The Effects of Urban Parameters on the Development of Urban Heat Island in Jalingo Metropolis: Analysis and Statistical Modeling

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Abstract

Urban Heat Island (UHI) has been a source of concern in recent years and different approaches have been employed to understand its nature, characteristics and implications. In this paper, analysis of spatial pattern of land surface temperature (LST) derived from remote sensing images used to examine effects of vegetation and water index, and built up density on LST of Jalingo metropolis, North East Nigeria was determined. Normalized difference vegetation index (NDVI) was used as an indicator for vegetation cover, normalized difference built-up index (NDBI) for level of urbanization indicator, while normalized difference water index (NDWI) for water index indicator. Landsat 8 data was used for the retrieval of LST, calculation of (NDBI), (NDVI) and (NDWI). The analysis showed that areas with high LST were located principally in central built-up areas. The results of assessment of relationship between LST with NDVI, NDWI and NDBI, showed a negative correlation between LST and NDVI and NDWI, and a positive correlation with NDBI; this means that green surfaces can reduce urban heat island (UHI) effect whereas built-up areas can strengthen the effect of UHI. It was concluded that NDVI, NDWI and NDBI could be used to investigate and predict Urban Heat Islands (UHI) and results may help city planners better prepare for possible impacts of urban environmental change.

Keywords: Land Surface Temperature (LST), Normalized Difference Built-up Index (NDBI), Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI) and Urban Heat Island (UHI),

Introduction

Urbanization has been found to contribute to global climate change in various ways and across multiple dimensions. Rapid urbanization has led to significant increase in land surface temperature (LST) which is governed by surface heat fluxes, (Laosuwan and Sangpradit, 2012). Structures of urban canopies and parameters such as building density, proportion of vegetation cover and materials control the development of urban heat island (UHI). Laosuwan and Sangpradit (2012) observed that urban heat island intensity is related to patterns of land use land cover (LULC) changes such as the modifications of vegetation, existing water body and built up density changes.

The introduction of computer applications in geography and environmental studies, coupled with the used of remote sensing and geographic information systems in the monitoring, studying evaluating and analysis of the environment, has greatly improved research work in geography and environmental studies. Several statistical packages such as SPSS and STATA have made statistical analysis easier with higher precision and high level of accuracy with minimal error.

Statistical modeling can provide useful quantitative information about the contribution of urban factors to UHI development and help better understanding of the causal relationship that help to assess and predict the formation and evolution of UHI phenomena. Land surface temperature measurements have been carried out by some researchers using National Oceanic and Atmospheric Administration (NOAA) and Advance Very High Resolution Radiometer (AVHRR) data (Streutker, 2002 and 2003) for urban temperature mapping in local scales. Recently, Landsat Thematic Mapper sensors (TMs) and Enhanced Thematic Mapper plus sensor (ETMs+), thermal infrared sensors (TIR) with resolutions (30m, 60m and 120m) particularly, have been utilized for heat island study and assessment of the factors affecting urban heat island, Aneesh, Rishabh, Neha, Sumit, Nivedita (2015); Balázes, Unger, Gál, Sümeghy, Geiger, Szegedi, (2009); Weng, Dengsheng, and Jacquelyn, (2004); Chen, Ren, Li and Ni (2009).

It is known that various vegetation indices obtained from remote sensing data can be used in the measurement of vegetation cover qualitatively and quantitatively (Purevdorj Tateishi, Ishiyama and Honda, 1998; Chen Wang, and Li, 2002). For example, the relationship between various vegetation indices and percentage vegetation cover has been created using regression analysis (Weng, 2011). Normalized Difference Vegetation Index (NDVI) is used for estimation of vegetation production and precipitation in semiarid areas (Streutker, 2002; Chen, Babiker, Chen, Komaki, Mohamed, and Kato, 2004), while the Normalized Difference Water Index (NDWI) was used for the determination of Vegetation Water Content (VWC) under physical principles (Gao, 1996). NDVI has been found to have limited capability for estimating VWC (Ceccato, Gobron, Flasse, Pinty and Tarantola, 2002), hence it is ideal to integrate NDVI and NDWI to represent the state of vegetation. Zha, Gao and Ni, (2003) has developed the Normalized Difference Built-up Index (NDBI) to classify urban and built-up areas. The utilization of NDVI, NDWI and NDBI could represent land cover types quantitatively so that the relationships between them and temperature can be established in UHI studies. It is against this background that this research was formulated to examine spatial structure and variations of surface temperatures in a medium size urban area in tropical Africa faced with numerous planning challenges and to link these temperature characteristics to characteristics of urban canopy.

Description of Study area

Jalingo Metropolis lies between latitude 8°52’ and 8°56’N of the equator while its longitudinal extent is 11°19’ and 11°24’E. According to 2006 National Population census, Jalingo has a population of 139,845 with a projected population growth rate of 3% (Shawulu, Adebayo, and Binbol, 2008). Using the population growth rate of 3%, the population of Jalingo was projected to be 197, 998 in 2017.

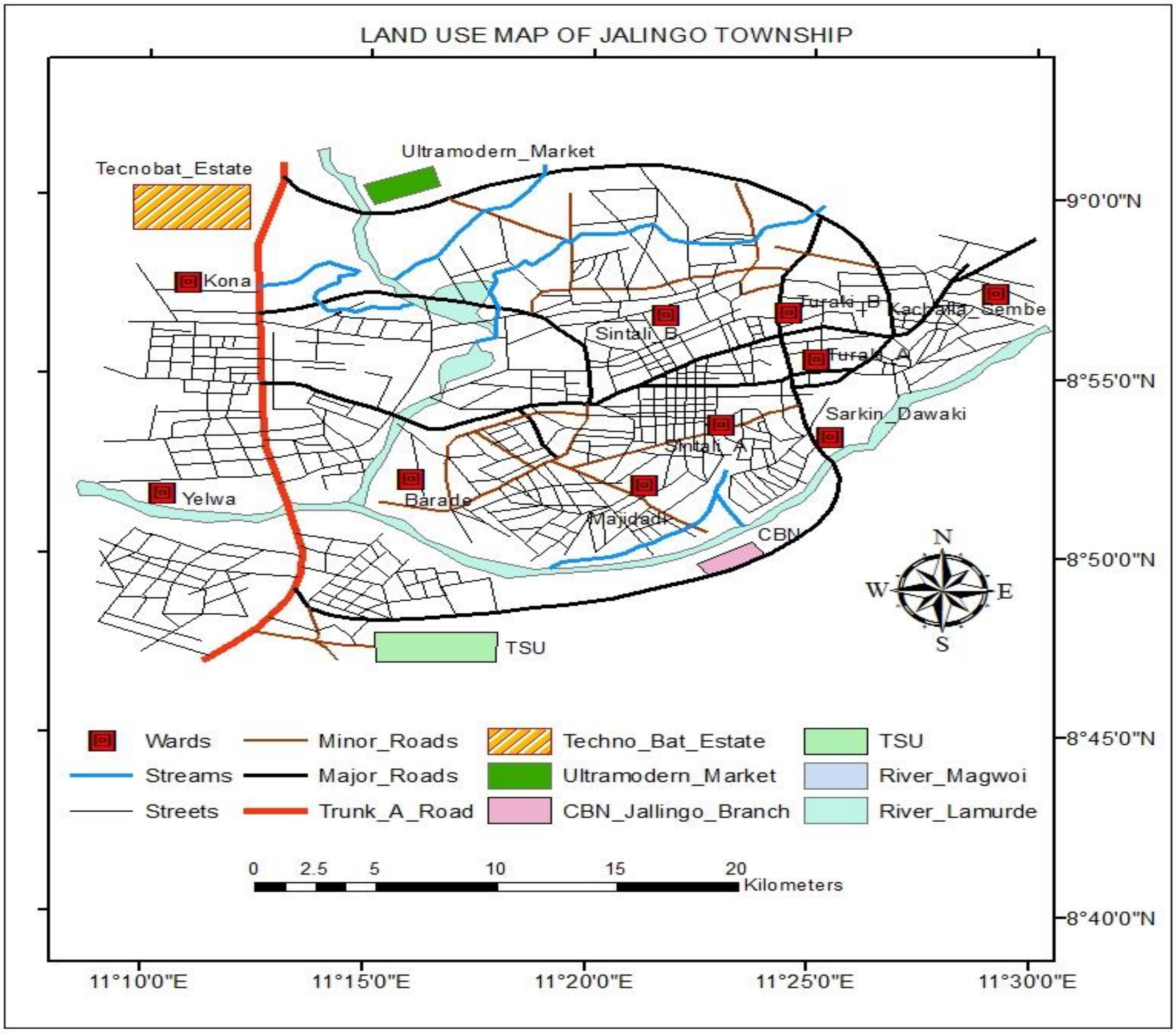


Fig 1: Land use map of the study area

Jalingo has tropical continental type of climate characterized by well-marked wet and dry seasons. The wet season usually begins around April and ends in October. The dry season begins in November and ends in March. The area has a mean annual rainfall of about 1,200mm^3 and annual mean temperature of about 29^{o}C. Relative humidity ranges between 60-70 per cent during the wet season to about 35 – 45 per cent in the dry season. The Temperature of Jalingo ranges from 29°C – 37°C, with an average mean of 32°C in the months of August and September. The coldest months are December and January.

The relief of Jalingo consists of undulating plain interspersed with mountain ranges with elevation ranging from 137ft to 914ft above sea level (a.s.l.). The peaks form the watershed for River Lamurde and other streams which drain into River Benue. The compact massif of rock outcrops (mountains) in Jalingo extends from Kona area through the border between Jalingo and Lau LGA down to Yorro and Ardo Kola LGAs in a circular form to Gongon area. Thus, giving a periscope semi-circle shape that is almost like a shield to Jalingo town, that it exerts a greater influence of katabatic and anabatic winds effects on the township which consequently may have the ability to modify the micro climate of the area. Jalingo metropolis is drained by two major rivers; Mayo-Gwoi and Lamurde, which take their sources from the mountain ranges in Yorro LGA and emptied their content into the Benue river system at Tau village. The Rivers Lamurde and Mayo Gwoi form a confluence in Jalingo town around Magami area. River Lamurde has extensive flood plain on both sides of the river (Oruonye, 2011).

Materials and Methods

In order to carry out this study, two sets of data were acquired; these are satellite images and auxiliary data. These include the Landsat 8 ETM+ data set acquired in 2018 from United States Geological Survey (USGS) website was used to derive LST, Administration boundary map of Jalingo from the geography department of Taraba State University (TSU), Jalingo and the Topographic map at scale 1:50000 for digitizing to create map of the study area.

Land Surface Temperature (LST) was derived from band 10 which is the thermal band from Landsat 8 using Geographic Information System (GIS) through the conversion of the Digital Numbers (DN) into radiance, then Kelvin and to Celsius degrees.

Land use land cover classification

The study area was categorized into thermal climate zones (TCZ) based on Asa, Joel and Zarma (2017). Thermal climate zones (TCZ) are regions of relatively uniform surface air temperature distribution across a horizontal scale of 10^2m to 10^4m (Stewart and Oke, 2009). They are differentiated based on surface properties that directly influence temperature such as building height-to-width ratio (H/W), Sky View Factor (SVF), Height of Roughness Element, Anthropogenic Heat Flux (QF), and Surface thermal Admittance. All field sites were defined by a 'circle of influence' (also known as source area or footprint) whose radius extends from meters to kilometers depending on instrument height, boundary layer conditions and surface geometry (Oke, 2004, 2006).

The classification was done after evaluating the physical nature of the urban terrain following the procedures laid down by Oke (2004, 2006). Given the spatial dimensions of local climate zones as imposed by the environment and the measurement set up for this study, field sites were parameterized using a radius of 300m by differentiating properties of the source area. The TCZ that best matched the measured or estimated properties of field sites was identified. Photographs were taken to substantiate matches between field sites and Oke's TCZ's. This is because different photographs alone can substantiate reasonable accurate matches between field site and Oke's TCZ since direct relationship between the measured properties and the zones data sheets ultimately supported a more objective and reducible outcome. The most important properties considered in this classification were the thermal admittance, canyon geometry (H/W) ratio, nature of the buildings, and height of roughness element, function and anthropogenic activities. Where site metadata were incomplete or poorly aligned as compared with that of Steward and Oke, the process of selecting — "best fit" zones became one of skilled judgment, knowledge of the field site and discretion of the researcher rather than automated matching.

Knowledge based detection method for LST, NDVI, NDWI AND NDBI

The normalized surface temperature was prepared using the following steps as outlined by, USGS (2016).

Step1: Conversion of DN Values to Radiance
The following equation was used to convert DN's to radiance units, expressed as:
Lλ = ((LMAXλ - LMINλ)/(QCALMAX-QCALMIN)) * (QCAL-QCALMIN) + LMINλ
Step2: Conversion from Radiance to Temperature in Degree Kelvin
The formula below was used for conversion of radiance to temperatures in degree Kelvin:

$$T = \frac{K2}{Ln\left(\frac{K1}{L\lambda}+1\right)}$$

T = Effective at-satellite temperature in Kelvin

K2 = Calibration constant 2 from Table
K1 = Calibration constant 1 from Table
Lλ = Spectral radiance in watts/(meter squared * ster * µm) USGS (2016)
Step3: conversion from Degree Kelvin to Degree Celsius

The derived temperature in degree Kelvin was then converted to degree Celsius using the formula: C=K-273.15 and UHI calculated.

Step 4: Isotherm interpolation

Isotherm for the derived UHI will be interpolated into isotherms using standard Kriging method and linear variogram model from the ArcGIS package for spatial interpolation and digitization (tracing) of the isotherm. This revealed the spatial distribution of the UHI in the study area in terms of isotherms.

Normalized difference vegetation index (NDVI) calculations

The first step in the calculation of normalized difference vegetation index (NDVI) was land-cover classification. Supervised classification was employed to categorize the images into high, medium and low density vegetation. Normalized Difference Vegetation Index (NDVI) was determined from the pixel values of the satellite image using the following equation (Gallo and Owen, 1999).

NDVI = *(IR –R) / (IR + R)* or

$$NDVI = \frac{TM\ Band\ 4 - TM\ band\ 3}{TM\ Band\ 4 + TM\ Band\ 3}$$

Where *IR* is the pixel value of the near-infrared band (0.72–1.1 ⌈m) and *R* is the pixel value of the visible red band (0.58–0.68⌈m).

Extracting built up density

Normalized Difference Built-up Index (NDBI) was used to extract built up density of the study area from the Landsat_8 image. NDBI was extracted using ArcGIS-Raster calculator functions of the spatial analyst tool using the equation;

NDBI = MIR – NIR / MIR + NIR or

$$NDBI = \frac{TM\ Band\ 5 - TM\ band\ 4}{TM\ Band\ 5 + TM\ Band\ 4}$$

Where NIR = Near Infrared Reflectance; MIR = Mid Infrared Reflectance (Aneesh et'al, 2015).

Normalized Difference Water Index (NDWI)

NDWI processes green and mid-infrared spectral bands to extract water areas (Xu, 2005). Hence, to remove water signatures from the output image of the study area and increase the spectral contrast among built-up area, bare land and other land cover classes, NDWI was used, it was extracted from the satellite images using the equation follow:

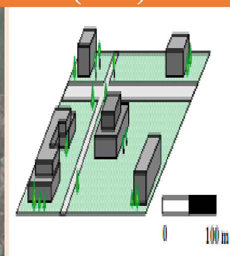
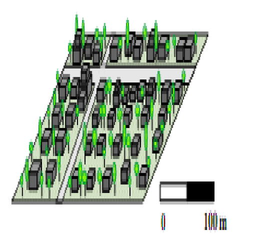
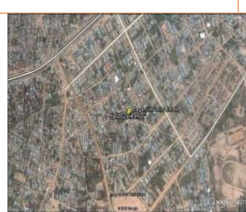
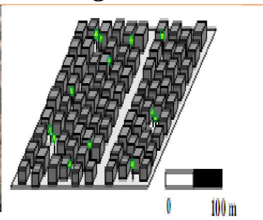
$$NDWI = \frac{TM\ Band\ 3 - TM\ band\ 7}{TM\ Band\ 3 + TM\ Band\ 7}$$

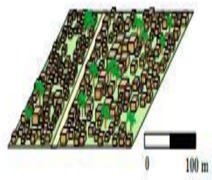
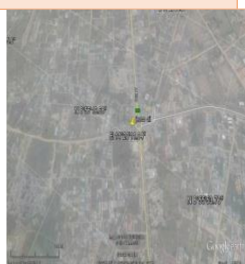
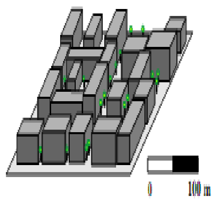
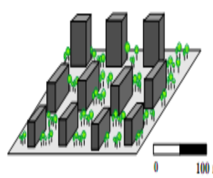
Stepwise regression approach was used to (i) identify parameters defining UHI intensity and (ii) model spatial structure and temporal variations in the study area.

Result of Findings

The result of findings shows that, Jalingo metropolis is represented in the thermal climate zones (TCZ) classified by Stewart and Oke (2009). Six of the TCZ identified in the study area include TCZ 9, TCZ 8, TCZ 7, TCZ 5, TCZ 3 and TCZ 2, (Table 1).

Table: 1. LandUse/LandCover Typology in Jalingo.

Site	Satellite view	Thermal climate zone (TCZ)	Site Photo	Zones properties and Site description
Site 1 (T.S.U Jalingo) **8°54'15.14" N 11°19'04.03" E** **Altitude=204.81m**		 **(TCZ 9) Open space**	 C.O.E Jalingo	**H/W %built[2]QF[3]** **1.75 30-40 5-10** **Large widely set, mid- rise buildings in an open place. Buildings vary in size, distribution height with abundant vegetations**
Site 2 (Technobat mile six) **8°57'53.38" N 11°22'22.93" E** **Altitude= 224.1m**		 (TCZ 7) Regular Housing	 Technobat	**0.70 40-70 10-15** **Low rise buildings that are detached. And the Buildings separated by yards, and set along medium width streets. Light traffic flow and uniform in design**
Site 3 (Magami) **8°54'36.00" N 11°20'49.92" E** **Altitude= 196.9m**		 (TCZ3)Compact Housing	 Magami	**1.30 >70 20-30** **Buildings densely packed and are low rise. Light traffic flow and Construction materials uniformly arranged.**
Site 4				**0.65 >65 >5**

(Anguwan N.T.A) **8°53'20.35" N 11°22'23.12" E** **Altitude= 226.8m**		 TCZ 8) Shanty town	 **Anguwan NTA**	**Buildings small and fragile, densely packed, separated by narrow streets and alleyways. Mostly unpaved, swampy compacted surfaces.**
Site 5 (Roadblock) **8°56'12.56" N 11°20'16.82" E** **Altitude= 211.8m**		 (TCZ 2) Old core	 Road block	**1.20 >80 30-50** **Buildings are often large and dense, attached or closet, and homogeneous in character with wide streets. Heavy traffic flow.**
Site 6 (Comm.quarters) **8°54'25.65" N 11°23'30.56" E** **Altitude= 213.4m**		 (**TCZ 5) Block housing**	 Comm. Q	1.60 <80 20-35 **Medium high rise** **buildings uniform in design (height and width), with heavy materials. Abundance of vegetation and open space among buildings with light traffic flow.**

Source: Asa *et al*, 2017

Descriptive Statistics of the Urban Parameters

Table 2 shows the statistical results of the urban parameters LST (ºC), NDVI, NDWI and NDBI. The result indicates that maximum LST in the study area is 37 ºC, minimum LST is 32.5 ºC, while the mean LST is 34.7 ºC and the standard deviation is 1.854. Normalize Difference Vegetation Index (NDVI) ranges from -0.052 to 0.165. The mean is -0.061 and standard deviation is 0.311. From the statistical result presented in Table 2, NDBI ranges from -0.18 to 0.299 with a mean of 0.154 and standard deviation of 0.135. On the other hand, the result shows that Normalize Difference Water Index (NDWI) ranges from -0.765 to -0.189 with a mean of -0.384 and a standard deviation of 0.260. The results imply that vegetation index in the city is below average NDVI which means there has been wide absence of vegetation and this could influence the development of UHI. Furthermore, the result of water index shows that the city contained few open water features which can define the turbidity of water in the area that can affect temperature distribution. High built up density observed in the city implies that most natural environment was replaced by artificial features such as pavements, interlock buildings among others. This may have consequential effect on temperature of the study area.

Table 2: Result of LST (ºC), NDVI, NDWI and NDBI Analysis

Parameters	Maximum	Minimum	Mean	Std. Deviation
LST (ºC)	37	32.5	34.725	1.854
NDBI	0.299	-0.18	0.154	0.135
NDWI	-0.189	-0.765	-0.384	0.260
NDVI	0.165	-0.052	-0.061	0.311

Land Surface Temperature (LST)

The result of the land surface temperature (LST) derived from Landsat 8 band 10 as can be seen in figure 2, shows LST value decrease from the city centre to the periphery as such high temperature value is recorded in the city center. This finding corroborates that of Balaze et al (2009) in Hungary and Aneesh et'al (2015) in India. The high temperature in the city center of the study area can be attributed to the high anthropogenic activities within the city center and the replacement of most natural land surface cover with artificial land covers such as concretes interlock roof tops, pavements and tarred roads coupled with smoke-from vehicle exhaust and population congestion which have the ability to increase anthropogenic heat flux that can raise temperatures of a place. On the other hand, the presence of natural surfaces in the rural periphery and low anthropogenic activities as a result of low population may account for the low temperature recorded in the periphery. The statistical result of LST is shown in Table 2.

Normalized Difference Vegetation Index (NDVI)

The result of Normalized Difference Vegetation Index is presented in figure 3 below. This the result revealed that lower values of NDVI is observed in high density built-up areas which includes commercial, residential and industrial areas within the city and higher NDVI values in agricultural fields and near water bodies as shown in figure 3. This finding is similar to Aneesh et al (2015), Savić S, Unger Gál, Milošević, Popov (2013) (2013) and Balaz et'al (2009). The high density built up in the study area are the TCZ (4) Anguwan NTA, Magami TCZ (3) as well as the

TCZ (5) Road Block and the market area in the heart of the study area. ATC area in the Eastern part of the map (fig.3) also shows low NDVI. This is not unconnected with the presence of the Taraba State University in the area which attracts more population that results in higher human activities. Table 2 shows the statistical results of NDVI.

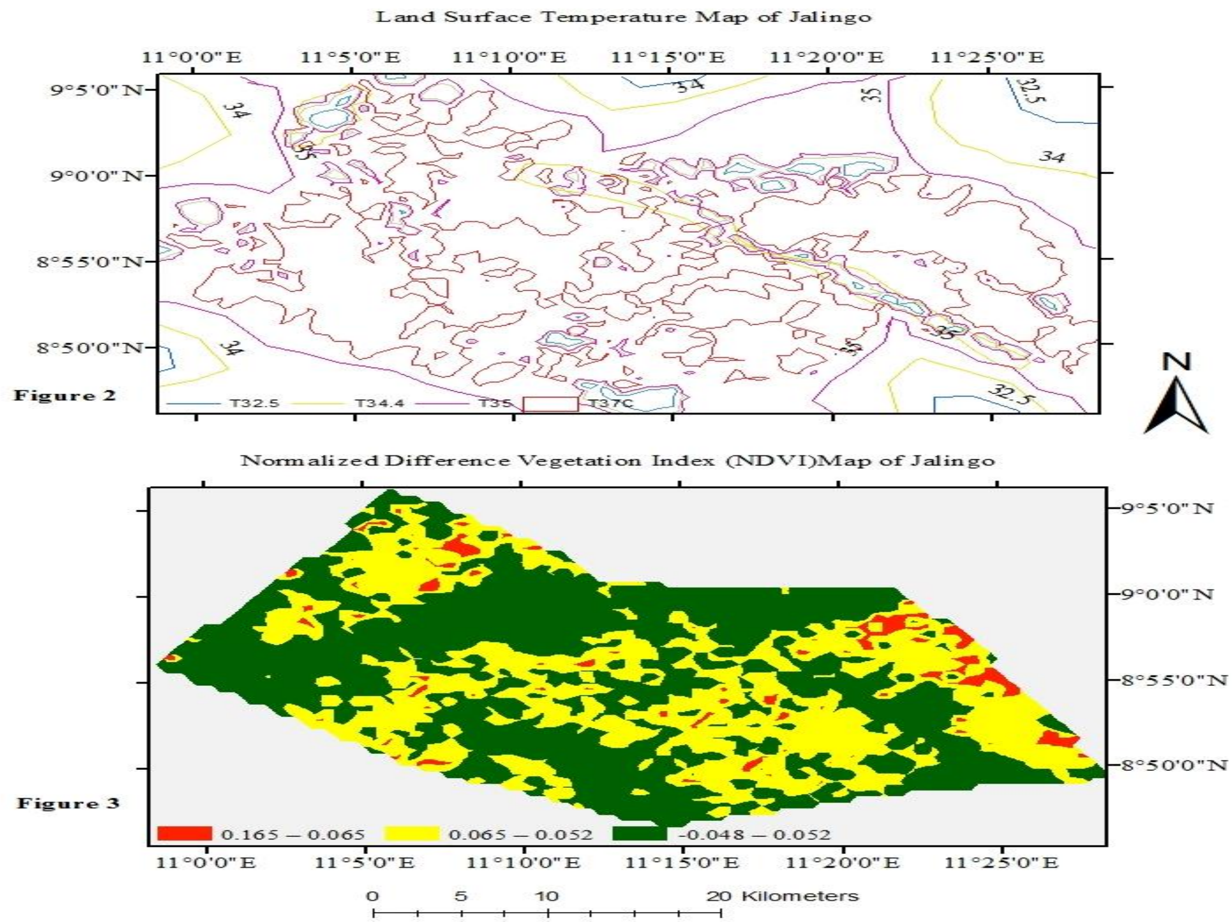


Fig. 2: LST Map and fig. 3 NDVI Map

Normalized Difference Built Index (NDBI)

Normalized Difference Built Index (NDBI) was extracted as can be seen in fig.4 below. It has been found that higher values of NDBI is observed in high density built-up areas which includes commercial, residential and industrial areas within the city and lower NDBI values in agricultural fields and water bodies as shown in figure 4. The statistical result of NDBI is presented in Table 2.

Normalized Difference Water Index (NDWI)

The use of Normalized Difference Water Index (NDWI) has been suggested by Ogashawara and Bastos (2012) for reducing the spectral confusion between built-up and bare areas, arguing that bare areas are likely to have a higher water content than built-up areas (impervious surfaces). NDWI was extracted and the result is presented in fig. 5. The results show that higher NDWI was found in mostly the agricultural fields near water bodies and TCZ 9. Thus, the study area can be said to show evidence of higher NDWI with the lowest recorded on the periphery of the study area. The lowest NDWI in the peripheries of the study area has to do with the higher built-up density recorded in those areas and the evidence of lower vegetation cover. Hence, this implies that areas with low NDWI are in few open water areas, thus the cooling effect of water body may not have impact on the temperature of the areas.

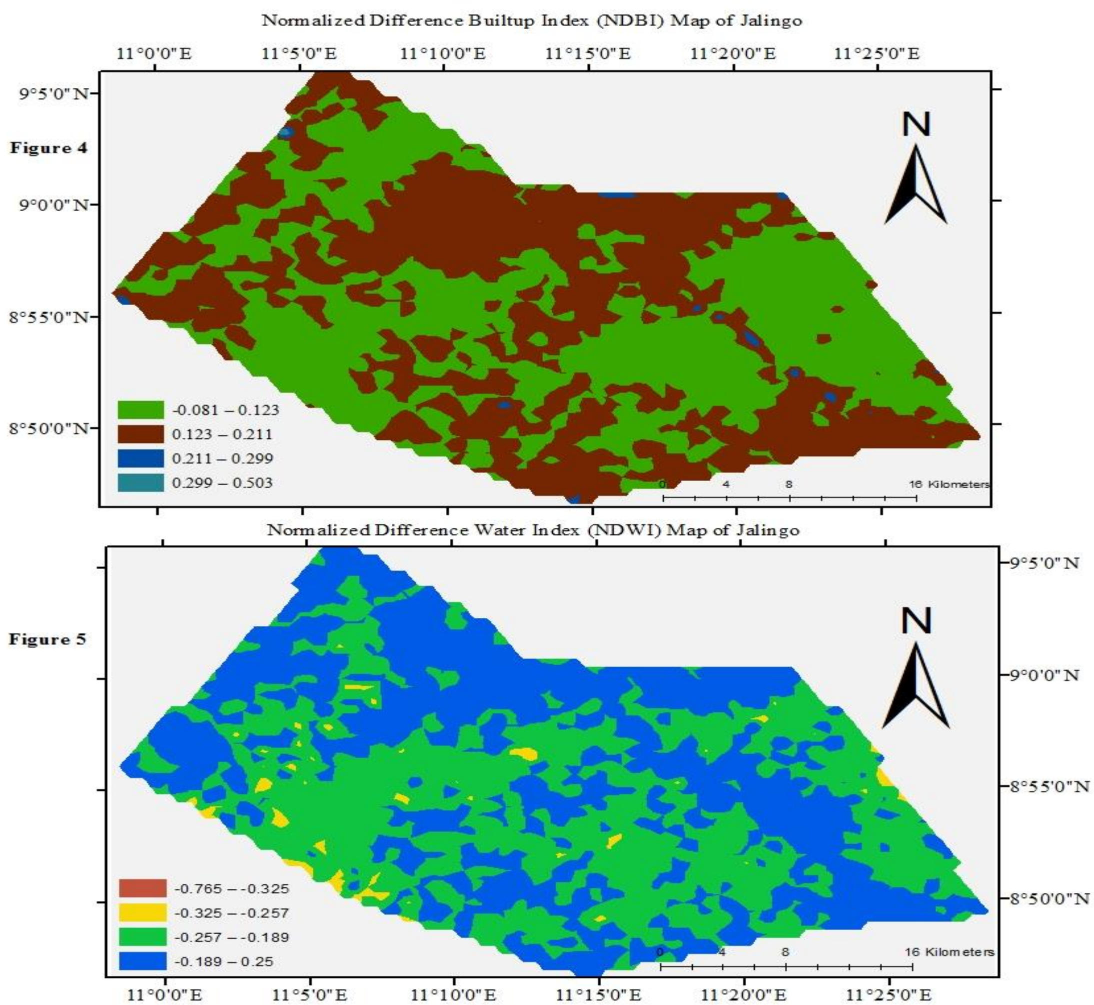


Fig. 4 NDBI map and Fig. 5 NDWI map

Relationship Between Urban Parameters and Land Surface Temperature

The relationship between LST and NDVI was calculated using Pearson correlation. The result (Table 3) shows negative correlation between LST and NDVI in the study area with a correlation coefficient of - 0.962 which is significant at 0.05% confidence level (2-tailed). It implies that as vegetation cover decreases, land surface temperature increases. Thus, areas of higher vegetation tend to have low temperatures. The result is similar to findings by Laosuwan and Sangpradit (2012) in their study on monitoring urban heat island in Thailand. It also agreed with the works of Kun and Zhuang (2008) in China who also reported a negative correlation between LST and NDVI in a study on comparative and combinative effects of urban heat island.

Table 3: Correlations between LST and NDVI

		LST	NDVI
LST	Pearson correlation	1	-.962*
	Sig. (2-tailed)		.038
	N	4	4
NDVI	Pearson correlation	-.962*	1
	Sig. (2-tailed)	.038	
	N	4	4

*. Correlation is significant at the 0.05 level (2-tailed).

Relationship between LST and NDBI

The relationship between LST and NDBI was calculated using Pearson correlation and the result is shown in Table 4 below. The result indicates a strong positive correlation which is significant at 0.01% level with a correlation coefficient of 0.998. The result therefore means an increase in the value of NDBI will subsequently increase land surface temperature in the study area. The result agrees with findings in other places by Aneesh et al (2015), Savić et al (2013), Sun, Lin, and Ou, (2007), Chen et al (2009) and Zhao and Wang (2002). In their separate studies, they found a strong positive correlation between LST and NDBI. Therefore, this study deduced that built-up density is an important factor affecting temperature in the study area.

Table 4: Correlations between LST and NDBI

		LST	NDBI
LST	Pearson correlation	1	.998**
	Sig. (2-tailed)		.002
	N	4	4
NDVI	Pearson correlation	.998**	1
	Sig. (2-tailed)	.023	
	N	4	4

**. Correlation is significant at the 0.01 level (2-tailed).

Relationship Between LST and Normalized Difference Water Index (NDWI)

Relationship between LST and Normalized Difference Water Index (NDWI) was calculated and the result is presented in Table 5 below. The result as shown in Table 5 indicates a strong negative correlation between LST and NDWI with a correlation coefficient of -0.869 which is significant at 0.05% level (2-tailed). Thus, the result means that as value of NDWI decreases, temperature values increase significantly. Thus, temperature increases with decreasing value of

NDWI. The result agrees with findings of Aneesh et al (2015), Zhao and Wang, (2002) and Gao, (1996).

Table 5: Correlations between LST and NDWI

		LST	NDWI
LST	Pearson correlation	1	-0.869*
	Sig. (2-tailed)		0.131
	N	4	4
NDVI	Pearson correlation	-0.869*	1
	Sig. (2-tailed)	0.131	
	N	4	4

*. Correlation is significant at the 0.05 level (2-tailed).

Trend of Relationship Between LST and the Urban Parameters

The trend of relationship between urban parameters and land surface temperature in the study area was determined using regression model and a scatter plot graphs were drawn for better understanding. The scatter plots of LST vs NDVI and LST vs NDBI and LST vs NDWI are presented in figures 6, 7 and 8 respectively. Regression analysis has been applied to find the trend of the relationship between LST with NDVI, NDBI and NDWI. It has been observed that there is a negative correlation of LST with both NDVI and NDWI, which interprets that higher NDVI and NDWI can reduce the effect of UHI. Thus, vegetation cover is an important parameter which affects the variations in surface temperature of the study area due to the difference in behaviour of land use/land cover types. Variations in surface temperature are very less in higher NDVI areas. The trend lines of scatter plots show negative relationship between LST and vegetation indices for the period of study. From figures 6, 7 and 8, it can be concluded that the relationship of mean LST with NDVI, NDBI and NDWI is linear and shows the negative relationship between mean LST and vegetation indices. The figures also show the coefficient of correlation (R^2) values of 72.1% and 82.4% for NDVI and NDWI respectively for the linear relationship.

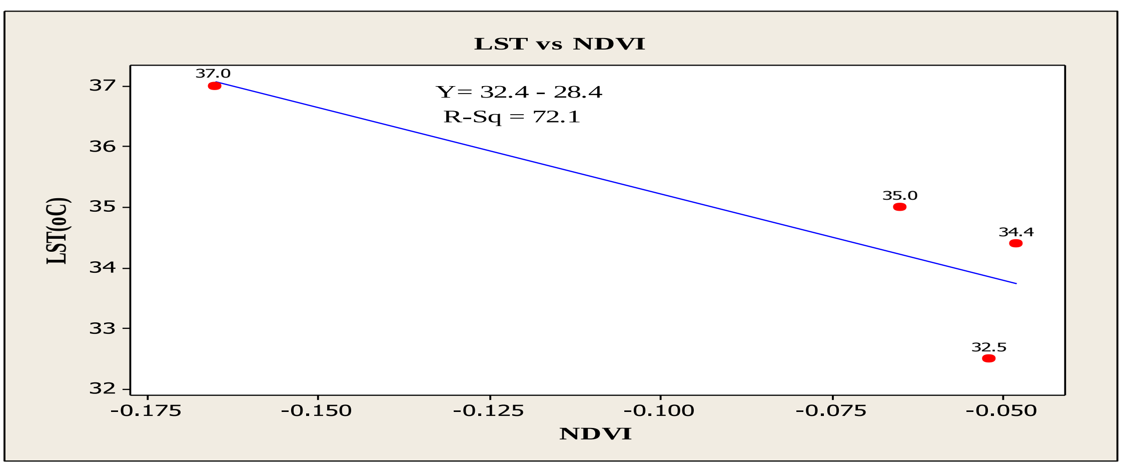


Fig. 6: Scatterplots of LST vs NDVI with the regression equation and coefficient

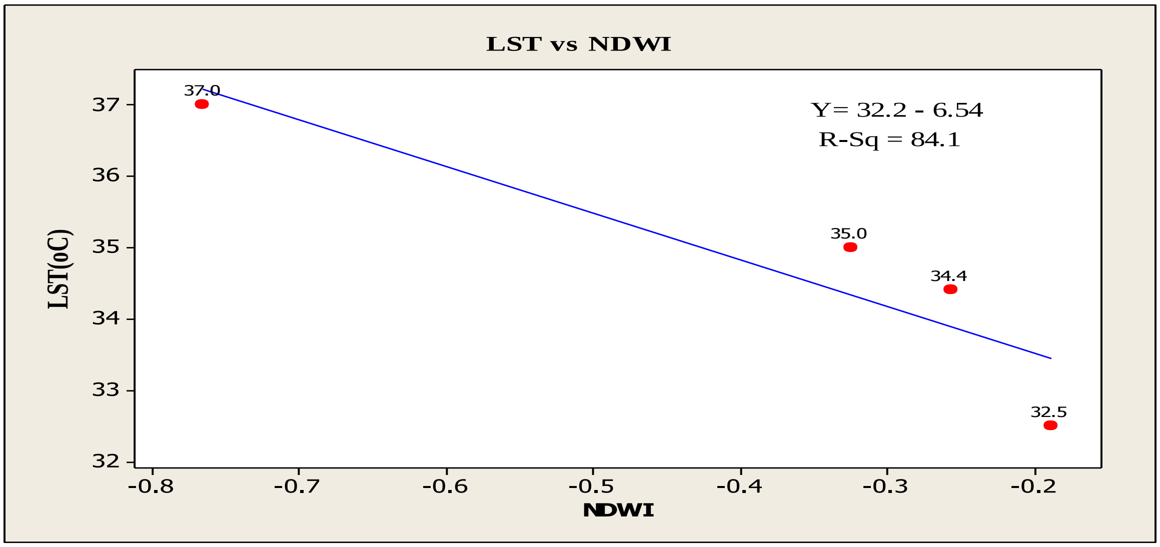


Fig. 7: Scatterplots of LST vs NDWI with the regression equation and coefficient

The scatterplots between LST vs NDBI relationship is shown in fig. 8. The same regression analysis which has been used in the two relations above is applied to find the relationship between LST and NDBI of the study area for the two periods. LST vs NDBI scatterplots show an irregular and compacted pattern and a rising trend can be observed. The analysis in the two previous cases above showed negative trend but here it has been found to show a positive correlation between LST and NDBI, which means that built-up areas can strengthen the effect of UHI. Whereas the higher vegetation covers at the periphery show relatively lower values of NDBI, the urban built up areas like roads, buildings, industries etc, have more imperviousness than the rural areas. Thus, it can be deduced that NDBI has a direct relationship with the imperviousness of the surface. The trend lines of scatter plots show linear and positive correlation between LST and NDBI along with the coefficient of correlation (R^2) of 96.5 for the linear relationship.

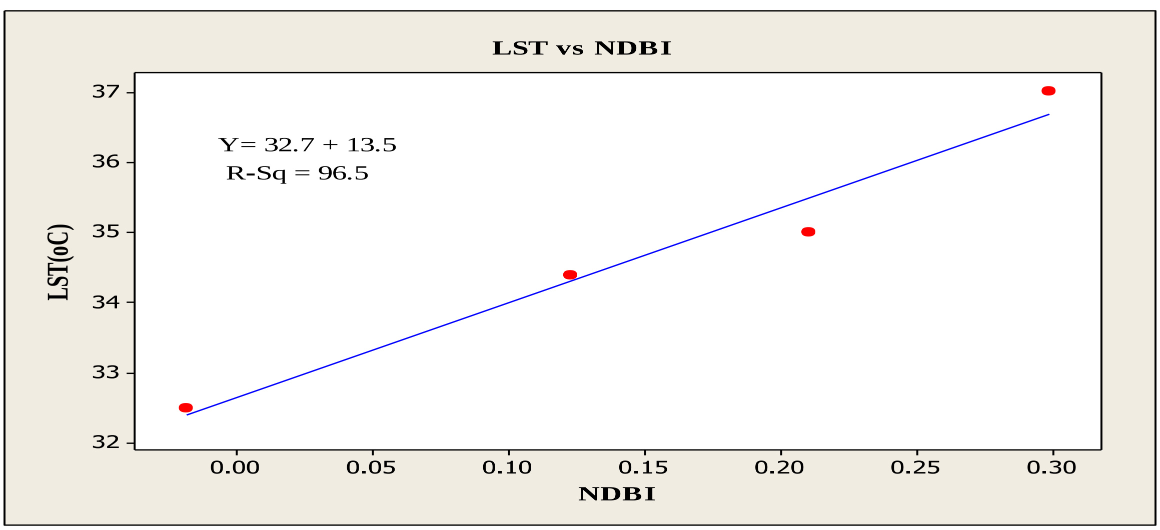


Fig. 8: Scatter plots of LST vs NDBI with the regression equation and coefficient

Conclusion

In this study, Landsat 8 data have been used for the derivation of four urban parameters i.e. LST, NDVI, NDWI and NDBI for Jalingo metropolis. The paper modeled the pattern of UHI distribution in the area and investigated individual relationships of LST with the three parameters (NDVI, NDWI and NDBI). The findings of the study revealed that highest temperatures were not only in the center of the city, but also in the outskirt, taking ATC area where the Taraba state University is located as example. The new built-up areas, because of fewer trees and green lands and more black asphalt concrete pavements, have higher surface temperature. Also the Central area of Jalingo extending from the market through Magami and Anguwan NTA areas have the most significant Urban Heat Island (UHI) effect and this can be attributed to the high level of anthropogenic activities going on in the area, closely packed buildings with dark surfaces, roads with asphalts on it and other materials with very low albedo. Rather than emitting, they absorb the greater part of the electromagnetic radiation that falls on them. The results of statistical analysis revealed negative correlation of LST with NDVI and NDWI, which means that green spaces and existence of water surface can reduce the effect of UHI and positive correlation between LST and NDBI which means that built-up areas can strengthen the effect of UHI. Thus, from the results, it was concluded that rapid urbanization and urban sprawling, absence of vegetation cover and low water index contributes to the major changes in the Land Surface Temperature. Therefore, built-up areas like residential, commercial and industrial mainly account for UHI effect. Finally, the results of regression analysis and scatterplots graph of each parameter with LST revealed a linear trend of relationship between all the parameters and LST. From the findings, it can be concluded that all the three parameters affect UHI significantly.

Recommendation

This study suggests that urban planners, decision-makers, and city managers formulate new policies and regulations that encourage residential, commercial, and industrial developers to include vegetation, such as trees, shrubs, and grass, when planning new construction. In particular, the city planning should adopt concept of green and blue city planning which may help create a conducive urban environment that offers many ecosystem benefits including cooling. These policies should include setting certain percentages of vegetation cover or numbers of small trees with height and crown coverage or shrubs before structures are built. This would prevent the clearing of land for built-up areas that typically leaves no vegetation cover, resulting in large areas of bare soils, buildings, and impervious surfaces. The concentration of these manmade surfaces elevates LST dramatically over the long run. Keeping existing vegetation or adding vegetation during construction offsets the heat retained by these surfaces. This is especially true for desert cities.

The study also recommends further study to identify other parameters that can affect the temperature of the study area so that a statistical model will be simulated for predicting and estimating urban heat island.

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