



ARTICLE

Beyond Urban Heat Islands: Linking Land Surface Temperature to Urban Air Pollution through Geospatial and Correlation Analytics

Yusuf Ahmed Yusuf^{1,2,3} , Helmi Zulhaidi Mohd Shafri^{1,3,*} , Kamil Muhammad Kafi^{4,5,*} ,
Siti Nur Aliaa Roslan^{1,3} and Jibrin Gambo^{3,6}

¹Department of Civil Engineering, Faculty of Engineering, Universiti Putra Malaysia, Serdang, Selangor, Malaysia

²Department of Environmental Management, Faculty of Earth and Environmental Sciences, Bayero University, Kano, Nigeria

³Geospatial Information Science Research Centre (GISRC), Faculty of Engineering, Universiti Putra Malaysia, Serdang, Selangor, Malaysia

⁴Department of Environment, Faculty of Forestry and Environment, Universiti Putra Malaysia, Serdang, Selangor, Malaysia

⁵Department of Urban and Regional Planning, Faculty of Earth and Environmental Sciences, Bayero University, Kano, Nigeria

⁶Department of General Studies, Binyaminu Usman Polytechnic, Hadejia, Nigeria

*Corresponding Authors: Helmi Zulhaidi Mohd Shafri. Email: helmi@upm.edu.my; Kamil Muhammad Kafi. Email: kmkafi.urp@buk.edu.ng

Received: 27 April 2026; Accepted: 16 July 2026; Published: 07 August 2026

ABSTRACT: Urbanization alters land surface characteristics, intensifies urban heat, and degrades air quality, posing significant environmental and public health challenges. This study investigated the relationship between urban land surface temperature (LST) and air pollution in Kano Metropolis, Nigeria, using Earth observation data, geospatial techniques, and correlation analysis. Land use/land cover (LULC) analysis revealed that built-up areas account for 67.4% of the metropolitan area, contributing to elevated land surface temperatures, particularly within the densely urbanized local government areas of Kano Municipal, Gwale, Ungogo, Dala, and Fagge, as demonstrated by the LST and Urban Heat Island (UHI) analyses. To evaluate the relationship between urban heat and air quality, Pearson correlation analysis showed strong and statistically significant positive relationships between LST and particulate matter, with $PM_{2.5}$ ($r = 0.74$, $p < 0.001$) and PM_{10} ($r = 0.61$, $p < 0.001$) exhibiting the strongest associations. In contrast, CO_2 , TVOC, and HCHO displayed weak and statistically non-significant relationships with LST. Air Quality Index (AQI) assessment further revealed that 53.6% of the metropolitan area experienced unhealthy air quality, with localized very unhealthy conditions concentrated around commercial cooking areas where biomass fuels are extensively used. These findings indicate that particulate pollution is closely associated with urban surface heating, whereas gaseous pollutants are comparatively less influenced by LST. Overall, the results demonstrate that rapid urbanization, increasing impervious surfaces, and anthropogenic emissions collectively contribute to elevated urban temperatures and deteriorating particulate air quality in Kano Metropolis. These findings provide valuable evidence to support sustainable urban planning through urban greening, the use of high-albedo materials, and cleaner cooking technologies to mitigate urban heat, improve air quality, and reduce public health risks in rapidly urbanizing cities.

KEYWORDS: Urban heat islands; air quality; remote sensing; Nigeria; public health; sustainable urban planning

1 Introduction

Urbanization, recognized by the United Nations as a key global trend, has resulted in over half of the global population living in urban areas. This rapid urban expansion presents notable environmental challenges, including the Land Surface Temperature (LST) and Urban Heat Island (UHI) effect [1,2]. The LST is

the temperature of the Earth's land surface derived from satellite thermal infrared data, reflecting the thermal characteristics of different land cover types. While UHIs are characterized by higher temperatures in urban areas compared to rural surroundings, driven by modified land surfaces, increased energy consumption, and reduced vegetation [3]. Additionally, urbanization intensifies outdoor air pollution, which is particularly detrimental in densely populated and underdeveloped regions [4]. In developing countries, unplanned urban growth often leads to urban sprawl, increased traffic emissions, and overburdened infrastructure [5,6]. By 2050, over 60% of Nigerians are expected to reside in urban areas, many in unplanned settlements [7]. The transformation of natural landscapes into impermeable surfaces alters solar radiation dynamics, exacerbating LST formation [8].

The UHI effect elevates urban temperatures by 2°C to 15°C compared to rural areas, with more severe impacts observed in arid and semi-arid regions [9]. Factors such as human activities, weather patterns, and land-use changes influence the intensity of UHIs [10]. UHIs affect surface temperatures, energy consumption, and air pollutant levels, posing health risks and altering atmospheric conditions [11]. Urban air pollution, stemming from transportation, industrial processes, and heating, further compounds these challenges. Pollutants such as PM_{2.5}, NO₂, and O₃ are associated with significant health risks [12]. The interplay between UHIs and outdoor air pollution creates additional risks to urban residents' health and well-being [13].

The relationship between LST and air quality is multifaceted, influenced by factors such as chemical reactions, emission sources, and atmospheric stagnation [14]. Elevated LST temperatures enhance ground-level ozone formation, while reduced air circulation leads to pollutant accumulation [15]. Although available evidence indicates that reductions in anthropogenic emissions may have influenced surface temperature and net radiative flux across these urban areas; however, the relationship has not yet been conclusively established [1].

The interaction between LST/UHIs and outdoor air pollution presents a multidimensional environmental challenge [16,17]. Elevated urban temperatures can catalyze photochemical reactions that increase ground-level ozone, while stagnant atmospheric conditions associated with UHI hinder the dispersion of pollutants, leading to their accumulation [14,15]. Urban zones with high population density and industrial activity often experience overlapping UHI and air pollution hotspots, intensifying public health risks [18]. Addressing these intertwined phenomena requires a detailed understanding of their spatial and temporal dynamics, particularly in rapidly urbanizing regions where data scarcity remains a persistent limitation.

Numerous studies have investigated UHI and LST dynamics using remote sensing, which enables consistent, large-scale monitoring of surface thermal conditions and land use/land cover change [8,19,20]. Despite increasing concerns over the environmental and health impacts of urbanization, limited research has examined the relationship between land surface temperature (LST) and ambient air pollution in rapidly urbanizing semi-arid cities of developing countries. Most previous studies have focused primarily on UHI characterization, with little attention to how surface thermal conditions interact with key air pollutants, particularly in semi-arid African cities. In addition, many studies estimate UHI intensity using mean LST values without an in-depth analysis of the impact of urban temperature differentials on public health, potentially limiting the scope of impact assessments. Given the rapid urban expansion, increasing impervious surfaces, and deteriorating air quality in Kano Metropolis, there is an urgent need to investigate these interactions to provide evidence for sustainable urban planning, climate adaptation, and public health interventions. The failure to account for this difference introduces significant uncertainty, particularly in regions where temperature variability across land cover types is pronounced.

2 Methods and Materials

2.1 Study Area

The Kano metropolitan area, located in northwest Nigeria, has a long history of important human settlements that date back thousands of years. This region, which is 472 m above sea level, covers latitudes $11^{\circ}25' \text{ N}$ to $12^{\circ}47' \text{ N}$ and longitudes $8^{\circ}22' \text{ E}$ to $8^{\circ}39' \text{ E}$ (See Fig. 1). The urbanised area is surrounded by Tofa, Madobi, Gezawa, and Dawakin Kudu and consists of eight Local Government Areas (LGAs): Kano Municipal, Gwale, Dala, Fagge, Tarauni, Nassarawa, and Ungogo. Two separate air masses, maritime air masses from the Atlantic Ocean and dry currents from the Sahara Desert, converge to shape the climate of Kano. High temperatures are the norm year-long, reaching highs of over 48°C from January to April. The area has three distinct seasons: a hot and dry season from March to mid-May, a cold and dry season from November to February, and a wet season from May to September with average monthly temperatures higher than 26°C [21–23].

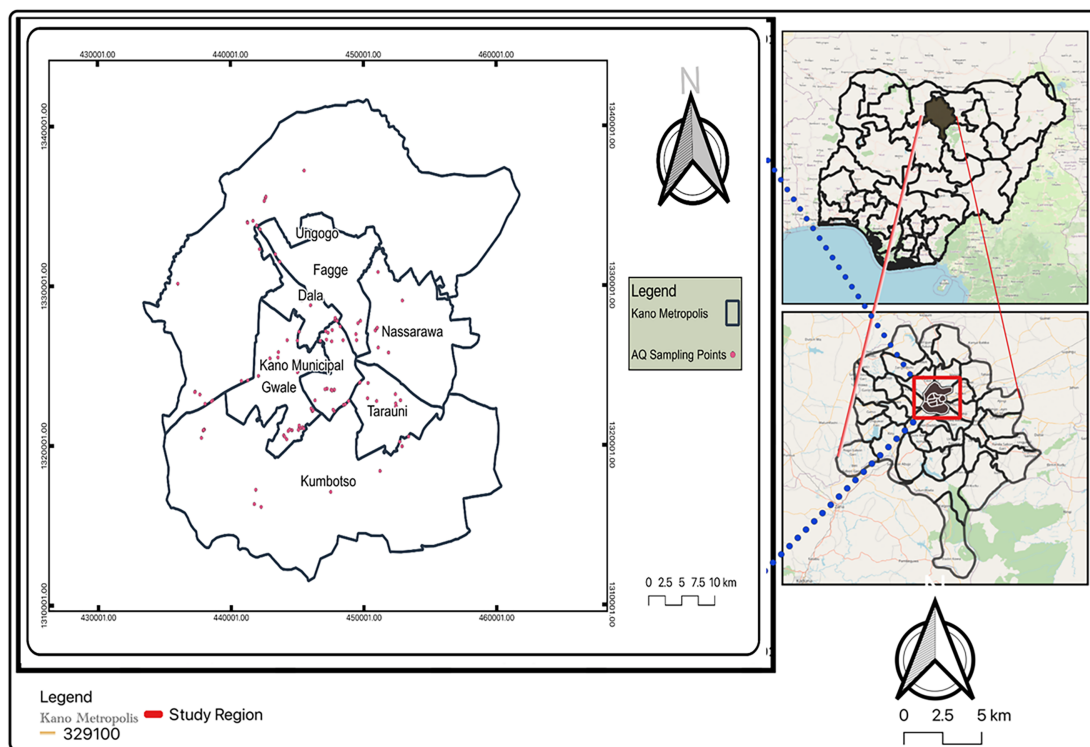


Figure 1: Study area showing the locations of air pollutant sampling points across Kano metropolis.

2.2 Methodology

The methodology used in this study integrates remote sensing techniques, ground-based air quality measurements and statistical modeling to assess the relationship between Land Surface Temperature (LST) and outdoor air quality in the Kano metropolis, Nigeria. The research framework follows a structured approach and ensures accuracy and reproducibility through a combination of data collection, pre-processing, analysis techniques and validation. The study used a multi-temporal analysis using Landsat Collection 2 satellite imagery, air quality measurements, and geospatial tools. The methodology was developed to quantify the intensity of the LST effect and its impact on air quality parameters such as CO_2 , particulate matter ($\text{PM}_{2.5}$ and PM_{10}), total volatile organic compounds (TVOC) and formaldehyde (HCHO). The study used advanced

image processing techniques, including land use and land cover classification (LULC), calculation of LST, and calculation of indices such as the Normalized Difference Vegetation Index (NDVI) and the Urban Thermal Field Variance Index (UTFVI) and Air quality on the ground. Fig. 2 depicts the methodological flowchart of the study.

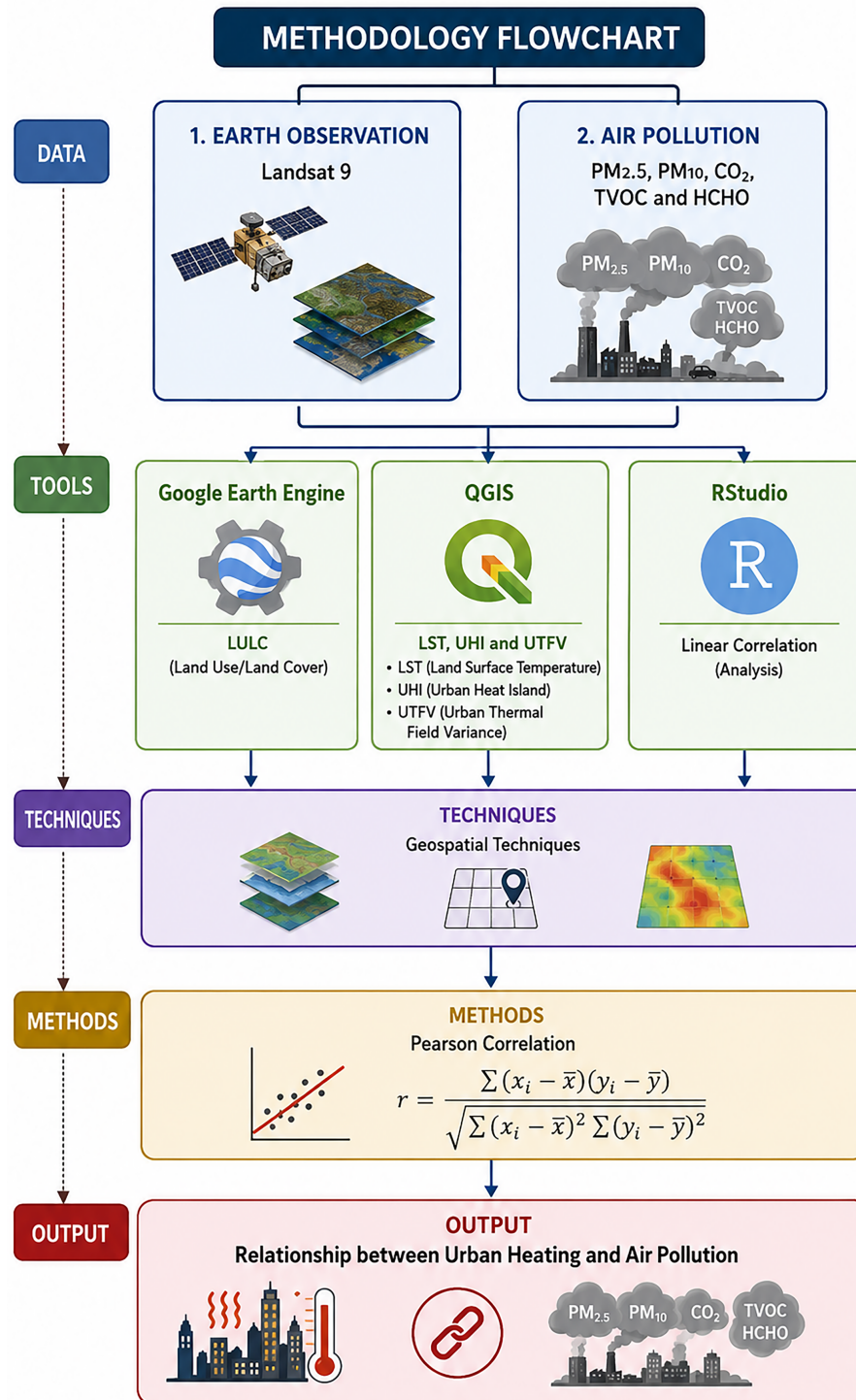


Figure 2: Methodological flowchart.

2.3 Data and Pre-Processing

2.3.1 Landsat Collection 2 Data

This study utilized data from Landsat Collection 2, which provides improved radiometric and geometric quality for Earth observation. The collection includes Level 1, Level 2, and Level 3 products from Missions 1 through 9, representing decades of environmental monitoring [24]. Level 1 products deliver top-of-atmosphere reflectance data, while Level 2 products, available for Missions 4 through 9, provide surface reflectance and temperature data derived through advanced atmospheric correction algorithms [24]. A key enhancement in Collection 2 is its improved geometric accuracy, achieved through integration with the Global Digital Elevation Model (GDEM) and other high-resolution elevation datasets. This integration minimizes positioning errors and ensures better alignment of multi-temporal data, facilitating reliable analyses of land-use and environmental changes over time [25]. Enhanced calibration and validation processes further improve data quality, making the collection well-suited for monitoring phenomena such as UHI and urban land cover changes. The Level 2 Surface Reflectance and Surface Temperature products, available since 1982, employ atmospheric correction models to mitigate the influence of aerosols, water vapor, and other atmospheric disturbances. These corrections enable precise calculation of indices such as the LST, which are essential for analyzing thermal anomalies, particularly in rapidly urbanizing areas [24]. Additionally, the U.S. Analysis Ready Data (ARD) products provide pre-processed datasets organized into standardized grids, facilitating efficient large-scale analyses such as long-term environmental monitoring and climate research [26]. For this study, Landsat 9 data were chosen due to their higher radiometric resolution and improved signal-to-noise ratio, which enhance the detection of thermal variations. Cloud-free images from the hot-dry season were prioritized to effectively capture UHI dynamics.

2.3.2 Air Pollution Data

To accurately assess the relationship between Land Surface Temperature (LST) and outdoor air quality in the Kano metropolis, a systematic and comprehensive air quality data collection approach was employed. The aim was to monitor a range of important pollutants, including carbon dioxide (CO₂), particulate matter (PM_{2.5} and PM₁₀), total volatile organic compounds (TVOC), and formaldehyde (HCHO). Environmental parameters such as temperature and humidity. These data were collected across different land use types, including residential, commercial, industrial, and vegetation areas, to ensure spatial representation and capture the variability of pollutant concentrations across the study region. The study was conducted during the hot and dry peak season (March to May 2025), a period known for high temperatures and minimal precipitation, which is crucial for understanding the intensification of UHIs and their impact on air quality. A total of 125 sampling points were collected to measure the concentrations of five air pollutants: PM_{2.5}, PM₁₀, CO₂, Total Volatile Organic Compounds (TVOC), and formaldehyde (HCHO) across Kano Metropolis.

Device Calibrations

The study employed a DM106A Air Quality Monitor and a JD-3002 Professional Air Quality Meter. Both instruments were supplied as factory-calibrated devices by the manufacturers and were operated according to the manufacturers' guidelines. Prior to each measurement campaign, the instruments were inspected, allowed to stabilize in a clean and well-ventilated environment, and verified for consistent operation. The instruments were also allowed an adequate warm-up period before data collection to ensure stable sensor performance. Although no laboratory recalibration was conducted during the study period, standard quality control procedures were implemented, including routine instrument checks, sensor stabilization, and repeated measurements across sampling locations to minimize observational errors.

These procedures are consistent with the operational recommendations provided by the manufacturers for field-based environmental monitoring.

The two handheld devices were used for real-time air quality and environmental data collection: the DM106A air quality monitor and the JD-3002 professional air quality meter. Each device was selected for its suitability to the study's requirements. DM106A Rechargeable Air Quality Monitor, as shown in Fig. 3A: This device measures PM_{2.5} and PM₁₀ concentrations, formaldehyde (HCHO), total volatile organic compounds (TVOC), temperature, humidity, and the air quality index (AQI). Using a third-generation laser sensor, it detects fine particles in the range of 0–999 µg/m³. HCHO and TVOC detection ranges are 0.001–1.999 mg/m³ and 0.001–9.999 mg/m³, respectively. It measures temperatures from –10°C to 50°C and humidity levels from 20% to 85% relative humidity (RH) with a fast measurement time of 1.5 s. Its compact size (164 mm × 69 mm × 44 mm) makes it portable and suitable for various environments. The JD-3002 Professional Air Quality Meter is shown in Fig. 3B. The JD-3002 measures CO₂, TVOC, HCHO, temperature, and humidity. It features an NDIR (Non-Dispersive Infrared) sensor for CO₂ detection in the range of 350–2000 ppm. TVOC and HCHO detection ranges are 0.000–2000 mg/m³ and 0.000–1000 mg/m³, respectively. It measures temperatures from 0°C to 90°C and humidity levels from 0% to 99% RH with 0.1 accuracy. Detection scores are visually categorized as “Excellent,” “Good,” or “Pollution” [27].



Figure 3: (A) DM106A air quality monitor, and (B) JD-3002 professional air quality meter.

2.3.3 Data Collection Strategy

Air quality measurements were taken at 50 locations across the Kano metropolis, representing diverse land use categories, including residential, industrial, commercial, and green spaces. Sampling occurred at three times of day (morning, afternoon, and evening) to capture diurnal variations in pollutant concentrations. Devices were placed approximately 1.5 m above ground level to measure pollutants at breathing height, and data were recorded for 10 min at each site. Measurements were georeferenced using GPS to ensure spatial precision, and averaged values minimized transient fluctuations [12,28].

2.4 Image Processing Techniques

Several image processing techniques were applied to the selected Landsat 9 data points. These techniques produce a series of images that are used to calculate various indices, including the digital elevation model (DEM), land surface temperature (LST), urban heat island (UHI), urban thermal feature vegetation index (UTFVI), and normalized difference Vegetation index (NDVI).

2.4.1 Land Surface Temperature Calculation (LST Derivation from Landsat 9)

The process of deriving LST involves converting the initial digital values (DNs) of the thermal data to LST values using the Landsat 9 Operational Land Imager (OLI) sensor [29]. This conversion involves the following steps:

Step 1:

Transformation to Spectral Radiance (SR):

$$L = \frac{L_{\max} - L_{\min}}{DN_{\max}} \times Band + L_{\min} \quad (1)$$

where;

L : Spectral Radiance—The amount of energy received per unit area per steradian per unit wavelength.

$L_{\max}$: Maximum Radiance—The maximum radiance value based on sensor calibration.

$L_{\min}$: Minimum Radiance—The minimum radiance value based on sensor calibration.

$DN_{\max}$: Maximum Digital Number—The maximum value of the digital number (DN) from the sensor.

$Band$: Digital number values from the thermal band of the Landsat image.

Step 2:

Conversion to at-sensor brightness temperature (BT)

The at-sensor brightness temperature was derived from the thermal band by assuming the Earth's surface behaves as a black body (emissivity = 1) while accounting for atmospheric absorption and emission along the sensor's path [30]. The required thermal constants were obtained from the image metadata file and applied using Eq. (2).

$$T = \frac{K_2}{\ln \left(\frac{K_1}{L_\lambda} + 1 \right)} - 273.15 \quad (2)$$

where;

T = At-sensor brightness temperature in Kelvin (K).

L_λ = TOA spectral radiance (Watts/(m²·srad·μm)).

K_1 = The calibration constant 666.09 in Watts/(m²·sr·μm).

K_2 = The calibration constant 1282.71 in degrees Kelvin.

Step 3:

The calculation of NDVI is a crucial process in assessing the LST for Landsat 9 images [31] (Shahfahad et al., 2020). Therefore, to determine the NDVI, Eq. (3) was used.

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

where;

NDVI: Normalised Difference Vegetation Index—A measure of vegetation health based on how plants reflect light at certain wavelengths.

NIR: Near-Infrared Band—The reflectance value from the near-infrared band of the Landsat image.

Red Band—The reflectance value from the red band of the Landsat image.

Step 4:

The Vegetation Proportion (PV) was established by employing the minimum and maximum values of the standardised Vegetation Index (NDVI) in accordance with the formula provided in Eq. (4), as specified by [32,33].

$$P_v = \left(\frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \right)^2 \quad (4)$$

where;

P_v : Vegetation Proportion—The proportion of vegetation cover within a pixel.

NDVI: Normalised Difference Vegetation Index—A measure of vegetation health.

$NDVI_{min}$ and $NDVI_{max}$: Minimum and Maximum NDVI—The minimum and maximum NDVI values in the dataset.

Step 5:

The Land Surface Emissivity (LSE) was determined through the use of Eq. (5) and the PV calculation, which was carried out in accordance with the methods outlined by [33].

$$LSE = 0.004 \times P_v + 0.986 \quad (5)$$

where;

LSE: Land Surface Emissivity—The efficiency of the surface in emitting thermal radiation.

P_v : Vegetation Proportion—The proportion of vegetation cover within a pixel.

Step 6:

Using Eqs. (6) and (7), the Land Surface Temperature (LST) was calculated in degrees Celsius for bands 10 and 11 through a rigorous mathematical process, as reported by [32–34].

$$LST = \frac{BT}{\left\{ 1 + \left[\frac{\lambda BT}{\rho} \right] \ln(LSE) \right\}} \quad (6)$$

where;

LST: Land Surface Temperature—The temperature of the Earth's surface.

BT: Brightness Temperature: Temperature calculated from radiance.

λ : Wavelength of Emitted Radiance—The wavelength corresponding to the thermal band used.

The value of the emitted radiance was calculated using Eq. (7) and the wavelength was measured.

$$\rho = h \frac{c}{\sigma} = 1.438 \times 10^{-2} \text{ m} \cdot \text{K} \quad (7)$$

where;

The following equation, which involves the Boltzmann constant (σ), Planck's constant (h), and speed of light (c), is expressed as 1.38×10^{-23} J/K, 6.626×10^{-34} Js, and 2.998×10^8 m/s, respectively [32,35].

2.4.2 Urban Heat Island Intensity (UHII)

Urban Heat Island Intensity (UHII) was calculated using the conventional urban–rural land surface temperature difference approach, which defines UHI as the excess temperature of urban surfaces relative to nearby rural reference surfaces. In this study, pixels classified as built-up areas from the land use/land cover map were considered urban pixels, while vegetated pixels located outside the dense metropolitan core were used as the rural reference class. The highest land surface temperatures were observed over both dense built-up surfaces and exposed barren land. However, only the temperature excess of built-up urban surfaces relative to the vegetated rural reference was interpreted as surface urban heat island intensity. The elevated temperatures over barren land reflect the thermal behavior of dry, sparsely vegetated surfaces in a semi-arid environment rather than urban heat island effects.

The mean land surface temperature of urban pixels ($\overline{LST}_{urban}$) and rural pixels ($\overline{LST}_{rural}$) was computed as:

$$\overline{LST}_{urban} = \frac{1}{n_u} \sum_{i=1}^{n_u} LST_i$$

$$\overline{LST}_{rural} = \frac{1}{n_r} \sum_{j=1}^{n_r} LST_j$$

where n_u and n_r represent the number of urban and rural pixels, respectively.

The overall surface urban heat island intensity was then calculated as:

$$UHII = \overline{LST}_{urban} - \overline{LST}_{rural}$$

A positive UHII value indicates that urban areas are warmer than the rural reference surfaces, confirming the presence of a surface urban heat island effect.

To generate a spatially explicit UHI map, pixel-level UHI values were also calculated as:

$$UHI_i = LST_i - \overline{LST}_{rural}$$

where UHI_i represents the local urban heat island intensity for pixel i . This approach allows identification of localized thermal hotspots while maintaining consistency with the standard urban–rural UHI definition.

2.4.3 Urban Thermal Field Variance Index (UTFVI)

In addition to UHII, the Urban Thermal Field Variance Index (UTFVI) was used to assess spatial thermal stress and ecological condition across the study area. Unlike UHII, which quantifies the temperature contrast between urban and rural surfaces, UTFVI provides a pixel-based measure of thermal deviation relative to the mean land surface temperature of the study area.

UTFVI was calculated as:

$$UTFVI = \frac{LST_i - \overline{LST}}{\overline{LST}}$$

where LST_i is the land surface temperature of pixel i , and $\overline{LST}$ is the mean land surface temperature of the entire study area.

The resulting UTFVI values were classified into ecological evaluation categories ranging from excellent to worst, following established thresholds reported in previous literature. In this study, UTFVI was used as a

complementary indicator of thermal stress and ecological quality, while UHII remained the principal metric for assessing the urban heat island effect.

2.4.4 CART Classification Technique

The Classification and Regression Tree (CART) technique was employed for the supervised classification of Land Use and Land Cover (LULC) using the pre-processed Landsat 9 imagery. CART is a non-parametric decision tree learning algorithm widely recognized for its robustness and flexibility in handling complex spatial data [30]. The method operates by recursively partitioning the dataset into homogeneous classes based on input predictor variables, such as spectral reflectance values from different Landsat bands. For this study, training samples representing four land cover categories—Urban, Vegetation, Water, and Barren land were selected based on visual interpretation of high-resolution Google Earth imagery and field validation points. The CART algorithm iteratively splits the data by selecting thresholds that minimize classification errors, resulting in a decision tree structure that effectively distinguishes between land cover types. This approach enhances classification accuracy, particularly in heterogeneous urban environments where spectral overlap among classes is common. The final LULC map produced using the CART classification formed the basis for subsequent analyses, including Land Surface Temperature (LST) derivation and Urban Heat Island (UHI) assessments.

2.5 Accuracy Assessment

LULC Classification Accuracy

To ensure accuracy, 20% of the training samples were assigned to each land use/land cover class (LULC). Classification accuracy was evaluated by selecting a random subset of 20% of the training dataset from the Google Earth images. Several precision metrics, including overall accuracy and user accuracy, were calculated to assess the reliability of the LULC classifications [30].

2.6 Analytical Methods

This study combined statistical analysis, geospatial mapping, and visual data representation to examine the relationship between LST effects and air quality. Pearson correlation was the primary statistical method, suitable for modeling these relationships. The model analyzed the impact of LST intensity on air quality indicators, including CO₂, TVOC, HCHO, PM_{2.5}, and PM₁₀, while accounting for land use types and population densities recorded during data collection. The regression model is represented by Eq. (8):

$$\text{Log} \left(\frac{P(Y \leq i)}{P(Y > j)} \right) = a_j + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_K X_K \quad (8)$$

where

$P(Y \leq i)$ is the probability of the dependent variable being at or below a certain category j , a_j are the intercepts, and $\beta_1, \beta_2, \dots, \beta_K$ are the coefficients for the independent variables $X_1, X_2, \dots, X_K$.

Data visualization techniques summarized and communicated the results. Tables displayed OLR results, including regression coefficients and p -values, while maps highlighted spatial patterns of LULC, LST, UHI, and UTFVI. Scatterplots illustrated the distribution of air quality metrics across LST intensities, identifying variations and outliers. This integrated approach facilitated a comprehensive assessment of LST impacts on air quality, providing accessible insights for policymakers and urban planners to support sustainable environmental management strategies for the Kano metropolis.

3 Results and Discussion

3.1 LULC of Metropolitan Kano

LULC analysis was performed using Landsat 9 image data and the CART classification method, which is based on classification and regression techniques. This study defined four classes: Urban, Vegetation, Water, and Barren Land. These are detailed in the methodology section of this study. The accuracy of the LULC map was assessed using a confusion matrix and overall classification accuracy, with the aim of determining the suitability of the proposed classes. The overall accuracy is 98.2%.

Four distinct land use/land cover (LULC) classes were identified across the study area [36], encompassing the eight local government areas that constitute Kano Metropolis. The LULC analysis revealed that built-up areas cover 353.7 km², representing 67.4% of the total land surface area of the metropolis. Fig. 4a illustrates the spatial distribution of the LULC classes generated using the Classification and Regression Trees (CART) algorithm.

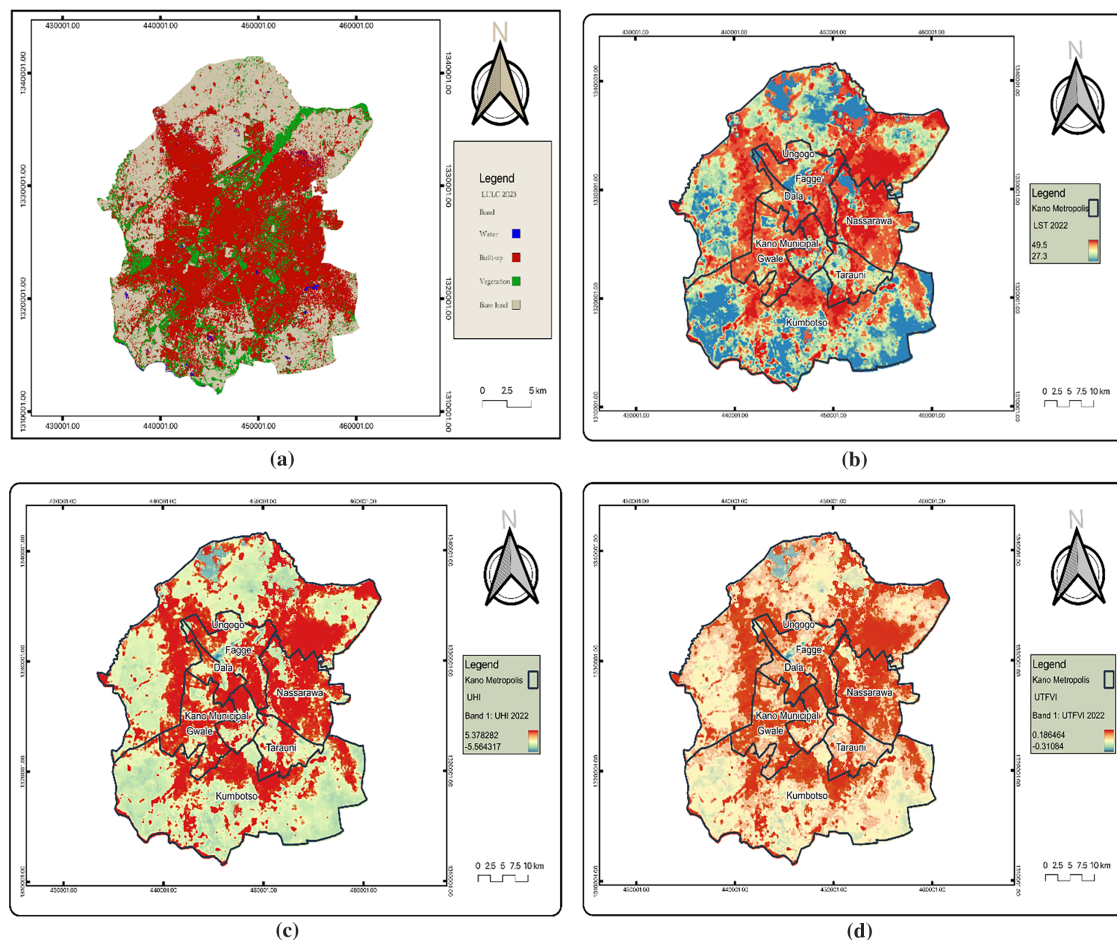


Figure 4: Showing (a) Land use and land cover for 2025, (b) Land surface temperature (c) Urban heat Island and, (d) Urban thermal field variance index for Kano metropolis.

3.2 Kano Urban Heating

The spatial distribution of Land Surface Temperature (LST) revealed that the highest temperatures were concentrated within the densely built-up and rapidly urbanizing parts of Kano, particularly in Kano

Municipal, Gwale, Ungogo, Dala, and Fagge (Fig. 4b). These areas are characterized by extensive impervious surfaces, high building density, limited vegetation cover, and the widespread use of low-albedo roofing and paving materials, all of which enhance solar heat absorption while reducing evapotranspirative cooling. Consequently, these urban characteristics increase heat storage, resulting in elevated surface temperatures and the development of localized UHI. In contrast, relatively lower LST values were observed in areas dominated by open spaces, agricultural land, and dense vegetation, where evapotranspiration and shading contribute to surface cooling.

The spatial pattern of the Urban Heat Island (UHI) further corroborates these findings (Fig. 4c). Distinct heat hotspots were identified within the urban core, particularly in neighborhoods characterized by dense building clusters and sparse vegetation cover. These hotspots reflect the cumulative effects of rapid urbanization, land cover modification, and the replacement of natural surfaces with heat-retaining materials. Collectively, the LST and UHI patterns demonstrate that urban morphology and land cover characteristics are the primary determinants of surface thermal conditions across Kano Metropolis.

The classification of the urban thermal field variance index (UTFVI) comprises six categories of the urban heat island phenomenon, ranging from low to high values. These categories correspond to the ecological evaluation index, with low values ranked as “Excellent” to extreme values ranked as “Worst” indications of the UTFVI. About 48% of the study area experienced the worst urban heat island index, while 12% was classified as having an excellent urban heat island. The remaining 40% were distributed among the other categories. The city centre was predominantly characterized by the strongest/worst urban heat island effect, whereas the surrounding suburban areas were largely classified as having no or excellent urban heat effect. This is consistent with the definition of the urban heat island effect. Additionally, barren lands outside the city, which lack green vegetation and development, were found to exhibit the worst urban heat island effect. This is consistent with the characteristics of the study location, which is semiarid. Areas with high vegetation cover in the city centre were found to have excellent UTFVI, as shown in the distribution of UTFVI in Fig. 4d.

3.3 Kano Urban Air Pollution

The Air Quality Index (AQI) assessment revealed that air quality across the Kano metropolitan area is generally poor, with the majority of locations falling within unhealthy categories. Approximately 53.6% of the study area recorded unhealthy AQI levels (101–200), indicating that air pollution poses a significant environmental and public health concern (See Fig. 5). These elevated AQI values were predominantly concentrated within densely populated neighborhoods and areas with unpaved roads, where frequent vehicular movement and the resuspension of road dust substantially increase particulate matter concentrations. In contrast, only about 20% of the study area exhibited good to moderate AQI conditions. These relatively cleaner environments were mainly located within sparsely populated and well-planned residential areas, such as Nasarawa and Bompai, which are characterized by better road infrastructure, lower traffic volumes, and relatively higher vegetation cover that enhances pollutant dispersion and deposition.

More concerning, the study identified localized very unhealthy (20%) and hazardous (6.3%) air quality conditions. Areas with very unhealthy AQI values (201–300) and hazardous AQI values (>300) were predominantly associated with Suya and Gurasa preparation spots, where the extensive use of firewood and charcoal for cooking releases large quantities of smoke and fine particulate matter into the atmosphere [27]. Continuous exposure to these pollution hotspots poses serious health risks [37], including respiratory diseases such as asthma, bronchitis, and chronic obstructive pulmonary disease (COPD), as well as cardiovascular disorders, impaired lung function, and an increased risk of premature mortality, particularly among children, older adults, and individuals with pre-existing medical conditions [1,20].

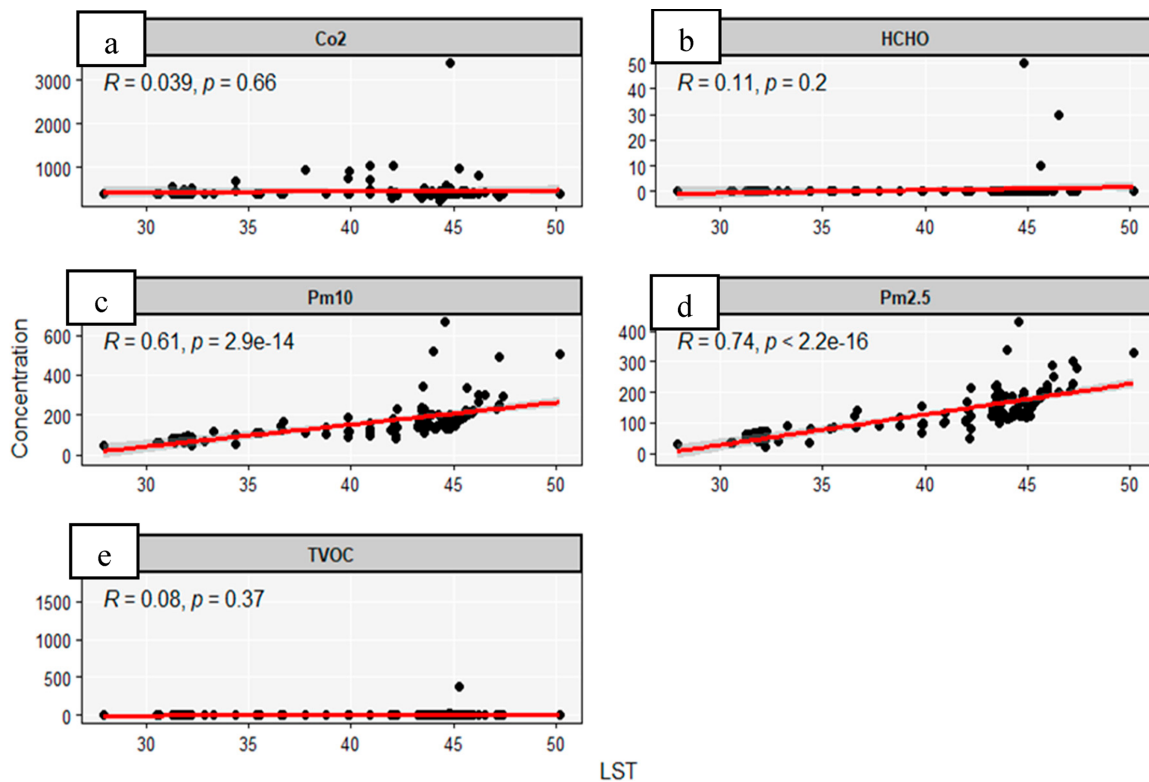


Figure 5: Scatter plots showing the pearson correlation between land surface temperature (LST) and air pollutants concentration across Kano Metropolis. (a) Carbon dioxide (CO₂), (b) Formaldehyde (HCHO), (c) Coarse particulate matter (PM₁₀), (d) Fine particulate matter (PM_{2.5}), and (e) Total volatile compounds (TVOC). The analyses were performed using the tidyverse and ggpubr packages in the R programming language.

The spatial distribution of gaseous pollutants revealed generally acceptable air quality conditions across the Kano metropolitan area (Fig. 5c,d). Approximately 95% of the monitored locations recorded CO₂ concentrations of around 350 ppm, while the remaining 5% ranged between 400 and 1000 ppm. Importantly, all observed CO₂ concentrations remained within internationally accepted indoor air quality guidelines, indicating adequate air quality with respect to carbon dioxide exposure. The slightly elevated CO₂ concentrations recorded at a few locations are likely attributable to localized human activities and reduced ventilation but do not constitute a significant health concern.

Similarly, TVOC and HCHO concentrations remained consistently low throughout the study area. About 99% of the sampled locations recorded TVOC concentrations of approximately 0.5 mg/m³, while 98% exhibited HCHO concentrations of approximately 0.04 mg/m³. These values are substantially below recommended exposure limits, suggesting minimal emissions of volatile organic compounds and formaldehyde across most parts of Kano. The generally low concentrations of these gaseous pollutants indicate that, unlike particulate matter, they currently pose a relatively low risk to ambient air quality and public health within the study area. Consequently, particulate pollution, rather than gaseous pollutants, represents the dominant air quality challenge requiring priority attention in Kano.

3.4 Air Pollutants Effects on Urban LST

The results of the correlation analysis between land surface temperature (LST) and individual air pollutants are presented in Fig. 5. Pearson's correlation coefficient (r) and the corresponding p-values were

used to evaluate the strength and statistical significance of the relationships [38]. Overall, the relationships ranged from weak and statistically non-significant to strong and statistically significant, with correlation coefficients ranging from $r = 0.039$ to $r = 0.74$ and p -values ranging from $p < 0.001$ to $p = 0.66$ across the five pollutants investigated. Among the pollutants, $PM_{2.5}$ and PM_{10} exhibited the strongest positive correlations with LST, with $r = 0.74$ ($p < 2.2 \times 10^{-16}$) and $r = 0.61$ ($p = 2.9 \times 10^{-14}$), respectively (see Fig. 5c,d). In contrast, CO_2 ($r = 0.039$, $p = 0.66$), TVOC ($r = 0.08$, $p = 0.37$), and HCHO ($r = 0.11$, $p = 0.20$) showed weak and statistically non-significant relationships with LST (See Fig. 5a,b,e). These findings suggest that land surface temperature is more closely associated with particulate pollutants than with gaseous pollutants. The strong positive relationships observed for $PM_{2.5}$ and PM_{10} indicate that fine and coarse particulate matter play an important role in shaping the surface thermal environment of Kano. Elevated particulate concentrations are primarily linked to anthropogenic activities [2,39]. These particles can accumulate on land surfaces through dry deposition, modifying surface radiative properties and the surface energy balance, thereby contributing to increased land surface temperatures under favorable climatic and meteorological conditions [40].

The observed positive relationship between LST and particulate matter in Kano is consistent with previous studies [41]. For example, Weng and Yang [42] reported a positive association between dust particles and LST in Guangzhou, China, while Suthar et al. [2] found that $PM_{2.5}$ was positively correlated with LST in Bengaluru, India. The consistency of these findings across cities in both developed and emerging economies suggests that particulate matter is an important contributor to elevated LST [43]. This relationship is largely driven by anthropogenic activities, including rapid urbanization, increasing vehicular traffic, fossil fuel combustion, industrial emissions, construction activities, and the loss of vegetation due to land use and land cover changes [20,37,44]. A study by Barau et al. [27] identified certain anthropogenic activities as the primary drivers of deteriorating air quality in Kano. Their study on urban air quality and smellscape revealed that emissions from fossil fuel and wood combustion at numerous Gurasa baking outlets and Suya (open-roasted meat) spots, together with traffic emissions and other commercial activities, were responsible for the poorest and most unhealthy Air Quality Index (AQI) conditions across the metropolitan area. These findings reinforce the present study by demonstrating that intense urbanization, high anthropogenic emissions, and thermally inefficient urban surfaces interact to simultaneously elevate particulate matter concentrations and LST in Kano, underscoring the need for integrated urban planning strategies that promote cleaner energy use, increased urban greening, and the adoption of high-albedo construction materials. These activities increase the concentration of particulate matter, which modifies the surface radiative and energy balance by enhancing heat absorption and reducing surface cooling [40].

Consequently, urban areas with elevated particulate matter concentrations tend to experience higher LST, reinforcing the UHI effect [45]. The coexistence of elevated LST and high concentrations of $PM_{2.5}$ and PM_{10} , particularly within the densely populated urban core of Kano, presents a dual environmental challenge with serious public health implications [41]. Prolonged exposure to particulate matter, especially under elevated thermal conditions, increases the risk of respiratory and cardiovascular diseases, heat-related illnesses [46], and reduced overall environmental quality [47].

The findings suggest that urban heat mitigation and air quality improvement should be addressed through integrated planning strategies. Priority should be given to expanding urban green infrastructure, increasing tree canopy cover, preserving open spaces, and promoting the use of high-albedo roofing and paving materials to reduce surface temperatures and enhance evapotranspiration [48,49]. Equally important are interventions aimed at reducing particulate emissions, including improved traffic management, the paving of untarred roads to minimize dust resuspension, stricter regulation of industrial and vehicular emissions, and the adoption of cleaner cooking fuels at Suya and Gurasa preparation sites. Together, these measures would not only mitigate urban heat island intensity but also reduce exposure to harmful particulate

matter, thereby improving environmental quality and safeguarding public health. These findings provide valuable evidence to support climate-responsive urban planning and air quality management policies in rapidly urbanizing cities such as Kano [18,19]. Collectively, these findings underscore the need for integrated urban planning and public health interventions to simultaneously mitigate urban heat and particulate pollution, thereby promoting healthier and more sustainable cities.

4 Conclusion

This study examined the relationship between urban land surface temperature (LST) and air pollution in Kano Metropolis using Earth observation data, geospatial techniques, and statistical analysis. Land use and land cover (LULC) classification identified four dominant land cover types—urban areas, vegetation, barren land, and water bodies—revealing that rapid urban expansion has substantially altered the city's surface characteristics. The LST and Urban Heat Island (UHI) analyses showed that the highest temperatures were concentrated within the densely built-up urban core, particularly in Kano Municipal, Gwale, Ungogo, Dala, and Fagge, whereas lower temperatures were associated with vegetated and agricultural areas. Similarly, the Air Quality Index (AQI) indicated that more than half of the metropolitan area experiences unhealthy air quality, with localized hazardous conditions occurring around commercial cooking areas where biomass fuels are extensively used.

Pearson correlation analysis further demonstrated that LST exhibited strong and statistically significant positive relationships with particulate matter ($PM_{2.5}$ and PM_{10}), whereas the relationships with CO_2 , TVOC, and HCHO were weak and statistically non-significant. These findings indicate that particulate pollution is more strongly associated with urban surface heating than gaseous pollutants, highlighting the combined influence of rapid urbanization, impervious surfaces, traffic emissions, biomass burning, and other anthropogenic activities on the urban thermal environment. The coexistence of elevated LST, intense UHI effects, and poor air quality within the urban core underscores the need for integrated urban planning and environmental management strategies.

The findings provide valuable evidence for policymakers and urban planners to implement interventions that simultaneously reduce urban heat and particulate pollution. Priority should be given to expanding urban green infrastructure, increasing tree canopy cover, adopting high-albedo building materials, paving untarred roads to reduce dust resuspension, improving traffic management, and promoting cleaner cooking fuels and technologies. Collectively, these measures have the potential to mitigate urban heat island effects, improve air quality, and reduce the burden of heat- and pollution-related health risks. Future research should incorporate seasonal observations, additional meteorological variables, and long-term monitoring to further elucidate the interactions between urban heat, land use change, and air pollution in rapidly urbanizing cities.

Since this study used air pollution data from a single study period, it does not capture the seasonal variability of land surface temperature and air pollution. Future studies should incorporate multi-seasonal observations covering both the dry and wet seasons to better characterize temporal variations and improve the robustness of the findings.

Acknowledgement: Not applicable.

Funding Statement: The authors received no specific funding for this study.

Author Contributions: Study conception and design were carried out by Yusuf Ahmed Yusuf, Helmi Zulhaidi Mohd Shafri and Siti Nur Aliaa Roslan. Data collection was conducted by Yusuf Ahmed Yusuf, Kamil Muhammad Kafi and Jibrin Gambo. Data analysis and interpretation of results were performed by Yusuf Ahmed Yusuf and Kamil Muhammad Kafi. The initial draft of the manuscript was prepared by Yusuf Ahmed Yusuf. Manuscript review was undertaken

by Kamil Muhammad Kafi. Visualization and validation were conducted by Helmi Zulhaidi Mohd Shafri, Kamil Muhammad Kafi and Siti Nur Aliaa Roslan. All authors reviewed and approved the final version of the manuscript.

Availability of Data and Materials: The datasets supporting the findings of this study are available from the corresponding authors upon reasonable request.

Ethics Approval: This study did not involve human participants, animals, or the collection of personal or sensitive data. The research was based solely on Earth observation data and environmental air quality measurements; therefore, ethical approval and informed consent were not required.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Parida BR, Bar S, Roberts G, Mandal SP, Pandey AC, Kumar M, et al. Improvement in air quality and its impact on land surface temperature in major urban areas across India during the first lockdown of the pandemic. *Environ Res.* 2021;199:111280. doi:10.1016/j.envres.2021.111280.
2. Suthar G, Kaul N, Khandelwal S, Singh S. Dynamics of land surface temperature: insights into vegetation, elevation, and air pollution in Bengaluru. *Remote Sens Appl Soc Environ.* 2024;33(2):101145. doi:10.1016/j.rsase.2024.101145.
3. Dewantoro BB, Khafid MA, Putra AA, Wicaksono AP, Andita FW. Identification of the impact of vegetation cover changes and the development of urban areas on Urban Heat Island using GIS and remote sensing: a case studies of Sleman regency, province of Yogyakarta. *IOP Conf Ser Mater Sci Eng.* 2021;1098(5):052023. doi:10.1088/1757-899x/1098/5/052023.
4. Barau AS. Land degradation and environmental quality decline in urban Kano. In: *Kano: the state, society and economy 1967–2017*. Abuja, Nigeria: Trans West Africa Limited; 2018. p. 141–70.
5. Mehta T, Ghoshal S, Mahajan Y, Sharma M, Neha K. Analysis of patterns of urban sprawl and surface urban heat island in solan town of Himachal Pradesh using remote sensing and GIS. *IOP Conf Ser Earth Environ Sci.* 2023;1110(1):012084. doi:10.1088/1755-1315/1110/1/012084.
6. Waleed M, Sajjad M, Acheampong AO, Alam MT. Towards sustainable and livable cities: leveraging remote sensing, machine learning, and geo-information modelling to explore and predict thermal field variance in response to urban growth. *Sustainability.* 2023;15(2):1416. doi:10.3390/su15021416.
7. African Development Bank Group. *Urbanization in Africa*. Abidjan, Côte d'Ivoire: African Development Bank Group; 2012.
8. Liu Y, Li Q, Yang L, Mu K, Zhang M, Liu J. Urban heat island effects of various urban morphologies under regional climate conditions. *Sci Total Environ.* 2020;743(2):140589. doi:10.1016/j.scitotenv.2020.140589.
9. Lam YF, Ong CW, Wong MH, Sin WF, Lo CW. Improvement of community monitoring network data for urban heat island investigation in Hong Kong. *Urban Clim.* 2021;37:100852. doi:10.1016/j.uclim.2021.100852.
10. García-Chan N, Licea-Salazar JA, Gutierrez-Ibarra LG. Urban heat island dynamics in an urban-rural domain with variable porosity: numerical methodology and simulation. *Mathematics.* 2023;11(5):1140. doi:10.3390/math11051140.
11. Shahmohamadi P, Che-Ani AI, Etessam I, Maulud KNA, Tawil NM. Healthy environment: the need to mitigate urban heat island effects on human health. *Procedia Eng.* 2011;20(18):61–70. doi:10.1016/j.proeng.2011.11.139.
12. World Health Organization. *Ambient (outdoor) air pollution*. Geneva, Switzerland: World Health Organization; 2022.
13. Li X, Zhou Y, Yu S, Jia G, Li H, Li W. Urban heat island impacts on building energy consumption: a review of approaches and findings. *Energy.* 2019;174(1):407–19. doi:10.1016/j.energy.2019.02.183.
14. Zhang M, Kafy AA, Xiao P, Han S, Zou S, Saha M, et al. Impact of urban expansion on land surface temperature and carbon emissions using machine learning algorithms in Wuhan, China. *Urban Clim.* 2023;47(6):101347. doi:10.1016/j.uclim.2022.101347.
15. Lai LW, Cheng WL. Air quality influenced by urban heat island coupled with synoptic weather patterns. *Sci Total Environ.* 2009;407(8):2724–33. doi:10.1016/j.scitotenv.2008.12.002.

16. Yang J, Wang Y, Xiu C, Xiao X, Xia J, Jin C. Optimizing local climate zones to mitigate urban heat island effect in human settlements. *J Clean Prod.* 2020;275:123767. doi:10.1016/j.jclepro.2020.123767.
17. Peng J, Ma J, Liu Q, Liu Y, Hu YN, Li Y, et al. Spatial-temporal change of land surface temperature across 285 cities in China: an urban-rural contrast perspective. *Sci Total Environ.* 2018;635:487–97. doi:10.1016/j.scitotenv.2018.04.105.
18. Liang Z, Huang J, Wang Y, Wei F, Wu S, Jiang H, et al. The mediating effect of air pollution in the impacts of urban form on nighttime urban heat island intensity. *Sustain Cities Soc.* 2021;74(4):102985. doi:10.1016/j.scs.2021.102985.
19. Acosta MP, Vahdatikhaki F, Santos J, Jarro SP, Dorée AG. Data-driven analysis of Urban Heat Island phenomenon based on street typology. *Sustain Cities Soc.* 2024;101(2):105170. doi:10.1016/j.scs.2023.105170.
20. Gupta P, Shukla DP. Implications of Russia-Ukraine war on land surface temperature and air quality: long-term and short-term analysis. *Environ Sci Pollut Res Int.* 2024;31(34):46357–75. doi:10.1007/s11356-024-32800-5.
21. Barau AS, Abubakar IR, Kafi KM, Olugbodi KH, Abubakar JI. Dynamics of negotiated use of public open spaces between children and adults in an African city. *Land Use Policy.* 2023;131(4):106705. doi:10.1016/j.landusepol.2023.106705.
22. Barau AS, Kafi KM, Sodangi AB, Usman SG. Recreating African biophilic urbanism: the roles of millennials, native trees, and innovation labs in Nigeria. *Cities Health.* 2023;7(2):213–23. doi:10.1080/23748834.2020.1763892.
23. Tanko IA, Suleiman YM, Yahaya TI, Kasim AA. Urbanisation effect on the occurrence of urban Heat Island over Kano Metropolis, Nigeria. *Int J Sci Eng Res.* 2017;8(9):293–9.
24. U.S Geological Survey. Landsat collection 2. In: *Landsat missions*. Reston, VA, USA: USGS; 2022 [cited 2026 Apr 27]. Available from: <https://www.usgs.gov/landsat-missions/landsat-collection-2>.
25. Earth Data. Landsat 9 to provide a wealth of data to the longest continuous global record of earth imagery. Washington, DC, USA: NASA; 2021 [cited 2026 April 14]. Available from: <https://www.earthdata.nasa.gov/news/feature-articles/landsat-9-provide-wealth-data-longest-continuous-global-record-earth-imagery>.
26. Dwyer JL, Roy DP, Sauer B, Jenkerson CB, Zhang HK, Lymburner L. Analysis ready data: enabling analysis of the landsat archive. *Remote Sens.* 2018;10(9):1363. doi:10.3390/rs10091363.
27. Barau AS, Kafi KM, Mu'allim MA, Dallimer M, Hassan A. Comparative mapping of smellscape clusters and associated air quality in Kano City, Nigeria: an analysis of public perception, hotspots, and inclusive decision support tool. *Sustain Cities Soc.* 2023;96(1):104680. doi:10.1016/j.scs.2023.104680.
28. Kafi KM, Gibril MB. GPS application in disaster management: a review. *Asian J Appl Sci.* 2016;4(1):63–9.
29. Koko AF, Han Z, Wu Y, Abubakar GA, Bello M. Spatiotemporal land use/land cover mapping and prediction based on hybrid modeling approach: a case study of Kano metropolis, Nigeria (2020–2050). *Remote Sens.* 2022;14(23):6083. doi:10.3390/rs14236083.
30. Kafi KM, Ibrahim S, Aliyu FU, Usman MA, Olugbodi KH. Impact of LULC spatial dynamics on incompatible mixed land use in Kaduna: a remote sensing and GIS risk analysis. *Eco Cities.* 2024;5(2):2818. doi:10.54517/ec.v5i2.2818.
31. Shahfahad, Kumari B, Tayyab M, Ahmed IA, Baig MRI, Khan MF. Longitudinal study of land surface temperature (LST) using mono- and split-window algorithms and its relationship with NDVI and NDBI over selected metro cities of India. *Arab J Geosci.* 2020;13(19):1040. doi:10.1007/s12517-020-06068-1.
32. Kafy AA, Faisal AA, Shuvo RM, Naim MNH, Sikdar MS, Chowdhury RR, et al. Remote sensing approach to simulate the land use/land cover and seasonal land surface temperature change using machine learning algorithms in a fastest-growing megacity of Bangladesh. *Remote Sens Appl Soc Environ.* 2021;21(4):100463. doi:10.1016/j.rsase.2020.100463.
33. Roy DP, Wulder MA, Loveland TR, Woodcock CE, Allen RG, Anderson MC, et al. Landsat-8: science and product vision for terrestrial global change research. *Remote Sens Environ.* 2014;145(1):154–72. doi:10.1016/j.rse.2014.02.001.
34. Kafy AA, Al-Faisal A, Mahmudul Hasan M, Sikdar MS, Hasan Khan MH, Rahman M, et al. Impact of LULC changes on LST in rajshahi district of Bangladesh: a remote sensing approach. *J Geogr Stud.* 2019;3(1):11–23. doi:10.21523/gcj5.19030102.
35. Rashid KJ, Islam S, Rahman MA. Ecological impact evaluation of urban heat island in Dhaka city; a spatio-temporal approach. *Res Sq.* 2021:1–25. doi:10.21203/rs.3.rs-307151/v1.

36. Kafi KM, Ponrahono Z, Ash'aari ZH, Barau AS. Flood risk prediction and modeling in Bauchi: leveraging machine learning models and explainable AI for urban resilience. *J Clim Chang Health*. 2025;26:100490. doi:10.1016/j.joclim.2025.100490.
37. Bala R, Pratap Yadav V, Nagesh Kumar D, Prasad R. Exploring the relationship of land surface parameters and air pollutants with land surface temperature in different cities using satellite data. *Adv Space Res*. 2024;74(7):2958–75. doi:10.1016/j.asr.2024.06.031.
38. Kafi KM, Ponrahono Z. Weather and climate extremes in Nigeria: modeling the perceived impact of spatial planning and community practices on windstorm and flood exposure using PLS-SEM and correlogram. *Int J Disaster Risk Reduct*. 2025;124:105554. doi:10.1016/j.ijdr.2025.105554.
39. Fuladlu K, Altan H. Examining land surface temperature and relations with the major air pollutants: a remote sensing research in case of Tehran. *Urban Clim*. 2021;39(6):100958. doi:10.1016/j.uclim.2021.100958.
40. Zhu L, Liu J, Cong L, Ma W, Ma W, Zhang Z. Spatiotemporal characteristics of particulate matter and dry deposition flux in the Cuihu wetland of Beijing. *PLoS One*. 2016;11(7):e0158616. doi:10.1371/journal.pone.0158616.
41. Mendez-Astudillo J, Caetano E, Pereyra-Castro K. Synergy between the urban heat island and the urban pollution island in Mexico City during the dry season. *Aerosol Air Qual Res*. 2022;22(8):210278. doi:10.4209/aaqr.210278.
42. Weng Q, Yang S. Urban air pollution patterns, land use, and thermal landscape: an examination of the linkage using GIS. *Environ Monit Assess*. 2006;117(1–3):463–89. doi:10.1007/s10661-006-0888-9.
43. Fang Y, Gu K. Exploring coupling effect between urban heat island effect and PM_{2.5} concentrations from the perspective of spatial environment. *Environ Eng Res*. 2022;27(2):200559. doi:10.4491/eer.2020.559.
44. Piracha A, Chaudhary MT. Urban air pollution, urban heat island and human health: a review of the literature. *Sustainability*. 2022;14(15):9234. doi:10.3390/su14159234.
45. Suthar G, Singhal RP, Khandelwal S, Kaul N. Spatiotemporal variation of air pollutants and their relationship with land surface temperature in Bengaluru, India. *Remote Sens Appl Soc Environ*. 2023;32(2):101011. doi:10.1016/j.rsase.2023.101011.
46. Sabrin S, Karimi M, Nazari R. Developing vulnerability index to quantify urban heat islands effects coupled with air pollution: a case study of Camden, NJ. *ISPRS Int J Geo Inf*. 2020;9(6):349. doi:10.3390/ijgi9060349.
47. Burns J, Boogaard H, Polus S, Pfadenhauer LM, Rohwer AC, van Erp AM, et al. Interventions to reduce ambient air pollution and their effects on health: an abridged Cochrane systematic review. *Environ Int*. 2020;135(1):105400. doi:10.1016/j.envint.2019.105400.
48. Adegun OB, Ikudayisi AE, Morakinyo TE, Olusoga OO. Urban green infrastructure in Nigeria: a review. *Sci Afr*. 2021;14(4):e01044. doi:10.1016/j.sciaf.2021.e01044.
49. Croce S, Vettorato D. Urban surface uses for climate resilient and sustainable cities: a catalogue of solutions. *Sustain Cities Soc*. 2021;75:103313. doi:10.1016/j.scs.2021.103313.