

Characterising Surface Urban Heat Island in Ibadan, Nigeria: Hot- Spot Clustering and Relationships With Vegetation and Land Cover

Opeoluwa Odeleye

mopeoluwa4@gmail.com

Federal University Lafia

Temitope Waheeb

University of Ibadan

Adewale Adeyefa

University of Ibadan

Research Article

Keywords: urban heat island, land surface temperature, hot-spot analysis, Getis-Ord Gi*, Ibadan

Posted Date: October 22nd, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-11060767/v1>

License: © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Additional Declarations: No competing interests reported.

Characterising Surface Urban Heat Island in Ibadan, Nigeria: Hot-Spot Clustering and Relationships With Vegetation and Land Cover.

Opeoluwa Odeleye^{1*}, Temitope Waheeb², Adewale Adeyefa²

¹Department of Geography, Federal University of Lafia, Lafia, Nigeria

²Department of Geography, University of Ibadan, Nigeria

**Corresponding author: mopeoluwa4@gmail.com, +234-8105725485*

Abstract

Rapid, often unplanned, urban growth in Nigerian cities is reshaping the surface energy balance and intensifying urban heat. This study characterises the Surface Urban Heat Island (SUHI) of Ibadan, one of the largest cities in West Africa, using Landsat thermal remote sensing, and examines how Land Surface Temperature (LST) relates to vegetation and to the spatial clustering of surface heat. LST and NDVI were derived for the 2025 dry season from Landsat 8 and 9 Collection 2 Level 2 Surface Temperature data, assembled as a cloud-masked median in Google Earth Engine, and all analysis was carried out in ArcGIS Pro. A metropolitan urban core was compared against a surrounding rural ring; the heat island was measured both as an urban-minus-rural difference and along urban-to-rural transects; the LST-NDVI relationship was quantified, and statistically significant heat clusters were identified with the Getis-Ord Gi* statistic. Mean LST across the study area was 35.03 degrees C, ranging from 27.84 to 47.60 degrees C. The urban core averaged 39.77 degrees C against 34.73 degrees C for the rural ring, giving a SUHI intensity of 5.04 degrees C, and the transect profiles showed surface temperature peaking over the built-up centre and falling toward the vegetated periphery. LST and NDVI were strongly negatively correlated ($r = -0.93$, $R^2 = 0.86$), with the regression $LST = 43.8 - 18.7 \times NDVI$. Hot-spot analysis identified statistically significant heat clustering over 25.1 percent of the study area, dominated by a high-confidence hot core covering about 345 square kilometres, while significant cold clusters (27.7 percent) occupied the vegetated surroundings. Mean LST by land cover ranked built-up (39.35 degrees C) and bare land (38.12 degrees C) warmest and vegetation (33.60 degrees C) and water (31.76 degrees C) coolest, a built-up to vegetation contrast of 5.75 degrees C. These results identify where targeted greening and cooler surfaces would deliver the greatest relief, and provide an evidence base for heat-aware urban planning in Ibadan.

Keywords: urban heat island; land surface temperature; hot-spot analysis; Getis-Ord Gi*; Ibadan

1. Introduction

Rapid urbanisation is transforming landscapes and local climate systems across the Global South, particularly in rapidly expanding cities of sub-Saharan Africa [1, 2, 3]. Converting vegetation, agricultural land, wetlands, and exposed soils into buildings, roads, and other impervious surfaces alters surface properties and the exchange of energy, moisture, and radiation between the land and atmosphere [2]. Built surfaces generally absorb and store more solar energy, while vegetation loss reduces shading and evapotranspiration, creating thermal contrasts between densely developed areas and their surroundings. As noted by Li et al. [3] and Liu et al. [4], these changes contribute to the development and intensification of Surface Urban Heat Islands (SUHIs), with global evidence showing substantial urban contributions to long-term surface warming and SUHI intensity.

Land Surface Temperature (LST) is a key indicator for examining urban thermal conditions because it represents the radiometric temperature of the land surface derived from thermal infrared observations. Its spatial variability is influenced by vegetation cover, soil moisture, emissivity, albedo, imperviousness and urban morphology [5, 6]. Consequently, Land Use Land Cover (LULC) changes associated with urban growth can alter the surface energy balance and produce marked spatial contrasts in LST. SUHI refers specifically to the relative warmth of urban surfaces compared with surrounding non-urban or rural surfaces and differs from the canopy-layer UHI, which is based primarily on air temperature. Recent global evidence demonstrates that surface and canopy UHIs have different magnitudes, trends and controlling factors, highlighting the need to distinguish between them in urban climate studies [7].

Thermal remote sensing provides an effective approach for investigating SUHI because satellite observations offer spatially continuous information on surface thermal conditions across large urban areas [5, 8]. Landsat imagery is particularly valuable for city-scale studies because its relatively fine spatial resolution enables thermal variations associated with neighbourhoods, land-cover classes and specific urban features to be examined [9]. Remote sensing therefore supports LST mapping, SUHI estimation and investigation of relationships among thermal conditions, vegetation and urban development. However, methodological choices involving urban–rural reference areas, image acquisition, cloud contamination and SUHI estimation can influence results [8, 10].

LST distribution is strongly associated with the composition and configuration of urban land cover. Vegetated surfaces promote cooling through evapotranspiration and shading, whereas concrete, asphalt, roofing materials and other impervious surfaces tend to absorb and retain heat. Water bodies may also have comparatively lower surface temperatures because of their heat capacity and evaporative properties. Systematic evidence identifies LULC as a major determinant of LST, with Landsat imagery, GIS, NDVI and built-up indices widely used to investigate these relationships [6]. NDVI is particularly useful for assessing vegetation abundance and vegetation–temperature relationships, although their strength varies with climate, vegetation type, soil moisture, urban density and spatial configuration [11].

Attention has increasingly shifted from average LST differences to the spatial organisation of urban thermal conditions. High and low temperatures often form concentrated patterns, with hotspots commonly associated with densely built-up districts, industrial areas, transport corridors and exposed surfaces, while cooler conditions occur around parks, forests, wetlands and water bodies. Local Climate Zone research demonstrates that variations in building density, height, openness and surface cover produce distinct thermal environments within cities [11, 12]. Identifying statistically significant hot and cold clusters can therefore provide more useful information for planning than relying solely on mean LST or simple urban–rural differences.

Elevated surface temperatures can increase heat exposure, reduce outdoor thermal comfort, increase cooling requirements and contribute to environmental vulnerability. The Intergovernmental Panel on Climate Change identifies urban heat as an important climate-related risk and recognises vegetation, street trees, green roofs and other nature-based solutions as measures for reducing heat through shading and evapotranspiration [13]. Effective mitigation, however, requires spatially explicit identification of areas experiencing the greatest thermal stress.

Ibadan provides an important setting for examining these processes because continued spatial expansion has transformed substantial areas of natural, agricultural and semi-natural land. Previous studies demonstrate clear relationships between urban land-cover transformation and surface temperature. Fashae et al. [14] reported substantial increases in urban land cover between 1984 and 2019, accompanied by pronounced LST increases and a strong negative relationship between vegetation abundance and surface temperature. Oni and Ibeabuchi [15] identified spatially varying LST patterns and urban heat areas, also reporting a negative relationship between NDVI and LST. Kasim et al. [16] found a strong association between LULC and LST, with the highest temperatures occurring in densely built-up areas. More recently, Ikuemonisan et al. [17] linked increasing built-up areas and declining vegetation with substantial LST increases, while Njoku and Tenenbaum [18] showed that vegetation and topographic characteristics also contribute to spatial LST variations.

Despite these contributions, detailed understanding of the spatial organisation of Ibadan's SUHI remains limited. Existing studies have largely examined LST change, LULC transformation, NDVI–LST relationships or general areas of elevated temperature, with limited attention to statistically significant concentrations of unusually high or low LST. The combined application of SUHI intensity, vegetation–temperature relationships, LULC characteristics and spatial hotspot statistics therefore remains insufficiently explored at the intra-urban scale. A spatially explicit framework can provide a more nuanced understanding of Ibadan's thermal heterogeneity and support targeted urban greening, land-use planning and heat-risk management.

Against this background, this study characterises the Surface Urban Heat Island of Ibadan, Nigeria, with emphasis on hot-spot clustering and its relationship with vegetation and land cover. Specifically, it seeks to: (i) examine the spatial distribution of land surface temperature (LST) across Ibadan using Landsat thermal observations; (ii) characterise SUHI intensity and spatial distribution using urban–rural contrasts and transect analysis; (iii) quantify the relationship between LST and vegetation using NDVI; (iv) examine

variations in LST among major land-cover categories; and (v) identify statistically significant hot and cold clusters of surface temperature.

2. Study Area

Ibadan, the capital of Oyo State, lies in south-western Nigeria and is centred at approximately latitude 7°23'N and longitude 3°55'E. It ranks among the most extensive urban areas in West Africa, with a dense, historically organic built-up core that grades outward into mixed residential development, cropland, and vegetated land toward a rural periphery. The city falls within the transition between tropical rainforest and Guinea savanna and experiences a tropical wet-and-dry climate, with a rainy season from about March to October and a dry season, dominated by the dry, dusty harmattan, from about November to February.

To capture both the urban core and its rural surroundings, the study area was defined as a rectangle centred on the metropolitan Ibadan boundary and extended outward by a 15 km buffer, covering about 2,130 square kilometres. The metropolitan polygon forms the urban core, while the ring of land between the metropolitan boundary and the rectangle edge provides the rural reference. Two transects, west-to-east and north-to-south, were drawn through the centre of the metropolitan area to profile the urban-to-rural temperature gradient. All layers were projected to WGS 84 / UTM Zone 31N (EPSG:32631) on a 30 m grid (Figure 1).

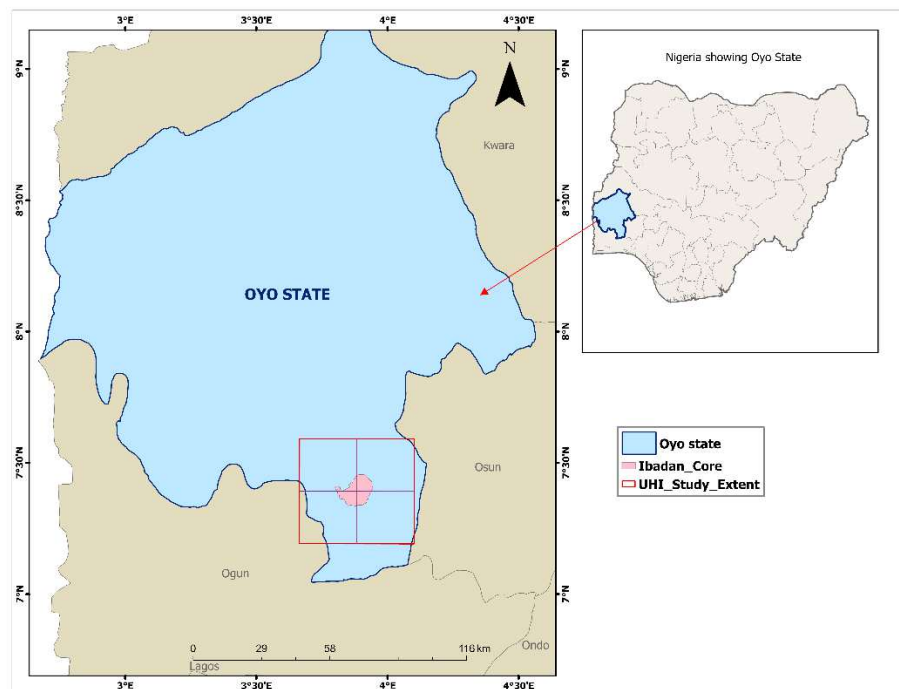


Figure 1. Study area. The main map shows metropolitan Ibadan (urban core), the surrounding 15 km rural ring, the rectangular study extent, and the west-to-east and north-to-south transects, projected to

WGS 84 / UTM Zone 31N. Insets show the location of Ibadan within Oyo State and of Oyo State within Nigeria. (Placeholder: replace with the ArcGIS Pro layout described in the accompanying guide.)

3. Materials and Methods

The workflow proceeded from study area definition to data assembly, followed by the derivation of thermal, vegetation, and land-cover products and analysis of the spatial heat pattern, as summarised in Figure 2. Landsat Collection 2 Level 2 data were used because the Level 2 Surface Temperature and Surface Reflectance products incorporate standardised processing and atmospheric corrections, supporting consistent and reproducible analysis across the Landsat archive [19]. Thermal processing and land-cover classification were carried out in Google Earth Engine, which provides access to the Landsat archive and enables large-scale geospatial processing [20]. Subsequent spatial analysis and cartographic production were performed in ArcGIS Pro using ArcPy. All datasets were projected to WGS 84 / UTM Zone 31N (EPSG:32631), an appropriate projected coordinate reference system for Ibadan, to ensure that distance and calculations were expressed in metres.

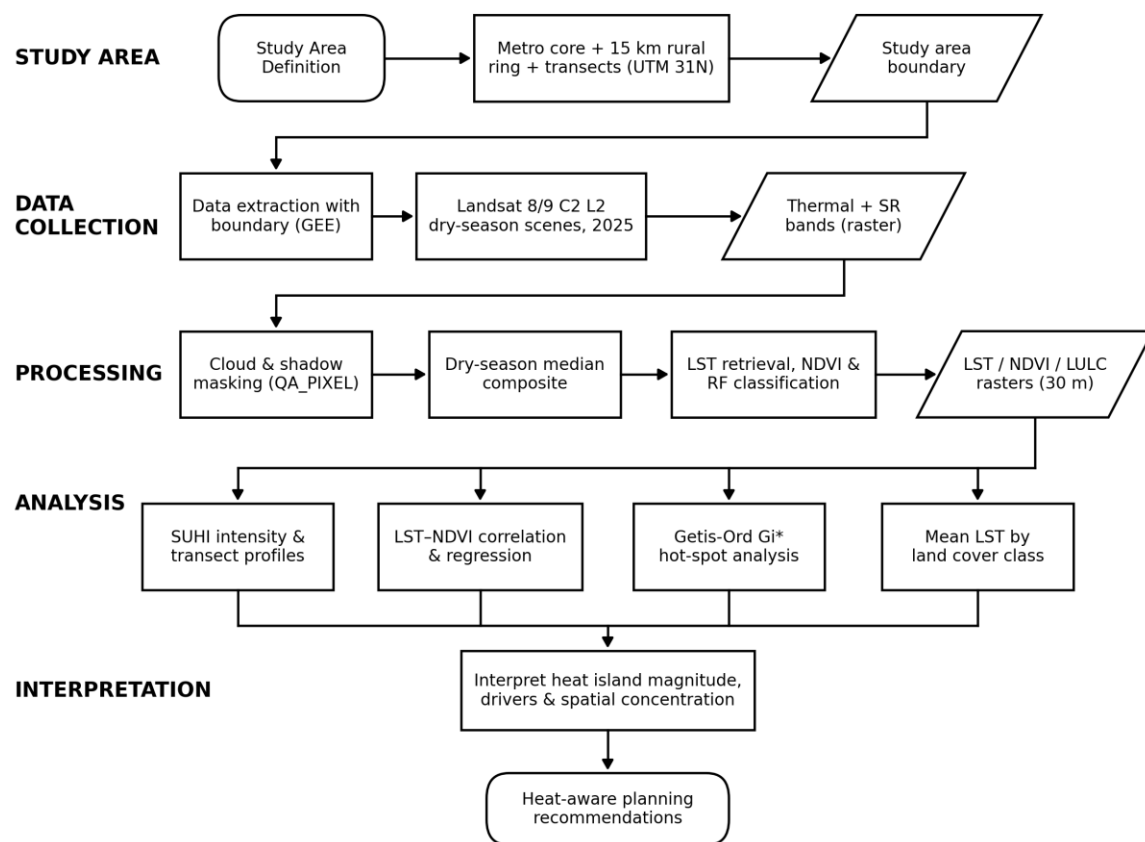


Figure 2. Methodological workflow, from study area definition and data acquisition through processing and analysis to interpretation and recommendations.

3.1 Data and study period

The datasets used in the study are summarised in Table 1 and their spatial distribution is shown in Figure 3. Land surface temperature (LST) and the Normalized Difference Vegetation Index (NDVI) were derived from Landsat 8 and Landsat 9 Collection 2 Level 2 scenes acquired during the 2025 dry season. The dry-season period, approximately from late November to February, was selected for three main reasons. First, cloud cover over Ibadan is generally lower during this period, increasing the availability of clear-sky thermal observations. Second, surface urban heat island (SUHI) patterns are more readily expressed under clear and relatively dry conditions, when differences in surface heating between built-up and vegetated areas are more pronounced. Third, restricting the analysis to a single season minimises seasonal variability and provides a more consistent basis for comparing spatial patterns of surface temperature and vegetation.

Because individual Landsat scenes may still contain cloud-contaminated pixels, all qualifying scenes within the study period were subjected to cloud masking and combined using a median compositing approach. The resulting composite provides a stable representation of the dry-season surface conditions by reducing the influence of residual clouds, anomalous observations, and scene-specific variability, rather than relying on observations from a single acquisition date.

Table 1. Characteristics of the datasets used in the study.

Dataset	Source/sensor	Resolution	Date/period	Role in analysis
Surface Temperature	Landsat 8/9 C2 L2 (TIRS)	30 m (thermal 100 m, resampled)	2025 dry season	LST retrieval
Surface Reflectance	Landsat 8/9 C2 L2 (OLI)	30 m	2025 dry season	NDVI computation
QA_PIXEL band	Landsat 8/9 C2 L2	30 m	2025 dry season	Cloud/shadow masking
Land cover	Landsat imagery, Random Forest (GEE)	30 m	2025	Mean LST by class
Metro boundary	Ward boundaries, from Grid3	Vector	2025	Urban core definition

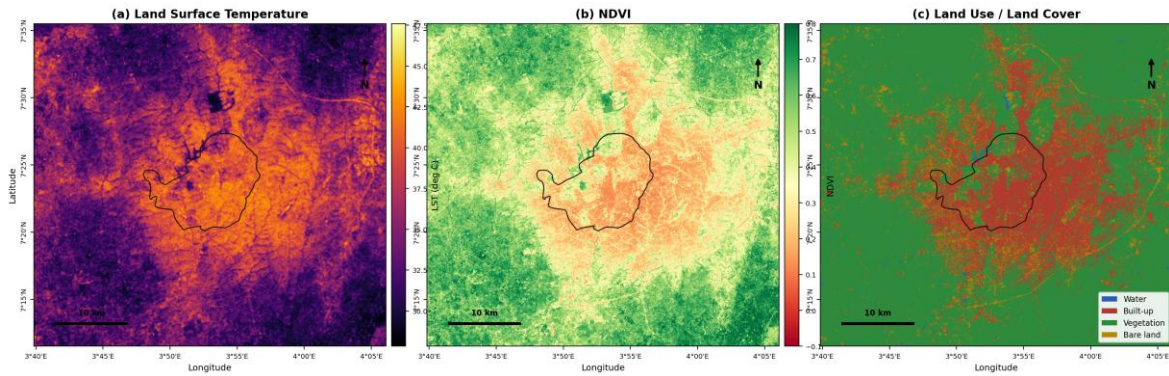


Figure 3. Input datasets for the analysis: (a) land surface temperature, (b) NDVI, and (c) land use / land cover for the 2025 dry season. The dark outline marks metropolitan Ibadan. Data in WGS 84 / UTM Zone 31N with the graticule labelled in degrees and minutes.

3.2 Land surface temperature retrieval

Land surface temperature was obtained from the Landsat Collection 2 Level 2 Surface Temperature product. This product is preferred over a manual retrieval because it applies a physically based single-channel algorithm with atmospheric correction and NDVI-derived emissivity in a consistent, validated implementation [21, 22], which reduces user-introduced error and ensures comparability across the Landsat 8 and 9 sensors. The archived integer values were converted to Kelvin and then to degrees Celsius using the published scale factor and offset (Equation 1):

$$LST(^{\circ}C) = (DN \times 0.00341802 + 149.0) - 273.15 \text{ ----- (Equation 1)}$$

where *DN* is the raw Surface Temperature digital number and the constants are the USGS-published scale factor and offset.

Cloud, cloud shadow, and dilated cloud were removed before compositing using the QA_PIXEL quality band (bits 1, 3, and 4), so that only clear-sky pixels contributed to the median. This masking is essential because cloud contamination produces spuriously cold pixels that would bias the thermal statistics.

3.3 Vegetation index

NDVI was computed from the Level 2 Surface Reflectance red and near-infrared bands as their normalised difference (Equation 2). NDVI is used because it is the standard, well-validated measure of vegetation abundance and is closely coupled to surface temperature through evapotranspiration and shading [23]:

$$NDVI = (NIR - Red) / (NIR + Red) \text{ ----- (Equation 2)}$$

where NIR and Red are the scaled surface-reflectance values in the near-infrared and red bands.

3.4 Land cover classification

A four-class land cover map, water, built-up, vegetation, and bare land, was produced in Google Earth Engine by supervised Random Forest classification of Landsat imagery for 2025. Random Forest was chosen because it is robust to noise, handles non-linear class boundaries well, and is widely used and accepted for medium-resolution land cover mapping. Training points were collected by the authors across the four classes, and classification accuracy was assessed against withheld reference samples, yielding an overall accuracy of 91% and a kappa coefficient of 0.75. The classified map supported the summary of mean LST by land cover type.

3.5 Study geometry and heat island measurement

To measure the heat island, the metropolitan Ibadan boundary was taken as the urban core and a 15 km buffer around it as the rural reference, together forming a rectangular study area of about 2,130 square kilometres centred on the city. A buffer-based rural reference is a standard and transparent way to define the non-urban baseline while keeping climate and terrain broadly comparable to the core. The surface urban heat island (SUHI) intensity was defined as the difference in mean LST between the urban core and the rural ring (Equation 3):

$$SUHI = LST\bar{(urban)} - LST\bar{(rural)} \text{ ----- (Equation 3)}$$

where the overbar denotes the zonal mean LST.

To show the gradient spatially, LST was sampled at 300 m intervals along a west-to-east and a north-to-south transect crossing the city centre, and plotted against distance from the centre. Transect profiling is a long-established way to visualise the urban-to-rural temperature transition directly.

3.6 LST–vegetation relationship

The relationship between LST and NDVI was quantified with the Pearson correlation coefficient and ordinary least squares regression (Equation 4) across all pixels valid in both layers, more than 2.36 million, so the relationship rests on the full population rather than a sample:

$$LST = a + b \times NDVI \text{ ----- (Equation 4)}$$

where b is the slope, quantifying the change in surface temperature per unit change in NDVI, and a is the intercept.

3.7 Hot-spot analysis

Statistically significant clusters of high and low surface temperature were identified with the Getis-Ord G_i^* statistic [24, 25], which tests whether high or low values cluster in space more than would be expected by chance (Equation 5):

$$G_i^* = [\sum w_{ij} x_j - \bar{X} \sum w_{ij}] / [S \sqrt{ (n \sum w_{ij}^2 - (\sum w_{ij})^2) / (n-1) }] \text{ ----- (Equation 5)}$$

where x_j is the LST at location j , w_{ij} is the spatial weight between locations i and j , $\bar{X}$ is the mean, S is the standard deviation, and n is the number of features.

A high positive G_i^* indicates a hot cluster and a low negative value a cold cluster.)

The 30 m LST surface was aggregated to a 150 m grid to give a computationally tractable point set before analysis, converted to points, and analysed with a fixed-distance conceptualisation of spatial relationships. Each point was classified at the 90, 95, and 99 percent confidence levels for hot and cold clustering, and the share of the study area in each class was computed.

4. Results

4.1 Spatial distribution of land surface temperature

The retrieved surface temperature is mapped in Figure 4, which shows a clear centre-to-edge pattern, with the warmest surfaces forming a broad core over the dense built-up centre and the coolest values over tree cover and water at the periphery. Across the study area, the mean LST was 35.03 degrees C, with a median of 34.60 degrees C, a minimum of 27.84 degrees C, and a maximum of 47.60 degrees C. The frequency distribution, summarised in Table 2 and plotted in Figure 5, is broad and slightly right-skewed, with the central 90 percent of pixels falling between 30.11 and 41.05 degrees C and a warm tail extending toward the built-up core.

Table 2. Summary of land surface temperature across the study area, Ibadan 2025.

Statistic	Value (degrees C)
Mean	35.03
Median	34.60
Standard deviation	3.44
Minimum	27.84
5th percentile	30.11
95th percentile	41.05
Maximum	47.60

Based on 2,365,368 valid pixels.

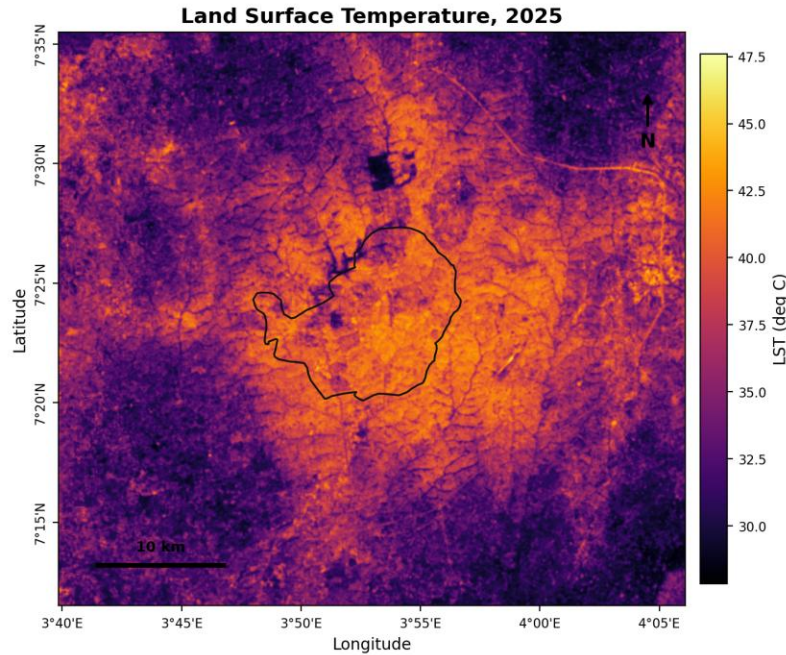


Figure 4. Land surface temperature of Ibadan for the 2025 dry season, with the metropolitan boundary (dark outline). The warm built-up core stands out against the cooler vegetated periphery. Data in WGS 84 / UTM Zone 31N with the graticule labelled in degrees and minutes.

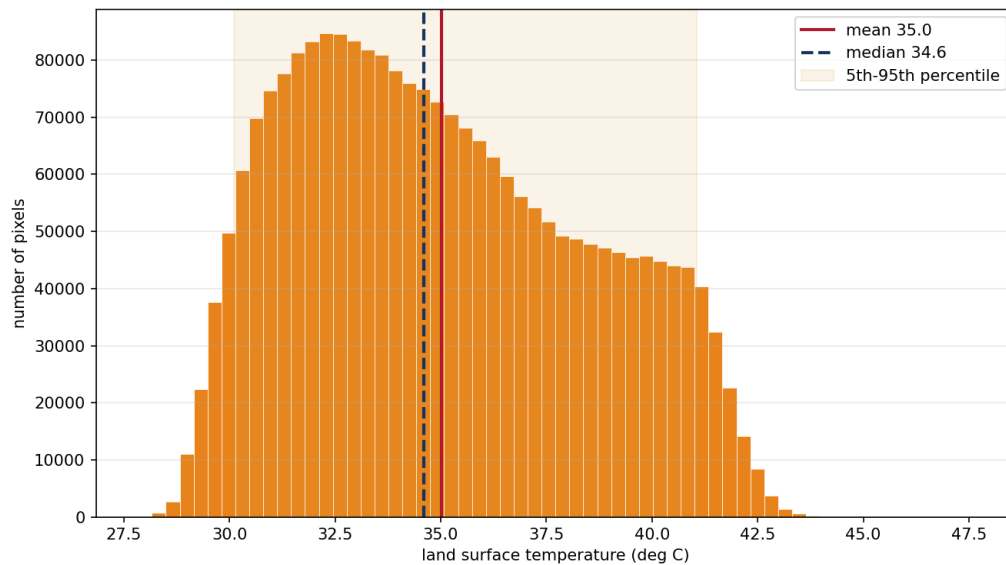


Figure 5. Frequency distribution of land surface temperature across the study area (mean 35.03 degrees C, median 34.60 degrees C). The shaded band marks the 5th to 95th percentile range.

To show the core-to-rural contrast directly, surface temperature was extracted along the west-to-east and north-to-south transects; the resulting urban heat island profiles are presented in Figure 6. Along both transects the temperature rises to a broad, elevated dome over the built-up centre, near and above 42 degrees C, and falls toward cooler values at the vegetated rural ends. The profiles confirm that the elevated temperatures

are concentrated over the urban core rather than distributed evenly, with pronounced cool troughs where the transects cross patches of dense vegetation or water.

Taken together, the map, the distribution and the transects describe a surface field with three consistent features. First, the spread of values is wide, a standard deviation of 3.44 degrees C and a 5th-to-95th-percentile range of nearly 11 degrees C, indicating strong internal contrast rather than a uniformly warm surface. Second, the right-skew of the distribution shows that the very high temperatures are confined to a limited part of the area, the warm tail, rather than being typical of the city as a whole. Third, the two transects, running west-to-east and north-to-south through the centre, both peak over the same built-up core and decline symmetrically toward the vegetated margins, so the warmth is organised around the city centre in every direction sampled. This spatial signature, a compact warm core embedded in a cooler vegetated surround, frames every result that follows and identifies the built-up centre as the focus of the surface heat island.

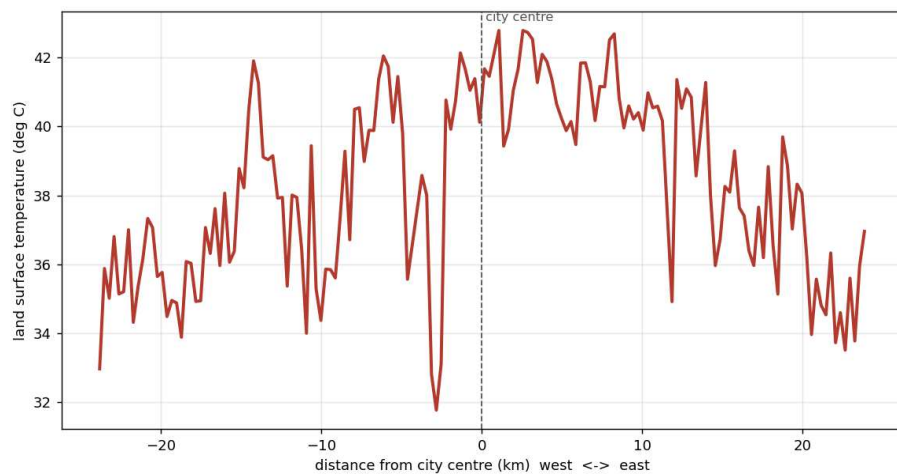


Figure 6a. Urban-rural land surface temperature profile along the west-to-east transect across Ibadan, 2025. Distance is measured from the city centre; the dashed line marks the centre.

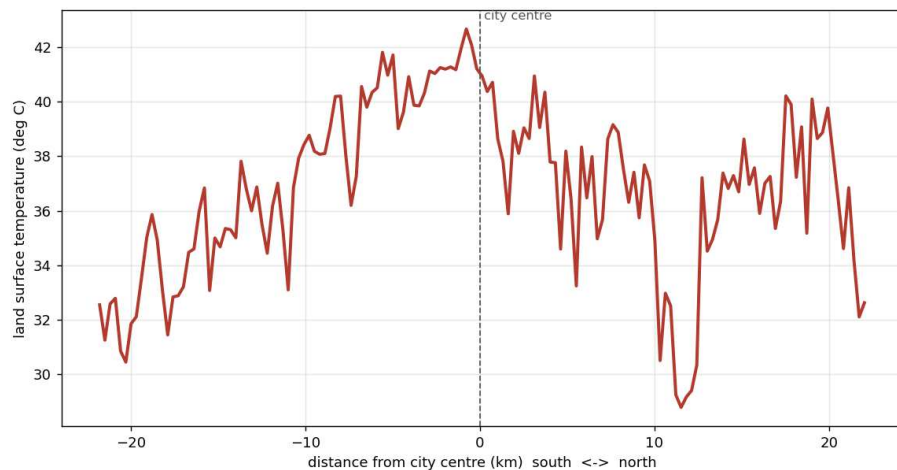


Figure 6b. Urban-rural land surface temperature profile along the north-to-south transect across Ibadan, 2025.

4.2 Surface heat island intensity

The SUHI intensity, defined as the difference in mean LST between the urban core and the rural ring, was 5.04 degrees C, the urban core averaging 39.77 degrees C against 34.73 degrees C for the rural ring (Figure 7). The scale of the contrast is reinforced by comparing the full temperature distributions of the two zones (Figure 8): the urban population of pixels is shifted markedly toward warmer values relative to the rural population, so the heat island is not merely a difference of averages but a systematic warming of the entire built-up surface.

The magnitude of the contrast can be placed on the same scale as the values in Table 2. The urban-core mean of 39.77 degrees C sits close to the 95th percentile of the whole-area distribution, while the rural-ring mean of 34.73 degrees C sits near the median, so the two zones occupy clearly separated parts of the temperature range rather than overlapping tails. The 5.04 degrees C separation is therefore not a marginal difference but a shift of roughly one and a half standard deviations between the core and the ring. Figure 8 makes the same point in distributional terms: the urban curve is displaced bodily toward higher temperatures, with only limited overlap with the rural curve, which means the warming applies across the built-up surface generally rather than being driven by a small number of extreme pixels. This distinction matters for interpretation, because a whole-population shift points to a surface-wide cause, the replacement of vegetated ground by impervious material, rather than to isolated hot objects.

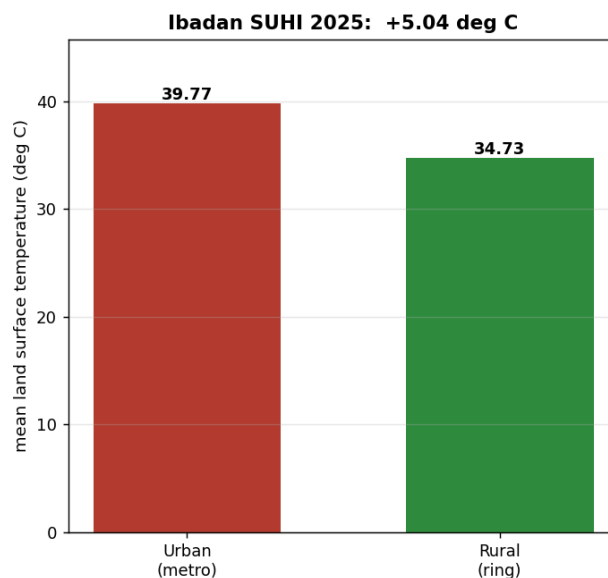


Figure 7. Mean land surface temperature of the urban core and the rural ring, Ibadan 2025. The urban-rural difference gives a surface urban heat island intensity of 5.04 degrees C.

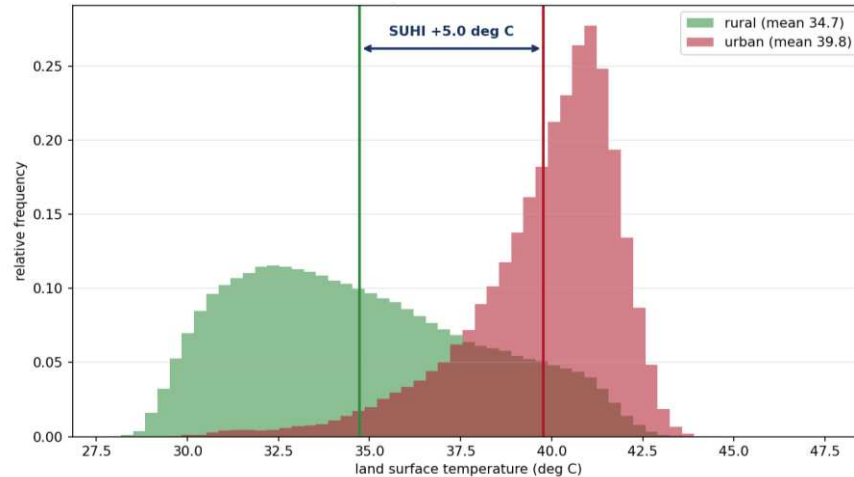


Figure 8. Urban and rural land surface temperature distributions, Ibadan 2025. The urban distribution (red) is shifted about 5 degrees C warmer than the rural distribution (green); the arrow marks the difference in means.

4.3 Relationship between LST and vegetation (NDVI)

The relationship between surface temperature and vegetation is shown in Figure 9. LST and NDVI were strongly negatively correlated, with a Pearson coefficient of $r = -0.93$ and a coefficient of determination of $R^2 = 0.86$, so vegetation abundance explained about 86 percent of the variation in surface temperature across the study area. The fitted regression was $LST = 43.8 - 18.7 \times NDVI$, which implies that an increase of 0.1 in NDVI is associated with a fall of about 1.9 degrees C in surface temperature. The strength of the association reflects the dominant control of vegetation cover on dry-season surface temperature, with the highest temperatures concentrated at the low-NDVI, built-up and bare end of the range.

The scatter in Figure 9 shows the association is not only strong but tight and near-linear across the full NDVI range, with points clustering closely about the fitted line rather than forming a diffuse cloud, which is why the coefficient of determination is high at 0.86. The negative slope of 18.7 degrees C per unit NDVI is steep, and its practical meaning is easiest to read in small steps: each rise of 0.1 in NDVI corresponds to about 1.9 degrees C of cooling, so the difference between sparsely vegetated ground at an NDVI near 0.1 and dense canopy near 0.6 amounts to roughly 9 to 10 degrees C of surface cooling. The densest concentration of points sits at the low-NDVI, high-LST corner, the built-up and bare surfaces, and thins toward the high-NDVI, low-LST corner occupied by vegetation and water. Because both variables are drawn from the same composite and the analysis uses the full pixel population rather than a sample, the relationship reflects the actual surface of the city rather than a subset, and it provides the quantitative bridge between the temperature field and the land cover results that follow.

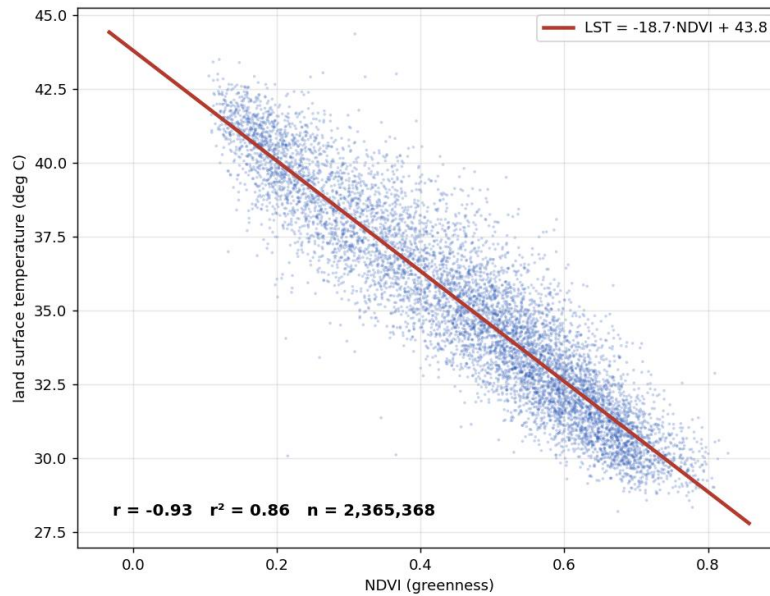


Figure 9. Relationship between NDVI and land surface temperature, Ibadan 2025 ($r = -0.93$, $R^2 = 0.86$, $n = 2,365,368$). The line is the ordinary least squares fit.

4.4 Temperature by land cover

Mean LST by land cover class is reported in Table 4 and shown in Figure 12, using an independent, locally trained four-class classification for 2025. Built-up land was the warmest class at 39.35 degrees C, followed closely by bare land at 38.12 degrees C. Vegetation, which covers most of the study area, was substantially cooler at 33.60 degrees C, and water was the coolest surface at 31.76 degrees C. The difference between the warmest built-up class and the vegetation class was 5.75 degrees C, closely matching the 5.04 degrees C zonal SUHI and reinforcing the strong LST-NDVI relationship: the same physical contrast between impervious and vegetated surfaces underlies all three results. The class shares are consistent with the city's form, vegetation dominating the study area at 73.1 percent, built-up land forming a compact 19.3 percent concentrated in the centre, bare land 7.2 percent, and water a small fraction.

Table 4 also reports the within-class variability, which sharpens the interpretation. The built-up and bare classes are not only the warmest in the mean, at 39.35 and 38.12 degrees C, but also relatively consistent, with standard deviations near 2.1 degrees C, indicating that impervious and exposed surfaces are reliably hot across the city rather than only in a few districts. Vegetation, at 33.60 degrees C, shows the widest spread, a standard deviation of 2.57 degrees C, reflecting the range from sparse grass to dense canopy captured within a single class. The ordering of the four classes is monotonic and matches the ordering expected from surface physics, warmest for the driest, most impervious surfaces and coolest for water and dense vegetation, with no crossover between classes. The disproportion between extent and thermal effect is the key observation: vegetation occupies 73.1 percent of the area yet defines the cool

background, while the compact 19.3 percent of built-up land, concentrated in the centre, accounts for the warm core, so a minority land cover exerts a majority influence on where the city is hottest.

Table 4. Mean land surface temperature by land cover class.

Land cover class	Share of area (%)	Mean LST (degrees C)	Std. dev.
Built-up	19.3	39.35	2.12
Bare land	7.2	38.12	2.09
Vegetation	73.1	33.60	2.57
Water	0.4	31.76	1.95

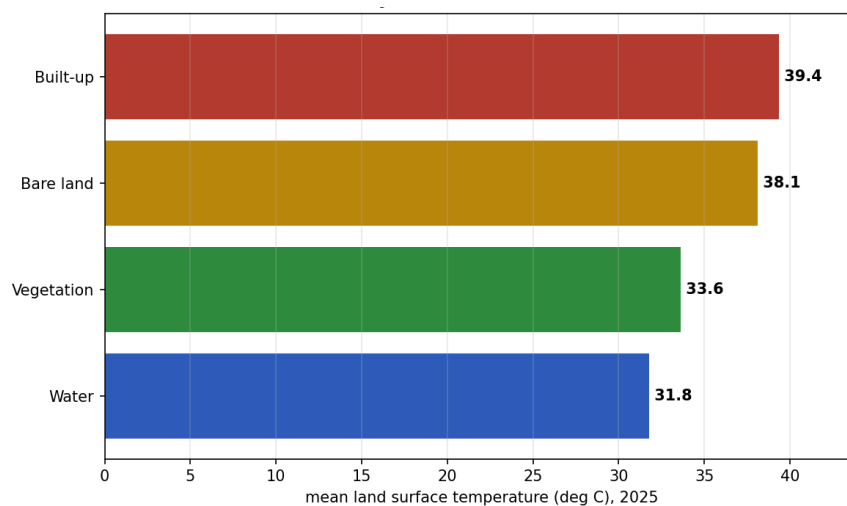


Figure 12. Mean land surface temperature by land cover class, Ibadan 2025, ranked from warmest (built-up) to coolest (water). Based on a locally trained four-class classification.

4.5 Hot-spot analysis of surface temperature

The Getis-Ord Gi* analysis, mapped in Figure 10, identifies where surface heat clusters at a statistically significant level. A large, coherent hot cluster covers the built-up core and extends outward along developed corridors, while significant cold clusters occupy the vegetated land to the south-west, north, and south-east. The distribution of the study area across the significance classes is reported in Table 3 and Figure 11. Significant hot clusters occupied 25.1 percent of the study area and significant cold clusters 27.7 percent, with the remaining 47.2 percent not significant. The hot clustering was dominated by the highest confidence level: 16.2 percent of the area, about 345 square kilometres, fell in the 99 percent hot class alone, indicating an intense and well-defined heat core rather than a diffuse warm zone. The cold clusters were more graded across confidence levels, consistent with a broader, softer cooling influence from the vegetated surroundings.

The full breakdown in Table 3 quantifies this asymmetry between hot and cold clustering. On the hot side, the significance is heavily front-loaded into the highest confidence class: of the 25.1 percent of the area that is a significant hot cluster, nearly two-thirds, 16.2 percent of the whole area or about 345 square kilometres, falls in the 99 percent class, with progressively smaller shares in the 95 and 90 percent classes. This top-heavy structure is the statistical signature of a single, dense, coherent heat core rather than many small scattered warm patches. The cold clustering, by contrast, is spread more evenly across the three confidence levels, 11.9, 10.1 and 5.7 percent, describing a broader and more gradual cooling that grades outward through the vegetated periphery. The 47.2 percent of the area that is not significant separates the two, forming a transitional zone between the hot core and the cold surroundings. Read alongside the land surface temperature map and the transect profiles, the hot-spot map converts the visual impression of a warm centre into a defined, mappable footprint that identifies precisely which districts carry a statistically significant heat load.

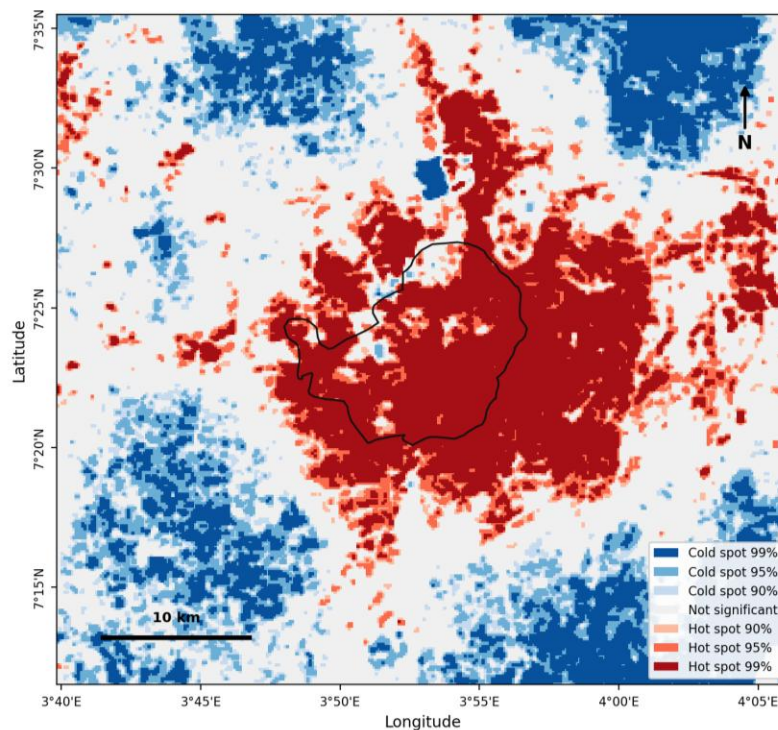


Figure 10. Statistically significant hot and cold clusters of land surface temperature (Getis-Ord Gi*), Ibadan 2025, with the metropolitan boundary. Red denotes significant hot clustering and blue significant cold clustering at the 90, 95, and 99 percent confidence levels. Data in WGS 84 / UTM Zone 31N with the graticule labelled in degrees and minutes.

Table 3. Distribution of the study area across the Getis-Ord Gi* significance classes, 2025.

Significance class	Share of area (%)	Area (km ²)
--------------------	-------------------	-------------------------

Hot 99%	16.2	345.0
Hot 95%	5.7	120.7
Hot 90%	3.3	69.9
Not significant	47.2	1004.9
Cold 90%	5.7	120.8
Cold 95%	10.1	215.5
Cold 99%	11.9	253.3
Significant hot (all)	25.1	535.6
Significant cold (all)	27.7	589.6

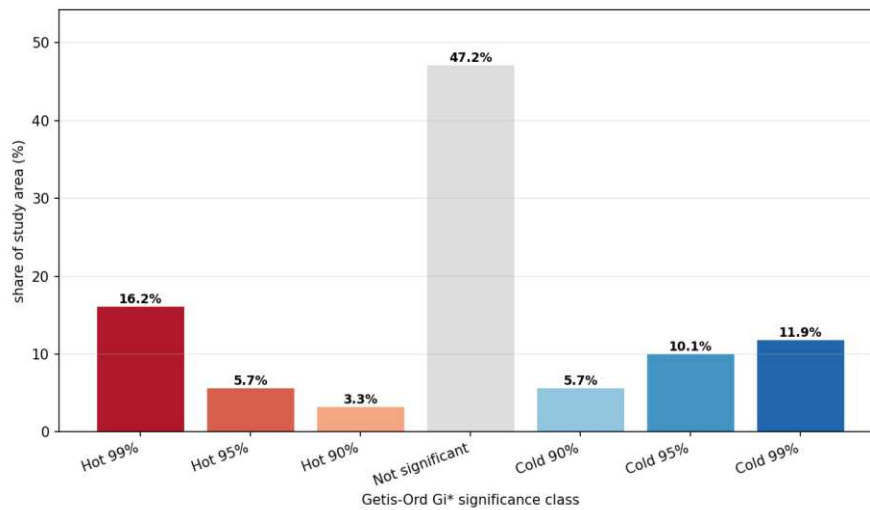


Figure 11. Share of the study area in each Getis-Ord Gi* significance class, Ibadan 2025. The hot side is dominated by the 99 percent confidence class.

5. Discussion

5.1 Spatial distribution of land surface temperature

The centre-to-edge pattern of surface temperature, with a mean LST of 35.03 degrees C and a warm core reaching 47.60 degrees C over the built-up centre, is the classic surface expression of urbanisation and matches the structure reported across tropical and sub-tropical cities. The broad, slightly right-skewed distribution, with a warm tail extending toward the built-up core, is consistent with the mixed thermal surface of a compact African city in which a small, intensely warm built-up centre is embedded in a cooler vegetated matrix. Comparable centre-to-periphery gradients have been documented for Nigerian cities, including Lagos [26], Abuja [27, 28] and Enugu [29], and for numerous cities worldwide [30, 31]. The magnitude of the maximum-to-minimum range, close to 20 degrees C, is characteristic of dry-season imagery, when senescent vegetation and exposed soils amplify the contrast between built and vegetated surfaces [32]. The dry-season timing therefore represents the period of greatest thermal differentiation and

provides a conservative, planning-relevant view of where the city is hottest. The whole-population basis of the estimate, more than 2.36 million pixels drawn from a single cloud-masked Level 2 composite, means the pattern is not an artefact of sampling and can be read as a robust representation of the 2025 dry-season surface field.

5.2 Surface heat island intensity

The SUHI intensity of 5.04 degrees C between the urban core and the rural ring, corroborated by the 5.75 degrees C difference between the built-up and vegetation land cover classes, is substantial and consistent with values reported for comparable cities. The agreement between two independent definitions of the urban-rural contrast, a zonal core-minus-ring difference and a land-cover-based difference, strengthens confidence in the estimate, since both converge on a similar magnitude. For Abuja, Koko et al. [27] documented a mean surface temperature rise from 30.7 degrees C in 1990 to 32.7 degrees C in 2019 alongside built-up expansion, and Obiefuna et al. [26] found that built-up and bare surfaces in Lagos warmed most while wetlands and vegetation moderated temperature. Earlier work in Enugu linked surface warming directly to vegetation loss [29], and continental and global assessments report surface heat island intensities of several degrees whose magnitude scales with the extent and compactness of impervious cover [30, 31, 33]. The distribution comparison in Figure 8 shows that the entire urban pixel population is shifted toward warmer values rather than a few extreme pixels raising the mean, so the heat island is a systematic warming of the built surface rather than a localised anomaly. The Ibadan value therefore falls squarely within the expected range for a large, compact, rapidly urbanising tropical city, while the transect profiles confirm that the elevated temperatures form a coherent dome over the core rather than scattered warm patches.

5.3 Relationship between LST and vegetation

The inverse relationship between LST and NDVI found here, with $r = -0.93$ and $R^2 = 0.86$, is one of the strongest reported for a tropical African city and sits at the upper end of the values documented in the wider literature. Weng, Lu and Schubring [23], in the foundational work on this relationship, reported correlations in the range of about -0.4 to -0.6 for Indianapolis; Yuan and Bauer [34] similarly found NDVI a strong but seasonally variable predictor of LST in Minneapolis-St Paul; and the global synthesis of Zhou et al. [33] confirms a consistently negative but variable association across cities. Within Nigeria, Koko et al. [27] reported a strong negative LST-NDVI relationship for Abuja, and studies in Lagos and other cities have found the same direction [26]. The particularly high coefficient obtained for Ibadan reflects three factors: the dry-season timing, when senescent and cleared vegetation maximises the thermal contrast between green and non-green surfaces [32]; the use of a whole-population analysis of more than 2.36 million pixels rather than a small sample; and the internal consistency of drawing both variables from the same cloud-masked Level 2 composite. The slope of -18.7 degrees C per unit

NDVI, equivalent to about 1.9 degrees C per 0.1 NDVI, is steeper than the values typically reported for temperate cities and indicates that vegetation loss in Ibadan carries a large thermal penalty. This should be read as evidence of the dominant control of vegetation cover on dry-season surface temperature rather than as sole causation, since surface material, soil moisture, emissivity and built-up density also contribute to the residual 14 percent of unexplained variance [34, 35].

5.4 Land cover controls on surface temperature

The ranking of land cover by temperature, built-up warmest at 39.35 degrees C, then bare land at 38.12 degrees C, then vegetation at 33.60 degrees C, and water coolest at 31.76 degrees C, reproduces the ordering documented across Nigerian and international cities and confirms the physical basis of the heat island. Built-up and bare surfaces absorb and store shortwave radiation and lack the evaporative cooling that vegetation provides, whereas water and dense vegetation remain cool through high heat capacity and evapotranspiration [35, 36]. The same ordering has been reported for Lagos, where built-up and bare surfaces were warmest and wetlands and vegetation coolest [26], and is implicit in the land-use-driven warming documented for Abuja and Enugu [27, 29]. The disproportion is striking: vegetation covers 73.1 percent of the study area, yet the compact 19.3 percent of built-up land generates the significant hot core, illustrating how strongly impervious surfaces dominate the urban thermal environment relative to their extent. The close match between the built-up-to-vegetation contrast of 5.75 degrees C and the zonal SUHI of 5.04 degrees C shows that the land-cover control and the urban-rural contrast are two expressions of the same physical process. The convergence of the land cover ranking, the SUHI intensity, the transect profiles and the LST-NDVI relationship on the same conclusion gives the study strong internal consistency and points directly to vegetation retention and surface materials as the levers for cooling.

5.5 Spatial concentration of surface heat

The hot-spot analysis adds a dimension that a single intensity value cannot convey. Statistically significant heat clustering covered a quarter of the study area (25.1 percent) and was strongly concentrated at the highest confidence level, with 16.2 percent of the area, about 345 square kilometres, in the 99 percent hot class. This indicates an intense, coherent heat core over the built-up centre rather than a diffuse warm zone, while the significant cold clusters (27.7 percent of the area), more evenly graded across confidence levels, occupied the vegetated periphery. Moving from average differences to the statistical organisation of the thermal field follows a growing body of work that applies local spatial autocorrelation statistics, in particular the Getis-Ord G_i^* statistic [24, 25], to urban temperature in order to locate priority zones for intervention. Framing surface heat in terms of significant clusters also connects the results to the local climate zone perspective [12], since the coherent hot core corresponds to the compact built zones of the city centre. The transect profiles reinforce this picture, showing a broad elevated dome

over the core with sharp cool troughs where the transects cross vegetated patches, confirming that the elevated temperatures are spatially concentrated rather than uniform. For Ibadan, this provides planners with a spatially explicit map of where significant heat is concentrated, allowing cooling measures to be targeted at the specific districts that carry the greatest thermal load rather than applied uniformly across the city.

5.6 Limitations

Several limitations should be noted. The analysis rests on a single dry-season composite for one year, so it characterises the current heat pattern rather than its seasonal or multi-year evolution; extending it across seasons and years would place the 2025 pattern in a temporal context. The composite is a cloud-masked median assembled from multiple scenes, so the absolute values are a dry-season representation rather than a single-instant measurement. The thermal band is acquired at 100 m and resampled to 30 m, which limits the detail of fine-scale features such as individual streets. Surface temperature differs from the air temperature that people experience, so the surface heat island described here is related to, but not identical with, thermal comfort at street level [35]. Finally, the land cover classification carries its own uncertainty, reflected in the reported accuracy, which propagates into the zonal statistics by class. These limitations qualify the interpretation but do not affect the main conclusions, which rest on very large pixel populations and are corroborated across several independent measures.

6. Conclusion

Using Landsat thermal data and analysis in ArcGIS Pro, this study characterised the surface urban heat island of Ibadan for the 2025 dry season and quantified its link to vegetation and its spatial clustering. Mean LST was 35.03 degrees C, the urban core was 5.04 degrees C warmer than the rural ring, and LST fell as NDVI rose with a correlation of -0.93 and a slope of -18.7 degrees C per unit NDVI. Statistically significant heat clustering covered a quarter of the study area and was dominated by a high-confidence hot core of about 345 square kilometres over the built-up centre. A locally trained land cover classification confirmed the surface control on temperature, with built-up and bare land the warmest classes and vegetation and water the coolest, a built-up to vegetation contrast of 5.75 degrees C. These findings reproduce the patterns established in the wider urban climate literature and in earlier Nigerian studies, and they give planners a clear, spatially explicit basis for targeting cooling interventions. Future work should extend the analysis across seasons and years, add a locally trained land cover breakdown of temperature, and relate surface temperature to air temperature and to population exposure.

7. Recommendations

The following recommendations follow directly from the specific findings of this study and are directed at urban planning and environmental management in Ibadan.

(1) Because built-up land was the warmest class at 39.35 degrees C and the 99 percent hot cluster covers about 345 square kilometres over the city centre, tree planting and green infrastructure should be concentrated first within that mapped hot core, where the thermal penalty and the cooling opportunity are greatest.

(2) Given the steep vegetation-cooling gradient, a fall of about 1.9 degrees C for every 0.1 rise in NDVI, even modest increases in green cover within the built-up core would yield measurable temperature reductions, so greening targets should be set in NDVI terms and monitored.

(3) Because bare land was almost as warm as built-up (38.12 degrees C), exposed and cleared surfaces should be revegetated or shaded rather than left open, and land clearing ahead of development should be minimised and kept brief.

(4) Since water and dense vegetation formed the coolest surfaces and the significant cold clusters at the periphery, existing water bodies and peri-urban vegetation should be protected from conversion, preserving the natural cooling reservoir that moderates the wider study area.

(5) Cool or reflective roofing and paving standards should be adopted in new development within the identified hot zones to reduce heat storage in the impervious surfaces that drive the 5 degree heat island.

(6) The land surface temperature and Getis-Ord hot-spot maps should be integrated into the city's land use planning and a heat-health early warning system, with priority given to densely populated, low-income neighbourhoods that fall within the significant hot clusters and combine high heat with low green cover.

(7) Monitoring should be extended across seasons and years and linked to air temperature and population exposure, so that the health burden of urban heat and the effect of interventions can be tracked over time.

Statements and Declarations

Funding

The authors declare that no funds, grants, or other support were received during the preparation of this manuscript.

Competing Interests

The authors have no relevant financial or non-financial interests to disclose.

Ethics, Consent to Participate, and Consent to Publish declarations: not applicable.

Author Contributions

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by Temitope Waheeb, Opeoluwa Odeleye and Adewale Adeyefa. The first draft of the manuscript was written by Opeoluwa Odeleye and Temitope Waheeb and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Data Availability

The Landsat Collection 2 Level 2 data used in this study are openly available from the United States Geological Survey. The derived datasets generated during the analysis are available from the corresponding author on reasonable request.

References

1. Waheeb T, Adeyefa A, Oguntinyinbo O. Pattern of air pollutants and land surface temperature in Nigeria using space-time pattern mining techniques. *Theoretical and Applied Climatology*. 2026. <https://doi.org/10.1007/s00704-026-06507-1>
2. Shen P, Zhao S, Ma Y, Liu S. Urbanization-induced Earth's surface energy alteration and warming: a global spatiotemporal analysis. *Remote Sensing of Environment*. 2023;284:113361. <https://doi.org/10.1016/j.rse.2022.113361>
3. Li L, Zhan W, Hu L, Chakraborty TC, Wang Z, Fu P, et al. Divergent urbanization-induced impacts on global surface urban heat island trends since 1980s. *Remote Sensing of Environment*. 2023;295:113650. <https://doi.org/10.1016/j.rse.2023.113650>
4. Liu Z, Zhan W, Bechtel B, Voogt JA, Lai J, Chakraborty T, et al. Surface warming in global cities is substantially more rapid than in rural background areas. *Communications Earth & Environment*. 2022;3:219. <https://doi.org/10.1038/s43247-022-00539-x>
5. Patel S, Indraganti M, Jawarneh RN. A comprehensive systematic review: impact of land use/land cover (LULC) on land surface temperatures (LST) and outdoor thermal comfort. *Building and Environment*. 2024;249:111130. <https://doi.org/10.1016/j.buildenv.2023.111130>
6. Eneche PSU, Atun F, Zeng Y, Pfeffer K. Robust drivers of urban land surface temperature dynamics across diverse landscape characters: an augmented systematic literature review. *Ecological Indicators*. 2024;163:112056. <https://doi.org/10.1016/j.ecolind.2024.112056>
7. Du H, Zhan W, Voogt JA, Lai J, Liu Z, Bechtel B, et al. Contrasting trends and drivers of global surface and canopy urban heat islands. *Geophysical Research Letters*. 2023;50(15):e2023GL104661. <https://doi.org/10.1029/2023GL104661>

8. Mishra V, Kumar P, et al. Remote sensing for urban heat island research: progress, current issues, and perspectives. *Remote Sensing Applications: Society and Environment*. 2024;33:101081. <https://doi.org/10.1016/j.rsase.2023.101081>
9. Li Z, Li ZL, Zhang Z, Liu Q, et al. Satellite remote sensing of global land surface temperature: definition, methods, products, and applications. *Reviews of Geophysics*. 2023;61(3):e2022RG000777. <https://doi.org/10.1029/2022RG000777>
10. Diem NK, Diem PK, Thien PM, Downes NK. Monitoring urban heat island spatial variability over urban structure types: a case study from a fast-growing city in the Vietnamese Mekong Delta. *IOP Conference Series: Earth and Environmental Science*. 2024;1345:012001. <https://doi.org/10.1088/1755-1315/1345/1/012001>
11. Yuan B, Li X, Zhou L, Bai T, Hu T, Huang J, et al. Global distinct variations of surface urban heat islands in inter- and intra-cities revealed by local climate zones and seamless daily land surface temperature data. *ISPRS Journal of Photogrammetry and Remote Sensing*. 2023;203:1-15. <https://doi.org/10.1016/j.isprsjprs.2023.08.012>
12. Stewart ID, Oke TR. Local climate zones for urban temperature studies. *Bulletin of the American Meteorological Society*. 2012;93(12):1879-1900. <https://doi.org/10.1175/BAMS-D-11-00019.1>
13. Intergovernmental Panel on Climate Change. *Climate change 2022: impacts, adaptation and vulnerability*. Cambridge: Cambridge University Press; 2022. <https://doi.org/10.1017/9781009325844>
14. Fashae OA, Adagbasa EG, Olusola AO, Obateru RO. Land use/land cover change and land surface temperature of Ibadan and environs, Nigeria. *Environmental Monitoring and Assessment*. 2020;192(2):1-18.
15. Oni F, Ibeabuchi U. Mapping urban heat island areas in Ibadan. *Journal of Management and Service Science*. 2023;3(2):1-15. <https://doi.org/10.54060/jmss.2023.25>
16. Kasim O, Agbola S, Oweniwe M. Land use land cover change and land surface emissivity in Ibadan, Nigeria. *Town and Regional Planning*. 2020;77:71-88. <https://doi.org/10.18820/2415-0495/trp77i1.6>
17. Ikuemonisan FE, Kayode YO, Ogunjo ST, Odubote OB, Okedeyi SA. Modeling heatwave trends from land cover dynamics using satellite observations and machine learning in Ibadan, Nigeria. *Discover Geoscience*. 2025;3:254. <https://doi.org/10.1007/s44288-025-00361-w>
18. Njoku EA, Tenenbaum DE. Quantitative assessment of the relationship between land use/land cover (LULC), topographic elevation and land surface temperature (LST) in Ilorin, Nigeria. *Remote Sensing Applications: Society and Environment*. 2022;27:100780. <https://doi.org/10.1016/j.rsase.2022.100780>
19. Earth Resources Observation and Science (EROS) Center. *Landsat 8-9 Operational Land Imager/Thermal Infrared Sensor Level-2, Collection 2 [dataset]*. Sioux Falls: U.S. Geological Survey; 2020. <https://doi.org/10.5066/P9OGBGM6>

20. Gorelick N, Hancher M, Dixon M, Ilyushchenko S, Thau D, Moore R. Google Earth Engine: planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*. 2017;202:18-27.
21. Jimenez-Munoz JC, Sobrino JA. A generalized single-channel method for retrieving land surface temperature from remote sensing data. *Journal of Geophysical Research*. 2003;108(D22):4688.
22. Sobrino JA, Jimenez-Munoz JC, Paolini L. Land surface temperature retrieval from LANDSAT TM 5. *Remote Sensing of Environment*. 2004;90(4):434-440.
23. Weng Q, Lu D, Schubring J. Estimation of land surface temperature-vegetation abundance relationship for urban heat island studies. *Remote Sensing of Environment*. 2004;89(4):467-483.
24. Getis A, Ord JK. The analysis of spatial association by use of distance statistics. *Geographical Analysis*. 1992;24(3):189-206.
25. Ord JK, Getis A. Local spatial autocorrelation statistics: distributional issues and an application. *Geographical Analysis*. 1995;27(4):286-306.
26. Obiefuna JN, Nwilo PC, Okolie CJ, Emmanuel EI, Daramola OE. Dynamics of land surface temperature in response to land cover changes in Lagos metropolis. *Nigerian Journal of Environmental Sciences and Technology*. 2018;2(2):148-159.
27. Koko AF, Yue W, Abubakar GA, Alabsi AAN, Hamed R. 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*. 2021;10(5):272.
28. Isioye OA, Ikwueze H, Akomolafe E. Urban heat island effects and thermal comfort in Abuja Municipal Area Council of Nigeria. *Ghana Journal of Geography*. 2020;12(1):130-157.
29. Adinna ENI, Enete IC, Okolie AT. Assessment of urban heat island and possible adaptations in Enugu urban using Landsat-ETM. *Journal of Geography and Regional Planning*. 2009;2(2):30-36.
30. Imhoff ML, Zhang P, Wolfe RE, Bounoua L. Remote sensing of the urban heat island effect across biomes in the continental USA. *Remote Sensing of Environment*. 2010;114(3):504-513.
31. Peng S, Piao S, Ciais P, Friedlingstein P, Ottle C, Breon FM, et al. Surface urban heat island across 419 global big cities. *Environmental Science & Technology*. 2012;46(2):696-703.
32. Weng Q. Thermal infrared remote sensing for urban climate and environmental studies: methods, applications, and trends. *ISPRS Journal of Photogrammetry and Remote Sensing*. 2009;64(4):335-344.
33. Zhou D, Xiao J, Bonafoni S, Berger C, Deilami K, Zhou Y, et al. Satellite remote sensing of surface urban heat islands: progress, challenges, and perspectives. *Remote Sensing*. 2019;11(1):48.

34. Yuan F, Bauer ME. Comparison of impervious surface area and normalized difference vegetation index as indicators of surface urban heat island effects in Landsat imagery. *Remote Sensing of Environment*. 2007;106(3):375-386.
35. Voogt JA, Oke TR. Thermal remote sensing of urban climates. *Remote Sensing of Environment*. 2003;86(3):370-384.
36. Oke TR. The energetic basis of the urban heat island. *Quarterly Journal of the Royal Meteorological Society*. 1982;108(455):1-24.