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Analysis of Landscape Dynamics Impacts on Micro-climate of Akure and its Environs

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ABSTRACT

Global surface temperature increase has contributed to the warming of our planet earth. Urban expansion in city centres has transformed the city landscape. This landscape transformation has led to temperature changes in the environments. This study thereby examined the contributions of landscape types to temperature variation in the study area. The sixteen years interval (1984, 2000 and 2016) temperature data and land use maps used in this study were extracted from Landsat images. The landscape dynamics assessment was carried out using spatial metrics in FRAGSTATS environment, Weight model was used to determine temperature contribution by each landscape type for each scenario. Results showed that built up areas and bare surfaces contributed to temperature increase over the years at increasing rate while vegetation cover had negative impacts. The effect of water on temperature was not consistent as it had the highest impact in 2000 and dropped in 2016.The Shannon's Index (SHI) values of 0.24, 0.31, and 0.61 for 1984, 2000 and 2016 respectively, revealed continued aggregate divergence of the built up and bare area segments, which is an indicator of increasing human activities that could lead to temperature increase. There was 0.054^{o}c average temperature decrease between1984 and 2000 and 0.861^{o}c increase between 2000 and 2016.This increase is close to the predicted 1.4^{o}c global mean temperature in the next century by the Inter-governmental Panel on Climate Change, which requires swift combating measure such as tree planting.

Keywords: Landscape; Urban expansion; Temperature; Environment; and Tree planting.

Introduction

Cities often exhibit higher mean average temperatures than surrounding rural areas (Kieron *et al.*, 2013).The urban setting including buildings, cities and infrastructure, represents one major set of factors that affect changes in climate, while at the same time support or provide opportunities for a livelihood. Some human activities in the cities today produce carbon and other gasses that can warm up the atmosphere (Joshi, 2015). Urbanization always given rise to a significant increase in environmental temperature. Economic growth and industrial processes that have replaced vegetation cover in the past four decades have resulted to various negative environmental impacts including pollution and Urban heat islands (UHI) (Joshi, 2015). Factors that contribute to this phenomenon include the thermal properties, height and spacing of buildings, the production of waste heat, air pollution, and differences in landscape (Kieron *et al.*, 2013).Landscape changes (LSC) is often regarded as the most important factor that influence the planet earth with associated effects on the global climate (Li *et al.*, 2014).

Landscape changes have become a central component in current strategies for managing natural resources and monitoring environmental variations (Agbor *et al.*, 2012). Several human activities have modified the landscapes and this development has had a deep effect on tour natural environment (Yang, 2001). Therefore, good knowledge of landscape change pattern has been a basic interest for researchers in global change (Southworth, 2004).Recently, scientists have continued to use remotely sensed data to enhance the accuracy of datasets which explain the distribution of land cover and impacts of its changes at different time and space (Agbor and Makinde, 2018; Makinde and Agbor, 2019).The characteristics of temperature as relate to landscape changes have been studied extensively over the years. For example, Xiao-Ling *et al.*, (2005) found that temperature changes are related to certain land-cover types, (Agbor and Makinde, 2018; Makinde and Agbor, 2019) also observed effects of changes in land use and land cover of Akure on the temperature distribution between 1984 and 2016, though did consider the contribution of each land cover type to the area's temperature variations, which is the main focus of this study. Bayes *et al*. (2013), found out that surface temperature changes are associated with vegetation and other land cover types dynamics in an environment. The results of multiple correlation and regression analyses indicate that surface temperature presents a positive correlation with built up and bare land areas and negative correlations with vegetation and water body. Past studies in the area examined the relationships between temperature and other land cover types as cited above, but did not critically determine the contribution of individual land cover type in the variations in temperature over the years. The purpose of this research work is therefore, to assess the changes in landscape types dynamics in Akure and its environs and investigate quantitatively the contributions of such changes to the microclimate of the area.

Materials and Methods

Study Area and Data

This study was carried out in Akure and its suburbs with Akure as the major dominating town. It lies between longitude 5°06'E to 5°38'E and between latitude 7°07'N to 7°37'N in South-west Nigeria. The three major settlements within the area include Apomu, Ipogun, and Akure (Figure. 1). The area covers about 161989.2 hectares. The area experiences warm humid tropical climate, with average rainfall of about 1420 mm per annum with the little short break in August. The rainfall in the area is seasonal with a short dry season occurring usually between December and March. the area is characterized by a principal rainy season occurring in May, June and first half of July, and a secondary rainy season in the latter half of September and October. The Annual average temperature of the area is 31.3°C and its mean annual relative humidity is about 82% (data based on 2014 data from the Nigerian Meteorological Agency). The area is characterized by rain forest Akure lies on a relatively flat plain of about 250 m above sea level within the Western Nigerian plains. The area towards Ado-Ekiti and Idanre are hilly and studded with large granite formation, rising to 410m and 496m above sea level respectively. The landscape of the region is relatively flat, this means it is located on a plain and is crested by a popular river called river Ala and owena dam (Aderoju *et al.*, 2013). The area is characterized by granitic formations said to be of volcanic origin, underlined by basement complex rocks, which are mostly impermeable gneisses and granites (Aderoju *et al*, 2013). The city had a

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population of less than 50,000 in 1952 and 70,641 in 1963 and was estimated as around 110,000 in 1980, the population increased to 484,798 in 2006. The other local government areas of Idanre and Ifedore where data were collected have population of 289,838 and 144,136 in 2006 respectively (National Bureau of Statistics, 2010). There are two major types of settlements within the study area and these are densed and linear settlements. The dense settlement is the type in the urban area of Akure where the buildings are concentrated with many social amenities such as stadium, schools, recreational centres, churches and mosques. The rural settlements such as Apomu and Ipogun are linear with buildings located along the roads in a linear form.

To quantitatively measure the direct contributions of each landscape type to local temperature in the study area, Landsat 5 TM image (1990); Landsat 7 ETM+ image (2003) amd OLI Landsat image (2016), were selected. Table 1 represents the dataset used in this study.

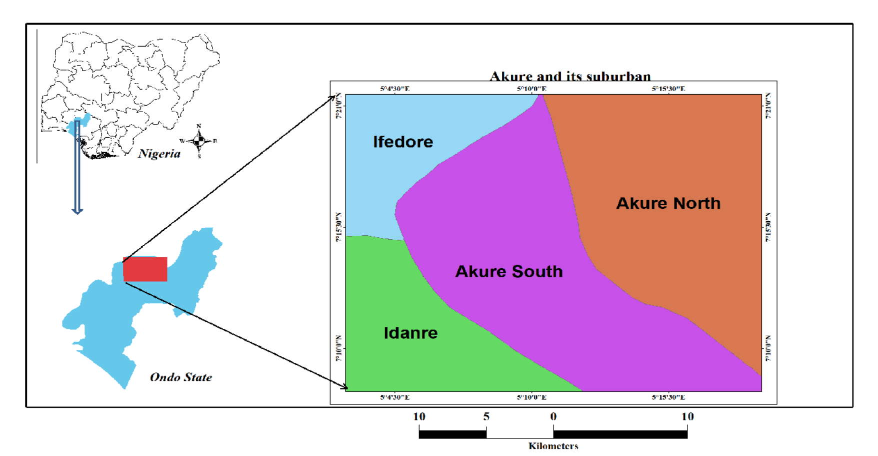


Figure **1:** Map of Ondo State Showing Study Area.

Table 1: Dataset used for this study

Satellite Sensor	Spatial resolution	Acquisitionyears	Path	Row	Source
Landsat 5, 7	30m x 30m	1990, 2003,	190	50	GLCF
Landsat 8	30m x 30m	2016	190	50	GLOVIS

The Landsat data covering the area for only dry season were downloaded from the NASA official website, processed and analyzed for studying the urban landscape changes and modification effects of such changes on local temperature (Xiao-Ling *et al.*, 2005)

Assessments of Landscape Patterns and Local Temperature

The landscape patterns were determined by first extracting the land use land cover from satellite images in different classes: built up, bare land, vegetation and water body. The land cover types were extracted in Idrisi software environment. The classified images served as inputs to determine clustering and diversity of each land cover type using the following indices: **D**iversity Indexes, Class area Index, Edge Contrast Index, Shape Index, Class Density, Fractal Dimension index, Nearest Index, Class Percentage Index, and Class Evenness Indexes. (Turner,1990a; Rajesh and Yuji, 2009 and Bharath *et al.*, 2012). These indexes have been used by ecologists to measure landscape composition. These are briefly described below.

Edge Contrast Index: Contrast means the magnitude of difference between adjacent patch types with respect to one or more ecological attributes at a given scale that are relevant to the organism or process under consideration (McGarigal *et al.*, 2012) The 'edge effects' of land cover classes are due to the degree of contrast between the classes. This index sums up the class perimeter lengths (m) and multiplies the sum by their corresponding contrast weights, divided by total class perimeter (m), multiplied by 100 (to convert to a percentage (equation 1)

$$ECON = \frac{\sum_{k=1}^{n}(p_{ijk} \bullet d_{ik})}{Pij}(100) \ldots\ldots\ldots\ldots 1$$

Shape Index:

This index describes the shape pattern of the class segments or patches. This is calculated by dividing patch perimeter (m) by the square root of patch area (m^2), adjusted by a constant to adjust for a square standard using raster inputs (Xianli *et al.*, 2014)

$$S_{Index} = \frac{0.25P_{ij}}{\sqrt{a_{ij}}} \ldots\ldots 2$$

SHAPE = 1 when the patch is circular (vector) or square (raster) and increases without limit as patch shape becomes more irregular.

Class Diversity (Shannon's) Index:

This measures the relative patch diversity of class p. This diversity index has been used by ecologists to measure landscape composition. The index equals minus the sum, across all patch types, of the proportional abundance of each patch type multiplied by that proportion (McGarigal *et al.*, 2012).

$$\text{SHDI} = -\sum_{i=1}^{n}(p_i \bullet \ln P_1) \ldots\ldots\ldots 3$$

SHDI = 0 when the landscape contains only 1 patch (that is., no diversity). SHDI increases as the number of different patch types (that is., patch richness, PR) increases and/or the proportional distribution of area among patch types becomes more equitable.

Simpson's Evenness Index

This measures the patch distribution and abundance of class *p*SIEI equals 1 minus the sum, across all patch types, of the proportional abundance of each patch type squared, divided by 1 minus 1 divided by the number of patch types. In other words, the observed Simpson's Diversity Index divided by the maximum Simpson's Diversity Index for that number of patch types. (Xianli *et al.*, 2014).

$$SEI = \frac{1-\sum_{i=1}^{n}(P_i^2)}{1-(\frac{1}{n})} \ldots\ldots\ldots\ldots 4$$

SIDI = 0 when the landscape contains only 1 patch (that is., no diversity) and approaches 0 as the distribution of area among the different patch types becomes increasingly uneven (i.e., dominated by 1 type). SIDI = 1 when distribution of area among patch types is perfectly even (that is., proportional abundances are the same).

Nearest Neighbour index:

This equals the distance (m) to the nearest neighboring patch of the same type, based on shortest edge-to-edge distance (McGarigal *et al.*, 2002).

$$N_n = h_{ij} \text{.......................5}$$

N_a>0, without limit.

Class Percentage (%Land)

This equals the sum of the areas (m^2) of all patches of the corresponding patch type, divided by total landscape area (m^2), multiplied by 100 (equation 6)to convert to a percentage); in other words, %LAND equals the percentage the landscape comprised of the corresponding patch type.

$$\%P = \frac{\sum_{j=1}^{n} a_{ij}}{A}(100)\text{.............6}$$

%LAND approaches 0 when the corresponding patch type (class) becomes increasingly rare in the landscape. %LAND = 100 when the entire landscape consists of a single patch type; that is, when the entire image is comprised of a single patch.

Fractal Dimension (FDim)

MPFD equals the sum of 2 times the logarithm of patch perimeter (m) divided by the logarithm of patch area (m^2) for each patch of the corresponding patch type, divided by the number of patches of the same type; the raster formula is adjusted to correct for the bias in perimeter (equation 7)(Li 1989).

$$FDim = \frac{\sum_{J=1}^{N}\left(\frac{2\ln(025P_{ij}}{\ln a_{ij}}\right)}{n_1}\text{....................7}$$

A fractal dimension greater than 1 for a 2-dimensional landscape mosaic indicates a departure from Euclidean geometry (that is., an increase in patch shape complexity). MPFD approaches 1 for shapes with very simple perimeters such as circles or squares, and approaches 2 for shapes with highly convoluted, plane-filling perimeters.

Edge Density (ED)

This is the sum of the lengths (m) of all edge segments involving the corresponding patch type, divided by the total landscape area (m^2), multiplied by 10,000 (to convert to hectares) (equation 8). If a landscape border is present, ED includes landscape boundary segments involving the corresponding patch type and representing true edge only.

$$ED = \frac{\sum_{K=1}^{N} e_{ik}}{A}(10{,}000)\text{....................8}$$

ED >0, without limit

ED = 0 when there is no class edge in the landscape;.

The surface temperatures were derived from the thermal bands of the images for each year using Equation 9. (Giannini *et al.*, 2015).

$$B_t = \left(\frac{K_2}{\ln\left(\frac{K_1}{A_r}+1\right)}\right) - 273.15 \quad \text{………….9}$$

where

B_t= º Kelvin, A_r =Top of Atmosphere radiance, K_1 and K_2 = thermal conversion constants from the metadata.(Agbor *et al.*, 2018).

Estimation of contributions by Landscape changes to Local Temperature

To assess the actual contribution of each land cover type to the temperature, temperature of every land use/cover type was calculated by averaging all corresponding pixel of a given land cover type. Considering the difference in temperature and atmospheric conditions between acquisition times of the Landsat images, The temperature intensity (equation 10) was used in our analysis, rather than absolute land surface temperature changes (Xiao-Ling *et al.*, 2005).

$$T_c = \frac{L\bullet T_a}{100} \text{........................10}$$

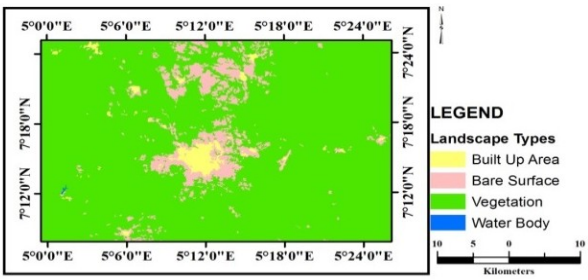
Where

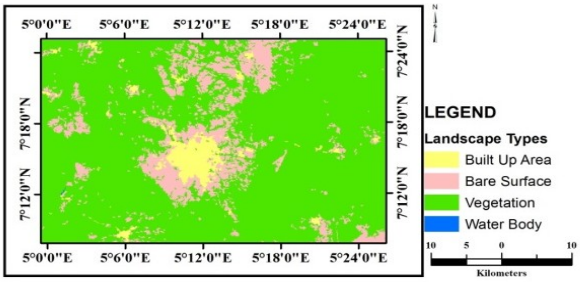
T_a is the difference between mean temperature across the years and total mean temperature l represents the weight of each landscape type. The mean temperatures were determined by up scaling 100 GPS points to the corresponding temperature signatures of thermal bands for the years considered.

Results and Discussions

Changes in landscape patterns

The Landscape change of Akure (between 1984 and 2016) was calculated from land use classes in the classified Landsat images (Figure 2). For each land use class, the spatial metrics change was calculated using FRAGSTAT. Table 2 shows that SHDI, SEI, NN, SI, FDim, CONI, NumP, ED and %Land changes between 1984 and 2016. The SHDI, SEI and SI increased over the years, while other landscape types were not consistent except the CONI that remained constant all through the years. Increased in SHEDI indicates multiplicity of class patches from 1984 to 2016 while the increase in SEI shows that the classes became more even. The values of the NN were indications that class patches were less dispersed in 1984, which increased in 2000 but reduced drastically in 2016. Fragmentation of the area reduced in 2000, which must have led to the increase in SEI at decreasing rate between 1984 and 2000 when compared to the changes in NumP between 2000 and 2016. Fragmentation was strengthened during this period, giving rise to a complex assemblage of isolated and diverse landscape patches and ecological processes. The Landscape mosaic exhibited patch shape complexity for the years with highest complexity in 2000. Associated with this are increased edge habitats and their effects (Couvillion, 2005), and greater loss of connectivity.





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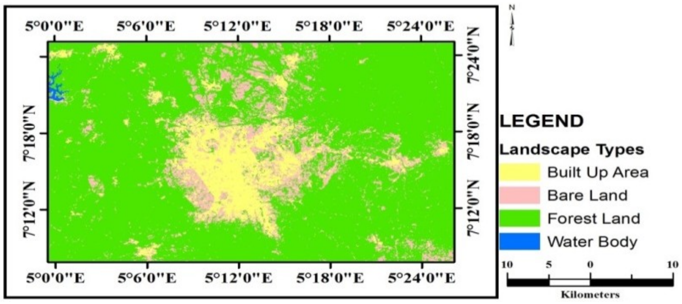

Figure 2: Landscape pattern in 1984, 2000 and 2016 respectively (Source: Makinde *et al*, 2019)..

Table 2 Metrics Values for each Landscape type between 1984and 2016

Date	Landscape metrics								
1984	SHDI	SEI	NN	SI	FDim	CONI	NumP	ED	%Land
All Classes	0.24	0.34	93.8	1.24	1.04	1	10530	18.86	-
Built Up	-	-	133.24	1.25	1.04	1	1106	2.65	2.27
Bare Surface	-	-	93.39	1.25	1.04	1	7672	17.08	11.5
Vegetation	-	-	53.15	1.21	1.03	1	1623	16.94	86.2
Water Body	-	-	288.75	1.11	1.02	1	129	0.03	0.04
2000									
All Classes	0.31	0.41	306.7	2.25	1.12	1	605	18.86	-
Built Up	-	-	940.58	2.13	1.12	1	72	2.65	3.64
Bare Surface	-	-	233.16	2.24	1.12	1	437	17.08	14.55
Vegetation	-	-	164.76	2.35	1.13	1	95	16.94	81.8
Water Body	-	-	1	2.9	1.18	1	1	0.03	0.01
2016									
All Classes	0.49	0.61	72.4	1.26	1.04	1	19847	69.83	-
Built Up	-	-	109.35	1.24	1.04	1	3334	16.5	8.5
Bare Surface	-	-	65.43	1.27	1.04	1	13102	68.49	24.92
Vegetation	-	-	54.1	1.27	1.04	1	3387	52.49	66.33
Water Body	-	-	1292.92	1.51	1.05	1	24	0.36	0.25

Mean temperature for Landscape types

Table 3: Mean temperatures of the Land Cover Types from 1984 to 2016.

LULC	1984	2000	2016	Total	Mean ^{O}C
Built-Up	32.8	30.9	32.5	96.2	32.07
Bare-Land	28.9	29.03	31.9	89.83	29.94
Vegetation	25.6	24. 7	28.7	78.37	26.12

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Water	23.7	23.6	26.6	73.9	24.63
Average	-	-	-	**28.19**	-

Table 3 summarizes the average surface temperature (ST) values by landscape types in the four periods. Clearly, the built-up land exhibited the highest ST, followed by bare soil, vegetation, and water body in all four periods. The findings signify that built-up areas increase surface temperature by replacing natural vegetation with non-evaporating, non-transpiring surfaces. Also mean temperature comparison of the different land cover in 2016 shows a great difference between them; Built up area has the highest temperature with 32.19^{0}C, followed by the bare surfaces with 31.9^{0}C, while Water bodies and Vegetation were 26.6^{0}C and 28.7^{0}C respectively. In addition, the ST increased for all land cover types over the periods. This research found that the temperature values ranged from about 14 ^{O}C to 36 ^{O}C. (figure 3).

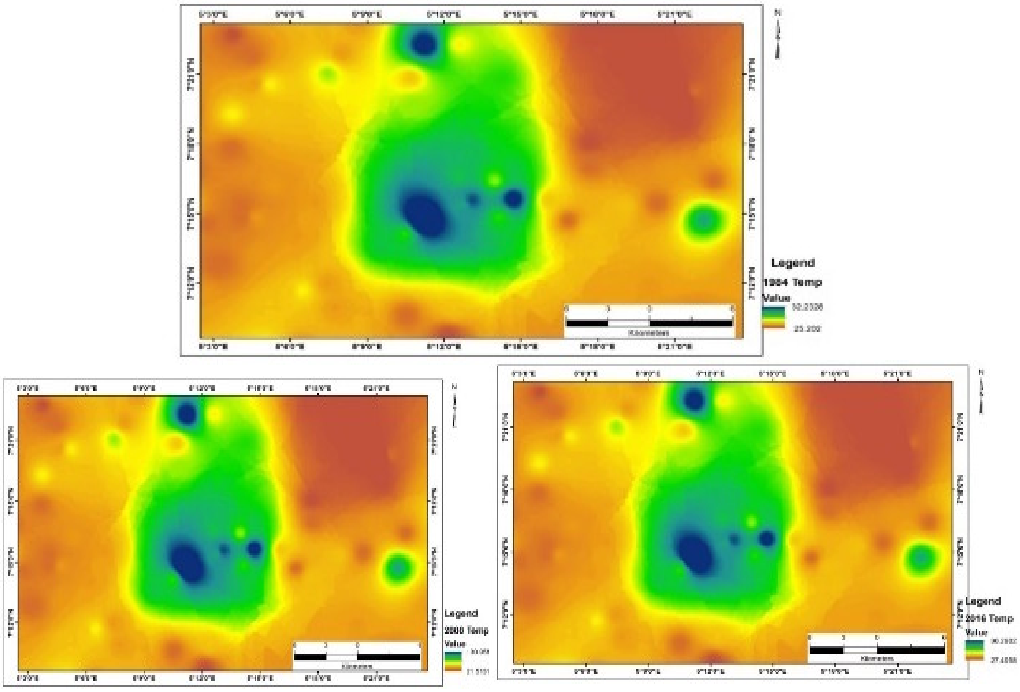

Figure 3: Temperature distribution in 1984, 2000 and 2016 respectively.

Landscape characteristics and effects on temperature

Quantifying the contribution of landscape types to local temperature, second level weight values was used. Further analysis considered other metrics statistics both at class and landscape levels. Using the statistics from the weight values (table 4), bare surface contributed most to the surface temperature of the area with the highest of 0.40°C followed by built up with the highest of 0.32°C. This development could be linked to large NumP values of both landscape types resulting to increased bare surface area and urban expansion Vegetation and water body values are negative indicating that they contributed to reduction in surface temperature, while built up and bare surface aided temperature increase by their positive values (Xiao-Ling *et al.,* 2005). The increase in temperature over the years (from table 3) could be attributed to increase in FDim, ED, and SI (Elif *et al.*, 2018). Class edge contrast structure describes by the CONI is a major factor in changing temperature. The relatively low contrast values over the years reflected in the high contrast level among all classes (Li and Chen, 2014). It is also good to state that the NumP values show vegetation was less fragmented in the year 2000 from base value of 1623 to 95 patches, thus the ability to mitigate temperature with least contributing effect to temperature increase between 1984 and 2000. This inference is based on the finding of Makinde *et al.* (2019), that reducing deforestation is an efficient method to mitigate urban heat island effect and human health effects of increased temperatures resulting from climate change and therefore, improve quality of life in urban areas. In contrast, the huge increase in vegetation segments from 95 in 2000 to 3387 in 2016 could not be unconnected to the increased mean temperature from 26.9°C in 2000 to 29.925°C in 2016 (table 4).Shannon's Diversity and Simpson's Evenness Indices, which explain fragmentation and patch distribution and abundance of class respectively, show similar trends, with both increasing throughout the period under study. Shannon's Diversity Index increased by 7percent (0.24 to 0.31) between 1984 and 2000, and a further 18 percent (0.31 to 0.49) between 2000 and 2016.Similarly, Simpson's Evenness Index, increased from 7 percent (0.34 to 0.41), between 1984 and 2000 to 20 percent (0.41 to 0.61), between 2000 and 2016. With both of these indices going towards one, the landscape showed more of fragmentation than aggregation between 1984and 2016. It could be added based on this information that ecological processes involving anthropogenic activities in the landscape increased throughout the study period. The existing increase in vegetation disaggregation calls for a more reasonable city layout and urban development to protect the city from severe heat index in the future. This agrees with (Balogun and Samakinwa, 2015) that the surface temperature of the urban environment of Akure has been increasing due to anthropogenic influence on the land use & land Cover pattern.

The percent increase in NumP, SHDI, SEI and %Land from 1984 to 2016 could be attributed to increased human activities (that characterized this period), in response to the economic and social reforms made across the entire country. Much of such activities could be credited to increase in impervious layers across the landscape. This increase in impervious surfaces could be attributed to increase in population, and economic growth (Balogun, 2015; Xu *et al.*, 2010).The observed decrease in NumP2000 does not indicate a reduction in human activities on the landscape such as urban expansion or agricultural activities, but could rather be the result of similar isolated patches joined to one another. Such aggregation of similar patches takes place when corridors are eliminated between similar patches, their connectivity increased, and their edges joined together. In the case of human habited areas for example, isolated settlements and villages may have joined to each other. The city itself assumed a more compact or organized expansion, rather than characterized by dispersed or isolated patches as major reason human settlements, especially in cities always contribute to increase in environmental heat island as shown in table 4 (Rajabi, 2014).

Table 4: Landscape types temperature contributions for the years under review

Landscape Types	TA	1984			2000			2016		
		W	Mean ^{o}c	T_c	W	Mean ^{o}c	T_c	W	Mean ^{o}c	T_c
Built-Up	3.88	2.23		0.09	3.60		0.14	8.19		0.32
Bare-land	1.75	11.16		0.195	14.6		0.26	22.78		0.40
Vegetation	-2.07	86.58		-1.79	81.80		-1.69	68.77		-1.42
Water	-3.56	0.03		-0.001	0.008		-0.0003	0.25		-0.009
Total T_c/W	-	100		-1.506	100		-1.5703	100		-0.709
Mean ^{o}c	-	-	27.75	-	-	26.9	-	-	29.925	-
Adjusted temperature	-	-	-	26.674	-	-	26.62	-	-	27.481

Conclusions and Recommendations

Changes in landscape structure have been recognized as a factor of local climate change. The resulting effects of the increased temperature have implications for human health and biophysical processes. The study presents some good findings regarding the impacts of landscape on ST, but also indicates that the relative impacts of landscape on ST vary in terms of structure and clustering of changing landscape. The results indicate that landscape composition influences temperature, but this relationship is not consistent for all areas and years. Where spatial configuration explains surface temperature, FDim and ED were quite handful. The class shape values appear very useful in explaining variations in surface temperature. The findings could be adopted for land use planning and policy making. In order to reduce the effects of temperature, planners must consider the composition and structure of the landscape. Future studies should expand the scope of this research by consider more landscape types in different study locations using higher resolution images.

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