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Full Length Research Article

ESTIMATION OF LAND SURFACE TEMPERATURE OF KADUNA METROPOLIS, NIGERIA USING LANDSAT IMAGES

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ABSTRACT
Understanding the spatial variation of Land Surface Temperature (LST), will be helpful in urban micro climate studies. This study estimates the land surface temperature of Kaduna metropolis, Nigeria. For the present study Landsat ETM+ images of 2001, 2006, 2009 and OLI 2015 was obtained from USGS of the study area. Normalized Difference Vegetation Index (NDVI) image was developed. The digital number of thermal infrared band is converted in to spectral radiance using the equation supplied by the Landsat user's hand book. The effective at-sensor brightness temperature is obtained from the spectral radiance using Plank's inverse function. The surface emissivity based on NDVI is used to retrieve the final LST. It was noted that 2006 has the highest maximum value with the highest mean value of 0.177 and standard deviation of 0.0903 while 2001 has the minimum value of NDVI. So also 2001 has the maximum value with highest mean value of 0.999 and standard deviation of 0.00161 while 2015 has the minimum value of surface emissivity. The coefficient determinant R^2 (0.837) show a strong positive correlation between mean of surface emissivity with date and season which shows downward trend in average over the study period. 2015 has the highest mean value of 39.42 with standard deviation of 1.92 of LST and coefficient determinant R^2 (0.46) show a positive correlation between mean of LST with date and season, with an upward trend in average LST over the study period. Lastly, NDVI is found to have negative correlation with LST. The Coefficient of determination (R^2) (0.66) of surface temperature with NDVI and surface emissivity show a better prediction power of land surface temperature.

Keywords: LST, NDVI, Surface Emissivity, Landsat images, Temperature.

1.0 INTRODUCTION
Land surface temperature can provide noteworthy information about the surface physical properties and climate, which plays a role in many environmental processes (Dousset and Gourmelon, 2003; Weng, et al., 2004). In order to monitor the rapid and recurrent changes of the global environment, Land Surface Temperature (LST), as the prime and basic physical parameter of the earth's surface, has been studied for over a decade. LST plays a key role in modelling the surface energy balance (Kalma, et al., 2008; Cammalleri, et al., 2012), and has a substantial impact on analysing the heat-related issues such as soil moisture, evapotranspiration, and urban heat islands(Srivastava, et al., 2013; Song, et al., 2013; Bateni, Entekhabi, and Castelli, 2013; Wong and Nichol, 2013; Bastiaanssen, et al., 1998). Regarding the lack of land surface temperature measured by weather stations, many studies have estimated the relative warmth of cities by measuring the air temperature, using land based observation stations, especially in developing countries, and Nigeria in particular (Obinna, et al., 2013). As it is traditionally measured in the field at sparsely located, field observation stations yielded discrete LST measurements (Obinna, et al., 2013). This approach has long been adopted in Nigeria. Discreet measurements of LST are usually not a good representative of the LST of an area (Obinna, et al., 2013). Furthermore, weather station based techniques produce point estimates where as remote sensing methods produce actual values (Owen, Carlson, and Gillies, 1998 and Weligepolage, 2005). More often this is done by extrapolating the air temperature data measured at weather station. Remote sensing might be a better alternative to the aforementioned methods (Ifatimehin, et'al 2010). The advantages of using remote sensed data are the availability of high resolution, reliable and repetitive coverage and proficiency of measurements of earth surface conditions (Owen, et al., 1998, Jakub et'al, 2015). Satellite-based thermal infrared (TIR) data is directly linked to the LST through the radiative transfer equation (National Aeronautic Space Agency, NASA 2015). The retrieval of the LST from remotely sensed TIR data has attracted much attention, and its history dates back to the 1970s (McMillin, 1975). Remote sensing is becoming a tool to reckon with in the evaluation and monitoring of environmental and ecological processes. Landsat is one of the most used data for environmental analysis. It is composed of seven bands for TM, eight for ETM and eleven for Landsat 8, they provide thermal data using just one long-wave infrared (LWIR) band, with a higher spatial resolution (NASA 2015). Although, there are other remote sensing data range from land observation to meteorological ones such as Modis, NOAA-17/AVHRR and Meteosat-9 (Jakub, et' al, 2016). But each of them has advantage over one another, for example Landsat has relatively high spatial resolution, more detailed land surface temperature pattern can be obtained, made it possible to study relationship between land surface temperature and different land use types and enables detection of single sources of the highest heat emission while meteosat-9 has too low spatial resolution in order to detect UHI's of smaller cities and not sufficient spatial resolution to assess UHI structure even in larger metropolis (Jakub, et' al, 2016). Nevertheless, the meteosat-9 has temporal resolution more than the Landsat, in addition some of the Landsat data have cloud cover and stripe from the sensor error (Jakub, et' al, 2016). Despite the availability of this information, few studies have been carried out to estimate this important climatic parameters for studying urban climatology (land surface temperature) in Nigeria for example (Shakirudeen and Gbolahan, 2015; Ifatimehin, et al., 2013; Zemba, 2010) but there is little or no studies carried out in Kaduna metropolis. Therefore, this research intended to bridge this gap which aims to estimate the land surface temperature of Kaduna metropolis.

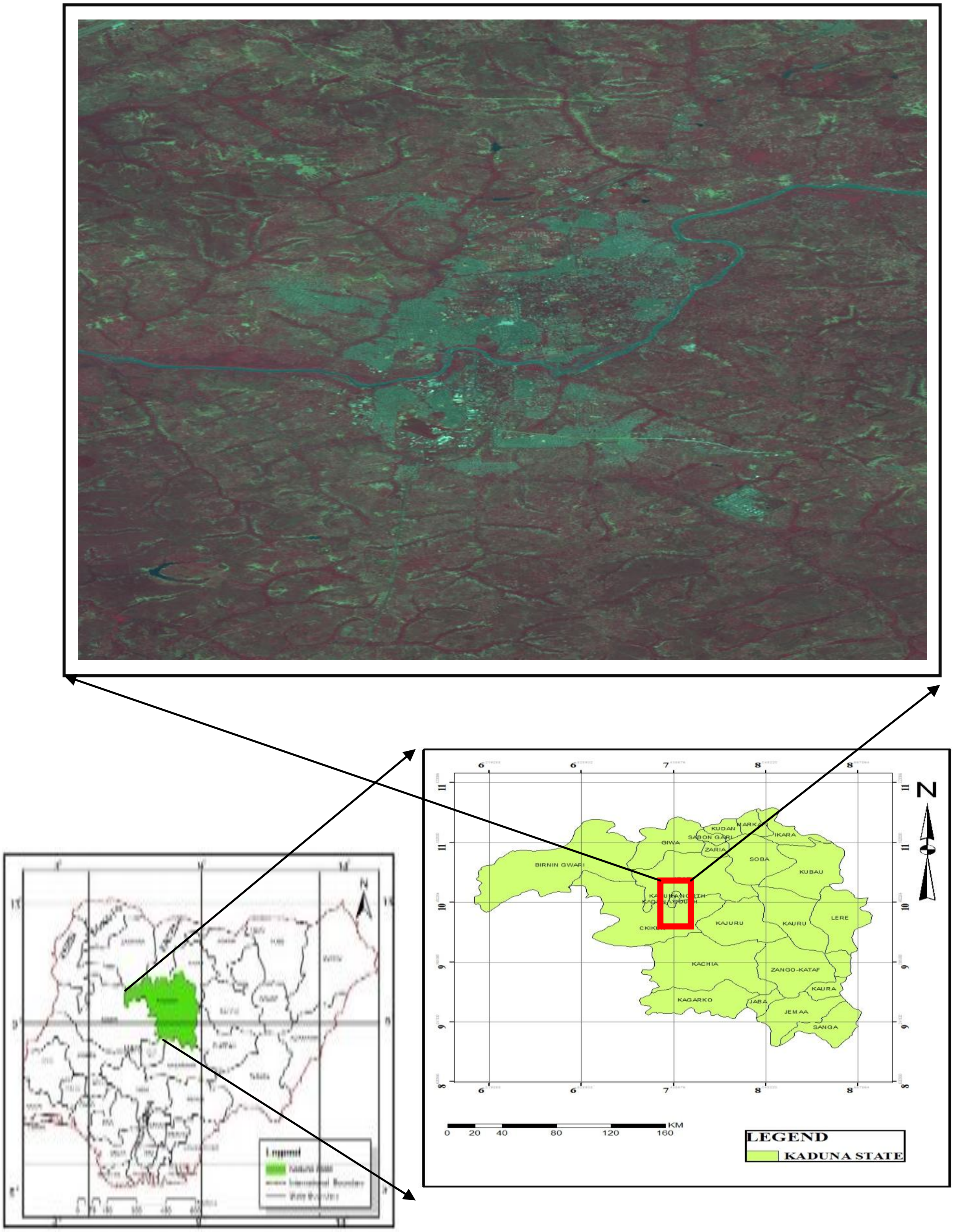

Figure 1: Composite Map of the Kaduna Metropolis

1.1 MATERIAL AND METHODOLOGY

1.1.1 STUDY AREA

Kaduna metropolis comprises of four (4) local government area in Kaduna state, which are Kaduna North, Kaduna South, Igabi and Chikun Local Government Area. It lies between latitude 10.25^{0}N to 10.75^{0}N and longitude 7.25^{0}E to 7.75^{0}E with an area of 3080.25km^2 shown in Figure 1.

1.1.2 MATERIAL

Material used in this research is Landsat data comprises of ETM and OLI obtained from USGS/LANDSAT, their properties are presented in Table 1 below

Table 1: Properties of Landsat Images Used

DATA	SENSOR	BANDS	RESOLUTION	DATE OBTAINED
Landsat-7	* ETM+	8	VNIR=30m TIR=60, PAN=15	2001-10-24
Landsat-7	*ETM+	8	VNIR=30m TIR=60, PAN=15	2006-11-07
Landsat-7	*ETM+	8	VNIR=30m TIR=60, PAN=15	2009-12-01
Landsat-8	*OLI	11	VNIR=30m, TIR=100, PAN=10	2015-04-30

Extracted from Metadata
ETM+ = Enhance Thematic Mapper Plus and OLI = Operational Land Imager

1.1.3 METHOD

To estimate the land surface temperature it comprise of various procedure and step that been describe by NASA. These procedure range from radiometric calibration and conversion of DN to radiance up to normalised difference vegetation index among other which are described below:

1.1.3.1 Radiometric Calibrations

In terms of atmospheric correction, the digital numbers (DN) of the ETM+ image were converted to normalized atmospheric reflectance using the equations below. The calibration parameters can be retrieved from the image head files and the NASA website.

$L_\lambda = \mathrm{GAIN} \times \mathrm{DN} \times \mathrm{BIAS}$-------------- (Eq. 1)

Where;
Lλ is the normalized atmospheric reflectance at a particular wavelength.

1.1.3.2 Conversion to At Sensor Spectral Radiance (Qcal - to- Lλ)

The digital number (DN) of thermal infrared band is converted in to spectral radiance (Lλ) using the equation supplied by the Landsat user's hand book, (NASA, 2004; NASA, 2015)

$L_\lambda = \left(\frac{\mathrm{LMAX-LMIN}}{\mathrm{QCALMAX-QCALMIN}}\right)\left(\mathrm{QCAL-QCALMIN}\right)+\mathrm{LMIN}$- (Eq. 2)

Where
LMAX = the spectral radiance that is scaled to QCALMAX in W/(m2 * sr * μm)
LMIN = the spectral radiance that is scaled to QCALMIN in W/(m2 * sr * μm)
QCALMAX = the maximum quantized calibrated pixel value (corresponding to LMAX) in DN = 255
QCALMIN= the minimum quantized calibrated pixel value (corresponding to LMIN) in DN = 1

1.1.3.3 Conversion to At-sensor Brightness Temperature (L λ -to- T)

The thermal band data (Band 6 on ETM+ and band 10 and 11 on OLI) can be converted from at-sensor spectral radiance to effective at-sensor brightness temperature. The conversion formula from the at-sensor's spectral radiance to at-sensor brightness temperature is:

$T = \frac{K2}{\ln\left(\frac{K1}{L\lambda}+1\right)}$ -------------------- (Eq.3)

Where:

T = Top of Atmosphere Brightness Temperature, in Kelvin.
Lλ = Spectral radiance (Watts/ (m2 * sr * μm))
K1 = Thermal conversion constant for the band (K1_CONSTANT_BAND_n from the metadata)
K2 = Thermal conversion constant for the band (K2_CONSTANT_BAND_n from the metadata)

Temperatures were converted from degree Kelvin into degree Celsius by subtracting 272.15 from the result, which is the conversion rate of kelvin to Celsius.

1.1.3.4 Derivation of NDVI Image

The NDVI image was computed for 2001, 2006, and 2009 from the band 3 and band 4 reflectance data while band 4 and band 5 for 2015, using the formula below:

$\mathrm{NDVI} = \frac{\mathrm{NIR-RED}}{\mathrm{NIR+RED}}$ ………… (Eq. 4)

Where,

NIR = the near infrared

RED = the red reflectance

1.1.3.5 Estimation of Land Surface Temperature (LST)

The final Land Surface Temperature (LST) is estimated using single window by the following equation:

$\mathrm{LST} = \frac{\mathrm{TB}}{1+\left(\lambda+\mathrm{TB}/\rho\right)\times\ln e}$ ----------- (Eq. 5)

Where,

λ is the wavelength of the emitted radiance which is equal to 11.5µm. ρ = h.c/σ, σ = Stefan Boltzmann's constant which is equal to 5.67 x 10-8 Wm-2 K -4, h = Plank's constant (6.626 x 10 -34 J Sec), c = velocity of light (2.998 x 108 m/sec) and ε is the spectral emissivity. In this study spectral emissivity is determined using the following equation

$$e = 0.004\mathrm{Pv} + 0.986 \text{----------- (Eq. 6)}$$

Where

Pv = proportion of vegetation and its computed from NDVI as follow:

$$\mathrm{Pv} = \left(\frac{\mathrm{NDVI}-\mathrm{NDVIMIN}}{\mathrm{NDVIMAX}-\mathrm{NDVIMIN}}\right)^2 \text{---------- (Eq. 7)}$$

All the procedures above (for estimating land surface temperature) were computed using map algebra function in Spatial Analyst in ArcGIS software.

1.2 RESULT AND DISCUSSION

1.2.1 Analysis of NDVI using Landsat Imagery

NDVI is one of the most widely used index whose applicability in satellite analysis and in monitoring of vegetation cover was sufficiently verified in the last two decades. The NDVI value of the pixels varies between -1 and +1. Higher values of NDVI indicate the richer and healthier vegetation. Figure 2 shows the spatial distribution of NDVI from the Landsat image. The NDVI values estimated are in the range of -0.592 to 0.397, for 2001, -0.281 to 0.478, for 2006, while 2009 having a range of -0.415 to 0.422 and -0.05 to 0.209 for 2015 clearly this show that 2006 has the highest maximum value while 2001 has the minimum value. In figure 4 show that 2006 has the highest mean value of 0.177 with standard deviation of 0.0903 while 2001 has the minimum value of 0.0054 with standard deviation of 0.113. The reason behind less NDVI values in 2015 could be attributed to the distortion of ecosystem due to the urbanization taken place.

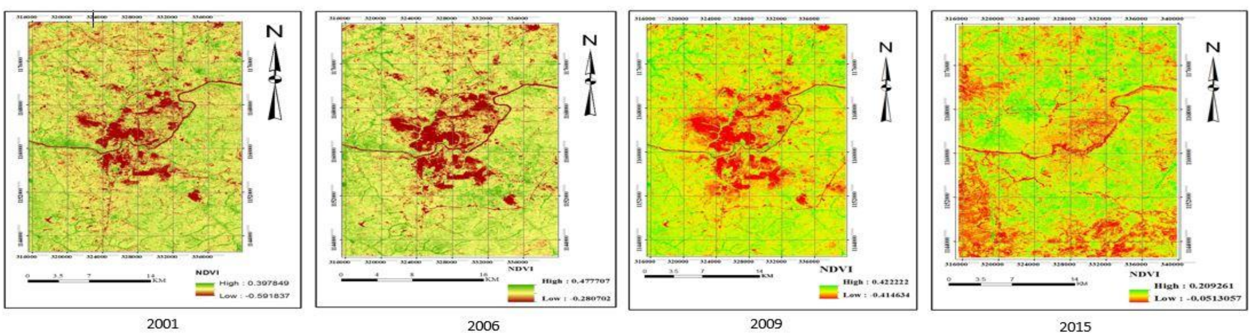

Figure 2: spatial distribution of NDVI from Landsat image of Kaduna metropolis

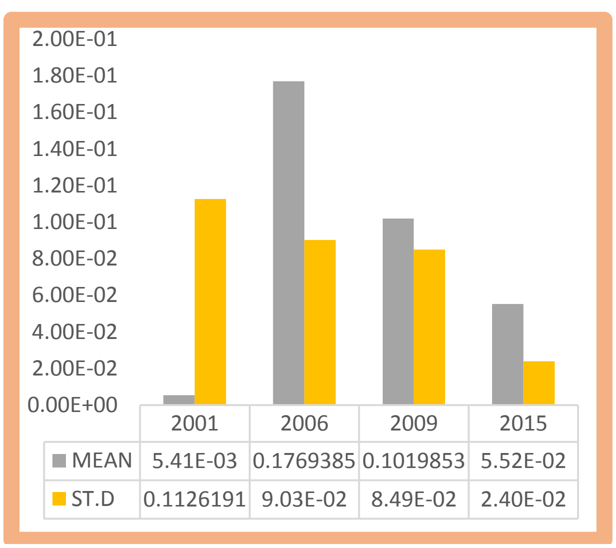

Figure 3: showing the difference in mean and standard deviation of NDVI

1.2.2 Analysis of Surface Emissivity

Satellite-sensed thermal infrared (TIR) data is the major source for estimating surface emissivity for a region. It is applicable to surface emissivity estimation from fine spatial resolution satellite data such as Landsat image TIR bands (Yang, 2003).The spatial distribution of surface emissivity from the Landsat image show in figure 4 below. The NDVI values estimated are in the range of 0.99 to 1.00 for 2001, 0.988 to 0.99 for 2006, while 2009 having a range of 0.986 to 0.989 and 0.986 to 0.987 for 2015 clearly this show that 2001 has the maximum value which reflect that some material are ideal that completely absorbs all incident radiation and converts it to internal energy, then emits (re-radiates) the absorbed energy at the maximum possible rate per unit area. While 2015 has the minimum value. In figure 4 show that 2001 has the highest mean value of 0.999 with standard deviation of 0.00161 while 2015 has the minimum value of 0.987 with standard deviation of 0.0000687. The coefficient determinant R^2 (0.837) show a strong positive correlation between mean of surface emissivity with date and season in which indicate that the equation can be used for estimating surface emissivity, it also show a downward trend in average over the study period.

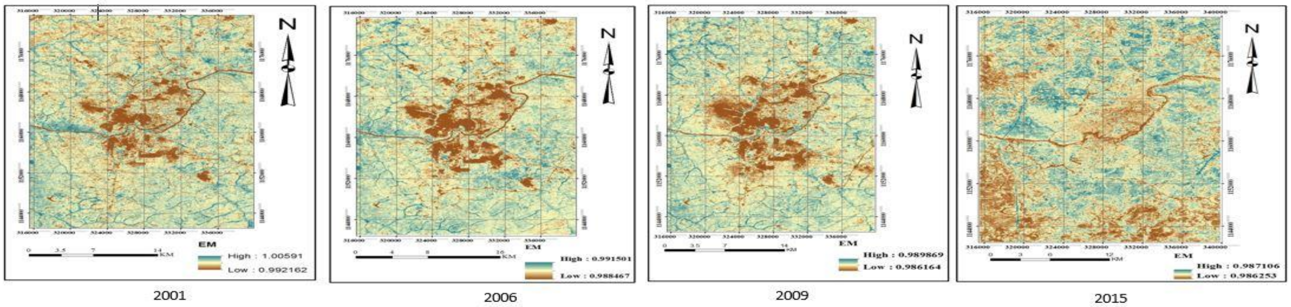

Figure 4: Spatial variation of surface emissivity of Kaduna metropolis

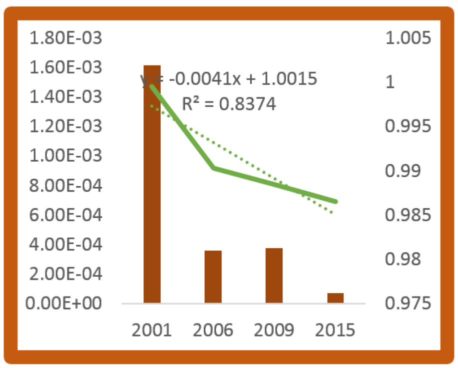

Figure 5: showing the difference in mean and standard deviation of surface emissivity

1.2.3 Land Surface Temperature

The LST of Kaduna metropolis revealed a temperature range between 18.76°C to 37.73°C in 2001, 15.67°C to 48.01°C in 2006, 17.66°C to36.03°C in 2009 and 28.14°C to 45.65°C show in (figure 7). 2015 has the highest mean value of 39.42 with standard deviation of 1.92 this implies that urban development does bring up surface temperatures by replacing natural vegetation with non-evaporating, non-transpiring surfaces such as bare land (soils), metal, tar, cemented buildings and concrete among other. The dry nature of these non-evapotranspirative materials in the urban environment is responsible for variation of land surface temperature. The coefficient determinant R^2 (0.46) show a positive correlation between mean of LST with date and season, it also shows an upward trend in average LST over the study period.

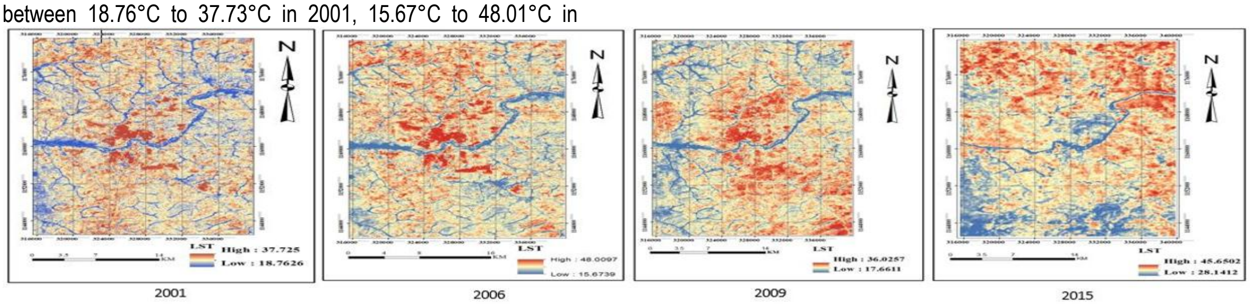

Figure 6: spatial variation of land surface temperature of study area.

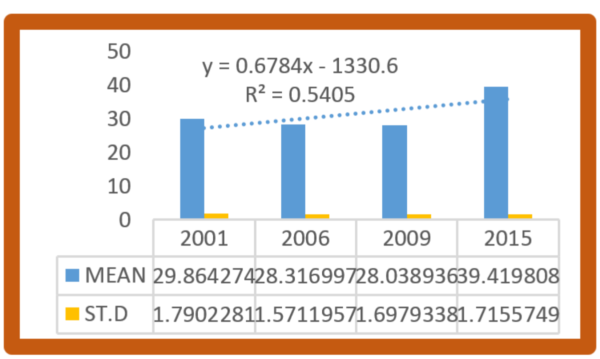

Figure 7: showing the difference in mean and standard deviation of surface temperature of study area.

1.2.4 Relationship between NDVI, surface emissivity and surface temperature:

Table 2 shows the correlation between NDVI, Surface Emissivity and land surface temperature. It is inferred that the entire variable have negatively correlated with one another. The strongest negative correlation between NDVI and surface emissivity follow by surface temperature and surface emissivity lastly and weak negative correlation between land surface temperature and NDVI. Table 6 shows the regression coefficient between surface temperature with NDVI and surface emissivity of the study area. Coefficient of determination (R^2) surface temperature with NDVI and surface emissivity show a better prediction power of land surface temperature. Furthermore, the NDVI and surface emissivity have significant impact on land surface temperature estimated using above mentioned method.

Table 2: Correlation Coefficient between Surface Temperature with Ndvi and Surface Emissivity

	LST	NDVI	EM
LST	1		
NDVI	-0.387	1	
EM	-0.409	-0.519	1

Table 3: Linear Regression for Predicting Surface Temperature.

Regression Statistics	
Multiple R	0.812
R Square	0.659
Adjusted R Square	-0.0237
Standard Error	5.463618166
Observations	4

1.3 Conclusion

Detailed information on land surface temperature in the Kaduna metropolis is lacking. Environmental satellite data provides a proficient and cheap way of estimating land surface temperature of an area. In this research, it shows the potential of remote sensing in studying land surface temperature of the Kaduna metropolis. However, the results above clearly show that the land surface temperature varies over space and time. As it's one of the important parameter for investigating urban morphology. This implies that, the more the urban development the high the land surface temperature. The study revealed the retrieval of Land Surface Temperature (LST) from the Surface Emissivity and Normalised Difference Vegetation Index (NDVI) is possible. Therefore, future work should focus on variation of land surface temperature over land use and land cover changes and how it can be applied in study the impact of urban micro – climate change on human comfort and aridity of Kaduna metropolis.

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