Modeling of Land Use and Land Cover Changes in Nsukka, Nigeria Using Remote Sensing and Geographic Information System

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***Abstract*—This study aimed to model LULC changes within the Nsukka Local Government Area of Enugu State. The objectives included analyzing the diverse LULC types in Nsukka from 1990 to 2020, assessing the extent of these changes over the same period, and predicting future LULC patterns for 2030 and 2100. The methodology involved a reconnaissance survey and the utilization of satellite imagery, specifically Landsat Thematic Mapper (TM) for 1990, Enhanced Thematic Mapper Plus (ETM+) for 2010, and Landsat-8 Operational Land Imager (OLI) for 2020. LULC maps were generated through supervised classification, identifying four primary classes: farmland, vegetation, bare land, and built-up areas. Findings revealed a consistent increase in built-up areas from 1990 to 2020, accompanied by a corresponding decline in vegetation and bare land within the study area. Future LULC predictions for 2030, 2050, and 2100 further indicate a continued expansion of built-up areas. Specifically, the simulation results from the CA–Markov model projected an increase in built-up area from 226.6 km² in 2020 to approximately 241.2 km² by 2030. The model further predicted that built-up areas would expand to approximately 310.4 km² by 2100, while other land uses are expected to continue decreasing in extent. These results underscore the urgent need for the urban planning and development authorities in Enugu State to adequately plan for the observed gradual urban growth. Proactive measures are essential within Nsukka Local Government Area and Enugu State to foster a better understanding of changing LULC patterns, thereby enabling more effective management of associated environmental challenges.**

***Index Terms*—Land Use and Land Cover, Urbanization, Deforestation, CA Markov Model**

I. NTRODUCTION

The integration of remote sensing (RS) and Geographic Information Systems (GIS) has become the cornerstone of contemporary land use and land cover (LULC) change analysis, with significant methodological advancements emerging in recent years. [1] demonstrated the effectiveness of Google Earth Engine (GEE) for monitoring ecosystem type changes in the upper Yellow River basin over the Tibetan Plateau, utilizing multi-temporal satellite data to achieve comprehensive spatial coverage. Similarly,[2] employed Random Forest classification of Landsat time series to analyze urban land use and land cover changes, highlighting the transition from traditional pixel-based methods to machine learning-enhanced approaches. The availability of high-resolution satellite imagery from Sentinel-2 and Landsat 8/9 has enabled researchers such as[3] to conduct detailed change detection studies with improved temporal resolution. These technological developments have facilitated long-term retrospective analyses, with studies by [4],[5] demonstrating the utility of RS/GIS integration for assessing hydrological impacts of LULC changes in watershed contexts. The consistent improvement in classification accuracies, now regularly exceeding 85% in urban applications, establishes RS and GIS as indispensable tools for environmental monitoring and sustainable land management.

Machine Learning and Advanced Classification Techniques. Recent literature has witnessed a paradigm shift toward machine learning (ML) algorithms for LULC classification and change detection, addressing the limitations of traditional parametric classifiers. [6] applied machine learning algorithms to quantify the impact of LULC changes on land surface temperature, demonstrating the capacity of these methods to capture complex environmental interactions.

The predictive modeling of LULC changes has evolved substantially through the integration of Cellular Automata (CA), Markov Chain analysis, and hybrid modeling frameworks. [7] applied the CA-based SLEUTH urban growth model to assess and predict urban expansion in the Kolkata Metropolitan Area, demonstrating the model's effectiveness for medium-term forecasting. Similarly, [8] utilized the SLEUTH model for urban growth simulations in Mangaluru, India, highlighting its applicability across different urban contexts and scales. [9] developed an integrated modeling approach combining CA, Markov chains, logistic regression, and weighted linear combination analysis for the Tabriz Metropolitan Area, simulating development scenarios until 2050. Recent comparative studies have evaluated model performance, with research showing that the SLEUTH model achieved 87% accuracy compared to 76% for CA-Markov in certain urban contexts. Additionally, [10] applied the Markov-FLUS model for multi-scenario simulation of land use change and ecosystem service value assessment. These predictive capabilities enable policymakers to evaluate potential consequences of unplanned development and design interventions that balance economic growth with environmental conservation.

A. The Study Area

Nsukka L.G.A. is one of the seventeen Local Government Areas in Enugu State, Nigeria. It has a total area of 495.87 km² and lies between latitudes $7^0$16'36.27"N and $7^0$33'20.81"N and longitude $6^0$42'00"E and $7^0$59'21.44"E (Fig 1). It shares boundaries with Igbo-Etiti L.G.A. to the south, Uzo-Uwani L.G.A. to the west, Udenu L.G.A. to the east, and Igbo-Eze North L.G.A. to the north, all within Enugu State. Nsukka had a population of 309,633 according to the 2006 Nigerian census.

The study area is characterized by a tropical rainforest climate (Köppen 'Af') with annual rainfall between 1750mm and 2000mm and consistently high temperatures ranging from 27°C to 28°C throughout the year. Due to its latitudinal position, the region experiences nearly vertical solar radiation and long daylight hours, resulting in intense solar radiation. However, actual insulation is modified by atmospheric absorption, cloud cover, rainfall, and harmattan haze. The combination of high temperatures (above 21°C) and high humidity (over 65%) year-round create uncomfortable conditions for human habitation, as perspiration evaporates slowly. Seasonal variations occur with drier conditions in January influenced by continental air masses, while April through September brings higher humidity from maritime air masses. Nsukka experiences three dry months with less than 6cm of rainfall monthly, though orographic influences from the Nsukka escarpment provide some modification to local precipitation patterns.

Geologically, the area is underlain by Nsukka shales from the Senonian stage (Coniacian, Santonian, and Campanian periods), which form part of the Cross River plains. The terrain features extensive hills on the western flank reaching 350-400 meters elevation with steep slopes, contrasting with lowlands to the east. Drainage occurs through seasonal streams and springs that dry up during the November-March dry season but swell during the April-October wet season, carrying significant debris that contaminates water supplies forcing residents in lower areas to travel uphill for cleaner water.

Shallow lithosol soils dominate the highland sandstone areas, sandy loam soils appear on escarpments, and alluvial and deep clayey soils characterize the depositional plains. Vegetation represents a transition zone between guinea savanna and rainforest, with dominant grass species (Hyparrhenium spp. and Andropogen spp.) covering most areas while forests persist as ribbon formations along stream valleys and depressions where favorable soil and groundwater conditions support tree growth.

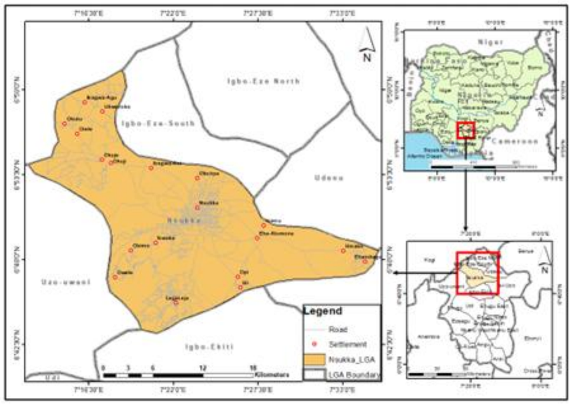

Fig 1. The Study Area
Source: Adopted from administrative map of Enugu State 2020.

II. MATERIALS AND METHODS

The primary materials utilized in this study consisted of multi-temporal satellite imagery from the Landsat mission. Specifically, the research employed Landsat Thematic Mapper (TM) for 1990, Enhanced Thematic Mapper Plus (ETM+) for 2010, and Landsat-8 Operational Land Imager (OLI) for 2020. Data collection and validation were further supported by a reconnaissance survey to ensure accuracy across the study area.

The types of data utilized for this study include the following: (i) administrative map of the study area, and (ii) Landsat satellite imageries. The administrative map was used to ascertain the boundaries of the study area, while the satellite images were employed to assess the land use and land cover characteristics of the study area. Specifically, Landsat 5, Landsat 7, and Landsat 8 imageries were used (Table 1). All Landsat data were downloaded via the USGS (United States Geological Survey) website as standard products, while the administrative maps of the study area were sourced from the Enugu State Ministry of Lands and Survey.

Table 1: Landsat Data characteristics

Date Acquired	Satellite	Spatial Resolution (m)	Path/Row
1990	Landsat 5	Bands 1-5,7: 30x30	188/55
2010	Landsat 7	Bands 1-5,7: 30x30	188/55
2020	Landsat 8	Bands 2-7: 30x30	188/55

A. Image Classification

Image training is the first and essential step in image classification; it is the process of careful selection of land use classes to be represented in the image. The LULC categories were identified as: (1) urban or built-up area, (2) vegetated areas (including forest, farmland, and shrub), (3) farmland, and (4) other (bare land). For this study, Landsat images were utilized in the identification of training samples of different land use classes as given above. This was followed by a supervised classification of the training samples. Spectral signature files were generated and used in supervised classification using a maximum likelihood algorithm. The spectral signatures included images created for each analysis year. LULC maps were produced for each of the three years, containing all five LULC types in each of the resulting maps.

B. The Landsat TM image Classification of 1990

The Landsat TM image of 1990 was classified into four land use/land cover categories. Farmland was classified with a lower producer's accuracy (81%) than other classes, as a result of errors particularly involving mixing with bare land. Built-up areas, vegetation, and bare land were classified with higher producer's accuracies of 91%, 90%, and 86%, respectively. The overall classification accuracy of the image was 87%, while the overall Kappa coefficient was 0.83 (Table2)

Table2. Accuracy Assessment Error matrix of 1990 Image Classification

	Vegetation	Farmland	Bareland	Built Up	Kappa	Producer's Accuracy	User's accuracy
Vegetation	91	5	0	4	0.88	90%	91%
Farmland	4	86	10	0	0.81	81%	86%
Bareland	1	13	81	5	0.75	86%	81%
Built up	5	2	3	90	0.87	91%	90%
Total	101	106	94	99			
Overall Classification Accuracy = 87%							
Overall, Kappa Statistics = 0.83							

Source: Author's analysis (2022)

C. Data Processing

All satellite images were free from scan lines except that of 2010, which required correction using the Fill No Data tool in the Raster Analysis extension of Quantum GIS 3.18 software. For the purpose of land use and land cover classification and image analysis, colour composite images of the study area were produced by stacking all the spectral bands of each year together in Idrisi Selva. Image subsetting was subsequently carried out using the same software, whereby the Landsat ETM images were imported into the GIS environment and the Area of Interest (AOI) was carved out using the coordinates of the study area. The Landsat TM image Classification of 2010

The Landsat ETM image (2010) was also classified into four land use/land cover categories with higher producer's accuracies. Built-up areas and bare land had the same producer's accuracy of 93%, while vegetation and farmland had 90% and 87%, respectively. The overall classification accuracy was much better (91%), and the overall Kappa coefficient was 0.88.

Table 3. Error matrix of 2010 Image Classification

	Farmland	Vegetation	Bareland	Built Up	Kappa	Producer's Accuracy	User's accuracy
Farmland	89	7	4	0	0.85	87%	89%
Vegetation	3	90	1	6	0.87	90%	90%
Bareland	10	1	88	1	0.84	93%	88%
Built up	0	2	2	96	0.95	93%	96%
Total	102	100	95	103			
Overall Classification Accuracy=91%							
Overall, Kappa Statistics = 0.88							

Source: Author’s analysis (2022)

D. The Landsat TM image Classification of 2020

In the classification of the Landsat 8 OLI image (2020), the producer's accuracy of bare land (81%) was lower than that of other classes, as a result of errors due to omission and misclassification to farmland, vegetation, and built-up areas. A lower producer's accuracy was also observed for built-up areas (83%) due to omission and misclassification to vegetation and bare land. The overall classification accuracy was 85%, while the Kappa coefficient was 0.79 (Table4).

Table 4. Error matrix of 2020 Image Classification

	Farmland	Vegetation	Bare land	Built Up	Kappa	Producer's Accuracy	User's accuracy
Farmland	91	4	5	0	0.88	86%	91%
Vegetation	8	77	5	10	0.71	90%	77%
Bareland	6	1	85	8	0.80	81%	85%
Built up	1	4	10	85	0.80	83%	85%
Total	106	86	105	103			
Overall Classification Accuracy = 85%							
Overall, Kappa Statistics = 0.79							

Source: Author’s analysis (2022)

E. Method of Data Analysis

To identify the various land use and land cover (LULC) types and determine the extent of their changes in Nsukka, downloaded satellite imageries were preprocessed and subjected to supervised classification using IDRISI Selva. The extent of each LULC class was computed in hectares using the Raster Calculator tool within the IDRISI software suite. To quantify the magnitude of change, a quasi-year’s image differencing technique was employed, involving the subtraction of the LULC extent of the base year (A) from the referenced year (B), expressed by the formula $E_T = B - A$. The annual rate of change was subsequently determined by dividing the total percentage change by the number of years in the study period. For the prediction of future LULC patterns for 2030, 2050, and 2100, the Land Change Modeler (LCM) and CA Markov modules in IDRISI

Selva and TerrSet were utilized. The process began by generating a Transition Probability Matrix (TPM), a Transition Area Matrix (TAM), and Transition Suitability Maps (TSM) through the cross-tabulation of multi-temporal images from 1990, 2010, and 2020. To ensure the model's reliability, a simulation for 2020 was first conducted using 1990 and 2010 data as calibration points; this result was then validated against the actual 2020 classified map using the Kappa Statistics Index. Following the confirmation of an acceptable Kappa index indicating high agreement between projected and observed data and the 2020 LULC map was used as the final base to forecast potential land cover dynamics for the years 2030, 2050, and 2100.

III. RESULTS AND DISCUSSION

The result of the spatial distribution of land use and land cover classes in 1990 showed that the farmland was scattered throughout the vegetated areas, suggesting an integrated agro forestry landscape pattern. Built-up areas were visibly concentrated in specific locations, corresponding to existing settlements and urban centers. The rsult also revealed distributed bare land, primarily occurring in isolated patches. This spatial pattern indicates that in 1990, Nsukka Local Government Area maintained a largely rural character with extensive forest cover and agricultural activities coexisting across the landscape. The result of this study agrees with that of [11] who examined land use and land cover changes in the Kodaikanal hills using multi-sensor satellite data to monitor changes in various land use/land cover classes using digital remote sensing techniques. Their study used LISS-III data of 2006 and 2011 and revealed that agriculture covered an area of 26.5%, representing a 9.5% decrease in agricultural land, while water bodies covered 1% and barren area increased. Forest classes also showed a decrease of 10%, with the present forest covering 38% of the study area. The decreased classes in agriculture and forest were converted to built-up area, which clearly shows population increase. The study further revealed that urban area has increased, whereas the area of cropland and plantation has decreased within the period 2006–2010.

A. 1990 Land use Land Cover Classification map of the Study area

The land use and land cover classification for 1990 derived from the TM satellite image indicates that vegetation was the dominant land cover type in the study area, accounting for 325.8 km² (67.3%), followed by farmland at 124.5 km² (25.7%). Built-up areas occupied 31.5 km² (6.5%), while bare land constituted the smallest proportion at 2.4 km² (0.5%). These statistics reveal that in 1990, the study area was predominantly characterized by natural vegetation, with agricultural activities representing the second major land use. The relatively low percentage of built-up areas (6.5%) suggests minimal urban development during this period, while the negligible extent of bare land (0.5%) indicates limited land degradation or exposed soil surfaces at the time.

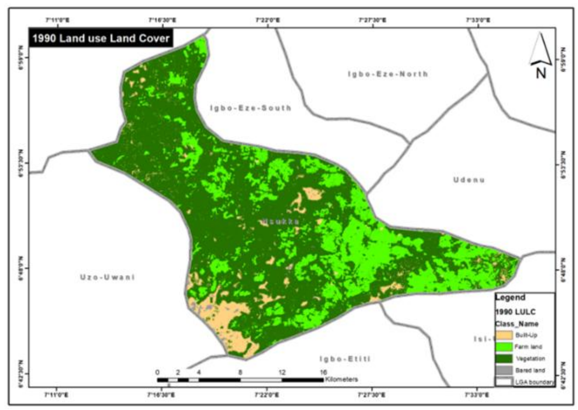

Fig 2.1990 Land use Land Cover Classification map of the Study area
Source: Author's GIS analysis (2022).

B. 2010 Land Use Land Cover Classification Mapping

The spatial distribution of land use and land cover classes in 2010 showed a radically altered landscape compared to 1990. Built-up now dominate the central and southern portions of the study area, forming extensive contiguous urban patches that indicate concentrated settlement expansion. Vegetation cover appears significantly fragmented and restricted to the peripheral and northern regions, suggesting isolation of remaining forest patches due to encroaching development. Farmland (light green) is interspersed throughout the landscape, often bordering built-up areas, which implies agricultural intensification at the urban-rural fringe. The visibly increased bare land patches are scattered across the map, particularly in areas adjacent to urban centers, indicating construction activities, land clearing, or degradation. This spatial pattern reflects the rapid urbanization of Nsukka Local Government Area between 1990 and 2010, with urban sprawl consuming previously vegetated and agricultural lands. The result of this study agrees with the work of [12] who assessed the dynamics in land use and land cover patterns in Calabar metropolis using thermal imageries for 2002, 2006, 2008, 2010, 2012, 2014, and 2016, obtained and processed using remote sensing and ArcGIS software in order to determine the changes that have occurred in the LULC in the study area. The overall accuracies of the LULC thematic maps were computed above 80 percent, which indicates an almost perfect agreement. The study reveals that LULC classes by the year 2016 have assumed different dimensions of change from their previous sizes in comparison to their current sizes. Land-use pattern changes in the study area were characterized by an increase in the built-up class and water bodies (though with a slightly negative change from 2010 to 2012) and a predominant negative trend in dense vegetation and bare land classes, thus indicating that future changing trends will pose a depleting threat to the overall LULC. The study also showed that the changing land use pattern of the area is capable of affecting certain characteristics of the environment, such as surface temperature.

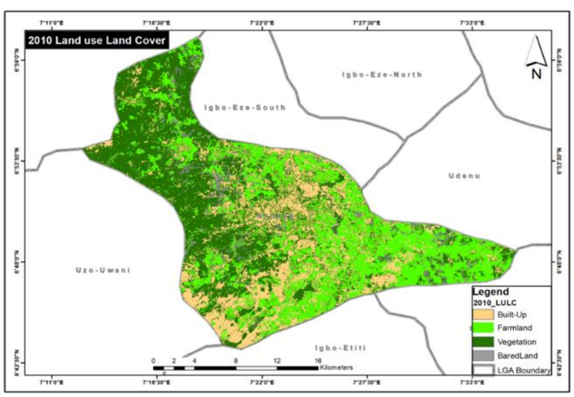

Fig 3. 2010 Land use Land Cover Classification map of the Study area

Source: Author's GIS analysis (2022).

C. 2020 Land Use Land Cover Classification Map

The spatial distribution of land use and land cover classes in 2020 showed extensive urbanization dominating the central and eastern portions of the study area. Built up areas formed a massive contiguous expanse centered around Nsukka, with development radiating outward in all directions, indicating consolidated urban growth and infilling of previously undeveloped spaces. Vegetation cover is severely restricted to the northwestern periphery and isolated patches, appearing as fragmented remnants of the formerly extensive forest cover. Farmland is interspersed throughout the landscape, particularly visible in transitional zones between the dense urban core and the remaining vegetated periphery, suggesting agricultural intensification at the urban fringe. The near-absence of bare land is visually apparent, with only minimal scattered patches detectable. This spatial pattern reflects the culmination of three decades of rapid urbanization in Nsukka Local Government Area, with the urban fabric now dominating the landscape and natural vegetation relegated to marginal areas. The result agrees with that of [13] who assessed land use/cover and its impacts, which play a crucial role in land use planning and formulation of sustainable land use policies. Their study used remote sensing data to map and predict land use/cover changes near Amman, where half of Jordan's population is living. Images of Landsat TM, ETM+, and OLI were processed and visually interpreted to derive land use/cover for the years 1983, 1989, 1994, 1998, 2003, and 2013. The study found that the main changes that altered the character of land use/cover in the area were the expansion of urban areas and the recession of forests, agricultural areas (after 1998), and rangelands. The findings of this study are also in conformity with those of Pande and Moharir (2014), who determined and identified changes in land use/land cover of Patur taluka in Akola district. The study was carried out through a remote sensing and GIS approach using SOI topo sheets, Landsat imagery of 2013, and IRS-1D-LISS-III 2007. The land use/land cover classification scheme was performed based on Survey of India topo sheets and satellite imageries. ArcGIS 10.1 software was used to prepare the LULC maps, and ground truth observations were also performed to check the accuracy of the classification scheme. The study classified land use into five categories on the basis of field study, geographical conditions, and remote sensing data. The study revealed a significant increase in built-up area, open forest, water body, wasteland, and other lands. Agricultural land decreased in 2013 as compared to 2007, though some changes were detected in land use/land cover analysis during the period 2007–2013.

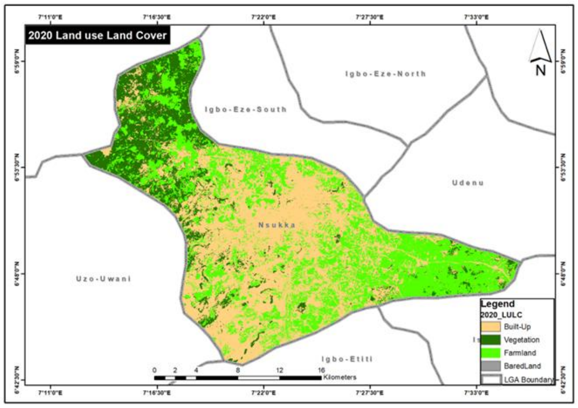

Fig4. 2020 Land use Land Cover Classification map of the Study area
Source: Author's GIS analysis (2022).

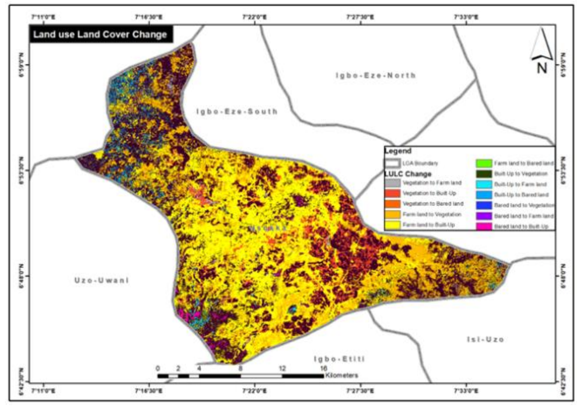

Fig 5. Extent of land use land cover changes of Nsukka from 1990-2020
Source: Author's GIS analysis (2022).

D. Extent of land use land cover changes of Nsukka from 1990-2020

The spatial pattern of land use/land cover change between 1990 and 2020 revealed extensive transformation across the study area. The result showed that agricultural lands have been the primary source of urban expansion, particularly in the central and eastern portions of the study area. The widespread distribution suggests a dispersed and fragmented pattern of urban growth, with development radiating from the original urban core of Nsukka. The result also revealed the progressive encroachment of human activities into previously forested regions. The concentration of bare land to built-up and Bare Land to Farmland in scattered locations suggests rehabilitation and utilization of previously degraded lands. The findings demonstrate that the study area has undergone massive urbanization over the 30-year period, with the built-up environment expanding at the expense of vegetation and agricultural lands. The evidence of this urban expansion can be clearly seen in the built-up maps of the study area to illustrate the progressive transformation from a predominantly vegetated landscape in 1990 to a heavily urbanized environment by 2020 (fig. 5)

E. 2030 Prediction of Land Use Land Cover Classification Map

The spatial distribution of predicted land use/land cover for 2030 showed extensive urbanization dominating the central and eastern portions of the study area, with built-up areas forming a massive contiguous urban mass that covers nearly half of the total landscape. The urban core of Nsukka appeared significantly expanded compared to 2020, with development radiating outward and consolidating previously fragmented settlements into a cohesive metropolitan area. Vegetation cover is restricted primarily to the northwestern periphery and isolated patches scattered throughout the landscape, appearing as fragmented remnants that constitute less than one-fifth of the study area. Farmland is interspersed throughout the landscape, particularly visible in transitional zones between the dense urban core and the remaining vegetated periphery, though its overall extent has diminished compared to 2020. The near-absence of bare land is visually apparent, with virtually no detectable patches remaining. This spatial pattern reflects the projected culmination of four decades of rapid urbanization in Nsukka Local Government Area, with the urban fabric dominating the landscape and natural vegetation relegated to marginal areas. The map suggests that by 2030, the study area will have transformed into a predominantly urbanized environment with limited green spaces, raising significant concerns for environmental sustainability, urban heat island effects, and the loss of ecosystem services previously provided by extensive vegetation cover. The fragmented distribution of remaining vegetation patches indicates potential isolation of forest remnants, which may threaten biodiversity and ecological connectivity. The visual comparison between this prediction and the historical maps (Fig 6) underscores the dramatic transformation expected to occur between 1990 and 2030, with urban areas expanding from 6.5% to nearly 50% of the landscape within a 40-year period.

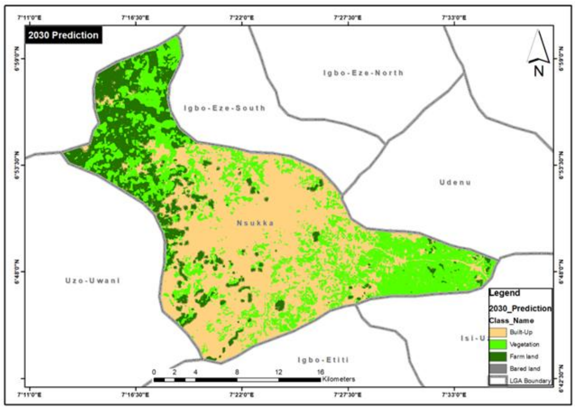

Fig 6. 2030 Prediction of Land use Land Cover Classification map of the Study area
Source: Author's GIS analysis (2022)

F. 2050 Prediction of Land Use Land Cover Classification Map

The spatial distribution of predicted land use/land cover for 2050 showed near-complete urbanization of the central and eastern portions of the study area, with built-up areas forming a dominant urban mass that covers more than half of the total landscape. The urban core of Nsukka appeared to have reached maximum expansion, with development filling in most available spaces and creating a highly consolidated metropolitan area that extends across the majority of the study area. Vegetation cover is severely restricted to the northwestern periphery and scattered isolated patches, appearing as fragmented remnants that constitute less than one-fifth of the study area, with many patches appearing smaller and more isolated than in the 2030 prediction. Farmland is visibly diminished compared to 2030, appearing as scattered patches interspersed throughout the urban fabric, particularly in transitional zones and areas unsuitable for intensive development. The complete absence of bare land is visually apparent, with no detectable patches remaining in the landscape. This spatial pattern reflects the projected culmination of six decades of rapid urbanization in Nsukka Local Government

Area, with the urban fabric dominating more than 50% of the landscape and natural vegetation relegated to marginal, protected, or inaccessible areas. The map suggests that by 2050, the study area will have transformed into a predominantly urbanized environment with severely limited green spaces, raising critical concerns for environmental sustainability, urban heat island effects, air quality degradation, and the loss of ecosystem services previously provided by extensive vegetation cover. The highly fragmented distribution of remaining vegetation patches indicates severe isolation of forest remnants, which threatens biodiversity, ecological connectivity, and the provision of habitat for wildlife species. The visual comparison between this prediction and the historical maps underscores the dramatic transformation expected to occur between 1990 and 2050, with urban areas expanding from 6.5% to over 50% of the landscape within a 60-year period, representing one of the most rapid urbanization rates documented in the region. This result suggests that the increase in built-up areas and continuous reforestation programs will contribute to the expected decrease in non-vegetated areas, exposed soils, landfills, and excavation sites. The city's expansion of built-up areas can be associated with various educational, socio-economic, and agricultural activities that have contributed to different change dynamics observed in the land cover. The availability of infrastructural, educational, and medical facilities in these districts will significantly increase the urban population and alter the city's land uses, thereby affecting the natural environment.

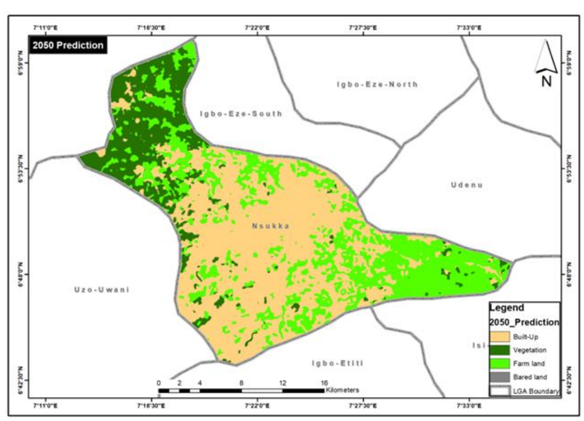

Fig7. 2050 Prediction of Land use Land Cover Classification map
Source: Author's GIS analysis (2022)

G. 2100 Prediction of Land Use Land Cover Map
The spatial distribution of predicted land use and land cover for 2100, showed near-total urbanization of the central, eastern, and southern portions of the study area, with built-up areas forming a dominant urban mass that covers nearly two-thirds of the total landscape. The urban core of Nsukka appears to have reached maximum expansion, with development filling virtually all available spaces and creating a highly consolidated metropolitan area that extends across the majority of the study area, leaving only fragmented remnants of natural and agricultural landscapes. Vegetation cover is severely restricted to the northwestern periphery and scattered, highly isolated patches throughout the landscape, appearing as small, disconnected remnants that constitute less than one-seventh (13.4%) of the study area. These vegetation patches appear significantly smaller and more fragmented than in the 2050 prediction, indicating severe habitat isolation and potential loss of ecological connectivity. Farmland is visibly diminished compared to 2050, appearing as scattered, disconnected patches interspersed throughout the urban fabric, primarily in areas unsuitable for intensive development or preserved for agricultural purposes. The complete absence of bare land is visually apparent, with no detectable patches remaining in the landscape. This spatial pattern reflects the projected culmination of over a century of rapid urbanization in Nsukka Local Government Area, with the urban fabric dominating nearly two-thirds of the landscape and natural vegetation relegated to marginal, protected, or completely inaccessible areas. The map suggests that by 2100, the study area will have transformed into a heavily urbanized environment with severely limited green spaces, raising critical concerns for environmental sustainability, urban heat island effects, air quality degradation, biodiversity loss, and the complete loss of ecosystem services previously provided by extensive vegetation cover. The highly fragmented and isolated distribution of remaining vegetation patches indicates near-total ecological disconnection, which threatens biodiversity, prevents wildlife movement, and eliminates the provision of habitat for most species. The visual comparison between this prediction and the historical maps (Fig 8) underscores the catastrophic transformation expected to occur between 1990 and 2100, with urban areas expanding from 6.5% to over 64% of the landscape within a 110-year period, representing one of the most dramatic urbanization rates documented in the region and potentially resulting in an urban environment with minimal natural areas and significantly compromised ecological functions.

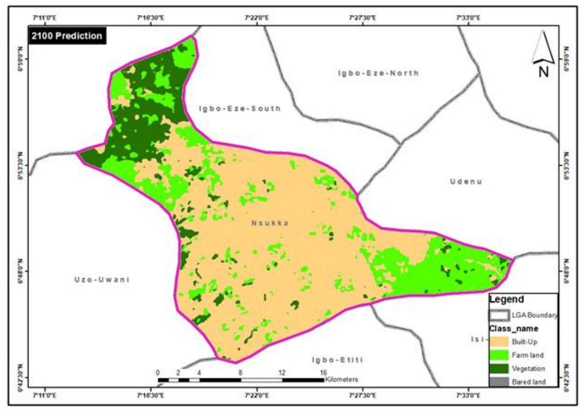

Fig 8. 2100 Prediction of Land use Land Cover prediction map of the Study Area Source: Author's GIS analysis (2022).

IV. CONCLUSION

For the past 30 years, the Nsukka Local Government Area (LGA) has experienced accelerated urban growth. This study successfully demonstrated the efficiency of the CA–Markov model in using remotely sensed data and GIS techniques to monitor LULC changes and predict future patterns. Such data are vital for informed decision-making in urban planning, as they provide the insights necessary to monitor growth and improve environmental sustainability. Although this study effectively predicted LULC for 2030, 2050, and 2100, it lacks up-to-date census data on population growth. Therefore, further research is needed to examine the relationship between land cover changes and population trends more closely. Incorporating demographic data will allow for a holistic understanding of long-term LULC dynamics and their implications for sustainable development. Based on the identified changing nature and rate of various land-use/land-cover types in the study area from 1990 to 2020, proactive measures should be taken by Nsukka

Local Government Area and Enugu State to better understand these changing patterns and manage associated environmental challenges. The management of the Ministry of Lands and Survey and Country Planning should adopt Remote Sensing and Geographic Information System techniques for efficient monitoring and control of encroachment, while the Urban Planning and Development Authority should adequately plan for gradual urban growth. Future research should focus on integrating high-resolution GIS and satellite remote sensing with socio-economic data to develop urban environmental monitoring and improve land use modeling techniques for predicting future change patterns.

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