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Spatiotemporal Influence of Land Use/Land Cover Change Dynamics on Surface Urban Heat Island: A Case Study of Abuja Metropolis, Nigeria

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Abstract: Rapid urbanization in cities and urban centers has recently contributed to notable land use/land cover (LULC) changes, affecting both the climate and environment. Therefore, this study seeks to analyze changes in LULC and its spatiotemporal influence on the surface urban heat islands (UHI) in Abuja metropolis, Nigeria. To achieve this, we employed Multi-temporal Landsat data to monitor the study area's LULC pattern and land surface temperature (LST) over the last 29 years. The study then analyzed the relationship between LULC, LST, and other vital spectral indices comprising NDVI and NDBI using correlation analysis. The results revealed a significant urban expansion with the transformation of 358.3 sq. km of natural surface into built-up areas. It further showed a considerable increase in the mean LST of Abuja metropolis from 30.65 °C in 1990 to 32.69 °C in 2019, with a notable increase of 2.53 °C between 2009 and 2019. The results also indicated an inverse relationship between LST and NDVI and a positive connection between LST and NDBI. This implies that urban expansion and vegetation decrease influences the development of surface UHI through increased LST. Therefore, the study's findings will significantly help urban-planners and decision-makers implement sustainable land-use strategies and management for the city.

Keywords: land use/land cover (LULC); urbanization; urban heat island (UHI); land surface temperature (LST); normalized difference vegetation index (NDVI); normalized difference built-up index (NDBI); Abuja Metropolis

1. Introduction

The world has recently witnessed an increased urban population due to perceived socio-economic opportunities in cities, contributing to rapid urbanization [1]. The global population in urban centers and cities has grown from 1.731 billion inhabitants (39.35%) in 1980 to 3.968 billion (53.91%) in 2015, and is further predicted to over 9.725 billion (68%) by 2050 [2]. The projection indicates that 35% of this growth is expected to occur in Africa and Asia in the next three decades. The consequence of this growth is the tremendous changes in land use/land cover (LULC) pattern and the alteration of various biophysical climatic conditions, particularly the Surface Urban Heat Island (UHI) that is measured using land surface temperature (LST) [3–5]. The transformation of land-use such as wetlands, vegetation, and agricultural areas into built-up and impervious surfaces can considerably influence LST [6]. Therefore, land use/land cover change dynamics are crucial factors influencing surface UHI due to the unique qualities (i.e., surface reflectance and roughness) attributed to each LULC category regarding its radiation and absorption energy [7]. Studies

of rapidly growing cities globally indicate an increased LST, which usually forms an urban heat island due to the dramatic changes in land-use associated with urbanization [8–10]. This growth has also contributed to high-energy demand that affects human health and wellbeing due to air pollution and greenhouse gas (GHG) emissions. Therefore, the study of LULC changes and their influence on surface UHI using land surface temperature as a key indicator is crucial in implementing policies and strategies aimed at mitigating the negative impacts of urban growth due to rapid urbanization.

The use of remotely sensed data and Geographical Information Systems has been widely considered as a responsive tool in urban climatic studies for achieving sustainable cities [11–14]. It provides an accurate, timely, and reliable method of measuring several spatio-temporal variations and indices in a cost-effective approach [15]. The use of satellite datasets provides a medium to high-resolution satellite imager capable of continually monitoring the earth's surface and atmosphere. Satellite-derived images are often utilized for the inventory and mapping of LULC changes [16–18]. The continuous availability of various satellite sensors such as Landsat 4 and 5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+), and Landsat 8 Operational Land Imager (OLI) has frequently been utilized to provide the necessary data for monitoring the recent changes in LULC and its influence on surface UHI [19–21]. The process involves using GIS techniques to quantitatively analyze previous LULC conditions in detecting changes related to the various satellite-derived indices [22–25].

Spectral indices from remotely sensed data usually give a comprehensive understanding of the relationship between LST, which is crucial in measuring surface UHI, and LULC conditions [26–28]. The most common satellite-derived indexes for estimating spatio-temporal variations of land surface temperature (LST) are the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Built-up Index (NDBI) [29,30]. These indices are indicators of LULC changes in the relationship with LST [31,32]. The correlation can be achieved using scatter plots and regression analysis. Previous studies have analyzed the different relationships between LULC, LST, NDVI, and NDBI. In Shenzhen city, located in China's Pearl River Delta, a negative correlation was established between NDVI and LST, while the connection between LST and NDBI was positive [30]. A study in Tehran's Metropolitan city indicated a negative correlation between vegetation index and land surface temperature [27]. Similar studies in Sivas city, Turkey [15], Egypt's greater Cairo region [19], and some megacities of southern Asia such as Bangkok (Thailand), Manila (Philippines), and Jakarta (Indonesia) [28] revealed significant interactions, more precisely negative correlation, between land surface temperature and NDVI and a positive correlation between LST and built-up surfaces. These results were predominantly attributed to the cities' continuous growth and expansion due to urbanization and socio-economic developments, which influenced land-use and regional climate changes. Studies on changes in LULC and surface UHIs help mitigate the adverse effects of climate change by analyzing the implications of various human activities and providing adaptive strategies aimed at sustainable management of land-use. [33], hence, helping significantly improvements in the liveability of cities.

Although several studies exist on LULC scenarios of selected cities in developing countries such as Nigeria [34–39], comprehensive studies on the spatiotemporal analysis of LULC changes and their influence on the surface UHI of Nigeria's rapidly growing cities are still relatively limited to non-existent. Abuja, Nigeria's capital and one of Nigeria's largest cities, has been under tremendous pressure over the last few decades due to rapid urbanization and population growth. Like many other developing megacities, the city has rapidly experienced various LULC changes, mainly an increasing built-up area and decreasing vegetation. The continuous alteration of land-uses for residential, commercial, and industrial activities often contributes to climate change, particularly global warming, through increased UHI. Therefore, to effectively reduce the surface UHI in Abuja Metropolitan, it is of utmost importance to study the LULC change scenario and its relationship with LST. The present study aims to monitor and analyze the spatio-temporal

trends of LULC changes and establish their relationship with the LST changes of Abuja Metropolis, Nigeria, using high-resolution satellite datasets and GIS techniques. More specifically, the study seeks to (i) map and analyze the various changes in the LULC pattern of Abuja metropolis over the last 29 years (i.e., 1990–2019); (ii) study the city's distribution of LST, NDVI, and NDBI; (iii) correlate and analyze LST with satellite-derived indices comprising NDVI and NDBI.

The study will help in advocating urban planning policies and adaptive strategies aimed at developing and improving the city's liveability. The study area overview alongside the materials and methods utilized for this study are discussed in Sections 2 and 3. Sections 4 and 5 present the results and discuss the study's findings. Finally, Section 6 highlights the concluding remarks and suggests pathways for future research.

2. The Study Area

Abuja, popularly called Federal Capital Territory (FCT), is Nigeria's capital city, situated in Nigeria's North-central region at about 840 m above mean sea level. It lies between Latitude 8°24' N and 9°28' N and Longitude 6°40' E and 7°45' E covering an area of approximately 7760 square kilometers (Figure 1). It has a tropical wet and dry climatic condition, i.e., non-arid, according to the Koppen-Geiger's classification, with an annual temperature ranging between 30–37 °C and a mean annual total precipitation of approximately 1650 mm per annum [40]. The metropolis experiences a warm, humid rainy season between April and October and a blistering dry season between November and March. The dry season's main features include dust-laden wind, harmattan haze, and intensified cold and dryness. The study area has a high altitude and undulating terrain that moderates the city's climatic conditions [41]. The Guinea-Savannah vegetation characterizes the city due to its abundant rainfall and strategic position between Nigeria's northern and southern ecological transitional zone type and has fertile agricultural land with maize, millet, guinea corn, and tubers as the dominant crops [42–44]. Abuja's metropolis has recently witnessed a continuous influx of populace due to its centrality and the deliberate establishment of government and private institutions, contributing to the development of satellite towns, and thereby expanding the urban area. The population has grown from within the city's metropolis to the fringes of the four (4) other area councils that comprise Kuje, Gwagwalada, Bwari, and Kwali. Studies have shown that Nigeria's high rural–urban migration and the relocation of the country's capital from Lagos to Abuja have contributed to the city's population increasing from 364,086 in 1991 to 759,547 in 1999 to 1,429,801 in 2006 [45]. The population is presently estimated to be over 3.2 million [46]. The United Nations Population Prospects estimates, that with the city's steady growth rate, Abuja is expected to have approximately 5.1 million inhabitants by 2030 [47]. This growth's consequences are land-use changes and microclimate modification due to urban heat island (UHI).

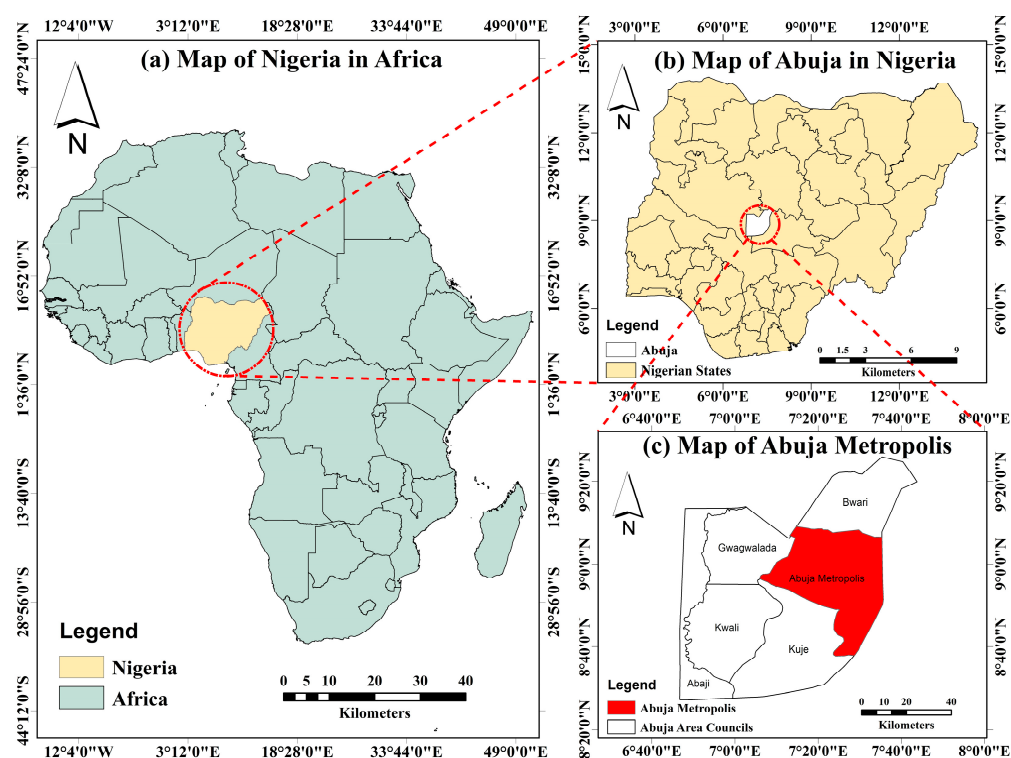


Figure 1. Location Map of Abuja Metropolis, Nigeria.

3. Materials and Methods

3.1. Data Acquisition and Pre-Processing

To identify the changes in LULC, LST, NDVI, and NDBI. We acquired an image for each year under study, i.e., 1990, 1999, 2009, and 2019, using various remotely sensed satellite images presented in Table 1. These images were downloaded without any cost from path 189, row 54 of the Earth Observing System of the United States Geological Survey (USGS) (<https://earthexplorer.usgs.gov>, accessed on 22 April 2021). We deliberately obtained datasets at an interval of 10 years to ensure uniformity between the time-nodes. However, the unavailability of the 1989 satellite data led to the utilization of the subsequent year's image. The datasets were acquired during the dry season, more precisely in January and February, to obtain cloud-free images, minimize seasonal effects, and ensure accurate image comparison. Studies indicate that spectral images acquired by satellite sensors are often affected by numerous factors such as sensor calibration, atmospheric absorption, scattering, and illumination geometry [48]. As a result, all the acquired images were subjected to radiometric calibration and geometric corrections to rectify the various surface reflectance variations due to the acquiring systems. This pre-processing operation improves atmospheric absorption/scattering, sensor sensitivity, topography and sun angle, scene illumination, and visible near-infrared wavelengths [49,50]. The pre-processed images were then employed to map LULC using visible light bands and LST using the thermal infrared band. Auxiliary data in the form of reference maps (Abuja Master Plan and land-use maps) were obtained from Abuja Geographic Information Systems (AGIS) and Federal Capital Development Authority (FCDA), which are government agencies responsible for the city's planning and development. However, the city's ground truth condition was analysed using Google earth imagery of 12th February 1990, 28th January 1999, 15th January 2009, and 4th February 2019 due to poor adherence to the master plan of the city [51].

Table 1. Details of Satellite Datasets used in the study.

Satellite Type/Sensor	WRS Path/Row	Date Acquired	Time (GMT)	Cloud Cover	Sun Azimuth	Sun Elevation	Thermal Conversion Constants	
							K ₁	K ₂
Landsat 4 TM	189/054	12/02/1990	09:22:25	6.00	121.5891	47.6548	671.62	1284.30
Landsat 5 TM	189/054	28/01/1999	09:29:13	3.00	128.8161	46.8722	607.76	1260.56
Landsat 7 ETM+	189/054	15/01/2009	09:39:52	3.00	135.0838	47.7213	666.09	1282.71
Landsat 8 OLI	189/054	04/02/2019	09:49:56	6.19	130.7612	51.8678	774.89	1321.08

3.2. Methods

3.2.1. LULC Classification

The classification of satellite images in urban centers and cities is considered a complex process due to its spectral heterogeneity [52–54]. Several classification methods have been employed in previous studies using remote sensing data and geospatial techniques to map satellite image pixels into various land use/land cover [55]. In this study, we employed Maximum Likelihood (ML) using the supervised classification method to classify LULC for the different study periods. ML is one of the most widely used methods for classifying LULC due to its high classification accuracy with appropriate selection of training data [56–59]. The study deliberately developed the city's LULC classification scheme after a careful study of relevant literature, reference maps, and field observations. The study area's land-use was then categorized into four (4) classes encompassing the built-up area, vegetation, barren land, and water bodies. The built-up areas represent all residential, commercial, industrial, and related urban infrastructural facilities. The vegetation class signifies agricultural lands and other grass-cover areas, while the barren land represents the city's non-inhabited areas, as described in Table 2.

Table 2. Description of LULC Classes in Abuja.

S/No	Land Use/Land Cover Classes	Description
1.	Urban/Built-Up Area	Covers residential, commercial, industrial developments, and infrastructural facilities.
2.	Vegetation	Comprises agricultural lands, natural vegetation, grassland, forest, trees, shrubs, parks, gardens, lawns, and other green areas
3.	Barren Land	Includes all non-vegetated land, bare soils, landfills and construction sites, quarries, gravel pits, and exposed open spaces.
4.	Water Bodies	Areas that comprise rivers, streams, ponds, lakes, reservoirs, wetland areas, swamps, irrigation and drainage canals

The main procedures for mapping the LULC classification include: (i) creating training samples, i.e., using polygons that represent the four LULC classes to be classified, (ii) using the satellite images to achieve supervised classification with the aid of maximum likelihood classification (MLC) and, (iii) evaluating the accuracy of the classified images using the Kappa coefficient [59–61].

3.2.2. Accuracy Assessment

A quantitative assessment was utilized to evaluate the study's land cover classification. For the Accuracy Assessment, the study employed a stratified random sampling approach to generate sample points of the study area. These samples were used to compare classified image pixels with reference data for each year. The validation/testing points

used for the accuracy assessment were independent of the training points used for image classification (i.e., different locations were selected for the training and validation). About 450 samples were created for each year to ensure the reliability of the results. Seventy percent of samples were used as training samples while 30% were used for validation. For each year, a minimum of 100 samples was created for each LULC class. The study then used the validation samples of the different years to assess the classified image accuracy. The results were statistically presented and analyzed using the confusion (error) matrix approach [61–64]. The confusion matrix is widely used for deriving analytical and descriptive data in classification accuracy. It comprises numbers displayed in columns and rows that present the various sample points (i.e., polygons, pixels, or pixel clusters) allocated to a specific land cover class relative to the class's actual ground condition [65]. The matrix has an overall accuracy comprising Producer and User Accuracy and Kappa coefficient (KC) as its assessment indices [64–67]. Producer Accuracy is the ratio of the total classified pixels in the error matrix diagonals to the total classified pixels in that category of the error matrix column. User Accuracy is the ratio of the total correctly classified pixels in the error matrix diagonals to the total classified pixels in that category of the error matrix row. Overall accuracy is the ratio of correctly classified pixels to the classified reference pixels. Finally, the Kappa index 'KC' was calculated as adopted by [68] using Equation (1).

$$\text{Kappa Coefficient (KC)} = \frac{N \sum_{i=1}^r x_{ii} - \sum_{i=1}^r (x_{i+} \times x_{+i})}{N^2 - \sum_{i=1}^r (x_{i+} \times x_{+i})}, \quad (1)$$

where N is the sum of pixels in the error matrix; r is the sum of columns/rows; x_{ii} is the value correctly classified pixels in the i th column and row; x_{+i} is the sum of pixels in the i th column; x_{i+} is the sum of pixels in the i th row, and N^2 is the square of the total number of pixels.

The Kappa Coefficient (KC) is a non-parametric index used in evaluating the level of agreement between pre-defined values and user-assigned value [69]. It has values between 0 and 1 with the result below 0.40, i.e., 40% demonstrating a weak agreement. A result ranging between 0.40 to 0.80 signifies a moderate agreement, while values above 0.80, i.e., 80%, signifies a good agreement [65]. Previous studies recommended the adoption of 80% as the minimum accuracy level for land use/land cover classification assessment [66,70].

3.2.3. Land Surface Temperature (LST) Retrieval

The study employed thermal infrared (TIR) bands to retrieve and map the study area's LST. This process uses a radiometric calibration technique that relies on an image header file, gain offset, solar radiation angle, and various calibration parameters. The procedure involves converting digital numbers (DNs) of thermal bands into spectral radiance values [71,72]. These values are then used in deriving the at-satellite (sensor) brightness temperature quantified in degrees Kelvin (°K), which were computed using thermal Conversion Constants [73–75]. The at-sensor brightness temperature values were further converted into degrees Celsius (°C) to derive the LST. The procedures used for the retrieval of LST are discussed below.

1. Conversion of DN to spectral radiance conversion

The DN of thermal infrared (TIR) bands were converted into spectral radiance with the aid of ArcGIS 10.7.1 image processing software using the Radiative Transfer Equation (RTE) presented in Equations (2) and (3) [76,77].

- For Landsat TM and ETM+

$$L_{\lambda} = \left(\frac{L_{\text{MAX}_{\lambda}} - L_{\text{MIN}_{\lambda}}}{Q_{\text{CAL}_{\text{MAX}}} - Q_{\text{CAL}_{\text{MIN}}}} \right) \times (Q_{\text{CAL}} - Q_{\text{CAL}_{\text{MIN}}}) + L_{\text{MIN}_{\lambda}}, \quad (2)$$

where L_{λ} is the value of spectral radiance; Q_{CAL} represents the DN value of the quantized calibrated pixel; $L_{\text{MAX}_{\lambda}}$ represents the value of spectral radiance in ($\text{Wm}^{-2}\text{sr}^{-1}\mu\text{m}^{-1}$)

scaled to Q_{CAL_MAX} ; L_{MIN_λ} represents the value of spectral radiance in ($Wm^{-2}sr^{-1}\mu m^{-1}$) scaled to Q_{CAL_MIN} ; Q_{CAL_MIN} and Q_{CAL_MAX} are the min. and max. DN values of the quantized calibrated pixels that correspond to L_{MIN_λ} and L_{MAX_λ} , respectively.

- For Landsat OLI/TIRS

$$L_\lambda = M_L \times Q_{CAL} + A_L, \quad (3)$$

where L_λ represents the top of the atmosphere spectral radiance in ($Wm^{-2}sr^{-1}\mu m^{-1}$); M_L is the rescaling factor for radiance multiplicative band obtained from metadata (i.e., Radiance_Mult_Band 10); Q_{CAL} is the DN value of the calibrated and quantized product pixel; and A_L is the rescaling factor for the radiance additive band obtained from metadata (i.e., Radiance_Add_Band 10).

2. Conversion of spectral radiance to TOA brightness temperature (B_T)

For this, spectral radiance values of the converted pixels digital numbers were used to extract the top of atmosphere (TOA) brightness temperature (B_T), also known as satellite-derived temperature, and expressed in Kelvin. Using uniform emissivity assumption, the brightness (sensor) temperature values were computed using Equation (4) [3,27,78].

$$B_T = \frac{K_2}{\ln\left(\frac{K_1}{L_\lambda} + 1\right)}, \quad (4)$$

where B_T is brightness temperature at the top of atmosphere (TOA) expressed in $^{\circ}K$; L_λ is the spectral radiance at TOA expressed in ($Wm^{-2}sr^{-1}\mu m^{-1}$); K_1 and K_2 are the retrieved metadata's thermal conversion constants (presented in Table 1).

3. Derivation of Land Surface Temperature from brightness temperature (B_T)

The study then derived the emissivity values of the corrected LST (in Kelvin) with the aid of at-satellite brightness temperature (T_B) using Equation (5) [3,27,79,80].

$$LST (^{\circ}K) = \frac{B_T}{\left[1 + \lambda \left(\frac{T_B}{E}\right) \ln(\epsilon)\right]}, \quad (5)$$

where B_T is the brightness temperature at-satellite (sensor); λ is the wavelength of emitted radiance (i.e., 11.5 μm in Band 6 for Landsat 4/5/7 and 10.8 μm in Band 10 for Landsat 8); E is $(h \times v)/s$ (1.4388×10^{-2} mK); h represents the Planck's constant (6.626×10^{-34} mK); v represents the velocity of light (2.998×10^8 m/s); s represents the Boltzmann constant (1.38×10^{-23} JK), and ϵ represents emissivity of the land surface.

We calculated the emissivity of the land surface (ϵ) in the study using Equation (6) [81]

$$(\epsilon) = N(P_v) + n, \quad (6)$$

where N is 0.004; n is 0.986; and P_v is the vegetation proportion expressed in Equation (7) [82].

$$P_v = \left(\frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}} \right)^2, \quad (7)$$

where $NDVI$ are the values of DN obtained from the $NDVI$ image; $NDVI_{max}$ and $NDVI_{min}$ are the highest and lowest DN values obtained from the $NDVI$ image.

Lastly, the study converted the Land Surface Temperature value (in Kelvin) into degree Celsius ($^{\circ}C$) using Equation (8) [27,79,81].

$$LST (^{\circ}C) = LST (^{\circ}K) - 273.15, \quad (8)$$

3.2.4. Normal Difference Vegetation Index (NDVI) Estimation

One of the most commonly used urban climate indicators in environmental studies is the Normalized Difference Vegetation Index ($NDVI$) [3,83], which serves as a reliable index

for extracting vegetation conditions of remotely sensed data [11]. Therefore, we employed the NDVI to examine the study area's vegetation distribution and extract emissivity values. The index is often associated with various other indices such as biomass, leaf area, and vegetation cover percentage and, as such, is closely related to the vegetation proportion (P_v) that is needed in calculating land surface emissivity (ϵ). The NDVI has values ranging between -1 and $+1$, where negative values indicate non-vegetated areas and positive values represent vegetated areas [84]. It is often calculated based on image pixels using the normalized difference between the near-infrared band (i.e., band 4 in Landsat TM and band 5 in Landsat OLI) and red band (i.e., band 3 in Landsat TM and band 4 in Landsat OLI) [28,85]. The NDVI of the study area was extracted using Equation (9) [79,80].

$$NDVI = \frac{NIR_{(Band\ 4,5)} - RED_{(Band\ 3,4)}}{NIR_{(Band\ 4,5)} + RED_{(Band\ 3,4)}}, \quad (9)$$

where $NIR_{(Band\ 4)}$ is $0.76\text{--}0.90\ \mu\text{m}$ (For Landsat 4–5 TM) and $NIR_{(Band\ 5)}$ is $0.85\text{--}0.88\ \mu\text{m}$ (For Landsat 8 OLI). $RED_{(Band\ 3)}$ is $0.63\text{--}0.69\ \mu\text{m}$ (For Landsat 4–5 TM and Landsat 7 ETM+) and $RED_{(Band\ 4)}$ is $0.64\text{--}0.67\ \mu\text{m}$ (For Landsat 8 OLI).

3.2.5. Normalized Difference Built-Up Index (NDBI) Estimation

The Normalized Difference Built-up Index (NDBI) is another vital urban climate indicator for environmental monitoring [3,68]. This serves as an effective method of mapping and analyzing land-uses by providing information on the spatial extent of built-up areas and impervious surfaces. The NDBI designates built-up area's density in unit pixel, with values ranging from positive 1 to negative 1. The negative values often signify vegetation, while the positive denotes built-up urban/impervious surfaces [3,28]. The NDBI was estimated using the mid and near-infrared bands presented in Equation (10).

$$NDBI = \frac{MIR_{(Band\ 5,6)} - NIR_{(Band\ 4,5)}}{MIR_{(Band\ 5,6)} + NIR_{(Band\ 4,5)}}, \quad (10)$$

where $MIR_{(Band\ 5)}$ is $1.55\text{--}1.75\ \mu\text{m}$ (For Landsat 4–5 TM and Landsat 7 ETM+) and $MIR_{(Band\ 6)}$ is $1.57\text{--}1.65\ \mu\text{m}$ (For Landsat 8 OLI). $NIR_{(Band\ 4)}$ is $0.76\text{--}0.90\ \mu\text{m}$ (For Landsat 4–5 TM and Landsat 7 ETM+) and $NIR_{(Band\ 5)}$ is $0.85\text{--}0.88\ \mu\text{m}$ (For Landsat 8 OLI).

The methodological flow chart illustrated in Figure 2 summarizes the several procedures used in this study.

3.2.6. Correlation Analysis

The study employed a correlation analysis to analyze LULC changes on surface UHI using the LST of Abuja Metropolis. We performed linear regression analysis using scatter plots of all four time nodes (i.e., 1990, 1999, 2009, and 2019) to examine the relationship between the different study variables. This was achieved by converting the study area's pixels into point data. These points' parametric values were then retrieved from the derived maps of the different periods using 1371 sample points for each period under consideration. Pearson's correlation coefficient ' r ' was further employed to effectively quantify and analyze the study's variables using Equation (11).

$$r = \frac{\sum_{i=1}^n (x_i - \bar{x}) \times (y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2} \times \sqrt{\sum_{i=1}^n (y_i - \bar{y})^2}}, \quad (11)$$

where r represents the Person's correlation coefficient; x represents the independent variables measuring the value of x_i ; y represents the dependent variable measuring value of y_i ; x_i and y_i represents the individual sample points indexed i ; while $\bar{x}$ and $\bar{y}$ represents the mean of the samples.

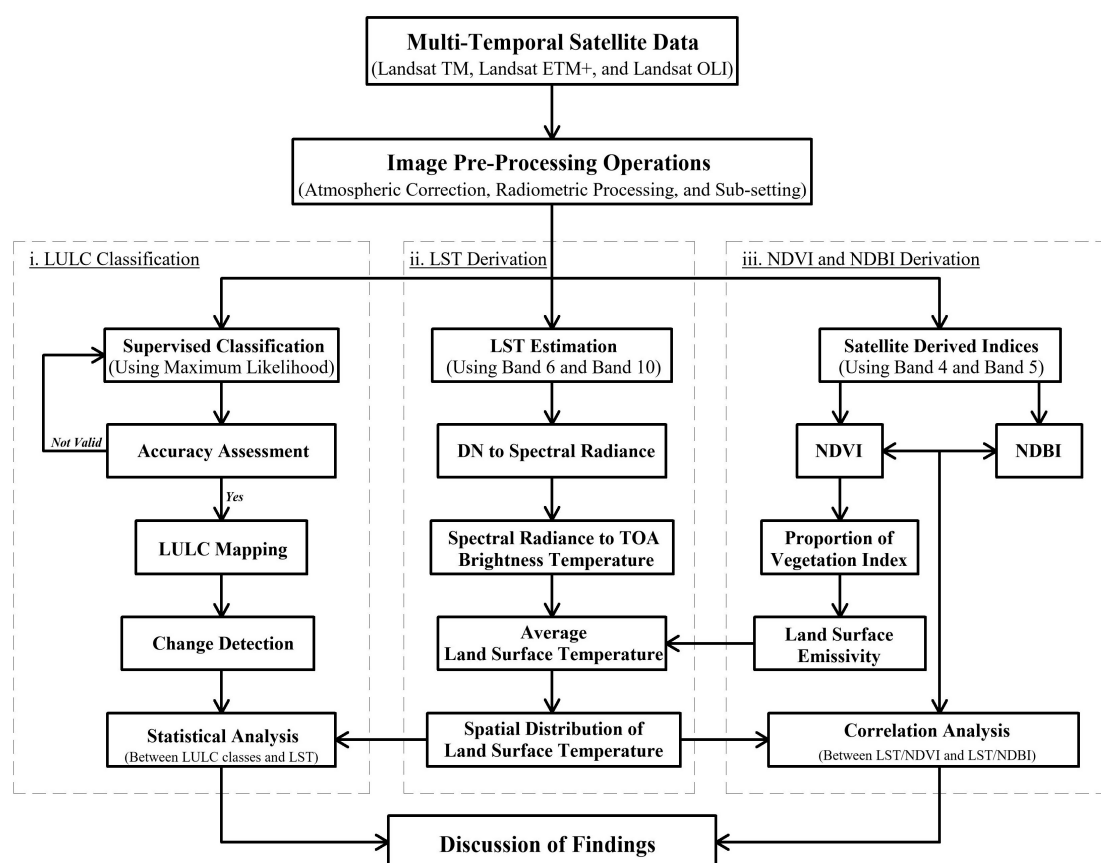


Figure 2. Methodological Flow chart of the study.

4. Results

This section presents and discusses the study's results. It analyzes the historical trend of LULC patterns, and distribution of LST, NDVI, and NDBI. The section also studies LULC changes and their influence on surface UHI by analyzing the city's LST variations with LULC classes, NDVI and NDBI.

4.1. Land Use/Land Cover Classification

The classified land cover maps of Abuja metropolis for the different periods (i.e., 1990, 1999, 2009, and 2019) are presented in Figure 3 and quantified in Table 3. The LULC were classified into four broad classes. These classes comprising built-up areas, vegetation, barren land, and water bodies, are the earlier defined land cover categories of the study area in Section 3.2.1. The metropolis covers approximately 1722.99 sq. km.

Table 3. Land use/land cover distribution in 1990, 1999, 2009, and 2019.

S/No	LULC Types	1990		1999		2009		2019	
		Area (sq. km)	Area (%)	Area (sq. km)	Area (%)	Area (sq. km)	Area (%)	Area (sq. km)	Area (%)
1.	Built-up Area	77.26	4.48	157.75	9.15	178.58	10.36	467.68	27.14
2.	Vegetation	447.94	26.00	319.91	18.57	274.38	15.92	195.61	11.35
3.	Barren Land	981.71	56.98	1151.28	66.82	1210.75	70.28	1005.84	58.38
4.	Water Bodies	216.08	12.54	94.05	5.46	59.28	3.44	53.86	3.13
5.	Total	1722.99	100	1722.99	100	1722.99	100	1722.99	100

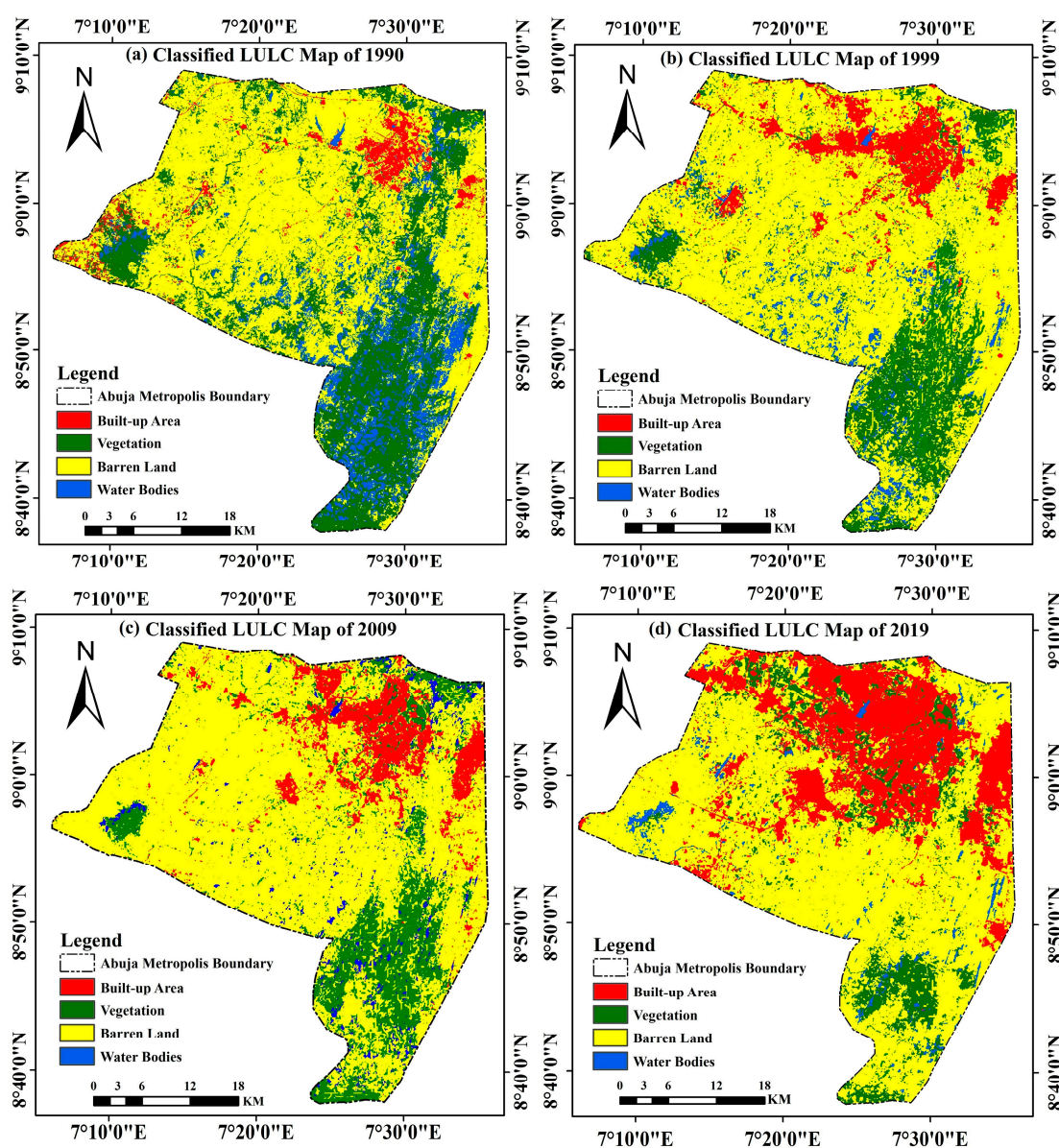
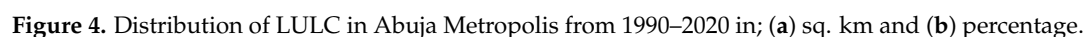


Figure 3. Classified land use/land cover maps of Abuja Metropolis in; (a) 1990, (b) 1999, (c) 2009, and (d) 2019.

The result reveals the built-up areas to have expanded the most among the four LULC classes in the metropolis. However, the city's vegetation cover decreased continuously throughout the study period. The gradual decrease in vegetation cover can be attributed to urban growth and human interference to the natural environment, which led to the continuous cutting down of forest areas to accommodate the populace's influx. The results indicate vegetation loss of about 252.33 sq. km (14.65%) during the study period due to various human activities. Barren land witnessed a slight increase from 1990 to 2019, which can mainly be attributed to the massive construction and urban development in the metropolis. The water bodies in the metropolis declined by approximately 162.22 sq. km (9.41%) between 1990 and 2019. The distribution of the individual LULC classes extracted from the four years' LULC classified maps are graphically presented in Figure 4a,b. The results show the study area to have undergone four epochs of notable change that might negatively affect the environment by influencing surface urban heat islands due to the various LULC changes.



As earlier stated, the land use/land cover pattern of Abuja metropolis was defined in four LULC classes that comprise built-up areas, vegetation, barren land, and water bodies. In this study, the Maximum Likelihood Algorithm (MLA) was employed for the LULC classification. The accuracy assessments of each year were evaluated using the error matrix that shows the correctly and incorrectly classified pixels as presented in Table 4. The producer accuracy and user accuracy of each LULC class in the different period is also shown in Table 5. The Kappa coefficient was further employed for the assessment of LULC classification accuracy. The overall accuracies of the four periods were above 90%, signifying a reliable land cover classification and a good agreement between classified maps and referenced maps [66,70]. Kappa coefficients ranging between 0.87 and 0.93 were observed during the study period.

(a) 1990 Confusion Matrix

(a) 1990 Confusion Matrix						
S/No	Land Cover Classes	Built-Up	Vegetation	Barren Land	Water Bodies	Total
1.	Built-up	469	60	23	0	552
2.	Vegetation	2	826	12	14	854
3.	Barren Land	11	98	531	0	640
4.	Water Bodies	0	1	0	332	333
Total		482	985	566	346	2379
Overall Accuracy = (2158/2379) = 90.71%						
Kappa Coefficient = 0.8710						
(b) 1999 Confusion Matrix						
S/No	Land Cover Classes	Built-Up	Vegetation	Barren Land	Water Bodies	Total
1.	Built-up	1033	32	12	0	1077
2.	Vegetation	60	537	22	1	620
3.	Barren Land	7	2	587	12	608
4.	Water Bodies	0	13	21	231	231
Total		1100	584	642	244	2570
Overall Accuracy = (2388/2570) = 92.92%						
Kappa Coefficient = 0.8984						

Table 4. Cont.

(c) 2009 Confusion Matrix						
S/No	Land Cover Classes	Built-Up	Vegetation	Barren Land	Water Bodies	Total
1.	Built-up	1259	1	4	29	1293
2.	Vegetation	6	787	122	29	944
3.	Barren Land	30	45	2275	5	2355
4.	Water Bodies	0	20	15	600	635
	Total	1295	853	2416	663	5227
Overall Accuracy = (4921/5227) = 94.15% Kappa Coefficient = 0.9146						
(d) 2019 Confusion Matrix						
S/No	Land Cover Classes	Built-Up	Vegetation	Barren Land	Water Bodies	Total
1.	Built-up	1219	3	17	3	1242
2.	Vegetation	63	683	1	0	747
3.	Barren Land	16	51	742	8	817
4.	Water Bodies	0	0	0	528	528
	Total	1298	737	760	539	3334
Overall Accuracy = (3172/3334) = 95.14% Kappa Coefficient = 0.9329						

Table 5. Producer and User accuracies of individual LULC classes.

S/No	Year	Producer's Accuracy (%)				User's Accuracy (%)			
		Built-Up Area	Vegetation	Barren Land	Water Bodies	Built-Up Area	Vegetation	Barren Land	Water Bodies
1.	1990	97.30	83.86	93.82	95.95	84.96	96.72	82.97	99.70
2.	1999	93.91	91.95	91.43	94.67	95.91	86.61	96.55	87.17
3.	2009	97.22	92.26	94.16	90.50	97.37	83.37	96.60	94.49
4.	2019	93.91	92.67	97.63	97.96	98.15	91.43	90.82	100.00

4.3. Change Detection Analysis

Remotely sensed data are useful in detecting and analyzing spatiotemporal changes in LULC. The analysis of land cover changes due to urban growth and rapid urbanization often helps monitor the negative effects of various human activities on the environment. The present study analyzed the LULC changes of the Abuja metropolis between 1990 and 2019 in five (5) different periods. These periods include: period 1 (1990–1999), period 2 (1999–2009), period 3 (2009–2019), period 4 (1990–2009), and period 5 (1990–2019). The study utilized the four identified (4) LULC classes to analyze the study area's mapping. The results are quantitatively presented in Table 6, showing each period's LULC change in sq. km and percentage.

The study revealed notable spatiotemporal LULC changes during the period, showing both negative and positive changes in the various LULC classes, which may influence the ecosystem and are likely to contribute to varying climatic conditions.

During period 1, the land use/land cover change was characterized by an expansion in the magnitude of built-up areas and barren land while vegetation cover and water bodies decreased significantly. These positive and negative changes may be attributed to the city's growth and development to an urban settlement due to the relocation of Nigeria's capital city to Abuja in 1991. During period 2, the study area witnessed a slight increase in built area by approximately 20.83 sq. km while barren land increased by about 59.47 sq. km. Vegetation and waterbodies continued along this decreasing trend in this period, declining

by 45.53 sq. km and 34.77 sq. km. During period 3, the metropolis witnessed an abrupt increase in built areas and a rapid decrease in barren land. Likewise, vegetation declined substantially during this period. The results suggest that water bodies experienced little or no significant change between 2009 and 2019 compared to other LULC classes due to human-induced activities.

Table 6. LULC change dynamics (statistics) of Abuja Metropolis from 1990 to 2019.

S/No	LULC Types	1990–1999		1999–2009		2009–2019		1990–2009		1990–2019	
		Area (sq. km)	Area (%)	Area (sq. km)	Area (%)	Area (sq. km)	Area (%)	Area (sq. km)	Area (%)	Area (sq. km)	Area (%)
1.	Built-up Area	80.49	4.67	20.83	1.21	289.10	16.78	101.32	5.88	390.42	22.66
2.	Vegetation	−128.03	−7.43	−45.53	−2.65	−78.77	−4.57	−173.56	−10.08	−252.33	−14.65
3.	Barren Land	169.57	9.84	59.47	3.46	−204.91	−11.90	229.04	13.30	24.13	1.40
4.	Water Bodies	−122.03	−7.08	−34.77	−2.02	−5.42	−0.31	−156.80	−9.10	−162.22	−9.41

The city's change detection result at an interval of 9 years (1990–1999), 19 years (1990–2009), and 29 years (1990–2019) revealed remarkable LULC changes. The study indicated an average annual change in built-up areas by approximately 8.94 sq. km, 5.33 sq. km, and 13.46 sq. km during the span of 9 years, 19 years, and 29 years. The city's barren land increased annually by 18.84 sq. km during the period between 1990–1999. However, this rate declined to 12.05 sq. km between 1990 and 2009. A decreasing trend of approximately 9.13 sq. km and 8.25 sq. km were observed annually in vegetation and water bodies between 1990 and 2009. Likewise, between 1990 and 2019, the city's vegetation and waterbodies declined annually by 8.70 sq. km and 5.59 sq. km, respectively.

Therefore, the LULC change scenarios of the study area suggest the development and expansion of built-up areas, depicting the rapid urban growth of the metropolis. This increase in built areas may have contributed to the negative changes in some LULC classes, as illustrated in Figure 5.

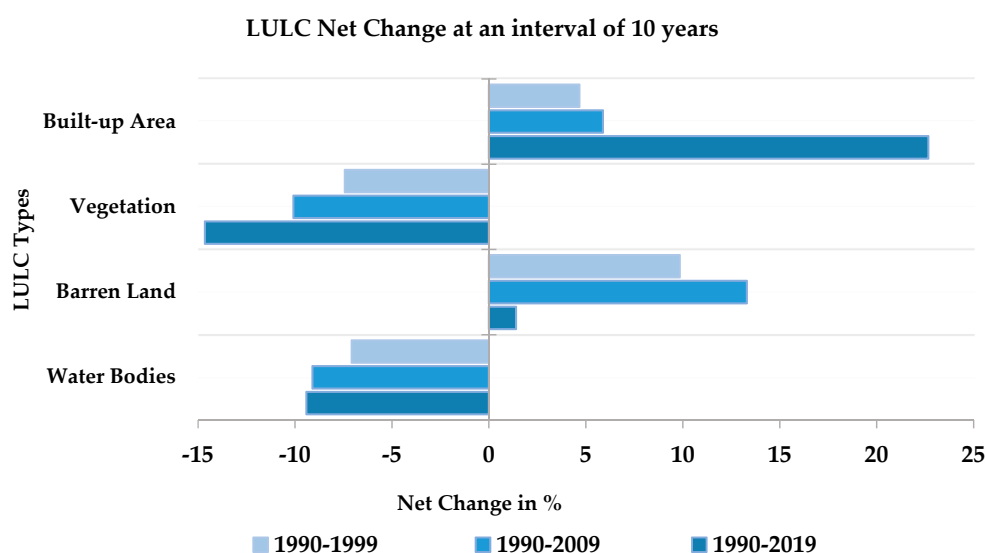


Figure 5. Net Changes in LULC types of Abuja Metropolis during three study periods.

Figure 6 shows the LULC transition map of the Abuja metropolis from 1990 to 2019 and the result presented in Figure 7. This indicates approximately 969.99 sq. km changes in the study area's different LULC classes over 29 years. The results show 301.24 sq. km (17.48%) of barren land converted into built-up areas as the highest land cover transition between 1990 and 2019. It was seconded by the transformation of 289.41 sq. km (16.80%) of vegetation into the barren land and subsequently followed by the conversion of 158.27 sq. km (9.19%) of water bodies into barren land. A moderate transition was observed in the

conversion of barren land into vegetation with 84.75 sq. km (4.92%), while 45.06 sq. km (2.62%) of vegetation was transformed to built-up areas. On the other hand, 23.64 sq. km (1.37%) of vegetation was converted into water bodies, and 22.62 sq. km (1.31%) of water bodies were converted to vegetation. A minuscule transition of 0.82 sq. km (0.05%) was seen in the transformation of built-up areas into water bodies.

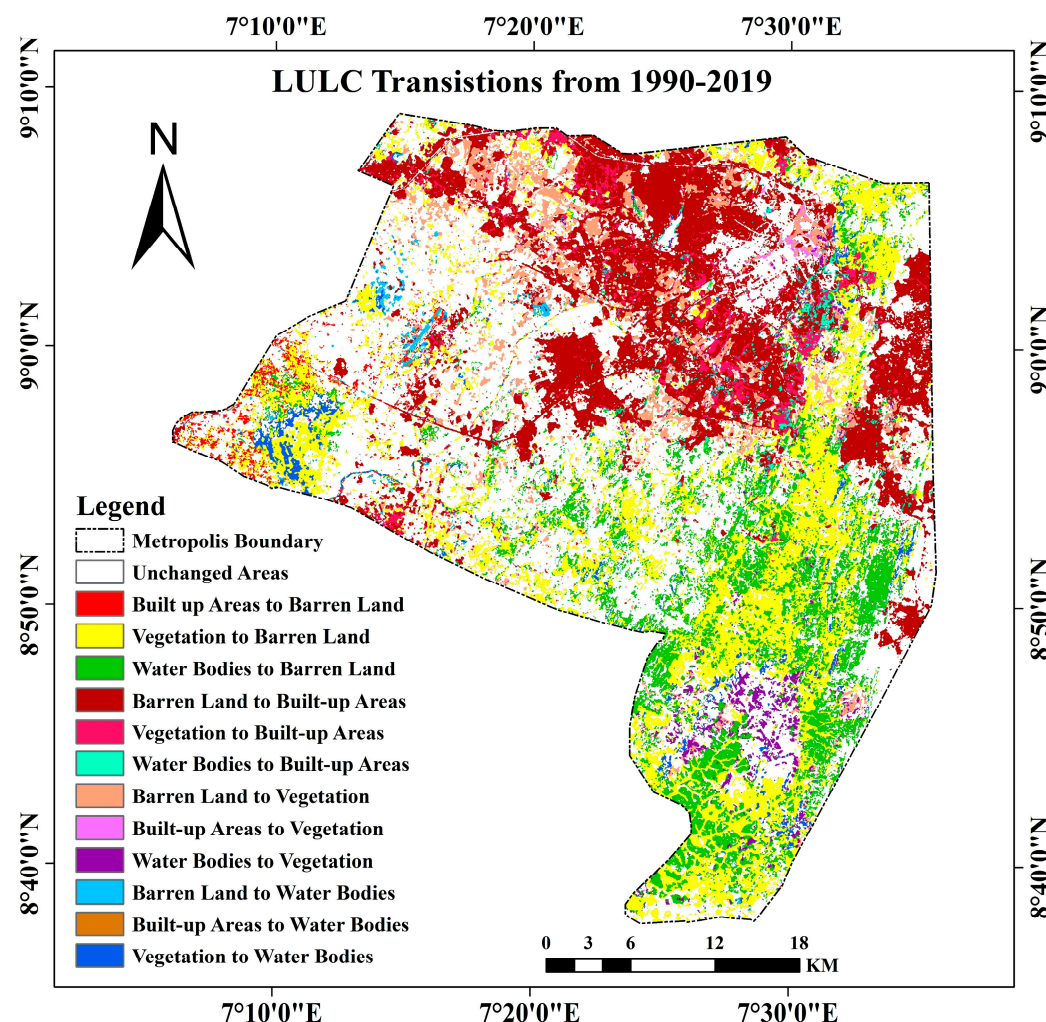


Figure 6. Land use/land cover transitions of Abuja Metropolis from 1990–2019.

4.4. LST Distribution and Its Relationship with LULC

The spatial distribution of LST in Abuja Metropolis for the years 1990, 1999, 2009, and 2019 were extracted as described in Section 3.2.3 and illustrated in Figure 8. The statistical data are presented in Table 7. The results indicate that the LST of Abuja metropolis ranged between approximately 20.30–37.11 °C, 21.50–44.46 °C, 20.55–46.34 °C, and 20.58–40.13 °C during the four distinct periods (i.e., 1990, 1999, 2009, and 2019, respectively). The result revealed a substantial increase in the mean LST of the metropolis from approximately 30.65 °C in 1990 to 32.69 °C in 2019. The LST analysis indicates that between 1990 and 1999, the mean LST of the metropolis has decreased by 0.25 °C. A similar decrease of 0.24 °C was observed between 1999 and 2009. However, the metropolis witnessed an increase in the mean LST with roughly 2.50 °C between 2009 and 2019. This result indicates a mean LST increase of about 2.04 °C over the last 29 years.

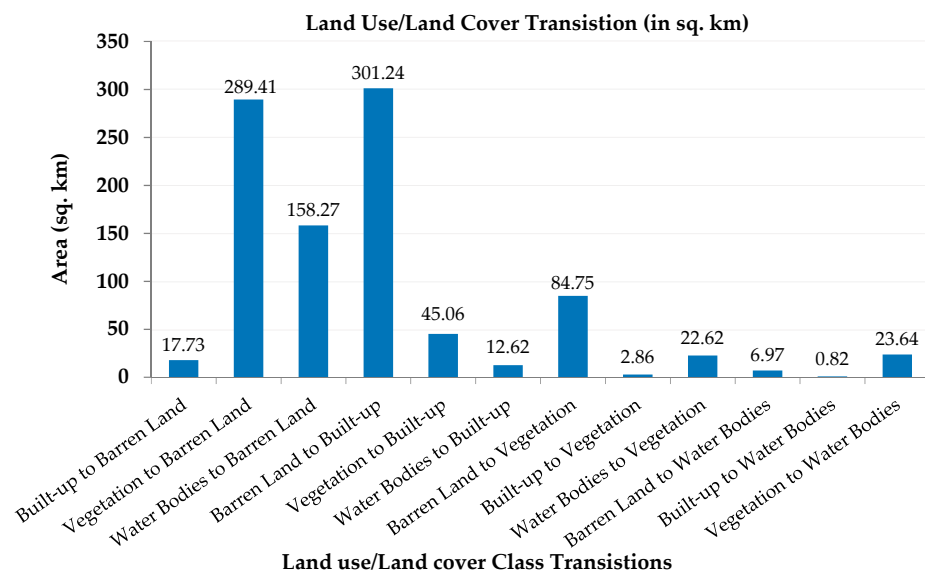


Figure 7. The LULC change transition of Abuja Metropolis in sq. km from 1990 to 2019.

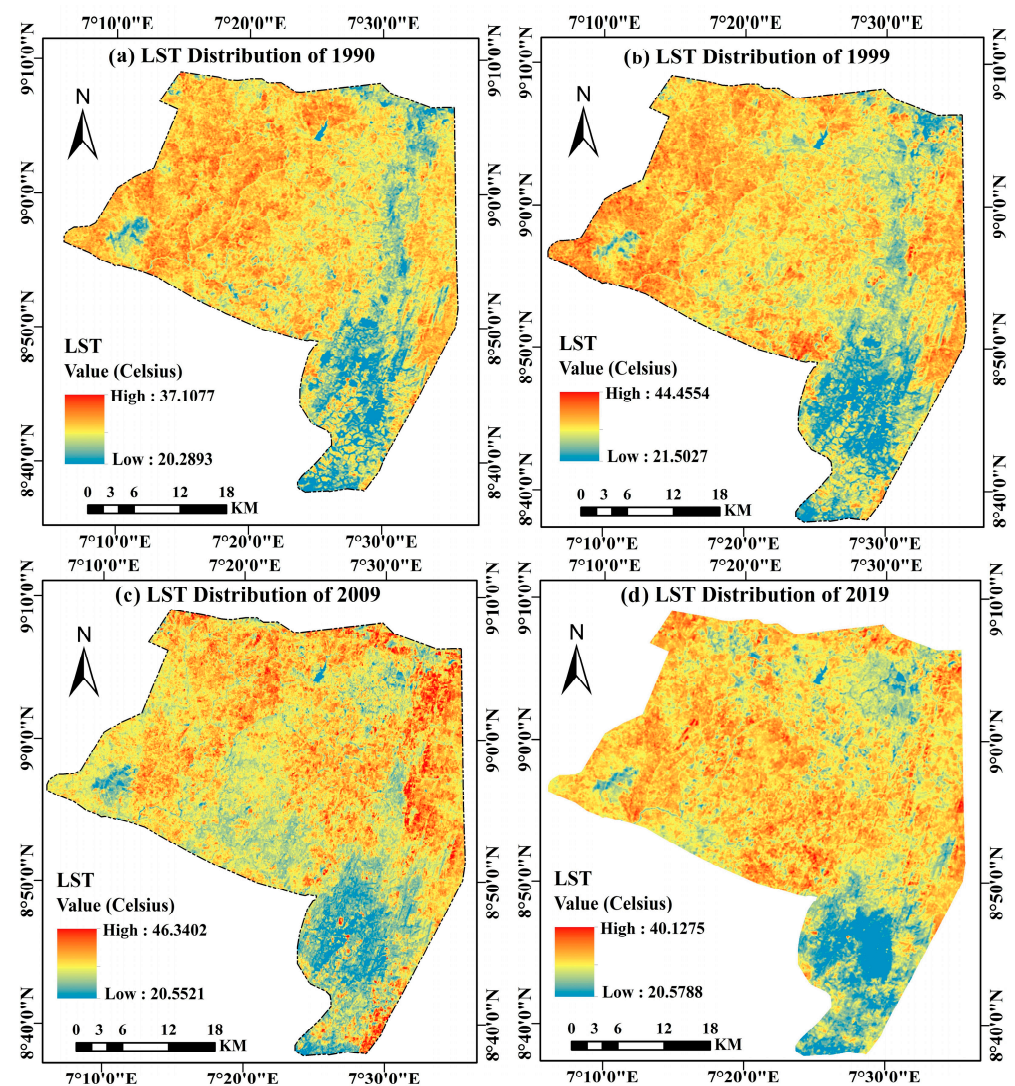


Figure 8. LST Distribution of Abuja Metropolis in; (a) 1990, (b) 1999, (c) 2009, and (d) 2019.

Table 7. Statistics of LST (°C) in Abuja Metropolis for the four periods between 1990 and 2019.

S/No	Acquisition Date	Land Surface Temperature (LST)			
		Minimum (°C)	Maximum (°C)	Mean (°C)	Standard Deviation
1.	12/02/1990	20.30	37.11	30.65	2.19
2.	28/01/1999	21.50	44.46	30.40	2.13
3.	15/01/2009	20.55	46.34	30.16	1.87
4.	04/02/2019	20.58	40.13	32.69	2.02

Therefore, to effectively analyze LST and LULC relationship, it is essential to study the thermal signature of individual land use/land cover classes [73]. In this study, the LST and LULC comparison was carried out using numerous sampling points. These points were selected to compare the four LULC classes with the LST values of the study area in 1990, 1999, 2009, and 2019. The mean LST values of each LULC class were computed by averaging the specific land cover category's image pixels. The results of the four distinct periods under consideration are presented statistically in Table 8.

Table 8. Mean LST values for each LULC type in Abuja Metropolis for the period between 1990 and 2019.

S/No	LULC Types	Mean LST (°C)				Mean LST Difference (°C)				
		1990	1999	2009	2019	1990–1999	1999–2009	2009–2019	1990–2009	1990–2019
1.	Built-up area	31.09	30.27	30.50	32.98	−0.82	0.23	2.48	−0.59	1.89
2.	Vegetation	28.18	27.44	28.05	29.67	−0.74	0.61	1.62	−0.13	1.49
3.	Barren Land	31.83	31.12	30.73	33.23	−0.71	−0.39	2.50	−1.10	1.40
4.	Water Bodies	30.15	30.09	29.21	30.65	−0.06	−0.88	1.44	−0.94	0.50

The mean LST value of the built-up areas was established to be 31.09 °C in 1990 and by 1999 this had reduced to 30.27 °C. However, it rose slightly to 30.50 °C in 2009 and further increased to 32.98 °C in 2019. The result clearly shows that the Abuja metropolis' built areas witnessed a higher mean LST of 1.89 °C in 2019 than in 1990. Analysis of the different periods indicates the mean LST in built-up areas has experienced the highest increase of 2.48 °C between 2009 and 2019. The mean LST for vegetation was 28.18 °C in 1990, and subsequently, in 1999, it reduced to 27.44 °C. However, the mean LST increased to 28.05 °C in 2009 and increased further to 29.67 °C in 2019. Therefore, it is evident that vegetation witnessed a rise of 1.49 °C in mean LST from 1990 to 2019. The result revealed that the mean LST of vegetation observed the most significant rise of 1.62 °C between 2009 and 2019. The mean LST value of barren land was 31.83 °C in 1990, which decreased slightly to 31.12 °C in 1999. The result showed a further decline to 30.73 °C in 2009 and a rapid increase to 33.23 °C in 2019. Therefore, it is apparent that barren land experienced various changes with a higher LST value of 1.40 °C in 2019 than in 1990. Additional analysis reveals that barren land has experienced the highest increase in mean LST of 2.50 °C from 2009 to 2019 and the lowest decrease of 0.39 °C from 1999 to 2009. The study also revealed the mean LST of water bodies in 1990 to be 30.15 °C, which decreased slightly to 30.09 °C in 1999. The mean LST further declined to 29.21 °C in 2009, but significantly increased to 30.65 °C in 2019. The result indicates an increase of 0.50 °C in the mean LST of water bodies from 1990 to 2019, signifying the lowest mean LST change during the study period.

4.5. NDVI and Its Relationship with LST

The derived maps of the Normalized Difference Vegetation Index of Abuja Metropolis are presented in Figure 9 which portrays the four different study periods, i.e., 1990, 1999, 2009, and 2019. The statistical results are quantified and presented in Table 9. The result revealed the highest NDVI values ranging between approximately 0.29 and 0.54, with such areas having mostly shrubs, grasslands, cultivated lands, and undeveloped natural

surfaces, while the lowest NDVI values ranged between -0.09 to -0.39 , with such areas covering mainly built-up areas, barren land, and water bodies.

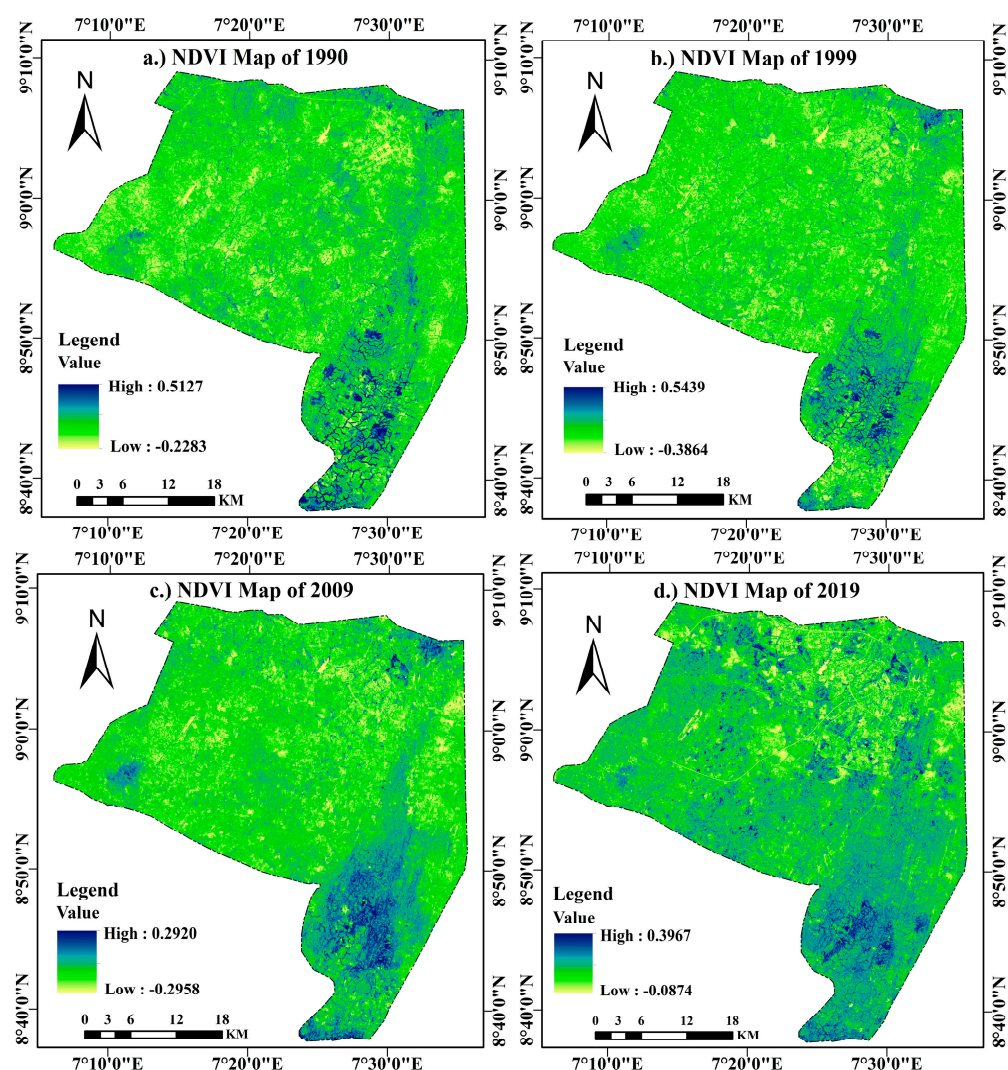


Figure 9. NDVI Spatial Distribution of Abuja Metropolis in; (a) 1990, (b) 1999, (c) 2009, and (d) 2019.

Table 9. Statistics of NDVI in Abuja Metropolis for the period between 1990 and 2019.

S/No	Acquisition Date	Normalized Difference Vegetation Index (NDVI)			
		Minimum	Maximum	Mean	Standard Deviation
1.	12/02/1990	-0.23	0.51	0.06	0.05
2.	28/01/1999	-0.39	0.54	0.09	0.07
3.	15/01/2009	-0.30	0.29	-0.03	0.05
4.	04/02/2019	-0.09	0.40	0.15	0.04

The results demonstrated the highest NDVI in the southern part and north-eastern fringes of the metropolis, mainly covered by forest areas and vegetation. To examine the relationship between LST and NDVI, we generated 1371 random sample points for each period's scattered plots (i.e., 1990, 1999, 2009, and 2019). The results are shown in Figure 10, indicating a negative relationship between the values of LST and NDVI in all four periods. The scatter plots analysis results show a considerable decline in the determination

coefficient during each period. This had a value (R^2) of approximately 0.42 in 1990, 0.40 in 1999, 0.38 in 2009, and 0.20 in 2019.

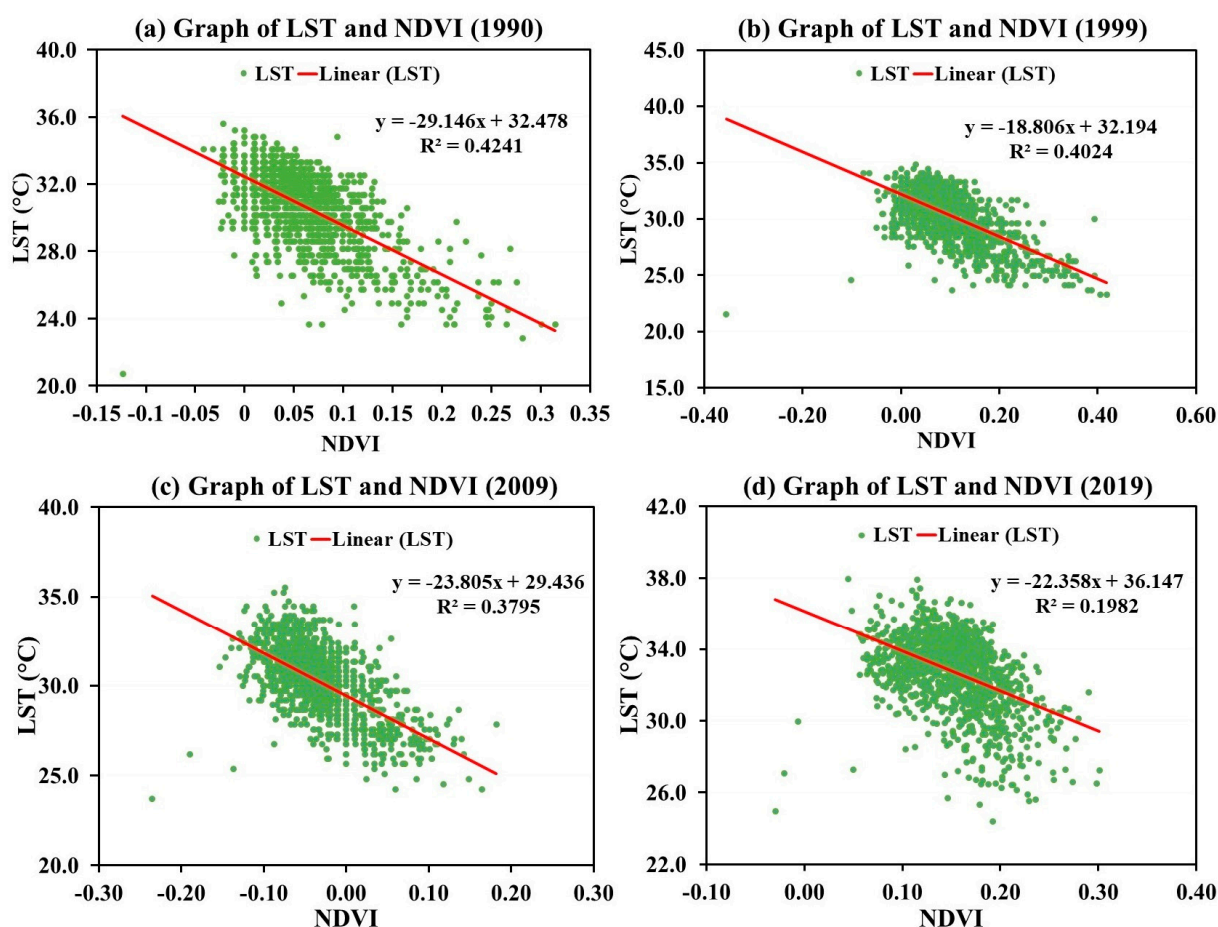


Figure 10. Relationship between LST and NDVI of Abuja Metropolis for; (a) 1990, (b) 1999, (c) 2009, and (d) 2019 using scattered plots.

4.6. NDBI and Its Relationship with LST

The spatiotemporal maps of the Normalized Difference Built-up Index of Abuja Metropolis are presented in Figure 11 and quantified in Table 10. The results of the different periods (i.e., 1990, 1999, 2009, and 2019) indicates that the metropolis' NDBI values ranges between approximately 0.65 to -0.25 in 1990, 0.77 to -0.96 in 1999, 0.66 to -0.54 in 2009, and 0.58 to -0.25 in 2019. These values represent the maximum and minimum NDBI for the different periods, respectively. Previous studies suggest that NDBI values greater than -0.22 represent land mainly occupied by built-up areas [3].

Table 10. Statistics of NDBI in Abuja Metropolis for the period between 1990 and 2019.

S/No	Acquisition Date	Normalized Difference Built-Up Index (NDBI)			
		Minimum	Maximum	Mean	Standard Deviation
1.	12/02/1990	-0.25	0.65	0.24	0.07
2.	28/01/1999	-0.96	0.77	0.28	0.08
3.	15/01/2009	-0.54	0.66	0.15	0.07
4.	04/02/2019	-0.25	0.58	0.04	0.05

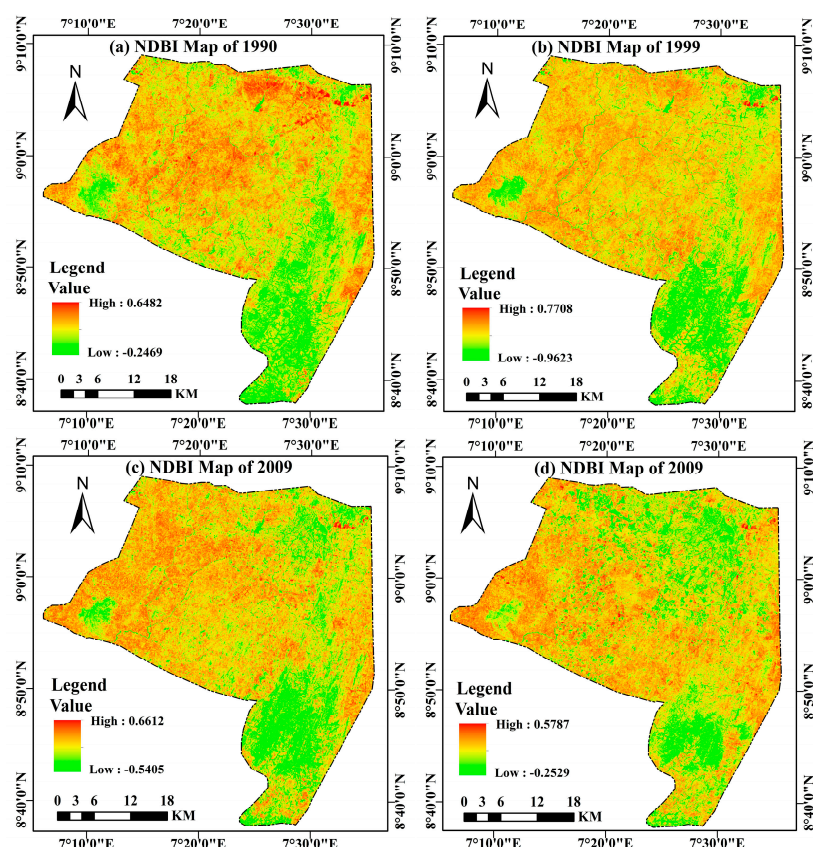


Figure 11. NDBI Spatial Distribution of Abuja Metropolis in; (a) 1990, (b) 1999, (c) 2009, and (d) 2019.

The graphical relationship between LST and NDBI is demonstrated in Figure 12. It shows a positive association between LST and built-up areas. The results indicate that lower LST values corresponded to lower NDBI, while higher LST values corresponded to built-up areas of high density.

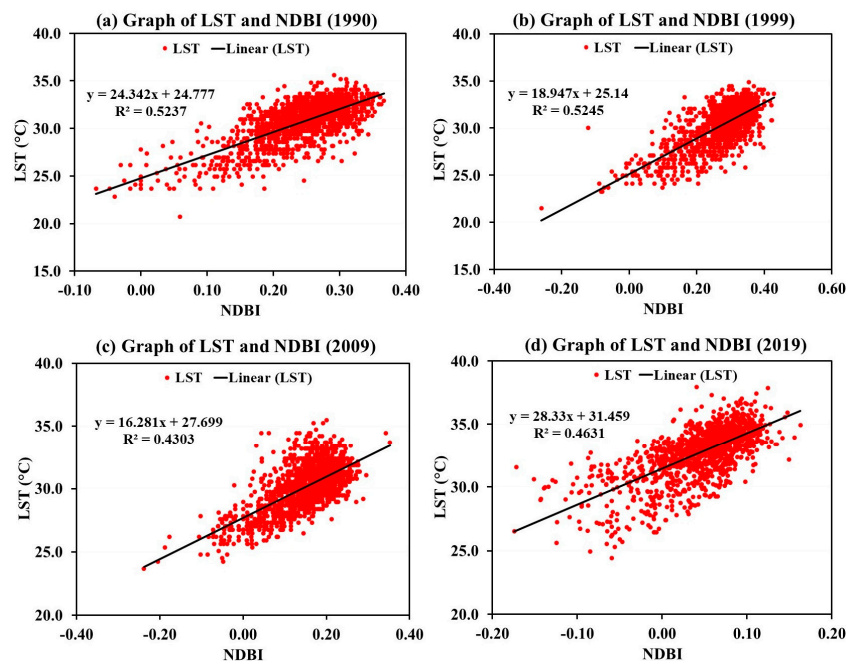


Figure 12. Relationship between LST and NDBI of Abuja Metropolis for; (a) 1990, (b) 1999, (c) 2009, and (d) 2019 using scattered plots.

5. Discussion

From the change detection results obtained, it is evident that urbanization coupled with socio-economic activities in Abuja metropolis may have contributed remarkably to the transition of natural surfaces into built areas. The results conform with previous studies, which suggest an increasing trend in the spatial extent of built-up/urban areas in developing countries such as Nigeria, Bangladesh, Egypt, and many others [6,19,37,39,68]. These are consequences of rapid urban growth and the quest for better living conditions. The development of urban areas has negatively affected the natural and built environment, contributing significantly to the increase in the land surface temperatures of cities [8,39,68].

The present study revealed the built-up area of Abuja Metropolis to have exhibited the most significant increase in the mean LST, followed by barren land, vegetation, and water bodies over the last 29 years. During the study periods between 1990 and 2019, the western, northwestern, eastern, and central parts of the study area exhibited the highest LST, with such areas corresponding to built-up areas and barren land. The southern parts of the metropolis exhibited the lowest LST, with such areas corresponding to vegetation and waterbodies. The lower LST values can be ascribed to the high evapotranspiration in vegetation that reduces land surface temperatures [86,87]. In contrast, the study attributes the higher values of LST in most areas of the metropolis to urban development and the replacement of natural vegetation with non-evaporative and non-transpiring surfaces that comprise construction sites for residential, commercial, and industrial development. The consequences of these land use/land cover changes play a significant role in the increased LST of the metropolis and contribute to Urban Heat Island development, as observed in similar studies [11,80,86,88,89].

Findings from the study area's NDVI indicate that the vegetation cover of Abuja metropolis tends to decrease with an increase in the alteration of the natural environment into other land uses, as found in some rapidly growing cities [11,29,32]. However, it is often challenging to use the NDVI to differentiate between LULC categories such as barren land and built-up areas due to their relative similarities [90,91]. Therefore, our study established the city's vegetation cover as areas with higher NDVI and lower LST. The results of NDVI shows a significant decrease over the last 29 years, which can be ascribed to the transformation of natural surfaces to built-up areas [15,27,92]. Due to the negative correlation between LST and NDVI during the different study periods, it is also apparent that the decrease in the vegetation of Abuja Metropolis has contributed substantially to the increase in land surface temperature of the city. This result aligns with similar studies in Anshun City, China [93], Colombo Metropolitan Area and Kandy City, Sri Lanka [8,9], Seoul Metropolis, Korea [94], Bahir Dar city, Ethiopia [86], and many others [15,27,83,85,88]. Their findings found that vegetation cover comprising forest areas, shrublands, green belts, and surfaces usually have lower LST within cities and urban centers due to the cool-island effect. Therefore, an increase in NDVI leads to a decrease in LST.

The study also observed a gradual increase in the city's NDBI, i.e., built-up areas, which can be mainly ascribed to urban growth, which has contributed to the reduction of the city's vegetation cover. This aligns with previous studies that reported positive NDBI representing built-up areas and negative NDBI signifying vegetation cover [3,30,83,85]. The positive correlation between LST and built-up areas conforms to earlier studies that revealed higher variation in the LST of impervious surfaces, i.e., mostly built-up areas and barren land/soil, compared to vegetated areas [31,88]. This implies that urban growth and land-use alterations have contributed substantially to the decline of vegetation, thereby increasing surface UHI through higher LST [8,15,87]. The development of surface UHI affects the environment and its inhabitants through increased demand for energy that adversely affects life quality and human health [32,95].

Therefore, it is of paramount importance for the city's authorities to implement the following land-use strategies to mitigate the increasing surface Urban Heat Island. These strategies include:

- i. Increasing the city's vegetation and tree cover: the increase in trees, shrubs, grasses, vines, and other smaller plants can significantly lower the city's land surface temperature by providing shading and cooling the urban environment through evapotranspiration. Other potential benefits of utilizing this strategy include reducing energy demand, reducing greenhouse gas emissions and air pollution.
- ii. Encouraging the use of green and cool roofs: the use of vegetative layers such as trees, plants, grasses, and shrubs on rooftops provides shading and removes heat through evapotranspiration. Cool roofs also help in reflecting heat and sunlight. Therefore, this strategy will mitigate the city's urban heat island by reducing roofs' surface temperature. It will also contribute significantly towards improving the thermal condition of the urban environment through reduced energy demand.
- iii. Adopting cool pavements as an alternative to the conventional impermeable surfaces: the use of cool pavements on parking lots, sidewalks, and streetways has the potential not only to store less heat than conventional paving materials but also to lower the city's surface temperature by reflecting more solar energy and enhancing water evaporation.
- iv. Implementing smart growth practices: the implementation of smart growth strategies can reduce the effect of urban heat through the design of urban spaces. This strategy covers wide-ranging conservative and developmental measures that seek to protect the natural environment and make the city more livable. It includes the creation of walkable, bike-friendly, transit-oriented, and mixed-use neighborhoods.

The recommended strategies align with the UHI cooling strategies of the U.S. Environmental Protection Agency [96]. Therefore, the city's planning authorities can effectively implement these initiatives through the deliberate enactment of zoning and other planning regulations.

6. Conclusions

The present study analyzed the spatiotemporal influence of LULC changes on the surface UHI of Abuja metropolis over the last 29 years (1990–2019) with the aid of multi-temporal satellite data. The change dynamics were mapped and quantified for four periods (1990, 1999, 2009, and 2019) using four different LULC classes comprising built-up areas, vegetation cover, barren land, and water bodies. To achieve the study's objectives, we examined the spatial distribution of LST, NDVI, and NDBI. We also studied the relationship between LST and the different LULC classes and the correlation between LST and land-use indices such as NDVI and NDBI. The LULC change analysis indicates a rapid urban growth in Abuja Metropolis with a considerable built-up area increase from 77.26 sq. km in 1990 to 467.68 sq. km in 2019. On the other hand, vegetation and water bodies decreased significantly during the study period by 252.33 sq. km and 162.22 sq. km, respectively. The most remarkable land cover transition in the metropolis was the conversion of barren land to built-up areas with an area of 301.24 sq. km. The LST analysis result revealed barren land and vegetation as the LULC classes with the highest and lowest LST during the study period. The mean LST also increased from 30.65 °C in 1990 to 32.69 °C in 2019. This suggests that the LST of the metropolis transformed along with changes in LULC. The most significant change in mean LST was observed in built-up areas with a 1.89 °C increase between 1990 and 2019. Similarly, the mean LST of vegetation cover, barren land, and water bodies increased by 1.49 °C, 1.40 °C, and 0.50 °C, respectively. Therefore, the result indicates a substantial LST increase in all the LULC classes. The study further revealed a negative relationship between LST and NDVI while establishing a positive relationship between LST and NDBI during the different periods. This implies that higher LST is experienced along with a decline in vegetation and an increase in built-up areas. This study's findings suggest that LULC changes in Abuja metropolis have substantially influenced the city's increase in LST, therefore contributing to the development of surface UHI. The present study only examined the historical period between 1990 and 2019. Therefore, further research is needed to investigate the city's future LULC change dynamics and

its potential LST variations using various geospatial-modeling techniques. The study concluded by recommending various strategies to mitigate the adverse influence of LULC changes by ensuring sustainable land-use practices.

Author Contributions: Conceptualization, Auwalu Faisal Koko; methodology, Auwalu Faisal Koko, and Ghali Abdullahi Abubakar; software, Auwalu Faisal Koko; validation, Ghali Abdullahi Abubakar, Wu Yue and Akram Ahmed Noman Alabsi; formal analysis, Auwalu Faisal Koko; writing—original draft preparation, Auwalu Faisal Koko; writing—review and editing, Ghali Abdullahi Abubakar, Wu Yue, Akram Ahmed Noman Alabsi and Roknisadeh Hamed; visualization, Auwalu Faisal Koko and Ghali Abdullahi Abubakar; supervision, Wu Yue; funding acquisition, Wu Yue. All authors have read and agreed to the published version of the manuscript.

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

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