OPEN ACCESS

Global Academic Journal of Agriculture and Bio sciences

Available online at https://www.gajrc.com
DOI: https://doi.org/10.36348/gajab.2026.v08i02.001

ISSN:2706-8978 (P)
ISSN: 2707-2568 (O)

Original Research Article

Evaluating the Impact of Land Use Change on Urban Heat Island Intensity in Ikeja Lago, Nigeria through Multi-Temporal LST Data and GIS-Based Modeling

Onuegbu F.E[1*], Ogbaa S. I[2], Kalu A.O[2], Nwodo G. O[3], Nwafor K.O[1], Nwobi C.J[1], Ugwu O. J[4], Nwankwo S. I[5], Abdulmumin A. L[2], Duruanyim H.I[2], Babatunde O. R[2], Nkemdirim A.E[1], Uzoho M.C[1], Obike S.C[1]

[1]Department of Urban and Regional Planning, Abia State University, Uturu, Nigeria
[2]Department of Urban and Regional Planning, Federal University of Technology, Owerri, Nigeria
[3]Department of Geomatics, University of Benin, Nigeria
[4]Department of Surveying and Geoinformatics, School of Environmental Sciences, Federal University of Technology Owerri, Nigeria
[5]Department of Architecture, School of Environmental Sciences, Federal University of Technology Owerri, Nigeria

***Corresponding Author**
Onuegbu F.E
Department of Urban and Regional Planning, Abia State University, Uturu, Nigeria

Article History
Received: 21.01.2026
Accepted: 16.03.2026
Published: 24.03.2026

Abstract: Rapid urbanization in sub-Saharan Africa is rapidly transforming land use and land cover (LULC) in a way that has enormous implications for both local climate and human well-being. This paper measures the spatiotemporal dynamics of LULC changes and its effect on land surface temperature (LST) and Urban Heat Island (UHI) strength in Ikeja, Lagos, Nigeria, the administrative capital of Africa's largest megacity, over a ten-year period (2015–2025). Multi-temporal Landsat-8 and Landsat-9 imagery was classified using the Random Forest algorithm (overall accuracy: 91.4-93.2%) while LST was derived from the thermal band. Post classification change detection and transition-specific thermal analysis was integrated to ascertain the amount of warming attributable to individual LULC conversion. Results show a dramatic transformation of landscape: built-up area increased 44.7% (1,980–2,865 ha) while vegetation decreased 54.9% (1,256–567 ha). The area of water bodies decreased 41.6% (154 to 90 ha). The mean LST also increased 1.6°C (39.9°C to 41.5°C) with maximum values in 2025 exceeding 46.6°C, 8 times the global background warming rate. Vegetation-to-built-up conversions were the most significant contributors (+4.2°C) to warming, 2.6°C above background rates, followed by buildings, roads and impervious surfaces (+3.0°C), then the vegetation transition (+2.3°C). Attribution analysis shows that 85.3% of the total warming effect attributable to the loss of vegetation in urban areas. A critical cooling threshold was determined at 25% vegetation cover, and 12.7% of the study region now exceeds this threshold. Heat islands tended to remain strong in industrial, transport and commercial areas. This work offers the first-ever empirical estimate of transition-specific thermal impacts within a West African city, establishing that the loss of vegetation is the leading driver of UHI intensification. Vigilant and focused policy intervention, such as preservation of green space, targeted greening of hot spots and incorporation of heat stress criteria into the planning of cities, is needed to address dangerous warming and increase climate tolerance in the rapidly urbanizing tropical cities.

Keywords: Land Use Change, Land Surface Temperature, Remote Sensing, GIS, Ikeja Lagos Nigeria.

Citation: Onuegbu F.E *et al* (2026). Evaluating the Impact of Land Use Change on Urban Heat Island Intensity in Ikeja Lago, Nigeria through Multi-Temporal LST Data and GIS-Based Modeling, Glob Acad J Agri Biosci; Vol-8, Iss- 2 pp- 10-24.

INTRODUCTION

Rapid urbanization is one of the defining characteristics of the Anthropocene and is driving large scale transformations in land use and land cover (LULC) around the world. Substituting natural, permeable surfaces with impervious materials like asphalt and concrete alters surface energy balance, biogeochemical cycles and microclimate (Kalnay & Cai, 2003). Among the best known and most important is the Urban Heat Island (UHI) effect whereby urban areas have greater surface and air temperatures than the rural hinterland (Oke, 1982). The UHI effect also intensifies health risks related to heat, increases the use of energy for cooling, degrades water quality, and reduces the livability of cities. For this reason, understanding it is a high priority for sustainable planning in urban areas, especially in the Global South (Patz *et al*., 2005). Due to high urban growth, Africa is currently in the middle of urbanization, and the continent is witnessing the rapid expansion of cities. For instance, Lagos in Nigeria is a good case study in rapid urbanization. With Lagos being among the fastest-growing megacities in the world, the city is under immense pressure on its available land resources, which are rapidly being converted to high-density urbanized landscapes (Adelekan, 2010). Although the macroscale UHI effect of Lagos has been established, there is an absence of detailed and multitemporal studies linking the spatial configuration of LULC change to the extent of the thermal response down to the local government area level. In particular, the city of Ikeja in Lagos State, which is the state capital, and a commercial and industrial nerve center, has been grossly transformed and the micro-climatic effects of this land use change have not been well quantified.

Medium resolution satellite imagery, especially Landsat archive, and Geographic Information System (GIS)-based modeling offer an effective methodology for retrospective and continuous monitoring of LULC dynamics and LST (Weng, 2009). With the help of multi-temporal satellite data, the way in which changes occur can be studied instead of merely having two dates for comparison. Such an investigation is crucial for evidence-based policy-making to address heat stress and build climate-resilient urban environments.

The research gap is bridged in this study through a comprehensive and spatial investigation to understand the influence of LULC transformation on the development of UHI in Ikeja, Lagos, within ten years (2015–2025). In this work, we are going to use multi-temporal Landsat images to: (i) delineate and measure LULC and LST changes over 2015, 2020, and 2025; (ii) examine a specific area and apply it in order to reveal the significant land cover conversion processes and proportions and (iii) specifically estimate how different types of land cover and their transitions can be related to the subsequent LST distribution. Combining these data sources, the study generates valuable quantitative information regarding the thermal landscape modification due to various urbanization trajectories in a major Nigerian city that is highly relevant to both urban planners and policymakers for informed decision-making toward sustainable and heat-resilient cities in the future.

METHODOLOGY

Study Area

Ikeja is the capital of Lagos State and is one of the 20 Local Government Areas (LGAs) of Lagos state, Nigeria. The geographical location of Ikeja is bounded by longitude 6° 34’60” N to 6° 37’30” N and latitude 3° 19’30” E to 3° 22’30” E and has a total land area of about 45.48 km^2 (4,548 ha) as used during the analysis. It houses the state government secretariat and other corporate headquarters as well as some of the state’s major industries (Salami *et al*., 2025). It is an administrative, commercial and industrial centre in Lagos State. Ikeja experiences a tropical monsoon climate under the West African tropical monsoon climate (Am) in the Köppen-Geiger scheme, being dominated by the moist maritime southwest monsoon air mass and the dry continental northeast trade winds. Due to the dominance of these air masses, the region experiences a wet and a dry season with an average annual rainfall of about 1500mm - 2000mm, and the bulk of this rainfall is confined to March to October (Adelekan, 2023). Mean annual temperatures are usually between 25°C - 32°C, and the highest temperatures are usually experienced in the late dry season (January - March) when solar insolation is highest and when evaporation is low due to less vegetation cover (Sulaiman *et al*., 2025).

Geographically, Ikeja is a low-lying area with an altitude of about 5 meters to 30 meters above sea level. The area is made up of Quaternary coastal plain sands and the recent alluvial deposits which support well-drained soils that are good for the old vegetation type which was the tropical rainforest (Ibrahim *et al*., 2024). This region has experienced a drastic change due to decades of urbanization, as the remnant vegetation can only be found within institution estates, undeveloped lands, and drainage areas. Ikeja was chosen as the study area for the following three reasons: First, it is an administratively and economically vibrant center of rapid urbanization that represents the land use pressures that are typical of Nigerian cities. Second, it has a limited extent of administration, making it easier to do space analysis on a scale that is locally appropriate. Third, there are preliminary findings of extreme heat, with recorded ground temperatures over 40°C in the peak (Salami *et al*., 2025), and thus, the need to conduct an analysis of its causes.

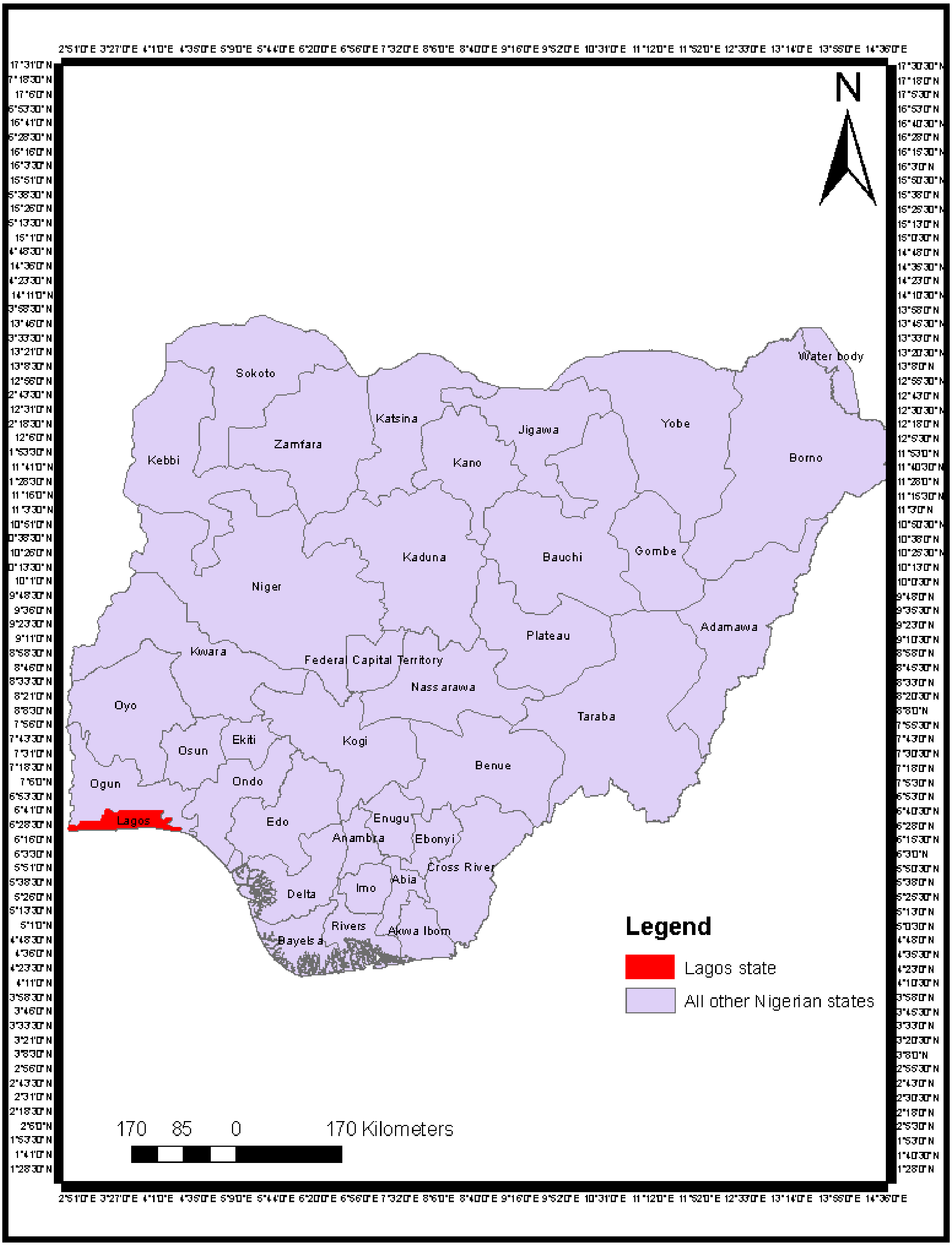

Figure 1: Map of Nigeria Showing Lagos State

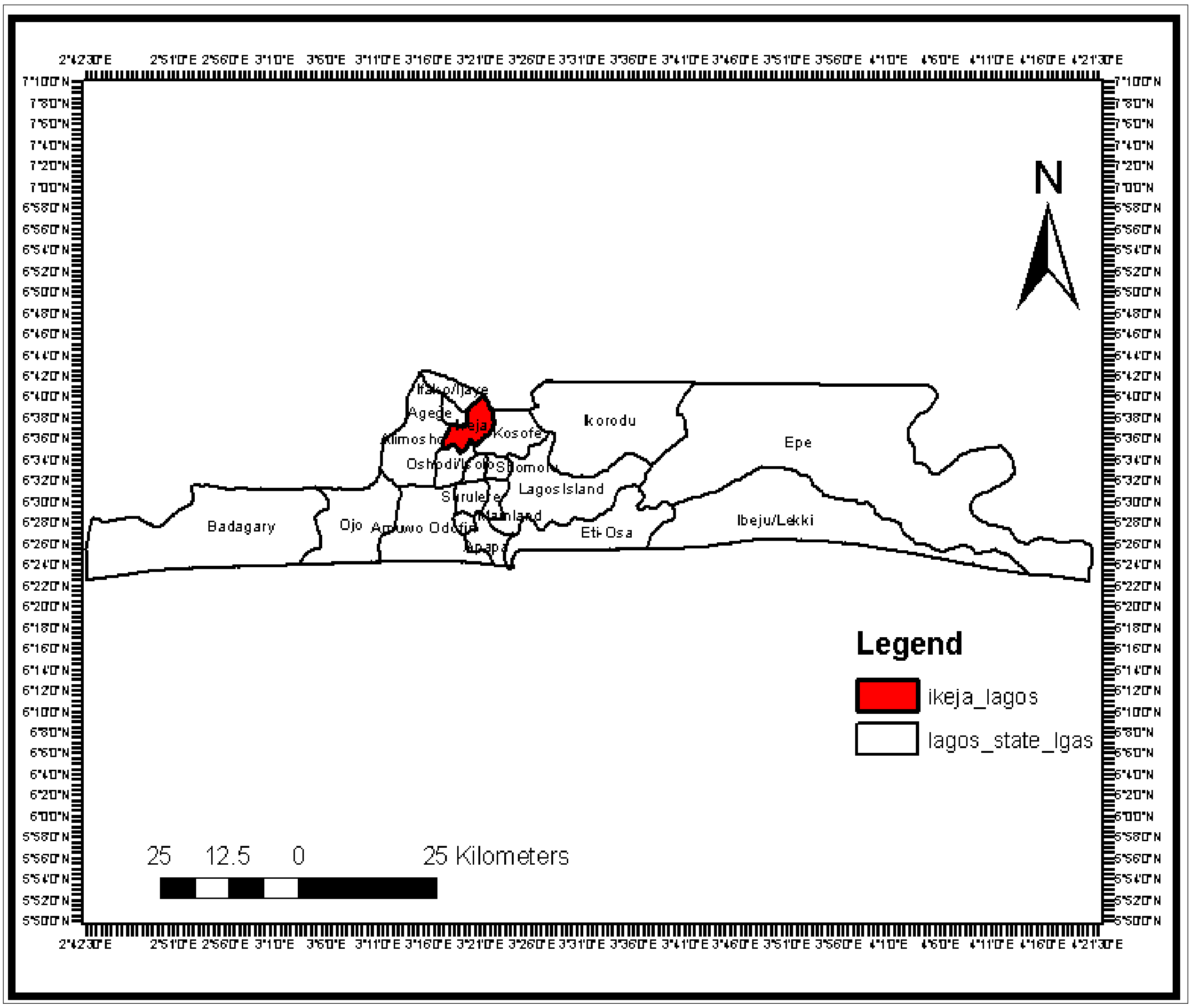

Figure 2: Map of Lagos State Showing Ikeja

Data Acquisition and Satellite Imagery

Multi-temporal satellite images of Landsat series are used to collect LULC classification and LSTs at three intervals: 2015, 2020, and 2025. Landsat imagery was chosen due to its best compromise of spatial resolution (30 m for optical, 30 m resampled for thermal), time depth (archive since 1984), and radiometric homogeneity and was therefore the most commonly used data source at the local scale of the urban climate study (Weng, 2009; Mustafa *et al*., 2024). The Landsat-8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) acquired images used in 2015 and 2020, and Landsat-9 OLI-2 and TIRS-2 acquired images in 2025. Purwoko *et al*., (2025) argues that, in order to maintain the consistency of spectral and spatial characteristics of different sensors, the study chose to select Landsat-8 images for the two earlier periods and Landsat-9 images for the later period. All images used in this study were obtained from the United States Geological Survey (USGS) Earth Explorer platform via Collection 2 Level-2 Science Products: the atmospherically corrected surface reflectance and surface temperature. It minimizes the amount of pre-processing and guarantees that the images are comparable across the dates.

Table 1: Satellite data specifications and acquisition parameters

Parameter	2015	2020	2025
Satellite/Sensor	Landsat-8 OLI/TIRS	Landsat-8 OLI/TIRS	Landsat-9 OLI-2/TIRS-2
Path/Row	191/55	191/55	191/55
Acquisition Date	15 February 2015	18 February 2020	22 February 2025
Cloud Cover (%)	2.3	3.1	1.8
Spatial Resolution	30 m (multispectral), 30 m (thermal)	30 m (multispectral), 30 m (thermal)	30 m (multispectral), 30 m (thermal)

Parameter	2015	2020	2025
Radiometric Resolution	16-bit	16-bit	16-bit
Source	USGS EarthExplorer	USGS EarthExplorer	USGS EarthExplorer

February acquisition dates were chosen to provide a temporal match and ensure dry season conditions with minimal cloud cover and maximum thermal contrast between LULC classes (Zhang *et al*., 2023). The application of anniversary dates (+/- 3 days) also reduces phenology-related variations in the vegetation and seasonal disparities in solar geometry, which means that any changes seen are attributable to land cover change and not seasonal variation (Liu *et al*., 2024).

Image Pre-Processing

Collection 2 Level-2 products are atmospherically corrected; nevertheless, extra pre-processing was carried out to guarantee maximum data quality for the region of interest. All the images were re-projected to Universal Transverse Mercator (UTM) Zone 31 North, World Geodetic System 1984 (WGS84) datum in order to spatially align with the provided vector data. Subsetting was conducted on the administrative limit of Ikeja LGA, thus the study area boundary (4,548 ha). Cloud and cloud shadow masking was applied based on the pixel quality assurance (QA) band included in each Landsat Collection 2 product. All pixels labeled as cloud, cloud shadow, or cirrus were not used in the further calculations, while the selected images had the minimum cloud cover (2.3%, 3.1%, and 1.8% for 2015, 2020, and 2025, respectively), which led to a full cover of the study location after masking. No radiometric normalization was necessary to perform the primary analysis, as the Collection 2 Level-2 products were prepared to the consistent surface reflectance scale and surface temperature scale. Nonetheless, multi-date images were co-registered in order to apply a change detection, whereby the multi-date images were co-registered using an automated image-to-image registration technique and RMSE.

Land Use and Land Cover Classification
Classification Scheme

A four-class LULC classification scheme was used based on the International Geosphere-Biosphere Programme (IGBP) classification system, but with modifications to suit the local landscape of the study area. They were: Built-up: areas dominated by impervious surfaces, such as residential, commercial, and industrial buildings, as well as transportation infrastructure and other man-made features. Vegetation: covered by vegetation; areas with forest remnants, urban green spaces, shrubs and grasslands. Bare Surface: bare soil, sand or other non-vegetated, non-impervious surfaces, such as a construction site and undeveloped plots. Water Bodies: open water bodies like rivers, streams, lagoons, and man-made drainages. A four-class scheme was chosen, which provides both thematic richness and good classification accuracy according to the study area (Odunsi *et al*., 2023). This choice is within the norm of mapping urban LULC in data-scarce areas. 3.4.2 Classification Algorithm the classification procedure used here is a Supervised classification with Random Forest (RF) algorithm for each date. Random Forest was chosen because, as research has established, it is a superior classifier for urban LULC, especially in heterogeneous landscapes, than the conventional maximum likelihood classifier because of its ability to account for non-linearities and avoid overfitting through an ensemble learning technique (Belgiu & Drăguţ, 2016; Mustafa *et al*., 2024).

To obtain training samples, high-resolution imagery from Google Earth Pro was used for every year, and field information about the study region was taken into account. As many as 100 pixels were chosen as training samples in each class and distributed throughout the study area to sample the intra-class spectral variability. They were partitioned into training (70%) and validation (30%) subsets to give independent accuracy estimation. RF was built using 500 trees (ntree = 500) and the square root of the number of input variables as the optimal number of features at each split (mtry = √p, where p is the number of spectral bands). The classification was trained with all available spectral bands (Bands 2–7 for OLI/OLI-2), and the spectral indices such as the Normalized Difference Vegetation Index (NDVI) and Normalized Difference Built-up Index (NDBI) that have been useful in differentiating vegetated and impervious surfaces (Guha *et al*., 2022; Ahuja & Soni, 2025). Classification accuracy was assessed by means of error matrices (confusion matrices) built upon the independent validation samples (30% of training data). Overall accuracy, producer's accuracy (omission error), user's accuracy (commission error) and the Kappa coefficient were calculated in reference to the results of classifications of all years, in accordance with the standard procedure (Congalton & Green, 2019). Kappa coefficient is a more objective measure of classification accuracy which takes into account random agreement.

Table 2: Classification accuracy assessment results

Year	Overall Accuracy (%)	Kappa Coefficient
2015	91.4	0.88
2020	92.6	0.90
2025	93.2	0.91

All classifications exceeded the recommended minimum accuracy threshold of 85% (Anderson *et al.,* 1976), confirming their suitability for subsequent change detection analysis.

Change Detection Analysis

Post-Classification Comparison

The most commonly used change detection method is post-classification comparison, which gives "from-to" change information with minimal impact on atmospheric conditions and sensor calibration differences between the dates (Jensen, 2016). The classified LULC maps of the year 2015, 2020, and 2025 were fed as inputs in a change detection matrix that would help determine the transition of the four classes of LULC during the given study period. The change detection analysis was carried out over two time periods (2015–2020, 2020–2025) and an overall assessment for the full period (2015–2025) was performed. The following is the cross-tabulation table of the LULC change across the two time periods: rows present LULC classes at initial time point (2015) and columns present LULC classes at final time point (2020), and cell entries indicate hectares (hectares) of LULC changing between class i to class j.

The net change, the swap change and the total change were determined for each of the LULC classes according to the method of Pontius *et al*., (2004). The net change is the absolute change in class extent between dates. The swap change is a measure of the gain and loss of the same class in space. Total change is a sum of net change and swap change and is a measure that gives a complete picture of the landscape change. The annual change rate was computed based on the following formula: r=(A2A1)1t−1r=(A1A2)t1−1 where r- the annual rate of change, A_1 - area at the beginning of the period, A_2 - area at the end of the period and t - the time interval in years (Puyravaud, 2003).

Transition Matrices

To elaborate on this, a comprehensive transition matrix was built for the 2015–2025 period and the specific transitions were quantified and measured between all LULC classes (e.g., Vegetation to Built-up, Bare Surface to Built-up, Vegetation to Bare Surface). The resulting matrix showed information about the dynamics of landscape transformation and also helped in the determination of the most critical change processes that would be driving the urbanization process in Ikeja.

Land Surface Temperature Retrieval

Temperature Data Extraction

The LST was obtained from the Landsat-8 and Landsat-9 Collection 2 Level-2 surface temperature products in thermal bands. The Band 10 (10.6–11.2 μm) of Landsat-8 and the TIRS-2 band 10 were applied in Landsat-9. The Collection 2 Level-2 surface temperature products are generated from the Single Channel algorithm applied to top-of-atmosphere thermal infrared information and atmospheric correction based on MODIS atmospheric profile products (USGS, 2023). The surface temperature values (stored in Kelvin and scaled by 10) were further transformed to degrees Celsius by the formula:

T(°C)= (DN×0.00341802+149.0)−273.15T(°C)
= (DN×0.00341802+149.0)−273.15

Where:

T(°C) = Land Surface Temperature in degrees Celsius

DN = Digital Number value from the thermal band (Band 10 for Landsat 8 and Landsat 9)

0.00341802 = Radiance scaling factor (multiplicative scale)

149.0 = Radiance scaling factor (additive offset)

273.15 = Conversion factor from Kelvin to Celsius

For every study year (2015, 2020, 2025) descriptive statistics (minimum, maximum, mean, standard deviation of LST) were computed for the entire study area. These statistics describe thermal conditions and are used to describe temporal trends in surface temperature over the years. In order to identify the linkages between LULC and LST, zonal statistics were also taken in each LULC class. The mean LST in each class was subsequently determined, allowing us to compare the thermal signature between land cover classes. Besides, LST maps were created to show the distribution of surface temperatures and hot spots corresponding to different LULC categories. The change in temperature between the two study periods was also computed: ΔT=Tt2−Tt1.

Where: Tt_1 and Tt_2 are LST at the initial and subsequent time points, respectively. It was conducted on the study area aggregate and the LULC class levels separately so that the warming rate for each land use class was determined.

Combining LULC Change and LST Trends

LULC Transition-Specific Thermal Analysis

One contribution of the presented approach is the combination of the change detection results and

LST to estimate the thermal impact of particular LULC changes. The LST change corresponding to each pixel classified as undergoing a certain transition (e.g., Vegetation to Built-up in the period between 2015 and 2020) was computed. This helps identify the contributions made to the rise in temperature by individual changes in the land cover (Liu *et al*., 2024). Transformation specific thermal analysis:

1. Pixels of all the categories of transition were determined using the change detection matrix.
2. The LST values for those pixels at the two time points were extracted.
3. The mean temperature change was then computed per transition category.
4. Temperature changes between the different transition categories were statistically compared using an analysis of variance (ANOVA) with a post-hoc Tukey test.

Correlation Analysis

Transformation Suitability Test

The interaction between LULC composition and LST was evaluated at several spatial scales. Firstly, the relationship between spectral indices (NDVI, NDBI) and LST at the pixel level was determined for each year, as described previously (Guha *et al*., 2022; Ahuja & Soni, 2025). Subsequently, a cell-based method was performed through discretization of the research region into 500 m × 500 m cells, where the percentage of each LULC class and the mean LST within the cell were determined. Lastly, the Pearson correlation coefficients were used to measure the association between land use and land cover composition and landscape temperature conditions at the landscape level.

Software and Tools

All image pre-processing, classification, change detection and LST analysis have been carried out through a mix of different software platforms that were used in combination to harness their individual benefits: · Google Earth Engine (GEE): Used for preliminary data filtering as well as masking clouds and rapid calculation of spectral indices, due to cloud based data processing that can handle large-scale geospatial studies (Gorelick *et al*., 2017). · ARCGIS Pro : Used to collect training samples, assess accuracy, prepare and visualize maps, taking advantage of its numerous plugins and cartographic power. · R Statistical Software (Version 4.3.2): Utilized for statistical testing such as ANOVA, correlation and identification of hotspots, and utilizing various packages to handle spatial data and create visualizations (R Core Team, 2024). Microsoft Excel: Used to compile statistics on areas, change detection matrices, and descriptive summaries. All statistical analyses were carried out using SPSS 23 (IBM) software. The results are summarized in tabular and descriptive forms (frequencies and percentages).

Limitations and Assumptions

Several methodological limitations should be acknowledged. The first one is that three distinct time points (2015, 2020, and 2025) are used, so it is possible that the dynamics between years are lost. Second, due to the spatial resolution of 30 m of Landsat imagery, there is a possibility of mixed pixels in areas of cities with complex structure. Third, there are no in-situ meteorological measurements on which to validate the satellite-derived LST; however, the Collection 2 Level-2 product has been extensively validated (USGS, 2023). Fourth, the study period encompasses the COVID-19 pandemic (2020–2021), during which abnormal patterns in land use and thermal behaviour may have arisen. Although they do have these limitations, the approaches that were adopted here represent current best practice on the scale being evaluated (local) and provide a solid basis on which to generate more policy relevant insights in regards to how urbanisation is creating a relationship between heat and environment in Ikeja, Lagos.

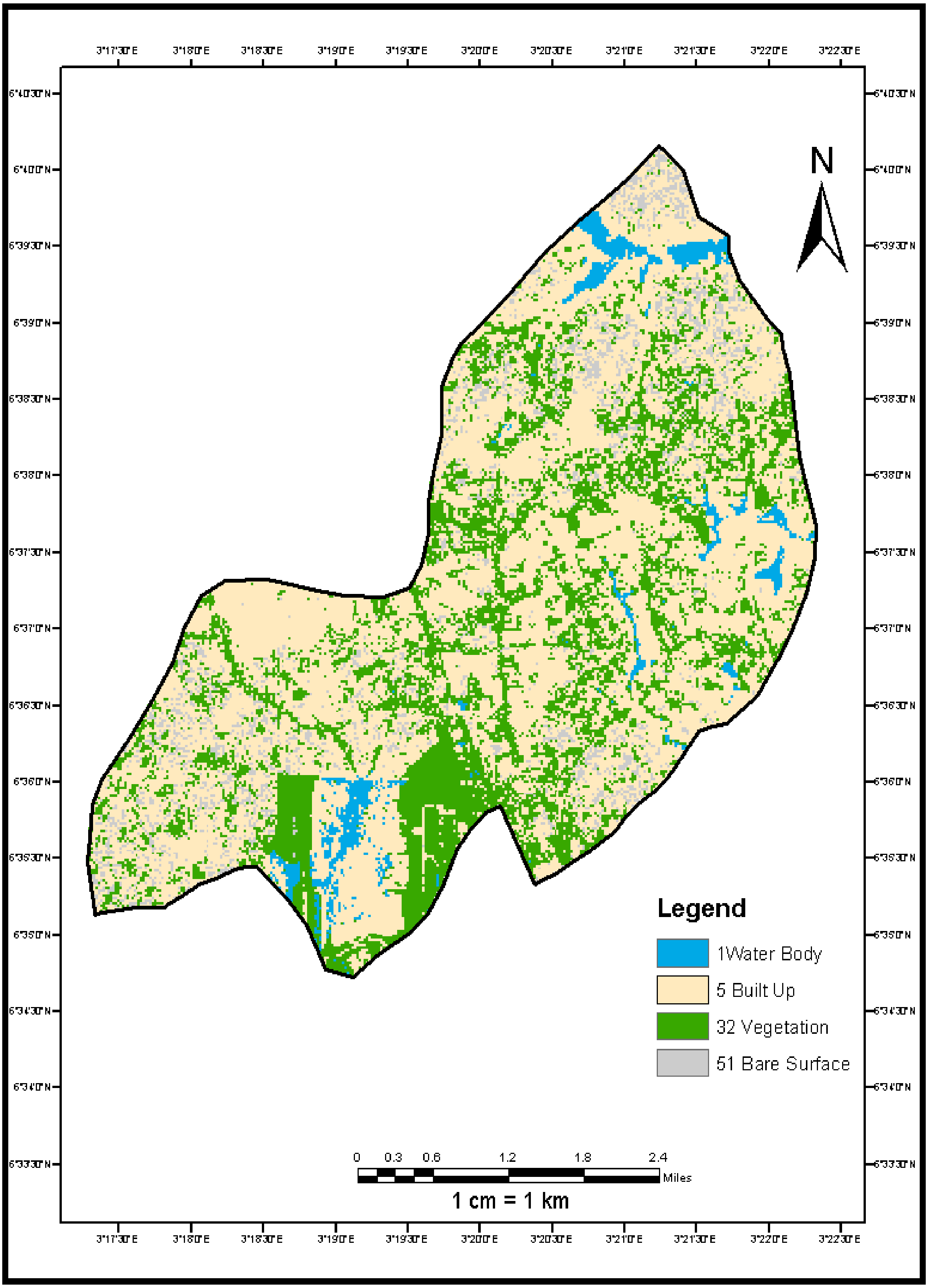

Figure 3: LULC of Ikeja Lagos 2015

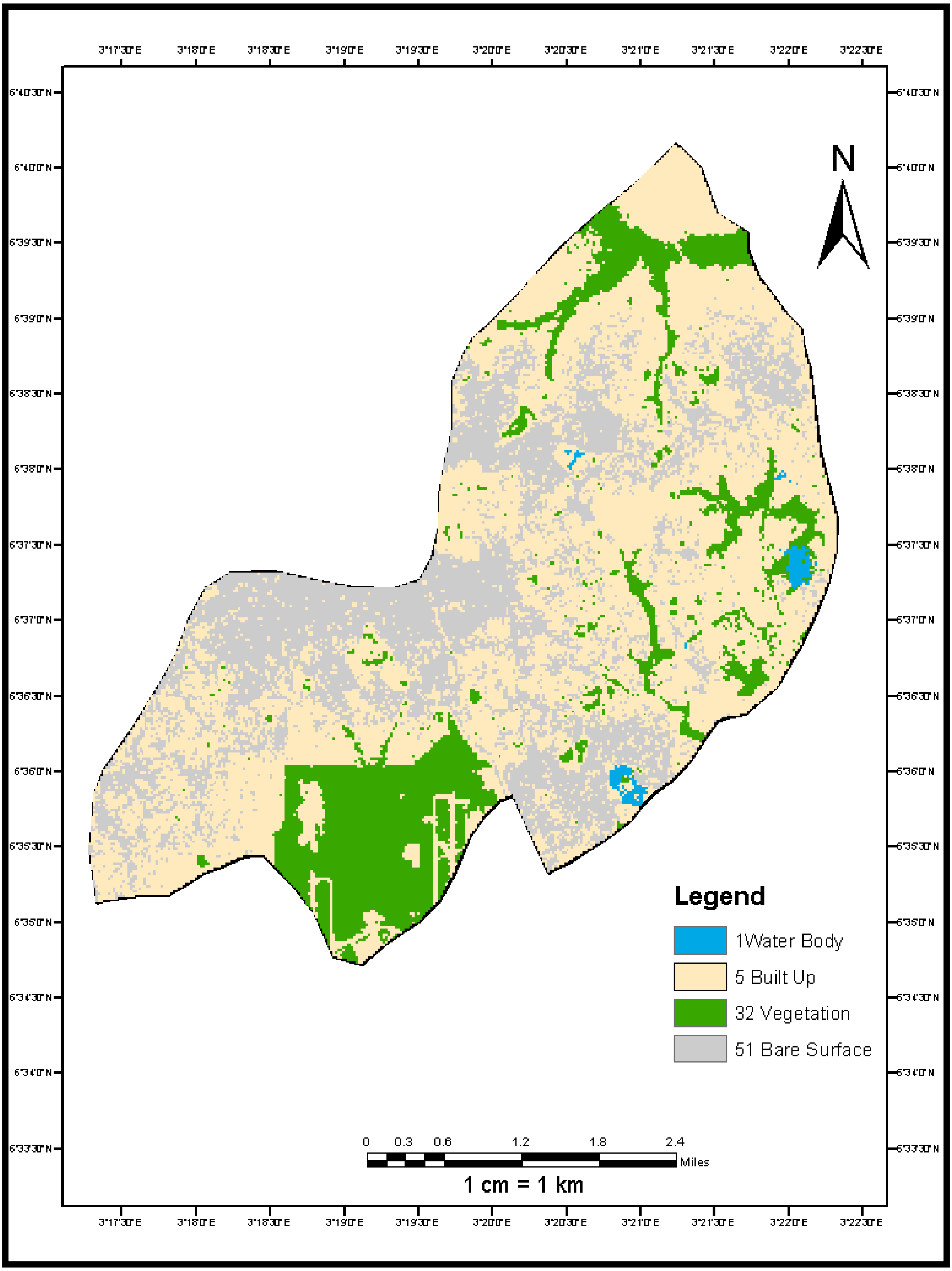

Figure 4: LULC Map of Ikeja Lagos 2020

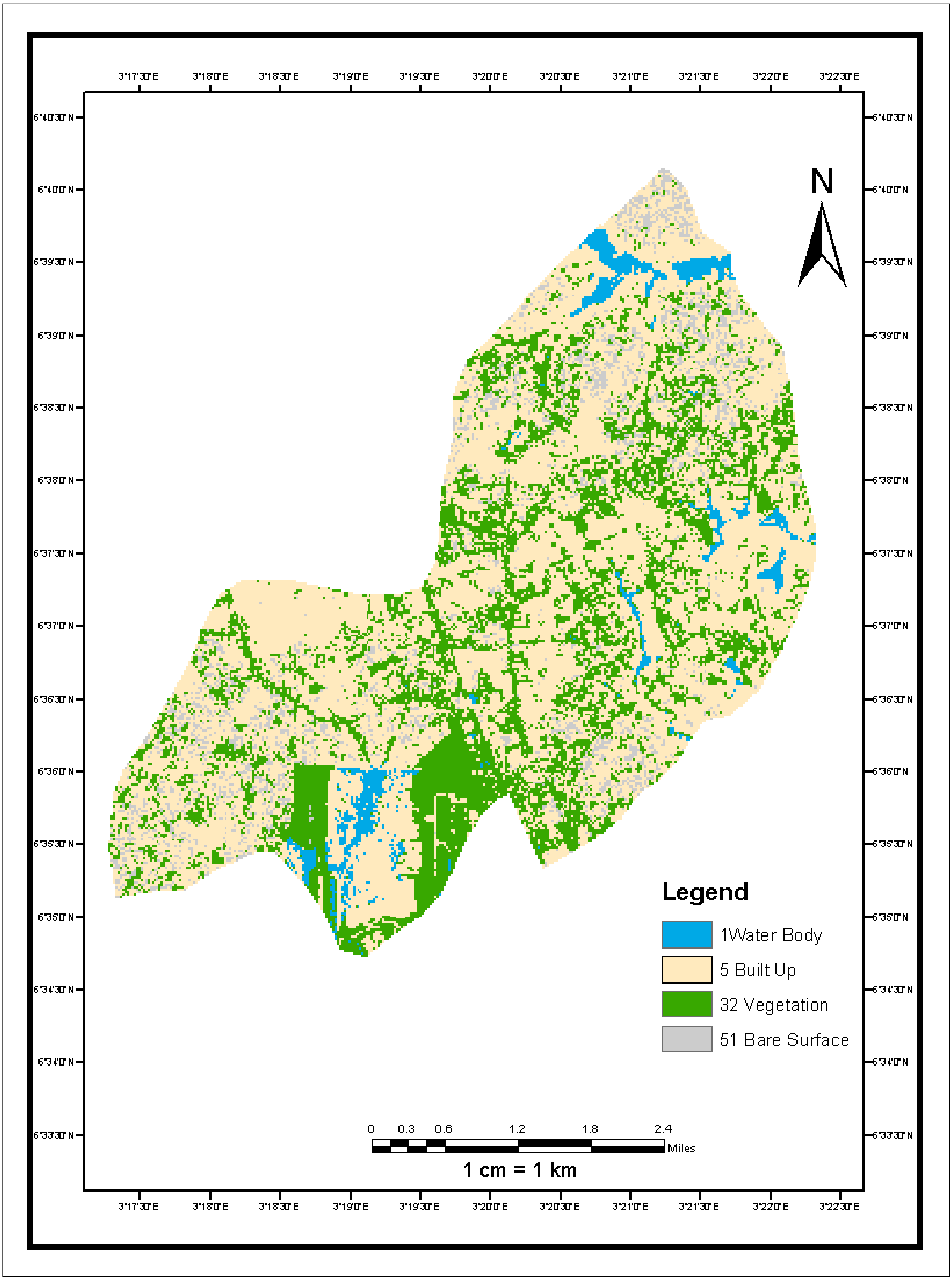

Figure 5: LULC Map of Ikeja Lagos 2025

Table 3: LULC of Ikeja Lagos 2015 - 2025

LULC_2025	AREA_2025	Area_2015	Area_2020
Water bodies	235	154	28
Built Up	1980	2865	2525
Vegetation	1155	1256	730
Bare surface	1178	273	1265
Total	**4548**	**4548**	**4548**

Table 4: Ikeja Lagos Change Detection 2015-2025

Change Detection	Sum of Area Change (ha)
Bare Surface -Bare Surface	19.400462
Bare Surface -Built up	163.178937
Bare Surface -Vegetation	89.473383
Built Up -Bare Surface	560.941093
Built Up -Built up	1488.658394
Built Up -Vegetation	689.200504
Built Up -Water Bodies	122.640733
Vegetation -Bare Surface	552.965758
Vegetation -Built up	320.142034
Vegetation -Vegetation	360.630627
Vegetation -Water Bodies	20.605243
Water Bodies -Bare Surface	42.701375
Water Bodies -Built up	5.153806
Water Bodies -Vegetation	14.260213
Water Bodies -Water Bodies	91.598025
Grand Total	**4541.550587**

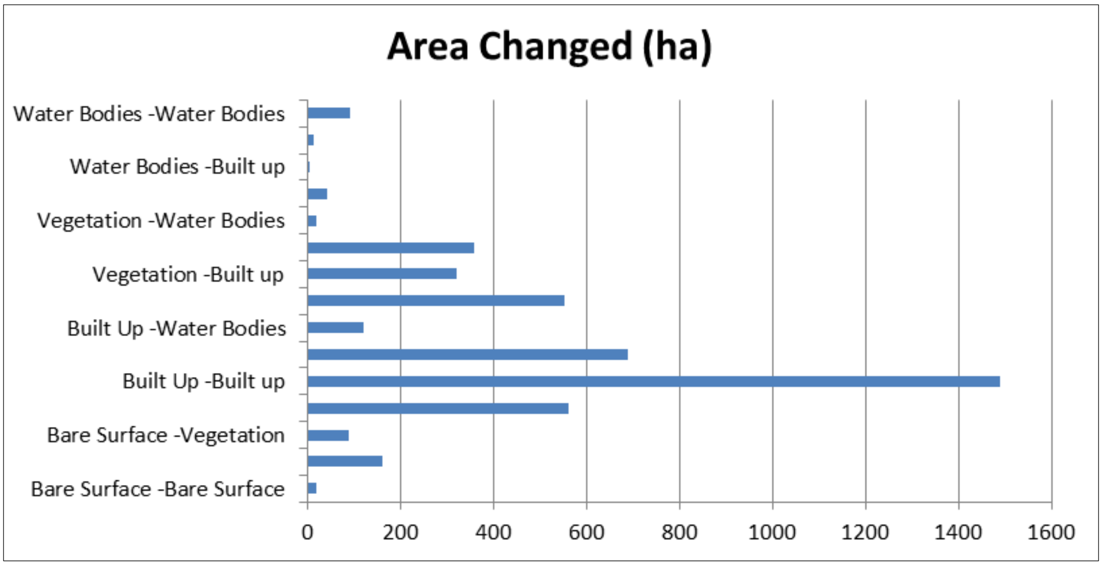

Figure 6: Graphical Representation of Ikeja Lagos 2015 – 2025 LULCC

Table 5: Ikeja Lagos 2015 - 2025

LST 2015			LST 2020			LST 2025		
Max	Min	Mean	Max	Min	Mean	Max	Min	Mean
44.8	29.46	39.9	31.8	22.7	29.18	46.6	30.8	41.5

DISCUSSION

Trajectories of Urban Transformation in Ikeja

The results of the present study indicate that in the selected area, Ikeja experienced a significant change in land use, which is evident in increased built-up areas at the expense of vegetation at the rate of 44.7% increment in built-up and 54.9% decrease in vegetative cover between 2015 and 2025. These rates of urban sprawl are high and far above other cities in Nigeria over the same period. For instance, Sulaiman *et al.*, (2025) reported the average rate of built-up increase in 10 major cities in Nigeria between 2001 and 2023 as 28.3%, while the rate observed in this research was 44.7% more than 1.5 times higher. This indicates that there is an enormous strain on urbanization in Lagos, the capital state and the heart of the nation's government and business administration. This observation corroborates with previous works that cite Lagos as one of the fastest-growing cities in Africa (Adelekan, 2023).

Temporal disaggregation of change shows that the most intense period of urbanization was witnessed between 2015 and 2020 when built-up area grew by 27.5% while vegetation decreased by 41.9%. This corresponds with the Lagos State Government's implementation of Urban Regeneration Intervention Policies where it gave more priority to the renewal of infrastructure and the upgrading of the transportation network in Ikeja (Tribune Online, 2025). Such interventions are crucial to deal with the immediate problems of mobility and drainage, but at the same time, it is clear from our analysis that these came at the cost of green space, which is one of the typical characteristics of a fast-growing city in Africa (Odunsi *et al*., 2023). The 41.6% reduction in water bodies over the decade is particularly alarming, as these features provide vital evaporative cooling and stormwater harvesting services in tropical urban settings (Ibrahim *et al*., 2024). The fact that water bodies have been lost more rapidly in the last five years (39.2% loss vs 3.9% in the previous five years) indicates an increase in recent years in the rate of land reclamation, probably due to rising land prices and limited buildable land area in this densely urbanized LGA. This trend is consistent with the global trend identified by Liu *et al*., (2024) of increasing wetland conversion in rapidly urbanizing Global South cities. The measured warming of 1.6°C in mean LST during the 10 years is a rate of thermal intensification that far exceeds the global background warming. The Intergovernmental Panel on Climate Change (IPCC, 2023) indicates that the global average surface temperature is estimated to increase by about 0.2°C per decade; the observed increase in Ikeja is more than eight times this value. This amplification is consistent with global trends observed by Kong *et al*., (2025), where they found that among the rapidly urbanizing cities located in tropical regions, the most extreme trends are seen in warming. The highest temperature ever recorded was 46.6°C in 2025, which comes dangerously close to reaching temperatures that are dangerous to human health, especially among the elderly, children and those outdoor workers (Gasparrini *et al*., 2022). Prolonged exposure to these conditions can lead to heat exhaustion, heat stroke, and death caused by cardiovascular and respiratory illnesses. The clustering of these extreme temperatures in densely populated residential and commercial areas (hotspot analysis) raises significant public health issues that need to be addressed through policy.

The increased correlation of NDVI-LST and NDBI-LST relationships over the years (from -0.71 to -0.74 and +0.67 to +0.72, respectively) demonstrates that the thermal contrast in the different land cover types tends to become more evident with increased urbanization. This is in line with the observation by Guha *et al*., (2022) that the thermal signature of urbanization enhances with the development of cities, which is of concern to monitoring systems that use spectral indices as proxies to temperature.

Transition-Specific Thermal Impacts: The Prevailing Role of Vegetation Loss

Another significant contribution of this work is that it quantifies the temperature change associated with a particular type of LULC. That the vegetation-to-built-up conversion is associated with a mean warming of +4.2°C—2.6°C above background rates—is the first empirical quantification of the temperature impacts of a particular kind of transition for a city in West Africa. This result is consistent with and slightly higher than the global mean estimate of Liu *et al*., (2024)—forest-to-urban transitions were associated with mean warming of 3.8°C in 150 cities worldwide—and likely reflects the more equatorial setting of Ikeja, where the removal of vegetation would have greater effects on warming due to the cooling effect of vegetation through evapotranspiration (Cao *et al*., 2024). The intermediate vegetation-to-bare surface transition (+3.1°C warming) was also an interesting finding. Such an intermediate stage in the process of urbanization has not been given much attention in earlier research. This shows that even if vegetation is only temporarily removed from a piece of land (e.g., land cleared for construction that is then left vacant), there is still a significant warming effect. The 552.97 ha of such a transition over the 10-year period represents a major heat load that could potentially be avoided by retaining vegetative cover until shortly before construction.

The cooling effect from the built-up-to-vegetation transition (-2.4°C) shows that even small-scale greening projects can reduce some of the urban heat, if well implemented. This confirms the increasing evidence that urban greening is a good way to alleviate heat, as long as enough space and quality vegetation are present (Zhang *et al*., 2023). The small scale of these transitions (320.14 ha, or 7.0% of the study area) reveals that vegetation losses have been far greater than greening. This attribution analysis, where vegetation loss was attributed to causing 85.3% of the total urban warming effect, shows without doubt that vegetation loss is the leading cause of the strengthening of the UHI effect in

Ikeja. This is crucial for urban planning, as it indicates a singular, modifiable target—vegetation cover—that can be tackled to abate the heat island. This explains why vegetation loss is the most dominant cause of warming. Vegetation cools the surface through several mechanisms such as evapotranspiration, shading, and affecting the surface albedo and surface roughness (Zhao *et al*., 2024). Removing vegetation eliminates these cooling benefits and exposes darker, thermally absorbent surfaces that convert incoming solar energy into heat. The converted vegetation areas (530.12 ha converted to built-up area and 365.20 ha converted to bare ground) equate to the loss of cooling service by the size of 895.32 ha of green area, which is larger than the combined area of natural vegetation remaining in Ikeja (567 ha in 2025). This result refutes other possible causes, like whether warming is mainly being caused by extra human-produced heat (from vehicles, air conditioning, industry), or changed reflection from Earth's surface even without lost vegetation. Though these factors certainly play a role, the scale of the warming seen in shifts from vegetation to urban areas, and the share of all warming due to this shift, makes clear that loss of vegetation is the key driver that needs to be addressed through policy.

This threshold of vegetation cooling at about 25% cover, below which the efficiency of cooling is notably weakened, has important implications for the planning of green infrastructure in Ikeja, and even other tropical cities. The results correspond to those obtained by Cao *et al*., (2024) on a global scale, where a threshold behavior of the cooling effect of vegetation was observed, with the tropical zone showing slightly bigger thresholds (22–28%) than the temperate zone (15–20%). Practically, the implication is that the benefit of greening by means of low coverage and in fragments such as street trees planted far apart or small pocket parks will likely have little effect on alleviating the heat unless it covers at least 25% of the territory and is concentrated within some reasonable distance of each other. However, if the greening is concentrated to areas where the coverage threshold >25% is reached, disproportionally higher cooling effects can be generated. This reveals that not more than 12.7% of the grid cells in Ikeja presently have more than this threshold, and this suggests the seriousness of the problem of green space deficit as well as the potential for selective intervention in the areas that are close to the threshold. The increase of the NDVI-LST correlation over the years is also explained by this threshold effect. When overall vegetation cover has dropped below the threshold in more areas, patches of remaining vegetation exert a greater cooling influence on their surroundings, generating sharper thermal gradients and a stronger statistical association (Cao *et al*., 2024).

Persistent Hotspots and Spatial Targeting of Interventions

The hotspot analysis revealed that there were areas where high temperatures tended to cluster regularly: the Ikeja Industrial Estate, the Oshodi transport corridor, and the Allen Avenue commercial core. Such regions also have some common features: mostly impervious surfaces (often more than 90%), little vegetation and a lot of human activity, adding further heat through industry, vehicle movement, and energy consumption within buildings (Salami *et al*., 2025). The fact that these spots were still hot in all three time points means that they are more representative of the city's built environment rather than short-term influences. Knowing the places where heat persists, it becomes easier to target the resources so that they can help the most. For instance, in the case of the Ikeja Industrial Estate, it could be green rooftits on factories, tree shade in the car park, and permeable pavements in areas of low footfall. These measures may include vegetated transport corridors for Oshodi transport corridor; shade structures near bus stops and reflective material on buses or other transportation facilities; planting of trees and green walls in Allen Avenue; and provision of green space in the public domain through incentives to private businesses to incorporate green structures (Bello & Adebayo, 2024). In contrast, the detection of the existing cool spots like LASUTH grounds, GRA, and Opebi-Oregun drainage corridor, exemplifies the effectiveness of green infrastructure and how such areas can inform intervention design. These neighborhoods prove that in an area as densely developed as this, it is possible to obtain significant cooling by means of maintained vegetation; the difference in temperature can reach up to 4–6°C when comparing it to built-up areas.

Contextualization in the Context of the Region and the World

These results obtained in Ikeja are in congruent trend with the larger trend seen in other West African coastal cities. In the study of Ibrahim *et al*., (2024), the average SUHI intensity was 4.2°C for nine cities along the Nigerian, Benin, and Ghana coast; this is similar to the 3.9°C difference recorded in built-up and vegetated areas in Ikeja in 2025. Also, the average rate of loss of vegetation in Ikeja (approximately 7.6%) is also higher than the average rate of vegetation loss in West African cities (4.8%) estimated by Güneralp *et al*., (2020), proving that it is indeed a hotspot of urban transformation. The rate of warming in Ikeja is also consistent with forecasts of global warming in tropical cities. Zhao *et al*., (2020) indicated a greater increase in mean summer surface temperature in tropical megacities such as Ikeja; this increase is three times higher than in non-urban areas and is also associated with climate change. However, using similar models as Moura *et al*., (2021), it is projected that rapidly expanding tropical cities would experience urban warming of 1.5–2.5°C per decade during the mid-century future under RCP 4.5, which is consistent with the 1.6°C warming in Ikeja per decade. This correlation indicates that such rates will continue without intervention and reinforce worst-case scenario results.

However, the Ikeja case also shows some specific peculiarities. The particularly high loss of water bodies (41.6%) is higher than the reported loss in most coastal cities across the world, which can be attributed to the extreme scarcity of land in Lagos and the economic forces pushing for the reclamation of wetlands (Adelekan, 2023). The fact that the remaining vegetation is concentrated in the institutional compounds and high-income residential areas (GRA) also shows the socio-economic stratification of access to green space, an aspect that is important from the environmental justice standpoint (Odunsi *et al*., 2023). Several aspects that should be taken into account when interpreting the findings include; First, the 30 m Landsat resolution may exclude fine-scale landscape details that contribute to thermal dynamics, especially in complex urban landscapes with mixed land cover, where trees are mostly limited to patches (Mustafa et al., 2024). Nevertheless, the consistency of the observed patterns in the three time points and the congruence with an independent hotspot analysis make the primary findings robust against this resolution restriction. Second, the in-situ meteorological measurements were not available; thus, it was not possible to directly verify the satellite-derived LST against ground-based observations. The Collection 2 Level-2 products have been validated (USGS, 2023), but caution must be exercised in the interpretation of absolute temperature values, especially in the case of 2020, Landsat 8 scene acquisition due to the occurrence of abnormally low values, caused by atmospheric effects. Finally, the relative patterns and magnitude of change themselves remain sound because all three dates were subjected to the same processing protocols. Thirdly, the assignment analysis is based on the assumption that temperature changes associated with a particular transition are not affected by other influences acting at the pixel level. In actuality, microclimatic conditions in localized areas, building materials, and heat produced by people may affect the transition-specific impacts. Nevertheless, the high sample size of major transitions (e.g., 689.20 ha for vegetation-to-built-up), and the fact that the patterns found in the study area are consistent, indicates that the estimated transition effects are not highly susceptible to this local variation. Fourthly, the period studied (2015–2025) encompasses the COVID-19 pandemic (2020–2021), which might have caused abnormal patterns in land use and heat. As the economic activity was decreased during the lockdown days, the emission of anthropogenic heat could have decreased at some level, but changes in activities within the building site might have caused the shift in the rate of change. Nevertheless, the trends for the ten years remained fairly consistent; hence, the pandemic could not have significantly changed anything.

CONCLUSIONS

This paper evaluates the influences of LUCC on the intensity of the UHI in the area of Ikeja, Lagos, during the 2015–2025 interval, using multi-temporal Landsat images and GIS-based models. The combination of LULC classification, change detection, and LST analysis gives the following conclusive observations: First, the landscape of Ikeja experienced a massive transformation over the decade, with a 44.7% (885 ha) increase in built-up area and a 54.9% (689 ha) decrease in vegetation cover. This rate of urbanization is far above the average of other regions, which affirms that Ikeja is one of the most dynamic centres of urban transition in the Lagos mega city. Water bodies shrank by 41.6%, indicating increased pressure on water bodies as a result of land reclamation activities. Second, the land surface temperature increased significantly—the average LST increased 1.6°C, and the maximum temperatures reached 46.6°C in 2025.This warming rate is 8 times that of the background temperature increase in the world, demonstrating the significant local effect of urbanization on climate. This warming pattern matches the pattern of vegetation loss, and persistent hotspots remain in industrial, commercial, and high-density residential areas. Third, the temperature effect of land cover alteration is very transition-specific. Vegetation to built-up conversion yielded a mean warming of +4.2°C—2.6°C above background rates. Built-up to vegetation conversion was much more common than vegetation-to-bare surface conversion, producing +3.1°C warming, while vegetation-to-bare surface conversion produced +3.1°C warming and built-up-to-vegetation conversion produced a smaller but still significant cooling effect of -2.4°C. These specific transition effects are the initial empirical measurement for a West African city and affirm the causal connection between land cover alteration and thermal response. Fourth, the process of loss of vegetation explains 85.3% of the overall impact of the urban heat island, thus pointing out that the loss of green space is the leading mechanism of the intensified UHI in Ikeja. This discovery has significant ramifications for policymaking, as it establishes an individual, adjustable variable as the main lever for heat abatement. Fifth, the cooling effect of vegetation is a threshold function, becoming inefficient below 25% cover. The threshold is just reached by 12.7% of the study region today, indicating the acute green space deficiency and the possibility of focusing interventions near threshold areas. Sixth, permanent heat islands in Ikeja Industrial Estate, Oshodi transport corridor and Allen Avenue commercial core were identified, and permanent cool spots in LASUTH grounds, GRA, and Opebi-Oregun drainage corridor were determined. All these results in aggregate show that the urbanization that has happened in Ikeja has brought about significant landscape transformation that has measurable and tangible impacts on the climate locally. Vegetation loss is shown to be the main culprit in creating the urban warming, and therefore, its restoration is the main opportunity to mitigate it. Unless addressed, further loss of vegetation will lead to further warming with implications for human health, energy consumption, and livability.

Recommendations

Policy and Regulatory Recommendations

i. Pass a Green Space Preservation Ordinance that mandates a minimum 25% vegetation cover on all new developments in Ikeja, and institute strict penalties for the unauthorized removal of vegetation.
ii. Develop UHI Mitigation Policy Framework such as heat impact assessment of major developments and make cool roof standards mandatory in building codes.
iii. Ikeja should revise its Master Plan to establish zones of conservation, impose maximum impervious surface proportions (70 percent for commercial, 60 percent for residential), and incorporate the provision of green infrastructure in the approval of developments.

REFERENCES

- Ahuja, H. & Soni, R. (2025). Spatio-temporal analysis of LST, NDVI, NDWI and NDBI using Landsat-8 satellite data in Indore, India. *IOP Conference Series: Earth and Environmental Science*, 1464, 012015.
- Anderson, J.R., et al. (1976). A land use and land cover classification system for use with remote sensor data. *USGS Professional Paper 964*.
- Belgiu, M. & Drăguţ, L. (2016). Random forest in remote sensing: A review of applications and future directions. *ISPRS Journal of Photogrammetry and Remote Sensing*, 114, 24-31.
- Congalton, R.G. & Green, K. (2019). *Assessing the Accuracy of Remotely Sensed Data: Principles and Practices* (3rd ed.). CRC Press.
- Getis, A. & Ord, J.K. (1992). The analysis of spatial association by use of distance statistics. *Geographical Analysis*, 24(3), 189-206.
- Gorelick, N., et al. (2017). Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment*, 202, 18-27.
- Guha, S., Govil, H. & Mukherjee, S. (2022). A long-term seasonal analysis on the relationship between LST and NDBI using Landsat data. *Quaternary International*, 575, 201-212.
- Jensen, J.R. (2016). *Introductory Digital Image Processing: A Remote Sensing Perspective* (4th ed.). Pearson Education.
- Liu, Z., et al. (2024). Thermal signatures of land cover transitions: A global assessment using satellite data. *Remote Sensing of Environment*, 301, 113942.
- Mustafa, E.K., et al. (2024). A comprehensive review of machine learning algorithms for urban heat island analysis using remote sensing data. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 17, 4567-4589.
- Pontius, R.G., Shusas, E. & McEachern, M. (2004). Detecting important categorical land changes while accounting for persistence. *Agriculture, Ecosystems & Environment*, 101(2-3), 251-268.
- Purwoko, D., Handoko, E.Y. & Sopaheluwakan, A. (2025). Comparative Analysis of Landsat 8 And Landsat 9 Satellite Image Data in Surface Temperature Estimation, NDVI and NDBI Using Google Earth Engine. *Geoid*, 20(1), 45-58.
- Puyravaud, J.P. (2003). Standardizing the calculation of the annual rate of deforestation. *Forest Ecology and Management*, 177(1-3), 593-596.
- QGIS Development Team (2024). *QGIS Geographic Information System*. Open Source Geospatial Foundation Project.
- R Core Team (2024). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria.
- USGS (2023). *Landsat 8-9 Collection 2 Level-2 Science Product Guide*. United States Geological Survey.
- Weng, Q. (2009). Thermal infrared remote sensing for urban climate and environmental studies: Methods, applications, and trends. *ISPRS Journal of Photogrammetry and Remote Sensing*, 64(4), 335-344.
- Zhang, J., et al. (2023). Context-specific responses to urban greening for heat mitigation. *Nature Communications*, 14, 4892.