Urbanization Effects on Land Surface Temperature in Soba Local Government Area, Kaduna State, Nigeria: A Spatio-Temporal Analysis

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Keywords: Land Surface Temperature; Urbanization Effects; Urban Heat Islands; LULC, Time Series

SUMMARY

Urbanization is a continuous and dynamic phenomenon that is mostly influenced by humans' direct interaction with the immediate environment. These interactions in most cases result in the alteration of land use land cover. Likewise, the environment where such urbanizations occur usually faces changes in climate resulting in temperature increase or simply termed Urban Heat Islands. The Urban Heat Islands (UHI) represent a global phenomenon arising from substantial alterations in land use and land cover. Consequently, the local climate and the surrounding environment have direct consequences from the urbanization effects. Our paper aims to study the effects of urbanization on land surface temperature in the Soba Local Government Area of Kaduna State for a period of over 20 years using noncontact surveying techniques and other ancillary data. The research relies on secondary data, specifically Landsat 8 OLI/TIRS and Landsat 7 ETM+ imagery, to extract information on land use and land cover changes over the two-decade span. The methodology involves the use of Landsat thermal images to determine land surface temperature, exploring the relationships between land use/land cover classifications, the Normalized Difference Vegetation Index (NDVI), and the Normalized Difference Built-up Index (NDBI) in relation to land surface temperature. These relationships are evaluated through correlation and linear regression analyses. Findings from the study show that in 2001, the mean temperature in the area was 30.29°C, which decreased to 29.01°C in 2011 and then to 29.65°C in 2021. Notably, the relationship between NDVI and land surface temperature shows a positive correlation, with correlation coefficient R^2 values of 0.348, 0.168, and 0.381 for the years 2001, 2011, and 2021, respectively. Similarly, the connection between NDBI and land surface temperature reveals a strong positive correlation, with R^2 values of 0.270 in 2001, 0.491 in 2011, and 0.376 in 2021. The significant increase in temperature and built-up areas in 2021 suggests potential health risks due to higher temperatures for residents. Considering that the minimum temperature in 2001 was lower than in 2021, it is reasonable to argue that Soba experienced an urban heat island effect during the period. The study recommends that the state government establish a consistent program for monitoring urban expansion and development in the study area, leveraging geospatial tools to enhance decision-making. Furthermore, it suggests conducting further research on this issue to gain a deeper understanding of the problem.

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1. INTRODUCTION

Urbanization is a concept that describes the human population living in separate parts of a clustered large area with various socioeconomic activities and alteration or conversion of the natural ecosystem into more useful scenarios. Population here is key because most of the natural settings in the immediate environment are influenced by human activities. Because of the importance of these human activities, the term urbanization also refers to the shift in population from rural to urban centers, the shifts or reductions in the number of people residing in rural areas that follow, and how communities adjust to these developments. In another way, urbanization refers to the rise in the percentage of the population residing in cities and the subsequent growth of city areas. According to McComb (2014), urbanization can also be defined as the physical expansion of urban areas brought about by suburban and rural migration. Similarly, Hussain *et al*, (2016) opined that urbanization is the social process that leads to the creation of cities or expansion of cities

Because of the direct link between infrastructural developments, socioeconomic well-being, and urbanization, there has been recent massive interest in conducting research on urbanization. Though rapid urbanization plays a vital role such as massive development, especially in population density and buildups, it also has direct impacts on natural vegetation, altering land covers (Kumar *et al*., 2012). Urban cores become warmer than the periphery, forming an Urban Heat Island (Srivastava *et al*., 2010).

According to Darren *et al*. (2020), land surface temperature (LST) is defined as the temperature measured at the interface between the earth's surface and the immediate/near-surface atmosphere. It influences the timing and rate of plant development and defines processes like the transfer of energy and water between the two. Latif (2014) states that the type of surface or object material and the amount of sunshine have an impact on LST. Purwanto *et al*. (2016) reported that temperature is influenced by the changes in Land cover and land use. Also, Human activity is modifying the characteristics of the land cover to support the expanding population by replacing vegetated areas with impermeable surfaces, which is contributing to climate change (Gill *et al*., 2007). Changes in land cover have therefore become one of the primary indicators of environmental vulnerability (Nzoiwu *et al*., 2017).

An urban area, volume, region, or metropolitan area that, as a result of human activity, experiences warmer or higher temperatures than its surrounding rural areas is known as an urban heat island (UHI). According to Kaplan *et al*. (2018), numerous researchers studying the UHI have employed remote sensing, which allows for surface temperature measurement. Likewise, Landsat TM and ETM were utilized by Weng, (2012) and Chen *et al*., (2006) to explore UHI.

Numerous researchers have conducted on Urbanization, LST, and UHI in recent years using various methodologies: Zhenhua *et al*. (2020) examined Urban sprawl in the two major cities of Shanghai and Tokyo using data from the MODIS/Aqua LST product, MYD11A2 006, for nine representative sites in the study areas from 2003 to 2018. Results revealed that as a result of Shanghai's higher rate of increase in impervious surfaces over the past several years than Tokyo's, led to Shanghai's urban sprawl being more pronounced, indicating the influence of urbanization on Land Surface Temperature (LST). Also, Varinder and Reet (2017) assessed the relationship between urbanization and the creation of urban heat islands as well as the reduction of plant cover. Furthermore, according to Hafoud *et al*. (2020), there is a positive correlation between urban land expansion and LST, suggesting that urban expansion benefits LST. Because of its high exposure to solar radiation, Ike *et al*. (2021) characterize Umuahia's land surface as hot and humid. Urbanization, according to Tanko *et al*. (2017), raised Kano Metropolis' LST by 80.5%, indicating a very strong positive association between urbanization and UHI.

Soba is a local government area of Kaduna state, which is experiencing tremendous growth in the last few decades and provides a striking representation of such land conversion, due to the rise in the urban sprawl that has been observed across the country in various cities (Avis, 2019). Urban development can alter the urban landscape structures and urban thermal environment. Timely and accurate information on the status and trends of urban ecosystems is crucial to developing strategies for sustainable development and improving the urban residential environment and living quality. Thus, developing techniques and enhancing the ability to monitor urban expansion and urban thermal environment is greatly desired. Over the past few years, remotely sensed data of various spatial, spectral, angular, and resolutions have been widely used to study Urban development and to retrieve land surface parameters, such as vegetation, built-up indices, and land surface temperatures, that are good indicators of conditions of an urban ecosystem.

In this study, geospatial tools are employed to analyze the impact of urbanization on urban land surface temperature variance in the Soba Local Government Area, to demonstrate the effects of Urban Heat Island (UHI) on geographical domains. The results are beneficial for policy decision-makers to have access to useful information on boosting vegetation cover to lessen the impact of UHI on the environment.

1.1 Study area

The study area Soba Local Government Area (LGA) is located in Kaduna State, the North-West geopolitical zone of Nigeria, and shares boundaries with the Makarfi, Sabon Gari, Zaria, Igabi, Kauru, and Ikara LGAs. It is geographically located between Latitude 10° 20’ 06’’ to 10° 59’ 60’’ North and Longitude 08° 03’ 32’’ to 08° 30’ 15’’ East of the equator (Figure 1).

It covers an area of 223,400 hectares (2,234.00 km^2). Its headquarters is in the Maigana town. The average annual temperature varies from 12°C to 35°C. The LGA`s estimated population is 319,843 as of 2022 and the projected population to be 431,468 by 2032 (National Population Commission, 2016).

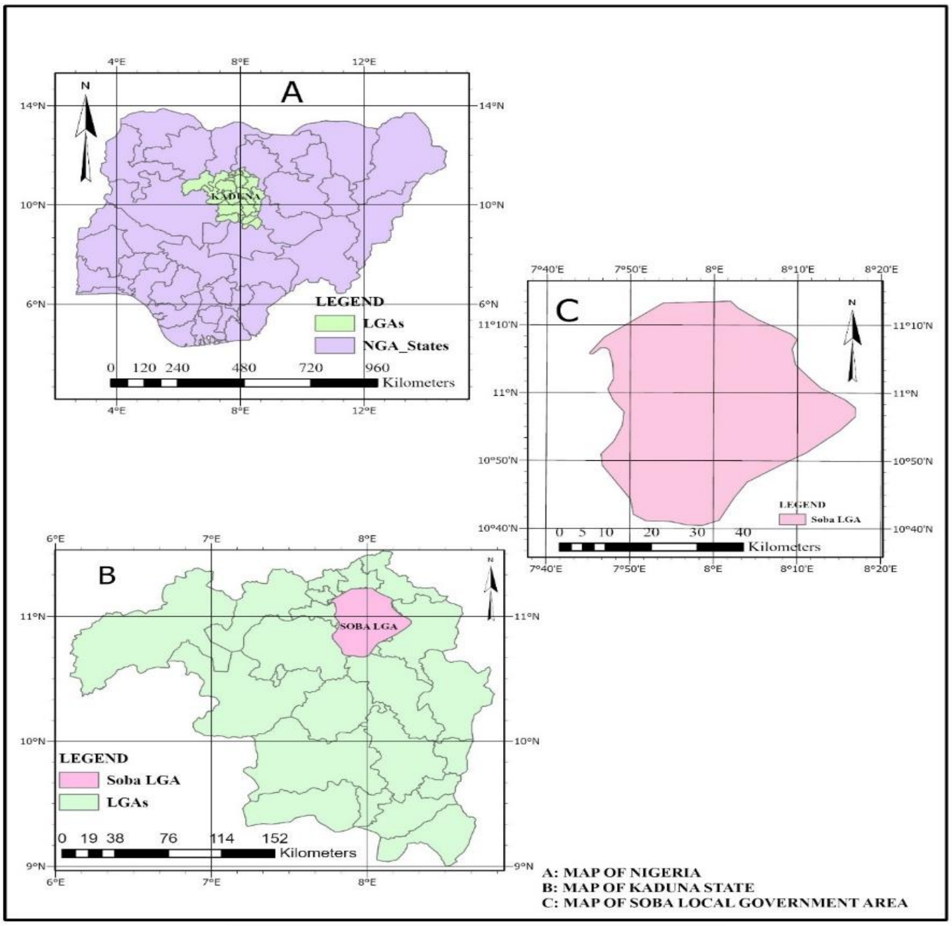


Figure 1: Locational map of the study area

2. MATERIALS AND METHODS

2.1 Materials

2.1.1 Data types and sources:

The data utilized consisted of both primary data and secondary data. Landsat satellite imageries were downloaded from the USGS in World Geodetic System 1984 (WGS84) projection coordination, with path and rows and other relevant metadata as shown in Table 1. Minimal cloud coverage was considered in choosing the right imageries. Preprocessing such as layer stacking, mosaicking, and sub-setting followed. The software used for this study are shown in Table 2.

Table 1: Landsat Data Characteristics

Data Type	Path/Row	Year	Resolution (m)	Date acquired by Satellite	Date Obtained
Landsat 7 TM	P189R052	2001	30	11th Dec. 2001	21st April 2022
Landsat 7 ETM+	P189R052	2011	30	21st Nov. 2011	21st April 2022
Landsat 8 OLI	P189R052	2021	30	11th Nov. 2021	21st April 2022

Table 2: Software and their Uses

Software	Uses
ArcGIS v10.7.1	For land cover classification, accuracy assessment, and the final product's visualization.
Envi 5.3	To sub-set the images and create the study's land use/land cover classes and accuracy assessment
Math Type	For mathematical formulas
Microsoft Office 2019	This was used for the write-up and the presentation of the research

2.2 Methods

The methodology followed the steps in Figure 2: from data acquisition, mosaicking which is needed where the study area falls within more than one swath as reported by (Guo *et al*., 2017), LULC classification, Urban Heat, Land surface temperature, and change detections.

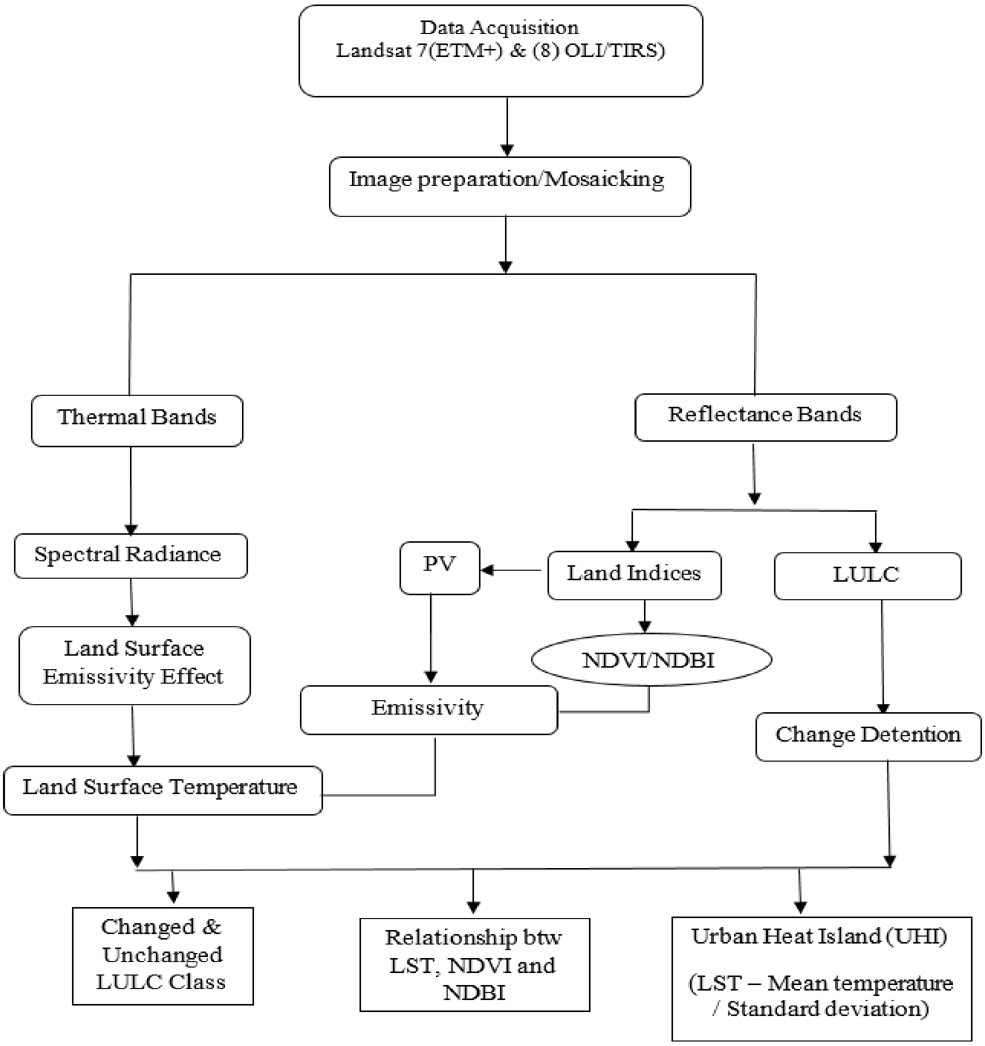


Figure 2: Study workflow

2.2.1 Land cover classification

The land cover for the Landsat imagery from 2001, 2011, and 2021 (Landsat 7 TM, ETM+, and Landsat 8 OLI/TIRS) was classified using supervised classification. The training sample manager (schema) was used to create the known land cover, and the cell signature values for each category of land cover, such as built-up, water, bare surface, forest, and agriculture. The producer's accuracy and the user's accuracy assessments, total accuracy, emissivity correction, and kappa coefficient were calculated.
False color composites (bands 4, 3, and 2 for Landsat 7 and bands 5, 4, and 3 for Landsat 8) were supervised and classified into the categories of agricultural land, built-up area, forest cover, Agricultural land, and bare surfaces (Table 3).

Table 3: Classification Scheme

Code	Land use/Landover	Description
1	Agricultural land	Lands used for farming (Plantation, Cropland orchard)
2	Built-up land	Lands used for residential, industrial, commercial, etc.
3	Grassland/ forest cover	Lands covered with natural vegetation (plant species)
4	Bare surfaces	Lands devoid of vegetation exposed soil
5	Water bodies	Areas with lakes, rivers, and streams.

2.2.2 Derivation of NDVI and NDBI

The amount and health of vegetation at the surface are gauged by the Normalized Difference Vegetation Index (NDVI). Values for NDVI range from -1 to +1. The equations below define the index (Isioye *et al.,* 2020).

$$NDVI = \frac{NIR - RED}{NIR + RED} \qquad 1.1$$

NIR and RED in Landsat 7 ETM+ represent, respectively, reflectance in the near-infrared (band 4) and red (band 3) regions of the electromagnetic spectrum in equation (1.1). Equation (1.2) includes the NDVI for Landsat 8 OLI/TIRS;

$$NDVI = \frac{Band5 - Band4}{Band5 + Band4} \qquad 1.2$$

Band 5 and Band 4 are, respectively, the reflectance bands in the near-infrared and red portions of the electromagnetic spectrum of the Landsat 8 Operation Land Imager (OLI) sensor (Adebayo *et al.,* 2017).

In this study, the NDBI (Zha *et al.*, 2005) was used to identify built-up areas. Equations (1.3) and (1.4) are used to construct the Normalized Difference Built-up Index (NDBI) from the Landsat ETM+ and OLI/TIRS data, respectively.

$$NDBI = \frac{Band4 - Band5}{Band4 + Band5} \qquad 1.3$$

$$NDBI = \frac{Band6 - Band5}{Band6 + Band5} \qquad 1.4$$

2.2.3 Land Surface Temperature (LST) retrieval

Many different types of literature have demonstrated that Landsat 7 (ETM+) band 6 (10.4 - 12.5 μm) and Landsat 8 (OLI/TIRS) band 10 (10.60 - 11.19 μm) and band 11 are adequate for capturing the complex intra-urban temperature changes, making it effective for urban climate study (Adebayo *et al*., 2017).

2.2.4 Urban Heat Island Estimation

The estimated Land Surface Temperature, mean temperature, and standard deviation were utilized to calculate the UHI. Urban heat island variations in the research area were analyzed using the following formula (Ma *et al.*, 2010):

$$UHI = \frac{Ts - Tm}{SD} \qquad 1.5$$

Where:

UHI = Urban Heat Island
Ts = Land surface temperature
Tm = Mean surface temperature
SD = Standard deviation

2.2.5 Growth rate:

The standard formula for calculating growth rate (Bob, 2002) is:

$$PR = \frac{(Vpresent - Vpast)}{Vpast} * 100$$

Where:

PR = Present Rate
Vpresent = Present or Future Value
Vpast = Past or Present Value

The annual percentage growth rate is simple the present growth divided by N, the number of years.

3. RESULTS AND ANALYSIS

3.1 Spatial Pattern of Land/Use and Land/Cover

Figures 3, 4, and 5 display the output of land use land cover classification maps in the Soba LGA. The total accuracy values for the classified images from 2001, 2011, and 2021 are displayed in Table 4. The overall accuracy of the classified data was determined based on 50 reference points. The highest spatial coverage as of 2001 was found on bare soil, followed by agricultural land, forests, and water bodies. But by 2021, built-up areas had grown by 0.79%, adding 123.768 hectares to the 1637.480 hectares covered in 2001 (Table 4).

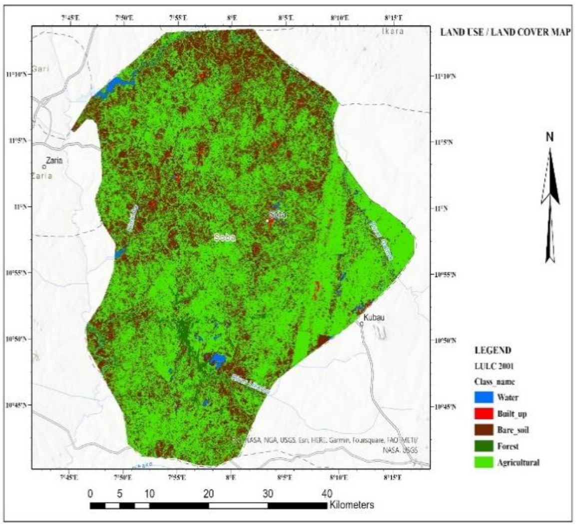


Figure 3: LULC classification map 2001

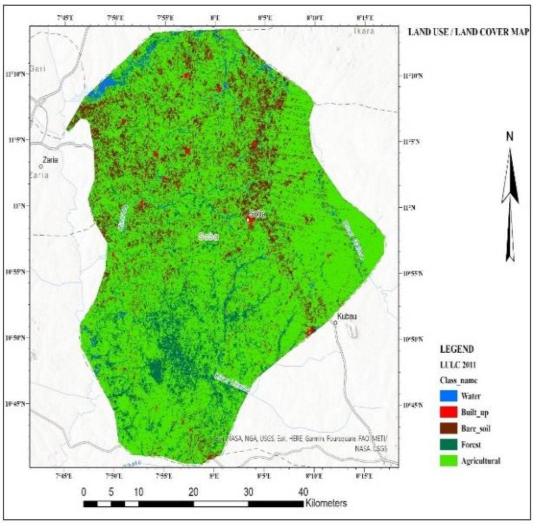


Figure 4: LULC classification map 2011

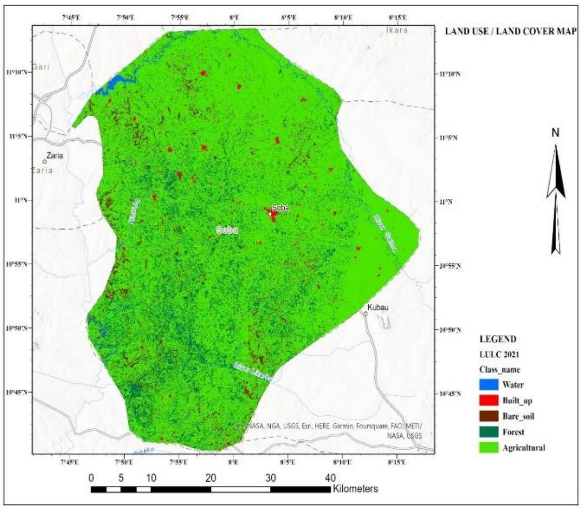


Figure 5: LULC classification map 2021

3.2 Changes in Land Cover from 2001 to 2021

From classification results, Agricultural land and bare soil occupied the most area in 2001, accounting for 63.63% and 32.27% of the total area, respectively (Table 4), most likely because there were not many people living there compared to the area's total land area. The high value of agriculture may be attributable to the fact that farming is the main occupation of the residents of the study area, who take advantage of the abundant land at their disposal. Additionally, only 2.30% of the area was covered by forests at this time. This could be explained by the increased proportion of bare soil; built-up areas made up just 0.73% of the total area, while water areas made up the majority of the remaining land.

However, from 0.73% in 2001 to 0.726% in 2011, there was a slight decrease in the built-up area, which may be attributable to an increase in water and forest cover of 1.36% and 9.21%, respectively. Unsurprisingly, agricultural land increased to 75.84% from 63.63% in 2001, while bare soil decreased to 12.85%. This decrease in bare soil could be attributed to an increase in water generated by the extension of water bodies, which can also lead to an increase in agricultural activities.

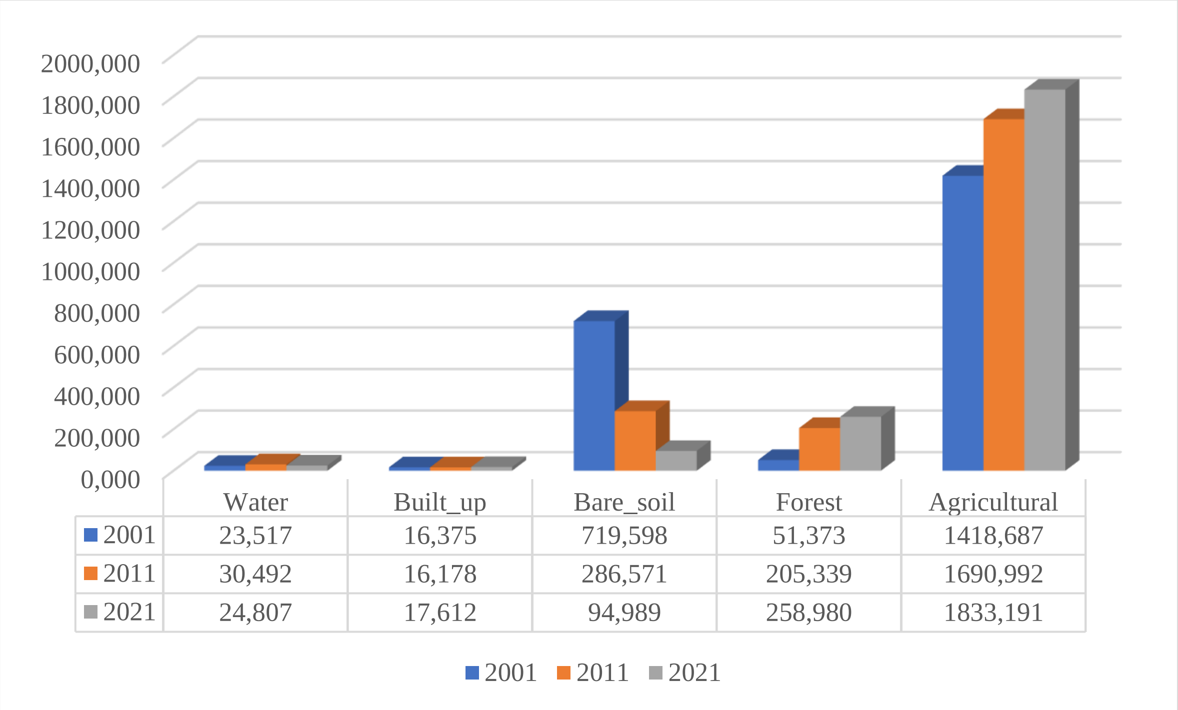


Figure 6: Land use and land cover classification chart 2001-2021

Table 4: Land use and cover classification of Soba LGA from 2001 to 2021

Class name	**2001 (Km²)**	**%**	**2011 (Km²)**	**%**	**2021 (Km²)**	**%**
Water	23.517	1.055	30.492	1.368	24.807	1.113
Built up	16.375	0.734	16.178	0.726	17.612	0.790
Bare soil	719.598	32.276	286.571	12.853	94.989	4.260
Forest	51.373	2.304	205.339	9.210	258.980	11.616
Agricultural land	1418.687	63.631	1690.992	75.844	1833.191	82.221
Total	**2229.550**	**100.000**	**2229.573**	**100.000**	**2229.579**	**100.000**

In 2021, agricultural land made up 82.22% of the total area, or 1833.191 km² (Figure 6), making it the highest and most used land cover. This may be due to an increase in the built-up area, which now has 0.79 % of the area compared to 0.73 %, and 0.72 % in 2001 and 2011, which may be attributed to the influx of residents into the area and may also be a factor in the study area's notable increase in farming or agricultural land. This may also possibly be related to the sharp decline of bare soil over that time, which went from 32.27% in 2001 and 12.85% in 2011, both of which covered bigger kilometer squares, to 4.26% in 2021, which only covered 94.989km² (Table 4 & Figure 6). Additionally, it was also noticed that the amount of forest cover increased to 11.61% in 2021, compared to 2011. This may be because farmlands that were left fallow were eventually taken over by forest, or it may be because more people planted trees in the study area to reduce wind howling. It was also observed that water levels decreased in 2021 by 1.11% compared to an increase in 2011 of 1.36% from 1.05% in 2001. This analysis demonstrates that the built-up area increased between 2001 and 2021, which may be due to residential area growth combined with an increase in anthropogenic activity levels in the area brought on by population growth or migration.

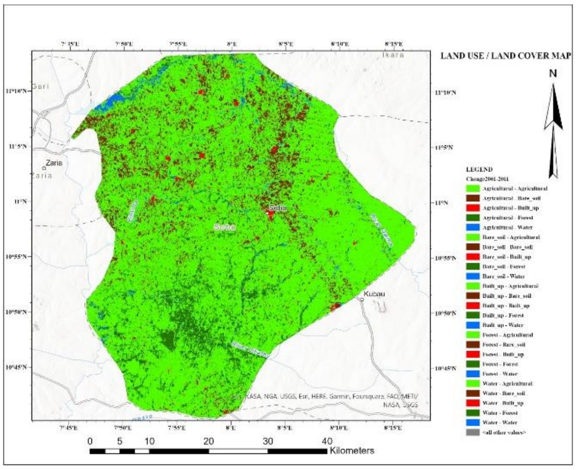
3.3 Cumulative Changes in Land Cover

3.3.1 Changes between 2001, 2011 and 2021

The cumulative changes seen in the study region are depicted in Figure 7. With an increase of 63.63% to 75.84% from 2001 to 2011, the area of agricultural land increased to 169099.16 hectares (Tables 4 and 5). By 2011, there were -43302.73 hectares lower in bare soil as a result of this expansion. An increase in farming activity and an increase in the area covered by trees (Forest) are two signs of this growth. In 2011, there was also a rise in the amount of land covered by water, by an additional 697.48 hectares. There was a -19.643 hectares loss in the area covered by built-up, which is 0.01% less than the 0.73% in 2001.

Table 5: Land use and cover classification of Soba LGA from 2001 to 2021

Class name	2001 (Hectares)	2011 (Hectares)	2021 (Hectares)	Diff 2001-2011	Diff 2001-2021
Water	2351.739	3049.226	2480.658	697.487	128.919
Built up	1637.480	1617.837	1761.249	-19.643	123.768
Bare soil	71959.841	28657.107	9498.925	-43302.734	-62460.916
Forest	5137.269	20533.920	25897.962	15396.651	20760.693
Agricultural land	141868.653	169099.166	183319.074	27230.513	41450.421



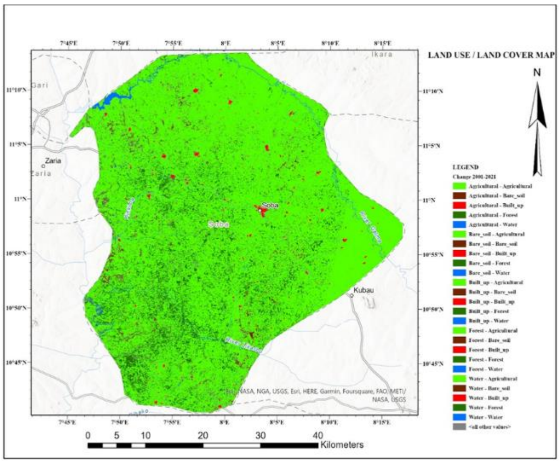


Figure 7: Area changes in LULC of 2001-2011 **Figure 8:** Area changes in LULC of 2001-2021

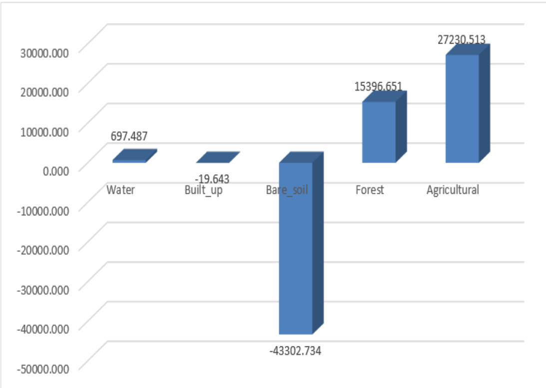
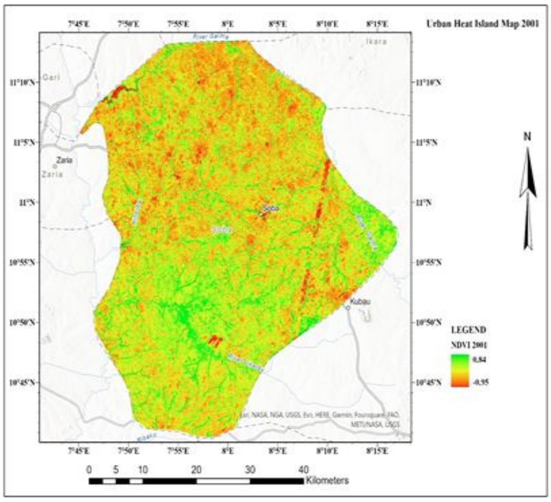


Figure 9: Cumulative LULC changes 2001-2011 **Figure 10:** Cumulative LULC changes 2001-2021

The process of land cover transfer is statistically illustrated by the Area change chart (Figures 9 & 10), which shows various transfer probabilities. The LULC map depicts the changes from 2001 to 2011 and from 2001 to 2021 were displayed in Figures 7 and 8. Water bodies and bare land decreased significantly between 2011 and 2021 by almost 14% between the two classes, with bare soil being the most affected. Built-up area increased by 0.06% between 2011 and 2021, occupying 1761.249 hectares, a difference of 123.768 hectares.

3.4 Effect of Urbanization on Vegetation

Using the NDVI, the distribution of vegetation within the research region was examined. The NDVI at the research site between 2001, 2011, and 2021 is depicted in Figure 11:12. The NDVI is one of the indexes that are most frequently used for satellite data analysis and monitoring vegetation cover. The values of the NDVI pixels range from -1 to +1. According to Isioye *et al.*, (2020), higher NDVI levels suggest vegetation that is both more abundant and healthier.



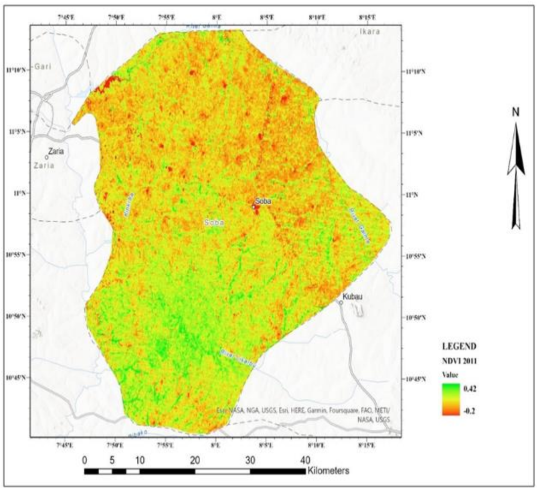


Figure 11: NDVI map of Soba for 2001 **Figure 12:** NDVI map of Soba for 2011

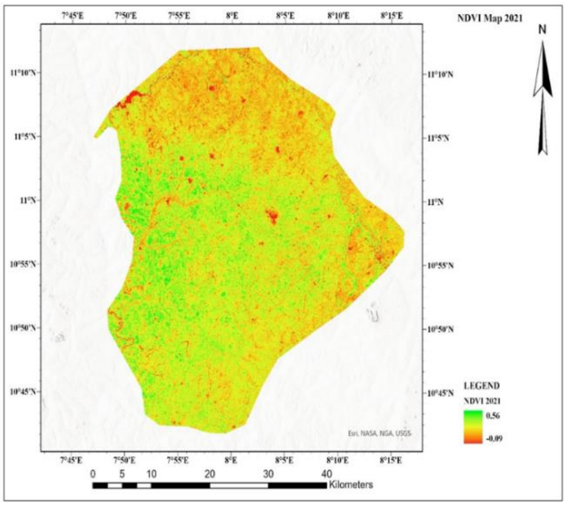


Figure 13: NDVI map of Soba for 2021

Using the Red and NIR bands of Landsat 7 and Landsat 8, NDVI maps were created for the years 2001, 2011, and 2021 to assess vegetation abundance. When compared to areas with low NDVI values, the high NDVI values show an abundance of vegetation (Figure 11). In 2001, the NDVI value ranged from -0.95 to 0.84, whereas in 2011, it was recorded that the value ranged from -0.2 to 0.42. Similar to this, it was noted that the NDVI values for 2021 ranged from -0.09 to 0.56 and were lower than they were in 2001. The NDVI value in Figure 13 reveals that lower NDVI values are associated with more developed places like Soba, Gimba, and Turawa, as well as rocks and bare surfaces, while higher NDVI values are associated with more naturally occurring surfaces, suggesting that urbanization does have an impact on the amount of vegetation.

3.5 Normalized Difference Built-up Index (NDBI)

In this study, the NDBI was used to identify built-up regions. According to the NDBI values displayed in Figures 14 – 16, positive NDBI values are linked to more developed settlements, and negative NDBI values are linked to less developed natural surfaces.

The NDBI values generally indicate that built-up areas have grown, whereas other land uses and land cover, particularly forest cover, have also increased and occasionally water decreased. Although the change was minimal, the numbers nonetheless indicate that built-up areas have grown. The study area's growing population and economic activity are the main causes of the increase of built-up areas generally, agricultural fields, and natural forests in particular. However, the key finding of this investigation was that the quantification of the NDBI could demonstrate a connection between changes in area size and land cover class.

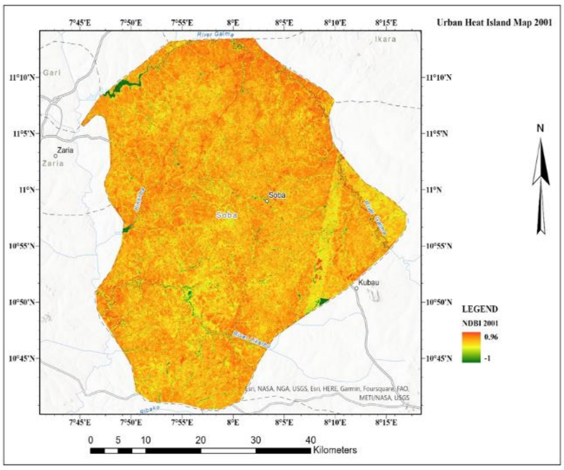


Figure 14: NDBI map for 2001

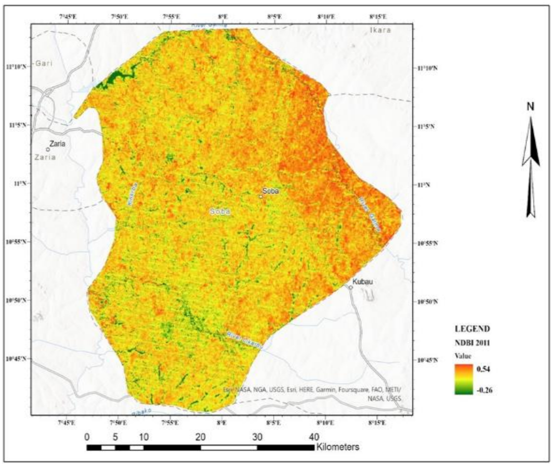


Figure 15: NDBI map for 2011

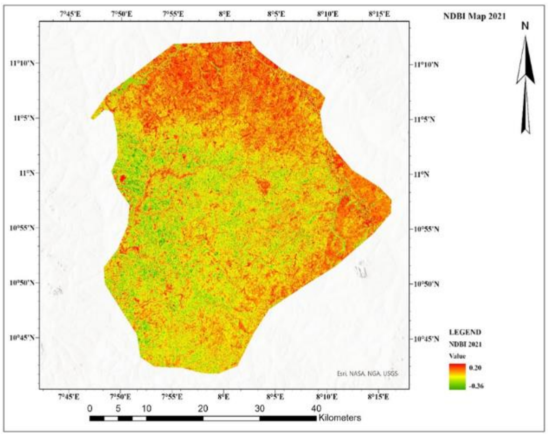
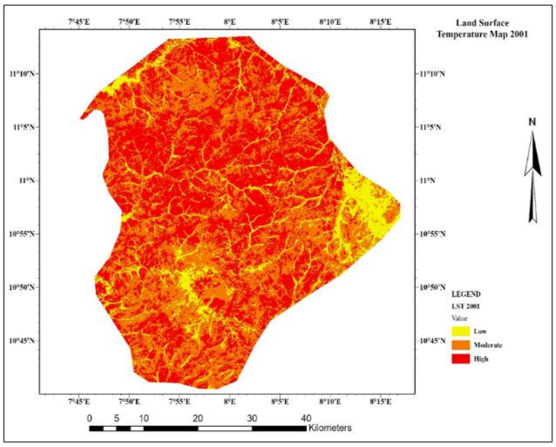


Figure 16: NDBI map for 2021

3.6 Spatial distribution of Land Surface Temperature (LST)

The analysis of data revealed that LST has increased significantly in the last twenty years (Table 6). The LST map was generated for November and December for the study area for each year. The year 2001 saw a temperature range of 18.22–48.93 °C. Large parts of the Local Government exhibited a high-temperature range of 31.4-48.9 °C due to the high presence of bare soil. While the vegetated area around the water body (river Galma, Likarbu, and Kinkiba) had a lower temperature of 18.3-28.9 °C, the region's built-up area was moderate with a temperature range of 29-30.3 °C. A decade later in 2011, LST range analysis revealed a temperature range of 17.92-48.93 °C.

There was a drop in the temperature range with the majority of the region experiencing moderate temperature due to the increase in water bodies and substantial increase in forest cover with a range of 28.7-30.2 °C. Similarly, as seen in the previous year the lower temperature in the study area were areas close to the rivers with a temperature range of 18-26.7 °C which was below that of 2001. Lastly, LST analysis for the Study area was done for the year 2021. The northwestern, northeastern, and as expected region's settlement areas temperature increased further with the temperature range of 32.85-48.88 °C which was the highest surface temperature in the area, furthermore, the central area of the study area had moderate temperature while the southwestern and southeastern of the study area has low temperature which may be due to the increase in forest cover (Table 4, Figure 5).



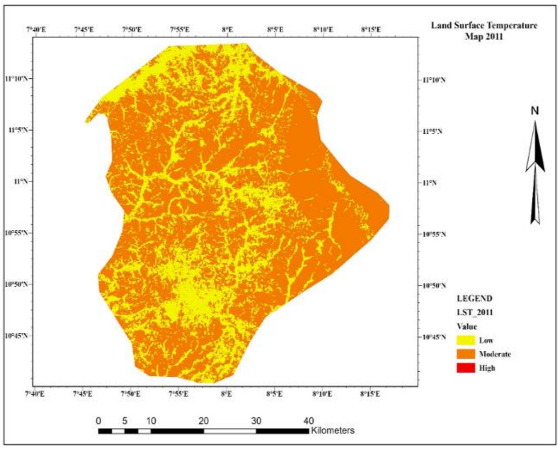
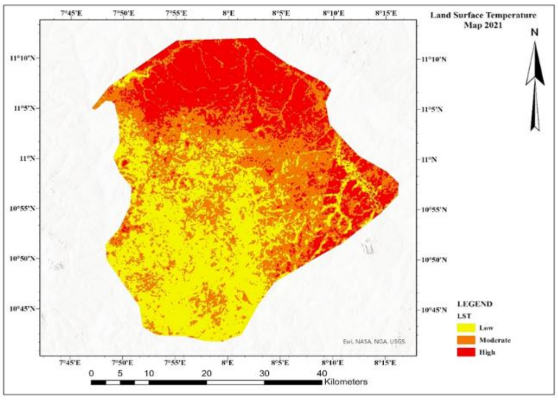


Figure 17: 2001 LST from Landsat ETM+7 **Figure 18:** 2011 LST from Landsat ETM+7



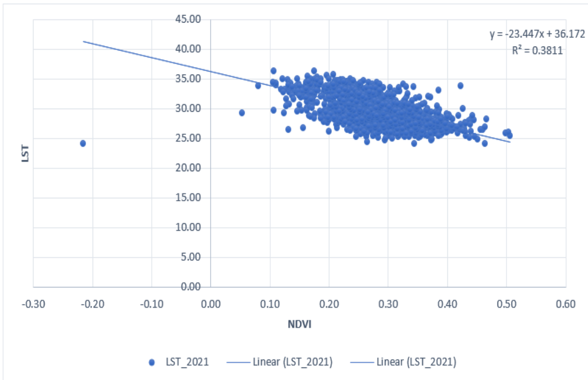


Figure 19: 2021 LST from Landsat 8 OLI/TIRS. **Figure 20:** 2021 Correlation between LST and NDVI

Table 6: LST statistics derived from Landsat images from 2001 to 2021

Year	Lowest Value	Highest Value	Mean	Standard Deviation
2001	18.22	48.93	30.29	1.46
2011	17.92	48.93	29.01	1.57
2021	22.33	48.88	29.65	2.50

Figure 25 illustrates the linear regression correlations between the elements and the relationship between LST and NDVI. It was found that there is a weak correlation between LST and NDVI. This suggests that the amount of LST that may be obtained at a specific place is influenced by the presence of vegetation, and it can be said that when vegetation is present, the temperature is lower than in an area that is built up.

4. CONCLUSION

From the findings, the temperature in the Soba local government has been noticeably rising from 2001 to 2021 because no two periods have the same average temperature. Based on the results, it may be concluded that the rising temperatures may be caused by increased development and a dearth of water bodies. To investigate the idea of UHI in that area, the LST was extracted using Landsat 7 ETM+ and Landsat 8 OLI/TIRS data. Because an increase in vegetation will lower temperature and vice versa, it was determined from the association between LST and NDVI that NDVI can be a measure control of LST. However, in this study, it was shown that there was a weak link between LST and NVDI. NDBI and LST had a positive association since the correlation showed that LST rose as the built-up area grew. It was discovered that during the years 2001, 2011, and 2021, there were significant changes in land cover and an equivalent rise in surface temperature. During this research work, some issues were encountered, such as incorrect NDVI values derived from 2001 images that were caused by incompatible levels of the downloaded Landsat images. To resolve this issue, another set of images was downloaded with the same level for the mosaicking. The 2011 images were also downloaded with scanlines, which caused delays in the research process. To fix this problem, another type of software called QGIS was used to remove the scanlines from the images. It is recommended that the State Government should regularly monitor urban growth in the study region; communities should prioritize the plantation of trees within the community centers, and providing helpful information on improving vegetation cover in the area will lessen the impact of UHI on the environment.

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