Heliyon 10 (2024) e31167

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

Assessing desertification vulnerability and mitigation strategies in northern Nigeria: A comprehensive approach

Ibrahim I. Yahaya [a,b], Yongdong Wang [a,*], Zhijie Zhang [c,d], Abubakar Y. Inuwa [e], Yazhou Zhao [a], Yuan You [a], Hamisu A. Basiru [g], Friday Uchenna Ochege [h], Zhou Na [a], Chukwuka P. Ogbue [a,b], Murad Muhammad [a,b], Yeneayehu F. Mihertu [a], Isah A. Tanko [f], Waseem Shoukat [a,b]

[a] *National Engineering Technology Research Center for Desert-Oasis Ecological Construction, Xinjiang Institute of Ecology and Geography, Chinese Academy of Sciences, Urumqi, 830011, China*
[b] *University of Chinese Academy of Sciences, Beijing, 100049, China*
[c] *School of Geography Development, The University of Arizona, Tucson, AZ, 85719, USA*
[d] *Aero Geophysical and Remote Sensing Centre of China Geological Survey Beijing, 100083, China*
[e] *Federal Polytechnic Daura Katsina State 820001, Nigeria*
[f] *Nigerian Meteorological Agency, National Weather Forecasting, and Climate Research Centre, Kano State, 700004, Nigeria*
[g] *Hussain Adamu Federal Polytechnic, Kazaure, Jigawa State, Nigeria*
[h] *Department of Geography and Environmental Management, University of Port Harcourt, PMB 5323 Choba, East-West, Port Harcourt, Nigeria*

A R T I C L E I N F O

Keywords:
Desertification
Vulnerability
Northern Nigeria
Land degradation
Spatial patterns
Trends

A B S T R A C T

Desertification constitutes a grave threat to the environmental and socio-economic stability of desertification frontline states in Northern Nigeria. From 2003 to 2020, this research comprehensively analyzes desertification vulnerability, integrating parameters such as NDVI, LST, TVDI, MSAVI, and Albedo. Key factors contributing to land degradation are identified, along with the spatial patterns and trends of desertification over the two-decade period. The consequences are profound, with Northern Nigeria's ecosystem experiencing a steady decline in vegetation cover. Agriculture, vital to the region's economy, faces increased aridity and reduced arable land, jeopardizing food security. Diminishing water resources exacerbates scarcity issues, placing additional strain on communities. These environmental changes lead to severe socio-economic implications, including displacement, loss of livelihoods, and heightened vulnerability to climate-related risks. Urgent, comprehensive, and strategic interventions are imperative. Policy recommendations underscore revising and enforcing land use regulations, promoting sustainable agricultural practices, and establishing monitoring systems to guide decision-making. This research contributes practical strategies to enhance the resilience of desertification frontline states, safeguard livelihoods, and align with Nigeria's sustainable development objectives. Findings from the study indicate that only a tiny percentage (6.7 %) of the study area remains unaffected by desertification. Moreover, 13.3 % exhibit light vulnerability, 20 % demonstrate moderate exposure, and 60 % fall into the severe (26.7 %) and compelling (33.3 %) vulnerability categories. These statistics underscore the gravity of desertification in the study area, emphasizing the urgent need for effective mitigation measures to address its impact comprehensively.

* Corresponding author.
E-mail address: wangyd@ms.xjb.ac.cn (Y. Wang).

https://doi.org/10.1016/j.heliyon.2024.e31167
Received 22 November 2023; Received in revised form 26 April 2024; Accepted 11 May 2024
Available online 20 May 2024

1. Introduction

1.1. A. an overview of desertification risk in the world

Desertification, as defined by the United Nations Convention to Combat Desertification (UNCCD, 1994), is "land degradation in arid, semiarid, and dry subhumid areas resulting from various factors, including climatic variation and human activities" [1]. This degradation, primarily caused by human activities like pollution, agriculture, and overgrazing [2], poses a severe threat to arid and semi-arid regions. These regions comprise about 41 % of the global surface area and are home to over 38 % of the world's population [3–5]. Desertification not only results in the loss of land productivity but also leads to socio-economic conflicts and necessitates international collaboration. It has emerged as a critical environmental issue that societies must address [6,7]. The complex process of desertification involves numerous environmental and human factors [8] and can cause irreversible changes over several decades, potentially permanent within human generational timescales [9]. Recent studies link desertification to losses in ecosystem services, defining it as "a persistent reduction in the capacity of ecosystems to supply services over extended periods" [10]. Dryland ecosystems support about 2 billion people, 90 % in developing countries, and are crucial for food security, carbon sequestration, and biodiversity. However, they are vulnerable to accelerated desertification, exacerbating food insecurity and lowering human well-being levels in these regions [10]. Economically, land degradation in drylands is estimated to cost developing countries 4–8% of their GDP (UN, 2011), putting a significant portion of the population at starvation [9]. The extent of regions affected by desertification varies widely due to differing definitions and methodologies in land degradation studies [11]. This variation is evident in the estimates of desertified land, ranging from 10 % to 71 %, with Africa and Asia being regions of particular concern [12–15]. Although some estimates might overstate the problem, there is a general consensus on the alarming rate of desertification and its impact on soil resources in arid and semi-arid rangelands and cultivated lands [14,15].

1.2. b. desertification risk Factors and their impact

To effectively combat and reverse the trend of desertification, utilizing tools that enhance our understanding of its dynamics is essential. A key factor in this regard is land use, which is closely linked to land cover and significantly influences the risk of desertification [8]. In line with the 2030 sustainable development goals set by the UNCDD, one critical step is to assess soil degradation patterns, pinpoint anomalies, and identify areas experiencing degradation [16]. In this scenario, monitoring and analyzing Land Use/Land Cover change (LULC) become indispensable for pinpointing current hot spots of desertification or soil degradation and projecting future trends related to land use patterns. Recent decades have seen an emphasis on spatially explicit models to decode the drivers of LULC changes [17,18]. Highlight that such models are potent in envisaging alternative future landscapes and conceptualizing experiments that deepen our understanding and quantification of pivotal processes. Therefore, deciphering these trends is vital for formulating effective policies, which should adapt based on the land use dynamics in areas prone to desertification [19]. Given the intricate interplay of physical, biological, and human factors in desertification, comprehending various feedback mechanisms in this process is of great interest. In particular, intensive land usage without proper soil management in delicate ecosystems may hasten the onset of desertification [20]; notable among such land use shifts are the transformation of natural vegetation into grazing land and the extension of agricultural fields [21,22]. Below, we outline several key desertification risk factors and their impact on human activities.

a. Natural Factors include extended droughts, diminished rainfall, and rising temperatures. Such changes compromise soil moisture and vegetation health, thereby increasing the susceptibility of land to desertification [23].
b. Anthropogenic Factors - LUCC: Human-driven factors, especially LUCC, significantly contribute to desertification, encompassing deforestation, agricultural practices, and overgrazing [24,25] Key aspects include:

- Deforestation and Overgrazing: These activities lead to notable declines in soil integrity and plant cover, essential for soil preservation. This vegetation loss aggravates soil erosion [26,27].
- Unsustainable Agricultural Practices: Practices such as over-cultivation, unsuitable irrigation, and overuse of agrochemicals impair soil health, often causing land abandonment and exacerbating desertification [28,29]Urbanization: The rapid conversion of fertile agricultural lands into urban and industrial zones disrupts local ecosystems, contributing to land degradation [30–32].

The ramifications of these factors are significant, leading to biodiversity loss, reduced agricultural yield, and increased difficulties for communities in affected areas. Furthermore, desertification contributes to climate change by lowering the land's carbon sequestration capacity and increasing greenhouse gas emissions [33].

1.3. C. overview of study area

Desertification in Nigeria, particularly in its northern region, represents a critical environmental and socio-economic challenge. The phenomenon predominantly affects the 'frontline states' – regions on the edge of the advancing Sahara Desert [34]. These states, grappling with the severe impacts of desertification, including Sokoto, Kebbi, Katsina, Kano, Jigawa, Yobe, Borno, Zamfara, Kaduna, Bauchi, Gombe, and Adamawa. Here's a brief overview of each:

Sokoto: Known for its arid climate, Sokoto faces significant desertification, impacting its largely agrarian economy and water scarcity. Kebbi: Bordering the Sahara, Kebbi experiences frequent droughts and land degradation, affecting agricultural productivity and food security. Katsina: Overgrazing and deforestation exacerbate land degradation in Katsina, threatening the livelihoods of many who depend on agriculture. Kano: As the most populous state in Nigeria, Kano confronts severe land degradation due to overuse of agricultural land and deforestation. Jigawa: Situated in the northwestern part of Nigeria, Jigawa's semi-arid conditions make it highly susceptible to desert encroachment, impacting local communities and farming practices. Yobe: Yobe faces acute water shortages and declining soil fertility due to desertification, disrupting local ecosystems and agriculture. Borno: Known for its vast arid lands, Borno is at the forefront of desertification challenges, with significant implications for its predominantly agrarian society. Zamfara: Desertification in Zamfara leads to a loss of arable land and pastures, exacerbating poverty and food insecurity. Kaduna: Although more diversified in its economy, Kaduna still faces the threat of desertification, particularly in its northern regions, affecting agriculture and natural resources. Bauchi: In Bauchi, the advancing desert has led to soil erosion and a decline in crop yields, impacting the state's agricultural output. Gombe: Gombe's proximity to the Sahel makes it vulnerable to desertification, with significant consequences for its environment and rural communities. Adamawa: Bordering Cameroon, Adamawa experiences significant environmental changes due to desertification, affecting its rich biodiversity and agricultural lands. For this research, we solely focus on seven of the desertification frontline states (Fig. 1)

1.4. D.reviews tools and methods to assess desertification risk/vulnerability

The Sahel region, facing severe desertification challenges exacerbated by two decades of drought [35] and human activities, is struggling with sustainable development. This issue is particularly acute in Nigerian states like Bauchi, Gombe, Borno, Yobe, Kano, Jigawa, Katsina, Sokoto, Zamfara, Kebbi, and Adamawa. The middle belt states, including Kaduna, Kwara, Kogi, Nasarawa, Niger, Plateau, Taraba, and the Federal Capital Territory, serve as buffer zones, absorbing migrations from these desertification-hit areas [36].

Northern Nigeria's susceptibility to desertification is widely recognized due to its geographical positioning. This study highlights that while climatic and geographic factors inherently place the region at risk, human-induced activities have escalated the situation, leading to drought and heightened desertification risk [37]. Furthermore, this study emphasizes the need to develop solutions for decreasing desertification risk, including spreading such strategies. This involves incorporating risk reduction methodologies addressing human-made risks into spatial planning and policy formulation [24]. Despite the critical nature of this integrated approach, especially given the region's vast expanse, there remains a lack of comprehensive desertification risk assessments in the frontline states.

There have been numerous studies examining the effects of desertification in northern Nigeria. For instance Ref. [35],discuss the development of early warning systems for agricultural drought assessment in Nigeria, employing spatiotemporal analysis using VHI [38]. Focus on desertification risk assessment in Bauchi, while [39] explore the impact of land cover changes [40,41]. delve into

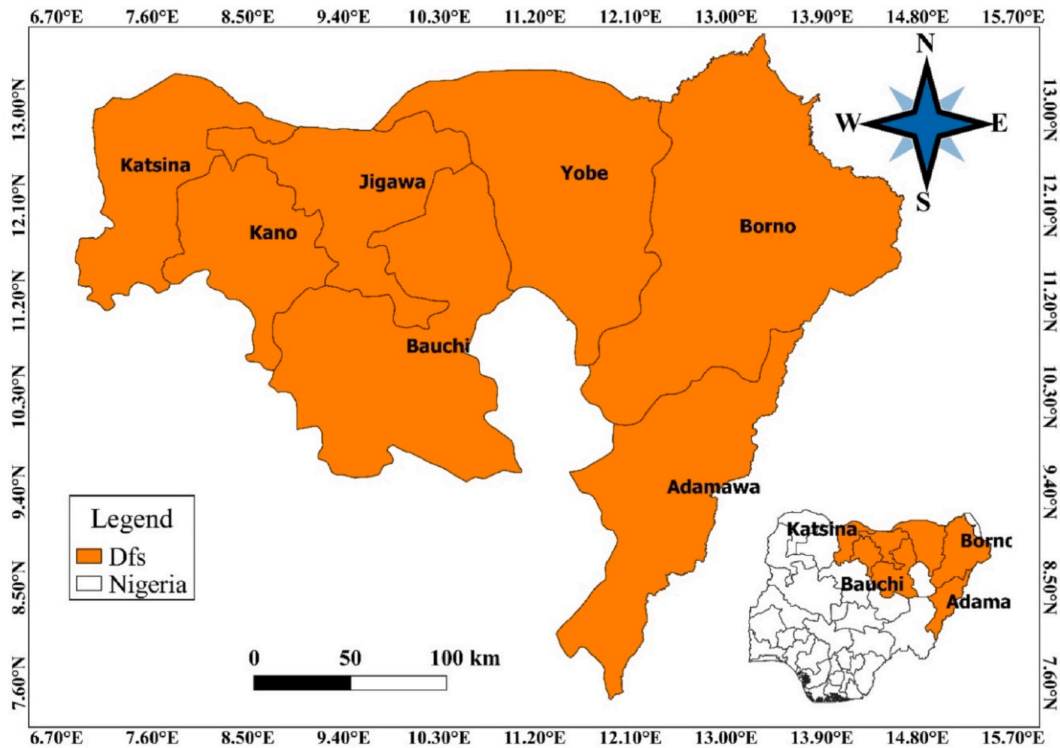

Fig. 1. Map of the study area.

assessing desertification sensitivity in Katsina and analyzing Land Cover Sensitivity to Desertification in the Maigatari Local Government Area, Jigawa State, respectively [42].

Our research builds upon these significant contributions by examining desertification in Nigeria from a broader perspective. Previous studies typically focused on individual states within the desertification frontline or employed a limited set of desertification indices combined with climatic and human factors for assessment. In contrast, our study utilizes a comprehensive approach, incorporating five desertification indices, land use land cover analysis, and climatic variables to thoroughly evaluate desertification vulnerability in Northern Nigeria. We pay particular attention to the seven frontline states most severely impacted by desertification. The findings of this study will be disseminated to local authorities to aid in the planning, management, and policy formulation aimed at combating desertification in these critical areas.

Due to the complexity of land desertification, a universal assessment index is unavailable [43–45] The study utilizes five specific indicators for desertification assessment: Surface albedo, modified soil-adjusted vegetation index (MSAVI), land surface temperature (LST), vegetation coverage (FVC), and temperature vegetation drought index (TVDI), as they have been shown to offer reliable and adaptable results [43,45] Additionally, the Normalized Difference Vegetation Index (NDVI) will be incorporated to enhance the assessment's accuracy. The primary goals of this research are to examine the desertification vulnerability index from 2003 to 2020, changes in land use and land cover from 2003 to 2020, and changes in meteorological parameters such as rainfall and temperature in the study area from 2003 to 2020.

2. Materials and methods

2.1. Data

To give an intuitive view of desertification vulnerability, climate change, and human activities, we used desertification indices mechanism comprising of 5 indices namely NDVI, LST, TVDI, Albedo, and MSAVI to grade desertification vulnerability into four classes: very severe, Severe, Moderate, light and No desertification. To verify the grading results we compared our results with the desertification vulnerability map of European Environment agency (EEA) https://www.eea.europa.eu/data-and-maps/figures/sensitivity-to-desertification-index-map [46,47]. To achieve the objectives of this study, the SNAP tool was used for the preprocessing and processing of remote-sensing images. Python 3.12. and ArcGIS 10.3 were used for statistical regression analysis and presentation of results, respectively. The process begins with downloading remote sensing data sourced from Google Earth imagery, https://earthengine.google.com/, which provides the foundational layers for assessing environmental conditions related to desertification. After acquisition, the data undergoes calibration to correct any sensor errors or biases.

Calibration ensures that the data accurately reflects the radiometric properties of the imaged area [48]. After that, we adjust the satellite data for the effects of the atmosphere on the reflectance values received by the satellite sensor. It is crucial for ensuring that the data accurately represents the surface conditions without atmospheric interference. Before further processing, the images are geometrically rectified to ensure that the spatial relationships and coordinates are accurate. This allows for proper alignment and

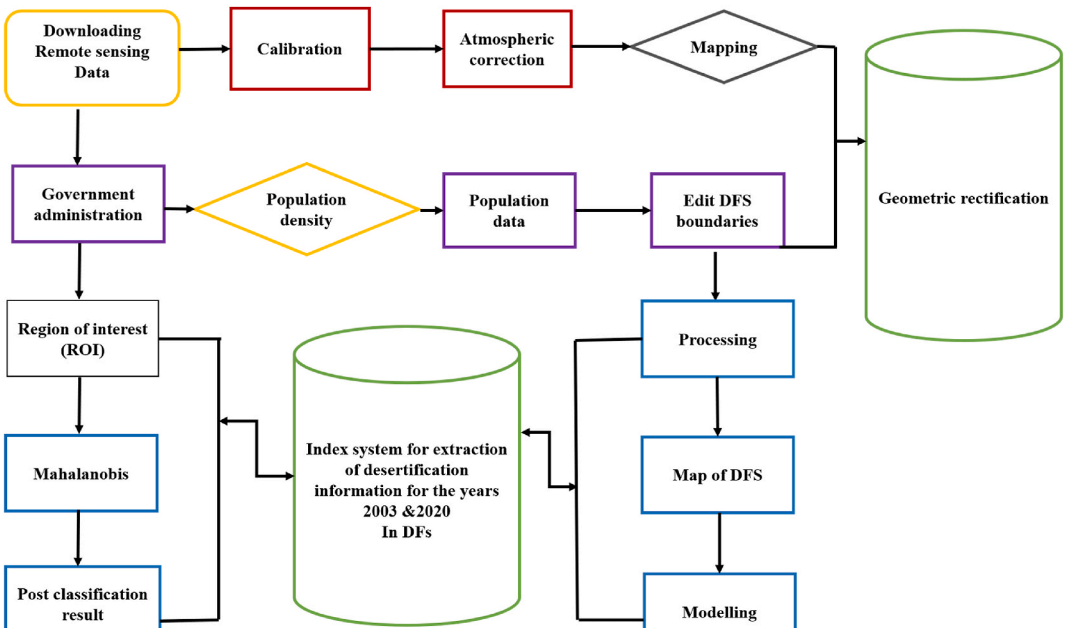

Fig. 2. Methodology's workflow chat.

comparison with other spatial data layers [49,50]. The data underwent a mapping phase where the processed data is used to create maps, likely of vegetation indices or land surface temperatures. It also includes editing DFS (Desertification Frontline States) boundaries, which involves adjusting the administrative or observational boundaries within the geographic information system (GIS) to ensure accuracy in the analysis. There is an integration of population data, which suggests an analysis of human factors in desertification. Population density metrics from government administration sources are combined with the remote sensing data, providing a socio-economic layer to the environmental analysis. A specific ROI is selected, which could mean focusing on areas within the DFS prone to or experiencing desertification.

Mahalanobis Distance: This statistical measure is used, possibly for classification purposes in this context. It may be used to identify the statistical distance of various pixels from a defined mean for different land cover classes, which aids in the post-classification of the results [51].

Index System for Desertification Information: A comprehensive index system extracts desertification information for 2000 and 2020. This system includes the indices mentioned in the methodology section, such as NDVI, MSAVI, Albedo, LST, and TVDI.

Processing to Map of DFS: The processed data is then used to create a Map of DFS, which visualizes the extent and severity of desertification in the selected ROI over the 20 years.

Modelling: Finally, the processed data and the generated maps are used for modeling. This could involve predictive modeling of future desertification trends or the impact of certain interventions. The modeling helps understand the dynamics of desertification and formulate strategies for mitigation or reversal (Fig. 2).

2.2. Methods

Desertification is a significant environmental challenge in Nigeria's Sudano-Sahel region, which spans from Senegambia to Somalia. This region, covering approximately 40 % of Nigeria's northern territory and situated between 10° and 14° N latitudes and 3° and 14° E longitudes, is commonly referred to as the "frontline states" [52]. These states, including Katsina, Zamfara, Sokoto, Kebbi, Kano, Jigawa, Yobe, Adamawa, and Borno, border the Sahelian Niger Republic and are majorly impacted by desert-like conditions, affecting an area of about 580,841 km^2 or 63.8 % of Nigeria's landmass [34,36,53,54]. Significantly, desertification affects around 30 million people, constituting 17 % of Nigeria's population, across 15 of its 36 states [55]. The contributing factors to this environmental issue include climatic changes and human activities. Environmental pressures in these regions stem from various sources, such as livestock demands, population growth, agricultural expansion, and the need for resources like fuelwood and construction materials [34,56,57]. Studies by Refs. [40,58] have used time-series data to depict the steady advancement of land degradation and desertification. Key climate elements such as yearly temperature, rainfall, and population density are highlighted as direct contributors to desertification [59–62]. This study aims to assess the desertification vulnerability index alongside changes in land use, land cover, and meteorological variables from 2003 to 2020. Using Landsat and MODIS data for their respective resolutions and coverage abilities, the research addresses a gap in the existing literature, particularly focusing on the desertification vulnerability indices in Northern Nigeria's frontline states. This aspect is critical given the urgent need for action to support the well-being of over 200 million Nigerians, including the 50 million residents in these affected states [63].

2.2.1. Decadal mean (% change from ordinary), frequency of rainfall, and temperature over the study area from 2003 to 2020

The following equation was used to calculate the cumulative decadal temperature and rainfall change from 2003 to 2020. as employed by Ref. [64], in identifying rainfall trends in Orissa State, India, spanning the twentieth century (1871–2006). The decadal metrological change is typically used to identify a rise or fall in climatic data over ten years or more.

$$A - \frac{B}{A} * 100 \quad (1)$$

Where A = Current Value

$$B = \text{Starting point} \quad (2)$$

2.3. Desertification extraction indices

2.3.1. Normalized difference vegetation index (NDVI)

NDVI spatial composite images are made to distinguish green vegetation from bare soils clearly. The Normalized Difference Vegetation Index (NDVI) quantifies the quantity and strength of vegetation on the land surface. NDVI values typically vary from −1.0 to 1.0; negative values denote clouds and water, positive values close to zero denote bare soil, and higher positive values of NDVI indicate sparse vegetation (0.1–0.5) to thick green foliage (0.6 and above). The red and NIR bands' reflectance values are measured and stored by the satellite's spectrometer or radiometric sensor on two different channels or pictures, and the values are then used to calculate the NDVI [65]. were the first to suggest NDVI, computed by dividing the difference between the red and near-infrared (NIR) channels by the sum of the two channels. The classification of NDVI (Normalized Difference Vegetation Index) is justified in assessing desertification vulnerability and land cover changes due to its role as a widely recognized indicator for monitoring vegetation health and cover. By categorizing NDVI values, it enables the identification of land degradation and desertification, quantification of land use changes, comparative analysis of trends, integration with other parameters, and informs policy and management decisions, making it an essential and versatile tool in understanding complex desertification processes and their environmental impacts.

$$\text{Or} : \text{NDVI} = \left(\frac{(\text{NIR} - \text{RED})}{\text{NIR} + \text{RED})}\right) \tag{3}$$

RED = the red portion of the electromagnetic spectrum (0.6–0.7 μm), and NIR = the near-infrared part (0.75–1.5 μm).

2.3.2. MSAVI: Modified Soil Adjusted Vegetation Index

Where other vegetation indices do not apply, the Modified Soil Adjusted Vegetation Index does. The MSAVI index is aimed to replace NDVI-NDRE when low vegetation hinders them from providing accurate data. Its value ranges from −1 to 1, and its spectral range is 405–14385.

$$2\text{NIR} + 1 - \sqrt{\left((2\text{NIR} + 1)^2\right)} - 8\left(\frac{\text{NIR} - \text{RED}}{2}\right) \tag{4}$$

2.3.3. Albedo

Albedo measures how much light a surface reflects. The albedo is equal to 1 if every surface is reflected. If 30 % is reflected, the albedo is 0.3. The amount of solar energy, or light, that enters Earth's atmosphere, ocean, or land surfaces is promptly reflected to space depending on the albedo of those surfaces. This might affect the climate [66].

$$\alpha = (1 - \text{D})\bar{\text{a}}(\theta\text{i}) + \text{D}\tilde{\bar{\text{a}}} \tag{5}$$

α = albedo

D = propose diffusion of elemination

$\bar{\text{a}}(\theta\text{i})$ = directional hemispherical reflectance at that solar zenith angle

$\tilde{\bar{\text{a}}}$ = bi hemispherical reflectance

2.3.4. Land surface temperature

One of the most critical factors in the physics of land surface processes at all scales is land surface temperature (LST). Since LST is becoming increasingly important, there is much interest in creating methods for measuring LST from space. However, retrieving LST is still challenging since the LST retrieval problem is ill-posed [67]. This study examines the current level of a few remote sensing algorithms used to forecast LST for frontline desertification states between 2003 and 2020. This is called the TOP of Atmospheric (TOA) spectral radiance calculation. Land Surface Temperature (LST) is included in assessing desertification vulnerability due to its role in indicating aridity, monitoring drought conditions, evaluating its impact on ecosystems and human well-being and its synergy with other parameters like NDVI and TVDI. LST helps to comprehensively understand and monitor the complex dynamics of desertification, making it a valuable component of the assessment process.

$$\text{TOA (L)} = \text{M}_\text{L} * \text{Q}_{\text{cal}} + \text{A}_\text{L} \tag{6}$$

M_L = Band-specific multiplicative rescaling factor from the metadata (RADIANCE_MULT_BAND_x, where x is the band number). Qcal = corresponds to band 10.

A_L = Band-specific additive rescaling factor from the metadata (RADIANCE_ADD_BAND_x, where x is the band number). TOA = 0.0003342 ∗ "Band 10" + 0.1 m. Therefore, the equation was solved using the Raster Calculator tool in ArcMap. TOA to Brightness Temperature conversion

$$\text{BT} = \frac{\text{K}_2}{\ln\left(\text{K}_1 / \text{L}\right) + 1)} - 273.15 \tag{7}$$

Where:

K_1 = Band-specific thermal conversion constant from the metadata (K1_CONSTANT_BAND_x, where x is the thermal band number). K_2 = Band-specific thermal conversion constant from the metadata (K2_CONSTANT_BAND_x, where x is the thermal band number). L = TOA Therefore, the radiant temperature is adjusted by adding the absolute zero (approx. 273.15 °C) to obtain the results in Celsius. Calculate the NDVI

$$\text{NDVI} = \frac{(\text{Band 5} - \text{Band 4})}{(\text{Band 5} + \text{Band 4})} \tag{8}$$

Note that the calculation of the NDVI is important because the proportion of vegetation (PV), which is highly related to the NDVI, and emissivity (ε), which is related to the PV, must be calculated.

$$\mathrm{NDVI} = \mathrm{Float}\frac{(\mathrm{Band}\ 5 - \mathrm{Band}\ 4)}{(\mathrm{Band}\ 5 + \mathrm{Band}\ 4)}$$

Calculating the proportion of vegetation P *V*.

$$\mathrm{P_V} = \frac{(\mathrm{NDVI} - \mathrm{NDVI}_{\min})}{(\mathrm{NDVI}_{\max} - \mathrm{NDVI}_{\min})} \tag{9}$$

In most cases (including ArcGIS, QGIS, ENVI, and Erdas Imagine), the lowest and maximum values of the NDVI image may be seen right there in the image. If not, you must access the raster's attributes to see those values. $\mathrm{P_V} = (\mathrm{NDVI} - 0.216901)$ Calculating Emissivity $\varepsilon = 0.004 * \mathrm{PV} + 0.986$ Applying the formula in the raster calculator, the value of 0.986 corresponds to a correction value of the equation. Calculate the Land Surface Temperature

$$\mathrm{LST} = \frac{\mathrm{BT}}{1 + 0.00115 * \frac{\mathrm{BT}}{(1.4388)}} * \mathrm{Ln}\,(\varepsilon)\Bigg)\Bigg) \tag{10}$$

Finally, apply the LST equation to obtain the surface temperature map.

2.3.5. TVDI

(Temperature Vegetation Dryness Index). The relationship between the vegetation index (NDVI) and land surface temperature (LST) is explained by this method [68], expressed below.

$$\mathrm{TVDI} = \left(\frac{\mathbf{Ts} - \mathbf{Tsmin}}{\mathrm{a} + \mathrm{b}\ \mathrm{NDVI} - \mathrm{Tsmin}}\right) \tag{11}$$

(Ts, Ts min, NDVI, a, and b: Regression Constanta Ts and NDVI hot edge triangles) Land surface temperature (Ts), minimum land surface temperature (Ts), and normalized difference vegetation index (NDVI). After obtaining TVDI, divide it into five categories: no

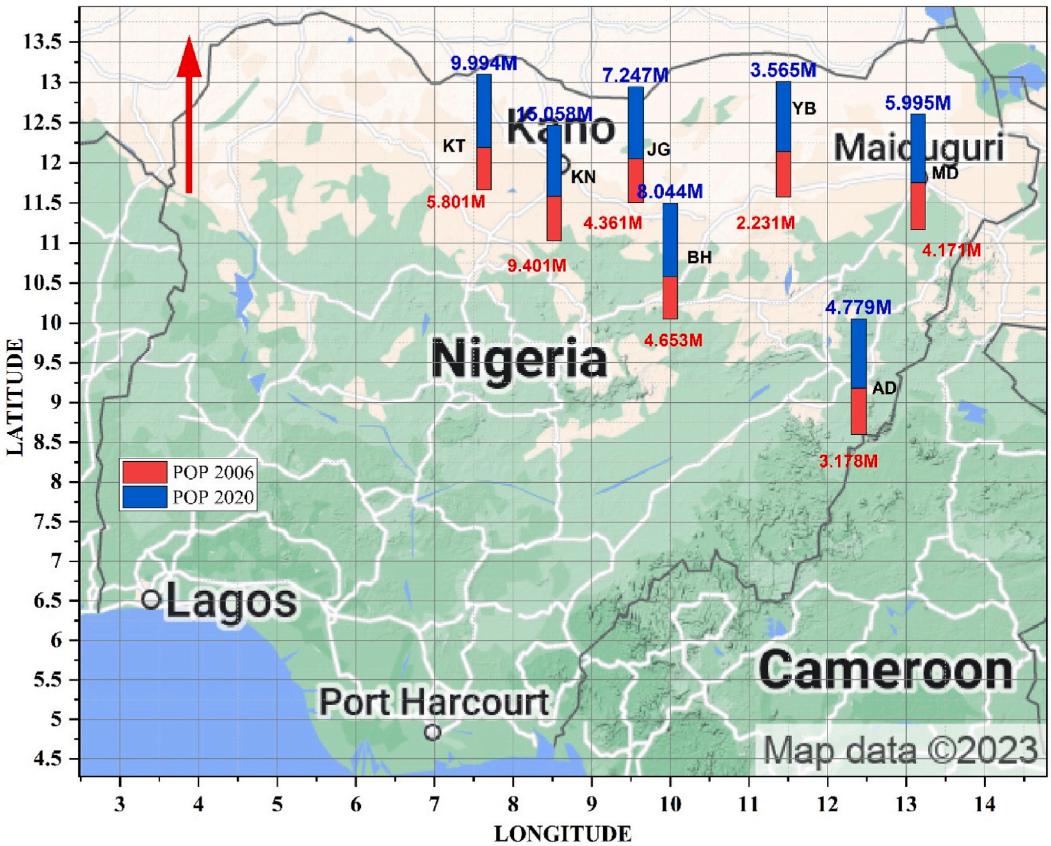

Fig. 3. Study area population projection from 2006 to 2020.

desertification (0.68–1), light desertification (0.58–0.68) and moderate desertification (0.51–0.58). Extremely severe (0–0.31) and severe (0–0.32).

2.3.6. Predicted population growth in desertification frontline states from 2006 to 2020

The cohort-component approach was used to generate population forecasts. In its most basic form, the cohort-component technique is written as:

$\mathbf{P}t + n = \mathbf{P}t + \mathbf{B}t, t + n - \mathbf{D}tn + \mathbf{M}t, t + n$ $\mathbf{P}t + n$ = the change in population that occurs from one time period to the next $\mathbf{P}t$ = population at the last census $\mathbf{B}t, t + n$ = live birth that occurred during the time interval t, t + n $\mathbf{D}t, t + n$ = death that occurred during the time interval t, t + n $\mathbf{M}t, t + n$ = net migration during the time interval t, t + n Where net migration is $\mathbf{M}t, t + n = \mathbf{I}t, t + n - \mathbf{O}t, t + n$ $\mathbf{I}t, t + n$ = in-migration during the interval $\mathbf{O}t, t + n$ = out-migration during the interval

$$\text{Population density} = \left\{ \frac{\text{total population}}{\text{total area}} \right\} \tag{12}$$

There are various population forecast methodologies. These include the bi-regional cohort-component model, a cohort component model using net migration figures, a cohort component model utilizing net migration rates, a composite net migration cohort component model merging net migration figures and net migration rates, and the Hamilton-Perry shortcut cohort model [69]. This study will use the cohort component approach to generate population forecasts based on the most recent official census data for all seven states from 2006 to 2020. The aim is to investigate the correlation between population growth and environmental pressures such as desertification. This analysis will highlight the impact of human activities and population pressure on environmental degradation and will have policy and future research implications.

3. Results and discussion

Human activity has significantly contributed to desertification in various parts of the world [70,71]. In Africa, the primary cause of desertification is the pressure of the human population, which leads to overexploitation and increased environmental strain. Over the past thirty years, the population of Africa has more than doubled to reach 708 million in 1994, growing at an annual rate of 3 %. Consequently, African farmers feed an additional 21 million people yearly, regardless of weather conditions. According to the most recent United Nations data interpreted by World Meter, Nigeria's population is alarmingly increasing, making it the most populous country in Africa and the seventh most populous worldwide. Nigeria has a population of 221,420,140 people, with a population density of 225 individuals per square kilometer (https://www.worldometers.info/world-population/nigeria-population/). In 2020, the population of Katsina state was projected to reach 9,994,288, starting from its 2006 base of 5,801,584.

Similarly, Kano, Jigawa, Borno, Adamawa, Yobe, and Bauchi states also experienced population growth during the projection period, reaching populations of 15,057,715, 7,246,906, 5,995,271, 4,778,877, 3,565,258, and 8,043,978 respectively (Fig. 3). The most noticeable population increase occurred in the northwestern states of Kano, Jigawa, and Katsina. However, population growth in the northeastern states was slightly lower than anticipated, possibly due to the impact of religious terrorism. This has resulted in the displacement of thousands of Nigerians. Boko Haram, a religious terrorist group, has caused destruction and loss of lives and rendered many people homeless [72]. The Nigerian economy relies heavily on agriculture [73]. Environmental degradation in Nigeria is diverse and unevenly distributed, including sheet erosion, mild gullies, biodiversity loss, drought, and soil degradation. These consequences can occur individually or together, impacting plant biodiversity, depleting protected areas, and reducing soil fertility [74]. Deforestation and fuel wood consumption worsen this problem in Northern Nigeria [75]. The northern region experiences aridity, drought, wind erosion, and vegetation changes, leading to visible desertification. Various agricultural regions in Nigeria exhibit extensive gully erosion and deforested land [73,76].

Deforestation, salinization, and loss of plant diversity are widespread throughout Northern Nigeria, with population growth and climate change being significant factors. As part of the Federal Government of Nigeria's efforts to protect the environment, a focus has been placed on addressing drought and desertification [77]. The research underscores Nigeria's agricultural dominance and varying degrees of environmental degradation. Northern Nigeria, characterized by aridity and prone to desertification, shows clear signs of ecological stress exacerbated by deforestation and intensive agriculture. This region is facing accelerated environmental degradation, with issues such as wind erosion and biodiversity loss. In response, the Federal Government of Nigeria has prioritized addressing drought and desertification. The study reviews government efforts and suggests enhancements within the National Policy on Environment framework. These include developing a national action program to combat desertification, raising public awareness about drought and desertification, strengthening institutional capacities, promoting sustainable agriculture and water management, encouraging community-led afforestation efforts, adopting efficient energy sources, and establishing early warning systems for drought [73].

3.1. Climatic variables

Climatic variables are essential in determining suitable habitats for species. Temperature is crucial for species' growth and survival, as each species thrives within specific temperature ranges. Precipitation, including rain and snow, is vital for maintaining soil moisture and water availability for flora and fauna. Humidity impacts species depending on their moisture requirements, while wind influences seed and pollen distribution and evaporation rates. Sunlight is vital for plant photosynthesis and affects the temperature, influencing various species. Atmospheric pressure also plays a role in shaping habitats by affecting weather patterns. These variables collectively determine the viability of habitats for different species, with changes in these factors potentially altering habitats and affecting biodiversity [78]. Climatic Variables directly influence individuals' growth, survival, reproduction, and movement, and these processes can be studied through experiments and sampling in the ocean. The combined impacts of these individual processes are observed at the population, community, or ecosystem level [79]. Climate assessments have been made in the past about the north-eastern area of Nigeria; according to a study by Ref. [3], their analysis suggests a decrease in rainfall and an increase in temperatures.

Moreover [80], propose that human activities and Climatic Variables play a role in land degradation in Northern Nigeria. This paper evaluates the study area's annual mean temperature and precipitation averages from 2003 to 2020. The analysis reveals consistently high temperatures in Kano, Katsina, and Jigawa regions. These areas recorded mean temperatures around 43 °C, with peak maximum temperatures reaching 44.05 °C in Kano, 43.6 °C in Katsina, and 44.54 °C in Jigawa. (Fig. 4).

The northeastern states, Borno, Adamawa, and Yobe, experience annual mean temperatures of 44.9 °C, 44.4 °C, and 44.2 °C, respectively. Borno recorded the highest maximum temperature mean of 45.48 °C in 2019 and 2010, while Adamawa reached its highest maximum mean temperature of 45.26 °C in 2016. Yobe State hit a maximum mean of 44.68 °C in 2010. On the other hand, Bauchi State maintains a mean annual temperature of 42.08 °C, with the highest maximum temperature at 42.76 °C in 2010. Notably, these seven desertification-affected states' annual temperatures have been persistently high for nearly a decade. This renders the study area highly vulnerable to land degradation and desertification, especially climate change.

The study area examined annual mean precipitation averages, unveiling that Kano, Katsina, and Jigawa had mean values of 631 mm, 707 mm, and 591 mm, respectively. On the flip side, the northeastern states—Borno, Adamawa, Yobe, and Bauchi—registered annual precipitations of 503 mm, 863 mm, 688 mm, and 854 mm, respectively, spanning from 2003 to 2020. (Fig. 5). A noteworthy observation is the significant increase in precipitation in the states of Kano, Katsina, Jigawa, Yobe, and Bauchi during 2020, marking an abnormal upward trend compared to the patterns observed in rainfall from 2003 to 2019. Conversely, Borno and Adamawa exhibit distinct patterns of annual rainfall distribution, particularly noticeable in 2008, 2010, and 2012, all with rainfall surpassing 800 mm per annum. Upon examining the distribution of precipitation and annual temperature in the study area, it becomes evident that 2010 recorded the highest maximum temperatures (Fig. 4) among the states while also experiencing the lowest annual rainfall (Fig. 5).

Fig. 6 illustrates changes in climatic variables, specifically rainfall, and temperature, across the study area from 2003 to 2020 for temperature and from 2003 to 2019 and 2003 to 2020 for precipitation. These changes stand out, notably the abnormal trends of increased rainfall in most states during 2020, possibly attributed to El Niño and La Niña events. El Niño and La Niña are climatic phenomena forming part of the El Niño-Southern Oscillation (ENSO) cycle, characterized by significant changes in the temperature of the Pacific Ocean [81,82]. El Niño, the warm phase, involves warming central and eastern tropical Pacific waters, leading to altered weather patterns like increased rainfall in some regions and droughts in others. In contrast, La Niña, the cool phase, is marked by the cooling of these ocean waters, resulting in weather effects opposite to those of El Niño, such as wetter conditions in Southeast Asia and drier weather in the southern United States. These phenomena occur irregularly, usually every two to seven years, and can significantly impact global climate, influencing precipitation, temperature, and storm patterns worldwide. According to Ref. [81], El Niño events

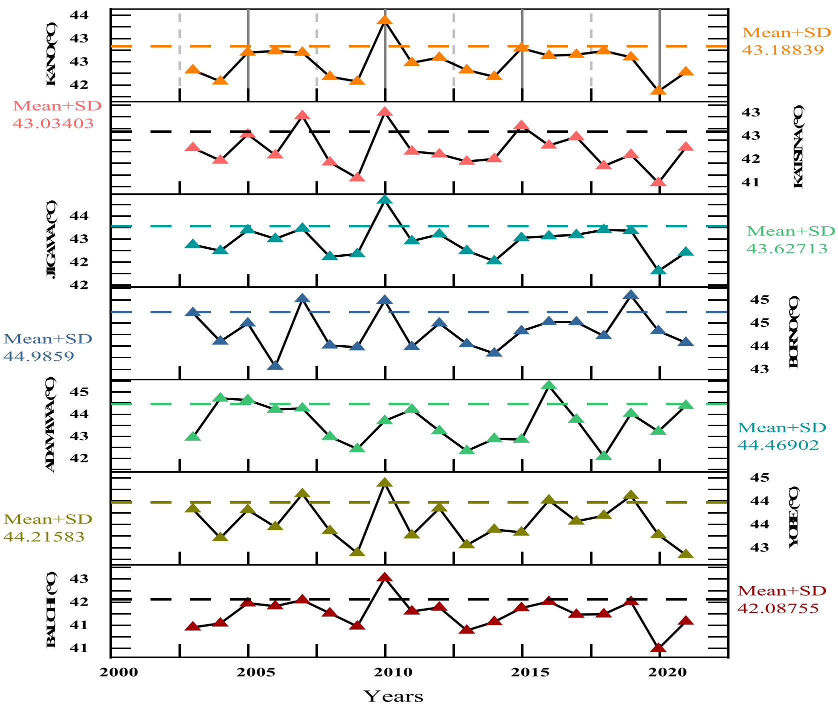

Fig. 4. Inter-annual temperature distribution of desertification frontline states from 2003 to 2020.

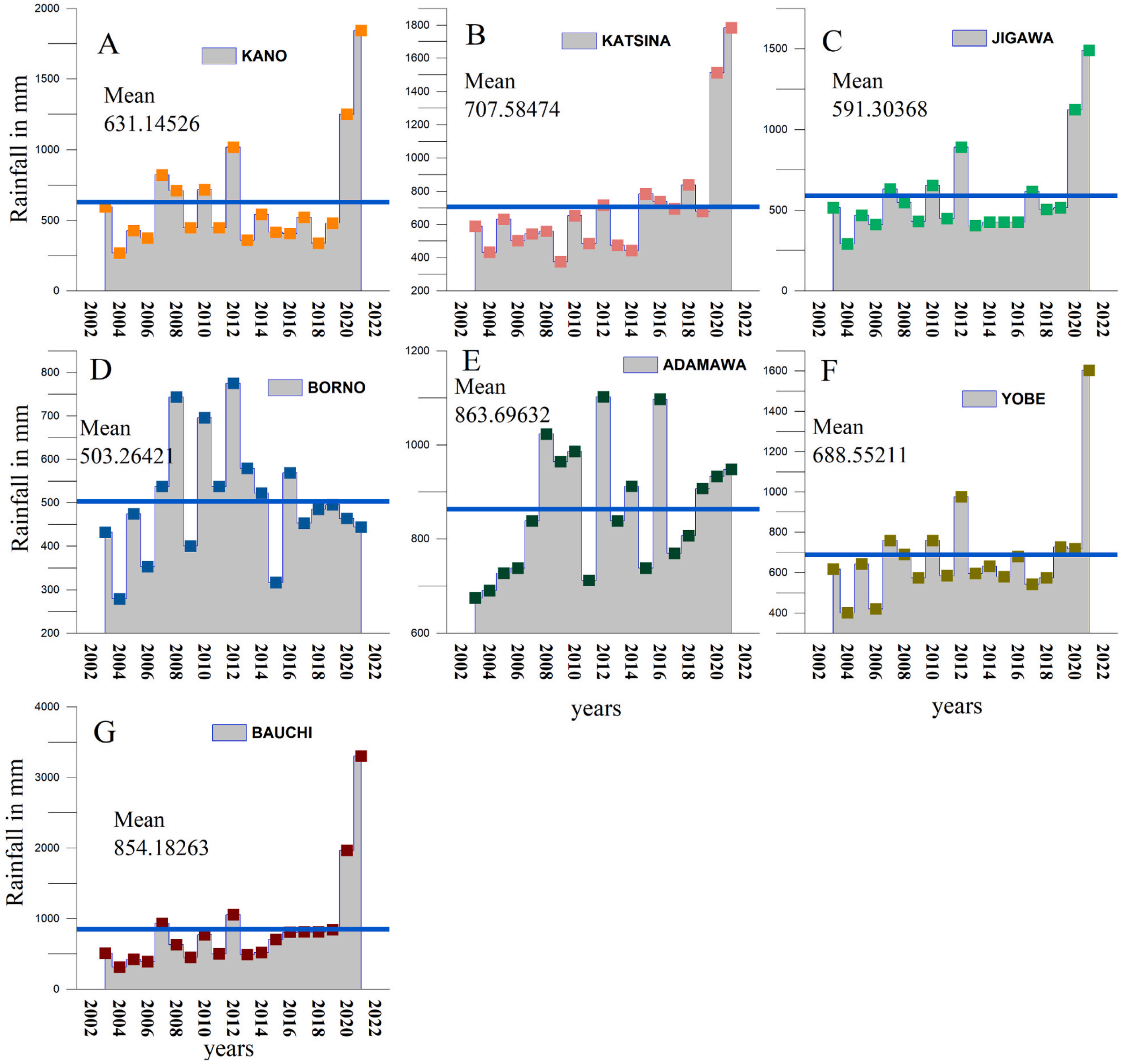

Fig. 5. Inter-annual rainfall distribution of desertification frontline states from 2003 to 2020 a)Kano b)Katsina c)Jigawa d)Borno e) Adamawa f) Yobe g)Bauchi.

occur every few years, It's crucial to note that these events don't follow a regular occurrence, with El Niño happening more frequently than La Niña. In Fig. 6, the orange bar represents the mean temperature changes of the states from 2003 to 2020, the blue bar indicates the first precipitation trends from 2003 to 2019, and the green curve represents the second precipitation changes from 2003 to 2020. As observed, the pattern of rainfall changes demonstrates an increasing trend, especially after incorporating the subsequent year of 2020, as indicated in (Table 1) below.

3.2. Land use land cover change (LUCC)

The analysis of land cover statistics highlights the prevalence of croplands in the desertification frontline states from 2003 to 2020 (Fig. 7&8). provide land cover maps of the desertification frontline states from 2003 to 2020. Table S1 provides information on the spatial distribution of land cover in the northern frontier states during this period. The findings reveal a decrease in barren area from 247.23414 km^2 in 2003 to 241.469386 km^2 in 2020. Similarly, water bodies experienced a reduction in coverage from 92.473607 km^2 in 2003 to 86.162107 km^2. In contrast, cropland coverage increased from 128628.9338 km^2 in 2003–131230.4984 km^2 in 2020, and urban areas expanded from 794.604644 km^2 to 890.979524 km^2. Additionally, croplands and natural vegetation coverage rose from

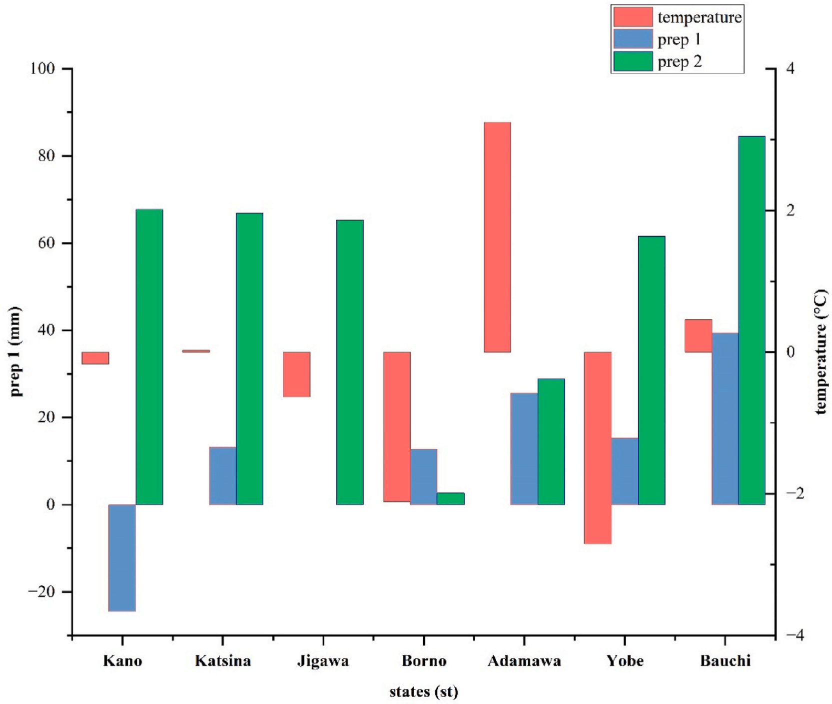

Fig. 6. changes in climatic parameters in the study area 2003–2020.

Table 1
Decadal precipitation and temperature change over the study area from 2003 to 2020 (Rainfall in mm).

Decadal temp change from 2003 to 2020 and precipitation change from 2003 to 2019 & 2003–2020			
States	Temperature	Rainfall (A)	Rainfall (B)
Kano	−0.1654	−24.436	67.73
Katsina	0.0235	13.178	66.9
Jigawa	−0.6333	0	65.302
Borno	−2.113	12.765	2.66
Adamawa	3.245	25.603	28.835
Yobe	−2.705	15.217	61.49
Bauchi	0.459	39.37	84.519

3968.437259 km^2 in 2003–6255.744018 km^2 in 2020. However, grasslands decreased from 126410.7129 km^2 in 2003–120330.4585 km^2, and permanent wetlands also experienced a reduction from 15.936525 km^2 in 2003 to 10.622056 km^2 in 2020 (see Fig. 8).

In this paper, thirteen land use classification classes are analyzed. However, the primary focus is observing the changes in the classes mentioned above. This information is of utmost significance for policymakers and various government agencies involved in monitoring ecological restoration and implementing measures to mitigate desertification in the frontline states of Northern Nigeria. The current situation of these states is crucial for understanding the progress made and the effectiveness of desertification mitigation efforts. Detailed information regarding these changes can be found in (Table 2).

3.3. Desertification indices assessment

In assessing desertification vulnerability in Northern Nigeria, the choice of specific parameters—such as NDVI (Normalized Difference Vegetation Index), LST (Land Surface Temperature), TVDI (Temperature-Vegetation Dryness Index), MSAVI (Modified Soil-Adjusted Vegetation Index), and Albedo—was grounded in well-established scientific principles and previous research findings. NDVI, a widely recognized remote sensing index, was selected to measure changes in vegetation cover and health due to its sensitivity to variations in plant biomass and greenness [83–85]. A lower NDVI value typically indicates reduced vegetation cover, a key indicator of desertification. LST and TVDI are essential in desertification assessment, providing critical information on land surface temperature and moisture conditions. High LST and low TVDI values often correlate with arid or degraded land, which is characteristic of desertification [86–88]. MSAVI, a modification of NDVI, is more robust in quantifying vegetation cover in regions with high soil brightness and arid conditions [89,90]. Its application in desertification studies helps mitigate the limitations of traditional NDVI in

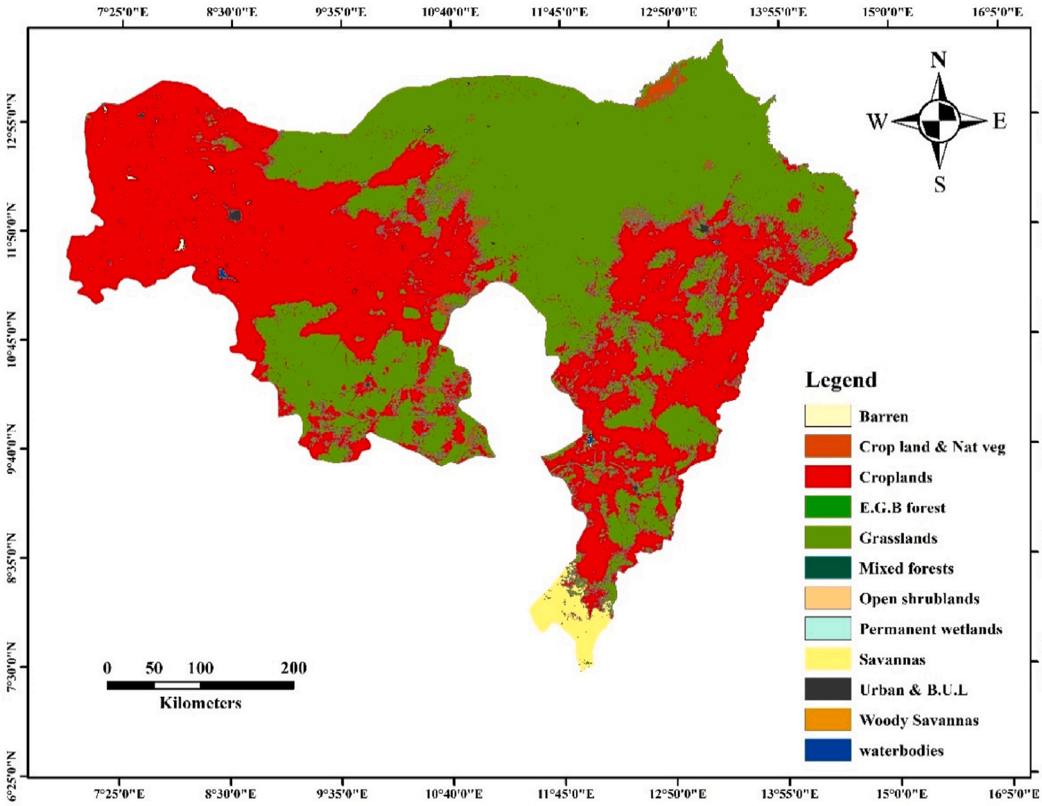

Fig. 7. Land use land classification change of the study area 2003.

such environments. Albedo, representing surface reflectivity, is a valuable indicator of land surface changes. Higher albedo values can indicate the presence of bare or degraded soil, a significant component of desertification [91–93]. These parameters have been extensively used in previous studies on desertification monitoring. They are recognized for their effectiveness in capturing changes in vegetation, land surface temperature, and land cover, which are critical indicators of desertification processes in various ecosystems [38,43]. By employing this set of parameters, we aimed to provide a comprehensive and robust assessment of desertification vulnerability in Northern Nigeria, ensuring the research's rigor and comparability with previous studies."

3.3.1. Land surface temperature

Land surface temperature (LST) refers to the radiative skin temperature of the land, which is determined by the absorption and emission of solar radiation. It measures the thermal radiance emitted by the land surface, where solar energy interacts with and warms the ground or the surface of vegetated areas. LST represents a combination of temperatures from both vegetation and bare soil. This characteristic of LST makes it a valuable indicator for studying energy partitioning at the boundary between the land surface and the atmosphere, and it is highly responsive to changes in surface conditions. Studies such as [94,95] have recognized the significance of LST in understanding and monitoring these dynamics. Based on the land surface temperature map, Katsina state exhibits a moderate level of desertification, with temperature values ranging from (308–308). In contrast, the outskirts of Kano state reveal a highly severe degree of desertification, with temperature values ranging from (309–310). It's crucial to note that the extreme ends of Kano, particularly the Folgore forest area, pose no significant threat of desertification, with temperature values ranging from (297–304) and (305–307). However, most of the state experiences severe desertification, potentially attributed to urban heat island effects stemming from population congestion and motor vehicle emissions [96].

Katsina state, positioned to the left of Kano, shows moderate and light desertification vulnerability with temperature values ranging from (305–307) and (308–308), respectively. Jigawa, situated on the right of Kano, exhibits severe vulnerability in approximately 60–75 % of the state (309–310). However, some of Jigawa's fringes face no desertification threats, with temperature values ranging from (297–304) and moving to the northeastern states, Yobe, Borno, Adamawa, and Bauchi present varying degrees of desertification vulnerability. Yobe state, adjacent to Borno on the right, experiences severe desertification in approximately one-third of its area, possibly due to moving dunes in the Yusufari local government area [3].

Neighboring Yobe, Borno state exhibits severe (309–310) and very powerful (311–313) degrees of desertification. Southward, Adamawa has variable levels of sensitivity to desertification, from negligible to extreme (297–313). Notably, the land surface temperature map (Fig. S1) reveals a gradual transition from the darkest green color at the extreme tail of Adamawa to light desertification, possibly influenced by climate change and human activities. Positioned between the northeastern and northwestern states, Bauchi

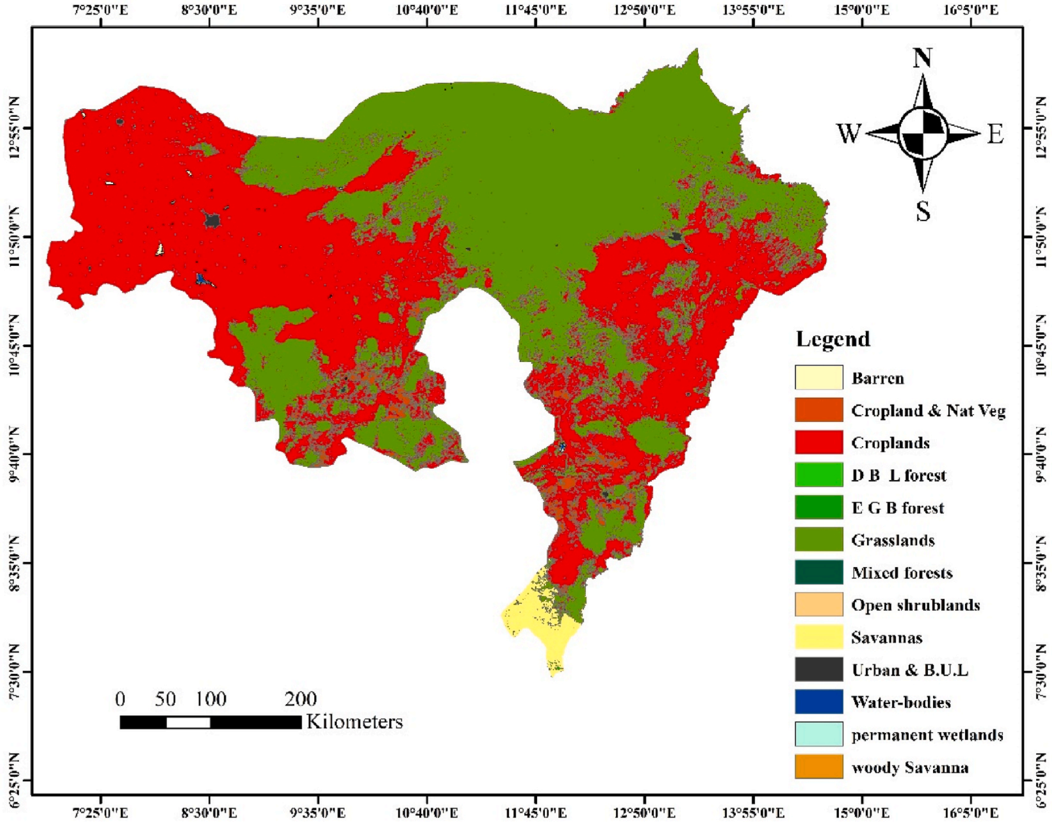

Fig. 8. Land use land classification change of the study area 2020.

Table 2
Spatiotemporal land use land classification of the desertification frontline states from 2003 to 2021.

S/N	Area (sq. km)	Class_2003	Area (sq. km)	Class_2020	2003–2020	Change Area (sq. km) 2003–2020
1	14.847499	E G B Forest	48.117041	E G B forest	E G B forest	−33.2695
2	0.246342	D B L Forest	26.53121	D B L forest	D B L forest	−26.2849
3	0.336831	Mixed Forest	6.92481	Mixed forests	Mixed forests	−6.58798
4	19.061747	Open shrub land	15.300576	Open shrub lands	Open shrub lands	3.761171
5	2.430846	Woody Savannah	19.107059	woody Savanna	woody Savanna	−16.6762
6	4195.803255	Savannah	4114.878425	Savannah	Savannah	80.92483
7	126410.7129	Grasslands	120330.4585	Grasslands	Grasslands	6080.254
8	15.936525	Permanent wetland	10.622056	permanent wetlands	permanent wetlands	5.314469
9	128628.9338	Croplands	131230.4984	Croplands	Croplands	−2601.56
10	794.604644	urban and B.U.L	890.979524	Urban & B.U.L	Urban & B.U.L	−96.3749
11	3968.437259	cropland & Nat. veg	6255.744018	cropland & Nat. veg	cropland & Nat. veg	−2287.31
12	247.23414	Barren	241.469386	Barren	Barren	5.764754
13	92.473607	water bodies	86.162107	Water-bodies	Water-bodies	6.3115

state is influenced by desertification vulnerability. Areas previously classified as light desertification gradually transition to moderate and severe degrees (309–313). Although Bauchi may be considered the least affected among the northeastern states, significant vegetation loss has been reported due to deforestation and climate factors [97].

(Fig. S2) illustrates improvements at the extreme ends of Katsina, Kano, and Bauchi states, transitioning from a moderate rate of desertification to the light desertification stage. Moving to the northeastern part of Adamawa state, it's observed that areas classified as light desertification in 2003 have progressed to moderate desertification, with temperature values ranging from (305–308) (Figs. S1 and S2). collectively indicate that only 6 % of the study area is not vulnerable to desertification. Approximately 13 % of the area is classified as having light vulnerability, 20 % as moderate vulnerability, 26 % as severe vulnerability, and 33 % as very severe vulnerability to desertification. These observations provide valuable insights into the extent and distribution of desertification vulnerability across the study area.

3.3.2. The Modified Soil Adjusted Vegetation Index

(MSAVI) is particularly useful when other vegetation indices may not provide accurate information about the extent of vegetation cover in a region. Its value ranges from (−1 to 1), with specific ranges indicating different stages of vegetation development. For instance, values from (−1 to 0.2) indicate bare soil, while values between (0.2 and 0.4) suggest the seed germination stage. The range of (0.4–0.6) corresponds to the leaf development stage. When the number surpasses 0.6, the Normalized Difference Vegetation Index (NDVI) should be used instead, as it indicates that the vegetation is dense enough to cover the soil effectively. Understanding the MSAVI index in desertification hotspots is critical (Fig. S3). illustrates the modified soil-adjusted vegetation index, indicating elevated values (close to 1) in the northeastern states of Bauchi, certain parts of Borno, and Adamawa (ranging from 0.95 to 1).

Additionally, specific areas show values between (0.84 and 0.94). In contrast, Kano, Jigawa, Katsina, Yobe, and the upper regions of Maiduguri exhibit low MSAVI values ranging from (0.45–0.69) in 2003, and from (0–0.45). Observations in 2020 reveal an expansion of low MSAVI values in regions that previously had higher MSAVI values in 2003. This expansion is particularly noticeable in parts of Borno, Adamawa, and some areas of Bauchi, signaling a gradual shift from light desertification vulnerability to moderate vulnerability. However, the same cannot be said for the northeastern parts of Kano, Katsina, and Jigawa, where areas previously classified as having light desertification vulnerability now exhibit severe vulnerability indices ranging from (0.92–0.94 to 0.07), respectively.

3.3.3. Albedo

Albedo refers to the fraction of sunlight diffusely reflected by a surface. It is measured on a scale from 0 to 1, where 0 corresponds to a black body that absorbs all incident radiation, and 1 represents complete reflection. Surface albedo, specifically, is defined as the ratio of radiosity (Je) to the irradiance (Ee) received by a surface; both are expressed as flux per unit area [98]. Surface albedo is influenced not only by the properties of the surface itself but also by the spectral and angular distribution of solar radiation reaching the Earth's surface [99]. Various surfaces exhibit different albedo ranges. For example, fresh asphalt has an albedo of approximately 0.04, while open ocean reflects around 0.06 of incident radiation. Worn asphalt has an albedo of approximately 0.12, and conifer forests typically range from (0.08–0.15) in albedo. Deciduous forests have albedo values ranging from (0.15–0.18), while bare soil typically reflects around 0.17 of incoming radiation. Green grass has an albedo of approximately 0.25, while desert sand has a higher albedo of 0.40. New concrete surfaces have an albedo of 0.55, whereas ocean ice typically ranges from (0.50–0.70). Fresh snow has a high albedo of 0.80, and aluminum surfaces reflect approximately 0.85 incident radiation. These albedo ranges provide insights into the reflective properties of different surfaces and are important for understanding how they interact with solar radiation.

The North Western states, such as Kano, manifest high, severe, and severe desertification vulnerability indices. In Kano, the range of classes spans from no desertification (0–0.34) at the far end of the Falgore Game Reserve to very severe vulnerability (0.53–1) at the city's outskirts. Moving to Jigawa state, it is segmented into moderate (0.44–0.54), severe (0.54–0.64), and very severe (0.64–1) desertification vulnerability categories. Notably, Jigawa state is gradually evolving into one of the most severely impacted states in the North Western region. Shifting focus to Katsina state, the desertification vulnerability is delineated into three classes based on the albedo index, ranging from severe (0.44–0.54) to moderate (0.54–0.64).

Transitioning to the North Eastern states, Yobe's northernmost border region is categorized with severe desertification vulnerability (0.64–1), whereas the southern end of the state undergoes a shift from moderate to severe vulnerability (0.44–0.64). In Borno state, the uppermost part experiences a severe to very severe level of desertification (0.54–1). At the same time, the extreme tail indicates a favorable stage, ranging from no desertification to light desertification in 2003.

However, according to the albedo map (Fig. S4), a significant portion of the Sambisa Forest, where dense vegetation is located, is projected to become moderately vulnerable to desertification in 2020. This shift can be attributed to human invasion and the ongoing conflict between the Boko Haram insurgency and the Nigerian army, leading to tree destruction and an increased susceptibility to degradation.

In Adamawa, Yola shares the same albedo index as Maiduguri, but the latter has been more adversely affected by changes. Maiduguri's transitions from light vulnerability to moderate vulnerability, with values ranging from (0.44–0.62) from 2003 to 2020, likely due to various factors, including conflict and environmental stressors.

According to (Fig. S4), Bauchi state exhibits vulnerability to desertification at its uppermost boundaries, classified as severe (0.54–1) and very severe (0.53–1) in 2002 and 2020, respectively. The southern part of Bauchi displays light desertification vulnerability, gradually shifting to moderate vulnerability in 2020, with values ranging from (0.44–0.53).

3.3.4. Normalized difference vegetation index (NDVI)

The Normalized Difference Vegetation Index (NDVI) is a commonly used metric for assessing the health and density of vegetation based on sensor data. It is calculated using measurements from specific spectral bands, typically the red and near-infrared bands, obtained from remote sensing platforms such as satellites. The NDVI metric is widely adopted in various industries due to its accuracy and strong correlation with the vegetation on the ground. The interpretation of NDVI values is straightforward. The index ranges from −1 to 1, with each value representing a different condition. An NDVI value of zero indicates an area where no vegetation is present. As vegetation increases in density and health, the NDVI value gradually increases towards one.

Consequently, areas with dense and healthy vegetation will have an NDVI close to one. Conversely, NDVI values less than zero suggest the absence of vegetation or the presence of non-photosynthetic surfaces such as water bodies. In such cases, an NDVI value of −1 is typically obtained, as in the case of an ocean. In summary, the NDVI is a valuable tool for quantifying vegetation health and density using remote sensing data. Its simplicity and interpretability make it a widely accepted metric in various applications, providing insights into vegetation cover and growth. Based on (Figs. S5 and S6, Tables S1 and S2), the NDVI values in the study area depict a consistently low vegetation cover in the North Western states of Kano, Katsina, and Jigawa for both 2003 and 2020. These states exhibit severe desertification vulnerability, with NDVI values ranging from (0.51–0.31) in 2003 and (0.49–0.31) in 2020.

In contrast, the North Eastern states of Bauchi, Borno, Adamawa, and Yobe present different characteristics. In 2003, Bauchi displayed light to moderate desertification vulnerability with NDVI values ranging from (0.58–0.5)1. However, by 2020, it transitioned from severe to severe vulnerability with values ranging from (0.51–0.31). Yobe demonstrated moderate to severe desertification vulnerability in 2003 (NDVI: 0.58 to 0.51), worsening to severe in 2020 (NDVI: 0.51 to 0.31). Adamawa shifted from no desertification to light desertification in 2003 (NDVI: 1 to 0.68), progressing to moderate, severe, and severe vulnerability in 2020 (NDVI: 0.49 to 0.31). Similarly, Borno showed a transition from light to moderate desertification in 2003 (NDVI: 0.68 to 0.58), evolving into severe to very severe vulnerability in 2020 (NDVI: 0.49 to 0.31).

The severity of desertification, particularly in terms of NDVI, is evident across the study area in 2003 and 2020. Factors such as population growth, human influence, climatic conditions, and war and conflict have likely contributed to the disruption of livelihoods and sustainability in these regions. These affected areas represent a significant portion of Nigeria's landmass, where approximately 70 % of agricultural activities sustaining the nation's food production occur.

The Normalized Difference Vegetation Index (NDVI) is crucial in assessing vegetation in the study area. Satellite photos with a resolution of 500 and 1000 m were retrieved to get this data. Although there may not be significant differences to infer between the NDVI images obtained at these resolutions, the statistical analysis reveals a consistency in the results. This consistency is reflected in (Tables S1 and S2), which present comparable data for 2003 and 2020, respectively.

3.3.5. Temperature Vegetation Dryness Index (TVDI)

The Temperature Vegetation Dryness Index (TVDI) is a land surface dryness index that utilizes the relationship between Land Surface Temperature (LST) and Normalized Difference Vegetation Index (NDVI) to assess the degree of drought [100,101]. It considers the changes and interrelation between NDVI and LST, considering their combined impact on soil moisture. TVDI considers the physical mechanisms involved in water stress and employs temperature as a time-sensitive indicator of water stress. However, it acknowledges that vegetation coverage can influence temperature when using temperature alone to monitor soil moisture. By integrating vegetation indices and surface temperature, TVDI can monitor soil moisture effectively by combining information from visible, near-infrared, and thermal infrared bands. This wider range of applicability enhances its usefulness in monitoring drought conditions (Fig. S7). depicts the TVDI map of Northern Nigeria's desertification frontline states. The TVDI range is specified as [0, 1], with 1 representing the dry side and 0 representing the wet side. Higher TVDI values indicate less soil moisture, indicating a more severe drought. The compositing technique selects the best observational data for TVDI analysis, ensuring the results' correctness and reliability (Table S1).

(Fig. S7), the TVDI map offers insights into the vulnerability of various states in Northeastern Nigeria. In Bauchi state, there is a noticeable transition in the vulnerability index from moderate to severe in 2003 (TVDI: 0.83 to 1) to a range encompassing light, moderate, and severe desertification statuses in 2020 (TVDI: 0.72 to 1).

Kano state displayed moderate desertification vulnerability in 2003 (TVDI: 0.72 to 0.93) and shifted to a combination of moderate, light, and severe vulnerability in 2020 (TVDI: 0.83 to 1). The exacerbation of TVDI vulnerability in 2020 can be attributed to widespread urbanization in the state, involving clearing vegetation and economic trees [37].

Jigawa state exhibited a range of moderate to very severe vulnerability in 2003 (TVDI: 0.72 to 1) but shifted to light and moderate vulnerability in 2020 (TVDI: 0.67 to 0.8). The improvement in the vulnerability index may be influenced by the occurrence of flooding in the area, as flooding can lead to the growth of vegetation such as grasses and shrubs.

Katsina state displayed light to moderate vulnerability in 2003 (TVDI: 0.72 to 0.83) and 2020 (TVDI: 0.67 to 0.8). While the vulnerability classes remained the same, the intensity of vulnerability was more pronounced in 2020, as indicated in (Table S2).

In Yobe state, there was a severe degree of vulnerability in 2003 (TVDI: 0.94 to 1), and in 2020, some parts of the state transitioned from moderate to severe vulnerability (TVDI: 0.8 to 0.92).

Borno state exhibited a high degree of vulnerability in 2003 (TVDI: 0.93 to 1), and by 2020, certain areas shifted from moderate to severe-to-very severe vulnerability (TVDI: 0.8 to 1).

In Adamawa state, severe vulnerability was evident in 2003, with the extreme tail showing a range from no desertification to light desertification (TVDI: 0.48 to 0.67). In 2020, an improvement is anticipated in the central part of the state, transitioning from a very severe to a severe degree of desertification vulnerability.

Based on the Temperature Vegetation Dryness Index (TVDI) analysis, it is observed that Adamawa state is the only state among the seven to encompass all five classes of the desertification vulnerability index. However, the proportions of no desertification and light desertification are relatively low compared to the remaining three classes, which range from moderate to severe vulnerability.

3.4. LST and NDVI regression

The correlation between NDVI and LST in the study area is illustrated in (Fig. S8 for 2003 &Fig. S9) for 2020. These figures unveil an inverse relationship between LST and NDVI. Notably, various studies, including those conducted by Refs. [102–104], have also observed and reported similar inverse correlations between LST and NDVI. The relationship between NDVI and LST in the study area is influenced by various factors such as rainfall, temperature, and vegetation cover. In regions with low mean annual rainfall of 600 mm, specifically in Kano, Katsina, and Jigawa, as shown in (Fig. 5), the peak value of the dry edge is observed in areas with bare soil. This means that these regions have limited vegetation cover. As the NDVI value increases and approaches 1, indicating higher vegetation density, the peak value of the dry edge reduces. This can be attributed to the higher evapotranspiration rate [100] where vegetation extracts moisture from the soil and releases it into the atmosphere through transpiration. This process helps to cool the surface and reduces the temperature, resulting in lower LST values. Overall, the combination of low mean annual rainfall, high temperatures, and limited vegetation cover in Kano, Katsina, and Jigawa regions contributes to higher LST values and a dry edge in the NDVI-LST relationship. The fitted curve in (Fig. S9), which represents the relationship between NDVI and land surface temperature (LST), may not be directly interpretable without the corresponding rainfall and temperature data in 2020. However, some inferences can be made from the graph by referring to the land surface temperature data (Fig. S1 & Fig. S9). It can be observed that NDVI is inversely correlated with land surface temperature, meaning that areas with lower vegetation cover tend to have higher temperatures, as indicated by the peak of the dry edge. As the edge's declines, indicating a decrease in land surface temperature, the NDVI value increases. This trend is particularly notable in some extreme ends of Adamawa, certain parts of Katsina, and select regions in Bauchi and Jigawa. The uneven characteristics of rainfall in the study area contribute to these variations. Even within the same states, different regions receive varying levels of precipitation. This variability in rainfall distribution affects water availability for vegetation growth and ultimately impacts the NDVI-LST relationship. The study by Ref. [105]. It provides insights into the uneven patterns of rainfall in the study area.

4. Discussions

4.1. Population growth and desertification

The study's findings emphasize the connection between population growth and desertification, specifically in Northern Nigeria's northwestern and northeastern states. This region is known for its dry and arid climate and has experienced significant demographic changes in recent decades. The data indicates a substantial increase in population in states like Katsina, Kano, and Jigawa. For example, Katsina's population was projected to reach nearly 10 million by 2020, a significant increase from its 2006 levels. This rapid population growth, particularly in urban areas, has put significant pressure on the natural environment. It has resulted in increased land exploitation for agricultural and urban development purposes. These human activities have, in turn, intensified land degradation and desertification. As shown by the land use change data, the expansion of croplands and urban areas indicates a significant alteration of the natural landscape, often at the expense of vegetation cover and water bodies. Furthermore, the study's analysis reveals that the northwestern states have shown more resilience despite their population growth than the northeastern states. In the northeastern states, the impact of religious terrorism, particularly by Boko Haram, has caused displacement and added environmental stress. This unrest has not only disrupted socio-economic activities but has also contributed to environmental degradation, as displaced populations often resort to unsustainable practices such as deforestation for fuel and shelter. The situation in the northeastern states is particularly alarming. The displacement of populations due to conflict, combined with the existing challenges of aridity and limited water resources, increases the vulnerability of these areas to desertification. The destruction and abandonment of agricultural lands and the loss of biodiversity and vegetation cover worsen the situation, creating a vicious cycle of degradation, poverty, and instability.

4.2. Land use changes

Based on an analysis of land use and land cover changes in the desertification frontline states of Northern Nigeria from 2003 to 2020, this study reveals important environmental transformations. Barren lands decreased from 247.23414 km^2 in 2003 to 241.469386 km^2 in 2020, while water bodies decreased from 92.473607 km^2 to 86.162107 km^2. On the other hand, there was a significant increase in croplands, expanding from 128628.9338 km^2 to 131230.4984 km^2, and urban areas, growing from 794.604644 km^2 to 890.979524 km^2. These land use changes are significant because they directly impact the region's vulnerability to desertification. The reduction in barren lands and water bodies, coupled with the increase in agricultural and urban areas, suggests a shift in land management practices driven by population growth and economic development. However, these shifts can lead to environmental degradation, including soil erosion, loss of biodiversity, and changes in hydrological cycles, all of which worsen the desertification process.

4.3. Comparison with previous studies

The findings indicate substantial changes in land cover within the northern boundary states of Nigeria during the two decades from 2003 to 2020. This research focused on this specific time frame to observe the population increase from 2006 to 2020. Although the official census took place in 2006, the research chose to project the population increase from 2006 to 2020 due to the rapid population growth observed in the study area, as supported by Refs. [88,106]. Furthermore, the deforestation of economically valuable trees and disturbances in the ecosystem resulted in reduced agricultural output, attributed to conflicts between insurgents and the Nigerian Army. This impact was observed through changes in NDVI and LST across areas such as the Sambisa forest in Maiduguri and Yankari Game Reserve in Bauchi, as documented by Refs. [107–109]Additionally, several articles have highlighted the shrinking of Lake Chad, a water source supporting around 50 million people across multiple countries, including Nigeria, Niger, Cameroon, and Chad [85]. As reported by Refs. [85,110], the reduction of the lake's size has exacerbated water-related crises. This aligns with the findings of our study, particularly in terms of land use and land cover (LUCC) spatial-temporal trends from 2003 to 2020. The study's results demonstrated an increase in temperature (Fig. 4), an uptick in Land Surface Temperature (LST) (see Figs. S1 and S2), and a decrease in vegetation cover over the two-decade period. These findings are consistent with prior research, including studies by Refs. [85,111–113], which have indicated the adverse effects of drought on farmers in the desertification frontline states of Bauchi, Yobe, Gombe, Adamawa, and Borno.

This analysis conducted in the present study is in line with the findings of [114], Who assessed the effects of desertification in Yobe

State. Jibril's assessment highlighted the severity of bare lands in Yobe, which aligns with the results obtained in this analysis. Yobe state is the worst affected among the seven states when considering various indices derived from LST, NDVI, TVDI, MSAVI, and NDVI. The consistency between the findings of this study and Jibril's assessment further strengthens the understanding of the extent and severity of desertification in Yobe state. According to Ref. [39], who conducted a desertification risk analysis and assessment in northern Nigeria, Bauchi state, in particular, was categorized based on its aridity index as having low, moderate, high, and very high desertification risk. The study revealed that there has been an increase in desertification risk, especially in areas that initially had low risk, such as southern Bauchi. It is concerning to note that areas with previously low risk were observed to have deteriorated and now exhibit high or very high-risk levels.

Additionally [97], highlighted the detrimental effects of deforestation in Bauchi state. This aligns with the findings from our NDVI analysis (Fig. S5, 500 m) and (Fig. S6, 1000 m), indicating a vegetation cover deterioration in Bauchi state from 2003 to 2020. These observations further support the notion of increased desertification and the need for effective measures to mitigate the negative impacts on the environment in Bauchi state. In the study conducted by Ref. [115], an assessment of drought and desertification in the Nigerian environment revealed that a significant portion of the country's land area is affected by desertification. Specifically, out of the total land area, approximately 909,890 km^2, about 580,841 km^2 (63.83 %) is impacted by desertification. The study identified climatic variability and anthropogenic activities, such as deforestation, extensive cultivation, overgrazing, cultivation of marginal land, bush burning, fuel wood extraction, faulty irrigation systems, and urbanization, as major causes of desertification. These findings align with the current analysis, as it was observed that only a small percentage (6.7 %) of the study area is not vulnerable to desertification. Furthermore, 13.3 % of the area exhibits light vulnerability, 20 % has moderate vulnerability, and a significant proportion of 26.7 % and 33.3 % falls into the categories of severe and very severe vulnerability, respectively. This emphasizes the severity of desertification in the study area and the urgent need for effective measures to mitigate its impact.

4.4. *Future prospective*

Given the extensive research on land use changes and desertification in Northern Nigeria, future research should prioritize exploring the relationship between demographic trends, climate variability, and land use practices. It is of utmost importance to thoroughly examine the long-term effects of these changes on local ecosystems and communities. Advanced remote sensing and GIS technologies are recommended to ensure accurate monitoring and predictive modeling of desertification processes. It is also crucial to engage in multidisciplinary research that integrates socio-economic factors, local knowledge, and environmental data to develop effective and sustainable land management strategies. Furthermore, the effectiveness of current policies and interventions in mitigating desertification and promoting sustainable land use should be thoroughly investigated. To enhance resilience to desertification while simultaneously ensuring food security and economic development, additional research can explore innovative solutions, such as climate-smart agricultural practices. It is crucial to adopt a holistic approach that improves our understanding of desertification dynamics in the region and contributes significantly to global efforts in combatting land degradation and promoting environmental sustainability.

5. Conclusions

A study on desertification in Northern Nigeria's frontline states from 2003 to 2020 found that only 6.7 % of the region remains unaffected by desertification. An additional 13.3 % is mildly vulnerable, 20 % are moderately vulnerable, and 60 % experience severe (26.7 %) to severe (33.3 %) vulnerability. This situation is largely due to the rapid population growth during this period, which has led to deforestation, urban expansion, increased carbon emissions, and urban heat island effects. These human activities are major contributors to land degradation in the area. The resulting environmental impacts include reduced vegetation, expanded croplands, diminished water bodies, and ongoing conflicts, particularly in the Northeast. This environmental deterioration is causing a decline in agriculture, a crucial sector for the region's economy, and increasing aridity and land scarcity, threatening food security. Additionally, dwindling water resources are worsening scarcity issues and putting immense pressure on local communities. The study acknowledges its limitations, particularly regarding data availability and quality, which could introduce uncertainties. Inherent in remote sensing and modeling approaches, these constraints may not fully capture the complex realities of desertification processes on the ground. Therefore, the study emphasizes the importance of ongoing research efforts to improve understanding of desertification dynamics and develop more reliable assessment tools and strategies for sustainable land use in Northern Nigeria.

Data availability

Data Availability Statement.
Has data associated with your study been deposited into a publicly available repository?
No.
Data included in article/supplementary material/referenced in article.

CRediT authorship contribution statement

Ibrahim I. Yahaya: Writing – original draft, Supervision, Software, Methodology, Investigation, Conceptualization. **Yongdong Wang:** Project administration, Funding acquisition, Data curation. **Zhijie Zhang:** Investigation. **Abubakar Y. Inuwa:** Investigation.

Yazhou Zhao: Data curation. **Yuan You:** Formal analysis. **Hamisu A. Basiru:** Investigation. **Friday Uchenna Ochege:** Investigation. **Zhou Na:** Formal analysis. **Chukwuka P. Ogbue:** Investigation, Formal analysis. **Murad Muhammad:** Data curation. **Yeneayehu F. Mihertu:** Investigation. **Isah A. Tanko:** Formal analysis, Data curation. **Waseem Shoukat:** Writing – original draft, Formal analysis.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:Ibrahim Inuwa Yahaya reports financial support was provided by Xinjiang Institute of Ecology and Geography. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The authors wish to thank the Integration and application of appropriate technologies for desertification control in Africa (Grant No. SAJC202108) and the key technical talent project of the Chinese Academy of Sciences (Research on desertification technology along the "Belt and Road") for financial support to do this paper. We also thank the support of the "Tianchi doctor program" of Xinjiang Uygur Autonomous Region in 2020.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2024.e31167.

References

[1] J. Huang, G. Zhang, Y. Zhang, X. Guan, Y. Wei, R. Guo, Global desertification vulnerability to climate change and human activities, L. Degrad. Dev. 31 (11) (2020) 1380–1391, https://doi.org/10.1002/ldr.3556.
[2] H., P. Yu, D. Han, S. Liu, X. Wen, Y. Huang, Jia, Soil quality assessment under different land uses in an alpine grassland, Catena 171 (2018) 208–287.
[3] E.S. Ibrahim, et al., Desertification in the Sahel region: a product of climate change or human activities? A case of desert encroachment monitoring in north-eastern Nigeria using remote sensing techniques, Geographies 2 (2) (2022) 204–226, https://doi.org/10.3390/geographies2020015.
[5] J. Huang, et al., Dryland climate change: recent progress and challenges, Rev. Geophys. 55 (3) (2017) 719–778, https://doi.org/10.1002/2016RG000550.
[6] C.A. Karavitis, et al., A desertification risk assessment decision support tool (DRAST), Catena 187 (June 2019) (2020) 104413, https://doi.org/10.1016/j.catena.2019.104413.
[7] H. Briassoulis, Combating Land Degradation and Desertification : the Land-Use Planning Quandary, 2019, pp. 1–26, https://doi.org/10.3390/land8020027.
[8] S. Wijitkosum, The impact of land use and spatial changes on deserti fi cation risk in degraded areas in Thailand, Sustain. Environ. Res. 26 (2) (2016) 84–92, https://doi.org/10.1016/j.serj.2015.11.004.
[9] P. D'Odorico, A. Bhattachan, K.F. Davis, S. Ravi, C.W. Runyan, Global desertification: drivers and feedbacks, Adv. Water Resour. 51 (2013) 326–344, https://doi.org/10.1016/j.advwatres.2012.01.013.
[10] MEA, Millennium Ecosystem Assessment, Ecosystems and Human Well- Being: Desertification Synthesis, World Resour. Institute, Washington DC, 2005.
[11] S. Un, The assessment of global trends in land degradation. In: Sivakumar RVK, Ndiang'ui N, editors. Climate and land degradation. Berlin Heidelberg: Springer-Verlag (2007) 1–38.
[12] E. Lepers, A. Janetos, R.S. Defries, A synthesis of information on rapid land-cover change for the period 1981 – 2000 3568 (February) (2005), https://doi.org/10.1641/0006-3568(2005)055.
[14] H. Jackson, S.D. Prince, Degradation of net primary production in a semiarid rangeland, Biogeosciences 13 (16) (2016) 4721–4734, https://doi.org/10.5194/bg-13-4721-2016.
[15] F. Qian, D. Lee, G. Nikolich, D. Koditschek, Rapid in-situ characterization of soil erodibility with a field deployable robot © 2018 American Geophysical Union . All rights reserved (2019) 1–22, https://doi.org/10.1029/2018JF004887.
[16] UNCCD, Neutralidad de la Degradación de las Tierras Programa de Establecimiento de Metas Establecimiento de metas para la neutralidad de la degradación de las tierras Guía técnica, 2016.
[17] P.H. Verburg, B. Eickhout, H. Van Meijl, A Multi-Scale , Multi-Model Approach for Analyzing the Future Dynamics of European Land Use, February 2008, 2014, https://doi.org/10.1007/s00168-007-0136-4.
[18] A. Veldkamp, E.F. Lambin, Predicting land-use change, Agric. Ecosyst. Environ. 85 (1) (2001) 1–6, https://doi.org/10.1016/S0167-8809(01)00199-2.
[19] P.H. Verburg, J.R.R. van Eck, T.C.M. de Nijs, M.J. Dijst, P. Schot, Determinants of land-use change patterns in The Netherlands, Environ. Plan. B Plan. Des. 31 (1) (2004) 125–150, https://doi.org/10.1068/b307.
[20] M. Gabriele, R. Brumana, M. Previtali, A. Cazzani, A combined GIS and remote sensing approach for monitoring climate change-related land degradation to support landscape preservation and planning tools: the Basilicata case study, Appl. Geomatics 15 (3) (2023) 497–532, https://doi.org/10.1007/s12518-022-00437-z.
[21] S. Wijitkosum, E Nvironment A Sia, July 2014, 2016, https://doi.org/10.14456/ea.2014.35.
[22] K. WijitkosumS, L. Kroutnoi, Yolpramote, Factors affecting the desertification in Huay Sai royal development study center, Thailand, J. Environ. Res. Dev. 7 (4) (2013) 1439.
[23] U. (2016). UNEP, WMO, Global Assessment of Sand and Dust Storms. United Nations Environment Programme, United Nations Environment Programme (UNEP), Nairobi, 2016.
[24] S. Wijitkosum, Reducing Vulnerability to Desertification by Using the Spatial Measures in a Degraded Area in Thailand, 2020.
[25] M.A.E. Abdelrahman, An overview of land degradation , desertification and sustainable land management using GIS and remote sensing applications, Springer International Publishing 34 (3) (2023), https://doi.org/10.1007/s12210-023-01155-3.
[26] P.F. Eswaran, H. Lal, R, Reich, Land degradation: an overview. Responses to land degradation, in: Proceedings of the 2nd International Conference on Land Degradation and Desertification, Khon Kaen, Oxford Press, New Delhi., 2001.
[27] S. Chakravarty, S. K, C, P, N. A, G. Shukl, Deforestation: causes, effects and control strategies, Glob. Perspect. Sustain. For. Manag. (2012), https://doi.org/10.5772/33342.

[28] W. Maetens, J. Poesen, M. Vanmaercke, How effective are soil conservation techniques in reducing plot runoff and soil loss in Europe and the Mediterranean? Earth-Science Rev. 115 (1–2) (2012) 21–36, https://doi.org/10.1016/j.earscirev.2012.08.003.
[29] B.T. Bestelmeyer, et al., Desertification , land use , and the transformation of global drylands in a nutshell, Safriel 2007 (2015) 28–36, https://doi.org/10.1890/140162.
[30] L. Cui, J. Shi, Urbanization and its environmental effects in Shanghai, China, Urban Clim. 2 (2012) 1–15, https://doi.org/10.1016/j.uclim.2012.10.008.
[32] Y. Tan, H. Xu, X. Zhang, Sustainable urbanization in China: a comprehensive literature review, Cities 55 (2016) 82–93, https://doi.org/10.1016/j.cities.2016.04.002.
[33] J. Baartman, G. Van Lynden, M.S. Reed, C.J. Ritsema, DESIRE REPORT Series Desertification and Land Degradation : Origins , Processes and Solutions, 2007. November.
[34] M.A. Falaki, H.T. Ahmed, B. Akpu, Predictive modeling of desertification in jibia local government area of Katsina state, Nigeria, Egypt. J. Remote Sens. Sp. Sci. 23 (3) (2020) 363–370, https://doi.org/10.1016/j.ejrs.2020.04.001.
[35] O. Adedeji, et al., Early warning systems development for agricultural drought assessment in Nigeria, Environ. Monit. Assess. 192 (12) (2020), https://doi.org/10.1007/s10661-020-08730-3.
[36] N.M. Gadzama, H.K. Ayuba, On major environmental problem of desertification in Northern Nigeria with sustainable efforts to managing it, World J. Sci. Technol. Sustain. Dev. 13 (1) (Jan. 2016) 18–30, https://doi.org/10.1108/WJSTSD-06-2015-0035.
[37] I. L, I.Y. Ibrahim, Y.D. Wang, N. Zhou, B.M. Ibrahim, D.D. Umar, Y. You, & nasir, "assessment of remote sensing on deforestation of economic tree species in wudil, Kano state, Nigeria.,", Appl. Ecol. Environ. Res. 21 (5) (2023) 4445–4474, https://doi.org/10.15666/aeer/2105_44454474.
[38] O.Y. Ekundayo, E.C. Okogbue, F.O. Akinluyi, A.M. Kalumba, I.R. Orimoloye, Spatiotemporal drought assessment using vegetation health index and standardized precipitation index over Sudano-Sahelian region of Nigeria, African Geogr. Rev. 40 (4) (2021) 412–424, https://doi.org/10.1080/19376812.2020.1841658.
[39] O. Joseph, A.E. Gbenga, D.G. Langyit, Desertification risk analysis and assessment in Northern Nigeria, Remote Sens. Appl. Soc. Environ. 11 (2018) 70–82, https://doi.org/10.1016/j.rsase.2018.04.012.
[40] P.C. Nwilo, D.N. Olayinka, C.J. Okolie, E.I. Emmanuel, M.J. Orji, O.E. Daramola, Impacts of land cover changes on desertification in northern Nigeria and implications on the Lake Chad Basin, J. Arid Environ. 181 (November 2018) (2020) 104190, https://doi.org/10.1016/j.jaridenv.2020.104190.
[41] G. James, I. Jega, D. Agency, H. Ahmad, D. Agency, O.O. Olojo, Assessment of Environmental Sensitivity to Desertification in Katsina State, November, 2018, https://doi.org/10.13189/eer.2018.060604. Nigeria.
[42] K. Hausa, Quantitative Assessment of Land Cover Sensitivity to Desertification in Maigatari Local Government Area, Jigawa State, Nigeria, 2020.
[43] L.S.M. Zhou Na, W.A.N.G. Yongdong, L.E.I. Jiaqiang, AHMEDOU Ould Soule, X.U. Xinwen, Alioune Fall, Determination of the status of desertification in the capital of Mauritania and development of a stretegy for combating it, J. Resour. Ecol 9 (3) (2018) 306–316, https://doi.org/10.5814/j.issn.1674-764x.2018.03.011.
[45] A.X. Liu, J. Wang, Z.J. Liu, et al., Monitoring Desertification in Arid and Semi-arid Areas of China with NOAA-AVHRR and MODIS Data. In Geoscience and Remote Sensing Symposium, 2005,", IEEE Int. Korea Seoul, no. IGARSS '05. Proceedings, 2005, pp. 2362–2364, 2005.
[46] R.H. Armon, Desertification and Desertification Indicators Classification (DPSIR), 2015, pp. 277–290, https://doi.org/10.1007/978-94-017-9499-2.
[47] O. Using, R. Sensing, I. Techniques, Quantitative Assessment of Desertification in an Arid Oasis Using Remote Sensing Data and Spectral Index Techniques, 2018, https://doi.org/10.3390/rs10121862.
[48] J. Im, J. Rhee, J.R. Jensen, M.E. Hodgson, An Automated Binary Change Detection Model Using a Calibration Approach, vol. 106, 2007, pp. 89–105, https://doi.org/10.1016/j.rse.2006.07.019.
[49] G. Verhoeven, M. Doneus, C. Briese, F. Vermeulen, Mapping by matching: a computer vision-based approach to fast and accurate georeferencing of archaeological aerial photographs, J. Archaeol. Sci. 39 (7) (2012) 2060–2070.
[50] N. Merkle, W. Luo, S. Auer, R. Müller, R. Urtasun, Exploiting deep matching and SAR data for the geo-localization accuracy improvement of optical satellite images, Rem. Sens. 9 (6) (2017) 586.
[51] M.S. Navin, L. Agilandeeswari, Comprehensive review on land use/land cover change classification in remote sensing, J. Spectr. Imaging 9 (2020).
[52] Federal Government of Nigeria, Great Green Wall for the Sahara and Sahel Initiative-National Strategic Action Plan (2012) 1–65. October, http://www.greatgreenwallinitiative.org.
[53] M.N. Thelma, Desertification in northern Nigeria : causes and implications for national food security, Peak J. Soc. Sci. Humanit. 3 (2) (2015) 22–31 [Online]. Available: https://www.peakjournals.org/sub-journals-PJSSH.htm.
[54] M. Tiffen, M. Mortimore, Questioning desertification in dryland sub-Saharan Africa, Nat. Resour. Forum 26 (3) (2002) 218–233, https://doi.org/10.1111/0165-0203.t01-1-00023.
[55] I.A. Jaiyeoba, No Title: Environment in Africa Atlases: Nigeria, J. A Paris, 2002, pp. 22–123.
[56] W. Cotthem, About Drought, Desertification and Poverty in the Dry Lands, 2007.
[57] D. Bashir, National Summit on the Environment: Greening the Environment for Sustainable Economic Development Held at Transcorp Hilton, vol. 20, Abuja on, 2008, pp. 1–17.
[58] E. Symeonakis, N. Drake, Monitoring desertification and land degradation over sub-saharan africa, Int. J. Rem. Sens. 25 (3) (2004) 573–592, https://doi.org/10.1080/0143116031000095998.
[59] H.N. Le Houérou, Man-made deserts: desertization processes and threats, Arid Land Res. Manag. 16 (1) (2002) 1–36, https://doi.org/10.1080/153249802753365296.
[62] A.I. Naibbi, B. Baily, R.G. Healey, P. Collier, Changing vegetation patterns in Yobe state Nigeria: an analysis of the rates of change, potential causes and the implications for sustainable resource management, Int. J. Geosci. 5 (1) (2014) 50–62, https://doi.org/10.4236/ijg.2014.51007.
[63] N.I. Medugu, M.R. Majid, F. Johar, Drought and desertification management in arid and semi-arid zones of Northern Nigeria, Manag. Environ. Qual. Int. J. 22 (5) (2011) 595–611, https://doi.org/10.1108/14777831111159725.
[64] J.P. Patra, A. Mishra, R. Singh, N.S. Raghuwanshi, Detecting rainfall trends in twentieth century (1871-2006) over Orissa State, India, Clim. Change 111 (3) (2012) 801–817, https://doi.org/10.1007/s10584-011-0215-5.
[65] R.E. Crippen, Calculating the vegetation index faster, Remote Sens. Environ. 34 (1) (1990) 71–73, https://doi.org/10.1016/0034-4257(90)90085-Z.
[66] M. Pearce, NASA goddard Institute for space studies (GISS) climate change research initiative (CCRI) applied research STEM curriculum unit portfolio, NASA Goddard Sp. Flight Cent. Off. Educ. NASA Goddard Inst. Sp. Stud. 212–678 (6038) (2018) 1–142 [Online]. Available: https://www.giss.nasa.gov/edu/res/Dulaney_EarthsEnergyBudgetUnitPlanPortfolio.pdf.
[67] Z.L. Li, et al., Satellite-derived land surface temperature: current status and perspectives, Remote Sens. Environ. 131 (2013) 14–37, https://doi.org/10.1016/j.rse.2012.12.008.
[68] A. Aisyah, E. Kusratmoko, A. Wibowo, The spread of dry area based on TVDI index (temperature vegetation dryness index), IOP Conf. Ser. Earth Environ. Sci. 311 (1) (2019), https://doi.org/10.1088/1755-1315/311/1/012006.
[69] T. Wilson, Evaluation of alternative cohort-component models for local area population forecasts, Popul. Res. Pol. Rev. 35 (2) (2016) 241–261, https://doi.org/10.1007/s11113-015-9380-y.
[70] IFAD, Dealing effectively with desertification will lead to a reduction in global poverty, Ecosyst. Hum. Well-Being, a Rep. Millenn. Ecosyst. Assess. (2020) 1–4 [Online]. Available: https://www.ifad.org/documents/38714170/39150184/Desertification+factsheet_e.pdf/40c0689e-a726-42ed-91c4-a5f79273ccd8#:~:text=IFAD'sveryexistencehasits,iscentraltoIFAD'swork.
[71] UN-OHRLLS, The Impact of Climate Change, Desertification and Land Degradation on the Development Prospects of Landlocked Developing Countries, 2015, pp. 1–59 [Online]. Available: http://unohrlls.org/custom-content/uploads/2015/11/Impact_Climate_Change_2015.pdf.
[72] C.T. Nwaoga, A.B. Okoli, F.C. Uroko, Self-acclaimed religious terrorism, refugee crisis, and the plight of internally displaced persons in Nigeria, Mediterr. J. Soc. Sci. 8 (3) (2017) 189–195, https://doi.org/10.5901/mjss.2017.v8n3p189.

[73] M. Nuraddeen, D. Salisu, M. Umar, S. Daura, Mitigation strategies to environmental degradation in Nigeria 4 (21) (2014) 38–52.
[74] M. David, Biodiversity and tropical forest assessment for Nigeria, USDA For. Serv. For. USAID/Bureau Africa. Washington, DC (2008) 118–119.
[75] A.I. Naibbi, Fuelwood and Vegetation Change in Northern Nigeria: An Exploration Using Remote Sensing (RS), Geographical Information Systems (GIS) and Field Reports. A thesis submitted in partial fulfilment of the requirements for the award of the degree of Doctor of P (2013).
[76] F. Forestry Management, Evaluation and Co-ordinating Unit, The Assessment of Vegetation and Land Use Changes in Nigeria. Between 1976/78 and 1993/95 (1998).
[77] F. Federal Government of Nigeria, National Action Program to Combat Desertification, Federal Ministry of Environment of Nigeria, 2006.
[78] T.H. Booth, Species choice, Encycl. For. Sci. (2004) 1–8.
[79] S. Rahmstorf, Abrupt climate change, in: J.H. Steele (Ed.), Encyclopedia of Ocean Sciences, second ed., Academic Press, Oxford, 2009, pp. 1–6, https://doi.org/10.1016/B978-012374473-9.00710-4. Second Edition.
[80] M. M. B., Land degradation in Northern Nigeria: the impacts and implications of human-related and climatic factors, Afr. J. Environ. Sci. Technol. 8 (5) (2014) 267–273, https://doi.org/10.5897/ajest2013.1584.
[81] A. Timmermann, et al., El niño–southern oscillation complexity, Nature 559 (7715) (2018) 535–545, https://doi.org/10.1038/s41586-018-0252-6.
[82] M.J. McPhaden, A. Santoso, W. Cai, Introduction to El Niño southern oscillation in a changing climate, El Niño South. Oscil. a Chang. Clim. (2020) 1–19.
[83] T.S. Purevdorj, R. Tateishi, T. Ishiyama, Y. Honda, Relationships between percent vegetation cover and vegetation indices, Int. J. Rem. Sens. 19 (18) (Dec. 1998) 3519–3535, https://doi.org/10.1080/014311698213795.
[85] I.R. Orimoloye, A.O. Olusola, O. Ololade, S. Adelabu, A persistent fact: reflections on drought severity evaluation over Nigerian Sahel using MOD13Q1, Arabian J. Geosci. 14 (19) (2021), https://doi.org/10.1007/s12517-021-08369-5.
[86] H. Duan, T. Wang, X. Xue, C. Yan, Dynamic monitoring of aeolian desertification based on multiple indicators in Horqin Sandy Land, China, Sci. Total Environ. 650 (2019) 2374–2388.
[88] K.O. Ogunjobi, Y. Adamu, A.A. Akinsanola, I.R. Orimoloye, Spatio-temporal analysis of land use dynamics and its potential indications on land surface temperature in Sokoto Metropolis, Nigeria, R. Soc. Open Sci. 5 (12) (2018), https://doi.org/10.1098/rsos.180661.
[89] F. Ahmad, Spectral vegetation indices performance evaluated for Cholistan Desert, J. Geogr. Reg. Plann. 5 (6) (2012) 165–172.
[90] K. McGwire, T. Minor, L. Fenstermaker, Hyperspectral mixture modeling for quantifying sparse vegetation cover in arid environments, Remote Sens. Environ. 72 (3) (2000) 360–374.
[91] M. Lamchin, et al., Assessment of land cover change and desertification using remote sensing technology in a local region of Mongolia, Adv. Space Res. 57 (1) (2016) 64–77.
[93] A.N. Zolotokrylin, L. Brito-Castillo, T.B. Titkova, Local climatically-driven changes of albedo and surface temperatures in the Sonoran Desert, J. Arid Environ. 178 (2020) 104147.
[94] A. Khan, S. Chatterjee, Y. Weng, Characterizing Thermal Fields and Evaluating UHI Effects, 2021, https://doi.org/10.1016/b978-0-12-819669-4.00002-7.
[95] T.N. Chase, R.A. Pielke, T.G.F. Kittel, R. Nemani, S.W. Running, Index 101 (1996) 7393–7408.
[96] T.I. Abdullahi, S.Y. M, Y. T. I, K. A. A, Urbanisation effect on the development of urban heat island over Kano metropolis Nigeria, Int. J. Sci. Eng. Res. 8 (9) (2017) 293–299 [Online]. Available: http://www.ijser.org.
[97] J. M. Abubakar James, T. Gundiri, Impact of deforestation on land surface temperature in northern part of Bauchi state, Nigeria, FUTY J. Environ. 14 (1) (2020) 22–31.
[98] K. Zimmerman, Developing the rendering equations, A Basic 2 (1998) 1–11 [Online]. Available: https://www.cs.princeton.edu/courses/archive/fall10/cos526/papers/zimmerman98.pdf.
[99] J.A. Coakley, Reflectance and albedo, surface, Encycl. Atmos. Sci. (2003) 1914–1923, https://doi.org/10.1016/b0-12-227090-8/00069-5.
[100] S. Chen, Z. Wen, H. Jiang, Q. Zhao, X. Zhang, Y. Chen, Temperature vegetation dryness index estimation of soil moisture under different tree species, Sustain. Times 7 (9) (2015) 11401–11417, https://doi.org/10.3390/su70911401.
[101] L. Meng, J. Li, Z. Chen, W. Xi, D. Chen, H. Duan, The calculation of TVDI based on the composite of pixel and drought analysis, Int. Arch. Photogramm. Remote Sening Spat. Inf. Sci. 38 (2008) 519–524.
[102] T.I.M. Ibrahim, S. Al-Maliki, O. Salameh, I. Waltner, Z. Vekerdy, Improving LST downscaling quality on regional and field-scale by parameterizing the DisTrad method, ISPRS Int. J. Geo-Inf. 11 (6) (2022), https://doi.org/10.3390/ijgi11060327.
[104] C. Jeganathan, N.A.S. Hamm, S. Mukherjee, P.M. Atkinson, P.L.N. Raju, V.K. Dadhwal, Evaluating a thermal image sharpening model over a mixed agricultural landscape in India, Int. J. Appl. Earth Obs. Geoinf. 13 (2) (2011) 178–191, https://doi.org/10.1016/j.jag.2010.11.001.
[105] S.B. Ogungbenro, T.E. Morakinyo, Rainfall distribution and change detection across climatic zones in Nigeria, Weather Clim. Extrem. 5 (1) (2014) 1–6, https://doi.org/10.1016/j.wace.2014.10.002.
[106] S. Mukhtar, Land use land cover change detection through remote sensing approach in Kano state Nigeria, Pyrex J. Geogr. Reg. Plan. 2 (2) (2016) 16–28 [Online]. Available: http://www.pyrexjournals.org/pjgrp.
[107] O.D. Elisha, NATURAL RESOURCES AND ENVIRONMENTAL SECURITY FOR SUSTAINING PEACEBUILDING IN NIGERIA, 2022.
[109] C. Onyia, Climate change and conflict in Nigeria: the Boko Haram challenge, Am. Int. J. Soc. Sci. 4 (2) (2015) 181–190.
[110] D.A. Okpara Ut, L.C. Stringer, Using a novel climate–water conflict vulnerability index to capture double exposures in Lake Chad, Reg Env. Chang 17 (2) (2017) 351–366.
[111] T.S. Cooper Pj, J. Dimes, K.P. Rao, B. Shapiro, B. Shiferaw, Coping better with current climatic variability in the rain-fed farming systems of sub-Saharan Africa: an essential first step in adapting to future climate change? Agric Ecosyst Env. 126 (1– 2) (2008) 24–35.
[113] M. V Wossen T, T. Abdoulaye, A. Alene, S. Feleke, A. Menkir, Measuring the impacts of adaptation strategies to drought stress: the case of drought tolerant maize varieties, J. Environ. Manag. 203 (2017) 106–113.
[114] M. Jibril, An assessment of the effects of desertification in Yobe state, Nigeria, Conflu. J. Environ. Stud. 1597–5827 (2012) 72–87 [Online]. Available: http://www.journalhome.com/cjes.
[115] T.E. Olagunju, Drought, desertification and the Nigerian environment: a review, J. Ecol. Nat. Environ. 7 (7) (2015) 196–209, https://doi.org/10.5897/jene2015.0523.

Further reading

[4] P. Taylor, Governing global desertification: linking environmental degradation, poverty and participation, Environ. Sci. 4 (4) (2007), https://doi.org/10.1080/15693430701198573, 249–249.
[13] G. Sterk, J.J. Stoorvogel, Desertification-Scientific versus political realities, Land 9 (5) (2020) 1–18, https://doi.org/10.3390/LAND9050156.
[31] Y. Liu, X. Huang, H. Yang, T. Zhong, Environmental effects of land-use/cover change caused by urbanization and policies in Southwest China Karst area – a case study of Guiyang, Habitat Int. 44 (2014) 339–348, https://doi.org/10.1016/j.habitatint.2014.07.009.
[44] G.K. Tripathy, T.K. Ghosh, S.D. Shah, Monitoring of desertification process in Karnataka state of India using multi-temporal remote sensing and ancillary information using gis, Int. J. Rem. Sens. 17 (12) (1996) 2243–2257, https://doi.org/10.1080/01431169608948771.
[60] H.J. Geist, E.F. Lambin, Dynamic causal patterns of desertification, Bioscience 54 (9) (2004) 817, https://doi.org/10.1641/0006-3568(2004)054[0817:dcpod]2.0.co;2.
[61] M. Falkenmark, J. Rockström, Building resilience to drought in desertification-prone savannas in Sub-Saharan Africa: the water perspective, Nat. Resour. Forum 32 (2) (2008) 93–102, https://doi.org/10.1111/j.1477-8947.2008.00177.x.
[84] S.W. Todd, R.M. Hoffer, D.G. Milchunas, Biomass estimation on grazed and ungrazed rangelands using spectral indices, Int. J. Rem. Sens. 19 (3) (1998) 427–438.

[87] L. Han, Z. Zhang, Q. Zhang, X. Wan, Desertification assessments in the Hexi corridor of northern China's Gansu Province by remote sensing, Nat. Hazards 75 (2015) 2715–2731.
[92] M. Lamchin, et al., Assessment of land cover change and desertification using remote sensing technology in a local region of Mongolia, Adv. Space Res. 57 (1) (2016) 64–77, https://doi.org/10.1016/j.asr.2015.10.006.
[103] A. Karnieli, M. Bayasgalan, Y. Bayarjargal, N. Agam, S. Khudulmur, C.J. Tucker, Comments on the use of the vegetation health index over Mongolia, Int. J. Rem. Sens. 27 (10) (2006) 2017–2024, https://doi.org/10.1080/01431160500121727.
[108] S.A. Adebisi, O.O. Azeez, R. Oyedeji, Appraising the effect of Boko Haram insurgency on the agricultural sector of Nigerian business environment, J. Law Gov. 11 (1) (2016) 15–26.
[112] M.A. Shiferaw B, K. Tesfaye, M. Kassie, T. Abate, B.M. Prasanna, Managing vulnerability to drought and enhancing livelihood resilience in sub-Saharan Africa: technological, institutional and policy options, Weather Clim. Extrem. 3 (2014) 67–79.