ISSN 2682-681X (Paper), ISSN 2705-4241 (Online) | http://unilorinjoger.com | https://doi.org/10.63745/joger.2025.12.30.009

JOURNAL OF GEOMATICS AND ENVIRONMENTAL RESEARCH
www.unilorinjoger.com

RESEARCH ARTICLE

# Geospatial Analysis of Land Surface Temperature and Multiple Spectral Indices in Kaduna Metropolis Using Remote Sensing

**Abdullahi, S. U. Akomolafe, E. A., Bukar, F. T., Makarfi, Y. I., & Ojonugwa, O. F.**

[1-3]Department of Geomatics, Ahmadu Bello University Zaria, Nigeria,
[4]Kaduna Geographic Information Service Kaduna, Nigeria,
[5]Regional Center for Space Science Education in Asia and Pacific, Beihang University, China.

Corresponding email: sadiyaabdullahimaidara@gmail.com

**Abstract**

*This study examines the spatial and temporal relationship between Land Surface Temperature (LST) and key spectral indices Normalized Difference Vegetation Index (NDVI), Normalized Difference Built-up Index (NDBI), and Normalized Difference Water Index (NDWI) in Kaduna Metropolis, Nigeria, for the years 2002, 2014, and 2024. Landsat 7 and Landsat 8 imagery were processed to derive LST and the three indices, while zonal statistics and correlation analyses were applied to assess long-term environmental changes. Results show that average LST increased from 34.89°C in 2002 to 36.59°C in 2024, reflecting rising thermal stress and increasing temperature homogenization across the city. NDVI values improved markedly over the study period, indicating gradual vegetation recovery, whereas NDBI declined, suggesting reduced built-up intensity or shifts in land cover composition. NDWI exhibited notable fluctuations, highlighting unstable surface moisture conditions. Correlation analysis revealed a persistent moderate negative relationship between LST and NDVI, a strengthening positive correlation between LST and NDBI, and a shift from positive to weak negative correlation between LST and NDWI. These patterns underscore the growing thermal influence of built-up areas and the continued cooling role of vegetation. The study recommends integrating green infrastructure and preserving water bodies as essential strategies for mitigating urban heat and enhancing climate resilience in Kaduna Metropolis.*

**ARTICLE HISTORY**
Received: 26th August, 2025
Accepted: 8th December, 2025
Published: 10th December, 2025

**KEYWORDS**
Land Surface Temperature (LST),
Spectral Indices
Urban Heat Dynamics
Remote Sensing
Kaduna Metropolis.

**Citation:** Abdullahi, S. U. Akomolafe, E. A., Bukar, F. T., Makarfi, Y. I., & Ojonugwa, O. F. (2025). Spatio-Temporal Analysis of Land Surface Temperature and Spectral Indices in Kaduna Metropolis Using Remote Sensing. *Journal of Geomatics and Environmental Research, 8(2). Pp87-98*

## 1. INTRODUCTION

Urbanisation and rapid land use/land cover (LULC) change continue to alter the thermal behaviour of cities worldwide, with significant implications for environmental sustainability and urban liveability. One of the most direct indicators of these changes is Land Surface Temperature (LST), which represents the radiative skin temperature of the Earth's surface as measured by satellite thermal sensors (Li *et al*., 2023). LST is widely applied in climate modelling, ecological monitoring, and urban planning because it reflects how different surface materials absorb, retain, and release heat (Mansourmoghaddam *et al*., 2024). As natural surfaces such as vegetation and water bodies are replaced with impervious materials like concrete and asphalt, cities typically experience elevated temperatures and the development of Urban Heat Island (UHI) conditions.

To quantify these surface changes, spectral indices derived from remote sensing particularly the Normalized Difference Vegetation Index (NDVI), Normalized Difference Built-up Index (NDBI), and Normalized Difference Water Index (NDWI) serve as reliable proxies for vegetation health, built-up intensity, and surface moisture, respectively (Roy & Bari, 2022; Sharma *et al*., 2022). Numerous studies have demonstrated that vegetation strongly mitigates LST, built-up areas intensify surface heating, and water bodies contribute cooling effects through evaporation (Xia *et al*., 2022: Rahimi *et al*., 2025). These relationships are well established in Europe, Asia, and North America (Li *et al*., 2023), and increasingly documented across rapidly growing African cities such as Accra, Nairobi, and Addis Ababa (Woldesemayat & Genovese, 2021; Frimpong *et al*., 2023; Mwangi, 2024).

In Nigeria, remote sensing research has expanded in major urban centres like Lagos and Abuja, where NDVI–LST and NDBI–LST interactions have been widely analysed (Koko *et al*., 2021); Alademomi *et al*., 2022). However, most of these studies focus on single indices or limited time periods, providing an incomplete picture of the simultaneous influence of vegetation, built-up surfaces, and water resources on urban thermal conditions. Secondary cities such as Kaduna, which are experiencing rapid population growth and unregulated development, remain understudied despite their high vulnerability to thermal stress and environmental degradation.

Kaduna Metropolis has undergone pronounced land transformation in recent decades, driven by expanding housing, transportation infrastructure, and industrial activity (Abubakar & Abdussalam, 2024; Danung *et al*., 2025). These changes have contributed to vegetation loss, fragmentation of water bodies, and increasing impervious surface coverage factors known to exacerbate urban heating. Yet, comprehensive geospatial assessments integrating LST with NDVI, NDBI, and NDWI remain limited for the city. This gap restricts the development of evidence-based strategies for climate-sensitive planning, green infrastructure design, and long-term environmental management.

Remote sensing platforms such as Landsat provide multispectral datasets suitable for deriving LST and spectral indices across multiple decades. Combined with GIS-based spatial analysis and statistical techniques such as Pearson correlation, these datasets enable robust evaluation of the strength and direction of relationships between thermal patterns and surface characteristics (Tiwari & Kanchan, 2024). Given the limited availability of continuous ground-based observational data in Kaduna, these geospatial approaches offer an essential means of characterising its evolving thermal environment.

This study, therefore, aims to conduct a multi-temporal geospatial analysis of the relationship between LST and key spectral indices NDVI, NDBI, and NDWI in Kaduna Metropolis for 2002, 2014, and 2024. By integrating satellite-derived indices, zonal statistics, and correlation analysis, the study provides an updated and comprehensive understanding of how vegetation, built-up surfaces, and surface moisture interact with urban heating over time. The findings will support data-driven recommendations for sustainable urban development, climate resilience, and environmental policy in Kaduna and similar mid-sized cities undergoing rapid transformation.

## 2.0 MATERIAL AND METHODS

### 2.1 Study Area

Kaduna Metropolis (Figure 1) is located between latitudes 10°23′–10°40′N and longitudes 7°18′–7°35′E, covering approximately 217.72 km². The area experiences a tropical continental climate characterised by distinct wet (April–October) and dry (November–March) seasons, with mean annual rainfall ranging from 1,000 to 1,500 mm (Okafor *et al*., 2024). The natural vegetation belongs to the northern Guinea savanna ecological zone, consisting of scattered trees, shrubs, and grasses; however, rapid urbanisation has altered much of the natural landscape (Abubakar & Abdussalam, 2024). The soils are predominantly ferruginous tropical soils that are moderately fertile and well drained (Zhi *et al*., 2025). Hydrologically, the metropolis is drained mainly by the Kaduna River and several tributaries, which play essential roles in urban water supply, irrigation, and stormwater management.

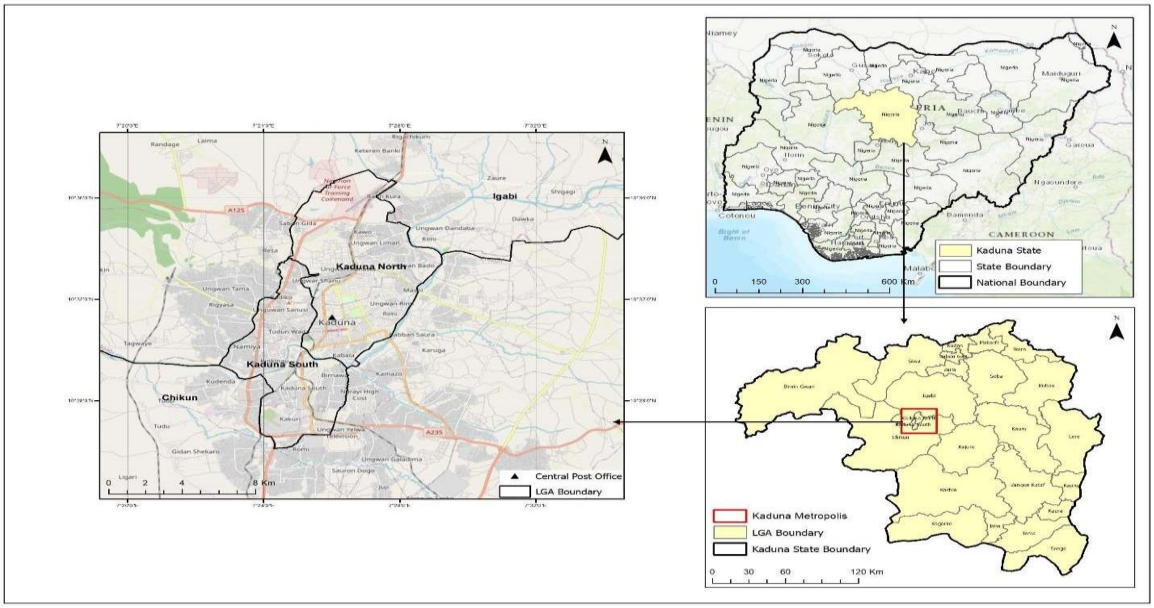



Figure 1. Map of Nigeria and the Kaduna metropolis indicating the location of the study area

### 2.2 Data Sources

Two primary datasets were used: multispectral satellite imagery and ancillary vector data (Table 1).

Table 1: Data Types and Sources

| SN | Data Type | Source | Years |
|---|---|---|---|
| **1** | Landsat 7 ETM+ and Landsat 8 OLI/TIRS | USGS EarthExplorer (https://glovis.usgs.gov/) | 2002, 2014, 2024 |
| **2** | Road network | GRID3 Nigeria (https://grid3.gov.ng/) | – |

Landsat scenes were selected based on minimal cloud cover (<10%), comparable acquisition months to reduce seasonal bias, and availability of both thermal and multispectral bands needed for index computation and LST retrieval.

### 2.3 **Image Pre-processing**

All satellite images were processed in ArcGIS 10.8 and subjected to Layer stacking of spectral bands, Radiometric and atmospheric correction using metadata scaling factors (Landsat Collection 2 L1), Subsetting to the Kaduna Metropolis boundary, and Conversion of digital numbers (DN) to top-of-Atmosphere (TOA) radiance. These steps ensured consistency across the three time periods.

### 2.4 Computation of Spectral Indices

Spectral indices were generated using the Raster Calculator in ArcGIS based on established formulas.

#### 2.4.1 Normalized Difference Vegetation Index (NDVI)

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

Where NIR and R are the infrared and red bands of Landsat 7 and 8, respectively. NDVI values range from -1 to +1, with higher values indicating healthier vegetation.

ISSN 2682-681X (Paper), ISSN 2705-4241 (Online) | http://unilorinjoger.com | https://doi.org/10.63745/joger.2025.12.30.009

### 2.4.2 Normalized Difference Built-Up Index (NDBI)

$$NDBI = \frac{SWIR - NIR}{SWIR + NIR}$$ (eqn. 2)

Where SWIR and NIR are the short-wave and infrared bands of Landsat 7 and 8, respectively. Positive NDBI values typically correspond to built-up/impervious surfaces.

### 2.4.3 Normalized Difference Water Index (NDWI)

$$NDWI = \frac{G - NIR}{G + NIR}$$ (eqn. 3)

Where G and NIR are the green and infrared bands of Landsat 7 and 8, respectively. Higher NDWI values indicate greater surface water presence or moisture content.

### 2.5 Land Surface Temperature (LST) Retrieval

LST was estimated using the thermal bands of Landsat 7 (Band 6) and Landsat 8 (Band 10) following standard procedures (Li *et al*., 2023; Mansourmoghaddam *et al*., 2024).

### 2.5.1 Conversion of DN to TOA Radiance

$$L_\lambda = ML \ X \ Q_{cal} + AL$$ (eqn. 4)

Where:

- $L_\lambda$ = TOA spectral radiance
- $ML$ = radiance multiplicative scaling factor
- $AL$ = radiance additive scaling factor
- $Q_{cal}$ = pixel digital number

### 2.5.2 Brightness Temperature (BT)

$$BT = \frac{K_2}{In\left(\frac{K_1}{L_\lambda}+1\right)}$$ (eqn. 5)

Where $K_1 \ and \ K_2$ are Landsat thermal constants.

### 2.5.3 Land Surface Emissivity (LSE)

Vegetation proportion ($P_v$) was estimated using NDVI:

$$P_v = \left(\frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}}\right)^2$$ (eqn. 6)

Then, the emissivity ($\varepsilon$) was computed as:

$$\varepsilon = 0.986 + 0.004P_v$$ (eqn. 7)

### 2.5.4 Final LST Calculation (in °C)

$$LST = \frac{BT}{1+\left(\frac{\lambda BT}{\rho}\right)In(\varepsilon)} - 273.15$$ (eqn. 8)

Where:

- λ = effective wavelength of emitted radiance (≈11.5 μm)
- $\rho = \frac{hc}{s} = 1.438 \times 10 - 2\,\mathrm{m.K}$

ISSN 2682-681X (Paper), ISSN 2705-4241 (Online) | http://unilorinjoger.com | https://doi.org/10.63745/joger.2025.12.30.009
Final LST maps were rescaled to Celsius.

### 2.6 Statistical and Spatial Analysis

#### 2.6.1 Zonal Statistics
Using the Zonal Statistics tool in ArcGIS, minimum, maximum, mean, and standard deviation values were extracted for LST, NDVI, NDBI and NDWI. This enabled comparison of temporal changes across 2002, 2014, and 2024.

#### 2.6.2 Correlation Analysis
Pairwise correlations between LST and each spectral index were computed using the Band Collection Statistics tool. Pearson correlation coefficients (r) quantified the strength of relationships, direction (positive/negative), and temporal trends across the three years. Correlation matrices were generated for each study year to assess how vegetation, built-up surfaces, and moisture interacted with surface temperature over time.

### 2.7 Map Production
Final thematic maps, including LST, NDVI, NDBI, and NDWI, were produced for all study years. Symbology was standardized using identical classification methods and colour scales to ensure comparability.

## 3.0 RESULTS AND DISCUSSION

### 3.1 Temporal Dynamics of LST, NDVI, NDBI, and NDWI

The spatial distribution and summary statistics of LST and the three spectral indices for 2002, 2014, and 2024 indicate substantial environmental changes across Kaduna Metropolis (Tables 2–5). The temporal patterns show a notable rise in surface temperature, improvements in vegetation health, and a decline in built-up intensity, and fluctuating moisture conditions.

Table 2: Land Surface Temperature Statistics for 2002, 2014 and 2024

| LST | Minimum | Maximum | Mean | Standard Deviation |
|---|---|---|---|---|
| 2002 | 20.8732 | 49.3726 | 34.8929 | 2.6717 |
| 2014 | 26.9629 | 45.4419 | 36.2628 | 2.406 |
| 2024 | 26.8889 | 44.0935 | 36.5898 | 2.1049 |

Table 3: Normalized Difference Vegetation Index Statistics for 2002, 2014, and 2024

| NDVI | Minimum | Maximum | Mean | Standard Deviation |
|---|---|---|---|---|
| 2002 | -0.5962 | 0.2794 | -0.1578 | 0.0684 |
| 2014 | -0.2809 | 0.507 | 0.2092 | 0.071 |
| 2024 | -0.2277 | 0.5803 | 0.2577 | 0.0904 |

Table 4: Normalized Difference Built-up Index Statistics for 2002, 2014 and 2024

| NDBI | Minimum | Maximum | Mean | Standard Deviation |
|---|---|---|---|---|
| 2002 | -0.3529 | 0.64 | 0.3191 | 0.0585 |
| 2014 | -0.3247 | 0.6408 | 0.0257 | 0.0549 |
| 2024 | -0.6408 | 0.3247 | -0.0257 | 0.0549 |

Table 5: Normalized Difference Water Index Statistics for 2002, 2014 and 2024

| NDWI | Minimum | Maximum | Mean | Standard Deviation |
|---|---|---|---|---|
| 2002 | -0.2105 | 0.6585 | 0.0525 | 0.0588 |
| 2014 | -0.4514 | 0.313 | -0.2363 | 0.0579 |
| 2024 | -0.4592 | 0.5012 | 0.0537 | 0.0462 |

**Land Surface Temperature (LST)**

Average LST increased consistently from 34.89°C (2002) to 36.26°C (2014) and 36.59°C (2024). Minimum LST rose by nearly 6°C across the study period (20.87°C to 26.89°C), indicating a warming of cooler peripheral zones. Maximum LST decreased from 49.37°C to 44.09°C, suggesting a reduction in extremely hot surfaces. The standard deviation declined from 2.67°C to 2.10°C, reflecting a more thermally uniform environment.

Rising mean LST combined with decreasing variability signals a shift toward generalized heat stress, a pattern similarly reported in studies from Accra (Frimpong *et al*., 2023) and Gaborone (Ouma *et al*., 2021), where rapid urban expansion increased overall temperature homogeneity.

**Normalized Difference Vegetation Index (NDVI)**

Vegetation conditions improved markedly. Mean NDVI transitioned from –0.1578 (2002) to 0.2577 (2024), while maximum NDVI rose from 0.2794 to 0.5803. Minimum NDVI values also increased, indicating fewer highly degraded vegetative surfaces.

This greening contrasts with trends in other Nigerian cities, such as Lagos, where NDVI has declined due to aggressive urban growth (Alademomi *et al*., 2022). The increase in Kaduna may reflect peri-urban re-vegetation, agricultural expansion around the city, or seasonal differences in imagery acquisition.

**Normalized Difference Built-up Index (NDBI)**

Contrary to expectations for a rapidly urbanizing city, mean NDBI declined from 0.3191 (2002) to –0.0257 (2024). Maximum NDBI values also dropped substantially. While this could suggest reduced impervious surface intensity, it is more likely related to shifts in land cover classification due to vegetation recovery, spectral confusion in mixed-pixel suburban areas, or urban expansion into vegetated zones with changing reflectance properties.

Comparable studies in Abuja and Nairobi report steady increases in NDBI over time (Koko *et al*., 2021; Mwangi, 2024), making Kaduna's declining trend unusual and warranting further investigation.

**Normalized Difference Water Index (NDWI)**

NDWI exhibited strong fluctuations: mean NDWI dropped from 0.0525 (2002) to –0.2363 (2014), then rebounded to 0.0537 (2024). Minimum values also became more negative in 2014 and 2024.

These patterns align with documented reductions in surface water availability in the Kaduna River system during 2010–2016 (Isa *et al*., 2023), possibly caused by seasonal changes, increased water extraction, or sedimentation.

**3.2 Correlation between LST and Spectral Indices**

Correlation analysis (Tables 6–8) provides insight into how vegetation, built-up areas, and surface moisture collectively influence thermal dynamics.

Table 6: Correlation Analyses of LST, NDVI, NDBI and NDWI for 2002

| | LST | NDVI | NDBI | NDWI |
|---|---|---|---|---|
| LST | 1 | -0.53785 | 0.31592 | 0.45766 |
| NDVI | -0.53785 | 1 | -0.51759 | -0.77327 |
| NDBI | 0.31592 | -0.51759 | 1 | 0.20474 |
| NDWI | 0.45766 | -0.77327 | 0.20474 | 1 |

Table 7: Correlation analyses of LST, NDVI, NDBI and NDWI for 2014

| 2014 | LST | NDVI | NDBI | NDWI |
|---|---|---|---|---|
| LST | 1.0000 | -0.5427 | 0.4740 | 0.4244 |
| NDVI | -0.5427 | 1.0000 | -0.5157 | -0.8375 |
| NDBI | 0.4740 | -0.5157 | 1.0000 | 0.3826 |
| NDWI | 0.4244 | -0.8375 | 0.3826 | 1.0000 |

Table 8: Correlation analyses of LST, NDVI, NDBI, and NDWI for 2024

| 2024 | LST | NDVI | NDBI | NDWI |
|---|---|---|---|---|
| LST | 1.0000 | -0.5103 | 0.6338 | -0.2467 |
| NDVI | -0.5103 | 1.0000 | -0.6656 | 0.4557 |
| NDBI | 0.6338 | -0.6656 | 1.0000 | -0.4385 |
| NDWI | -0.2467 | 0.4557 | -0.4385 | 1.0000 |

**LST and NDVI**

LST shows a consistent moderate negative correlation with NDVI across the three years: - 0.54 (2002), –0.54 (2014), and –0.51 (2024). This pattern confirms the cooling role of vegetation and is consistent with global findings (Rahimi *et al*., 2025; Xia *et al*., 2022). The slight weakening in 2024 may reflect the fragmentation of vegetated areas or the increased dominance of moderately vegetated zones.

**LST and NDBI**

The correlation strengthened substantially over time: 0.32 (2002), 0.47 (2014), and 0.63 (2024). This indicates that built-up surfaces increasingly influence heat accumulation. The rising association aligns with findings from Lagos (Alademomi *et al*., 2022) and Addis Ababa (Woldesemayat & Genovese, 2021), which link the expansion of impervious surfaces to higher LST. The trend also suggests that even though mean NDBI values declined, the built-up areas that do exist have become thermally dominant, possibly due to denser construction materials, reduced tree shading, or intensification of urban activities.

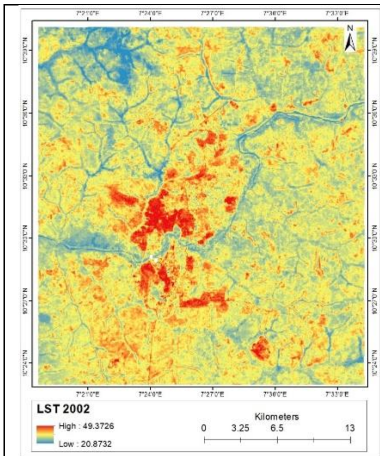
**LST and NDWI**

The relationship shifted from moderately positive to weakly negative: 0.46 (2002), 0.42 (2014), and –0.25 (2024). The positive correlations in 2002 and 2014 may reflect evaporation-driven heating in moist soil or riverine areas. By 2024, the negative correlation suggests reduced surface water extent or lower moisture levels, consistent with the NDWI rebound but still weak overall. Globally, NDWI typically exhibits a negative correlation with LST (Kamran *et al*., 2024), reinforcing that Kaduna's earlier positive values are anomalous and may be influenced by hydrological variability or mixed-pixel effects near urban–river interfaces.

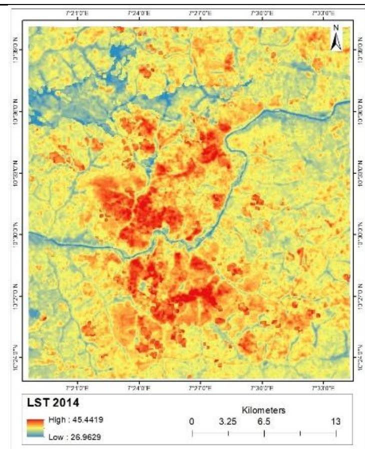
ISSN 2682-681X (Paper), ISSN 2705-4241 (Online) | http://unilorinjoger.com | https://doi.org/10.63745/joger.2025.12.30.009

**Inter-index Relationships**

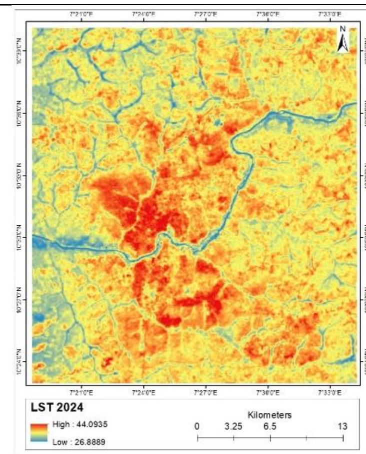
NDVI and NDBI remained moderately to strongly negatively correlated, strengthening from –0.52 (2002) to –0.67 (2024), reflecting continued trade-offs between vegetation and built-up areas. NDVI and NDWI showed a strong negative correlation in 2002 and 2014 but became moderately positive in 2024 (0.46), indicating a recent trend where vegetation and moisture co-occur more frequently (e.g., riparian restoration or agricultural expansion). NDBI and NDWI shifted from weak positive (2002, 2014) to moderately negative in 2024 (–0.44), suggesting built-up areas have become increasingly associated with dry surfaces. Figure 2 presents the Maps of LST, NDVI, NDBI, and NDWI for 2002, 2014, and 2024.



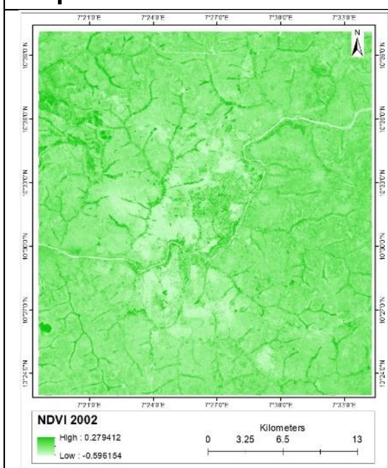

**Map of LST in 2002**



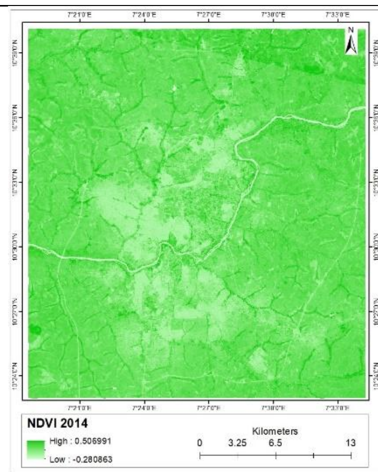

**Map of LST in 2014**



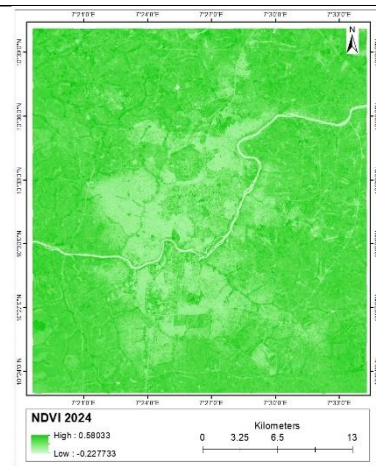

**Map of LST in 2024**




**Map of NDVI in 2002**




**Map of NDVI in 2014**




**Map of NDVI in 2024**

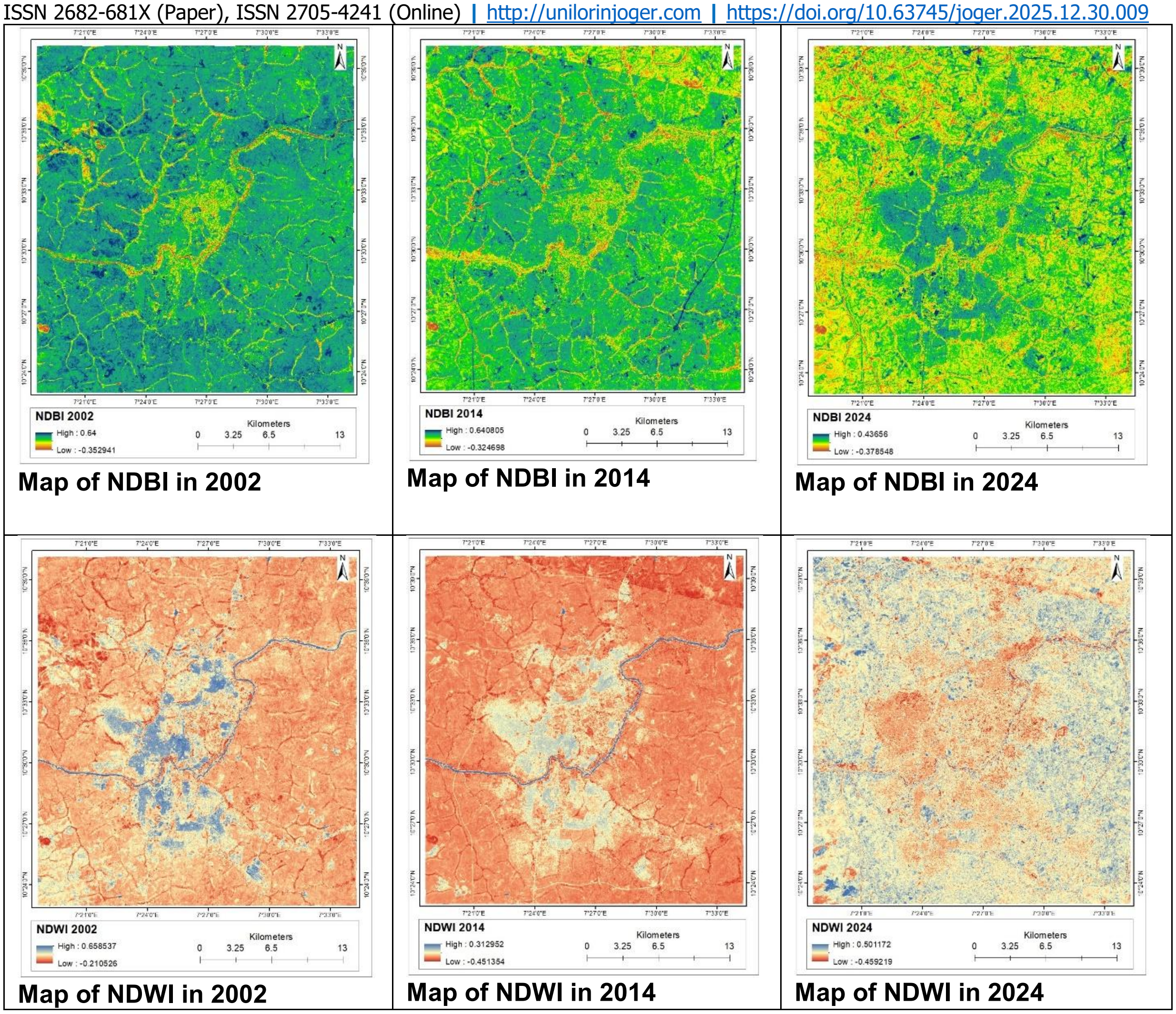



Figure 2: Maps of LST, NDVI, NDBI, and NDWI for 2002, 2014, and 2024

### 3.3 Overall Interpretation

Across the two decades, Kaduna Metropolis exhibited rising thermal stress, consistent with regional warming patterns, improved vegetation, which partly counterbalances heat but remains insufficient to offset warming trends, Increasing thermal dominance of built-up surfaces, as shown by the strengthening LST–NDBI correlation and Hydrological instability, consistent with fluctuating NDWI patterns and weakening cooling effects of water bodies.

These findings highlight the intensifying influence of impervious surfaces and the critical importance of expanding green and blue infrastructure. The relationship patterns align with similar studies in tropical African cities but also reveal unique trends such as declining mean NDBI and shifting NDWI–LST correlations that underscore Kaduna's complex and evolving urban landscape.

## 4.0 CONCLUSION

This study assessed the multi-temporal relationship between Land Surface Temperature (LST) and key spectral indices NDVI, NDBI, and NDWI in Kaduna Metropolis for 2002, 2014, and 2024 using Landsat imagery and geospatial analysis. The findings show a clear increase in average LST over the two-decade period, indicating a progressively warmer and more thermally uniform urban environment. Although vegetation cover improved, as reflected in the rising NDVI values, this greening has not been sufficient to counteract the overall warming trend. The persistent negative correlation between LST and NDVI reaffirms the cooling role of vegetation and underscores its critical importance in moderating the urban thermal environment.

Built-up surfaces exhibited a declining mean NDBI but a steadily strengthening positive correlation with LST, demonstrating that the impervious areas that remain have become increasingly influential in driving urban heat. Moisture conditions fluctuated significantly, with NDWI patterns suggesting hydrological instability and weakened cooling influence from surface water, particularly by 2024. Together, these trends reveal a landscape undergoing rapid transformation, where vegetation gains coexist with intensified thermal contributions from built-up areas and inconsistent water availability.

The study highlights the urgent need for climate-responsive urban planning in Kaduna Metropolis. Priority should be placed on expanding and protecting green infrastructure such as urban forests, street trees, parks, and vegetated corridors to reduce heat exposure and support ecological resilience. Preservation and restoration of water bodies are equally essential for enhancing microclimatic cooling and improving urban hydrological stability. Furthermore, the increasing thermal dominance of built-up areas calls for the adoption of heat-mitigating design strategies, including reflective roofing materials, permeable pavements, and improved building layouts that promote ventilation.

Finally, the integration of geospatial monitoring into routine planning processes is crucial to enable timely assessment of environmental change and guide sustainable development decisions. The insights provided by this study contribute valuable evidence for urban heat mitigation, land-use planning, and climate-resilience strategies in Kaduna and other rapidly urbanizing cities facing similar environmental pressures.

**Recommendations**

The study recommends expanding urban green infrastructure through tree planting, parks, and vegetated corridors to reduce surface temperatures, while also protecting and restoring water bodies to stabilise moisture levels and support cooling. Heat-mitigating urban design measures such as reflective roofing, permeable pavements, and climate-sensitive building materials should be adopted to minimise heat retention in built-up areas. Routine geospatial monitoring of LST and related indices should be integrated into urban planning processes to guide evidence-based development decisions. Stronger development control policies are needed to prevent excessive impervious surface growth and ensure a minimum vegetation cover in new developments. In addition, community engagement should be encouraged to promote urban greening, water conservation, and environmental stewardship at the local level.

**Limitations and Future Research**

This study is limited by the use of three single-date Landsat images, which do not capture seasonal variations; future research should employ multi-seasonal or annual time-series data. The spectral indices may be affected by mixed-pixel effects in heterogeneous urban areas, suggesting the need for higher-resolution imagery in subsequent studies. LST estimation relied on generalized atmospheric and emissivity assumptions, and future work should incorporate more detailed atmospheric correction or in-situ validation. The analysis did not integrate socio-economic factors, which should be explored to better understand human–environment interactions influencing urban heat. Finally, advanced modelling approaches such as machine learning and scenario-based simulations are recommended to predict future thermal patterns under different urban-growth conditions.

## REFERENCES


Abubakar, M. L., & Abdussalam, A. F. (2024). Geospatial analysis of land use changes and wetland dynamics in Kaduna Metropolis, Kaduna, Nigeria. *Scientific World Journal, 19*(3), 687–696.

Akintayo, T., Bello, S. A., Ugwu, S. J., & Mwali, C. N. (2022). Determination of groundwater potential areas in Kaduna Metropolis, Kaduna, Nigeria. *FUDMA Journal of Sciences, 5*(4), 194–204.

Alademomi, A. S., Okolie, C. J., Daramola, O. E., Akinnusi, S. A., Adediran, E., Olanrewaju, H. O., *et al*. (2022). The interrelationship between LST, NDVI, NDBI, and land cover change in a section of Lagos metropolis, Nigeria. *Applied Geomatics, 14*(2), 299–314.

Danung, I. J., Ategbe, D., Abubakar, A. U., & Uthman, I. B. (2025). Temporal land use change along two road infrastructure: A comparative analysis of Yakowa and Yar'adua Ways, Kaduna Metropolis, Nigeria. *International Journal of Built Environment and Earth Science.*

Dapke, P. P., Nagare, S. M., Quadri, S. A., Bandal, S. B., Gaikwad, R. M., & Baheti, M. R. (2025). Seasonal analysis of vegetation, moisture, urbanization, and land surface temperature (LST) using NDVI, NDMI, NDWI, and NDBI indices: A case study of Sillod, Maharashtra. In *2025 International Conference on Computational, Communication and Information Technology (ICCCIT)* (pp. 753–760). IEEE.

Frimpong, B. F., Koranteng, A., & Opoku, F. S. (2023). Analysis of urban expansion and its impact on temperature using remote sensing and GIS techniques in the Accra Metropolis in Ghana (1986–2022). *SN Applied Sciences, 5*(8), 225.

Isa, Z., Sawa, B. A., Abdussalam, A. F., Ibrahim, M., Babati, A. H., Baba, B. M., *et al*. (2023). Impact of climate change on climate extreme indices in Kaduna River Basin, Nigeria. *Environmental Science and Pollution Research, 30*(31), 689–712.

Kamran, J. G., Faizah, C. R., Shuib, R., & Tahereh, N. (2024). Spatial and temporal water pattern change detection through the Normalized Difference Water Index (NDWI) for initial flood assessment: A case study of Kuala Lumpur 1990 and 2021. *Journal of Advanced Research in Fluid Mechanics and Thermal Sciences, 114*(1), 178–187.

Koko, A. F., Yue, W., Abubakar, G. A., Alabsi, A. A. N., & Hamed, R. (2021). Spatiotemporal influence of land use/land cover change dynamics on surface urban heat island: A case study of Abuja Metropolis, Nigeria. *ISPRS International Journal of Geo-Information, 10*(5), 272.

Li, Z., Wu, H., Duan, S., Zhao, W., Ren, H., Liu, X., *et al*. (2023). Satellite remote sensing of global land surface temperature: Definition, methods, products, and applications. *Reviews of Geophysics, 61*(1).

Mansourmoghaddam, M., Rousta, I., Ghafarian Malamiri, H., Sadeghnejad, M., Krzyszczak, J., & Ferreira, C. S. S. (2024). Modeling and estimating land surface temperature (LST) using remote sensing and machine learning: Case study of Yazd, Iran. *Remote Sensing, 16*(3), 454.

Mwangi, P. (2024). Evaluating the spatio-temporal distribution of nitrogen dioxide, land surface temperature and NDVI in Nairobi City County. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, X-3-2024*(4), 37–44.

Obateru, R. O., Okhimamhe, A. A., Fashae, O. A., Schürmann, A., Teucher, M., & Conrad, C. (2025). Insights into landscape structure change in urbanising rainforest and Guinea Savanna ecological regions of Nigeria. *Environmental Management, 75*(5), 16–38.

Okafor, G. C., Ogbu, K. N., Agyekum, J., Limantol, A. M., & Larbi, I. (2024). Rainfall projections under different climate scenarios over the Kaduna River Basin, Nigeria. *Discover Environment, 2*(1), 89.

Ouma, Y. O., Tjitemisa, T., Segobye, M., Moreri, K., Nkwae, B., Maphale, L., *et al*. (2021). Urban land surface temperature variations with LULC, NDVI and NDBI in semi-arid urban environments: Case study of Gaborone City, Botswana (1989–2019). In N. Chrysoulakis, T. Erbertseder & Y. Zhang (Eds.), *Remote Sensing Technologies and Applications in Urban Environments VI* (p. 6). SPIE.

Rahaman, Z. A., Kafy, A. A., Saha, M., Rahim, A. A., Almulhim, A. I., Rahaman, S. N., *et al*. (2022). Assessing the impacts of vegetation cover loss on surface temperature, urban heat island and carbon emission in Penang city, Malaysia. *Building and Environment, 222*, 109335.

Rahimi, E., Dong, P., & Jung, C. (2025). Global NDVI–LST correlation: Temporal and spatial patterns from 2000 to 2024. *Environments, 12*(2), 67.

Roy, B., & Bari, E. (2022). Examining the relationship between land surface temperature and landscape features using spectral indices with Google Earth Engine. *Heliyon, 8*(9).

Sharma, M., Bangotra, P., Gautam, A. S., & Gautam, S. (2022). Sensitivity of normalized difference vegetation index (NDVI) to land surface temperature, soil moisture and precipitation over district Gautam Buddh Nagar, UP, India. *Stochastic Environmental Research and Risk Assessment, 36*(6), 79–89.

Tiwari, A. K., & Kanchan, R. (2024). Analytical study on the relationship among land surface temperature, land use/land cover and spectral indices using geospatial techniques. *Discover Environment, 2*(1), 1.

Woldesemayat, E. M., & Genovese, P. V. (2021). Monitoring urban expansion and urban green spaces change in Addis Ababa: Directional and zonal analysis integrated with landscape expansion index. *Forests, 12*(4), 389.

Xia, H., Chen, Y., Song, C., Li, J., Quan, J., & Zhou, G. (2022). Analysis of surface urban heat islands based on local climate zones via spatiotemporally enhanced land surface temperature. *Remote Sensing of Environment, 3*, 112972.

Zheng, Y., Tang, L., & Wang, H. (2021). An improved approach for monitoring urban built-up areas by combining NPP-VIIRS nighttime light, NDVI, NDWI, and NDBI. *Journal of Cleaner Production, 328*, 129488.

Zhi, L., Abdullahi, U., Zhang, Q., Wang, X., & Li, X. (2025). Dynamics of ecosystem services driven by land use change under natural and anthropogenic trajectories in the Kaduna River Basin, Nigeria. *Land, 14*(4), 706.