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Impact of Land Use Change on Urban Heat Island in Etsoko West, Southern Nigeria

Medina Omo Kadiri[a], Gift Oluwatodimu Fabolude[b], Nura Umar Kura[c*]

[a] Department of Plant Biology and Biotechnology,
University of Benin,
Benin City.

[b] Department of Environmental Management and Toxicology,
Faculty of Life Sciences,
University of Benin,
Benin City.

[c*] Department of Environmental Environmental Sciences,
Faculty of Sciences,
Federal University Dutse,
Nigeria.

Email: nuraumar@fud.edu.ng

Abstract
The phenomenon of urbanization and population growth is a major global concern, as both emerging and old cities continue to expand, particularly in developing countries. Nigeria's urban population has grown dramatically over the last five decades, resulting in shrinking green spaces and urban forest, as well as increased urban island heat. As a result, this study looked into the existing and predicted land use and land cover (LULC), as well as land surface temperature change in Etsako West LGA of Edo State, Nigeria. The supervised maximum likelihood classification method was used to classify the town into four classes using Landsat data from 1987, 2001, and 2020. Similarly, LULC for the year 2040 was predicted using the Markov and CA-markov models. The Landsat Project manual was used to extract the land surface temperature. It was discovered that the built-up area increased over time, from 28.1 km² in 2001 to 103.07 km² in 2020, with a projected 166.93 km² in 2040. Furthermore, forestland decreased throughout time, but the decline was more pronounced in 2020, with decline of twice that of 2001. Cultivated/grassland land has increased over time and is expected to continue to do so in 2040, but surface water hasn't changed significantly. The average land surface temperature climbed from 25.67 °C in 1987 to 32.39 °C in 2020. The environmental impact of urban sprawl and rising urban heat cannot be overstated, as it includes both direct and indirect human and environmental consequences. As a result, eco-friendly strategies were recommended in ensuring sustainable urban growth and reducing urban island heat.

Keywords: Urban heat island; Landcover/Land use; Remote sensing; GIS; environment

INTRODUCTION
Emerging cities, as well as large cities and metropolitan areas, are experiencing the effects of urbanisation and population growth (Kuddus *et al*, 2020). Urban sprawl has a number of negative consequences such as; depletion of natural resources, increase in land surface

**Author for Correspondence*

temperature, and increase in pollution (Mittal, 2013). It has been predicted that, more than half of the world's population would be living in cities by 2050, thus, fast population expansion and urbanisation in emerging countries like Nigeria is a major environmental problem (Onaiwu, 2021). The environmental impacts of land use change are the results of the urbanization process. On one hand, the urbanization and people migration to urban areas in search of greener posture, help in lifting hundreds of millions of people out of poverty, on the other hand, it is believed to be responsible for grave environmental consequences which offer huge societal challenges, such as arable land decline (Yuan, *et al.*, 2022), raised ecological challenges (Abass, *et al.*, 2018), such as destructions of hydrological and ecological environment, urban heat-island effects (Zheng, *et al.*, 2021; Chatterjee & Majumdar, 2022). Though researchers have shown that, only four percent of the world's total land surface is urban area however, it still holds tremendous effects on both physical and social environment (Yuan, *et al.,* 2022). Similarly, urban expansion is responsible for depletion of natural resources, loss of biodiversity and destruction of natural landscape as well as affecting human health among other problems (Chatterjee & Majumdar, 2022).

Nigeria's urban population has expanded significantly over the last five decades, with a 50% urbanisation rate (Fox., *et al* 2015). This expansion is generally influenced by rural-urban migration and population growth (Avis, 2019). Established cities with accumulated trunk infrastructures, such as Lagos and Benin City, are experiencing significant urban expansion, due to shifting of rural communities to urban (Onaiwu, 2021). Urbanization is known to have tremendous effects on all components of the ecosystem. For example, the quality of water, air, and soil are known to be affected by urbanization and sensitive ecosystems like wetlands and forestry more often than not altered by these changes. Moreover, the impacts of urban growth can be felt by human social environment and economy, leading to environmental disasters such as flooding and erosion (UNDRR, 2013). Furthermore, land surface temperature increases due to declining green spaces and urban forest which can have diverse effects on the entire ecosystem (Fonseka., *et al* 2019).

Geographical Information system (GIS) and remote sensing have been shown to be reliable in analysing urban expansion and supporting urban planners in formulating environmentally friendly strategies (Saied, 2013). Land use changes, future projections, and land surface temperature have all been studied using satellite data from numerous sources, including the United States Geological Survey (USGS), which provides Landsat spectral data collected by remote sensing devices (Wang *et al,* 2020). This technique will be used to evaluate changes in land use, land cover, future projections, and land surface temperature trends in the Estako west local government area (LGA) of Edo State, Nigeria.

METHODOLOGY

Study area

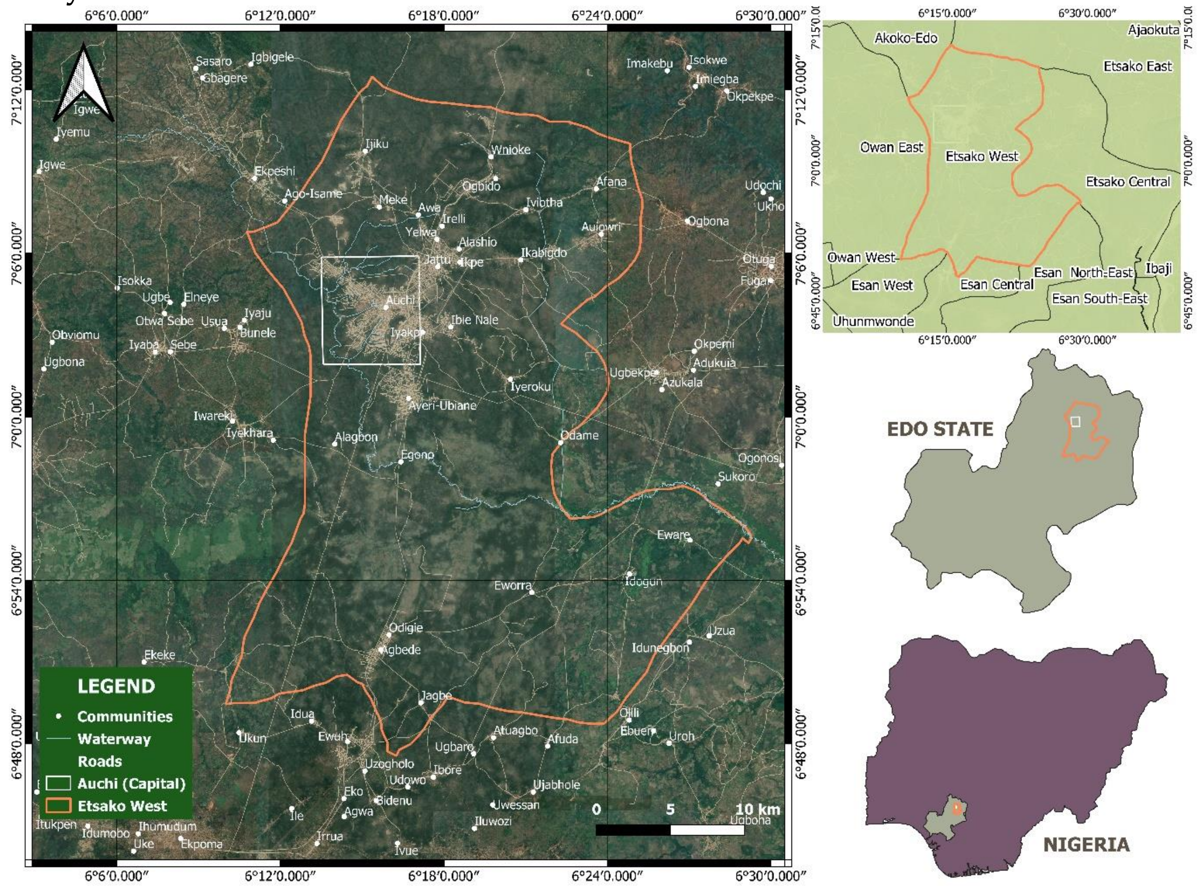

Figure 1: Map showing study area

Etasako West LGA lies between latitudes 6° 46′ 59.297′′ – 7° 11′ 23.007″ N and longitude 6° 8′ 35.943′′ – 6° 28′ 18.389′′. It is situated in the northern part of Edo State surrounded by Etsako East LGA, Etsako Central LGA, Akoko-Edo LGA and the entire Esan area. The centre of urbanization in the LGA is the capital (Auchi) which is joined by Jattu, Ughiole and South-Ibie to form an urban forum (Onaiwu, 2015). The population of the LGA was 260,700 according the 2006 population census with farming being the major occupation. The LGA falls under the sub-humid tropical climate according to Ibanga *et al*. (2021) with the area experiencing an average minimum temperature of 20^{0}C and maximum of 34^{0}C with a rainfall peak of 243.7mm in the first bi-modal peak, 282.2mm in the second peak and a total of 1602.5 mm per annum.

FLOW CHART OF PROCEDURE

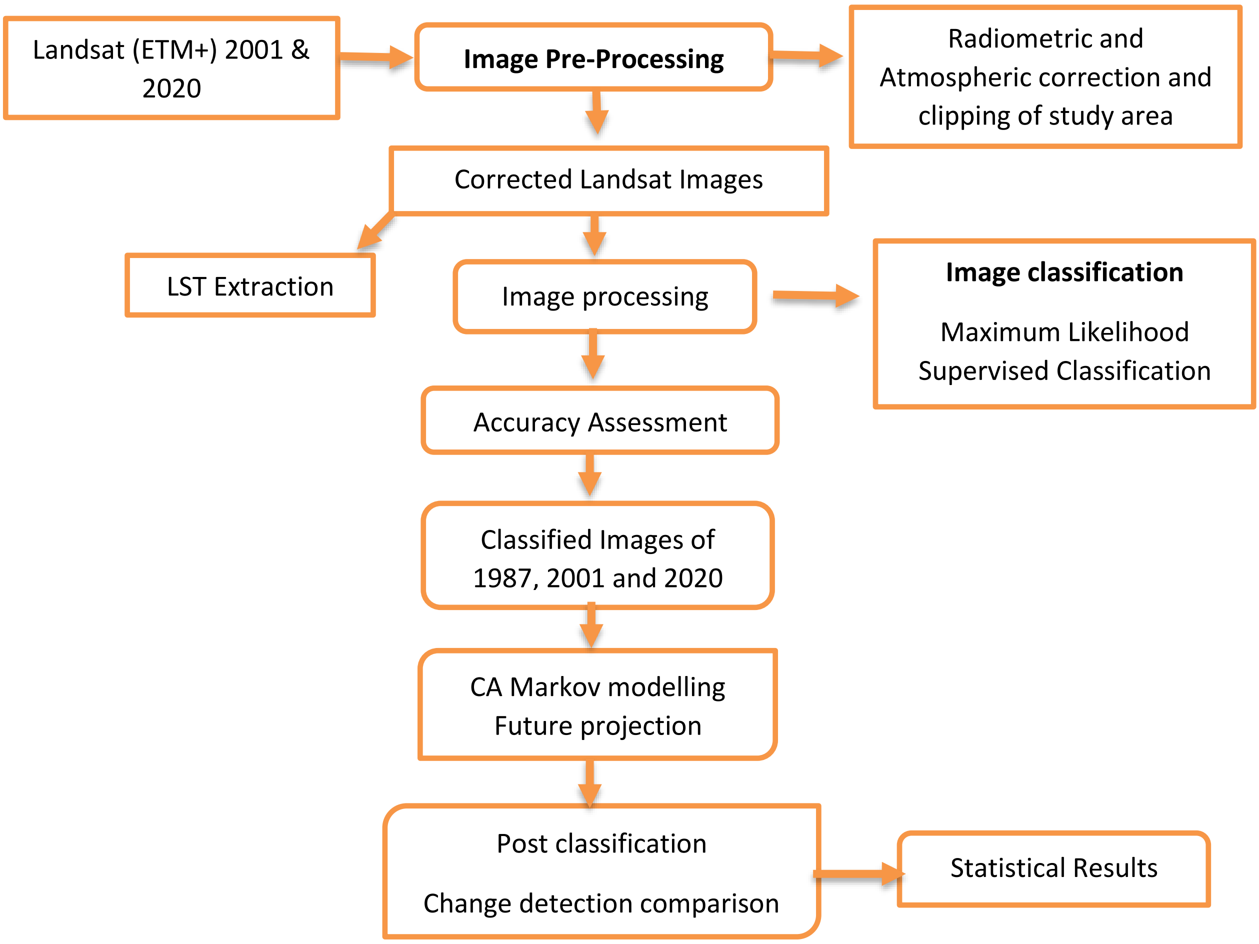

Figure 2: Methodology framework of study

Satellite data acquisition and image processing

Landsat satellite (Landsat 5,7,8) data were obtained from the United States Geological Survey (USGS) database at (http://earthexplorer.usgs.gov/). Table 1 presents the metadata for all imageries collected. Due to cloud cover concerns in the tropical region, data was collected in a 20-year average interval. Imageries with less than 10% cloud over were collected. It is a difficult task to perform classification analysis without radiometric and atmospheric correction thus, it is important to perform image pre-processing to ensure similar spatial resolution and radiometric calibration (Hishe *et al.,* 2021). Image pre-processing was carried out using the ENVI 5.2 FLAAH (Fast Line of Sight Atmospheric Analysis Hypercube) tool which help convert raw DN (Digital number) to reflectance values before clipping out the study area from each scene.

Table 1: Attributes of the downloaded satellite imageries

Attributes	**1987**	**2001**	**2020**
Sensors	Landsat 5 TM+	Landsat 7 ETM+	Landsat 8 OL1/TIRS
Path/row	188/54	188/54	189/56
Spatial resolution	30 m	30 m	30 m
Data of acquisition	27-01-1987	09-01-2001	22-1-2020

Image classification and accuracy

In this study, the Maximum Likelihood classification method was utilized as it has been demonstrated to be accurate and commonly utilized (Chen and Stow, 2002). The imageries were classified into four land use/land cover classes (Built-up, Forest, Cultivated/grassland, and Water). The imageries were classified using ground control points using the Supervised Maximum Likelihood classification tool in ENVI 5.2, as shown in table 2. Using these sampling points, each pixel is allocated to the class with the highest probability or maximum likelihood (Richards, 1999). Then, Confusion matrix, which describes the connection between a reference data and the classified map, was used to determine the accuracy of each classified image (Comber, 2013). A high-resolution image was used to acquire the reference data (Google Earth image) (Khwarahm, *et al.*, 2021). The accuracy result shows the accuracy of the producer and the user, as well as the overall accuracy and the Kappa coefficient. The error matrix was used to create all of these accuracy values. The multivariate Kappa coefficient depicts the probability of ground truth data and classification map agreement ranging from 0 to 1 (Esaid *et al.*, 2018).

Table 2: Land Use Land Cover Class adopted and number of training samples per class

Class	Description	Number of samples (1987)	Number of samples (2002)	Numbers of samples (2020)
Built-up Area	A concrete structure such as residential, industrial, roads and other uses.	40	41	42
Water Bodies	Reservoirs and rivers	30	32	32
Cultivated/grassland	Agriculture, grass vegetation and crop land	49	50	50
Forest land	Forest cover (trees)	50	45	53

Future modelling (Markov and CA-Markov model)

Future LULC maps were created by first building a transitional matrix between a previous and later LULC map. The Markov model was used to produce this transition matrix. It is a well-liked model that generates a two-period transition area matrix and transition probability matrix (Biswas et al, 2019). The transition matrix is critical for modelling future scenarios that are dependent on the pixel-by-pixel state of both the current and previous image (Khwarahm, *et al*, 2020). A transition matrix was created utilizing the 2001 and 2020 classified LULC maps in order to model for the next 20 years starting in 2020. The Land Use Modeller tool in TerrSet 17.0 software was used for this. The Cellular Automata Model (CA model) was used to simulate spatial allocation of the LULC class once the probability matrix was generated. Based on the derived probability matrix, the CA model predicts a new spatial distribution of LULC classes (Khwarahm, *et al.*, 2020). The CA-modeller in TerrSet 17.0 software was also used to calibrate the 2040 LULC map for this study.

Measurement of Land Surface Temperature (For Landsat 5 &7)

LST for Landsat 5 and 7 was obtained by converting digital number (DN) to Spectral radiance utilizing radiant actors in Land metadata reference values according to the equation published by the Landsat Project Science Office (2002). This stage extracts the brightness of the surface temperature, which is then transformed to kinetic temperature using the Eq2 equation (Artis and Carnahan 1982)

Lλ = ((LMAXλ - LMINλ)/(QCALMAX-QCALMIN)) * (QCAL-QCALMIN) + LMINλ --------------------------Eq. 1

L_λ represents spectral radiance (watts/ (m^2*srad*µm)), LMAX and LMIN are spectral values from the Landsat image metadata. QCALMAX and QCALMIN are also calibrated values extracted from the Landsat Image Metadata while K1 and K2 are defined constants.

$$LST = \frac{T}{1+w\times[\left(\frac{T}{p}\right)\times\ln(e)]}$$ ……………………………………Eq. 2

Where T is At-Satellite Brightness Temperature, w = wavelength of emitted radiance of the thermal infrared band, e = land surface emissivity, which ranges from 0.99–1.01 and p is given as: $\frac{h\times c}{s\ (1.438\times10^{-2}\ m\ K)}$ …………………………Eq 3

Where h, s and c are Planck's constant (6.626×10^{-34} Js), Boltzmann Constant (1.38×10^{-23} J/K) and velocity of light (2.998×10^{8} m/s), respectively.

For Landsat 8, At-satellite brightness temperature was gotten from spectral radiance adopting thermal constants as provided in the metadata file using equation 4. Land surface emissivity (e) was extracted using equation 5 before final LST calculation using Eq 2

$$T = \frac{K_2}{ln(\frac{K_1}{L_\lambda}+1)}$$ ……………………………………..Eq. 4

L_λ Represents spectral radiance, while K1 and K2 are predefined constants.

$e = (0.004\times P_v) + 0.986$ ……………………. Eq. 5

Where

$P_v = (\frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}})^2$ ………………………..Eq. 6

RESULTS

LULC change result in Etsako West Local Government, Edo State

Etsako West Local Government Area of Edo State spans 950 square kilometres. the results shows that Land Use and Land Cover of the area as follows: urban land use grew linearly from 1987 to 2020 (figure 3 and 4). The urban area grew nearly fourfold from 28.10 km^2 in 1987 to 103.07 km^2 in 2020 (figure 3 and 4), and this trend is projected to continue as the CA-Marvol modeling projects that urban land use would grow to around 166.93 km^2 by 2040. Furthermore, between 1987 and 2001, grassland cover/agriculture land use did not develop much, but between 2001 and 2020, grassland cover/agriculture land use rose by 262.99 km^2 (figure 3). Moreover, it was discovered that forest cover was deteriorating, with a large loss of 266.46km^2 of land between 2001 and 2020. The CA-Marvol model predicts that while grass/cultivated land may not change significantly, forest land would depreciate by 53.47km^2 from 2020 to 2040. Finally, unlike other classes, surface water class did not show any major changes over the years studied (figure 3 and 4).

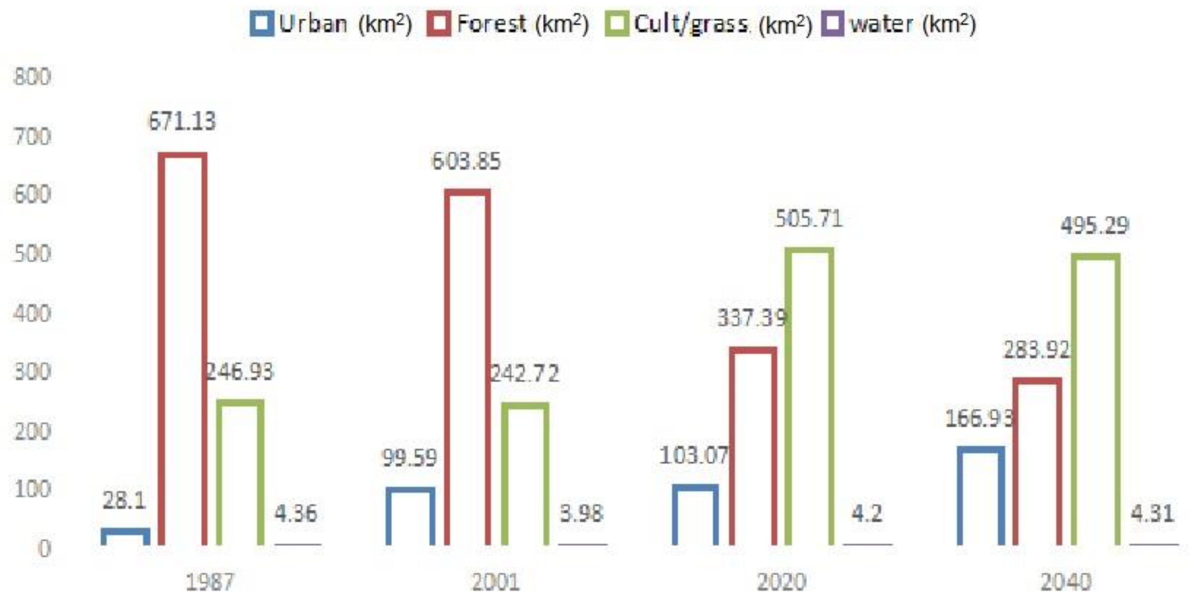

Figure 3: A bar chart showing changes in LULC classes of Etsako West LGA.

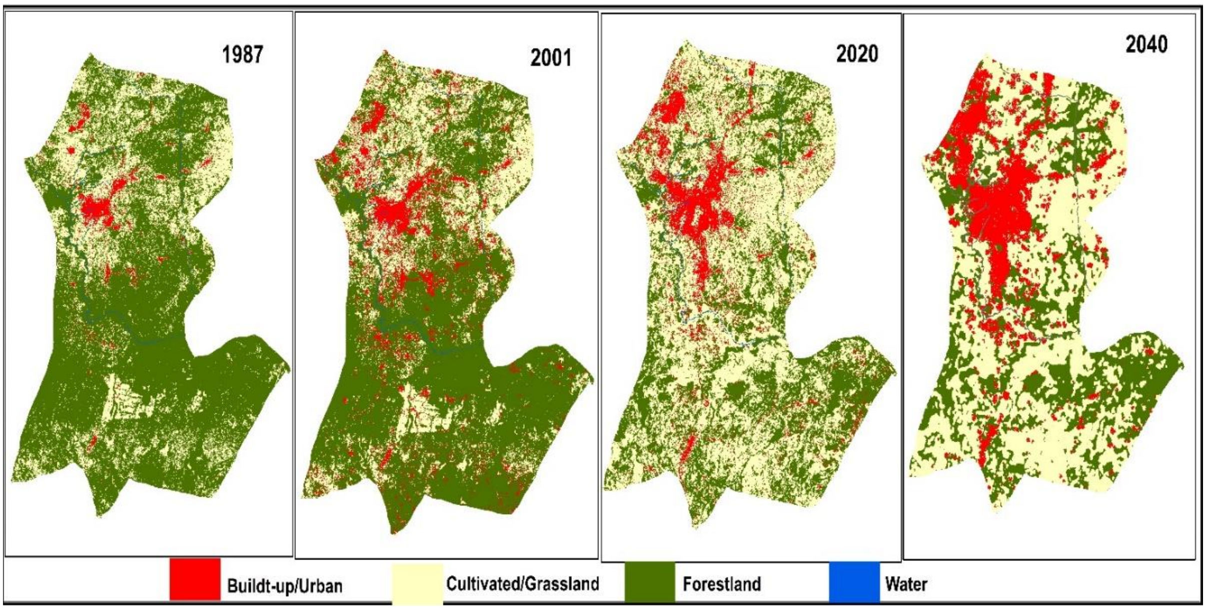

Figure 4: Spatial Distribution of LULC in Etsako West LGA, Edo State Nigeria.

LULC of AUCHI

The estimated LULC of Etsako west's capital (Auchi) shown in Figure 5. It spanned 53.21 km^2. The urban class grew steadily and in a linear pattern, as it rose from 10.76km^2 to 17.75km^2 between 1987 and 2001, and then further grew to 24.70km^2 in 2020. Whereas, grassland/cultivated land found in the most area in 1987, underwent no major changes between 2001 and 2020. Forest land in the Capital drastically depreciated from 12.89km^2 in 2001 to 6.27km^2 in 2020, indicating an influence of urbanization. Finally, the Capital, like the rest of the Etsako west area, saw no notable changes in surface water throughout the course of the year (table 3).

Table 3: Area of LULC classes for the Auchi, Etsako West capital.

Years	Urban (km²)	Forest (km²)	Cultivated/grass(km²)	water(km²)
1987	10.76	15.43	21.81	1.81
2001	17.75	12.89	17.37	1.73
2020	24.70	6.27	17.03	1.78

Accuracy Assessment

The User's accuracy, Producer's accuracy, Kappa coefficient and Overall accuracy were extracted for all LULC map generated. The LULC map for 2020 had the highest Overall accuracy of 94.80% and Kappa coefficient of 0.91. While the 1987 and 2001 maps had Kappa coefficient values of 0.85 and 0.86 respectively (table 4). Generally, the lowest User's accuracy was recorded in 1987 for the Cultivated/grassland class while the highest was recorded in 1987 for the Water class. Finally, the highest Producer's accuracy was also recorded for the water class in 1987 and the lowest still in 1987 for the forest class all of which are within the acceptable limit (Khwarahm, *et al.*, 2021).

Table 4: Kappa coefficient, producer, user and overall accuracy for all classified images from 1987 – 2020

Class	1987		2001		2020	
	User's Accuracy	Producer's Accuracy	User's Accuracy	Producer's Accuracy	User's Accuracy	Producer's Accuracy
Urban	94.99	92.34	90.84	92.72	94.99	96.60
Forest	88.74	85.82	88.00	89.50	92.20	89.74
Grassland	87.99	94.52	94.35	88.82	94.34	92.85
Water	99.99	99.9	94.48	96.54	96.22	99.29
Overall Accuracy (%)	89.81		90.87		94.80	
Kappa Coefficient	0.85		0.86		0.91	

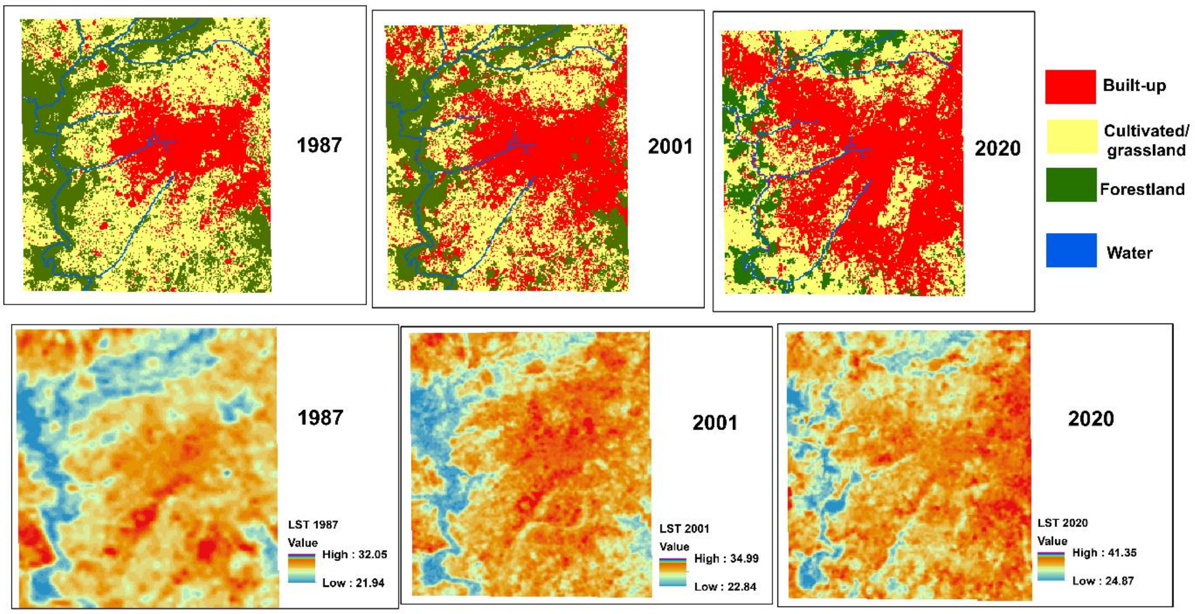

Figure 5: LULC and LST distribution of Auchi

Land Surface Temperature

Figure 5 shows the spatial distribution of Land surface temperature in Etsako West With an average temperature increased over time from 1987 to 2020. In 1987, average LST was 25.67 ^{o}C while the minimum and maximum LST was 20.18^{o}C and 34.46 ^{o}C respectively. However, in 2001, average LST increased to 26.49 ^{o}C with a minimum LST of 21.29 and Maximum LST of 43.11^{o}C. Moreover, in 2020 average LST further increased in to 32.39 ^{o}C with a minimum and Maximum LST of 24.36 ^{o}C and 42.23 ^{o}C respectively. Finally, LST was also extracted for the Capital (Auchi) as shown in fig 5. Average LST increased from 26.50 ^{o}C in 1987 to 28.57 ^{o}C in 2001 and further increased to 32.35 ^{o}C in 2020.

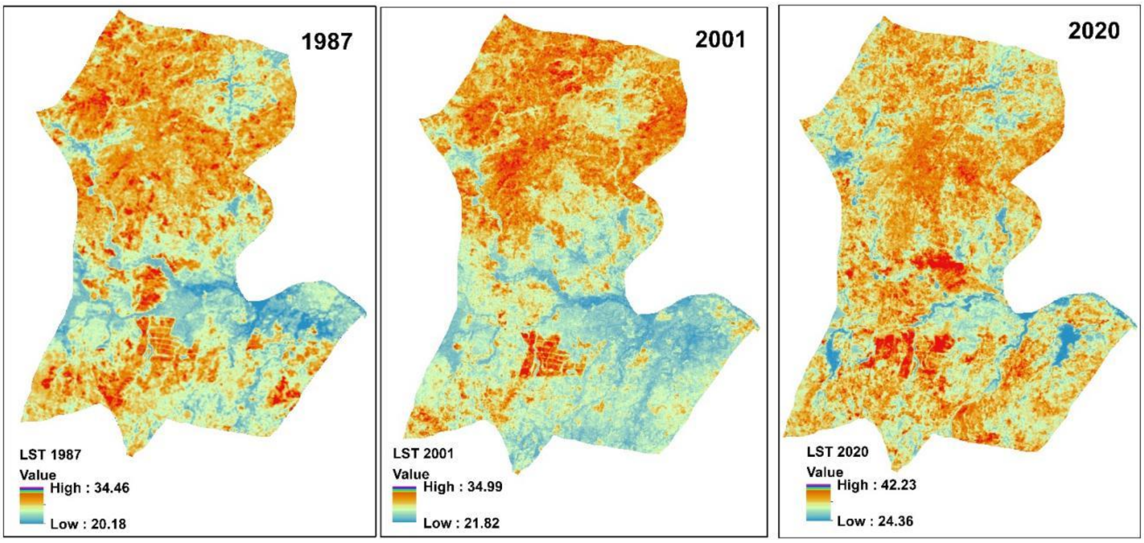

Figure 6: Spatial distribution of Land Surface Temperature in Etsako West Local Government

DISCUSSION

This study analysed the changes in Land Use and land cover (Built up, Forestland, cultivated/grassland and water) and LSTof Etsako West over a period of 33 years. The area experienced a steady growth in built-up areas over the past 33 years (figure 3, 4 and table 3). From the findings, the urban area increased by 74.97km^2 within an average of 30 years and predicted to further increase by 63.86km^2 in the next 20 years from now based on the CA Markov's Model/ transition matrix (Table 3).

The increase in urban or built-up areas is majorly due to increasing population of a given place (Satterthwaite *et al.*, 2010). Etsako West population increased from 126,112 to 260,700 between 1991 to 2016 with an annual population change of 2.7 % and population density of 275.9/km^2 according to the 1991 and 2006 national census. Thus, increase in population leads to increase in built up area and consequentially affects the natural resources such as forest and surface water resources (Mittal and Mittal, 2013). In addition, the pressure on natural resources in urban areas directly and indirectly leads to increase in pollution (Air, water and land), loss of biodiversity, increase in urban heat, and increase chances of flood and erosion (Ohwo and Abotutu, 2015). As reported by Ibanga *et al.* (2021) that about 70% of the population in Etsako west are farmers by occupation and the dominant environmental disasters in the town are flooding and erosion, with the recent 2019 flooding event owing to agricultural water stress (Ibanga *et al.*, 2021). Moreover, the increase in agricultural water in 2019 corroborates the results of this study with the massive expansion of cultivated/grassland in 2020. Therefore, the sudden growth in cultivated/grassland that doubled in 2020 can be attributed to increased pressure to satisfy the growing population of the town (Pandey & Khare, 2017). All communities in Auchi experienced linear growth across the main road apart from Auchi which experienced growth from its core to other areas. The growth in the capital town can be attributed to social establishments and institutions such as Auchi Polytechnic, numerous Secondary Schools, Hotels etc. Thus, the quest for education and jobs within and around the institution directly affects the expansion of the town capital which increased by 13.94km^2 within 33 years period of this study (Turok & McGranahan, 2013). Furthermore, deforestation in urban areas was not only attributed to the felling of trees for development but also expansion of built-up areas into natural habitat which includes forest (Gourmelon, 2016).

Results from this study show that, most of the depleted forest land were converted to grassland/cultivated land especially in the southern part of the town (figure 4 and 5). However, the capital experienced significant growth leading to increased deforestation within the town capital. Edo State is endowed with high valued forest tree species such as *Triplochiton scleroxylon* and *Milicia excelsa* which makes lumbering and timber processing a major economic activity in the state (Olayiwola and Igbavboa, 2014). Therefore, with the increase in both legal and illegal lumbering without afforestation plans, forest lands are heavily depleted and species diversity richness reduces over time. Although tropical regions are dominated by native species that have high regeneration rates, this regeneration is often altered by unregulated human activities (Lawer *et al.*, 2013).

With the recent report on the fact that native species have high carbon sequestering ability than exotic species replacing natural forests, the heavy depletion of forests in Etsako L.G.A should be checked for effective climate change mitigation actions (Daalder, 2021). In addition, surface water had no substantial changes over time, and this may be due to the fact that such land use are not usually replaced by urban development or other land use activities in emerging cities. However, developments in urban areas are major concerns for water quality as activities from increasing agricultural practice, transportation and point source industrial processes contributes largely to chemical and biological changes of surface and groundwater resources (Camara *et al.,* 2019). Moreover, water bodies in urban areas are often affected by siltation which is caused by improper management of drainage system thereby reducing the size of water bodies and posing a threat to aquatic biodiversity (Dudgeon, 2012). Similarly, one of the most significant environmental impacts of urbanisation is the increase in urban heat (Chatterjee & Majumdar, 2022). This impact owes to increasing structures such as buildings and roads that absorb and re-emit the radiation from sun. These surfaces tend to absorb more heat than other natural areas such as water and forestlands (Chapman *et al,* 2013). Furthermore, in tropical regions, it has been proven that temperature has increased over time and urban areas experienced more heat than other areas owing to increasing urban density (Marcotullio *et al,* 2021). This supports the Land Surface Temperature (LST) analysis result of this study (Figure 5 and 6). The mean LST increased by 0.82 ^{0}C from 1987-2001 while mean LST increased by 5.9 ^{o}C between 2001 and 2020. The massive increase in LST in 2020 can be attributed to increased built-up structures, exposed barren land and cultivated/grassland was evident from the LULC results of this study (Grigoraș & Urițescu, 2019). As expected, among all analysed years, the capital of the L.G.A experienced slight increase in LST over time (Figure 5). The impact of increased urban heat includes increased indoor and outdoor discomfort for humans, recirculation of pollutants, increase energy consumption and impairment of water quality (EPA, 2021). LULC study is incomplete without an accuracy assessment (Abdelkareem *et al.,* 2018). Therefore, accuracy test was carried out for this study using the confusion matrix.

The overall accuracy for all years studied was ≥ 89.81% while the Kappa coefficient was ≥ 0.85 thus, satisfying the analysis as excellent (Khwarahm, *et al.*, 2021).

CONCLUSION

This study investigated LULC and LST temperature change for Etsako West L.G.A of Edo State Nigeria. The LULC analysis utilized the supervised maximum likelihood classification method based on four classes which are built-up, forest, Cultivated/grassland and water for the year 1987, 2001 and 2020. The resulting changes of the LULC were then utilized to predict changes for 2040 using the Markov/CA-Markov modelling. Urban area and cultivated/grassland expanded significantly over time particularly the cultivated/grassland in 2020 while the forest land depreciated over time but there were no substantial changes in surfaces water over time. The general trend is expected to continue in 2040 as it was predicted that the urban land and cultivated/grassland will continue to increase due to increase in population but if afforestation plans are not implemented, the forest land will further depreciate. In the case of capital of the L.G.A, the result for all classes observed were similar but experienced the highest urban growth from its core to surrounding areas. Land surface temperature increased over time in Etsako West Local Government Area, with slight increase in the capital, Auchi. The impact of increasing land use and land surface temperature affect s all components of the environment. Therefore, it is recommended that eco-sensitive urban plans such as development of green spaces, effective town planning and use of eco-friendly building materials are initiated.

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