INFLUENCE OF CLIMATE VARIABILITY ON BIOMASS DENSITY OF SOUTH WEST NIGERIA: A CASE STUDY OF OYO AND OGUN STATES

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ABSTRACT
The study aims at examining the influence of climate variability on the biomass density of Oyo and Ogun States. Past records of rainfall and temperature data for the 1981 to 2010 covering the study area were acquired and used for climate variability analysis. The Normalized Difference Vegetation Index (NDVI) data from Advanced Very High Resolution Radiometer (AVHRR) (1981 -1999) and Moderate Resolution Imaging Spectroradiometer (MODIS) (2000 - 2010) satellites were employed for the Biomass analysis. These set of data were converted to grid points and extracted to statistical software for correlation and PCA (Principle Component Analysis). The decadal analysis for each location revealed that Alabata recorded highest rainfall (103.21 mm) in 2000 and 98.285 mm in 1990, in 1980 and 1990 the same location recorded a temperature of 32.31 ^{0}c with a slight decrease to 32.27 ^{0}c in 2000. Biomass showed a steady decline from 0.68 (1980) to 0.67 (1990) and 0.46 (2000). Eggua recorded highest rainfall of 99.26 mm in 2000 followed by 1990 (91.63 mm) and the lowest in 1980 (76.013 mm). However, temperature was consistent for 1980 and 1990 (32.36 ^{0}c). Biomass had a steady decline from 0.66 in 1980 to 0.64 in 1990 to 0.43 in 2000. Idode recorded 102.26 mm rainfall in 1980 and it increased to 104.115 mm in 2000 and in 1990 it decreased to 102.03 mm. Temperature ranges from 34.05 ^{0}c in 1980 and 1990 to 31.77 ^{0}c in 2000. NDVI decline in biomass across the decade from 0.64 in 1980 to 0.61 in 1990 to 0.33 in 2000. Irawo relatively had a low rainfall throughout the 3 epochs 1990 (94.36 mm) 2000 recorded 96.57 mm and 93.62 mm in 1980. Temperature was however consistent for 1980 and 1990 (31.91 ^{0}c) with a slight decrease in 2000 to 31.79 ^{0}c. Biomass was reduced for the 3 decades from 0.60 in 1980 to 0.57 in 1990 to 0.33 in 2000. Despite the general and consistent increases recorded in rainfall between 1980s and 2000s epochs, rainfall anomaly was consistently below normal for Eggua and Irawo in the decades 2000s. The study concludes that the continual increase in temperature has led to reduction in biomass of the study area.

Keywords: Biomass, Anomaly, Temperature, Rainfall, NDVI.

INTRODUCTION

Africa is most likely the continent in the world with the highest vulnerability to climate variations (Schneider, *et al* 2007). This vulnerability does not exempt agriculture as it is one of the sectors highly vulnerable to impacts of climate change. The vulnerability in this sector is manifested through occurrence of extremes events such as increased drought, flood severity, more intense storms, shifts in the timing and distribution of rainfall, warmer temperatures, and secondary effects such as increased pest and disease pressure (FAO, 2010). All this now have effect on the food security status of the continent alongside other problems facing the continent which is occurring on top of rapid population growth, fast-paced urbanization, land-use change, conflict, and degradation of critical environmental services that underpin food and livelihood security. (Speziale, and Geneletti, 2014).

Intergovernmental Panel on Climate Change (IPCC, 2001) states that vulnerabilty is the degree to which a system is susceptible to or unable to cope with adverse effects of climate change, including climate variability and extremes'. Most often, vulnerability is represented by a suite of socio-economic, political and environmental factors that represent the sensitivity and exposure of population to climate hazards (Brooks, *et.al.* 2005).

The change in climate possesses a serious threat to human lives and properties. It has over the years caused increase in global temperature and reduction in rainfall. These will however lead to a general reduction in vegetal biomass in the world. According to Whyte, 1995, forest is especially vulnerable to the effects of climatic change through temperature stress, changes in precipitation, increase in pests and decrease in competition from other ecosystems.

A Declarations of the United Nations on disaster management (Hyogo Framework for Action 2005-2015) states that 'the starting point for reducing disaster risk and for promoting a culture of disaster resilience lies in the knowledge of hazards and the physical, social, economic and environmental vulnerabilities to disasters that most societies face, and of the ways in which hazards and vulnerabilities are changing in the short and long term followed by action on the basis of that knowledge' (UN, 2005). The understanding of vulnerability to climate change is therefore a key step towards managing risk/hazard related to climate variability and achieving environmental sustainability. (Rehman, 2017)

Rainfall and temperature are the major climatic factors that directly influence vegetation growth, it follows that the higher rainfall the higher the vegetation index, and on the other hand the higher the temperature the lower the vegetation index. Past research have shown these relationships, (Nightingale and Phinn, 2003; Funk and Brown, 2005). Several global and regional studies have previously investigated the relationship between NDVI and climatic factors in different parts of the world.

Many studies have used NDVI to monitor the temporal response of vegetation to climatic fluctuations in the USA (Di *et al*., 1994, Yang *et al*., 1997), in Africa (Tucker *et al*., 1983, 1985, Justice *et al*. 1986, Townshend and Justice 1986, Malo and Nicholson 1990, Davenport and Nicholson 1993, Nicholson and Farrar 1994, Anyamba and Eastman 1996), in India (Srivastava *et al*., 1997), and at a global scale (Schultz and Halpert 1993); but only a few studies have examined spatial patterns of NDVI as they relate to climate variation (Tucker *et al*., 1985, Nicholson and Farrar 1994). Temporal variations of NDVI are closely related to precipitation and there is a strong linear (Malo and Nicholson, 1990) or log-linear (Davenport and Nicholson, 1993) relationship between NDVI and precipitation in cases where monthly or annual precipitation is within a certain range (500-1,000mm/yr). The relationship between NDVI and rainfall regionally varies due to variation in properties such as vegetation type, temperature and soil background (Nicholson and Farrar, 1994).

As every conflict has many causes, and people do not automatically start fighting when the weather heats up, and drought and desertification ensues. Drawing lines of causation between climate change and conflict requires caution hence a basic causal mechanism links climate change with violence in Nigeria. Climate change in Nigeria has led to growing shifts in temperature, rainfall, storms, and sea levels. These climatic challenges, left unaddressed, had thrown already stressed resources such as land and water into even shorter supply. Moreover, poor responses to resource shortages could have serious negative secondary effects, including more sickness and hunger, fewer jobs, and poor economic growth, which in turn could open the door to more violence. Indeed, in a few conflict-prone states in Nigeria such as Plateau state, has long being affected by conflict by the farmers and herdsmen, also in recent times Benue State has been recording series of conflicts. First, land scarcity, Second factor is water shortage and scarcity. Odoh and chilaca, 2002 reported a break of conflict 5 times in 2002 which lead to loss of many lives, properties and farm produce while many fled their homes.

The impacts from the climatic variations within the study area could be measured by determining the anomalies recorded on the temperature, rainfall, and the NDVI, the result thus, shows the possible vulnerability of the either to humans or animals.

MATERIALS AND METHODS

Study Area

The studied settled pastoral communities include Alabata in Odeda LGA and Eggua in Egbado North (Yewa North) LGA both in Ogun State, and Irawo in Atisbo LGA and Idode in Oyo East LGA of Oyo State. Since the pastoralists traverses a large area in search of pasture and water for their herds, the study area is, therefore, described in the context of the larger geographic area that provides the actual and potential operating space for settled agro- pastoralists. Thus, the area adopted for the study covers the states of Ogun and Oyo States in Southwest Nigeria. This covers about 42,900km^2 and is roughly defined by Latitudes 6^o 30' and 9^{o}15' N and Longitudes 2^{o}45' and 4^{o}30' E.

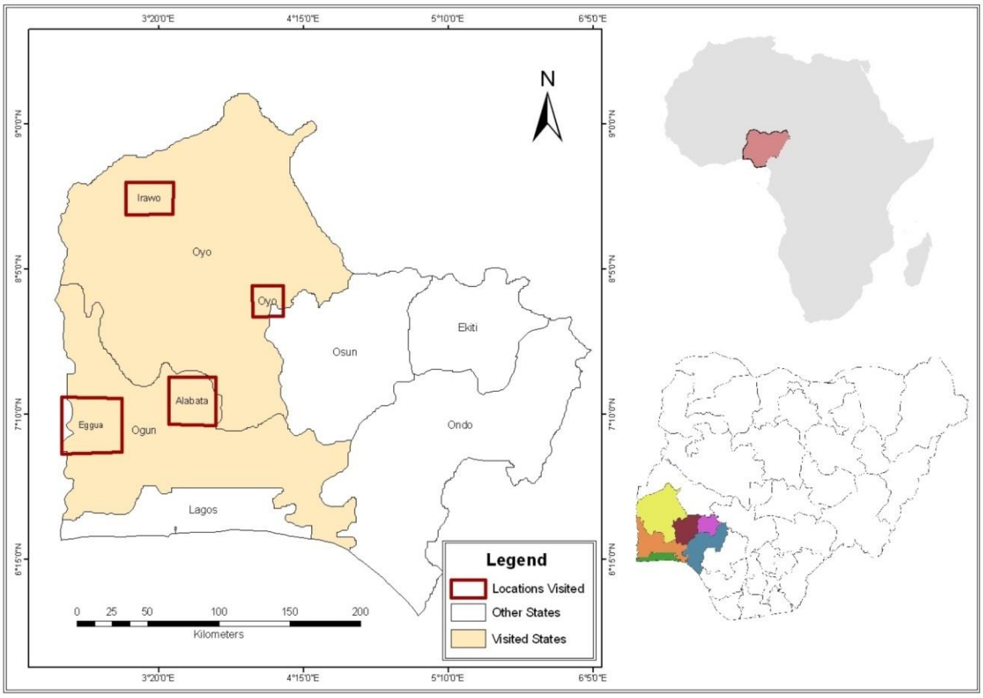


Fig 1: Map of the Study Area

Table 2: Data used for climate and vegetation indices analysis

Data	Resolution	Source	Date	Usage
Monthly Rainfall data		NIMET		Rainfall Variability
Monthly Temperature Data		NIMET		Temperature Variability
Monthly NDVI Composite images NOAA - AVHRR	8km /8bit	NOAA-AVHRR acquired from Clarks Lab	1981 - 1999	NDVI Values Extraction
Monthly NDVI Composite MODIS Images	1km/16bits	Moderate Resolution Imaging Spectrometer (MODIS) acquired from Clark Labs	2000-2009	NDVI Values Extraction

Climatic Data Processing

The monthly rainfall and temperature data for nine stations in the southwest Nigeria from 1981 - 2010 was obtained from the Nigerian Meteorological Agency (NIMET). In order to improve the spatial analysis and interpolation, additional climate data was sourced for three stations adjacent station in Benin Republic. Table 3 shows the stations for which data were accessed.

Table 3: Meteorological stations for which data was accessed

SN	Station	Lon	Lat	Years for which data is available
1	Iseyin	3.58549	7.98167	1982-2010
2	Shaki	3.3747	8.6947	1984-2010
3	Bida	5.99836	9.05513	1980-2010
4	Lokoja	6.71486	7.81282	1980-2010
5	Oshogbo	4.54461	7.76675	1980-2010
6	Ilorin	4.53645	8.51135	1980-2010
7	Ibadan	3.89073	7.3763	1980-2005
8	Abeokuta	3.30152	7.16694	1981-2006
9	Akure	5.18377	7.23955	1980-2006
10	Save	2.47000	8.03000	1980-2000
11	Kandi	2.62000	9.35000	1980-2000
12	Bohicon	2.07000	7.17000	1980-2000

A uniform time frame (1982-2010) was adopted for both climate and vegetal change analysis. The rainfall and temperature data were analyzed for spatial and temporal averages and anomalies including annual, decadal, and seasonal averages, anomalies and trends. The results were converted into spatially explicit data using surface interpolation methods. This is important to facilitate easy integration of the climate data with NDVI and other spatial datasets to facilitate spatially-explicit inferences as well as collocation analysis of the integrated dataset. A surface interpolation function creates a continuous surface from sampled point values thus predicting a value for any geographic point. The Inverse Distance Weighted (IDW) model was used to create a continuous surface from the analyzed rainfall and temperature data. The IDW uses weighted moving average point with some zone of influence for the calculation of grid values through the area of analysis. This method assumes that the variable being mapped decreases in influence with distance from its sampled location.

The mathematical interpretation of IDW is that the values assigned for the estimation of points are going to be determined by the values of the neighbors, each of them weighted according to the inverse of the distance between the estimation points and the neighbor being considered, elevated to the second power. The relation is expressed in the formula below;

$$\frac{\sum^{n} W_j C_j}{\sum_{j=1}^{n} W_j} \quad \text{--} \quad (1)$$

Where $W_j = \frac{1}{(D_{je})^2}$

C_e = the concentration of value for the estimation point

D_{je} = distance from the estimation point to the j_{th} neighbor

W_j = weight given to each sample obtained by the inverse of square the distance between the estimation point and the j_{th} neighbor.

Biomass data Processing

The close coupling between rainfall and the growth of vegetation has made it possible to utilize NDVI data as proxy for the land surface response to precipitation variability (Anyamba and Tucker 2005, Neigh *et al*. 2008) and vegetation biophysical properties (Stow *et al*. 2004). The NDVI provides a measure of the amount and vigor of vegetation at 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. Time series NDVI can, therefore, provide a proxy for estimating multi-temporal changes in vegetation.

The NDVI is calculated from two channels of the AVHRR sensor, the near-infrared (NIR) and visible (VIS) wavelengths, using the following algorithm:

NDVI = (NIR - VIS)/(NIR + VIS) --(2)

Global Monthly NDVI maximum value composite images for 1981 - 2010 was used. The NDVI data came in two series, the first is from the Advanced Very High Resolution Radiometer (AVHRR). It is an 8km resolution monthly NDVI composite images which covered the period of 1981 - 1999. The radiometric resolution is signed 8-bit (values from -128 to +128), with 1800 and 3600 rows and columns respectively. Its production and distribution were funded by NASA's Mission to Planet Earth Program. The data which is also downloadable from the NASA Goddard DAAC ftp site was supplied by Clark Labs, Worcester, MA, USA. The data was re-projected from Goode Interrupted Homolosine Projection to Geographic Projection in using Idrisi software at the Clark Labs. To convert the data values -128 to +128 to the traditional NDVI data range (-1 to +1), 128 is subtracted from the cell values and the result is divided by 128.

The global monthly NDVI data values for 2000-2010 are from the NASA MODIS CMG monthly NDVI data. Derived from the MODIS (Moderate Imaging Spectrometer), these data were processed by NASA Goddard from the Terra Sensor projected on a 0.05 degree Climate Modeling Grid (CMG). The data format is in binary integer, with 7200 columns and 3600 rows. It has a spatial resolution of 1km and a radiometric resolution of *16 bit signed integer*, which has a theoretical range of values from -32,768 to +32,768. According to The Center for Earth Observation, Yale University the documented data range is from with a fill value of -3000 and to convert these numbers to the traditional NDVI data range (-1 to +1), cell values are divided by 10,000.

The processing of the NDVI data include image subsetting, value rescaling and image summarization using image calculator. The NDVI images are global and the area of interest (AOI) (i.e. southwest Nigeria) has to be subset from the global image. This was done by exporting the NDVI images to ArcGIS software where they were clipped; using the ‘Extract by Mask’ tool from ArcGIS Toolbox and the AOI was clipped to an AOI polygonal shape file.

The original NDVI values range is 0-255 for the AVHRR and -2000 to +10000 for the MODIS NDVI datasets. Since NDVI values are expected to range from -1 to +1, the NDVI values had to be rescaled. Thus, image calculator (which is an algebraic and mathematical operation tool within Idrisi Taiga software) was used to rescale the NDVI values.

For the AVHRR dataset series, the rescale was done using:

$N_n = (N_0 - 128)/128$--(3)

And for the MODIS dataset series, the rescale was done using:

$N_n = N_0 /10000$---(4)

Where
N_n = New NDVI image values
N_0 = Original NDVI image values

Using the image calculator function of Idrisi Taiga software, the time-series NDVI data were analyzed for annual, seasonal, and decadal averages and anomalies. For the seasonal mapping, four seasons - DJF (December, January, February), MAM (March, April, May), JJA (June, July, August), and SON (September, October, November) was used.

After computing the normalized scores the index is constructed by giving either equal weight to all indicators.

Normalization was carried out in Microsoft excel workbook, using the standardized formula in the formula menu.

Obviously, the indicators normalized by using functional relationship to be in the same units and scales. This methodology is adopted from the UNDP’s Human Development Index (HDI) (UNDP, 2006). That is, done in order to obtain figures which are free from the units and also to standardize their values to lie between 0 and 1.

When equal weights are given, the use simple average of all the normalized scores to construct the vulnerability index by using the formula:

VI = RF+T+NDVI

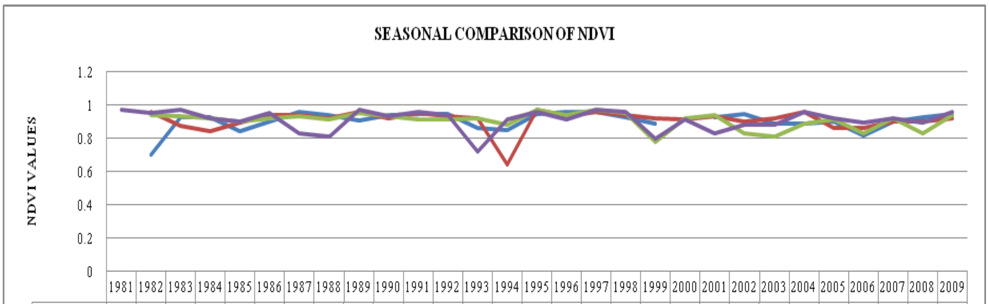
Where,
VI = Vulnerability Index
RF = Rainfall
T = Temperature
NDVI = Normalize Diference Vegetation Index

Finally, the vulnerability indices are used to rank the different regions in terms of vulnerability. A region with highest index is said to be most vulnerable and it is given the rank 1, the region with next highest index is assigned rank 2 and so on.

RESULTS AND DISCUSSION

NDVI Responses across the Seasons

Figure 4 shows the average seasonal NDVI from 1982 to 2009. Although the vegetation index for the four seasons seems not very distinct, some seasons at various years still show a remarkable mean value. MAM, JJA and SON on the average have a strong NDVI values. This can be explained by the fact that April and May are the beginning of rainfall and the crop season. In June, July and August the farmlands will be covered with crops. These may have given these two seasons the strong NDVI values.



	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
DJF		0.70	0.93	0.93	0.84	0.90	0.96	0.94	0.91	0.94	0.95	0.95	0.86	0.85	0.95	0.96	0.96	0.93	0.89		0.93	0.95	0.89	0.89	0.90	0.82	0.90	0.93	0.95
MAM		0.96	0.87	0.84	0.89	0.94	0.94	0.92	0.96	0.92	0.95	0.93	0.92	0.64	0.97	0.93	0.96	0.94	0.92	0.91	0.93	0.90	0.92	0.96	0.86	0.86	0.90	0.90	0.92
JJA		0.94	0.93	0.92	0.90	0.92	0.93	0.91	0.95	0.93	0.91	0.91	0.92	0.88	0.97	0.94	0.97	0.95	0.78	0.92	0.94	0.83	0.81	0.89	0.91	0.83	0.92	0.83	0.94
SON	0.97	0.95	0.97	0.92	0.90	0.95	0.83	0.81	0.97	0.93	0.96	0.94	0.72	0.91	0.96	0.91	0.97	0.96	0.80	0.91	0.83	0.88	0.88	0.96	0.92	0.89	0.92	0.89	0.96

Figure 4: Average seasonal NDVI from 1982 to 2009

SON marks the end of the rains and also characterized by crop harvesting. The lower NDVI for DJF is consistent with the season being characterized by a dry period of little or no rainfall, high temperature, and burning of grasses and woodlands especially in the savanna areas.

Seasonal NDVI Anomaly

Figures 5a-h shows the average seasonal NDVI anomalies for the study area. The years 1981 to 1999 had the greatest changes most of which were to the negative axis. The direction of anomalies for DJF and MAM for the decades 1980s and 1990s was significantly negative. These recovered significantly in the years 2000 to 2009. JJA denotes the peak of the rainy season in the study area. Hence, years of negative anomaly were very few for JJA in all the three decades. SON denotes the approach of the cessation of rains and transition to the dry season. The NDVI signal shows significant negative anomalies in the period 1981 to 1999. Just like the JJA, NDVI shows significant positive anomalies for SON in the period 2000-2009.

In essence, it can be generally inferred that the vegetation was more disturbed in the decades 1980s and 1990s than 2000s. This also suggests a significant vegetal recovery in the decades 2000s from the perturbation of the 1980s and 1990s. This inference is consistent with increased rainfall experienced in the decades 2000s compared to the 1980s and 1990s. This is also consistent with the findings of Lauwaet *et al.* (2009), Stow *et al.* (2004) and Nicholson (2000) on vegetation recovery in the West Africa Sahel which has been linked with recovery of rainfall in the region after the drought of the 1970s and 1980s. This looks like cheering news for pastoralists as it suggests that the range is greener now than it was in the last two decades.

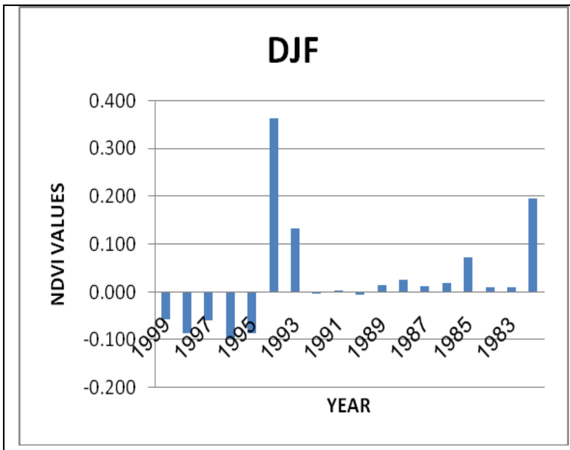


Fig 5a: Seasonal NDVI anomalies for DJF 1982-1999

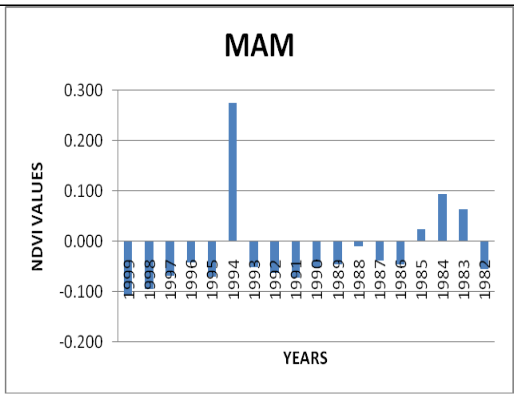


Fig 5b: Seasonal NDVI anomalies for MAM 1982-1999

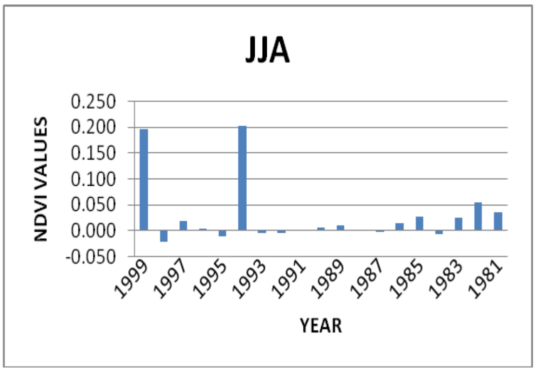


Fig 5c: Seasonal NDVI anomalies for JJA 1982-1999

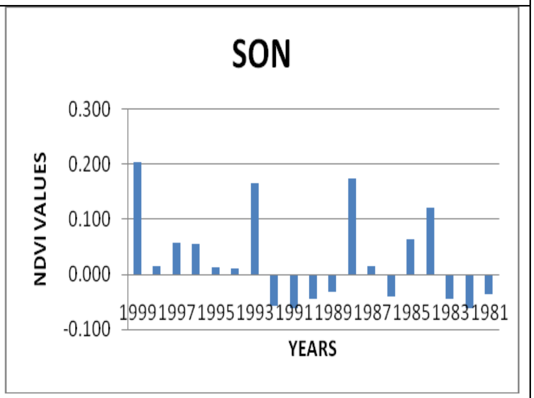


Fig 5d: Seasonal NDVI anomalies for SON 1982-1999

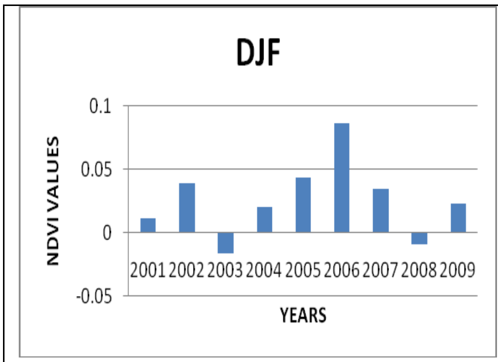


Fig 5e: Seasonal NDVI anomalies for DJF 2000-2009

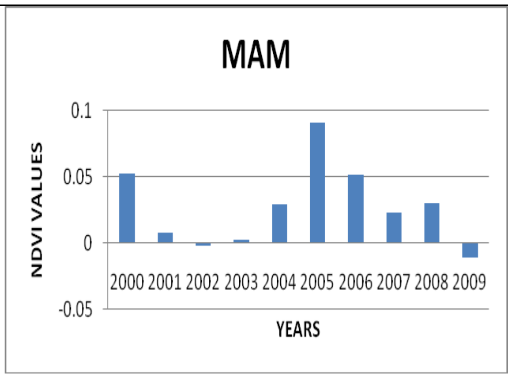


Fig 5f: Seasonal NDVI anomalies for MAM 2000-2009

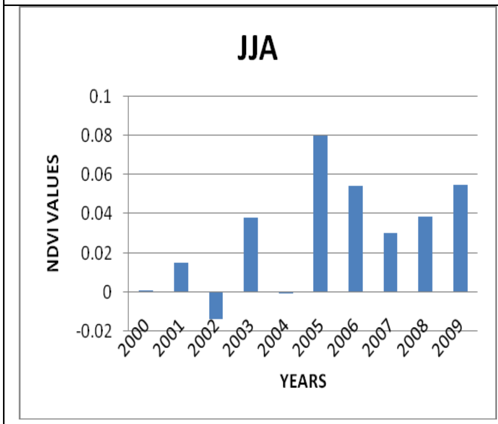


Fig 5g: Seasonal NDVI anomalies for JJA 2000-2009

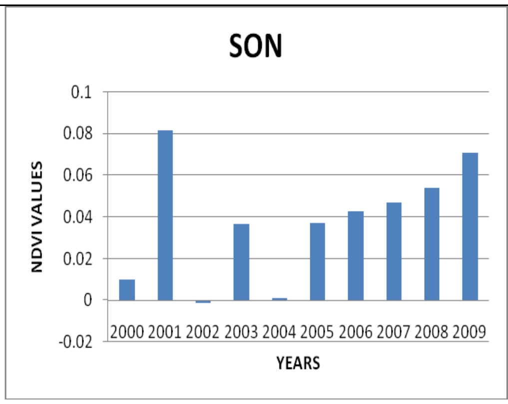


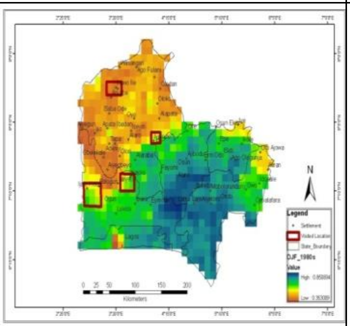
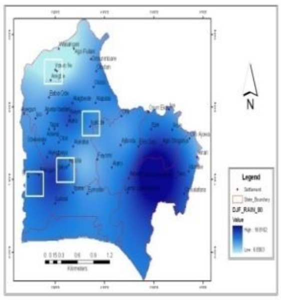
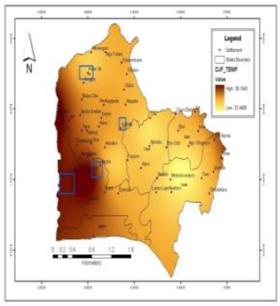
Fig 5h: Seasonal NDVI anomalies for JJA 2000-2009

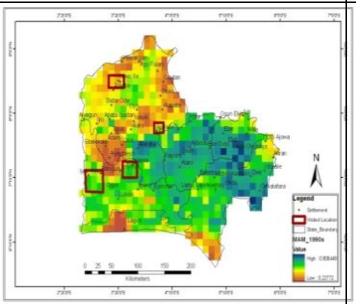
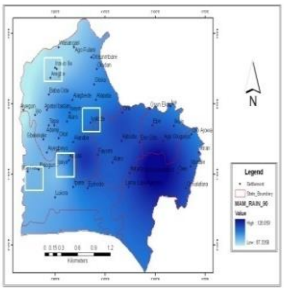
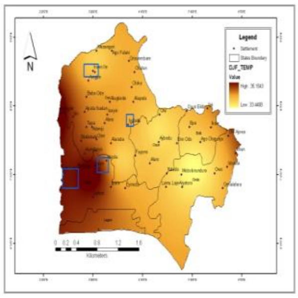
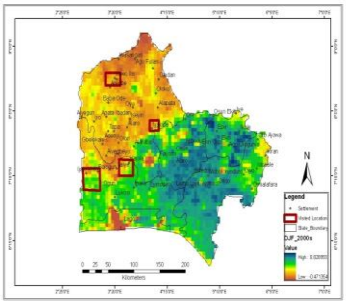
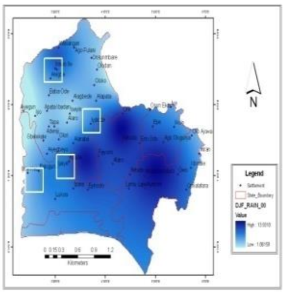
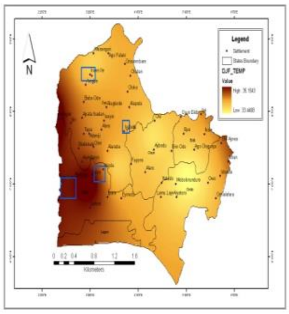
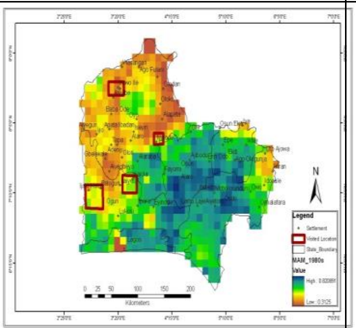
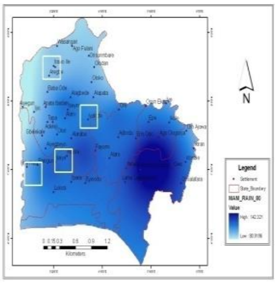
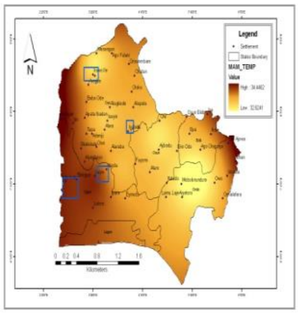
NDVI Response to Precipitation and Temperature

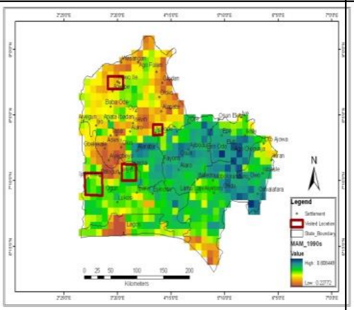
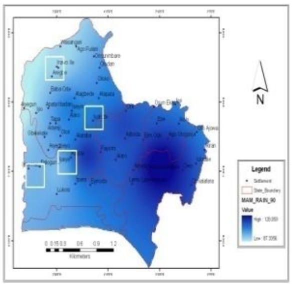
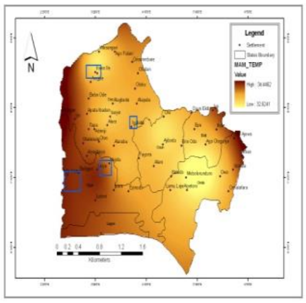
Generally, NDVI responds positively to rainfall but negatively to temperature. A correlation matrix was carried out to show these relationships. (See appendix I). From the correlation it was very clear that all through the seasons that NDVI correlated with rainfall positively while it had a negative correlation with temperature. Bayarjagal *et. al*. (2002) have also shown a greater possibility of using NDVI values derived from NOAA AVHRR data to monitor the occurrences of dry and wet seasons over the arid and semi-arid regions of Mongolia. Just as it were, the findings of the present study shows the possibility of using NDVI data derived from NOAA AVHRR data for studies on vegetation dynamics and in monitoring the occurrences of dry and wet conditions over south western Nigeria.

Areas that receive higher rainfall are more likely to be associated with areas with higher vegetal cover and by extension strong NDVI signal. In the same way dry and warmer areas are less likely to support strong vegetal growth which reflects in low NDVI signal. However, stronger relationships between NDVI and rainfall over different regions have been reported from earlier studies (Wang *et al*., 2003 Foody, 2003). Foody (2003) studied the relationships between NDVI & rainfall over North Africa and Middle East using NOAA AVHRR data over the period from 1986 to 1993 and reported a r value of above 0.9.

Expectedly, the spatial distribution of average NDVI values over the seasons in the study area was most strongly influenced by precipitation accumulated throughout the rainy season. In most cases, the strongest relationships were between NDVI compared to accumulated precipitation for the rainy and planting season which cuts across MAM and JJA. Figure 7 depicts the seasonal NDVI compared with the seasonal average rainfall and temperature across space for the study area.

NDVI	RAINFALL	TEMPERATURE
		
DJF 1980s	**DJF 1980s**	**DJF 1980s**

NDVI	RAINFALL	TEMPERATURE
		
DJF 1990s	**DJF 1990s**	**DJF 1990s**
		
DJF 2000s	**DJF 2000s**	**DJF 2000s**
		
MAM 1980s	**MAM 1980s**	**MAM 1980s**

NDVI	RAINFALL	TEMPERATURE
		
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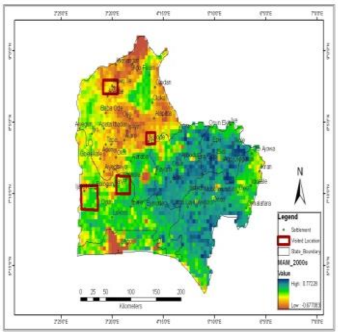	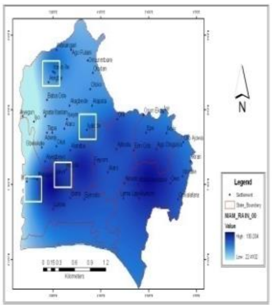	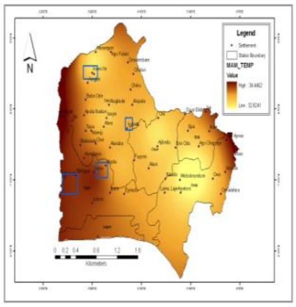
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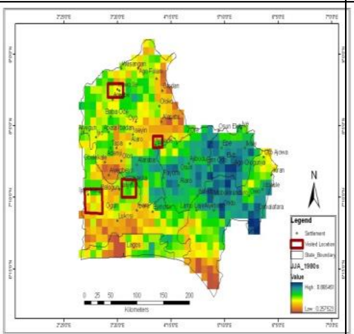
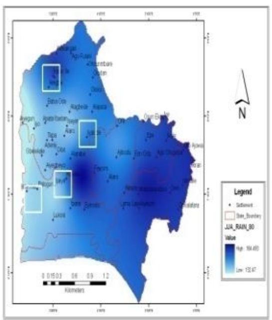
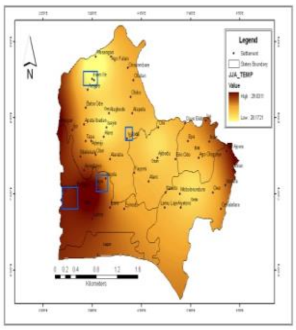
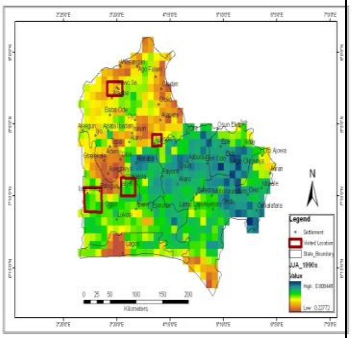
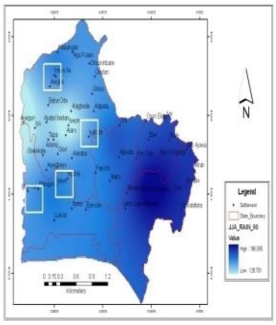
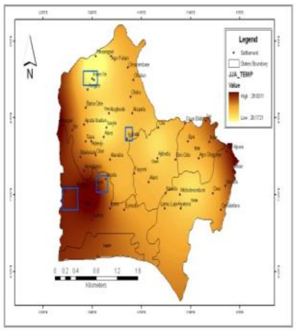
		
JJA 1980s	**JJA 1980s**	**JJA 1980s**

NDVI	RAINFALL	TEMPERATURE
		
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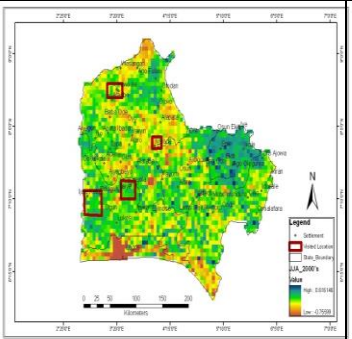
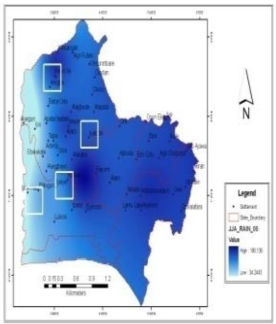
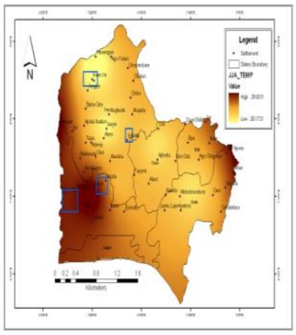
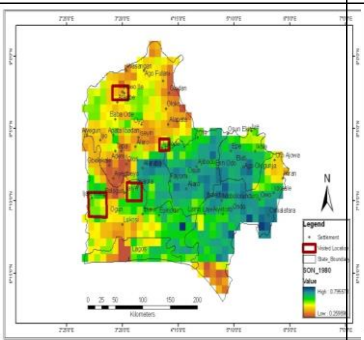
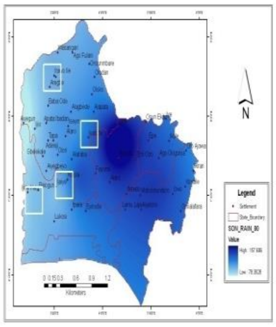
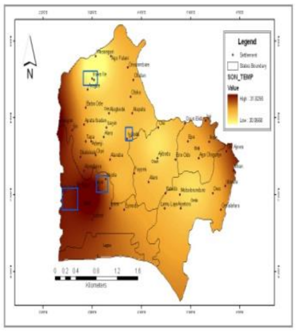
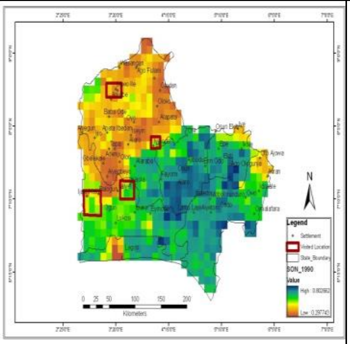
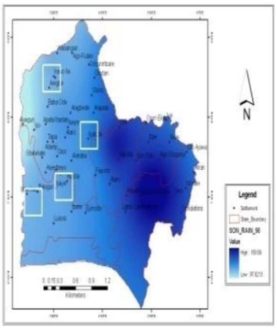
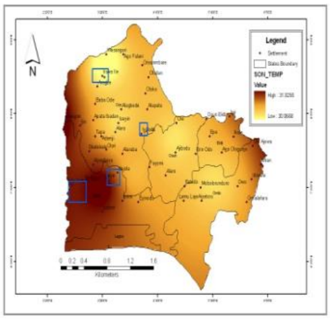
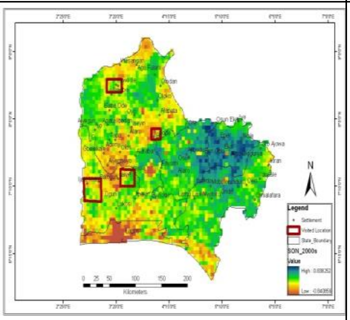
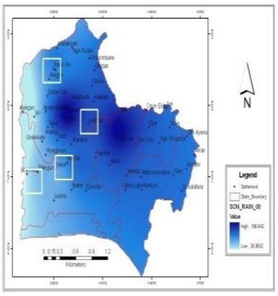
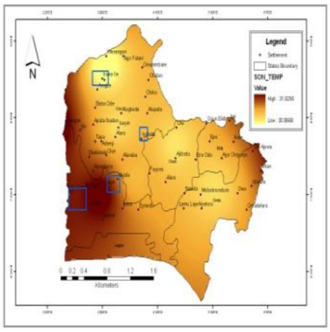
		
JJA 2000s	**JJA 2000s**	**JJA 2000s**
		
SON 1980s	**SON 1980s**	**SON 1980s**

NDVI	RAINFALL	TEMPERATURE
		
SON 1990s	**SON 1990s**	**SON 1990s**
		
SON 2000s	**SON 2000s**	**SON 2000s**

Vulnerability analysis

The biophysical characteristics of the study area shows the anomalies of each of the biophysical variables that were computed as the potential impacts on the agro-pastoralist, which then showed the degree of vulnerability of the pastoralist. This assessment is captured in table 4.

Table 4: Vulnerability Index

	NDVI	TEMP	RF	VI	Rank
OYO	1.05	0.29	1.34	2.69	1
IRAWO	1.07	0.27	1.34	2.67	2
ALABATA	0.90	0.23	1.32	2.44	3
YEWA	0.86	0.23	1.10	2.19	4

The VI above shows changes in the various biophysical parameters within the various settlements visited, the analysis uses the weighted and ranked model to compute the exposures of the various settlements to different biophysical parameters. The result shows that Oyo is the most vulnerable with a Vulnerability index of 2.69 and thus ranked the number, followed by Irawo with a 2.67 vulnerability index. This could be explained by the fact that these two settlements are more stable in terms of their residency, and also what could explain further their level of vulnerability is the fact that those two locations are more of agricultural areas where the land is being cultivated for food crops thus, reducing the biomass available in the area for cattle feeding. As the settlements get more developed, the lesser their coping strategies will be. This will result in compelling these agro-pastoralists to abandon their cattle and settle down for crops cultivation. Hence it can be concluded that the frequency of change of location may also help in improving their resilience especially in the face of the inadequate pasture and unavailability of water.

On the other hand, the settlement at Yewa shows to be less vulnerable to changes in climate and biomass, from table 4 above Yewa has a vulnerability index of 2.19 and thus ranked the fourth vulnerable location within the four-location visited. The earlier discussion that the impact of the rainfall and temperature directly reflects on the biomass (NDVI). A lower temperature with a high rainfall will surely give a high index of biomass, while a higher temperature and a lower rainfall will give low index of biomass.

CONCLUSION

The research carried out to uncover the vulnerable aspects of the agro-pastoralist within the south western part of Nigeria has revealed that the agro-pastoralists are gradually being exposed to the impacts of climate change, with the fluctuations in rainfall duration and intensity and continual increase in temperature. With the biophysical characteristics of the study carried with the use of remote sensing data, the rainfall data, temperature and NDVI data for over a 30-year period has shown that the climate over the years has been fluctuating thus given the Fulani herdsmen concern over their cattle. NDVI shows the health status of the vegetation at a given point in time thus, the result of the NDVI for the study area was generally in a good health condition but though the luxuriant of the vegetation is highly dependent on the abundant rainfall and lower temperatures.

In regards to the biophysical, Irawo the NDVI values for this area was very low when compared to the areas within the study area. Thus, it is considered the most vulnerable that is as a result of the fact that the lands have been highly opened up to agricultural activities, and the Fulani herdsmen are settled permanently thus their ability not to move out in search of greener lands makes them very vulnerable. Oyo (Oyo East) is the most vulnerable area.

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