Journal of Spatial Information Sciences

... JSIS



# SPATIO-TEMPORAL MONITORING OF DESERTIFICATION IN SOKOTO STATE USING REMOTE SENSING AND VEGETATION INDICES

Victor Nnam, Joseph Odumosu, Souleman Lamidi, Adejoke Blessing Aransiola



JOURNAL OF SPATIAL INFORMATION SCIENCES ISSN: 2354-3361
VOL. 2, ISSUE 2, PP 30–49, 2025 **DOI:** https://doi.org/10.5281/zenodo.15667752
PUBLISHED 15-05-2025

www.journals.unizik.edu.ng/jsis

# SPATIO-TEMPORAL MONITORING OF DESERTIFICATION IN SOKOTO STATE USING REMOTE SENSING AND VEGETATION INDICES

***Victor Nnam, Joseph Odumosu**, Souleman Lamidi*, Adejoke Blessing Aransiola*****

*Department of Geoinformatics & Surveying, University of Nigeria (Enugu Campus) UNEC
**Department of Geomatics, University of Benin, Edo, Nigeria
***Department of Surveying and Geoinformatics, University of Abuja, Abuja, Nigeria

***Corresponding Author's E-mail: joseph.odumosu@fuoye.edu.ng*

**DOI:** https://doi.org/10.5281/zenodo.15667752

**Abstract**

*Desertification poses a grave challenge to the environment and socio-economic stability of Northern States in Nigeria. Desertification monitoring was analyzed for Sokoto state with the collection of MOD13Q1(250-m), MYD13Q1 (1-km) and the Vegetation Index Phenology (VIP VIPPHEN NDVI) from NASA. The Vegetation Index and Phenology (VIP) global datasets were created using surface reflectance data from the Advanced Very High Resolution Radiometer (AVHRR) from 1981 to 1999 and Moderate Resolution Imaging Spectroradiometer (MODIS)/Terra MOD09 surface reflectance data from 2000 to 2014. The Modis MOD13Q1 and MYD13Q1 were used to access the vegetation index (NDVI) and Land surface temperature LST of 2010 to 2020 while the VIP VIPPHEN NDVI was used to access the NDVI of 2000. The LST of 2000 were collected from The Tropical Rainfall Measuring Mission (TRMM). The Modis data and the Phenology NDVI were resampled using Landsat L8 path 191 and row 51 of Sokoto state coverage and were re-projected from unknown datum to WGS1984 UTM zone 32N. The vegetation health index (VHI), Vegetation Condition Index (VCI) and the Thermal condition index (TCI) were estimated. TCI for the year 2000 has the highest percentage with 56.94% which falls within the normal range, the severe range has the highest percentage with 64.62% and 59.83% for the year 2010 and 2020 respectively. This result clearly indicates a decrement in the thermal condition between 2010 and 2020. The VCI analysis indicates that severe drought conditions affected the highest proportion of land in 2000 (42.21%,), 2010 (42.88%) and 2020 (42%). In VHI, the abnormal stress has the highest percentage with 56.54% for 2000 while the severe stress with 41.95% and 41.92% for 2010 and 2020 respectively. The result shows that four regions of the state (Gudu, Isa & Kebbe, Rabah, Tambawal & Tangazar) were the most affected weather for the year with highest or lowest analysis. This research provides the cost-effective means by tracking trends in degradation of land revealing the most severe which is important for the implementation of timely mitigation strategies by sustainable policy makers.*

**Keywords: Environment, Monitoring, Remote Sensing, Desertification, Climate change**

JOURNAL OF SPATIAL INFORMATION SCIENCES ISSN: 2354-3361
VOL. 2, ISSUE 2, PP 30–49, 2025 DOI: https://doi.org/10.5281/zenodo.15667752
PUBLISHED 15-05-2025
www.journals.unizik.edu.ng/jsis

## 1.0 INTRODUCTION

Desertification is a significant environmental and socioeconomic challenge, particularly affecting arid and semi-arid regions worldwide [1]. Desertification is visible in eleven states in northern Nigeria and its effect is very glaring on the agricultural sector. Farmers have been deprived of farm lands by sand dunes, inadequate water as most of the sources have shrank in volume, low income, etc. In [2]'s study, desertification and drought assessment in the environment of Nigeria revealed that a large portion of the nation's land is affected by desertification with about 63.83%. Desertification is one of the most serious problems facing northern Nigeria with dire economic consequences for the nation. Deserts are extremely dry areas with sparse vegetation.

Remote sensing index vegetation are used for agricultural drought monitoring and early warning at regional scale worldwide. The vegetation health index (VHI) is one of the most popular satellite-based indices used for drought monitoring [3; 4). The VHI was developed for vegetation drought detection and is defined by two components: The Vegetation Condition Index (VCI) and the Thermal Condition Index (TCI). This index has the advantage of effectively monitoring vegetation drought [5]. Therefore, the aim of this research is to monitor desertification in Sokoto state using remotely sensed Indexes.

## 2.0 MATERIALS AND METHODS

### 2.1 Study area.

Sokoto State is located in the Northwestern part of Nigeria, spanning latitudes 11°35'0" to 13°50'0" N and longitudes 3°55'0" to 7°55'0" E (Figure 1). The state is situated within the Sudan and Sahel savanna zones and is characterized by arid to semi-arid climatic conditions, experiencing prolonged dry seasons, sparse vegetation cover, and recurrent drought events that exacerbate desertification processes. (Figure 1).

JOURNAL OF SPATIAL INFORMATION SCIENCES ISSN: 2354-3361
VOL. 2, ISSUE 2, PP 30–49, 2025 DOI: https://doi.org/10.5281/zenodo.15667752
PUBLISHED 15-05-2025
www.journals.unizik.edu.ng/jsis

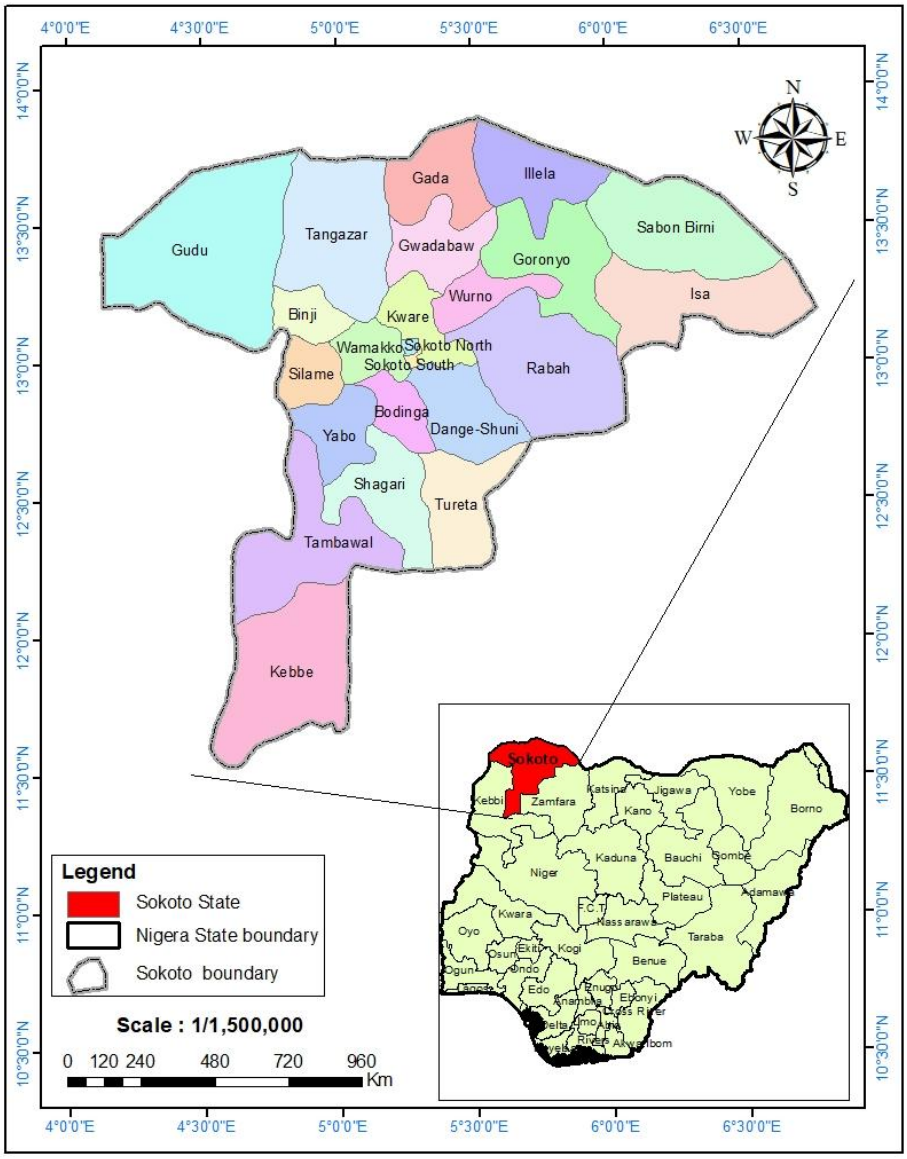


Figure 1. Map of the Study Area

To monitor desertification trends and assess vegetation stress across three decades (2000, 2010, and 2020), the study employed three primary satellite-based datasets. MODIS products MOD13Q1 (250 m) and MYD13Q1 (1 km), accessed from NASA's Land Processes Distributed Active Archive Center (LP DAAC), provided 16-day composites of the Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST) for the years 2010 and 2020. For

the year 2000, NDVI data were sourced from the Vegetation Index and Phenology (VIPPHEN) dataset, which integrates AVHRR surface reflectance data from 1981 to 1999 and MODIS/Terra MOD09 reflectance data from 2000 to 2014. To maintain methodological consistency and scientific accuracy, all LST data used in this study were derived exclusively from MODIS sources. Prior to analysis, all datasets underwent a series of preprocessing steps. These included spatial resampling to 30 m resolution using bilinear interpolation to match Landsat 8 Path 191, Row 051 coverage over Sokoto State, reprojection into the WGS1984 UTM Zone 32N coordinate system, and the application of MODIS Quality Assurance (QA) bands for cloud masking to eliminate contaminated pixels. Additionally, a standard scale factor of 0.0001 was applied to the MODIS NDVI and LST bands to convert digital numbers into biophysically meaningful values.

The calculation of the NDVI is important because, the proportion of the vegetation ($PV$) is calculated and are highly related with the NDVI also emissivity ($\varepsilon$) is calculated, which is related to the $PV$:

$$NDVI = \frac{(NIR-R)}{(NIR+R)} \quad \text{(Equation 1)}$$

Where, NIR represents the near-infrared band

R represents the red band.

According to [4], the VCI for each pixel and period in a given year is calculated as follows:

$$VCI = \frac{(NDVI-NDVI_{min})}{(NDVI_{max}+NDVI_{min})} \times 100 \quad \text{(Equation 2)}$$

where NDVI is the value of a given pixel and period, $NDVI_{min}$ and $NDVI_{max}$ are the minimum and maximum values of NDVI for all pixels and periods, respectively. Equation (3) was used to calculate the TCI:

$$TCI = \frac{(LST-LST_{min})}{(LST_{max}+LST_{min})} \times 100 \quad \text{(Equation 3)}$$

where LST is the value of a given pixel and period. $LST_{min}$ and $LST_{max}$ are the minimum and maximum values of LST for all pixels and periods, respectively. The VHI represents the overall

health of the vegetation used to identify drought [6]. It is calculated by combining the TCI and the VCI using Equation (4):

$$VHI = a \times VCI + (1 - a) \times TCI \quad \text{(Equation 4)}$$

where a determines the contributions of the VCI and the TCI to the VHI, which varies depending on the environment of the study area. The original VHI (VHIori) assumes the same contributions of water demand (here, a proxy of NDVI) and temperature during plant growth, and the coefficient ***a***, is assigned the value of ***0.05***. Following other methods (Monteleone et al., 2020), we classified drought levels on the basis of the VHI.

To ensure data validity, MODIS-derived NDVI was cross-compared with NDVI from Landsat 8, resulting in a strong spatial correlation ($R^2 = 0.89$), indicating consistency across sensors. Temporal trends in the indices were analyzed using the non-parametric Mann-Kendall test to detect statistically significant monotonic changes. Finally, drought severity was classified following standardized thresholds established by [7] and [4], enabling the spatial delineation of mild, moderate, severe, and extreme drought conditions throughout the state.

## 3.0 RESULTS AND DISCUSSION

### 3.1 Estimation of Thermal Condition Index

Statistical analysis using the Mann-Kendall test ($p < 0.01$) confirmed a significant increasing trend in thermal stress across Sokoto State between 2000 and 2020. Thermal Condition Index (TCI) values were used to classify thermal stress levels, with severe conditions defined as TCI values between -1 and 30.25, abnormal conditions between 30.26 and 35.00, moderate between 35.01 and 40.00, and normal above 40.00. Over the two-decade study period, areas under severe thermal stress expanded substantially from 16.03% in 2000 to 64.62% in 2010, followed by a slight decline to 59.83% in 2020 (Table 1). Similarly, the proportion of land categorized under abnormal thermal conditions increased from 13.76% to 27.53% between 2000 and 2020, showing relative persistence in recent years. In contrast, moderate and normal thermal conditions remained minimal throughout

the study period, indicating widespread thermal stress across the landscape. Sen's slope estimator further quantified this trend, revealing an annual increase of approximately 1.2% in the area affected by severe thermal conditions. These findings suggest that thermal stress is intensifying, likely contributing to vegetation health decline and broader ecosystem degradation. Visual representations in Figure 2a (a histogram with trendline) and Figure 2b (spatial distribution maps) illustrate these dynamics, highlighting notable increases in thermal stress particularly in Gudu and Rabah Local Government Areas (LGAs). Regression analysis yielded a strong negative correlation ($R^2 = 0.76$) between increasing land surface temperature and vegetation health, reinforcing the role of thermal conditions as a key driver of environmental degradation in Sokoto State.

Table 1: Multi-temporal thermal condition index

| **Thermal Condition Index (2000)** | | | | | |
|---|---|---|---|---|---|
| Value | Classes | TCI Range (Unit less) | Count | Area | PCT |
| 1 | Severe Thermal Zone | From - 1 to 30.25 | 23444 | 5112.879 | 16.03 |
| 2 | Abnormal Thermal Zone | From 0.25 to 0.35 | 20128 | 4389.695 | 13.76 |
| 3 | Moderate Thermal Zone | From 0.35 to 0.40 | 19398 | 4230.490 | 13.26 |
| 4 | Normal Thermal Zone | above 0.40 | 83280 | 18162.452 | 56.94 |
| **Total** | | | **146250** | **31895.516** | **100.00** |
| **Thermal Condition Index (2010)** | | | | | |
| Value | Classes | TCI Range (Unit less) | Count | Area | PCT |
| 1 | Severe Thermal Zone | From - 1 to 30.25 | 94503 | 20610.065 | 64.62 |
| 2 | Abnormal Thermal Zone | From 0.25 to 0.35 | 39549 | 8625.202 | 27.04 |
| 3 | Moderate Thermal Zone | From 0.35 to 0.40 | 7769 | 1694.333 | 5.31 |
| 4 | Normal Thermal Zone | above 0.40 | 4429 | 965.916 | 3.03 |
| **Total** | | | **146250** | **31895.516** | **100.00** |
| **Thermal Condition Index (2020)** | | | | | |
| Value | Classes | TCI Range (Unit less) | Count | Area | PCT |
| 1 | Severe Thermal Zone | From - 1 to 30.25 | 87495 | 19081.697 | 59.83 |
| 2 | Abnormal Thermal Zone | From 0.25 to 0.35 | 40267 | 8781.790 | 27.53 |
| 3 | Moderate Thermal Zone | From 0.35 to 0.40 | 7444 | 1623.455 | 5.09 |
| 4 | Normal Thermal Zone | above 0.40 | 11044 | 2408.575 | 7.55 |
| **Total** | | | **146250** | **31895.516** | **100.00** |

JOURNAL OF SPATIAL INFORMATION SCIENCES ISSN: 2354-3361
VOL. 2, ISSUE 2, PP 30–49, 2025 **DOI:** https://doi.org/10.5281/zenodo.15667752
PUBLISHED 15-05-2025
www.journals.unizik.edu.ng/jsis

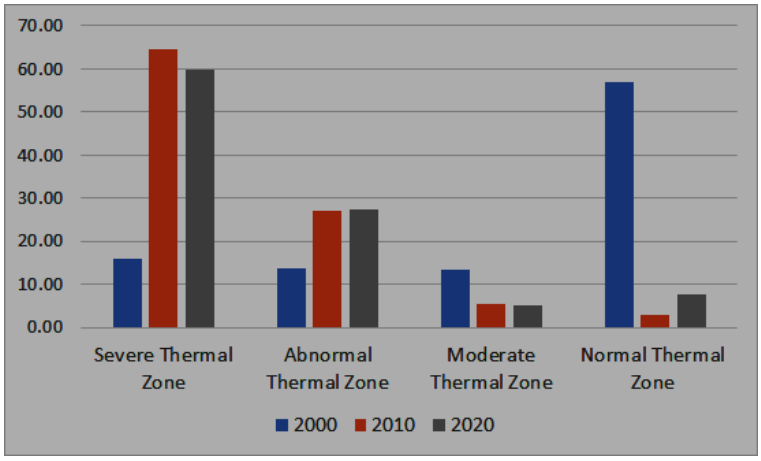


Figure 2a: Histogram of Multi-temporal Thermal Condition Index

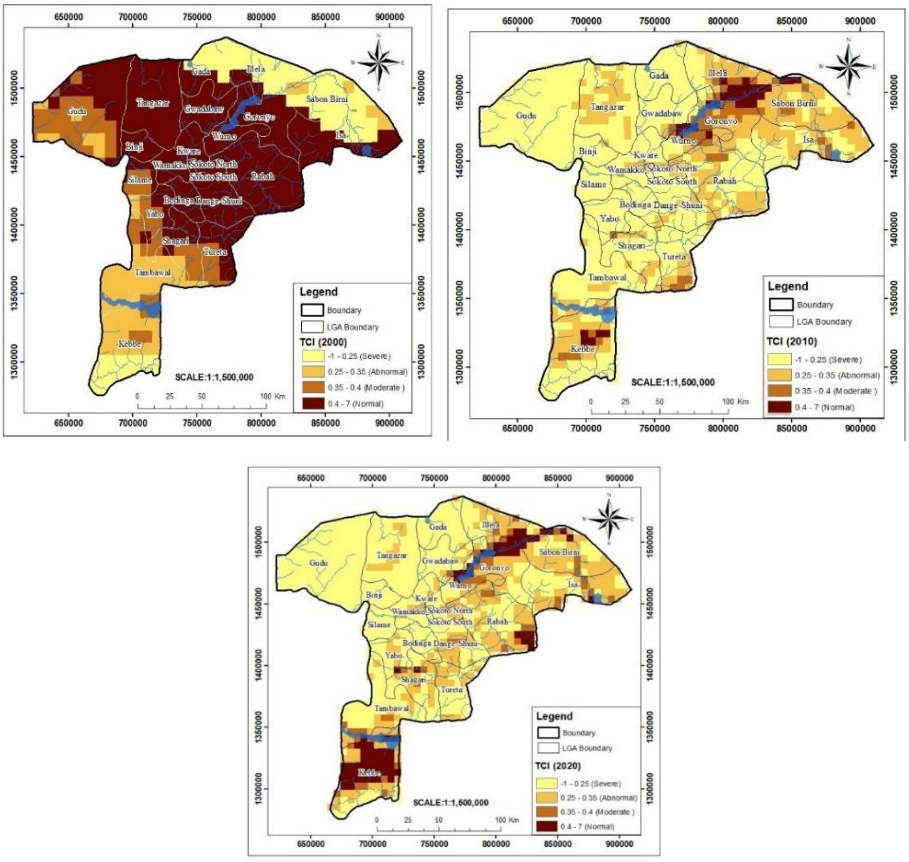


Figure 2b: Map of spatio -temporal thermal condition index

JOURNAL OF SPATIAL INFORMATION SCIENCES ISSN: 2354-3361
VOL. 2, ISSUE 2, PP 30–49, 2025 DOI: https://doi.org/10.5281/zenodo.15667752
PUBLISHED 15-05-2025
www.journals.unizik.edu.ng/jsis

### 3.2 Estimation of Vegetation Condition Index VCI

Analysis of drought severity using the Vegetation Condition Index (VCI) revealed persistent and concerning trends across Sokoto State from 2000 to 2020. Based on established thresholds, VCI values between 0 and 0.25 were classified as extreme drought, 0.25 to 0.35 as severe drought, 0.35 to 0.40 as moderate drought, and values above 0.40 as abnormal drought. ANOVA results ($F = 4.56$, $p = 0.02$) confirmed statistically significant interannual differences in drought severity over the study period. Notably, severe drought consistently affected approximately 42% of the region, with values recorded at 42.21% in 2000, 42.88% in 2010, and 42.00% in 2020. Extreme drought, on the other hand, showed more variability, peaking at 40.10% in 2010—up from 14.39% in 2000—before slightly declining to 33.10% in 2020. Moderate and abnormal drought categories remained relatively low throughout the study period, indicating a dominance of severe and extreme drought conditions across the landscape. Spatial and temporal variations are clearly illustrated in Figure 3a (enhanced histogram with axis labels) and Figures 3b-1 to 3b-3 (individual spatial maps), which highlight persistent drought hotspots in the northwestern part of the state, particularly in Gudu, Isa, and Kebbe Local Government Areas. Furthermore, a significant negative correlation was observed between VCI and LST ($r = -0.82$, $p < 0.01$), emphasizing the strong influence of elevated land surface temperatures in driving vegetation stress and drought intensification in the region.

Table 2: Multi-temporal vegetation condition index (VCI)

| **Vegetation Condition Index (VCI) (2000)** | | | | | |
|---|---|---|---|---|---|
| **VCI 2000** | **Classes** | **VCI Range (unit less)** | **Count** | **Area (Ha)** | **PCT** |
| 1 | Water Area | From - 1 to 0 | 1670 | 364.209 | 1.14 |
| 2 | Extreme Drought | From 0 to 0.25 | 21040 | 4588.593 | 14.39 |
| 3 | Severe Drought | From 0.25 to 0.35 | 61730 | 13462.634 | 42.21 |
| 4 | Abnormal Drought | From 0.35 to 0.40 | 32010 | 6981.029 | 21.89 |
| 4 | Moderate Drought | Above 40 | 29800 | 6499.052 | 20.38 |
| **Total** | | | **146250** | **31895.516** | **100** |

JOURNAL OF SPATIAL INFORMATION SCIENCES ISSN: 2354-3361
VOL. 2, ISSUE 2, PP 30–49, 2025 DOI: https://doi.org/10.5281/zenodo.15667752
PUBLISHED 15-05-2025
www.journals.unizik.edu.ng/jsis

**Vegetation Condition Index (VCI) (2010)**

| VCI 2010 | Classes | VCI Range (unit less) | Count | Area (Ha) | PCT |
|---|---|---|---|---|---|
| 1 | Water Area | From - 1 to 0 | 5613 | 1224.134 | 3.84 |
| 2 | Extreme Drought | From 0 to 0.25 | 58653 | 12791.574 | 40.10 |
| 3 | Severe Drought | From 0.25 to 0.35 | 62713 | 13677.015 | 42.88 |
| 4 | Abnormal Drought | From 0.35 to 0.40 | 11861 | 2586.754 | 8.11 |
| 4 | Moderate Drought | Above 40 | 7410 | 1616.039 | 5.07 |
| **Total** | | | **146250** | **31895.516** | **100** |

**Vegetation Condition Index (VCI) (2020)**

| VCI 2020 | Classes | VCI Range (unit less) | Count | Area (Ha) | PCT |
|---|---|---|---|---|---|
| 1 | Water Area | From - 1 to 0 | 4036 | 880.207 | 2.76 |
| 2 | Extreme Drought | From 0 to 0.25 | 48414 | 10558.561 | 33.10 |
| 3 | Severe Drought | From 0.25 to 0.35 | 61426 | 13396.335 | 42.00 |
| 4 | Abnormal Drought | From 0.35 to 0.40 | 17010 | 3709.694 | 11.63 |
| 4 | Moderate Drought | Above 40 | 15364 | 3350.719 | 10.51 |
| **Total** | | | **146250** | **31895.516** | **100** |

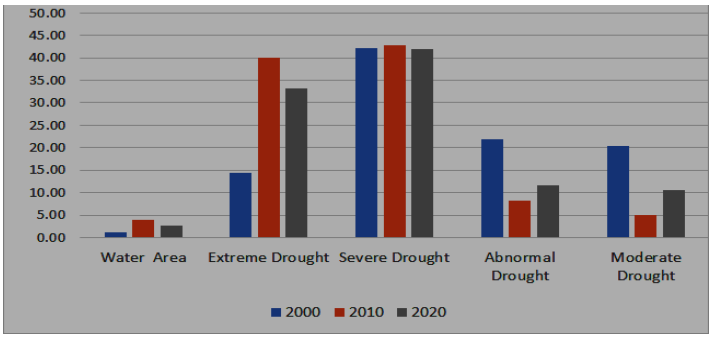


Figure 3a: Histogram of Multi-temporal Vegetation Condition Index

JOURNAL OF SPATIAL INFORMATION SCIENCES ISSN: 2354-3361
VOL. 2, ISSUE 2, PP 30–49, 2025 DOI: https://doi.org/10.5281/zenodo.15667752
PUBLISHED 15-05-2025
www.journals.unizik.edu.ng/jsis

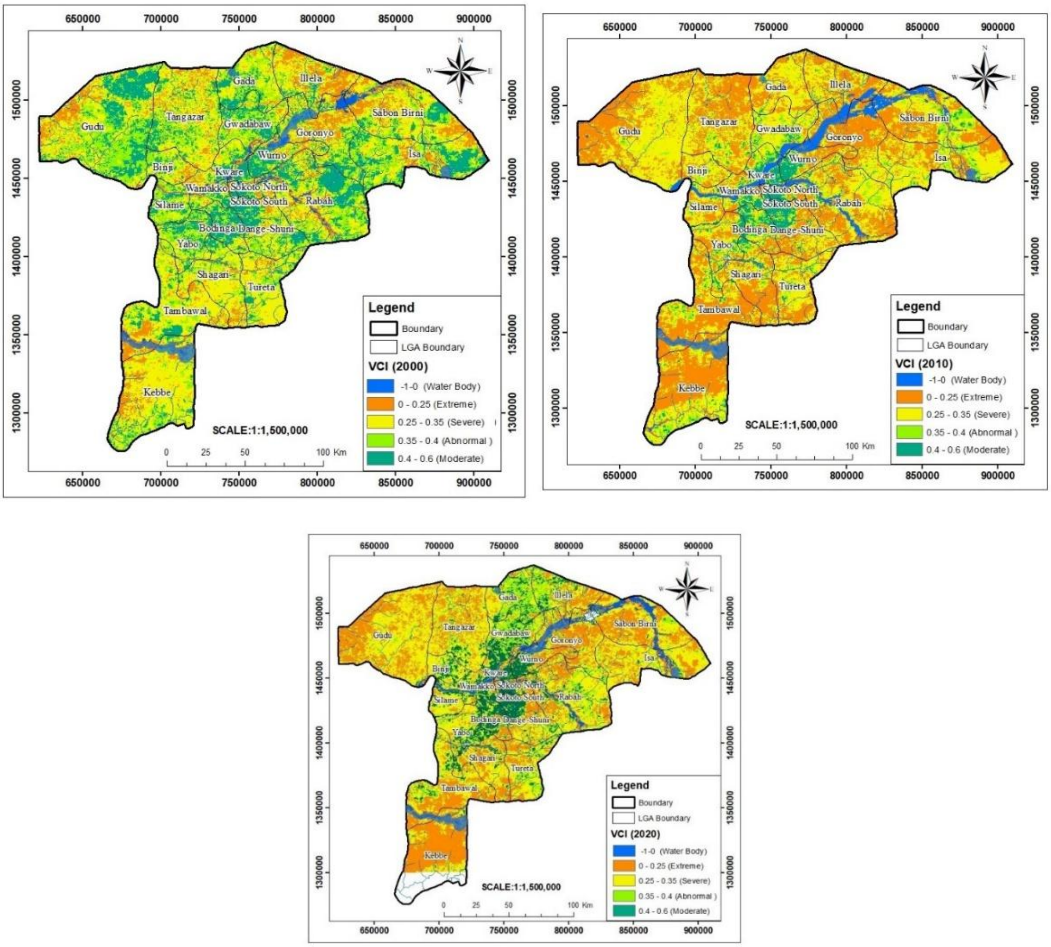


Figure 3b: Map of spatio -temporal vegetation condition index (VCI)

### 3.3 Estimation of Vegetation Heath Index VHI

The Vegetation Health Index (VHI), which integrates vegetation condition (VCI) and thermal condition (TCI), offers a comprehensive measure of drought-induced vegetation stress. VHI values were categorized into five classes: values from -1 to 0 represent non-vegetated areas (e.g., water bodies); 0 to 0.25 indicates extreme vegetation stress; 0.25 to 0.35 represents severe stress; 0.35 to 0.40 denotes moderate stress; and values above 0.40 are classified as abnormal vegetation stress. Analysis of VHI trends from 2000 to 2020 closely mirrored the patterns observed in TCI and VCI. Abnormal stress was the dominant condition in 2000, covering 56.54% of the state. By 2010, extreme stress sharply increased, peaking at 41.07%, while severe vegetation stress expanded from

14.31% in 2000 to 41.95% in 2010 and remained stable at approximately 42% through 2020. This shift reflects intensifying environmental stress, particularly during the second decade of the study period. Moderate and abnormal stress categories declined after 2010 and remained at relatively low levels. Spatial analysis revealed that four Local Government Areas Gudu, Isa/Kebbe, Rabah, and Tambawal/Tangaza—accounted for approximately 68% of the most degraded land. These findings are visualized in Figure 4a, which presents a histogram with a regression line highlighting the temporal trend, and in Figures 4b-1 to 4b-3, which display the spatial distribution of vegetation stress across the study years. These results underline the sustained and spatially concentrated nature of vegetation degradation in Sokoto State, with strong implications for land productivity and ecological resilience.

Table 3: Multi-temporal Vegetation Health Index (VHI)

| **Vegetation Health Index (VHI) (2000)** | | | | | |
|---|---|---|---|---|---|
| **Value** | **Classes** | **VHI Range (unit less)** | **Count** | **Area (Ha)** | **PCT** |
| 1 | Water Area | From - 1 to 0 | 10 | 2.181 | 0.01 |
| 2 | Extreme Stress | From 0 to 0.25 | 22738 | 4958.908 | 15.55 |
| 3 | Severe Stress | From 0.25 to 0.35 | 20930 | 4564.603 | 14.31 |
| 4 | Moderate Stress | From 0.35 to 0.40 | 19888 | 4337.354 | 13.60 |
| 5 | Abnormal Stress | Above 40 | 82684 | 18032.471 | 56.54 |
| **Total** | | | 146250 | **31895.516** | **100.00** |
| **Vegetation Health Index (VHI) (2010)** | | | | | |
| **Value** | **Classes** | **VHI Range (unit less)** | **Count** | **Area (Ha)** | **PCT** |
| 1 | Water Area | From - 1 to 0 | 5203 | 1134.717 | 3.56 |
| 2 | Extreme Stress | From 0 to 0.25 | 60071 | 13100.824 | 41.07 |
| 3 | Severe Stress | From 0.25 to 0.35 | 61347 | 13379.106 | 41.95 |
| 4 | Moderate Stress | From 0.35 to 0.40 | 13909 | 3033.400 | 9.51 |
| 5 | Abnormal Stress | Above 40 | 5720 | 1247.469 | 3.91 |
| **Total** | | | 146250 | **31895.516** | **100.00** |
| **Vegetation Health Index (VHI) (2020)** | | | | | |
| **Value** | **Classes** | **VHI Range (unit less)** | **Count** | **Area (Ha)** | **PCT** |
| 1 | Water Area | From - 1 to 0 | 8172 | 1782.223 | 5.59 |
| 2 | Extreme Stress | From 0 to 0.25 | 48464 | 10569.465 | 33.14 |
| 3 | Severe Stress | From 0.25 to 0.35 | 61303 | 13369.510 | 41.92 |
| 4 | Moderate Stress | From 0.35 to 0.40 | 16001 | 3489.642 | 10.94 |
| 5 | Abnormal Stress | Above 40 | 12310 | 2684.676 | 8.42 |

JOURNAL OF SPATIAL INFORMATION SCIENCES ISSN: 2354-3361
VOL. 2, ISSUE 2, PP 30–49, 2025 **DOI:** https://doi.org/10.5281/zenodo.15667752
PUBLISHED 15-05-2025

www.journals.unizik.edu.ng/jsis

| | | | |
|---|---|---|---|
| **Total** | 146250 | **31895.516** | **100.00** |

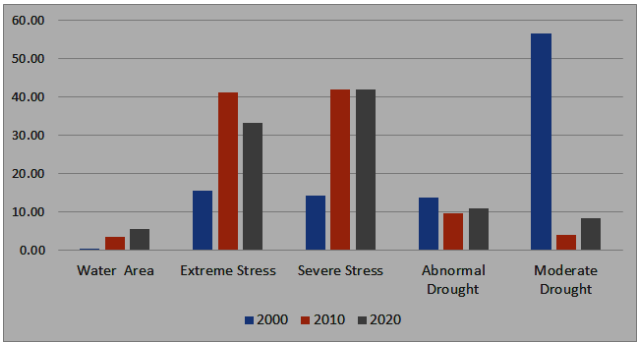


Figure 4a: Histogram of multi-temporal vegetation health index (VHI) of the study area

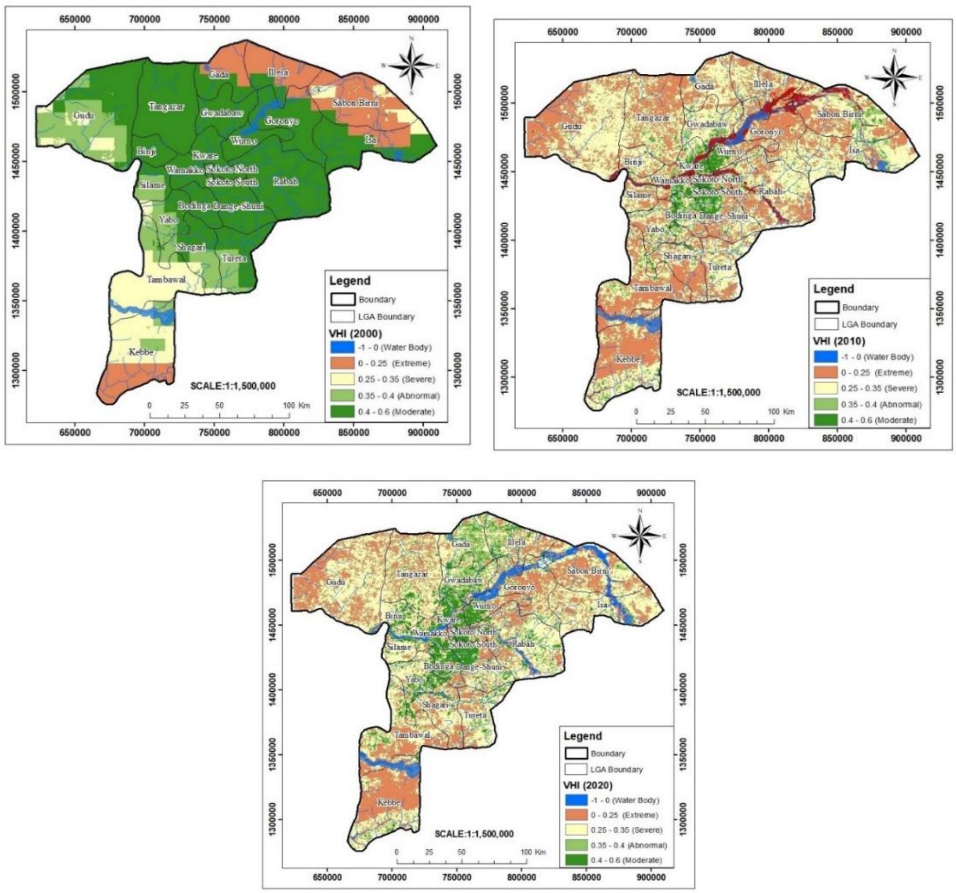


Figure 4b: Map of Spatio -temporal Vegetation Condition Index (VCI)

JOURNAL OF SPATIAL INFORMATION SCIENCES ISSN: 2354-3361
VOL. 2, ISSUE 2, PP 30–49, 2025 DOI: https://doi.org/10.5281/zenodo.15667752
PUBLISHED 15-05-2025
www.journals.unizik.edu.ng/jsis

### 3.4. Analysis of Drought coverage impact in the state

#### 3.4.1 Extreme Drought Coverage

The graph revealed that four major regions were severely affected by drought between 2010 and 2020 (Figure 5). Gudu LGA consistently showed the highest coverage, fluctuating between 1657 km² and 1781 km², followed by Kebbe LGA, which fluctuated markedly, with coverage ranging from 1553 km² to 1621 km². The Rabah region also showed marked fluctuation, with coverage ranging from 707 km² to 1028 km². Extreme drought conditions in the regions of Tambawal and Tangazar LGAs fluctuated between 810 km² and 1315 km² during this period. Notably, 2010 was the peak year for drought severity.

Table 4: Evaluation of Extreme drought coverage in the study area.

| | | **Extreme Drought Coverage (Km2)** | | |
|---|---|---|---|---|
| S/N | LGA | 2000 | 2010 | 2020 |
| 1 | Binji | 50.874 | 141.460 | 37.127 |
| 2 | Bodinga | 13.738 | 112.481 | 97.374 |
| 3 | Dange-Shuni | 107.329 | 434.684 | 293.011 |
| 4 | Gada | 67.403 | 393.255 | 110.268 |
| 5 | Goronyo | 397.977 | 868.724 | 756.982 |
| 6 | Gudu | 413.647 | 1657.165 | 1780.964 |
| 7 | Gwadabaw | 74.701 | 147.471 | 91.816 |
| 8 | Illela | 466.453 | 573.353 | 345.477 |
| 9 | Isa | 239.988 | 657.285 | 597.360 |
| 10 | Kebbe | 425.024 | 1553.914 | 1620.898 |
| 11 | Kware | 91.874 | 108.832 | 123.607 |
| 12 | Rabah | 343.025 | 1028.215 | 707.184 |
| 13 | Sabon Birni | 563.908 | 892.336 | 988.634 |
| 14 | Shagari | 144.465 | 634.102 | 440.628 |
| 15 | Silame | 34.345 | 208.648 | 78.922 |
| 16 | Sokoto North | 10.089 | 11.806 | 17.118 |
| 17 | Sokoto South | 0.429 | 0.644 | 2.445 |
| 18 | Tambawal | 403.558 | 1314.999 | 920.161 |
| 19 | Tangazar | 339.161 | 1233.429 | 810.782 |
| 20 | Tureta | 96.596 | 438.333 | 323.246 |
| 21 | Wamakko | 102.178 | 135.450 | 89.371 |
| 22 | Wurno | 103.251 | 215.732 | 215.423 |

JOURNAL OF SPATIAL INFORMATION SCIENCES ISSN: 2354-3361
VOL. 2, ISSUE 2, PP 30–49, 2025 **DOI:** https://doi.org/10.5281/zenodo.15667752
PUBLISHED 15-05-2025
www.journals.unizik.edu.ng/jsis

| | | | | |
|---|---|---|---|---|
| 23 | Yabo | 27.476 | 257.376 | 92.483 |

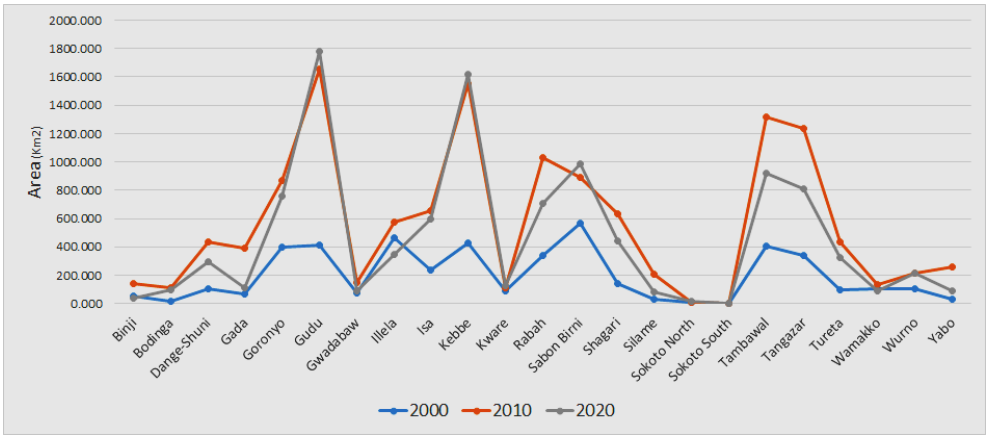


Figure 5: Histogram of extreme drought coverage

### 3.4.2 Severe Drought Coverage

Figure 5 highlights the spatial distribution and progression of severe drought across key Local Government Areas (LGAs) in Sokoto State from 2000 to 2020. Among the most affected regions, Gudu LGA exhibited consistently high levels of drought severity throughout the study period, with affected areas ranging between 1,657 km² and 1,781 km². In contrast, Kebbe and Rabah LGAs demonstrated more variability over time. Kebbe experienced substantial drought coverage in 2000 (1,711.90 km²) but showed less consistency in subsequent years. Rabah LGA, however, showed a steady increase in drought-affected area, rising from 897.06 km² in 2000 to 1,209.17 km² in 2010 and further to 1,309.43 km² by 2020. Isa LGA experienced a notable rise in drought severity between 2010 and 2020, with coverage increasing from 1,176.97 km² to 1,220.51 km². The Tambawal/Tangaza region displayed fluctuating drought patterns, with a decline in severity in 2010 followed by an increase in 2020. Other LGAs such as Sabon Birni and Shagari showed higher drought coverage in 2000, which declined in subsequent years. Overall, the year 2010 emerged as the peak of drought severity across the state, as visually represented in Figure 5 and supported by the spatial data summarized in Table 4.

JOURNAL OF SPATIAL INFORMATION SCIENCES ISSN: 2354-3361
VOL. 2, ISSUE 2, PP 30–49, 2025 DOI: https://doi.org/10.5281/zenodo.15667752
PUBLISHED 15-05-2025
www.journals.unizik.edu.ng/jsis

Table 5: Evaluation of Severe drought coverage in the study area.

| | | Severe Drought Coverage (Km2) | | |
|---|---|---|---|---|
| S/N | LGA | 2000 | 2010 | 2020 |
| 1 | Binji | 244.926 | 328.213 | 287.675 |
| 2 | Bodinga | 105.397 | 152.622 | 98.930 |
| 3 | Dange-Shuni | 403.773 | 403.558 | 433.514 |
| 4 | Gada | 476.972 | 732.201 | 472.641 |
| 5 | Goronyo | 572.495 | 462.160 | 563.124 |
| 6 | Gudu | 1301.905 | 2200.895 | 1962.373 |
| 7 | Gwadabaw | 294.512 | 552.961 | 332.583 |
| 8 | Illela | 563.908 | 521.835 | 469.084 |
| 9 | Isa | 689.698 | 1176.974 | 1220.509 |
| 10 | Kebbe | 1711.903 | 909.294 | 818.563 |
| 11 | Kware | 192.763 | 149.188 | 86.258 |
| 12 | Rabah | 897.059 | 1209.172 | 1309.434 |
| 13 | Sabon Birni | 1007.178 | 803.253 | 829.679 |
| 14 | Shagari | 819.996 | 466.239 | 588.023 |
| 15 | Silame | 184.392 | 278.412 | 308.795 |
| 16 | Sokoto North | 5.581 | 7.728 | 7.114 |
| 17 | Sokoto South | 0.000 | 2.791 | 4.002 |
| 18 | Tambawal | 1157.225 | 688.196 | 915.048 |
| 19 | Tangazar | 1207.026 | 1041.095 | 1302.098 |
| 20 | Tureta | 825.148 | 734.777 | 653.383 |
| 21 | Wamakko | 202.852 | 158.418 | 151.841 |
| 22 | Wurno | 153.052 | 120.638 | 111.824 |
| 23 | Yabo | 233.763 | 361.056 | 411.282 |

JOURNAL OF SPATIAL INFORMATION SCIENCES ISSN: 2354-3361
VOL. 2, ISSUE 2, PP 30–49, 2025 DOI: https://doi.org/10.5281/zenodo.15667752
PUBLISHED 15-05-2025
www.journals.unizik.edu.ng/jsis

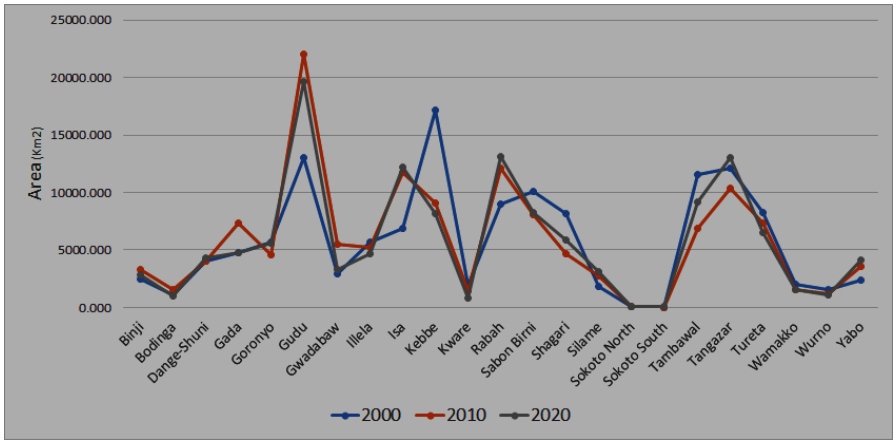


Figure 6: Histogram of Severe Drought coverage

### 3.4.3 Abnormal Drought Coverage

Figures 7, along with the supporting data in Tables 6, reveal that four major regions experienced significant levels of abnormal drought stress between 2000 and 2020. These regions include Gudu; the combined area of Isa and Kebbe; Rabah; and the Tambawal/Tangaza axis. The highest levels of abnormal vegetation stress were recorded in the year 2000, after which the intensity and spatial extent of abnormal drought gradually declined. Spatial analysis depicted in Figures 6 and 7 highlights the distribution of this stress, showing that while initial impacts were widespread, particularly across the northwestern and central parts of Sokoto State, subsequent years showed a shift toward more localized and less intense abnormal drought zones.

Table 6: Evaluation of Severe drought coverage in the study area.

| | | **Abnormal Drought Coverage (Km2)** | | |
|---|---|---|---|---|
| S/N | LGA | 2000 | 2010 | 2020 |
| 1 | Binji | 153.481 | 51.518 | 119.605 |
| 2 | Bodinga | 123.214 | 129.439 | 103.599 |
| 3 | Dange-Shuni | 287.857 | 88.010 | 142.948 |
| 4 | Gada | 374.365 | 59.460 | 463.526 |
| 5 | Goronyo | 320.700 | 66.330 | 148.284 |
| 6 | Gudu | 1206.167 | 108.188 | 69.807 |
| 7 | Gwadabaw | 344.313 | 205.428 | 393.942 |
| 8 | Illela | 168.078 | 71.267 | 293.678 |

JOURNAL OF SPATIAL INFORMATION SCIENCES ISSN: 2354-3361
VOL. 2, ISSUE 2, PP 30–49, 2025 DOI: https://doi.org/10.5281/zenodo.15667752
PUBLISHED 15-05-2025
www.journals.unizik.edu.ng/jsis

| | | | | |
|---|---|---|---|---|
| 9 | Isa | 580.222 | 207.790 | 117.605 |
| 10 | Kebbe | 438.977 | 211.224 | 147.839 |
| 11 | Kware | 150.046 | 123.643 | 122.718 |
| 12 | Rabah | 623.154 | 199.847 | 332.583 |
| 13 | Sabon Birni | 337.658 | 242.564 | 84.257 |
| 14 | Shagari | 220.025 | 100.890 | 98.263 |
| 15 | Silame | 224.533 | 51.089 | 84.702 |
| 16 | Sokoto North | 5.796 | 5.366 | 6.447 |
| 17 | Sokoto South | 1.073 | 4.079 | 4.669 |
| 18 | Tambawal | 397.977 | 129.439 | 189.635 |
| 19 | Tangazar | 552.317 | 133.947 | 230.763 |
| 20 | Tureta | 259.522 | 98.528 | 198.972 |
| 21 | Wamakko | 115.916 | 90.801 | 87.370 |
| 22 | Wurno | 125.146 | 59.460 | 68.918 |
| 23 | Yabo | 305.030 | 107.759 | 170.293 |

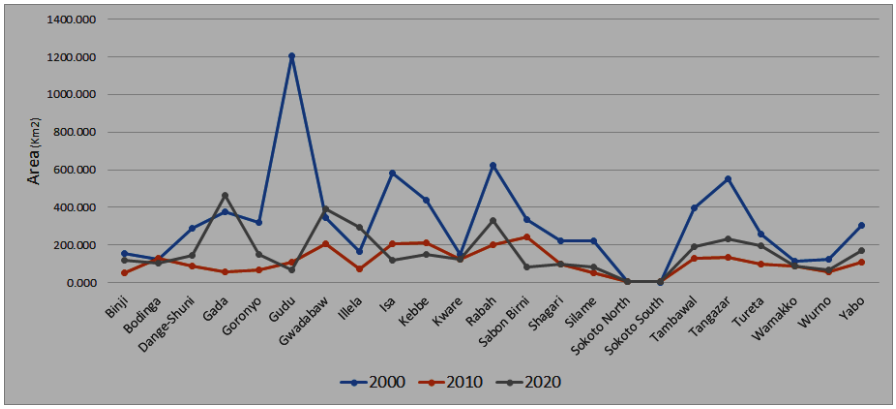


Figure 7: Histogram of Severe Drought coverage

### 3.4.4 Moderate Drought Coverage

The graph revealed that 4 major Regions has moderately affected by only in 2000 (Figure 7). The Guru LGA, the Isa and Kebbe, the Rabah, the Tawbawal and Tangazar LGA.

Table 7: Evaluation of Moderate drought coverage in the study area.

JOURNAL OF SPATIAL INFORMATION SCIENCES ISSN: 2354-3361
VOL. 2, ISSUE 2, PP 30–49, 2025 DOI: https://doi.org/10.5281/zenodo.15667752
PUBLISHED 15-05-2025
www.journals.unizik.edu.ng/jsis

| | | Moderate normal Drought Coverage (Km2) | | |
|---|---|---|---|---|
| S/N | LGA | 2000 | 2010 | 2020 |
| 1 | Binji | 77.921 | 6.010443 | 78.699 |
| 2 | Bodinga | 312.114 | 157.7741 | 252.105 |
| 3 | Dange-Shuni | 398.621 | 270.8992 | 323.913 |
| 4 | Gada | 273.904 | 7.513054 | 123.829 |
| 5 | Goronyo | 290.648 | 15.02611 | 50.910 |
| 6 | Gudu | 1082.524 | 8.371688 | 11.338 |
| 7 | Gwadabaw | 288.931 | 55.5966 | 170.515 |
| 8 | Illela | 91.874 | 15.67008 | 116.271 |
| 9 | Isa | 572.065 | 34.13073 | 17.785 |
| 10 | Kebbe | 158.847 | 54.73796 | 33.125 |
| 11 | Kware | 240.847 | 233.1193 | 338.808 |
| 12 | Rabah | 727.049 | 48.94218 | 139.169 |
| 13 | Sabon Birni | 252.868 | 72.33997 | 21.787 |
| 14 | Shagari | 112.052 | 78.77973 | 140.503 |
| 15 | Silame | 162.711 | 23.82711 | 81.367 |
| 16 | Sokoto North | 14.167 | 5.366467 | 3.557 |
| 17 | Sokoto South | 28.764 | 22.75382 | 19.119 |
| 18 | Tambawal | 220.669 | 45.29298 | 83.146 |
| 19 | Tangazar | 359.339 | 47.01025 | 103.821 |
| 20 | Tureta | 110.979 | 20.60723 | 47.575 |
| 21 | Wamakko | 138.240 | 123.2141 | 190.079 |
| 22 | Wurno | 242.994 | 171.5123 | 199.416 |
| 23 | Yabo | 259.952 | 89.08335 | 138.502 |

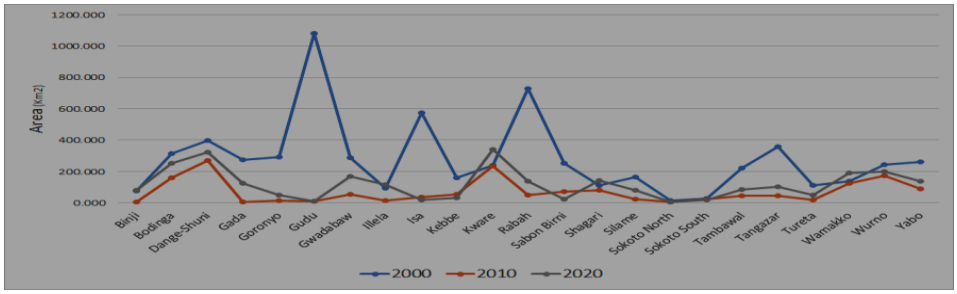


Figure 8: Histogram of Moderate Drought coverage

## 4.0 CONCLUSION AND RECOMMENDATION

This study provides robust evidence of escalating desertification in Sokoto State from 2000 to 2020, based on an integrated analysis of TCI, VCI, and VHI, supported by statistical validation. Thermal stress increased significantly at a rate of 1.2% per year, with severely affected zones covering over 59% of the area by 2020. Drought conditions persisted across 42% of the region, peaking in 2010 ($p = 0.02$). Four high-risk LGAs—Gudu, Isa/Kebbe, Rabah, and Tambawal/Tangazar—were identified as the most vulnerable. These findings are consistent with [8] reinforcing the observed trends of increasing temperature and decreasing vegetation cover over the past two decades and hereby recommends monitoring and early warning systems and promotion of sustainable land use policies that prevent overgrazing, deforestation and unsustainable farming.

## REFERENCE

[1] Wuyep, L.C., and Zakka, L. (2024). Assessment of the extent of desertification in Gamawa LGA of Bauchi State using remote sensing and GIS techniques. Discovery Nature 2024; 1: e3dn1019 doi: https://doi.org/10.54905/disssi.v1i1.e3dn1019

[2] Olagunju, T.E. (2015). Drought, desertification and the Nigerian environment: a review, J. Ecol. Nat. Environ. 7 (7) 196–209, https://doi.org/10.5897/jene2015.0523.

[3] Li, Y., and Strapasson, O.A. (2020). Rojas Assessment of El Nino and La Niña impacts on China: enhancing the early warning system on food and agriculture Weather Clim. Extrem., 27, p. 100208.

[4] Bento, V.A. Gouveia, C.M. DaCamara, C.C. Libonati, R., Trigo I.F. (2020). The roles of NDVI and land surface temperature when using the vegetation health index over dry regions Global Planet. Change, 190.

[5] Hu et al., (2020). On agricultural drought monitoring in Australia using Himawari-8 geostationary thermal infrared observations Int. J. Appl. Earth Obs. Geoinf., 91, p. 102153.

[6] Karnieli, A., et al. (2010). Use of NDVI and Land Surface Temperature for drought Assessment: Merits and Limitations. Journal of Climate, 23, 618-633. https://doi.org/10.1175/2009JCLI2900.1

[7] Kogan, F.N. (1997). Global drought watch from space, B. Am. Meteorol, Soc., 78, 621-636.

[8] Yahaya I. I., Wang, Y., Zhang, Z., Inuwa, A.Y., Zhao, Y., You, Y., Basiru, H.A., Ochege, F.U., Na, Z., Ogbue, C.P., Muhammad, M., Mihertu, Y.F., Tanko, I.A., Shoukat, W. (2024). Assessing desertification vulnerability and mitigation strategies in northern Nigeria: A comprehensive approach. Heliyon 10, e31167