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Spatio-Temporal Dynamics of Urban Green Space and Temperature in Ado-Ekiti Metropolis, Nigeria

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Abstract
The Nexus between the Urban Green Space (UGS) and Land Surface Temperature (LST) helps to formulate policy for sustainable management of UGS where there is an urban sprawl like Ado Ekiti. However, there is a dearth of information on UGS and LST in Ado-Ekiti. Therefore, this study adopted remote sensing and geographic information system techniques to determine the dynamics and nexus between UGS and LST as well as investigating the perceived factors responsible for the UGS changes in Ado-Ekiti metropolis, Nigeria with a view to providing relevant information for sustainable management of the UGS and mitigating the Urban Heat Island. Landsat imageries of 1987 (TM), 1998 (ETM) and 2019 (OLI) were obtained. Map of Ado-Ekiti was georeferenced and digitized to obtain its shapefile. The maximum likelihood algorithm of supervised classification in ArcGIS was used to classify Landsat imageries. The shapefile was superimposed on the classified imageries and clipped for the determination of land use land cover sizes. The LST was extracted from the imageries by converting the digital numbers to the surface temperature. Correlation analysis was used to determine the nexus between the UGS and LST. Four land use land cover: green spaces, built-up area, water bodies and bare land, were identified in the Ado-Ekiti metropolis. The UGS decreased from 74.4% in 1987 to 38.7% in 2019. Similarly, water bodies reduced from 0.9% in 1987 to 0.1% in 2019 respectively. However, built-up area and bare land increased from 21.9% and 2.9% in 1987 to 51.1% and 10.5% in 2019 respectively. The LST in Ado-Ekiti metropolis increased from 22.1°C in 1987 to 30.5 °C in 2019 respectively. The Built-up area and bare land had the highest LST values compared with UGS and water body in all the years. The relationship between the UGS dynamics and LST was negatively correlated with r2 ranging from -0.51 to -0.83. By the year 2049, the vegetation would have reduced to 36.0% while built-up and bare land would have increased to 52.4%. on the other hand, water with no significant change.

Keywords: *Land use land cover change, urban green space change, geographic information system, land surface temperature, Spatio-temporal*

Introduction

Urban greenspace is the publicly managed vegetative areas within an urban environment such as forested land, wilderness, street trees, parks, gardens, backyard gardens, geological formations, coastal areas and agricultural lands (McIntyre *et al.*, 2000). There has been growing interest in green space research as it has a positive influence on human well-being and livelihood. The loss of green belts surrounding large cities leads to profound and irreversible changes in the local landscape, lowers air quality and exerts a negative influence on local residents and social interactions (Szezepanska and Senetra, 2019). Baycan-Levent *et al*. (2009) grouped all the urban green space values into five categories (a) ecological values: intrinsic natural value, genetic diversity value, life-support value; (b) economic values: market value; (c) social values: recreational value, aesthetic value, cultural symbolization value, historical value, character-building value, therapeutic value, social interaction value, substitution value; (d) planning values: instrumental/structural value, synergetic and competitive value; (e) multidimensional values: scientific value, policy value. Increased urbanization has effects on the urban microclimate. The absence of green spaces is characteristic of most contemporary cities globally. Various construction works, deforestation activities and other anthropogenic activities take place in the cities. These lead to alterations in the landform equilibrium of the city terrains, affecting the microclimate.

Urbanization is rapidly evolving throughout the world. It is an inevitable process that goes along with economic development and rapid population growth. According to UN, (2007), 70 percent of the global population will live in urban areas by 2050 as cities now house slightly more than half of the world's population. According to Rimal, (2011), when the residential and commercial land uses at the peripheral of metropolitan areas are converted to green environment, this is considered to be a sign of regional economic liveliness whose benefits are increasingly unbiased against ecosystem impacts. Urbanization processes in Ado-Ekiti metropolis is evolving and have generated some geomorphological impacts in the city. The increase in infrastructural development in this city has transformed the city and the land use pattern into a more vibrant urban settlement. The expansion of the city both demographically and physical spatially has affected the plant biodiversity and the rapid population growth has impacted negatively on plant conservation. The unavailability of updated and current information about the urban green changes leads to poor management and environmental planning. Alo and Akindele (2011) reported that information in the forestry sector was scarce or where available, may not be up-to-date. Therefore, the status, extent and changes over time of UGS in Ado-Ekiti are not currently known. Although previous studies on land use land cover measurement in Ado-Ekiti metropolis focused on qualitative analysis, that is, changes in land use land cover changes in terms of spacing increased pollution and waste generated (Oriye, 2013). However, there is limited information on the quantitative aspect of UGS in the study area. Therefore, this study aimed at determining the changes and nexus between UGS and temperature between 1987 and 2019 in Ado – Ekiti metropolis, Nigeria.

Methodology

Study Area

Ado-Ekiti metropolis is located on latitudes 7° 35' N and 7° 39' N of the Equator and Longitudes 5° 10' E and 5° 19' E of the Greenwich Meridian. It is situated to the North of Ikere-Ekiti, West of Are-Ekiti and Afao-Ekiti, East of Iyin-Ekiti and Igede-Ekiti, and south of Iworoko-Ekiti (Figure 1). The low relief and gentle gradient characteristics of Ado-Ekiti favour agricultural and construction activities and make much of the metropolis susceptible to erosion and flood hazards during the rainy season (Awosusi and Jegede 2013). Ado-Ekiti has a plan metric area of about 884km^2. Geologically, the region lies entirely within the pre-Cambrian basement complex rock group, which underlies much of Ekiti State (Awosusi and Jegede 2013). The temperature of this area is almost uniform throughout the year, with very little deviation from the mean annual temperature of 27°C. February and March are the hottest 28°C and 29° C respectively, while June with a temperature of 25°C is the coolest (Adebayo, 1993; Nwatu, 2018). The mean annual total rainfall is 1367 mm with a low co-efficient variation of about 10%. Rainfall is highly seasonal with well-marked wet and dry seasons. The wet season is from April to October, with a break in August.

Data collection

Image Acquisition and Classification

Landsat imagery data were downloaded from USGS Earth Explorer. The Thematic Mapper (TM) imagery of 1984, 1998 (ETM) and Operational Land Imager (OLI) imagery of 2019 were downloaded (Table 1). The spatial resolution of Landsat imageries is 30 m. They were used for image classification. Vector data used includes the shapefile of Ado-Ekiti metropolis, which was digitized. This study utilized the Maximum Likelihood Classification Algorithm for the classification of imageries into two land cover categories; Forested and Non-Forested (built-up, water and bare surface) classes (Table 2).

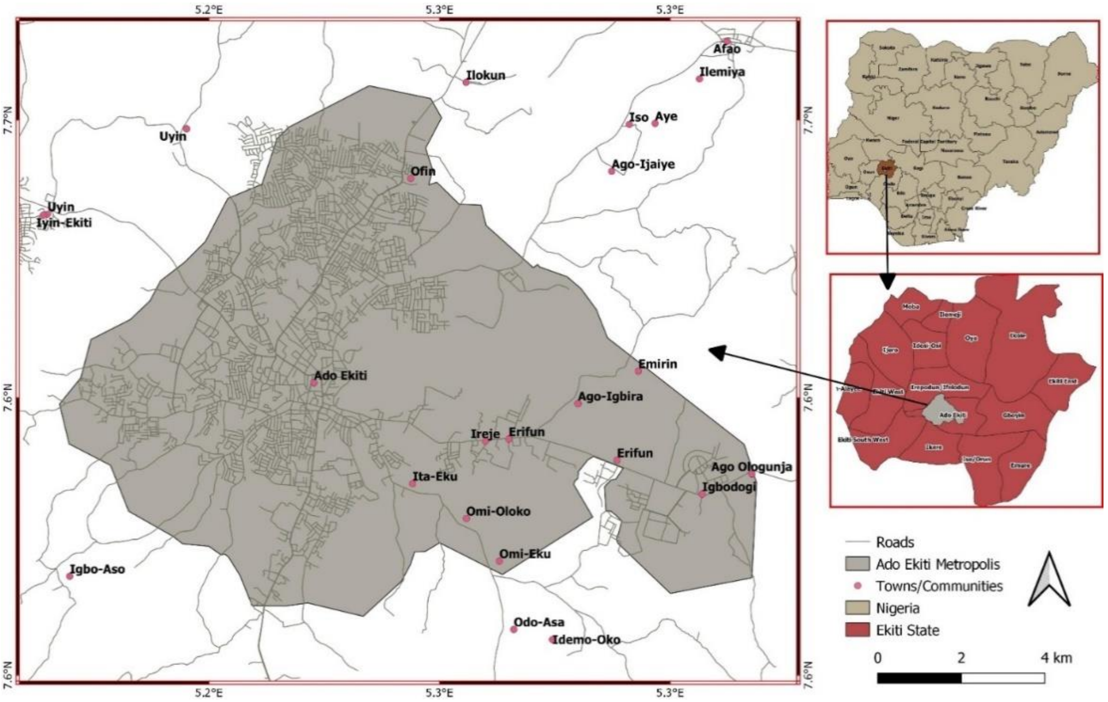

Figure 1: Ado-Ekiti metropolis
Source: Adapted from Abegunde et al. (2018)

Table 1: Satellite data for the study

Satellite id	Year	Sensor id	Path/row	Spatial resolution
Landsat 5	1987	TM	190/55	60 m
Landsat 7	1998	ETM	190/55	30 m
Landsat 8	2019	OLI/TIRS	190/55	30 m

Table 2. *Adopted modified version of the Anderson scheme of land use/cover classification.*
Source: Monica Cavinaw Geography, (2007)

LULC Categories	Description
Built-up area	Residential, commercial and services, transportation, communications, and utilities, industrial and commercial areas
Vegetation	Cropland, orchards, vineyards, nurseries, and confined feeding operations, plantation and mixed forest
Bare land	Sandy areas, barely exposed rock, transitional area and open land
Waterbody	Streams, lakes, and reservoirs

The change detection was carried out by comparing the independently classified images of different intervals. It aided in identifying the rate of change in percentage that has occurred within the selected years.

Average Rate of Change = $\frac{Y_2 - Y_1}{T_2 - T_1}$ ….. (eq. 2)

To achieve this, the area in hectares and the percentage of each year was determined. This was calculated using equations 1 to 3:

$\%\Delta$ in year = $\frac{Y_2 - Y_1}{Y_1} \times 100$ …………… (eq. 1)

%Average Rate of Change = $\frac{\text{Average Rate of Change}\left(\frac{\text{ha}}{\text{yr}}\right)}{\text{Years Difference}} \times 100$ …..…. (eq. 3)

Where: $Y_2 - Y_1$ is the observed change; T_2- T_1 is the difference between the final period and the initial period; Y_2 is the ending year; Y_1 is the starting year.

Accuracy assessment was carried out to determine the level of error in the classification. This involves comparing the classified and actual reference unit, an error matrix table was formed. According to Olofsson *et al.*, (2013), the matrix reveals errors of commission and omission. The User accuracy (Ua) and Producer accuracy (Pa) and overall statistics were calculated. To determine the accuracy of image classification, kappa statistics were used, which measures the agreement between the reality and the model predictions or to know if the error matrix values represent a result significantly better than random (Jensen 1996, Congalton 1991). It was computed using equation 4.

$$k = \frac{N\sum_{i=I}^{r} x_{ii} \sum_{i=I}^{r} x_{ii}\,(x_{i+}\, x_{+i}\,)}{N^2 - \sum_{i=I}^{R}(x_{i+}\, x_{+i}\,)} \quad \ldots\ldots \text{(eq.4)}$$

where N = total number of sites in the matrix; R = number of rows in the matrix; x_i = number in row i and column i; x_{+i} = total for row i; x_{i+} = total for column i; x_{ii} = total number in row i column I

Land cover modelling using Markov

Lopez *et al.,* (2011) explained that Markov chains follow stochastic process models which give the probability of one variable such as built-up changing to another (vegetation) within a given certain time period. TerrSet Clark lab IDRIS software land change modeler was used for the land cover prediction. The first step was to analyze the earlier land use land cover to generate the transition probability of each land cover category to change to another category. The Ca-Markov model was run to predict the change for each class in the year 2049 by using two land use/cover in 1998 and 2019 derived from satellite images.

Land Surface Temperature Determination

Images were processed in units of absolute radiance using 32-bit floating-point calculations. These values were converted to 16-bit integer values in the finished Level 1 product. They were converted to spectral radiance using the radiance scaling factors provided in the metadata file.

Conversion of Digital Number (DN) to Top of Atmosphere Radiance (TOA) using equation 5

$$L\lambda = M_L \times Q_{cal} + A_L \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(eq. 5)}$$

$L\lambda$ is the spectral radiance at the sensor [W/(m2 sr μm)]; M_L represents the band-specific multiplicative rescaling factor (0.0003342); Q_{cal} is the Level 1 pixel value in DN for Band 10 for Landsat 8 and Band 6 for Landsat 5 and 7; A_L is the band-specific additive rescaling factors (0.1).

TIRS Top of Atmosphere Brightness Temperature (BT)

Thermal Infrared Sensor data can also be converted from spectral radiance (as described above) to brightness temperature, which is the effective temperature viewed by the satellite under an assumption of unity emissivity (equation 6).

$$BT = \frac{K2}{ln\,(\frac{K1}{L\lambda}+1)} - 273.15 \ldots\ldots\ldots\ldots \text{(eq. 6)}$$

*where: BT= Top of atmosphere brightness temperature (K) where: Lλ = TOA spectral radiance (Watts/(m2 * srad * μm)); K1 = Band-specific thermal conversion constant from the metadata (K1_CONSTANT_BAND_x, where x is the thermal band number); K2 = Band-specific thermal conversion constant from the metadata (K2_CONSTANT_BAND_x, where x is the thermal band number)* (Suresh *et al.,* 2016).

NDVI Method for Emissivity Correction

Landsat visible and near-infrared bands will be used for calculating the Normalised Difference Vegetation Index (NDVI). The calculation of the NDVI is important because, it determines the proportion of the vegetation (Pv) and consequently, the emissivity € of the area under investigation (equation 7) (Suresh *et al.,* 2016).

$$NDVI: \frac{\text{NIR (Band)5} - \text{R (Band 4)}}{\text{NIR (Band)5} + \text{R (Band 4)}} \ldots\ldots \text{(eq. 7)}$$

Where NIR (Band 5) represents near-infrared (Band 5) in Landsat 8 (Band 4 in Landsat 5 and 7) and R represents the red band (Band 4) in Landsat 8 (Band 3 in Landsat 5 and 7)

The Proportion of Vegetation P_v was calculated using equation 8. This method for calculating P_v suggests using NDVI values for vegetation and soil ($NDVI_v$ = 0.5 and $NDVI_s$ = 0.2) to apply in global conditions.

$$P_v = \left(\frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}}\right)^2 \ldots\ldots\ldots\ldots \text{(eq. 8)}$$

Emissivity

The error correction is

E = 0.04 x P_v + 0.986 ………………(eq. 9)
Retrieving the Land Surface Temperature/Emissivity-Corrected Land Surface Temperature TS (Equation 9)

$$TS = \frac{TB}{1+[\left(\frac{\lambda \text{ x TB}}{P}\right) x \ln(\varepsilon)]} \text{ ………………(eq. 9)}$$

Where TS = LST; λ = wavelength of emitted radiance (11.345 for TM/ETM and 11.5 µm for OLI), ρ = h×c/ σ (1.438 ×10-2 m K); σ = Boltzman constant (1.38 ×10-23 J/K); h = Planck's constant (6.626×10-34 J s); c = velocity of light (2.998 ×108 m/s); ε = denotes emissivity

All these processes were carried out using ArcMap software (Suresh *et al.*,2016).

Determination of the relationship between Normalized Difference Vegetation Index and climatic factors (Temperature)

The correlation analysis was carried out between urban green space (NDVI) and surface temperature to know the degree and the direction of the relationship between them. With 100 randomly selected points, excluding water features as water has a negative correlation with NDVI according to studies. Therefore, this study adopted Pearson "r" correlation was used (equation 10).

$$r = \frac{N\sum xy-(\sum x)(\sum y)}{\sqrt{((N(\sum x^2)-(\sum(x)^2)(N(\sum y^2)-(\sum(y)^2))}}$$

……….. (eq. 10)

Where:

r = Correlation Coefficient; X = Independent variable, which is the Land-use classes in decreasing order of reflective capacity; Y = Dependent variable, which is the land surface temperature readings associated with each class; N = Observations.

The regression analysis was run in Statistical Packages for Social Sciences (SPSS). **Results**

Table 3 showed the land cover classification in the study area from 1987 to 2019 and the map presentation from figure 3 to 5.

Table 3: *Land Cover Classification (1987, 1998 and 2019)*

	1987		**1998**		**2019**	
Classes	Area (km²)	Area (%)	Area (km²)	Area (%)	Area (km²)	Area (%)
Green Spaces	71.1	60.0	58.7	49.6	45.9	38.7
Built-Up	13.1	11.1	40.1	33.9	60.5	51.1
Bare Land	33.5	28.3	19.5	16.4	12.4	10.5
Water Body	0.8	0.7	0.1	0.1	0.1	0.1
Total	118.5	100	118.5	100	118.5	100

Land Use Land Cover Transition

Figure 6a-6d showed the transition in the land use land cover of Ado-Ekiti metropolis between 1987 and 2019.

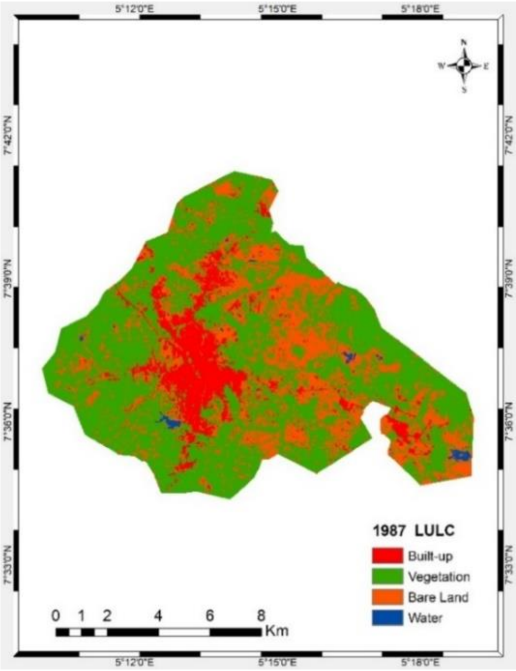

Figure 3: *Land cover changes for year 1987*

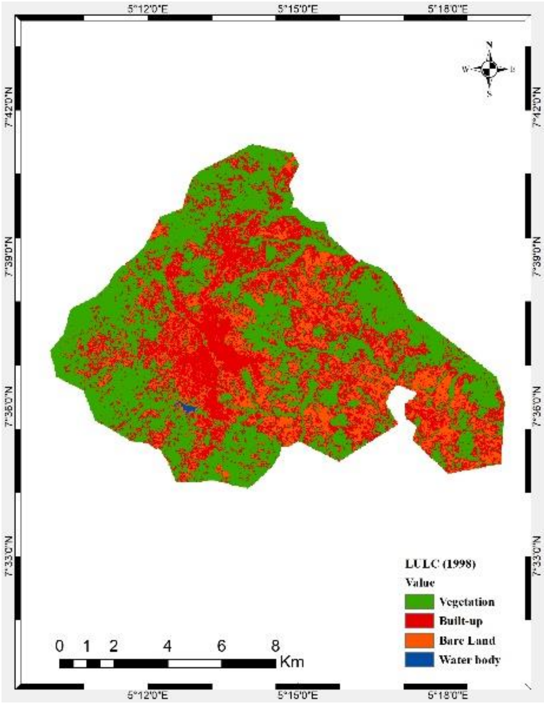

Figure 4: *Land cover changes for year 1998*

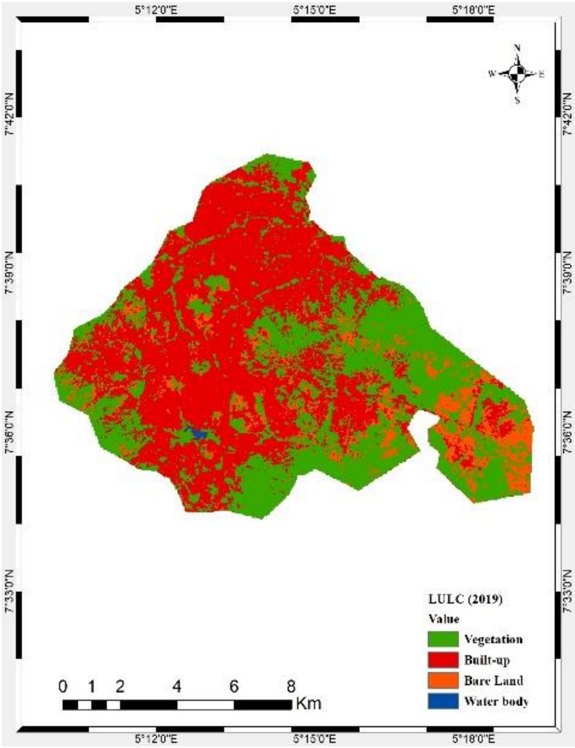

Figure 5: *Land cover changes for year 2019*

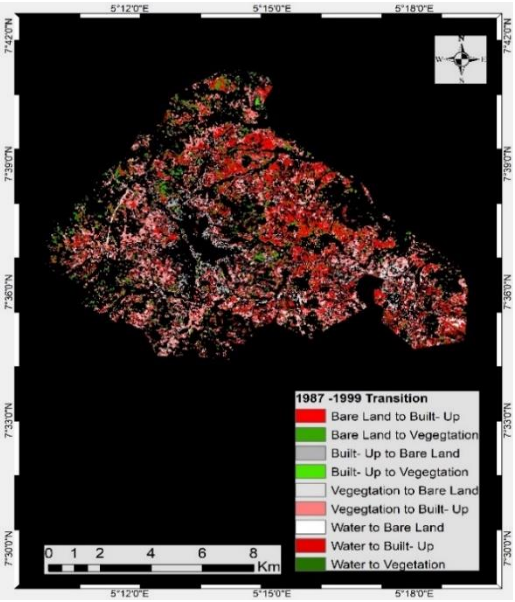

Figure 6a. *Land Cover transition from 1998 to 2019*

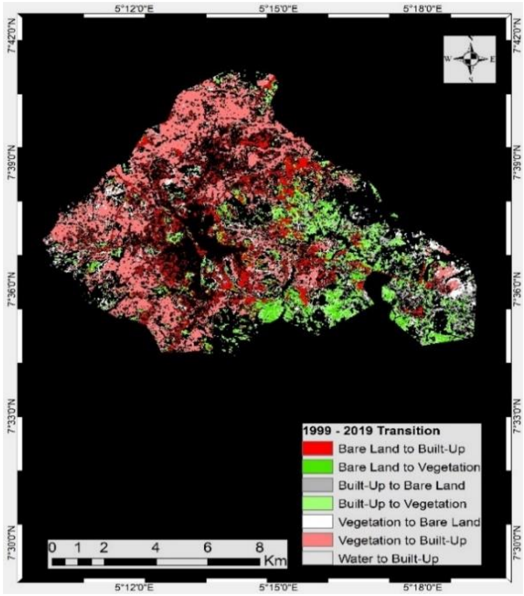

Figure 6b. *Land cover transition from 1987 to 1998*

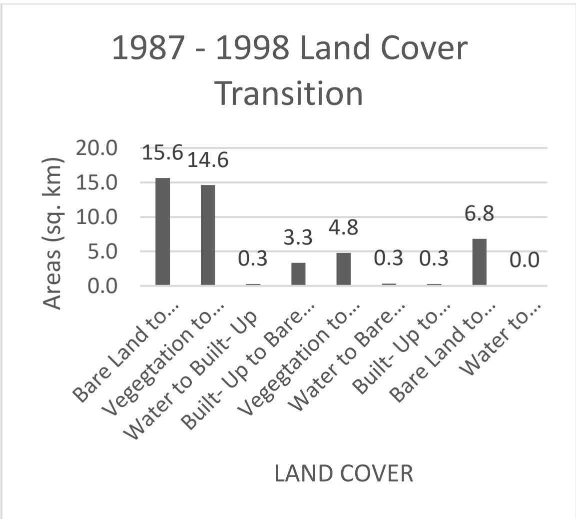

Figure 6c. *Land Cover transition from 1987 to 1998*

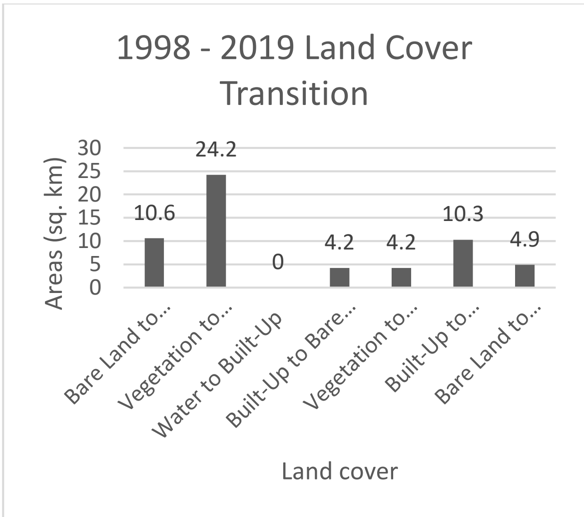

Figure 6d. *Land cover transition from 1998 to 2019*

Image Accuracy Assessment

Table 4 indicates classification accuracy for user's accuracy (Ua), and producer's accuracy (Pa).

Table 4: *1987, 1998 and 2019 Error matrix*

LULC	**1987**	**1998**	**2019**
	Pa Ua	***Pa, Ua***	***Pa, Ua***
Green spaces	85, 77.3	81.8, 85	90.9, 100
Built-up	75, 88.2	100, 85	83.3, 100
Bare Surface	68.2, 75	88.9, 80	93.3, 70
Water body	85, 73.9	87, 100	100, 95
Kappa statistics	0.87	0.79	0.85
Overall accuracy	78.1%	88.75%	91.3%

Surface Temperature of Ado-Ekiti metropolis

Figures 7-9 showed the spatial distribution of surface temperature from 1987 to 2019.

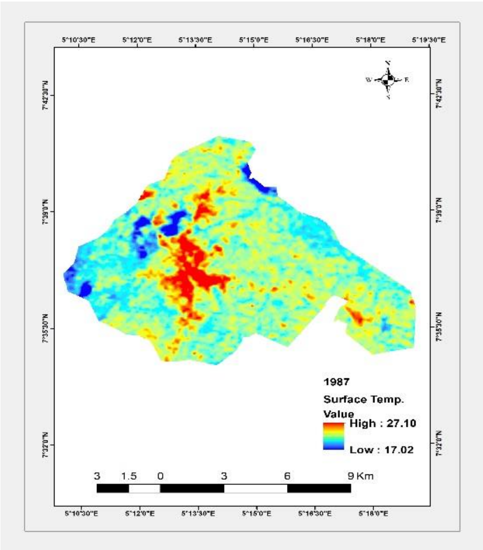

Figure 7: *Land surface temperature for year 1987*

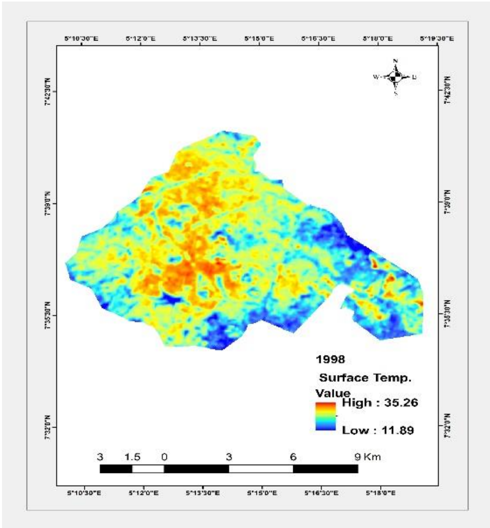

Figure 8: *Land surface temperature* ***for year 1998***

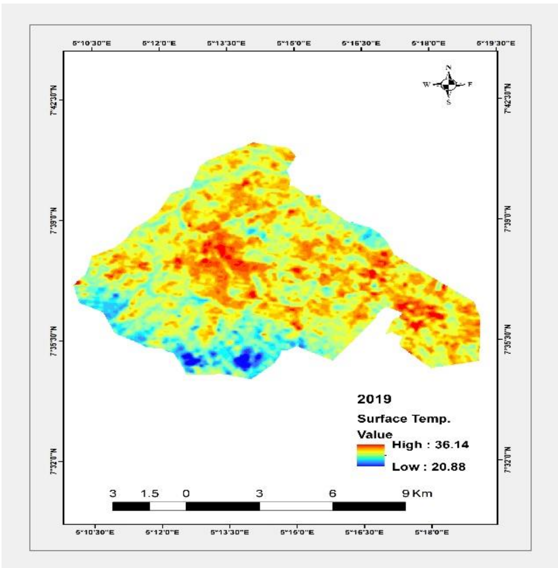

Figure 9: *Land surface temperature for year 2019*

Temperature variation among different land cover classes

Table 5: *Variation in temperature in land cover of the Study Area*

	Temperature		
LULC	**1987°C**	**1998 °C**	**2019°C**
Green Spaces	27.1	30.2	31.9
Built-Up	33.2	34.3	35.2
Bare Soil	28.5	31.9	31.9
Water Body	25.0	25.3	25.9

Normalized Difference Vegetation Index (NDVI)

Figure 9 – 11 showed the study area greenness index carried out, Normalized Difference Vegetation Index (NDVI).

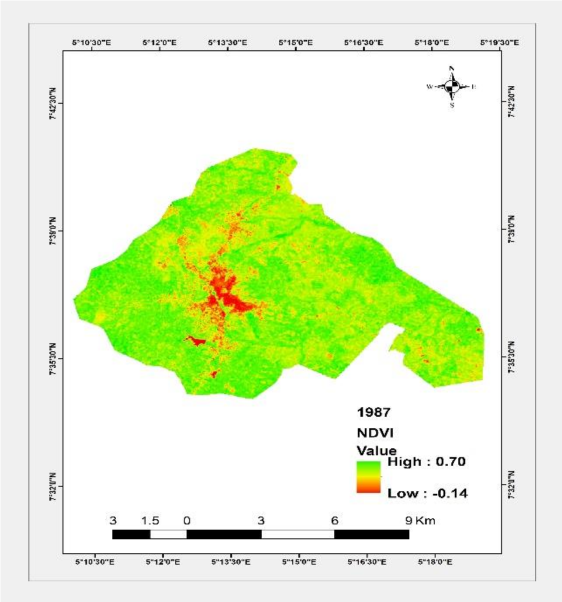

Figure 10: *NDVI for1987*

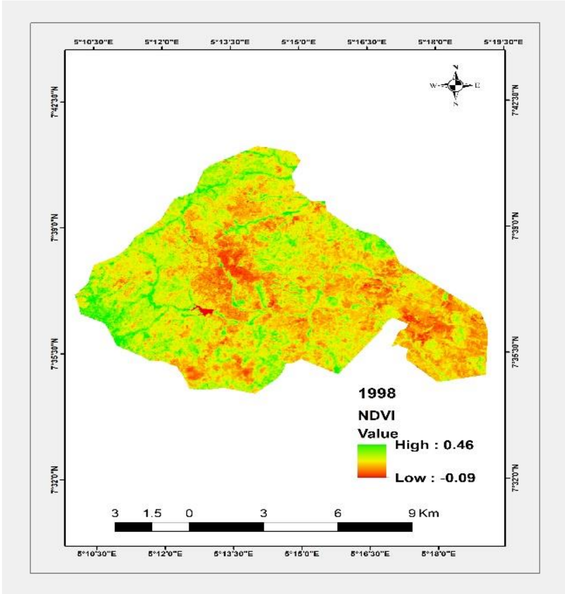

Figure 11: *NDVI for1998*

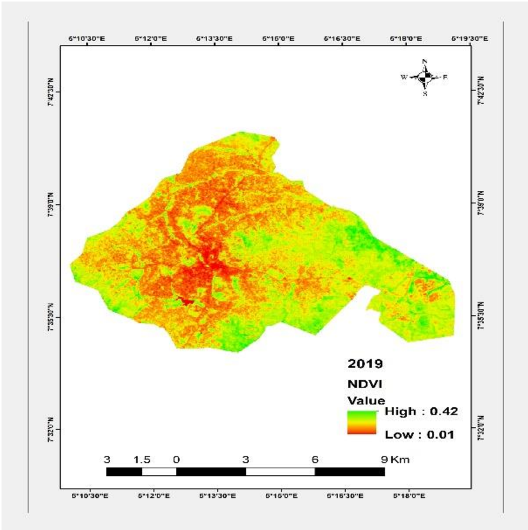

Figure 12: *NDVI for 2019*

Relationship between Urban Green and Surface Temperature (ST)

The correlation coefficient for the years considered in this study is shown in Table 6.

able 6. Correlation between UGS and ST

Year	Correlation Value (R^2)	*P* value
1987	-0.51	0.00
1998	-0.57	0.00
2019	-0.83	0.00

Source: field survey, 2019

Projected Land cover for 30 years (2049)

Table 7 showed the probability of the land covers to change to another category for both 1987 to 1998 and 1998 to 2019.

	Built-up	*Bare Land*	*Vegetation*	*Water*
1987 -1998				
Built-Up	0.5686	0.3523	0.0792	0.0000
Bare Land	0.5557	0.2089	0.2354	0.0000
Vegetation	0.3628	0.1305	0.5067	0.0000
Water	0.5120	0.3219	0.1299	0.0362
1998 -2019				
Built-Up	0.5814	0.1084	0.3101	0.0000
Bare Land	0.5678	0.1262	0.3056	0.0005
Vegetation	0.4922	0.0892	0.4186	0.0000
Water	0.1026	0.0041	0.0080	0.8853

Table 8. Projected Land Cover for 2049

Land Cover	**Area (Km^2)**	**Percentage (%)**
Built-Up	62.1	52.4
Bare Land	13.6	11.5
Vegetation	42.7	36.0
Water	0.1	0.1

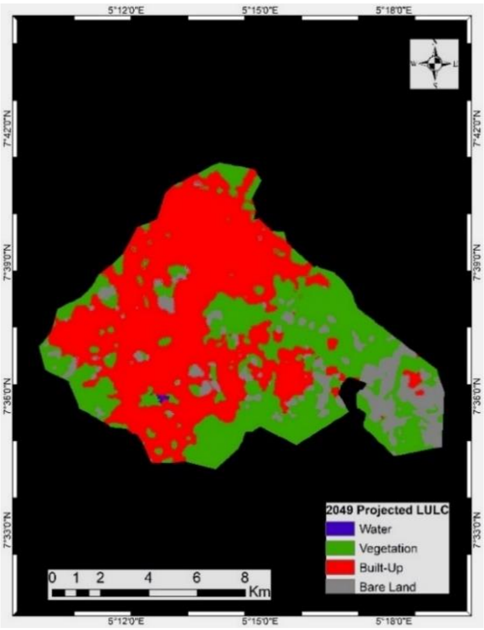

Figure 12. Predicted Land cover for 2049

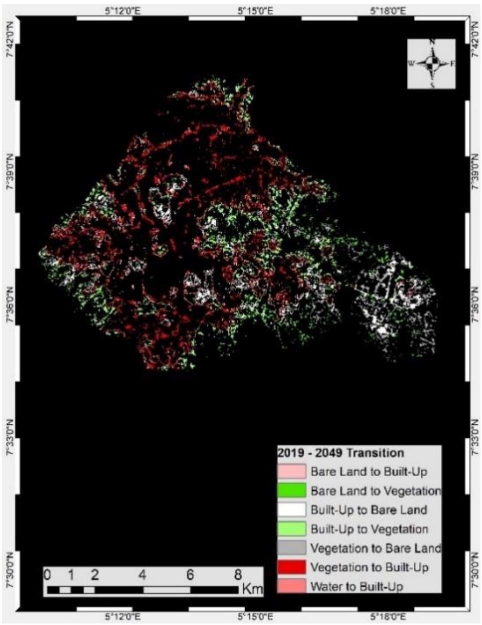

Figure 13. Predicted land cover transition for 2049

Table 7. Transition probability matrix for 1987 -1999 and 1999 - 2019

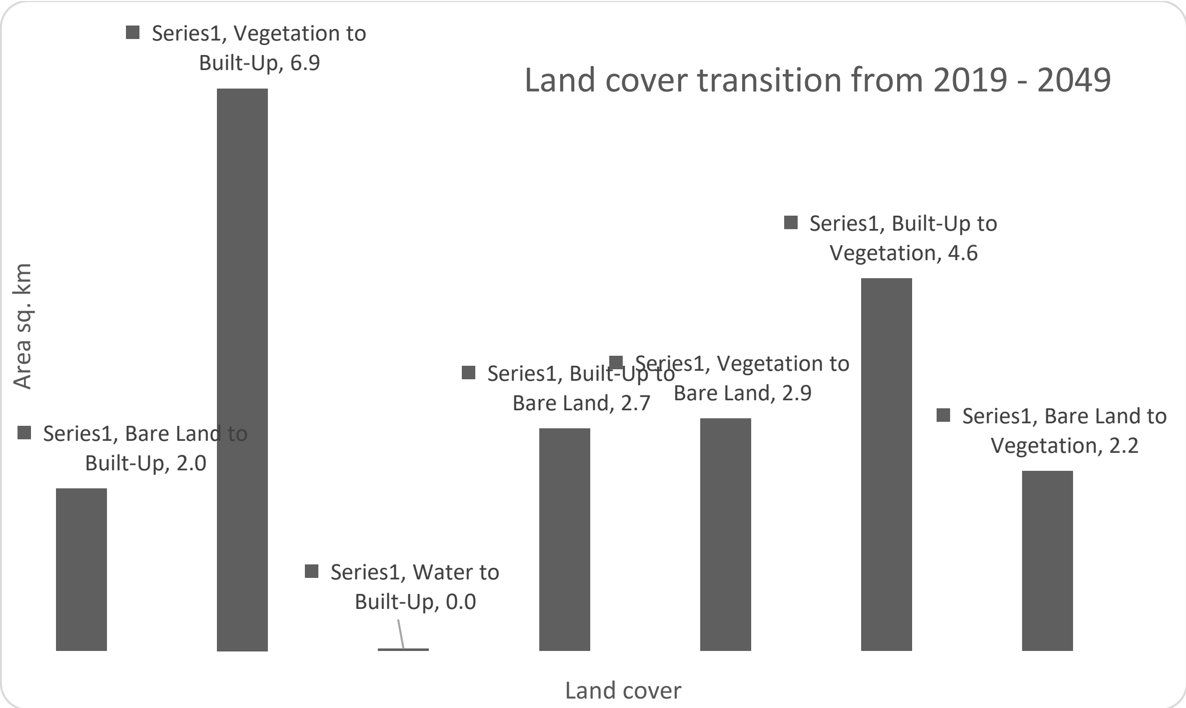

Figure 14. Predicted land cover transition for 2049

Discussion and Conclusion

There was a significant loss in UGS and bare land in Ado-Ekiti from 60% and 28.3% in 1987 to 38.7% and 10.5% in 2019. This loss in UGS is gained by built-up area, which consequently increased from 11.1% in 1987 to 51.1% in 2019 respectively. The percentage change in the UGS in Ado Ekiti metropolis between 1987 (60%) and 1998 (49.6%) was more than the changes recorded between 1998 (49.6%) and 2019 (38.7%). The high percentage change recorded between 1987 and 1998 was as a result of the creation of Ekiti State in 1996 from the old Ondo State which was already populated. As a result, there was rural-urban drift to Ado-Ekiti as the capital of Ekiti State, thereby increasing the social infrastructures and amenities in Ado-Ekiti. Therefore, an increase in population growth within the metropolis led to an increase in demand for land for infrastructural developments and other human-related activities which affected the green spaces in the study area. This is in line with the findings of Agboola (2019), that a considerable change in the pattern and process of land use in Ado-Ekiti metropolis had an effect on its land cover. This is also corroborated by Kong and Nakagoshi (2005) and Anqi and Edwin (2019) that UGS reduction was influenced by urban sprawl, which also increase the population and consequently increased the built-up area. Similarly, Alo and Aturamu (2014) argued that an increase in infrastructure and population significantly reduces forestland. Our result indicated a drastic reduction in UGS which is a threat to biodiversity conservation, an increase in land surface temperature of the city and harsh climatic conditions.

Land Use Land Cover Transition

Figure 6a-6c showed the transition in the land use land cover of Ado-Ekiti metropolis between 1987 and 2019. It showed the land cover that change to another land cover over the years (Figure 2a-2b). According to Figure 2c, from 1987 to 1998, vegetation and bare land had the highest transition to built-up with an area of 14.6 km^2 and 15.6 km^2 respectively. 4.8 km^2 of vegetation also changed to bare land whereas 6.8 km^2 of bare land changed to vegetation. From 1998 to 2019, a total area of 27.3 km^2 and 4.2 km^2 of vegetation transitioned to built-up and bare land respectively (Figure 2c). 10.6 km^2 of bare land also changed to built-up and 4.9 km^2 to vegetation. Area covered by built-up area increased from 1984 through

1998 to 2019. The changes in land use are similar to the report of Agboola (2019) that both in population size and spatial coverage, Ado-Ekiti has experienced continuous and unprecedented growth. And this is attributed to factors such as rural-urban migration, residential development, economic growth and pattern of transportation routes (Anqi and Edwin, 2019).

Image Accuracy Assessment

The accuracy assessment gives the user's accuracy (Ua), producer's accuracy (Pa), Kappa statistics (k) and overall accuracy for the years considered for the land use land cover trend analysis. Table 4 indicates classification accuracy for user's accuracy (Ua), and that producer's accuracy (Pa) was greater than 50%. The kappa statistics that show the level of accuracy for 1987, 1998 and 2019 were 0.87, 0.79 and 0.85 respectively. The overall accuracy for 1987, 1998 and 2019 were 78.1%, 88.75% and 91.3% respectively.

Surface Temperature of Ado-Ekiti metropolis

Figures 7-9 show the spatial distribution of surface temperature from 1987 to 2019, recorded that the highest average temperature (30.5°C) was observed in 2019. This was followed by 1998 with an average temperature of (23.6 °C) and 1987 with average an temperature of (22.1°C).

Temperature variation among different land cover classes

Built-up had the highest temperatures 33.2°C, 34.4°C and 35.2°C for 1987, 1998 and 2019 respectively. This was followed by bare soil and green spaces with 28.5°C and 27.1°C, 31.9°C and 30.2°C, as well as 31.9°C and 31.9°C in 1987, 1998 and 20219 respectively. This is because of the presence of paved surfaces and open surfaces. However, the lowest temperature was recorded for a water body with 25.0°C, 25.3 and 25.9°C in 1987, 1998 and 2019 respectively.

Relationship between Urban Green and Surface Temperature (ST)

From 1987 to 2019, the surface temperature increased from an average temperature of 22.1°C to 30.5°C (Figure 7-9). This can be said to be due to loss of vegetation that helps in reducing the adverse effect of direct solar radiation through shade and evapotranspiration on the soil, and the properties of impervious materials that contribute to the absorption of solar energy, causing surfaces, and the air above them, to be warmer in urban areas than those in rural surroundings. Inu (2015) discovered that the mean temperature is also influenced by the increase or decrease in built-up and vegetation cover in a proportional and aggregate way. That is, an increase in the built-up has a negative effect on the temperature. Built-up and bare surfaces had the highest temperature from 1987 to 2019 compared to other land cover types, that is, vegetation and water body This variation in temperature of different land cover types are due to the presence of buildings, structures, metals that affect the amount of radiation received and emitted by urban infrastructure. According to Figure (9-11), from 1987 to 2019, the vegetation index of the study area revealed that the vegetation decreases over the years due to the conversion of land cover. The built-up areas had the lowest (negative values) due to the presence of urbanization.

The negative correlation values indicate that there was a negative relationship between NDVI and ST throughout the years considered (Table 6). This is in line with the findings of Fareda *et al* (2020) that there is a negative correlation between LST and NDVI which implies that the higher the LST, lower the vegetated area. This implies that the increase in the surface temperature over the years of study was contributed to by the loss of urban green space. When the temperature of an urban region is higher than its rural surrounding, it is known as a phenomenon called Urban Heat Island. This is supported by the result of Awuh *et al.*, (2019) that changes in land cover greatly influence the spatial distribution of land surface temperature.

Projected Land cover for 30 years (2049)

Figure 12 showed the 30 years projected land cover for Ado-Ekiti metropolis. Table 8 showed that vegetation would have reduced to 42.7 (36%), built-up and bare land would have increased to 62.1 (52.4%) and 42.7 (11.5%) respectively. According to Figure 14, the land area of built-up and bare land that will be converted to vegetation are 4.6 km^2 and 2.2 km^2 respectively. But these are comparatively lower to the area loss in vegetation (6.9 km^2 and 2.9 km^2) that would be gained by built-up and bare land respectively.

Conclusion

There was variation in urban green space and bare land in Ado-Ekiti between 1987 and 2019 with a significant decrease over the years. However, the built-up area took over the loss by urban green space and bare land. The surface temperature of the study area also witnessed an increase which could be related to an increase in the built-up due to changes in the land use affecting the land cover. There is a need for urban greening and environmental education on maintaining trees wherever they are located for the sustainability of the environment.

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