

Multi-Indicator Assessment of Desertification Dynamics in Kebbi State, Nigeria

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ABSTRACT

This study assessed desertification in Kebbi State over a 32-year period (1991-2023) using a multi-indicator approach comprising thirteen indicators. Vegetation indicators included the Normalized Difference Vegetation Index (NDVI), Modified Soil-Adjusted Vegetation Index (MSAVI), and Normalized Difference Moisture Index (NDMI). The Modified Normalized Difference Water Index (MNDWI) was used to extract surface water. Soil indicators included the Normalized Difference Salinity Index (NDSI) and the Topsoil Grain Size Index (TSGI). Land use and land cover indicators were the Normalized Difference Built-Up Index (NDBI) and the Normalized Difference Bareness Index (NDBaI). Climate indicators included Land Surface Temperature (LST), Air Temperature (TMP), Precipitation (PRE), Aridity Index (AI), and Surface Albedo. We computed Remote sensing indices from Landsat 4 TM and Landsat 8 OLI/TIRS for 1991 and 2023, respectively, and obtained climate data from the Climate Research Unit (CRU) gridded datasets. Results revealed a decline in vegetation and moisture conditions. Maximum NDVI decreased from 0.4695 to 0.3925, and MSAVI declined from 0.5931 to 0.5637. NDMI reduced from 0.5271 to 0.2388, and MNDWI from 0.3215 to 0.1375. Soil salinity declined, with NDSI decreasing from 0.3661 to 0.1019 and TSGI from 0.6356 to 0.4399, indicating a shift to fine soil. Built-up intensity increased as NDBI rose from 0.7180 to 0.7354, while surface bareness (NDBaI) declined from 0.7411 to 0.6065. Climatic stress intensified: maximum LST decreased from 64.04°C to 56.26°C, mean temperature increased from 29.28°C to 30.34°C, annual precipitation declined from 1232.33 mm to 1004.80 mm, and AI declined from 0.96 to 0.65. Surface albedo increased from 0.2589 to 0.3020, indicating increased land exposure and degradation. This study underscores the effectiveness of employing a multi-indicator framework for desertification monitoring and understanding its dynamics in Kebbi State and other semi-arid regions.

Keywords: Desertification, Multi-Indicator, Kebbi State, Spatio-temporal, Remote Sensing

1.0 INTRODUCTION

Desertification is a critical global challenge that threatens sustainable development, affecting an estimated 3.2 billion people and reducing about 10 percent of global GDP annually (UNCCD, 2017a). The United Nations Convention to Combat Desertification (1994) defines it as land degradation in arid, semi-arid, and dry sub-humid areas, collectively known as drylands, resulting from many factors, including human activities and climatic variations. The above definition is comprehensive and has been formally and widely used, since then, for multiple studies on desertification around the world. Pimm and John (2023) defined it as the process by which natural factors and human activities such as climate change, deforestation, overgrazing, poverty, political instability, and unsustainable irrigation practices reduce the biological productivity of drylands, threatening all dryland ecosystems, including deserts, grasslands, and scrublands, without necessarily expanding existing deserts.

The drivers of desertification are factors that trigger desertification processes. The relative roles of climatic and human drivers of desertification are location-specific and evolve over time (Mirzabaev et al.,

2019). An analysis in China found that a combination of socio-economic factors and, to a lesser extent, climate drove desertification in drylands, but the relationships among factors are complex and vary by region (Huang & Zhai, 2023). In Nigeria, desertification is less a function of climate change, but more a product of human activities driven by poverty, population growth, and failed government policies (Ibrahim et al., 2022). According to the United Nations Convention to Combat Desertification (UNCCD, 2017b), many interrelated factors contribute to desertification, including population growth, demands for greater production, technologies that increase resource exploitation, and climate change. The direct drivers are either natural (e.g., earthquakes, landslides, drought, and floods) or anthropogenic (i.e., human-induced); human-induced drivers such as deforestation, wetland drainage, overgrazing, unsustainable land use practices, and the expansion of agricultural, industrial, and urban areas (i.e., land use change) continue to be the most significant proximate cause of land degradation.

Desertification is a critical environmental and socioeconomic challenge in arid and semi-arid areas, which ultimately results in the continuous decline or

loss of biodiversity or land productivity (Xu et al., 2024). Admittedly, the effects of desertification on biodiversity are mainly due to drought, limited nutrients, high salinity, intense sunlight, wind erosion and unstable environmental conditions. (Islam et al., 2024). The socio-economic impacts of desertification include poverty (Nwer et al., 2021), food security (AbdelRahman, 2023), human health (Manikandan & Joseph, 2022), conflict (Bello & Kazibwe, 2023), infrastructure (Karmaoui et al., 2022), and migration (Hermans & McLeman, 2021).

An indicator is a parameter or value derived from parameters that describe the state of a phenomenon (European Environment Agency [EEA], 2019). Desertification indicators are parameters that are used to assess the potential risk of desertification, and the selection of indicators is based on their applicability and sensitivity to desertification processes (Kosmas et al., 2014). Different indicator sets and approaches have been developed to monitor and assess desertification from national to global scales (Mirzabaev et al., 2019).

Remote sensing (RS) involves using sensors to record the electromagnetic radiation reflected or emitted by objects. The information collected through RS can be used to create digital maps, assess environmental conditions, manage resources, and ensure public safety (Singh, 2022). RS technology has provided researchers with a novel method of monitoring desertification (Yang et al., 2022). According to Rivera-Marin et al. (2022), the use of remote sensing for desertification studies dates back to 1991. From 2015 to 2020, more than 40 articles were published each year, showing a recent increase in the use of remote sensing techniques and their availability for monitoring desertification. Spatio-temporal analysis involves examining data that includes both spatial and temporal components (Barazzetti, 2024). It involves examining spatial patterns of geographic objects or events over time (Lee, 2023). Many studies have explored the methods of spatio-temporal analysis and applied spatio-temporal data analysis techniques to various fields (Aliero et al., 2022; Chen et al., 2024; Ding & Xingming, 2021; Hu et al., 2024; Meng et al., 2024; Molekoa et al., 2022; Musa et al., 2022; Shafiq et al., 2025; Ullah et al., 2022; Yang et al., 2022; Zhao et al., 2023).

Desertification has reached an alarming state in Nigeria. The frontline desert-threatened states of Nigeria constitute 40% of the landmass (Gadzama & Ayuba, 2016). Desertification has become one of Nigeria's most pronounced ecological disasters, affecting arid and semi-arid areas. This phenomenon is more pronounced in the northern region, particularly the 11 frontline states (Adamawa, Bauchi, Borno, Gombe, Jigawa, Kano, Katsina, Kebbi, Sokoto, Yobe, and Zamfara states) of Nigeria, which share borders with the Niger Republic, and is attributed to a range of

natural and anthropogenic factors. Rampant felling of trees for fuelwood, unsustainable agriculture, and overgrazing, coupled with unfavourable climatic conditions, are among the key factors that aggravate the desertification phenomenon (Ibrahim et al., 2022).

Globally, several studies have advanced our understanding of desertification; however, notable gaps remain. Research has often focused on regions such as North Africa, China, and the Mediterranean (Lamaamri et al., 2023; Meng et al., 2024; Wang et al., 2024), while limited attention has been paid to localized desertification dynamics in West Africa. In Nigeria, existing studies have primarily focused on broader regional analyses covering states such as Sokoto, Yobe, Katsina, and Zamfara. Despite these efforts, Kebbi State, an ecologically sensitive and agriculturally reliant region, has remained largely underexplored.

A study by Xu (2023) focused on the significance of applying remote sensing, specifically NDVI, land cover classification, and spectral mixture analysis (SMA), to improve efficiency in desertification monitoring. Results showed the efficiency of applying remote sensing in desertification monitoring. Another study by Aliero et al. (2022) assessed Spatiotemporal Land Cover Change and Vegetation Degradation Using Remote Sensing in Kebbi State, Nigeria. The study used NDVI from 1986 to 2016. The results illustrated a decline in dense vegetation and shrubs/built-up, while farmland, grass land/bare land increased, and water bodies remained unchanged. Expansion of farmland due to population growth and socio-economic demands, including fuelwood consumption and endemic poverty, was identified as the major driver. Falaki et al. (2020) and Nwilo et al. (2020) used LULC to measure the extent and predict desertification in the Jibia Local Government Area of Katsina State, Nigeria. Yang et al. (2022) used NDVI, albedo, MSAVI, and rainfall data to analyze changes and identify the driving factors of desertification in the Sahel. Agbaje et al. (2020) used NDVI, DEM, and a mix of qualitative data to identify areas affected by desertification.

Moreover, prior research has largely utilized coarse- or medium-resolution satellite datasets (e.g., MODIS and Landsat) and basic image classification techniques, often focusing on single indicators such as NDVI, LST, or SAVI. While valuable, these approaches fall short in capturing the multidimensional nature of desertification, particularly its interaction with climatic and anthropogenic drivers. Furthermore, many studies have limited temporal scope, with few offering a long-term perspective spanning multiple decades.

Recent studies (e.g., Rajendram and Patel, 2021; Zhao et al., 2023) have underscored the importance of integrating multiple indices, including vegetation, soil,

and climate, to better understand desertification processes. Rivera-Marín et al. (2022) also identified similar methodological gaps by reviewing 384 publications on desertification studies using remote sensing from 1960 to 2021 globally and recommended using multiple indicators.

Against this background, this study adopts a holistic spatio-temporal framework to assess desertification in Kebbi State over a 32-year period (1991-2023) by employing 13 biophysical and climate indicators: Normalized Difference Vegetation Index (NDVI), Modified Soil Adjusted Vegetation Index (MSAVI), Normalized Difference Moisture Index (NDMI), Modified Normalized Difference Water Index (MNDWI), Normalized Difference Salinity Index (NDSI), Topsoil Grain Size Index (TGSi), Normalized Difference Bareness Index (NDBaI), Normalized Difference Built-up Index (NDBI), Land Surface Temperature (LST), Temperature (TMP), Precipitation (PRE), Aridity Index (AI), and Albedo was extracted to paint a clear picture of the phenomenon.

The primary objective of this study is to conduct a multi-indicator assessment of desertification dynamics in Kebbi State, Nigeria, to understand their dynamics, identify hotspot areas, and support targeted mitigation planning.

2.0 MATERIALS AND METHODS

2.1 Study Area

Kebbi State is located in the northwestern part of Nigeria between Latitudes 10°0'0" N and 13°0'0" N of the Equator and Longitudes 3°0'0" E and 6°0'0" E of the Greenwich Meridian (Figure 1). The state shares an extensive border with the Republic of Niger to the North and Republic of Benin to the west, with many

intercultural and ethnic linkages. It is internally bordered to the North-East by Sokoto State, to the East by Zamfara State, and to the south by Niger State. It has a total landmass of about 37,699 square kilometers, of which 36.46 percent is made up of farmland (Kebbi State Government, 2018). The state was created from part of Sokoto State in 1991 (Blench, 2020).

Kebbi has a tropical wet and dry savannah climate, with rainfall ranging from 733mm in the north to 1,045mm in the south, concentrated between April and October, and a mean annual temperature of 31.3°C (Kebbi State Government, 2018). The soils are predominantly ferruginous tropical types, prone to erosion, fertile alluvial fadama soils in the river valleys (Kebbi State Government, 2018). Vegetation varies from the Sudan Savannah in the north to Northern Guinea Savannah in the south, though cultivation, grazing, and fuelwood exploitation have heavily degraded it (Britannica, 2024). The geology consists of sedimentary formations of the Sokoto Rima Basin and Precambrian basement complex rocks, with generally low, undulating relief at elevations between 148 and 495 m. Major hydrological features include the Niger and Rima Rivers and Kainji Lake, which covers a large part of the southeastern boundary (Kebbi State Government, 2018).

Administratively, the state has 21 local government areas and four emirates (Gwandu, Argungu, Yauri, and Zuru), with a population of approximately 5.56 million (2022 projection), growing at 3.4% annually (City Population 2022; Kebbi State Government, 2018). Agriculture is the dominant occupation, engaging 80% of the population, making the state highly vulnerable to the impacts of desertification (Britannica, 2024).

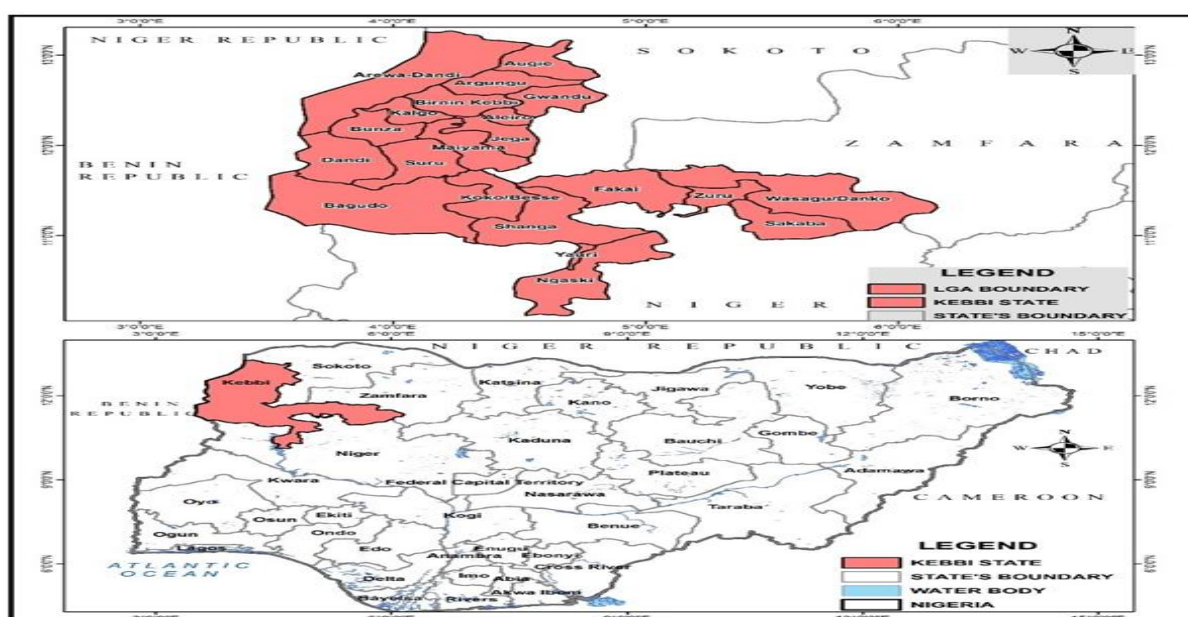


Figure 1: Geographic location of Kebbi State

Source: Adopted and Modified from the Administrative Map of Nigeria, 2024

2.2 Data Collection

Table 1 presents the types and sources of data used in this study. This study adopted a multi-temporal geospatial approach covering the period 1991–2023. The data used for the analysis, include Landsat imagery (TM 1991 and OLI/TIRS 2023), Google Earth, CRU high-resolution gridded climate data, and administrative shapefiles. Thirteen desertification indicators (NDVI, MSAVI, NDMI, MNDWI, NDSI, TGSI, NDBaI, NDBI, LST, temperature, precipitation, aridity index, and albedo) were utilized. These indicators were processed in ArcMap 10.8 and analyzed to detect spatio-temporal changes.

Landsat 4 TM for 1991 and Landsat 8 OLI/TIRS for 2023 were downloaded from the United States Geological Survey (USGS) website <http://www.earthexplorer.usgs.gov>, respectively. High-resolution Gridded climate data on Temperature, precipitation, and Potential Evapotranspiration (PET) for 1991 and 2023 were downloaded from the Climate Research Unit (CRU) website <https://crudata.uea.ac.uk/cru/data/hrg>. The administrative boundary (Shapefile) of the study area was acquired from the Humanitarian Data Exchange website <https://data.humdata.org> for sub-setting.

Table 1: Types and Sources of Data

S/N	Dataset	Source	Description	Purpose
1	Administrative maps	https://data.humdata.org	Administrative Shapefiles	Image Sub setting
2	Landsat 4 TM (1991)	https://www.earthexplorer.usgs.gov	Seven-band multispectral image acquired by TM sensor (30m resolution)	Extraction of spectral indices
3	Landsat 8 OLI/TIRS (2023)	https://www.earthexplorer.usgs.gov	Eleven spectral bands acquired from OLI/TIRS sensors (30m resolution).	Extraction of spectral indices
4	CRU high-resolution gridded climatic data	https://crudata.uea.ac.uk/cru/data/hrg	Gridded Air Temperature, Precipitation, and PET data (0.5x0.5 degree resolution)	Extraction of Temperature, precipitation, and PET indices

2.3 Data Analysis

2.3.1 Spatio-temporal pattern of desertification indicators in the study area between 1991 and 2023.

This was achieved using the following steps:

2.3.1.1 Mosaicking and Clipping of Landsat Data

We mosaicked (merged) five paths and rows covering the study area in ArcMap 10.8 for 1991 and 2023, respectively. The paths and rows 190/052, 190/053, 191/051, 191/052, and 191/053 were then clipped using the study area boundary shapefile.

2.3.1.2 Extraction of Spectral Indices

The raster calculator in ArcMap was used to compute the spectral indices as follows:

1. NDVI: NDVI was calculated using equation 1; and the NIR and RED bands were used: bands 4 and 5 (for Landsat 8) and bands 4 and 3 (for Landsat 4), respectively.

$$NDVI = \frac{NIR - RED}{NIR + RED} \quad (1)$$

where: NIR - light reflected in the near-infrared spectrum
RED - light reflected in the red range of the spectrum

2. MSAVI: MSAVI was calculated as the ratio between the R and NIR values with an inductive L function applied to maximize the

reduction of soil effects on the vegetation signal, as shown in equation 2.

$$MSAVI = \frac{2 * NIR + 1 - \sqrt{(2 * NIR + 1)^2 - 8 * (NIR - R)}}{2} \quad (2)$$

3. NDMI was calculated as the ratio of NIR and SWIR values, as shown in equation 3.

$$NDMI = \frac{(NIR - SWIR)}{(NIR + SWIR)} \quad (3)$$

4. MNDWI: MNDWI was calculated as the ratio between the green and short-wave infrared bands to identify water bodies, as shown in Equation 4.

$$MNDWI = \frac{(GREEN - SWIR)}{(GREEN + SWIR)} \quad (4)$$

5. For soil salinity, the NDSI was computed for each year using equation 5, which requires the red and NIR bands, bands 3 and 4 and bands 4 and 5 for Landsat 4 and 8, respectively.

$$NDSI = \frac{[Red - NIR]}{[Red + NIR]} \quad (5)$$

6. For soil texture, the TGSI was computed for each year using equation 6, which requires the red, blue, and green bands, that is, bands 3, 2, and 1 for Landsat 4 and bands 4, 3, and 2 for Landsat 8.

$$TGS I = \frac{(Red-Blue)}{(Red+Blue+green)} \quad (6)$$

7. NDBI: For built-up areas, the normalized difference built-up index (NDBI) was computed using the NIR and SWIR bands to emphasize built-up areas in Equation 7.

$$\text{NDBI} = \frac{(\text{SWIR} - \text{NIR})}{(\text{SWIR} + \text{NIR})} \quad (7)$$

8. AI: The aridity index (AI) was calculated using the formula in equation 8.

$$AI = \frac{P}{PET} \quad (8)$$

where P is precipitation, and PET is potential evapotranspiration.

9. **ALBEDO:** The albedo requires the use of five bands as indicated in equation 9. The albedo for each Landsat image acquired was computed where bands 1,3,4,5 and 6 for Landsat 7 and bands 2,4,5,6, and 7 for Landsat 8 as Blue, Red, NIR, SWIR1, and SWIR2 were used respectively.

$$\text{ALBEDO} = (0.356 * B1) + (0.130 * B2) + (0.373 * B3) + (0.085 * B4) + (0.072 * B5) - 0.018) / 1.016$$

(9)

10. For the derivation of LST,

The multiplicative scale factor and additive offset for Landsat Collection 2, Level 2 products (C2 L2) were used to obtain the actual LST in °C from the processed surface temperature bands (i.e., Band 6 ST and Band 10 ST) for 1991 and 2023, respectively (equations 10 and 11). The multiplicative Scale Factor and the Additive Offset were both obtained from the metadata file.

For Landsat 4 TM;

$$\text{LST (}^{\circ}\text{C)} = \frac{(\text{LT04_L2SP_02_T1_ST_B6.TIF} * 0.003418}{02 + 149) - 273.15} \quad (10)$$

Where;

Multiplicative Scale Factor

```
“TEMPERATURE_MULT_BAND_ST_B6” =
0.00341802
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Additive Offset

“TEMPERATURE_ADD_BAND_ST_B6” = 149.0
For Landsat 8 OLI/TIRS;

$$\text{LST (}^{\circ}\text{C)} = (\text{"LC08_L2SP_02_T1_ST_B10.TIF"} * 0.00341802 + 149) - 273.15 \quad (11)$$

Where;

Multiplicative Scale Factor

“TEMPERATURE_MULT_BAND_ST_B10” =
0.00341802

Additive Offset

“TEMPERATURE_ADD_BAND_ST_B10” = 149.0

11. For Bare land, the bareness index (NDBaI) was computed using the thermal band (band 6 for Landsat 7 and band 10 for Landsat 8) and the SWIR band (band 5 for Landsat 5 and band 6 for Landsat 8), as shown in equation 12.

$$\text{NDBaI} = \frac{(\text{SWIR} - \text{TIR})}{(\text{SWIR} + \text{TIR})} \quad (12)$$

For built-areas, Normalized Difference Built-up Index (NDBI) was computed using NIR and SWIR bands to emphasize built-up areas in equation 13.

$$\text{NDBI} = \frac{(\text{SWIR} - \text{NIR})}{(\text{SWIR} + \text{NIR})} \quad (13)$$

3.0 RESULTS AND DISCUSSION

3.1 Spatio-Temporal Pattern of Desertification Indicators in Kebbi State (1991 and 2023)

This section presents the spatiotemporal pattern of desertification indicators for 1991 and 2023.

3.1.1 Normalized Difference Vegetation Index (1991-2023)

NDVI values declined from a range of -0.3661 to 0.4695 in 1991 to -0.1019 to 0.3925 in 2023 (Fig. 2a, b), indicating deterioration in vegetation cover and biomass over the study period. Higher NDVI values reflecting areas with dense vegetation were observed predominantly in the central and southern zones. The decrease in NDVI supports findings from (Aliero *et al.*, 2022; Salisu *et al.*, 2024). Also, Yahaya *et al.* (2024) highlighted a decrease in NDVI, depicting a consistently low vegetation cover in the northwestern states of Kano, Katsina, and Jigawa for both 2003 and 2020.

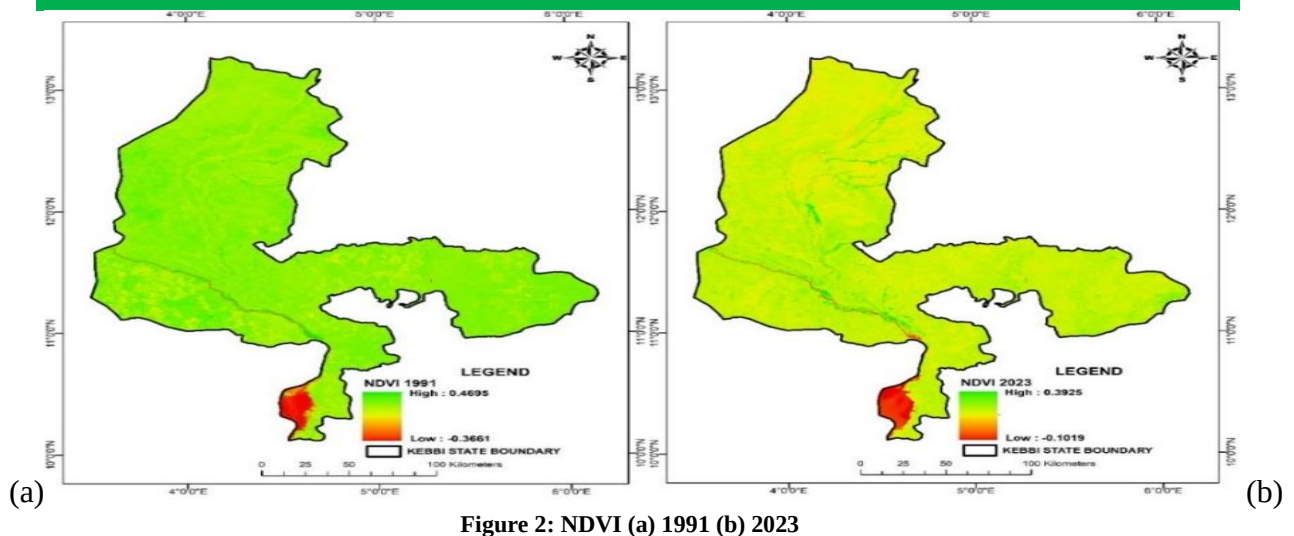


Figure 2: NDVI (a) 1991 (b) 2023

3.1.2 Modified Soil Adjusted Vegetation Index (1991-2023)

MSAVI similarly decreased from a range of -0.4855 to 0.5931 in 1991 to -0.2213 to 0.5637 in 2023 (Fig. 3a, b). The general decrease in MSAVI values from 1991 to 2023 reflects vegetation degradation across the state. The MSAVI aligned with the NDVI, confirming true

vegetation stress without the influence of soil. The decrease in MSAVI over the last three decades also aligns with findings from *Yang et al. (2022)*, who observed similar vegetation loss in the Sahelian zone where population pressures, agricultural expansion, and deforestation exacerbate desertification trends.

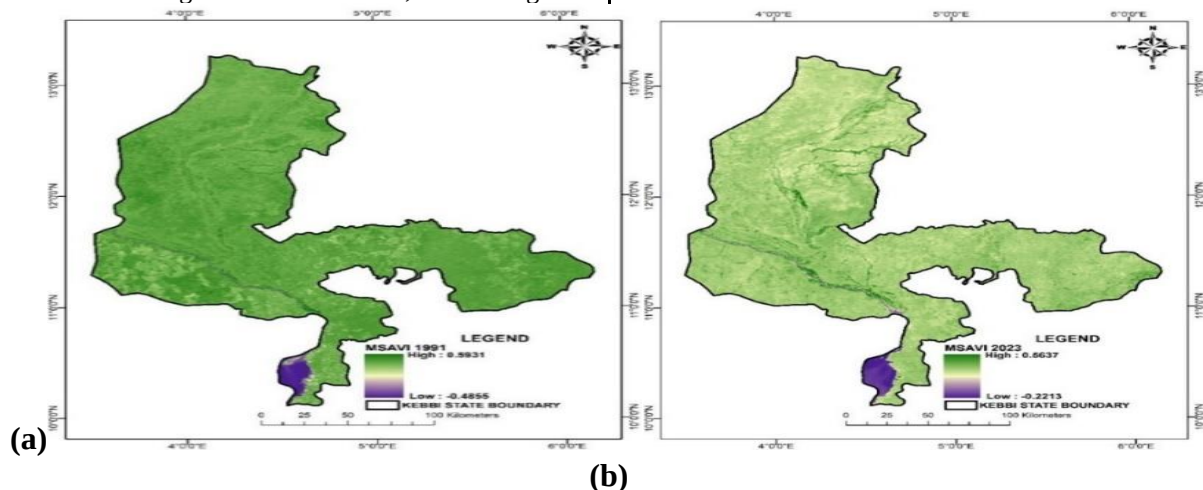


Figure 3: MSAVI (a) 1991 (b) 2023

3.1.3 Normalized Difference Moisture Index (1991-2023)

NDMI decreased from a range of -0.7180 to 0.5271 in 1991 to -0.5130 to 0.2388 in 2023 (Fig. 4a, b). The highest NDMI values were found in the southwestern and central areas of Kebbi State, indicating relatively moist and fertile areas. The northern and northeastern parts of the state, however, had very low NDMI values,

suggesting severe soil dryness and water stress. This decrease in NDMI values suggests declining moisture availability and increasing drought stress, particularly in the northern and central regions. The findings aligned with those of *Hu et al., (2024)*, who observed an 18% decline in moisture level between 1993 and 2023 in Zhenjiang city, located in Jiangsu province of China.

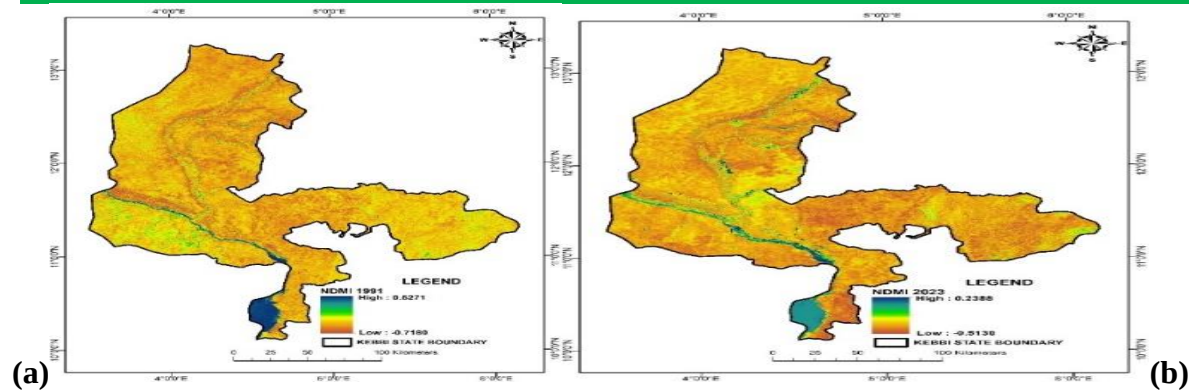


Figure 4: NDMI (a) 1991 (b) 2023

3.1.4 Modified Normalized Difference Water Index (1991-2023)

The MNDWI decreased from range of -0.7480 to 0.3215 in 1991 to -0.6454 to 0.1375 in 2023 (Fig. 5a, b), indicating reduced surface water availability and declining moisture conditions across the study area. These findings align with findings by (Getaneh *et al.*,

2024; Molekoa et al., 2022). Additionally, research by Yahaya et al. (2024) in Northern Nigeria has shown a reduction in available water resources over time, often linked to increasing desertification and climate variability, particularly in the Northeast region, putting immense pressure on local communities.

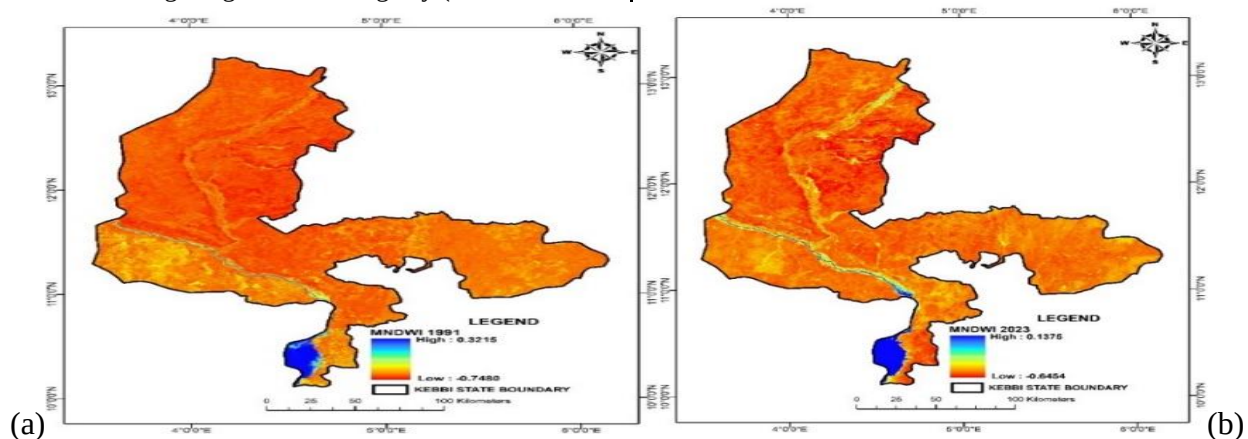


Figure 5: MNDWI (a) 1991 (b) 2023

3.1.5 Normalized Difference Salinity Index (1991-2023)

The NDSI values ranged from -0.4695 to 0.3661 in 1991 to -0.3925 to 0.1019 (Fig. 6a, b). This decline in maximum and minimum NDSI values implies a reduced surface salinity due to land cover changes and further land degradation over the period. These

findings also align with *Musa et al. (2022)* who observed a negative trend in salinity between 2000 and 2020 in neighbouring Gusau, Zamfara State reflecting broader changes in salinity. On the contrary, *Zhao et al. (2023)* observed a rising trend in salinity, attributed to the prevailing dry climate and low precipitation in his study area.

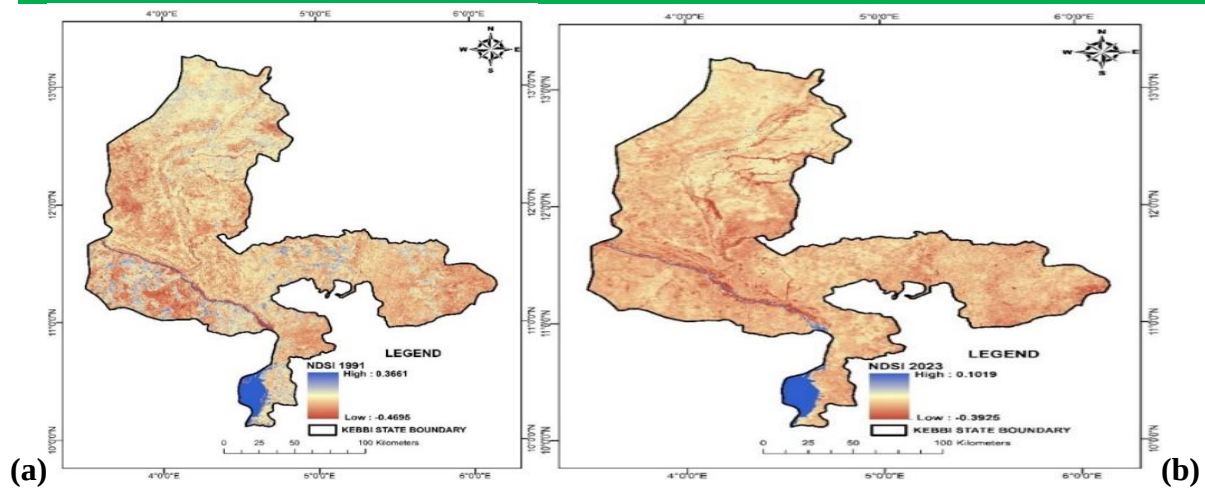


Figure 6: NDSI (a) 1991 (b) 2023

3.1.6 Topsoil Grain Size Index (1991-2023)

The TGSi values ranged from a minimum value of -0.3732 to 0.6356 in 1991 to -0.1666 to 0.4399 (Fig. 7a, b). The high values indicate that soils with a greater proportion of sand predominate across the state, especially in the northern and central regions, while the southern regions have lower TGSi values. This notable decrease in the maximum TGSi values indicates an improvement in the quality of the topsoil and a shift toward finer-grained soils, particularly in the northern

regions, and at the same time a corresponding spread of coarse sandy soil in the south and south-eastern regions. These findings are similar to those obtained by (Geloogerdi *et al.*, 2023; Kumar *et al.*, 2022; Mihi *et al.*, 2022), where low TGSI values reflect clayey or vegetated soil with minimal wind erosion, and higher TGSI values correspond to increased sand content (coarse soil surface) and reduced clay content, indicating severe degradation.

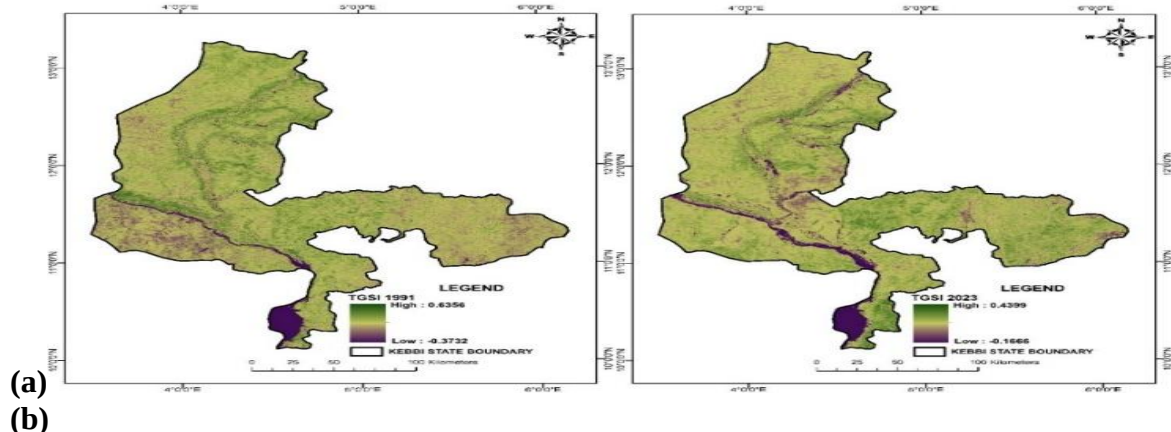


Figure 7: TGSi (a) 1991 (b) 2023

3.1.7 Normalized Difference Bareness Index (1991-2023)

The NDBal values ranged from a maximum of 0.7411 to a minimum of -0.4481 in 1991 and 0.6065 to -0.1990 (Fig. 8a, b), reflecting a significant presence of bare soil across the region. This decrease suggests a slight reduction in bare soil due to rapid urban expansion and an increase in vegetation, especially in areas along river valleys, due to intensified agricultural activities.

These results align with the research by *Mail (2017)*, where bare land slightly decreased as some areas transitioned into crusted soil. *Shafiq et al., (2025)* observed a contrasting increase in bare land areas. Additionally, *Guha and Govil, (2022)* detected that the built-up area and bare land have increased at a very high rate (78.37 km² in 27 years) due to rapid land conversion of green areas, which also corresponds to the findings of the present study.

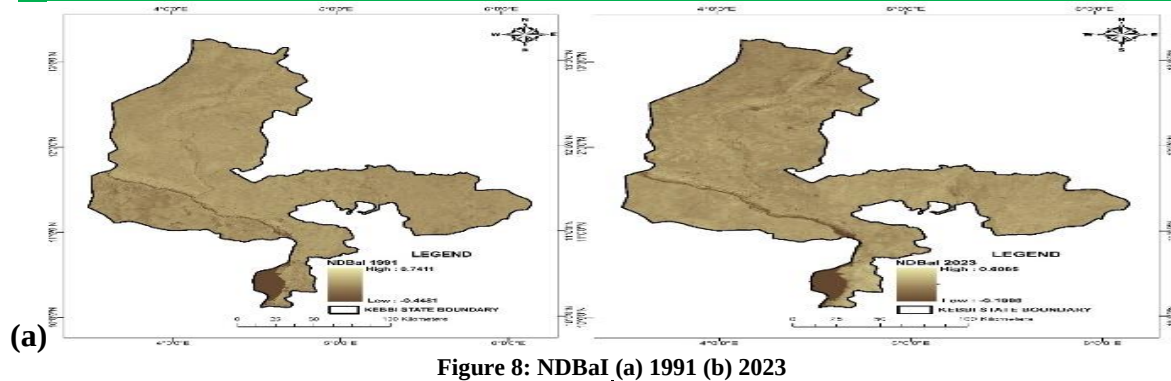


Figure 8: NDBal (a) 1991 (b) 2023

3.1.8 Normalized Difference Built-up Index (1991-2023)

NDBI values ranged from 0.7180 to -0.5271 in 1991 and 0.7354 to -0.2055 (Fig. 9a, b). This increase in maximum NDBI values indicates that built-up areas have increased in Kebbi State over the period under consideration. Also, the increase in the minimum values further suggest expansion is due to the conversion of non-built-up areas such as forests or

grasslands. These findings are consistent with the results of Mail (2017), where built-up areas expanded slightly from 2.16% to 2.76%. Additionally, Singgalen (2024) reported a substantial increase in built-up areas on Kakara Island, signifying significant urban expansion likely driven by socio-economic development, which also corresponds to the findings of the present study.

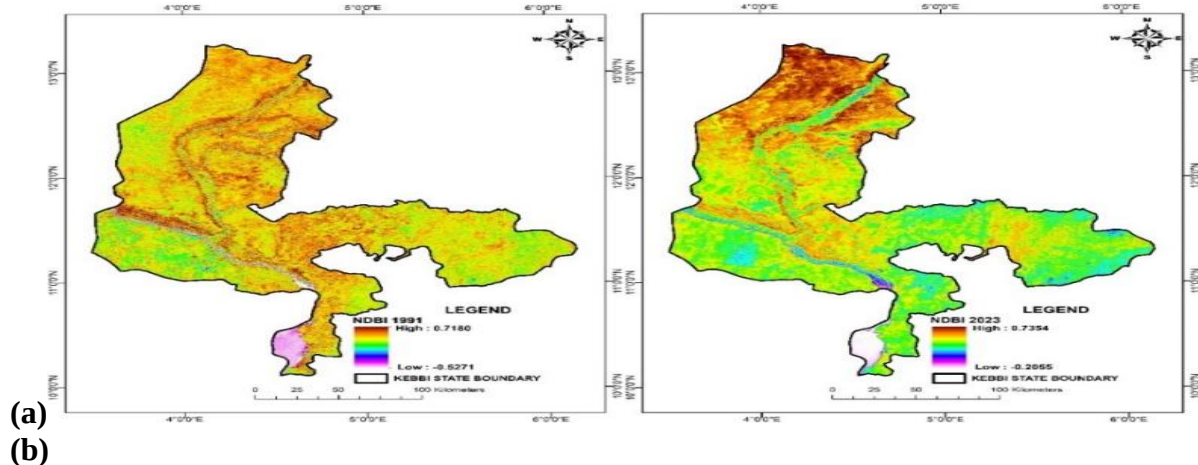


Figure 9: NDBI (a) 1991 (b) 2023

3.1.9 Land Surface Temperature (1991-2023)

LST values ranged from a minimum of 24.31°C to a maximum of 64.04°C in 1991 and a minimum of 27.73°C to a maximum of 56.26°C (Fig. 10a, b), indicating pronounced surface heating particularly in the northern and eastern parts of the state. There was a decrease in the maximum value, but the sustained high values reflect intense solar radiation leading to higher

surface heating. The increase in minimum value, suggests a general warming trend across previously cooler zones due to changes in land cover. These findings align with *Arnous and Mansour (2022)* study in the Suez Canal Region, where a maximum and minimum LST of 64°C and 5°C in 1984, and 57°C and 13°C in 2018 were recorded respectively.

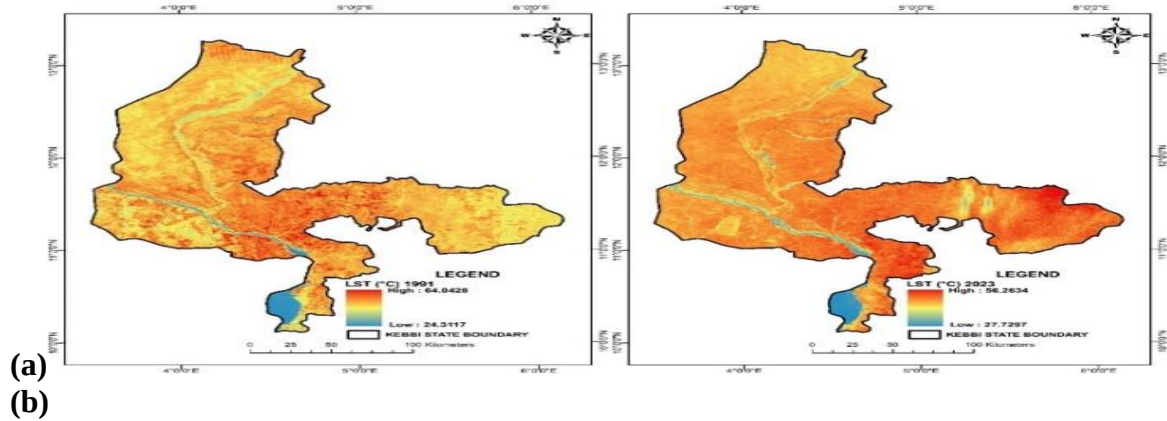


Figure 10: LST (a) 1991 (b) 2023

3.1.10 Air Temperature (1991-2023)

Air temperature increased from a maximum 29.28°C in 1991 to 30.34°C in 2023 (Fig. 11a, b). This increase in both maximum and minimum temperature indicates a shift in climate, which is consistent with the global

warming trend (*Daramola and Xu (2022); Mirzabaev et al., 2019*). Similarly, *Yahaya et al. (2024)* observed temperature increases across Northern Nigeria, highlighting an area-specific response to global climate shifts.

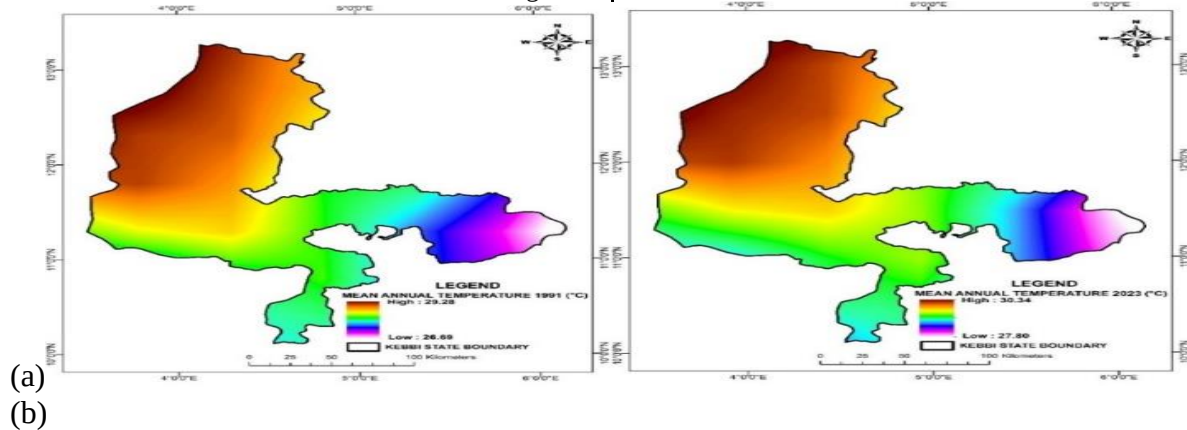


Figure 11: Temperature (a) 1991 (b) 2023

3.1.11 Precipitation (1991-2023)

Annual precipitation declined significantly from a maximum of 1232.33 mm in 1991 to 1004.8 mm in 2023 (Fig. 12a, b). This suggests a shift in weather patterns as a result of climate change. *Daramola & Xu*

(2022) revealed that precipitation generally decreased over the drylands. They also observed intense warming in the areas where precipitation decreased, suggesting the effect of reduced evaporative cooling

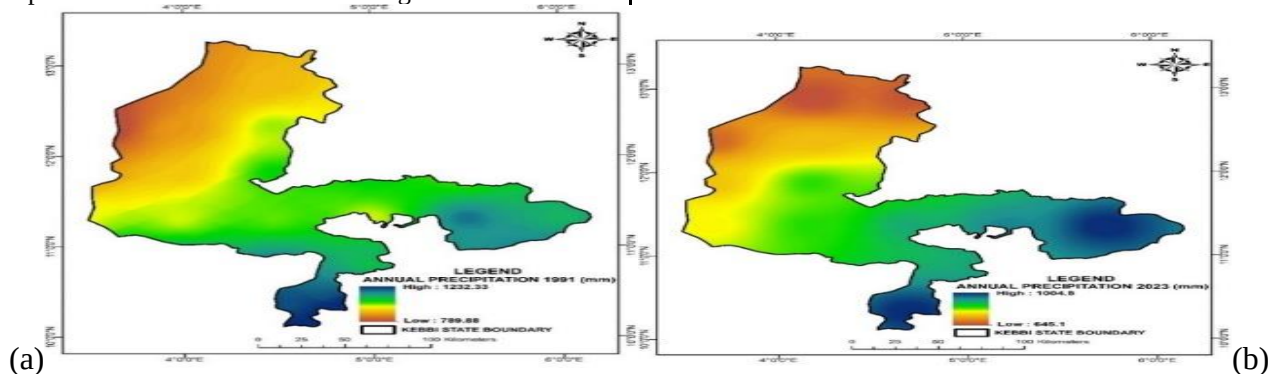
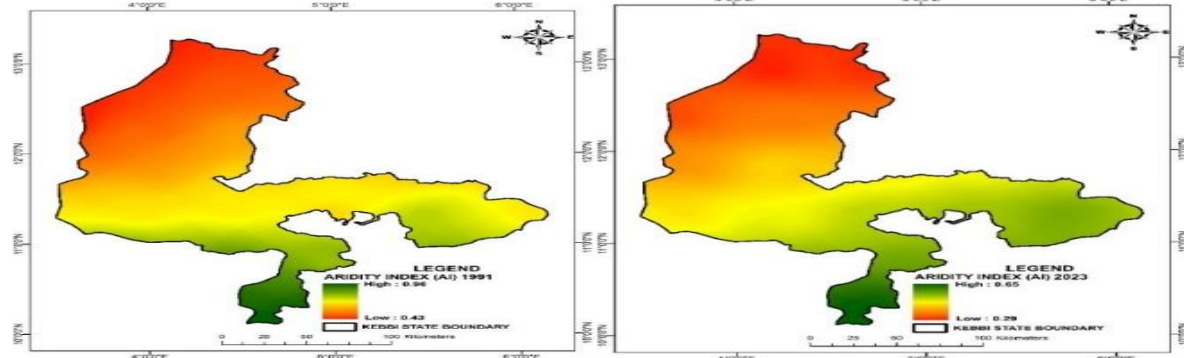


Figure 12: Precipitation (a) 1991 (b) 2023

3.1.12 Aridity Index (1991-2023)

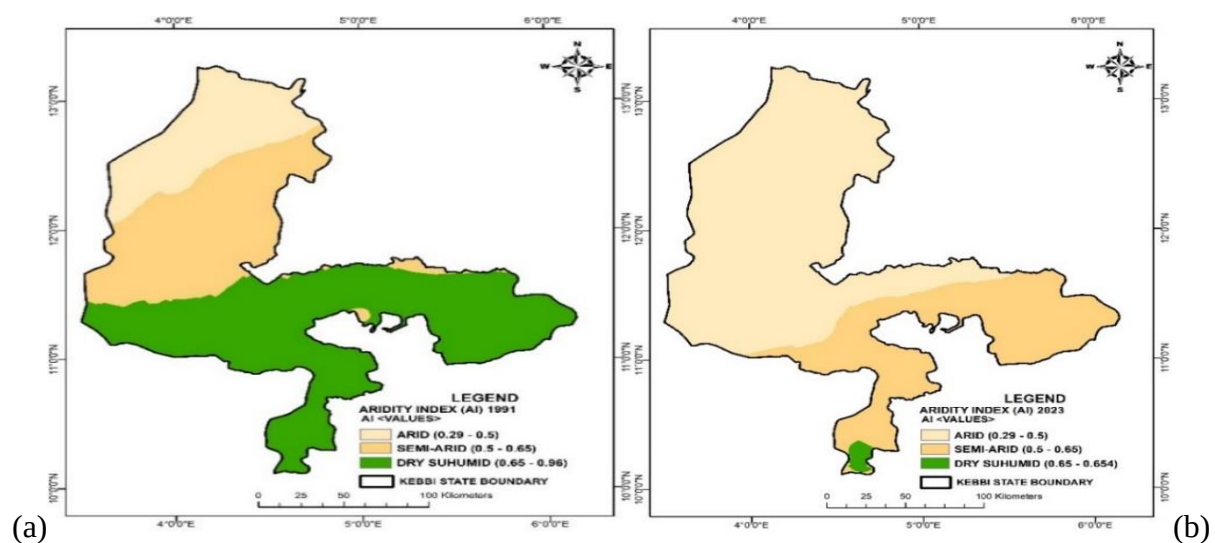
AI values decreased from a maximum of 0.96 in 1991 to 0.65 in 2023 (Fig. 13a, b). This reduction in AI values implies increasing drier conditions across the state, aligned with that of *Ullah et al. (2022)*. Further classification of AI based on *UNEP (1997)*; *Zomer et al. (2022)* thresholds showed that in 1991, 7018.69 ha (19.18%) of the total land mass fall under arid, 11262.18 ha (30.77%) falls under semi-arid and 18315.03ha (50.05%) under dry subhumid respectively (Fig. 14a). By 2023, 24597.89ha (67%) falls under arid, 11675.32ha (32%) under semi-

arid and 322.69ha (1%) under dry subhumid areas (Fig. 14b).(a)



(b)

Figure 13: Aridity Index AI (a) 1991 (b) 2023



(a)

(b)

Figure 14: Classified AI based on UNEP (1997), Trabucco and Zomer (2022) (a) 1991 (b) 2023

3.1.13 Albedo (1991-2023)

Albedo values increased from 0.0842-0.2589 in 1991 to 0.0982-0.3020 in 2023 (Fig. 15a, b), suggesting potential degradation of vegetative cover and increased

in exposed, compacted soils. These findings are consistent with *Bluestein et al. (2025)*, which report that albedo in the Sahel increased from 0.14 to 0.35 due to desertification during the 20th century.

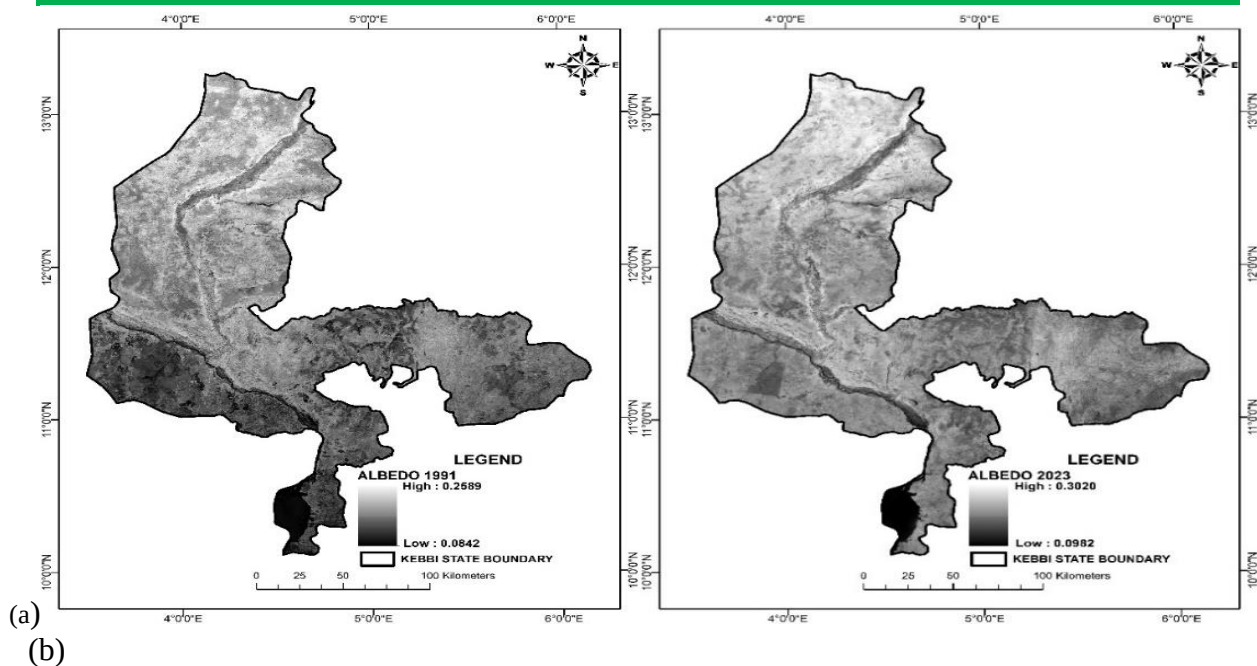


Figure 15: Albedo (a) 1991 (b) 2023

4.0 CONCLUSION

This study assessed the dynamics of desertification indicators in Kebbi State between 1991 and 2023 using a multi-indicator remote sensing and climate data approach. The results reveal an overall intensification of desertification conditions, characterized by declining vegetation and surface moisture, reduced precipitation, increasing air temperature and aridity, expansion of built-up areas, and increased surface albedo. The substantial decline in the Aridity Index, together with the expansion of arid areas from 19.18% in 1991 to 67% in 2023, indicates a marked shift towards drier conditions across the state. Although some indicators, such as NDSI and NDBaI, declined, their changes alongside the other indicators show the complex and spatially variable nature of desertification. The study highlights the effectiveness of a multi-indicator approach for identifying desertification dynamics and provides a useful basis for targeted land restoration, sustainable land-use management, and continuous monitoring of vulnerable areas in Kebbi State and other semi-arid regions of northern Nigeria.

DECLARATIONS

Conflict of interest: The author declares no conflict of interest.

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DATA AVAILABILITY: Landsat data are publicly available from the United States Geological Survey,

and climate data are available from the Climate Research Unit (CRU) Of the University of East Anglia.

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