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Original paper

Land use dynamics and mangrove degradation in the Niger delta region

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Abstract: Land use dynamics describes the changes occurring in an area which can be approximated from a land use and land cover map (LULC). This research aims to assess how the mangrove forest in the Niger Delta Region has degraded. Landsat imagery of 1987, 2002, and 2022 were used to create LULC maps from which change detection of the area derived from supervised classification technique, were investigated. The classification accuracy was determined and the result shows that for 1987, 2002, and 2022 the accuracy score are 82.16%, 82.16%, and 83.97%, respectively and the corresponding kappa coefficients for the epochs are 75.63%, 75.63%, and 78.43%. The producer and user accuracy are high for all the classes except grassland and urban areas. The change detection result showed a net loss in mangrove, grassland, and water bodies between 1987 and 2002 with significant gains for urban and woodlands however significant losses were revealed in the mangrove, woodlands, water bodies, and grassland with gains in only the urban settlement between the 2002 and 2022 study period. The result also revealed that the mangrove forest cover has seen a consistent loss in the two study periods. The Niger Delta Region is a key component of the global climate system and our research provides an accurate assessment of the land use dynamics and the mangrove degradation in the region.

Keywords: GIS, Niger delta, Mangrove, remote sensing, land cover

1. Introduction

One of the most vital ecosystems on earth is a delta, sometimes known as a wetland, a swamp or a marsh. They are necessary for carrying out a variety of ecosystem functions, including controlling food production, preserving biodiversity, raising fish, storing carbon, regulating aquifer discharge, controlling floods, and providing habitat for several endangered species (Barbier et al., 1997; Okonkwo et al., 2015). This ecosystem supports a huge percentage of the human population globally even while just occupying a little less than 1% of the earth's surface (Ericson et al., 2006). The major contributing factor to the migration of people to these areas includes the fertile lands for agriculture, the biodiversity within this ecosystem as well and the ease of movement through the waterways. This ecosystem support for agrarian activities also puts it at the frontier of addressing the global food security menace (Nababa et al., 2020).

The Niger Delta Region (NDR) is the largest delta in Africa (Goudie, 2005; Okonkwo et al., 2015; Nababa et al., 2020) and is characterized to habituate different types of land covers such as grassland, woodlands, ponds, mangroves etc. The delta is also home to Africa's greatest oil reserves and has been instrumental in Nigeria's GDP growth since the 1970s (Kuenzer et al., 2014). According to reports, the mangrove forest in the Niger Delta is the most exploited in the world. This area is also known as a global biodiversity hot spot and is considered to be the second most vulnerable habitat in Africa (Food and Agriculture Organization, 1997). The vulnerability of this region can be attributed to the rapid phase of economic expansion, facing several environmental difficulties, which are exacerbated by anthropocentric forces such as petroleum activities, economic development, and demographic shifts (Osei et al, 2006). As prominent as the Delta is, it can be vulnerable to hazards from factors such as sea level rise, industrialization and so many other anthropogenic factors especially tropical deltas like the Niger Delta.

The NDR habituates the third-largest mangrove forest in the world and the largest in Africa (Kuenzer et al., 2014; Nababa et al., 2020). It is important to highlight that mangrove swamps are at the heart of a delicate and complex ecosystem that is critical for fishing enterprises as well as sources of employment and income for local residents. The mangrove habitats many of the country's key wildlife and plants and is recognized as the most important commercially rich ecological zone (Okonkwo et al., 2015). Mangrove forests are very important ecosystem with their provisions through aquatic species shelter and breeding grounds, carbon sequestration and adaptation, such as stabilizing coastline erosion, lowering storm surges, and limiting inland soil salinization (Brander et al., 2012; Siikamäki et al., 2012; Clough, 2013; Kuenzer et al., 2013). However, mangroves are common in developing and underdeveloped nations and are more sensitive to climate change (Chow, 2018). With the evident importance of mangrove forests and the posing threats of rising sea level, global warming and coastal erosion, their degradation need to be monitored, mapped and comprehended to provide appropriate policies for their management and make progress toward meeting Sustainable Development Goals (Chow, 2018).

However, mapping land cover dynamics and investigating mangrove degradation is only practicable using remote sensing and Geographic Information System (GIS) derived Land Use and Land Cover data. The data, with their spatial details, are also important for environmental preservation and spatial planning (Rwanga et al., 2017). Remote sensing

(RS) is a primary source of numerous types of thematic data that are essential for GIS analysis, such as data on LULC characteristics which are also needed for policy, corporate, and administrative objectives. Aerial and Landsat satellite photos are examples of widely used remote sensing data utilized to assess the distribution of LULC and to update existing geospatial data. RS when combined with GIS delivers more usable information on land cover and land use degradation can be estimated from this integration. The importance of RS in GIS has grown dramatically since the advent of remote sensing technologies and image processing software (Merchant et al., 2009). Such land use change and mangrove degradation could be monitored using remote sensing data, which offers the advantages of a synoptic view, repeating coverage, cost-effectiveness, and availability. The essential assumption for employing remote sensing data is that a change in an object's condition must result in a change in radiance value (Mas, 1999), a phenomenon that can explicitly define any slight change in the land use and land cover within an area. Hence, it is embracement for this research.

Nonetheless, there have been several studies of the NDR land cover dynamics and mangrove degradation (James et al., 2007; Onojeghuo and Blackburn, 2011; Kuenzer et al., 2014; Ayanlade and Drake, 2016) but the results have been conflicting mostly in terms of the accuracy of the classification which makes the result unreliable or the study generalizing the degradation on the entire forest class except for (Nababa et al., 2020) whose study narrowed the investigation to mangrove degradation but covered 25 years, but then, in this present research, study period spans over three decades which will provide a sense to validate all the previous studies carried out in this region as well as provide an updated land cover state of the NDR. In similar research, Hauser et al. (2020) combine Google Earth Engine (GEE's) capabilities, including its entire Landsat-7 and Landsat-8 archives and cutting-edge classification approaches, with a post-classification temporal analysis to optimize land use classification results into gap-free and consistent data in Ngoc Hien District, Ca Mau Province, Vietnamese Mekong delta. The study's conclusions is that the net change in mangrove forests from 2001 to 2019 is 0.01% per year in the studied region. Aslan et al. (2021) discovered that 62% of the 96,298 ha of mangrove forests in the Mahakam Delta in Indonesia were deforested during the study period in their study to evaluate the spatiotemporal dynamics of large area mangrove deforestation, aquaculture pond building, and subsequent abandonment of ponds, primarily for building shrimp and fish ponds. Achionye et al. (2018) examined the land-use and land-cover transition of the Warri vegetation zone of the NDR over the last four decades using Landsat imageries for 1975, 1987, and 2015 with the aid of RS techniques and GIS. The results showed that the use of supervised classification produced satisfactory results in terms of distinguishing Built-up areas, Water bodies, and Mangrove and Non-mangrove vegetation. Nababa et al. (2020) were able to accurately measure land cover patterns in the NDR over 25 years by using the Google Earth Engine (GEE) cloud computing platform to estimate spatial-temporal Landsat-based metrics in three epochs (1988, 2000 and 2013). Their findings revealed that mangroves, lowland rainforests, and freshwater forests all suffered net losses during the study period, whereas built-up areas nearly increased. Furthermore, the findings provide a crucial quantification of the land cover changes in the NDR, as well as the first exact evaluation of the spatial extent of the region's degraded mangroves. These studies have justified the threats facing the mangroves globally and in NDR, precisely and further illustrate the capability of RS and GIS technology in mapping and monitoring the land cover dynamics and mangrove degradation. However, a further dive to utilize the derived LULC maps for monitoring change detection and mangrove degradation is greatly dependent on the accuracy of the classification. Accuracy of classification is often quantified by overall accuracy score, kappa coefficients, the user's accuracy and the producer's accuracy which were all the engaged validation techniques embraced in this paper and formed an important component of this research.

The goal of this work is to demonstrate the dynamism in land cover in the NDR between 1987 and 2022, as well as to investigate the extent of Mangrove forests degradation in the region. This was accomplished by pursuing the following objectives: Mapping the key land cover classes (i.e. Mangrove, Rain forest/woodland, grassland, water bodies and urban areas) across the NDR using Landsat data from three epochs, (1987, 2002, and 2022); validating the classification performance of the model using the overall classification accuracy, kappa coefficient, user accuracy, and producer accuracy scores; and determining the extent of mangrove degradation from 1987 to 2002 and from 2002 to 2022. The necessity to align with as many other NDR studies as possible so that comparisons could be made between them and the availability of Landsat imagery led to the use of data between the epochs. Proven to be the most often used supervised classification method, the maximum likelihood classification model, which is based on the premise that the training data statistics in each band are normally distributed (Richards et al., 2006) was used to derive the classification maps for this research. Akinyemi (2005) used this model to track land use patterns in the south-western region and Ojigi (2006) examined multiple supervised classification methods to track landscape changes in Abuja and findings show that the maximum likelihood algorithm outperformed the other methods (i.e. minimum distance, parallelepiped, and fisher's classifications model) tested.

2. Study area

The Niger Delta Region (shown in Fig. 1) is located in southern Nigeria, where the River Niger divides into numerous tributaries that flow into the Atlantic Ocean. It is Africa's largest river delta and home to the world's fifth-largest mangrove forest. The region includes nine southern states: Cross River, Akwa Ibom, Abia, Imo, River, Bayelsa, Delta, Edo, and Ondo, and is home to around 40 ethnic groups and over 250 dialects. However, the study region for this article only includes a portion of Bayelsa State. The Niger Delta Region is widely recognized as Nigeria's sole oil-producing region. They have also been a significant contributor to the country's Gross Domestic Product (GDP).

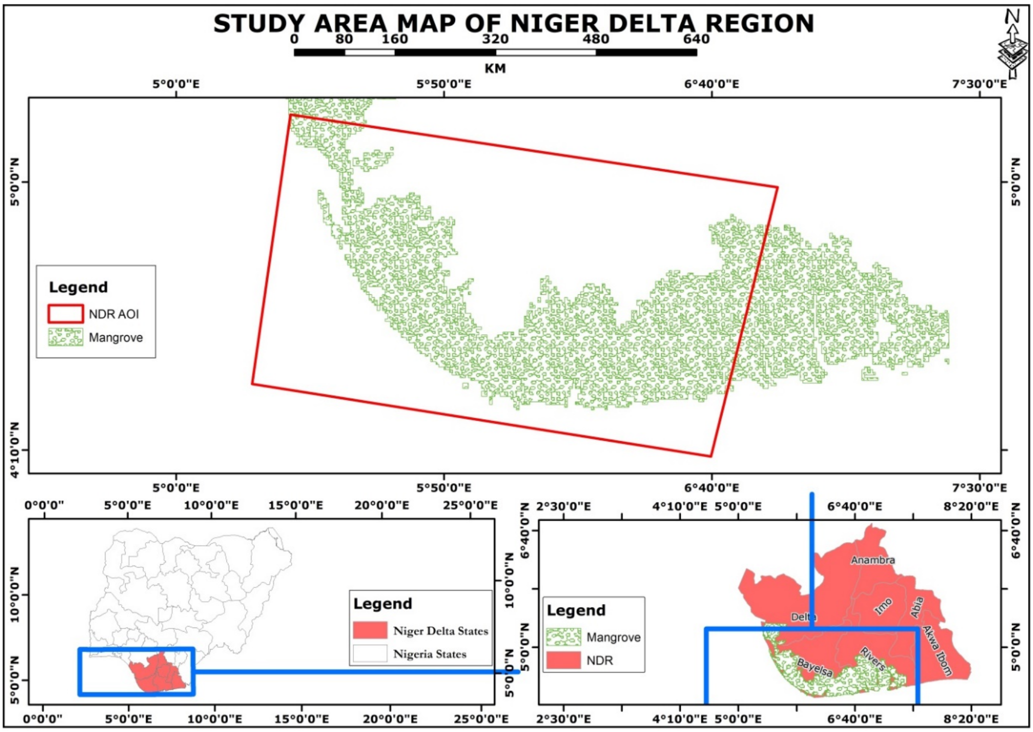

Fig. 1. Study area map

3. Methodology

3.1. Methods

The paper covers three sections: 1) Land cover classification mapping and accuracy assessment of the land cover classification 2) Change detection in the region and 3) Mangrove degradation.

The research began by mapping the main land cover types in three epochs focused around 1987, 2002, and 2022, and assessed land cover change and mangrove degradation in the two respective periods (i.e. 1987 to 2002 and 2002 to 2022). The choice of this epoch is to cover as many years as have been covered in previous studies so that a comparison of results could be made between them. The chosen classes were: Water, urban (i.e.,built-up), rainforest/woodland mangroves, and grassland. The choice of the classes was based on our knowledge of the area and previous research. The maximum likelihood classification model was used and post-classification accuracy assessment was carried out to make sure the classification maps were appropriate for further analysis. Afterwards, the change in the same land cover in different years was determined to investigate the changes in the area coverage. This was examined by grouping the epochs into two groups (i.e. 1987–2002 and 2002–2022). The methodology workflow in Figure 2 illustrates how the three stages of this research have been achieved.

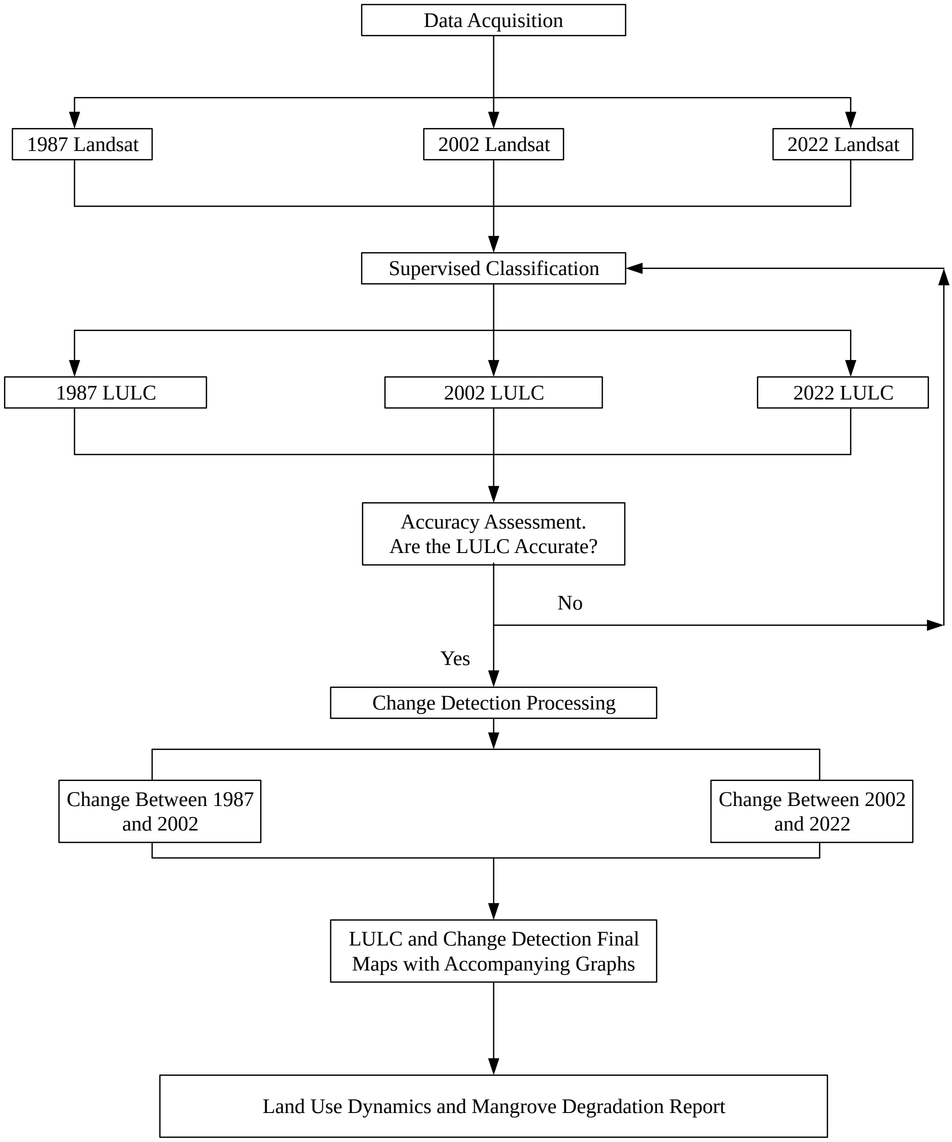

Fig. 2. Methodological workflow

3.2. Data source

In this work, three Landsat imagery were acquired from the United States Geological Survey USGS website. All the data were acquired for the same month and during the dry season. The research spans three epochs. This study relied heavily on satellite datasets for the change detection analyses. Table 1 shows details of the dataset used. ENVI 5.3 and ArcGIS 10.7.1 were used for geoprocessing all the data while further statistical analyses were done using Microsoft Excel.

Table 1. Datasets and the sources

Data	Data Source	Resolution	Acquisition Date
Landsat Imagery	USGS Earth Explorer	30 m	1987/DEC/21 2002/DEC/30 2022/DEC/29
Administrative Map	CESRA	–	–

3.3. Land cover classification

In this investigation, the maximum likelihood model of the supervised classification technique on ENVI 5.3 software was used. According to Eastman (2003), supervised categorization occurs when the user develops the spectral signatures of known categories, such as urban and forest, and then the software assigns each pixel in the image to the cover type to which its signature is most comparable. The first step in supervised classification is to identify the locations that will serve as training grounds for the various land cover classes. The training samples were chosen in accordance with Landsat Image and Google Earth, wherein, areas that coincide with the identified land cover class are labelled accordingly. Prior pixel labelling is then performed on the selected training sites. The band 7, 5 and 3 were first initiated to create the true color composite map for easy identification of the land cover class for the pixel selection. The study area was classified into five classes (Urban, Water, Grassland, Mangrove and Rain forest/Woodland). Without an accuracy or accurate assessment, land use classification is incomplete (Lillesand et al., 2008). The kappa coefficient is a measurement index for accuracy that was developed by remote sensing societies in the early 1980s (Congalton and Mead, 1983). Since then, it has been the accepted standard for field data validation and picture training (Rosenfield and Fitzpatrick-Lins, 1986; Congalton and Green, 2009). It has been used as an all-encompassing assessment index for classification accuracy in numerous studies (Rashid et al., 2011; Ghebrezgabher et al., 2016; Ochege and Okpala-Okaka, 2017). ENVI Software's overall accuracy score and kappa coefficient command were used to assess the overall agreement of the error matrix from the training session performed on all satellite images. In the categorized image of the research region, a total of 100 points (locations) were formed and utilized for the accuracy assessment.

3.4. Change detection

A method for detecting post-classification changes was used. Although the accuracy of post-classification methods is dependent on the accuracy of individual classifications and is subject to error propagation, the classification of each date of imagery builds a historical series that can be easily updated and used for purposes other than change detection. As a result, the LULC maps created were adjudged to be very accurate based on the overall accuracy score and the kappa coefficient. Furthermore, because each image is identified independently, this method overcomes difficulties caused by variations in sensor properties, atmospheric effects, solar illumination angle, sensor view angle, and vegetation phenology between dates. The change detection command on ENVI 5.3 was used to determine the level of change within the study area for the three epochs. Furthermore, the results of change detection statistics are contained in Table 6, which shows how the trend of the various land cover classes has changed within the period of the study. The Bar chart created using Microsoft Excel illustrates the result showing the analysis of the mangrove forest degradation.

4. Result and discussion

4.1. Land use mapping

The areas covered by individual land cover classes have been computed (Table 2). From the output, it can be seen that in 1987, the rainforest covered the largest part of the study area with 5581.3671 km^2. This was also noticed to have increased to 5751.1836 km^2 in 2002 just to be reduced back to 5392.5930 km^2 twenty years later in 2022 which is even less than the initial size in 1987. The mangrove forest in the area saw or shows a negative trend between 1987 and 2022 where the area covered was initially 3971.1213 km^2 in 1987 to 3911.6169 km^2 in 2002 in 2022 showing a decline to 3775.2327 km^2 in 2022. Grassland also followed a similar trend as it went from 1250.1324 km^2 in 1987 to 1164.3669 km^2 in 2002. In 2022, the grassland covered an area of 711.5148 km^2. Urban area in the NDR experienced a positive change as in 1987 the area covered was 117.5886 km^2 then increased to 149.823 km^2 in 2002 and in 2022, the area covered rose to 1204.6464 km^2. The water bodies in the NDR saw a decline and this could be attributed to the oil spillage going on in the region. The water bodies in the area covered 685.3068 km^2 in 1987, 628.5258 km^2 in 2002 and 521.5509 km^2 in 2022. The water bodies can be seen (Figs. 3–5) flow out from the Atlantic Ocean and the rain forests as well as the mangroves are majorly in those areas characterized by many tributaries of the Atlantic Ocean.

Table 2. Area Covered by the Land Use Classes

Land Use Class	Area Covered (km^2)		
	1987	2002	2022
Mangrove	3971.1213	3911.6169	3775.2327
Rain Forest/Woodland	5581.3671	5751.1836	5392.593
Grassland	1250.1324	1164.3669	711.4932
Water	685.3068	628.5258	521.5509
Urban	117.5886	149.823	1204.6464
Total Area	11605.5162	11605.5162	11605.5162

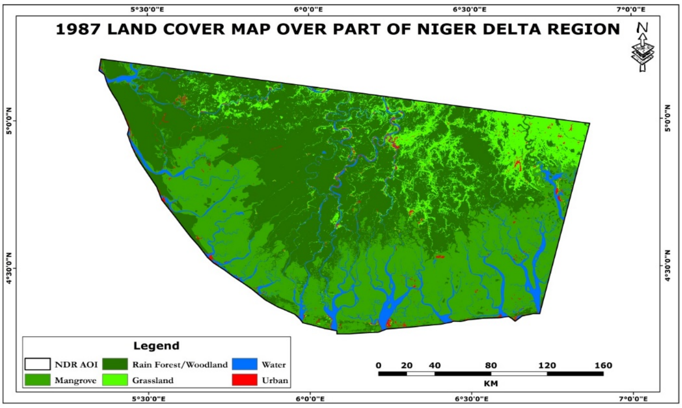

Fig. 3. Land cover map of 1987

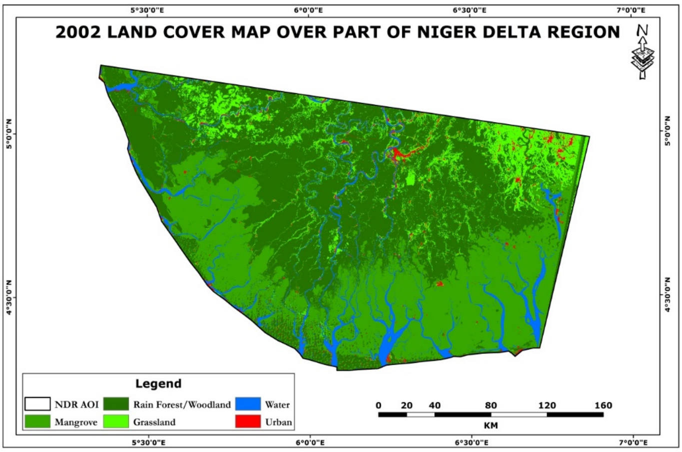

Fig. 4. Land cover map of 2002

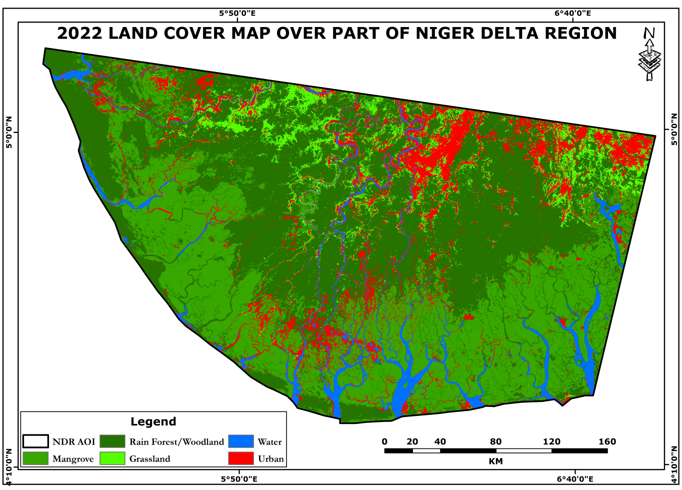

Fig. 5. Land cover map of 2022

4.2. Validation of classification

Accuracy evaluation is one of the most crucial last steps in the classification process. The goal of accuracy evaluation is to quantify how well pixels were sampled into the correct land cover classes. Furthermore, for accuracy evaluation pixel selection, the primary emphasis was on locations that could be identified on Landsat high-resolution images, Google Earth, and Google Maps.

The accuracy evaluation results for the various years – 1987, 2002, and 2022 – are 82.16%, 82.16%, and 83.97%, respectively. The corresponding kappa coefficients for the epochs are 75.63%, 75.63% and 78.43% (Tables 3–5). These scores show that the developed land cover maps are accurate enough to be further used to carry out post-classification change detection analysis. The producer accuracies (PA) and user accuracies (UA) for all the land cover classes are contained in Tables 3–5.

Table 3. 1987 error matrix

Land Use Class	Water	Rain Forest/ Woodland	Mangrove	Urban	Grassland	PA	UA
Water	97	0	0	9	0	96.69	98.65
Rain Forest/ Woodland	0	89	13	50	48	89.39	68.60
Mangrove	3	4	86	27	2	85.92	87.77
Urban	0	0	1	0	4	0.00	0.00
Grassland	0	7	1	14	46	46.15	64.86
Total	100	100	100	100	100		
Overall Classification Accuracy			82.16%				
Kappa Coefficient			75.63%				

Table 4. 2002 error matrix

Land Use Class	Water	Rain Forest/ Woodland	Mangrove	Urban	Grassland	PA	UA
Water	96	0	0	5	0	96.03	99.32
Rain Forest/ Woodland	0	92	15	50	54	91.67	66.85
Mangrove	4	1	85	23	2	84.51	90.23
Urban	0	0	1	5	0	4.55	50
Grassland	0	8	0	18	44	44.23	62.16
Total	100	100	100	100	100		
Overall Classification Accuracy			82.16%				
Kappa Coefficient			75.63%				

Table 5. 2022 error matrix

Land Use Class	Water	Rain Forest/ Woodland	Mangrove	Urban	Grassland	PA	UA
Water	91	0	0	0	0	91.39	100
Rain Forest/ Woodland	6	95	17	36	25	95.45	70
Mangrove	0	3	81	5	0	80.99	95.83
Urban	3	0	2	59	23	59.09	40.63
Grassland	0	2	0	0	52	51.92	93.1
Total	100	100	100	100	100		
Overall Classification Accuracy			83.97%				
Kappa Coefficient			78.44%				

4.3. Change detection

Tables 6–7 show the differences generated from comparing categorized Landsat photos from 1987, 2002, and 2022. The change detection analysis was carried out for two different spans of years they are; between 1987–2002 and 2002–2022. In this work, negative values indicate degradation while positive values show an improvement in the land cover class. The change detection results show that grassland degraded by 85.7655 km^2 between 1987 and 2002, while rainforest, also known as woodland, grew from 5581.3671 km^2 in 1987 to 5751.1836 km^2 in 2002, indicating a total improvement of 169.8165. This is reinforced by the steady decline of mangrove forests, which fell from 3971.1213 km^2 in 1987 to 3911.6169 km^2 in 2002. Water bodies have also changed, reducing from 685.3068 km^2 in 1987 to 628.5258 km^2 in 2002. This is due to the severe oil spillage that has been happening since the discovery of crude oil in the region. The urban area saw a net change with improvements by 32.2344 km^2 where the initial area of 117.5886 km^2 in 1987 increased to 149.823 km^2 in 2002.

Table 6. Change in areas between 1987 and 2002

Land Use Class	Area Covered (km^2)		
	1987	2002	Difference
Mangrove	3971.1213	3911.6169	–59.5044
Rain Forest/ Woodland	5581.3671	5751.1836	169.8165
Grassland	1250.1324	1164.3669	–85.7655
Water	685.3068	628.5258	–56.781
Urban	117.5886	149.823	32.2344
Total Area	11605.5162	11605.5162	

The change detection results in Table 7 show that grassland lost 452.8521 km^2 between 2002 and 2022, while rainforest reduced from 5751.1836 km^2 in 2002 to 5392.5930 km^2 in 2022, indicating a total loss of 358.5906 km^2 as against the trend in the change recorded between 1987 and 2002. The mangrove forest also shows a decrease in its area, which reduced from 3911.6169 km^2 in 2002 to 3775.2327 km^2 in 2022. The water body also recorded noticeable changes in its area covered, reducing from 628.5258 km^2 in 2002 to 521.5509 km^2 in 2022. The urban area is the only land cover class that recorded an increase. The urban area settlement increased from 149.823 km^2 in 2002 to 1204.6464 km^2 in 2022.

Table 7. Change in areas between 2002 and 2002

Land Use Class	Area Covered (km^2)		
	1987	2002	Difference
Mangrove	3911.6169	3775.2327	–136.3842
Rain Forest/ Woodland	5751.1836	5392.593	–358.5906
Grassland	1164.3669	711.4932	–452.8737
Water	628.5258	521.5509	–106.9749
Urban	149.823	1204.6464	1054.8234
Total Area	11605.5162	11605.5162	

4.4. Mangrove degradation

The mangrove degradation data has been extracted from the contingency matrices derived for change detection. The result of this analysis shows the total mangroves that existed between 1987–2002 and 2002 and 2022. Between 1987 and 2002, the mangrove covers experienced a loss of 346.477 km^2 of which have been converted to other land classes that include 36.8154 km^2 to a water body; 16.7391 km^2 to urban settlement; 8.1324 km^2 to grassland and 284.7897 km^2 to rain forest causing a decrease in the mangrove to 3624.723 km^2. In summary, within the space of fifteen years mangrove forest in the Niger Delta Region has degraded by approximately 347 km^2. At the beginning of 2002, the mangrove covered 3911.507 km^2 and 715.329 km^2 of this area had been lost to other land classes twenty years later in 2022. Of this change, 440.8083 km^2 has changed to rain forest; 236.8719 km^2 to urban areas; 27.4689 km^2 has changed to water body and 10.1799 km^2 of the mangrove covers has been changed to grassland. Just before the beginning of 2023, the mangrove cover in the Niger Delta Region has been degraded to remain at 3196.178 km^2. The distribution of the mangrove degradation is illustrated in Figure 6 and Figure 7.

Accurate land cover estimates also enabled a more thorough land change analysis, which included an assessment of change dynamics and change detection in a crucial component of the Niger Delta Region and its mangrove forests. The mangrove forest of the Niger Delta is a major source of oil and gas resources. As a result, it is highly vulnerable to oil and gas extraction activities such as land clearing, dredging, construction

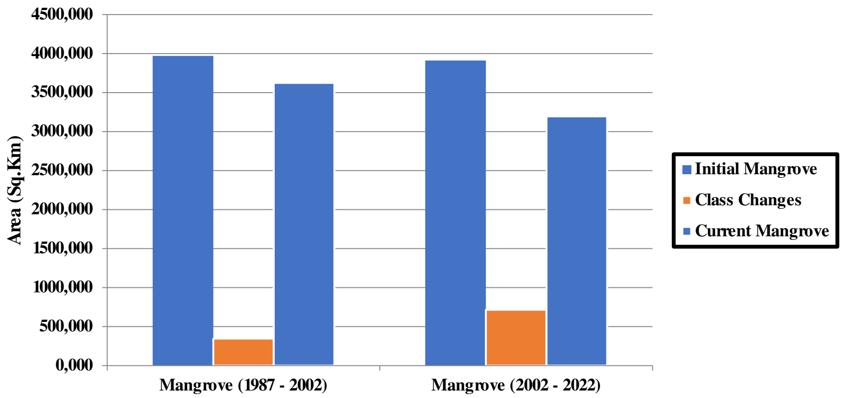

Fig. 6. Chart of the degraded mangrove forest in NDR

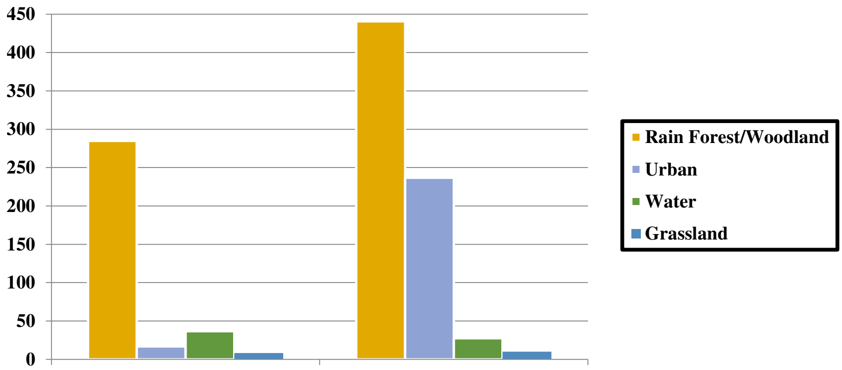

Fig. 7. Distributed land cover class from degraded mangrove forest

of flow stations, pipe and seismic lines, well blowouts, leakages or corrosion, equipment failure, error during operation or maintenance, accidents during transportation, sabotage, and so on, as well as urbanization, selective logging, and the proliferation of the invasive Nipa palm species (Nypa fruticans) that cause forest destruction and deforestation. The land cover change and change detection analysis revealed that degraded mangroves grew during both research periods and mangrove losses outweighed increases. The effects of fast urbanization and oil extraction activities are to blame for mangrove deterioration in this area. This further shows conformity with the result obtained by Nababa et al., (2020).

5. Conclusion

The Niger Delta Region (NDR) is a significant ecosystem that provides several benefits to the millions of people that live there. Despite its undeniable value, it is under threat of degradation, primarily as a result of human pressure, and particularly as a direct result of operations associated with the region's large oil and gas deposits. Understanding the scope of the problem necessitates an accurate assessment of the region's land cover dynamics, which can only be accomplished with cutting-edge remote sensing and GIS technologies. The region harbours the third-largest mangrove in the world and the largest in Africa. This ecosystem contributes to the climate system of the earth and is home to some species of plants and animals. To completely understand, monitor and map the extent of the dynamism in the ecosystem requires the integration of remotely sensed imagery and Geographic Information System (GIS) hence, preempting this study.

In this study, we have accurately utilized ENVI and ArcGIS Pro to extract Spatio-temporal information required to assess the land cover change and degradation of mangroves in NDR from Landsat imagery for a period traversing 35 years. We considered grouping the epochs in to two groups of years for the change detection analysis and the mangrove degradation (i.e. 1987 to 2002 and 2002 to 2022, representing the first case and second case, respectively) and classifying the land cover into five classes (urban, mangrove forest, rain forest/woodland, water and grassland). In the first case (i.e. between 1987 and 2002), the rain forest/woodland and the urban areas recorded total gain in area coverage, the water bodies, mangrove and grassland demonstrated net loss between the year. Between 2002 and 2022, the mangroves, rain forest/woodland, grassland, and water bodies all demonstrated a net loss while the urban areas have greatly increased between the last 20 years. Summarily, they was a consistent loss of forest types (rain forest/woodland, mangroves, grassland) and consistent net gain in the urban class throughout the 35 years of the study. Further findings showed that mangrove has been lost consistently over the 3 decades with the most loss occurring between 2002 and 2022 and this could attributed to the increase in population in this areas leading to increase exploitation of the mangrove trees for their economic benefits. This is supported as most of the mangroves were converted to urban settlement between 2002 and 2022 from the analysis, demonstrating a case of increase in population and increase in industrialization as well. Conclusively, in both scenerios of mangrove degradation investigation, the results reveals insistent net loss in mangrove. Our results demonstrate consistency with the findings of other studies in this situation and offer a useful estimate of the land cover dynamics in the NDR. Such evaluations are essential for developing the successful policies required for managing natural resources like mangroves.

Recommendation

The Niger Some of the recommendations identified by the author include

1. Because optical vision is likely to be influenced by clouds, more studies into the application of microwave remote sensing techniques in the region should be investigated.
2. The government should closely oversee the operations of crude oil exploration businesses in this region, and their actions should be closely monitored, with erring corporations prosecuted or arrested.
3. The mangrove study should be continued since it is crucial to meeting a number of Sustainable Development Goals and reaching Land Degradation Neutrality by 2030, as proposed by the United Nations LDN Target Setting Programme.

Author contributions

Conceptualization: I.O.I., T.H., S.O.A.; collection and assembly of data: I.O.I.; data analysis and interpretation: I.O.I., S.O.A.; article writing: I.O.I.; writing – review and editing: T.H.; critical revision and final approval of the article: T.H.; supervision: I.O.I., S.O.A.

Data availability statement

The data that supports the outcome of this research are available upon request.

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