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Impact of Impervious Surface Area on Land Surface Temperature in Minna, Niger State, Nigeria

Bolarin O. A., Muhammed M. and Hassan A.B.

Department of Geography, Federal university of Technology, Mina
olatejubol@gmail.com, (07062544543 corresponding Author)

ABSTRACT

Rapid urbanization in Minna due to population increase has led to the conversion of natural vegetal cover into impervious surface area (ISA). The study aimed at the Impact of Impervious Surface Area on Land Surface Temperature in Minna with the objective of 'Deriving Land Surface Temperature (LST), analyze the relationship between Impervious Surface Area (ISA), Vegetation and Land Surface Temperature (LST) of Minna. Landsat images of 2006, 2011 and 2016 were used to create the Normalised Different Built-up Index (NDBI) for impervious surfaces, and NDVI for Vegetation. Erdas 2014 and Arc Map 10.2 were used to extract the values which served as the range for the Indices, i.e. NDBI and NDVI. The extracted temperature data of thermal band of Landsat 7ETM+ for 2006, 2011 and 2016 were used to assess the relationship between NDBI and NDVI and LST estimation. Multiple Linear Regression and Correlation statistical analysis was used to know the relationship between NDBI, NDVI and LST. The correlation results between NDBI and LST shows a positive relationship, with a critical value for 2006, 2011 and 2016 as 0.838274, 0.99561 and 0.862733 respectively. Between LST and NDVI, it shows a negative critical value for 2006, 2011, 2016 to be -0.93395, -0.77712 and -0.72158 respectively. The coefficient of determination (R^2) obtained from NDBI, NDVI and LST is 0.99134267, 0.866741512 and 0.881626705 for 2006, 2011 and 2016 respectively. The R^2 values shows that as Impervious Surface Area increases, LST also increases. The study concluded that persistent warm anomaly over the years is due to Impervious Surface Area (ISA) increase in area extent which influences surface energy exchange and other environmental processes which can be used to determine the strength of Urban Heat Island (UHI) and monitor the global climate.

Key words: Impervious Surface area, Land Temperature

1. INTRODUCTION

Impervious surface is generally defined as any materials that water cannot infiltrate and is primarily associated with human activities and habitation through construction of roads and building. Impervious surface has long been recognized as an important variable in many urban or environment related studies, such as in urban land use classification. Adedayo, (2015) earlier reported that Impervious Surface Area (ISA) could be an indicator of the degree of urbanization and environmental quality. Understanding changes in ISAs is important for a wide range of environmental applications such as watershed impact assessment, rainfall run-off volume, duration and intensity, ground water recharge and base flow storm analysis, stormflow and flood frequency. Angel *et al.*, (2005) stated the concerns for unwieldy urban expansion typically castigated as "sprawl" have recaptured the attention of both policy makers, academics and, more recently, voters during the last decade. Impervious land cover has long been characteristic of urban areas, but has only recently emerged as an environmental indicator. Natural resource planning using impervious surface coverage as a framework can be a pragmatic and effective way of addressing a host of complex urban environmental issues particularly those related to the land surface temperature (Jr & Gibbons, 2007).

Conversion of land to feed and shelter the growing human enterprise has been one of the primary modes for human modification of the global environment. Over the coming decades, expansion and intensification of agriculture, growth of urban areas, and extraction of timber and other natural resources will likely accelerate to satisfy demands of increasing numbers of people at higher standards of living.(Defries, 2004).

The growth of urban areas has a significant impact on land use by replacing areas of vegetation with residential and commercial areas and their related infrastructure; this escalates the land surface temperature (LST) (Rasul & Ibrahim, 2017).

The most significant environmental impact resulting from the modification of the physical properties of the land surface due to land conversion (i.e., transformation of land cover from one class to a completely different class) is the changes in land surface temperature (LST) and atmospheric temperature (Deng & Wu, 2013). Surface temperature are affected surface energy change, anthropogenic heat discharge, building energy consumption and atmospheric pollution. They can be detected at a large geographical scale (urban–rural surface temperature difference) which is known as urban heat island (Lu & Weng, 2006). Deng & Wu., (2013) appraised that the earlier method of assessing surface temperature variability involved the simulation of Urban Heat Island (UHI) phenomenon and its spatial pattern using governing equations for fluid mechanics such as an energy balance equation, etc, together with in-situ measurements or laboratory experimental data. The main simulation models they pointed out were: energy balance models (Xiao *et al.*, 2008) and dynamic numerical simulation methods (Yuan *et al* .,2008), and also mentioned the use of sheltered thermometer above a flat grassy and well ventilated surface to estimating surface-air temperature.

Oloukoi *et al.*, (2014) recently assessed the urban heat island in Akure, Nigeria, West Africa, using Radiative Transfer Method as an effective way of estimating LST using Landsat 7 ETM+. Rapid urban growth which occurred in Duhok City due to enhanced political and economic growth made Rasul & Ibrahim, (2017) to investigate the effect of land use changes on LST; this study depends on data from three Landsat images. The study outcome proved that the changes in land use/cover have a significant role in the escalation of land surface temperatures. The highest temperatures were associated with barren land and built-up areas, ranging from 47°C, 50°C, 56°C while lower temperatures were related to water bodies and forests, ranging from 25°C, 26°C, 29°C respectively, in 1990, 2000 and 2016. The study also proved that NDVI and NDWI correlate negatively with low temperatures while NDBI and NDBAI correlate positively with high temperatures.

Bernales *et al*., (2016) carried out a research to examine the relationship between LST and LULC as well as to create a model that can predict LST using class-level spatial metrics from LULC,

LST was derived from a Landsat 8 image and LULC classification was derived from LiDAR and Orthophoto datasets.
Rapid urbanization in Minna due to population increase has led to the conversion of natural vegetal cover into impervious surface area (ISA). The study aimed at the Impact of Impervious Surface Area on Land Surface Temperature in Minna with the objective of 'Deriving Land Surface Temperature (LST), analyze the relationship between Impervious Surface Area (ISA), Vegetation and Land Surface Temperature (LST) of Minna.

2. STUDY AREA

Minna is located in Niger State. It is the headquarters of Chanchaga Local Government area and capital of the state respectively. It lies in the middle belt of Nigeria and falls within the temperate humid regions of the country. Minna is situated in the tropical hinterland and in the Guinea savannah zone. It lies between Latitude 09° 40' 7.63" N to Latitude 09° 39' 59.72" N and longitude 06° 30' 0.32" E to Longitude 06° 36' 34.05" N. Minna lies on a valley bed (i.e. lowland) bordered to the east by Paida hill stretching eastwards towards Maitumbi and essentially savannah and quite conducive for farming. It bordered Wushishi and Gbako to the west, Shiroro to the North, Paikoro to the East, Katcha to the South. (Aminu 2010

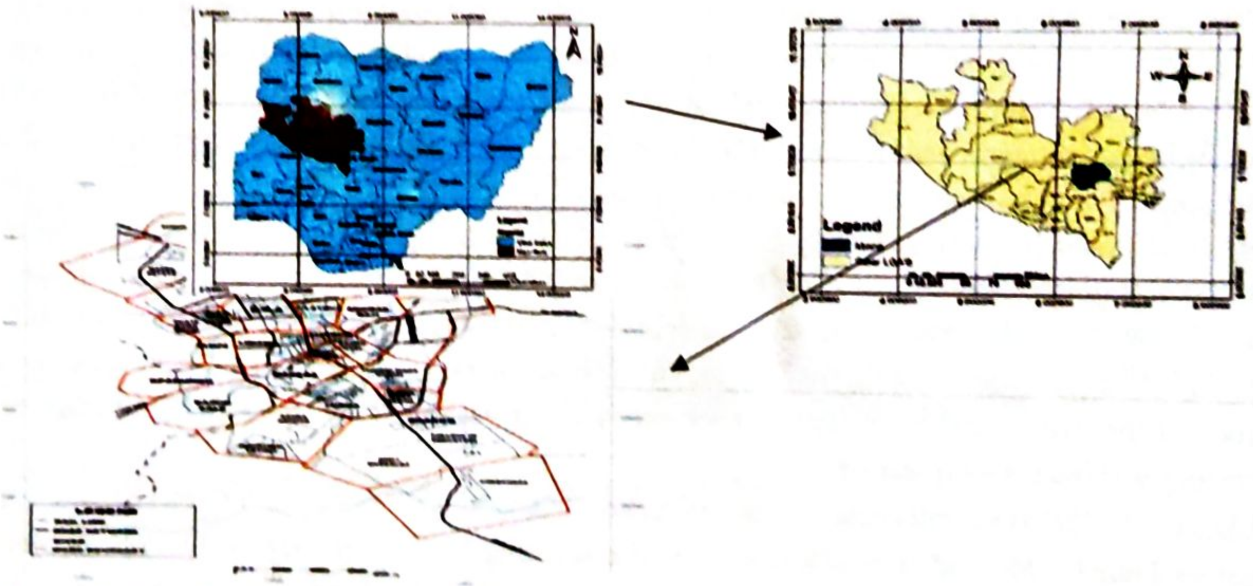

Figure 1: Location map of the study area

3. METHODOLOGY

3.1 Data Sources and Types

The data type used is mainly secondary data, satellite Remote Sensing image (Land-sat7 ETM+) to be precise, which was downloaded from www.earthexplorer.usgs.go

3.2 Landsat7 ETM+SENSOR DETAILS

Table 3.1: Spectral and spatial characteristics of the Landsat 7 ETM + multispectral scanner (adapted from http://landsat.usgs.gov)

Band Name	Bandwidth (μm)	Resolution (m)	Combinations Bands
Band 1 Blue	0.45 – 0.52	30	Color 4,3,2
Band 2 Green	0.52 – 0.60	30	Infrared
Band 3 Red	0.63 – 0.69	30	Natural color 3,2,1
Band 4 NIR	0.77 – 0.90	30	False color 5,4,3
Band 5 SWIR 1	1.55 – 1.75	30	False color 7,5,3
Band 7 SWIR 2	2.09 – 2.35	30	False color 7,4,2
Band 8 Pan	0.52 – 0.90	15	
Band 6 TIR	10.40 – 12.50	30/60	

3.3 Creation of NDVI and NDBI

Although there are various indices, in this study Normalized Difference Built-up indices, (NDBI) generated using Edars 2014 was considered.

NDBI was generated from the Landsat 7 ETM+ Thematic Mapper (TM) which revealed the spectral response of built-up lands because built-up shows a higher reflectance in the mid infra-red (MIR) wavelength range than in the near infra-red (NIR). The mathematical expression for NDBI is given in equation 1 (Chan *et al.*, 2008).

$$NDBI=\frac{MIR-NIR}{MIR+NIR} \qquad \text{.......................... (1)}$$

3.4 Deriving land surface temperature for estimation of LST with Landsat Thermal Infrared Band

The thermal infrared (TIR) bands are generally useful for assessing the temperature difference between the city and its surrounding rural areas (i.e., UHI phenomenon).

For this study, pre- determined land surface emissivity of the LULC types according to Mallick *et al.* (2008) was used to derive the Land Surface Temperature (LST) image.

During radiometric calibration, pixel values (Q) from raw, unprocessed thermal bands for the Landsat images used was converted to spectral radiance using 32-bit floating-point calculations. The absolute radiance values in the Landsat data that was employed for this research are scaled to 8-bit for Landsat 7 ETM+, Q calmax = 255 (http://landsat.usgs.gov).

The conversion from Qcal back to at-sensor spectral radiance (Lλ) requires the following equations below;

$$L\lambda = \left(\frac{LMAX\lambda - LMIN\lambda}{Qcalmax - Qcalmin}\right)(Qcal - Qcalmin) + LMIN\lambda \; ....(2) \quad \text{Or}$$

$$L\lambda = G_{rescale} * Q_{cal} + B_{rescale} \; ....(3)$$

Where:

$$G_{rescale} = \left(\frac{LMAX\lambda - LMIN\lambda}{Qcalmax - Qcalmin}\right) ....(4)$$

$$B_{rescale} = LMIN\lambda - \left(\frac{LMAX\lambda - LMIN\lambda}{Qcalmax - Qcalmin}\right) Qcalmin \; \ldots\ldots\ldots\ldots\ldots..(5)$$

Where:

$$Qcal = qunatized\ calibrated\ pixel\ value\ [DN]$$
$$Qcalmin = Minimum\ quantized\ calibrated\ pixel\ value\ corresponding\ to\ LMIN\lambda\ [DN]$$
$$Qcalmax = Maximum\ quantized\ calibrated\ pixel\ corresponding\ to\ LMAX\lambda\ [DN]$$

Lλ = Spectral radiance at the sensor's aperture [W/(m^2srμm)]

LMINλ = Spectral at sensor radiance that is scaled to $Qcalmin$ [W/(m^2srμm)]

LMAXλ = spectral at sensor radiance that is scaled to $Qcalmax$ [W/(m^2srμm)]

$G_{rescale} = Band - specific\ rescaling\ bias\ factor$ [W/(m^2srμm)]

3.5 Conversion to At-Satellite Brightness Temperature

For Landsat thermal bands, the conversion of DN to At-Satellite Brightness Temperature is given by 'Landsat Handbook

Where: K1 = Band-specific thermal conversion constant (in watts/meter squared * ster * μm), K2 = Band-specific thermal conversion constant (in kelvin), Lλ is the Spectral Radiance at the sensor's aperture, measured in watts/ (meter squared * ster * μm).

Table 3.2: The K1 and K2 constant for Landsat sensors are provided in the image metadata file.

	Landsat 7 ETM+
K1 (watts/meter squared * ster * μm)	666.09
K2 (Kelvin)	1282.71

LST image was converted to Celsius image using the equation (6)

LST (celcius) = LST (kelvin)-273.15....... (6)

4. RESULT AND DISCUSSION

4.1 Extracted Land Surface Temperature (LST) of 2006, 2011 and 2016

The extracted LST map of 2006, 2011 and 2016 is presented in Figures 4.1, 4.2 and 4.3 respectively. It is represented by color Green, Orange and Red, the Green color ranges from dark green to light Green, where the Dark Green symbolizes area with high Vegetation and concentrated plant, and also symbolizes area with cool or moderate temperature with little or no impervious surface present on it.

The Orange color symbolizes areas with no much vegetation and with little Built-up areas which makes the area moderately warmer than the surroundings.

The Red color symbolizes areas with high concentration of impervious surface areas indicating high concentrations of Built-up, which makes the area warmer than the surroundings.

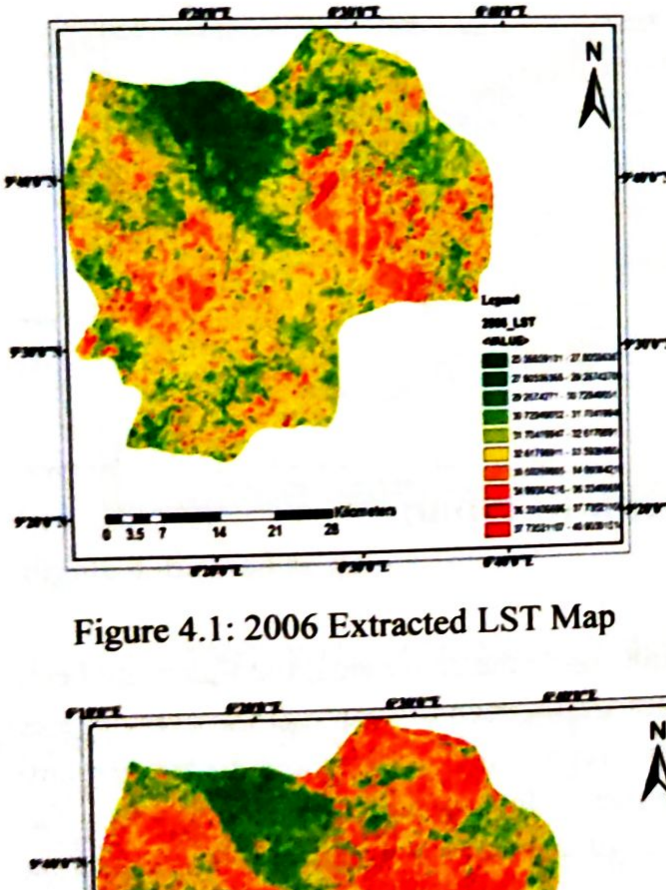

Figure 4.1: 2006 Extracted LST Map

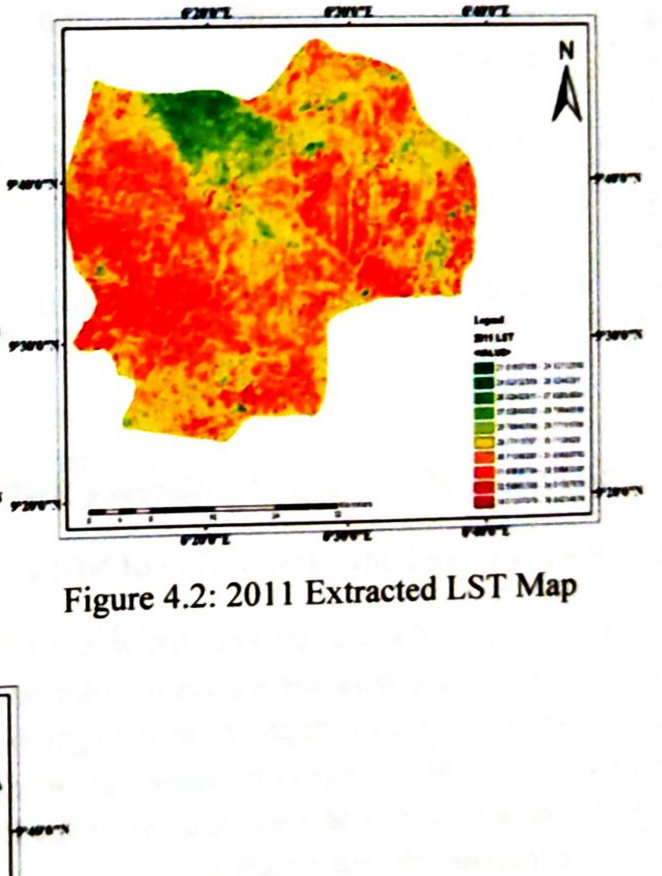

Figure 4.2: 2011 Extracted LST Map

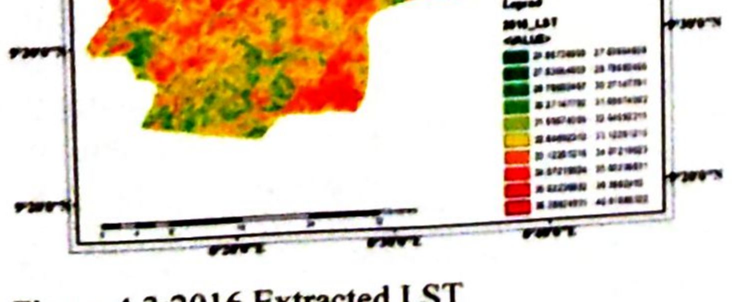

Figure 4.3:2016 Extracted LST

4.1.1 Extracted Land Surface Temperature (LST) Value of 2006, 2011 and 2016

Table 4.1 shows temperature values ranges from 27.805 to 40.903^{0}c for 2006, a ranges of 24.821 to 36.842^{0}c and it ranges from 27.836^{0}c to 40.010^{0}c for 2016. The derived LST Values range shows category and the level of Vegetation to Impervious Surface area, which implies areas that are cool as a result of the presence of Vegetation, areas that are moderately warm as a result of the presence of little Vegetation with little Built-up, and areas that are warm as a result of concentration of impervious surfaces or Built-up area is having larger percentage of the LULC of such region.

Table 4.1: Extracted Land Surface Temperature (LST) Value of 2006, 2011 and 2016

S/N	2006 (^{0}C)	2011 (^{0}C)	2016 (^{0}C)
1	27.805	24.821	27.836
2	29.267	26.824	28.786
3	30.729	27.826	30.271
4	31.704	28.769	31.696
5	32.618	29.771	32.646
6	33.593	30.713	33.122
7	34.994	31.657	34.072
8	36.334	32.599	35.022
9	37.735	34.013	36.388
10	40.903	36.842	40.010

4.3 Derivation of Normalized Difference Built-up Index (NDBI)

4.3.1 2006, 2011 and 2016 Derivation of NDBI

The figure 4.4, 4.5 and 4.6 determines the level of Built -up in the study area, the figure are been delineate by different colors, the shades of color ranges from Green to Red, and the every colors represent a feature. Areas with presence of Vegetation is represented in green and the temperature of that area is cool, the orange color represents where there's little or no Vegetation in which the place experience moderate temperature, while the Red color represents areas with no Vegetation which is warmer than the surrounding.

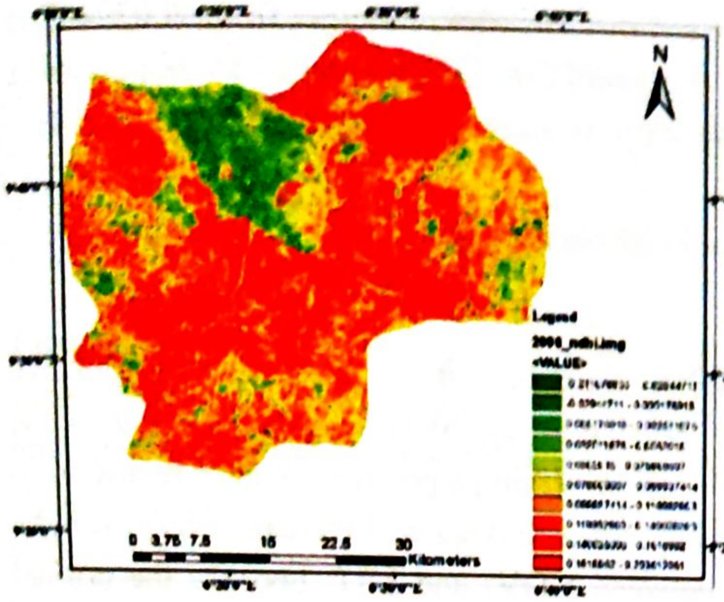

Figure 4.4: 2006 NDBI

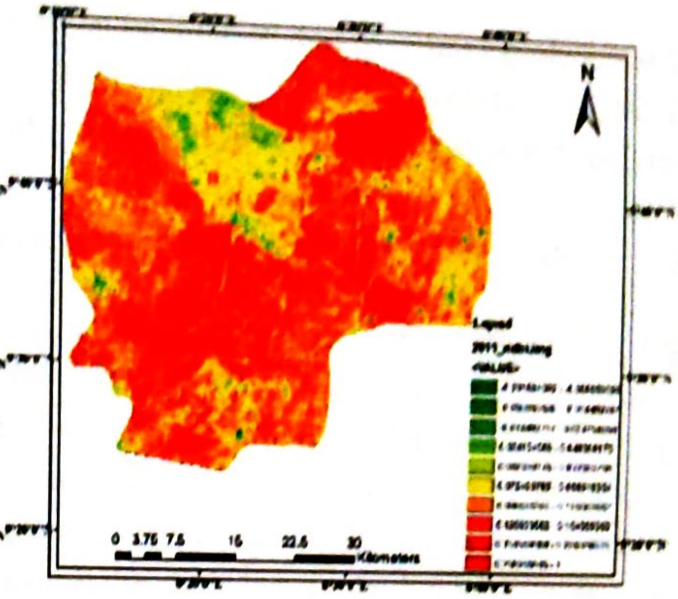

Figure 4.5: 2011 NDBI

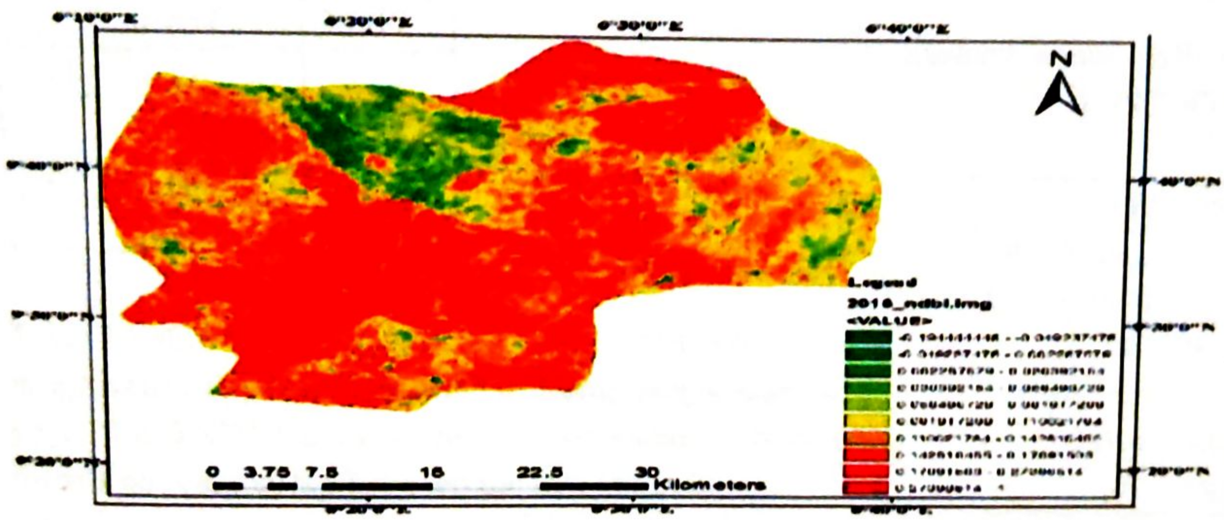

Figure 4. 6: 2016 NDBI

Table 4.2: 2006, 2011 and 2016 Extracted NDBI Values

2006	2011	2016
-0.029447	-0.08696	-0.0492
0.0051769	-0.01449	0.00229
0.0325117	0.024155	0.03039
0.0562018	0.048309	0.0585
0.0780696	0.072464	0.08192
0.0999374	0.096618	0.11002
0.1199829	0.125604	0.14281
0.1400284	0.154589	0.17092
0.1618962	0.256039	0.27397
0.2530121	1	1

Table 4.2 shows the variation in the land cover classes built up index, it ranges from -0.029447 to 0.2530121, -0.08696 to 1 and -0.0492 to 1 form the years 2006, 2011 and 2016 respectively, implying that as the values move from -0 to 1 the built up is increasing between 2006 and 2016

4.6 Relationship between Impervious Surface land surface temperature of Minna.

4.6.1 2006 Regression Analysis

Regression analysis of 2006 image, LST and NDBI variables, shows a significance positive relationship between LST and NDBI, the "P-Value" obtained from 2006 is 2.42401E-05, which is less than the critical value (0.25) at 99% confident level. Indicating a positive level of relationship between NDBI and LST, i.e. the increase in Impervious Surface Area will increase LST, from the same table (4.3) indicate a negative relationship between NDVI and LST, because the critical Value is greater than the P-Value (0.781398).

Table 4.3: 2006 Regression Analysis
SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.99566193
R Square	0.99134267
Adjusted R Square	0.98886915
Standard Error	0.42345834
Observations	10

ANOVA

	df		*MS*	*F*	*Significance F*
Regression	2	143.7339516	71.8669758	400.7817985	6.03731E-08
Residual	7	1.255218756	0.179316965		
Total	9	144.9891703			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	29.3517519	0.812483128	36.12598327	3.23452E-09	27.4305346	31.27296922
NDBI	47.1395835	4.804214918	9.812130459	2.42401E-05	35.77942043	58.49974664
NDVI	-1.2119316	4.202365091	-0.28839274	0.781398705	-11.14894598	8.725082839

Table 4.4: 2006 LST and NDBI correlation

	NDBI	*LST*
NDBI	1	
LST	0.99561	1

Table 4.4 shows how stronger the relationship is by carrying out a correlation analysis on the variables which was attained at 0.99561 which is equivalent to 99%, indicating a strong level of relationship between the variables, because the value obtained is greater than 0.25 which is the critical value.

Table 4.5: 2006 LST and NDVI

	LST	*NDVI*
LST	1	
NDVI	- 0.93395	1

Table 4.5 shows correlation of LST and NDVI variables which the was attained at -0.93395 which is equivalent to -93%, indicating a strong insignificant level of relationship between the variables i.e. LST and NDVI, because the value obtained is less than 0.25 which is the critical value, meaning there's no relationship between the two variables.

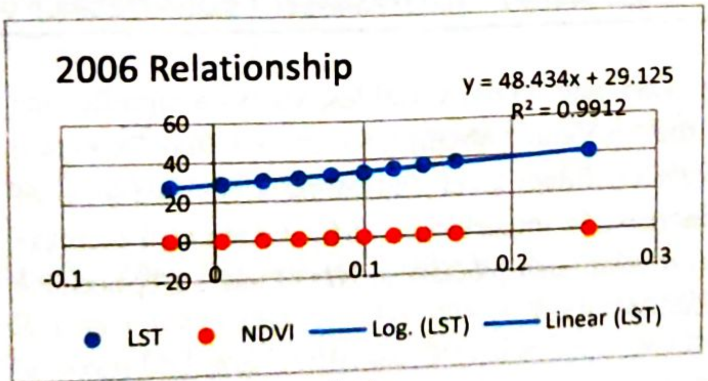

Figure 4.7: 2006 Correlation

Figure 4.7 summarizes the relationship by correlation which shows that increment in impervious surface Area will increase LST.

2011 Regression Analysis

Table 4.6: 2011 Regression Analysis

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.930989534
R Square	0.866741512
Adjusted R Square	0.828667658
Standard Error	1.477409055
Observations	10

ANOVA

	Df	*SS*	*MS*	*F*	*Significance F*
Regression	2	99.37891904	49.68945952	22.76474344	0.000863838
Residual	7	15.2791626	2.182737515		
Total	9	114.6580816			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	29.81471486	0.649368223	45.91341833	6.07741E-10	28.27920301	31.3502267
NDBI	6.933907364	1.86614703	3.715627576	0.007499079	2.521170841	11.34664389
NDVI	-5.098071784	1.73672883	-2.935444899	0.021854351	-9.204782894	-0.99136067

Regression analysis carried out on 2011 image, LST and NDBI variables, shows a significance positive relationship between LST and NDBI, the "P-Value" obtain from 2011 is 0.007499079, which is less than the critical value (0.25) at 99% confident level. Indicating a positive level of relationship between NDBI and LST, i.e. the increase in Impervious Surface Area will increase LST, from the same table (4.6) indicate a negative relationship between NDVI and LST, because the critical Value is greater than the P-Value (0.021854351).

Table 4.7: 2011 LST and NDBI correlation

	NDBI	*LST*
NDBI	1	
LST	0.838274	1

Table 4.7 shows the result of the relationship and how it further buttress relationship to know how stronger the relationship is by carrying out a correlation analysis on the variables which was attained at 0.838274, equivalent to 83% and indicating a strong level of relationship between the variables, because the value obtained is greater than 0.25 which is the critical value.

Table 4.8: 2011 LST and NDVI correlation.

	NDVI	*LST*
NDVI	1	
LST	- 0.77712	1

Table 4.8 shows the relationship attained at -0. 0.77712 equivalent to -77%, indicating a strong level of relationship between the variables, because the value obtained is less than 0.25 meaning there's no relationship between the two variables.

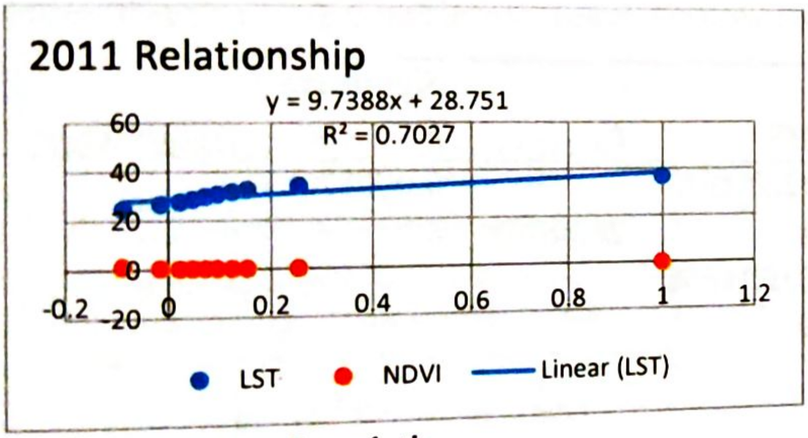

Figure 4.8: 2011 Correlation

Figure 4.8 summarizes the relationship by correlation which shows that increment in impervious surface Area will increase LST.

4.6.2 2016 Regression Analysis

Regression analysis for 2016 image on LST and NDBI shows a significance positive relationship between LST and NDBI, the "P-Value" obtained from 2016 is 0.002425917, which is less than the critical value (0.25) at 99% confident level. This indicates a positive level of relationship between NDBI and LST implying that an increase in Impervious Surface Area will increase LST, from the same table (4.9) indicate a negative relationship between NDVI and LST, because the critical Value is greater than the P-Value (0.02470206).

Table 4.9: 2016 Regression Analysis

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.938949788
R Square	0.881626705
Adjusted R Square	0.847805763
Standard Error	1.421923308
Observations	10

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	105.409896	52.7049481	26.06748	0.000570674
Residual	7	14.1530613	2.02186589		
Total	9	119.562958			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	32.25836486	0.67336586	47.9061486	4.518E-10	30.66610762	33.8506221
NDBI	8.147979583	1.76360184	4.62007887	0.0024259	3.977723912	12.31823525
NDVI	-4.84622379	1.70065925	-2.8496148	0.0247021	-8.86764389	-0.82480369

Table 4.10: 2016 LST and NDBI correlation

	NDBI	*LST*
NDBI	1	
LST	0.862733	1

Table 4.10 shows the result of the relationship and how it further buttress relationship to know how stronger the relationship is by carrying out a correlation analysis on the variables which the was attain at 0.862733 which is equivalent to 86%, indicating a strong level of relationship between the variables, because the value obtained is greater than 0.25 which is the critical value.

Table 4.11: 2016 LST and NDVI correlation

	NDVI	*LST*
NDVI	1	
LST	-0.72158	1

Table 4.11 shows the result of the relationship and how it further buttress relationship to know how stronger the relationship is by carrying out a correlation analysis on the variables which the was attained at -0.72158 which is equivalent to -72%, indicating a strong level of relationship between the variables, because the value obtained is less than 0.25 which is the critical value. It means there's no relationship between the two variables.

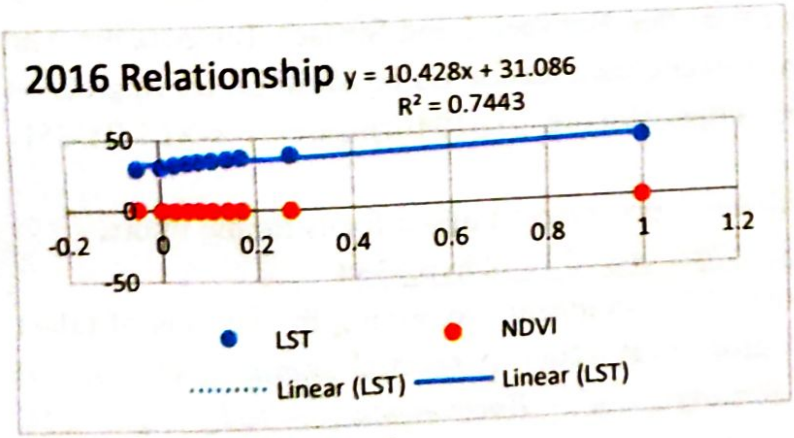

Figure 4.9: 2016 Correlation

Figure 4.9 summarizes the relationship by correlation which shows that increment in impervious surface Area will increase LST.

5.1 CONCLUSION

Increase in population, Civilization and urbanization are the major push and pull factors that increases the level of human activities which brought about changes in the different LULC classes,. Increase in Built-up area decreases other land use type which decreases the vegetation and Farm Land which could help in minimizing the LST. Based on this could be deduced that persistent warm anomaly over the years is due to ISA increase in extent. Thus, increase in ISA influences surface energy exchange and other environmental processes which can be used to determine the strength of UHI and monitor the global climate. The study shows and proof that there's correlation between ISA and LST, because an increment in ISA will increase LST, there's also a strong relationship between ISA and LST because the goodness of fit is very strong and close to 100%. The stretch in urban sprawl has resulted in temperature variation across the major towns and cities in Nigeria, which extend to the study area Minna metropolis.

It is recommended that; as there is advancement in level of technology which brings about improvement in standard of living resulting into erection of impervious infrastructural built-up, environmentalist and Scientist should find a way of replacing impervious surfaces with pervious surfaces, since there's a great need to beautify the environment. Decision makers can use the information presented in this study in various governmental and private sectors such as energy management, urban planning, environmental sustainability and other socio-economic applicatio

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