Science Forum (Journal of Pure and Applied Sciences)

Journal Homepage: https://atbuscienceforum.com.ng/index.php/jpas

Spatiotemporal Assessment of Climate Change Using Land Surface Temperature and NDVI Dynamics in Bauchi LGA, Nigeria: A Geospatial Analysis

JIKA Hilary Terkula [1], MOHAMMED Jibril[1,2]

[1]Sustainable Procurement Environmental and Social Standards Enhancements Center of Excellence, Abubakar Tafawa Balewa University Bauchi, Nigeria.

[2]Chemical Engineering Department, Faculty of Chemical Engineering, Abubakar Tafawa Balewa University Bauchi, Nigeria.

Abstract

Rapid land-use and land-cover (LULC) changes driven by urban expansion, agricultural intensification, and deforestation have significantly altered surface thermal dynamics across many sub-Saharan African cities, posing serious challenges to environmental sustainability and climate resilience. This study investigates the spatiotemporal variations of Land Surface Temperature (LST) and the Normalized Difference Vegetation Index (NDVI) in Bauchi Local Government Area (LGA), Nigeria, over three epochs (2013, 2018, and 2023) to evaluate the influence of vegetation cover changes on surface thermal conditions. Remote sensing datasets and geospatial analytical techniques were employed to quantify temporal changes in LST and NDVI, while correlation and regression analyses were used to assess the strength and direction of their relationship. Results indicate a persistent increase in LST across the study area between 2013 and 2023. By 2018, the spatial extent of cooler thermal zones had markedly decreased, accompanied by expanding warming zones associated with vegetation loss and increased exposure of bare surfaces. In 2023, cool thermal signatures became highly restricted, while most of the study area exhibited elevated surface temperatures, indicating a diminished capacity for natural thermal regulation. NDVI analysis revealed a progressive decline in vegetation cover and ecosystem productivity, with extensive vegetated areas observed in 2013 becoming increasingly fragmented and degraded by 2018 and 2023. Regression analysis confirmed a consistent inverse LST–NDVI relationship throughout the study period. NDVI explained only 0.64% of LST variability in 2013 (R^2 = 0.0064), increased to 26.32% in 2018 (R^2 = 0.2632), and declined to 13.05% in 2023 (R^2 = 0.1305) when LST reached 43–47°C. These findings underscore the urgent need for urban greening, land restoration, and climate-adaptive planning strategies to support SDGs 13 and 15.

Keywords
Land Surface Temperature;
Vegetation Cover;
Remote Sensing;
Urban Heat;
Climate Change.

ISSN 1119-4618
JPAS
Faculty of Science, ATBU Bauchi

Corresponding Author: JIKA Hilary Terkula., [1]Sustainable Procurement Environmental and Social Standards Enhancements Center of Excellence, Abubakar Tafawa Balewa University, P.M.B 0248 Bauchi, Nigeria. Email: htjika.pg@atbu.edu.ng

1.0 Introduction

Climate change is one of the greatest environmental problems that the world faces now, and its effects differ from place to place and from time to time. In semi-arid areas of sub-Saharan Africa, the impacts are very severe because of the combined effects of the climate, degradation of the environment, and the people's inability to cope with the changes. Being part of the Sudano-Sahelian zone, Nigeria is undergoing changes in its temperature and rainfall patterns availability, though real local climate analyses are hindered by lack of long-term and spatially continuous meteorological data [Pettorelli et al. 2018]. That means, satellite technology has become a crucial tool to observe the changes of the earth's surface climate in those places where ground data are not available [Zhang et al. 2021].

Land Surface Temperature (LST) and the Normalized Difference Vegetation Index (NDVI) are the two most commonly used biophysical parameters for documenting climate-related environmental changes. LST measures the radiative temperature of the Earth's surface and can be used as an indicator of the energy balance processes at the surface level directly [Li et al. 2020]. NDVI which is computed by using the red and near-infrared parts of the spectrum, very well reflects vegetation condition, amount of green biomass and photosynthetic regions, a very good measure of the state of the ecosystem [Rahimi et al. 2025].

The relationship between these parameters is based on well-known vegetation-temperature interactions: through evapotranspiration, vegetation affects the LST, the surface roughness and albedo are the other factors; However, how much the vegetation is stressed thermally will determine its productivity and presence in a given area [Weng et al. 2019; Mohammed & Lorestani, 2025]. When temperature increases to a level that the plant cannot tolerate, its productivity will decrease which results in less NDVI and less cooling through plants. However, LST will go up and the positive feedback loop that makes the surface becoming warmer is set in motion again [Zhang et al. 2021; Liu et al. 2022]. Such feedback loops do get very strong in semi-arid areas and in fact, even the little vegetation that disappears will cause large thermal effects [Li et al. 2020].

Worldwide empirical studies show that LST and NDVI are very useful tools for monitoring climate. A recent worldwide evaluation by Rahimi et al. (2025) has shown that, from 2000 to 2024, NTVI-LST correlations were A lot negative in statistically in more than 80% of the world's terrestrial ecosystems, so confirming that increased vegetation density cools the surface with the evaporative process. In a similar vein, Li et al. (2020) established that LST anomalies based on satellite data for decades greatly matched the locations of observed long-term changes in the climate, mainly in arid and semi-arid zones where the destruction of vegetation intensifies surface warming. Time-series analysis, trend detection methods like the Mann Kendall test, and correlation analysis have become the regular ways of quantifying spatial-temporal climate dynamics, and are most fitting for regions with a scarcity of data like North-East Nigeria [Dissanayake et al. 2019; Hussain et al. 2019]. Looking at Nigeria, a number of studies have used geospatial techniques to evaluate urban and peri-urban climate dynamics.

Abubakar et al. (2024) revealed that LST Much increased while NDVI decreased A lot in Kaduna Metropolis, finding that these changes resulted from urbanization and land cover conversion. However, studies in non-metropolitan Local Government Areas (LGAs) are scarce, although it is proven that settlement and infrastructure development result in localized warming detectable through LST even in areas not yet fully urbanized [Weng et al. 2019]. Bauchi LGA, North-East Nigeria, is a good example of this. The area experiences a semi-arid climate, a mix of agricultural and rangeland systems, and rising human pressures due to urban expansion, vegetation clearance, and infrastructural development. All these activities change the surface energy balance and are major contributors to surface warming. But there is no quantified evidence of climate-driven changes at the surface level in Bauchi LGA.

This research's theoretical foundation is based on Surface Energy Balance Theory from which the researcher explains how the energy coming from the sun is distributed at the Earth's surface into three main components namely sensible heat, latent heat, and ground heat [Li et al. 2020]. Besides, Spatiotemporal Systems Theory considers environmental things as systems that change dynamically across the dimension of space and time [Dissanayake et al. 2019]. The third theoretical support is Urban Heat Island Theory that is concerned with explaining how the decrease in the amount of vegetation and the increase in the surface of impermeable materials are factors leading to the elevation of surface temperatures in towns or cities compared to rural areas [Weng et al. 2019]. In total, these theories enable NDVI to be placed as a mediating variable that links land cover changes to LST variability, Because of this providing support for thorough climate change studies.

Because the observed patterns fit well with Sustainable Development Goals (SDGs) like SDG 13 (Climate Action), SDG 15 (Life on Land), and SDG 11 (Sustainable Cities), there is a pressing demand for spatially explicit, data-driven researches to finance climate-resilient planning [Fashae et al. 2020]. Even though Bauchi LGA is not a fully urban area, the presence of climate changes and land surface fluctuations points to a slow environmental change in which the strength of the ecosystem decreases while the sensitivity to environmental pressure increases. Effects do not come from a single cause but from connected interactions that determine the local situation.

For this reason, this paper intends to carry out a climate change evaluation in Bauchi LGA based on geospatial analysis of LST and NDVI changes over the period 2013 to 2023. Corresponding to the main aim, this work shall be carried out through: (1) examination of spatiotemporal distribution features of LST and NDVI;(2) the identification of long-term trend with the aid of Mann-Kendall test and Sen's slope estimator; and (3) the assessment of NDVI-LST interactions to locate climate change hotspots. The combination of remote sensing, statistical trend analysis, and GIS-based mapping methods, this study furnishes proof to back up specific measures such as afforestation, sustainable agriculture, and urban green infrastructure that contribute to surface warming alleviation and ecological resilience enhancement in Bauchi LGA.

2.0 Methodology and Materials

2.1 The Study Area

Bauchi Local Government Area lies in Bauchi state, North-East Nigeria in the Sudan–Sahel savanna ecological zone. The LGA is located approximately between 9°30′ N – 10°15′ N latitudes and 9°30′ E – 10°15′ E longitudes Fig.1. It is predominantly flat to gently rolling with an elevation above average sea level ranging from 600 to 700m. Bauchi LGA experiences unimodal climatic regime with a short rainy period of May to September and a long dry period of October to April. Rainfall is between 700 and 900 mm per year on average and yearly and seasonal temperatures frequently exceed 30°C, with dry season temperatures frequently over 40°C.

The climate in this area makes it very susceptible to increased temperature and stress to plants. Vegetation in the study area is mainly Sudan savanna (grasses, shrubs and isolated trees), which is increasingly under threat from the encroaching agricultural frontier, fuelwood harvesting, grazing and the presence of settlements. The LGA is highly vulnerable to climate variability and climate change, as most of the population relied on rain-fed agriculture and natural vegetation as their means of livelihood (Ayanlade et al., 2018; Abubakar et al., 2024). The features have contributed to the decision of Bauchi LGA as a suitable area for the localized evaluation of climate change using LST and NDVI.

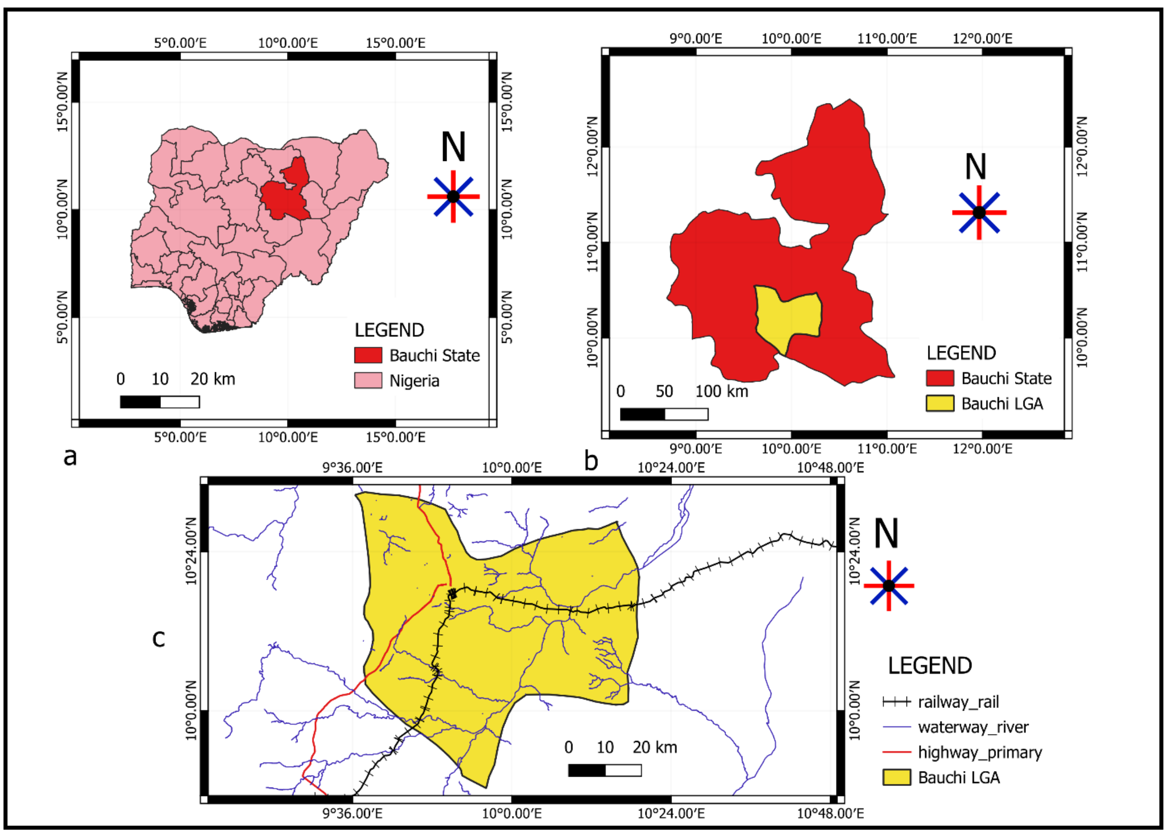


Figure 1: Map of the study area showing (a) Nigeria (b) Bauchi State (c) Bauchi Local Government Area.

2.2 Satellite Data

Data used for this research are mostly multitemporal satellite images from Landsat and MODIS systems. The moderate spatial resolution (30m) and the large historical archive of Landsat was selected for comprehensive spatial analysis of vegetation and surface temperature trend. Complementing Landsat data, MODIS data products based on the robust and reliable nature of the data, offered high temporal resolution, with a special focus on time-series analysis and trend analysis (Wan et al., 2015).

The Land Surface Temperature (LST) data were obtained using thermal infrared bands of the Landsat sensors and near infrared reflectance and red bands to calculate NDVI. The temporal span of the data will cover 3 quinquennials in 2013, 2018 and 2023, which will allow the identification of longer-term climate trends in line with previous studies on climate around the world in semi-arid regions (Li et al., 2020). Data coverage for Mann Kendall trend analysis and Sen's slope is from 2013 to 2023.

2.3 Software and Analytical Tools

Data processing and analysis will be performed with QGIS for spatial analysis and production of maps, Modis plugins for image processing and spectral analysis, and Google Earth Engine (GEE) to efficiently manage large multi-temporal datasets. Data will be analysed statistically using R package.

2.4 Determination of LST

The algorithm employed for the derivation of LST is given in equation 1. This algorithm needs the parameters of transmittance, emissivity and mean atmospheric temperature. (Qin et al., 2001). The algorithm was applied to thematic Infrared Band (TIR) bands that is band 6 and band 10 of Landsat 8 data respectively

$$T_s = \frac{[a(1 - C - D) + [b(1 - C - D) + C + D]T_1 - D * T_a]}{C} \dots\dots\dots\dots\dots\dots.1$$

Where $T_s = LST$; a=-67.35531; b=0.4558606; $C = \varepsilon_i * \tau_i$; $D = (1 - \tau_i)[1 + (1 - \varepsilon_i) * \tau_i]$

$\varepsilon_i = Emissivity$ $\tau_i = Transmissivity$

2.4.1 Digital Number to radiance values

The data from Landsat 8 was used to obtain the spectral radiance values by converting the digital numbers. This spectral reflectance values were obtained by using equation 2 on thermal band 6 and band 10. The band specific information of the satellite data is store in the metadata.

$$L_\lambda = M_L * Q_{Cal} + A_L \dots\dots\dots\dots\dots\dots.2$$

L_λ=TOA spectral radiance (W/(m^2*srad*µm))

ML=Band specific multiplicative rescaling from the metadata (RADIANCE_MULT_BAND_x where x is the band number)

A_L= Band specific additive rescaling factor from metadata (RADIANCE_ADD_BAND_x where x is the band number)

Q_{Cal}=Quantized and calibrated standard product pixel values (DN)

2.4.2 Convert to brightness temperature

The inverse of the Plank function is used to get the brightness temperature from the spectral radiance value (Sospedra et al., 1990). Equation 3 given below

$$T = \frac{K_2}{\ln\left(\frac{K_1 * \varepsilon}{L_\lambda} + 1\right)} \dots\dots\dots\dots\dots\dots 3$$

Where T=temperature in Kelvin, K_1 and K_2 become a coefficient determine by the effective wavelength of the satellite and are obtained from metadata; L_λ and ε has earlier been define in equation 1 and 2.

2.4.3. Atmospheric Transmittance

Gases and aerosols make up the air in the atmosphere. These compositions can absorb or scatter radiation in its way to the thermal imaging system (Holst, 2000). Atmospheric transmittance, T(ʌ), is the percentage of the electromagnetic radiation at wavelength transmitted through the atmosphere without being absorbed or scattered along the way given in equation 4 below.

$$I(\lambda) = I_o(\lambda)\exp\left(-\tau(\lambda)\right)$$

$$T(\lambda) = \frac{I(\lambda)}{I_o(\lambda)} = \exp\left(-\tau(\lambda)\right) \dots\dots\dots\dots\dots\dots 4$$

Where I_o(ʌ) is the incident spectral radiance at the top of the atmosphere.

I(ʌ) is the spectral radiance after atmospheric transmission.

2.4.4 Emissivity

Van de Griend and Owe (1993) calculated emissivity using equation 5 below when the value of NDVI is between 0.157 to 0.727 or using Table 1.

$$\varepsilon_i = 1.0094 + 0.0047 ln\,(NDVI) \dots\dots\dots\dots\dots\dots 5$$

Table 1:Values of NDVI for calculation of land surface emissivity (After Zhang et al.,2006)

NDVI	Land Surface Emissivity
NDVI < - 0.185	0.995
- 0.185 ≤ NDVI < 0.157	0.970
0.157 ≤ NDVI ≤ 0.727	1.0094 + 0.047ln (NDVI)
NDVI > 0.727	0.990

2.5 Normalized Difference Vegetation Index (NDVI)

Rouse et al., (1974) calculated the NDVI using the reflectance values of the Near Infrared (NIR) and Red spectral bands as given in the equation 6 below

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)} \ldots\ldots\ldots\ldots\ldots\ldots .6$$

Where NIR is reflectance in the near infrared band and Red is the reflectance in the red band
For urban vegetation classes (Table 2 below), Hashim et al., 2019 used NDVI

Table 2:Urban vegetation classes and NDVI value (After Hashim et al., 2019)

SN	Vegetation Classes	Description	NDVI Value
1	Non-Vegetation	Baren areas, build up areas, road network	-1 to 0.199
2	Low Vegetation	Shrub and grassland	0.2 to 0.5
3	High Vegetation	Temperate and Tropical urban forest	0.501 to 1.0

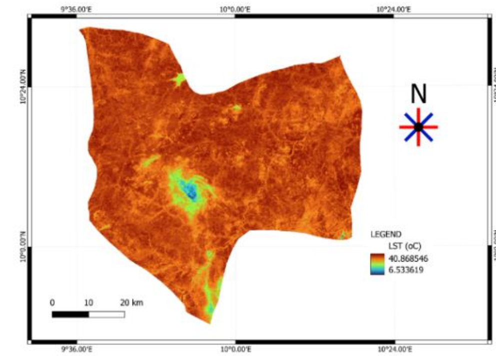
3.0 Results and Discussions

3.1 Spatiotemporal Patterns of Land Surface Temperature

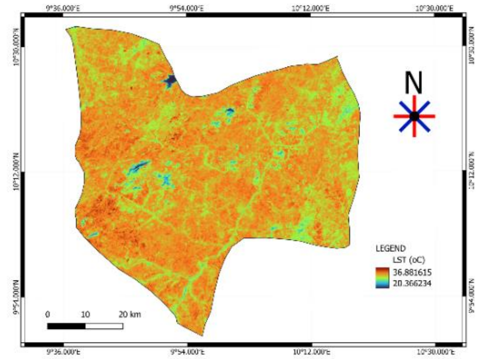
The surface temperature in Bauchi LGA has increased consistently over the three survey years (2013, 2018 and 2023). By 2013 Fig,2A there was a lot of heat, but there are still some areas that are cooler, particularly in the central region. The lower surface temperature readings are associated with areas of increased plant density and ground water holding capacity. These greener areas release moisture into the air, and provide shade, having a natural ability to cool down their surroundings.

In the year 2018, changes in temperature distribution are well seen in Fig.2B. Cooler areas are reduced in size greatly and are increasingly surrounded by warmer areas that intensify over time. As the vegetation decreases, and more bare ground is exposed, there is less natural cooling. For 2023, almost all space is reported as having temperatures above normal. Long-term surface changes are now established in small pockets, which do not warm up Fig 2C. As temperature increases the land's capacity to handle heat seems to be diminishing, which has a direct impact on both nature and humans.

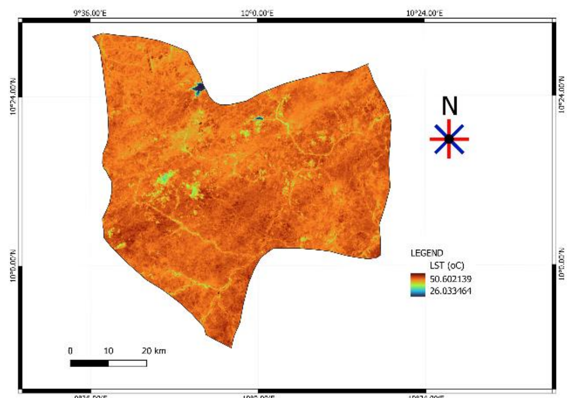
The evidence of SDG 13 suggests there is increasing evidence of climate change in certain regions. As surface temperature increases, so will the health strain when the weather is hot; crop yields will decline; and natural systems will become more fragile, making local adaptation to such changes even more urgent over time. Such trends, though not significant in its size, do have significance when looked at from a regional perspective.



A



B



C

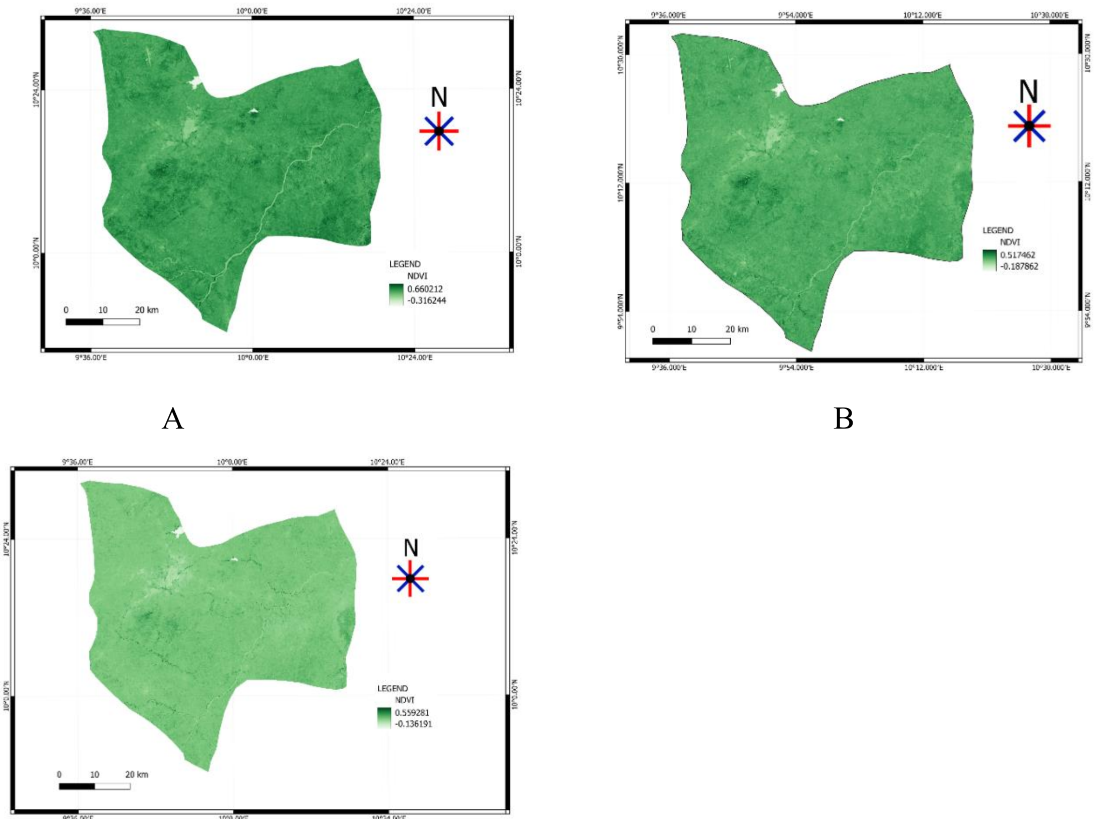
Fig. 2: Spatial distribution of LST in Quinquennial (2013 A, 2018 B and 2023C)

3.2 Spatiotemporal Changes in Vegetation Cover (NDVI)

The NDVI values showed a gradual decrease in signs of greener terrain from 2013 to 2023 across Buchi LGA. In Fig.3A there is still a wide band of healthy plant cover around the beginning of the decade, under steady green signals. Once such conditions were available, natural systems were allowed to function and capture carbon, hold the earth and balance the water. These patterns were evident in the later years and were seen as thinning.

In 2018, some signs of plant stress are observed, with the appearance of patchy patterns in the different locations, and the NDVI readings decrease slightly Fig. 3B. These spot s are oriented closely together where surface heat is more intense, indicating that heat is possibly being applied to green cover.

In 2023, greener loss deepens, while weaker signals are spread wider, reflecting thinner and less active growth that extends farther than ever Fig.3C. In 2023, greener loss deepens and weaker signals spread wider, with thinner and less active growth extending farther than ever. This is a transition from stable plants to the increase in stress and breakdown. As conditions change, long-term land health and natural systems face growing risks. There is an urgency to protect inland environments in the face of the degradation in green cover, given the connection of this indicator to Target 15 of SDGs. As plant layers become thinned, species diversity also declines while the strength of the soil diminishes in its ability to maintain communities and ecological stability.



A B

C

Figure 3: Spatial distribution of NDVI in Quinquennial (2013 A, 2018 B and 2023 C)

3.3 Correlation Between LST and NDVI

To determine the effect of vegetation cover on the thermal condition of the surface in the study area, the correlation between LST and NDVI was analyzed for the three time periods of 2013, 2018 and 2023. The type and intensity of the relationship between the two variables were evaluated using the correlation and regression analysis, based on the scatter plots. The regression lines had negative slopes for all the years analyzed, indicating a negative correlation between vegetation density and land surface temperature. This implies that areas with higher vegetation cover had lower surface temperatures, and those with less vegetation and/or urban development had relatively higher temperatures.

3.3.1 LST-NDVI Correlation for 2013

The 2013 correlation assessment resulted in the regression formula: y2=2.8655x+36.077with a coefficient of determination of: R^2=0.0064 Fig.3. There is very weak negative correlation between LST and NDVI in 2013. The R^2 value is very low, meaning that NDVI explained less than 1% of the variability in LST. The slope of the regression was negative, showing that a rise in vegetation cover was associated with a slight decrease in temperature, but the relationship was not statistically significant and spatially variable.

This weak interaction could be due to the fairly uniform vegetation conditions throughout the study area in 2013 or the effects of other environmental factors like variations in soil moisture, exposed surfaces, human heat sources, and urban materials. Variability in vegetation-induced thermal reaction is further supported by the range of the data points around NDVI values between ~0.30 and ~0.45, and LST values between 33 and 38 degrees Celsius, during this period. Results show that in 2013 the vegetation only had a moderate effect on surface temperature.

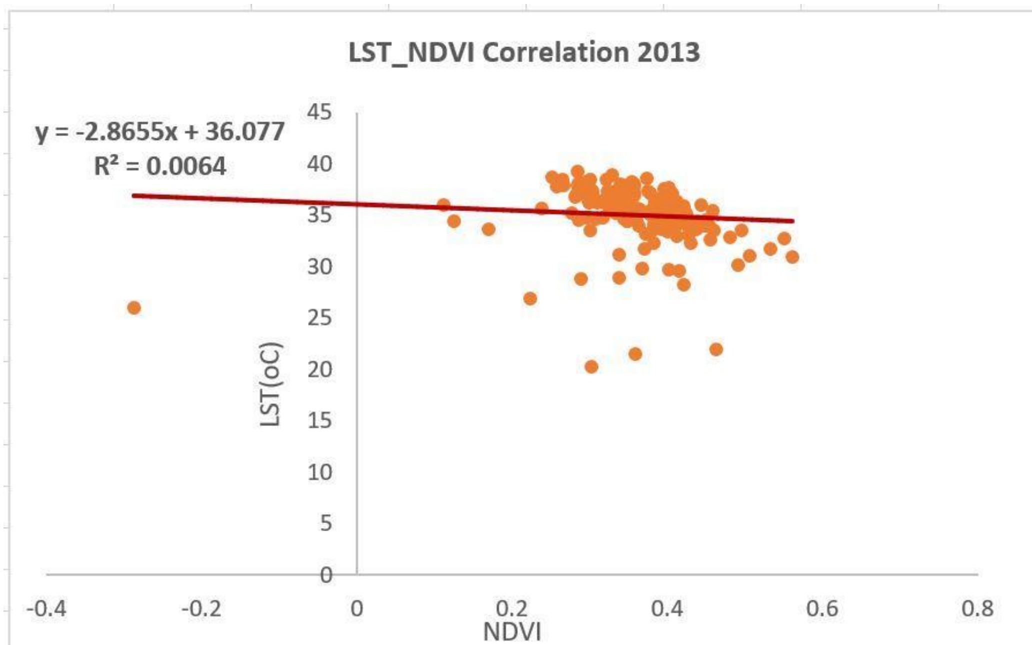


Figure 3: LST and NDVI Correlation in the study area for 2013

3.3.2 LST-NDVI Correlation for 2018

The regression formula for the 2018 results is represented as: y2=-17.861x+35.801 with R^2=0.2632; while in 2013, there was a moderate positive correlation between the NDVI and LST Fig.4. The negative slope shows that the higher the vegetation density, the more pronounced the decreases in surface temperature. The R^2 value of 0.2632 indicates that 26.3% of the LST variability can be explained by vegetation cover changes. This enhanced connection indicates that vegetation emerged as a more important influencing factor of thermal conditions in 2018. More dense vegetation is likely to have caused increased shading and evapotranspiration in the regions, which is likely to have reduced the amount of heat retained on the ground surface. Conversely, NDVI low regions were associated with bare ground, urban development or degraded land cover, which contributed to higher temperatures. The wider temperature spread at the lower NDVI values also indicate greater land cover variation and particular temperature anomalies in the study area.

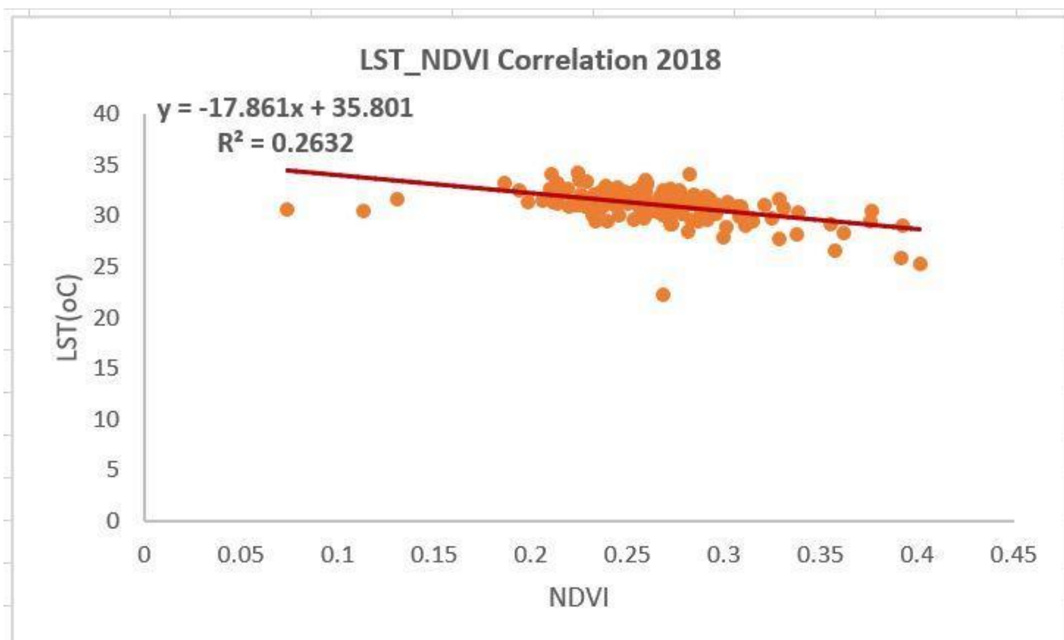


Figure 4: LST and NDVI Correlation in the study area for 2018

3.3.3 LST-NDVI Correlation for 2023

The 2023 regression model was presented as: y2=16.322x+48.609 with: R^2=0.1305 Fig 5. The analyses from 2023 revealed a negative correlation between vegetation cover and land surface temperature; nevertheless, the strength of this correlation decreased compared to 2018. Based on the R^2 value, it is hypothesized that approximately 13.1% of the variation in LST was explained by NDVI. Although plant life remains a factor in reducing surface temperatures, the loss of explanatory power suggests that other environmental and human factors have become increasingly important in driving thermal variability in 2023. The observed rise in LST (43C to 47C) may suggest to higher urbanisation, declining land quality, increased impervious surfaces, reduced soil moisture, and increased climate warming effects. The prevalent negative slope is still making an ecological point that vegetation helps to reduce thermal stress in the study area.

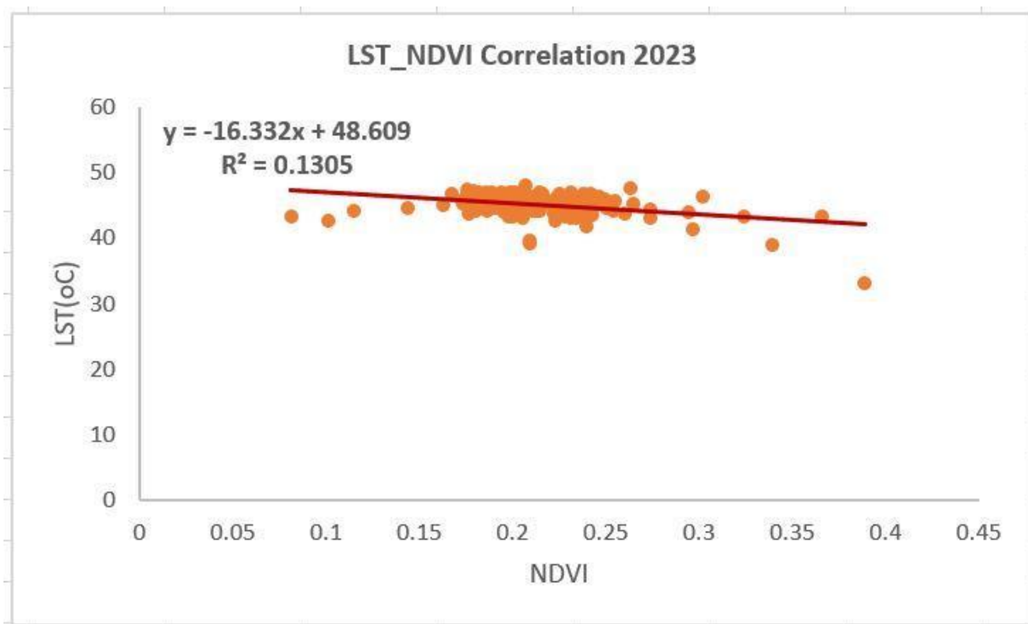


Figure 5: LST and NDVI Correlation in the study area for 2013

Conclusion

This study demonstrates a significant spatio-temporal increase in Land Surface Temperature (LST) and a concurrent decline in vegetation cover, represented by the Normalized Difference Vegetation Index (NDVI), across Bauchi Local Government Area between 2013 and 2023. The observed trends indicate a progressive deterioration of the thermal–vegetation equilibrium, reflecting increasing environmental stress within the study area. The temporal analysis revealed that areas characterized by reduced vegetation density consistently exhibited higher surface temperatures, highlighting the critical role of vegetation in regulating local microclimatic conditions.

Regression analysis confirmed a persistent inverse relationship between LST and NDVI throughout the study period, indicating that vegetation loss contributes substantially to surface warming. Although the strength of this relationship varied over time, the influence of vegetation cover on temperature dynamics became increasingly pronounced, evolving from a relatively weak effect in 2013 to a moderate influence in 2018 and intensifying further by 2023. This trend suggests that anthropogenic activities such as urban expansion, land-use conversion, deforestation, and increasing infrastructure development, combined with climatic variability, have significantly altered the land surface energy balance of the area.

The substantial increase in LST recorded in 2023, coupled with widespread vegetation degradation, signifies that the environmental conditions in Bauchi LGA are approaching a critical threshold. Continued warming and vegetation loss may exacerbate ecological degradation, reduce agricultural productivity, intensify heat-related health risks, diminish biodiversity, and undermine local food security. These findings underscore the urgent need for integrated environmental management strategies, including afforestation and reforestation programmes, urban greening initiatives, sustainable land-use planning, and climate-resilient development policies. Implementing such measures will be essential for mitigating environmental degradation, enhancing ecosystem resilience, and supporting the attainment of Sustainable Development Goals (SDGs) 13 (Climate Action) and 15 (Life on Land) in Bauchi LGA and other semi-arid urban environments across Nigeria.

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