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Mapping Spatiotemporal Land Use Land CoverDynamics of Yewa South LGA of Ogun State for Urbanization Monitoring

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ABSTRACT: *This research examines the Spatio-temporal changes of land use/ Land cover(LULC) and its effect on Land Surface Temperature (LST)in Ilaro town in Ogun state, Nigeria from historical remote sensing dataset (Landsat TM, ETM+ and OLI imageries acquired on 1990, 2000, 2010, 2018). Three sets of Landsat images were classified into five land use /land cover classes (built up, bare lands, vegetation and cultivated/mixed vegetation) using supervised classification algorithm in ENVI and ARCGIS. The result demonstrated that historical remote sensing images can be used to investigate change in LULC and also how the LULC affects the surface temperature of thestudy area. For each year, the surface temperature of the different classes was recorded, and the changes were noted.Landsat 8 OLI, Landsat 7ETM+ and Landsat 5 TM, were used for the LULC mapping and Land Surface Temperature analysis. The urban thermal field variance index (UTFVI) was applied to measure the thermal comfort level of the city. Results show that during the observed period, the study area experienced a gradual increasing rate in mean LST especially between 2000 and 2018 (>5% per annum).Findings showed that there are changes in Land use pattern in Ilaro changed between 1990 and 2018; about 20km^{2}of thick vegetation was lost due to rapid urbanization in the town and built up areas increased rapidly by more than 70 percent. This change in LULC pattern significantly increased the amount of heat emitted in the metropolis, with more than 10^{0}C increase (40%) between 1990 and 2000 and 5^{0}C increase (9%) between 2000 and 2018. It is concluded that effective measures need to be taken to control the menace of rapid rise in LST in Ilaro town, which includes afforestation, preservation of water bodies and reduction of the amount of bare surfaces.*

Keywords: *Land Surface Temperature, Land Use/Land Cover,Urban Heat Island, Urban Thermal Field Variance Index,*

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I. INTRODUCTION

Land use and land cover are two essentials unfolding the terrestrial environment in connection with both natural as well as anthropogenic activities (Bender, Boehmer, Jens , & Schumacher, 2005; Mendoza, et al., 2010).As a result of the growing impacts on global environments, it has become important for land use planners to extract, detect, monitor and predict land use/cover changes (LULCCs)(Vahid & Esmail, 2016). An accurate estimation of these land use/land cover changesare essential for improved understanding of its impacts on climatic and environmental systems, to enable the implementation of appropriate environmental management practices(Abu Yousuf, et al., 2019).The use to which land is being put to is one of the most important fields of human induced environmental transformation. Observation of the physical environment reveals the problem of the urban transformation in the land cover of the study area. The process of urbanization involves the growth of urban population and built-up areas(Kassahun & Tegegne , 2018). Ilaro is the largest town in and the headquarters of Yewa South Local Government of Ogun State. From its inception to the time it became a local government headquarters, there has been enormous changes in its land cover. These changes are noticeable both within and without, and invariably have had some effects on the lives of human dwellers in it. These transformations have adversely affected and will still affect development of the town; population increase has caused increased in volume and size of refuse dump sites, the transformation is paving way for urban slum, urban shift etc. These adversities requires spatio temporal investigation into the trend of the transformation for sustainable development.

Spatiotemporal analysis does not only provide information on spatial expansion or development across the landscape but also serve as vital source of information on the rate of expansion, likely causes of the expansion, etc., all of which have great implication on developmental planning.

In other to mitigate the negative effects of the town's expansion, there is need for adequate programme and policies that can foster its sustainable development. The essence of this is to encourage and monitor development in a way that it will not damage the environment for the incoming generations. Thesepolicies should include taking appropriate inventory of the available resources, planning for their present and future uses and classifying the land uses.

Classification of land uses (LU classification) is a common method to identify different types of ground cover, where the application of machine learning (ML) based supervised-classification techniques has growing significance(Laura , et al., 2019). Thematic mapping of LULC is commonly based on a number of image classification techniques(Lu & Weng, 2007).

Todate,themostwidelyusedclassificationmethodsandassociatedalgorithmsfallinto a number of categories—supervised and unsupervised, parametric and nonparametric, hard and soft (fuzzy) classification, or per-pixel, sub pixel and per field categories(Abu Yousuf, et al., 2019).

With the advent of satellite imageries, it is now very easy to perform land use and land cover analysis. In the early 70s, different satellites were launched into the space, these satellites consistently provide earth imageries, and one of these satellites provides the Landsat imageries. Landsat with the help of USGS has provided an archive of imageries, up till 1970, which helps different researchers to monitor the earth environment and understand how the world changed over the years, which is very integral in Land use land cover analysis. Land use / land cover are often used simultaneously; however, they are two different terms. Land use refers to the way in which land has been used by humans and their habitats for economic activities, while Land cover refers to the physical individuality of the Earth's surface, which is captured by vegetation, soil, water bodies and other physical features of the land. Changes in Land use/land cover is one of the integral factors that influences the world ecosystem, for example conversion of a forested area to built up, would mean affects the supply of oxygen and cause an imbalance in the world ecosystem. Land use or land cover changes is not driven by anthropogenic factors alone, sometimes they are driven by natural factors such as disasters like flood, hurricane etc. It is imperative and important therefore, that subsequently changes in land use and land cover must be monitored, so as to understand the dynamics of our environment.

Urbanization in the study area in the past decade has reduced the amount of vegetation cover and has a direct impact on land surface temperature. These include the growth or degradation of surface vegetation and changes in the land surface, which affect regional and global climate by producing changes in the surface energy budgets(Abu Bakar, Pradhan, Usman , & Abdullahi , 2016). There has been changes in the physical landscape, roads, building and other infrastructures thus replacing open land and vegetation. The conversion of these physical environment to built ups or bare surfaces has increased the Land surface temperature (LST) and this is mainly due to increase in concentrated human activities, paved land cover or barren lands in the area.

Urbanization could change not only the mechanism of the energy balance on urban surfaces but also sea breeze system in large coastal cities(Effat & Hassan, 2014)&(Tokairin, Sofyan , & Kitada, 2010).Due to the Urbanization, Urban Heat Island (UHI) phenomenon expanded (Effat & Hassan, 2014).

The urban heat island (UHI) is a phenomenon whereby urban regions experience warmer temperatures than their rural, undeveloped surroundings(Roth, 2013).As the urban area increases, there is increase in the use of manmade materials, at the same time anthropogenic heat production is on the increase, thus the main causes of UHI. This has led tothe understanding that increased urbanization is the primary cause of the urban heat island(Abbas, Jason, & Tristan, 2017).

UHI have effects on the quality of lives. These can be evaluated using a number of thermal comfort indices, some of which are the temperature humidity index (THI), the physiological equivalent temperature(Moser-Reischl, , et al., 2018), the wet-bulb globe temperature (WBGT), and the urban thermal field variance index (UTFVI)(Kakon, et al., 2010;Matzarakis, et al., 1999; Willett & Sherwood, 2012;Zhang, et al., 2006).

In this study, the trend of development of atmospheric UHI through changes in temperature and UHI index over time was explored and the impact of UHI on the quality of urban life in the area (from 1990 -2018) based on the UTVFI was evaluated using remote sensing and GIS.

Satellite data such as the Landsat with temporal, spatial and spectral characteristics affords us the opportunity to study the rise in temperature of the study area over different years (temporal resolution).

II. MATERIALS AND METHOD

1.1 Study area

Ilaro town is situated in Ogun state Nigeria, south western region of Nigeria. It lies between Latitude and Longitude. Ilaro town houses about 57,850 people, Ilaro town is the headquarters of the Yewa south Local government, now known as Yewaland. Ilaro is about 50km from Abeokuta, Ogun state capital. Daily temperature of Ilaro town ranges between an average minimum 23 °C to a maximum of 34.2 °C.Farming is one major occupation of the dwellers of Ilaro town, they produce crops such as cocoa, coffee, kolanuts, oranges, pineapples, cassava, yam, rice etc. Ilaro soils are mostly loamy and humus and rich in manure which supports of these crops. Also Ilaro dwellers (Yewa/Egbado people) produce timber, as a result of the thick forest in the town.

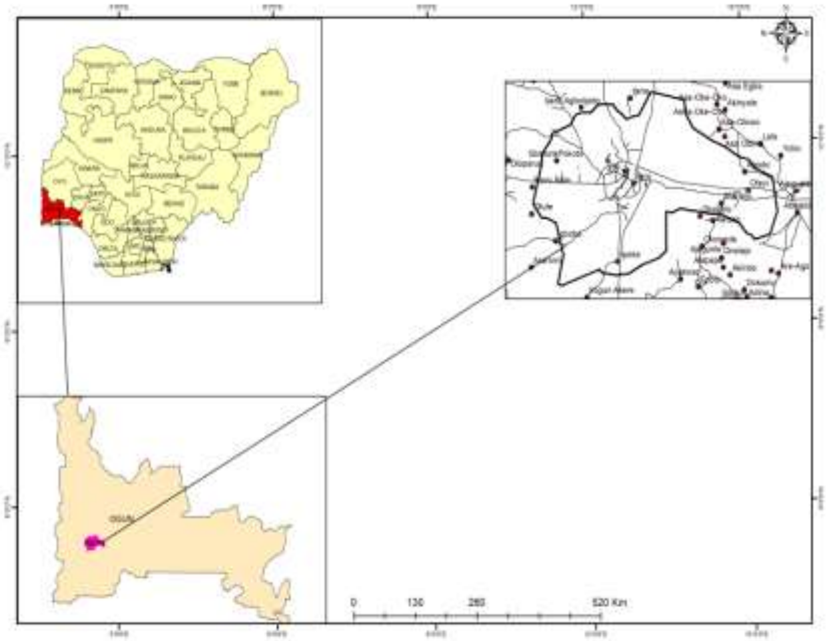

Figure 1: Map of the Study area

Flow chart

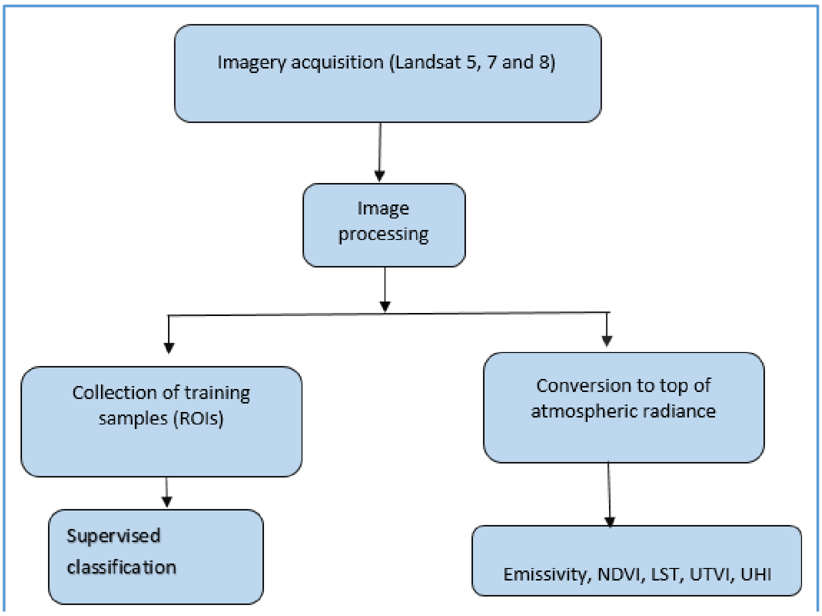

Figure 2: Flow process of the study

1.2 Data

For the purpose of this research, remotely sensed imagery of Landsat TM, ETM and Landsat OLI imageries were used. The imageries used were acquired in 1990, 2000, 2010 and 2018. Landsat TM with spatial resolution of 40 meters, Landsat ETM of spatial resolution of 30 meters and Landsat OLI of 28 meters' spatial resolution were used to detect the changes. Landsat imageries are acquired in scenes, for the study area a single Landsat scene was used. The imageries were obtained from the USGS website, these datasets were all acquired in the dry season, to minimize cloud cover. Cloud cover inhibits perfect result, as the cloud would mask the real object on ground, and even affect the quality of the research procedure.

1.3 Image processing, Data Description and Data Preparation

Remotely sensed imageries need to be corrected for radiometric and geometric distortion.Most satellite imageries errors such as the geometric errors are corrected at the ground receiving station.However, some errorsneed to be corrected by the user, such ascloud removal or reduction, line dropout removal etc. The Landsat imageries were corrected before embarking on the research. Most Landsat 7 dataset have line dropout errors whichhave been corrected in this study, for better accuracy. Also several image processing techniques were applied to enhance visual perception; composite bands, sub-setting, layer stack etc.
This image processing helped in image interpretation, which is an important aspect while performing supervised image classification algorithm.

Table 1: Satellite Data Information

Satellite	Time	Path/Row	Bands used	Spatial resolution
Landsat 5(Thematic mapper)	November 1990	191/55	Visible band (1,2,3), NIR: Band 4, SWIR: 7, TIR: Band 6	30mx 30m
Landsat 7(Enhanced Thematic mapper)	November 2000, 2010	191/55	Visible bands:1,2,3 NIR: Band4, SWIR: Band 5, TIR: Band 6	30mx 30m
Landsat 8 Operational land imager/ thermal infrared sensor	November 2018	191/55	Visible bands:2,3,4 NIR: Band 5, SWIR: Band6, 7,9 TIR:Bands10 and 11	30mx 30m

1.4 Land Use Land Cover Classification

Image classification refers to the process of assigning pixels to a defined class. There are different ways of classifying an image, the two major techniques are the supervised and unsupervised classification. The supervised classification method was adopted in this study.Supervised classification uses the spectral signature that is defined in the training set. For example, it determines each class on what it resembles most in the training set. The common supervised classification algorithms are maximum likelihood and minimum-distance classification.

Using the ENVI 5.3 classic software, regions of interests, ROI were created. These ROIs were used as training sites or training points whereby the computer uses the training points to classify the imagery. The classification algorithm used for this research is the maximum likelihood classification. This is because this algorithm assumes that the statistics for each class in each band are normally distributed and calculates the probability that a given pixel belongs to a specific class. The study identified four (4) land cover classes in the study area; Bare surface/soil, Riperian vegetation or thick vegetation (forest), Light vegetation and Built up.

Table 2: Land Use land Cover types in the study area

	LULC	Description
1	Built up	Settlements and buildings
2	Bare surface/bare soil	Cultivated land, cleared land
3	Thick vegetation(forest/riparian vegetation	Forest, tree canopy
4	Light vegetation	Grasslands and shrubs

III. RESULTS AND DISCUSSION

3.1 Land Use land Cover Change

Land Use land Cover maps were produced for the different years and the accuracy of the classification technique was determined by comparing the classification output with ground truth data. This technique is called accuracy assessment and it is used to validate the result of the image classification. Based on the LU/LC cover classification technique used, a temporal land use and land cover change between the year 1990 and 2018, was prepared using the cross tabulation technique. This was done using the ENVI 5.3 classic software, by selecting the post classification tab. The cross tabulation method overlays newer classified image on older images, to produce the changes and loses between the two images.

Table 3: Cross tabulation for LU/LC between 1990 and 2018

Area in (Square Km)	LU/LC 1990 - 2018					
	Built up	Thick forest/ Riparian Vegetation	Light vegetation	Bare surface/soil	Row Total	Class Total
Built Up	3.85	116.68	7.4	2.59	130.53	130.53
Bare surface	1.67	14.77	19.27	3.51	39.22	39.22
Light vegetation	0.18	18.76	19.08	0.91	38.93	38.93

Riparian Vegetation/ thick vegetation	0.07	27.14	20.94	0.77	48.92	48.92
Class Total	5.76	177.35	66.69	7.79	0	0
Class Changes	1.91	150.22	47.61	4.27	0	0
Image Difference	124.76	-128.43	-27.76	31.43	0	0

Table 4: Cross tabulation for LU/LC between 1990 and 2000

Area in (Square Km)	**LU/LC 1990 - 2000**					
	Built Up	Thick forest/Riparian vegetation	Light vegetation	Bare Surface	Row Total	Class Total
Built Up	2.45	0.22	0.47	0.85	3.99	3.99
Vegetation	0.53	139.25	25.35	1.64	166.77	166.77
Riparian Vegetation	0.02	24.13	20.61	1.01	45.76	45.76
Bare surface	2.77	13.76	20.27	4.29	41.08	41.08
Class Total	5.76	177.35	66.69	7.79	0	0
Class Changes	3.31	153.23	41.34	3.5	0	0
Image Difference	-1.78	-131.6	100.08	33.29	0	0

Table 5: Cross tabulation for LU/LC between 2000 and 2010

Area in (Square Km)	**LU/LC 2000 - 2010**					
	Built Up	Thick forest/Riparian vegetation	Light vegetation	Bare Surface	Row Total	Class Total
Built Up	3.99	0	0	0	3.99	3.99
Vegetation	0	166.77	0	0	166.77	166.77
Riparian Vegetation	0	0	45.76	0	45.76	45.76
Bare surface	0	0	0	41.08	41.08	41.08
Class Total	3.99	166.77	45.76	41.08	0	0
Class Changes	0	166.77	45.76	41.08	0	0
Image Difference	0	-121.01	-4.68	125.69	0	0

Table 6: Cross tabulation for LU/LC between 2010 and 2018

Area in (Square Km)	**LU/LC 2010 - 2018**					
	Built Up	Thick forest/Riparian vegetation	Light vegetation	Bare Surface	Row Total	Class Total
Built Up	0	0	0	0	0	0
Vegetation	126.05	0	0	0	126.05	126.05
Riparian Vegetation	0	51.19	0	0	51.19	51.19
Bare surface	0	0	59.75	0	59.75	59.75
Class Total	0	0	0	20.6	20.6	20.6
Class Changes	126.05	51.19	59.75	20.6	0	0
Image Difference	0	0	0	0	0	0

3.2 Accuracy Assessment

Accuracy assessment of the Land Use Land cover classification was obtained for each year from 1990, 2000, 2010, and 2018using a confusion matrix, which compare, on a class-by-class basis, the relationship between known reference data (ground truth) and the corresponding results of the classification procedure. Kappa coefficient is calculated using equation

$$K = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}(x_i + Xx_{+1})}{N^2 - \sum_{i=1}^{r}(x_{ii} Xx_{+1})}$$

(Adam, 2011)

Where:

r = Number of rows/columns in confusion matrix
Xii = Number of observation in row i and column i
Xi+ =Total number of row i
X+I = Total number of column i
N = Number of observations

The overall classification accuracy is obtained by dividing the total number of correctly classified samples by the total number of reference samples. It is the percentage of correctly classified samples of an error matrix. It is calculated using equation:

$$\text{Overall accuracy} = \frac{1}{N} \sum_{k-1}^{n} a_{kk}$$ (Banko, 1998)

Accuracy Assessment for 1990
Overall Accuracy = Sum of the elements along the major diagonal divide by the total numberof reference pixels (818/1021) = 80.1175%
Kappa Coefficient = 0.5464

Table 7: Accuracy Assessment for 1990

Class	**Commission**	**Omission**	**Commission**	**Omission**
	(Percent)	(Percent)	(Pixels)	(Pixels)
Built Up (Red)	4.55	20.25	3/66	16/79
Thick Forest/Riparian Vegetation	2.82	20.15	19/673	165/819
Light vegetation	63.92	18.58	163/255	21/113
Bare surface	66.67	10.00	18/27	1/10

Accuracy Assessment for 2000
Confusion Matrix: 2000
Overall Accuracy = (392/408) = 96.0784%
Kappa Coefficient = 0.9178

Table 8: Accuracy Assessment for 2000

	Ground Truth (Percent)			
Class	Built Up	Riparian Vegetation	Bare surface	Total
Built Up (Red)	100	0.00	13.33	12.01
Riparian Vegetation	0.00	98.58	0.00	67.89
Bare surface	0.00	1.42	86.67	20.10
Total	100.00	100.00	100.00	100.00

Accuracy Assessment for 2010
Confusion Matrix: 2010
Overall Accuracy = (640/661) = 96.8230%
Kappa Coefficient = 0.9544

Table 9: Accuracy Assessment for 2010

Class	**Commission (%)**	**Omission (%)**	**Commission**(Pixels)	**Omission**(Pixels)
Built up (Red)	0.00	3.41	0/85	3/88
Bare Surface	4.29	1.27	7/163	2/158
Light Vegetation	2.78	3.11	8/288	9/289
Riparian Vegetation/thick vegetation	4.80	5.56	6/125	7/126

Accuracy Assessment for 2018
Confusion Matrix: 2018
Overall Accuracy = (539/549) = 98.1785%
Kappa Coefficient = 0.9724

Table 10: Accuracy Assessment for 2018

Class	**Commission(%)**	**Omission (%)**	**Commission**(Pixels)	**Omission**(Pixels)
Built Up (Red)	0.47	0.94	1/211	2/212
Bare surface	2.38	1.20	2/84	1/83
Light vegetation	20.59	0.00	7/34	0/27
Riparian Vegetation/thick vegetation	0.00	3.08	0/220	7/227

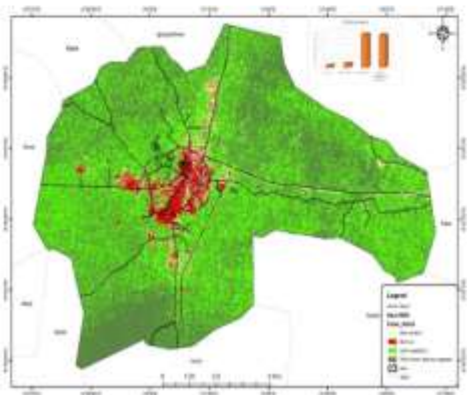

Figure 3: Land Use Land cover in 1990

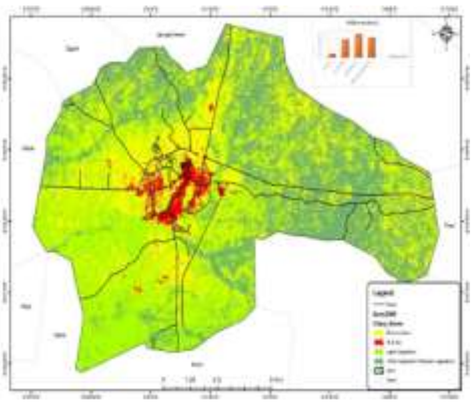

Figure 4: Land Use Land cover in 2000

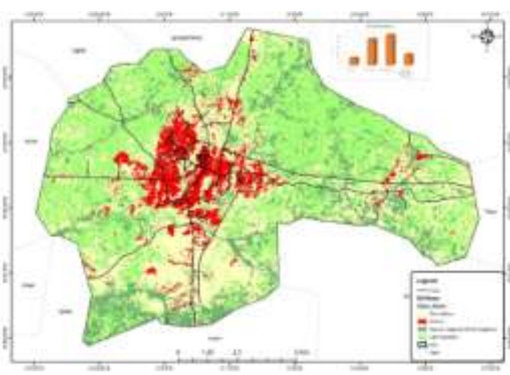

Figure 5: Land Use Land cover in 2010

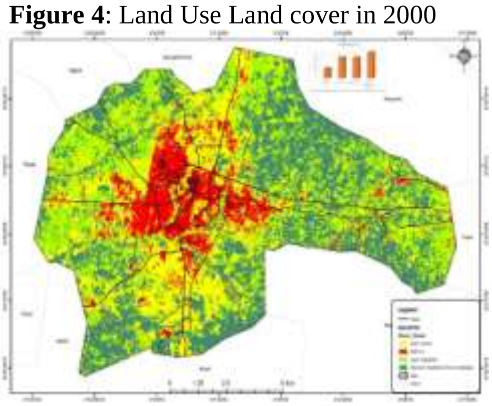

Figure 6: Land Use Land cover in 2018

The maps above show the changes that occurred in Ilaro town between 1990 and 2018. The changes are better visualized in the tables below.

Table 11: Areas covered by each Land Use / Land Cover class for each year.

Land use/Land cover type	**1990 (Km^2)**	**2000 (Km^2)**	**2010 (Km^2)**	**2018 (Km^2)**
Built up	3.987918	5.763718	13.69881	18.173086
Bare Surface	7.784108	41.048254	51.125829	39.185914
Light vegetation	66.605235	54.33862	59.66458	38.880049
Riparian vegetation/thick vegetation	64.890863	45.669132	20.554634	48.804874

Result from the research showed that between 1990 and 2000, built up increased by 1.7759 square kilometers while thick vegetation reduced by 19 square kilometers. Between 1990 and 2018, built up areas in Ilaro town had tripled.This implies that forest and lots of green cover had been reduced. Built up areas and bare surfaces are concentrated in the metropolis of the town. Between 1990 and 2018, most of the thick vegetation cover have been reduced to light or thin vegetation and most of the light vegetation have been converted to bare soil and built up.

Figure 7: Land Use Land Cover Inventory of the study Area

3.3 Land-Use/Land Cover (LULC) based on Land Surface Temperature (LST)

The Land surface temperature of a place is how hot the surface of that place would feel to touch.Figures 8-11 show the maximum and minimum land surface temperaturesbetween 1990 and 2018 and table 11 show the changes in the Land surface temperature for the different LU/LC.

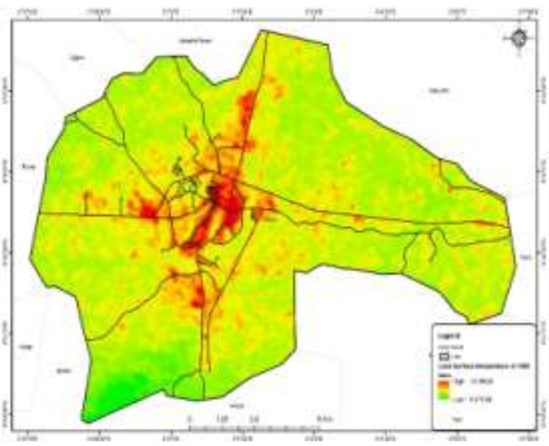

Figure 8: LST distribution in 1990

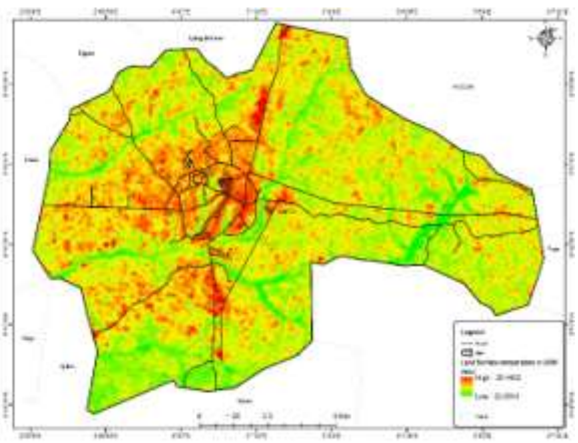

Figure 9: LST distributionin 2000

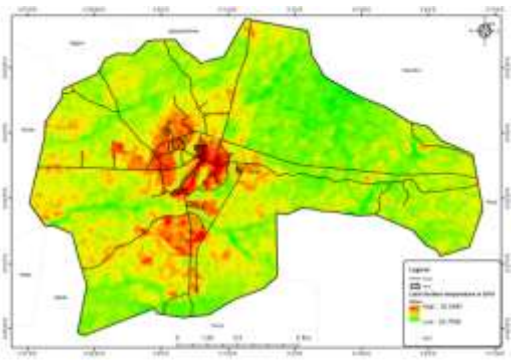

Figure 10: LST distributionin 2010

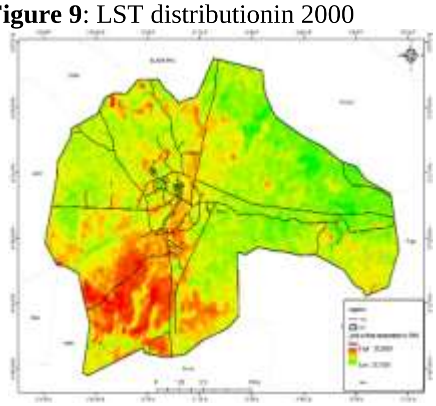

Figure 11: LST distributionin 2018

Table 12: Changes in the Land surface temperature

	Land Surface Temperature (LST)			
Land Use/Land Cover (LULC)	**1990**	**2000**	**2010**	**2018**
Built Up	12.738614	30.077009	32.971878	33.75209
Riparian/ thick forest	5.896029	24.598423	25.35343	28.555384
Light vegetation	8.38	26.618078	26.28	28.015749
Bare surface/soil	11.307416	29.588655	31.900617	31.664524

There is increase in Land surface temperature in built up areas from 1990 to 2018.Between the year 1990 and 2000, the land surface temperature doubled as a result of increasing urbanization and decreasing vegetation cover. The increase in bare surfaces imply that green cover reduces, which has a direct impact on the Land surface temperature of the area.

3.4 Variation of LST with LULC Change

The figure below shows the changes in Land surface temperature with changing Land use and Land cover type.

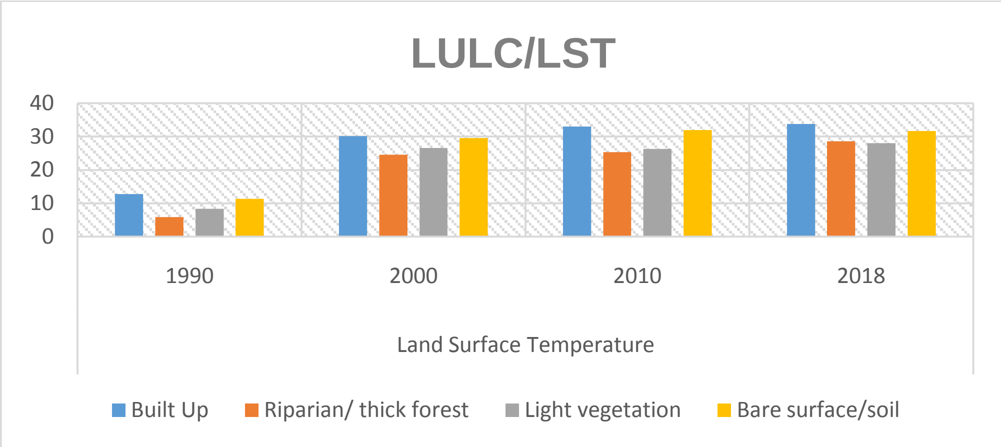

Figure 12: Changes in LST with changing LULC type.

3.4.1 Urban Thermal Field Variance Index (UTFVI), Urban Heat-Island (UHI) Effect and Ecological Conditions from the LST of Ilaro town

Urban thermal field variance index was applied to determine the thermal and ecological comfort level of the city. Several urban heat islands (UHIs) were extracted as the most heated zones within the city boundaries due to increasing anthropogenic activities.The urban thermal field variance index (UTFVI) is commonly used to express the urban heat island effect. It can be calculated by

$$UTVI = \frac{T_S - T_{mean}}{T_S} \qquad \text{(Zhang, et al., 2006)}$$

where T_s = LST in certain point of the map

T_{mean} = the corresponding mean temperature of the whole town.

UTFVI = Urban Thermal Field Variance Index;

LST = surface temperature of certain point in °C (temperature of points in a certain Land use or land cover type),

The result of UTVI is classified into six (6) classes where each class corresponds to the ecological index. This is to be able to illustrate the level of urban heat island effectively.

Table 13: Urban Heat Island IntensityClassification Index

Urban Thermal Field Variance Index (UTFVI)	**Urban Heat Island Phenomenon (UHI)**	**Ecological Evaluation Index (EEI)**
<0	None	Excellent
0.000–0.005	Weak	Good
0.005–0.010	Middle	Normal
0.010–0.015	Strong	Bad
0.015–0.020	Stronger	Worse
> 0.020	Strongest	Worst

Table 14: UTFVI for the study area between 1990 and 2018

UTVI(1990)	UTVI(2000)	UTVI(2010)	UTVI(2018)
3.259112821	11.1519869	7.027437201	7.702281332
-2.009573033	-8.8433371	-8.663189331	-35.05379713
-18.62222222	-34.935437	-13.14	-20.68726477
4.564197535	13.3966849	8.810823404	13.80004044

Tables 14 – 17 show the correlation between each land use land cover class, with the Urban Thermal field variance index(UTFVI) and the corresponding ecological conditions for each value. The tables showed that the thick forest and light vegetation zones had the best ecological index throughout the study years while built up and bare surfaces has the worst. This implies that there has been rapid urbanization from 1990 till 2018. This urbanization is attributable to the high employment opportunities and admission rate into the country's major cement factory and the most sought after federal polytechnic that are situated in the area. The location of these factory and institution has brought about migration of workers and students to settle down in the town. This influx of migrants and students thus increased demand for housing and infrastructure in the area, hence increasing the built up and bare surface areas.

Table 15: LULC, UTVI and Ecological Conditions from the LST of the study area in 1990

Land Use/Land Cover	UTVI(1990)	UHI PHENOMENON	Ecological index
Built Up	3.259112821	strongest	Worst
Riparian/ thick forest	-2.009573033	None	Excellent
Light vegetation	-18.62222222	None	Excellent
Bare surface/soil	4.564197535	strongest	worst

Table 16: LULC, UTVI and Ecological Conditions from the LST of the study area in 2000

Land Use/Land Cover	UTVI(2000)	UHI PHENOMENON	Ecological index
Built Up	11.1519869	strongest	Worst
Riparian/ thick forest	-8.8433371	None	Excellent
Light vegetation	-34.935437	None	Excellent
Bare surface/soil	13.3966849	strongest	worst

Table 17: LULC, UTVI and Ecological Conditions from the LST of the study area in 2010

LandUse/land Cover	UTVI(2010)	UHI PHENOMENON	Ecological index
Built Up	7.027437201	strongest	Worst
Riparian/ thick forest	-8.663189331	None	Excellent
Light vegetation	-13.14	None	Excellent
Bare surface/soil	8.810823404	strongest	worst

Table 18: LULC, UTVI and Ecological Conditions from the LST of the study area in 2018

LandUse/Land Cover	UTVI(2018)	UHI PHENOMENON	Ecological index
Built Up	7.702281332	strongest	Worst
Riparian/ thick forest	-35.05379713	None	Excellent
Light vegetation	-20.68726477	None	Excellent
Bare surface/soil	13.80004044	strongest	worst

IV. CONCLUSION AND RECOMMENDATION

This paper looks at the dynamic effects of Land Use Land Cover on Land Surface Temperature in Ilaro, Yewa South LGA area of Ogun state. The present trend of land use changes within the study area has visible environmental impacts on the surrounding natural resources and the ecosystems.From the study Ilaro town has witnessed rapid urbanization from the year 1990 till 2018, thereby reducing the amount of thick vegetation or forests in the area. Built ups and Bare surfaces or bare soil now accounts for a very integral figure in the total land use or land cover of the town. Land surface temperature shows an increasing trend in built up areas and bare surfaces between the year 1990 and 2018. Generally, there has been a subsequent increase in land surface temperature across the different land use and land cover types. Land surface temperature increases with decreasing vegetation cover and increasing built up or bare surfaces. The study had an overall classification accuracy of 92.8% and kappa coefficient of 0.848. The kappa coefficient is rated as substantial and hence the classified image found to be fit for further research. This work highlights the importance of using remote sensing for environmental changes research. Remote sensing data such as satellite imagery, has temporal, spatial and spectral characteristics, which gives it an edge over in-situ techniques.Therefore, to prevent the increase in the Land surface temperature, destruction of vegetation cover should be prohibited, more trees need to be planted, and deforestation should be reduced to the barest minimum.

To improve the thermal environment around buildings and mitigate UHI, it is suggested to use the material of lower absorptivity, higher reflectivity, and larger thermal conductivity(Xu, Bruelisauer, & Berger, 2017)

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