Geosfera Indonesia
p-ISSN 2598-9723, e-ISSN 2614-8528
available online at : https://jurnal.unej.ac.id/index.php/GEOSI
Vol. 9 No. 2, August 2024, 101-121

https://doi.org/10.19184/geosi.v9i2.45185

Research Article

Assessment of Agricultural Drought Using Vegetation Condition Index and Vegetation Health Index in Niger River Basin, Nigeria

Muhammad Lawal Abubakar[1,2,*], **Muhammad Sambo Ahmed**[1,2], **Auwal Farouk Abdussalam**[1,2]
[1]Department of Geography, Kaduna State University, Kaduna, Nigeria
[2]Climate Research Group, Kaduna State University, Kaduna, Nigeria
*Corresponding author, email : muhdlawal@kasu.edu.ng

ARTICLE INFO

Received :
24 December 2023

Revised :
29 March 2024

Accepted :
2 April 2024

Published :
23 June 2024

ABSTRACT

Soil moisture indicates the dryness of the ground surface. This phenomenon is directly tied to vegetation quality and Land Surface Temperature in a specific place. As a result, these characteristics indirectly describe the dryness of the ground surface. This study assessed agricultural drought in Niger River in Nigeria. Data used include MODIS driven MOD13Q1 (NDVI), and MOD11A2 (LST) datasets obtained from Land Processes Distributed Active Archive Center. These datasets were used to compute Vegetation Condition Index (VCI) and Vegetation Health Index (VHI) in Niger River Basin, Nigeria. Additionally, correlation and regression analyses were used to check the relationship between LST and NDVI. Results revealed that the mean NDVI for the year 2002 is 0.494, 0.477 in 2007, 0.468 in 2012, 0.458 in 2017 and 0.430 in 2022. The mean LST in Niger River Basin for year 2002 is 32.28 ^{o}C, 32.12 ^{o}C in 2007, 32.35 ^{o}C in 2012, 33.20 ^{o}C in 2017 and 33.41 ^{o}C in 2022. For the statistical relationship between NDVI and LST, results exhibited negative correlation, with -0.33 in 2002, -0.43 in 2007, -0.42 in 2012, -0.36 in 2017 and -0.27 in 2022. For the VCI results, findings revealed that the mean VCI in the basin was 83.73 in 2002, 64.26 in 2007, 56.76 in 2012, 45.32 in 2017, and 14.93 in 2023. Also, the VHI results revealed that the mean VHI in the basin was 75.44 in 2002, 69.54 in 2007, 61.02 in 2010, 37.22 in 2017 and 18.87 in 2022. The study therefore concluded that vegetation is decreasing in the basin, while land surface temperature is increasing.

Keywords: Vegetation Health Index, Vegetation Condition Index, Soil Moisture, Niger River Basin

INTRODUCTION

Soil moisture is an essential element of the environment, modulating crop production, hydrological cycle and meteorology via its influence on surface water exchange and heat and through comprehensive soil–vegetation–atmosphere continuum (Pradhan, 2019; Srivastava et al., 2023). It is an important variable in understanding water cycle, weather prediction, and water resources management, particularly in agriculture because it is an indicator of agricultural drought (Ryu et al., 2021). Furthermore, understanding various biogeochemical processes is heavily reliant on soil moisture content (Wang et al., 2015), because it allows us to monitor the land surface's mass and energy balance, which includes transpiration, surface overflow, soil formation and solute movement, and precipitation (Wang et al., 2021). Soil moisture fluctuates widely across spatial and temporal scales due to the complexity of environmental conditions and their multimodal influences.

Soil moisture influences the distribution of rainfall into stream flow, surface overflow, infiltration, and groundwater inflow (Ghajarnia et al., 2020). Consequently, soil moisture is key to understanding crop water stress and in estimating yield, because it is a very good indicator of general soil conditions (Yang et al., 2023). It is in this regard that agricultural drought is loosely used to refer to soil moisture deficit (Huang et al., 2020).Thus, changes in soil moisture, especially decrease or loss, is as a result of drought, and can disrupt the regular interchange between vegetation and the biogeochemical constituents of the soil (Amiri et al., 2020).

All over the world, irrigation and rainfed agriculture are the most common agricultural practices, with irrigated farmlands accounting for 18% of the world's total farmlands and 40% of its overall agricultural production, and rainfed farmlands accounting for 82.2% of the world's entire farmlands and 60.0% of its overall agricultural production (United Nations Commission on Sustainable Development (UNCSD), 2020). In the Niger River Basin particularly, over 70% of the population lives in places where food security is dependent on unpredictable rainfall (Olatunji, 2023). Elsewhere in sub-Saharan Africa, drought poses a serious threat to food security and is a factor in declining crop yields globally and fiscal deficits (Yang et al., 2023). Additionally, semi-arid climate regions will continue to grow in size, which make crop yields and socioeconomic development more difficult (Cetin et al., 2023). Therefore, irrigation system should be efficient in order to ensure adequate food production. In addition, climate change effects already apparent to the unaided eye worldwide. Flooding and drought events, two hydrological phenomena associated to climate change, have recently escalated. Researchers issue a warning that these phenomena will only get worse (Furtak & Wolińska, 2023).

Historically, the Niger River Basin has been experiencing drought due to decreasing rainfall since 1970s (Ogunrinde et al., 2023; Olatunji, 2023). This has led to devastating hydrological and meteorological drought in the region (Oloruntade et al., 2017). Additionally, this extreme is not a recent occurrence, because available records showed frequent drought events in the past with various intensities, leading to famine resulting from crop failure (Murtala et al., 2018). Furthermore, large part of the country is within the Sudano-Sahelian Savannah, a region characterized by dryness and low rainfall (Medugu et al., 2011). In addition, drought analysis between 1900 and 2013 suggested that severe droughts in Northern Nigeria caused enormous socioeconomic and environmental consequences (Masih et al., 2014).

Field measurements of soil moisture can offer comparatively precise estimation of soil moisture, but these methods are constrained by the need for a number of instruments, which may be difficult to gather in order to sufficiently study a broad region (Pradhan, 2019). Additionally, such measurements are more suitable for a relatively small geographic area. Hence, due to technological advancement in remote sensing, several methodological approaches have been used to determine soil moisture. These include numerous methods such as the Temperature Vegetation Dryness Index (TVDI) and Normalized Difference Moisture Index (NDMI) (Gao et al., 2011; Maduako et al., 2017; Meng et al., 2008; Przeździecki et al., 2023); Temperature Vegetation Precipitation Dryness Index (TVPDI), remote sensing derived Vegetation Condition Index (VCI) (Ali et al., 2023; Dutta et al., 2015; Wei et al., 2020); Empirical Standardized Soil Moisture Index (ESSMI) and Comprehensive Agricultural Drought Index (CADI) (Carrão et al., 2016; Yang et al., 2023).

Moderate Resolution Imaging Spectroradiometer (MODIS) has different datasets that have been used in environmental monitoring (Wassie et al., 2022). For example, the MODIS (MCD12Q1) has been used in land use and land cover evaluation (Kloos et al., 2021), while MODIS (MOD13Q1) has been used in vegetation assessment and drought monitoring (Fathi-Taperasht et al., 2022), by integrating the MODIS (MOD11A2) land surface temperature datasets. These different datasets have been used to compute drought indices such as Temperature Condition Index (TCI), Vegetation Condition Index (VCI),and the Vegetation Health Index (VHI) for assessment of soil moisture all over the world (de Lima et al., 2023; Shamloo et al., 2022; Tran et al., 2023).

The Niger River Basin Development Authority was created to focus on food production through irrigation, in order to realize the country's close relationship between food and water security (Babatolu et al., 2014). The area is known for agricultural production; however, periodic droughts are threatening food security in the region. A few researchers focused on the assessment of meteorological drought in the basin (Okpara, 2022), soil moisture assessment (Badou et al., 2019). Thus, there are limited studies on the spatial and temporal variations of agricultural drought in the Niger River Basin. Therefore, the goal of this paper is to estimate soil moisture by combining vegetation and temperature in the Niger River Basin, and account for the physical characteristics of soil moisture. This study aims to examine the spatiotemporal variation of vegetation and land surface temperature, and to estimate agricultural drought using a combination of LST and NDVI to calculate VCI and VHI. This study is crucial in investigating how the spatial organization of soil moisture functions and use the knowledge gained to help food security, conservation efforts, restoration, and future land-use planning.

STUDY AREA

The Niger River Basin is located in Nigeria between latitude 7°4’13” and 11°28’30” North of the Equator and between longitudes 2°40’32” and 8°51’5” East of the Greenwich Meridian (See Figure 1). Climate of the basin is influenced by northeasterly trade winds moving southwards, and the southwesterly winds moving northwards, which influence the seasonal movement of the ITCZ. Annual Mean temperature in the basin ranges from 22°C in the northeastern part to 27 °C in the southern part (Nigerian Meteorological Agency, 2018). The northern part of the basin records about 100mm, while the southern part records up to 1300mm across two defined seasons (Bello, 1987). Elevation of the basin in the south is about 600m and up to 1200m in the north, separated by the Niger River, with the highlands serving as the source of most of the tributaries of the River Niger. Major tributaries of the river include River Kaduna, Kampe, Swashi, Moshi, Awon, River Kontagora, River Mariga, the Eku River and Oyun (Babatolu & Akinnubi, 2014). Apart from the Niger drain, the basin is characterized by the guinea savanna which declines as you move northward due reduced rainfall amount (Adekunle et al., 2015).

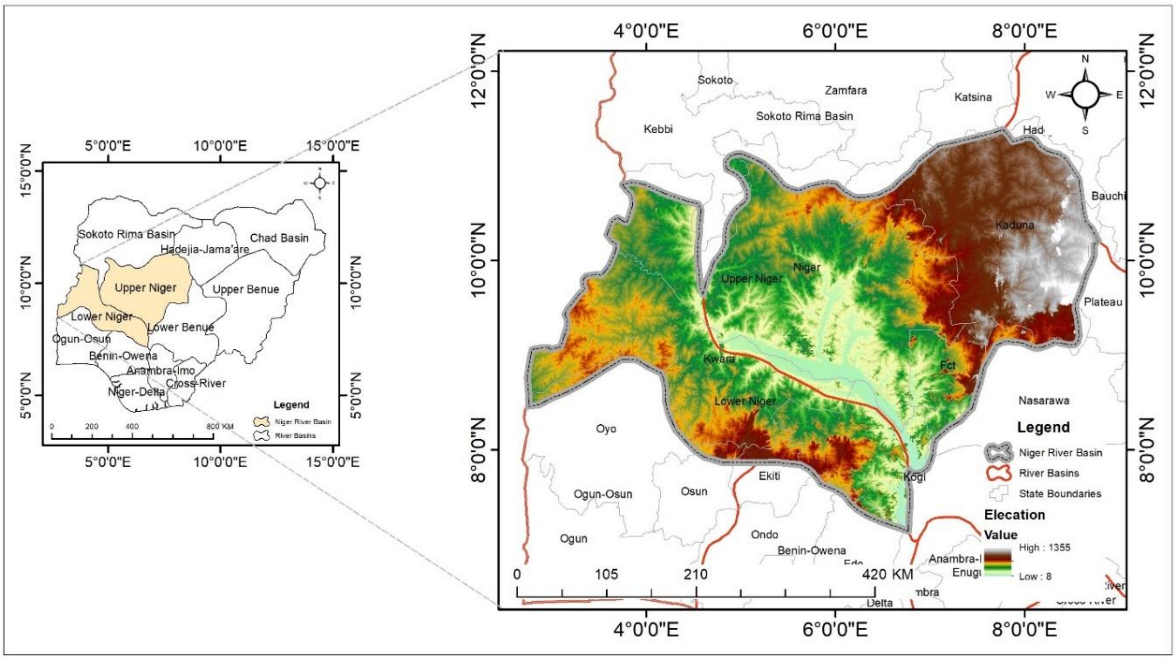


Figure 1. Study Area

METHODS

Data Sources

This study used datasets from pre-processed Moderate Resolution Imaging Spectrometer (MODIS). The MOD13Q1, a 16-day average NDVI with 250m spatial resolution (Figure 2). MOD11A2, an 8-day average Land Surface Temperature (LST), with 1km spatial resolution (NASA, 2023). These MOD13Q1 and MOD11A2 were resampled using ArcGIS Pro. The MODIS derived vegetation and LST indices have been used in global monitoring of drought (Xie & Fan, 2021). The average annual values of the NDVI and LST were obtained from Land Processes Distributed Active Archive Center (LP DAAC) using Google Earth Engine and processed using ArcGIS Pro.

Drought Monitoring

To determine the variation in soil moisture in Niger River Basin, Nigeria, vegetation condition and vegetation health indices were applied. According to Zeng et al. (2022), the VCI for a particular year is calculated using Equation 1.

$$VCI = \frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \tag{1}$$

Where, NDVI is the value of vegetation in a referenced period, and NDVImin and NDVImax are the lowest and highest values of NDVI for all pixels and years. In order to compute the Temperature Condition Index (TCI) (Patel et al., 2012), the following formula was used (Equation 2) :

$$TCI = \frac{LST_{max} - LST}{LST_{max} - LST_{min}} \tag{2}$$

Where, LST is the value of surface temperature for referenced period. LSTmin and LSTmax are the lowest and highest values of LST for all the periods. According to Karnieli et al. (2019), the VHI is regarded as the overall health of the vegetation, and it is applied in identifying drought. A combination of VCI and TCI are used to calculate VHI as follows (Equation 3):

$$VHI = a\ x\ VCI + (1 - a)\ x\ TCI \tag{3}$$

Where, a as certain the influences of the VCI and the TCI to the VHI, which varies in the basin, due to various factors in the environment. The original VHI (VHIori) presumes that water demand and temperature have the same contribution to plant growth. Using other approaches by Monteleone et al. (2020), VHI was used as the basis to classify level of droughts in the Niger River Basin. Furthermore, the VHI ranges from 0 to 100, indicating vegetation changes from extremely poor (0) to excellent (100). Average conditions are colored yellow (50), which changes to brown and dark brown when the vegetation conditions decline (Table 1).

Table 1. Drought classification using vegetation health index (Fathi-Taperasht et al., 2022)

Drought type	VHI
Extreme drought	<0.1
Severe drought	0.1-0.2
Moderate drought	0.2-0.3
Mild drought	0.3-0.4
No drought	>0.4

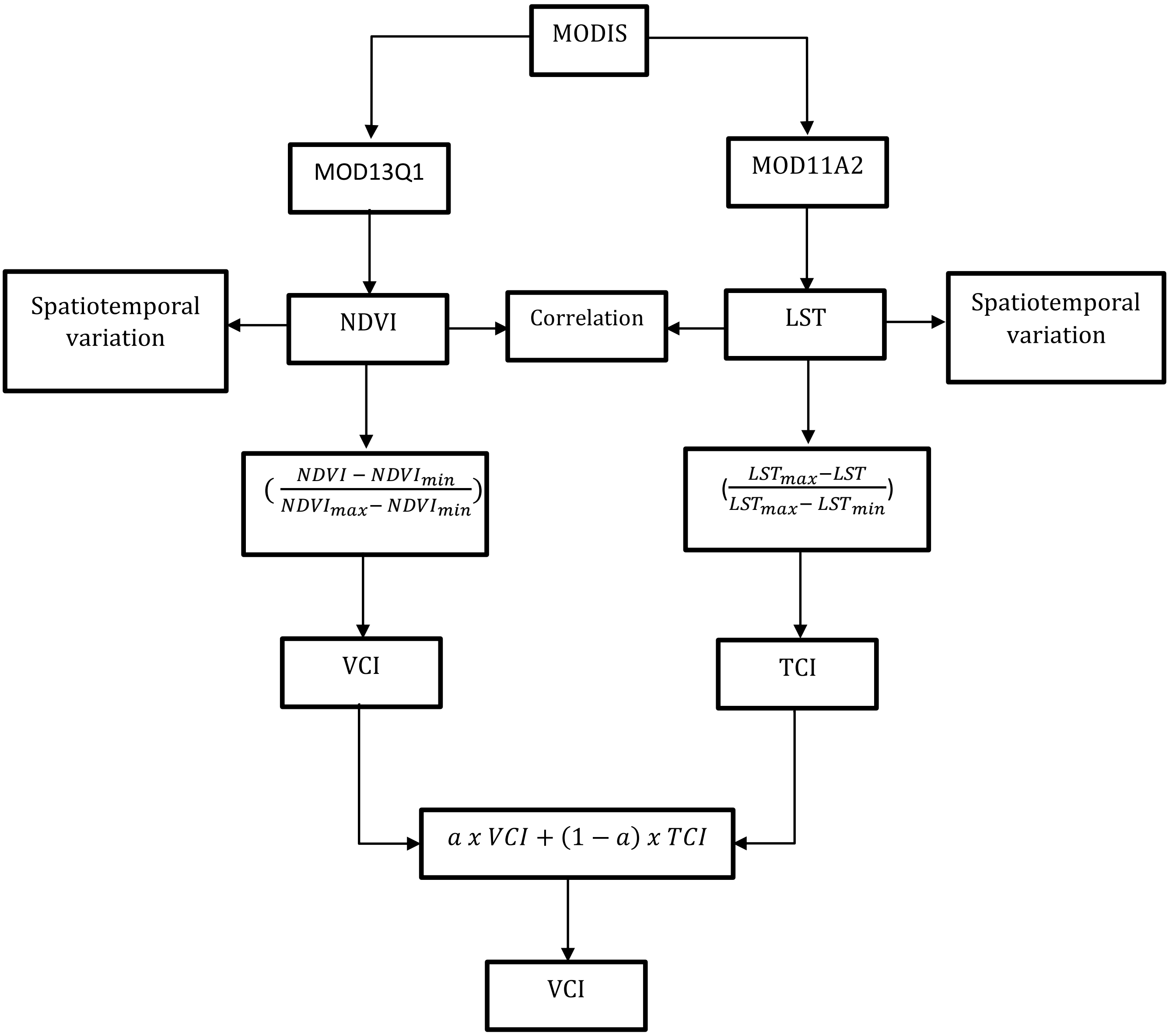


Figure 2. Research Framework

Statistical Analysis

To examine the interconnection between vegetation and land surface temperature in Niger River Basin, Nigeria, the NDVI and LST for the years 2002, 2007, 2012, 2017 and 2022 were extracted to multipoint on ArcGIS Pro. These points were exported as comma delimited (.csv) format and were correlated using Pearson Moment Correlation. Results of Pearson correlation coefficient varies between −1 and +1; with positive values indicating a direct relationship, and negative values indicating an inverse relationship between two variables (Fathi-Taperasht et al., 2022). Any coefficient $|r| \geq 0.7$ indicates a strong association (Ismail et al., 2024). This was carried out using Multi-Environment Trial Analysis (metan) package on R-Studio.

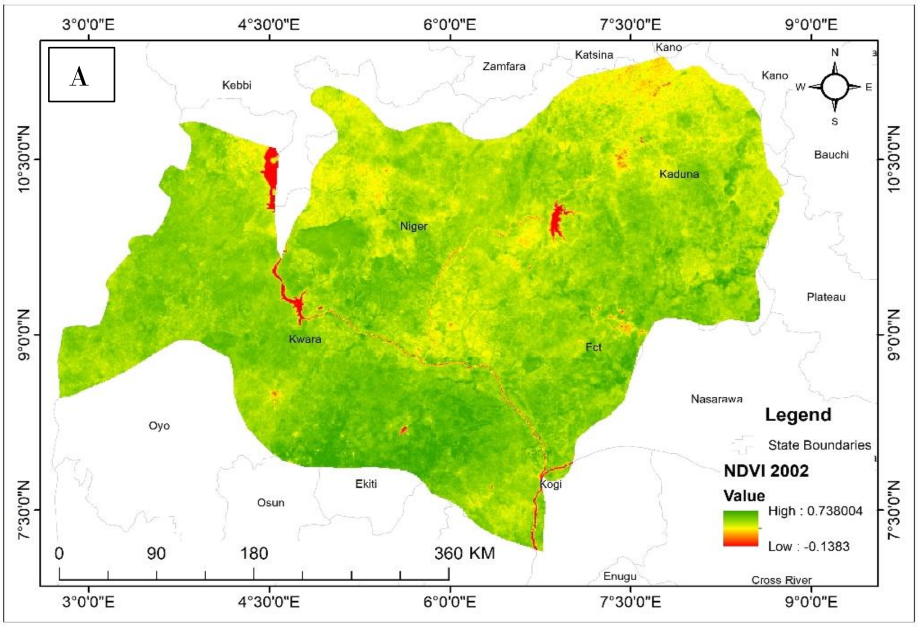
RESULTS AND DISCUSSION

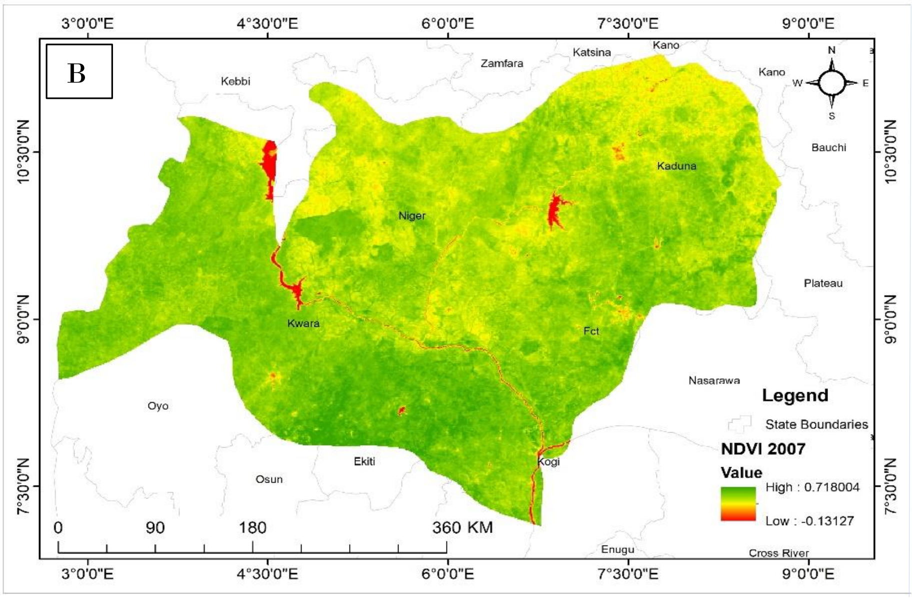
Spatiotemporal Variation in Vegetation Using Normalized Differential Vegetation Index in Niger River Basin, Nigeria

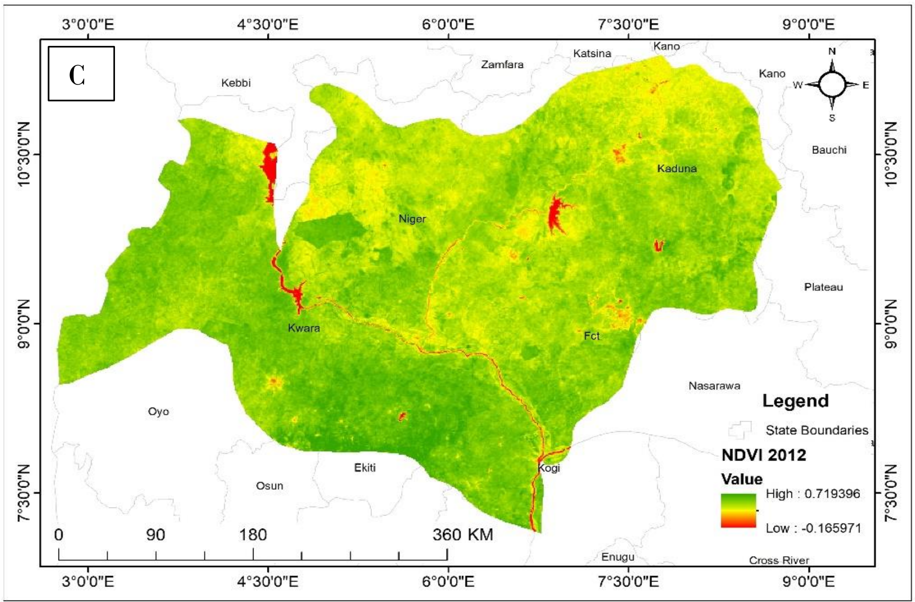
This study analyzed the vegetation change for the years 2002, 2007, 2012, 2017 and 2022. The results are shown in Figure 3. The NDVI index ranges from -1 to 1. The lower the value of the NDVI, the poorer the vegetation condition, while the higher the NDVI value, the healthier the vegetation. In 2002, the mean annual NDVI was calculated from MOD13Q1 using Google Earth Engine. Figure 3a shows the spatial variation of NDVI in the Niger River Basin. The lowest NDVI was -0.1383 and the highest was 0.738. Low NDVI values are red, while high NDVI values are colored green. Lowest NDVI values were found along the Niger and Kaduna Rivers, Shiroro Dam and within the urban areas, while the highest values were concentrated towards the southwestern part of the basin. In 2007, Figure 3b the lowest NDVI value was -0.131 and the highest was 0.718. NDVI with lowest values were dominated along the Niger and Kaduna Rivers, Shiroro Dam and within the urban areas, while the maximum value is concentrated towards the southern part of the study area. This loss of vegetation has been identified as a driver of land degradation in the area (Adenle et al., 2022).

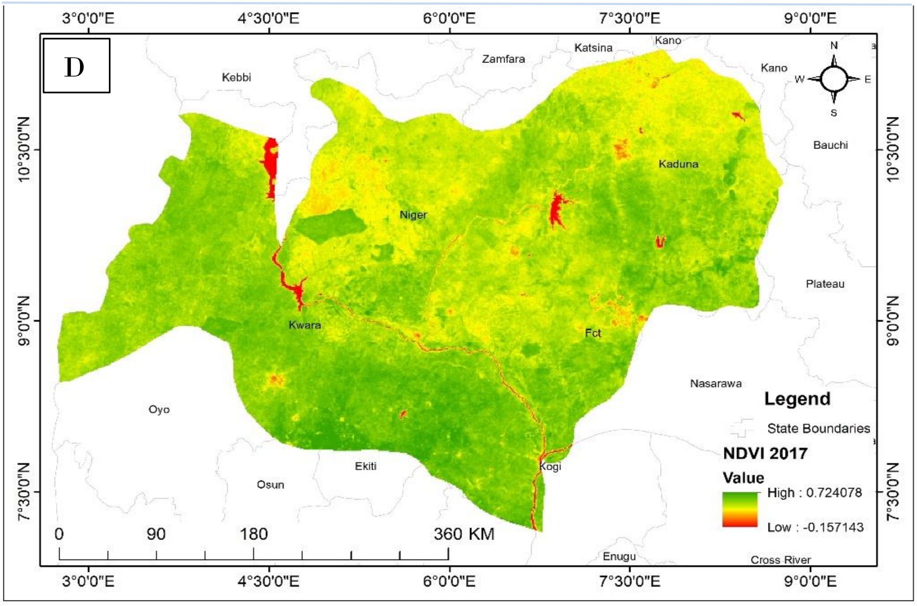
In 2012, Figure 3c the minimum value for this year is -0.166 and the maximum value is 0.719. This revealed loss of vegetation around the Northwestern part of the basin, close to Lake Kainji. Northern part of Shiroro LGA, Mashegu and most southern part of the basin have a very healthy vegetation. For the year 2017, Figure 3d revealed that the minimum NDVI value for this year is -0.157 and the maximum value is 0.724. This indicate an increasing density compared to 2012. Northern part of Shiroro LGA, Mashegu and most southern part of the basin have a very healthy vegetation. The density of the vegetation increased in southern part of Kaduna State, and western part of Niger State. The maximum value of the NDVI is shown around the southern part of the basin.

Finally, for the year 2022, Figure 3e revealed the minimum NDVI value of -0.117, and a maximum value of 0.677, indicating a significant decrease from 2017. The maximum value of NDVI diffuses from the southern part to the western part of the basin. Lowest NDVI values are found along the water bodies, followed by the urban areas. This agrees with the findings of Ogbue et al. (2024) that there is a variation in the spatial distribution of vegetation in the Niger River Basin., but disagrees with the results of Agbo et al. (2023), which indicated an increase in vegetation across all ecological zones in Nigeria.




B
3°0'0"E
4°30'0"E
6°0'0"E
7°30'0"E
9°0'0"E
10°30'0"N
9°0'0"N
7°30'0"N
Kebbi
Zamfara
Katsina
Kano
Kano
Bauchi
Kaduna
Niger
Plateau
Kwara
Fct
Nasarawa
Oyo
Osun
Ekiti
Kogi
Enugu
Cross River
Legend
State Boundaries
NDVI 2007
Value
High : 0.718004
Low : -0.13127
0 90 180 360 KM


C
3°0'0"E
4°30'0"E
6°0'0"E
7°30'0"E
9°0'0"E
10°30'0"N
9°0'0"N
7°30'0"N
Kebbi
Zamfara
Katsina
Kano
Kano
Bauchi
Kaduna
Niger
Plateau
Kwara
Fct
Nasarawa
Oyo
Osun
Ekiti
Kogi
Enugu
Cross River
Legend
State Boundaries
NDVI 2012
Value
High : 0.719396
Low : -0.165971
0 90 180 360 KM


D
3°0'0"E
4°30'0"E
6°0'0"E
7°30'0"E
9°0'0"E
10°30'0"N
9°0'0"N
7°30'0"N
Kebbi
Zamfara
Katsina
Kano
Kano
Bauchi
Kaduna
Niger
Plateau
Kwara
Fct
Nasarawa
Oyo
Osun
Ekiti
Kogi
Enugu
Cross River
Legend
State Boundaries
NDVI 2017
Value
High : 0.724078
Low : -0.157143
0 90 180 360 KM

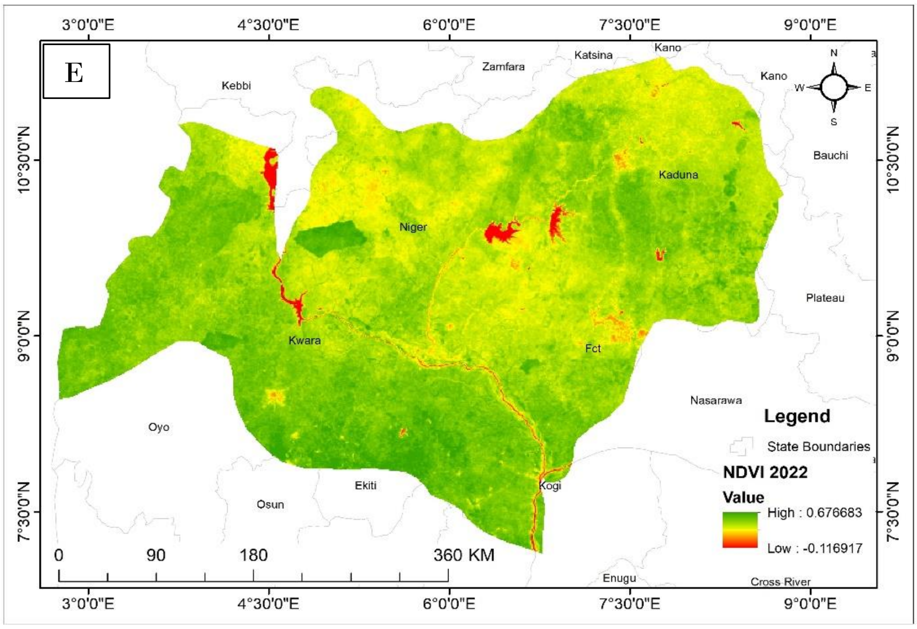
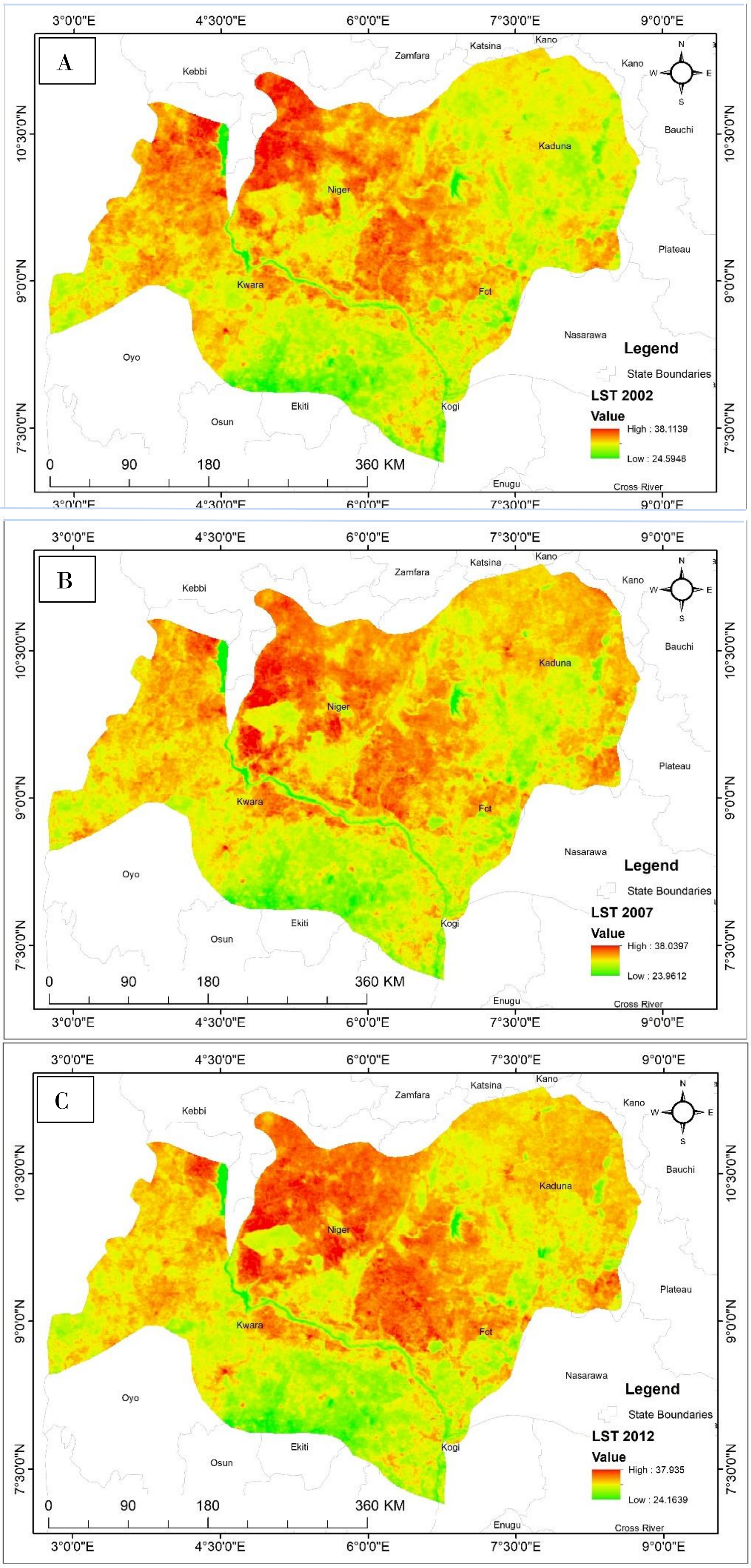


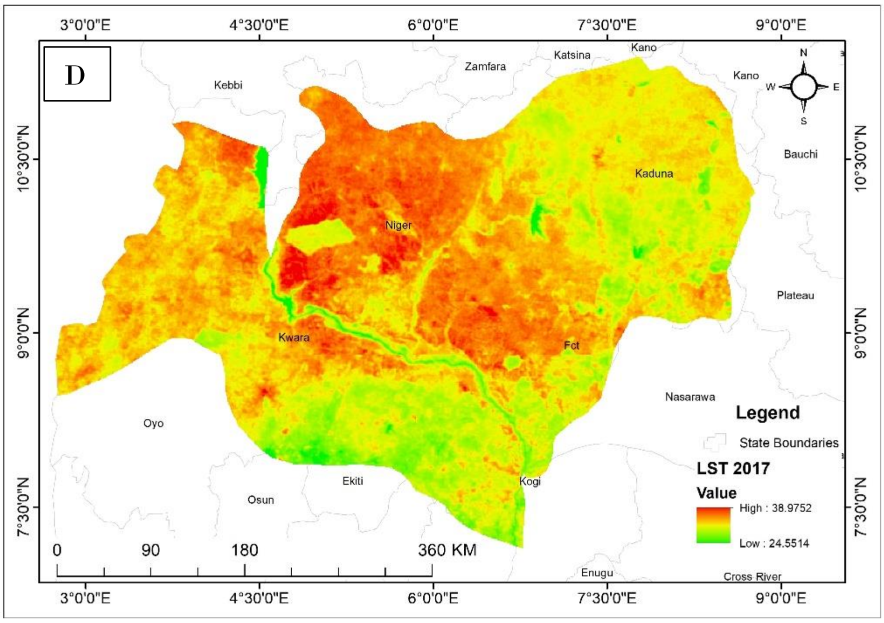
Figure 3. Spatial and temporal variation of vegetation using NDVI, A: 2002, B: 2007, C: 2012, D: 2017 and E: 2022

Spatiotemporal Variation in Land Surface Temperature in Niger River Basin, Nigeria

The Land Surface Temperature of Niger River Basin for the year 2002, 2007, 2012, 2017 and 2022 was estimated. The results are shown in Figure 3. The LST index shows the surface temperature in degree Celsius (°C). Pixels with minimum LST values reveal that the areas have low surface temperature, represented by the color green, while the red color indicate high LST values, indicating areas with high surface temperature. This is represented by the color red.

In 2002, Figure 4a shows that the lowest LST was 24.59 °C and the highest was 38.11 °C. The high LST is from the central part of the basin to the North Western Part. The water bodies, and southern part of the basin have the lowest land surface temperature. Studies have previously reported that the basin experienced warm years between 2001 and 2010 (Babatolu & Akinnubi, 2013). In 2007, Figure 4b shows that the lowest LST was 23.96 o °C, the highest was 38.04 °C with a standard deviation of 1.70 °C. Water bodies have the lowest LST, while the urban areas show high LST. For the distribution of the LST, the lowest values were around the eastern and southern part of the basin. This is because the region is having healthier vegetation compared to the northern part of the basin (Seun et al., 2022). In 2012, Figure 4c shows that the minimum LST for this year is 24.16 °C, the maximum value is 37.94 °C with a standard deviation of 1.89 °C. In the year 2017, the minimum LST for this year is 24.55 oC, the maximum value is 38.97 °C with a standard deviation of 1.96 oC. Lastly, for the year 2022, the minimum LST for this year is 23.12 °C, the maximum value is 39.01 °C with a standard deviation of 2.2 °C. This indicate a significant rise in the land surface temperature in the basin. Previous studies have also established that LST is negatively linked with soil moisture (Nguyen et al., 2022).


A
3°0'0"E
4°30'0"E
6°0'0"E
7°30'0"E
9°0'0"E
10°30'0"N
9°0'0"N
7°30'0"N
Kebbi
Zamfara
Katsina
Kano
Kano
Bauchi
Kaduna
Niger
Plateau
Kwara
Fct
Nasarawa
Oyo
Osun
Ekiti
Kogi
Enugu
Cross River
N
S
E
W
0
90
180
360 KM
Legend
State Boundaries
LST 2002
Value
High : 38.1139
Low : 24.5948
B
LST 2007
High : 38.0397
Low : 23.9612
C
LST 2012
High : 37.935
Low : 24.1639



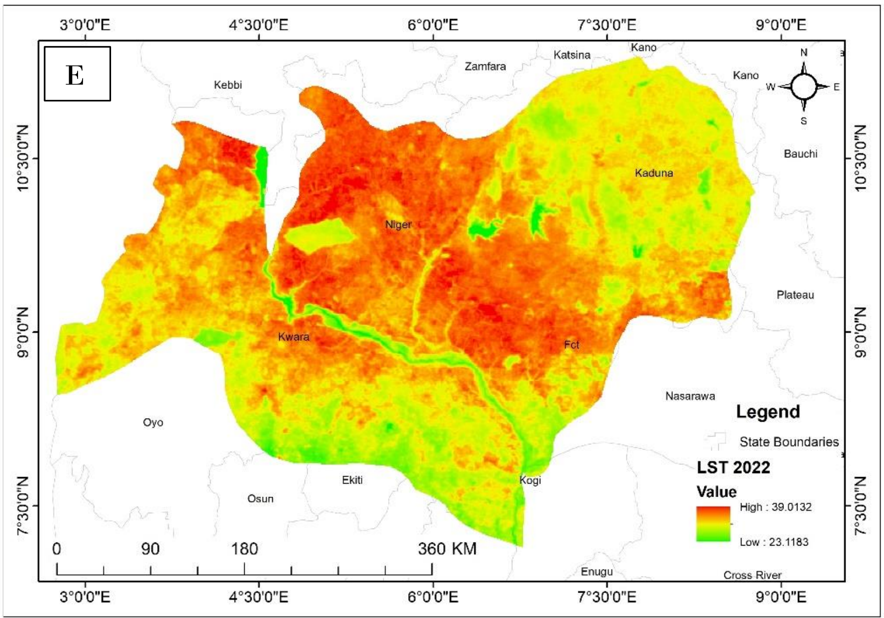


Figure 4. Spatial and temporal variation of Land Surface Temperature (LST) , A= 2002, B= 2007, C=2012, D= 2017 and E=2022

Relationship Between Vegetation and Land Surface Temperature in Niger River Basin, Nigeria

Statistical analysis is important in analyzing different attributes. In this study paper, we extracted points from LST and NDVI image pixel values, that is, 270,183 for each study period, and correlated them using Pearson Correlation Coefficient. For the year 2002, the correlation coefficient between NDVI and LST is -0.33, indicating a weak negative correlation, which is significant at $p<0.001$. for the year 2007, the correlation coefficient between NDVI and LST is -0.431, indicating a negative correlation. In the year 2012, the coefficient was -0.423, indicating a negative correlation. This agrees with Alademomi et al. (2022) that vegetation significantly influences land surface temperature. The correlation coefficient between NDVI and LST for the year 2017 was -0.362, indicating a negative correlation. Finally, the correlation coefficient between NDVI and LST for the year 2022 was -0.272, indicating a weak negative correlation. For all the five epochs, findings revealed a negative correlation between NDVI and LST, which means that places with healthy vegetation have low surface temperature. This agrees with the findings of Thakur et al. (2024) and Buzhani et al. (2023) that vegetation is negatively correlated with land surface temperature. The result is shown in Figure 5.

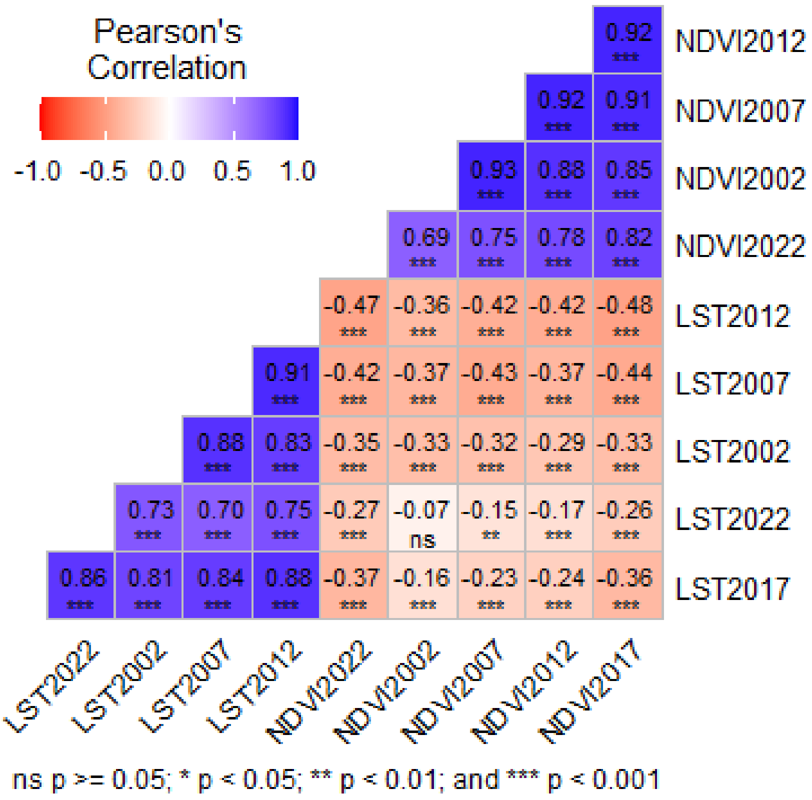
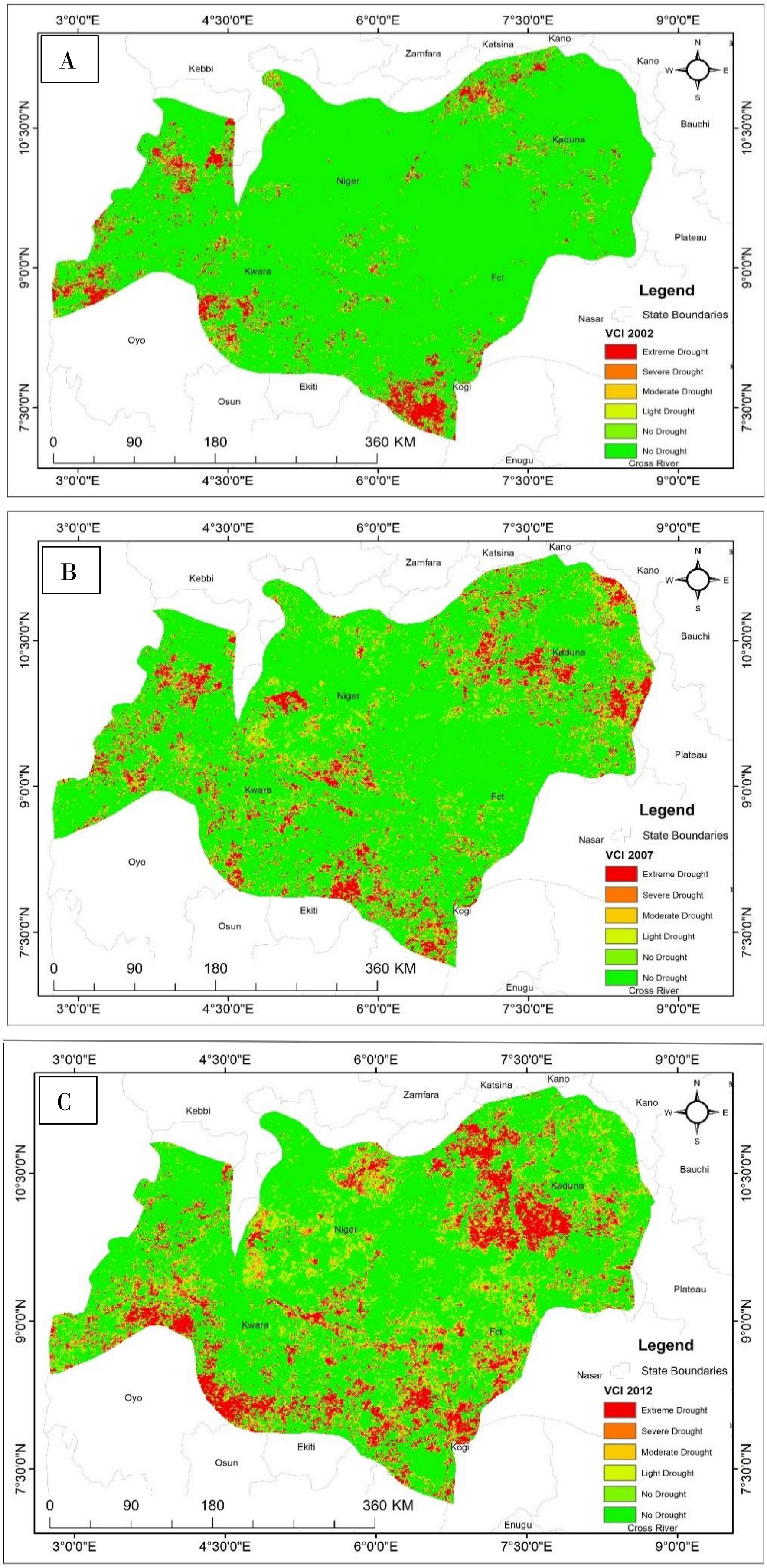


Figure 5. Correlation coefficient between NDVI and LST for the years 2002 to 2022

Spatiotemporal Variation of Soil Moisture using Temperature Vegetation Dryness Index in Niger River Basin, Nigeria

To examine the agricultural drought in Niger River Basin, the VCI and VHI were employed. Results are presented in Figure 6 and Figure 7. For the year 2002, Figure 6a the VCI revealed that most of the basin had a very healthy vegetation, only the southern part and the southwestern of the basin experienced severe to extreme drought with VCI value of less than 20%. The mean value of VCI in 2002 is 83.73, indicating a very healthy vegetation.

For the year 2007, more areas within the basin experienced agricultural drought as shown in Figure 6b. The northeastern and southwestern parts of the basin had VCI values below 20%. The mean value of the VCI is 64.26. This indicate a decreasing trend in vegetation condition, which means low soil moisture amount. For the year 2012, the mean VCI is 56.76. Areas that experienced agricultural drought increased, with the entire southern part of the basin experiencing water stress, as well as the southeastern and northern part. This water stress further deteriorates in 2012, with the southwestern part, as well as the northern part experiencing severe stress. The VCI further decreased in 2017 having a value of 45.32, indicating a further deteriorating crop conditions in the basin. In the year 2022 the VCI dropped to 14.93. The basin experienced the worst agricultural drought. Only locations close to water bodies had healthy vegetation, with some locations bordering the forests.


A
3°0'0"E
4°30'0"E
6°0'0"E
7°30'0"E
9°0'0"E
10°30'0"N
9°0'0"N
7°30'0"N
Kebbi
Zamfara
Katsina
Kano
Bauchi
Kaduna
Niger
Plateau
Kwara
Fct
Nasar
Oyo
Osun
Ekiti
Kogi
Enugu
Cross River
0 90 180 360 KM
N
S
E
W
Legend
State Boundaries
VCI 2002
Extreme Drought
Severe Drought
Moderate Drought
Light Drought
No Drought
No Drought
B
VCI 2007
C
VCI 2012

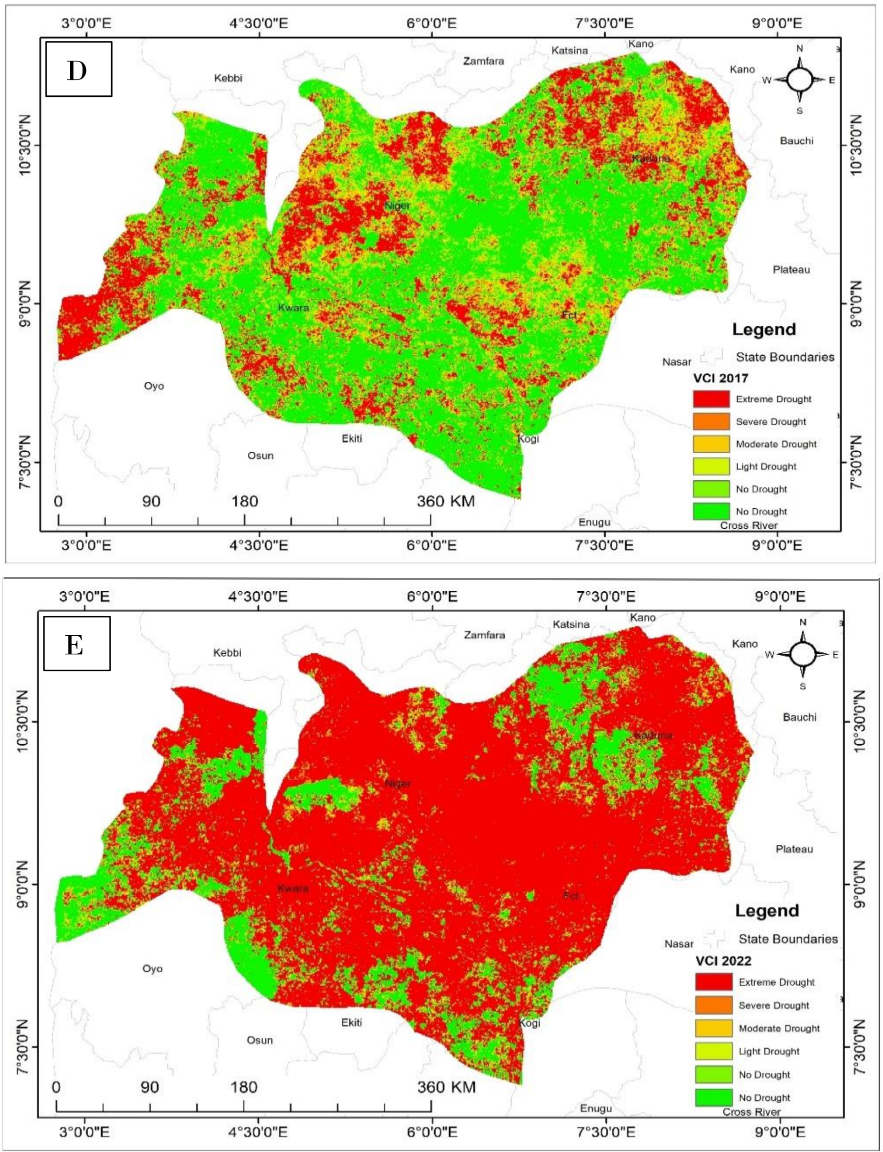
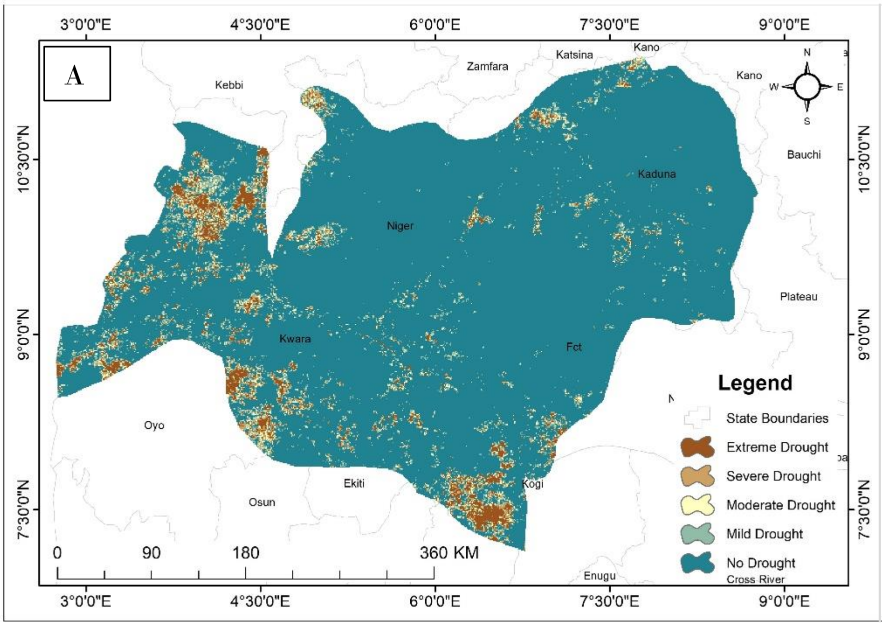
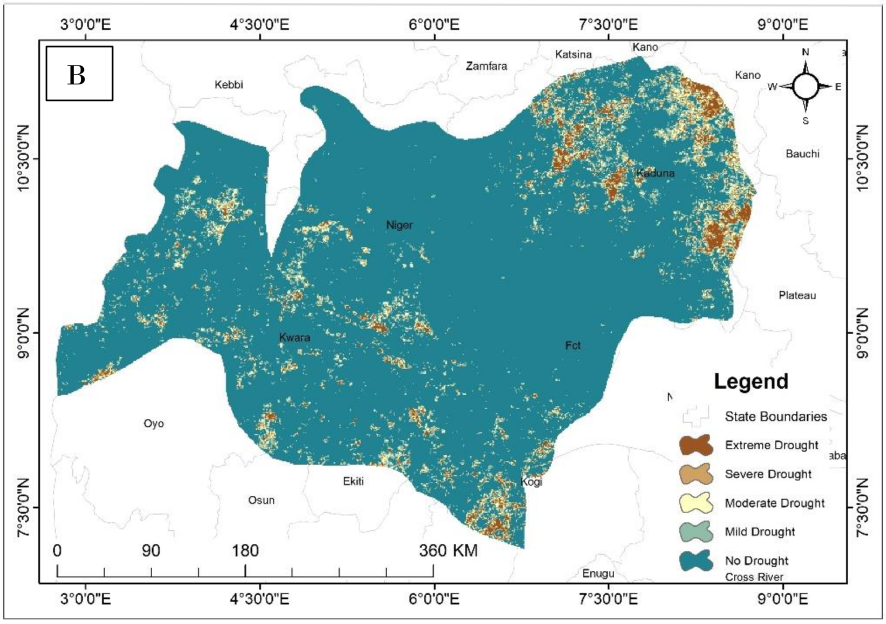


Figure 6. Spatial and temporal variation of Vegetation Condition Index (VCI), A=2002, B=2007, C= 2012 D=2017 and E= 2022

For the vegetation health index (VHI), results from 2002 to 2022 are shown in Figure 7. For the year 2002, Figure 7a revealed that the VHI that most of the basin had a very healthy vegetation. Areas around Lokoja and most southern and southwestern part of the basin revealed a water stress. This agrees with the findings of Kehinde and Umar (2021) that the region is having low soil moisture, but the soil moisture is improves moving southwards. The average VHI was 75.44% and STD of 26.15. This shows a very healthy vegetation without water stress. In 2007, the southern and northeastern part of the basin experienced acute water stress. The mean VHI for the period is 69.54%, and the STD is 24.27. This indicates that crop farmers experienced water shortage within the period (Ibanga et al., 2022).

This water stress worsened in 2012, with most of the northeastern and southwestern parts of the basin suffered severe agricultural drought, this may be attributed to declining rainfall within the period (Ogunrinde et al., 2019), which led to meteorological drought in the basin (Oloruntade et al., 2017). The mean VHI was 61.02%, while the standard deviation was 25.68. In 2017, Figure 7d revealed that most parts of the basin experienced severe agricultural drought, with the central part of the basin having a relatively healthy vegetation, while the northeastern part continue to experience water stress. This in line with Luo et al. (2023) that soil moisture varies spatially. The mean VHI in 2017 was 37.22%, indicating a deteriorating condition, and the standard deviation is 24.28. Finally, the worst agricultural drought in the basin occurred in 2022, as most part of the basin had VHI values of less than 40%. Overall, the average VHI for the year 2022 was 19.87%, with a standard deviation of 27.38. Previous studies had established that low values of VHI can be directly attributed to increasing surface temperature (Dutta et al., 2015; Masitoh & Rusydi, 2019).





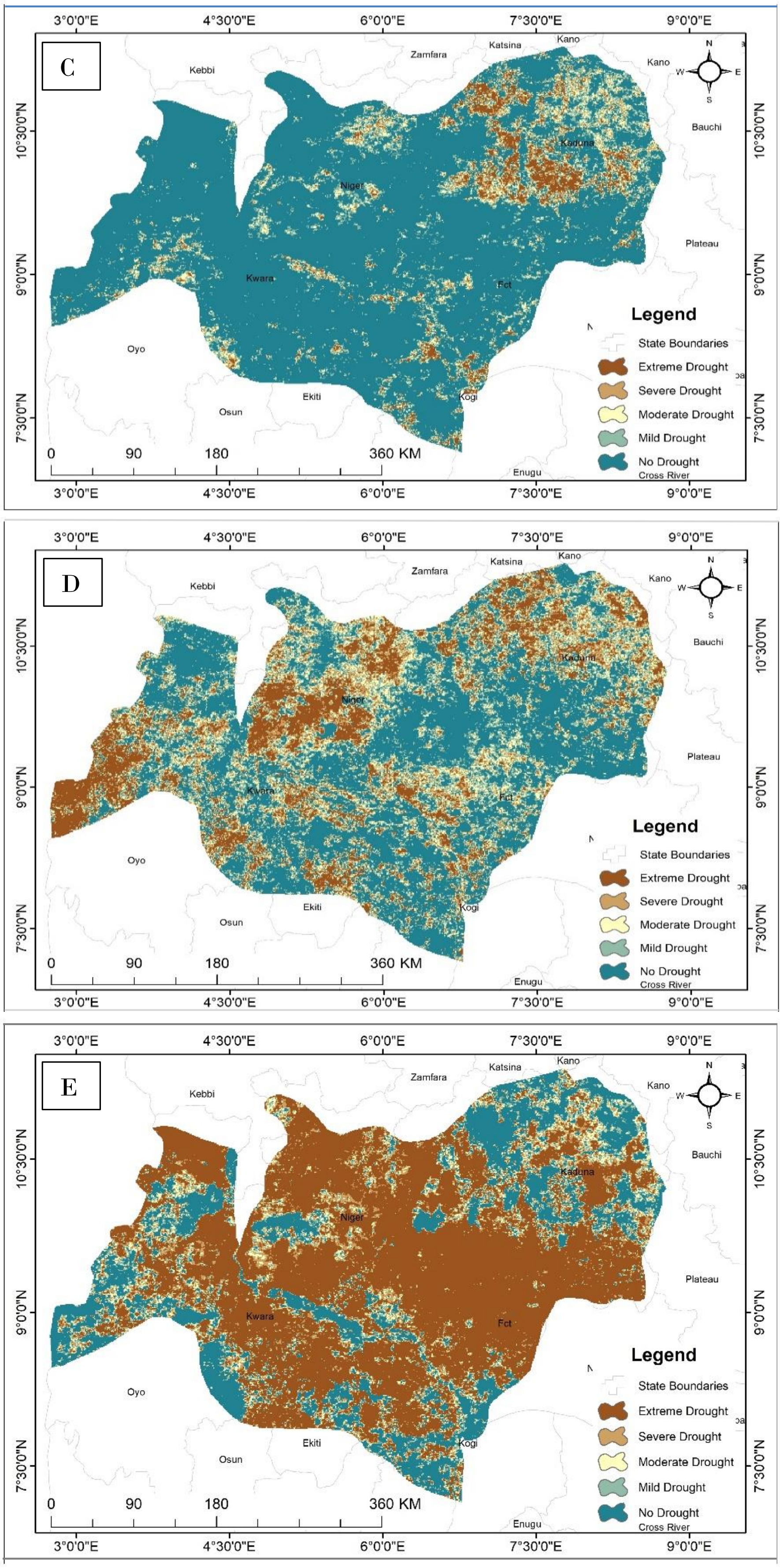


Figure 7. Spatial and temporal variation of Vegetation Health Index (VHI), A=2002, B=2007, C= 2012, D=2017 and E=2022

CONCLUSION

Monitoring and evaluation of agricultural drought is critical to food security, especially in tropical humid climate (Aw). In this paper, we used remote sensing indices to investigate the correlation between vegetation and land surface temperature in Niger River Basin. Mainly, we employed VH index, which computed the roles of VCI and TCI, pixel by pixel. This basically identified the relative influences of vegetation conditions and temperature within the basin for agricultural drought. Additionally, this study assessed the response of vegetation to drought, in order to have a better understanding of the impact of drought on vegetation. This study revealed the area is experiencing decline in vegetation, and a gradual increase in land surface temperature. Additionally, both VCI and VHI revealed that the basin is experiencing severe crop stress within the period under study. Increase in surface temperature, which is significantly influencing agricultural is attributed to climate change. Thus, adequate attention should be paid to continuous monitoring and evaluation of drought in the basin in order to develop early warning system.

ACKNOWLEDGMENTS

The authors acknowledge the National Aeronautics and Space Administration and the United States Geological Survey Agency for the data used in this research. We also acknowledge the Climate Research Group of Kaduna State University for their support.

DECLARATIONS

Conflict of Interest

We declare no conflict of interest, financial or otherwise.

Ethical Approval

On behalf of all authors, the corresponding author states that the paper satisfies Ethical Standards conditions, no human participants, or animals are involved in the research.

Informed Consent

On behalf of all authors, the corresponding author states that no human participants are involved in the research and, therefore, informed consent is not required by them.

DATA AVAILABILITY

Data used to support the findings of this study are available from the corresponding author upon request.

REFERENCES

Adekunle, O. A., Oladipo, F. O., & Busari, I. Z. (2015). Factors affecting farmers' participation in irrigation schemes of the Lower Niger River Basin and Rural Development Authority, Kwara State, Nigeria. *South African Journal of Agricultural Extension, 43*(2), 2015. https://doi.org/10.17159/2413-3221/2015/v43n2a353

Adenle, A. A., Boillat, S., & Speranza, C. I. (2022). Key dimensions of land users' perceptions of land degradation and sustainable land management in Niger State, Nigeria. *Environmental Challenges*, 8, 100544. https://doi.org/10.1016/J.ENVC.2022.100544

Agbo, E. P., Nkajoe, U., Edet, C. O., & Ali, N. (2023). Identification of trends of key parameters affecting vegetation over Nigeria's vegetation zones using innovative trend analysis. *Environmental Earth Sciences, 82*(20), 464. https://doi.org/10.1007/s12665-023-11141-5

Alademomi, A. S., Okolie, C. J., Daramola, O. E., Akinnusi, S. A., Adediran, E., Olanrewaju, H. O., Alabi, A. O., Salami, T. J., & Odumosu, J. (2022). The interrelationship between LST, NDVI, NDBI, and land cover change in a section of Lagos metropolis, Nigeria. *Applied Geomatics, 14*(2), 299–314. https://doi.org/10.1007/s12518-022-00434-2

Ali, S., Basit, A., Umair, M., Makanda, T. A., Khan, F. U., Shi, S., & Ni, J. (2023). Spatio-temporal variations in trends of vegetation and drought changes in relation to climate variability from 1982-2019 based on remote sensing data from East Asia. *Journal of Integrative Agriculture, 22*(10). https://doi.org/10.1016/J.JIA.2023.04.028

Amiri, M., Jafari, R., Tarkesh, M., & Modarres, R. (2020). Spatiotemporal variability of soil moisture in arid vegetation communities using MODIS vegetation and dryness indices. *Arid Land Research and Management, 34*(1), 1–25. https://doi.org/10.1080/15324982.2019.1573441

Babatolu, J. S., & Akinnubi, R. T. (2013). Surface Temperature Anomalies in the River Niger Basin Development Authority Areas, Nigeria. *Atmospheric and Climate Sciences, 03*(04), 532–537. https://doi.org/10.4236/acs.2013.34056

Babatolu, J. S., & Akinnubi, R. T. (2014). Influence of Climate Change in Niger River Basin Development Authority Area on Niger Runoff, Nigeria. *Journal of Earth Science & Climatic Change, 05*(09). https://doi.org/10.4172/2157-7617.1000230

Babatolu, J. S., Akinnubi, R. T., Folagimi, A. T., & Bukola, O. O. (2014). Variability and Trends of Daily Heavy Rainfall Events over Niger River Basin Development Authority Area in Nigeria. *American Journal of Climate Change, 03*(01), 1–7. https://doi.org/10.4236/ajcc.2014.31001

Badou, D. F., Diekkrüger, B., & Montzka, C. (2019). Validation of satellite soil moisture in the absence of in situ soil moisture: the case of the Tropical Yankin Basin. *South African Journal of Geomatics, 7*(3), 243. https://doi.org/10.4314/sajg.v7i3.3

Bello, N. J. (1987). An assessment of water supply for agriculture in the Niger River Basin Development Authority Area, Nigeria. *Agricultural and Forest Meteorology, 40*(2), 109–121. https://doi.org/10.1016/0168-1923(87)90001-3

Buzhani, F. I., Sadr, M. K., Sobhanardakani, S., Lorestani, B., & Cheraghi, M. (2023). Remote sensing assessment of multi-year drought vulnerability of agriculture in Kangavar, Kermanshah Province, Western Iran. *Natural Hazards, 120*(4). https://doi.org/10.1007/s11069-023-06354-7

Carrão, H., Russo, S., Sepulcre-Canto, G., & Barbosa, P. (2016). An empirical standardized soil moisture index for agricultural drought assessment from remotely sensed data. *International Journal of Applied Earth Observation and Geoinformation, 48*, 74–84. https://doi.org/10.1016/J.JAG.2015.06.011

Cetin, M., Sevik, H., Koc, I., & Zeren Cetin, I. (2023). The change in biocomfort zones in the area of Muğla province in near future due to the global climate change scenarios. *Journal of Thermal Biology, 112*. https://doi.org/10.1016/J.JTHERBIO.2022.103434

Chere, Z., & Debalke, D. B. (2023). Modeling agricultural drought based on the earth observation-derived standardized precipitation evapotranspiration index and vegetation health index in the northeastern highlands of Ethiopia. *Natural Hazards, 120*(3). https://doi.org/10.1007/s11069-023-06320-3 de Lima, S. C., Neto, J. M. d. M., Lima, J. P., de Lima, F. C., & Saboya, L. M. F. (2023). Response of semi-arid vegetation to agricultural drought determined by indices derived from MODIS satellite. *Revista Brasileira de Engenharia Agrícola e Ambiental, 27*(8), 632–642. https://doi.org/10.1590/1807-1929/AGRIAMBI.V27N8P632-642

Dutta, D., Kundu, A., Patel, N. R., Saha, S. K., & Siddiqui, A. R. (2015). Assessment of agricultural drought in Rajasthan (India) using remote sensing derived Vegetation Condition Index (VCI) and Standardized Precipitation Index (SPI). *The Egyptian Journal of Remote Sensing and Space Science, 18*(1), 53–63. https://doi.org/10.1016/J.EJRS.2015.03.006

Fathi-Taperasht, A., Shafizadeh-Moghadam, H., & Kouchakzadeh, M. (2022). MODIS-based evaluation of agricultural drought, water use efficiency and post-drought in Iran; considering the influence of heterogeneous climatic regions. *Journal of Cleaner Production*, 374, 133836. https://doi.org/10.1016/J.JCLEPRO.2022.133836

Fathi-Taperasht, A., Shafizadeh-Moghadam, H., Minaei, M., & Xu, T. (2022). Influence of drought duration and severity on drought recovery period for different land cover types: evaluation using MODIS-based indices. *Ecological Indicators, 141*, 109146. https://doi.org/10.1016/J.ECOLIND.2022.109146

Furtak, K., & Wolińska, A. (2023). The impact of extreme weather events as a consequence of climate change on the soil moisture and on the quality of the soil environment and agriculture – A review. *CATENA, 231*, 107378. https://doi.org/10.1016/J.CATENA.2023.107378

Gao, Z., Gao, W., & Chang, N. Bin. (2011). Integrating temperature vegetation dryness index (TVDI) and regional water stress index (RWSI) for drought assessment with the aid of LANDSAT TM/ETM+images. *International Journal of Applied Earth Observation and Geoinformation, 13*(3), 495–503. https://doi.org/10.1016/j.jag.2010.10.005

Ghajarnia, N., Kalantari, Z., Orth, R., & Destouni, G. (2020). Close co-variation between soil moisture and runoff emerging from multi-catchment data across Europe. *Scientific Reports, 10*(1), 4817. https://doi.org/10.1038/s41598-020-61621-y

Huang, J., Zhuo, W., Li, Y., Huang, R., Sedano, F., Su, W., Dong, J., Tian, L., Huang, Y., Zhu, D., & Zhang, X. (2020). Comparison of three remotely sensed drought indices for assessing the impact of drought on winter wheat yield. *International Journal of Digital Earth, 13*(4), 504–526. https://doi.org/10.1080/17538947.2018.1542040

Ibanga, O. A., Idehen, O. F., & Omonigho, M. G. (2022). Spatiotemporal variability of soil moisture under different soil groups in Etsako West Local Government Area, Edo State, Nigeria. *Journal of the Saudi Society of Agricultural Sciences, 21*(2), 125–147. https://doi.org/10.1016/J.JSSAS.2021.07.006

Ismail, R. B. Y., Bozorg-Omid, F., Osei, J. H. N., Pi-Bansa, S., Frempong, K. K., Ofei, M. K., ... & Dadzie, S. K. (2024). Predicting the environmental suitability for Anopheles stephensi under the current conditions in Ghana. *Scientific Reports, 14*(1), 1116.. https://doi.org/10.1038/s41598-024-51780-7

Karnieli, A., Ohana-Levi, N., Silver, M., Paz-Kagan, T., Panov, N., Varghese, D., Chrysoulakis, N., & Provenzale, A. (2019). Spatial and seasonal patterns in vegetation growth-limiting factors over europe. *Remote Sensing, 11*(20), 2406. https://doi.org/10.3390/rs11202406

Kehinde, M. O., & Umar, A. T. (2021). Assessment of soil moisture storage in nigeria using climatic water budgeting approach. *Ghana Journal of Geography, 13*(1), 167–202. https://doi.org/10.4314/gjg.v13i1.9

Kloos, S., Yuan, Y., Castelli, M., & Menzel, A. (2021). Agricultural drought detection with modis based vegetation health indices in southeast germany. *Remote Sensing, 13*(19), 1–24. https://doi.org/10.3390/rs13193907

Luo, X., Li, S., Yang, W., Liu, L., Shi, Y., Lai, Y., Yu, P., Yang, Z., Luo, K., Zhou, T., Yang, X., Wang, X., Chen, S., & Tang, X. (2023). Spatio-temporal changes in global root zone soil moisture from 1981 to 2017. *Journal of Hydrology, 626*, 130297. https://doi.org/10.1016/J.JHYDROL.2023.130297

Maduako, I. N., Ndukwu, R. I., Ifeanyichukwu, C., & Igbokwe, O. (2017). Multi-Index Soil Moisture Estimation from Satellite Earth Observations: Comparative Evaluation of the Topographic Wetness Index (TWI), the Temperature Vegetation Dryness Index (TVDI) and the Improved TVDI (iTVDI). *Journal of the Indian Society of Remote Sensing, 45*(4), 631–642. https://doi.org/10.1007/s12524-016-0635-9

Masih, I., Maskey, S., Mussá, F. E. F., & Trambauer, P. (2014). A review of droughts on the African continent: A geospatial and long-term perspective. *Hydrology and Earth System Sciences, 18*(9), 3635–3649. https://doi.org/10.5194/HESS-18-3635-2014

Masitoh, F., & Rusydi, A. N. (2019). Vegetation Health Index (VHI) analysis during drought season in Brantas Watershed. *IOP Conference Series: Earth and Environmental Science, 389*(1). https://doi.org/10.1088/1755-1315/389/1/012033

Medugu, N. I., Majid, M. R., & Johar, F. (2011). Drought and desertification management in arid and semi-arid zones of Northern Nigeria. *Management of Environmental Quality: An International Journal, 22*(5), 595–611. https://doi.org/10.1108/14777831111159725

Meng, L., Li, J., Chen, Z., Xi, W., Chen, D., & Duan, H. (2008). The Calculation of TVDI Based on the Composite of Pixel and Drought Analysis. *The International Archives of the Photogrammetry, Remote Sening and Spatial Information Sciences, 38*, 519–524.

Monteleone, B., Bonaccorso, B., & Martina, M. (2020). A joint probabilistic index for objective drought identification: the case study of Haiti. *Natural Hazards and Earth System Sciences, 20*(2), 471-487. https://doi.org/10.5194/nhess-20-471-2020

Murtala, M., Iguisi, E. O., Ibrahim, A. A., Yusuf, Y. O., & Inobeme, J. (2018). Spatio - temporal analysis of drought occurrence and intensity in northwest zone of nigeria. *Dutse Journal of Pure and Applied Sciences, 4*(1), 111–129.

NASA. (2023). MOD13Q1 - MODIS/Terra Vegetation Indices 16-Day L3 Global 250m SIN Grid. Retrieved from https://ladsweb.modaps.eosdis.nasa.gov/missions-and-measurements/products/MOD13Q1

Nguyen, H. H., Cho, S., & Choi, M. (2022). Spatial soil moisture estimation in agro-pastoral transitional zone based on synergistic use of SAR and optical-thermal satellite images. *Agricultural and Forest Meteorology, 312*, 108719. https://doi.org/10.1016/j.agrformet.2021.108719

Nigerian Meteorological Agency (NIMET). (2018). *Daily Meteorological Variables. In Nigerian Meteorological Agency*. NiMET.

Ogbue, C., Igboeli, E., Ajaero, C., Ochege, F. U., Yahaya, I. I., Yeneayehu, F., You, Y., & Wang, Y. (2024). Remote sensing analysis of desert sensitive areas using MEDALUS model and GIS in the Niger River Basin. *Ecological Indicators, 158*, 111404. https://doi.org/10.1016/J.ECOLIND.2023.111404

Ogunrinde, A. T., Oguntunde, P. G., Akinwumiju, A. S., & Fasinmirin, J. T. (2019). Analysis of recent changes in rainfall and drought indices in Nigeria, 1981–2015. *Hydrological Sciences Journal, 64*(14), 1755–1768. https://doi.org/10.1080/02626667.2019.1673396

Ogunrinde, A. T., Oguntunde, P. G., Akinwumiju, A. S., Fasinmirin, J. T., Adawa, I. S., & Ajayi, T. A. (2023). Effects of climate change and drought attributes in Nigeria based on RCP 8.5 climate scenario. *Physics and Chemistry of the Earth, 129*, 103339. https://doi.org/10.1016/j.pce.2022.103339

Okpara, J. N. (2022). *Composite Index-Based Early Warning System for Drought Monitoring in The Niger River Basin of West Africa*. FUT Akure.

Olatunji, W. B. (2023). *Drought Management Initiatives (Issue May).* Niger Basin Authority.

Oloruntade, A. J., Mohammad, T. A., Ghazali, A. H., & Wayayok, A. (2017). Analysis of meteorological and hydrological droughts in the Niger-South Basin, Nigeria. *Global and Planetary Change, 155*, 225–233. https://doi.org/10.1016/j.gloplacha.2017.05.002

Patel, N. R., Parida, B. R., Venus, V., Saha, S. K., & Dadhwal, V. K. (2012). Analysis of agricultural drought using vegetation temperature condition index (VTCI) from Terra/MODIS satellite data*. Environmental Monitoring and Assessment, 184*, 7153-7163. https://doi.org/10.1007/s10661-011-2487-7

Pradhan, N. R. (2019). Estimating growing-season root zone soil moisture from vegetation index-based evapotranspiration fraction and soil properties in the Northwest Mountain region, USA. *Hydrological Sciences Journal, 64*(7), 771–788. https://doi.org/10.1080/02626667.2019.1593417

Przeździecki, K., Zawadzki, J. J., Urbaniak, M., Ziemblińska, K., & Miatkowski, Z. (2023). Using temporal variability of land surface temperature and normalized vegetation index to estimate soil moisture condition on forest areas by means of remote sensing. *Ecological Indicators, 148*, 110088. https://doi.org/10.1016/J.ECOLIND.2023.110088

Ryu, S., Kwon, Y. J., Kim, G., & Hong, S. (2021). Temperature vegetation dryness index-based soil moisture retrieval algorithm developed for geo-kompsat-2A. *Remote Sensing, 13*(15). https://doi.org/10.3390/rs13152990

Seun, A. I., Ayodele, A. P., Koji, D., & Akande, S. O. (2022). The potential impact of increased urbanization on land surface temperature over South-West Nigeria. Current Research in *Environmental Sustainability, 4*, 100142. https://doi.org/10.1016/J.CRSUST.2022.100142

Shamloo, N., Sattari, M. T., & Apaydin, H. (2022). Agricultural drought survey using MODIS-based image indices at the regional scale: case study of the Urmia Lake Basin, Iran. *Theoretical and Applied Climatology, 149*(1–2), 39–51. https://doi.org/10.1007/S00704-022-04023-6/METRICS

Srivastava, H. S., Sivasankar, T., Gavali, M. D., & Patel, P. (2024). Soil moisture estimation underneath crop cover using high incidence angle C-band Sentinel-1 SAR data. *Kuwait Journal of Science, 51*(1), 100101. https://doi.org/10.1016/J.KJS.2023.07.007

Taloor, A. K., Manhas, D. S., & Kothyari, G. C. (2021). Retrieval of land surface temperature, normalized difference moisture index, normalized difference water index of the Ravi basin using Landsat data. *Applied Computing and Geosciences, 9*, 100051. https://doi.org/10.1016/j.acags.2020.100051

Thakur, P. K., Samant, S. S., Verma, R. K., Saini, A., & Chauhan, M. (2024). Monitoring forest cover changes and its impact on land surface temperature using geospatial technique in Talra Wildlife Sanctuary, Shimla, India. *Environment, Development and Sustainability*, 1-30. https://doi.org/10.1007/s10668-023-04347-x

Tran, T. V., Bruce, D., Huang, C. Y., Tran, D. X., Myint, S. W., & Nguyen, D. B. (2023). Decadal assessment of agricultural drought in the context of land use land cover change using MODIS multivariate spectral index time-series data. *GIScience & Remote Sensing, 60*(1), 1. https://doi.org/10.1080/15481603.2022.2163070

United Nations Commission on Sustainable Development (UNCSD). (2020). *Comprehensive assessment of the freshwater resources of the world. Report of the Secretary-General*. Retrieved from http://www.un.org/esa/ sustdev/sdissues/water/water documents

Wang, H., Magagi, R., Goïta, K., Colliander, A., Jackson, T., McNairn, H., & Powers, J. (2021). Soil moisture retrieval over a site of intensive agricultural production using airborne radiometer data. *International Journal of Applied Earth Observation and Geoinformation, 97*, 102287. https://doi.org/10.1016/J.JAG.2020.102287

Wang, T., Wedin, D. A., Franz, T. E., & Hiller, J. (2015). Effect of vegetation on the temporal stability of soil moisture in grass-stabilized semi-arid sand dunes. *Journal of Hydrology, 521*, 447–459. https://doi.org/10.1016/j.jhydrol.2014.12.037

Wassie, S. B., Mengistu, D. A., & Birlie, A. B. (2022). Agricultural drought assessment and monitoring using MODIS-based multiple indices: the case of North Wollo, Ethiopia. *Environmental Monitoring and Assessment, 194*(10), 1–25. https://doi.org/10.1007/S10661-022-10455-4/METRICS

Wei, W., Pang, S., Wang, X., Zhou, L., Xie, B., Zhou, J., & Li, C. (2020). Temperature Vegetation Precipitation Dryness Index (TVPDI)-based dryness-wetness monitoring in China. *Remote Sensing of Environment, 248*, 111957. https://doi.org/10.1016/j.rse.2020.111957

Xie, F., & Fan, H. (2021). Deriving drought indices from MODIS vegetation indices (NDVI/EVI) and Land Surface Temperature (LST): Is data reconstruction necessary? *International Journal of Applied Earth Observation and Geoinformation, 101*, 102352. https://doi.org/10.1016/j.jag.2021.102352

Yang, C., Liu, C., Gu, Y., Wang, Y., Xing, X., & Ma, X. (2023). A novel comprehensive agricultural drought index accounting for precipitation, evapotranspiration, and soil moisture. *Ecological Indicators, 154*, 110593. https://doi.org/10.1016/J.ECOLIND.2023.110593

Zeng, J., Zhang, R., Qu, Y., Bento, V. A., Zhou, T., Lin, Y., Wu, X., Qi, J., Shui, W., & Wang, Q. (2022). Improving the drought monitoring capability of VHI at the global scale via ensemble indices for various vegetation types from 2001 to 2018. *Weather and Climate Extremes, 35*, 100412. https://doi.org/10.1016/j.wace.2022.100412