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DYNAMICS OF LAND COVER CHANGE IN THE ANAMBRA RIVER BASIN OF NIGERIA AND IMPLICATIONS FOR SUSTAINABLE LAND MANAGEMENT

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Abstract: Land cover change and its consequences such as environmental degradation and biodiversity loss pose significant global challenges, including in Nigeria's Anambra River Basin. This study focuses on monitoring, predicting and understanding land cover changes in the basin from 1987 to 2018, with projections up to 2030. It explores the intricate relationship between population growth and land cover dynamics, aiming to contribute to sustainable land management practices and align with the Sustainable Development Goals (SDGs) for 2030. Using a combination of neural network classification and the CA-Markov model, the study analyses historical land cover data to identify significant transformations. Between 1987 and 2018, bare lands increased by 29%, vegetation increased by 14%, built-up areas increased by 128% and waterbodies increased by 10%, whereas there was a 58% decline in the extent of wetlands. The most significant transformation occurred in the wetlands, with a total of 1819.46 km^2 being converted to various land cover types. The results demonstrate remarkable shifts characterised by rapid urbanisation, substantial wetland loss and a decline in vegetation cover. Expectedly, population growth is found to be closely linked to the expansion of built-up areas while negatively impacting other land cover types. These findings underscore the urgent need for sustainable land management strategies that balance the demands of growing populations with the preservation of natural ecosystems and biodiversity. Furthermore, the study provides future projections that offer crucial insights for decision-makers involved in land use planning, biodiversity conservation and sustainable development.

Key words: land cover, neural network, cellular automata Markov model, population growth, Sustainable Development Goals

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Introduction

Land cover change has emerged as a critical global challenge due to escalating human activities and population growth (Beeson 2010, FAO 2019, Barbier 2021, Singh et al. 2022). It is a primary driver of environmental degradation, posing significant implications for ecosystem

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sustainability and human well-being (Mertens, Lambin 2000, Foley et al. 2005, Mamun et al. 2013, Metternicht. 2017, Fu et al. 2018, Li et al. 2022). As human populations expand and development intensifies, the conversion of natural landscapes into urban areas, agricultural fields, and industrial zones leads to the loss of vital habitats and disruption of ecological processes. This transformation profoundly affects ecosystem functioning and presents formidable sustainability challenges across sectors such as agriculture, water resources, and climate regulation.

In Nigeria, the situation has become increasingly alarming, with significant land cover change occurring particularly within river basins, resulting in biodiversity loss and environmental degradation (Imarhiagbe et al. 2020). As the seventh most populous country in the world (UN DESA 2017), Nigeria experiences rapid population growth, exerting immense pressure on land cover. This growth has triggered substantial alterations in land cover, leading to environmental degradation and biodiversity loss nationwide (Brody 2003, Gordon et al. 2009, Biitir, Nara 2016, Wubie et al. 2016, Asenso Barnieh et al. 2020, Herrmann et al. 2020).

The Anambra River Basin, characterised by extensive agricultural and industrial activities, has witnessed notable changes in land cover. The population growth in the states comprising the basin has fuelled demands for housing, infrastructure development, and urban expansion, resulting in the conversion of natural land cover and further exacerbating environmental degradation.

However, the scarcity of research on evaluating current and projected changes within the Anambra River Basin hampers the identification of critical areas requiring conservation and management interventions. It is imperative to prioritise concerted efforts to address the ongoing population growth trend and its associated impacts on land cover change, particularly within the Anambra River Basin. These efforts are vital to foster sustainable development, mitigate biodiversity loss, and combat environmental degradation, aligning with the Sustainable Development Goals (SDGs) for 2030.

This research is the culmination of a long-term analysis of land cover change in the Anambra River Basin of Nigeria, utilising a combination of neural network classification and the well-established CA-Markov model (Nwilo et al. 2021). In the present study, we showcase results from the multi-decadal investigation of land cover change and land cover transitions between 1987 and 2018 and provide future projections for 2030. Additionally, the relationship between land cover and population growth is assessed, and recommendations are proffered for sustainable land use practices in the region. We aim to shed light on the dynamics of land cover change within the basin. Summarily, this article addresses the following research questions:

1. What land cover changes have occurred within the Anambra River Basin between 1987 and 2018?
2. How do population growth and land cover relate within the Anambra River Basin?
3. What are the predicted changes in land cover within the Anambra River Basin for 2030?

By addressing these research questions, we aim to contribute valuable insights into land cover change dynamics in the Anambra River Basin, emphasising the urgent need for sustainable land use practices in the region to achieve the SDGs for 2030.

Study area

The Anambra River Basin is predominantly situated in the southeastern geopolitical region of Nigeria (Fig. 1) and encompasses the Anambra River and its associated drainage systems, constituting a significant component of the region's inland waters (Nwani, Ude 2005). Given Nigeria's projected population increase from 208 million in 2020 to 419 million by 2058 (Chamie 2022), the Anambra River Basin is expected to experience increased human pressures on land cover and natural resources. The basin, covering approximately 11,000 km^2 (Fig. 1), extends from the Ankpa hills and merges with the River Niger at Onitsha. It exhibits a diverse range of biophysical characteristics, with elevations ranging from a maximum of approximately 594 m a.s.l. to a minimum of −2 m b.s.l. Intersecting eight states, namely Abia, Anambra, Benue, Delta, Enugu, Imo, Edo, and Kogi, the Anambra River Basin hosts abundant natural resources, including substantial deposits of coal and lignite, along with

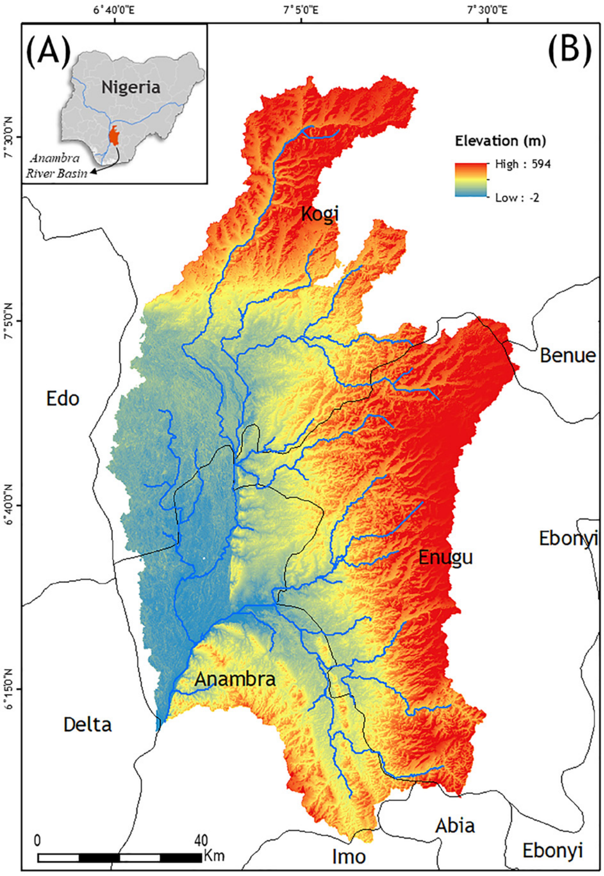

Fig. 1. Map of Nigeria showing the location of the Anambra River Basin (A). Map of the Anambra River Basin showing the relief pattern and state boundaries (B).

significant hydrocarbon potential. Notably, the basin is estimated to possess around 10 trillion cubic feet of gas reserves. It experiences two distinct seasons: a dry season from October/November to March and a rainy season from April to September/October. These seasonal variations correspond to the hydrological regimes, with dry and flood phases observed in the region. Its climatic conditions further complement the basin's biophysical attributes. It maintains an annual mean maximum temperature of 32°C and an annual mean minimum temperature of 24.5°C. The area receives an accumulative annual rainfall ranging from 1900 mm to 2707 mm (Akafor, Obiezue 2004).

In addition to its natural characteristics, the Anambra River Basin supports a growing population and diverse land uses. Agriculture employs over 60% of the population of South-eastern Nigeria and is the backbone of the economy in the region (Ogoke 2023). Within the Anambra River Basin, agriculture serves as the primary land use, encompassing activities such as forestry, fishing, farming, field crop production, and animal pasture. The region's agricultural and fishery projects, including the World Bank's rice initiatives, exemplify the immense potential within the basin. The Anambra-Imo River Basin and Rural Development Authority was established for sustained development and resource management.

Given the dynamic interplay of biophysical features, climatic patterns, and human activities, performing a spatiotemporal characterisation of the Anambra River Basin is imperative. Understanding the basin's evolving dynamics and changes over time is crucial for effective planning, management, and sustainable development of the area. By studying the basin's spatiotemporal aspects, valuable insights can be gained regarding its ecological integrity, water resources, land use patterns, and potential impacts on the surrounding communities.

Materials and methods

The workflow diagram of the methodology is presented in Figure 2, and the essential stages are discussed in the following sections.

Data acquisition and pre-processing

The dynamics of land cover in the study area were examined using Landsat satellite imagery from three approximate periods: 1987, 2000, and 2018. Six Landsat scenes covering the study area were downloaded from the United States Geological Survey website (USGS 2023) in GeoTIFF format. Table 1 provides an overview of the characteristics of the Landsat imageries employed in the analysis.

The population data for the states within the river basin, spanning the years 2006–2018, were sourced from the National Bureau of Statistics website (NBS 2023). These population datasets are instrumental in understanding demographic changes and their potential influence on regional land cover dynamics. By utilising these resources, we aim to gain a comprehensive understanding of the changes in land cover over time and explore any potential correlations with population dynamics in the study area.

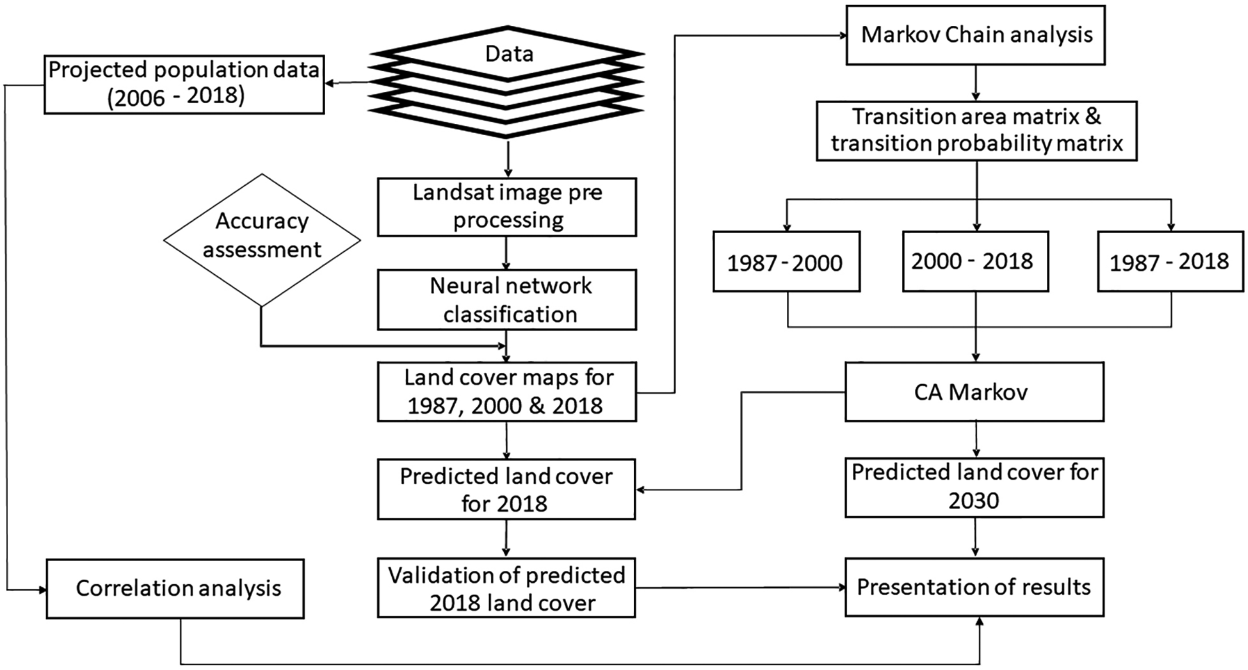

Fig. 2. Workflow diagram of the methodology.

Table 1. Characteristics of the Landsat imageries.

Landsat mission	Path/row	Acquisition date	Spatial resolution [m]	Band composition
Landsat 4–5 TM (Thematic Mapper)	188/55	04.01.1986	30	4–3–2
	188/56	21.12.1987		
Landsat 7 ETM+ (Enhanced Thematic Mapper)	188/55	17.12.2000	30	5–4–3
	188/56	09.01.2001		
Landsat 8 OLI/TIRS (Operational Land Imager/Thermal Infrared Sensor)	188/55	09.01.2018	30	6–5–4
	188/56	25.01.2018		

Selection of classification scheme

During image interpretation, the following five classes were detected, following the Level I classification scheme of Anderson et al. (1976): vegetation, wetland, waterbody, built-up area, and bare land (described in Table 2).

Table 2. Land cover classification scheme.

S/N	Land cover class	Description
1	Vegetation	Cropland and pasture fields, grassland and fallow land
2	Wetland	Marsh or swamp
3	Waterbody	Inland rivers, ponds and small lakes
4	Built-up area	Residential, commercial and industrial areas; settlements; and transportation infrastructure
5	Bare land	Tilled farmland, sand-filled land and rocky area

Neural network classification

In recent years, the field of land cover classification has witnessed the development of various techniques, with neural networks emerging as a particularly accurate and effective method (Jansen et al. 2009). The application of neural networks for extracting land cover information from remotely sensed data has been widely demonstrated by researchers (Frizzelle, Moody 2001, Muchoney, Williamson 2001, Tatem et al. 2001, Benediktsson, Sveinsson 2003, Jensen, Binford 2004, Al-Hameedi et al. 2021, 2022,).

The utilisation of neural networks as a classification method offers compelling justifications. Firstly, neural networks have demonstrated a remarkable ability to handle complex patterns and relationships within data. They can capture intricate non-linearities and subtle interactions, enabling them to effectively discriminate between different land cover classes based on their unique spectral characteristics and spatial patterns. This capability makes neural networks well-suited for accurately categorising land cover types from remotely sensed imagery. Additionally, neural networks operate in a supervised learning framework, leveraging labelled training samples to train the network's parameters. This characteristic allows for the exploitation of prior knowledge and expert input in the classification process. By utilising a large and diverse training dataset, neural networks can learn to recognise intricate patterns and generalise well to unseen data, enhancing their performance in land cover classification tasks.

Accuracy assessment

The importance of conducting an accuracy assessment in image classification cannot be overstated as it plays a crucial role in establishing the confidence and reliability of the obtained results (Gashaw et al. 2017). A comprehensive approach was employed in this study to ensure a robust evaluation of the land cover output. Specifically, a stratified random sampling technique was implemented, considering the different land cover classes within the study area.

The ground-truth points used for accuracy assessment were thoughtfully distributed across the study area using the stratified random sampling approach. The aim was to ensure that each land cover class was adequately represented, accounting for the inherent heterogeneity of the landscape. High-resolution imagery from Google Earth served as the basis for identifying suitable locations for ground-truth points.

The well-established Cochran's formula for stratified random sampling (Cochran 1977) was employed to ascertain an appropriate sample size for the study:

$$n = \frac{(\sum w_i s_i)^2}{[S(\hat{O})^2] + (1 / N)\sum w_i s_i^2} \approx \left(\frac{\sum w_i s_i}{S(\hat{O})}\right)^2 \quad (1)$$

where:
- N represents the number of units in the region of interest,
- $S(\hat{O})$ denotes the standard error of the estimated overall accuracy we aim to achieve,
- W_i represents the proportion of the mapped area corresponding to class i,
- S_i represents the standard deviation of stratum i, calculated as $S_i = \sqrt{U_i(1 - U_i)}$.

The formula was pivotal in determining the number of samples required to ensure a representative and statistically significant representation within each stratum. The overall accuracy is given by:

$$\text{Overall accuracy} = \frac{\text{Total number of correct classified points}}{\text{Total number of points}} \times 100 \quad (2)$$

The total number of correctly classified points is the number of points with the same class values from the classification output and the ground truth, while the total number of points is the number of random points created. The kappa coefficient was also calculated. Kappa tests are used to measure the accuracy of classification as the test accounts for all elements in the confusion matrix, including diagonal elements (Halmy et al. 2015). The kappa test is a measure between predefined producer rating and user-assigned rating, which can be expressed as follows:

$$K = \frac{P(A) - P(E)}{1 - P(E)} \quad (3)$$

where:
- *P(A)* is the number of times the *k*-raters agree, and
- *P(E)* is the number of times the *k*-raters are expected to agree only by chance (El-Kawy et al. 2011, Pontius, Millones 2011, Hua 2017).

Meanwhile, user accuracy can be defined as the probability of a pixel on the image representing a class on the ground. The producer's accuracy indicates the probability of a pixel being correctly classified and is mainly used to determine how well an area can be classified (Pontius, Millones 2011).

Land cover prediction with CA-Markov model

The CA-Markov model is well established for use in land cover prediction (e.g., Nath et al. 2020, Beroho et al. 2023, Rani et al. 2023). The process of land cover prediction using the CA-Markov model involved several steps. Firstly, the classified images were converted to an ASCII data format to ensure compatibility with Clark Labs' IDRISI software. The ASCII file was then imported into the IDRISI environment and converted to an *.rst format. Subsequently, the reclass tool was utilised to reclassify the raster, assigning numerical values to different land cover classes.

A transition probability matrix was generated. The process required selecting the earliest year's reclassified image as the first image, while the latest year's reclassified image was selected as the second. The resulting probability matrix was labelled with the prefix 'output' and included the conditional probability values. The period forward and the epochal difference between the two images were specified, while the proportional error value was set to 0.00.

The prediction of land cover for 2030 involved a two-step process. Initially, the land cover of 2018, referred to as predicted 2018, was predicted. This prediction served as a basis for comparing the performance of the model with the actual data obtained from Landsat-based classification. The transition probability matrix for 1987–2000, suitability maps and a 5 × 5 contiguity filter were employed, and a comparison was conducted between the classified and predicted maps of 2018.

The classified 2018 map was utilised as a base map for further predictions, after which the transition probability matrix for the period 2000–2018 was employed to simulate the land cover for 2030.

Land cover change analysis and population growth

A post-classification detection method was utilised to perform the land cover change detection. The *calculate geometry* function in ESRI's ArcMap™ was employed to calculate the coverage areas of the land cover classes. The resulting data on coverage areas were then transferred to the Microsoft Excel workspace for additional analysis. In parallel, population data from 2006 to 2016 were obtained and used to project the population figures for 2017 and 2018. The projection of population figures followed the formula provided by George et al. (2004):

$$Nt = Pe^{(r \times t)} \tag{4}$$

where:
- Nt represents the future population,
- P is the present population,
- e is the base of the natural logarithms (2.71828),
- r is the annual growth rate,
- t is the time or period involved.

Results

Assessment of land cover change

The assessment of land cover change reveals significant transformations in the study area over the years. Figure 3 depicts the land cover maps for 1987, 2000 and 2018, providing a visual representation of the changes that occurred. Furthermore, Table 3 presents the areal distribution of land cover for the three respective years, offering quantitative insights into the changes.

Table 4 presents the land cover change at three study intervals: 1987–2000, 2000–2018 and 1987–2018. Figure 4 shows a graphical representation of the percentage changes.

Between 1987 and 2000, there was an observable increase in built-up areas, expanding from 168.28 km^2 (1.51% of the study area) to 201.42 km^2 (1.80%). This trend continued, with built-up areas further growing to 382.87 km^2 (3.42%) by 2018. Concurrently, wetlands experienced a notable decline from 2479.71 km^2 (22.18%) in 1987 to 1102.15 km^2 (9.86%) in 2000. The decrease continued, reaching 1047.99 km^2 (9.37%) in 2018. The area of bare land increased from 118.29 km^2 (1.06%) in 1987 to 185.03 km^2 (1.66%) in 2000 but subsequently decreased to 153.02 km^2 (1.37%) in 2018. Vegetation, which exhibited the largest cover throughout the years, expanded from 8373.33 km^2 (74.89%) in 1987 to 9643.82 km^2 (86.27%) in 2000. However, vegetation coverage decreased slightly to 9549.34 km^2 (85.43%) by 2018. Waterbody experienced a marginal increase from 41.18 km^2 (0.3%) in 1987 to 46.06 km^2 (0.41%) in 2000 but slightly decreased to 45.38 km^2 (0.41%) by 2018.

During the period from 1987 to 2000, there was a significant gain in bare land (56.41%), built-up areas (19.69%), waterbody (11.85%) and vegetation (15.17%), whereas wetlands experienced a substantial loss of 55.55%. From 2000 to 2018, there was a decline in bare land (17.3%),

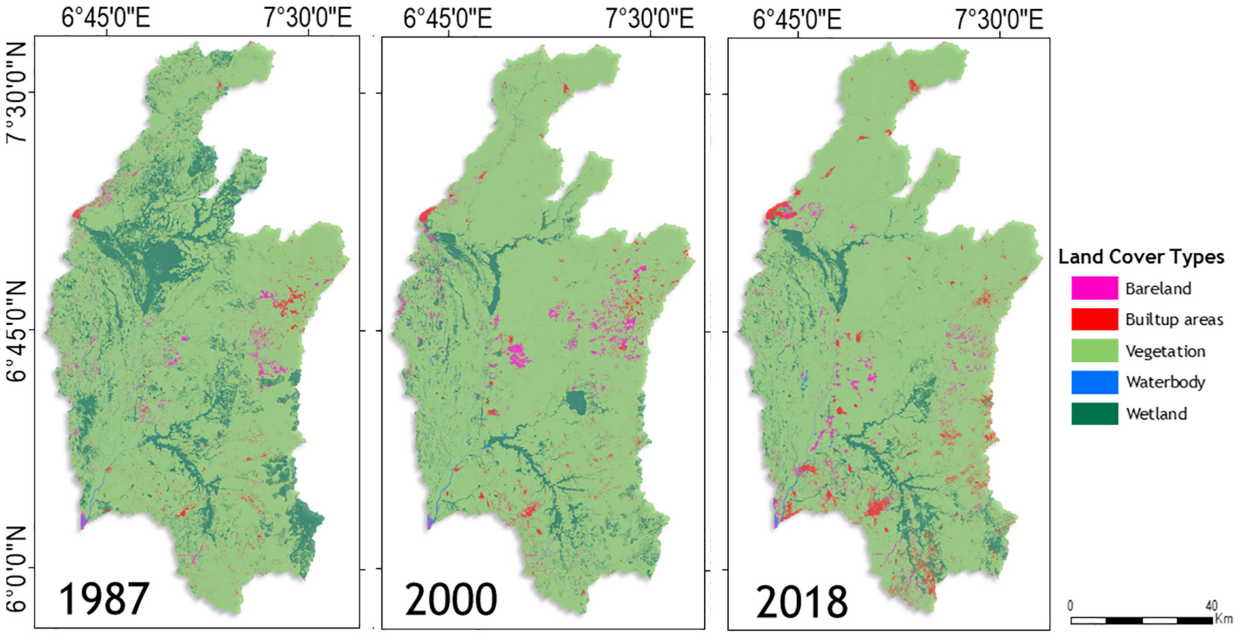

Fig. 3. Anambra River Basin land cover maps for 1987, 2000 and 2018.

Table 3. Land cover distribution for 1987, 2000 and 2018.

Land cover class	1987		2000		2018	
	[km²]	[%]	[km²]	[%]	[km²]	[%]
Waterbody	41.18	0.37	46.06	0.41	45.38	0.41
Built-up area	168.28	1.51	201.42	1.80	382.87	3.42
Wetland	2479.71	22.18	1102.15	9.86	1047.99	9.37
Vegetation	8373.33	74.89	9643.82	86.27	9549.34	85.43
Bare land	118.29	1.06	185.03	1.66	153.02	1.37
Total	11,180.80	100.00	11,178.48	100.00	11,178.58	100.00

Table 4. Areal changes in land cover in 1987–2000, 2000–2018 and 1987–2018.

Land cover class	1987–2000		2000–2018		1987–2018	
	[km²]	[%]	[km²]	[%]	[km²]	[%]
Waterbody	4.88	11.85	−0.68	−1.49	4.19	10.20
Built-up areas	33.14	19.69	181.45	90.09	214.59	127.52
Wetland	−1377.57	−55.55	−54.16	−4.91	−1431.73	−57.74
Vegetation	1270.49	15.17	−94.49	−0.98	1176.01	14.04
Bare land	66.73	56.41	−32.01	−17.3	34.72	29.36

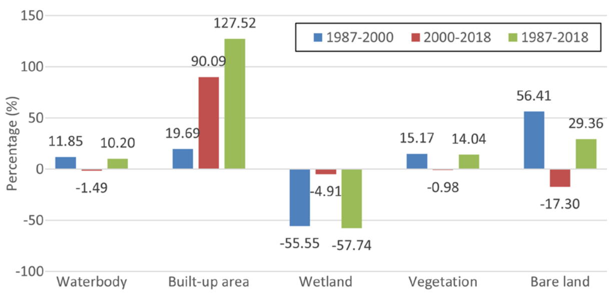

Fig. 4. A comparison of positive and negative changes in land cover; 1987–2000 in blue, 2000–2018 in orange and 1987–2018 in grey colours.

wetland (4.91%), vegetation (0.98%) and waterbody (1.49%), while built-up areas experienced a substantial increase of 90.09%. From 1987 to 2018, there was an increase in bare land (34.72 km², 29.36%), vegetation (1,176.01 km², 14.04%), built-up areas (214.59 km², 127.52%) and waterbody (4.19 km², 10.20%). However, wetlands experienced a considerable loss of 1431.73 km² (57.74%).

The accuracies for 1987, 2000 and 2018 classifications were 87.85%, 85.33% and 91.27%, with kappa coefficients of 0.84, 0.81 and 0.87, respectively.

Transition probability matrix

The transition probability matrix provides valuable insights into the likelihood of land cover conversions within specific periods in the Anambra River Basin. Figure 5 presents summaries of the probability matrix, focusing on the major land cover change between 1987–2000, 2000 –2018 and 1987 – 2018, respectively.

In the analysis of the transition probabilities between 1987 and 2000 (Fig. 5A), it is observed that the probability of a waterbody remaining as a waterbody was 46%. Meanwhile, the probability of bare land converting to vegetation was relatively high at 81%. Additionally, the probability of vegetation remaining unchanged was 90%, indicating considerable stability in vegetation cover during this period. There was a relatively low probability of vegetation transitioning to built-up areas (2%). In terms of wetlands, there was a 16% probability of them remaining unchanged, while the probability of wetlands converting to vegetation was notably high at 82%. Figure 5B shows that between 2000 and 2018, the probability of wetlands remaining unchanged was 64%, while the probability of wetlands changing to vegetation was 32.10%. The probability of built-up areas remaining unchanged was 53%, while the probability of built-up areas changing to vegetation was 45%. Figure 5C shows that between 1987 and 2018, vegetation had the highest probability of 92% remaining as vegetation. In contrast, waterbody, built-up area, wetland and bare land had probabilities of 73%, 51%, 43% and 17%, respectively, to remain unchanged.

Land cover change transition matrix

The land cover transition matrices presented in Tables 5–7 provide detailed information on the transformations between different land cover classes during specific time intervals: 1987–2000, 2000–2018 and 1987–2018.

Analysing the land cover change between 1987 and 2018 (Table 7), it is evident that the wetland area experienced the most significant transformation, with a total of 1819.46 km^2 being converted to various land cover types, including

Table 5. Transition matrix of land cover change (km^2), 1987–2000.

Land cover class		2000					
		Waterbody	Built-up area	Wetland	Vegetation	Bare land	Total
1987	Waterbody	23.69	0.44	3.63	12.10	1.25	41.11
	Built-up area	0.08	57.63	0.78	105.20	4.38	168.07
	Wetland	5.94	3.66	697.13	1761.91	9.48	2478.13
	Vegetation	13.88	132.32	394.69	7676.33	150.77	8367.99
	Bare land	2.45	7.18	5.37	84.07	19.09	118.17
	Total	46.04	201.24	1101.60	9639.61	184.97	11,173.46

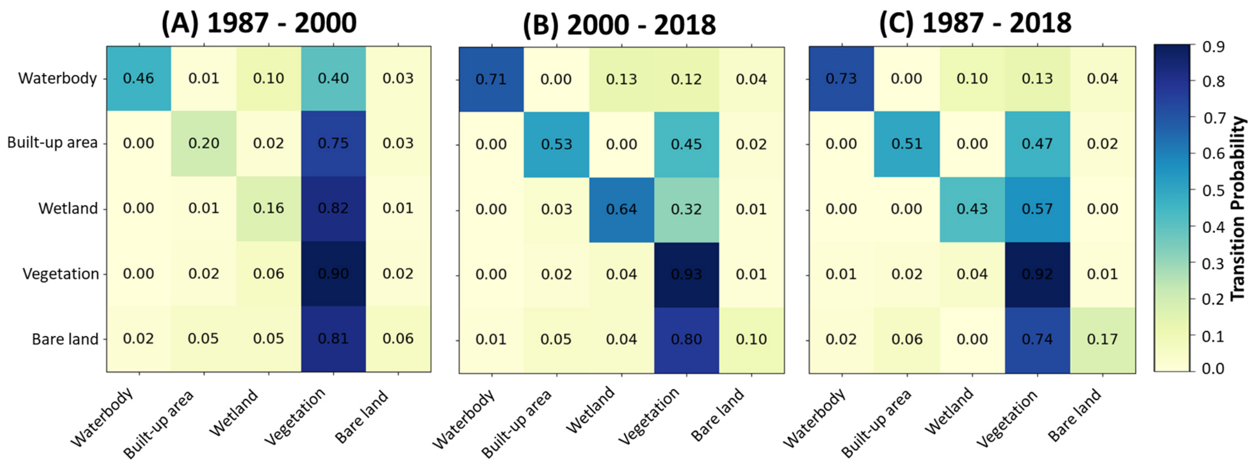

Fig. 5. Transition probability matrix for land cover maps from 1987 to 2000 (A). Transition probability matrix for land cover maps from 2000 to 2018 (B). Transition probability matrix for land cover maps from 1987 to 2018 (C).

Table 6. Transition matrix of land cover change (km^2), 2000–2018.

Land cover class		2018					
		Waterbody	Built-up area	Wetland	Vegetation	Bare land	Total
2000	Waterbody	28.20	0.26	6.79	9.16	1.645	46.05
	Built-up area	0.06	87.57	1.99	107.46	4.26	201.34
	Wetland	3.55	33.66	603.10	452.36	9.34	1102.00
	Vegetation	12.27	252.50	427.42	8825.93	124.78	9642.90
	Bare land	1.30	8.70	8.61	153.48	12.92	185.01
	Total	45.37	382.69	1047.92	9548.39	152.95	11,177.31

Table 7. Transition matrix of land cover change (km^2), 1987–2018.

Land cover class		2018					
		Waterbody	Built-up area	Wetland	Vegetation	Bare land	Total
1987	Waterbody	21.07	0.48	4.37	13.86	1.34	41.11
	Built-up area	0.05	54.21	1.68	108.71	3.44	168.09
	Wetland	6.03	43.47	658.79	1755.70	14.26	2478.25
	Vegetation	16.07	277.59	380.86	7570.97	122.78	8368.28
	Bare land	2.13	6.86	1.88	96.24	11.06	118.17
	Total	45.35	382.62	1047.57	9545.48	152.89	11,173.89

waterbodies, built-up areas, vegetation and bare land. During the same period, 103.098 km^2 of bare land transitioned to built-up areas and vegetation. Moreover, approximately 277.59 km^2 and 122.78 km^2 of vegetation changed into built-up areas and bare land, respectively. These transformations highlight the dynamic nature of land cover within the Anambra River Basin, illustrating the substantial shifts between different land cover categories over the examined period.

Specifically examining the land cover transitions between 1987 and 2000 (Table 5), it can be observed that a significant portion of wetlands, measuring 1761.91 km^2, transformed into vegetation. Similarly, a total of 427.42 km^2 of vegetation was converted into wetlands between 2000 and 2018 (Table 6).

Validation of land cover prediction

The validation of land cover prediction is a crucial step in ensuring the credibility and applicability of the CA-Markov model's outputs. By comparing the predicted results with classified land cover information, potential limitations and areas of improvement for the model can be identified. This information can be valuable for refining the model and enhancing its accuracy in future applications.

A comparison was made between the predicted land cover output for 2018 and the classified land cover derived from imagery to assess the accuracy of the land cover prediction generated by the CA-Markov model. The prediction for 2018 was obtained using the transition probability matrix calculated for the period from 1987 to 2000. The results of this validation process are presented in Figure 6.

Figure 6 provides a clear overview of the comparison between the classified and predicted values for different land cover categories, namely waterbodies, wetlands, vegetation, bare land and built-up areas. The analysis reveals a close alignment between the classified and predicted values for waterbodies, wetlands, vegetation and bare land. These categories demonstrate a consistent correspondence between the predicted land cover and the observed land cover derived from the imagery data.

However, there is a notable difference in the predicted area for built-up areas compared to the classified values, with a discrepancy of 182.89 km^2. This disparity can be attributed to the model's limited sensitivity in accurately capturing small and scattered patches of built-up areas. The model's performance in predicting the extent and distribution of built-up areas appears less accurate than other land cover categories.

In terms of overall performance, the accuracy assessment indicates a satisfactory outcome for the CA-Markov model in simulating future land cover. The model achieved an overall accuracy of 91.60%, reflecting the percentage of correctly predicted land cover categories and a kappa

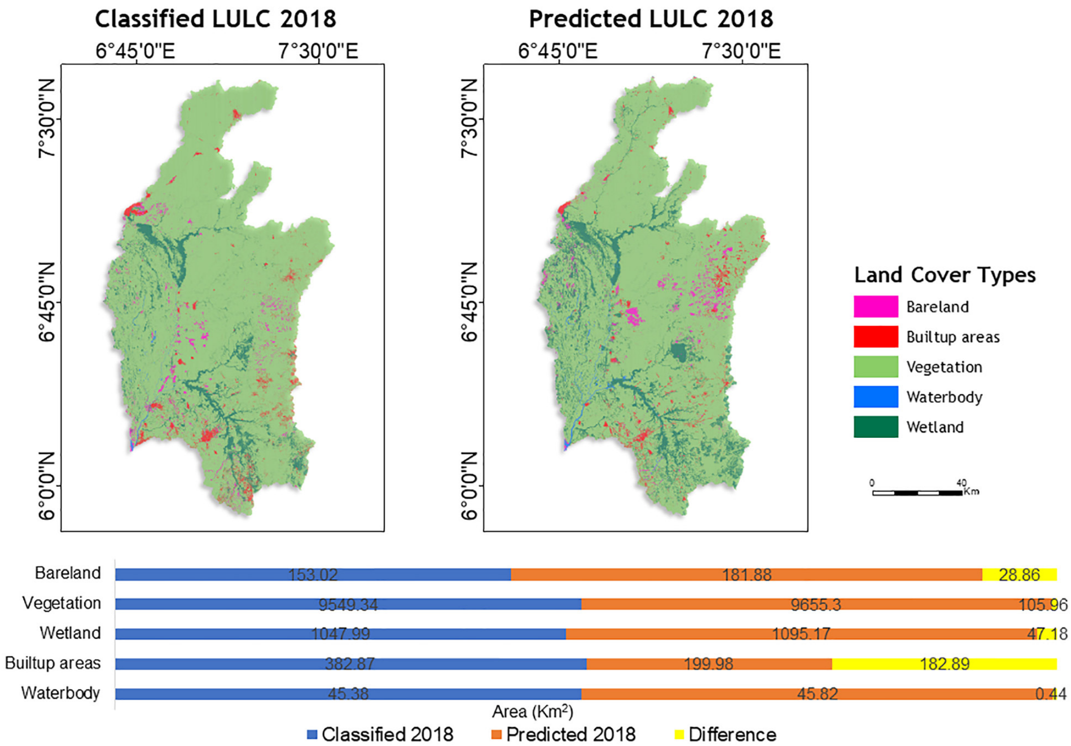

Fig. 6. Comparison between the classified land cover of 2018 and the predicted land cover of 2018.

coefficient of 0.87, which measures the agreement between predicted and observed land cover beyond what could be expected by chance alone.

Future land cover prediction

The future land cover prediction for the study area was conducted using the CA-Markov chain model. The resulting distribution of land cover classes for the year 2030 is visualised in Figure 7, providing a comprehensive overview of the projected changes in land cover across the study area.

Figure 7 illustrates the spatial distribution of different land cover categories, including waterbodies, wetlands, vegetation, bare land and builtup areas, as projected by the CA-Markov chain model for 2030. This visualisation offers valuable insights into the expected changes in the land cover composition and patterns over the specified time frame, aiding in understanding the future landscape dynamics and potential environmental impacts.

Furthermore, Table 8 presents a detailed summary of the projected land cover change between 2018 and 2030. It provides quantitative information regarding the transitions and transformations anticipated to occur within this period. The table shows the magnitude of changes for

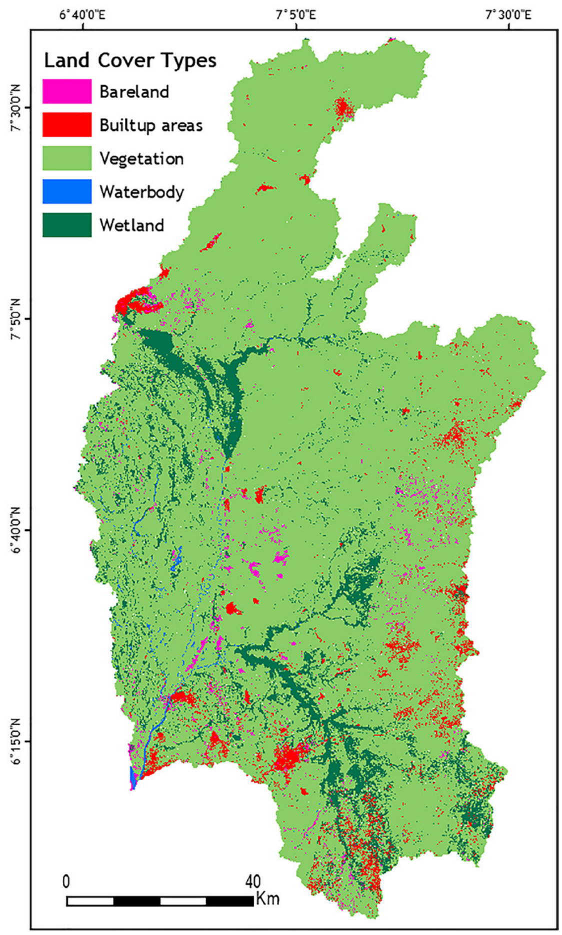

Fig. 7. Projected land cover for 2030.

Table 8. Comparison between land cover for 2018 and the projected land cover for 2030.

Land cover class	2018	Projected 2030
Waterbody	45.38	44.59
Built-up area	382.87	377.93
Wetland	1047.99	1035.37
Vegetation	9549.34	9572.94
Bare land	153.02	148.06
Total	11,178.58	11,178.90

each land cover category, shedding light on the expected gains, losses and shifts in land cover across the study area.

Relationship between land cover and population growth

The relationship between land cover types and population growth in the study area was examined using Pearson's correlation coefficient, and the results are summarised in Table 9. This analysis aimed to understand the association between population dynamics and different land cover categories within the basin.

The findings revealed a strong positive correlation (r = 1.0) between population and built-up areas, indicating that as the population increases, there is a corresponding increase in built-up areas, suggesting urbanisation and the expansion of human settlements. The strong positive association implies that population growth is a driving force behind the expansion of built-up areas, possibly due to the need for housing, infrastructure development and other urban amenities to accommodate the growing population.

On the other hand, a strong negative correlation (r = −0.99) was observed between population and bare land, waterbody, wetland and vegetation, implying that these land cover types tend to decrease as the population increases. The negative association suggests that population growth has a detrimental impact on these land cover categories.

Discussion

The main objective of this study was to assess the dynamics of land cover change in the Anambra River Basin using a combination of neural network classification and the CA-Markov model. By employing these modelling techniques, we aimed to investigate the changes in land cover within the basin between 1987 and 2018 and to provide future projections for the year 2030. Additionally, we sought to examine the relationship between population growth and land cover within the study area. The integration of these objectives allowed us to gain a comprehensive understanding of the land cover dynamics and their implications for sustainable land management in the Anambra River Basin.

The assessment of land cover change revealed significant transformations in the Anambra River Basin over the examined period. The analysis indicated increased built-up areas and a decline in wetlands, with vegetation maintaining the largest cover throughout the years. These changes have important implications for the basin's ecosystems and sustainability. The expansion of built-up areas signifies urbanisation and the growth of human settlements, which can lead to various environmental challenges such as habitat fragmentation, loss of biodiversity and increased pressure on resources. The decline in wetlands raises concerns about the loss of valuable ecosystems that provide critical services such as flood regulation, water purification and support for unique flora and fauna.

The stability and slight decrease in vegetation cover indicate the importance of preserving and managing the remaining natural areas to ensure ecological balance, carbon sequestration and the provision of ecosystem services. Additionally, the negative correlations between population growth and various land cover categories highlight the

Table 9. Correlation relationship between population and land cover.

	Population	Built-up area	Bare land	Waterbody	Wetland	Vegetation
Population	1	1.000**	−0.998**	−0.999**	−0.998**	−0.999**
Built-up area	1.000**	1	−0.998**	−0.999**	−0.998**	−0.999**
Bare land	−0.998**	−0.998**	1	1.000**	1.000**	1.000**
Waterbody	−0.999**	−0.999**	1.000**	1	1.000**	1.000**
Wetland	−0.998**	−0.998**	1.000**	1.000**	1	1.000**
Vegetation	−0.999**	−0.999**	1.000**	1.000**	1.000**	1

** Correlation is significant at the 0.01 level (two-tailed).

detrimental impact of population expansion on bare land, waterbodies, wetlands and vegetation.

These findings emphasise the need for sustainable land management practices and conservation efforts within the Anambra River Basin. It is crucial to implement measures to mitigate the negative effects of urbanisation, protect remaining wetlands, promote reforestation and afforestation initiatives and manage land use to balance human needs with ecological integrity.

By understanding the land cover changes and their implications, policymakers, land managers and local communities can make informed decisions and develop strategies to ensure the long-term sustainability and resilience of the Anambra River Basin's ecosystems and promote harmonious coexistence between human activities and the environment. These efforts align with the SDGs for 2030, particularly those related to sustainable cities and communities (SDG 11), climate action (SDG 13), life on land (SDG 15) and partnerships for the goals (SDG 17).

Our study's findings on land cover change dynamics in the Anambra River Basin align with and contribute to the existing body of research conducted in similar regions. Several studies have explored land cover change in Nigeria and other African countries, shedding light on the drivers and impacts of these transformations. However, our study provides additional insights by employing a combination of neural network classification and the CA-Markov model, which enhance the accuracy and predictive capabilities of land cover change analysis.

Our findings are consistent with previous studies that have observed an increase in built-up areas and a decrease in wetlands over time (Assefa et al. 2021, Li et al. 2022). This trend reflects the rapid urbanisation and expansion of human settlements within the Anambra River Basin, driven by population growth and economic development. While several studies have primarily relied on traditional land cover classification methods, our study benefits from applying advanced techniques such as neural networks and the CA-Markov model. This approach allows for a more insightful and detailed analysis of land cover change dynamics, capturing subtle changes and predicting future transformations.

Additionally, our study provides a comprehensive assessment of the relationship between land cover change and population growth in the Anambra River Basin. We found a strong positive correlation between population and built-up areas, indicating the role of population growth as a key driver of urban expansion (Mahtta et al. 2022). Moreover, the negative correlations between population and other land cover categories, such as vegetation, bare land, waterbody and wetland, emphasise the detrimental impacts of population growth on these natural land cover types (Mugari, Masundire 2022).

Integrating the neural network and CA-Markov models in our study contributes to the accuracy of land cover change predictions. By validating our model's outputs against classified land cover information, we have demonstrated its credibility and applicability in simulating future land cover scenarios. Although our model exhibits a slight limitation in accurately capturing small and scattered patches of built-up areas, the overall accuracy and kappa coefficient indicate satisfactory performance in predicting land cover change (Sankarrao et al. 2021).

This study builds upon previous research on land cover change in similar regions by employing advanced modelling techniques and providing new insights into the relationship between population growth and land cover dynamics. The application of neural network classification and the CA-Markov model enhances the accuracy and predictive capabilities of land cover change analysis (Girma et al. 2022), contributing to a better understanding of the drivers and implications of land cover transformations in the Anambra River Basin.

The findings of this study on land cover change in the Anambra River Basin between 1987 and 2018 have several implications for land management, conservation and sustainable development in the region. The significant transformations observed, such as the expansion of built-up areas and the decline of wetlands, bare land and vegetation, highlight the need for proactive measures to address the negative effects of land cover change.

One important implication is the increasing urbanisation and population growth driving the expansion of built-up areas. This rapid urbanisation can lead to various challenges, including increased demand for housing, infrastructure development and encroachment on natural habitats. Therefore, effective land management strategies should be implemented to ensure sustainable urban development, including proper urban planning, the protection of green spaces and the promotion of compact and efficient land use patterns.

The decline in wetlands, bare land and vegetation raises concerns about the loss of ecosystem services and biodiversity. Wetlands play a crucial role in flood regulation, water purification and supporting diverse plant and animal species. The decrease in wetlands can negatively impact the hydrological balance and increase the region's vulnerability to flooding. Therefore, conservation efforts should focus on preserving and restoring wetland areas, considering their ecological significance and ability to provide essential ecosystem services.

The following recommendations can be made to mitigate the negative effects of land cover change and promote sustainable land use practices in the Anambra River Basin:

Implement land use planning and zoning regulations

The Anambra State Government should develop a comprehensive land use plan for the river basin in collaboration with local communities. This plan should designate protected zones around key waterbodies and wetlands, such as the Otuocha wetland, to restrict development in these ecologically sensitive areas. Strict enforcement of zoning regulations is necessary, for example establishing at least 500 m buffer zones along riverbanks where agriculture and settlements are prohibited (Ziegler 1993, Chung 1994, Huang, Daberkow 1996, Nel 2016).

Enhance public awareness and education

Local non-profits should launch community outreach campaigns to educate farmers on sustainable techniques and discourage activities like deforestation close to riverbanks. Awareness programmes in schools can foster conservation values in younger generations. Broadcasting public service announcements on local radio can also reach a broad audience with messages on sustainable land use practices (Sola 2014).

Encourage sustainable agriculture practices

The Anambra State agricultural agencies should actively promote climate-smart techniques by providing training, materials and financial incentives to farmers. These could include agroforestry, no-till farming and using cover crops. Pilot projects demonstrating sustainable practices can be implemented in key farming areas like Ayamelum (National Research Council 2010).

Strengthen collaboration and governance

A multi-stakeholder forum involving government, communities, Non-Governmental Organisations and local researchers should be established to oversee land use planning and programmes in the basin. This can enhance coordination, knowledge sharing, monitoring and transparent decision-making. The forum should meet regularly to review land use regulations, conservation initiatives and emerging best practices (Hossain 2015).

Limitations and future directions

While this study provides valuable insights into land cover change and their relationship with population growth in the Anambra River Basin, it is important to acknowledge several limitations. These limitations present opportunities for future research and improvement in land cover analysis and prediction.

Firstly, the accuracy and reliability of the land cover analysis are influenced by certain data limitations, including classification errors and temporal gaps in imagery data. To enhance the accuracy of the analysis, future studies could incorporate multi-temporal datasets and advanced remote sensing techniques. Additionally, the inclusion of ground-truth data and field surveys for validation and calibration would be beneficial.

Secondly, the CA-Markov model used in this study assumes that past land cover conditions and transition probabilities are the sole factors influencing land cover change. This approach neglects the potential influences of socioeconomic factors, policy interventions and climate change. To improve the realism and accuracy of the model, it would be valuable to integrate additional variables and drivers into the analysis.

Furthermore, it is worth noting that this study focused solely on the Anambra River Basin between 1987 and 2018. Expanding the spatial scope and extending the temporal scope of future research would capture larger-scale processes and interactions, providing a more comprehensive understanding of land cover change.

Although the study addresses environmental implications, it is important for future research to assess the socioeconomic and ecological impacts of land cover change using impact assessment methodologies. This broader perspective would provide a more holistic understanding of the consequences of land cover change.

Finally, stakeholder engagement and participatory approaches should be emphasised to align land cover analysis and management strategies with the needs of local communities. Incorporating the knowledge and perspectives of local communities would enhance the effectiveness of land cover analysis and contribute to more sustainable land management strategies.

Conclusions

The assessment of land cover changes in the Anambra River Basin between 1987 and 2018 has provided valuable insights into the dynamics of land transformation, the relationship with population growth and future projections for 2030. Between 1987 and 2018, bare lands increased by 29%, vegetation increased by 14%, built-up areas increased by 128% and water bodies increased by 10%, whereas there was a 58% decline in the extent of wetlands. The most significant transformation occurred in the wetlands with a total of 1819.46 km^2 being converted to various land cover types. These findings have significant implications for achieving the SDGs in the region and contribute to informed decision-making regarding land management, biodiversity conservation and sustainable development. The analysis revealed substantial growth in built-up areas, indicating urbanisation and the expansion of human settlements, which can pose challenges to environmental sustainability. The decline of wetlands emphasises the loss of crucial ecosystems and raises concerns about the availability of ecosystem services such as flood regulation and water purification. The slight decrease in vegetation cover underscores the importance of sustainable land management practices to preserve natural habitats and mitigate the negative impacts of human activities.

Understanding the relationship between land cover types and population growth is vital for achieving SDGs, particularly Goal 11 (Sustainable Cities and Communities) and Goal 15 (Life on Land). As the population increases, the expansion of built-up areas intensifies, while other land cover categories such as bare land, waterbodies, wetlands and vegetation tend to decrease. This highlights the need to balance urban development with the conservation of natural areas, ensuring the provision of essential ecosystem services and the preservation of biodiversity. The future land cover projections for 2030 provide valuable information for policymakers and stakeholders to guide their actions towards sustainable development. By considering the implications of land cover change and population growth, decision-makers can formulate strategies aligned with the SDGs. These strategies may include implementing effective land use planning and zoning regulations to ensure sustainable urban development (SDG 11), enhancing public awareness and education on sustainable land management practices (SDG 4 – Quality Education), promoting sustainable agriculture techniques to reduce land degradation (SDG 2 – Zero Hunger) and strengthening collaboration and governance among stakeholders (SDG 17 – Partnerships for the Goals).

While this study has contributed valuable insights into land cover change and their implications, it is important to acknowledge its limitations. Factors such as data availability, model assumptions and spatial–temporal constraints can affect the accuracy and generalisability of the findings. Future research should address these limitations by incorporating higher-resolution imagery, integrating additional variables, expanding the spatial and temporal scope, conducting impact assessments and engaging stakeholders more effectively. By considering the recommendations and strategies proposed in this study, stakeholders can work towards achieving the SDGs for 2030 in the Anambra River Basin. The preservation of natural ecosystems, sustainable land management practices and the integration of environmental considerations into development planning are essential for ensuring a sustainable and resilient future, where the needs of human populations are balanced with the conservation of land resources, biodiversity and ecosystem services.

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Author's contribution

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