SPC Journal of Environmental Sciences, 8 (1) (2026) 46-55

SPC Journal of Environmental Sciences

Website: www.sciencepubco.com/index.php/JES
https://doi.org/10.14419/ekwa2n59
Research paper

Spatio-Temporal Assessment of Green Infrastructure Dynamics And Urban Heat Island Mitigation Using Remote Sensing And GIS: Evidence from Owerri Urban, Nigeria

Chukwudi Andy Okereke [1] *, Prince Chinomso Onuoha[2]

[1] *Department of Surveying and Geoinformatics, Imo State University, Owerri*
[2] *Department of Estate Management, Federal Polytechnic, Nekede, Owerri*
**Corresponding author E-mail: andyokereke@gmail.com*

Received: 14-07-2026 , Accepted: 16-07-2026, Published: 23-08-2026

Abstract

Rapid urbanisation has accelerated the loss of urban green infrastructure in many cities of the Global South, intensifying Urban Heat Island (UHI) effects and posing significant challenges to sustainable urban development. Despite growing interest in the cooling role of urban vegetation, limited attention has been given to integrating long-term green infrastructure dynamics with thermal remote sensing to support spatially explicit planning interventions in rapidly expanding secondary cities. This study evaluated the spatio-temporal distribution of Green Infrastructure (GI) and its influence on urban thermal conditions in Owerri Urban, Nigeria, using multi-temporal Landsat imagery acquired in 2000, 2015, and 2025. Green Infrastructure maps, Normalized Difference Vegetation Index (NDVI), and Land Surface Temperature (LST) were derived and analysed alongside correlation, multiple linear regression, and spatial overlay techniques to investigate vegetation–temperature interactions and identify priority greening zones. The results revealed a substantial decline in Green Infrastructure from 72.22% in 2000 to 26.43% in 2025, accompanied by a corresponding increase in non-green areas and progressively higher land surface temperatures. Statistical analysis showed a strong negative relationship between NDVI and LST ($r = -0.772$, $p < 0.001$), while the regression model explained 72.9% of the spatial variation in LST ($R^2 = 0.729$), confirming that vegetation density and built-up intensity are the principal determinants of urban thermal conditions. Spatial overlay analysis further identified priority greening zones where strategic vegetation restoration is expected to provide the greatest cooling benefits. This study demonstrates that integrating green infrastructure assessment with thermal remote sensing and spatial prioritisation provides a practical decision-support framework for climate-responsive urban planning. The findings highlight the importance of protecting and expanding urban green infrastructure as a nature-based solution for mitigating Urban Heat Islands, for strengthening climate resilience, and advancing sustainable urban infrastructure.

Keywords: *Green Infrastructure; Urban Heat Island; Land Surface Temperature; Remote Sensing; Sustainable Urban Planning; Owerri Urban.*

1. Introduction

As cities continue to expand, natural landscapes are increasingly transformed into impervious surfaces such as buildings, roads, and paved infrastructure. Although these developments support economic growth and accommodate rising populations, they also alter the natural energy balance of urban environments by reducing vegetation cover, limiting evapotranspiration, and increasing heat absorption and storage [22] [35]. One of the most visible consequences of these changes is the Urban Heat Island (UHI) phenomenon, whereby urban areas experience significantly higher surface and atmospheric temperatures than their surrounding rural environments [3] [5]. The persistence of elevated urban temperatures contributes to increased energy demand, deteriorating air quality, heightened heat-related health risks, and reduced environmental quality, particularly in rapidly developing cities where urban expansion often occurs with limited ecological planning [8].

The growing recognition of these challenges has shifted attention towards green infrastructure as a sustainable and nature-based approach to improving urban environmental conditions. Green infrastructure encompasses interconnected natural and semi-natural features, including urban forests, wetlands, grasslands, agricultural landscapes, and other vegetated spaces that collectively provide essential ecosystem services within urban environments [33]. Beyond their ecological value, these landscapes play a significant role in regulating urban microclimates through mechanisms such as shading, evapotranspiration, carbon sequestration, and improved air circulation. Numerous studies have demonstrated that areas with higher vegetation density generally exhibit lower land surface temperatures, highlighting the importance of preserving and expanding urban green infrastructure as an effective strategy for mitigating Urban Heat Island effects while simultaneously supporting biodiversity conservation, climate adaptation, and sustainable urban development [16] [28] [29] [32].

Despite the recognised environmental benefits of urban vegetation, maintaining adequate green infrastructure has become increasingly difficult in many developing countries experiencing rapid and often uncontrolled urban growth. Population increase, housing demand, infrastructure expansion, and commercial development have accelerated the conversion of vegetated landscapes into impervious built-up surfaces [19]. This transformation is particularly evident across many African cities where urban planning has struggled to keep pace with demographic growth. Consequently, green spaces are frequently fragmented or completely replaced by residential, commercial, and transportation infrastructure, reducing the capacity of urban ecosystems to moderate thermal conditions [5] [14] [31]. As vegetation declines and impervious surfaces expand, cities become increasingly vulnerable to elevated land surface temperatures, heat stress, flooding, and other climate-related environmental hazards.

Although previous studies have examined land use and land cover change, vegetation dynamics, or urban thermal environments independently, relatively few have integrated these components to evaluate how long-term changes in green infrastructure influence Urban Heat Island intensity within rapidly urbanising secondary cities [12]. Existing studies also tend to emphasise the mapping of vegetation or temperature without translating these findings into spatially explicit information that can support urban planning decisions. Consequently, there remains limited empirical evidence identifying where vegetation loss has most strongly contributed to thermal stress and where future green infrastructure interventions would produce the greatest environmental benefits. Addressing this knowledge gap is particularly important for cities such as Owerri, where continued urban expansion is expected to intensify pressure on remaining vegetated landscapes.

Therefore, this study evaluates the spatio-temporal dynamics of green infrastructure and their relationship with Urban Heat Island patterns in Owerri Urban, Nigeria, using multi-temporal Landsat imagery acquired in 2000, 2015, and 2025. Green infrastructure was derived from classified land-use data, while vegetation density and thermal characteristics were quantified using the Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST), respectively. The study further examines the statistical relationship between vegetation and urban thermal conditions using the 2025 dataset and identifies priority locations where future greening interventions could contribute most effectively to Urban Heat Island mitigation.

2. Materials and Methods

2.1. Study area

The study was conducted in Owerri Urban, the administrative and commercial capital of Imo State in southeastern Nigeria. Owerri Urban comprises the three Local Government Areas of Owerri Municipal, Owerri North, and Owerri West, and has experienced rapid physical expansion over the past three decades due to population growth, increasing commercial activities, infrastructural development, and rural–urban migration [13] [26]. The city lies within the humid tropical rainforest climatic zone and is characterized by two distinct seasons: the wet season, typically extending from April to October, and the dry season from November to March.

Owerri experiences relatively high annual rainfall, warm temperatures throughout the year, and abundant natural vegetation. However, continuous urban development has progressively transformed large portions of natural and agricultural landscapes into residential, commercial, and transportation infrastructure [2] [21]. This extensive land conversion has substantially altered the spatial distribution of urban vegetation and increased the extent of impervious surfaces, creating favourable conditions for the development of Urban Heat Island (UHI) effects. The combination of rapid urbanisation, declining vegetation cover, and increasing thermal stress makes Owerri Urban an appropriate case study for investigating the role of green infrastructure in mitigating urban heat.

2.2. Data sources

Multi-temporal Landsat satellite imagery acquired in 2000, 2015, and 2025 was used to evaluate changes in green infrastructure and land surface temperature within the study area. The satellite datasets were selected because they provide a consistent long-term record suitable for environmental change detection and urban climate studies. The principal datasets used in this research included Landsat imagery for 2000, 2015, and 2025 and the administrative boundary of Owerri Urban for image clipping and spatial analysis.

2.3. Green infrastructure mapping

The land use maps were utilised to derive Green Infrastructure (GI) through the aggregation of vegetated land-cover classes into a single green infrastructure layer, while built-up, bare surfaces and other non-vegetated classes were grouped as non-green infrastructure. Green infrastructure was derived from the existing land use/land cover datasets through thematic reclassification. Vegetated land-cover classes, including natural vegetation and other ecologically functional green spaces, were grouped into a single Green Infrastructure (GI) category, while built-up areas, bare land, and other non-vegetated surfaces were classified as Non-Green Infrastructure. Water bodies were retained as an independent class due to their distinct thermal characteristics. The resulting green infrastructure maps were produced for the years 2000, 2015, and 2025. Area statistics were subsequently computed to quantify the spatial extent and proportional coverage of each class. Temporal changes in green infrastructure were assessed by comparing the area occupied by each class across the three observation years. The net change in area for each land-cover class was computed using Equation (1):

$$\Delta A = A_{t_2} - A_{t_1} \quad (1)$$

Where ΔA is the change in area (km²), A_{t1} is the area at the initial year, and A_{t2} is the area at the subsequent year. To determine percentage change, Equation (2) was applied:

$$\%Change = \frac{A_{t_2} - A_{t_1}}{A_{t_1}} \times 100 \quad (2)$$

2.4. Land surface temperature retrieval

Land Surface Temperature (LST) was derived from the thermal infrared bands of the Landsat imagery following standard satellite-based thermal retrieval procedures. Digital Number (DN) values were converted to top-of-atmosphere spectral radiance and subsequently transformed into at-sensor brightness temperature. Surface emissivity was estimated using the Normalized Difference Vegetation Index

(NDVI), allowing brightness temperature to be corrected to obtain actual land surface temperature values [1] [24] [30] [33]. For Landsat 7 imagery, spectral radiance was computed using Equation (3):

$$L_\lambda = \left(\frac{L_{Max}-L_{min}}{QCAL_{max}-QCAL_{min}}\right)(DN - QCAL_{min}) + L_{min} \quad (3)$$

L_λ = Spectral radiance ($Wm^{-2}sr^{-1}\mu m^{-1}$), DN = Digital Number, L_{MAX} = Maximum Spectral Radiance , L_{MIN} = Minimum Spectral Radiance , $QCAL_{MAX}$ = Maximum Quantized Calibrated Pixel Value , $QCAL_{MIN}$ = Minimum Quantized Calibrated Pixel Value

For Landsat 8 and Landsat 9 imagery, spectral radiance was obtained using Equation (4):

$$L_\lambda = M_l \times Q_{cal} + A_l \quad (4)$$

Where: M_L = Radiance Multiplicative Scaling Factor, A_L = Radiance Additive Scaling Factor, Q_{cal} = Quantized Calibrated Pixel Value (DN)

Brightness Temperature (BT) was calculated via Equation (5):

$$BT = \frac{K_2}{ln\left(\frac{K_1}{L_\lambda}+1\right)} \quad (5)$$

Where: BT = Brightness Temperature (K), Lλ = Spectral Radiance, K1 and K2 = Thermal Calibration Constants (for Landsat 5 and 7, K1=607.76 and K2=1260. 56. For Landsat 8 and 9, K1=774.89 K2=1321.08)
The final Land Surface Temperature was calculated using Equation (6):

$$LST = \frac{BT}{1+\left(\frac{\lambda BT}{14380}\right)ln(\varepsilon)} - 273.15 \quad (6)$$

Where: LST = Land Surface Temperature (K), BT = Brightness Temperature (K), λ = Effective Wavelength of Thermal Band, ε = Land Surface Emissivity, 14380 = Constant derived from Planck's Law

2.5. Normalized difference vegetation index (NDVI)

Vegetation conditions were assessed using the Normalized Difference Vegetation Index (NDVI), which exploits the contrast between near-infrared and red reflectance to quantify vegetation density and vigour. The NDVI was calculated using Equation (7):

$$NDVI = (NIR - RED) / (NIR + RED) \quad (7)$$

2.6. Green infrastructure change detection and spatial overlay analysis

The temporal dynamics of green infrastructure were evaluated through post-classification comparison of the reclassified Green Infrastructure maps for 2000, 2015, and 2025. Percentage change was computed to evaluate the magnitude of landscape transformation, while comparative analysis between successive periods (2000–2015 and 2015–2025) provided insights into the rate of urban expansion and vegetation decline. The Green Infrastructure layer was combined with the classified Land Surface Temperature map to identify areas where vegetation corresponded with different thermal conditions. Similarly, classified NDVI and LST maps were integrated using the Combine tool to evaluate the interaction between vegetation density and urban thermal patterns.

2.7. Correlation/regression analysis and priority greening zone analysis

To quantify the relationship between vegetation and urban thermal conditions, statistical analyses were performed using the 2025 datasets. Random sample points were generated across the study area, and corresponding NDVI and LST values were extracted from the raster datasets. Pearson's correlation analysis was employed to determine the strength and direction of the relationship between vegetation density and land surface temperature. Subsequently, a simple linear regression model was developed using LST as the dependent variable and NDVI as the independent variable to evaluate the extent to which vegetation explains variations in urban thermal conditions. Priority locations for future green infrastructure development were identified through the interpretation of the NDVI–LST overlay map. Areas characterised by low vegetation density and high land surface temperatures were classified as priority greening zones because of their elevated thermal vulnerability and limited ecological capacity to regulate urban temperatures.

3. Results

3.1. Spatio-temporal dynamics of green infrastructure

The analysis of Green Infrastructure (GI) revealed a substantial transformation of the urban landscape in Owerri between 2000 and 2025 (Table 1). Green infrastructure occupied 387.676 km² (72.22%) of the study area in 2000 but declined to 297.724 km² (55.47%) by 2015 before decreasing further to 141.889 km² (26.43%) in 2025. Conversely, non-green areas expanded from 147.769 km² (27.53%) in 2000 to 388.193 km² (72.32%) by 2025, indicating a major conversion of vegetated landscapes into built-up and other impervious surfaces. Water bodies increased only marginally throughout the study period and occupied less than two percent of the total land area.
The change detection analysis demonstrates that Owerri experienced a net loss of 245.787 km² of green infrastructure, representing a 63.40% reduction over the twenty-five-year study period. In contrast, non-green areas recorded a net gain of 240.424 km², equivalent to a 162.71% increase. Temporal comparison further indicates that vegetation loss accelerated considerably after 2015. Between 2000 and 2015, green infrastructure declined by approximately 23%, whereas the subsequent decade recorded a decline exceeding 52%, suggesting an intensified rate of urban expansion and landscape transformation.

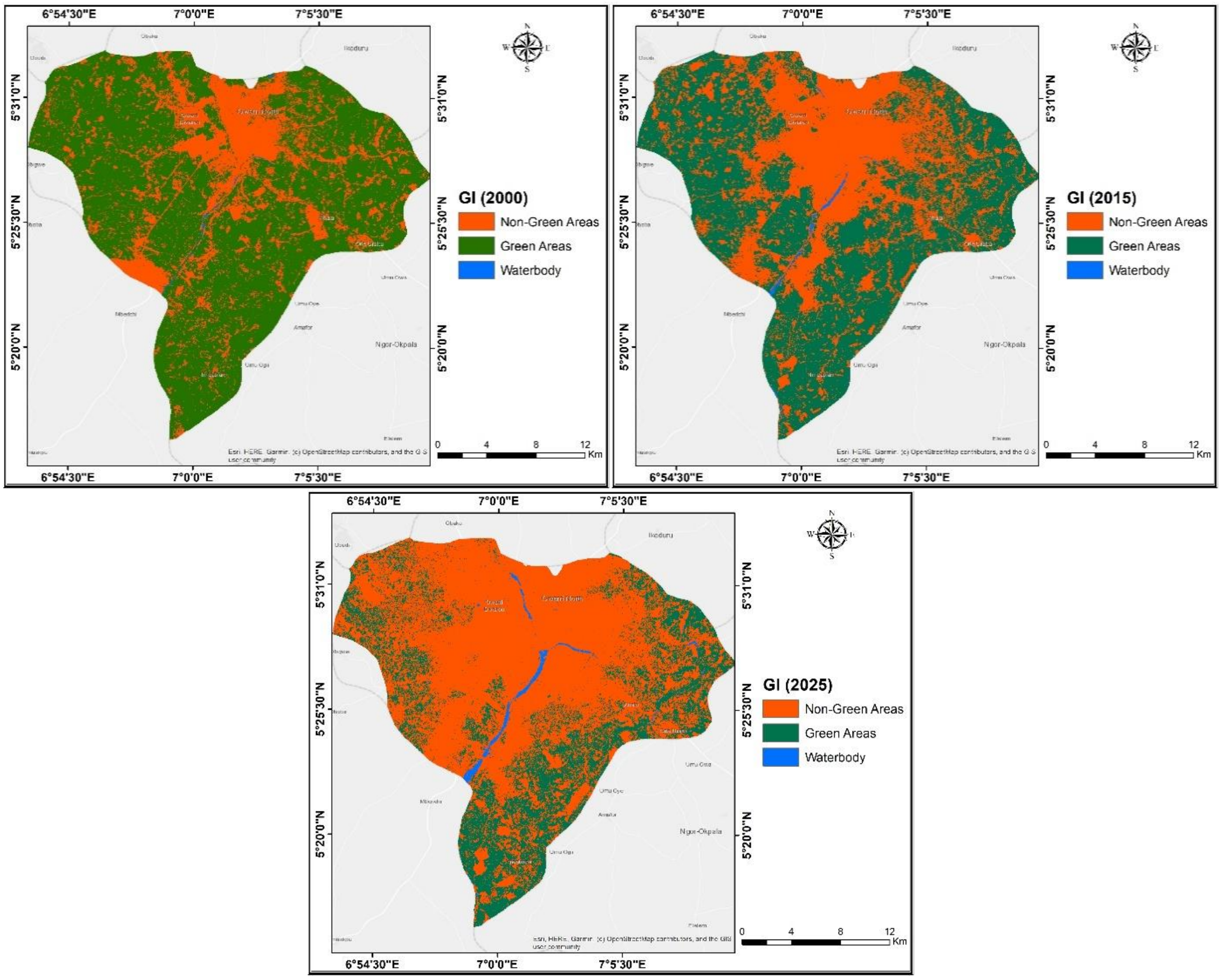

Fig 1: Map showing Green Infrastructure Changes (2000-2025)

Table 1: Spatio-Temporal Distribution of Green Infrastructure in Owerri Urban (2000–2025).

Land Cover Class	2000 Area (km²)	2000 (%)	2015 Area (km²)	2015 (%)	2025 Area (km²)	2025 (%)	Net Change (km²)	% Change
Non-Green Areas	147.769	27.53	236.786	44.11	388.193	72.32	+240.424	+162.71
Green Areas	387.676	72.22	297.724	55.47	141.889	26.43	-245.787	-63.40
Waterbody	1.320	0.25	2.256	0.42	6.683	1.25	+5.363	+406.20
Total	536.765	100.00	536.766	100.00	536.765	100.00	—	—

3.2. Spatio-temporal variation in land surface temperature and vegetation conditions

The temporal analysis of Land Surface Temperature (LST) indicates a progressive warming of the urban environment between 2000 and 2025 (Table 2). Mean LST increased from 26.02°C in 2000 to 28.45°C in 2015 before reaching 29.24°C in 2025, representing an overall increase of approximately 3.22°C during the study period. Maximum temperatures also increased from 34.54°C to 35.74°C, while the standard deviation rose slightly in 2025, suggesting greater spatial variability in thermal conditions across the city.

In contrast, vegetation density exhibited a continuous decline throughout the study period (Table 3). Mean NDVI decreased from 0.459 in 2000 to 0.264 in 2015 and further to 0.189 in 2025, indicating substantial degradation of vegetated landscapes. The progressive reduction in NDVI corresponds closely with the observed decline in Green Infrastructure, confirming that urban expansion has significantly diminished vegetation density within Owerri Urban [9] [12] [37]. The inverse temporal behaviour of NDVI and LST demonstrates the environmental consequences of rapid urbanisation. As vegetation cover decreased, land surface temperatures increased ($r = -0.59$), reflecting the replacement of permeable and vegetated surfaces with impervious materials capable of absorbing and storing larger quantities of solar radiation. This finding is consistent with the established understanding that vegetation provides an important cooling mechanism through shading and evapotranspiration, whereas impervious urban materials intensify thermal accumulation and contribute to Urban Heat Island formation [23] [25] [31] [34].

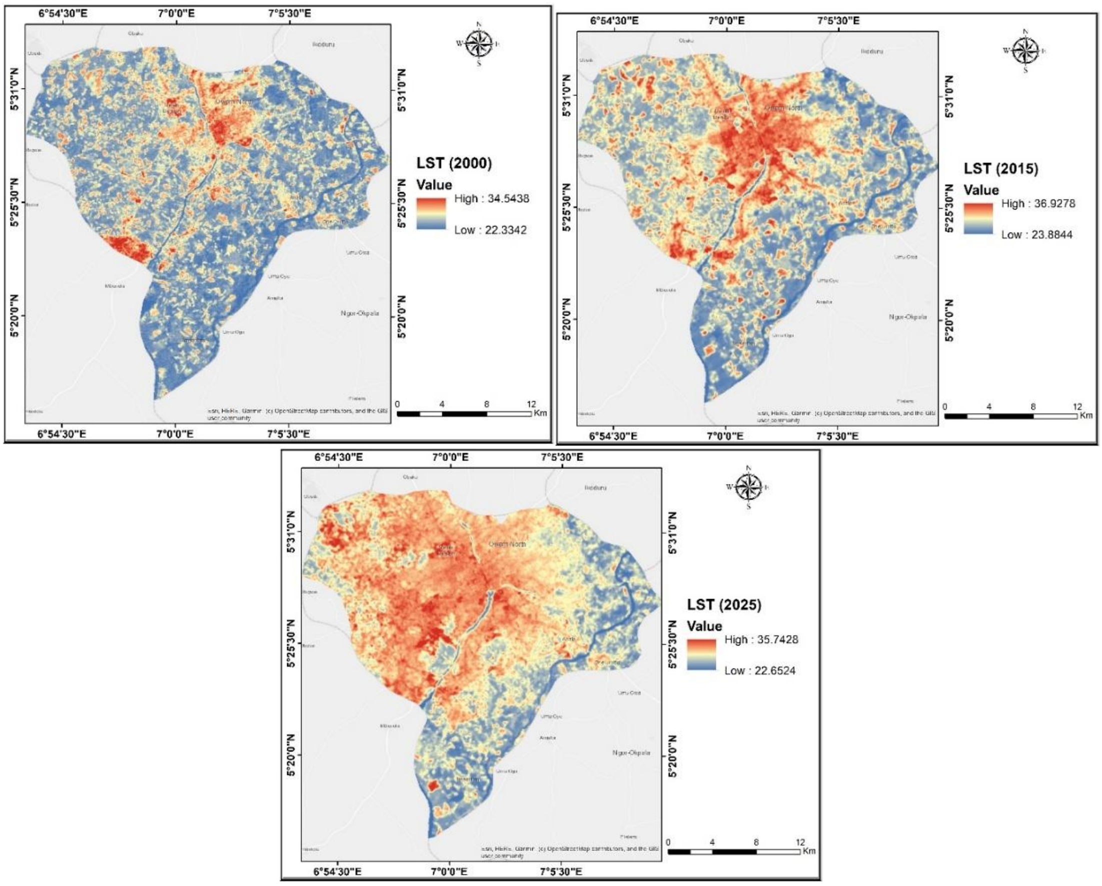

Fig 2: LST Variations between 2000 and 2025 in Owerri Urban

Table 2: LST Changes between 2000 and 2025 in Owerri Urban

Year	Min (°C)	Max (°C)	Mean (°C)	SD (°C)
2000	22.334	34.540	26.017	1.800
2015	23.884	36.927	28.446	1.752
2025	22.652	35.742	29.240	2.002

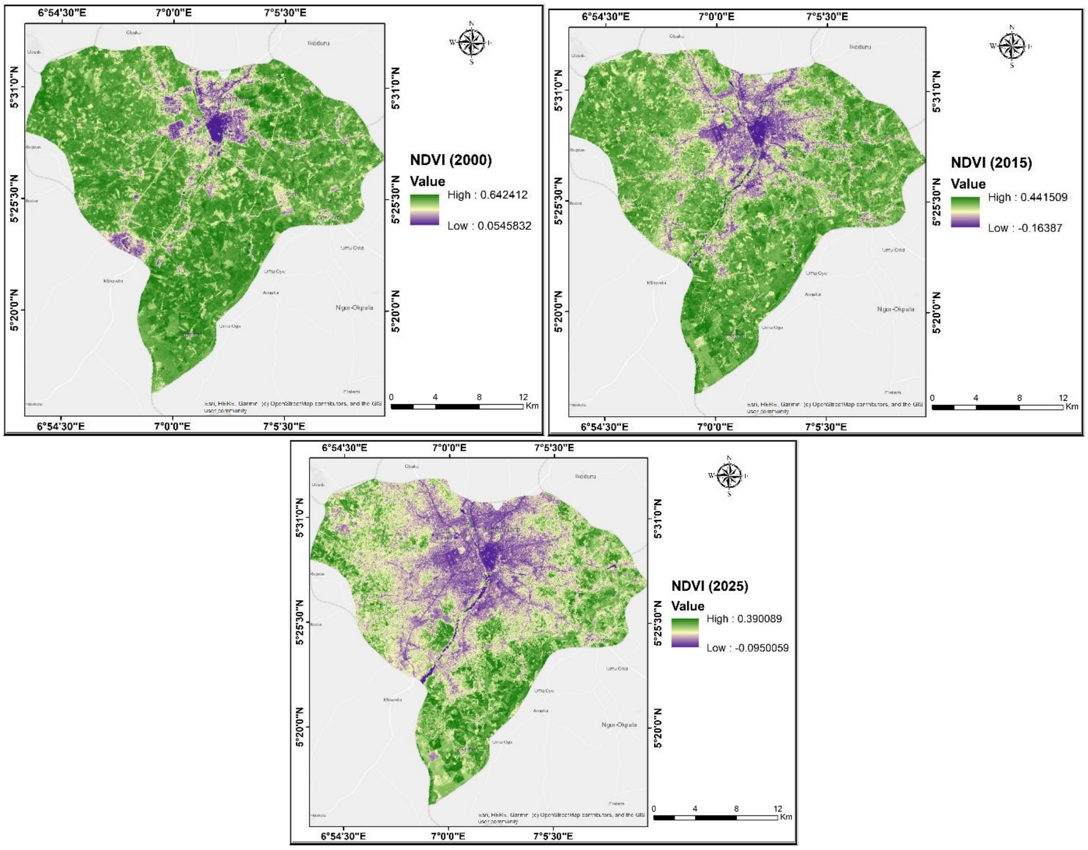

Fig 3: NDVI Variations in Owerri Urban (2000 – 2025)

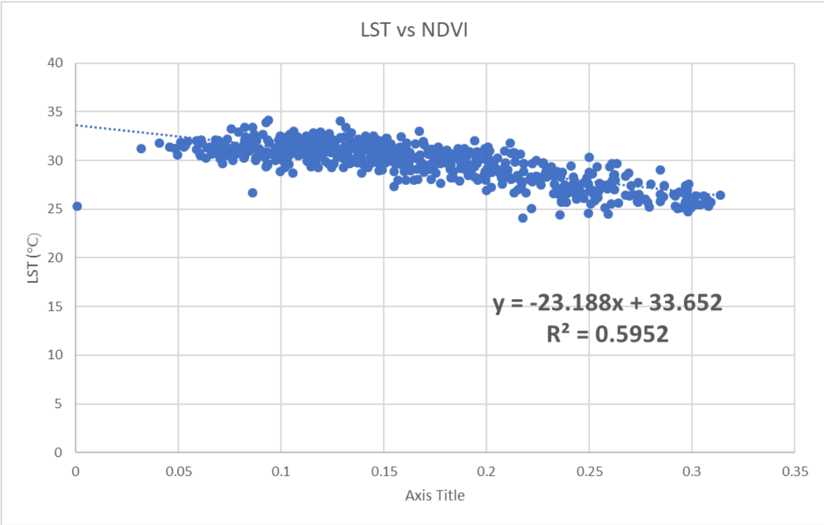

Fig 4: Relationship between LST and NDVI

Table 3: NDVI Statistics (2000–2025).

Year	Min	Max	Mean	SD
2000	0.0545	0.6420	0.4590	0.0780
2015	-0.1638	0.4415	0.2630	0.0679
2025	-0.0950	0.3901	0.1880	0.0635

3.3. Relationship between green infrastructure and urban heat island

The statistical analysis performed revealed a strong inverse relationship between vegetation density and land surface temperature. Pearson's correlation coefficient indicated a strong negative correlation ($r = -0.772$, $p < 0.001$) between NDVI and LST (Table 4), confirming that areas characterised by higher vegetation density generally experienced lower surface temperatures. The multiple linear regression model further demonstrated that vegetation and built-up intensity significantly explained spatial variations in land surface temperature. The model produced an R^2 value of 0.729 (Table 5), indicating that approximately 72.9% of the observed variation in LST was explained jointly by NDVI and NDBI. Both predictors were statistically significant ($p < 0.001$). NDVI exhibited a negative regression coefficient ($\beta = -0.215$, $B = -6.470$), confirming its cooling influence on urban temperatures, whereas NDBI showed a positive coefficient ($\beta = 0.665$, $B = 20.396$), demonstrating that increasing built-up intensity substantially elevated land surface temperatures (Table 6).

Table 4: Pearson Correlation Analysis between NDVI and Land Surface Temperature (2025)

Variable	Pearson Correlation (r)	p-value	Sample Size (N)	Interpretation
NDVI vs LST	-0.772	<0.001	600	Strong negative and statistically significant relationship

Table 5: Multiple Linear Regression Results for Predicting Land Surface Temperature

Statistic	Value
Multiple Correlation (R)	0.854
Coefficient of Determination (R^2)	0.729
Adjusted R^2	0.728
Standard Error of Estimate	1.026
F-statistic	801.563
Significance (p-value)	<0.001

Table 6: Multiple Linear Regression Model Examining the Influence of Vegetation Density (NDVI) and Built-Up Intensity (NDBI) on Land Surface Temperature in Owerri Urban

Predictor	B	Standardized β	t-value	p-value	Interpretation
Constant	31.233	—	172.611	<0.001	Model intercept
NDVI	-6.470	-0.215	-5.542	<0.001	Increasing vegetation significantly reduces LST
NDBI	20.396	0.665	17.132	<0.001	Increasing built-up intensity significantly increases LST

Spatial overlay analysis supported these statistical findings. Areas classified as Green–Very Cool and Green–Cool represented environmentally stable zones where vegetation effectively moderated urban temperatures (Table 7). Conversely, Non-Green–Hot and Non-Green–Very Hot combinations corresponded to densely developed neighbourhoods with limited vegetation and pronounced Urban Heat Island characteristics [10] [32] [36]. Similarly, the NDVI–LST overlay revealed that areas characterised by high vegetation density consistently coincided with lower thermal conditions, whereas locations with sparse vegetation exhibited elevated surface temperatures, reinforcing the important role of green infrastructure in regulating the urban thermal environment (Table 8).

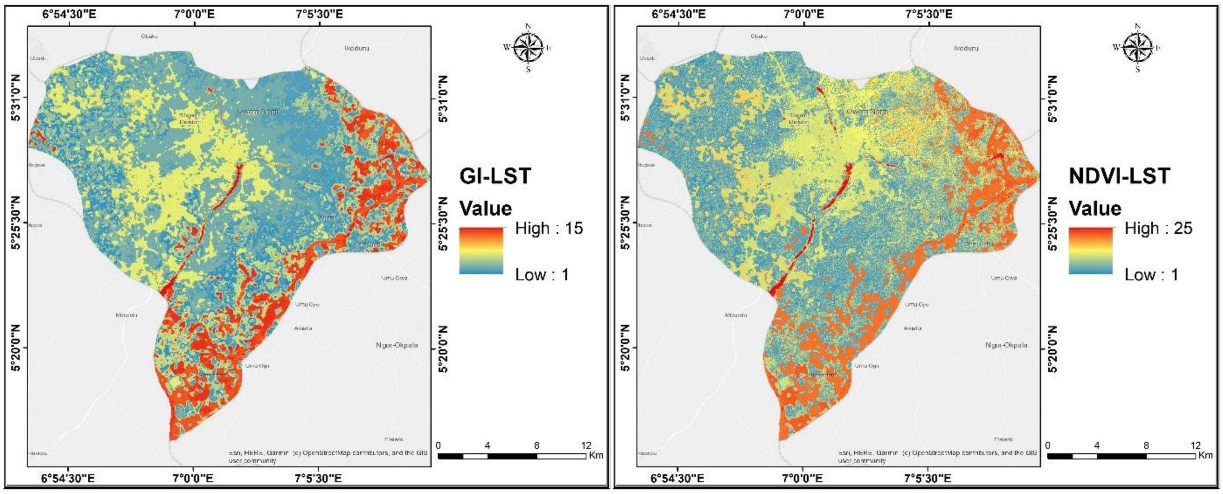

Fig 5: LST Overlay Analysis with Green Infrastructure and Vegetation Health

Table 7: Classification and Interpretation of GI–LST Overlay Values.

Overlay Value	Green Infrastructure	LST Class	Environmental Interpretation
1	Green	Very Cool	Excellent Green Cooling Zone – Dense green infrastructure effectively suppresses surface temperature.
2	Green	Cool	Healthy Green Area – Vegetated area with good cooling performance.
3	Green	Moderate	Moderately Stable Green Area – Vegetation present but experiencing moderate thermal conditions.
4	Green	Hot	Heat-Stressed Green Area – Green infrastructure exists but is under elevated thermal stress, possibly due to surrounding urbanization.
5	Green	Very Hot	Critically Stressed Green Infrastructure – Vegetation present but unable to offset extreme heat.
6	Non-Green	Very Cool	Cool Non-Green Surface – Typically water bodies or shaded impervious surfaces.
7	Non-Green	Cool	Moderately Cool Built Environment – Non-vegetated area with relatively low surface temperature.
8	Non-Green	Moderate	Transition Urban Zone – Intermediate thermal conditions with limited vegetation.
9	Non-Green	Hot	Urban Heat Zone – Built-up area with high surface temperature and limited vegetation.
10	Non-Green	Very Hot	Severe Urban Heat Island (Highest Priority for Greening) – Highly impervious, vegetation-deficient area experiencing extreme thermal stress.

Table 8: NDVI–LST Overlay and Interpretation

Overlay Values	Interpretation
1–8	Healthy vegetation with strong cooling effect.
9–15	Transitional areas where vegetation provides only partial cooling.
16–20	Vegetation-deficient areas experiencing increasing thermal stress.
21–25	Critical Urban Heat Island zones requiring priority greening interventions.

3.4. Spatial distribution of priority greening zones

The Priority Greening Zone analysis identified substantial spatial variation in the need for future green infrastructure interventions across Owerri Urban (Table 9). Approximately 117.491 km² (21.89%) of the study area was classified as Low Priority, representing locations where vegetation conditions remain relatively stable and thermal stress is comparatively limited. Moderate Priority areas occupied 320.230 km² (59.66%), indicating extensive transitional landscapes where strategic enhancement of green infrastructure could improve thermal regulation. The remaining 99.036 km² (18.45%) was classified as High Priority, representing areas characterised by sparse vegetation and elevated land surface temperatures that require immediate ecological intervention.

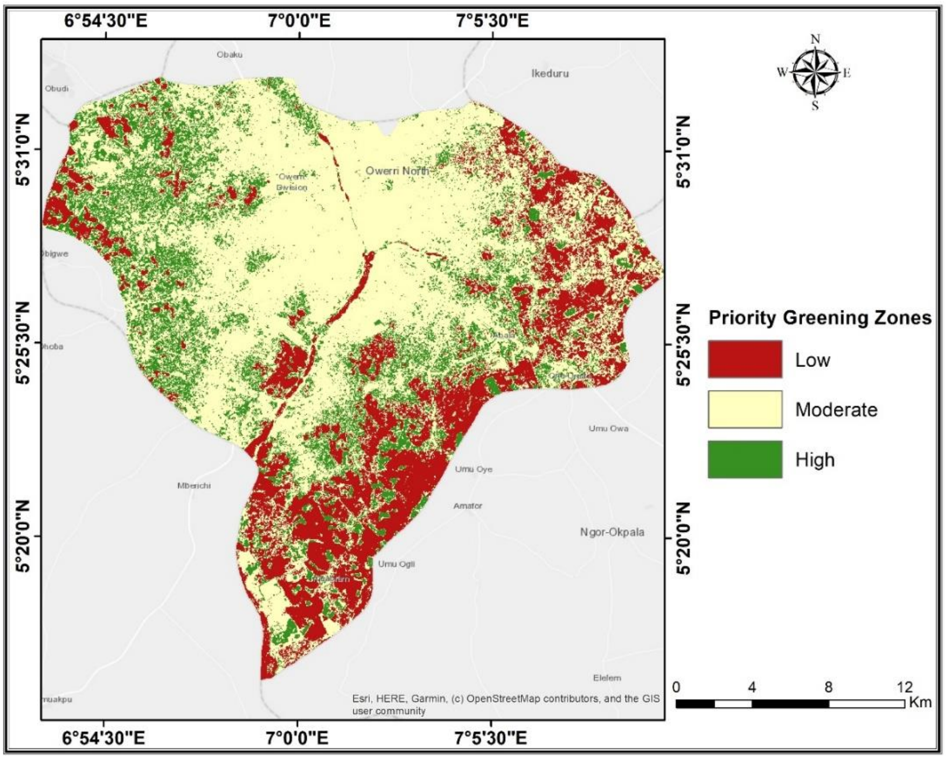

Fig 6: Green Priority Zone Map

Table 9: Green Priority Areas Composition (Area and Percentage)

Priority Level	Area (km²)	Percentage (%)
Low	117.491	21.89
Moderate	320.230	59.66
High	99.036	18.45
Total	536.757	100.00

4. Discussion

The findings of this study demonstrate that rapid urbanisation has fundamentally altered the ecological structure of Owerri Urban, transforming large areas of vegetated land into impervious surfaces over the past twenty-five years. Beyond representing a physical expansion of the city, this transformation signifies a progressive loss of ecological infrastructure responsible for regulating the urban environment. The substantial reduction in green infrastructure observed during the study period therefore reflects not only landscape modification but also a decline in the city's natural capacity to regulate its microclimate and sustain environmental quality [14].

The accelerated rate of vegetation loss after 2015 suggests that recent urban development has occurred with limited integration of ecological considerations into land-use planning. Similar trends have been reported in rapidly urbanising cities across Sub-Saharan Africa, where increasing population, housing demand, commercial expansion, and infrastructure development have contributed to widespread conversion of vegetated landscapes into built-up areas [11] [15] [17]. However, the significance of the present study extends beyond documenting land-cover change. Linking long-term green infrastructure dynamics with thermal characteristics demonstrates how continued urban expansion progressively reduces the ecological resilience of secondary cities and increases their vulnerability to climate-related thermal stress.

The temporal analysis of vegetation and land surface temperature further revealed a clear inverse relationship between urban greening and thermal conditions. As green infrastructure and vegetation density declined between 2000 and 2025, land surface temperatures increased consistently across the study area, indicating that the replacement of vegetated surfaces with impervious materials has intensified Urban Heat Island (UHI) conditions. The statistical analyses reinforce this observation, with the strong negative correlation between NDVI and LST ($r = -0.772$, $p < 0.001$) and the regression model ($R^2 = 0.729$) confirming that vegetation density and built-up intensity are the principal determinants of spatial temperature variation in Owerri Urban. These findings agree with previous studies that have consistently reported vegetation as one of the most effective natural regulators of urban thermal environments [4] [6] [20]

A major contribution of this study is the integration of Green Infrastructure mapping, NDVI, Land Surface Temperature, statistical modelling, and spatial overlay analysis into a single planning-oriented framework. Rather than assessing vegetation dynamics or Urban Heat Islands independently, the study demonstrates how remotely sensed environmental information can be translated into practical planning decisions [7] [18]. The Green Infrastructure–LST and NDVI–LST overlay analyses clearly show that areas with dense vegetation consistently experience lower thermal conditions, while densely built-up neighbourhoods correspond to elevated surface temperatures [27]. Building on these relationships, the Priority Greening Zone analysis identifies locations where future greening interventions are expected to achieve the greatest environmental benefits.

The broader implications of this study extend beyond Urban Heat Island mitigation to sustainable urban infrastructure and low-carbon development. Green infrastructure should be regarded as an essential component of urban infrastructure because of its capacity to simultaneously enhance climate resilience, improve environmental quality, conserve biodiversity, regulate stormwater, and contribute to carbon sequestration. Consequently, the continued decline of urban vegetation observed in Owerri represents not only an environmental concern but also a strategic planning challenge. This study provides a transferable framework for integrating ecological infrastructure into urban development planning by demonstrating how remote sensing and GIS can support evidence-based identification of priority greening areas. Such an approach aligns with the principles of nature-based solutions and Sustainable Development Goal 11, while offering practical guidance for developing climate-resilient and low-carbon cities throughout Nigeria and the wider Global South.

5. Conclusion

This study evaluated the spatio-temporal distribution of Green Infrastructure (GI) and its role in mitigating Urban Heat Island (UHI) effects in Owerri Urban using multi-temporal Landsat imagery. The findings revealed a substantial decline in green infrastructure accompanied by a corresponding increase in land surface temperature, demonstrating the significant influence of urban expansion on the city's thermal environment. The strong inverse relationship between NDVI and LST, together with the regression analysis, confirmed that vegetation plays a critical role in regulating urban temperatures, while increasing built-up surfaces intensity thermal conditions. Combining Green Infrastructure mapping, thermal remote sensing, statistical analysis, and spatial overlay techniques provides robust evidence that preserving and enhancing urban vegetation is fundamental to mitigating Urban Heat Island effects in rapidly urbanising cities.

Beyond assessing environmental change, this research demonstrates how remote sensing and GIS can support evidence-based urban planning by identifying Priority Greening Zones where future interventions are likely to achieve the greatest cooling benefits. The integrated analytical framework developed in this study contributes to the growing body of knowledge on sustainable urban infrastructure by linking long-term green infrastructure dynamics with climate adaptation and low-carbon urban development. The findings provide practical guidance for planners and policymakers in Owerri and other rapidly growing cities across the Global South, highlighting that the protection, restoration, and strategic expansion of green infrastructure should be embedded within urban development policies to enhance climate resilience, improve environmental quality, and promote more sustainable Cities.

References

[1] Ajayi, O. O., Adepoju, O. M., James, G. K., Jega, I., Salami, V. T., Aderoju, O. M., & Adedeji, O. I. (2022). Geospatial assessment of urban development on land surface temperature in Abuja, Nigeria. Journal of Environmental Studies, 7(2), 287–293.

[2] Anzaku, I. M., Ishaya, K. I., & Ogah, A. T. (2021). Identification and characteristics of gully erosion in North Central Nigeria: Case study of Nasarawa State. International Journal of Environmental Studies and Safety Research, 6(1), 19–38.

[3] Asgarian, A., Amiri, B. J., & Sakieh, Y. (2015). Assessing the effect of green cover spatial patterns on urban land surface temperature using a landscape metrics approach. Urban Ecosystems, 18(1), 209–222. https://doi.org/10.1007/s11252-014-0387-7.

[4] Awuh, M. E., Japhets, P. O., Officha, M. C., Okolie, A. O., & Enete, I. C. (2019). A correlation analysis of the relationship between land use and land cover/land surface temperature in Abuja Municipal, FCT, Nigeria. Journal of Geographic Information System, 11(1), 44–55. https://doi.org/10.4236/jgis.2019.111004.

[5] Beele, E., Aerts, R., Reyniers, M., & Somers, B. (2024). Spatial configuration of green space matters: Associations between urban land cover and air temperature. Landscape and Urban Planning, 249, 105121. https://doi.org/10.1016/j.landurbplan.2024.105121.

[6] Castro, A., Nijanthan, K., Vignesh, B., Kumar, G., Kumar, R., Anthiny, J., & Sugnathan, P. (2022). Mapping and forecasting the land surface temperature in response to the land use and land cover changes using machine learning over the southernmost Municipal Corporation of Tamil Nadu. Research Square, 1–21. https://doi.org/10.21203/rs.3.rs-2085948/v1.

[7] Cecilian Nkechi, B., Babatunde, A., Dera, B. P., & Daniel, O. (2024). Impact assessment of urban heat island on land use/land cover in Owerri Metropolis using geospatial technique. International Journal of Advances in Engineering and Management (IJAEM), 6(9), 462–473. https://doi.org/10.35629/5252-0609462473.

[8] du Toit, M. J., Hahs, A. K., & MacGregor-Fors, I. (2021). The Effect of Landscape History on the Urban Environment: Past Landscapes, Present Patterns. Springer International Publishing. https://doi.org/10.1007/978-3-030-67650-6_3.

[9] Essien, E. (2023). Urban theories and urbanization perspectives in cities across Nigeria. Environmental Research Communications, 5(8), 085001. https://doi.org/10.1088/2515-7620/acefb4.

[10] Gallo, K. P., McNab, A. L., Karl, T. R., Brown, J. F., Hood, J. J., & Tarpley, J. D. (1993). The use of a vegetation index for assessment of the urban heat island effect. International Journal of Remote Sensing, 14(11), 2223–2230. https://doi.org/10.1080/01431169308954031.

[11] Guha, S., & Govil, H. (2020). Land surface temperature and normalized difference vegetation index relationship: A seasonal study on a tropical city. SN Applied Sciences, 2(10), 1661. https://doi.org/10.1007/s42452-020-03458-8.

[12] Guo, G., Wu, Z., Cao, Z., Chen, Y., & Zheng, Z. (2021). Location of greenspace matters: A new approach to investigating the effect of the greenspace spatial pattern on urban heat environment. Landscape Ecology, 36(5), 1533–1548. https://doi.org/10.1007/s10980-021-01230-w.

[13] Ifeanyi, B., Nkiru, C., & Awka, U. (2024). Comprehensive GIS-based flood risk assessment of vulnerable areas in Anambra State, Nigeria. World Journal of Innovation and Modern Technology, 8(4), 1–23.

[14] Ishrak, M. F., Adam, J. M., Jay, L. N., & Yu, W. (2026). Urban land use efficiency in the United States: Assessing UN 2030 Sustainable Development Goals. Geographies, 6(21), 1–22. https://doi.org/10.3390/geographies6010021.

[15] Koko, A. F., Wu, Y., Abubakar, G. A., Alabsi, A. A. N., Hamed, R., & Bello, M. (2021). Thirty years of land use/land cover changes and their impact on urban climate: A study of Kano Metropolis, Nigeria. Land, 10(11), 1106. https://doi.org/10.3390/land10111106.

[16] Mauder, M., Foken, T., & Cuxart, J. (2020). Surface-energy-balance closure over land: A review. Boundary-Layer Meteorology, 177(2–3), 153–182. https://doi.org/10.1007/s10546-020-00529-6.

[17] Mwangi, P. W., Karanja, F. N., & Kamau, P. K. (2018). Analysis of the relationship between land surface temperature and vegetation and built-up indices in Upper-Hill, Nairobi. Journal of Geoscience and Environment Protection, 6(1), 1–16. https://doi.org/10.4236/gep.2018.61001.

[18] Naim, M. N. H., & Kafy, A. A. (2021). Assessment of urban thermal field variance index and defining the relationship between land cover and surface temperature in Chattogram city: A remote sensing and statistical approach. Environmental Challenges, 4, 100107. https://doi.org/10.1016/j.envc.2021.100107.

[19] Narzary, M., Dey, P., Riming, T., Handique, A., & Patnaik, S. K. (2026). GIS-based assessment of thermal dynamics and urban heat island effects in response to land use changes in Ziro Valley, Arunachal Pradesh, India. Discover Geoscience, 4(62), 1–25. https://doi.org/10.1007/s44288-026-00447-z.

[20] Obiefuna, J. N., Okolie, C. J., Nwilo, P. C., Daramola, O. E., & Isiofia, L. C. (2021). Potential influence of urban sprawl and changing land surface temperature on outdoor thermal comfort in Lagos State, Nigeria. Quaestiones Geographicae, 40(1), 5–23. https://doi.org/10.2478/quageo-2021-0001.

[21] Ogundolie, O. I., Olabiyisi, S. O., Ganiyu, R. A., Jeremiah, Y. S., & Ogundolie, F. A. (2024). Assessment of flood vulnerability in Osun River Basin using AHP method. BMC Environmental Science, 1(1), 1–21. https://doi.org/10.1186/s44329-024-00009-z.

[22] Peng, J., Hu, Y., Dong, J., Liu, Q., & Liu, Y. (2020). Quantifying spatial morphology and connectivity of urban heat islands in a megacity: A radius approach. Science of the Total Environment, 714, 136792. https://doi.org/10.1016/j.scitotenv.2020.136792.

[23] Pooja, H., Rajeshwari, K. S., Kaddi, S. S., Cai, A., Selveraj, V., & Kumari, T. (2025). AI-driven solutions for achieving SDGs: Harnessing machine learning to address global sustainability challenges. International Journal of Environmental Sciences, 11(15), 1981–1989. https://doi.org/10.64252/by6egg73.

[24] Puttanapong, N., Luenam, A., & Jongwattanakul, P. (2022). Spatial analysis of inequality in Thailand: Applications of satellite data and spatial statistics/econometrics. Sustainability, 14(7), 3946. https://doi.org/10.3390/su14073946.
[25] Rabie, A. B., Elhag, M., & Subyani, A. (2025). Remote sensing, GIS, and machine learning in water resources management for arid agricultural regions: A review. Water, 17(21), 3125. https://doi.org/10.3390/w17213125.
[26] Rowland, A., & Ebuka, A. O. (2024). Assessing the impact of land cover and land use change on urban infrastructure resilience in Abuja, Nigeria: A case study from 2017 to 2022. Structure and Environment, 16(1), 6–17. https://doi.org/10.30540/sae-2024-002.
[27] Shahfahad, Talukdar, S., Rihan, M., Hang, H. T., Bhaskaran, S., & Rahman, A. (2022). Modelling urban heat island (UHI) and thermal field variation and their relationship with land use indices over Delhi and Mumbai metro cities. Environment, Development and Sustainability, 24(3), 3762–3790. https://doi.org/10.1007/s10668-021-01587-7.
[28] Shaker, R. R., Altman, Y., Deng, C., Vaz, E., & Forsythe, K. W. (2019). Investigating urban heat island through spatial analysis of New York City streetscapes. Journal of Cleaner Production, 233, 972–992. https://doi.org/10.1016/j.jclepro.2019.05.389.
[29] 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, 21. https://doi.org/10.1007/s44274-023-00021-1.
[30] Wang, Z., Shi, Y., & Zhang, Y. (2023). Review of desert mobility assessment and desertification monitoring based on remote sensing. Remote Sensing, 15(18), 4412. https://doi.org/10.3390/rs15184412.
[31] Xie, M., Wang, Y., Chang, Q., Fu, M., & Ye, M. (2013). Assessment of landscape patterns affecting land surface temperature in different biophysical gradients in Shenzhen, China. Urban Ecosystems, 16(4), 871–886. https://doi.org/10.1007/s10668-013-0325-0.
[32] Yu, X., Liu, Y., Zhang, Z., & Xiao, R. (2021). Influences of buildings on urban heat island based on 3D landscape metrics: An investigation of China's 30 megacities at micro grid-cell scale and macro city scale. Landscape Ecology, 36(9), 2743–2762. https://doi.org/10.1007/s10980-021-01275-x.
[33] Zeng, F. F., Feng, J., Zhang, Y., Tsou, J. Y., Xue, T., Li, Y., Yi, R., & Li, M. (2021). Comparative study of factors contributing to land surface temperature in high-density built environments in megacities using satellite imagery. Sustainability, 13(24), 13812. https://doi.org/10.3390/su132413706.
[34] Zhang, K., Chen, Y., Wang, W., Wu, Y., Wang, B., & Yan, Y. (2023). A method for remote sensing image classification by combining Pixel Neighbourhood Similarity and optimal feature combination. Geocarto International, 38(1), 2158948. https://doi.org/10.1080/10106049.2022.2158948.
[35] Zhou, J., Menenti, M., Jia, L., Gao, B., Zhao, F., Cui, Y., Xiong, X., Liu, X., & Li, D. (2023). A scalable software package for time series reconstruction of remote sensing datasets on the Google Earth Engine platform. International Journal of Digital Earth, 16(1), 988–1007. https://doi.org/10.1080/17538947.2023.2192004.
[36] Zhu, Q., Zeng, M., Jia, P., Guo, M., Liang, X., & Guan, Q. (2024). Measuring the urban sprawl based on economic-dominated perspective: The case of 31 municipalities and provincial capitals. Geo-Spatial Information Science, 27(4), 1272–1289. https://doi.org/10.1080/10095020.2023.2202201.
[37] Zhu, Y., Geiß, C., So, E., Bardhan, R., Taubenböck, H., & Jin, Y. (2024). Urban expansion simulation with an explainable ensemble deep learning framework. Heliyon, 10(7), e28318. https://doi.org/10.1016/j.heliyon.2024.e28318.