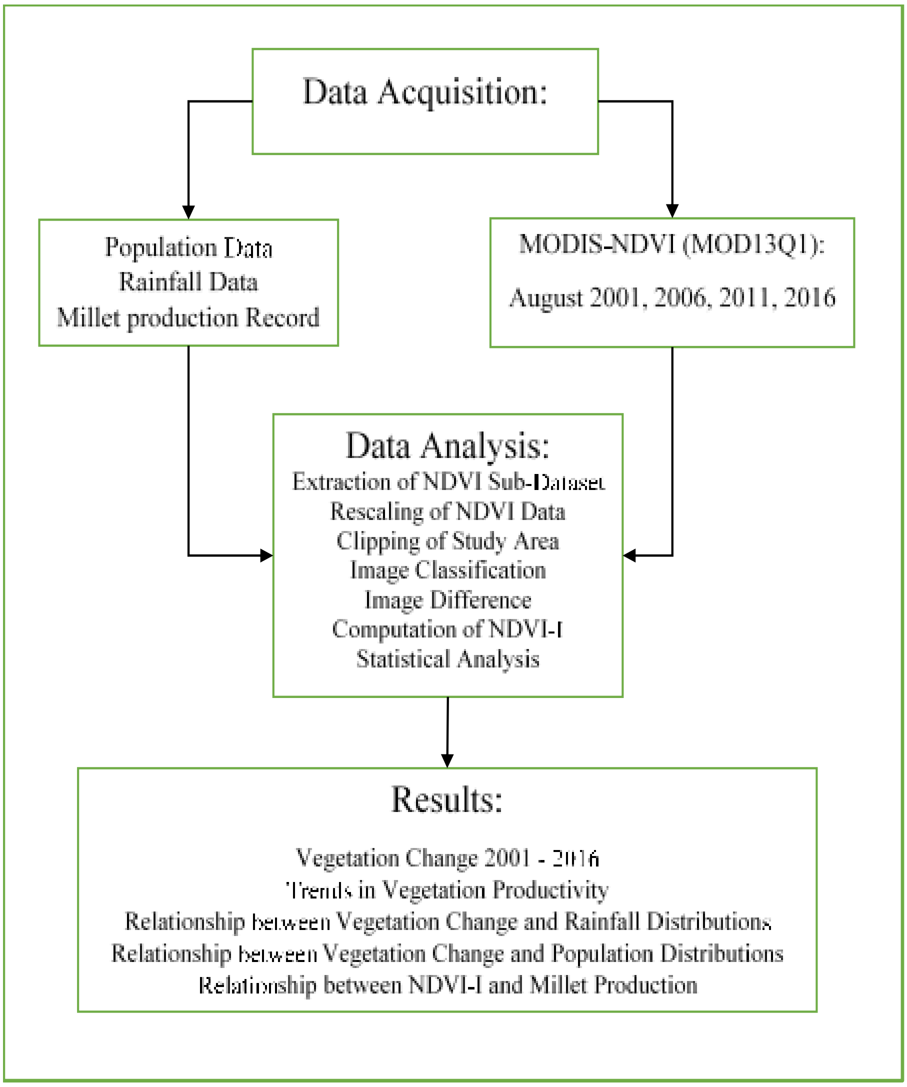

Fig. 2: Flow chart of Research Methodology

RESULTS AND DISCUSSIONS

Spatial Distribution of Vegetation

The results of the analysis indicate a gradual but persistent decline in the spatial distributions of vegetation in the area. Figures 3 and 4, show the trends in the spatial distributions of the vegetation in the area, in the month of august from 2001 to 2016. From the two figures, it is evident that, the spatial distribution of vegetation cover is persistently declining from 66% in 2001 to 51% in 2016. This represent close to 23% decline in the spatial distribution of vegetation within 16 years period. The month of August represents a period during which the vegetation cover is densest and greenest in the study area, as is usually the peak of both rainy season, as well as the vegetation growing season in the area.

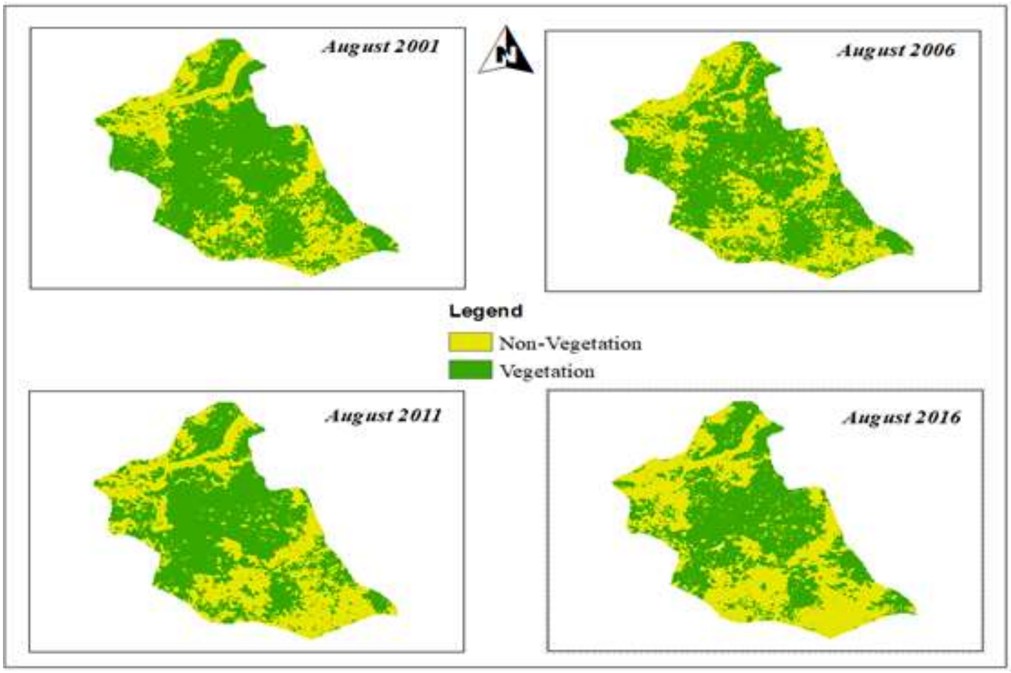

Fig. 3: Spatial Distribution of Vegetation 2001 – 2016

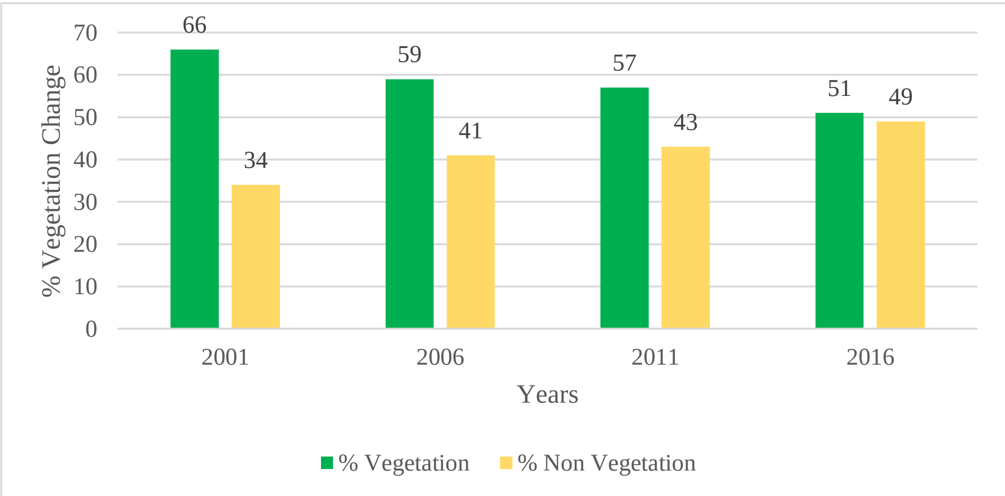

Fig. 4: Percentage of Vegetation Cover 2001 - 2016

Many drivers of change could also be responsible for the above change including climate change and variability. This is because amount and distribution of rainfall affects vegetation growth and distribution as well as its seasonal phenological cycles. Comparing the above change with the total annual rainfall reveals a strong positive correlation coefficient of r = 0.90 as indicated by figure 5.

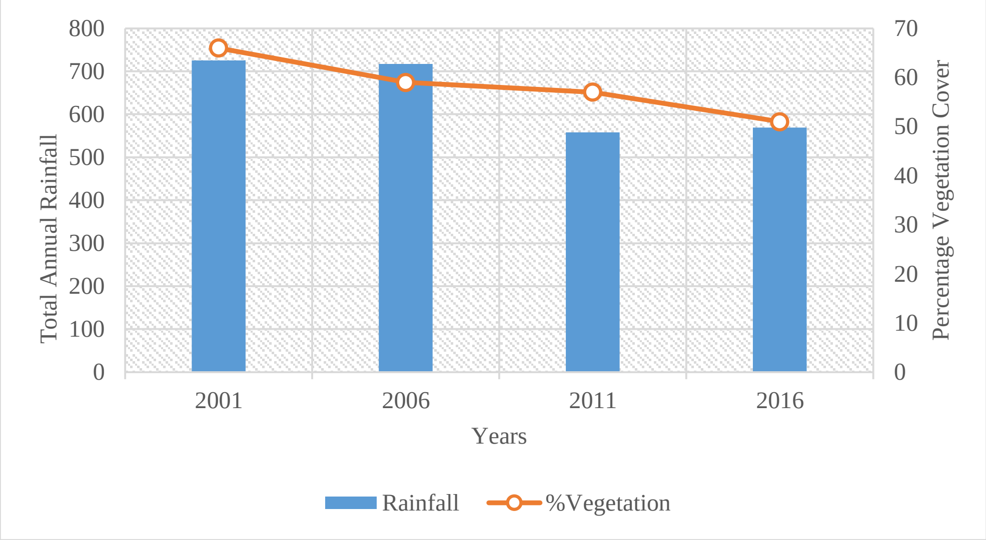

Fig. 5: Relationship between Total Annual Rainfall and Vegetation Cover.

Figure 5 revealed a decline in the total annual rainfall of the study area from 725.6 millimetres in 2001 to 569.2 millimetres in 2016. This correspond with a similar decrease in the percentage of vegetation cover from 66% in 2001 to 51% in 2016. This is a confirmation of the influence and the negative impact of climate change on the spatial distribution of vegetation cover which could also affect the entire ecosystem of the study area. Over the recent decades, dryland areas world over are experiencing climate change mostly in the form of increasing temperature and declining rainfall both in form of amounts and durations including high frequency of extreme events such as drought, flooding as well as violent wind and rainstorm (IPCC 2013). Sokoto Close-settled Zone as part of global dryland ecosystems also experience these symptoms of climate change which to a very large extent, affects both health and spatial distribution of ecosystem particularly the vegetation components.

Another important driver of change that interact with and compound the influence of climate change in changing the vegetation of the area is the rapid population growth in the area. The total population of the six Local Government Areas that make up the study area based on the 1991 National Population Census, stands at 777, 915 people. This has increased to 1,111,773 people during the 2006 National Population Census and projected to 1,468,055 people in the year 2016 (NPC, 2016). This rapid increase in the population of the area act as an impetus that fueled other drivers of change that in themselves contributed in changing the ecosystem of the area and also aggravated the processes of climate change. Population growth for example increases the demand for food and urban infrastructures that lead to land conversions in favour of agriculture and urban expansion to cater for the increasing population. This will no doubt affect vegetation distribution negatively in particular and the entire ecosystem of the area in general. Moreover, increase in population also increases the rate of exploitation and consumption of environmental resources as well as discharge of bye products from both domestic and industrial sources including greenhouse gasses, which aggravates climate change processes, which in turn, affects different components of ecosystem negatively including vegetation. Thus, population growth is one of the indirect drivers of ecosystem change in the area and shows a strong or near perfect negative correlation with vegetation distributions in the study area (r = -0.99) as depicted by figure 6.

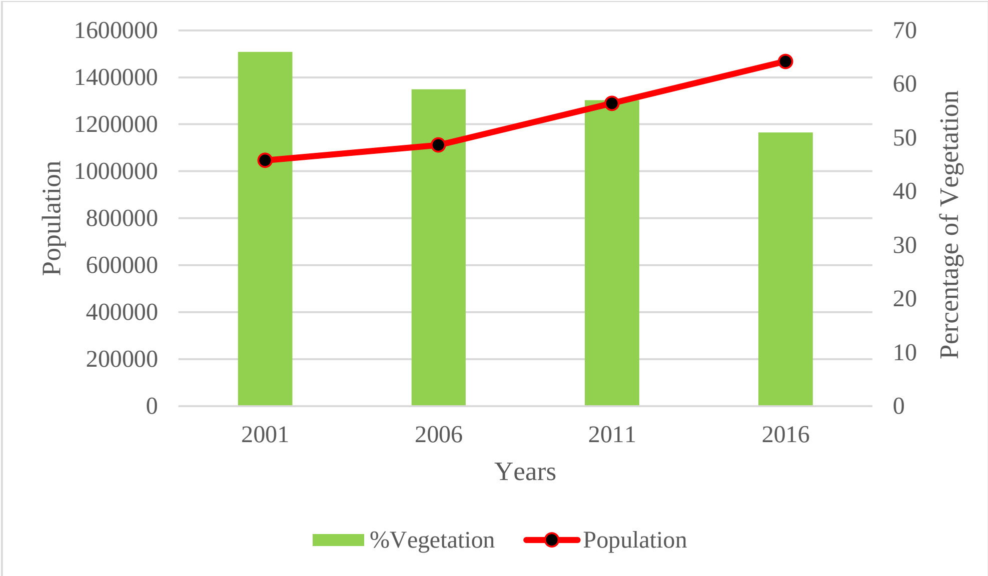

Fig. 6: Relationship between Population Growth and Vegetation Distribution.

Other drivers of vegetation change in the study area includes over grazing, fuel wood sourcing, bush burning and desert encroachment all of which presents serious ecological, social and economic consequences (Mohammed, 2015; Olagunju, 2015).

However, the rate at which the vegetation cover changes, varies from place to place and time to time depending on the interaction of different drivers causing the change both natural such as climate change and variability as well as anthropogenic drivers such as demographic, economic, cultural as well as technological changes. Figures 7 and 8 indicate the spatio-temporal rate of vegetation change. From the two figures, it is clear that, more surface land area is experiencing decreasing vegetation cover. For example, between the periods of 2001 to 2006, 7% of the total land area experienced an increase in vegetation cover, 14% experiences a decrease in vegetation cover while 79% of the land surface remains unchanged. From 2006 to 2011, 11% of the total land area recorded an increase in vegetation cover, 13% recorded a decrease in vegetation cover and 76% of the total land area remains unchanged. Furthermore, from 2011 to 2016, only 5% of the total land area recorded an increase in vegetation cover, while 12% recorded a decrease in vegetation cover and 83% remain unchanged.

Finally, on the whole, from 2001, to 2016, only 4% of the total land area recorded an increase in vegetation cover, while 19% recorded a decrease in vegetation cover and 77% remains unchanged. Thus, the trend is generally toward a declining vegetation cover, which is capable of changing many processes of ecosystem particularly, in view of the important roles of vegetation in supporting and stabilizing ecosystem. This will in turn, negatively affects the livelihood and economic development of the inhabitant of the area due to their over dependence on ecosystem for their sustenance, livelihood and overall development,

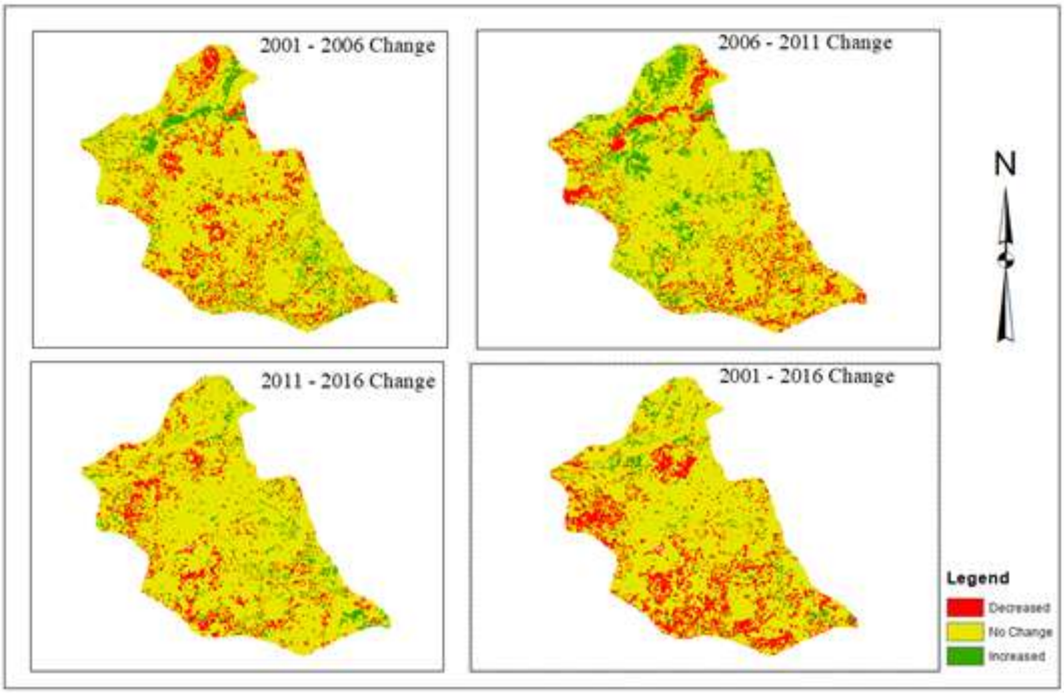

Figure 7 Vegetation Cover Change 2001 – 2016.

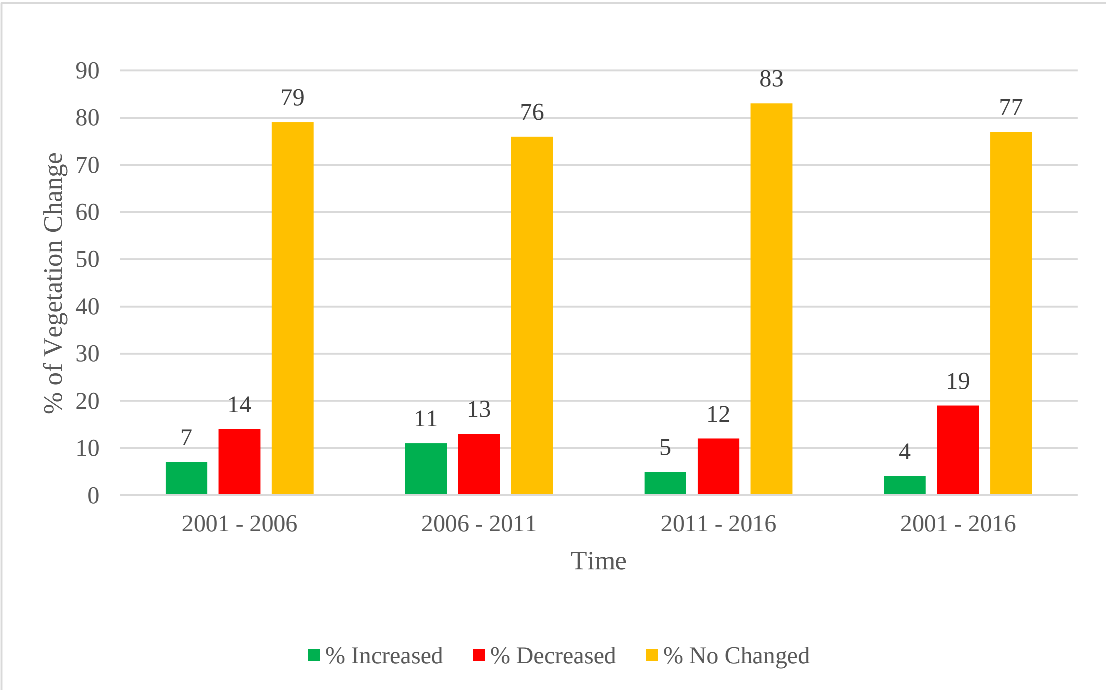

Fig. 8: Rate of Vegetation Change 2001 – 2016.

The temporal variation in the rate of change could be attributed to the interplay of many drivers of change including natural climatic variability and other anthropogenic drivers, as well as the degree of exposure, response and resilience of the ecosystem to such drivers of change. Increasing intensity of these drivers generally increases vulnerability of ecosystem and weaken its resilience, leading to persistent negative changes which is the situation observed in the study area.

Vegetation Productivity

In the same way with the vegetation distribution, there is also gradual but persistent decline in the vegetation productivity in the area as depicted by the annual distribution of integral

NDVI in the area. Figure 9, shows both the inter-annual variability and gradual decline in the vegetation productivity. Based on the figure, the vegetation productivity in the area declined from 0.71 in 2000 to 0.41 in 2016 representing over 40% decline in the vegetation productivity within the period. These types of change in ecosystem are usually gradual and often unnoticeable unless conscious efforts are made to assess and monitor them, but their cumulative long-term impacts could be very devastating to both the ecosystem and livelihood of the area. These are usually subtle changes that take place within the state of vegetation communities that are beyond the normal phenological cycles (Vogelmann et al., 2012).

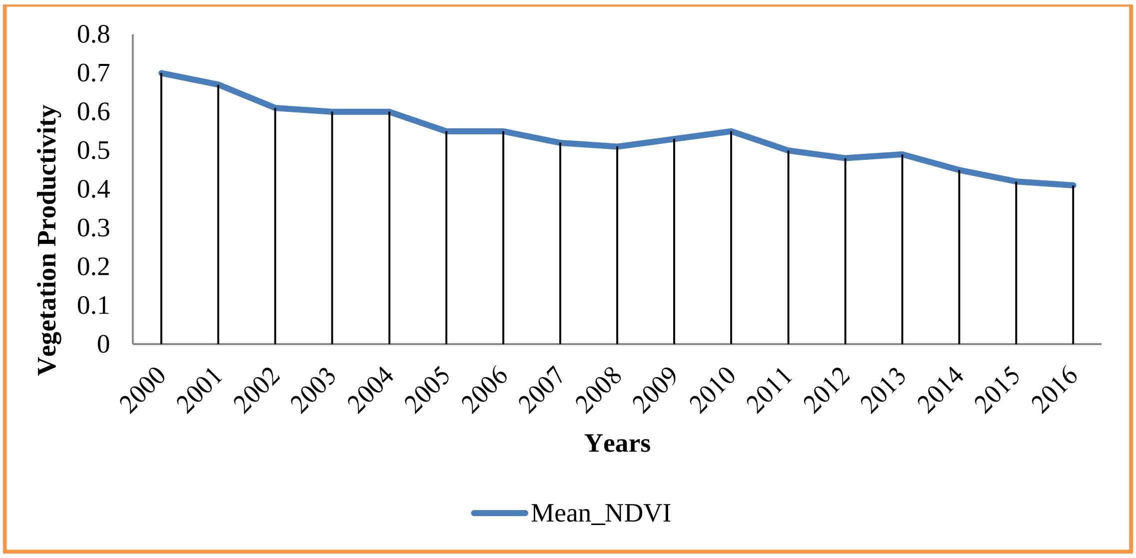

Fig. 9: Trend in vegetation productivity 2000 – 2016.

This result is further supported by the report of the Millennium Ecosystem Assessment (2005), which reported land degradation in the form of declining biological and economic productivity of the land as the major ecosystem change in dryland ecosystem, noting that, over 10% of the global dryland ecosystems are degraded (Millennium Ecosystem Assessment 2005).

Many drivers of change in ecosystem, both natural and anthropogenic as well as direct and indirect drivers of change could be responsible for the above change. However, in order to assess the role of climate change on the observed decline in vegetation productivity, the trend in vegetation productivity was correlated with the annual distribution of rainfall which is the major critical climatic element that influences the growth and productivity of vegetation in the study area. To do this however, the mean NDVI integral were rescaled by multiplying them with 1000 in order to have a common scale with the annual rainfall distribution for effective comparison. The result in figure 10, shows a positive relationship between annual rainfall distribution and vegetation productivity with the correlation coefficient of 0.43. This indicates that, climate change and variability is one of the strong drivers of change and determinants of vegetation productivity in the dryland ecosystem of the Sokoto Close-settled zone of North-western Nigeria.

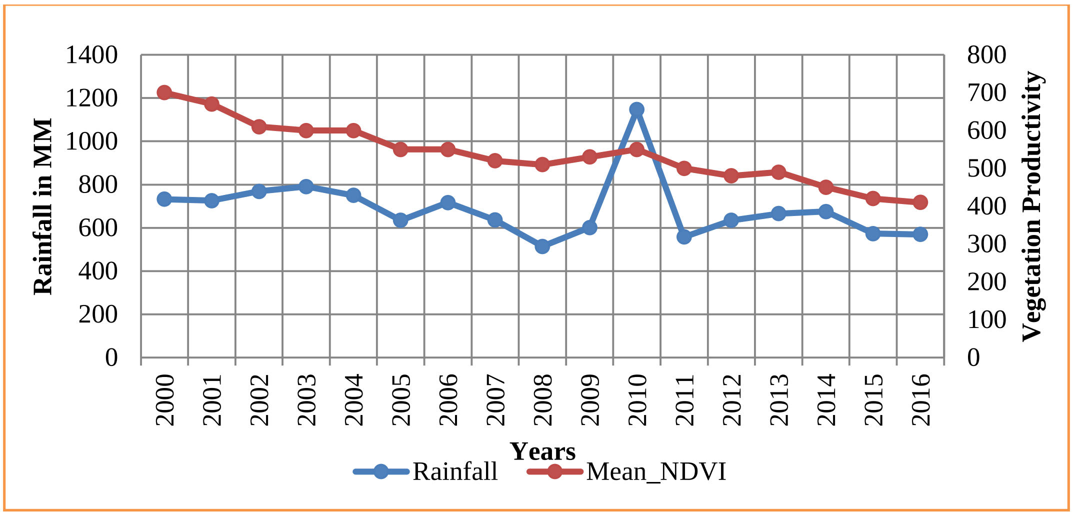

Fig. 10: Correlation between Rainfall Distributions and Vegetation Productivity

However, in order to validate the above result, there is need to establish a relationship between the mean NDVI integral and vegetation productivity in the study area. In the absence of field measured ANPP of the study area, annual crop yield was used as a surrogate of ANPP. Annual crop yield has been established to have a positive correlation with both NDVI and ANPP (Chang 2002; Jat *et al*., 2012; Li *et al*., 2007; Panda *et al*., 2010; Paruelo *et al*., 2013). For this reason, annual millet yield of the study area was correlated with mean NDVI integral to validate the above result. Millet is the major crop produced in the study area through rain fed agriculture. Figure 11 revealed a strong positive correlation between the mean NDVI integral (Mean NDVI-I) and the estimated annual production of millet in the study area, with a correlation coefficient of 0.88.

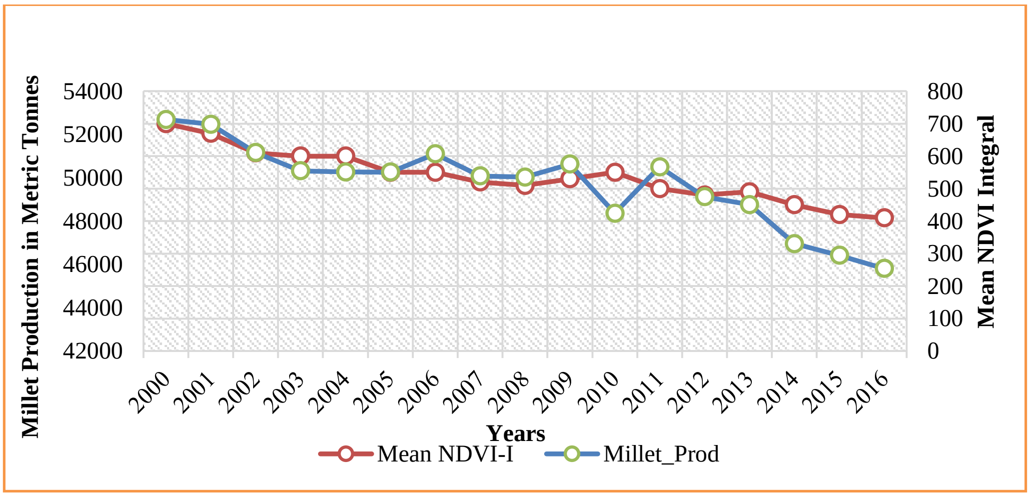

Fig. 11: Relationship between NDVI-I and Millet Productivity

CONCLUSION AND RECOMMENDATIONS

The result of this study indicated a gradual but persistent decline in both the spatial distribution and productivity of vegetation in the Sokoto Close-settled Zone, Northwestern Nigeria. The spatial distribution of vegetation in the area declined from 66% of the total land surface in 2001 to 51 % in 2016, representing close to 23% decline. This shows a strong positive correlation with rainfall distribution (r = 0.90) and a near perfect negative correlation with population growth in the area (r = -0.99). Similarly, vegetation productivity in the area decline from 0.70 in 2000 to 0.41 in 2016, representing over 40% decline, which shows a strong positive correlation with annual rainfall distributions in the area over the same period (r = 0.43). These confirmed the influence of climate change and variability on the vegetation dynamics of the area, which is also capable of changing the structure and functions of the ecosystem of the area. These types of change although operate gradually and not easily noticed, their cumulative effects over the years can have a significant impact on both the ecosystem, supply of ecosystem good and services as well as the livelihoods and sustainable development of the area. For example, declining vegetation cover can increase soil exposure to erosion by the action of wind and running water as well as dessert encroachment. This in turn could lead to loss of agricultural and grazing lands, decline in food production, depletion of surface and subsurface water hunger, increasing poverty, malnutrition and diseases. To mitigate and avert these negative development therefore, require a concerted efforts and collaborations from all stake holders including government at all levels, individuals, private and public as well as international organisations though such measures as public awareness, protection of marginal lands, sustainable farming and land management practices, afforestation, provision of alternative sources of energy and the use of alternative means of livelihoods with minimal negative impacts on the ecosystem of the area. A system also need to put in place for effective and frequent monitoring and assessment of the state of ecosystem in order to guide policies and actions and to assess the effectiveness of mitigation measures.

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