Early warning systems development for agricultural drought assessment in Nigeria

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Abstract The existing drought monitoring mechanisms in the sub-Saharan Africa region mostly depend on the conventional methods of drought monitoring. These methods have limitations based on timeliness, objectivity, reliability, and adequacy. This study aims to identify the spread and frequency of drought in Nigeria using Remote Sensing/Geographic Information Systems techniques to determine the areas that are at risk of drought events within the country. The study further develops a web-GIS application platform that provides drought early warning signals. Monthly NOAA-AVHRR Pathfinder NDVI images of 1 km by 1 km spatial resolution and MODIS with a spatial resolution of 500 m by 500 m were used in this study together with rainfall data from 25 synoptic stations covering 32 years. The spatio-temporal variation of drought showed that drought occurred at different times of the year in all parts of the country with the highest drought risk in the northeastern parts. The map view showed that the high drought risk covered 5.98% (55,312 km^2) of the country's landmass, while low drought risk covered 42.4% (391,881 km^2) and very low drought risk areas 51.5% (476,578 km^2). Results revealed that a strong relationship exists between annual rainfall and season-integrated NDVI ($r^2 = 0.6$). Based on the spatio-temporal distribution and frequency of droughts in Nigeria, drought monitoring using remote sensing techniques of VCI and NDVI could play an invaluable role in food security and drought preparedness. The map view from the web-based drought monitoring system, developed in this study, is accessible through localhost.

Keywords Drought · NOAA-AVHRR · NDVI · MODIS · Spatio-temporal

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Introduction

Early warning systems are globally becoming a prerequisite for an effective disaster reduction implementation plan. These are ensembles of toolkits needed to ensure a proactive design that could tackle headlong the impact of natural disasters be it flood, fire, hurricane, drought, dust storm, pest and diseases, etc. The design of early warning systems varies and the components are largely different. However, the basic idea behind a

typical early warning design is to act as surveillance and be able to detect or model natural disasters. Generally, the incidence of natural disasters affects both living and non-living things and the extent of damage caused is of concern as they are becoming amplified in the light of the changing climates especially in sub-Saharan Africa (SSA).

Across SSA, the imprints of various natural disasters are devastating since the sub-continent is largely made up of vulnerable individuals and communities due to various reasons stemming from but are not limited to poor governance, weak infrastructures, little or absence of insurance, and latitudinal location. As these natural disasters become more pronounced, livelihood support is being threatened as a greater percentage of the population within the sub-Saharan African region engages in various forms of farming activities. The sub-continent is largely agrarian, and hence, any disruption to the pattern and regime of various agro-climatological variables such as rainfall disrupts not only farming practices but means of livelihoods. It has been posited that SSA will receive the highest impact from the changing climates especially in terms of frequency and magnitude of natural disasters (Kaul 2013).

Droughts are periods of either water shortages, persistent rainfall anomalies which most often than not creates economic losses and adverse social inconveniences (Stahle et al. 2000; Wan et al. 2004 ; Orimoloye et al. 2020). Drought is a generic term and can be classified into four various parts, these are meteorological, hydrological, agricultural, and socioeconomic (Wilhite et al. 1986). Various definitions abound for meteorological drought, but it can be simply described as a period of prolonged dryness. Hydrological drought has to do with the hydrology of a particular area and is often described as a period of persistence in water shortages as a result of rainfall anomalies. Agricultural drought, on the other hand, looks at the influence of meteorological drought on agricultural practices and products. Agricultural drought is concerned with deficits in water supply, soil moisture, potential evapotranspiration, variation in groundwater levels, precipitation anomalies, etc., and tries to connect these with agricultural activities. Socioeconomic drought is more concerned with the impact of the other three types of drought on various socioeconomic activities (Wilhite et al. 1986). This study is concerned with agricultural drought, hereafter referred to as drought, by linking meteorological indicators to vegetation performance.

The greenness of most plants is closely linked to the prevailing meteorological indicators. The ratio between water surplus and water deficit in a certain region determines the drought condition of the area. The continuous deficit in the water balance for a given area is an indication of a drought condition (ICID 1996) and this is a situation when there is a perpetual record of below-average precipitation for some time. The persistence of a below-average precipitation condition within a given area impacts negatively on the ecosystem and most often than not creates a water-stressed environment. Water-stressed environments are largely intolerant to both humans and plants thereby leading to a modification of the natural environment. Across most sub-Saharan vegetal zones, acute water shortages have been creating new socio-ecological realities that are alien to the environment. These realities are becoming more pronounced in light of the changing climate and various anthropogenic activities.

In most global south countries, the ability to effectively manage drought especially in tropical zones is a great challenge. Most global south countries are battling with various issues such as weak institutions, corruption, population explosion amongst various anthropogenic factors (Thenkabail et al. 2002; Shiferaw et al. 2014) coupled with limited data and poor information networks. These issues are limiting the capacity and capability to confront the pressures from drought and other natural disasters. Furthermore, for sub-Saharan countries, there is a need to protect the degraded ecosystems, secure human livelihoods, and sustain the balance of payments as most countries within the region have a large agricultural-dependent economy. Therefore, there is a need to develop proactive measures and designs to combat natural disasters such as drought within sub-Saharan Africa. For most SSA countries such as Nigeria, drought assessment and monitoring efforts have been further hampered due to reliability on meteorological data, which is not only very tedious and time-consuming to collect (Oladipo 1993: Akeh et al. 2000; Bashir 2008; Binbol and Edicha 2012; Abdulrahim et al. 2013; Adeaga 2013) but not always available as and when due. Consequently, on an annual basis, millions of properties are destroyed and lives are lost before the needed information is delivered to the appropriate decision-makers for eventual dissemination to the end-users (Kandji et al. 2006). There is, therefore, the need to leverage on remotely sensed products that are freely available to help in the design and monitoring

of a proactive platform to combat drought and its attendant consequences. In more technological-driven nations, remote sensing products are used to close the gap between decision-makers and end-users (Bhuiyan et al. 2006a, b; Chopra 2006; Wilhite et al. 2000; Richter et al. 2008; Gebrehiwot et al. 2011; Wu et al. 2013; Han et al. 2020; Schwarz et al. 2020). Remotely sensed products across various satellite platforms provide continuous datasets that provide the opportunity to understand and predict the occurrence, onset, duration, and magnitude of drought (Thiruvengadachari and Gopalkrishna 1993; Qin et al. 2008; Wan et al. 2004; Klisch and Atzberger 2016; Fashae et al. 2017; Dai et al. 2020; dos Santos et al. 2020; Mehr et al. 2020; Orimoloye et al. 2019). Remote sensing techniques and products provide a unique avenue to consistently monitor and forecast drought in a timely and efficient manner (Johnson et al. 1993; Jain 2009). Most of these products are open-source and of global coverage which makes it very useful for data-scarce countries and middle- and low-income countries such as Nigeria. This study, therefore, aims to map the spread and frequency of drought in Nigeria using remote sensing/GIS techniques. To achieve the stated aim, the study will analyze seasonal changes in vegetation cover of Nigeria due to variation in rainfall between 1981 and 2012, develop a model to link AVHRR and MODIS for effective drought monitoring, assess the spatio-temporal distribution of drought in Nigeria (1981–2012), and then establish a web-based environmental information system for drought monitoring within a GIS environment.

Drought: indices and Web-GIS

Drought indices are effective in developing early warning systems as they combine meteorological and hydrological factors (Lohani and Loganathan 1997; Wilhite et al. 2000; Mehr et al. 2020). These indices are used to predict crop yield (Kumar and Panu 1997; Kogan and Unganai 1998; Park et al. 2004; Gu et al. 2008; Ogunlade et al. 2010; Caccamo et al. 2011; Sona et al. 2012; Wu et al. 2013; Dai et al. 2020; Dantas de Paula et al. 2020), for comparative studies across different areas (Alley 1985; Dai et al. 2004; Wan et al. 2004; Bhuiyan et al. 2006a, b; Gu et al. 2007; Qin et al. 2008; Klisch and Atzberger 2016), to determine the distribution of relief in drought-affected areas (Torry 1986; Wilhite et al. 1986; Samra 2004; Nyong et al. 2013),

and in the estimation of drought termination (Karl et al. 1987; Han et al. 2020). Several drought indices for monitoring, estimation, and forecasting of drought are available such as the Palmer Drought Severity Index (PDIS) and the Standard Precipitation Index (SPI) (Palmer 1965; Qin et al. 2008; Caccamo et al. 2011; Wu et al. 2013; Gebrehiwot et al. 2011; Han et al. 2020; Huang et al. 2020; Mehr et al. 2020; Peng et al. 2020). However, these indices have inherent limitations such as their suitability for agricultural drought measurements and role in runoff estimations (Alley 1985; Dai et al. 2004; Narsimhan 2004; Bhuiyan et al. 2006a, b).

To overcome some of the aforementioned limitations in drought estimation, in recent years, remote sensing data has been used to monitor agro-climatic conditions, the state of the agricultural fields, and vegetation cover and to estimate crop yields globally. In particular, the Advanced Very High-Resolution Radiometer (AVHRR) Normalized Difference Vegetation Index (NDVI) information has been used in vegetation monitoring, crop yields assessment, and forecasting (Hayes et al. 1982; Benedetti and Rossini 1993; Quarmby et al. 1993; Unganai and Kogan 1998; Kogan et al. 2003). The National Oceanic and Atmospheric Administration's (NOAA) AVHRR together with the Moderate Resolution Imaging Spectroradiometer (MODIS) satellite series provides an archival and current record of NDVI data that can be used to predict crop yield (Prasad et al. 2007). Also, with 36 bands available from MODIS ranging from 0.4–14.4 μm, there is a wide range of vegetal indices such as but not limited to NDVI, Vegetation Condition Index (VCI), and Temperature Condition Index (TCI), which can be computed to further aid the understanding of drought conditions on vegetation performance (Wan et al. 2004; Gu et al. 2007; Lingtong Du et al. 2013; Klisch and Atzberger 2016; Kumar et al. 2018; Huang et al. 2020). Furthermore, effective water management (Mohammadi et al. 2020, Mohammadi and Mehdizadeh 2020) most often than not requires efficient drought monitoring, evaluation, and forecasting especially in tropical environments such as SSA.

The global increase in the use of information technology has witnessed tremendous growth in the merger between spatial data and mobile applications. This merger has created more dynamic and efficient geospatial data that can be handheld and much more user friendly. Gradually, there is a shift away from binary maps into more dynamic and evolving maps that provides end-users with the information needed per time

as the web-based Geographic Information Systems (Web-GIS) platforms. Web-GIS which allows for the dissemination of information using web-based applications allows flexibility in the information displayed by enabling end-users to query and analyze geographic data through a web browser interface (Bonnici 2005). The framework for a Web-GIS platform consists of a server and a client. The server and the client are web-based and they can provide information through mobile applications or desktops (Khan and Adnan 2010). This study therefore integrates drought assessment into a web-based GIS platform from a localhost to provide timely and up-to-date drought monitoring and forecast across Nigeria.

Study area

Nigeria is one of the most populous countries in Africa with an estimated population of over 160 million and a total land area of 923,773 km². Nigeria's coastline is 853 km in length, and the country is richly endowed with abundant natural resources. Specifically, the country has one of the largest deltas in the world, located in the southern part of the country (Fig. 1). Nigeria's most expansive topographical region is that of the valleys of the Niger and Benue River valleys with coastal plains to the west and east of these river valleys (Jeje 1970). The rainfall distribution is characterized by low rainfall in the northern part which gradually increases towards the southern part of Nigeria as a result of continentality. Nigeria's rainfall is characterized by the movement of trade winds, and this influences the vegetation pattern across the country (Fashae et al. 2017). Ecologically, the Nigerian landscape from the north to the south comprises savannas, forests, freshwater, and mangrove swamps. (Fig. 2). The Sudano-Sahelian zone of the country, approximately between latitude 11° N and 14° N (Fig. 1), has been constantly battling with desertification as a result of latitudinal location (Fashae et al. 2017).

Methodology

Satellite data (AVHRR and MODIS) were used in this study to establish a reporting system for evaluating and tracking the development of historic drought in Nigeria. Rainfall data for 30 years from 1981–2012 were

retrieved from various meteorological stations in Nigeria. AVHRR's image data from the NOAA-14 and MODIS satellites provided daily radiance data, which was pre-processed to estimate monthly images of the maximum composite value (MVC).

Spatial analyses

Satellite data characteristic and acquisition

Monthly NOAA-AVHRR NDVI pathfinder images of 1 km by 1 km of spatial resolution and MODIS of 500 m by 500 m of spatial resolution were used. The "AVHRR" sensor captures radiance data in five spectral bands including visible red (0.58–0.6 μm), near-infrared (0.725–1.1 μm), mid-infrared (3.55–3.93 μm), and two thermal infrared bands (10.3–11.3 μm, and 11.5–12.5 μm). Four bands are useful for this analysis along with NDVI, due to unresolved calibration issues with the mid-infrared band (Smith et al. 1997).

Preprocessing

The procedure for deriving monthly MVCs includes examining the daily radiance values for each wave band, along with the NDVI values, for each pixel per month. The highest daily radiance/NDVI value is established and maintained in a month; this minimizes cloud effect problems typical of single-date remote sensing studies (Eidenshink and Faundeen 1994). Corrections for atmospheric attenuation (e.g., dust or haze) and distortions are further carried out on the data (Kogan and Zhu 2001; Cracknell 1997). Likewise, radiometric and geometric corrections were also carried out. Nigeria was extracted from these images and then resampled to ensure the resize pixel of the dataset. Thirty-two year monthly images (January-December) from 1981–2012 were rescaled to get the NDVI values ranging from + 1 to − 1 by using the following expression:

$$(NDVI_i - 128) \times 0.008 \qquad (1)$$

where $NDVI_i$ is NDVI for the $i$month; the entire processing of the NOAA data was done using Idrisi Taiga
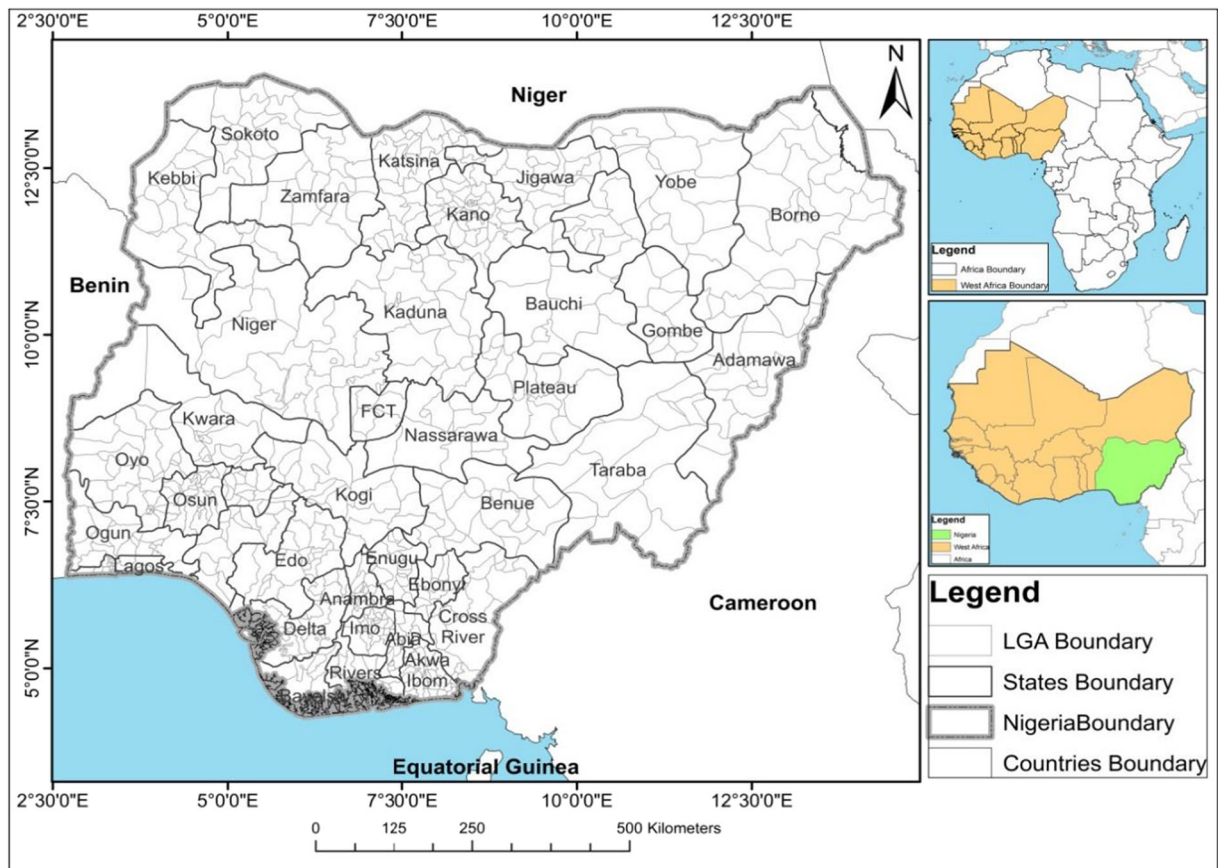
Fig. 1 Map of the study area

Post Processing of Satellite Imagery

For NOAA-AVHRR, NDVI is universally defined as (Lillesand and Kiefer 1994):

$$NDVI = \frac{NIR - RED}{NIR + RED} \qquad (2)$$

where NIR is the near infra-red band and Red is the red band in the electromagnetic spectrum.

To derive the seasonal pattern for NDVI from 1981 to 2000, average NDVI for each year was computed by using the following expression:

Average NDVI

$$x = \frac{JAN\_NDVI + FEB\_NDVI + \ldots\ldots\ldots\ldots DEC\_NDVI}{12} \qquad (3)$$

where NDVIx is NDVI for "x" year and JAN_NDVI, FEB_NDVI …. DEC_NDVI stands for NDVI for particular months in "x" year.

Mean NDVI for 32 years was computed using:

$$Mean\ NDVI = \frac{Avg\ NDVI81 + AvgNDVI82 + \ldots.AvgNDVI2012}{32} \qquad (4)$$

where *Avg NDVI*81 ... *AvgNDVI*2012 stands for the yearly average NDVI values for the 32 years.

Vegetation Condition Index (Fig. 2) was computed by using the following expression:

$$VCI = \frac{100*(NDVI - NDVImin)}{(NDVImax - NDVImin)} \qquad (5)$$

where NDVI, NDVImax, and NDVImin are the smoothed maximum NDVI, multi-year maximum NDVI, and multi-year minimum NDVI respectively for each grid cell.

According to Kogan (1997), different degrees of drought severity is indicated by VCI below 50% and VCI of 35% is a threshold for extreme drought. Based on this, the VCI values obtained were reclassified into
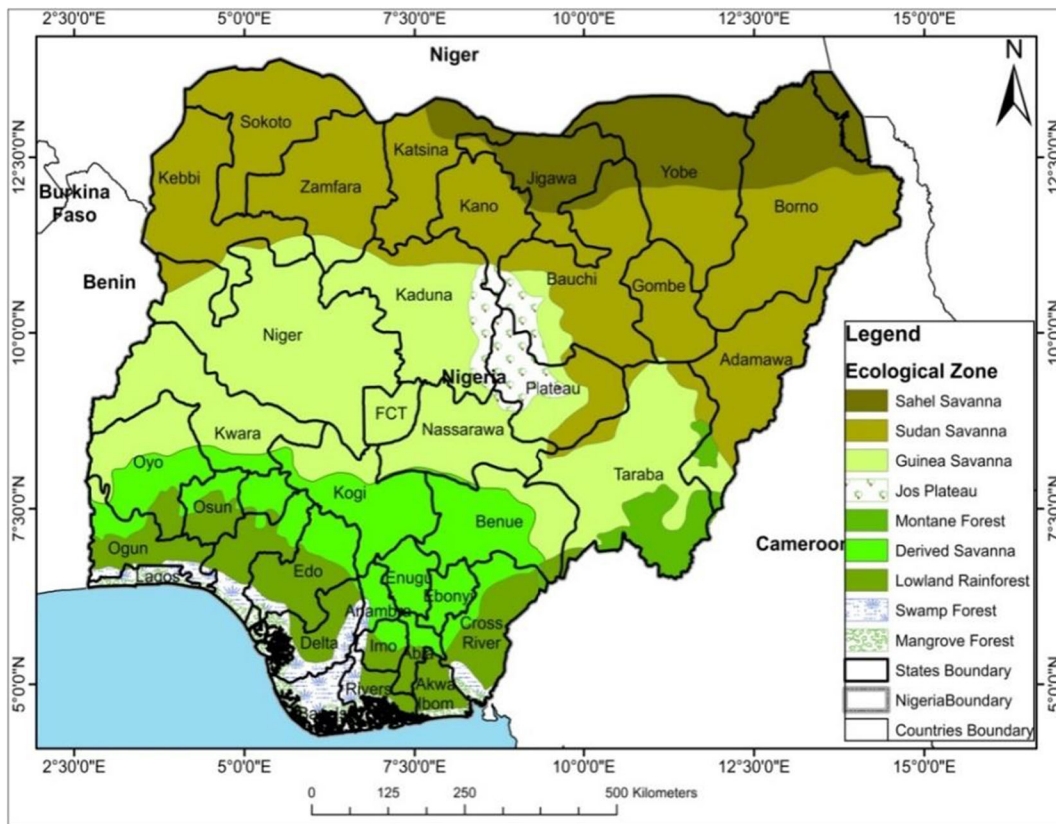
Fig. 2 Map showing agro-ecological zones of Nigeria

drought severity as 50 to 100%, normal to above normal condition (wet); < 50 to 35%, moderate drought; <35 to 0% severe drought.

Meteorological data

Rainfall data were collected at 25 synoptic stations across the Nigeria area over 32 years (1981–2012) from automated rain gauges. Data from some other rainfall stations in the study area were not used because their validity could not be verified. To derive the seasonal pattern of rainfall for 1981–2012, the average rainfall for each year was computed by using the following expression:

Average RAINx

$$= \frac{JAN_{RAIN} + FEB_{RAIN} + MAR_{RAIN} + \dots DEC_{RAIN}}{12}$$

$$(6)$$

where RAINx is rainfall for x year and JAN_{RAIN}, FEB_{RAIN} …. DEC_{RAIN} stands for RAIN for particular months in that year.

The average rainfall for 32 years was then computed by using the following expression:

Average RAINx

$$= \frac{Avg\ Rain1981 + Avg\ Rain1982 \dots Avg\ Rain\ 2012}{12}$$

$$(7)$$

where $Avg\ Rain1981$, $Avg\ Rain1982$, … $Avg\ Rain2012$ stand for the yearly average RAIN value for 32 years. The location of the rainfall stations was plotted using ArcGIS 10 software and the data were interpolated using the "Inverse Distance Weighting (IDW)" technique since variation in rainfall is more influenced by local factors.
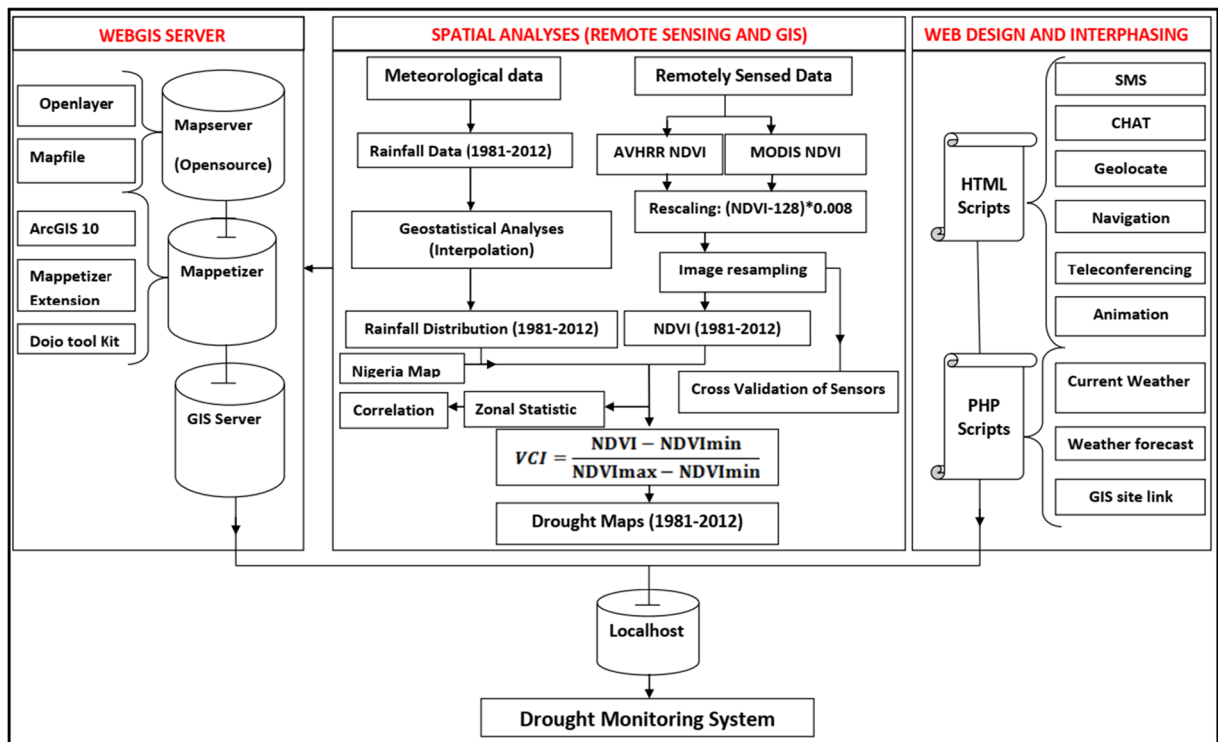
Fig. 3 Schematic diagram showing the methodology for the study

Web design and interface

PHP (Hypertext Preprocessor) code which is a server-side scripting language designed for web development was used to design the web page and was integrated into the HTML (HyperText Markup Language) (see Appendix). The two web scripts were used to synchronize some additional tools to the environmental information system such as Emergency SMS, Weather update, teleconferencing, geolocate tool, and live chat (Jing et al. 1999). The difference between a usual web application and a web mapping application is the necessity of a server that can work with spatial data (Huang et al. 2001; Janicki et al. 2016). Mapserver and Mappetizer were the two Web GIS software used for this study. The mappetizer is a licensed web-GIS tool which is an extension in ArcGIS 10 and the MapServer is open-source software. Both the mappetizer and the MapServer were used to create a web-based map, and the entire component was integrated to create a web-based Environmental Information System (EIS) (Kropla 2005; Sandinska and Bandrova 2015). The process of the client-server concept in web mapping applications used in this study is described as follows: the web GIS receives a request from the client (web browser); it reads the map file (a file where the map file are described); it draws and saves the map according to the definitions in the map file; it reads the template (html) and replaces the substitute string with the current value; it sends the rendered image map to a web server; then the webserver sends data to the web browser of the end-user.

Statistical analyses

A correlation and regression analysis between observed rainfall and NDVI was carried out. Spatial regression was performed to simulate the AVHRR image from MODIS imagery. A typical regression model is expressed as:

$$y = ax + b \tag{8}$$

where y is the independent variable, a is the intercept and b is the slope

Results

Rainfall and NDVI

The rainfall pattern (seasonal) and NDVI for the period 1981–2012, as depicted in Fig. 4, reveals a strong relationship between NDVI and rainfall ($R^2 = 0.64$). The result showed that as rainfall increased from 631 mm, NDVI increases and reaches up to a range of 0.5. The NDVI suggests relatively healthy vegetation. It was also observed, however, that at around 1800 mm of rainfall, there was no further increase in NDVI. This could be because there is some sort of inverse relationship between NDVI and rainfall events at the level of saturation (Chopra 2006).

Furthermore, from Fig. 5a, b, the Northern part of Nigeria, most especially the North-Eastern parts of Nigeria, with very low rainfall amounts (less than 500 mm/year, Fig. 5a), have the lowest NDVI values (Fig. 5b). Conversely, the Southern part of Nigeria with high rainfall (greater than 2000 mm /year) has the highest NDVI (Fig. 5).

For example, the southern part of Nigeria experienced high rainfall amount of about 3000 mm which corresponds to a high NDVI within the range of 5 (Fig. 5) while stations in the northern part received the least amount of rainfall (500 mm) and the least NDVI values (Fig. 5). This establishes the fact that there is a high dependence of NDVI (i.e., vegetation conditions) on rainfall (Damizadeh et al. 2001). This singular fact suggests that vegetation performance and response are linked to a well-received good amount of rainfall and vice versa. However, disaggregating the mean monthly rainfall and mean monthly NDVI across various agro-ecological zones in Nigeria (Fig. 6a–i) showed a positive correlation between annual rainfall and season-integrated NDVI. However, there appeared to be a varied relationship in different ecological zones. The correlation between the zones located in the northern and southern parts of the country showed differences (Fig. 6a–i).

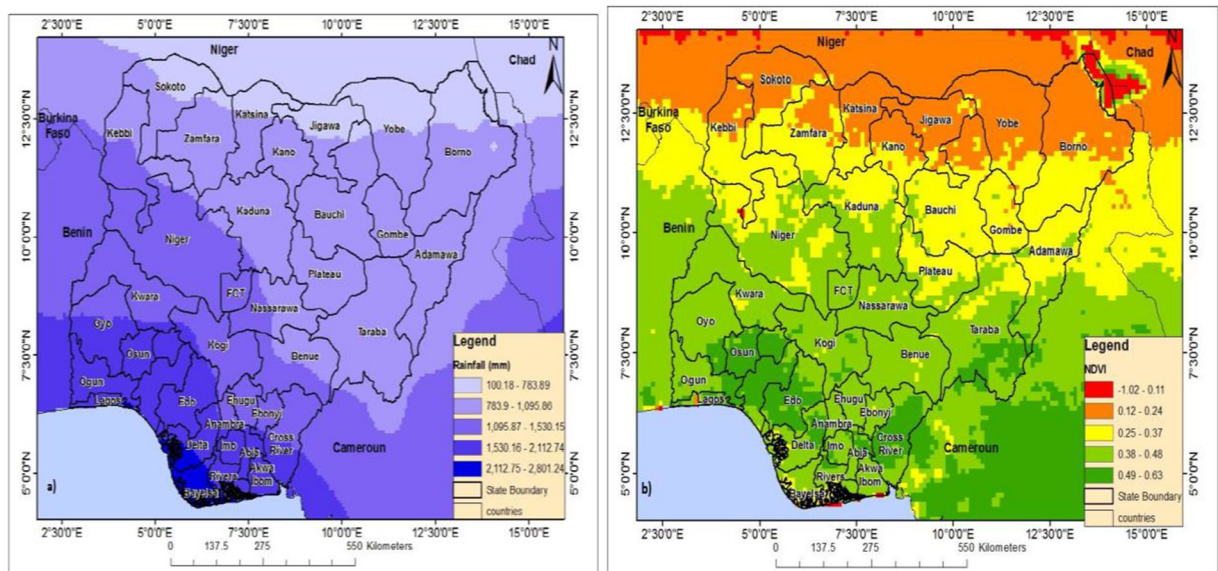### Drought in Nigeria (1981–2012)

Table 1 and Fig. 7 show the spatio-temporal pattern of drought severity in Nigeria using the Vegetation Condition Index (VCI). It was observed that drought occurred in the country at different times of the year, most especially in the northern part of Nigeria. In 1981, the northern fringes of Nigeria, running from the north-eastern to the north-western part of the country   and smaller pockets around the country, experienced a mildly severe drought.

From Fig. 7, the greater part of the country was not severely affected by drought (86.41%), while the low severe drought area was about 13.57% (Fig. 6 in 1981). In 1985 (Fig. 7), highly affected drought areas covered 4.72%; low severe drought covered 46.06%, while the no drought areas covered 49.23% (Table 1). The areas with low severe drought in terms of coverage have the highest coverage, but combining the high and low coverage extent for 1985 reveals over half of areas are affected all over the country. The highly severe area is
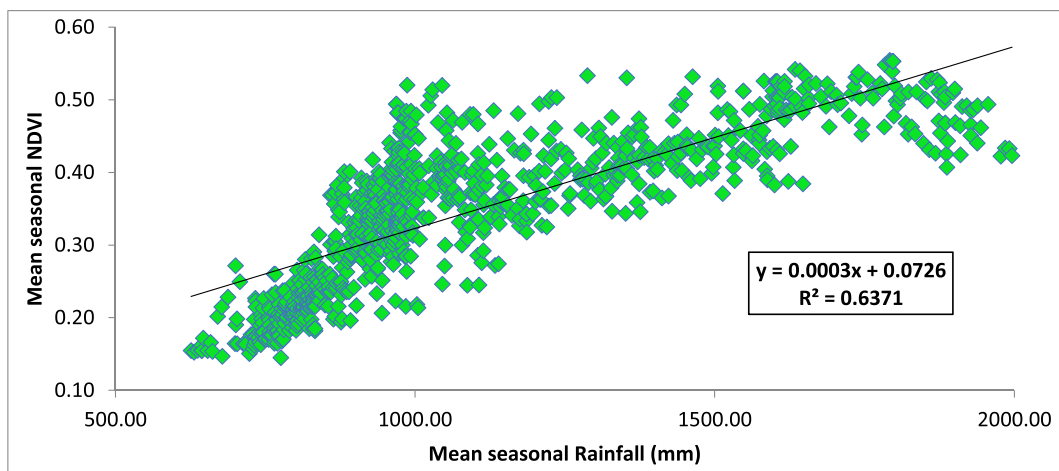
Fig. 4 Relationship between monthly mean NDVI and rainfall (1981–2012)

Fig. 5 a Spatial distribution of average rainfall for Nigeria (1981–2012). b Spatial distribution of average NDVI for Nigeria (1981–2012)

confined to the north-eastern part of the country, specifically Yobe and Borno States. The low severe drought areas spread over the north-west and some part of north-central. In the year 1989, high severe drought areas covered 7.06%; low severe drought areas covered 36.27%; while the areas with no drought covered 56.67% (Table 1). The high severe drought areas were still confined to the north-eastern part of the country, specifically Yobe and Borno States. As posited by Abaje et al. (2013), the decade (1980–1989) witnessed the persistence of drought in the zone beginning in 1981 (Fig. 7). The year 1993 as shown in Fig. 6 reveals areas severely affected by drought.

These include areas located in the Northeastern region of Nigeria and a few patches of drought as observed in Sokoto State (North-western). From Fig. 7, almost all the northern states were affected by drought with the degree between moderate to severe drought in 1991–1994. For 1997 and 2001 (Fig. 7), there remained persistent drought in Yobe and Borno States covering about 3.51% of the total landmass; some parts of Sokoto, Katsina, and Zamfara States were also affected by drought. The central areas in Nigeria did not experience intense drought in 2005 while the southern part experienced no severity of drought having a spatial extent of about 24.39%. Drought appeared to be prevalent in the year 2009 affecting about 51% (Table 1) of the total area (Fig. 7). During 2012, drought persisted in the Northeastern part while the areas that were not

severely affected by drought had a wider spatial distribution (Fig. 7). Overall, the result showed that there is a low correlation in some of the ecological zones across the country, most especially the zones located in the extreme northern and southern parts of Nigeria (Fig. 8), while zones with strong correlation are in the central part of Nigeria indicating that rainfall remains the major source of water for plant growth.

Inter-sensor relationships

To link NDVI$_{modis}$ with NDVI$_{avhrr}$ involves establishing a relationship between the two products (Fig. 9). This enables a continuous flow of data to enhance the drought assessment. A country-wide link is established between the NDVI values of MODIS and AVHRR. This is expressed as:

$$NDVI_{MODIS} = 0.010 + 0.905 NDVI_{AVHRR} \qquad (9)$$

Also, relationships were developed for specific months (Table 2) and the result showed that there is a strong correlation ($r^2 > 0.95$) for the individual months. Equation (9) and Table 2 present important models that link the two sensors and facilitates the monitoring of vegetation conditions for drought in a continuous manner, overtime and well into the future.
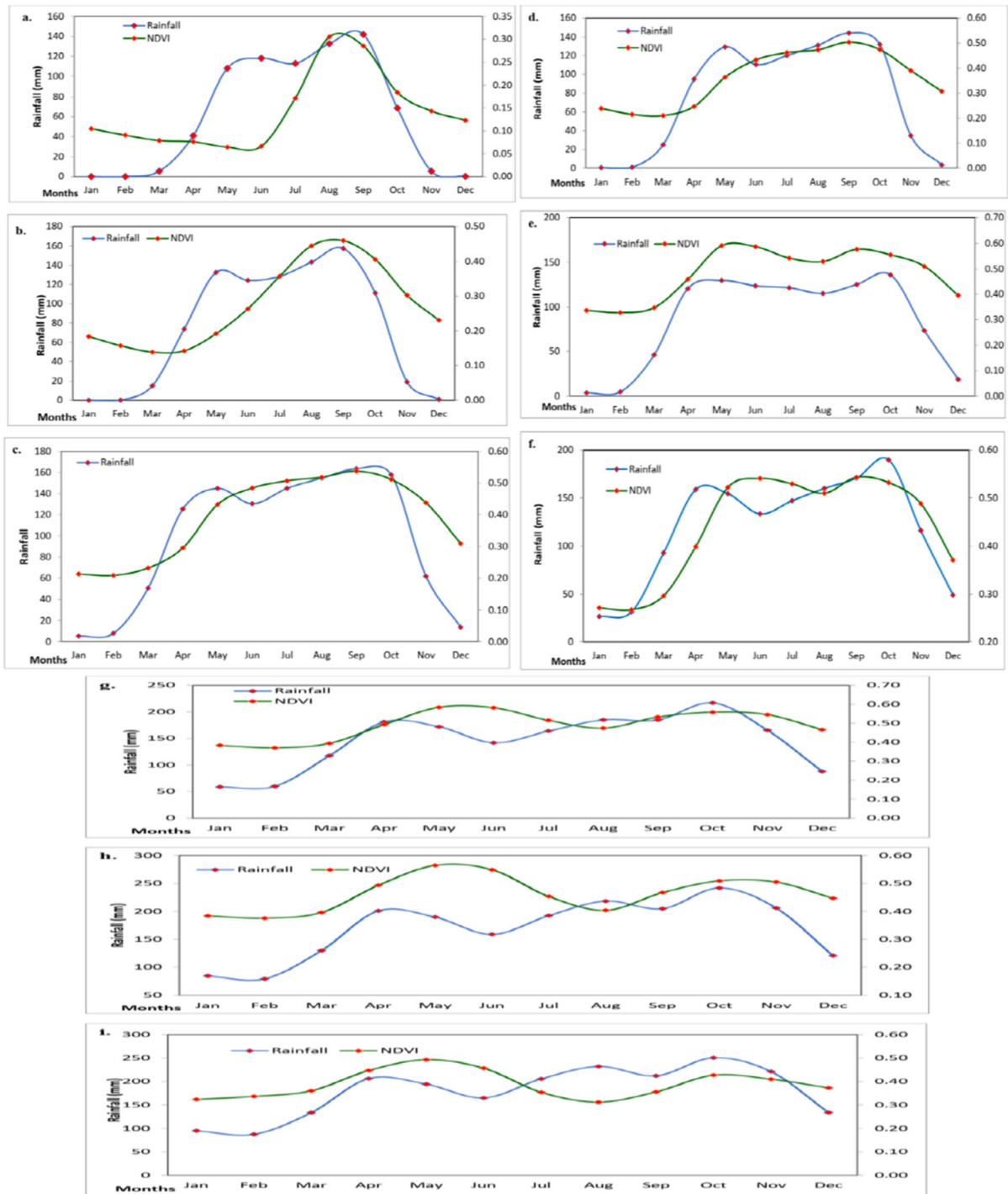
Fig. 6 Relationship between the monthly variation of NDVI and rainfall in Nigeria. **a** Sahel Savanna. **b** Sudan Savanna. **c** Guinea Savanna. **d** Jos Plateau. **e** Montane Forest. **f** Derived Savanna. **g** Rainforest. **h** Freshwater. **i** Coastal Zone

Table 1 Areas affected by drought (1981–2012)

Year	High drought severity (km^2)	High drought severity (%)	Low drought severity (km^2)	Low drought severity (%)	No drought severity (km^2)	No drought severity (%)
1981	246.21	0.03	125,319.95	13.57	798,206.84	86.41
1985	43,578.84	4.72	425,447.69	46.06	454,746.46	49.23
1989	65,219.09	7.06	335,078.44	36.27	523,475.47	56.67
1993	79,053.89	8.56	357,712.69	38.72	487,006.43	52.72
1997	30,378.37	3.29	225,193.50	24.38	668,201.13	72.33
2001	81,328.23	8.80	628,753.92	68.06	213,690.86	23.13
2005	38,944.69	4.22	577,189.73	62.48	307,638.58	33.30
2009	492,964.43	53.36	396,060.03	42.87	34,748.55	3.76
2012	49,367.53	5.34	558,355.30	60.44	316,050.17	34.21

Discussion

NDVI and rainfall

As presented in Fig. 4, the result showed a very low correlation ($r^2 = 0.290$) between rainfall and vegetation in the Sahel savanna zone located in the northern part of Nigeria. This result is in line with the study conducted by Anyamba and Tucker (2005). In their study (Anyamba and Tucker 2005) on the analysis of Sahelian vegetation dynamics using "NOAA-AVHRR NDVI data from 1981–2003, they posited that a mutual relationship exists between rainfall patterns and NDVI values as a result of the movement of the Inter-Tropical Convergence Zone (ITCZ). This observation was initially affirmed by Nicholson et al. (1990) in their study on a comparison of vegetation response to rainfall in the Sahel and East Africa using normalized difference vegetation index from NOAA-AVHRR. Similarly, in this study, rainfall within this agro-ecological zone is characterized by a low amount in December, January and February (DJF) which is the harmattan period while rainfall is at the peak (141.9 mm) in September. The Sudan savanna (Fig. 5a) also experienced a relatively low correlation ($r^2 = 0.45$), and the monthly variation exhibits a similar pattern as the other savanna zones. In the savanna regions, areas with exceptionally low NDVI-rainfall correlation identify sites where vegetation cover is damaged and land degradation is going on (Li et al. 2004). The Sudano-Sahelian region of Nigeria

is under threat; various crises ongoing within the Sudano-Sahelian region of Nigeria, especially the Sahel, point to the fact that the spatial spread of drought is affecting livelihood and human sustainability. Obioha (2008) in his study on climate change, population drift, and violent conflict over land resources in Northeastern Nigeria posited strongly that most of the crises within this region are environmentally induced largely as a result of increasing desertification [drought-like conditions]. The persistence of drought within the region has accounted for, among other things, the continued shrinking of the Lake Chad, the constant clashes over wetlands and other water support systems, the communal clashes and widespread increase in the rate of Fulani pastoralism into other parts of the country. These socio-hydrological indicators are pointers to the state of the water-stressed agro-ecological zone. The Guinea savanna and derived savanna (Fig. 6c and f) located at the central part of Nigeria remain the only savanna zone that showed strong correlation ($r^2 > 0.7$) and rainfall amount has increased to 180 mm while the maximum NDVI value has also increased to 0.5 as compared to the rainfall and vegetation value in other ecological zones especially the Sudan and Sahel. The other agro-ecological zones that exhibit a high correlation between rainfall and vegetation in Nigeria are the montane forest ($r^2 = 0.84$), Jos plateau ($r^2 = 0.64$), and the lowland rainforest ($r^2 = 0.588$) (Fig. 6e, d, g, respectively). The freshwater and mangrove zones as shown in Fig. 6 h and i respectively exhibit the highest amount of rainfall in
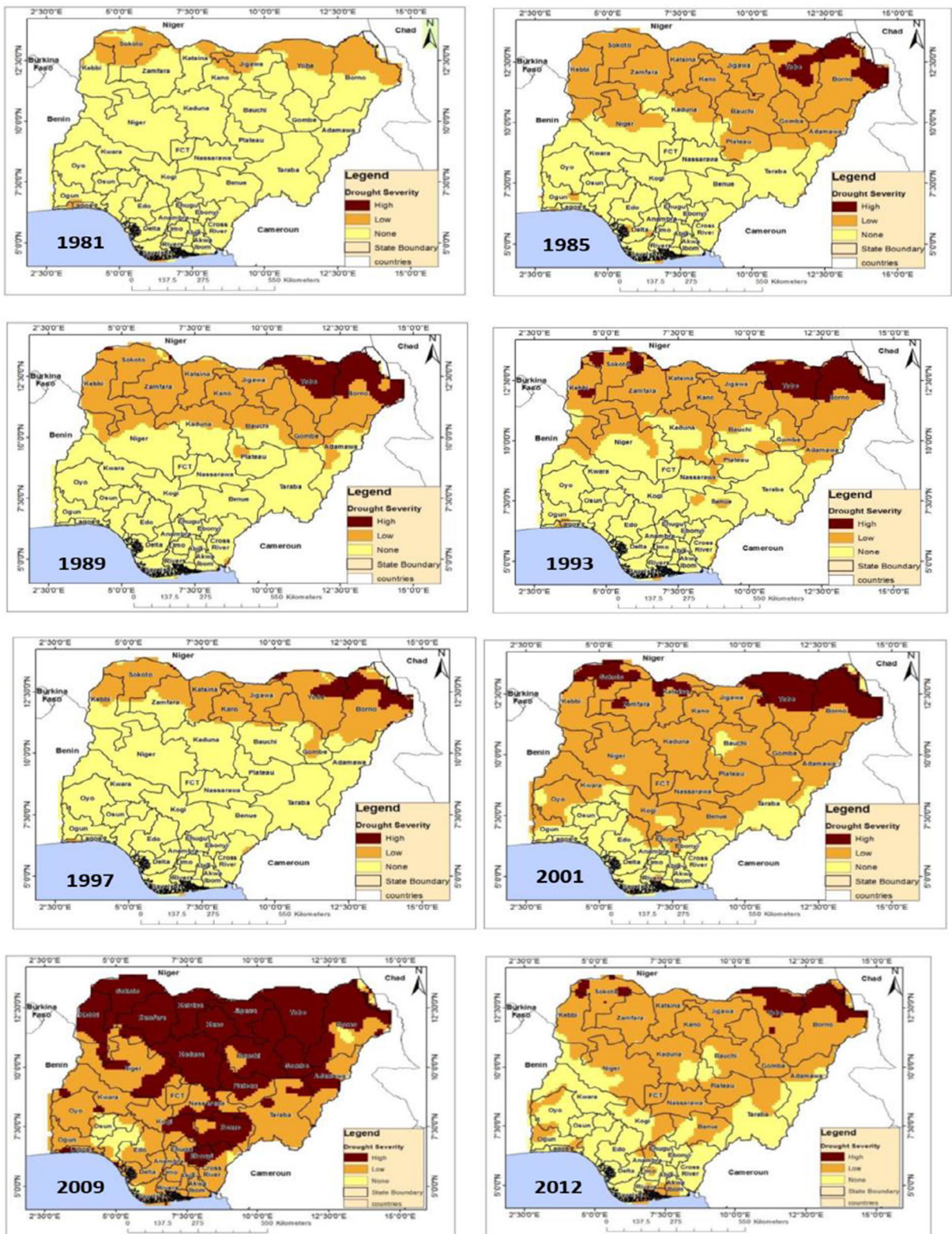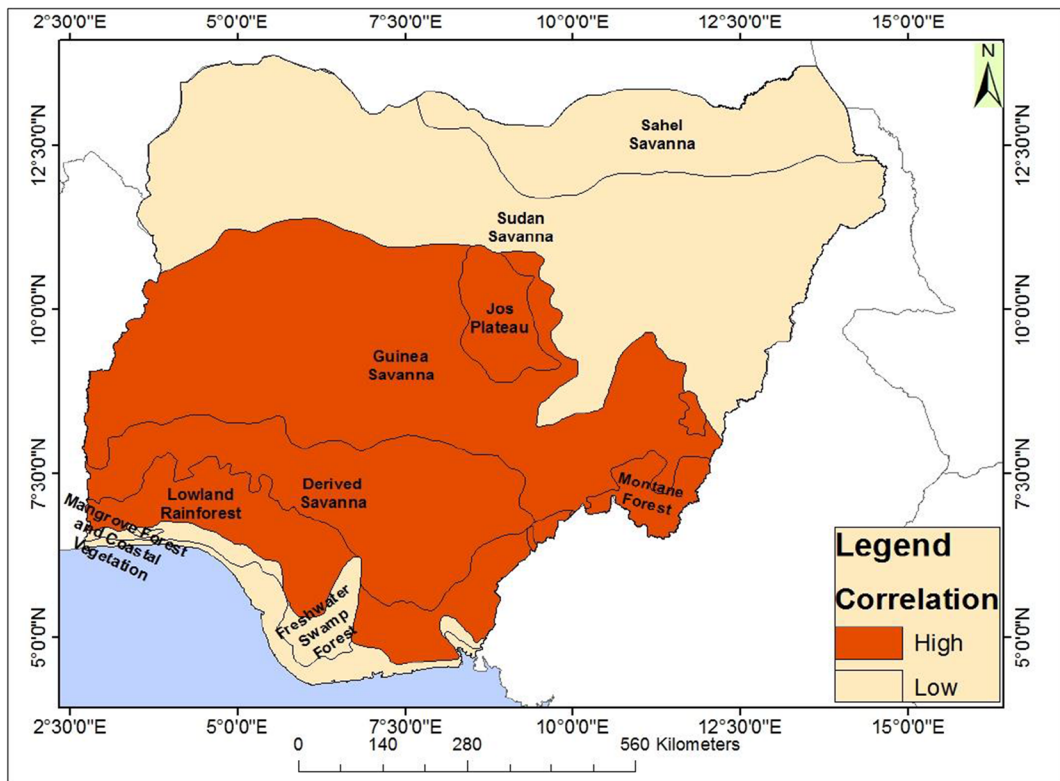
**Fig. 7** Map showing spatio-temporal pattern of drought incidence in Nigeria

Fig. 8 Map of Nigeria showing the correlation between rainfall and NDVI across agro-ecological zones

the zones and showed a low correlation between rainfall and NDVI. As discussed by Nicholson et al. (1990), the authors concluded that it appears NDVI might not be a sensitive indicator of rainfall in regions that are closer to the coast. This is because as rainfall increases, NDVI and presumably canopy density increases until this saturation is reached and NDVI thereafter remains constant despite increasing rainfall" (Nicholson et al. 1990).

An examination of the occurrence of drought in Nigeria shows that the extreme northern parts and north-eastern parts are more susceptible to severe drought. This is in good agreement with earlier researches that claim that these areas are prone to drought and desertification (Oladipo 1990, 1993; Ayuba 2007). The drought risk areas consist of Borno and parts of Yobe while other northern parts which comprise about ten (10) states are also at risk of drought with a spatial extent of 42.4% of the study area. According to Oladipo (1993), the northern region is prone to drought and this has been a very serious ecological problem due to
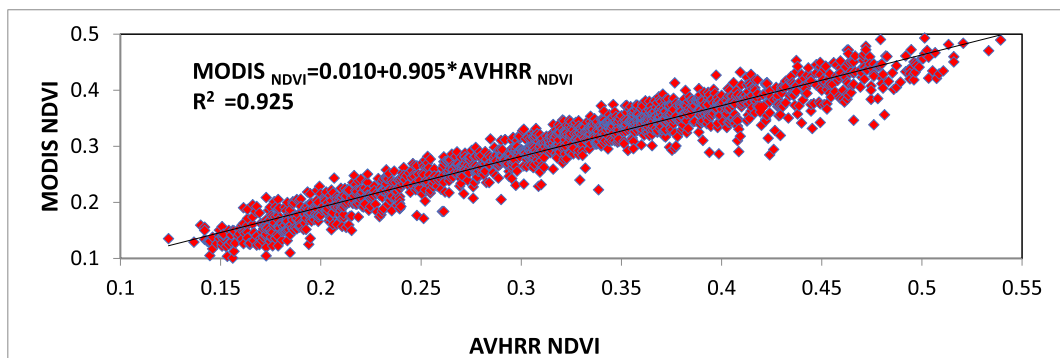
**Fig. 9** Relationship between $MODIS_{NDVI}$ and $AVHRR_{NDVI}$

Table 2 Relationship between 500-m MODIS NDVI Data and resampled 500-m AVHRR NDVI values for individual months

| Months	Model	R^2
January	$MODIS_{NDVI} = 1.593898 + 0.91513 AVHRR_{NDVI}$	0.990214
February	$MODIS_{NDVI} = 1.354615 + 0.959118 AVHRR_{NDVI}$	0.994184
March	$MODIS_{NDVI} = 4.633088 + 0.885415 AVHRR_{NDVI}$	0.986472
April	$MODIS_{NDVI} = 2.570693 + 0.885415 AVHRR_{NDVI}$	0.992139
May	$MODIS_{NDVI} = 0.633280 + 0.980332 AVHRR_{NDVI}$	0.991352
June	$MODIS_{NDVI} = 1.346658 + 0.990225 AVHRR_{NDVI}$	0.991033
July	$MODIS_{NDVI} = 0.520454 + 1.041241 AVHRR_{NDVI}$	0.992139
August	$MODIS_{NDVI} = 1.790612 + 0.999229 AVHRR_{NDVI}$	0.992139
September	$MODIS_{NDVI} = 0.014885 + 1.04218 AVHRR_{NDVI}$	0.988762
October	$MODIS_{NDVI} = 0.410682 + 1.001856 AVHRR_{NDVI}$	0.992054
November	$MODIS_{NDVI} = 1.501708 + 0.969129 AVHRR_{NDVI}$	0.994395
December	$MODIS_{NDVI} = 0.900312 + 1.041901 AVHRR_{NDVI}$	0.975651

various factors due to latitudinal location, rainfall anomalies, etc. On the other hand, areas with very low drought risk are located in the southern part of Nigeria with a spatial extent of 476,579 km^2 (Fig. 10).

Inter-sensor relationships

In an attempt to validate the equations in Table 2 and Fig. 8, the entire country, Nigeria, is used as a point of
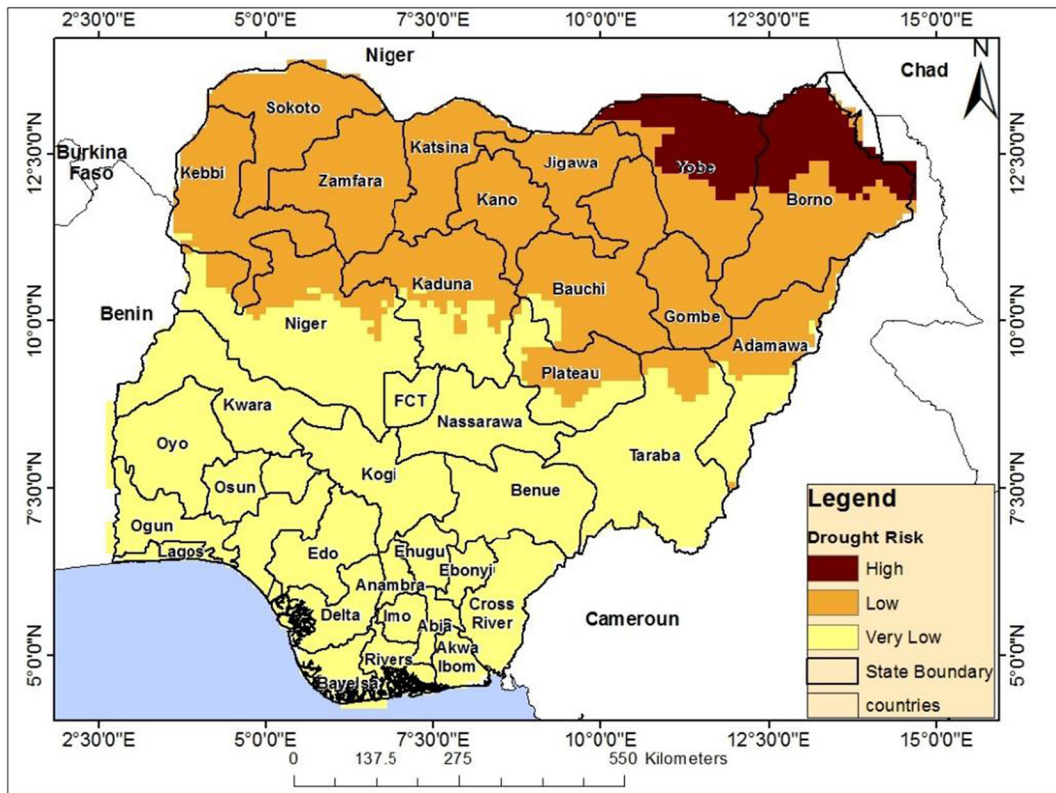

Fig. 10 Drought risk map of Nigeria
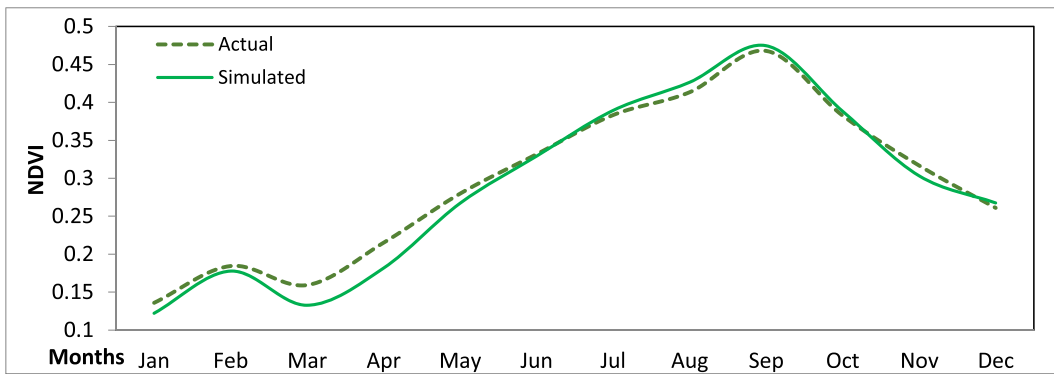
Fig. 11 Actual and simulated NDVI$_{MODIS}$ for Nigeria

reference. The variation between actual NDVI and the simulated NDVI as presented in Fig. 11 suggests little or no difference between the observed and simulated NDVI values (Fig. 11). It is clear from the result (Fig. 11) that there exists the same pattern of variation in NDVI across the months. The distance between the two models could be attributed to uncertainties in model estimations (Thenkabail et al. 2013). Furthermore, a comparison of observed and simulated values in the study area showed (Fig. 12) the amount of similarity between these two NDVI values (99%). Overall, the image (Fig. 12) reveals clear similarities in the NDVI magnitude and spatial distribution across the country. Specifically, low values of NDVI were observed in the northern part while the

highest NDVI value was observed in the southwestern part of the country (Fig. 12). The level of similarity will repeat itself for other months and this model can be adapted for other regions in sub-Saharan Africa especially within the Sudano-Sahelian zone.

Web-based environmental information system

Figure 13 showed the web-based environmental information system platform and its component for effective monitoring of drought. The platform with a domain name (NEMS.com) is available on a localhost that gives access to the public to any part in the world. The weather section interface gives a platform where people can access the
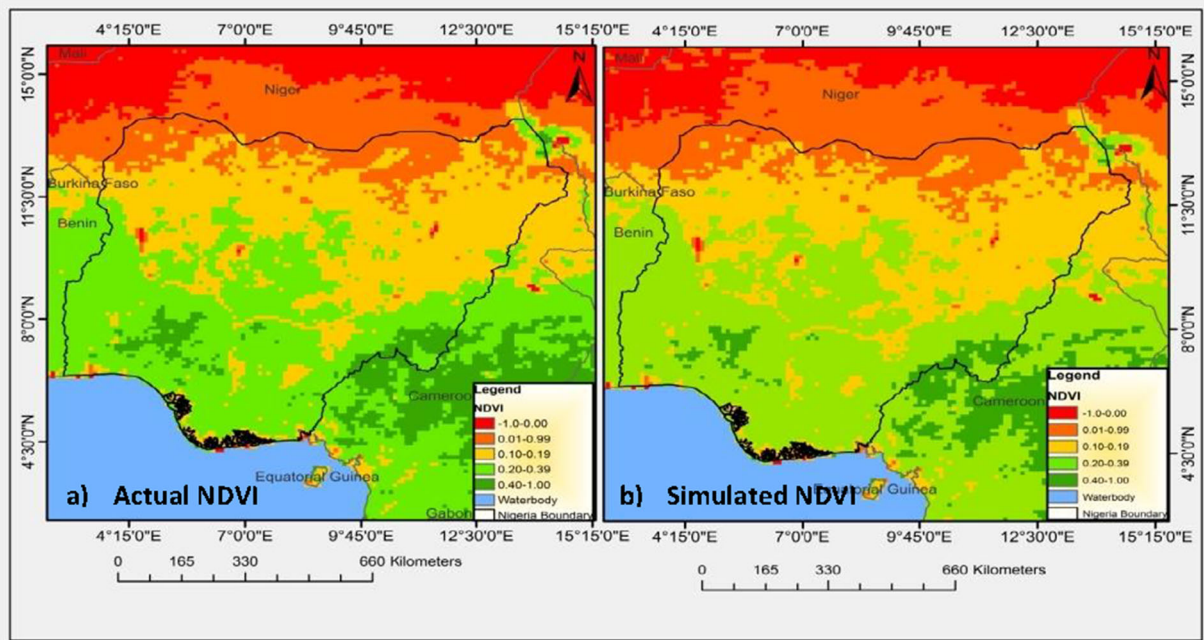
Fig. 12 Spatial distribution of actual (**a**) and simulated values (**b**) of NDVI for Nigeria
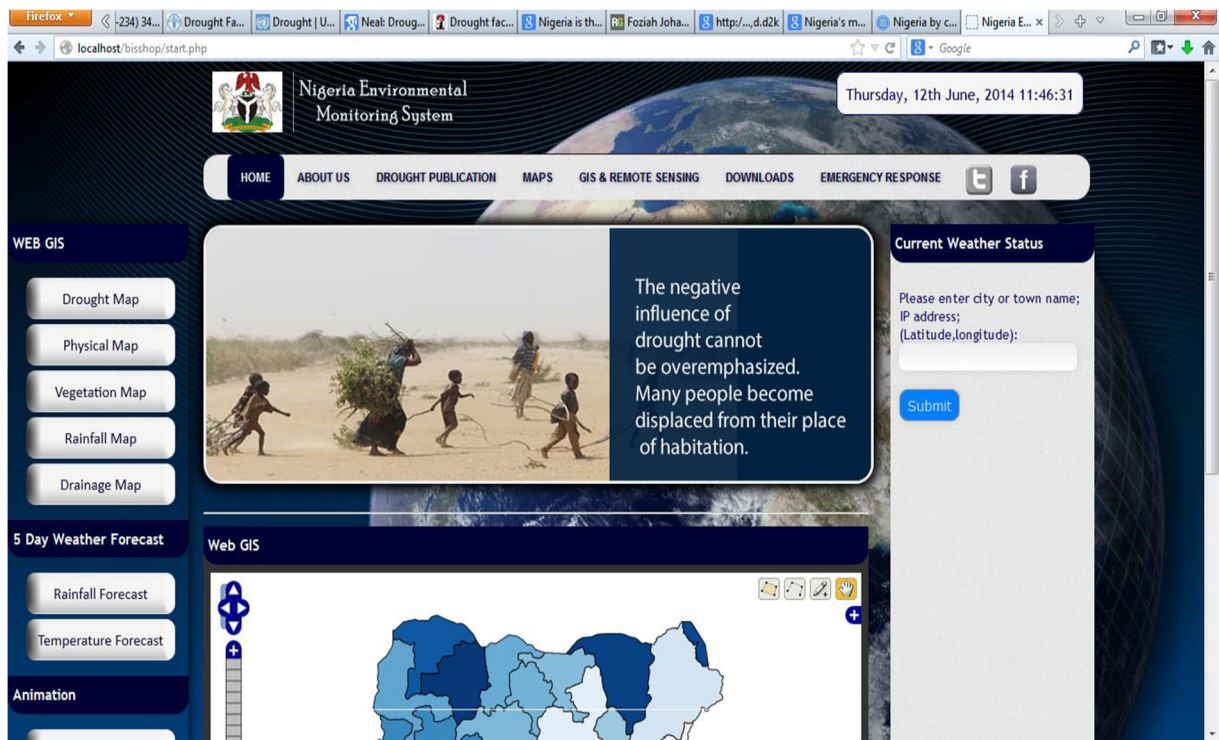
Fig. 13 The home page of the web-based drought early warning system for Nigeria

current weather report of any location in Nigeria by inputting the name or the coordinate of the area of

interest. The emergency response section is divided into three sections which are the SMS, chat, and
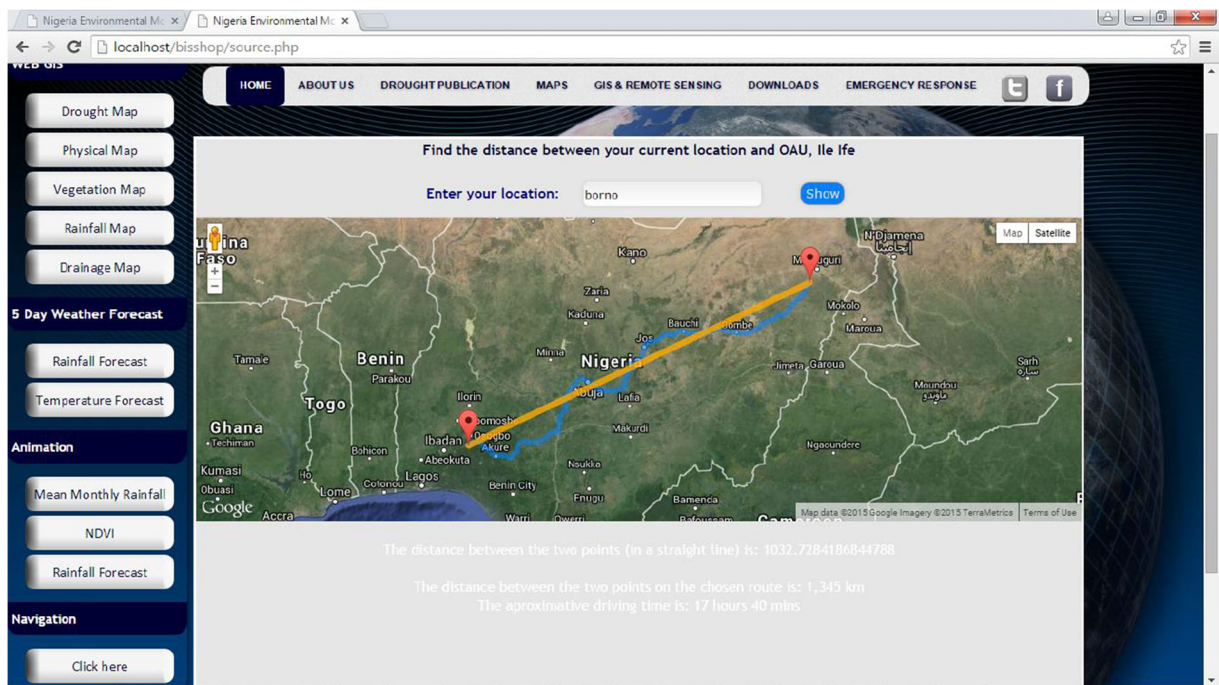

Fig. 14 The web-based drought early warning system interface displaying the navigation tool across Nigeria

Teleconferencing. The section grants users access to report any case of environmental challenges that may occur in any part of the country in real-time.

The navigation platform showed the path and direction to any location affected by drought from the research laboratory. For example, as shown in Fig. 14, the result showed that the distance to Borno State which is a drought-prone area from a named location is about 1345 km and the shortest route to get to the location is displayed. The platform also provides several tools to query data. Using the search tool, features can be selected and their information is displayed by entering part or all of their names in the search box. It must be noted that Query tools are common features available in most web mapping applications (Fig. 14). The web-based cancer atlas developed by MacEachren et al. (2008) features an interface that allows users to query the database based on the cancer type, site, gender, race, age, stage, and time. The query returns a choropleth map based on the settings made by the user. The search and query tools provided by Singh et al. (2012), in their Web-Based GIS platform, are very similar to the NEMS.

Conclusion

Globally, it has been identified that drought adversely affects human livelihood and development. It also impacts negatively on the natural environment. The impact of drought varies across regions of the world depending on various factors. However, in sub-Saharan Africa, SSA, drought has created socio-ecological reactions ranging from water stress, water war, migration, loss of farmlands, famine, hunger, and wars. It has also affected the economic performance of most countries within SSA and agricultural productivity is largely hampered. Importantly, this study has shown that NDVI pattern across space and time has strong ties to rainfall distribution especially for countries in tropical environments.

Secondly, the study also developed and validated drought assessment methods through the integration of distinct two distinct sensors. The developed model and framework (calculating NDVI from AVHRR and integrating into MODIS (500 m)) can be applied in data-scarce regions such as we have in SSA. Furthermore, this study by employing the use of time-series satellite data presented the spatio-temporal variation of drought at different times of the year in all parts of the country

during the study period with the highest drought risk in the north-eastern parts. The maps and tables showed that high drought risk covered 5.98% (55,312 km^2) of the total nation's landmass, while low drought risk covered 42.4% (391,881 km^2) and very low drought risk areas 51.5% (476,578 km^2).

Thirdly, this research goes further to develop a geospatial approach, a form of drought early warning for the country to assess the dynamics of drought in near real-time. The availability of open-source applications enabled the development of a web-based platform to monitor drought across the country. The map view from the web-based drought monitoring system, developed in this study, is accessible through the localhost (www.NEMS.com). Considering, on the one hand, the spread and frequency of droughts in the region, and the lack of accurate ground climate observations and technological ability to deal with droughts—on the other hand, such a system has enormous potential for preparedness for drought and a benchmark for early warning systems for drought.

Finally, this study calls for action to implement national strategies to mitigate drought that include effective monitoring of drought and early warning systems using geospatial data, a suitable method of impact assessment and mitigation measures to mitigate potential impacts, and national policies on the drought that encourage a more proactive approach to manage drought. Taking into account the spread and severity of droughts in Nigeria, monitoring of droughts using VCI and NDVI remote sensing techniques may play an invaluable role in food security and preparedness for drought.

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