OSUN GEOGRAPHICAL REVIEW

Journal of the Department of Geography,
Osun State University, Osun State, Nigeria

Volume 6, 2024

ISSN: 2695 - 1959

Published by the
Department of Geography, Osun State University,
Osun State, Nigeria

CONTENTS

OSUN GEOGRAPHICAL REVIEW
Published by the Department of Geography, Osun State University, Osun State, Nigeria
ISSN: 2695 - 1959 Volume 6, 2024; 84 - 94

CHARACTERIZATION OF THE IMPACT OF URBAN DEVELOPMENT ON DEFORESTATION AND FOREST DEGRADATION IN AKURE ENVIRON, ONDO STATE NIGERIA

***O. O. Fabiyi and O. Fajilade**
Department of Forestry and Wood Technology, Federal University of Technology Akure, Nigeria
**Corresponding author's email: seyifabiyi@gmail.com*

Abstract
The paper characterized the nature, trends, and future projection of the impacts of urban development on the land-use conversion of forest cover in Akure environment. The study analyzed the land use and land cover (LULC) changes in Akure environment over the past 40 years and projected the potential influence of future development on the forest cover in the study area. LULC transitions were mapped from years between 1991 and 2023 using Landsat data. The years were divided into 4 epochs within the time frame, 1991, 2002, 2016, and 2023 based on major developmental policy shifts. The results showed that between the periods of investigation, dense vegetation massively decreased from 561Sqkm to 166 Sqkm of total land cover, while built-up areas grew from 34sqkm to 162sqkm. The decrease in Vegetation cover was also accounted for by the increase in the bare surface from 132 Sqkm to 430sqkm. The bare surfaces largely include infrastructure development, land preparation for new development, and exposed rock outcrops from mining activities. Transition modeling done using the CA-Markov model predicts that built-up area would increase to 209sqkm, bare land increased to 447sqkm while dense vegetation decreased to 138 Sqkm in the year 2033. The study predicted that land conversion for urban development will continue dislocating the ecological balance between soft and hard landscape in Akure environ and this will further contribute to increased emission and reduction in carbon sequestration. The paper recommended ecological balance backed by concrete policy from the government that encourages urban green, urban agriculture, and the introduction of green corridors in urban infrastructure to enhance carbon sinks in the city.

Keywords: Landuse conversion, Forest degradation, Deforestation, Change detection, Urban development.

Introduction

Global Forest watch put deforestation in Nigeria at 163 Kha/year with 12% tree cover lost between 2001 and 2002. The major deforestation agents are urban development and agricultural land use. Urban development with its twin sister industrialization has been postulated as the agent of economic growth in most developing countries (Fabiyi, 2022,). Forest has been defined as a region with density of woodland which cohabited by a variety of living beings including man, plants, animals and other micro-organisms (Mfon, 2003). Humans in the quest for development intervene and utilize the forest resources in their pursuit of clothing, food, medicine, and other functions (Ahmed & Aliyu, 2019, Fabiyi, 2022). Man's demand for knowledge, education, and development has significantly influenced the land use of the world and the development that happens over time. Land use and land cover changes are prevalent in more urban areas than rural areas globally, with the potential to cause severe environmental impacts. These changes could result from natural or anthropogenic activities that affect the structure, function, and composition of ecosystems, leading to forest degradation and deforestation. According to Wang *et al*. (2018), the evaluation of LULC change is a study of environmental change that is more directly related to the growth of settlement, farming, fast urbanization, and deforestation. Urbanization has caused land transformation from one type to another and land cover modification which has altered a large proportion of the earth's land surface, and this is driven by the goal of meeting humanity's immediate needs from natural resources (Meyer and Turner, 1992; Vitousek *et al*. 1997).

Land use and land cover change (LULC) is a modification of the Earth's surface that is mostly caused by human activities (Li et al., 2023). Urban areas are experiencing fast growth, and this is due to the socioeconomic growth of different areas in the world, according to the World Bank (2023), over 50% of the world's population lives in urban areas and this is predicted to increase by 1.5% by 2045. With the increasing rate of human modification of land for different purposes largely for urban development and infrastructure, the current rate of land use and land change is greater than ever in history.

Deforestation is the transition of forest to non-forest land use either as a deliberate removal of trees for urban development or agriculture (Tejaswi, 2007). Deforestation is categorized as one of the major global issues in the world today (Manjula *et al*. 2011) existing literature shows that economic growth and persistent urbanization is an unavoidable global phenomenon that initiates urban encroachment into agricultural lands and forest lands (Azadi et al., 2011; Paul and McKenzie, 2013). Although urbanization cannot be stopped it can be controlled to reduce its adverse effect on the environment and vegetation cover.

Remote sensing and geographic information systems play a critical role in the assessment of land use changes, providing accurate and reliable information on land cover and land use changes, and has been used by several researchers to examine land cover changes in urban areas (Fabiyi 2006,2007,2011, Okwori and Fabiyi, 2016). Talukdar *et al*. (2020) noted that machine learning classifiers have become popular in recent years due to their ability to process large amounts of data quickly and accurately. The use of remote sensing in this study will provide accurate information on land use and land cover changes in the study area and enable policymakers to make informed decisions on land use planning and conservation.

Despite several attempts to measure urban expansion in recent decades and its environmental repercussions, researchers have paid little attention to quantifying the effects of urban growth on deforestation. To address the influence of urban expansion on deforestation, we must first understand how urban areas have evolved and how they affect the physical environment, especially biodiversity and land degradation. The study utilized remote sensing and GIS techniques to characterize the effects of urban expansion on deforestation and forest degradation in Akure environs.

Study Area

Akure comprises of two major local government areas (Akure South and Akure North LGAs) in Ondo State southwestern Nigeria. The area has a tropical humid climate with two distinct seasons, rainy and dry seasons. Akure South has an area of 338 km2 and Akure North has an area of 667 km^2. Akure North occupies the northern part and Akure South occupies the southern part. The areas are located between Latitude 7°05'N and 7°20'N and Longitude 5°05'E and 5°25'E. Figure 1 shows the map of the study area. In Akure, the average annual temperature is 25.8 °C. During the hot season, which lasts about two months from late January to late March with the daily maximum temperatures exceeding 30 °C frequently. March is the warmest month of the year, with an average high temperature of 30.5 °C and a low temperature of 22 °C at night. A daily maximum temperature of less than 27.8 °C is usual throughout the cold season, which lasts from mid-June to early October. August is the coldest month of the year with average lows of 20.5 °C and highs of 26.6 °C.

The annual rainfall total in Akure North and South is 2,548 mm (100.3 in). The rainy season lasts around 9 months, from February 6 to November 24, with a mean of 31 days of at least 12.7 mm rainfall. September has the highest average rainfall in Akure, with an average of 228.6 mm. The year's rainless season lasts more than two months, from November 24 to February 6. January is the driest month, with an average rainfall of 5.1mm inches. Between 1975 and 2015, both Akure North and Akure South had tremendous population growth, with Akure North increasing by 246.2% and Akure South increasing by 158.4%. This implies a significant shift in demographics throughout the years. Akure South has a greater population (500,226) than Akure North (126, 07). However, the gender distribution is generally balanced in both locations, with only minor differences in the proportions of male and female inhabitants. Akure South has a somewhat higher median age (21.7 years) than Akure North (20.4).

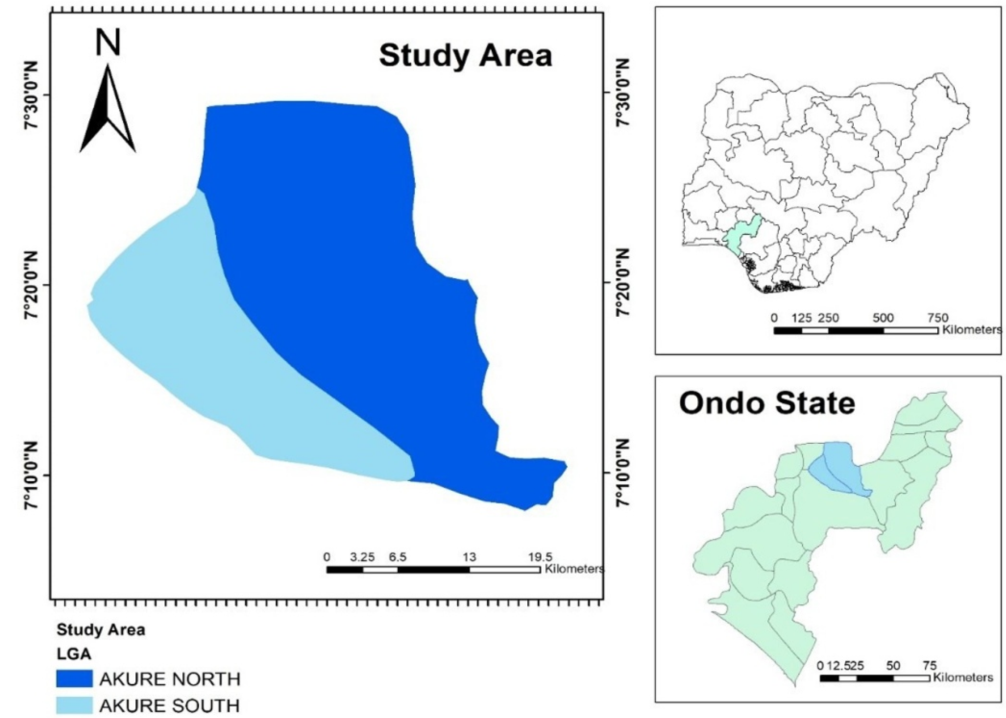

Figure 1: Map showing Akure South and Akure North

This means that Akure South's population is somewhat older on average.

Materials and Method

Materials

Remote sensing and GIS techniques are used in data collection and this method ensured a comprehensive assessment of the land use and land cover changes in the study area. Multitemporal satellite images (Landsat) of four epochs from 1983 to 2023 were used for this study, Landsat Thematic Mapper (TM), Landsat ETM+ (Enhanced Thematic Mapper), and Landsat Operational Land Imager (OLI). Different Landsat image series were used to capture the four temporals (epochs) of the LULC assessment condition of 1991, 2000, 2016, and 2023. The data was downloaded and accessed from the USGS Earth Explorer website and the open-access hub (https://earthexplorer.usgs.gov/).

Methods

Supervised classification:

Supervised classification was used in this study to categorize the different land cover types in the land area. Supervised classification is a remote sensing approach that uses a collection of training data to identify pixels inside an image. Five major classes were considered for the study which includes Built up, Bare land, Rock outcrop(which were grouped as urban land areas in the study area), Dense vegetation, and Sparse vegetation although agricultural land and fallow land were classified as sparse vegetation due to the difficulty of differentiating these classes on Landsat image because of their spatial resolution(the study was to extract the impact of urban development on the deforestation and forest degradation). The classification scheme used for this study is shown in the table1.

Accuracy assessment:

An accuracy assessment assesses the validity of classified images based on item groups. Accuracy is a measure of the agreement between a correct standard and an unknown-quality image classification. Confusion matrix is used to determine accuracy assessment and it includes overall accuracy, user accuracy, producer accuracy, and kappa data. The Kappa coefficient was calculated using equation (Wynne et al., 2021). Mishra *et al.* (2016) defined poor agreement as a kappa coefficient value below 0.4, moderate agreement as 0.4-0.8, and excellent agreement as greater than 0.8.

Table 1: A classification scheme for study purpose

Classification	Landuse	Description
Forest	Dense Vegetation	Land cover where trees and plants are abundant and Healthy
	Sparse Vegetation	Land cover where there is a low density of vegetation
Urban Development	Built-Up	Land cover types associated with manmade structures, such as buildings, roads, and infrastructure.
	Earth Crust (Rocky areas)	Land cover associated with rocks and hills exposed which are being exploited by humans as quarry or other mining extraction
	Bare Land	Land cover where the ground is not covered by vegetation or other types of land area. leaving the soil exposed including areas exposed for infrastructure or building operations and infrastructure development and other hard landscapes in the study area.

$$K = \frac{N\sum r\ i= 1\ Xii - \sum r\ i=1\,(Xi+)\,(X\ +\ i)}{N2\sum r\, i=1\ (Xi+)\ (X+1)}$$

Where r is—rows number in the matrix, Xii—number of observations in row i and column I (the

diagonal elements), X + i and Xi+—the marginal totals of row i and column I, respectively, and N—observations number.

Land cover change detection: This study compared changes in urban land use and vegetation cover between 1983 and 2023 among 4 transition epochs using change detection analysis techniques in ArcGIS.

Land cover change prediction: The CA-Markov model was used to predict urban expansion and impact on vegetation cover from 2023 to 2033 based on the algorithms used severally by authors such as (Weng, 2002; Mansour *et al.*, 2020; Fu *et al.*, 2022; Khwarahm *et al.*, 2021and Nouri *et al.*, 2014).

Results

The result showed progressive growth of the built-up area, and bare surfaces over the years as shown in Figure 2 and Table 2 the increasing land consumption for urban development resulted in a high reduction in vegetation cover in the area.

Dense vegetation was 559.3 Sqkm in 1991 but grossly reduced to 221.53 Sqkm in 2002. There was a slight increase in 2016 to 311.09 which is a bit suspicious judging from the accuracy assessment achieved in the 2016 dataset (58%, the lowest in the dataset) in 2023 vegetation reduced 166.6Sqkm. The reduction in dense vegetation is a combined consequence of deforestation and forest degradation. We further looked at the sparse vegetation changes and observed that spare vegetation peaked in 2002 with 341.3 Sqkm and was lowest in 2023 with only about 203.8sqkm remaining. The forest cover in Akure environment is steadily reducing while urban development is steadily on the increase.

Urban built-up area was only 34.18 Sqkm in 1991 but increased to 55.84 in 2022. A sudden increase was noticed in 2016 when urban growth tripled to about 141.49 Sqkm and in 2023 urban development was 2161.1Sqkm. The bare land which is another measure of urban development steadily increased from 125.3 Sqkm in 1991 to 352.3 Sqkm in 2002, 332.15 in 2016 Sqkm and 430.51 Sqkm in 2023. Therefore in 2023 urban development (built-up area and Bare surfaces) accounted for a total of 592.97Sqkm in the study area while vegetation cover greatly reduced during the period.

Table 2: Class area statistics in Km^2 and Percentage

LULC Type	1991		2002		2016		2023	
	km^2	%	km^2	%	km^2	%	km^2	%
Bare land	125.36	12.46	352.36	35.03	332.15	33.02	430.51	43.04
Built up	34.18	3.40	55.84	5.55	141.49	14.07	162.46	16.15
Dense vegetation	559.36	55.60	221.53	22.02	311.09	30.92	166.83	16.58
Sparse vegetation	252.43	25.09	341.36	33.93	178.83	17.78	203.84	20.26
Rock outcrop	35.57	3.54	35.72	3.55	43.54	4.33	42.71	4.34

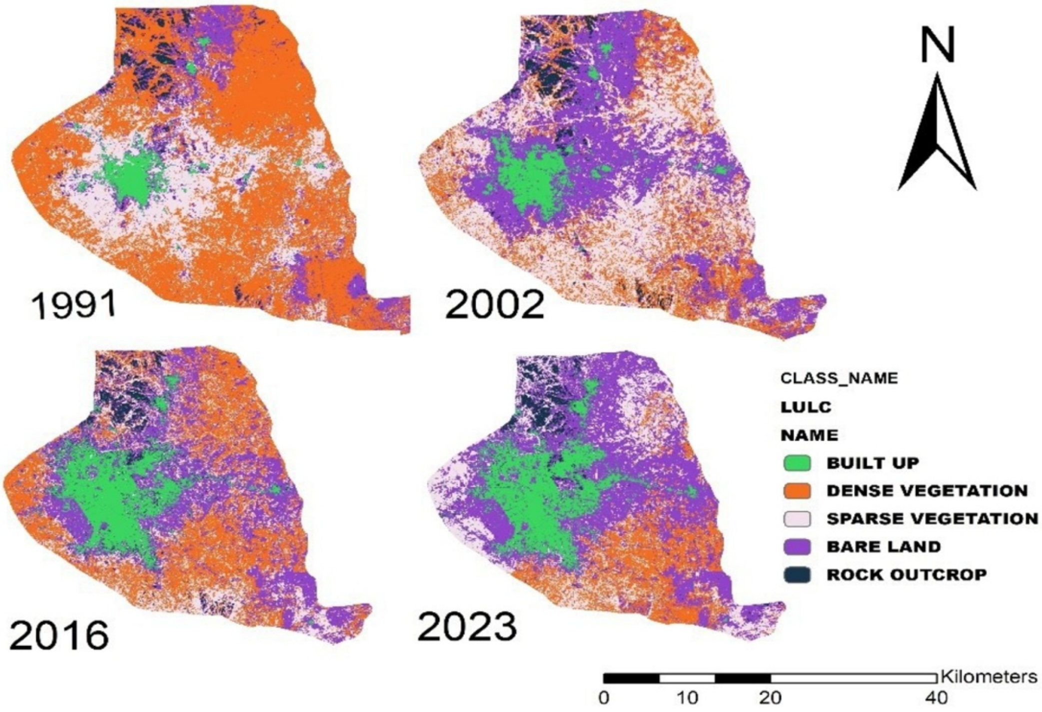

Figure 2: LULC map of the 4 epochs

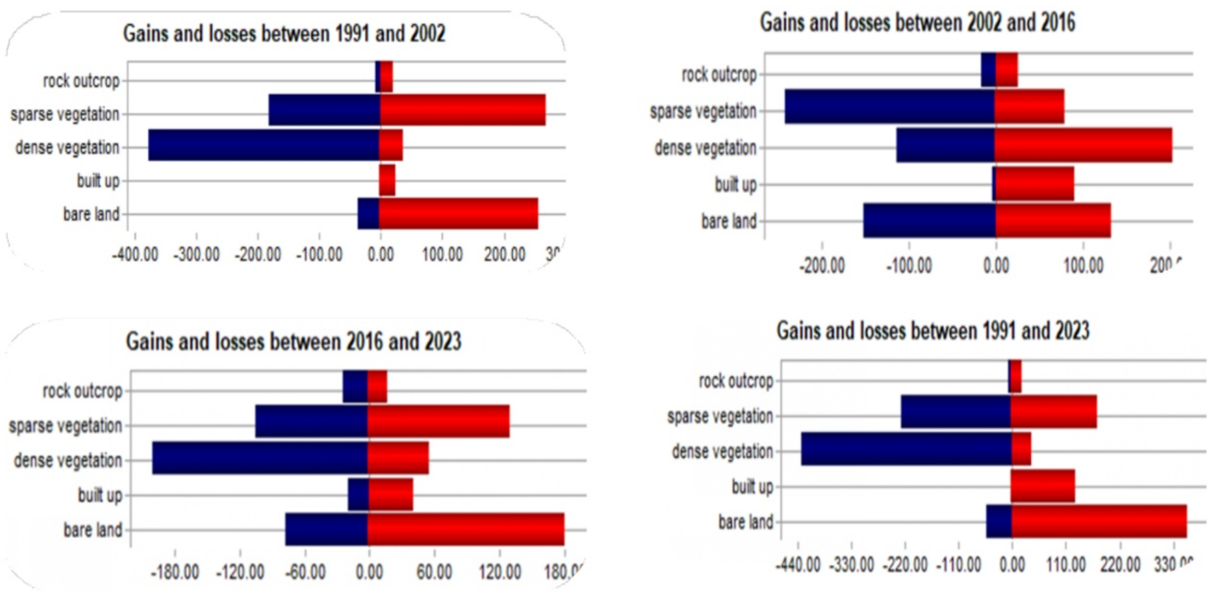

Figure 3: Net gain and loss for each change analysis

The expansion of built-up areas shows development over time, this increase might be due to population expansion, rising housing demand, and other urban development initiatives within the study area. The expansion of bare land represents a shift away from natural ecosystems and towards urbanization, agricultural expansion, and infrastructural development. Figure 2 represents the pictorial representation of the historical LULC maps over 40 years showing the different classifications as represented in the legend. Both Figure 2 and Table 2 indicate that the major land use and land cover in Akure North and Akure South is urban development and bareland with vegetation, such as fallow agricultural land.

Accuracy assessment of the classified images:

The accuracy of the classified image was done using the confusion/error matrix generated for each LULC classification in 1991, 2002, 2016, and 2023 classified maps. The overall accuracy percentage comes directly from the confusion matrix by taking the ratio of correctly classified pixels to the total sample size. Table 4 shows the overall accuracy of the classified images, 68%, 65%, 58%, and 63% for 1991, 2002, 2016, and 2023 respectively which indicates a moderately accurate model for all the data. It shows that the least-correctly classified data was in 2016. This was partly due to the lack of a cloud-free scene for the year 2016.

Sitthi *et al* (2016) explained that LULC map accuracy is carried out by establishing an error matrix that compares the classified map with a reference classification map. The outcomes of the investigation are consistent with the research of Temesgen *et al* (2018) in the Dera District and

Olujide et al (2018) in Akure who have done similar investigations. The accuracy assessment falls within the range of accuracy for Land Change Modeler and Landsat images (Rimal et al, 2018).

Table 3: Overall Accuracy for each year

Year	Overall accuracy
1991	68%
2002	65%
2016	58%
2023	63%

Land use change detection

Transition potential modeling provides a robust approach to analyzing LULC transition patterns in LULC between 2 different years (Maguire *et al*, 2005). Cross-tabulation measures changes and conversions between land cover maps. The tables below show outlined frequencies along the transition probability matrix of the diagonal, indicating the likelihood of the LULC class remaining unaltered (persistence) between earlier and later land cover maps.

Built-up area increased from 341.18 km2 in 1991 to 55.84 km2 in 2002, an increase of 21.66 km2 with the major contribution from sparse vegetation, due to urbanization. Dense vegetation decreased substantially from 561.09 km2 in 1991 to 221.46 km2 in 2002 with 140km2 transitioned to sparse vegetation and 106km changed to bare land. At the interval, the 2 prevalent land uses were bareland and sparse vegetation which increased from 254.41km2 in 1991 to 341.28km2 in 2002 and bare land increased significantly from 132.32km2 in 1991 to 352.29km2 in 2002. The prevalence of sparse vegetation and bare land in 2002, indicates readily available land resources that could be converted for urban development, facilitating the outward expansion of cities.**Table 5:** Change analysis 2002-2016

Urban expansion led to an increase in built-up area from 55.83 km2 to 141.49 km2, an increase of around 86 km2. Also, there was an increase in dense vegetation from 221.3973 to 310.7835, with contributions from transitioning bare land (35.14 km2) and sparse vegetation (167.2 km2). This suggests concurrent urbanization and regeneration of some vegetation areas in the study area during this period. Despite remaining the most prevalent land cover type, bare land area slightly decreased. The prevalent land use in 2016 was a combination of bare land (331.9 km2) and dense vegetation (310.78 km2).

The built-up area continued to increase from 141.4845 km2 to 162.4599 km2, an additional expansion of around 21 km2, driven by ongoing urbanization processes. Also, dense vegetation decreased substantially from 310.6926 km2 to 166.7889 km2, with significant portions transitioning to sparse vegetation (111.25 km2) and bare land (86.45 km2). This indicates deforestation or degradation of forested areas. Bare land experienced a notable increase from 331.8795 km2 to 430.4163 km2, majorly due to the conversion of previously vegetated areas. Sparse vegetation also moderately increased from 178.5402 km2 to

Table 4: Change analysis 1991-2002

		2002 (sqkm)					
		Bare land	Built up	Dense v	Sparse	Rock	TOTAL
1991	Bare land	94.6323	9.5139	12.4677	4.7556	10.9503	132.3198
	Built up	3.3228	30.7449	0.0009	0.0009	0.1071	34.1766
	Dense veg.	106.7337	0.855	183.7953	263.4012	6.3135	561.0987
	Sparse Veg.	140.7978	13.7376	24.6051	73.0701	2.2014	254.412
	Rock outcrop	6.8031	0.9846	0.5877	0.0486	16.1424	24.5664
	TOTAL	**352.29**	**55.84**	**221.46**	**341.28**	**35.72**	**1006.57**

Table 5: Change analysis 2002-2016

		2016(sqkm)					
		Bare land	Built up	Dense v	Sparse	Rock	TOTAL
2002	Bare land	199.13	67.67	35.14	33.64	16.64	352.22
	Built up	3.94	51.13	0.01	0.24	0.51	55.83
	Dense veg.	59.27	6.69	106.28	45.25	3.92	221.39
	Sparse Veg.	58.48	13.58	167.20	98.16	3.79	341.21
	Rock outcrop	11.11	2.43	2.15	1.34	18.67	35.69
	TOTAL	**331.93**	**141.49**	**310.78**	**178.62**	**43.54**	**1006.35**

Table 6: Change analysis 2016-2023

		2023(sqkm)					
		Bare land	Built up	Dense v	Sparse	Rock	TOTAL
2016	Bare land	263.74	30.16	16.79	18.23	1.97	331.87
	Built up	17.61	122.21	0.02	0.26	1.39	141.48
	Dense veg.	80.45	0.88	110.13	111.25	3.99	310.69
	Sparse Veg.	58.42	2.29	38.98	65.13	13.72	178.54
	Rock outcrop	12.20	9.93	0.88	0.89	18.63	43.54
	TOTAL	**430.42**	**162.46**	**166.79**	**203.77**	**42.70**	**1006.13**

Table 7: Change analysis 1991-2023

		2023					
		Bare land	Built up	Dense v	Sparse	Rock	TOTAL
1991	Bare land	71.9904	23.1813	9.9189	10.638	16.5444	132.273
	Built up	2.4174	31.4784	0.0144	0.0189	0.2421	34.1712
	Dense veg.	227.8548	30.7872	128.4885	165.2931	8.5464	560.97
	Sparse Veg.	121.9995	74.6928	28.1655	27.405	2.1204	254.3832
	Rock outcrop	6.2523	2.3229	0.2475	0.4806	15.2541	24.5574
	TOTAL	**430.4844**	**162.4626**	**166.8348**	**203.8356**	**42.7074**	**1006.355**

203.7654 km2, with (111.25km2) transitioning from dense vegetation. Overall, the patterns indicate continued urban expansion accompanied by a decline in dense vegetation cover and an increase in bare land during this period.

Table 7 shows the substantial reduction in dense vegetation from 560km^2 in 1991 to 166km^2 in 2023. The major transition contributing to this loss was 165km^2 changing from dense vegetation to sparse vegetation, 31km2 changing to built-up, and the most significant change of

227.85km2 to bare land. The built-up area grew substantially from 34km^2 in 1991 to 162km^2 in 2023. The majority of this increase was the transition from bare land, sparse vegetation, and dense vegetation which includes 23km^2, 74km^2, and 31km^2 respectively. Bare land increased from 132km^2 in 1991 to 430km^2 in 2023. The major contribution to the increase in bare land is the conversion of 227 km2 dense vegetation to bare land.

Figure 3 shows the net gain and loss over the 32 years from 1991 to 2023. The study area has gone through significant land cover transformations driven by human activities like fast-paced and uncontrolled urbanization, deforestation, and agricultural expansion. The transition of dense vegetation to bare land, sparse vegetation, and built-up areas shows the impact of human-caused land-use changes, resulting in the loss of dense vegetation cover within the study region during this period.

Prediction of future land use

Table 8 shows extensive loss of dense vegetation which is expected, based on the rapid urban development. It is estimated that only 114 km2 of dense vegetation will remain in 2033. This large, expected decline of dense vegetation highlights the need for conservation efforts in urban regions to improve the flow of the ecosystem. It is also recommended that urban green should be adopted in the built-up area to increase the forest cover and moderate the local climate in the study area. Built-up area is expected to expand significantly to 209 km^2 and the main gain is 26km^2 transitioning from bare lands, indicating development pressure on agricultural/fallow areas near settlements. The built-up area is predicted to continue expanding at the expense of bare lands and vegetation cover because it has been observed from the data that as vegetation changes to bare land the conversion of bare land to built-up increases.

The predicted continued loss of forests in the study area matches predictions for broader Nigeria, with FAO 2020 estimating annual deforestation rates between 2-5% will lead to complete forest depletion in key states by 2050 without interventions (Tubiello *et al.*, 2021).

Overall, the Table shows trends of urban expansion and vegetation loss expected to continue based on past trajectories. The data provides a basis to simulate ecological impacts and plan mitigating policies.

Discussion

The study showed the significant impacts of Urban development represented as built-up area and bare surfaces on the vegetation cover in the study area. It demonstrated that urbanization is one of the major drivers of deforestation in capital cities like Akure where there is a high concentration of Government and private investment in brick and mortar. The forest resources are threatened in any urban area that

Table 8: LULC area cover prediction for 2033

		2033(sqkm)					
		bare land	built up	dense veg.	sparse veg.	rock	Total
2023	bare land	364.78	26.27	13.92	14.76	10.68	430.42
	built up	4.03	158.12	0	0	0.31	162.46
	dense veg	27.09	0.85	114.82	23.55	0.48	166.79
	sparse veg.	42.64	22.90	10.26	127.96	0	203.77
	rock outcrop	9.63	1.06	0.08	0.23	31.71	42.70
	Total	**447.03**	**209.19**	**139.09**	**166.49**	**42.17**	**1006.13**

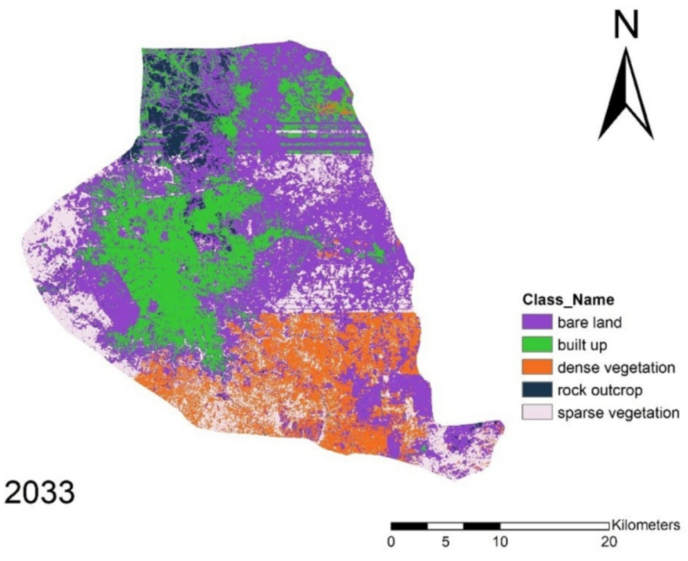

Figure 4: Predicted LULC in the study area in 2033

doubles as both an administrative and commercial center in the region which is the case in akure. The rapid expansion of urban areas, fueled by population growth and socioeconomic development, has led to the conversion of forested lands into built-up areas and other land uses.

The rise in built-up areas and bare land over the study period represents a significant shift toward urbanization, agricultural expansion, and residential development. The increase in built-up areas from 1991 to 2023 can be driven by factors such as population increase, housing demand, and urban development, which is consistent with the worldwide urbanization trend (Mansour *et al*, 2020). However, the alarming decline of dense vegetation and sparse vegetation reveals potential environmental effects that might have a detrimental influence on biodiversity, ecological services, and community well-being (Chitrakar *et al*, 2017; Gibbs and Salmon, 2015). The result is consistent with research that shows that fast urbanization leads to the conversion of natural land to built-up areas, hence contributing to land degradation (Idowu *et al*, 2023; Alademomi *et al*, 2020). The increase in bare land points to deforestation, urban expansion, and agricultural land clearing as contributing factors (Wubie *et al*., 2016; Araya and Cabral, 2010; Wang *et al*, 2018) Deforestation is mostly caused by poor law enforcement and population increase (Lennert *et al*, 2020).

This trend shows the need for conservation efforts and sustainable urban planning to mitigate the impact of urbanization on deforestation, this study shows the necessity of sustainable urban planning and conservation techniques to balance growth and environmental preservation (Olubi

and Fadamiro, 2022; Laros and Jones 2014). In summary, the study demonstrates the significant impact of urbanization on deforestation in the study area. The rapid expansion of urban areas, driven by population growth and socioeconomic development and how it has led to the conversion of forested lands into built-up areas, bare lands, and agricultural areas, resulting in substantial deforestation and loss of dense vegetation cover.

Conclusion

This research analyzed historical and future land use and cover patterns from 1991 to 2033. The land cover change data from 1991 to 2023 provides evidence that urbanization has been a major driver of deforestation in the study region over the past three decades and the projected LULC situation suggests that the covering will persist in the future. The substantial increase in built-up areas, coupled with the significant loss of dense vegetation cover, clearly shows the impact of urban expansion on vegetation. As development grew to accommodate increasing populations and economic activities, large areas of dense vegetation were cleared to make way for residential, commercial, and infrastructure development.

While urbanization is a necessary process for economic growth and development, the data shows that it has come at a significant environmental cost in the form of deforestation and habitat loss. The reduction in vegetation cover not only impacts biodiversity but also has implications for climate change mitigation, soil erosion, and other ecological processes. What is clear from this study is that climate and environmental change impact would continue to increase if nothing is done to bring a balance between urban development and environmental conservation. The government needs to implement policies to promote green infrastructure, biodiversity conservation, and sustainable urban development to help reduce the intense pressure of urban development on forest resources.

References

Alademomi, A. S., Okolie, C. J., Daramola, O. E., Agboola, R. O., & Salami, T. J. (2020). Assessing the relationship of LST, NDVI and EVI with land cover changes in the Lagos Lagoon environment. *Quaestiones Geographicae*, *39*(3), 87-109.

Araya, Y. H., & Cabral, P. (2010). Analysis and modeling of urban land cover change in Setúbal and Sesimbra, Portugal. *Remote Sensing*, *2*(6), 1549-1563.

Azadi, H., Schoonbeek, S., Mahmoudi, H., Derudder, B., De Maeyer, P., & Witlox, F. (2011). Organic agriculture and sustainable food production system: Main potentials. *Agriculture Ecosystems & Environment*, *144*(1), 92-94.

Beroho, M., Briak, H., Cherif, E. K., Boulahfa, I., Ouallali, A., Mrabet, R., ... & Aboumaria, K. (2023). Future scenarios of land use/land cover (LULC) based on a CA-markov simulation model: case of a mediterranean watershed in Morocco. *Remote Sensing*, *15*(4), 1162.

Chitrakar, R., Baker, D. and Guaralda, M., 2017. Emerging challenges in the management of contemporary public spaces in urban neighborhoods. *Archnet-Ijar*, *11*(1), pp.29-43.

De Lucia, G., Lapegna, M., & Romano, D. (2022). Towards explainable ai for hyperspectral image classification in edge computing environments. *Computers and Electrical Engineering*, *103*, 108381.

Ellis, C. D., Lee, S. W., & Kweon, B. S. (2006). Retail land use, neighborhood satisfaction and the urban forest: an investigation into the moderating and mediating effects of trees and shrubs. *Landscape and Urban Planning*, *74*(1), 70-78.

Fabiyi O.O. (2011)., Change actors' analysis and vegetation loss from remote sensing data in parts of the Niger Delta region. *Journal of Ecology and the Natural Environment* Vol. 3(12), pp. 381-391,

Fabiyi O.O (2007) 'Analysis of change- agents in urban land use transition; example

From Ibadan city, Nigeria'. *Journal of Environment and culture* Vol4 (2). pp.23-43.

Publisher: Dept of Archeology and Anthropology, University of Ibadan. Nigeria

Fabiyi O.O. (2006)., Urban Land Use Change Analysis of a Traditional City from Remote Sensing Data: The Case of Ibadan Metropolitan Area, Nigeria *Humanity & Social Sciences Journal 1 (1): 42-64, 2006*

Fu, F., Deng, S., Wu, D., Liu, W., & Bai, Z. (2022). Research on the spatiotemporal evolution of land use landscape pattern in a county area based on the CA-Markov model. *Sustainable Cities and Society*, *80*, 103760.

Ghosh, D., Karmakar, M., Banerjee, M., & Mandal, M. (2021). Evaluating the rate of change and predicting the future scenario of spatial pattern using Markov chain model: a study from Baghmundi CD Block of Purulia district, West Bengal. *Applied Geomatics*, *13*, 249-260.

Gibbs, H.K. and Salmon, J.M., 2015. Mapping the world's degraded lands. *Applied geography*, *57*, pp.12-21.

Gidey, E., Dikinya, O., Sebego, R., Segosebe, E., & Zenebe, A. (2017). Cellular automata and Markov Chain (CA_Markov) model-based predictions of future land use and land cover scenarios (2015–2033) in Raya, northern Ethiopia. *Modeling Earth Systems and Environment*, *3*, 1245-1262.

Hua, A. K. (2017). Application of CA-Markov model and land use/land cover changes in Malacca River watershed, Malaysia. *Applied Ecology & Environmental Research*, *15*(4).

Idowu, K., Olayanju, O., Ogbeta, C. and Mobolaji, D., 2023. Monitoring and Modelling of Urban Sprawl in Osogbo Metropolis, using GIS and Remote Sensing. *coou African Journal of Environmental Research*, *4*(2), pp.92-112.

Khwarahm, N. R., Najmaddin, P. M., Ararat, K., & Qader, S. (2021). Past and future prediction of land cover land use change based on earth observation data by the CA–Markov model: a case study from Duhok governorate, Iraq. *Arabian Journal of Geosciences*, *14*(15), 1-14.

Laros, M. and Jones, F., 2014. The state of African cities 2014: re-imagining sustainable urban transitions.

Lennert, J., Farkas, J.Z., Kovács, A.D., Molnár, A., Módos, R., Baka, D. and Kovács, Z., 2020. Measuring and predicting long-term land cover changes in the functional urban area of Budapest. *Sustainability*, *12*(8), p.3331.

Li, Y., Liu, W., Feng, Q., Zhu, M., Yang, L., Zhang, J., & Yin, X. (2023). The role of land use change in affecting ecosystem services and the ecological security pattern of the Hexi Regions, Northwest China. *Science of The Total Environment*, *855*, 158940.

Mansour, S., Al-Belushi, M. and Al-Awadhi, T., 2020. Monitoring land use and land cover changes in the mountainous cities of Oman using GIS and CA-Markov modeling techniques. *Land use policy*, *91*, p.104414.

Mansour, S., Al-Belushi, M., & Al-Awadhi, T. (2020). Monitoring land use and land cover changes in the mountainous cities of Oman using GIS and CA-Markov modeling techniques. *Land use policy*, *91*, 104414.

Meyer, W. B., & Turner, B. L. (1992). Human population growth and global land-use/cover change. *Annual review of ecology and systematics*, *23*(1), 39-61.

Mishra, P., Zaphu, V.V., Monica, N., Bhadra, A. and Bandyopadhyay, A., 2016. Accuracy assessment of modis fractional snow cover product for eastern Himalayan catchment. *Journal of the Indian Society of Remote Sensing*, *44*, pp.977-985.

Nouri, J., Gharagozlou, A., Arjmandi, R., Faryadi, S., & Adl, M. (2014). Predicting urban land use changes using a CA–Markov model. *Arabian Journal for Science and Engineering*, *39*, 5565- 5573.

Okwori A.A. & Fabiyi O.O. (2016) Factors Influencing Land Modification in Central Nigeria: Case study of Central Area of kaduna. International Journal of Advanced studies in Ecology, Development and Sustainability Vol 4(2)

Olubi, A.R. and Fadamiro, J.A., 2022. Implications of Urbanization on Sustainable Cities'

Developments in Nigeria. *European Journal of Development Studies*, *2*(4), pp.4-13.

Olujide, H.M., Amoo, N.B., Oguntayo, S.M., Aroge, S.K. and Amoo, A.O., 2018. Geospatial analysis of land use and land cover dynamics in Akure, Nigeria. *Dutse Journal of Pure and Applied Sciences*, *4*(1), pp.379-393.

Paül, V., & McKenzie, F. H. (2013). Peri-urban farmland conservation and development of alternative food networks: Insights from a case-study area in metropolitan Barcelona (Catalonia, Spain). *Land use policy*, *30*(1), 94-105.

Rimal, B., Zhang, L., Keshtkar, H., Haack, B.N., Rijal, S. and Zhang, P., 2018. Land use/land cover dynamics and modeling of urban land expansion by the integration of cellular automata and Markov chain. *ISPRS International Journal of Geo-Information*, *7*(4), p.154.

Sitthi, A., Nagai, M., Dailey, M., & Ninsawat, S. (2016). Exploring land use and land cover of geotagged social-sensing images using naive bayes classifier. *Sustainability*, *8*(9), 921.

Talukdar, S., Singha, P., Mahato, S., Pal, S., Liou, Y. A., & Rahman, A. (2020). Land-use land- cover classification by machine learning classifiers for satellite observations—A review. *Remote Sensing*, *12*(7), 1135.

Tejaswi, G. (2007). Manual of deforestation, degradation, and fragmentation using remote sensing and GIS. FAO: Food and Agriculture Organization of the United Nations, strengthening monitoring, assessment, and reporting on sustainable forest management in Asia (GCP/INT/988/JPN).

Temesgen, H., Wu, W., Legesse, A., Yirsaw, E. and Bekele, B., 2018. Landscape-based upstream- downstream prevalence of land-use/cover change drivers in southeastern rift escarpment of Ethiopia. *Environmental monitoring and assessment*, *190*, pp.1-15.

Tubiello, Francesco N., Kevin Karl, Alessandro Flammini, Johannes Gütschow, Griffiths Obli-Layrea, Giulia Conchedda, Xueyao Pan et al. "Pre- and post-production processes along supply chains increasingly dominate GHG emissions from agri-food systems globally and in most countries." *Earth System Science Data Discussions* 2021 (2021): 1-24.

Vitousek, P. M., Mooney, H. A., Lubchenco, J., & Melillo, J. M. (1997). Human domination of Earth's ecosystems. *Science*, *277*(5325), 494-499.

Wang, C., Wang, Y., Wang, R., & Zheng, P. (2018). Modeling and evaluating land-use/land-cover change for urban planning and sustainability: A case study of Dongying city, China. *Journal of Cleaner Production*, *172*, 1529-1534.

Wang, J., Lin, Y., Glendinning, A., & Xu, Y. (2018). Land-use changes and land policies evolution

in China's urbanization processes. *Land use policy*, *75*, 375-387.

Weng, Q. (2002). Land use change analysis in the Zhujiang Delta of China using satellite remote sensing, GIS, and stochastic modeling. *Journal of environmental management*, *64*(3), 273- 284.

Wubie, M.A., Assen, M. and Nicolau, M.D., 2016. Patterns, causes, and consequences of land use/cover dynamics in the Gumara watershed of lake Tana basin, Northwestern Ethiopia. *Environmental Systems Research*, *5*(1), pp.1-12.

Wynne, J. J., Jenness, J., Sonderegger, D. L., Titus, T. N., Jhabvala, M. D., & Cabrol, N. A. (2021). Advancing cave detection using terrain analysis and thermal imagery. *Remote Sensing*, *13*(18), 3578.

Yang, J., Chang, J., Wang, Y., Li, Y., Hu, H., Chen, Y., ... & Yao, J. (2018). Comprehensive drought characteristics analysis based on a nonlinear multivariate drought index. *Journal of Hydrology*, *557*, 651-667.