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Land Use and Land Cover Change Dynamics in the Niger Delta Region of Nigeria from 1986 to 2024

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Abstract: Land Use and Land Cover Change (LULCCs) shapes catchment dynamics and is a key driver of hydrological risks, affecting hydrological responses as vegetated land is replaced with urban developments and cultivated land. The resultant hydrological risks are likely to become more critical in the future as the climate changes and becomes increasingly variable. Understanding the effects of LULCC is vital for developing land management strategies and reducing adverse effects on the hydrological cycle and the environment. This study examines LULCC dynamics in the Niger Delta Region (NDR) of Nigeria from 1986 to 2024. A supervised maximum likelihood classification was applied to Landsat 5 TM and 8 OLI images from 1986, 2015, and 2024. Five land use classes were classified: Water bodies, Rainforest, Built-up, Agriculture, and Mangrove. The overall accuracy of the land use classification and Kappa coefficients were 93% and 0.90, 91% and 0.87, 84% and 0.79 for 1986, 2015, and 2024, respectively. Between 1986 and 2024, built-up and agriculture areas substantially increased by about 8229 and 6727 km^2 (561% and 79%), respectively, with a concomitant decrease in mangrove and vegetation areas of about 14,350 and 10,844 km^2 (−54% and −42%), respectively. The spatial distribution of changes across the NDR states varied, with Delta, Bayelsa, Cross River, and Rivers States experiencing the highest decrease in rainforest, with losses of 64%, 55, 44%, and 44% (5711 km^2, 3554 km^2, 2250 km^2, and 1297 km^2), respectively. The NDR's mangroves are evidently under serious threat. This has important implications, particularly given the important role played by mangrove forests in regulating hydrological hazards. The dramatic decrease in the NDR mangrove and rainforest could exacerbate climate-related impacts. The study provides quantitative information on LULCC dynamics that could be used to support planning on land management practices in the NDR as well as sustainable development.

Keywords: mangrove; rainforest; land use change detection; hydrological hazards; land use drivers; supervised classification; Africa

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1. Introduction

The earth's natural resources are being disrupted by human activities. Those regions with high human population densities often face particularly intense degradation [1]. Global sustainability challenges, such as climate change, biodiversity loss, and food insecurity, are often linked to the land use and land cover change (LULCC) taking place. LULCC can have both undesirable and desirable effects on sustainability challenges, depending on the direction of the change and the components that change [2]. For example, rehabilitating degraded agricultural areas to forests can support increased biodiversity, alongside climate change mitigation. However, such changes may not support food security goals.

Land plays a significant role in the global carbon cycle, as a natural carbon sink for anthropogenic CO_2 emissions [3]. Carbon emissions from LULCC are impacting on the global carbon cycle and have deep effects on the feedbacks from the land surface to the climate by changing the interactions of heat, moisture, momentum, trace gases, and albedo [4]. Numerous emission reduction scenarios that aim to achieve the Paris Agreement rely on considerable LULCC to reduce GHG emissions through ecosystem conservation and the creation of CO_2 sinks via reforestation and afforestation [5]. However, at the same time, deforestation continues [6]. For example, despite their abundant carbon and non-carbon benefits, more than half of the world's mangroves have been devastated. Between 1996 and 2020, the global loss of mangroves was 5245 km^2 (3.4%), while Africa lost 152.2 km^2 (2.15%) over the same period [7]. Such changes are undermining the environment's effectiveness in delivering key ecosystem services, particularly flood prevention, and the capacity of these forests to sequester carbon and mitigate climate change [8]. At the same time as this LULCC, the global population is set to increase substantially. The world's population reached 8 billion in November 2022, [9] although there are considerable differences in the projected future trends of populations across regions and countries, with sub-Saharan African countries (Nigeria being the most populous) projected to have most of the increase [10]. More people require more housing, roads, and services, leading to vegetation losses and land use changes toward urban development. At the same time, increased demand for food will cause forested and mangrove lands to be cleared for farming, causing soil degradation, erosion, and loss of biodiversity.

This demographic shift looks set to exacerbate LULCC under a business-as-usual scenario as demand for natural resources increases. This demand will have a powerful influence on economies, welfare, health systems, housing, and infrastructural needs worldwide [11]. Increasing human populations have already driven substantial expansion of urban areas and fast depletion of agricultural land and floodplains, with impacts on water bodies and wetlands. These changes have had a considerable influence on flood dynamics and associated hydrological hazards such as changes in runoff, erosion, risk of flooding, recharge rates, water quality, and salinity intrusion in coastal areas [12]. Understanding these effects and the drivers of global LULCC has thus become a major focus, particularly in areas of Nigeria such as the Niger Delta Region (NDR), where exposure to increasing human activities has dramatically altered the land cover. Subsequent intensification or reduction in the extent of certain land cover types due to unsustainable land use practices will further degrade the natural capital of the NDR [13].

Detection and modelling of LULCC can provide important information that can inform better natural resource management and sustainable land management practices under changing conditions, guiding environmental assessment, territorial and urban planning, and agricultural production management [14]. This study aims to understand the historical and present patterns of land use change in the following states of the NDR: Akwa Ibom, Bayelsa, Cross River, Delta, and Rivers, from 1986–2024. These states are often affected by flooding arising from high rainfall and river discharge emanating from LULCC [15]. Considering such a large spatial-scale approach is vital to understanding the changes in LULCC across the region.

1.1. Land Cover Change in the Niger Delta Region

The main land use in the NDR is agriculture, consisting of cassava, yam, corn, vegetables, banana and plantain cultivation, fodder for animal husbandry, and forestry [4]. Deforestation arises from logging for timber, cutting of firewood for domestic use, and the clearing of land for agricultural practices [16]. These drivers are contributing to land cover change, with subsequent impacts on the hydrology of the region. Oil exploration is also a major factor contributing to land cover change in the NDR. Land clearing, dredging, construction of flow stations, pipes, and seismic lines, well blowouts, leakages or corrosion, equipment failure, errors during operation or maintenance, accidents during transportation, and sabotage, have all contributed to the NDR's forest degradation (Figure 1) [8].

Figure 1. Highly degraded mangroves in Port-Harcourt city in the Niger Delta (4.7817600° N, 7.01368° E). Photographs taken in 2023 by the lead author.

Built-up areas have almost doubled in size (from 1990 km^2 in 1988 to 3730 km^2 in 2013) [17] and are predicted to almost double from 11% in 2003 to 20% by 2060. The significant rise in the urban land category from 550 km^2 in 2003, projected to about 988 km^2 in 2060, demonstrates anticipation of a clear change in land cover.

Mangroves support complex social–ecological systems. Recognizing socioeconomic situations linked with reducing losses and increasing gains remains challenging, although important [18]. The NDR supports the biggest mangrove forest in Africa, representing about 5% of the world's total mangroves, and is the third largest mangrove forest in the world, with an area of about 36,000 km^2 [19]. Over 70 uses of mangroves have been found in the region, including fishing, firewood, building materials, flood protection, medicine, leisure, and tourism [19]. Local populations depend on the mangrove to supply most of their needs, primarily fuel wood, meadow, wood, wild fruits, and medicinal herbs [20]. The NDR mangrove forest, nevertheless, has experienced rapid deterioration over the years. According to Dan-Jumbo, the NDR's low-lying rainforests, as well as the freshwater forests, have seen net losses over the period 1986–2013 (mangrove net loss: ~500 km^2; woodland net loss: ~1400 km^2) [21]. Population growth in the NDR has resulted in deforestation impacting the mangrove ecosystem's functioning. Most communities in the NDR still depend on wood fuel as their primary energy source [22]. This has led to the continuous deforestation of mangrove forests in the region, affecting the livelihoods of local and Indigenous communities who directly depend on the ecosystem for their subsistence, leading to increased poverty and displacement [23].

Furthermore, threats such as poorly regulated industrial and economic development, overharvesting, land conversion, fuel wood and charcoal, wetland dredging, and reclamation, and the spread of alien and invasive Nipa palm (*Nypa fruticans*) are among the leading causes of mangrove degradation [8]. Together with repeated oil spills and leakages, the degradation of the mangrove ecosystem has undermined the condition of the NDR such that its role as a barrier providing natural protection from erosion and floods [19] is being lost. The loss of forests is making the NDR much more susceptible to water pollution, depletion of fertile soil, and coastal storms [19]. Mangrove threats, whether through human activities or natural disturbances, have led to forest degradation and loss, affecting the biodiversity and the structural integrity of the NDR ecosystem and highlighting their need for protection. Therefore, mangrove restoration has become a priority in major policy discussions linked to climate action, especially in the NDR, with regard to river discharge and sea level rise.

1.2. Managing the Impacts of LULCC

Changes in land cover have a strong effect on the hydrological cycle, especially in coastal areas. LULCC alters the natural flow of water and the procedures that regulate it. For example, deforestation can lead to amplified runoff and reduced soil moisture retention [24]. Changes in land use patterns impact the vulnerability to flooding and climate-related risks and create economic, and social challenges in the NDR [25]. Flooding and erosion are the major hydrological hazards in the region, arising from high rainfall. Over 70% of the rainfall occurs in the NDR between April to November. This creates the potential for flooding, as the water table depth differs from less than 1.5 m in the estuaries to about 8 m at the apex of the Niger Delta. These hazards threaten the NDR and will be amplified in the future by increased climatic variability [26].

Nigeria has policies and regulations in place that cut across the environment, climate change, forest, and petroleum sectors, but the country still struggles to address most of the environmental problems in the Niger Delta. The efficiency of the present regulatory framework in Nigeria has been questioned, with experts pointing to inadequate enforcement, weak penalties for non-compliance, and a lack of coordination among regulatory agencies [27]. Scholars have applied many methods, including remote sensing and GIS [28], to detect and model environmental dynamics at different levels in the NDR to try to inform improved policies and regulations. This study contributes to this growing body of knowledge.

Timely and accurate LULCC classification is an important feature for monitoring the changes in natural resources and urban development [29]. This study provides evidence for LULCC and changes in multiple NDR states over the period 1986–2024, using a supervised classification. Findings could be useful for monitoring and managing land use changes, contributing to policy-making processes across the study region.

2. Materials and Methods

2.1. Descriptions of the Study Area

The NDR is situated in southern Nigeria, on the Gulf of Guinea, West Africa (Figure 2). Politically, the region comprises nine states: Bayelsa, Delta, Rivers, Akwa Ibom, Cross River, Edo, Aba, Imo, and Ondo. The Bayelsa, Delta, Rivers, Akwa Ibom, and Cross River States are often affected by flooding when there is heavy rainfall. The climate is tropical and humid, with annual rainfall ranging from 2400 to 3500 mm yr^{-1} and average temperatures of 26 °C. The main rainy season begins in April and lasts through to November.

Figure 2. The study region. Source: map prepared by the lead author.

The NDR is topographically diverse and has a coastline of 470 km. It is characterized by several ecological zones, with mangrove swamps, freshwater swamps, forests, and lowland rainforests with a rich diversity of plant and animal species [30]. With a total area of 112,106 km^2, it is a biodiversity hotspot due to its rich variety of plant and animal species [31].

2.2. Remote Sensing Data

The present study employs the analysis of time series remote sensing images to understand long-term changes across five selected NDR states. Remote sensing has become widely used given readily accessible data, global coverage at various scales and resolutions, and broad applicability for quantifying, mapping, and detecting land use changes for planning land conservation, management, and development [32,33]. A unique character of remote sensing is its multi-sensor capability, which improves the capacity for mapping different elements of the earth system and different land classes. Such features include monitoring human influences on vegetation and hydrological responses, especially along the coast [34]. Optical sensors capture the electromagnetic spectrum over near-infrared (NIR) and shortwave infrared (SWIR) wavelengths, with data from, e.g., Landsat, MODIS, or Sentinel-2 sensors. Remote sensing imagery has a wide range of spatial resolutions (e.g., low resolution of 30–250 m per pixel (MODIS), medium resolution of 5–30 m per pixel (e.g., Landsat), and high-resolution of 0–5 m per pixel (e.g., Dove or Sentinel).

Landsat is a renowned satellite imagery system that provides optical data and has been extensively used to monitor forests, urban areas, water bodies, and agricultural lands [33]. Landsat provides long-term data continuity, reasonable spatial resolution, comprehensive spectral capabilities, high radiometric quality, global coverage, and cost-effectiveness.

Landsat is highly suitable for study regions where resources are limited [35,36]. In this research, we selected Landsat images because they are freely accessible and highly suitable for monitoring water bodies and urban expansion [37]. Landsat provides long-term data continuity, and has a multi-band sensor which can be applied to separate out different land use classes [38].

2.3. Data Selection and Pre-Processing

The study examined LULCC using satellite images to analyze changes in land cover in the NDR from 1986 to 2024, using Landsat 5 Thematic Mapper (TM) and the Landsat 8 Operational Land Imager (OLI) data. This study used data from the United States Geological Survey Earth Explorer, https://earthexplorer.usgs.gov/ (accessed on 28 September 2023). Many criteria were considered to acquire the most reliable imagery possible and to display a high level of agreement over periods. Those criteria include atmospheric and radiometric corrections. Therefore, we used the Surface Reflectance (SR) product collection 2 to improve the comparison between several images over the region [39].

Despite the benefits of Landsat, challenges persist, such as ensuring cloud-free conditions (less than 10%). Therefore, seasonal variations were accounted for when selecting satellite images for classification due to the topography of the NDR. The NDR has a rainy and a dry season. We acquired the imagery during December and January of the selected years, focusing on the dry season, during which the skies are clearer, thus avoiding cloud cover and radiation differences. Landsat 5 was launched on 1 March 1984, and the first cloud-free imagery was available in 1986. The study, therefore, selected 1986 as the first study year. Landsat 8 was launched on 11 February 2013, and cloud-free imagery was available for 2015, so this year was chosen for the middle period, while 2024 was chosen as the most recent year for which images are available. These images were downloaded as GeoTIF files, comprising bands 1 to 7.

Path and row numbers allowed for easy location and identification of scenes for the various years within the study region (Table 1).

Table 1. Landsat images used in this study: resolution and sensors.

Acquisition Dates	Path/Row	Spatial Resolution	Satellite Sensor
19 December 1986	187/055; 187/056; 188/055; 188/057; 188/056; 188/057; 189/056; 189/057; 190/056.	30 m	LM5
14 January 2015	187/055; 187/056; 188/055; 188/057; 188/056; 188/057; 189/056; 189/057; 190/056.	30 m	OLI
30 December 2024	187/055; 187/056; 188/055; 188/057; 188/056; 188/057; 189/056; 189/057; 190/056.	30 m	OLI

The downloaded images were mosaicked to combine multiple satellite images into a single, seamless image. We ensured that spectral values were uniform across the mosaic before classification. The satellite images were sub-setted using a shapefile of Nigeria downloaded from https://diva-gis.org/data.html (accessed on 13 April 2023). Figure 3 describes the various steps taken for the analysis of Landsat imagery in ArcGIS Pro 3.1.0.

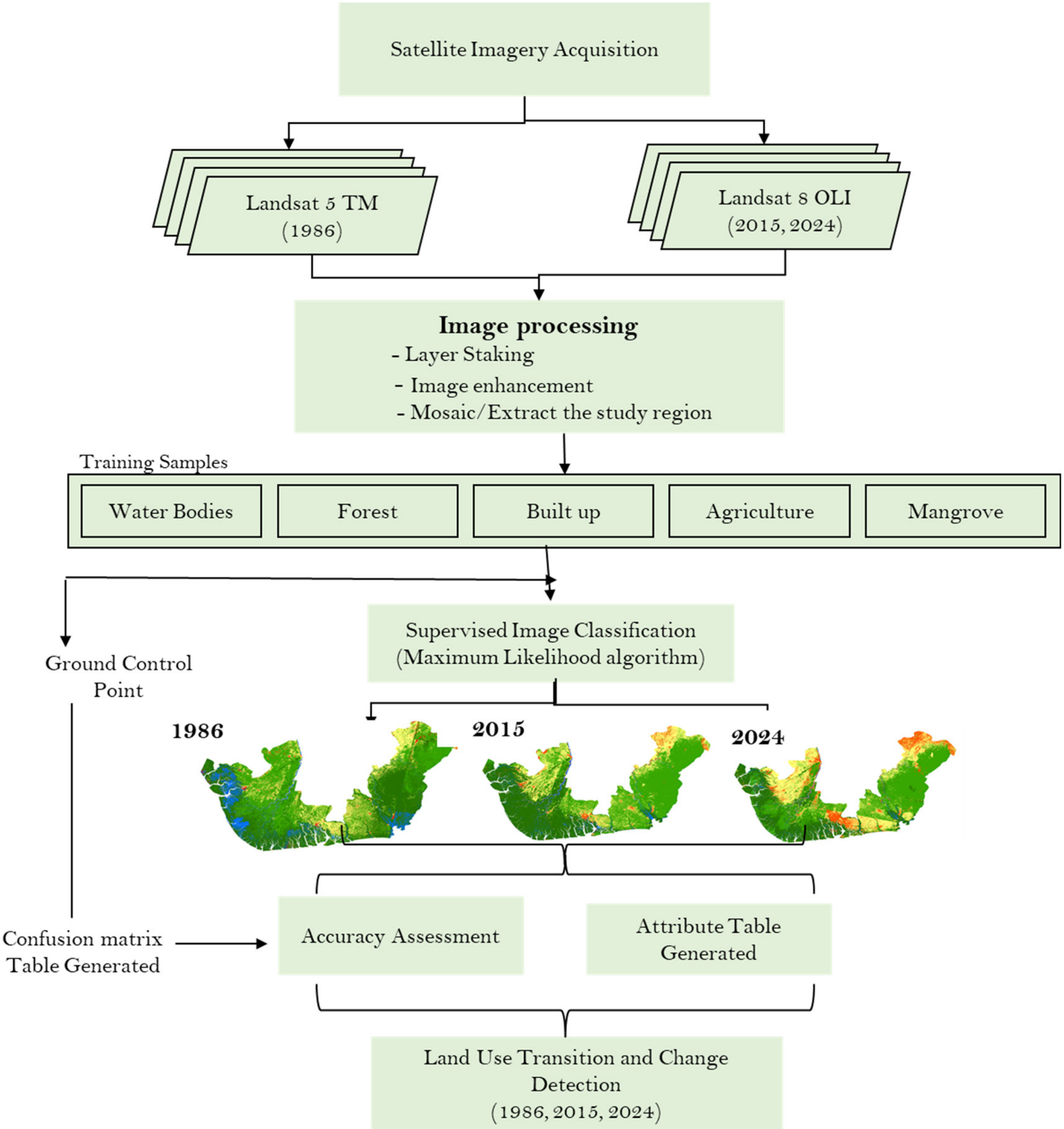


Figure 3. The process/steps taken for land use change analysis in the NDR from 1986–2024.

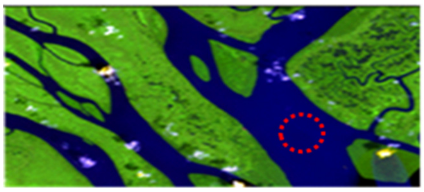
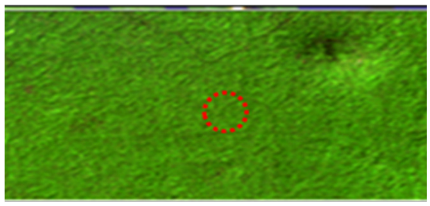
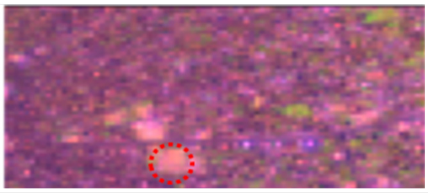
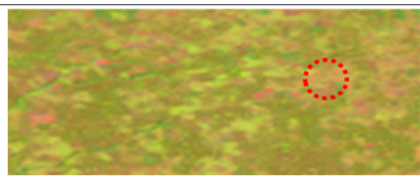
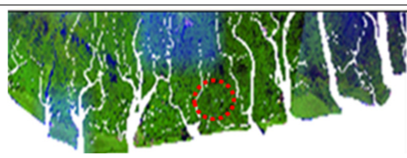
2.4. Land Use Classification

After image pre-processing for preparing the LULCC maps for the three time periods, the study used a supervised classification method. According to [40], the accuracy of a classified image is linked to the quality of the training sample defined for the study. For each land cover type, 100 training samples were selected to ensure a balanced representation among different classes. A total of 500 samples were chosen per map using polygons in ArcGIS Pro 3.1.0 based on visual interpretation. These samples were then verified with Google Earth and ground observations and were distributed across the study region. The classification process was conducted in three steps: training sample selection, classification, and accuracy assessment using training samples across the NDR. We adopted a method to classify the land cover into five representative classes that reflect the study region: water body, rainforest, built-up, agriculture, and mangrove, using the samples in Table 2. The first seven bands of the Landsat 5 TM and 8 OLI images were utilized for LULCC classification.

The classification of the pixels was done manually through the specification of various pixel values or spectral signatures associated with each class [41] by choosing representative sample locations of a known cover type. The process created a map with each pixel assigned to a class based on its multispectral composition. The study distinguishes mangroves from other vegetation by their unique spectral characteristics and the application of specific indices to separate them, such as the Mangrove Vegetation Index (MVI) [42,43]. The MVI has been developed to differentiate mangroves from other vegetation types with the use of green, NIR, and SWIR bands.

$$MVI = \frac{SWIR - Red}{SWIR + Red} \tag{1}$$

Table 2. List of land use classes, their description, and examples of training pixels (shown by red dotted circles).

Land Classes	Description	Example Pixels
Water Bodies	Rivers, small ponds, streams, and reservoirs are blue pixels in the image. Riparian vegetation is not included in the water bodies.	
Rainforest	A large area of mostly trees.	
Built-Up	A large area of mostly settlement.	
Agriculture	A large area of farmland with grass and woody plants smaller than a tree.	
Mangrove	A shrub or tree that grows mainly in coastal saline or brackish water.	

In this study, the supervised image classification technique of the Maximum Likelihood Classification (MLC) algorithm was utilized. MLC determines the statistical probability for each pixel to fit one of the land use and land cover classes. The technique assumes that the statistics for each class in each band are normally distributed and calculates the probability that a given pixel belongs to a specific class [44]. Built on Bayes' theorem, the principal procedure for MLC identifies where the cells in each class sample are regularly distributed in the multidimensional space [1]. According to [2], MLC has higher accuracy in detecting land cover classifications, particularly for the identified training sample. Ref. [45] noted that MLC is a decision-theoretic approach to classification when compared with

Random Forest and Support Vector Machines because the class with the highest likelihood of generating the observed pixel values is assigned to the pixel.

Three LULCC maps were created to be able to visually trace the changes in the land cover between the years 1986, 2015, and 2024.

2.5. Accuracy Assessment

Accuracy assessments were used to validate the LULCC classification. The accuracy assessment process determines whether the image pixels are well classified or misclassified from the remotely sensed data and intuitively reflects the classification connection between the data for assessment and the reference data [46]. A confusion matrix or error matrix is used for the accuracy assessment, based on GCPs, a classification scheme, a sampling type, a spatial autocorrelation, and the size and unit of the sample. One hundred and fifty GCPs were used to validate each of the classified maps. The confusion matrix evaluates the user accuracy, producer accuracy, and overall accuracy of kappa statistics. Kappa estimation was carried out by calculating the coefficient of agreement and is mathematically represented as shown in Equations (2)–(5):

User's Accuracy

$$X = \frac{Number\ of\ classified\ pixels\ in\ each\ category}{Total\ number\ of\ classified\ pixels\ in\ the\ category\ (Column\ Total)} \times 100 \quad (2)$$

Producer's Accuracy

$$X = \frac{Number\ of\ classified\ pixels\ in\ each\ category}{Total\ number\ of\ classified\ pixels\ in\ the\ category\ (Row\ Total)} \times 100 \quad (3)$$

Overall Accuracy

$$X = \frac{Total\ number\ of\ correct\ classified\ pixels\ (Diagonal)}{Total\ number\ of\ reference\ pixels} \times 100 \quad (4)$$

$$K = \frac{N \sum_{i=1}^{n} T_{ii} - \sum_{i=1}^{n} (T_{i+} T_{+i})}{N^2 - \sum_{i=1}^{n} (T_{i+} T_{+i})} \quad (5)$$

where N = total number of points, n is the type number of land cover data in the confusion matrix, Tii is the number of land types correctly classified in the confusion matrix, $Ti+$ displays the sum of the categories in the classified data, and $T+i$ shows the sum of category i in the measured or reference data.

The error matrix was created by comparing the classification results to the reference dataset. The confusion matrix displays the sum of the correctly classified values, which are situated diagonally in the confusion matrix from upper left to lower right (Table 3 and Figure 4 in the Results section), and the reference values describe the overall accuracy.

Table 3. The confusion matrix, showing the overall accuracy assessment.

Accuracy Assessment Point for 1986								
Class Value	**Water Bodies**	**Rainforest**	**Built-Up**	**Agriculture**	**Mangrove**	**Total**	**U_Accuracy**	**Kappa**
Water Bodies	8	2	0	0	0	10	80%	0
Rainforest	0	39	0	0	1	40	98%	0
Built-up	0	0	10	0	0	10	100%	0
Agriculture	0	1	0	12	0	13	92%	0
Mangrove	1	3	0	0	38	42	90%	0

Table 3. *Cont.*

Accuracy Assessment Point for 1986								
Class Value	**Water Bodies**	**Rainforest**	**Built-Up**	**Agriculture**	**Mangrove**	**Total**	**U_Accuracy**	**Kappa**
Total	9	45	10	12	39	115	0%	0
P_Accracy	89%	87%	100%	100%	97%	0%	93%	0
Kappa	0	0	0	0	0	0	0	0.90
Accuracy Assessment Point for 2015								
Class Value	**Water Bodies**	**Vegetation**	**Built-Up**	**Agriculture**	**Mangrove**	**Total**	**U_Accuracy**	**Kappa**
Water Bodies	9	0	0	0	1	10	90%	0
Rainforest	1	42	0	2	0	45	93%	0
Built-up	0	1	9	0	0	10	90%	0
Agriculture	0	0	1	16	0	17	94%	0
Mangrove	3	1	0	0	21	25	84%	0
Total	13	44	10	18	22	107	0%	0
P_Accuracy	70%	95%	90%	89%	95%	0	91%	0
Kappa	0	0	0	0	0	0	0	0.87
Accuracy Assessment Point for 2024								
Class Value	**Water Bodies**	**Vegetation**	**Built-Up**	**Agriculture**	**Mangrove**	**Total**	**U_Accuracy**	**Kappa**
Water Bodies	10	0	0	0	0	10	100%	0
Rainforest	0	36	0	1	2	39	92%	0
Built-up	0	4	11	0	0	15	73%	0
Agriculture	0	9	0	14	1	24	58%	0
Mangrove	0	0	0	0	19	19	100%	0
Total	10	49	11	15	22	107	0	0
P_Accuracy	100%	73%	100%	93%	86%	0	84%	0
Kappa	0	0	0	0	0	0	0	0.79

2.6. Change Detection

LULCC detection techniques were applied extensively to understand changes over the different years of imagery to identify and quantify areas of change in the land cover [41]. LULCC detection was carried out by comparing the classified results of 1986, 2015, and 2024, determining the extent of change and the degree of expansion or reduction in the land cover resulting from the classification. The percentage change in LULCC was calculated using the following equation (Equation (6)):

$$P_i = \frac{(L_i - B_i)}{B_i} \times 100 \quad (6)$$

where P_i is the percentage change in LULCC class. L_i means "previous year (1986)". The most current year (2024) is B_i. The change in class is divided by the covered area of the year (2024) and multiplied by 100.

3. Results

3.1. Accuracy Evaluation

The accuracy assessment and kappa statistics were 93% and 0.90, 91% and 0.87, and 84% and 0.79 for 1986, 2015, and 2024, respectively (Table 3 and Figure 4). This shows high confidence in the LULCC classification and change detection in the study region.

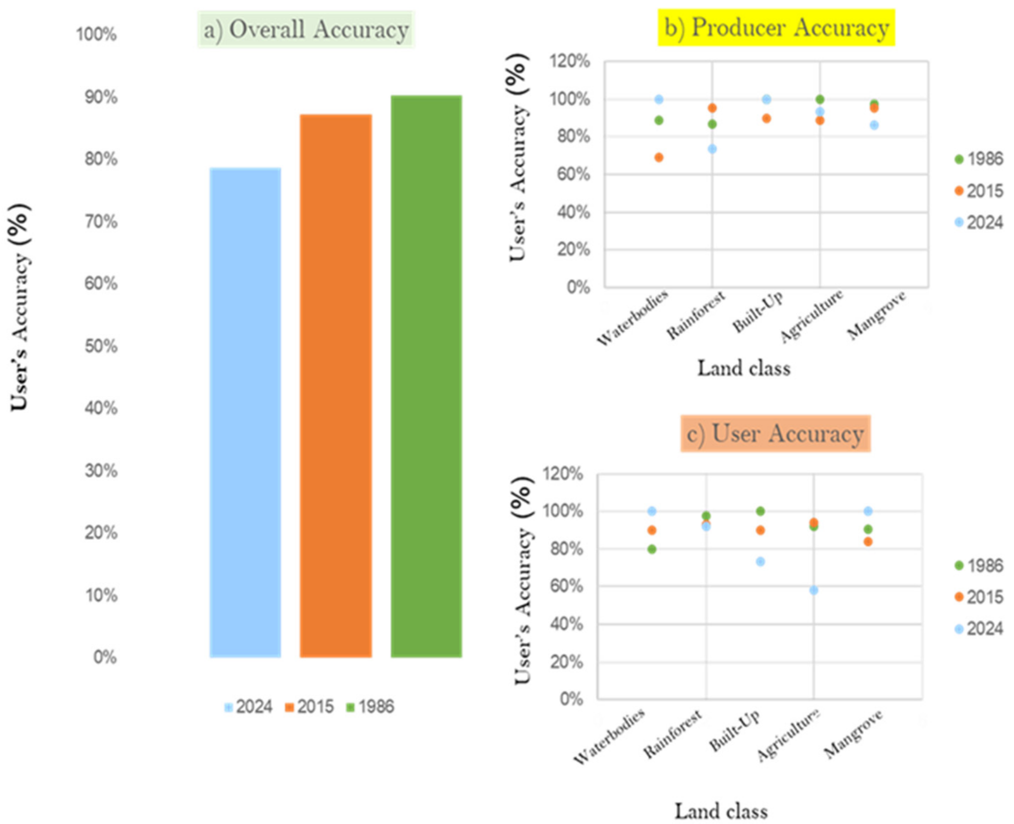


Figure 4. Graphical representation of the accuracy assessment of the LULCC classification over the three-term period of 1986, 2015, and 2024: (**a**) Overall accuracy, (**b**) Producer accuracy, and (**c**) User accuracy.

3.2. Change in Land Cover from 1986 to 2024 in the NDR

Land cover maps and land cover changes are shown in Figures 5–8. Figure 5 shows the noticeable changes in the LULCC of the study area. The proportions of each land type have changed over the study period. For instance, water bodies covered around 6.5%, 3.1%, and 1.9% in 1986, 2015, and 2024 respectively; rainforested areas covered 38.4%, 36.5%, and 27.6% across the study years; built-up land covered around 2.2%, 9.9%, and 18.5% across the three years; agriculture covered 12.9%, 20.8%, and 29.07%; and mangrove covered 40.0%, 29.8%, and 22.9%, respectively. The study observes overall changes in land cover patterns and the conversion of natural land cover to human-modified landscapes, as rapid development took place between 1986–2015 and 2015–2024.

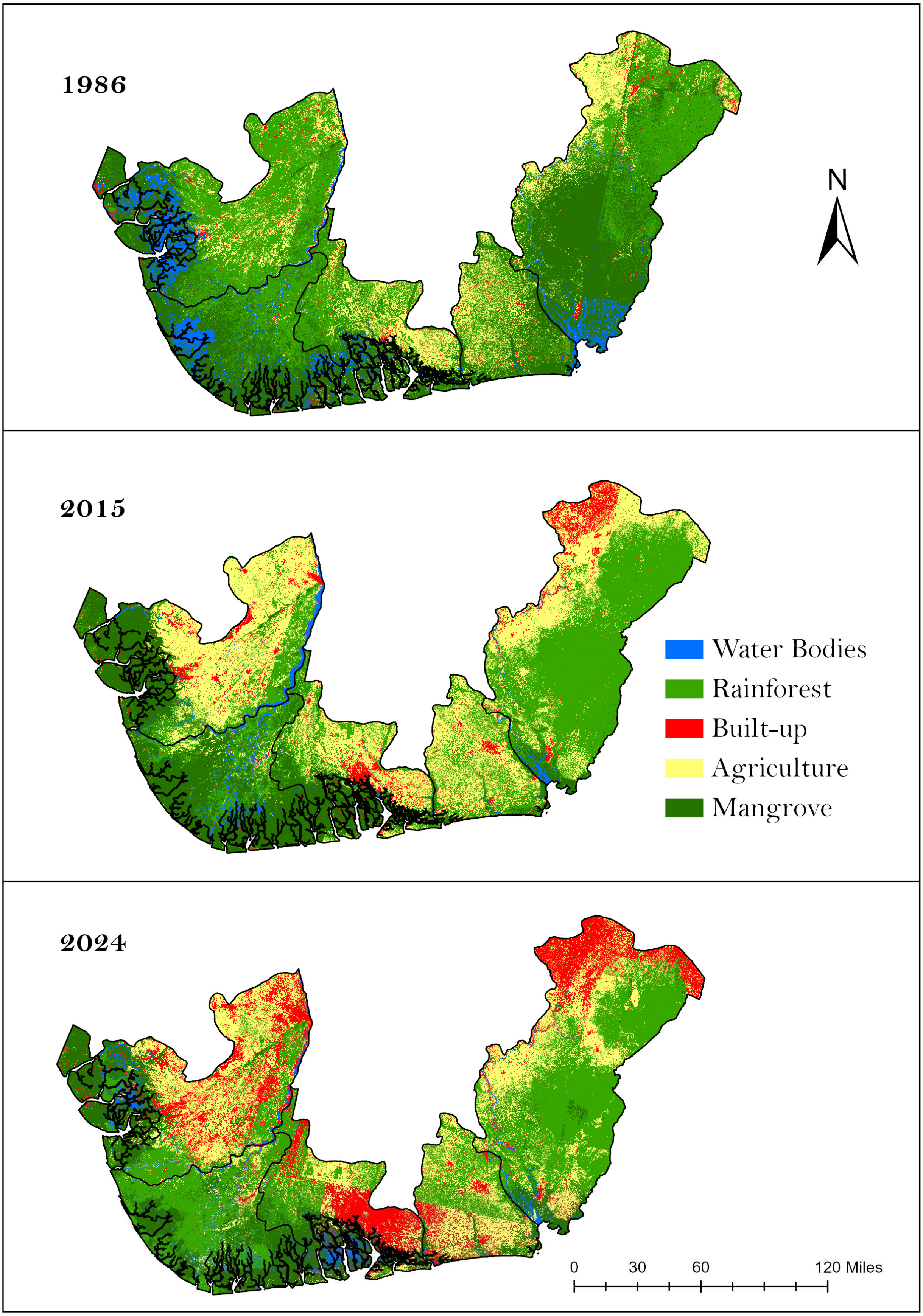


Figure 5. Land use/land cover change maps from 1986, 2015, and 2024 across the NDR.

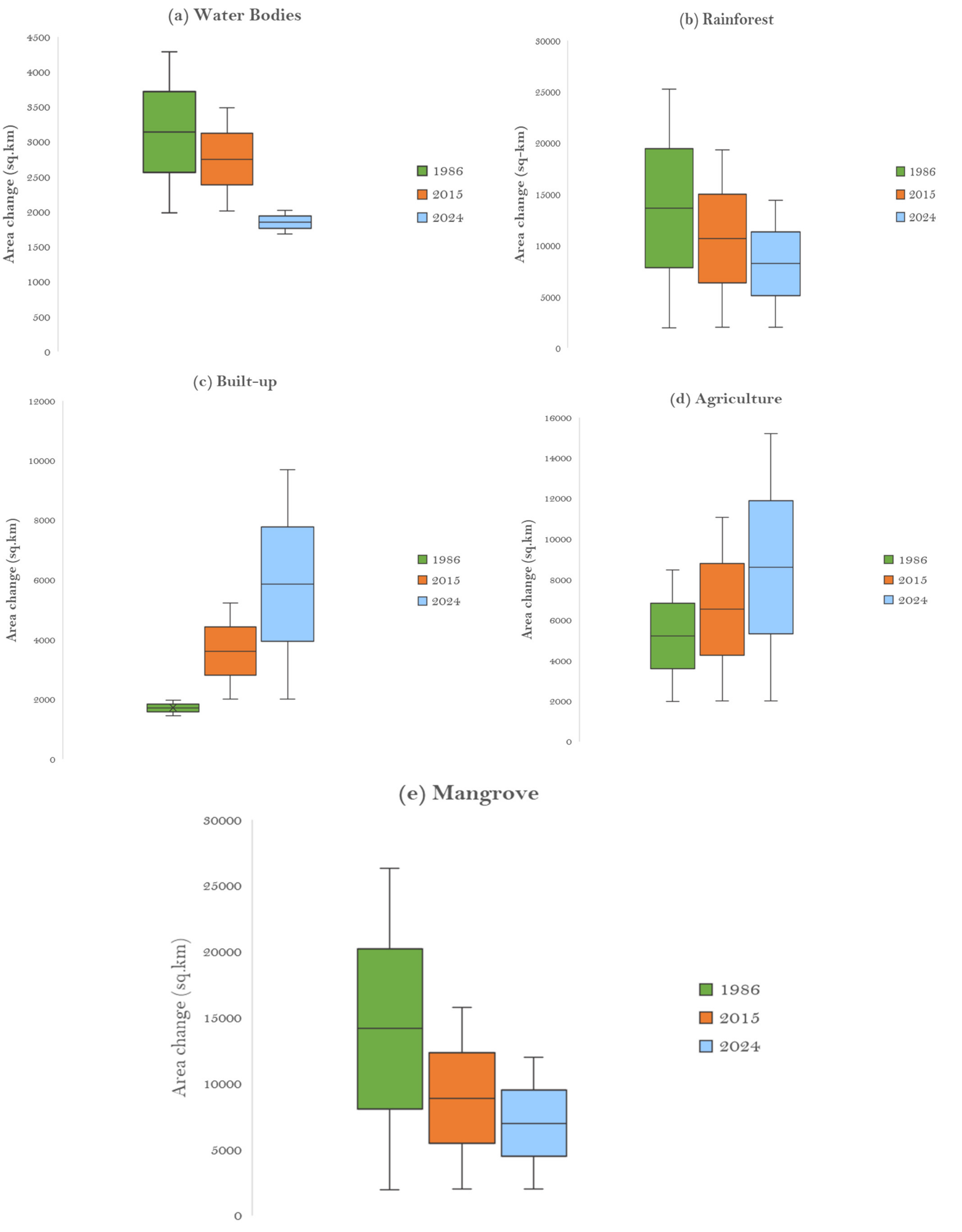


Figure 6. Graphical representation of the changes in land cover for the training sample where (**a**) represents water bodies, (**b**) agriculture, (**c**), rainforest (**d**) built-up area, and (**e**) mangrove for the three-term period across the study region.

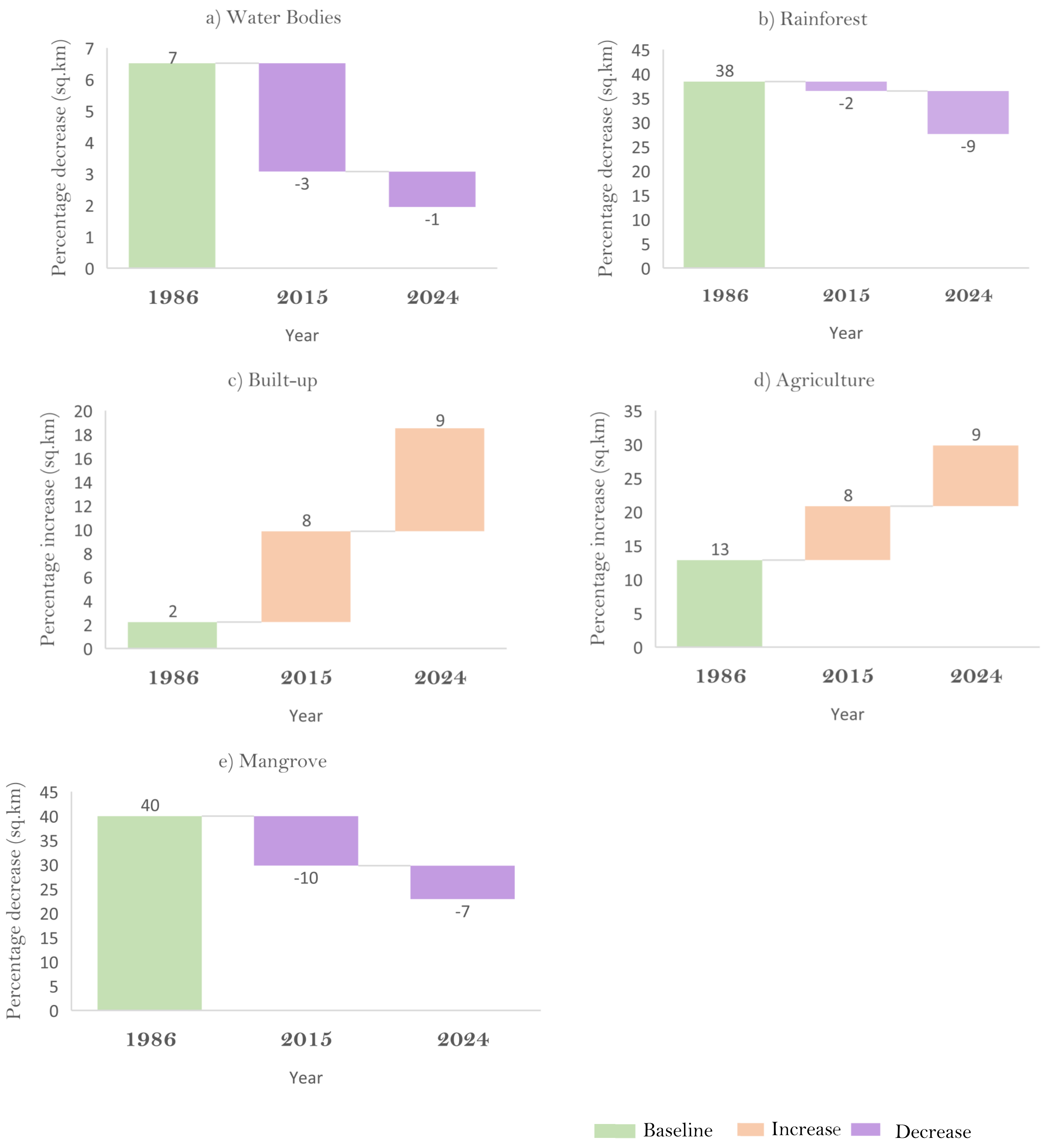


Figure 7. Situation of each land class across the three-term period in the NDR.

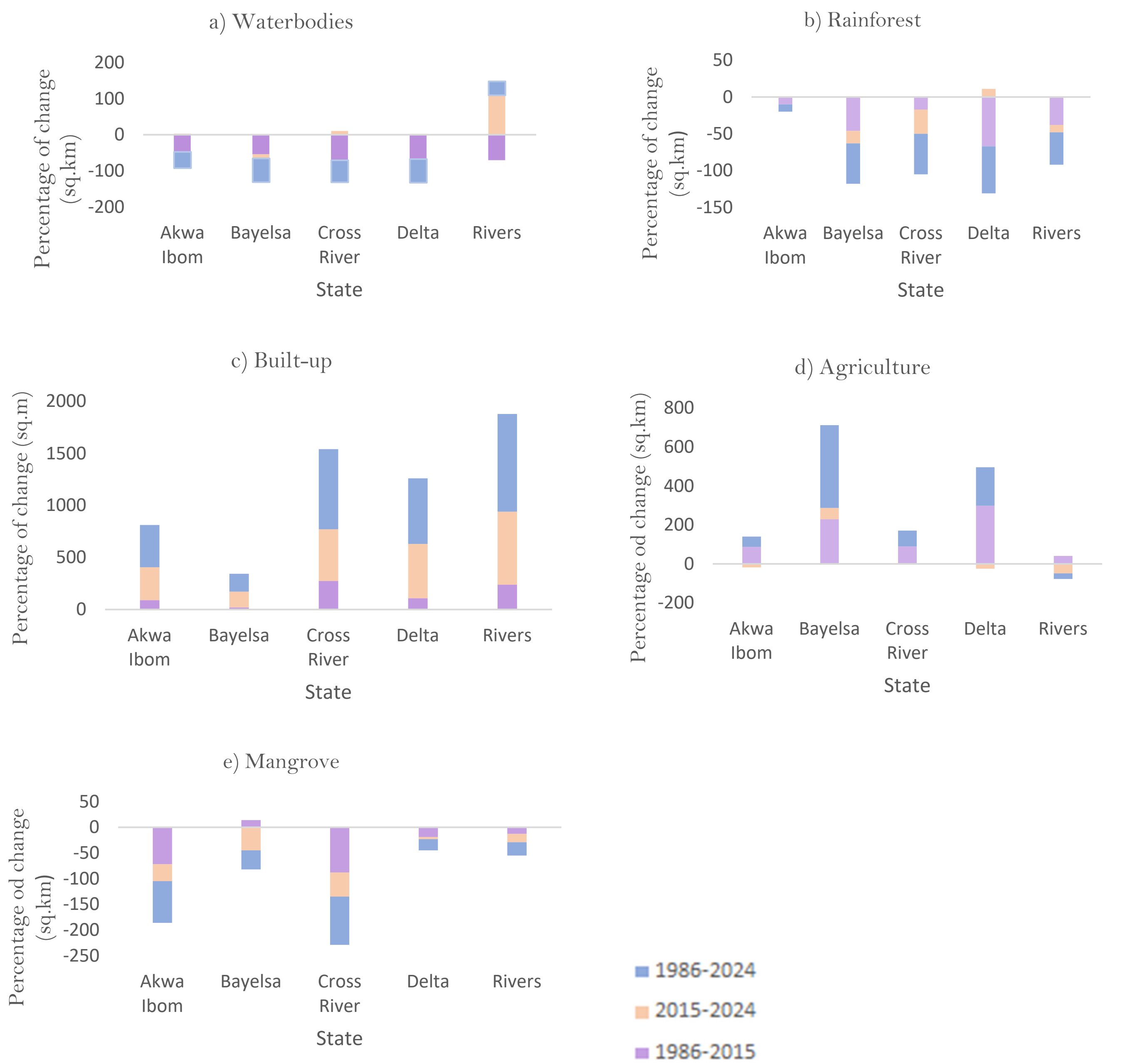


Figure 8. Percentage change in each land class from 1986 to 2024 across the NDR in the states included in this study.

3.3. Observed Changes

The spatial analysis was conducted to assess the patterns of LULCC and overall changes from 1986 to 2024. Change detection was done post-classification using the classified maps to show the transition among defined land cover classes. The results displayed a fundamental change across the NDR (Table 4). Across the entire study period, from 1986 to 2024, the built-up and agriculture classes have substantially increased by about 8229 and 6727 km^2 (561.54% and 79.4%, respectively), resulting in a decrease in mangrove and rainforest of about 14,350 and 10,844 km^2 (54.51 and 42.88%, respectively).

Table 4. Land use area and change detection from 1986–2024.

Land Use Classes	Land Use Area (km^2)			Change Detection (km^2)		
	1986	2015	2024	1986–2015	1986–2024	2015–2024
Water Bodies	4291.00 (6.5%)	1629.0 (3.1%)	1015,9.0 (1.9%)	−2662.0 (−62.0%)	−3275.1 (−76.3%)	−613.1 (−37.6%)
Rainforest	25,289.22 (38.41%)	19,345.81 (36.5%)	14,444.96 (27.6%)	−5943.4 (−23.5%)	−10,844.3 (−42.9%)	−4900.8 (−25.3%)
Built-up	1465.42 (2.22%)	5231.14 (9.9%)	9694.42 (18.5%)	3765.7 (257.0%)	8229.0 (561.5%)	4463.3 (85.3%)
Agriculture	8474.76 (12.9%)	11,065.16 (20.8%)	15,202.06 (29.0%)	2590.4 (30.6%)	6727.3 (79.4%)	4136.9 (37.4%)
Mangrove	26,326.79 (40.0%)	15,801.48 (29.8%)	11,976.19 (22.9%)	−10,525.3 (−40.0%)	−14,350.6 (−54.5%)	−3825.3 (−24.2%)

The results showed the decreasing coverage of the water bodies class over time. Overall, from 1986 to 2024, water bodies decreased about 3275 km^2 (76.32%). The greatest increase in land cover change was noticed in built-up and agriculture classes. The analysis showed dramatic LULCC in the category of built-up surfaces, exerting incredible pressure on non-built-up surfaces across the NDR mangrove area.

The results of the changes in the situation of each land class showed a large increase in agriculture and built-up land, while the rainforest and mangrove areas showed a steady net decrease by both 2015 and 2024. Water bodies showed slight decreases across the study period (Figure 7). The change detection shows that the NDR has experienced fast changes in the rainforest and mangrove (−42.9% and −54.5%, respectively) from 1986–2024.

Rivers State had the largest overall increase in built-up area across the five states for 1986–2024, at 939.56% (2114.0 km^2), followed by Cross River 770% (2934 km^2). The overall increase in agriculture was largest in Bayelsa for 1986–2024 at 424.81% (548 km^2), followed by Delta 197.34% (3.789 km^2). However, the overall decrease in the rainforest was most noticeable in Delta, Bayelsa, Cross River, and Rivers, which saw losses of 64%, 55%, 44.9%, and 44.3% (5711 sq km, 2250 km^2, 3554.0 km^2, and 1297 km^2), respectively. Cross River saw the largest losses in mangroves of 93.7% (8805.0 km^2) from 1986–2024, followed by Akwa Ibom at 81.8% (1746 km^2). It was further observed that the area of water bodies in all states decreased in the range of 45.1–65.7%, except for Rivers State, where the water bodies increased by 38.5% Table 5. The expansion of the built-up and agricultural areas has nevertheless, overall, resulted in the decrease in the water bodies, rainforests, and mangroves across the study states.

Table 5. Changes in each land use class by states across the years.

Region	Year	Waterbodies Changes		Rainforest Changes		Built-Up Changes		Agriculture Changes		Mangrove Changes	
		km^2	%	km^2	%	km^2	%	km^2	%	km^2	%
Akwa Ibom	1986–2015	−54.0	−47.8	254.0	−10.0	180.0	88.7	1540.0	86.8	−1966	−72.6
	2015–2024	3.0	5.1	−265.0	0.5	644.0	168	−602.0	−18.2	220.0	−33.4
	1986–2024	−51.0	−45.1	−11.0	−10.4	824.0	405	938.0	52.9	−1746	−81.8

Table 5. *Cont.*

Region	Year	Waterbodies Changes		Rainforest Changes		Built-Up Changes		Agriculture Changes		Mangrove Changes	
		km²	%	km²	%	km²	%	km²	%	km²	%
Bayelsa	1986–2015	−685.0	−54.5	−444.0	−46.2	17.0	18.7	295.0	228.7	815.0	14.3
	2015–2024	−141.0	−24.7	2694.0	−17.0	139.0	128.7	253.0	59.7	−2947	−45.3
	1986–2024	−826.0	−65.7	2250	−55.4	156.0	171.4	548.0	424.8	−2132	−37.4
Cross River	1986–2015	−550.0	−71.1	5860	−17.7	1043	273.8	2809.0	88.8	−9362	−88.1
	2015–2024	78.0	34.8	−2306	−33.1	1891.0	132.8	−221.0	−3.7	557.0	−47.0
	1986–2024	−472.0	−61.0	3554	−45	2934.0	770.1	2588.0	81.8	−8805	−93.7
Delta	1986–2015	−1203.0	−67.7	−6051	−67.8	502.0	108.0	5722.0	298.0	1032	−19.0
	2015–2024	40.0	7.0	340.0	11.8	2426.0	250.9	−1933.0	−25.3	−873	−4.3
	1986–2024	−1163.0	−65.4	−5711	−64.0	2928.0	629.7	3789.0	197.3	159	−22.4
Rivers	1986–2015	−260.0	−70.5	−1502	−38.3	535.0	237.8	841.0	40.5	358	−12.5
	2015–2024	402.0	108.9	205	−9.8	1579.0	207.8	−1438.0	−49.3	−749	−15.6
	1986–2024	142.0	38.5	−1297	−44.3	2114.0	939.6	−597.0	−28.8	−391.0	−26.2

4. Discussion

A good understanding of the land cover change in the NDR is essential for formulating effective management approaches in the future. This study has comprehensively analyzed the LULCC from 1986–2024 to understand land dynamics in the NDR. The changes in the forested area to increasingly built-up and agricultural areas correspond with similar studies in the region that also reported a dramatic decrease in mangroves within the same period [47], which, according to the literature [8], could affect the livelihoods of local communities who rely on the mangrove system for their survival. These changes reflect urban expansion influenced by the increase in population in the study region. [47] reported that the Niger Delta's population in 2023 was 42,436,000, compared to 31,200,000 in 2006, based on data from the National Population Commission (NPC), as reported by [48].

The decrease in the rainforest and mangrove area in the NDR is further driven by urban development and oil and gas exploration [49,50]. Rainforest and mangrove degradation can be assumed to have a severe influence on ecosystem delivery in the Niger Delta. The built-up area expansion from 1986–2024 (561.5%) across the NDR is worrisome; as Uchegbulam reported, the built-up area in the NDR is anticipated to continue increasing due to the movement of people to the region because of its socioeconomic activities [51]. Rivers State noticed a larger overall increase in built-up areas (compared to the other states. This can be attributed to Rivers having the highest population across the region (Table 6) [48].

Table 6. The population of selected Niger Delta states based on NPC census returns in 2006.

State	Population
Akwa Ibom	3,920,208
Bayelsa	1,703,358
Cross River	21,000
Delta	4,098,391
Rivers	5,185,420

The greater increase in built-up expansion could also be because many oil and gas companies are situated in Rivers, moving the state away from agriculture to industrial development. It is equally observed that agriculture has increased from 1986 to 2024 (79.4%), particularly in Bayelsa State, as the growing population exerts a larger demand for food. Siloko reported a growing concern about the linkages between changes in the environment and development issues like poverty [23]. He argued that poverty across the NDR could have contributed to the expansion of agricultural land, thereby decreasing the forested areas over the years. The majority of the population in the NDR depends on agriculture, and the development of sustainable land management practices requires proper identification of drivers to minimize the LULCC in the region [52].

Land use changes have substantial links to climate change, mostly because they influence carbon emissions [52]. Thus, mitigating the impacts of LULCC on the climate is of great importance across the NDR [19]. Management of land use change through sustainable agriculture, green urban development, conservation, and replanting in the NDR can meaningfully increase capacities to absorb carbon and increase the extent of the carbon sink across the region. The LULCCs identified in this study highlight that the NDR should take a new development pathway focusing on more sustainable land use and land cover to realize the country's promised carbon emission reduction targets.

The consequence of land use changes on plant and animal distributions and overall biodiversity across the study area is a great concern [53]. The NDR usefully provides green infrastructure and offers potential for ecosystem-based adaptation in support of sustainable development and nature-based solutions to global challenges [54]. Previous research reported that species are naturally destroyed every year in the NDR, but that if the current trend of destruction by human activities continues, the extinction rate will double the natural rate, leading terrestrial species to be impacted more often by the end of the century, as reported by [55]. Land use and land cover changes have significant inferences for natural capital across the NDR, and thus for Nigeria as a whole. According to [56], the unsustainable management of NDR resources especially as related to oil production could significantly affect the quality of regional habitats and thus give rise to a decline in biodiversity across the region. Changing ecosystems and the services they provide can either deplete or enhance natural capital. The degradation of natural capital components, together with the loss of wetlands, and forests, has led to deterioration in the provision of many vital ecosystem services, including the loss of protection from flooding and coastal storms [19].

LULCC is closely related to the increasing impacts of hydrological hazards that may arise from high rainfall, sea level rise, river flows, and storms. In addition, the changes in land cover across the NDR can disturb the natural hydrological cycle, leading to altered sediment transport and disrupted aquatic ecosystems. The NDR mangroves act as natural barriers that reduce the impacts of such hazards by absorbing much of the wave energy in storms and storm surges. The decreasing area of mangroves and rainforests can lead to an increase in the flow of excess water, resulting in flooding and damage to property and infrastructure across the region [55]. An increase in surface runoff is possibly due to a decrease in rainfall interception due to land clearing and tree removal, which reduces canopy cover [57]. Odoh and Nwokeabia highlight the susceptibility of the study region to flooding due to low-gradient slopes and the expansion of built-up areas that reduce infiltration, which have introduced challenges for flood management across the region [58]. The changes in land cover as presented in this paper are anticipated to have significantly altered hydrological processes, affecting how water moves through the environment and leading to increased frequency and intensity of flood hazards across the study region.

Managing the consequences of LULCC across the NDR is of great importance, especially in Delta, Bayelsa, Cross River, and Rivers States as these have experienced the largest reduction in rainforest. These changes have important implications for ecosystems, climate, biodiversity, and human livelihoods. An integrated policy approach that balances the requirements of human populations with the health of ecosystems is needed across the study region. In addition, a recent study [59] reported that climate change adaptation and mitigation policies are urgently needed to increase resilience and build adaptive capacity across the NDR, considering the increasing loss of biodiversity and the growing effects of climate change. Hazards such as river overflow are already happening in the NDR, and action will need to be obligatory to mitigate these deteriorating effects. The Government of Nigeria needs to be aware of the implications of LULCC and the growing risks, particularly to human wellbeing and ecosystem functioning, and needs to make long-term decisions relating to the NDR and its infrastructure.

5. Conclusions

Accurate and reliable information on land use and land cover dynamics is vital for the sustainable management of the NDR. This research aimed to understand the changing distribution of various land cover types and their potential influence, considering that the NDR is one of the rapidly growing regions in Nigeria. The research found that between 1986 and 2024, built-up and agriculture areas substantially increased by about 561% and 79%, respectively, with a concomitant decrease in mangrove and rainforest areas of about 54% and 42%, respectively. Rainforest and mangrove areas have decreased substantially over the study period, largely being replaced with built-up and agriculture land classes across the Niger Delta. Changes across the states were not consistent, with Delta, Bayelsa, Cross River, and Rivers States experiencing the highest decrease in rainforest, with losses of 64%, 55%, 45%, and 44%, respectively.

Mangrove restoration is becoming more extensively recognized as a significant approach for mitigating and adapting to the effects of climate hazards. The land use analysis will be valuable for making policies and management plans to realize better sustainable land management practices in the study area and to identify where opportunities for restoration could be found, as well as areas in which greater legal protection of mangroves could be useful. The findings from the study imply that the relevant stakeholders as well as the Nigeria government need to take necessary action to manage LULCC, as well as wetland and mangrove restoration and protection, to address the rapid development and changes in the land use pattern in the NDR. The decrease in the mangrove, forest areas, and water bodies in the NDR are anticipated to intensify runoff in the region, enhancing flood risk and impacts on livelihoods across the study region.

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