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Land-Cover Change and Predictive Modeling of Urban Heat Dynamics in Kano, Nigeria

Yusuf Ahmed Yusuf[1,2,3], Helmi Zulhaidi Mohd Shafri[1,3*], Siti Nur Aliaa Roslan[1,3], Jibrin Gambo[3,4]

[1]Department of Civil Engineering, Faculty of Engineering, Universiti Putra Malaysia (UPM), PMB 43400 Serdang, Selangor
[2]Department of Environmental Management, Bayero University Kano (BUK), Nigeria. PMB 3011 Kano, Kano
[3]Department of Civil Engineering and Geospatial Information Science Research Centre (GISRC), Universiti Putra Malaysia (UPM), PMB 43400 Serdang, Selangor
[4]Department of General Studies, Binyaminu Usman Polytechnic, Hadejia, Nigeria

*Corresponding author: helmi@upm.edu.my

Abstract – Urbanisation profoundly alters land-use and land-cover (LULC) patterns, often intensifying urban heat island (UHI) effects and threatening sustainable development. In rapidly growing semi-arid cities such as Kano Metropolis, Nigeria, these dynamics remain underexplored. This study investigates the relationship between LULC transitions and urban thermal dynamics over nearly four decades (1984 - 2023), while also forecasting future changes. Multi-temporal Landsat imagery was classified using the Classification and Regression Tree (CART) algorithm, achieving overall accuracies ranging from 92.1% to 98.5% and Kappa coefficients exceeding 0.85. Vegetation and built-up indices, including the Normalised Difference Vegetation Index (NDVI) and Normalised Difference Built-up Index (NDBI), were analysed alongside Land Surface Temperature (LST) to assess urban heat patterns. Predictive modelling employed the Cellular Automata Artificial Neural Network (CA-ANN) approach, which was validated with an overall accuracy of 92% and a Kappa coefficient of 0.86. Results show that built-up areas expanded from 43.06 km² (2.93%) in 1984 to 381.79 km² (25.95%) in 2023, an almost 800% increase, while bare land declined by 23.2%. Mean LST rose from 39.7°C in 1984 to 41.5°C in 2023, with peak values exceeding 52°C in 2010. A strong positive correlation was found between NDBI and LST (r = 0.57), while NDVI showed a negative correlation with LST (r = -0.32), highlighting the cooling effect of vegetation. Model simulations predict continued urban expansion through 2050, with built-up areas increasing by 6.5% and further intensification of UHI effects if unchecked. These findings emphasise the urgent need for sustainable urban planning, including the preservation of vegetation cover, the development of green infrastructure, and climate-sensitive construction practices. The study offers critical insights for policymakers and urban planners seeking to mitigate thermal stress and foster climate-resilient urban development in sub-Saharan Africa.

Keywords *– LULC, Land Surface Temperature (LST), Urban Heat Island (UHI), NDVI, NDBI, CA-ANN, Sustainable Urban Development*

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1.0 Introduction

The rapid expansion of urban areas has significantly influenced environmental patterns globally. Urbanisation often replaces natural landscapes with built environments, resulting in considerable ecological and climatic effects. A key outcome of this transformation is the urban heat island (UHI) effect, whereby urban areas experience higher temperatures than surrounding rural regions due to the replacement of vegetation and permeable surfaces with impervious materials such as buildings, roads, and pavements. These land-use and land-cover (LULC) changes not only affect local climates but also exacerbate broader environmental challenges, including increased energy demand and health risks associated with higher temperatures. Understanding how LULC changes influence urban thermal dynamics is essential for addressing these issues and fostering sustainable urban development in rapidly growing cities (Feng et al., 2024; Kassomenos & Begou, 2022; Liu et al., 2020). The intensification of the UHI effect has been associated with rising land surface temperatures (LST), elevated energy consumption, and increased public health risks, particularly in cities with rapid infrastructure growth and dense populations. In regions with accelerated urbanisation, such as South and Southeast Asia, Latin America, and Africa, balancing economic development with environmental sustainability has become an urgent priority. Research shows that urban centres in these regions face the dual challenge of supporting population growth while minimising the adverse impacts of urbanisation on climate and health (Hsu & Rodríguez, 2024; Fang et al., 2024; Nieuwenhuijsen, 2016). Consequently, sustainable urban planning has gained significant attention as a strategy to promote growth while maintaining ecological integrity and enhancing climate resilience, especially in regions vulnerable to UHI intensification.

In sub-Saharan Africa, this challenge is especially acute. Urban centres are expanding at unprecedented rates; however, research on the thermal consequences of these land-use and land-cover (LULC) changes remains limited. Many existing studies focus on tropical or temperate regions, overlooking the distinct dynamics of semi-arid environments, where sparse vegetation, soil type, and climatic variability influence heat patterns in different ways. This lack of localised evidence makes it difficult for policymakers to anticipate and manage the ecological and health implications of urban growth in African cities. In Nigeria, the relationship between LULC changes and urban thermal patterns is particularly relevant due to the country's rapid urbanisation and substantial population growth. Kano Metropolis, one of Nigeria's largest and most densely populated cities, exemplifies these dynamics. With over five million residents, Kano has undergone significant LULC changes in recent decades, driven by demographic pressures and economic activities. These transformations have replaced vast areas of natural vegetation and bare land with built environments, raising concerns about the UHI effect and its potential long-term implications for public health, energy use, and overall urban livability (A et al., 2017a; Emmanuel Ayila, 2014). Despite the importance of this issue, research on UHI effects in sub-Saharan Africa is limited, and the specific interactions between LULC transitions and urban thermal patterns in rapidly urbanising cities, such as Kano, are not well understood. This study aims to address these gaps by providing data-driven insights to inform sustainable urban planning practices tailored to the region's unique environmental and urbanisation trends.

While many studies have examined the UHI effect and LULC changes in cities worldwide, substantial gaps remain in understanding these relationships in semi-arid, rapidly urbanising regions of sub-Saharan Africa. Most existing research has focused on urban heat and land-use changes in developed or tropical cities, often overlooking semi-arid environments where different vegetation densities, soil types, and climate patterns affect thermal dynamics (Chakraborty & Lee, 2019; García-Chan et al., 2023; Moazzam et al., 2024). In Kano Metropolis, the rapid conversion of bare land and vegetation into built-up areas provides a distinct context for studying UHI effects. This transformation has altered the local microclimate, resulting in temperature increases that could impact public health, urban livability, and sustainability. However, limited data and predictive modelling in such contexts pose challenges for policymakers in forecasting and addressing the environmental impacts of urban expansion in semi-arid climates (Sajadzadeh & Ghorbanileylestani, 2024). Another critical research gap lies in the lack of predictive modelling for future LULC changes and their associated UHI impacts in semi-arid regions like Kano. Although urban heat studies often employ predictive tools to model UHI intensification in tropical and temperate zones, few studies apply these methods to sub-Saharan African cities, depriving decision-makers of essential insights for managing thermal and ecological stressors. This study aims to fill this gap by utilising remote sensing and advanced predictive modelling to analyse UHI and LULC changes in Kano, providing valuable information for urban planners and policymakers.

Recent work continues to clarify how land-use/land-cover (LULC) change influences surface urban heat island (SUHI) patterns through the loss of vegetation and expansion of impervious cover. Global and regional syntheses show the now-familiar signal: NDVI correlates negatively with LST, while NDBI shows a positive association, with implications for planning and heat-risk management. New analyses also emphasise modelling choices (e.g., OLS vs. GWR) and sensor/orbit trade-offs when interpreting SUHI dynamics, reinforcing the need for locally validated approaches in rapidly urbanising regions (Cetin et al., 2024; Eshetie, 2024). Evidence from semi-arid African cities has grown, though it remains thinner than for temperate settings. Studies in Kano, Nigeria, and Kaduna, Nigeria, report intensified SUHI linked to the conversion of bare/vegetated land to built-up areas, with NDVI-LST cooling and NDBI-LST warming relationships consistent with the broader literature. Parallel work in Ethiopia (Addis Ababa; multi-decadal Landsat series) and northern Ghana (Tamale) similarly attributes rising LST to urban expansion and declining vegetation cover, underscoring common mechanisms across the Sahel-to-Sudan belt despite local morphological differences (Sensing et al., 2024; Usman et al., 2025; Yiran et al., 2025). In predictive LULC modelling, recent studies have increasingly adopted Cellular Automata–Artificial Neural Network (CA-ANN) frameworks, often implemented via MOLUSCE in QGIS, to simulate transition potentials and forecast urban growth. These models, validated against observed changes, perform well in anticipating near-term expansion fronts and testing mitigation scenarios (e.g., green infrastructure retention). The recent literature shows CA-ANN's portability across contexts and its value for policy-relevant "what-if" analyses when paired with robust accuracy assessment (Ong'ondo et al., 2025). Methodologically, this study's LST retrieval and UHI interpretation align with established foundations. Landmark reviews explain how thermal remote sensing resolves urban surface processes and why SUHI reflects urban–rural energy-balance differences. For Landsat-based LST, classic single-channel formulations (Qin et al., 2001; Sobrino et al., 2004) and newer practical refinements provide the theoretical and empirical basis for converting radiance/brightness temperature to LST. Meanwhile, the USGS Collection-2 documentation details scale factors and K1/K2 conversions for Level-1 and Level-2 products. For comparability across urban forms, the Local Climate Zones (LCZ) framework remains the standard for classifying morphology and contextualising SUHI intensity (Qin et al. 2001; Voogt and Oke 2003).

This study aims to bridge existing research gaps by investigating the relationship between LULC changes and urban thermal patterns in Kano Metropolis over 39 years (1984–2023) through remote sensing data and predictive modelling. The study's primary objectives are as follows: Assess LULC Changes: Quantify LULC changes in Kano Metropolis from 1984 to 2023, focusing on the conversion of bare land and vegetation into built-up areas and analysing the spatial and temporal distribution of these changes. Analyse Urban Thermal Patterns: Identify spatial and temporal trends in land surface temperature (LST) and correlate these trends with LULC changes, highlighting regions with increased UHI effects and examining associations with demographic and economic factors. Evaluate Thermal and Vegetative Indices: Investigate the relationship between LST trends and spectral indices such as the Normalised Difference Built-up Index (NDBI) and Normalised Difference Vegetation Index (NDVI) to understand how vegetation and built-up areas affect urban thermal dynamics (Guha et al., 2020). Predict Future LULC and UHI Trends: Forecast future LULC changes and their potential impact on urban heat patterns through 2050 using Cellular Automata-Artificial Neural Networks (CA-ANN) modelling to inform sustainable urban planning practices. Provide Sustainable Planning Recommendations: Offer recommendations for sustainable urban development in Kano Metropolis, emphasising the role of green spaces, sustainable construction practices, and climate adaptation measures to improve urban livability and resilience. Through these objectives, this research aims to enhance the understanding of UHI effects in semi-arid, rapidly urbanising regions and provide essential insights to support sustainable development strategies in Kano and similar urban centres across sub-Saharan Africa.

1.1 Study Area

The study was conducted in Kano Metropolis, the capital of Kano State in northwestern Nigeria. Situated between latitudes 11° 25'N and 12° 47'N and longitudes 8° 22'E and 8° 39'E, Kano is one of the largest commercial cities in Nigeria. Covering approximately 5,700 square kilometres, it encompasses eight Local Government Areas (LGAs): Kano Municipal, Gwale, Dala, Fagge, Tarauni, Nassarawa, and Ungogo (A et al., 2017b; Emmanuel Ayila, 2014), as shown in Figure 1. Historically, Kano has been a significant commercial hub since pre-colonial times and remains crucial to the regional economy (Mustapha et al., 2014). With a population exceeding five million, it is the country's second-largest city. Kano's climate is classified as tropical wet and dry (Aw) under the Köppen climate classification system, characterised by high temperatures throughout the year, often exceeding 43°C during the hot, dry season. The region experiences three distinct climatic seasons: a cool dry season from November to February, a hot dry season from March to mid-May, and a wet season from June to October (Aliyu, 2008; Tanko et al., 2017). Kano's geographical location, climatic conditions, and rapid urbanisation make it an ideal case for studying the effects of land-use and land-cover changes on urban thermal patterns.

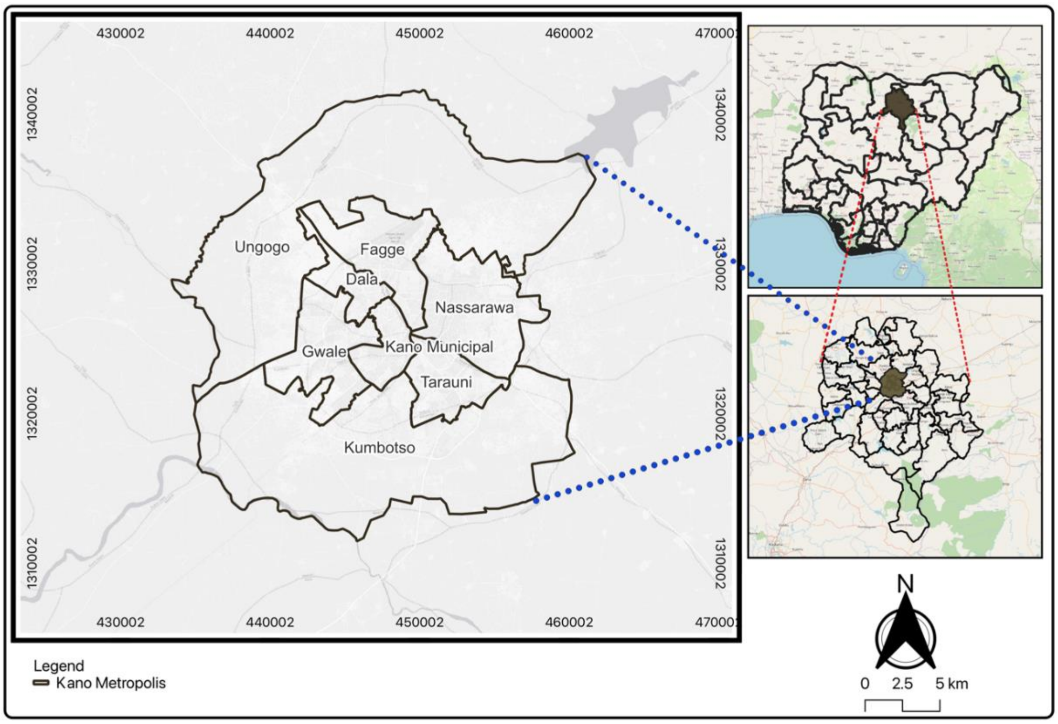

Figure 1: Map of the study area

2.0 Materials and Methods

2.1 Data Collection

The study utilised multi-temporal satellite imagery from Landsat 4, 5, 7, and 9 obtained from the Landsat Collection 2 dataset, spanning the period from 1984 to 2023. Cloud-free images between March and May, during the dry season, were selected to minimise cloud interference and ensure clear visibility of land-cover changes. These years were chosen to represent key stages in Kano's urban expansion: the early pre-urbanisation period (1984), the onset of rapid growth (2000), accelerated expansion (2010), and the most recent condition (2023).

2.2 Sensors and Bands Used

Landsat 4–5 TM and Landsat 7 ETM+: Multispectral bands (Blue, Green, Red, NIR, SWIR1, SWIR2) at 30 m resolution; Thermal Band 6 at 120 m (resampled to 30 m). Landsat 9 OLI/TIRS: Multispectral bands at 30 m; Thermal Bands 10 and 11 at 100 m (resampled to 30 m). Indices Computed: Normalised Difference Vegetation Index (NDVI), Normalised Difference Built-up Index (NDBI), and Urban Thermal Field Variance Index (UTFVI). These were chosen because of their proven sensitivity to vegetation, impervious surfaces, and ecological stress in semi-arid cities.

2.3 Data Pre-processing: Image Correction and Calibration

All images were pre-processed on Google Earth Engine (GEE), including radiometric calibration, atmospheric correction, and cloud masking using the QA band, with the following steps:

- Atmospheric Correction: Landsat surface reflectance data were used, incorporating corrections for atmospheric distortions to ensure accurate radiance and reflectance values.
- Geometric Correction: All images were co-registered to a uniform coordinate system (WGS84/UTM Zone 32N) to maintain spatial accuracy across the entire dataset.
- Cloud Masking: The 'CLOUD QA' band from the Landsat Collection 2 dataset was utilised to mask clouds and cloud shadows, ensuring that only cloud-free pixels were included in the analysis (Kafy et al., 2020; Orieschnig et al., 2021).

2.4 Land-use and Land-cover (LULC) Classification: Classification and Regression Tree (CART) Algorithm

The Classification and Regression Tree (CART) algorithm was employed to classify the Landsat imagery into distinct land-use and land-cover (LULC) categories. CART is a decision tree algorithm that recursively splits the dataset based on Gini Impurity, generating nodes that optimally separate the classes (see Equation 1). This approach ensures accurate classification of various LULC types across the entire study period. LULC classification was performed using the Classification and Regression Tree (CART) algorithm.

Classes Defined

Built-up Areas: – residential, commercial, and industrial structures with impervious surfaces.
Vegetation: – agricultural fields, grasslands, and sparse shrubs.
Bare Land: – exposed soil, sand, and degraded surfaces with minimal vegetation.
Water Bodies: – rivers, ponds, and reservoirs.

Variables in CART Equations: The splitting function used Gini Impurity, where:

$$\text{Gini Impurity} = 1 - \sum_{i=1}^{n} p_i^2 \tag{1}$$

Where p_i represents the probability of each class (Kafy et al., 2021)

The following steps were undertaken:

- **Training Data Collection:** Training samples were gathered using a stratified random sampling method for each land-cover class (e.g., built-up area, vegetation, bare land, and water). Ground truth data from field surveys and historical records were used to validate the classification. Training samples for each class were collected using stratified random sampling, which combined historical high-resolution imagery with ground truth points gathered during field surveys conducted in 2022–2023. Approximately 300 reference points were used per class.
- **Model Training:** The CART algorithm was trained on 80% of the labelled dataset, using spectral bands (e.g., NIR, SWIR) and indices (e.g., NDVI, NDBI) as input features.
- **Validation:** The remaining 20% of the dataset was used for validation. Classification accuracy was assessed through a confusion matrix, and both overall accuracy and the Kappa coefficient were calculated to ensure robustness. The overall accuracy exceeded 90% for all classified years (1984, 2000, 2010, and 2023).
- **Features Used in Classification:** Spectral bands (Red, NIR, SWIR1, SWIR2), NDVI, and NDBI were employed as predictor variables to improve class separability, especially between vegetation and built-up areas.

2.5 Calculation of Indices

To assess urban thermal patterns and land-cover changes, the Normalised Difference Vegetation Index (NDVI) was computed using the following formula, Equation 2:

$$\mathrm{NDVI} = \frac{(\mathrm{NIR}-\mathrm{R})}{(\mathrm{NIR}+\mathrm{R})} \tag{2}$$

The NDVI was used to evaluate vegetation health and density, where higher NDVI values represent denser vegetation. NDVI played a key role in assessing the cooling effect of vegetation on urban heat (Alademomi et al., 2020; Guha et al., 2020; Malik et al., 2019; Marzban et al., 2018).

The Normalised Difference Built-up Index (NDBI) was calculated to map built-up areas, using the following formula in equation 3:

$$\mathrm{NDBI} = \frac{(\mathrm{SWIR}-\mathrm{NIR})}{(\mathrm{SWIR}+\mathrm{NIR})} \tag{3}$$

Where:

- SWIR represents the reflectance in the shortwave infrared band, and
- NIR represents the reflectance in the near-infrared band.

NDBI was crucial for identifying impervious surfaces, such as buildings and roads, which contribute to heat absorption and exacerbate urban heat island (UHI) effects (Tesfamariam et al., 2023).

The Urban Thermal Field Variance Index (UTFVI) quantifies the relationship between land surface temperature (LST) and urban heat island (UHI) intensity, providing insights into the ecological impacts of urbanisation. The UTFVI is calculated using the following formula in equation 4:

$$\mathrm{UTFVI} = \frac{T_s - T_m}{T_s} \tag{4}$$

Where T_s In the formula for the UTFVI, T_s represents the land surface temperature (LST), and T_m is the mean LST of the area. Higher UTFVI values indicate stronger urban heat island (UHI) effects and more stressed urban environments. Thresholds are applied to classify urban areas into different ecological states based on thermal conditions (Kafy et al., 2021). The UTFVI quantifies the UHI effect and categorises urban areas into thermal stress zones, as shown in Table 1, providing insights into the environmental health of the urban ecosystem.

Table 1: UTFVI and ecological evaluation index thresholds (Faisal et al., 2021; Kafy et al., 2021)

Urban thermal field variation index	Urban heat island phenomenon	Ecological evaluation index
< 0	None	Excellent
0.000 – 0.005	Weak	Good
0.005 – 0.010	Middle	Normal
0.010 – 0.015	Strong	Bad
0.015 – 0.020	Stronger	Worse
>0.020	Strongest	Worst

These thresholds help evaluate the severity of thermal stress in urban environments, enabling urban planners to identify areas that require ecological interventions.

2.6 Land Surface Temperature (LST) Calculation

The Land Surface Temperature (LST) was derived from the thermal bands of Landsat imagery through several steps. The Digital Number (DN) values from Band 6 were first converted into radiance using the following equation 5:

$$L = \frac{(L_{max} - L_{min})}{Q_{max}} \times (DN - Q_{min}) + L_{min} \tag{5}$$

Where $L_{max} - L_{min}$ and Q_{max} are sensor-specific calibration constants. (Faisal et al., 2021; Fatemi & Narangifard, 2019; Ramaiah et al., 2020).

The radiance was then converted to temperature in Kelvin using equation 6:

Conversion to Brightness Temperature (Kelvin):

$$T_k = \frac{K_1}{1n\,(\frac{K_2}{RTM6}+1)} \tag{6}$$

Where K1=1260.56K1=1260.56 and K2=607.66K2=607.66. The temperature was further converted to Celsius using equation 7:

$$T_{\propto} = T_k - 273 \tag{7}$$

This approach was adapted for Landsat 9, using specific constants for its sensors (Koko et al., 2022a; Tesfamariam et al., 2023).

2.7 Predictive Modelling for Future LULC Changes

The Cellular Automata–Artificial Neural Network (CA-ANN) modelling approach was employed to simulate and predict future land-use and land-cover (LULC) changes up to 2033 and 2050. This approach was chosen for its ability to accurately simulate spatial-temporal changes by incorporating both historical land-use data and topographical features. Software and Plugin: Implemented in QGIS 3.28 (Firenze) using the MOLUSCE (Modules for Land Use Change Evaluation) plugin, version 4.0.

- Input Data: Historical LULC maps from 2000, 2010, and 2023 were used as input layers, along with geophysical variables such as slope, elevation, and population density.
- Model Training and Calibration: The CA-ANN model was trained using the MOLUSCE plugin in QGIS. The model predicted transition probabilities between LULC classes based on historical data and environmental factors. The model's accuracy was evaluated using Kappa statistics and overall classification accuracy, both of which exceeded 90%.
- Validation Strategy: The model's performance was validated by comparing the predicted LULC map for 2023 with actual LULC data. The Kappa coefficient of 0.86 indicated a strong agreement between the predicted and actual LULC distributions. The predicted and actual LULC distribution using the following formulas in equations 8 and 9:

$$\text{Overall Accuracy} = \frac{\text{sum of correctly classified pixels}}{\text{total reference pixels for that category}} \times 100 \tag{8}$$

$$\text{User Accuracy} = \frac{\text{correctly classified pixels for a category}}{\text{total reference pixels for that category}} \times 100 \tag{9}$$

To avoid redundancy, accuracy metrics are reported in the Results section. Here, the validation approach is described. LULC Classification Validation: Independent reference samples (20% of the dataset) were used to generate confusion matrices, which reported the overall accuracy and the Kappa coefficient.

Predictive Modelling Validation: The CA–ANN predictions for 2023 were compared against an independently classified LULC map for 2023. This "actual" map was derived directly from Landsat 9 imagery, not from training inputs, ensuring independent validation.

LST Validation: Ground-based temperature records were unavailable; therefore, direct validation of LST retrieval was not performed. Instead, results are interpreted within the context of established Landsat-based LST methods and recent literature acknowledging the absence of in-situ thermal validation for many African cities.

The Cellular Automata (CA)–Artificial Neural Network (ANN) model, used to predict future land-use and land-cover (LULC) patterns up to 2050, was validated using QGIS, achieving an overall accuracy of 92%. The rationale for utilising CA-ANN lies in its ability to simulate spatial-temporal LULC changes with high precision by integrating historical land-use data and topographical features (Faisal et al., 2021). The model's reliability was further strengthened by the MOLUSCE plugin, which incorporates multiple validation metrics, including Kappa statistics. These metrics provide robust evaluations of the model's predictive accuracy and consistency.

2.8 Remote Sensing Indices Selection Justification

The selection of indices such as NDVI and NDBI is based on their established roles in assessing vegetation cover and built-up areas, both of which are crucial for understanding urban heat dynamics. NDVI is essential for identifying dense vegetation areas, which mitigate urban heat by reducing surface temperatures through evapotranspiration (Guha et al., 2020). In contrast, NDBI is effective in detecting built-up regions where impervious surfaces contribute to elevated surface temperatures, intensifying the urban heat island (UHI) effect. These indices were selected for their reliability in distinguishing different LULC types, which is critical for developing accurate predictive models of urban heat dynamics. The inclusion of the Urban Thermal Field Variance Index (UTFVI) enhances the analysis by quantifying the urban heat effect and its relationship to ecological health. This provides a more comprehensive understanding of the impacts of UHI. Recent studies, such as Cevik Degerli and Cetin (2023), have validated UTFVI as a key indicator of ecological stress in urban environments. Figure 2 shows the methodological flowchart.

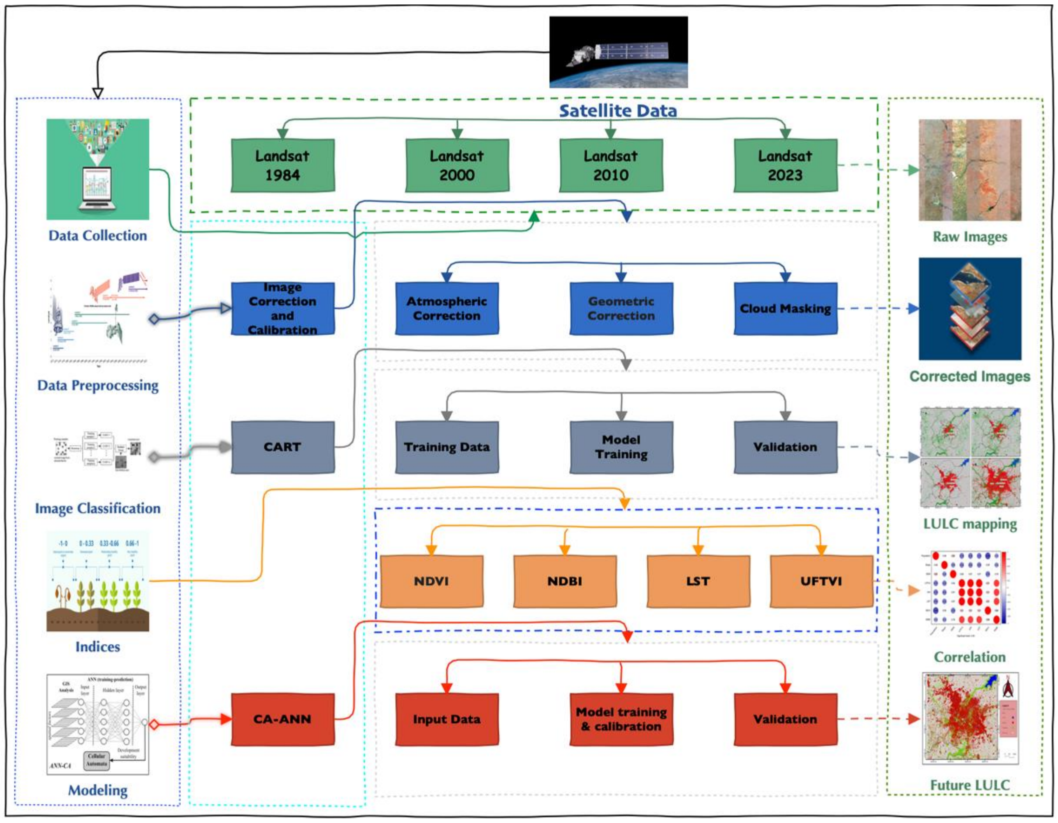

Figure 2: Methodological Flowchart

3.0 Results

3.1 Land-use and Land-cover (LULC) Classification Trends

3.1.1. Temporal Analysis of LULC Changes (1984–2023)

Over the past 39 years, the Kano Metropolis has undergone significant changes in land cover. Built-up areas expanded nearly eightfold from 43.06 km² (2.9%) in 1984 to 381.79 km² (25.9%) in 2023, reflecting rapid population growth and urban sprawl. This expansion primarily occurred at the expense of bare land, which declined by 23.2%, while vegetation cover remained relatively stable, with only a slight net reduction. This trajectory illustrates a distinctive semi-arid urbanisation pattern: unlike tropical cities where vegetation loss dominates, in Kano, the conversion of bare land to impervious built-up surfaces is the primary driver of urban change. This pattern has direct implications for thermal dynamics, since impervious surfaces strongly amplify heat retention. Figure 3 and Table 2 present the classification results for four key years: 1984, 2000, 2010, and 2023.

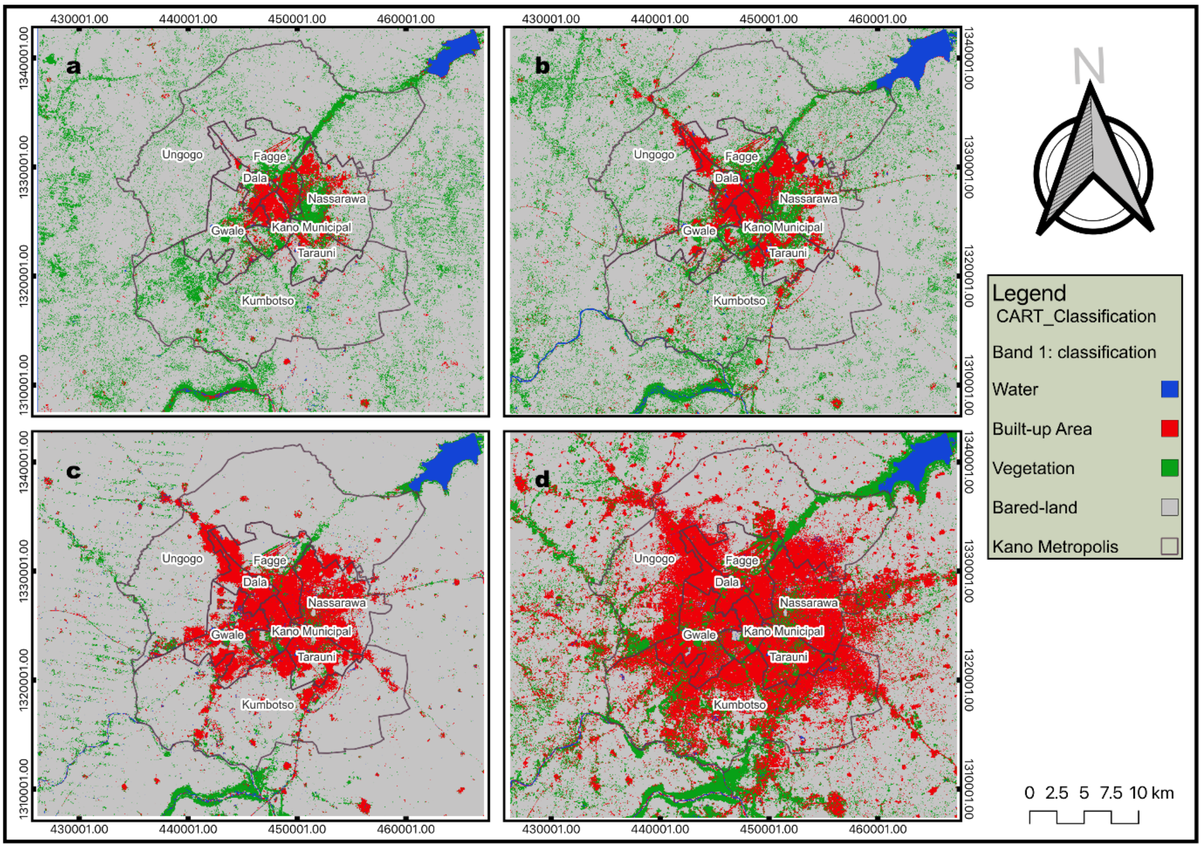

Figure 3: Depicts the distribution of Land Use and Land Cover (LULC) classes in the study areas over four different time periods: (a) 1984, (b) 2000, (c) 2010, and (d) 2023

Table 2: Distribution of LULC classes in the study area from 1984 to 2023

LULC Class	1984 (km²)	2000 (km²)	2010 (km²)	2023 (km²)	% Change (1984–2000)	% Change (2000–2010)	% Change (2010–2023)	% Change (1984–2023)
Water	19.31	23.46	26.05	24.29	0.28	0.18	-0.12	0.34
Built-up Area	43.06	84.56	144.5	381.79	2.82	4.07	16.13	23.02
Vegetation	192.29	203.9	68.41	189.46	0.79	-9.21	8.23	-0.19
Bare land	1216.62	1159.36	1232.32	875.74	-3.89	4.96	-24.24	-23.17

The overall classification accuracy for these years remained consistently high, with accuracies of 96.19%, 92.12%, 96.26%, and 98.48% for each year, respectively. Built-up Areas: The most significant change was the rapid expansion of built-up areas, increasing from 43.06 km² (2.93%) in 1984 to 381.79 km² (25.95%) in 2023. This represents an almost 800% increase in urbanisation, reflecting substantial infrastructural development in the region. Bare Land and Vegetation: Simultaneously, bare land coverage decreased by 23.17%, shrinking from 1,216.62 km² (82.69%) in 1984 to 875.74 km² (59.52%) in 2023. Vegetation cover saw a slight net decrease from 192.29 km² (13.07%) in 1984 to 189.46 km² (12.88%) in 2023, indicating growing pressure on green spaces due to urban expansion. The rapid growth of built-up areas, particularly between 2010 and 2023, corresponds to population growth and economic development in Kano, highlighting the critical need for sustainable urban planning to balance urbanisation with environmental sustainability.

3.1.2. Classification Accuracy

The CART classification achieved high accuracy across all benchmark years, with overall accuracies exceeding 92% and Kappa coefficients above 0.85. Table 2 presents the distribution of accuracy assessment results.

Table 3: Classification Accuracy from 1984 to 2023

Year	Overall accuracy	Kappa Coefficient
1984	98.67%	0.97
2000	92.06%	0.85
2010	98.96%	0.98
2023	96.80%	0.95

3.2 Land Surface Temperature (LST) Analysis

3.2.1. Temporal Patterns of LST (1984–2023)

Land surface temperature (LST) increased significantly over the study period. As shown in Table 4, the mean LST rose from 39.72°C in 1984 to 41.54°C in 2023, with a peak of 44.50°C recorded in 2010. The maximum LST observed in 2010 reached 52.85°C, highlighting the intensifying heat in the urban core, while the minimum temperature in 2023 dropped to 22.00°C in areas with substantial vegetation cover and water bodies. The increase in LST is closely linked to the urban heat island (UHI) phenomenon, where urbanised areas experience higher temperatures compared to surrounding rural areas. The spatial distribution of UHI consistently shows that built-up areas recorded higher temperatures than vegetated and bare land regions. This pattern underscores the role of impervious surfaces in absorbing and retaining heat, amplifying the UHI effect in rapidly urbanising areas like Kano.

Table 4: Minimum, Maximum, Mean, and SD of LST distribution in the study area from 1984 to 2023

Item/ Year	1984	2000	2010	2023
Min	24.20	12.24	11.69	22.00
Max	47.70	47.21	52.85	46.82
Mean	39.72	39.23	44.50	41.54
SD	1.80	2.76	2.6	2.30

3.2.2. LST and Spectral Indices Relationship

To further investigate the impact of urbanisation on thermal patterns, the relationship between land surface temperature (LST) and spectral indices such as NDVI and NDBI was analysed. The results demonstrated an inverse relationship between NDVI and LST, indicating that areas with dense vegetation exhibited lower surface temperatures. In contrast, a strong positive correlation was observed between NDBI and LST, showing that built-up areas with impervious surfaces significantly contribute to higher temperatures. These findings emphasise the crucial role of vegetation in mitigating urban heat and underscore the contribution of urbanisation to the intensification of the urban heat island (UHI) effect. Mean LST increased from 39.7°C in 1984 to 41.5°C in 2023, with a peak of 44.5°C in 2010. Maximum surface temperatures exceeded 52°C in dense urban cores, while cooler zones (<25°C) persisted in vegetated and water-rich areas. The observed inverse relationship between NDVI and LST ($r = -0.32$) confirms the cooling effect of vegetation. In contrast, the positive correlation between NDBI and LST ($r = 0.57$) highlights the role of impervious surfaces in amplifying heat.

3.3 Urban Thermal Field Variance Index (UTFVI) and Ecological Health

3.3.1. UTFVI Trends (1984–2023)

The Urban Thermal Field Variance Index (UTFVI) was calculated over the study period to assess the ecological stress resulting from the urban heat island (UHI) effect. Table 5 classifies urban areas based on thermal stress levels, ranging from "None" (indicating excellent ecological health) to "Strongest" (indicating the worst ecological conditions) as depicted in Figure 4. UTFVI results show a progressive increase in ecological stress. In 1984, only 3.5% of the city fell into the "worst" category (UTFVI > 0.020), while by 2023, this had risen to 18.3%, concentrated in newly urbanised zones.

- 1984: In this year, 23.46% of the study area experienced low thermal stress (UTFVI < 0.005), while only 3.48% of the area showed severe thermal stress (UTFVI > 0.02).
- 2023: By this year, the proportion of areas under severe thermal stress (UTFVI > 0.02) had risen to 18.31%, particularly in rapidly urbanising zones, reflecting the deteriorating ecological conditions due to urban expansion.

These findings highlight the increasing ecological stress driven by urbanisation and emphasise the urgent need for sustainable interventions to mitigate the negative impacts of the UHI effect on urban environments.

Table 5: Distribution of the UHI phenomenon with their respective ecological evaluation index of UTFVI in the study area from 1984 to 2023

Urban Thermal Field Variation Index	Urban Heat Island Phenomenon	Ecological Evaluation Index	Area (in sq km)				Net Change (in %)			Overall Changes (in %)
			1984	2000	2010	2023	1984 - 2000	2000 - 2010	2010 - 2023	
< 0	None	Excellent	546.19	155.81	434.48	474.91	-26.53	18.94	2.75	-4.84
0.000 – 0.005	Weak	Good	99.36	51.23	59.4	38.84	-3.27	0.56	-1.40	-4.11
0.005 – 0.010	Middle	Normal	113.38	508.68	64.02	40.26	26.87	-30.22	-1.61	-4.97
0.010 – 0.015	Strong	Bad	123.97	514.28	109.26	40.94	-8.43	7.43	-4.64	-5.64
0.015 – 0.020	Stronger	Worse	126.64	162.93	170.24	145.16	2.47	0.50	-1.70	1.26
>0.020	Strongest	Worst	461.74	78.35	633.88	731.17	-26.06	37.76	6.61	18.31

This pattern demonstrates that rapid urban growth directly intensifies ecological stress, reinforcing the urgency of incorporating vegetation preservation and climate-sensitive design into urban planning.

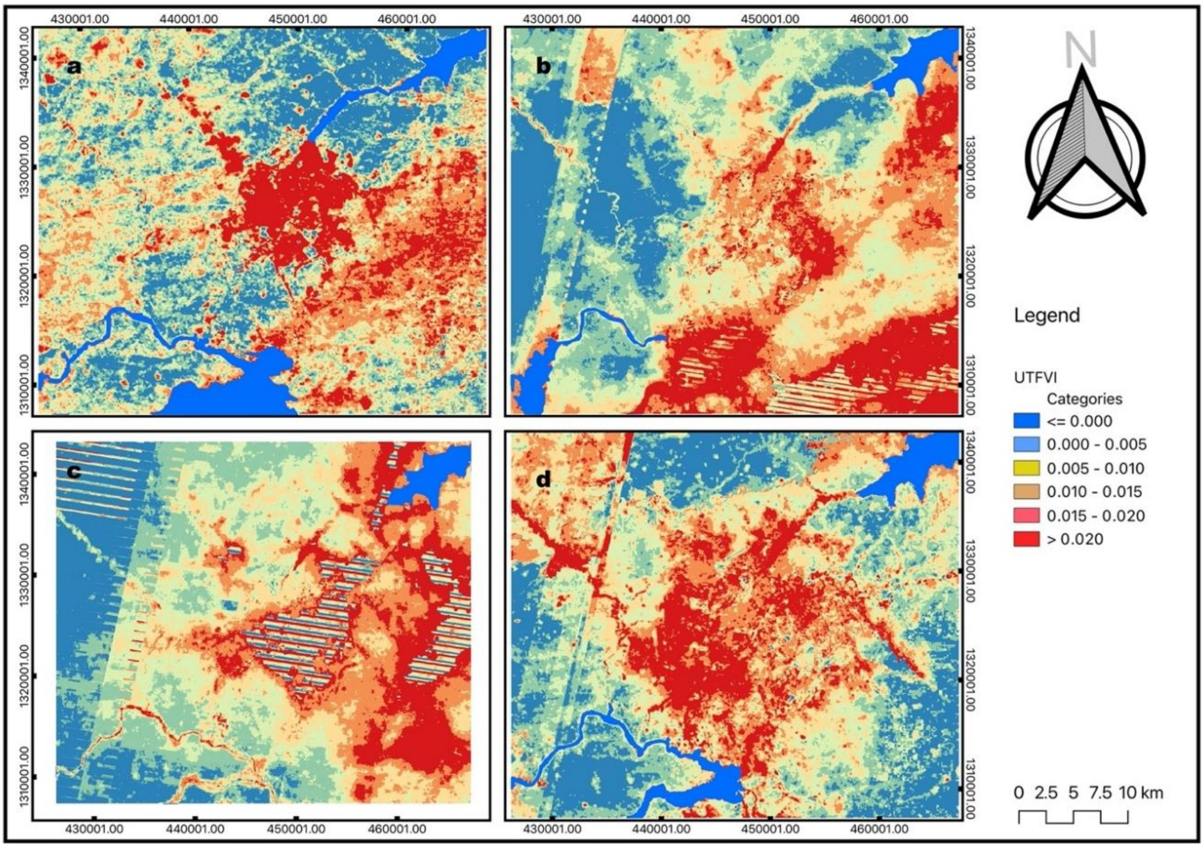

Figure 4: Dry season UTFVI distribution in the study area (a) 1984, (b) 2000, (c) 2010 and (d) 2023

3.3.2. Ecological Implications

The significant increase in UTFVI values from 1984 to 2023 reflects a decline in urban ecological health, with a growing proportion of areas experiencing high thermal stress. This trend highlights the urgent need for urban greening initiatives, such as expanding parks and increasing vegetative cover, to enhance ecological conditions and mitigate the adverse effects of the urban heat island (UHI) phenomenon. Implementing these strategies is crucial for improving the livability of urban spaces and fostering climate resilience in rapidly urbanising regions.

3.4 Statistical Analysis: Pearson's Correlation

3.4.1. Correlation Between Environmental Variables and LST

Pearson's correlation analysis was conducted to explore the relationships between key variables, including population density (Pop), slope, Digital Elevation Model (DEM), urban thermal field variance index (UTFVI), urban heat island (UHI), LST, NDVI, and NDBI. The correlation matrix is presented in Table 6 and visually summarised in Figure 5.

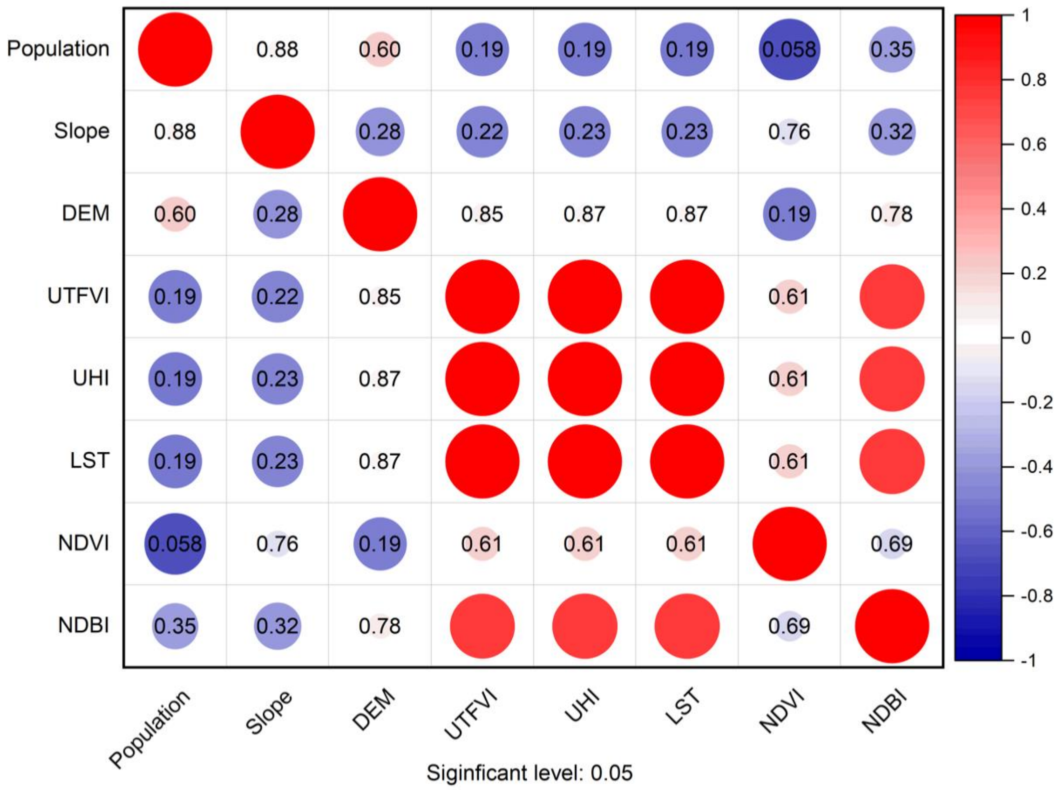

Figure 5: Pearson's correlation plot

- Population Density and Vegetation (NDVI): A moderate negative correlation was observed between population density and NDVI (-0.32), suggesting that areas with higher population densities tend to have reduced vegetation cover.
- LST and UHI/UTFVI: LST was strongly correlated with UHI (1.00) and UTFVI (0.99), indicating that LST is a direct driver of the UHI effect in Kano. As urban areas expanded, so did the intensity of UHI, with built-up regions showing the most significant increases in thermal stress.
- DEM and LST: A weak positive correlation was found between DEM and LST (0.21), suggesting that higher elevations in the study area are slightly warmer, though not as significantly as low-lying urban areas.
- NDBI and UHI/LST: A moderate positive correlation was found between NDBI and both UHI and LST (0.57), reinforcing the finding that built-up areas with impervious surfaces contribute to elevated temperatures.

These correlations highlight the influence of urbanisation on thermal dynamics, particularly the role of impervious surfaces and reduced vegetation in exacerbating urban heat effects.

Table 6: Pearson's correlation

	Pop	**Slope**	**DEM**	**UTFVI**	**UHI**	**LST**	**NDVI**	**NDBI**
Pop	1.00	0.07	0.18	-0.05	-0.08	-0.08	-0.32	-0.09
Slope	0.07	1.00	-0.10	-0.02	-0.03	-0.03	-0.01	-0.04
DEM	0.18	-0.10	1.00	0.24	0.21	0.21	-0.19	0.14
UTFVI	-0.05	-0.02	0.24	1.00	0.99	0.99	0.23	0.57
UHI	-0.08	-0.03	0.21	0.99	1.00	1.00	0.21	0.57
LST	-0.08	-0.03	0.21	0.99	1.00	1.00	0.21	0.57
NDVI	-0.32	-0.01	-0.19	0.23	0.21	0.21	1.00	-0.12
NDBI	-0.09	-0.04	0.14	0.57	0.57	0.57	-0.12	1.00

3.4.2. Interpretation of Correlation Results

The statistical results confirm that urban expansion, as reflected by NDBI, is strongly associated with rising LST and the intensification of the urban heat island (UHI) effect. The negative correlation between NDVI and LST highlights the cooling effect of vegetation, emphasising the importance of preserving green spaces in urban planning. Moreover, the strong correlations between LST, UHI, and UTFVI indicate that UHI intensification is directly linked to rising surface temperatures and declining vegetation, making urban areas increasingly vulnerable to thermal stress. These findings underscore the necessity for sustainable urban development strategies that integrate vegetation to mitigate the negative impacts of urbanisation on thermal dynamics.

3.5 Predictive Modelling of Future LULC and Thermal Patterns

3.5.1. LULC Predictions for 2033 and 2050

The CA–ANN model predicts continued urban expansion, with built-up areas expected to grow by 6.5% between 2023 and 2050, primarily at the expense of bare land. Vegetation cover is projected to remain relatively stable, with a slight increase by 2050, possibly reflecting the impact of greening initiatives.

Unless urban greening is actively implemented, Kano will face more pronounced UHI effects, with higher surface temperatures and increased ecological stress. This highlights the importance of integrating predictive models into planning decisions to pre-empt adverse outcomes. Using the Cellular Automata-Artificial Neural Network (CA-ANN) model, land-use and land-cover (LULC) changes were projected for 2033 and 2050, as shown in Figures 6 and 7. The model, validated with a Kappa coefficient of 0.86 and an overall accuracy of 92%, predicted continued urban expansion, accompanied by a reduction in vegetation and an increase in bare land.

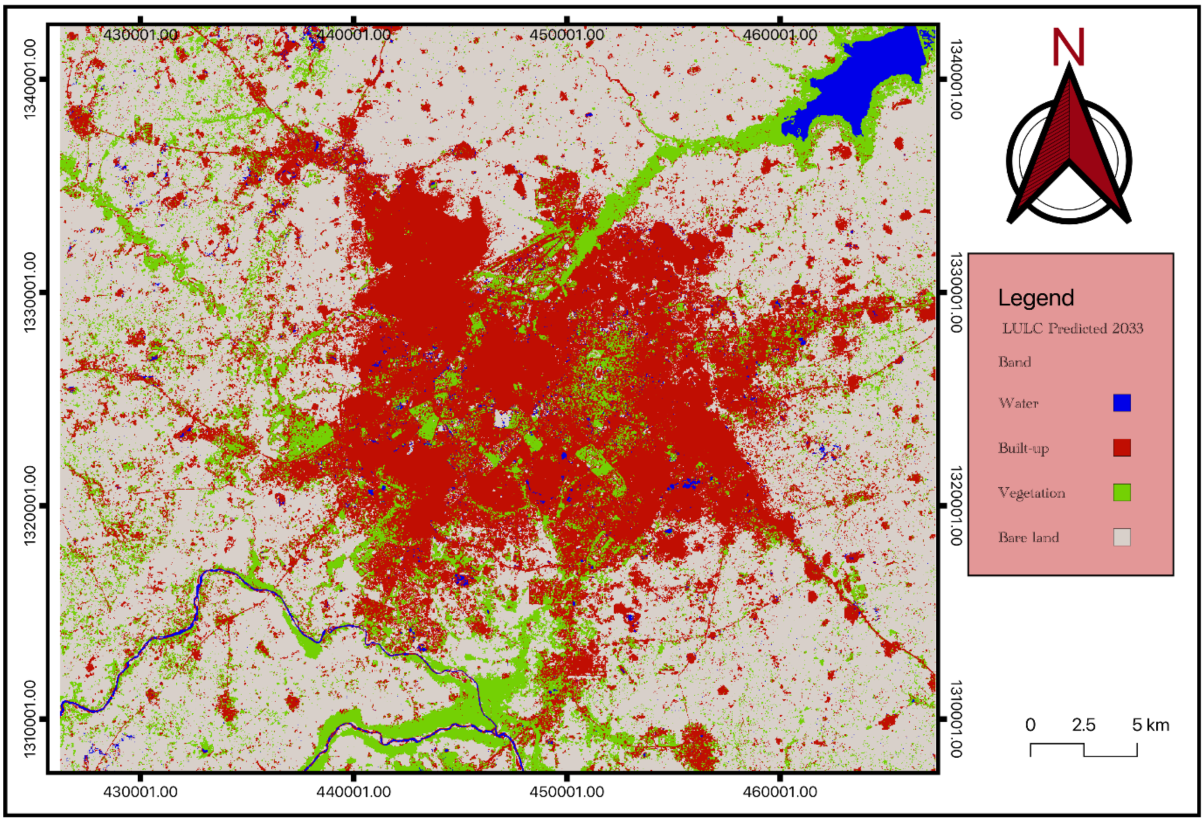

Figure 6: Simulated LULC for 2033 in the study area

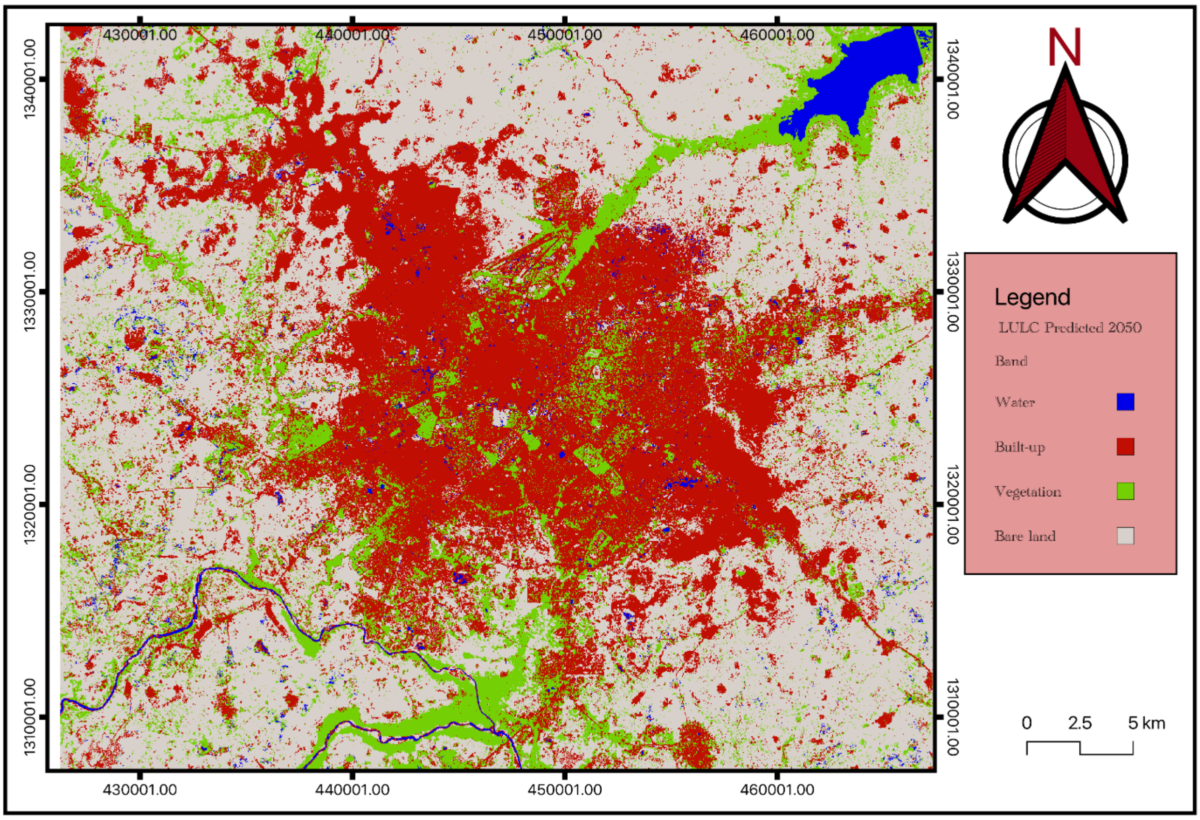

Figure 7: Simulated LULC for 2050 in the study area

- 2033 Projections: Built-up regions are projected to increase by 1.45%, while bare land is expected to decrease by 1.59%. Vegetation cover is forecasted to experience a slight decline of 0.03%. See Table 7.
- 2050 Projections: The trend continues, with built-up areas anticipated to expand by an additional 5.02%, resulting in a net reduction of bare land by 7.41%. Interestingly, vegetation cover is predicted to increase slightly by 0.30%, possibly reflecting urban greening initiatives. See Table 8.

These projections highlight the persistent urbanisation in Kano Metropolis and stress the need for sustainable development strategies that balance urban growth with ecological conservation.

Table 7: LULC simulation Validation of CA model for 2023 and 2050

Prediction Year	QGIS- MULUSCE Plugin module			
	% of Correctness	K - overall	K - histo	K - loc
2033	91.49	0.85	0.89	0.95
2055	92.34	0.86	0.89	0.96

Table 8: Change in LULC classes from 2023 to 2033 and 2050

LULC	2023		2033		2050		Net Change (%)		Overall Change (%)
	Area (sqkm)	Area (%)	Area (sqkm)	Area (%)	Area (sqkm)	Area (%)	2023 - 2033	2023 - 2050	
Water	24.29	1.65	26.81	1.82	31.22	2.12	0.17	0.47	0.64
Built-up	381.79	25.95	403.11	27.40	455.64	30.97	1.45	5.02	6.47
Vegetation	189.46	12.88	188.95	12.84	194.42	13.21	-0.03	0.34	0.30
Bare Land	875.74	59.52	852.42	57.94	790	53.69	-1.59	-5.83	-7.41

3.5.2. Implications of Predictive Modelling on Urban Heat

The predicted LULC changes for 2033 and 2050 suggest that the urban heat island (UHI) effect is likely to intensify as urban areas continue to expand. The increase in built-up areas, alongside the reduction in bare land, is expected to contribute to higher surface temperatures, particularly in densely populated regions. This projection underscores the urgent need for sustainable urban planning strategies that incorporate green infrastructure to mitigate the future impacts of the

UHI effect and enhance climate resilience. Implementing these measures will be essential to promoting a balanced approach to urban growth, while minimising thermal stress on both urban populations and ecosystems.

4.0 Discussion

4.1 Comparison with Previous Studies

This study demonstrates a clear relationship between land-use/land-cover (LULC) changes and the intensification of the urban heat island (UHI) effect in Kano Metropolis. The expansion of built-up areas and reduction of bare land over the last four decades have contributed significantly to the observed increase in land surface temperature (LST). As urbanisation progresses, impervious surfaces, such as roads and buildings, replace natural vegetation, leading to higher heat retention and exacerbating the UHI effect. While vegetation cover did decline slightly, it was not the primary driver of temperature increases; instead, the conversion of bare land to built-up areas had the most pronounced thermal impact. The negative correlation between NDVI and LST ($r = -0.32$) highlights the cooling effect of vegetation, and the positive correlation between NDBI and LST ($r = 0.57$) demonstrates how urban expansion increases thermal stress through impervious surfaces. These results align with studies in similar semi-arid regions, suggesting that land use is a primary determinant of urban thermal dynamics in these contexts. The notable growth in built-up areas, from 2.93% in 1984 to 25.95% in 2023, mirrors trends observed in other rapidly urbanising cities such as Lagos, Nigeria, and Dhaka, Bangladesh, where urban expansion has been closely linked to rising surface temperatures and the intensification of the UHI phenomenon (Derdouri et al., 2021; Fang et al., 2024; Karen C. Seto et al., 2012). These findings are consistent with existing research, which identifies urbanisation as a key driver of increasing land surface temperatures (LST), primarily due to the replacement of natural vegetation with impervious surfaces, such as buildings and roads, that trap and emit heat.

The negative correlation between NDVI and LST observed in this study aligns with the work of Guha et al. (2020), which showed that areas with higher vegetation cover experience lower temperatures due to the cooling effects of evapotranspiration. This underscores the critical role of green spaces in mitigating UHI effects and highlights the importance of vegetation for cooling urban environments, a conclusion well-supported by previous studies. However, the relatively small decrease in vegetation in Kano (-0.19% over 39 years) differs from the more substantial vegetation losses seen in other cities. This disparity may be due to the preservation of agricultural lands and parks in Kano, which still provide some cooling effects, although these are insufficient to offset the rapid urbanisation.

Another key finding is the link between the expansion of built-up areas and increasing urban thermal stress, as indicated by rising Urban Thermal Field Variance Index (UTFVI) values. Similar findings have been reported by Cevik Degerli and Cetin (2023), who observed declining ecological health in rapidly growing urban areas due to increased thermal stress. This study contributes to the body of literature by demonstrating how the growth of built-up regions in Kano has exacerbated thermal stress, particularly in densely populated areas.

The predictive modelling of future LULC changes points to a continued increase in built-up areas and a corresponding decrease in bare land and vegetation by 2050. These projections align with other studies that predict an intensification of the UHI effect if current urbanisation trends persist. However, unlike many studies that attribute rising LST primarily to vegetation loss, our findings suggest that in Kano, the conversion of bare land to built-up areas will play a more significant role, given that vegetation losses have been relatively modest compared to the substantial urban expansion.

4.2 Unique Insights and Discrepancies

The significant increase in UHI intensity observed in Kano corresponds closely with the spatial growth of urbanised areas and the decline in bare land. The Urban Thermal Field Variance Index (UTFVI) revealed a significant increase in thermal stress between 1984 and 2023. While the correlation between LST and UHI intensity is strong ($r = 1.0$), the relationship between population density, LULC changes, and thermal dynamics is more complex. The positive correlation between NDBI and LST ($r = 0.57$) suggests that urban sprawl is directly linked to the intensification of heat stress, a finding also reported in other rapidly urbanising semi-arid cities. However, caution is needed when interpreting the causes of vegetation changes. While bare land has decreased significantly, the reduction in vegetation cover is relatively small, suggesting that external factors, such as agricultural practices or land-use policies, may have contributed to this change. As semi-arid regions like Kano often rely heavily on agriculture, the dynamics between urbanisation and agricultural land use merit further study. This contrasts with trends in the other areas, where urbanisation has typically led to substantial reductions in green spaces. The modest decline in vegetation in Kano may be explained by its semi-arid climate, where natural vegetation is already sparse, and much of the land was categorised as bare before rapid urbanisation began. This highlights the importance of considering local climatic and environmental factors when evaluating the impacts of land-use and land-cover

(LULC) changes on thermal patterns. Another possible explanation for this discrepancy is the presence of agricultural lands within the metropolitan area, which have been preserved to some extent due to their economic importance. The conservation of these lands has likely mitigated the typical vegetation loss associated with urban expansion. However, our predictive models indicate that, if unchecked, continued urban growth will likely result in the conversion of these agricultural lands into built-up areas by 2050, which would further exacerbate urban heat island (UHI) effects. An additional noteworthy finding is the projected increase in vegetation cover by 2050 (by 0.30%), an unusual result compared to predictions for other urban areas. This projection may reflect potential urban greening initiatives or afforestation programs, which have gained traction in recent years as part of global and national climate resilience strategies. However, it is important to interpret these projections cautiously, as the successful implementation of such green infrastructure projects depends on political will, financial investment, and effective execution.

4.3 Limitations of CA-ANN Predictions

The Cellular Automata–Artificial Neural Network (CA-ANN) model demonstrated its utility in forecasting future LULC changes and UHI trends. However, its predictions should be viewed with caution. The model primarily relies on historical LULC data and environmental variables (e.g., proximity to roads, population density), which may not fully account for future policy interventions or external development pressures. The projected growth in built-up areas (an increase of 6.5% by 2050) assumes that current urban expansion trends will persist. Still, policy changes (e.g., zoning regulations or urban green spaces) could significantly alter these predictions. Additionally, climate change and global development trends may introduce uncertainties into future land-use projections, especially since these models do not fully account for non-local influences, such as international investment flows and global trade patterns.

4.4 The Role of Other Urban Factors in UHI

While the study primarily focused on LULC changes, other urban factors, such as transportation infrastructure, building materials, and energy consumption, also contribute to the UHI effect. High-density transport networks, for example, can exacerbate heat stress by increasing the extent of impervious surfaces and generating localised heat through vehicular emissions. Similarly, construction materials such as concrete and asphalt absorb more heat than natural landscapes, thereby intensifying urban thermal conditions. These factors should be considered when developing comprehensive UHI mitigation strategies, such as the use of cool roofs, green building practices, and sustainable transport systems. The complex interplay between these urban factors and LULC changes underscores the need for integrated urban planning that considers both ecological and infrastructural aspects to combat UHI effectively.

4.5 Implications for Sustainable Urban Development

The findings underscore the necessity for sustainable urban planning in the Kano Metropolis, particularly in light of the anticipated intensification of UHI effects. Urban planners must prioritise the integration of green infrastructure such as parks, green roofs, and urban forests to reduce the UHI impact. Furthermore, sustainable building materials and cooling technologies should be promoted to mitigate the thermal effects of impervious surfaces. Ensuring that urban growth does not come at the expense of ecological health is critical to climate resilience, particularly in semi-arid cities that already face significant thermal stress and resource limitations. The significant increase in built-up areas and the intensification of urban heat island (UHI) effects highlight the urgent need for urban planning practices that prioritise climate resilience and ecological health. Without proactive interventions, continued urban expansion will likely exacerbate surface temperatures, resulting in detrimental effects on public health, energy consumption, and ecological stability.

The negative correlation between NDVI and LST underscores the critical role of green spaces in mitigating urban heat. Urban planners should prioritise the preservation and expansion of parks, urban forests, and other vegetative areas as integral components of development strategies. The predicted increase in vegetation cover by 2050, as suggested by the model, should be actively promoted through policies encouraging urban greening initiatives. These could include afforestation, green roofs, and the establishment of green belts, which have been shown to lower LST and enhance urban livability. The strong positive correlation between NDBI and LST highlights the importance of sustainable building practices that reduce the use of impervious materials and incorporate heat-reflective designs. Policies should promote the adoption of energy-efficient building materials, cool roofing technologies, and increased tree cover around buildings to reduce the heat absorption capacity of built-up areas. These measures could significantly mitigate the UHI effect while improving the energy efficiency of urban environments.

The projected expansion of built-up areas by 2050 emphasises the need for careful land-use planning to ensure that future urban growth does not come at the expense of essential green spaces and agricultural lands. Zoning regulations should be updated to mandate green infrastructure in new developments, and incentives should be provided for developers who incorporate sustainable practices into their projects. Preserving agricultural lands near urban centres is also crucial for maintaining ecological balance, supporting food security, and reducing the adverse effects of urbanisation. This study emphasises the importance of integrating urban planning with climate change adaptation policies. Local governments must consider the environmental and public health implications of urbanisation when developing long-term expansion plans. Urban heat management strategies, such as increasing vegetation cover, enhancing urban water bodies, and constructing climate-resilient infrastructure, should be included in climate action plans to help cities address the challenges of rapid urbanisation. Integrating these strategies into broader climate resilience frameworks will be essential for promoting sustainable urban growth.

5.0 Conclusion

This study highlights the significant impact of land-use/land-cover (LULC) changes on the urban heat island (UHI) effect in the Kano Metropolis, Nigeria, over 39 years. Our findings show that urban expansion, primarily through the conversion of bare land into built-up areas, has led to increased land surface temperatures (LST) and intensified UHI effects. The positive correlation between Normalised Difference Built-up Index (NDBI) and LST, coupled with the negative correlation between Normalised Difference Vegetation Index (NDVI) and LST, underscores the role of vegetation in cooling urban environments, while built-up areas amplify heat. Predictive modelling further projects significant urban growth through 2050, emphasising the ongoing challenges of balancing urbanisation with sustainable development. The study also emphasises the importance of integrating green infrastructure and sustainable urban planning into future urban development strategies to mitigate the escalating UHI effects and promote climate resilience in rapidly urbanising regions. Measures such as preserving vegetation and adopting cooling technologies are critical to improving urban livability in semi-arid cities like Kano.

However, several limitations need to be considered when interpreting the results and applying them to other contexts. First, the predictive modelling relied heavily on historical data and environmental variables, but did not fully account for future policy interventions or the impacts of climate change. This uncertainty means that the projections for 2033 and 2050 are contingent on current trends continuing without significant policy changes or external disruptions. Additionally, LST validation was not performed due to the absence of ground-based thermal data, and therefore, the retrieved LST values should be interpreted with caution.

Finally, while urban factors such as building materials and transportation were acknowledged, they were not fully integrated into the model, limiting the comprehensiveness of the UHI effect analysis.

These limitations suggest that future studies should incorporate more localised data, including ground truth measurements for LST, and consider policy changes and other urban dynamics, such as construction practices and transportation infrastructure. Further research could also focus on testing UHI mitigation measures to evaluate their effectiveness in real-world scenarios, particularly in semi-arid and rapidly urbanising cities across sub-Saharan Africa.

5.1 Implications for Sustainable Urban Development

The findings highlight the urgent need for sustainable urban planning that prioritises climate resilience. Urban expansion must be balanced with the preservation and enhancement of green spaces to mitigate the UHI effect and reduce ecological stress. Policies that promote the use of sustainable building materials, urban greening initiatives, and heat-reflective infrastructure are essential for improving urban livability. Furthermore, land-use planning and zoning regulations must ensure that future developments incorporate climate adaptation strategies to protect public health and maintain ecological stability.

5.2 Future Research Directions

While this study contributes valuable insights into the nexus between LULC changes and urban thermal dynamics, further research is needed in several key areas:

1. Localised UHI Mitigation Strategies: Future research should focus on identifying and testing localised urban heat mitigation strategies, such as the effectiveness of urban greening initiatives, green roofs, and cool pavement technologies, particularly in semi-arid regions like Kano.
2. Socio-Economic Factors and Informal Urbanisation: Investigating the socio-economic drivers behind informal settlements and unplanned urban sprawl could provide deeper insights into the rapid urbanisation patterns observed. This could help inform policy interventions aimed at managing urban growth more sustainably.
3. High-Resolution Thermal Analysis: Conducting more granular studies of LST at the neighbourhood level would enable the identification of specific UHI hotspots, allowing for more targeted and effective interventions to mitigate the adverse effects of rising urban temperatures.

4. Longitudinal Impact of Green Infrastructure: Long-term studies on the effectiveness of green infrastructure in reducing UHI effects, particularly in rapidly urbanising regions, are needed to assess the potential of urban greening as a sustainable solution to urban thermal challenges.

In conclusion, this study emphasises the critical need for well-balanced urban expansion policies that integrate ecological considerations into urban planning. As cities continue to grow, the findings from this research provide a valuable foundation for decision-makers seeking to promote sustainable, climate-resilient urban development.

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Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this paper.

Authors' Contribution

Yusuf Ahmed Yusuf designed the research, conducted data collection and conducted the analysis. Helmi Zulhaidi bin Mohd Shafri supervised the research, provided the methodological framework and contributed to the overall design of the study. Siti Nur Aliaa binti Roslan assisted with data processing, contributed to the interpretation of results and provided editorial input. Jibrin Gambo contributed to data collection in Kano and provided contextual insights into the study area. All authors read and approved the final version of the manuscript.

Data Availability

The data supporting the findings of this study will be made available from the corresponding author upon reasonable request.

Funding Declaration

The authors declare that no funding was received for this research.

References

A, T. I., M, S. Y., I, Y. T., & A, K. A. (2017a). Urbanisation Effect on the Development of Urban Heat Island Over Kano Metropolis Nigeria. International Journal of Scientific & Engineering Research, 8(9). http://www.ijser.org

A, T. I., M, S. Y., I, Y. T., & A, K. A. (2017b). Urbanisation Effect on the Development of Urban Heat Island Over Kano Metropolis Nigeria. International Journal of Scientific & Engineering Research, 8(9). http://www.ijser.org

Alademomi, A. S., Okolie, C. J., Daramola, O. E., Agboola, R. O., & Salami, T. J. (2020). Assessing the relationship of LST, NDVI and EVI with land cover changes in the Lagos Lagoon environment. Quaestiones Geographicae, 39(3), 87–109. https://doi.org/10.2478/quageo-2020-0025

Aliyu, S. B. (2008). An Appraisal of Climate Change Risks and Institutional Adaptation Strategies in Kano State. 50th Annual Conference of the Association of Nigerian Geographers (ANG), 8, 103–112. https://doi.org/10.13140/2.1.2947.5523

Cetin, Mehmet, Mehtap Ozenen Kavlak, Muzeyyen Anil Senyel Kurkcuoglu, Gulsah Bilge Ozturk, Saye Nihan Cabuk, and Alper Cabuk. 2024. "Determination of Land Surface Temperature and Urban Heat Island Effects with Remote Sensing Capabilities: The Case of Kayseri, Türkiye." Natural Hazards 120(6):5509–36. doi: 10.1007/s11069-024-06431-5.

Cevik Degerli, B., & Cetin, M. (2023). Evaluation of UTFVI index effect on climate change in terms of urbanisation. Environmental Science and Pollution Research, 30(30), 75273–75280. https://doi.org/10.1007/s11356-023-27613-x

Chakraborty, T., & Lee, X. (2019). A simplified urban-extent algorithm to characterise surface urban heat islands on a global scale and examine vegetation control on their spatiotemporal variability. International Journal of Applied Earth Observation and Geoinformation, 74(October 2018), 269–280. https://doi.org/10.1016/j.jag.2018.09.015

Derdouri, A., Wang, R., Murayama, Y., & Osaragi, T. (2021). Understanding the Links between LULC Changes and SUHI in Cities: Insights from Two-Decadal Studies (2001–2020). Remote Sensing, 13(18), 3654. https://doi.org/10.3390/rs13183654

Eshetie, Seyoum Melese. 2024. “Exploring Urban Land Surface Temperature Using Spatial Modelling Techniques: A Case Study of Addis Ababa City, Ethiopia.” Scientific Reports 14(1):1–16. doi: 10.1038/s41598-024-55121-6.

Emmanuel Ayila, A. (2014). Statistical Analysis of Urban Growth in Kano Metropolis, Nigeria. International Journal of Environmental Monitoring and Analysis, 2(1), 50. https://doi.org/10.11648/j.ijema.20140201.16

Faisal, A. Al, Kafy, A. A., Al Rakib, A., Akter, K. S., Jahir, D. M. A., Sikdar, M. S., Ashrafi, T. J., Mallik, S., & Rahman, M. M. (2021). Assessing and predicting land use/land cover, land surface temperature and urban thermal field variance index using Landsat imagery for Dhaka Metropolitan area. Environmental Challenges, 4. https://doi.org/10.1016/j.envc.2021.100192

Fang, Q., Liu, C., Ren, Z., Fu, Y., Fan, H., & Wang, Y. (2024). Fine-Scale Spatiotemporal Analysis of Urban Heat Island Dynamics in the Central Yunnan City Cluster. https://doi.org/10.21203/rs.3.rs-3926408/v1

Fatemi, M., & Narangifard, M. (2019). Monitoring LULC changes and its impact on the LST and NDVI in District 1 of Shiraz City. Arabian Journal of Geosciences. https://doi.org/10.1007/s12517-019-4259-6

Feng, R., Liu, S., Wang, F., Wang, K., Zhengchen, R., & Wang, D. (2024). Future urban ecological land transition and its implications for high-heat exposure in China. Sustainable Cities and Society, 111, 105590. https://doi.org/10.1016/j.scs.2024.105590

Jain, Madhavi. 2024. “Future Land Use and Land Cover Simulations with Cellular Automata-Based Artificial Neural Network: A Case Study over Delhi Megacity (India).” Heliyon 10(14):e34662. doi: 10.1016/j.heliyon.2024.e34662.

García-Chan, N., Licea-Salazar, J. A., & Gutierrez-Ibarra, L. G. (2023). Urban Heat Island Dynamics in an Urban–Rural Domain with Variable Porosity: Numerical Methodology and Simulation. Mathematics, 11(5), 1140. https://doi.org/10.3390/math11051140

Guha, S., Govil, H., & Diwan, P. (2020). Monitoring LST-NDVI Relationship Using Premonsoon Landsat Datasets. Advances in Meteorology, 2020. https://doi.org/10.1155/2020/4539684

Hsu, C.-K., & Rodríguez, D. A. (2024). A comparison of heat effects on road injury frequency between active travelers and motorised transportation users in six tropical and subtropical cities in Taiwan. Social Science & Medicine, 117333. https://doi.org/10.1016/j.socscimed.2024.117333

Kafy, A.-A., Kafy, A. Al, Faisal, A.-A., Al-Faisal, A., Hasan, M. M., Sikdar, M. S. I., Sikdar, Md. S., Khan, M. H. H., Rahman, M., Rahman, M. M., & Islam, R. (2020). Impact of LULC Changes on LST in Rajshahi District of Bangladesh: A Remote Sensing Approach. https://doi.org/10.21523/gcj5.19030102

Kafy, A. Al, Faisal, A. Al, Rahman, M. S., Islam, M., Al Rakib, A., Islam, M. A., Khan, M. H. H., Sikdar, M. S., Sarker, M. H. S., Mawa, J., & Sattar, G. S. (2021). Prediction of seasonal urban thermal field variance index using machine learning algorithms in Cumilla, Bangladesh. Sustainable Cities and Society, 64. https://doi.org/10.1016/j.scs.2020.102542

Kassomenos Pavlos and Begou, P. (2022). The Impact of Urban Overheating on Heat-Related Morbidity. In M. Aghamohammadi Nasrin and Santamouris (Ed.), Urban Overheating: Heat Mitigation and the Impact on Health (pp. 39–80). Springer Nature Singapore. https://doi.org/10.1007/978-981-19-4707-0_3

Karen C. Seto, Burak Güneralp, & Lucy R. Hutyra. (2012). Global forecasts of urban expansion to 2030 and direct impacts on biodiversity and carbon pools. Proceedings of the National Academy of Sciences, 109(40), 16083–16088.

Koko, A. F., Han, Z., Wu, Y., Abubakar, G. A., & Bello, M. (2022). Spatiotemporal Land Use/Land Cover Mapping and Prediction Based on Hybrid Modeling Approach: A Case Study of Kano Metropolis, Nigeria (2020–2050). Remote Sensing, 14(23). https://doi.org/10.3390/rs14236083

Liu, P., Jia, S., Han, R., Liu, Y., Lu, X., & Zhang, H. (2020). RS and GIS Supported Urban LULC and UHI Change Simulation and Assessment. Journal of Sensors, 2020. https://doi.org/10.1155/2020/5863164

Malik, M. S., Shukla, J. P., & Mishra, S. (2019). Relationship of LST, NDBI and NDVI using Landsat-8 data in Kandaihimmat Watershed, Hoshangabad, India. Indian Journal of Geo-Marine Sciences. https://www.semanticscholar.org/paper/330257c6a59f76e9c032307e2c0288b294adc346

Marzban, F., Sodoudi, S., & Preusker, R. (2018). The influence of land-cover type on the relationship between NDVI–LST and LST-Tair. International Journal of Remote Sensing. https://doi.org/10.1080/01431161.2017.1402386

Moazzam, M. F. U., Kim, S., & Lee, B. G. (2024). Cities in the heat: Unveiling the urbanised impacted surface urban heat island of South Korea’s metropolises. Remote Sensing Applications: Society and Environment, 36, 101271. https://doi.org/10.1016/j.rsase.2024.101271

Mustapha, A., Yakudima, I. I., Alhaji, M., Nabegu, A. B., Adamu, F., Dakata, G., Umar, Y. A., & Musa, B. U. (2014). Overview Of The Physical And Human Setting Of Kano. Researchjournal's Journal of Geography, 1(5), 1–12. http://www.academia.edu/8127400/Overview_of_Physical_and_Human_Setting_of_Kano_Region_Nigeria

Nieuwenhuijsen, M. J. (2016). Urban and transport planning, environmental exposures and health-new concepts, methods and tools to improve health in cities. In Environmental Health: A Global Access Science Source (Vol. 15). BioMed Central Ltd. https://doi.org/10.1186/s12940-016-0108-1

Orieschnig, C. A., Belaud, G., Venot, J. P., Massuel, S., & Ogilvie, A. (2021). Input imagery, classifiers, and cloud computing: Insights from multi-temporal LULC mapping in the Cambodian Mekong Delta. European Journal of Remote Sensing, 54(1), 398–416. https://doi.org/10.1080/22797254.2021.1948356

Ong'ondo, Frank Juma, Shrinidhi Ambinakudige, Philista Adhiambo Malaki, Hafez Ahmad, Qingmin Meng, Domnic Kiprono Chesire, Kuria Anthony, and Yahia Said. 2025. "Monitoring and Prediction of Land Use and Land Cover Using Remote Sensing and CA-ANN." Rangeland Ecology and Management 102:160–71. doi: 10.1016/j.rama.2025.06.015.

Qin, Z., A. Karnieli, and P. Berliner. 2001. "A Mono-Window Algorithm for Retrieving Land Surface Temperature from Landsat TM Data and Its Application to the Israel-Egypt Border Region." International Journal of Remote Sensing 22(18):3719–46. doi: 10.1080/01431160010006971.Sensing, Remote, Kaduna Polytechnic, Kaduna Polytechnic, and Thermal Remote. 2024. "Journal of Agricultural & Env. Sci. Research 2024." 6(1):147–62.

Ramaiah, M., Avtar, R., & Rahman, M. M. (2020). Land cover influences on LST in two proposed smart cities of india: Comparative analysis using spectral indices. Land, 9(9). https://doi.org/10.3390/LAND9090292

sajadzadeh, H., & ghorbanileylestani, fatemeh. (2024). The Effect of Vegetation on Reducing the Urban Heat Island (Case Study: Karaj City). Motaleate Shahri. https://doi.org/10.22034/urbs.2024.140477.5005

Singh, N., Singh, S., & Mall, R. K. (2020). Urban ecology and human health: implications of urban heat island, air pollution and climate change nexus. In Urban Ecology (pp. 317–334). Elsevier. https://doi.org/10.1016/B978-0-12-820730-7.00017-3

Sobrino, José a., Juan C. Jiménez-Muñoz, and Leonardo Paolini. 2004. "Land Surface Temperature Retrieval from LANDSAT TM 5." Remote Sensing of Environment 90(4):434–40. doi: 10.1016/j.rse.2004.02.003.

Tanko, I. A., Suleiman, Y. M., Yahaya, T. I., & Kasim, A. A. (2017). Urbanisation Effect on the Development of Urban Heat Island Over Kano Metropolis Nigeria. International Journal of Scientific & Engineering Research, 8(9), 293–299.

Tesfamariam, S., Govindu, V., & Uncha, A. (2023). Spatio-temporal analysis of urban heat island (UHI) and its effect on urban ecology: The case of Mekelle city, Northern Ethiopia. Heliyon, 9(2). https://doi.org/10.1016/j.heliyon.2023.e13098

Thanvisitthpon, N. (2023). Statistically Validated Urban Heat Island Risk Indicators for UHI Susceptibility Assessment. International Journal of Environmental Research and Public Health, 20(2), 1172. https://doi.org/10.3390/ijerph20021172

Usman, Muhammad, Janet E. Nichol, Ayman M. Abdallah, and Muhammad Bilal. 2025. "Characterising the Urban Heat Island in a Low-Rise Indigenous City Using Remote Sensing." Urban Climate 61:102433. doi: 10.1016/j.uclim.2025.102433.

Voogt, J. .., and T. .. Oke. 2003. "Thermal Remote Sensing of Urban Climates." Remote Sensing of Environment 86(3):370–84. doi: 10.1016/S0034-4257(03)00079-8.

Yiran, Gerald Albert Baeribameng, Michael Kpakpo Allotey, Christopher Sormeteyema Boatbil, and Iris Ekua Mensimah Fynn. 2025. "Combining Remote Sensing Applications and Local Knowledge in Understanding Urban Heat in a Semi-Arid Region: A Case Study of Tamale's Thermal Landscape." Local Environment 1–19. doi: 10.1080/13549839.2025.2486298.