Ethiopian Journal of Environmental Studies & Management 17(2): 244 – 256, 2024
ISSN:1998-0507 doi: https://ejesm.org/doi/v17i2.9
Submitted: June 18, 2024 Accepted: August 3, 2024

LAND USE/LAND COVER CHANGE PROJECTION FOR THE YEAR 2050: AN ASSESSMENT OF LAGOS STATE, NIGERIA

***AMAECHI, C.F., OGBEMUDIA, O.S. AND OKODUWA, A.K.**
Department of Environmental Management and Toxicology, Faculty of Life Sciences, University of Benin, PMB 1154, Benin City, Nigeria
*Corresponding author: chika.amaechi@uniben.edu

Abstract

This study employed geographic information systems (GIS) and remote sensing techniques to analyze land use and land cover (LULC) changes in Lagos State from 2002 to 2022 and to project LULC changes for the year 2050. ENVI 5.3 was utilized for supervised classification via the maximum likelihood technique, categorizing Lagos State into six distinct classes: built-up areas, bare land, wetlands, forest, grassland, and water bodies. Subsequently, the IDRISI-TerrSet software CA-Markov model was employed to predict land use patterns for the year 2050. The classification accuracies for 2002 and 2022 were 89.87% and 87.50%, respectively, with kappa coefficients of 0.86 and 0.83, which are considered acceptable. From 2002 to 2022, the built-up area increased by 26.6 km², bare land decreased by 110 km², wetland area decreased by 96 km², forest area decreased by 449 km², grassland area increased by 11 km², and water bodies decreased by 133 km². The projections for year 2050 indicate that from 2022 to 2050, built-up land will increase by 664 km², bare land will increase by 0.7 km², wetlands will decrease by 1.5 km², forests will decrease by 7.6 km², grasslands will increase by 7 km², and water bodies will decrease by 3 km². The findings of this study will assist environmental managers in making well-informed decisions to promote resilient urban growth and sustainable development in Lagos State.

Key Words: *Land Use/Land Cover, Projection, CA-Markov, Sustainable Development*

Introduction

Urban centres worldwide are experiencing rapid development due to unprecedented population growth (Wu *et al*., 2012; Mosammam *et al*., 2017; Pawe *et al*., 2018; Bagheri *et al*., 2023; Miah *et al*., 2024). This expansion is driven by the increasing demand for urban amenities. By 2050, 68% of the world's population is projected to reside in metropolitan areas, with significant growth expected in Asia and Africa (Kookana *et al*., 2020).

Lagos State, Nigeria's largest urban center, has experienced remarkable growth due to its socioeconomic significance (Gandy, 2006; Wang and Maduako, 2018). Rapid urban development and the formation of informal settlements have increased the frequency and severity of floods. By 2050, urbanization is expected to exacerbate these flooding incidents (Jongman *et al*., 2012). Factors such as unplanned development, inadequate stormwater drainage, and weak enforcement of planning laws have contributed to flooding in neighborhoods such as Agege, Ebute Metta, Mushin, Oshodi-Isolo, Apapa, Surulere, Ikeja, Ajeromi-Ifelodun, and Alimosho (Adelekan, 2016). Deforestation is another major environmental issue affecting LULC in Lagos State (Okorie, 2012; Azeez, 2023). Driven by agriculture, logging, and urbanization, deforestation leads to the conversion of forested areas into agricultural fields, pastures, or urban landscapes. This results in habitat destruction, carbon emissions, and soil erosion (Amaechi *et al*., 2023; Foley *et al*., 2005; Olsson *et al*., 2019).

The year 2050 is a crucial milestone due to projections of significant demographic and environmental changes (United Nations, 2018; Wang *et al*., 2021; Enoh *et al*., 2023). Understanding these trends is essential for sustainable development planning (Amaechi *et al*., 2024). The projections for 2050 offer a forward-looking perspective to help policymakers and environmental managers mitigate the adverse effects of rapid urbanization and environmental degradation. Lagos has experienced rapid physical expansion driven by population growth, economic activities, and infrastructure development. The demand for housing, commercial spaces, and transportation networks has led to significant land cover changes.

Many previous studies have focused on specific aspects of LULC without providing a holistic view that includes future projections using advanced techniques such as the CA Markov model. This study aims to fill this gap by analyzing and predicting LULC changes adopting remote sensing and GIS techniques. GIS is crucial for studying LULC changes due to its ability to handle large datasets, perform spatial analyses, and visualize complex data patterns (Okoduwa and Amaechi, 2024). Scholars have widely used GIS to map urban expansion, analyze environmental impacts, and project future land cover scenarios (Ahmad *et al*., 2017; El-Hattab, 2016; Fenta *et al*., 2017, Amaechi *et al*., 2024). For instance, Karakus *et al*. (2015) and Zhou *et al*. (2020) utilized GIS to identify urbanization trends and support decision-making processes. Domingo *et al*. (2021) and Akdeniz *et al*. (2022) demonstrated how GIS can aid in sustainable urban planning by providing spatially explicit information.

This study aims to predict LULC changes in Lagos State with the following objectives: (1) classify LULC for the years 2002 and 2022, (2) determine the net change during this period, and (3) predict LULC for 2050 adopting the CA Markov model. The results will be instrumental in environmental management and in guiding relevant governance policies for sustainable development in Lagos State.

Materials and Methods

Description of the Study Area

Lagos State (Figure 1) lies in the southwestern part of Nigeria. It is situated within Latitudes 6^{o} 22′N and 6^{o} 45′N and Longitudes 2^{o} 42′E and 4^{o} 22′E (Atomode, 2021). It is the smallest state in the Federation and occupies an area of 3,577 square kilometers, of which 22% or 787 square kilometers are made up of Lagoons and Creeks (Akanni, 2010; Osoba, 2012). Additionally, Lagos State is bordered by the Republic of Benin in the West, Ogun State in the North and East, and the Atlantic Ocean in the South (Onilude and Vaz, 2021). Agege, Alimosho, Apapa, Ifako-Ijaye, Ikeja, Kosofe, Mushin, Oshodi-Isolo, Somolu, Eti-Osa, Lagos Island, Lagos Mainland, Surulere, Ojo, Ajeromi-Ifelodun, Amuwo-Odofin, Badagry, Ikorodu, Ibeju-Lekki, and Epe are among the 20 local government areas that make up Lagos State (Amaechi *et al.*, 2024).

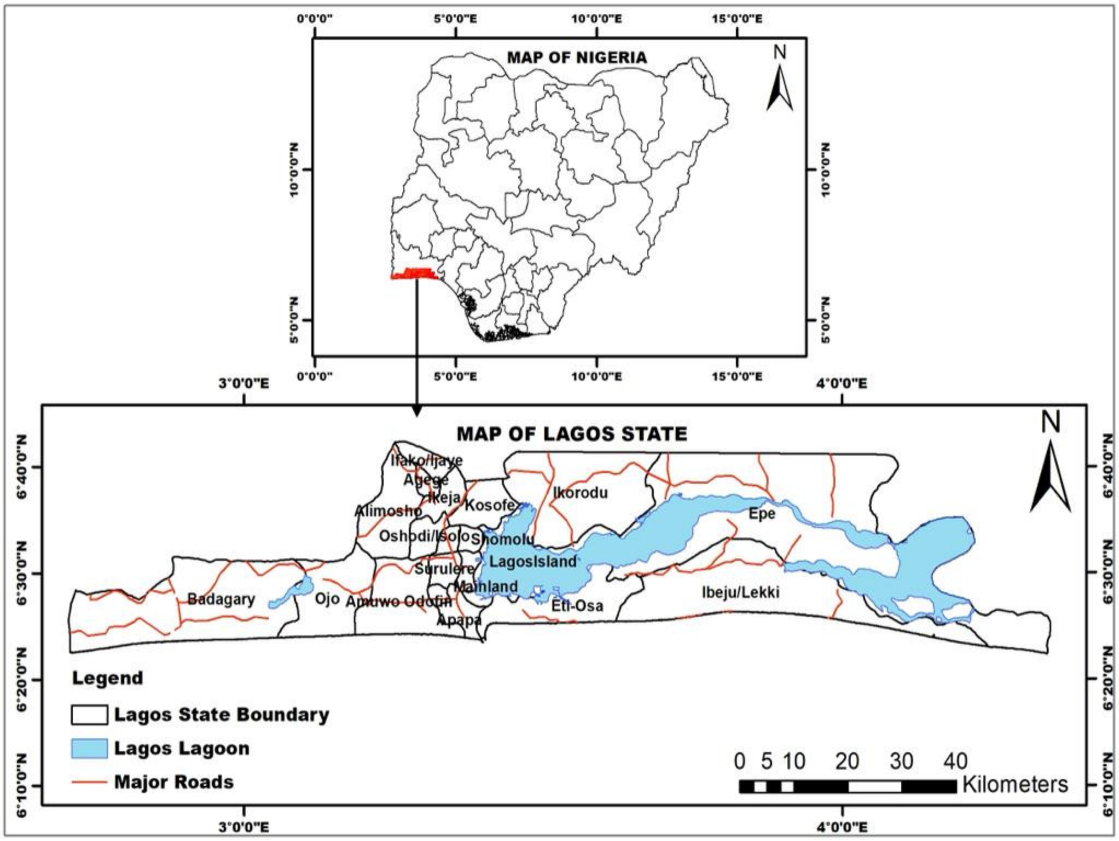

Fig. 1: Map of the study area (Lagos State)

Lagos has been expanding since the colonial era (Agbola and Agunbiade, 2009), and it is expected that by 2025, it will have a population of 18.8 million, surpassing several cities across the world (Heilig, 2012). Lagos is a commercial center with a seaport that functions as an international commerce hub (Williams, 2008). Thus, Lagos is the economic hub of Nigeria, accounting for 85% of the industrial sector, 65% of the financial sector, and 75% of the workforce (Ogunbiyi, 2011, Onilude and Vaz, 2021).

Data Acquisition

Landsat 5 ETM+ (Enhance Thematic Mapper plus) (2002) and Sentinel 2 (2022) data were utilized in this study. The data were collected using the Google Earth Engine. To ensure high image quality, only images with less than 10% land and scene cloud cover were selected for download.

Software Utilized

ENVI 5.3 was used for image preprocessing, image classification, accuracy assessment, postclassification processing, thematic change detection, and statistical analysis (Amaechi *et al*., 2024). ArcGIS 10.3 was used for editing the boundaries of the study area, conducting postclassification processing, designing map layouts, and creating visualizations. For future projections, CA Markov Model in IDRISI-TerrSet 17.0 software was utilized. The primary aim of the Markov model is to predict the extent of land use alterations and assess future land development stability within a particular region of interest in the form of a matrix, as presented in Table 3 (Hamad *et al*., 2018). By incorporating the CA-Markov model from IDRISI TerrSet 17.0 software into the study, seamless integration of cellular automaton filters and Markov processes was achieved. The prediction of land use change state was accomplished through the utilization of conversion tables (transition matrix) and the conditional probability derived from the conversion map. The study flowchart for LULC modeling is shown in Figure 2.

Image Preprocessing

Andualem *et al*. (2018) emphasized the significance of preprocessing satellite images for change detection. This crucial step aims to eliminate noise and enhance the interpretability of image data, which is essential for conducting time series analysis (Yichun *et al*., 2008). For this study, preprocessing operations were adopted, which included radiometric and atmospheric correction, as well as image enhancement and masking of the study area (Igben and Eregare, 2022). These operations were performed using the ENVI 5.3 FLAASH tool.

Image Classification

Maximum likelihood supervised classification was used to categorize the Landsat and Sentinel-2 images into six classes: built-up areas, bare land, water bodies, wetlands, grassland, and forestland (Table 1). For this process, training signature samples were carefully selected. Based on these samples, the study area was classified into distinct LULC classes. Various band combinations were utilized to enhance the visual interpretation of these classes in the images.

Table 1: LULC classification names, descriptions, and numbers of trained samples for each class of the Landsat and Sentinel datasets

Class	Description	Number of samples (2002)	Number of samples (2022)
Built-up Area	Areas with buildings, and infrastructure.	67	56
Bare land	Land that is devoid of significant vegetation.	45	38
Wetland	Water-saturated area.	54	65
Forest	Land covered predominantly by trees.	53	67
Grassland	Land dominated by grasses with few or no trees present.	39	43
Water bodies	Lakes and rivers.	35	34

Assessment of Accuracy

With the aid of the ground truth image tool and confusion matrix in the ENVI software, the accuracy of the classified images from 2002 and 2022 was evaluated. This assessment technique compares the classified land cover classes with the ground truth data using reference data based on Comber's (2013) methodology. The findings include the kappa coefficient, which rates classification accuracy on a scale from 0 to 1, as well as overall accuracy, producer's accuracy, and user's accuracy (Table 2). High-resolution Google Earth images for each year served as the basis of ground truth data for this investigation (Amaechi *et al*., 2024).

Table 2: Accuracy Assessment: User, Producer, Overall Accuracy, Kappa Coefficient.

Class	User accuracy	Producer accuracy	User accuracy	Producer accuracy
	2002		2022	
Built -up	92.41	94.14	92.45	93.91
Bare land	94.13	97.70	85.75	87.39
Wetland	94.76	95.35	86.61	88.30
Forestland	88.37	89.10	84.78	87.85
Grassland	91.87	92.65	85.87	86.87
Water bodies	83.65	85.32	89.34	87.26
Overall Accuracy (%)	89.87		87.50	
Kappa Coefficient	0.86		0.83	

Table 3: Probability Matrix

	Cl. 1	Cl. 2	Cl. 3	Cl. 4	Cl. 5	Cl. 6
Cl. 1	0.0000	0.2000	0.2000	0.2000	0.2000	0.2000
Cl. 2	0.6014	0.2052	0.0001	0.1500	0.0420	0.0013
Cl. 3	0.1781	0.1711	0.0009	0.4509	0.1707	0.0283
Cl. 4	0.1873	0.1777	0.0007	0.4593	0.1730	0.0019
Cl. 5	0.2991	0.2337	0.0006	0.3500	0.1152	0.0014
Cl. 6	: 0.0757	0.0496	0.0036	0.1242	0.0122	0.7347

where Cl 1 = built-up land, Cl 2 = bare land, Cl 3 = wetland, Cl 4 = forestland, Cl 5 = grassland and Cl 6 = water bodies.

Results and Discussion

Table 4 shows the LULC classes in Lagos from 2002–2050. In 2002, the built-up area covered 737 km^2, representing 20% of the total land area, which increased to 1,514 km^2, representing 42% of the total land area in 2022. Bare land, in 2002, covered an area of 161 km^2, representing 4% of the total land area, which decreased to 51 km^2, representing 1% of the total land area in 2022. In 2002, wetlands covered an area of 158 km^2, representing 4% of the land area, which further decreased to 62 km^2, representing 2% of the land area in 2022. Furthermore, forests in 2002 covered an area of 1,232 km^2, representing 34% of the total land area, which decreased to 783 km^2, representing 22% of the total land area in 2022. In 2002, grassland covered an area of 662 km^2, representing 18% of the total land area, which increased to 673 km^2, representing 19% of the total land area in 2022. The water bodies in 2002 covered an area of 651 km^2, representing 18% of the land area, which decreased to 518 km^2, representing 14% of the land area in 2022. For the projected year 2050, the built-up area will occupy an area of 2,178 km^2, representing 60% of the land area, and bare land will occupy an area of 76 km^2, representing 2% of the land area. Wetlands will occupy an area of 7 km^2, representing less than 1% of the land area; forests will occupy an area of 510 km^2, representing 14% of the land area; grasslands will occupy an area of 420 km^2, representing 12% of the land area; finally, water bodies will occupy an area of 410 km^2, representing 11% of the land area.

Table 4: LULC change of Lagos State: 2002 to 2022 and Future Projection (2050)

LULC Types	Total Area covered for each year in Km^2 and percentage (%)					
	2002	**%**	**2022**	**%**	**2050**	**%**
Built up	737	20%	1514	42%	2178	60%
Bare land	161	4%	51	1%	76	2%
Wetland	158	4%	62	2%	7	0%
Forest	1232	34%	783	22%	510	14%
Grassland	662	18%	673	19%	420	12%
Water bodies	651	18%	518	14%	410	11%

Table 5 presents comprehensive LULC net changes from 2002–2050. From 2002–2022, the built-up class increased by 21.6% (777 km^2). Bare land decreased by 3.1% (110 km^2). Wetland decreased by 2.7% (96 km^2), forest decreased by 12.5% (449 km^2), grassland increased by 0.3% (11 km^2), and water bodies decreased by 3.7% (133 km^2). From 2022–2050, the built-up class increased by 18.4% (664 km^2). Bare land increased by 0.7% (25 km^2). Wetland decreased by 1.5% (55 km^2), forest decreased by 7.6% (273 km^2), grassland decreased by 7% (253 km^2), and water bodies decreased by 3% (108 km^2).

Table 5: LULC net change in km^2 and percentage (%)

LULC Types	Net change 2002-2022 (km^2)	Net change 2002-2022 (%)	Net change 2022-2050 (km^2)	Net change 2022-2050 (%)
Built up	777	21.6	664	18.4
Bare land	-110	-3.1	25	0.7
Wetland	-96	-2.7	-55	-1.5
Forest	-449	-12.5	-273	-7.6
Grassland	11	0.3	-253	-7.0
Water bodies	-133	-3.7	-108	-3.0

The study's LULC geospatial map (Figure 3) for Lagos State in 2002 indicated built-up areas within the Agege, Ifako, Mushin, Mainland, Etiosa, and Oshodi local government areas. Bare land patches can be observed in Ojo and Badagry. Wetlands occur in the Kosofe and Eastern Epe regions. Forestland was the most common type of land cover feature, with denser occurrences in Epe and Ibeju/Lekki. Grassland was primarily observed in the Epe area. Grassland was also observed in Badagry and Ojo. Water bodies occurred in the Epe, Lagos Island, and Ibeju-Lekki local government areas.

Furthermore, the findings of the LULC map of Lagos State in 2022 (Figure 4) revealed more built-up areas occurring within Ojo, Agege, Ifako, Mushin, Mainland, Etiosa, and Oshodi, with some built-up areas in parts of Obeju-Lekki, Badagry and Epe. More barren land occurs in the northern region of Kosofe, and the eastern region of Ibeju-Lekki. Areas covered with wetlands reduced in 2022, as built-up areas are rapidly developing, leading to a reduction in formerly visible wetlands. The dense forestland observed in 2002 within the Epe and Ibeju/Lekki regions drastically decreased as built-up land began to occur within both local government areas.

Grassland areas were formerly observed on the Epe axis in 2002 and decreased in size due to built-up areas. Reduced amounts of grassland area were observed in Ibeju-Lekki, Epe, and Ikorodu. Water bodies largely occurred in the regions of the Epe, Lagos Island, and Ibeju-Lekki. Wetlands have given way to water bodies completely in the eastern region of the Epe. In addition, the wetland observed in 2002 in Kosofe completely disappeared by 2022 (Figure 4). Factors that must have led to the reduction in forest cover between 2002 and 2022 include population growth and urbanization (Musetsho *et al*., 2021), agricultural expansion (Lambin and Meyfroidt, 2011), infrastructure development (Laurance *et al*., 2009), deforestation, and forest degradation (Amaechi *et al*., 2023).

Future predictions for LULC for Lagos State in 2050 (Figure 5) revealed a massive built-up area within all the respective local government areas of Lagos State. Some patches of grassland are projected to occur within the Ibeju-Lekki and Epe regions (Figure 5). The Lagos population is expected to exceed 30 million by 2030 and reach over 60 million by 2050 (Enoh *et al*., 2023). With this increase in population, it is projected that by 2050, Lagos will become the world's third largest megacity after selected cities in China and India (UN-Habitat, 2006; Faisal Koko *et al*., 2021).

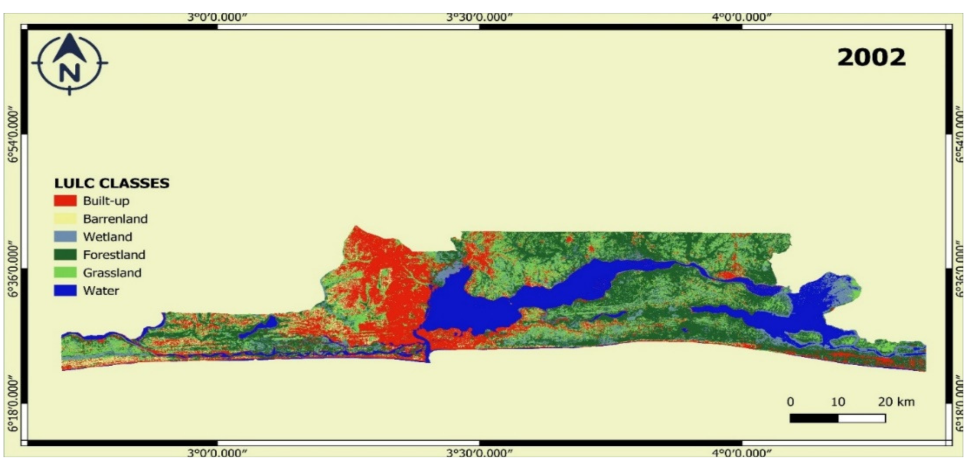

Fig. 3: Land Use-Land cover geospatial map for Lagos State 2002

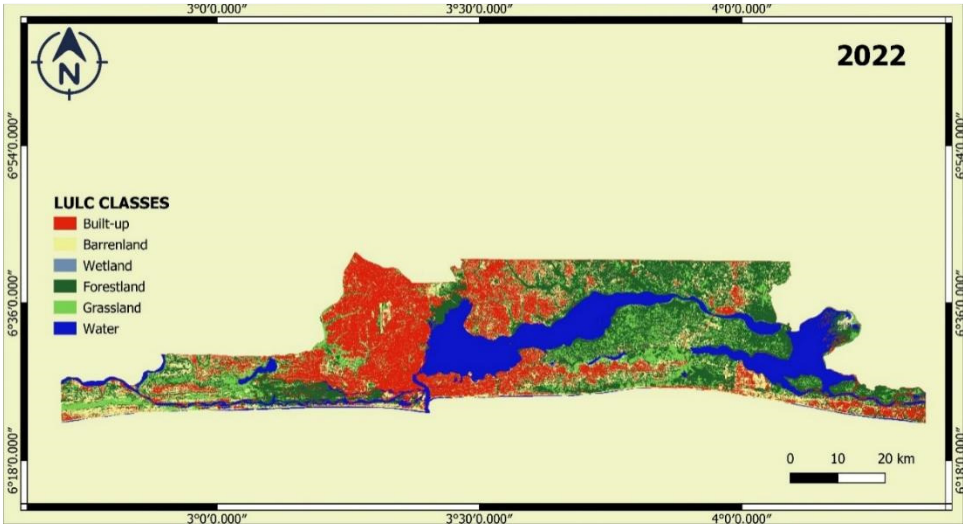

Fig. 4: Land Use-Land cover geospatial map for Lagos State 2022

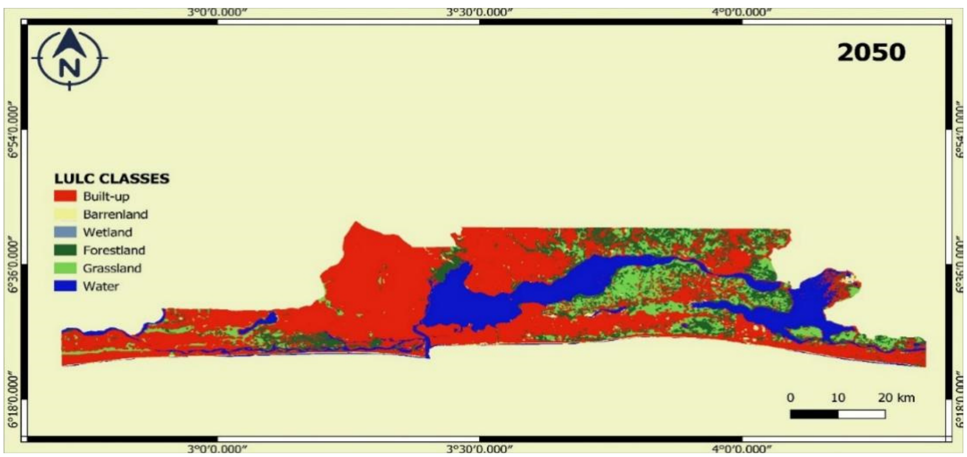

Fig. 5: Land Use-Land cover geospatial map for Lagos State 2050

Koko *et al*. (2020) projected LULC geospatial maps for 2050 in Zaria city, Nigeria, and indicated that urbanization, deforestation, and the expansion of agricultural activities will likely continue to transform forested areas into built-up land over the next 30 years. Similarly, research by Khawaldah *et al*. (2020) in the Irbid Governorate forecasts an ongoing increase in built-up areas from 2015 to 2030 and 2050. Another study by Rani *et al*. (2023) in Bathinda predicts a decrease in bare land by 2050. Additionally, wetland areas are expected to shrink, which will pose challenges for irrigation and groundwater reservoir sustainability. Debnath *et al*. (2023) reported that the amount of agricultural land in the Koch Bihar urban agglomeration would decline significantly by 2050, while the built-up area would grow dramatically.

Without measures to curb unsustainable urban development, ongoing expansion threatens to reduce the nation's forest coverage, hindering progress toward achieving Sustainable Development Goals (SDGs) 11 (sustainable cities and communities), 13 (climate action), and 15 (life on land) (Amaechi *et al*., 2024). In Lagos State, it is crucial to manage rapid urban growth and expansion to balance urban development with the preservation of the natural environment.

Conclusion

By 2050, the state of Lagos will become an almost completely built-up area, which will lead to poor air and water quality, urban heat islands, and biodiversity loss. Implementing and enforcing efficient environmental planning rules in Lagos is crucial to curbing a city's urban sprawl. It should be mandatory for homeowners associations to ensure the planting of trees and grass. Building taller houses to allow for better vertical land utilization enables the efficient and sustainable use of land, helps to conserve land resources, reduces urban sprawl and helps to maintain a balance between built-up areas and natural elements. The implementation of successful conservation strategies to safeguard forested regions is pivotal for preserving biodiversity.

References

Adelekan, I,O. (2016). Flood risk management in the coastal city of Lagos, Nigeria. *Journal of Flood Risk Management*, 9(3): 255–264.

Agbola, T. and Agunbiade, E.M. (2009). Urbanization, slum development and security of tenure: The challenges of meeting millennium development goal 7 in Metropolitan Lagos, Nigeria. Urban population-environment dynamics in the developing world: Case studies and lessons learned, 77-106.

Ahmad, F., Goparaju, L. and Qayum, A. (2017). LULC analysis of urban spaces using Markov chain predictive model at Ranchi in India. *Spatial Information Research*, 25(3): 351–359.

Akanni, C.O. (2010). Spatial and Seasonal Analyses of Traffic Related Pollutant Concentrations in Lagos Metropolis, Nigeria. *African Journal of Agricultural Research*, 5(11): 1264 – 1272.

Akdeniz, H.B., Sag, N.S. and Inam, S. (2022). Analysis of Land Use/Land cover changes and prediction of future changes with Land Change Modeler: Case of Belek, Turkey. *Research Square*, 10: 1-28.

Amaechi, C.F., Enuneku, A.A., Okhai, S.O. and Okoduwa, K.A. (2023). Geospatial Assessment of Deforestation in Federal Capital Territory Abuja, Nigeria from 1987 to 2021. *Journal of Applied Sciences and Environmental Management*, 27(11): 2457-2461.

Amaechi, C.F., Enuneku, A., Amadi, U.S. and Okoduwa, A.K. (2024). Effects of COVID-19 Policy on Air Quality in Lagos State, Nigeria. *Applied Environmental Research*, 46(1). https://doi.org/10.35762/AER.2024008.

Amaechi, C.F., Enuneku, A.A., Okhai, S.O. and Okoduwa, K.A. (2023). Geospatial Assessment of Deforestation in the Federal Capital Territory Abuja, Nigeria from 1987 to 2021. *J. Appl. Sci. Environ. Manage*., 27(11): 2457-2461.

Amaechi, C., Ugwu, V. and Okoduwa, A. (2024). Geospatial Assessment of Land Use/Land Cover of the Federal Capital Territory: A Case Study for the Year 2050. *Ethiopian Journal of Environmental Studies and Management*, 17(1): 95-109.

Amaechi, C.F., Ugwu, V.C. and Okoduwa, A.K. (2024). Geospatial Assessment of Land Use/ Land Cover of the Federal Capital Territory: A Case Study for the year 2050. *Ethiopian Journal of Environmental Studies and Management*, 17(1): 95-109. https://ejesm.org/doi/v17i1.8.

Andualem, T.G., Belay, G. and Guadie, A. (2018). Land use change detection using remote sensing technology. *Journal of Earth and Climatic Change*, 9:1-6.

Ashiru, A.R. and Waziri, O.O. (2008). Analysis of Intra-Urban Traffic Problems in Nigeria: A Study of Lagos Metropolis. *Indonesian Journal of Geography*, 40(1): 41-51.

Atomode, T.I. (2021). Analysis of Intra-Urban Freight Traffic Pattern in Lagos State, Nigeria. 17(1): 9-19. DOI: 10.36108/ijss/1202.91.0120

Azeez, O.O. (2023). An assessment of the effects of deforestation on biodiversity in OJO local government area of Lagos State, Nigeria. *Global Journal of Ecology*, 8(2): 075-080.

Bagheri, B. and Soltani, A. (2023). The spatio-temporal dynamics of urban growth and population in metropolitan regions of Iran. *Habitat International*, 136: 102797.

Comber, A., See, L., Fritz, S., Van der Velde, M., Perger, C. and Foody, G. (2013). Using control data to determine the reliability of volunteered geographic information about land cover. International *Journal of Applied Earth Observation and Geoinformation*, 23, 37- 48.

Debnath, M., Islam, N., Gayen, S.K., Roy, P.B., Sarkar, B. and Ray, S. (2023). Prediction spatiotemporal (2030 and 2050) land-use and land-cover changes in Koch Bihar urban agglomeration (West Bengal), India, using artificial neural network-based Markov chain model. *Modeling Earth Systems and Environment*, 1-22.

Domingo, D., Palka, G. and Hersperger, A.M. (2021). Effect of zoning plans on urban land-use change: A multi scenario simulation for supporting sustainable urban growth. *Sustainable Cities and Society*, 69: 102833.

El-Hattab, M.M. (2016). Applying post-classification change detection technique to monitor an Egyptian coastal zone (Abu Qir Bay). *Egyptian Journal of Remote Sensing and Space Sciences*, 19(1), 23–36.

Enoh, M.A., Njoku, R.E. and Okeke, U.C. (2023). Modeling and mapping the spatial–temporal changes in land use and land cover in Lagos: A dynamics for building a sustainable urban city. *Advances in Space Research*, 72(3): 694-710.

Enoh, M.A., Njoku, R.E. and Okeke, U.C. (2023). Modeling and mapping the spatial–temporal changes in land use and land cover in Lagos: A dynamics for building a sustainable urban city. *Advances in Space Research*, 72(3): 694-710.

Faisal Koko, A., Yue, W., Abdullahi Abubakar, G., Hamed, R. and Noman Alabsi, A.A. (2021).

Analyzing urban growth and land cover change scenario in Lagos, Nigeria using multi-temporal remote sensing data and GIS to mitigate flooding. *Geomatics, Natural Hazards and Risk*, 12(1): 631-652. DOI: 10.1080/19475705.2021.1887940

Fenta, A.A., Yasuda, H., Haregeweyn, N., Belay, A.S., Hadush, Z., Gebremedhin, M.A. and Mekonnen, G. (2017). The dynamics of urban expansion and land use/land cover changes using remote sensing and spatial metrics. International Journal of Remote Sensing, 38(14), 4107–4129.

Foley, J.A., Defries, R., Asner, G.P., Barford, C., Bonan, G., Carpenter, S. R., Helkowski, J. H. (2005). *Global consequences of land use. Science*, 309(5734): 570-574.

Gandy M. (2006). Planning, anti-planning, and the infrastructure crisis facing metropolitan Lagos. In: Murray MJ, Myers GA, editors. Cities in Contemporary Africa. New York: Palgrave Macmillan; p. 247–264.

Hamad, R., Balzter, H. and Kolo, K. (2018). Predicting land use/land cover changes using a CA Markov model under two different scenarios. *Sustainability*, 10(10): 3421.

Heilig, G.K. (2012). World urbanization prospects: the 2011 revision. United Nations, Department of Economic and Social Affairs (DESA), Population Division, Population Estimates and Projections Section, New York, 14, 555.

Igben, J.L. and Eregare, E.F. (2022). Predictive analysis of future rainforest covers depletion in Oghara, Delta state, Nigeria. *Discovery*, 58(314): 89-96.

Jongman, B., Ward, P.J. and Aerts, J.C. (2012). Global exposure to river and coastal flooding: Long term trends and changes. *Global Environmental Change*, 22(4): 823-835.

Karakus, C.B., Cerit, O. and Kavak, K.S. (2015). Determination of land use/cover changes and land use potentials of Sivas city and its surroundings using geographical information systems (GIS) and remote sensing (RS). Procedia Earth and Planetary Science, 15, 454–461.

Khawaldah, H.A. (2016). A prediction of future land use/land cover in Amman area using GIS-based Markov Model and remote sensing. *Journal of Geographic Information System*, 8(03): 412–427.

Koko, A.F., Yue, W., Abubakar, G.A., Hamed, R. and Alabsi A.A.N. (2020). Monitoring and Predicting Spatio-Temporal Land Use/Land Cover Changes in Zaria City, Nigeria, through an Integrated Cellular Automata and Markov Chain Model (CA- Markov). *Sustainability*, 12: 10452-10473.

Kookana, R.S., Drechsel, P., Jamwal, P. and Vanderzalm, J. (2020). Urbanisation and emerging economies: Issues and potential solutions for water and food security. *Science of the Total Environment*, 732: 139057.

Lambin, E.F. and Meyfroidt, P. (2011). Global land use change, economic globalization, and the looming land scarcity. *Proceedings of the National Academy of Sciences*, 108(9): 3465-3472.

Laurance, W.F., Goosem, M. and Laurance, S.G. (2009). Impacts of roads and linear clearings on tropical forests. *Trends in ecology and evolution*, 24(12): 659-669.

Miah, M.T., Fariha, J.N., Kafy, A.A., Islam, R., Biswas, N., Duti, B.M., ... & Salem, M.A. (2024). Exploring the nexus between land cover change dynamics and spatial heterogeneity of demographic trajectories in rapidly growing ecosystems of south Asian cities. *Ecological Indicators*, 158: 111299.

Mosammam HM, Nia JT, Khani H, Teymouri A, Kazemi M. (2017). Monitoring land-use change and measuring urban sprawl based on its spatial forms: the case of Qom city. *Egyptian Journal of Remote Sensing and Space Sciences*, 20(1): 103–116.

Musetsho, K.D., Chitakira, M. and Nel, W. (2021). Mapping land-use/land-cover change in a critical biodiversity area of South Africa. *International Journal of Environmental Research and Public Health*, 18(19): 10164.

Ogunbiyi, T. (2011). Giving Lagos a Special Status. Vanguard Newspaper. Available online: http://www.vanguardngr.com/2011/08/giving-lagos-a-special-status/ (accessed on 8 January 2024).

Okeke, F. (2012). Nigeria: FCC Condemns Nepotism. Daily Trust. 2012. Available online: http://allafrica.com/stories/201211160413.html (accessed on 25 January 2024).

Okoduwa, A. and Amaechi, C.F. (2024). Exploring Google Earth Engine, Machine Learning, and GIS for Land Use Land Cover Change Detection in the Federal Capital Territory, Abuja, between 2014 and 2023. Applied *Environmental Research*, 46(2). https://doi.org/10.35762/AER.2024029.

Okorie, F.C. (2012). A Spatio-temporal analysis of deforestation in Epe and its environs (Lagos, Nigeria). *International Journal of Science, Environment and Technology*, 1(5): 548-562.

Olsson, L.H., Barbosa, S., Bhadwal, A., Cowie, K., Delusca, D., Flores-Renteria, K., Hermans, E., Jobbagy, W., Kurz, D., Li, D. and Sonwa, J., Stringer, L. (2019). Land Degradation. In: Climate Change and Land: an IPCC special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems [P.R. Shukla, J. Skea, E. Calvo Buendia, V. Masson-Delmotte, H.-O. Pörtner, D. C. Roberts, P. Zhai, R. Slade, S. Connors, R. van Diemen, M. Ferrat, E. Haughey, S. Luz, S. Neogi, M. Pathak, J. Petzold, J. Portugal Pereira, P. Vyas, E. Huntley, K. Kissick, M. Belkacemi, J. Malley, (eds.)].

Onilude, O.O. and Vaz, E. (2021). Urban sprawl and growth prediction for Lagos using GlobeLand30 data and cellular automata model. Sci, 3(2), 23.

Osoba, S.B. (2012). Appraisal of Parking Problems and Traffic Management Measures in Central Business District in Lagos, Nigeria. *Journal of Sustainable Development*, 5(8): 105 – 115.

Pawe, C.K. and Saikia, A. (2018). Unplanned urban growth: land use/land cover change in the Guwahati Metropolitan Area, India. *Geografisk Tidsskrift-Danish Journal of Geography*, 118(1): 88-100.

Rani, A., Gupta, S.K., Singh, S.K., Meraj, G., Kumar, P., Kanga, S., ... & Dogančić, D. (2023). Predicting future land use utilizing economic and land surface parameters with ANN and Markov Chain models. *Earth*, 4(3): 728-751.

UN-Habitat. (2006). State of the world's cities 2006/7. The Millennium Development Goals, and urban sustainability: 30 years shaping the habitat agenda. London and Sterling: United Nations Human Settlements Programme.

United Nations. (2018). 68% of the world population projected to live in urban areas by 2050, says UN. Department of Economic and Social Affairs. Available online at https://www.un.org/development/desa/en/news/population/2018-revision-of-world-urbanization prospects.html. Accessed March, 17 2023.

Wang, J. and Maduako, I.N. (2018). Spatio-temporal urban growth dynamics of Lagos Metropolitan Region of Nigeria based on Hybrid methods for LULC modeling and prediction. *European Journal of Remote Sensing*, 51(1): 251–265.

Wang, S.W., Munkhnasan, L. and Lee, W.K. (2021). Land use and land cover change detection and prediction in Bhutan's high altitude city of Thimphu, using cellular automata and Markov chain. Environmental Challenges, 2, 100017.

Williams, L. (2008). Bradt Guide: Nigeria. Connecticut: The Globe Prequot Press Inc.: Guildford, CT, USA. Available online: http://books.google.com/books?id=fwuQ71ZbaOcC&pg=PA110#v=onepage&q&f=false (accessed on 10 January 2024).

Wu, K.Y. and Zhang, H. (2012). Land use dynamics, built-up land expansion patterns, and driving forces analysis of the fast-growing Hangzhou metropolitan area, eastern China (1978–2008). *Applied Geography*, 34: 137-145.

Yichun, X., Zongyao, S. and Mei, Y. (2008). Remote sensing imagery in vegetation mapping: A Review. Journal of Plant Ecology, 1(1):9-23.

Zhou, Y., Varquez, A.C.G. and Kanda, M. (2019). High-resolution global urban growth projection based on multiple applications of the SLEUTH urban growth model. *Scientific Data*, 6(1): 34.