Vulnerability Assessment of Drought over Borno State, Nigeria using Geospatial Technique

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Nigeria is experiencing unfriendly climate condition which has a negative impact on the welfare of millions of people. The need to assess the vulnerability of drought across areas in Nigeria, especially in the Sudan and Sahel region is timely. This study investigated the effectiveness of remote sensing-based drought assessment, examined the relations between rainfall and vegetation indices and identified the most drought vulnerable areas using remote sensing (RS) and GIS in Borno State. Landsat images of years 2010, 2015 and 2020 were downloaded from USGS site. Geometric and atmospheric corrections were performed to adjust the terrain displacement and improve the reflective properties of the image data. Normalized Difference Vegetation Index (NDVI) and Normalized Condition Index (NCI) data were performed on the satellite images. Result of this study indicates NDVI, for the three epochs recorded; non-vegetation as 0.6%, 9.61% and 17.13%. Shrub/Grass was 96.6%, 82.50% and 78.34%, dense vegetation was 2.8%, 9.4% and 4.53%. The drought analyses of (NCI) recorded the following; extreme drought 2.3%, 6.06%, 9.99%, severe drought; 2.52%, 13.54%, 28.5%, Moderate drought: 69.1%, 52.6%, 41.64%, No drought: 4.34%, 3.44%, 3.34% while wet drought: 21.7%, 24.4% and 18.43%. At 95% significance level, the extreme drought indicates an increase trend pattern of about 1.8%, the moderate drought indicates a decreasing trend pattern about 9.4% while the severe drought indicated an increasing trend of about 5.3%. Climate parameters (Rainfall and temperature) were used to validate the outcome of NDVI and NCI. The findings indicated that the study area is highly prone to drought, which has affected the agricultural sector and land conservation of the state. Hence, the authority responsible for the state environment management should put in place strategies that can enhance water efficiency, improve resilience and reduce drought vulnerability.
Keywords: Drought Mitigation Normalised Vegetation Difference Index, Normal Condition Index, Standard Precipitation Index, Climate Parameters

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Introduction

One of the most well-known environmental threats is drought (Vicente-serrano *et al.*, 2020). It happens when there is a severe lack of precipitation, which in turn leads to hydrological imbalances that in turn have an effect on the productive systems of the land. Both high and low, necessarily imply rainfall locations are equally susceptible to drought (Um *et al.*, 2017). It threatens not just agricultural output, but also the surrounding environment and human civilization (Gidey *et al.*, 2018). Due to its slow, insidious nature, drought is classified as a natural catastrophe (Ayoade 1988; Chopra, 2006). According to the research presented by Liu *et al.* (2018), drought has a gradual onset, a steadily increasing intensity, and a tendency to continue for a considerable amount of time despite the fact that it has ended. Orbital images from the National Aeronautics and Space Administration (NASA) reveal that between the early 1960s and 1986, substantial decertification occurred on about 900,000 km^2 of former tropical grass-land in the area of Africa owing to frequent drought occurrences (Samuel *et al.*, 2013). One-third of Africa's population, according to Bates *et al.* (2008), resides in regions prone to drought. As the Sahel area was ravaged by drought in the early 1970s, this phenomenon has grown more common over much of Africa. According to research by Dai *et al.* (2004), yearly rainfall totals in West Africa dropped by over 40% between the years 1968 and 1990 compared to the 30 years between 1931 and 1960. This means that households in the African Savannah are very sensitive to drought because of the prevalence of drought in the area.

The agricultural sector, plant life, human and animal populations, and the local economy were all negatively impacted by the recent drought because of the water crisis. As droughts may last for years and affect vast areas continually, they have a significant effect on regional food production, population longevity, and economic performance over huge regions or nations (Dutta *et al.*, 2015). Droughts on a global scale have become more common in recent years, with devastating effects on economies, ecosystems, and the lives of tens of millions of individuals (WMO, 2004). Worldwide, droughts harm more people than any other natural catastrophe, and they cost an average of \$6-8 billion each year to address (Melaku, 2013). Many records exist of droughts in Northern Nigeria that led to famines, including the droughts of 1903 and 1911-1913 (Shiru *et al.*, 2018). The years 1919, 1924, 1935 1951–1954, 1972–1985, 1984–1985, 2007, and 2011 all experienced drought as well (Abaje *et al.*, 2013; Tarhule & Woo, 1997). The rising human population, overgrazing, over-cultivation, and the widespread poverty have all contributed to making the situation worse (Eze, 2017). Agriculture is the major industry in the area. In addition, cereal crops including wheat, sorghum, sorghum berries, and millet have made the area famous (Eze, 2017). Since most farms in Nigeria, and especially in the northern region, rely on rainwater for irrigation, their output is very susceptible to weather fluctuations (Tiamiyu *et al*., 2015).

Homesteads in the area get a bountiful grain and livestock harvest in years with above average precipitation. In contrast, when rainfall is inadequate, families suffer from crop failure and low crop output, which ultimately results in starvation, hunger, and death (both human and animal) (Eze *et al.*, 2018). According to Eze (2018), the drought of 1972–1973 caused the deaths of around 300,000, One-third of Nigeria's overall cattle population perished during this time period in the region's north and northeast. Also, in 1987, massive crop losses were observed in several areas of northern Nigeria, especially in the Sahel region, as a result of drought (Mortimore *et al.*, 2009). Significant opportunities exist for detecting, tracking, and evaluating drought conditions thanks to the integration of remote sensing data with in-situ technologies (Berhan *et al.*, 2011).

Borno State, over the years has experienced significant drought conditions, exacerbating the ongoing humanitarian crisis in the region. Prolonged dry spells front severely affected agriculture, reducing food production and increasing water scarcity. Coupled with security challenges from insurgency, drought amplified food insecurity and displacement issues. Climate change and deforestation further worsened the environmental degradation, putting more pressure on livelihoods in the region (WHO, 2020).

The Normalized Difference Vegetation Index (NDVI) and Normalized Condition Index (NCI) are preferred for drought assessment because NDVI captures vegetation health by measuring greenness, and NCI reflects environmental stress conditions. These indices provide accurate, scalable monitoring of drought effects on ecosystems (Almouctar *et al.*, 2020). Therefore, this research seeks to assess the level of drought susceptibility and vulnerability in Borno state using the integration of remote sensing and GIS based technique

Study Area

Borno State is located within latitude 10^0 N and 14 N and longitude 11^0 30' E and 14^0 45' E. The State has an area of 61, 435sq km having borders with Republic of Niger to the north, Republic of Chad to the northeast and Cameroon Republic to the east and Adamawa State to the south, Gombe State to the southwest and Yobe State to the west. It comprised 27 local Government Areas. The state of Borno lies approximately 321m (1053.15 feet) above sea level. It has a tropical steppe weather with average daily highs of around 32.530 degrees Fahrenheit, or about 3.07% warmer than the rest of Nigeria (Etim, 2018). Around 17.06% of the year's total precipitation falls in the state of Borno, with an average of 36.69mm throughout 62.27 rainy days. Acacia (the source of gum Arabic), baobab, dragonfly beans, shea butter, dang palm, and kapok tree are all typical of the Sudan savannah flora found in Borno State.

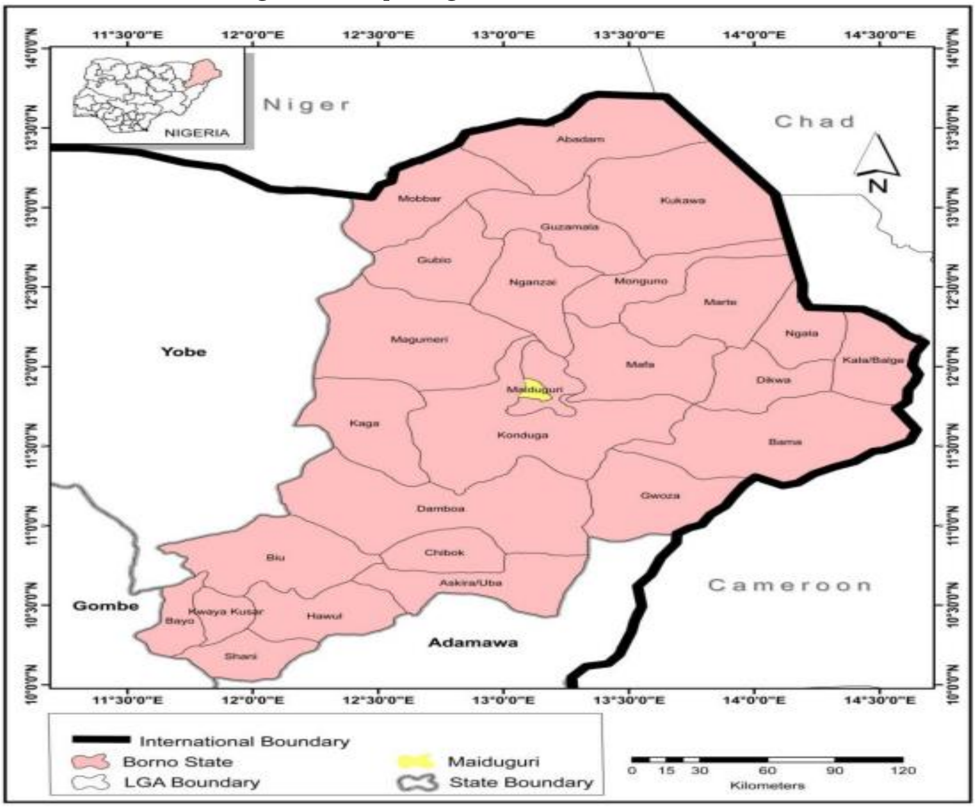


Figure 1: Study Area (Etim, 2018)

Research Methodology

The research explores four main processes: data gathering, data processing, data analysis, and the display of various maps, charts, and tables defining the research outcome. The research uses Normalized Difference Vegetation Index (NDVI), Normalized Condition Index (NCI) and Standard Precipitation Index (SPI) algorithms to evaluate the degree of drought sensitivity of the study area. The work flow for research is depicted in Figure 2.

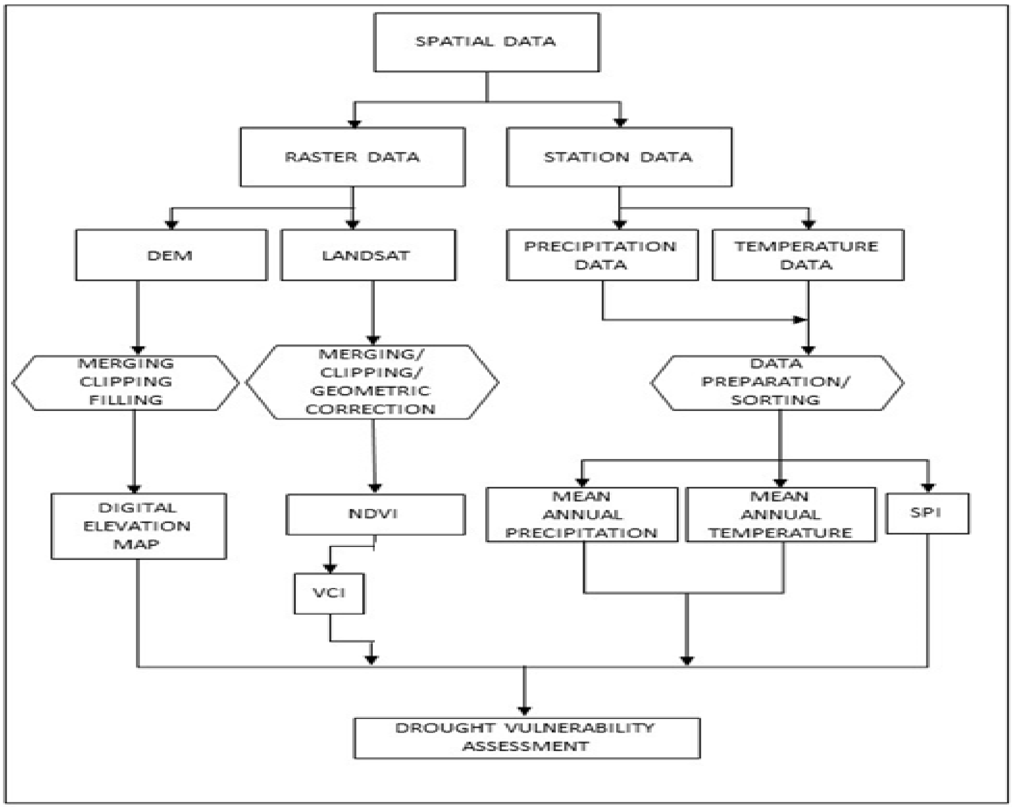


Figure 2: Schematic flow chart of the study

Data acquisition

The satellite datasets were download from United States Geological Survey (USGS). LANDSAT 7 and 8 were explored for the research. The LANDSAT 8 collection covers the years 2015 and 2020, the LANDSAT 7 collection covered the year 2010. The path and row of the image datasets obtained was 184-052, 185-051,185-052, 185-053, 185-051, 186-052, and 186-053. Table1 presents the attributes of the data utilized in the study.

Table 1: Data Used for the Research

Data	Sources	Epochs	Resolution/scale
Satellite Image (Landsat)	United States Geological Survey (USGS)	2010, 2015 &2020	30m
SRTM Digital Elevation Model (DEM)	United States Geological Survey (USGS)	2020	30m
Administrative Map	Office of the surveyor general of the federation OSGOF	1977	1:300,000
Climate Parameters	Nigeria Meteorological Agency (NiMet)	10years	

The DEM data used was from the SRTM 1 Arc Seconds dataset, which has a resolution of 30m. The administrative map of the study area was retrieved from the office of surveyor general of the federation (OSGOF). Due to the large study area, the image was downloaded in strips and mosaic to make a whole for each epoch, the mosaic process aid in facilitates the image data relativity and orientation combinations (Francisco & Brain, 2007). Image clipping was performed to ensured and maintain the image data intensity taking reference from the administrative layer of the map.

The image was projected to WGS 1984 UTM Zone 33 to align with the spatial position of the study area and to enable planimetric area calculation. Geometric correction of Satellite images data was implemented to remove the effects of terrain displacement and restore the correct proportions and geometry to objects in the scene, shape and rotation of the Earth (Green *et al.*, 2014). This simply means that the image's spatial orientation does not `correspond to its actual position on the ground (Fawz *et al.,* 2006). Radiometric distortion correction was carried out by converting digital number (DN) to radiance values. Top atmospheric correction of all the bands of Landsat images is required to avoid the path of noise, this technique firstly convert the DN value to the atmospheric radiance using the following equation

$$L\lambda = \frac{SR_k \ *DN}{DN_{max}} \qquad 1$$

Where SR_k the saturated radiance of K^{th} band, DN is the digital number, and DN_{max} is the maximum possible value of a pixel

Image classification

Supervised image classification was explored where training site of the features to be classified was carefully selected making used of the base map as referenced and ground trothing survey. Maximum likelihood was used as the classifier algorithm, this was informed base on its metric property and it degree of classification accuracy (Lillisand & Kiefer, 2016). The vegetation's patches were classified into three categories based on the threshold of -1 to 0.1, 0.1 to 0.4, and 0.4 and above. The first threshold identifies areas with no vegetation, the second identifies areas with shrubs and grasses, and the last identifies areas with dense vegetation.

Nigeria Meteorology Agency (NiMet) data

Climate data such as Temperature and Precipitation was retrieved from NiMet, headquarter Abuja, Nigeria. The data range was ten years (2011 to 2020). Spatial distribution map was plotted to show the climate data distribution across the study area. Figure 3 depicts the threshold categories adopted for this research.

Standard precipitation index (SPI)

The standard precipitation index map was produced using the precipitation data retrieve from NiMet. The observation data was explored by applying the Inverse Distance Weighting. The use of the geo-statistical wizard was employed for this purpose. The point shape file was used as the point dataset while the XY and average precipitation were used for the required parameters. Table 2 depicts the rainfall threshold ranges adopted for the research.

Table 2: Threshold for Precipitation Index

S/N	CATEGORY	THRESHOLD
i	Near normal	-1 to +1
ii	Moderately normal	+1 to 1.5
iii	Very wet	1.5 to 2.0
iv	Extremely wet	2.0 to Max

Source: Edo, 2020

Normalized Difference Vegetation Index (NDVI)

The NDVI works with an already defined formula stated below;

$$\text{NDVI} = \frac{NIR-RED}{NIR+RED} \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..\ (2)$$

Where NIR = band 4 in LANDSAT 7 and band 5 in LANDSAT 8

RED = band 3 in LANDSAT 7 and band 4 in LANDSAT 8 (Makario, 2019)

So, the mosaicked band 3 and 4 for LANDSAT 7, and that of band 4 and 5 for LANDS AT 8 were introduced into the equation. The raster calculator was used to apply the equation. The parameters in the NDVI equation were used, and the NDVI for the year 2010, 2015 and 2020 was calculated and maps were created.

Vegetation Condition Index (VCI)

The vegetation condition index was achieved by applying equation 2. It helps to describe the level of drought severity considering the condition of the vegetation within the study area

$$\text{VCI}=(\frac{NDVIi-NDVImin}{NDVImax-NDVImin})\text{x}100 \ \ldots\ldots\ldots\ldots\ (3)$$

Where

VCI: vegetation condition index

NDVIi: Normalized deference Vegetation Index of a particular year.

NDVImin: minimum Normalized Deference Vegetation Index of the years in consideration.

NDVImax: maximum Normalized Deference Vegetation Index of the years in consideration. The maximum and the minimum NDVI are calculated using the cell statistical toolbox which makes use of the already produced NDVI for each period considered (Makario, 2019). Table 2 depicts the categories adopted for the VCI. The raster image data was reclassified into 5 major categories, the extreme drought, severe drought, moderate drought, no drought, and wet.

Table 3: Thresholds used for the NCI

S/N	CATEGORY	THRESHOLD
I	Extreme Drought	<10%
Ii	Severe Drought	10% - 20%
Iii	Moderate Drought	20% - 35%
Iv	No Drought	35% - 50%
V	Wet	>50%

Source: Inia, 2020

Accuracy assessment

it was not possible to assess the site for field ground truth. However, Google Earth images can be used for validation instead of ground visits which saves time and money. However, the classification accuracy assessment was conducted. Accuracy assessment used to find the user and producers accuracy. In the context of information extraction by image analysis, accuracy "measures the agreement between a standard assumed to be correct and a classified image of unknown quality". The equation was used to calculate Kappa coefficient (K) as shown in Equation 4,

$$K = \frac{[N\sum_{i=1}^{r} X_{ij} - \sum_{i=1}^{r}(X_i * X_j)]}{N^2 - \sum_{i=1}^{r}(X_i * X_j)} \quad \ldots\ldots\ldots\ldots 4$$

Where N is the total number of same point and X is the element in row i and column j (Bhatta, 2008).

Forecasting using least squares regression model

The forecast was executed using a simple least square regression method to find the line (or curve) that best fits the sets of data points. It works by minimizing the sum of the squared differences between the observed (y) values and the values predicted by the regression line for each corresponding (x) value.

$$y = mx + b \quad \ldots\ldots\ldots\ldots\ldots 5$$

Where: (m) is the slope of the line (coefficient of x), (b) the y-intercept (the point where the line crosses the y-axis).

Result and Discussion

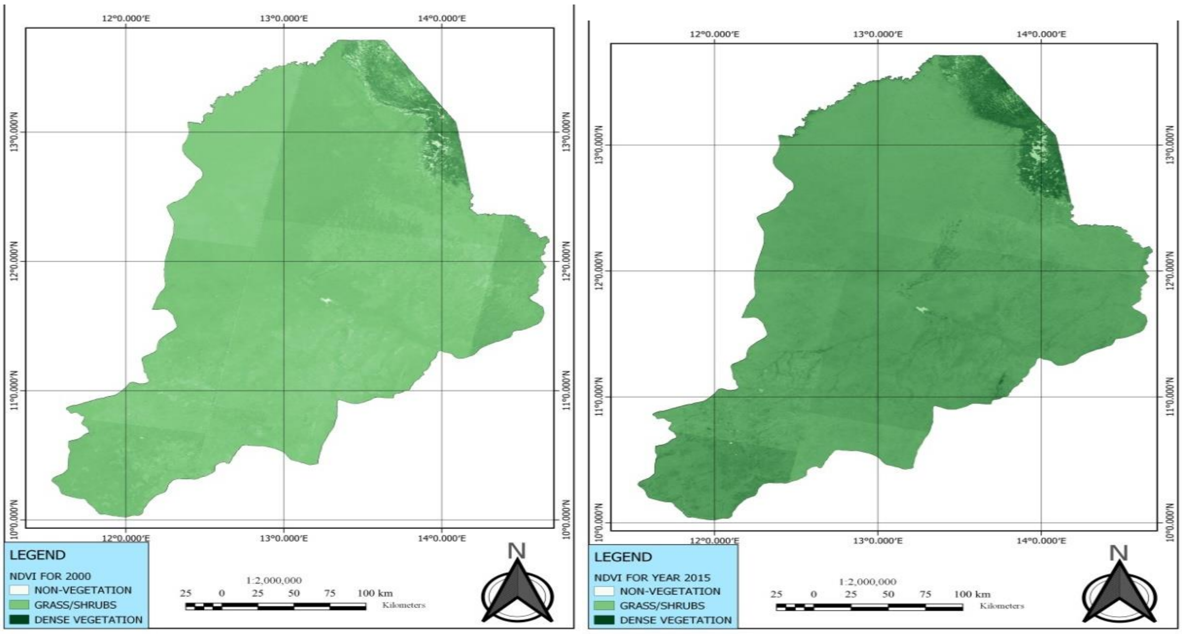
Table 4 and Figures 3a, 3b, and 3c show the vector statistical data and NDVI maps of study area for the year 2010, 2015 and 2020 respectively.

From 3a, the shrubs/grasses patch recorded the highest percentage coverage of about 96.96%, dense vegetation area covering a total of 2.8%, and non-vegetation category recorded the lowest of about 0.63%. However, the percentage of grass/shrubs is relative to the other categories, the large disparity is likely influence by climate condition of the study area. High temperature and low precipitation which is a function of climate condition of the Borno state (Ishaku & Majid, 2010). At the second epoch, (Figure 3b), the non-vegetation category recorded a gentle rise from 0.63% in the year 2010 to 9.61% in the year 2015. Shrub/Grass category recorded a decrease of about 14.1% when compared to the previous epoch. The dense vegetation recorded an increasing trend pattern of about 6.65% in the year 2015. The rise and fall of the patches are subject to climatic variation and to some extent, infrastructural development in the state in-term of built-up areas and increase in agricultural activities.

In the year 2020, the non-vegetation patch recorded an increasing trend pattern of about 09.08%. The shrub/grass patch recorded a decreasing trend of about 4.16% while dense vegetation patch recorded a decreasing trend of about 4.92%. According to Global Historical Climate and Weather data (GHCWD) (2020), Borno State falls under subtropical steppe climate condition, having limited amount of precipitation and high temperature of about 3.07% higher than Nigeria average. Another factor that could exacerbate the decrease of vegetation category in the state could be influence by lack of security has made many indigenes to lose hold of their livelihood, rendering farmer inactive and increasing restiveness among youth, the above may account for the drastic reduction in vegetation areas (Eludoyin & Adelekan 2012).

Table 4: Vector Data of study area for the Year 2010, 2015 And 2020

2010				2015			2020		
Categories	%	U.A	P.A		U.A	P.A		U.A	P.A
Non-Vegetation	0.6	82.34	61.02	8.05	87.14	70.3	17.47	76.81	67.73
Shrub/Grass	96.6	74.14	59.92	82.5	72.34	66.6	76.34	69.62	61.66
Dense Vegetation	2.8	81.23	60.03	9.45	74.05	68.2	6.19	61.04	57.56
U.A	User Accuracy								
P.A	Producer Accuracy								
Overall Accuracy and kappa coefficient									
2010	81.56%, 0.7465								
2015	88.45%, 0.8145								
2020	80.97%, 0.7132								



(a) (b)

Figures 3a and 3b: Normalised Diffeernce Vegetation Index Of Borno State For The Year 2010 and 2015

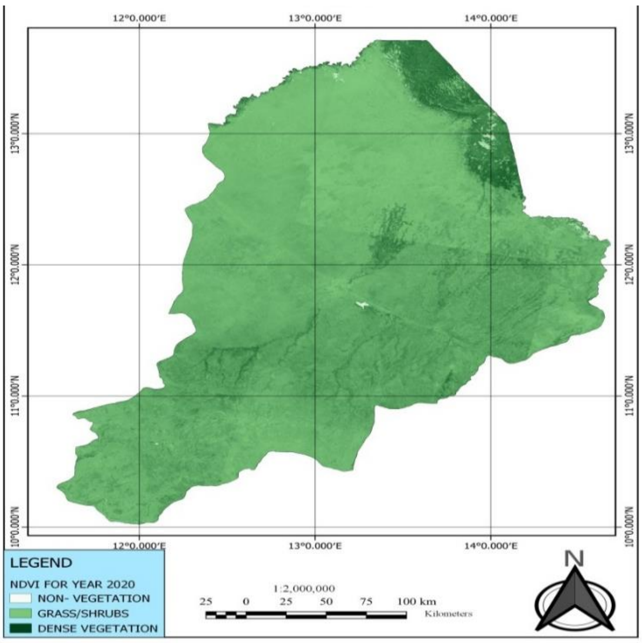


Figure 3b: Normalized Difference Vegetation Index of Borno State for the year 2020

Figure 4 depicts the bar chat representation of the change dynamics between the three epochs (2010, 2015 and 2020). The red bar represents regions devoid of vegetation, such as water, bare earth surface, rocks, structures, highways, and other man-made features. The dark green bar denotes dense vegetation, whereas the yellow bar symbolizes the category of shrubs and grasses. The comparison's outcome validates which categories during the course of the last eleven (11) years have gained and lost area coverage.

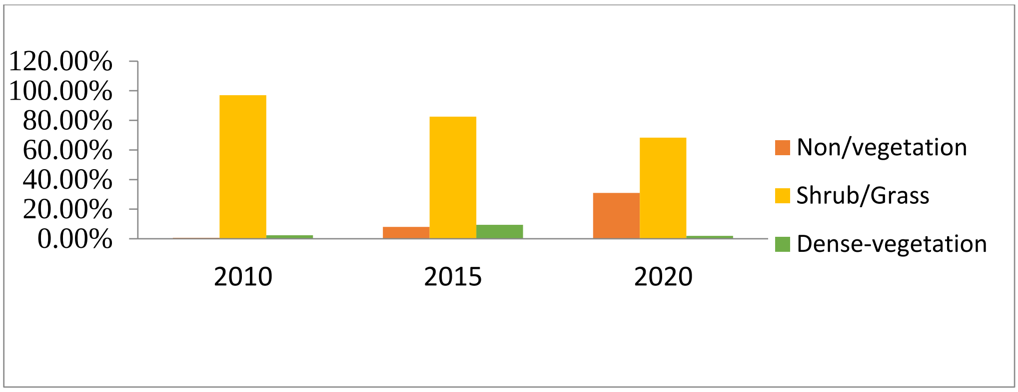


Figure 4: Magnitude of NDVI in Borno State.

Table 5 depicts the vegetation condition index (NCI) of the study area. Figures 5a, b, c, show the maps for the three epochs. NCI indices was used to assess the vegetation health and drought stressed based areas. The table depicts that moderate drought patch recorded the highest values of about 69% for the year 2010. The wet patches also recorded about 22% coverage area of the state, apart from several small rivers across the state, Lake Chad is located at the north eastern part of the state is playing significant role in the development of the surrounding villages especially in agriculture business (Ibrahim *et al.*, 2010). Extreme drought and severe drought recorded 2.3% and 2.52% respectively while the no drought patch recorded 4.34% area of the total coverage. At the second epoch, the extreme drought patch recorded an increase of about 3.72% when compared with the previous epoch, while the severe drought patches recorded an upward growth of about 10.98%. The moderate drought patches recorded a decreasing trend of about 16.5% as at the year 2015. The water bodies patches increased at about 3%, the increase could be associated to period (months) at which the image was downloaded (raining season). The non-drought patches recorded 3.4% of the total area covered.

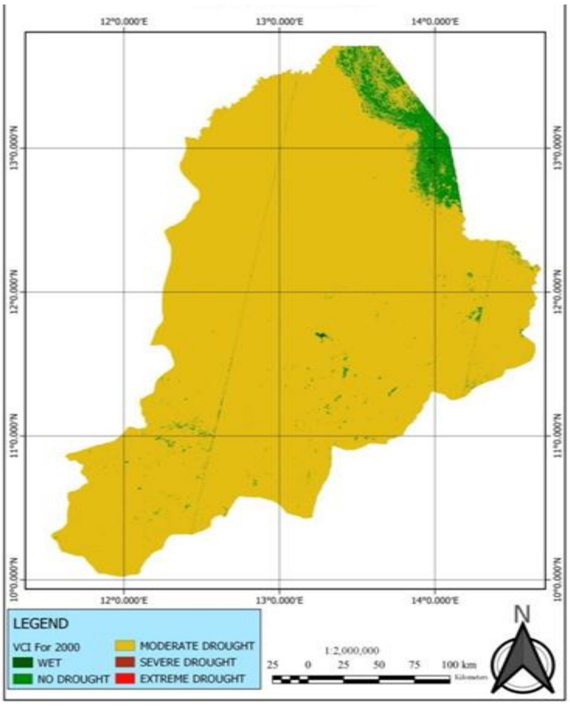
At the third epoch (2020), the patch of extreme drought recorded an increase trend of about 3.93% when compared to VCI map of the year 2015, severe drought patch recorded an increasing trend of about 15%, doubling what was obtained at the previous epoch. The rapid change could be a function of the position of Borno state, which is greatly influenced by convention air-masses (Uchechukwu *et al.*, 2017). The hot trade wind from the north eastern part of the country have contributed to the increase of severe drought patches observed. The moderate patches recorded a sharp decrease about 10.98% when compared to VCI map of 2015. The wet patches recorded decrease in trend pattern of about 7.87%. The drop in area of wet patch could be attributed to agricultural activities.

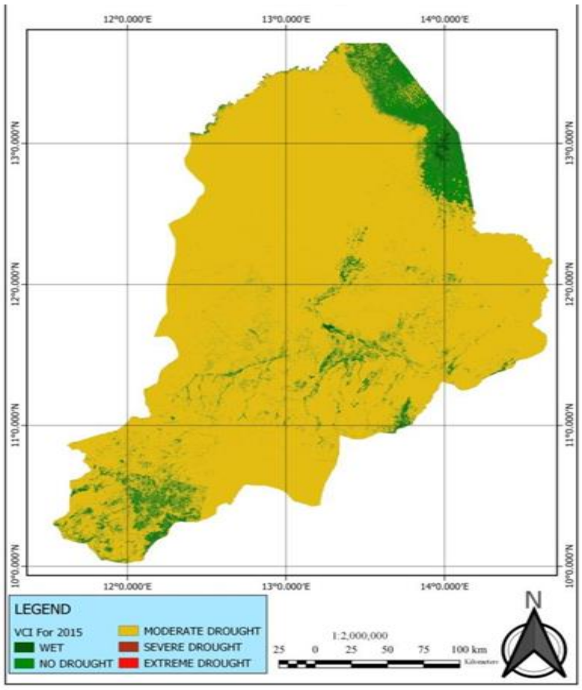
Table 5: Vector Statistic Data of NCI of Borno State for the Years 2010, 2015 and 2020

	2010			2015			2020		
Drought Patches	%	U.A	P.A	%	U.A	P.A	%	U.A	P.A
Extreme	2.34	76.95	66.56	6.06	91.34	71.04	9.99	90.01	79.91
Severe	2.52	81.71	69.54	13.5	85.62	78.56	28.5	83.23	76.54
Moderate	69.1	96.01	78.52	52.6	81.04	87.21	41.64	84.57	74.08
No Drought	4.34	70.32	61.14	3.44	90.91	69.34	3.34	80.34	73.87
Wet	21.7	66.51	58.83	24.4	84.07	71.63	16.53	88.78	71.84
U.A									
P.A									

Overall accuracy and Kappa coefficient

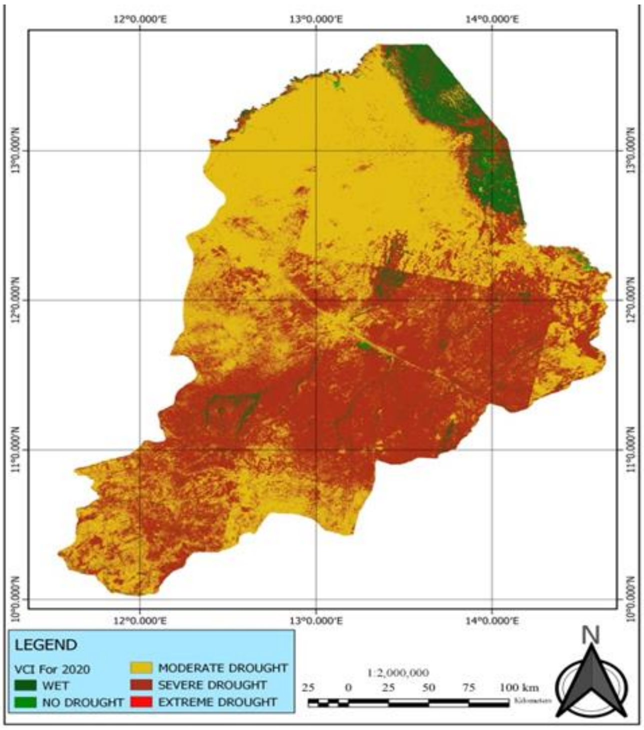
2010	76.74%, 0.7015
2015	87.49%, 0.8414
2020	89.35%, 0.8624





(a) (b)

Figures 5a, b: Normalised Condition Index of Borno State For The Year 2010 and 2015



(c)

Figure 5c: Normalised Condition Index of Borno State for the Year 2020

Figure 6 depicts the bar chart showing the magnitude change of VCI over the three epochs. The extreme and severe drought recorded a positive change (gain) all through the epochs. It indicates that there were increase in each category relatively to change in each year. The moderate drought patches recorded a sharp drop from the first epoch to the third epoch. The sharp drop in the moderate patches and the increase in the extreme and severe patches may be attributed to climate change and other anthropogenic factors. No-drought patches recorded little change between the years in review.

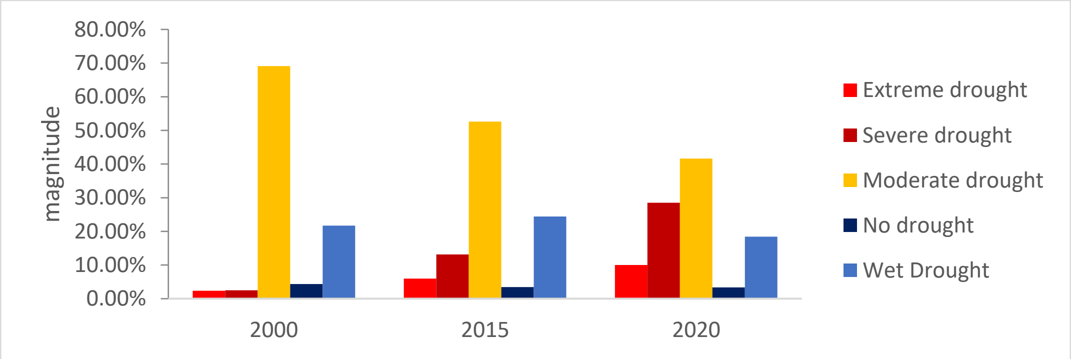


Figure 6: Loss and Gains Chat Representation of NCI for Borno State

Future prediction of vegetation condition index patches

The rate of change of each patch (extreme, severe, moderate, no and wet drought) were predicted using extrapolation method. There areas were determined in percentage for the next ten (10) years making the year 2025. The prediction bar chat depicted in Figure 7 indicates that the moderate patches have compensated for the severe and extreme drought condition. While the moderate drought was decreasing, the severe and extreme drought were increasing. This is of concern, as it extended effect will cut across other sectors of the economy of the state

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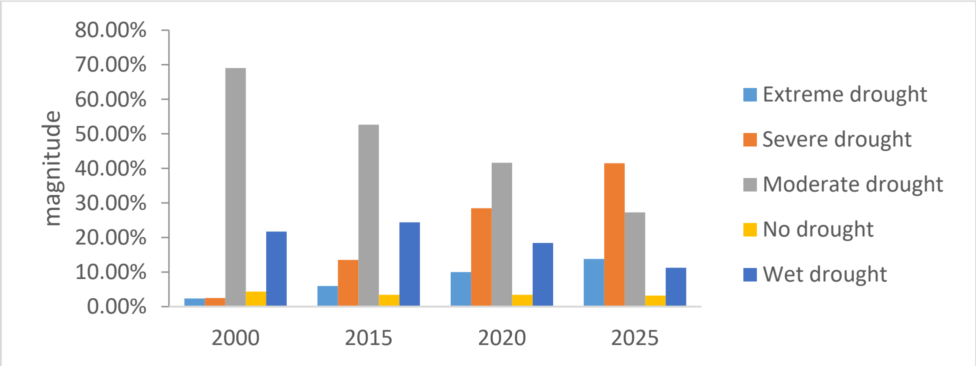
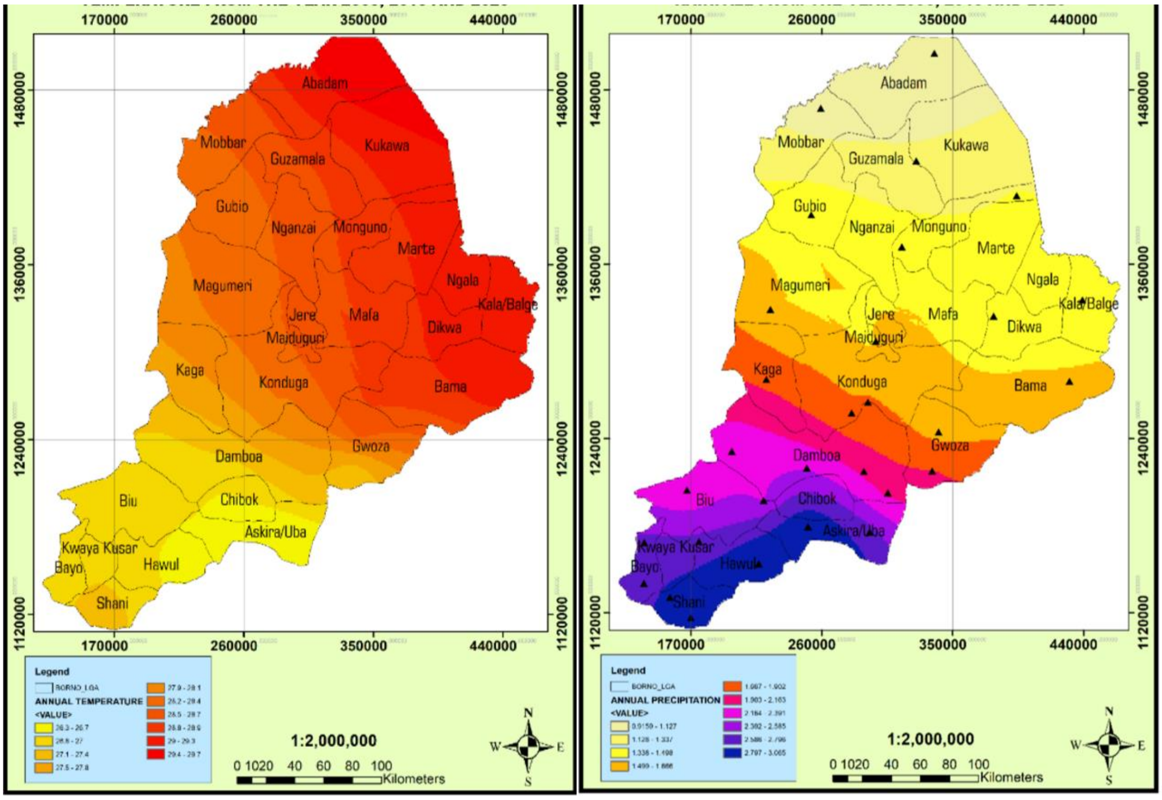


Figure 7: Projection of Patches to the Year 2025

Climatic parameters (precipitation and temperature)

Figures 8a and 8b depict the mean annual temperature and precipitation spatial distribution maps for the span of ten (10) years across the whole local government areas that constitute Borno State. The highest temperature range as depicted in Figure 8a, was recorded in the northern part of the state, with a gradual decrease toward the southern regions. The highest average annual temperatures were observed to fall within the 29.4°C to 31°C range, while the lowest average temperatures ranged between 27.5°C and 28.1°C. This have also justified the severity of the state of climate condition observed using VCI indices. Unlike the flow of temperature direction been observed in the state, the opposite was the case of precipitation. The southern region recorded high precipitation index when compared to the northern region of the state. The highest average annual precipitation range were between 28cm -31cm while the lowest was between the ranges of 05cm-13cm. The above outcome justified the outcome of the NDVI result obtained. This was further verified using the standard precipitation indices (SPI) to determine the level of precipitation at each of the region.



(a) **(b)**

Figure 8a,b. Spatial Distribution of Temperature and Precipitation across Borno State

Figure 9 depicts the SPI of Borno State. The SPI outcome further classifying the level and direction of drought within the study area. The above figure gives a clearer view on the precipitation distribution across the study area (Borno state). According to World Bank Climate Change Knowledge Portal (WB, 2020), Borno state is more of a subtropical region, most of it area lies along Sahel savannah. This accounts for the precipitation distribution rate throughout the state. It also indicates that the northern region of the state is more prone to drought, the drought prone areas descend from the northern region to the south, making the southern region less prone.

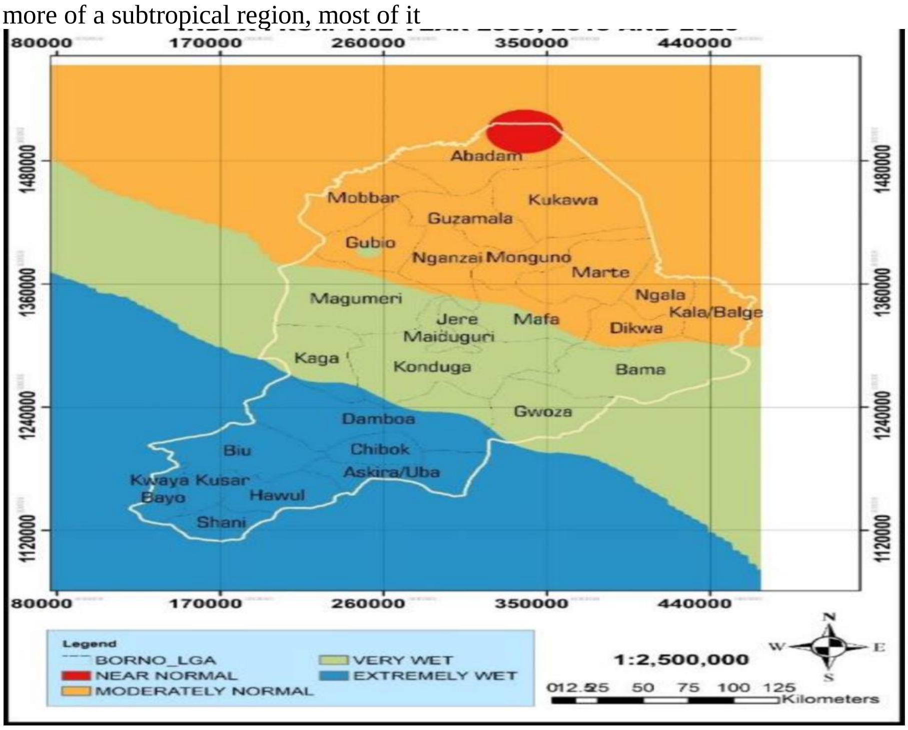


Figure 9: Standard Precipitation Index for Borno State

Conclusion

Northern Nigeria, particularly Borno State is frequently affected by drought (WHO, 2020). The gravity of drought decreased down south of the state. The Temporal and spatial extents and characteristics of drought can be noticed, monitored and mapped from remotely sensed data and vegetation indices algorithm. The Remote Sensing based drought indices were effective in drought assessment in the arid and semi-arid areas. The present study has revealed that drought vulnerable areas can be delineated using Normalized Difference Vegetation Index and Vegetation Condition Index which proved to be sensitive indicator of drought conditions. In addition, Standardized Precipitation Index from the Nigeria meteorological agency (NiMet), rainfall data was effectively used in drought assessment in Borno State. The temporal variation of NDVI values were closely related with rainfall to validate how vegetation stress condition was changing with the variability of rainfall. The present study shows the occurrence of moderate drought is reducing relative to the increase of extreme and severe drought, this really calls for concern. The rate of percentage increase in drought was influenced by the climate change. Within the eleven years of the study period, the drought was observed in different years and most experienced in the up northern region of the state. Therefore, it can be concluded that Borno State is highly prone to drought. The drought vulnerability map of the State shows that State is within the drought vulnerability range from moderate to extreme vulnerable.

The findings of this study can be used for improvement of drought monitoring scheme and to strategically plan on the best adaptive measures to be used in managing situation. Taking into account the spatial extension and frequency of drought and lack of timely ground data observations, the application of remotely sensed data has played a key role in drought assessment, monitoring and drought prediction.

Based on the findings of the study, the following recommendations are suggested for future studies:

i. There is the need to develop a way of streamlining data in real time (climate parameters) in order to constantly measure the climate change (drought) over time. This will aid in fast tracking drought condition across the state.
ii. It is found that the northern and north-eastern parts of the study areas have lost vegetation as indicated on the NDVI map. It is evident that the drought in different years affected the state largely dependent on rainfall. Therefore, disaster-risk management activities are needed. These are preparedness, prevention and response or mitigation phases.
iii. Remedial actions could be implemented before and after the occurrence of drought. Timely updated information about the prevalence of drought is important.

Further investigations are needed to improve the findings from this by incorporating other indices like Drought Severity Index (DSI) and other factors for determining drought vulnerable areas. These include; population density, poverty index and water resources.

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