

Vegetation, Built-up Intensity and Land Surface Temperature: A Multi-Temporal Analysis of Urban Change in Ilorin, Nigeria

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Abstract

Rapid urbanisation alters vegetation cover, built-up intensity, and surface thermal conditions; however, these relationships may change as urban landscapes evolve. This study examines the spatio-temporal relationships among the Normalised Difference Vegetation Index (NDVI), Normalised Difference Built-up Index (NDBI), and Land Surface Temperature (LST) in Ilorin Metropolis, Nigeria, using Landsat observations from 2005, 2015, and 2025. Landsat Collection 2 Level-2 imagery was processed in Google Earth Engine to derive NDVI, NDBI, and LST, followed by spatial overlay and simple linear regression to evaluate their relationships. The results indicate substantial urban surface transformation, with built-up land increasing from 7,007.87 ha (3.57%) in 2005 to 28,981.44 ha (14.76%) in 2025. Mean NDVI ranged from 0.327 in 2005 to 0.386 in 2015 and returned to 0.327 in 2025, while mean NDBI increased from 0.039 to 0.091. Mean LST rose progressively from 38.34°C in 2005 to 39.58°C in 2015 and 40.64°C in 2025, representing an overall increase of 2.30°C. NDVI demonstrated negative associations with LST, with R^2 values of 0.3149, 0.4647, and 0.0966, whereas NDBI exhibited positive associations with R^2 values of 0.4298, 0.4314, and 0.2409 for the respective years. The declining explanatory power of both indices by 2025 suggests increasing complexity in the urban thermal environment. These findings underscore the value of multi-temporal Earth observation for monitoring urban thermal change and highlight the importance of vegetation conservation and impervious-surface management as key elements of climate-sensitive urban planning.

Keywords: NDVI; NDBI; Land Surface Temperature; Urbanisation; Ilorin Metropolis.

1. Introduction

Rapid urbanisation alters the composition and physical properties of land surfaces, affecting surface reflectance, moisture availability, heat storage, and the partitioning of available energy. These modifications generate pronounced spatial contrasts in Land Surface Temperature (LST), especially when vegetated, moisture-retaining surfaces are replaced by built-up materials. Satellite-based thermal remote sensing is increasingly employed to characterise urban thermal environments, as it enables spatially continuous observations across metropolitan areas. Recent methodological reviews underscore the utility of remotely sensed LST for analysing urban thermal patterns and highlight key distinctions between surface-based and atmospheric measures of urban heat (Han *et al.*, 2023; Zhao *et al.*, 2025).

Vegetation condition and built-up intensity represent two critical aspects of surface transformation. The Normalised Difference Vegetation Index (NDVI) quantifies vegetation abundance and condition spectrally, while the Normalised Difference Built-up Index (NDBI) characterises the spectral dominance of built-up surfaces. Integrating these indices with LST is a widely adopted method for investigating the relationship between urban land-cover characteristics and surface thermal conditions. Studies in African cities such as Abuja and Kano have consistently reported negative NDVI–LST and positive NDBI–LST relationships, illustrating the effectiveness of these indices in diagnosing the thermal impacts of urban expansion (Koko *et al.*, 2021a; Koko *et al.*, 2021b).

However, the relationships between spectral indices and

LST are neither spatially nor temporally invariant. Vegetation cooling and built-up-surface warming result from complex interactions among land-cover composition, urban morphology, soil moisture, topography, atmospheric conditions, and spatial scale. Recent research demonstrates that the relative influence of NDVI, NDBI, and other urban-form variables can vary substantially across seasons and urban contexts. Reviews of urban heat mitigation also emphasise the combined effects of vegetation, water, surface materials, and urban geometry (Han *et al.*, 2023; Zhao *et al.*, 2025). Therefore, a strong bivariate relationship observed in one period should not be interpreted as a persistent physical control throughout subsequent stages of urban development.

This issue is especially pertinent to Ilorin, where prior research has revealed significant temporal and spatial variability in the relationship between land-use/land-cover (LULC) composition and LST. Njoku and Tenenbaum (2022) reported that LULC accounted for approximately 26–64% of LST variation in Ilorin from 2002 to 2020, with thermal conditions differing across land-cover classes and observation periods. These findings suggest that urban thermal behaviour in Ilorin cannot be fully explained by land-cover change alone and that the strength of observed relationships fluctuates over time.

The growing availability of analysis-ready Landsat products has enhanced the reproducibility of multi-temporal urban thermal studies. Landsat Collection 2 Level-2 products offer surface reflectance and surface-temperature datasets produced through standardised processing procedures. The surface-temperature product integrates thermal observations, emissivity, and atmospheric auxiliary data, and its digital numbers must be scaled appropriately before conversion to physical temperature values (USGS, 2024). The combination of these products with cloud-based platforms such as Google Earth Engine enables consistent processing of multi-temporal satellite observations and supports scalable urban environmental monitoring.

Although research on satellite-derived urban thermal conditions is expanding, evidence from medium-sized tropical African cities remains limited. Nigerian studies have established the relevance of NDVI, NDBI, and LST for assessing urban environmental transformation in cities such as Abuja, Kano, and Ilorin. However, most analyses have focused on single periods or have interpreted index–temperature relationships without evaluating changes in explanatory strength over time (Koko *et al.*, 2021b; Njoku & Tenenbaum, 2022). This gap highlights the need for

temporally consistent assessments that differentiate persistent relationships from those whose strength varies as urban landscapes become more heterogeneous.

Ilorin serves as an appropriate case study for such an assessment, as its metropolitan landscape encompasses established urban districts, rapidly developing peripheral corridors, agricultural zones, riparian environments, and residual vegetation. These diverse land-surface conditions offer an opportunity to investigate whether the relationships among vegetation, built-up intensity, and surface temperature have remained stable during ongoing urban transformation.

Accordingly, this study investigates the spatial and temporal relationships among NDVI, NDBI, and LST in Ilorin Metropolis for the years 2005, 2015, and 2025. The specific objectives are to: (i) characterise the spatial and temporal behaviour of NDVI, NDBI, and LST; (ii) quantify the pairwise associations between NDVI–LST and NDBI–LST; (iii) evaluate temporal changes in the explanatory strength of NDVI and NDBI for LST; and (iv) interpret the observed patterns in the context of climate-sensitive urban planning.

The principal contribution of this study is not limited to confirming the anticipated negative association between vegetation and LST or the positive association between built-up intensity and LST. Instead, it assesses whether the strength of these relationships changes across successive stages of urban transformation. By employing a consistent analytical framework across three observation years, the study offers evidence supporting a dynamic interpretation of spectral controls on urban surface temperature. The regression results are interpreted as spatial associations rather than causal estimates, acknowledging that NDVI and NDBI serve as partial proxies within a complex urban thermal system. This distinction enhances the scientific interpretation of the findings and provides a more robust foundation for utilising Earth-observation indicators in urban environmental planning.

2. Materials and Methods

2.1 Study area

The study area encompasses Ilorin Metropolis in Kwara State, North-Central Nigeria, including Ilorin West, Ilorin East, and Ilorin South Local Government Areas (Figure 1). The delineated boundary extends from approximately 8°20'00" to 8°44'00"N and 4°32'00" to 5°00'00"E. Ilorin serves as a regional administrative, educational, commercial, and transport hub. The region

experiences a tropical savanna climate with distinct wet and dry seasons. The Asa River and its associated drainage corridors represent significant ecological and hydrological features.

The selected study area is suitable for analysis due to its diverse composition, which includes dense built-up areas, institutional and commercial districts, peri-urban developments, agricultural land, riparian vegetation, and open surfaces. This heterogeneity facilitates the examination of relationships among vegetation, impervious surfaces, and surface temperature. Previous research has documented significant land use/land cover (LULC) and land surface temperature (LST) relationships in Ilorin, thereby providing empirical justification for extending the analysis to a paired Normalised Difference Vegetation Index (NDVI) and Normalised Difference Built-up Index (NDBI) framework (Njoku & Tenenbaum, 2022).

2.2 Research design and analytical framework

A longitudinal geospatial observational design was implemented. This approach compares three standardised observation years, 2005, 2015, and 2025, treating each year as a discrete snapshot of the coupled land-cover and thermal system. The workflow includes: (i) acquisition and quality screening of Landsat Collection 2 Level-2 data; (ii) spatial standardisation and masking; (iii) calculation of NDVI and NDBI; (iv) extraction of Level-2 surface temperature; (v) generation of descriptive statistics and spatial products; (vi) correlation and simple regression analysis; and (vii) comparative interpretation across years (Figure 2).

The design is intentionally parsimonious. NDVI and NDBI are employed as explanatory proxies due to their physical interpretability, reproducibility across Landsat generations, and direct association with vegetation and built-up spectral responses. However, these

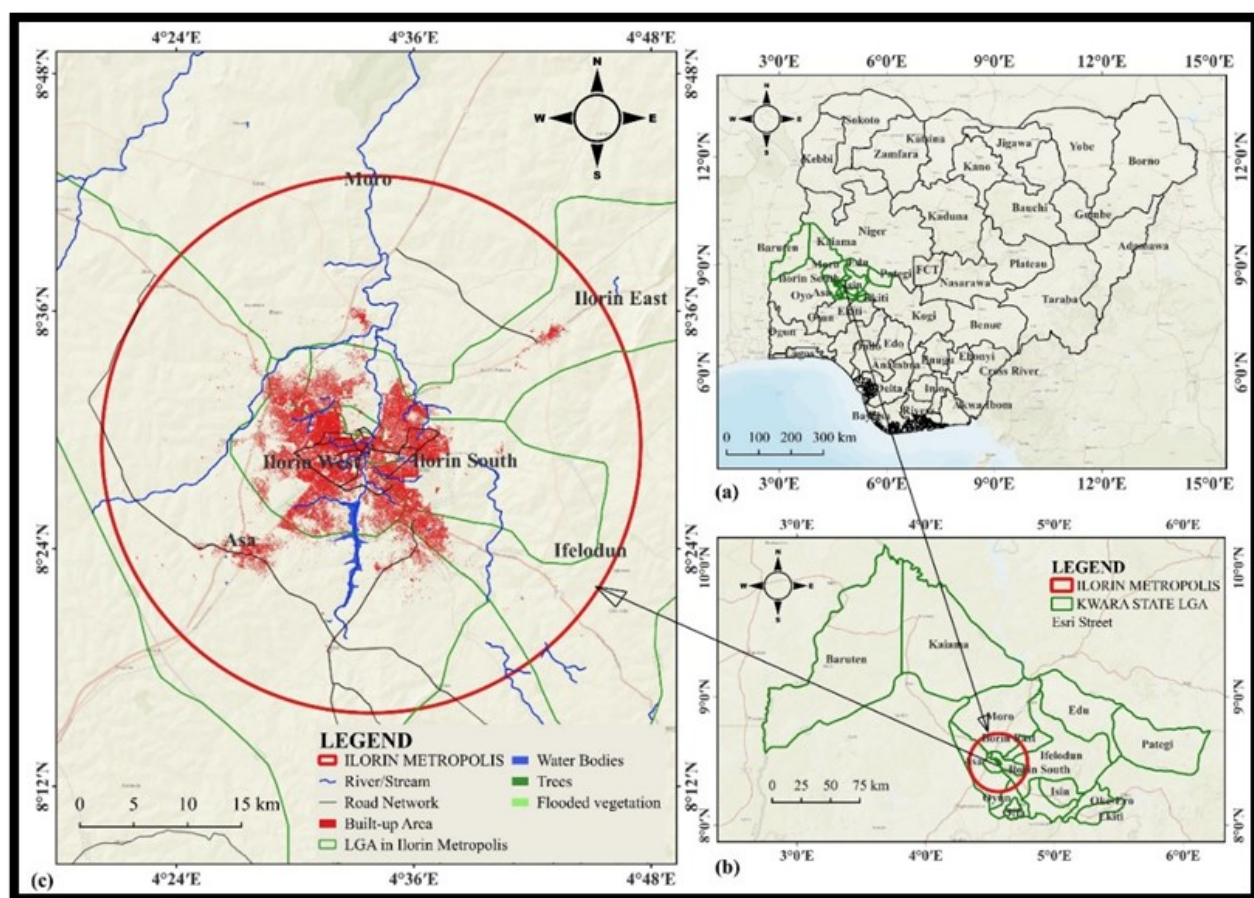


Figure 1. Location of Ilorin Metropolis, Kwara State, Nigeria.

Source: Authors' GIS Analysis

indices are not considered exhaustive determinants of land surface temperature (LST). This approach is supported by evidence indicating that LST in Ilorin is also influenced by land use/land cover (LULC) aggregation and other spatial controls, as well as by broader urban-climate literature that highlights the significance of morphology and atmospheric conditions (Njoku & Tenenbaum, 2022; Han *et al.*, 2023; Zhao *et al.*, 2025).

Figure 2 summarises the full analytical sequence; Table 1 documents the data sources; Equations (1)–(3) define the derived variables; Table 2 reports index statistics; Table 3 reports LST statistics; Figure 7 presents the regression diagnostics; and Table 4 provides the comparative regression results.

2.3 Satellite data and preprocessing

The analysis used multi-temporal Landsat Collection 2 Level-2 imagery to characterise vegetation, built-up conditions and land surface temperature (LST) across three temporal epochs. Landsat 7 Enhanced Thematic Mapper Plus (ETM+) imagery was used to represent the 2005 epoch, while Landsat 8 Operational Land Imager/Thermal Infrared Sensor (OLI/TIRS) imagery was used for 2015 and 2025. The corresponding Google Earth Engine collections were LANDSAT/LE07/C02/T1_L2 and LANDSAT/LC08/C02/T1_L2, respectively. We selected Collection 2 Level-2 products because they provide atmospherically corrected surface reflectance and surface temperature products within a consistent

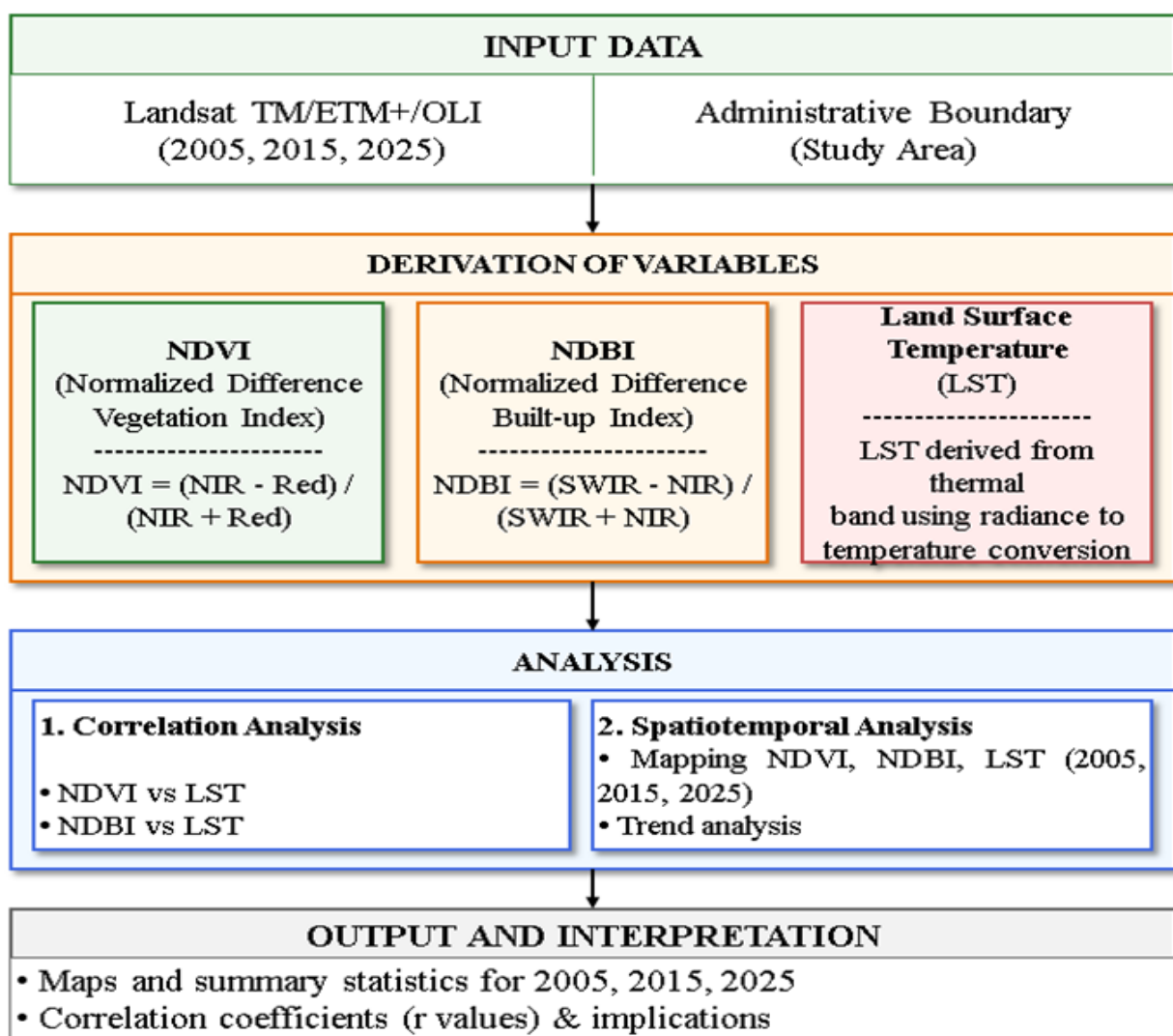


Figure 2. Analytical framework for evaluating relationships among NDVI, NDBI and Land Surface Temperature.

Source: Authors' Conceptualisation

processing framework at 30-m spatial resolution.

For the 2005 epoch, we considered Landsat 7 ETM+ scenes acquired between 1 January 2004 and 31 December 2006, whereas for the 2015 and 2025 epochs, we used Landsat 8 scenes acquired between 1 January and 31 December 2015 and 1 January and 31 December 2025, respectively. The image collections were spatially restricted to the Ilorin Metropolis boundary and filtered using scene-level cloud-cover thresholds of <100% for the 2005 epoch and <10% for the 2015 and 2025 epochs. After applying these filters, we combined the available scenes for each epoch using a pixel-wise median composite to obtain a representative image for subsequent analysis.

We removed pixel-level cloud and cloud-shadow contamination using the QA_PIXEL quality-assessment band. Specifically, we excluded pixels flagged for high-confidence cloud (bit 3) or high-confidence cloud shadow (bit 4) before compositing. The QA_PIXEL band is part of the Landsat Collection 2 Level-2 products and provides bit-packed information on pixel-level conditions affecting data quality.

The retained optical bands were converted from Collection 2 scaled digital numbers to surface reflectance using equation 1.

$$R = (DN \times 0.0000275) - 0.2 \quad (1)$$

while the thermal bands were converted to land surface temperature in Kelvin using equation 2.

$ST(K) = (DN \times 0.00341802) + 149.0$ and subsequently converted to degrees Celsius by subtracting 273.15. These scaling procedures follow the USGS specifications for Landsat Collection 2 Level-2 products.

Because Landsat 7 ETM+ imagery contains scan-line-corrector-off (SLC-off) data gaps during the 2005 epoch, the resulting median composite was further subjected to a focal-mean neighbourhood operation with a radius of two pixels to fill remaining gaps. We applied this operation only to the 2005 composite. The processed composites were subsequently clipped to the Ilorin Metropolis boundary and used to derive NDVI, NDBI and LST at 30-m spatial resolution.

Table 1 summarises the multi-temporal Landsat datasets employed for the analysis. Landsat 5 TM was used to represent the 2005 baseline, Landsat 8 OLI/TIRS for 2015, and Landsat 8 OLI-2/TIRS-2 for 2025. All datasets were standardised to 30 m spatial resolution, enabling consistent derivation and comparison of NDVI, NDBI and LST across the three observation years

2.4 Derivation of spectral indices

2.4.1 Normalised Difference Vegetation Index (NDVI)

The Normalised Difference Vegetation Index (NDVI) was calculated from surface reflectance using the contrast between near-infrared (NIR) and red wavelengths (Equation 3).

$$NDVI = \frac{NIR - Red}{NIR + Red} \quad (3)$$

where **NIR** and **Red** represent surface reflectance in the near-infrared and red bands, respectively. NDVI exploits the contrasting spectral response of vegetation, which generally absorbs red radiation while strongly reflecting near-infrared radiation. It therefore provides a relative indicator of vegetation abundance and greenness, rather than a direct measurement of biomass or physiological condition (Rouse *et al.*, 1974; Huang *et al.*, 2021).

The band combinations were selected according to the sensor corresponding to each temporal epoch. For 2005, Landsat 7 ETM+ SR_B4 and SR_B3 were used as the NIR and red bands, respectively, whereas Landsat 8 OLI/TIRS SR_B5 and SR_B4 were used for the 2015 and 2025 epochs, respectively. These band assignments correspond to the spectral configurations of the respective Landsat sensors. All calculations were performed using scaled Landsat Collection 2 Level-2 surface-reflectance data. Collection 2 surface-reflectance products provide atmospherically corrected, 30-m data designed to facilitate consistent analysis across Landsat observations, with the Collection 2 reflectance scaling factor applied before spectral-index computation (U.S. Geological Survey [USGS], 2020, 2026).

2.4.2 Normalised Difference Built-up Index (NDBI)

The Normalised Difference Built-up Index (NDBI) was calculated following the spectral contrast proposed by Maloney *et al.* (2024) as in Equation 4

$$NDBI = \frac{SWIR - NIR}{SWIR + NIR} \quad (4)$$

Table 1. Landsat datasets and preprocessing parameters used for the analysis

Parameter	2005 epoch	2015	2025
Sensor	Landsat 7 ETM+	Landsat 8 OLI/TIRS	Landsat 8 OLI/TIRS
GEE collection	LE07/C02/T1_L2	LC08/C02/T1_L2	LC08/C02/T1_L2
Acquisition period	1 Jan 2004–31 Dec 2006	1 Jan–31 Dec 2015	1 Jan–31 Dec 2025
Cloud-cover threshold	<100%	<10%	<10%
Cloud mask	QA_PIXEL bits 3 and 4	QA_PIXEL bits 3 and 4	QA_PIXEL bits 3 and 4
Composite method	Median	Median	Median
Gap filling	Focal mean, 2-pixel radius	Not applied	Not applied
Optical bands	SR_B1–SR_B5	SR_B2–SR_B6	SR_B2–SR_B6
NIR band	SR_B4	SR_B5	SR_B5
Red band	SR_B3	SR_B4	SR_B4
SWIR band	SR_B5	SR_B6	SR_B6
Thermal band	ST_B6	ST_B10	ST_B10
Spatial resolution	30 m	30 m	30 m

Source: Authors' analysis based on Landsat Collection 2 Level-2 products; USGS

where **SWIR** denotes shortwave-infrared surface reflectance and **NIR** denotes near-infrared surface reflectance. For the 2005 Landsat 7 ETM+ imagery, we used SR_B5 and SR_B4 as the SWIR and NIR bands, respectively. For both 2015 and 2025 Landsat 8 OLI/TIRS imagery, we used SR_B6 and SR_B5 as the SWIR and NIR bands, respectively. The formulation follows the original NDBI approach developed for Landsat imagery by Maloney *et al.* (2024). NDBI was interpreted as a spectral indicator of built-up surface dominance rather than a direct measure of imperviousness. Positive or relatively high NDBI values can also occur over bare or dry surfaces because of their spectral response in the shortwave-infrared and near-infrared regions. Accordingly, we interpreted NDBI alongside NDVI, LST, and the spatial distribution of land-cover characteristics rather than using it as an isolated measure of urbanisation.

2.5 Land Surface Temperature retrieval

Land Surface Temperature (LST) was derived from the Landsat Collection 2 Level-2 Surface Temperature (ST) product rather than reconstructed independently from the raw thermal digital numbers. This approach provides a consistent, documented surface-temperature product across the Landsat datasets used in the study. USGS Collection 2 Level-2 products provide surface temperature in Kelvin, with a scale factor of 0.00341802 and an additive offset of 149.0. The ST product is generated using the Landsat Level-2 surface-temperature processing framework and is available for Landsat 7 ETM+ and Landsat 8 OLI/TIRS within the periods relevant to this study.

In the GEE implementation, the thermal bands were first converted from scaled digital numbers to Kelvin as in Equation 5.

$$ST(K) = DN \times 0.00341802 + 149.0 \quad (5)$$

The resulting temperature was then converted to degrees Celsius by subtracting 273.15 (Equation 6).

$$LST(^{\circ}C) = [DN \times 0.00341802 + 149.0] - 273.15$$

For the 2005 epoch, the thermal variable was obtained from ST_B6 of Landsat 7 ETM+, whereas ST_B10 of Landsat 8 OLI/TIRS was used for both 2015 and 2025. These band selections correspond to the thermal bands specified in the GEE processing workflow. The calculation used the Collection 2 scaling factors specified by USGS for Level-2 Surface Temperature products.

The resulting LST surfaces for each temporal epoch using the minimum, maximum, mean, and standard deviation was summarised. The statistics was then used to characterise temporal changes in surface thermal conditions across Ilorin Metropolis.

The analysis distinguishes between land surface temperature (LST) and atmospheric air temperature. LST represents the radiometric temperature of the land surface retrieved from thermal infrared observations and should not be interpreted as a direct measurement of near-surface air temperature (Chakraborty *et al.*, 2021; Li *et al.*, 2023). Accordingly, spatially elevated LST values are referred to primarily as surface thermal hotspots. The term surface urban heat island (SUHI) is used where the analysis specifically concerns the spatial manifestation of elevated urban surface temperatures relative to surrounding non-urban areas (Shi *et al.*, 2021; Li *et al.*, 2023). This distinction reflects the conceptual separation between satellite-derived surface thermal observations and atmospheric urban heat-island conditions characterised using near-surface air-temperature observations (Chakraborty *et al.*, 2021).

2.6 Statistical analysis

Pearson correlation and ordinary least-squares (OLS) simple linear regression were used to quantify the relationships between NDVI and LST and between NDBI and LST for each observation year. For each year, 1,000 spatial observations were sampled from the corresponding raster datasets and used as the analytical observations. The same procedure was applied independently to the 2005, 2015 and 2025 datasets to facilitate temporal comparison. For a generic predictor X and LST response

Y , the fitted OLS relationship was expressed as in Equation 7.

$$LST_i = \beta_0 + \beta_1 X_i + \varepsilon_i \quad (7)$$

where LST_i is the observed land surface temperature at observation i , X_i represents either NDVI or NDBI, β_0 is the regression intercept, β_1 is the estimated change in LST associated with a one-unit change in the predictor, and ε_i is the residual error. Pearson's correlation coefficient (r) was used to describe the direction and strength of the linear association, while the coefficient of determination (R^2) was used to quantify the proportion of variation in LST accounted for by the fitted one-predictor relationship.

The statistical analysis was interpreted primarily in terms of direction, magnitude and temporal variation in association, rather than causal effects. A positive regression coefficient indicates that higher values of the predictor are associated with higher LST, whereas a negative coefficient indicates an inverse association. Similarly, a larger R^2 indicates greater explanatory strength of the bivariate linear relationship within the sampled observations. However, R^2 does not establish that changes in NDVI or NDBI independently caused changes in LST. This distinction is important because the variables are spatially structured and may be jointly related to land cover, urban morphology, topography and other environmental factors. Previous work in Ilorin has likewise demonstrated that relationships between urban environmental variables can vary spatially, indicating the importance of interpreting non-spatial regression results as measures of association rather than causal effects (Njoku & Tenenbaum, 2022).

For each year and predictor, the analysis therefore reports the Pearson correlation coefficient (r), regression slope (β_1), intercept (β_0), coefficient of determination (R^2) and sample size ($N = 1,000$). Reporting these statistics together provides a more complete description of the temporal changes in the NDVI–LST and NDBI–LST relationships than relying on R^2 alone.

2.7 Spatial analysis and interpretation

Spatial overlay was used to examine the co-location of NDVI, NDBI and LST across the three observation years. The three variables were interpreted jointly to identify spatial configurations associated with contrasting surface thermal conditions. Areas characterised by relatively high NDVI and lower NDBI were interpreted as potentially cooler vegetated landscapes, whereas areas exhibiting low NDVI, high NDBI and high LST were identified as surface-thermal hotspot configurations. This integrated interpretation reduces reliance on either NDVI or NDBI as a standalone indicator because NDBI may also respond to bare or dry surfaces, while NDVI varies with vegetation type, density and moisture conditions.

The spatial patterns were further examined in relation to the major urban development corridors and ecological features evident in the mapped distributions. These geographical patterns were used to contextualise the observed relationships and identify locations where urban expansion, vegetation conditions and elevated surface temperature spatially coincide. However, corridor-level patterns were interpreted as spatial associations rather than causal relationships, because no formal spatial-statistical test was undertaken to establish causal effects or spatial dependence at the corridor scale.

Google Earth Engine (GEE) was used for satellite-data processing, image compositing, spectral-index derivation and LST extraction, while ArcGIS Pro was used for raster processing, spatial overlay, statistical data preparation and cartographic visualisation. Integrating these platforms provided a consistent workflow for examining the temporal and spatial relationships among vegetation condition, built-up surface characteristics and land surface temperature (Gorelick *et al.*, 2017).

3. Results and Discussion

3.1 Spatio-temporal dynamics of NDVI and NDBI

The spatial distribution of NDVI reveals substantial changes in vegetation condition and configuration across Ilorin Metropolis between 2005 and 2025 (Figure 3). In 2005, relatively high NDVI values were more widely distributed across the metropolitan landscape. By 2025, higher NDVI values were increasingly concentrated in peripheral, riparian and agricultural areas, while lower and intermediate values became more prominent across the expanding urbanised areas. This pattern indicates a progressive reorganisation and fragmentation of vegetated

surfaces rather than a uniform decline in vegetation condition.

The descriptive statistics support the spatial interpretation and reveal that the temporal trajectory of mean NDVI was not monotonic. Mean NDVI increased from 0.327 in 2005 to 0.386 in 2015, then returned to 0.327 in 2025. The standard deviation rose from 0.065 to 0.079 in 2015 and remained relatively high at 0.071 in 2025. These findings do not support the conclusion that vegetation condition continuously declined during the study period. Instead, they indicate increasing spatial heterogeneity and redistribution of vegetation characteristics across the metropolis. The contraction and fragmentation of high-NDVI areas, as shown in Figure 3, provide more insight than the met metropolitan mean alone.

NDBI displayed a contrasting spatial pattern. In 2005, relatively high NDBI values were concentrated around established urban areas, expanding along major development corridors by 2015 and 2025 (Figure 4). The mean NDBI changed only slightly from 0.039 in 2005 to 0.040 in 2015, then increased to 0.091 in 2025. The maximum NDBI also rose from 0.208 in 2005 to 0.237 in 2025. This marked increase in the 2025 mean indicates a stronger spectral dominance of built-up or built-surface conditions in the later observation period.

The contrasting spatial configurations of NDVI and NDBI are consistent with patterns of urban surface transformation. However, the two indices should not be interpreted as mathematical complements or as direct measures of mutually exclusive land-cover components. At 30-m spatial resolution, mixed pixels may contain combinations of vegetation, exposed soil and built surfaces, while spectrally similar bare or dry surfaces can also produce relatively high NDBI responses (Liu *et al.*, 2022; Alegbeleye *et al.*, 2024). Recent evidence further indicates that no single built-up spectral index consistently separates impervious surfaces from bare land across different environmental settings (Liu *et al.*, 2022; Ipadeola & Babalola, 2025). Therefore, interpretation of increasing NDBI is more robust when undertaken alongside independently classified LULC and the spatial distribution of LST, rather than treating NDBI as a direct measure of impervious-surface abundance.

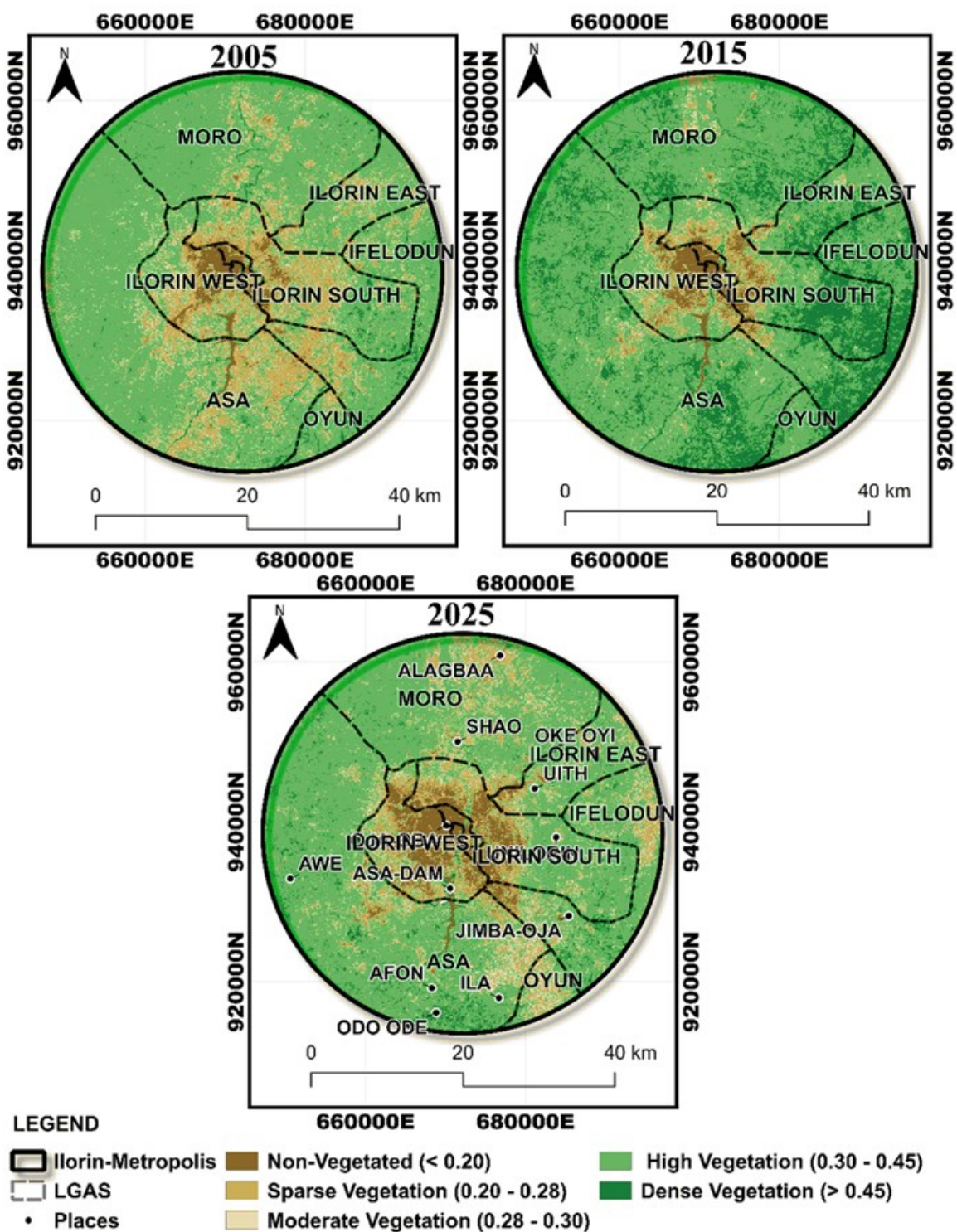


Figure 3. Spatial distribution of NDVI in Ilorin Metropolis for (a) 2005, (b) 2015 and (c) 2025.

Source: Authors' GIS analysis (2026)

3.2 Spatio-temporal dynamics of Land Surface Temperature

Figure 5 presents the continuous spatial distribution of Landsat-derived LST across Ilorin Metropolis for 2005, 2015 and 2025. The maps reveal pronounced spatial heterogeneity, with relatively elevated surface temperatures concentrated within and around established urbanised areas and expanding development corridors, while comparatively lower temperatures occur more frequently within vegetated, peripheral and water-associated landscapes.

The temporal statistics indicate a systematic increase in surface temperature across the three observa-

tion epochs. Mean LST increased from 38.34 °C in 2005 to 39.58 °C in 2015 and 40.64 °C in 2025, representing an overall increase of 2.30 °C. Maximum LST increased from 48.84 °C to 51.64 °C, while the minimum increased from 28.63 °C to 31.42 °C. The simultaneous increase in the minimum, mean, and maximum indicates that the observed thermal shift was not restricted to isolated extreme-temperature locations but involved a broader upward displacement of the surface-temperature distribution.

The standard deviation of LST also increased from 3.57 °C in 2005 to 3.91 °C in 2015 and 4.18 °C in 2025. This increase indicates greater spatial dispersion of surface temperature by 2025 and is consistent with an increasingly

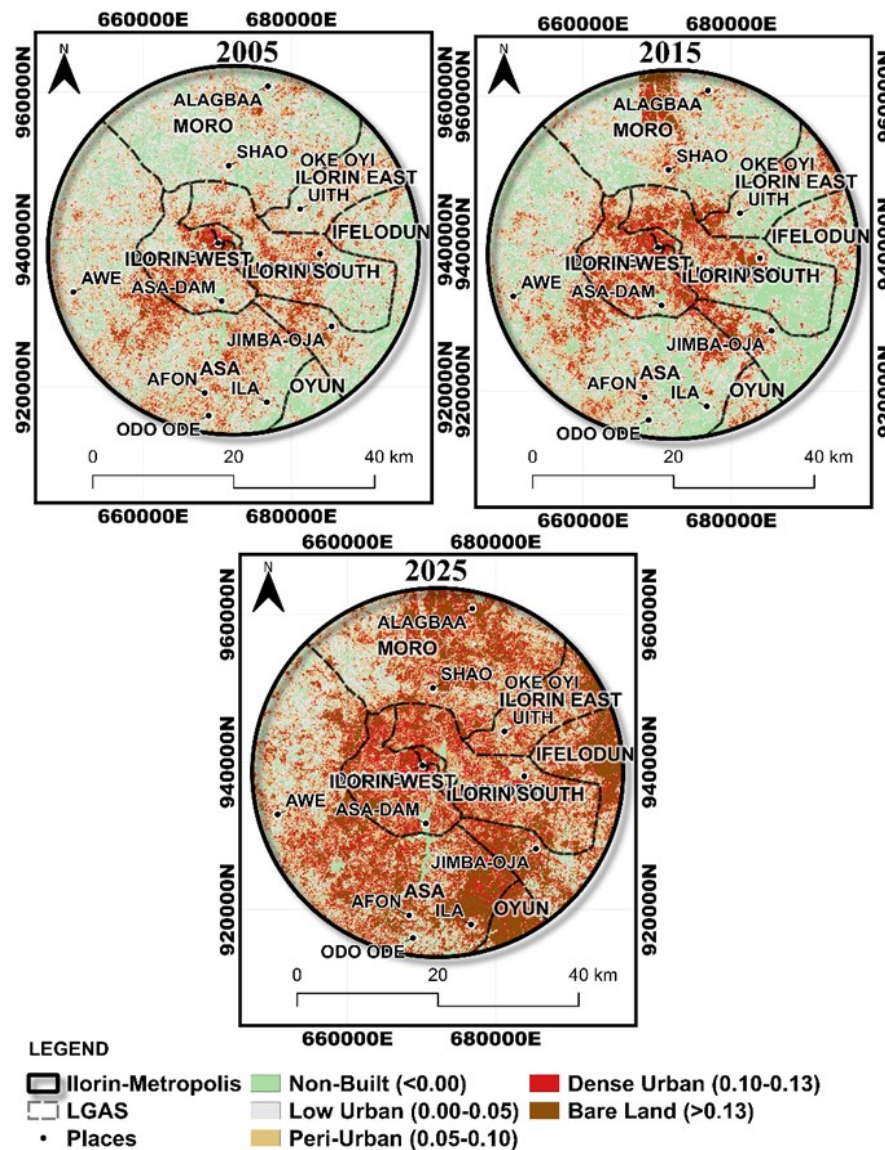


Figure 4. Spatial distribution of NDBI in Ilorin Metropolis for (a) 2005, (b) 2015 and (c) 2025.

Source: Author's GIS analysis (2026)

heterogeneous metropolitan surface in which densely developed areas coexist with residual vegetation, water bodies and peri-urban landscapes.

These results should nevertheless be interpreted as changes in surface thermal conditions, rather than direct evidence of changes in atmospheric air temperature. Landsat Collection 2 Surface Temperature measures land-surface temperature, and the USGS product provides it as a surface-temperature variable in Kelvin before scaling and conversion.

To facilitate interpretation of the continuous LST surface, the temperature data were subsequently classified into five intensity categories—Very Low, Low, Moderate, High and Very High—as shown in Figure 6. Figure 5 therefore communicates the continuous spatial thermal gradient, whereas Figure 6 provides a categorical representation of thermal intensity and the spatial distribution of potential thermal hotspots.

The classified pattern shows that relatively high and very high LST classes are concentrated primarily around developed portions of the metropolis, whereas lower-intensity classes occur more frequently within vegetated and water-associated areas. This spatial correspondence is consistent with established differences in the thermal and surface-energy properties of urban land-cover types. Vegetation can moderate surface temperature through shading and evapotranspiration, with evapo-

transpiration partitioning available surface energy towards latent rather than sensible heat fluxes (Wong et al., 2021; Li et al., 2022; Yang et al., 2023). Conversely, the replacement of natural surfaces by impervious materials can modify surface moisture availability, energy partitioning and heat storage, thereby contributing to higher LST under favourable conditions (Ding et al., 2023; Guo et al., 2022). These mechanisms provide a physical basis for the spatial associations observed among LST, NDVI and NDBI, but do not, by themselves, establish causality in the present observational analysis.

3.3 Statistical relationships between NDVI, NDBI and LST

The statistical analysis demonstrates contrasting relationships between the spectral indices and LST across the three observation years (Figure 7; Table 4). NDVI exhibited a negative association with LST in all three years, indicating that locations with relatively higher vegetation-index values generally corresponded to lower surface tem-

peratures. The coefficient of determination (R^2) was 0.3149 in 2005, 0.4647 in 2015 and 0.0966 in 2025. The strongest one-predictor relationship therefore occurred in 2015, whereas the association was substantially weaker in 2025. The negative NDVI–LST relationship is consistent with extensive remote-sensing evidence showing that veg-

Table 2. Summary statistics of NDVI and NDBI for 2005, 2015 and 2025

Year	Index	Minimum	Maximum	Mean	SD
2005	NDVI	−0.111	0.538	0.327	0.065
2005	NDBI	−0.176	0.208	0.039	0.054
2015	NDVI	0.005	0.604	0.386	0.079
2015	NDBI	−0.188	0.212	0.040	0.060
2025	NDVI	0.075	0.561	0.327	0.071
2025	NDBI	−0.199	0.237	0.091	0.053

Source: Authors' Statistical analysis (2026)

etation-related surface characteristics are generally associated with lower LST, although the magnitude of the relationship varies spatially and temporally (Guha & Govil, 2021; Shi et al., 2021; Li et al., 2023).

The reduction in NDVI–LST R^2 in 2025 should not be interpreted as evidence that vegetation ceased to exert a thermal influence. Rather, it indicates that NDVI alone accounted for a smaller proportion of the spatial variation in LST in the 2025 observations. Similar weakening of LST–NDVI relationships over time has been reported in multi-temporal urban analyses, highlighting that the relationship is not necessarily stable across observation periods (Guha & Govil, 2021). The result is compatible with a progressively more heterogeneous urban surface in which LST is also associated with surface materials, urban morphology, soil moisture, shading and other factors not represented by a single vegetation index (Shi et al., 2021; Li et al., 2023). Thus, the decline in R^2 represents a reduction in the explanatory strength of the one-predictor statistical relationship, rather than evidence of the disappearance of vegetation-related thermal effects. NDBI displayed the opposite relationship, with a positive association with LST across all three years. The R^2 values were 0.4298 in 2005, 0.4314 in 2015 and 0.2409 in 2025. NDBI therefore provided a stronger one-predictor fit than NDVI in 2005 and 2025, while the two relationships were relatively similar in 2015. This positive NDBI–LST association is consistent with multi-city evidence showing that built-up intensity is an important contributor to spatial LST variability, particularly in tropical and warm-climate settings (Li et al., 2022). However, the reduction in NDBI–LST R^2 from approximately 0.43 in 2005 and 2015 to 0.24 in 2025 similarly indicates that NDBI alone explained a smaller proportion of LST variability in the most recent observation period. Taken together, the results suggest that the relationships between individual spectral indices and LST became less well represented by simple bivariate models in 2025, pointing towards increasing complexity in the spatial controls of surface temperature.

The 2025 regression output provides an illustrative quantitative result: the NDBI–LST relationship produced $r = 0.491$, $R^2 = 0.241$, a slope of 23.566 and an intercept of 38.558, based on 1,000 observations. These values indicate a positive linear association, but

they should not be interpreted as evidence that a one-unit increase in NDBI directly causes a 23.566 °C increase in LST. The regression describes an empirical association within the sampled spatial observations.

The reduction in NDBI–LST R^2 from 0.4314 in 2015 to 0.2409 in 2025 similarly indicates that NDBI alone became less effective at accounting for the spatial variance in LST. This does not imply that built-up surfaces became thermally irrelevant. Rather, it suggests that the thermal environment increasingly reflects a combination of interacting surface and urban characteristics.

The combined results demonstrate three important characteristics of the Ilorin thermal landscape. First, vegetation and built-up spectral conditions exhibit opposing associations with LST. Second, neither relationship remains statistically constant through time. Third, the reduction in R^2 for both indices in 2025 indicates that a single spectral predictor provides an increasingly incomplete representation of the spatial variability of LST. The results therefore support a multivariate interpretation of urban surface thermal conditions, rather than attributing temperature variation to NDVI or NDBI independently.

3.4 Integrated spatial relationship and planning significance

Figure 8 integrates the spatial distributions of NDVI, NDBI and LST to identify locations where the three variables exhibit coherent spatial patterns. The overlay indicates that areas with relatively higher NDVI and lower NDBI generally coincide with lower LST, whereas areas with lower NDVI and higher NDBI tend to coincide with elevated LST. The integrated pattern therefore provides a spatial synthesis of the relationships observed separately in Figures 3–6 and quantitatively assessed in Figure 7.

The principal value of Figure 8 is not the creation of a new quantitative index, but the identification of co-located environmental conditions. Areas where vegetation is relatively prominent and the built-up spectral signature is comparatively limited tend to exhibit cooler surface conditions, whereas areas characterised by reduced vegetation and stronger built-up signatures tend to correspond with warmer surfaces. This convergence strengthens the interpretation obtained from the individual maps because the three spatial variables indicate a broadly consistent surface-thermal configuration. Such relationships are physically plausible given the recognised cooling effects of vegeta-

tion through shading and evapotranspiration and the influence of urban surface characteristics on energy partitioning and heat storage (Wong et al., 2021; Fu et al., 2022; Ji et al., 2024).

Nevertheless, the result requires cautious interpretation. The spatial overlay demonstrates co-location and association rather than an independently estimated causal effect of vegetation or built-up intensity on temperature. Moreover, NDBI may respond to exposed or dry soil, while NDVI is sensitive to vegetation type, density and moisture conditions. Consequently, the integrated pattern should be understood as a screening representation of surface conditions rather than a definitive causal model.

From an urban-environmental management perspective, the findings indicate that thermal mitigation in

Ilorin can be considered alongside vegetation conservation, protection of existing green and riparian areas, and management of unnecessary expansion of impervious surfaces. The persistence of relatively cooler vegetated areas suggests that retaining existing vegetation networks may complement the creation of additional green spaces. Such an approach is consistent with recent evidence that the thermal performance of urban greenery depends not only on its presence but also on its type, configuration, spatial distribution and surrounding urban form (Wong et al., 2021; Fu et al., 2022; Kumar et al., 2024).

The Landsat-derived indicators also provide a practical screening framework for urban environmental monitoring. Because NDVI, NDBI and LST can be repeatedly derived from Earth-observation imagery, their

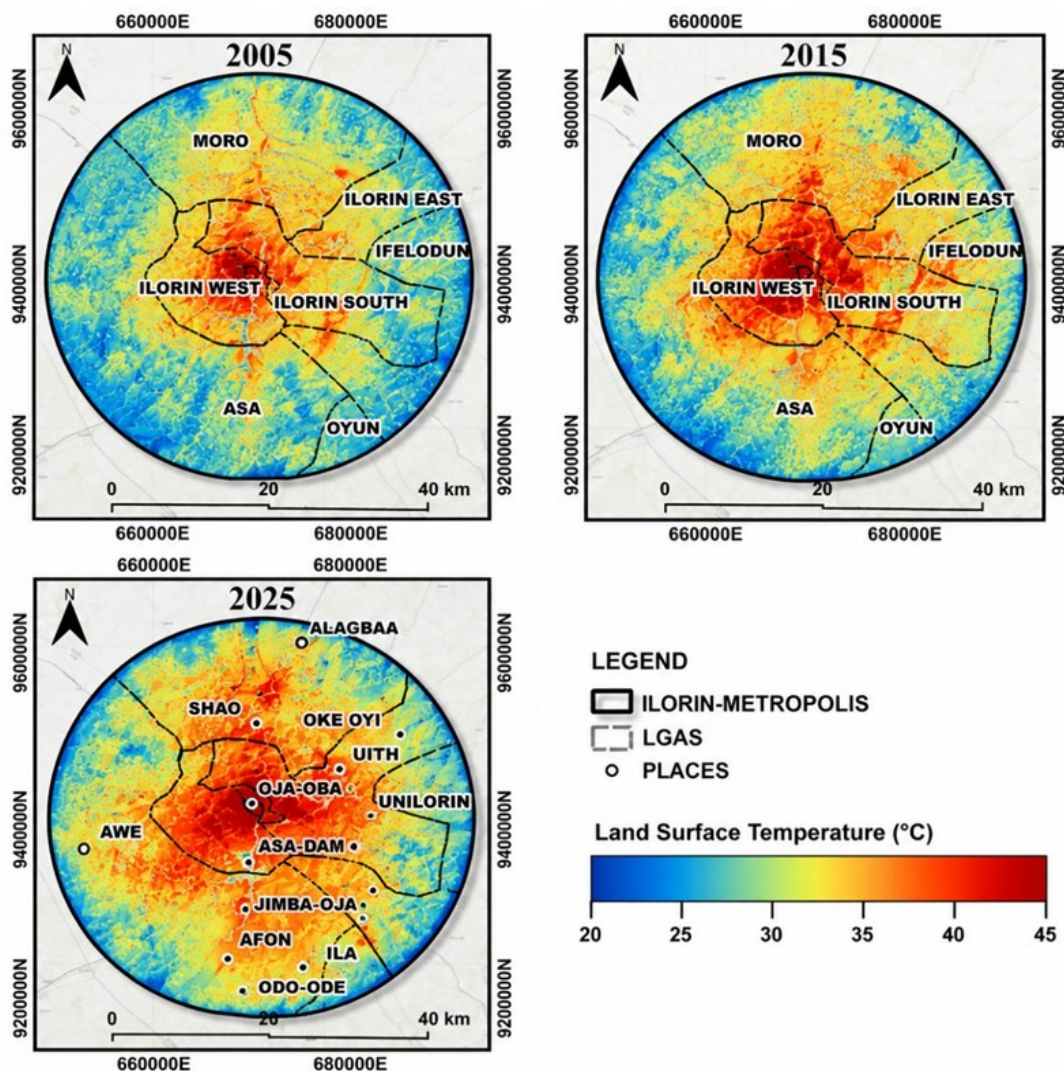


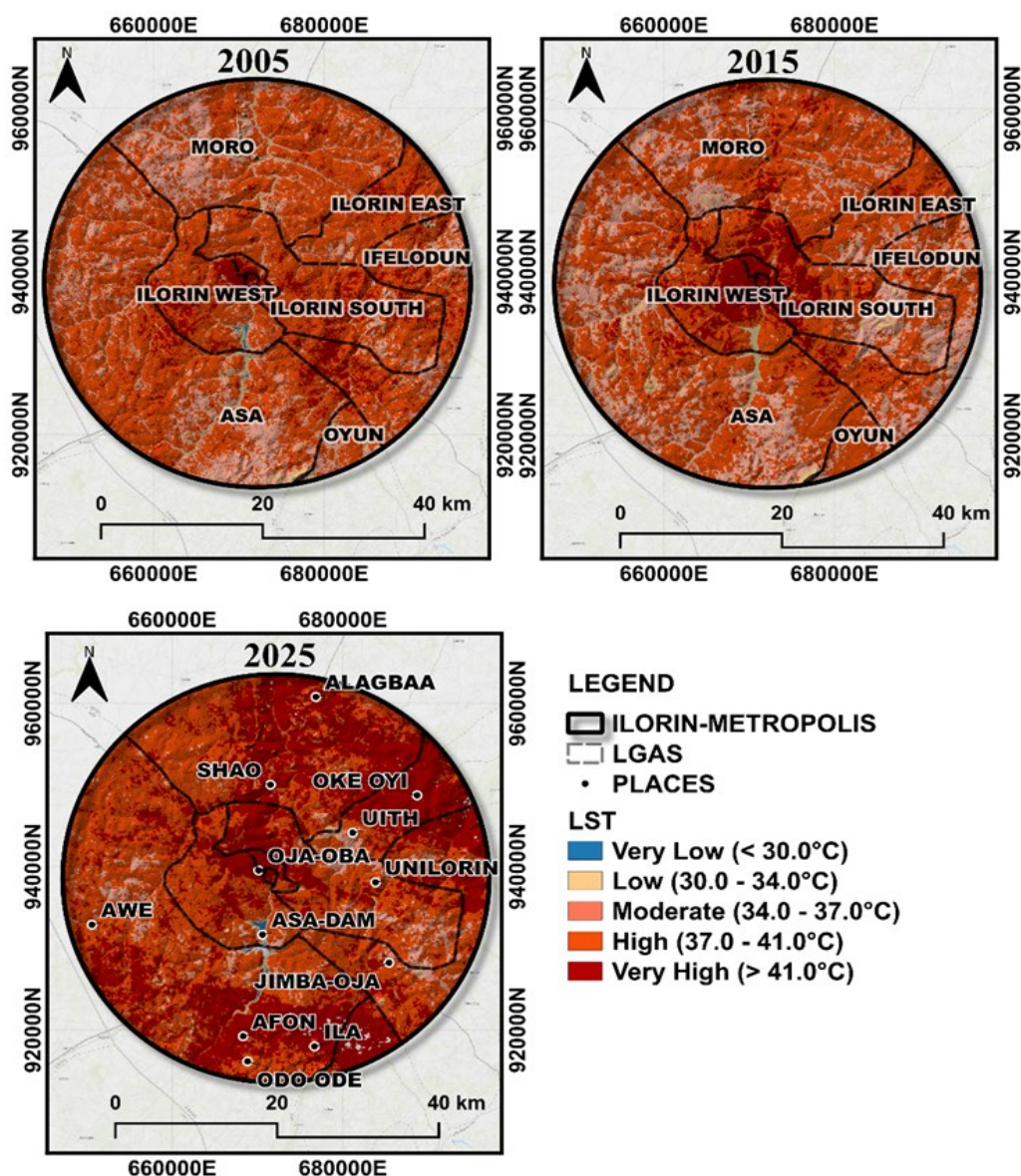
Figure 5. Spatial distribution of Land Surface Temperature in Ilorin Metropolis for (a) 2005, (b) 2015 and (c) 2025.

Source: Authors' GIS analysis (2026)

Table 3. Summary statistics of Landsat-derived Land Surface Temperature

Statistic	2005	2015	2025
Minimum (°C)	28.63	29.87	31.42
Maximum (°C)	48.84	50.31	51.64
Mean (°C)	38.34	39.58	40.64
Standard deviation (°C)	3.57	3.91	4.18

Source: Authors' Statistical analysis (2026)

**Figure 6. Land Surface Temperature intensity classes in 2005, 2015 and 2025.**

Source: Authors' GIS Analysis (2026)

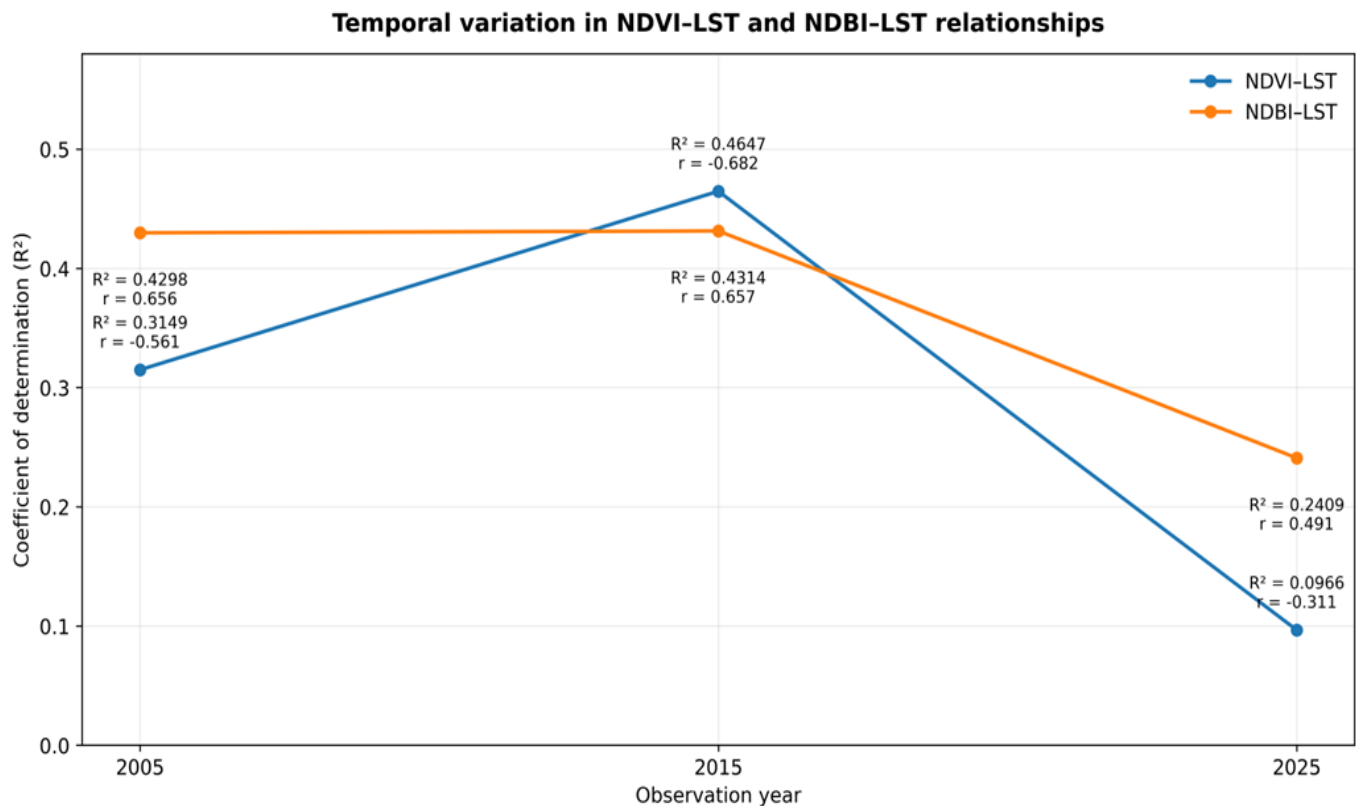


Figure 7. Scatterplots illustrating the relationships between LST and (a–c) NDVI and (d–f) NDBI for 2005, 2015 and 2025.

Source: Authors' Statistical Analysis (2026)

combined use can help identify locations requiring more detailed investigation of vegetation condition, shading, surface permeability and thermal characteristics. Google Earth Engine further supports the efficient processing of multi-temporal satellite observations over metropolitan areas, facilitating repeatable environmental monitoring at broad spatial scales.

The planning interpretation should, however, remain proportional to the evidence. The analysis characterises remotely sensed surface thermal conditions rather than human heat exposure, thermal comfort or heat-related health risk. It therefore provides a physical surface-thermal evidence layer that can inform urban environmental monitoring and planning but should not be interpreted as a complete assessment of climate vulnerability or human heat risk.

3.5 Limitations and methodological considerations

Consider these limitations when interpreting the results:

1. 30-m spatial resolution of Landsat can produce mixed pixels containing combinations of roofs, roads, vegetation, exposed soil and other materials, particularly within heterogeneous urban neighbourhoods.
2. The LST represents land-surface temperature and should not be treated as a direct substitute for near-surface air temperature or human thermal exposure.
3. The study compares three temporal epochs rather than providing a continuous annual time series. The differences observed therefore represent changes between the selected observation periods rather than a complete description of year-to-year thermal variability.
4. The differences in acquisition timing and atmospheric or meteorological conditions may contribute to inter-annual variation in LST and spectral indices. The results should therefore be interpreted primarily as multi-temporal spatial evidence rather than as a controlled estimate of the effect of urbanisation.
5. The NDVI-LST and NDBI-LST models are intention-

Table 4. Comparative regression performance for NDVI–LST and NDBI–LST

Relationship	2005 R^2	2015 R^2	2025 R^2	Temporal interpretation
NDVI–LST	0.3149	0.4647	0.0966	Negative association; strongest one-predictor fit in 2015
NDBI–LST	0.4298	0.4314	0.2409	Positive association; stronger than NDVI in 2005 and 2025

Source: Authors' Statistical Analysis (2026)

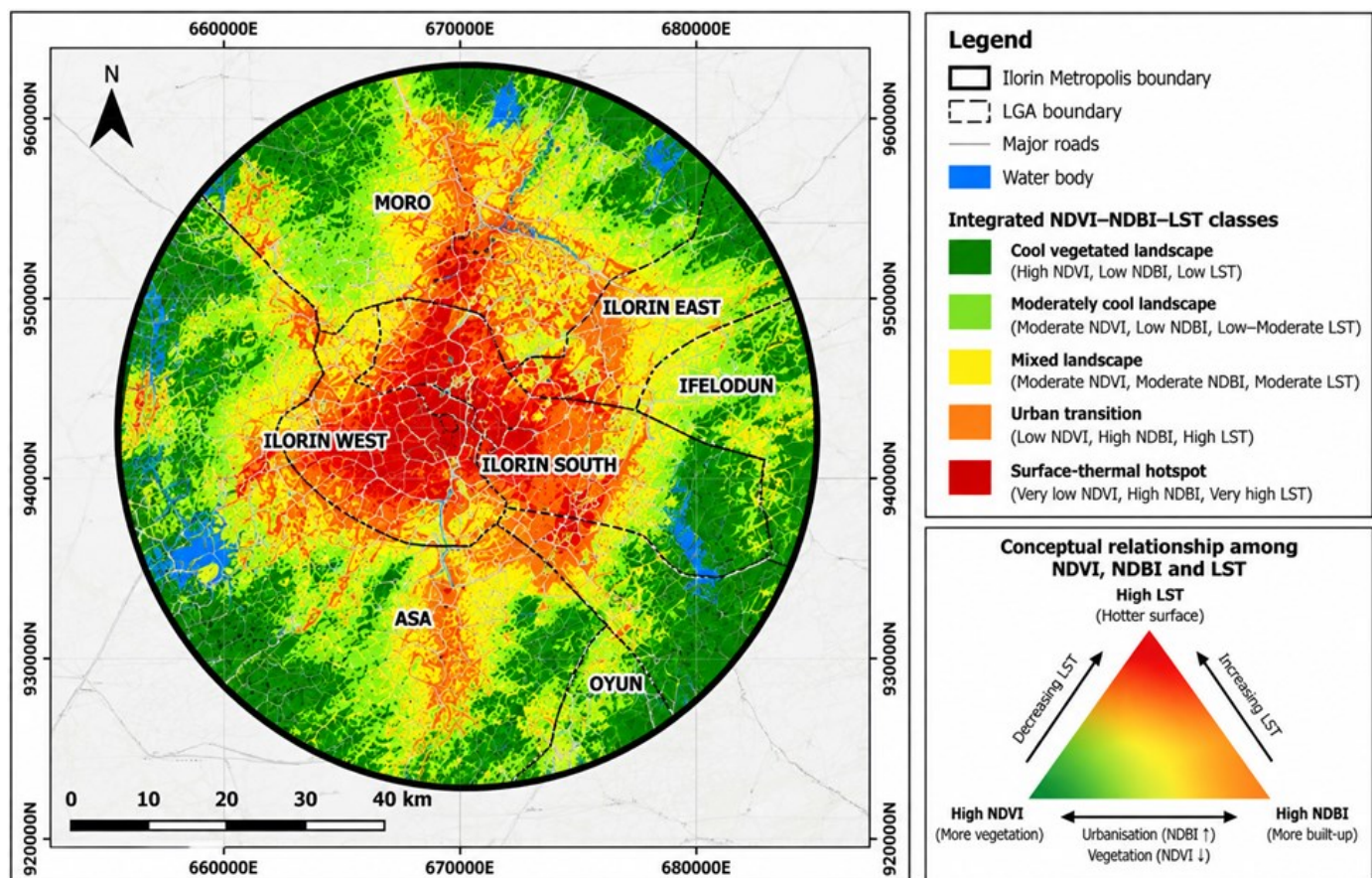


Figure 8. Integrated spatial relationship among NDVI, NDBI and Land Surface Temperature in Ilorin Metropolis.

Source: Authors' GIS Analysis (2026)

ally simple one-predictor relationships. They do not simultaneously account for urban morphology, soil moisture, topography, surface materials, atmospheric conditions, or other variables that may influence LST. The decline in R^2 observed for both relationships in 2025 reinforces this limitation and indicates that neither index independently captures the full complexity of the metropolitan thermal environment.

6. The regression observations are spatially distributed, and neighbouring pixels may not be statistically independent. Consequently, Pearson correlation and OLS results are descriptive and comparative measures of spatial association, not causal estimates. Using 1,000 observations per year provides a consistent analytical sample size across the three epochs, but the regression results should not be interpreted as if the observations constituted 1,000 independent experimental units.

4. Conclusions

This study examined the spatial and temporal relationships among NDVI, NDBI and Landsat-derived LST in Ilorin Metropolis for 2005, 2015 and 2025. The results reveal a substantial reorganisation of the metropolitan surface, characterised by changes in vegetation distribution, increasing built-up spectral dominance and progressively higher surface temperatures.

Mean LST increased from 38.34 °C in 2005 to 40.64 °C in 2025, while the maximum increased from 48.84 °C to 51.64 °C. The increase in standard deviation from 3.57 °C to 4.18 °C also indicates greater spatial heterogeneity in surface thermal conditions. The LST maps demonstrate that elevated surface temperatures increasingly coincide spatially with developed and rapidly transforming areas, whereas comparatively cooler conditions persist more frequently in vegetated and water-associated landscapes.

The statistical analysis confirms contrasting associations between the spectral indices and LST. NDVI was negatively associated with LST, with R^2 values of 0.3149, 0.4647 and 0.0966 for 2005, 2015 and 2025, respectively. NDBI exhibited positive associations, with corresponding R^2 values of 0.4298, 0.4314 and 0.2409. The temporal variation in these values demonstrates that the strength of the pairwise relationships is not constant. By 2025, neither NDVI nor NDBI alone explained most of the observed spatial variation in LST, emphasising

the multivariate nature of the urban surface thermal environment.

The principal scientific implication is therefore that NDVI and NDBI should be treated as complementary indicators of urban surface conditions rather than as independent causal explanations of LST. Their greatest analytical value emerges when their spatial patterns are considered jointly with LST and land-cover information.

Ilorin, the findings support a planning approach that combines vegetation conservation, protection of existing green and riparian networks, and management of impervious-surface expansion. The integrated spatial evidence provides a practical Earth-observation basis for screening areas where vegetation retention or enhancement and surface-sensitive urban planning may be particularly relevant. However, because the study measures surface temperature rather than air temperature or human exposure, these findings should be treated as a surface-thermal evidence base for planning, not a complete urban heat-risk assessment.

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Disclosure Statement

The authors declare that there are no conflicts of interest regarding the publication of this paper. The research was conducted solely for academic and scientific purposes as part of the doctoral research activities of the first author within the Department of Surveying and Geoinformatics.

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