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Spatiotemporal Assessment of Wetland Ecosystem: Integrating Terrain and Population Dynamics for Sustainable Planning

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Abstract
Wetlands are crucial in environmental sustainability, supporting biodiversity, water purification, flood control, and climate regulation. However, these ecosystems are increasingly threatened by anthropogenic activities and urban expansion. This study explores using remote sensing and GIS tools to assess wetland changes over time for conservation planning. Landsat imagery from 1990, 2000, 2013, and 2024 was processed in ENVI 6.0 using supervised classification with Maximum Likelihood Classification (MLC). Accuracy assessment was conducted through confusion matrices, while thematic change detection identified areas of wetland loss. Ancillary datasets, the Digital Elevation Model (DEM) and WorldPop population density layers, were analyzed using ArcGIS Pro. The results revealed a consistent decline in wetland coverage, with a corresponding rise in population density and encroachment in low-lying areas. Wetland zones at lower elevations showed greater susceptibility to conversion, often replaced by built-up or agricultural land. The integration of ancillary data proved critical for understanding the spatial drivers behind wetland degradation. The findings contribute to the growing body of knowledge on sustainable land use and emphasize the relevance of spatial tools in conserving ecologically sensitive areas.

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1. Introduction

Wetlands are important natural areas that support the environment, economy, and communities. However, human activities damage these areas, causing them to shrink and lose their benefits. (EPA, 2018; UN-Habitat, 2010). The modification and conversion of large natural, or agricultural, areas to built-up areas, can lead to loss of forests and wetlands, air quality impairment, increase in impervious surfaces, reduced aquifer recharge, flooding, ecosystem, and landscape fragmentation, as well as biodiversity loss (Fasona *et al*., 2007; Seifolddini & Mansourian, 2014) [16, 29]. Globally, wetland conservation has gained increased attention due to the alarming rate at which these ecosystems are being degraded by anthropogenic activities, particularly urbanization, land reclamation, and infrastructure development (Oyedepo & Oluyege, 2024; Peng *et al*., 2024) [25, 26]. In Nigeria, they are declining due to rapid urbanization, land reclamation, and climate change (Ogunlade & Oluwole, 2022) [22]. Fadipe *et al*., (2024) [8] observed that Lagos State is a prime example of this problem since significant wetland degradation has been brought on by the growth of real estate, people, and infrastructure. Over the past three decades, sand-filling, uncontrolled housing projects, and industrialization have significantly reduced the amount of wetland in Ikorodu, a rapidly urbanizing district inside Lagos State (Idowu *et al*., 2020; Ubaekwe & Engwoh, 2020; Fadipe *et al*, 2024) [11, 32, 8]. Remote sensing (RS) and Geographic Information Systems (GIS) are essential tools in environmental monitoring and wetland conservation, enabling researchers to detect, classify, and analyze land use and land cover (LULC) changes over time. (Fasona *et al*., 2007; Klemas, 2011; Obiefuna *et al*., 2013; Tochukwu, 2024) [16, 14, 31]. However, geospatial analysis alone is insufficient to explain the drivers of environmental change (Oseni *et al*., 2020; Ju & Bohrer, 2022) [24, 12].

Integrating ancillary datasets like census records, land tenure information, and hydrological datasets offers a more comprehensive understanding of wetland degradation (Dong *et al*., 2014; Kaplan & Avdan, 2017) [6, 13]. Prior research focusing on wetlands that includes ancillary data is limited in the study area (Gilbert & Shi, 2023; Fadipe *et al*., 2024; Oyedepo & Oluyege, 2024) [10, 25, 8]. This study employs Landsat-based remote sensing techniques to analyze wetland degradation in Ikorodu over 34-year intervals from 1990 to 2024, alongside elevation and population density (ancillary dataset). It offers data-driven insights for wetland conservation and ecosystem sustainability.

2. Study Area

This study was conducted for the Ikorodu Local Government Area (LGA). It is located in the southwest part of Lagos state, Nigeria (Figure 1) at latitude 6.6194° N and longitude 3.5105° E. Nigeria generally experiences two main seasons: a dry season and a rainy season. The dry season, characterized by lower rainfall and humidity, typically lasts from November to April. The rainy season, with more rainfall, usually begins in May and continues through October (Climate Change Knowledge Portal, 2021). Lagos is the most urbanized city in Nigeria, Africa's most populous country (Gilbert & Shi, 2023) [10]. According to UN World Urbanization Prospects, Ikorodu had a population of 8,645 in 1950, and current estimates place Ikorodu's population at 1,145,220 in 2024 with a 4.75% annual change from the previous year (WPR, 2024). Ikorodu LGA shares borders with Ogun State to the north, the Lagos Lagoon to the south, and the town of Agbowa-Ikosi in Lagos State's Epe Division to the east (Onuoha *et al*., 2025) [23]. Due to social, economic, and environmental effects, Ikorodu is Lagos State‘s most peri-urbanized community (Mokunfayo & Babatunde, 2018) [17]. These characteristics make the study area an interesting location for land cover analysis. In Ikorodu, vegetation (primarily forests, grasslands, and other plant life) is a significant landscape component, particularly in the rural areas and along the lagoon. Wetlands, like swamps and mangroves, also play a crucial role, especially along the Lagos Lagoon and surrounding areas (Odunuga *et al*., 2018) [21].

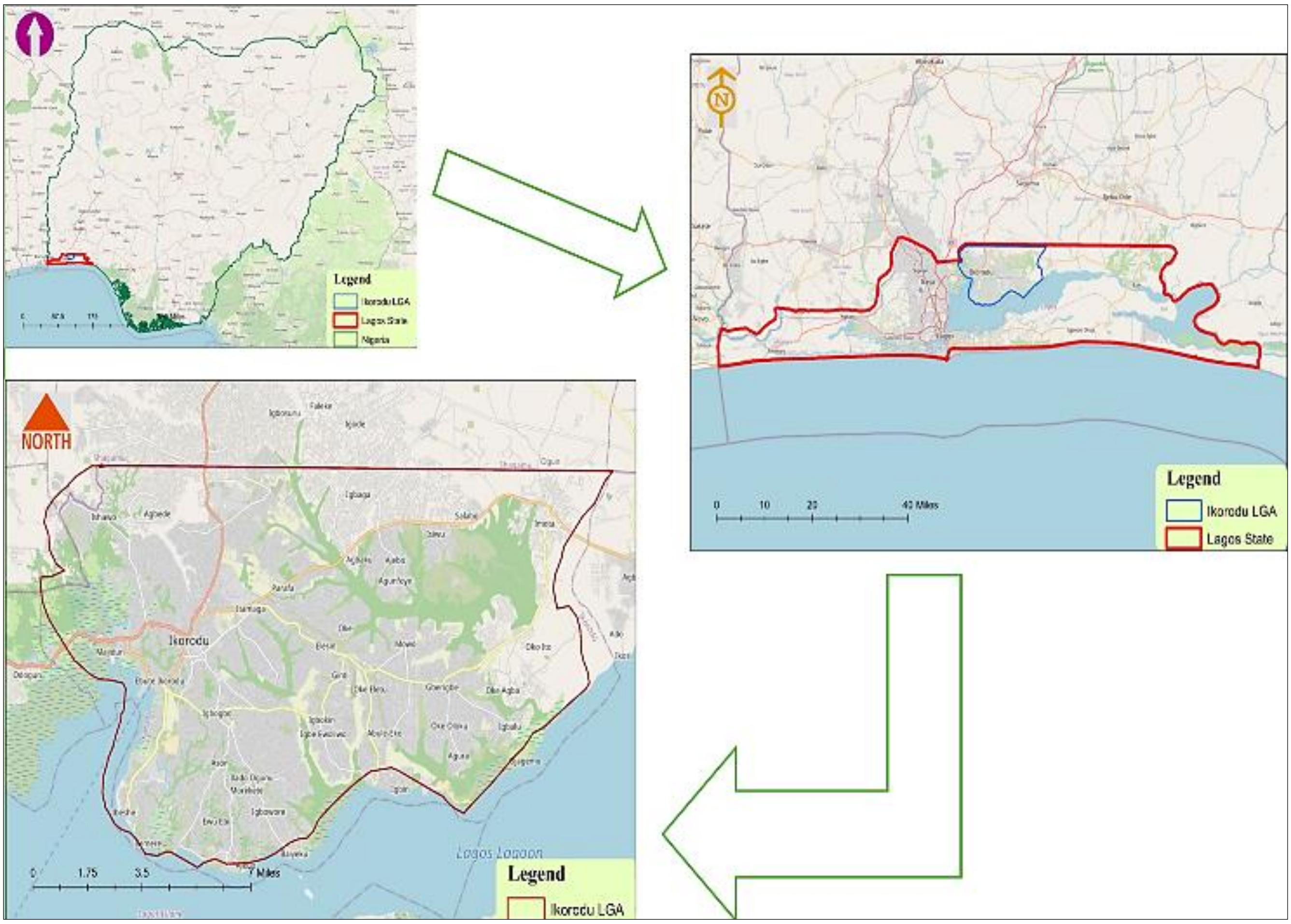


Fig 1: The locations of both Lagos State and Ikorodu Local Government Area (LGA) on the map of Nigeria.

3. Materials and Methods

This study utilized four Landsat scenes corresponding to the years 1990, 2000, 2013, and 2024 (Table 1) to examine spatiotemporal changes in wetland cover. Specifically, Landsat 4 Multispectral Scanner (MSS) data were used for 1990, Landsat 7 Enhanced Thematic Mapper Plus (ETM+) for 2000, Landsat 8 Operational Land Imager (OLI) for 2013, and Landsat 9 Operational Land Imager 2 (OLI-2) for 2024. All imagery was acquired from the United States Geological Survey (USGS) Earth Explorer platform as Level 2 surface reflectance products, which are atmospherically corrected and georeferenced to ensure spatial consistency (USGS, 2023). The boundary shapefile (publicly available) was acquired from the Nigeria Office of Surveyor General of the Federation (OSGOF). The near-global digital elevation model (DEM) of Earth's land surface, providing detailed elevation data, was collected by the Shuttle Radar Topography Mission (SRTM). Population density, defined as the number of people per square kilometer based on country totals, was adjusted to match the corresponding official United Nations population estimates. It represents the estimated population density per grid cell and is supplied by Woldpop. Information on the ancillary data, population density, and SRTM is also presented in Table 1. The SRTM data is designed to have a vertical accuracy of approximately 16 meters (90% confidence). This means that at 90% confidence, you can expect the SRTM elevation data to be within 16 meters of the true ground elevation (Mukul *et al.*, 2017) [18].

Table 1: Showing the date and spatial resolutions of the dataset. It includes both satellite imagery and ancillary data

NAME	Date	Spatial resolution
Landsat 4	1990/12/27	30 m (16% cloud cover)
Landsat 7	2000/02/06	30 m (7% cloud cover)
Landsat 8	2013/12/18	30 m (0.01% cloud cover)
Landsat 9	2024/12/08	30 m (0% cloud cover)
SRTM (DEM)	2005/02/01	3-Arc (Non-void filled) ~90m
SRTM (DEM)	2012/10/01	3-Arc (Void filled) ~90m
SRTM (DEM)	2014/09/23	1-Arc (Second Global) ~30m
Population density (UN Adjusted)	2000	1 km
Population density (UN Adjusted)	2013	1 km
Population density (UN Adjusted)	2020	1 km

3.1 Land Cover Classification

The land cover classification was carried out using the Maximum Likelihood Classifier (MLC) in ENVI 6.0 (Figure 2). Before classification, preprocessing was conducted to prepare all datasets for classification and analysis. Landsat images were subset to the study area using the Ikorodu boundary shapefile. Training and validation data were derived from visually interpreted regions of interest (ROIs), representing key land cover types, including wetlands, urban vegetation, and water. Google Earth Pro imagery was used to identify the ROIs in the Landsat imagery. Each Landsat image was classified independently, using spectral bands 1–7 for Landsat 4 and 7 and bands 2–7 for Landsat 8 and 9 to exclude the coastal band (USGS, 2023). The MLC algorithm assumes a normal distribution of class signatures and assigns each pixel to the class with the highest probability. Classified maps were validated using reference points and confusion matrices. The specific years for the 34-year interval period were 1990, 2000, 2013, and 2024. The year 2013 was substituted for 2010 because of the scan line error in 2010, and using 2024 was to depict the most recent development as of the time of this analysis.

3.2 Accuracy Assessment

An accuracy assessment (Figure 2) was conducted to validate the classification results of each Landsat scene. A confusion matrix was generated in ENVI using independently collected ground truth samples from the Landsat imagery as validation datasets for the four years. Google Earth Pro imagery was used to identify ground truth samples in the Landsat imagery. The samples were randomly stratified across all land cover classes, ensuring adequate representation. All pixels for both the training and validation datasets for each feature across the four years were above 700 pixels. Metrics, including overall accuracy, users' and producers' accuracy, and the Kappa coefficient, were computed to evaluate classification performance. An overall accuracy threshold of at least 85% was targeted, in line with standard remote sensing protocols (Congalton & Green, 2009) [4]. Discrepancies in class assignments were analyzed to refine training data for future iterations. Accuracy assessment ensured the reliability of the change detection and spatial analysis results.

3.3 Change Detection Analysis

Change detection (Figure 2) was performed to quantify land cover transformations over three decades (1990–2024). The classified Landsat images from each year (1990, 2000, 2013, and 2024) were compared using ENVI's Thematic Change Detection tool, which computes pixel-by-pixel transitions between defined classes. This enabled the identification of spatiotemporal dynamics in wetland cover, including degradation, expansion, or conversion to other land uses. A change matrix was generated for each decadal interval to quantify gains, losses, and persistence of land cover types. These outputs were crucial for understanding the patterns and drivers of wetland loss. The analysis was restricted to consistently classified pixels, and ambiguous or mixed classes were excluded to improve accuracy. This method supports multi-date comparisons and provides robust statistics for land management and policy formulation (Lu *et al.*, 2004).

3.4. Impact analysis

Population density data provided a proxy for human pressure, while DEM helped identify elevation-related constraints to wetland distribution. Zonal Statistics as a Table was employed in ArcGIS Pro to quantify the relationship between DEM and population density. This process served as the impact analysis (Figure 2) in this study. After ensuring the alignment of all datasets through the Project Raster tool, Zonal Statistics was applied using the classified map as the zone raster. This method calculated statistical measures such as mean, sum, and standard deviation of the value raster within each land cover class. Only the mean was used for comparison in this study. The resulting table provided a detailed comparison of environmental and demographic attributes across classes.

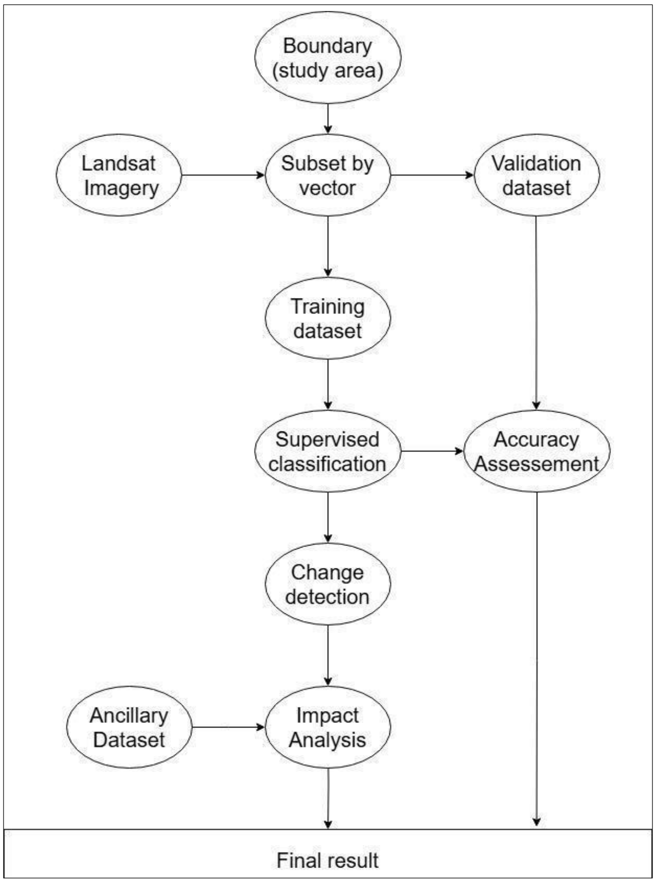
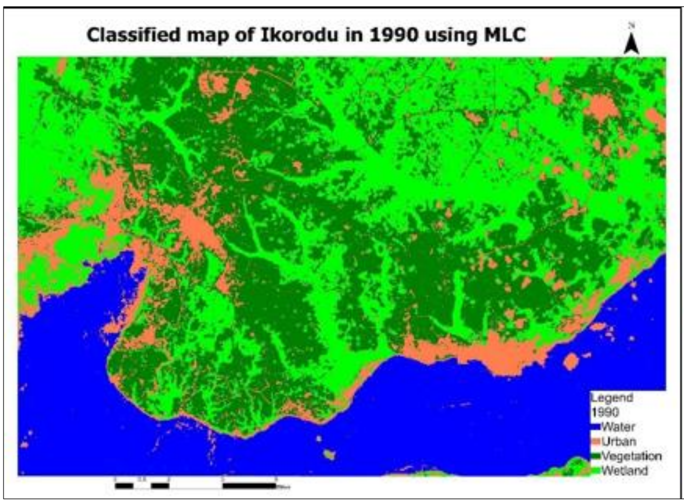


Fig 2: Showing the methodology flowchart for this study.

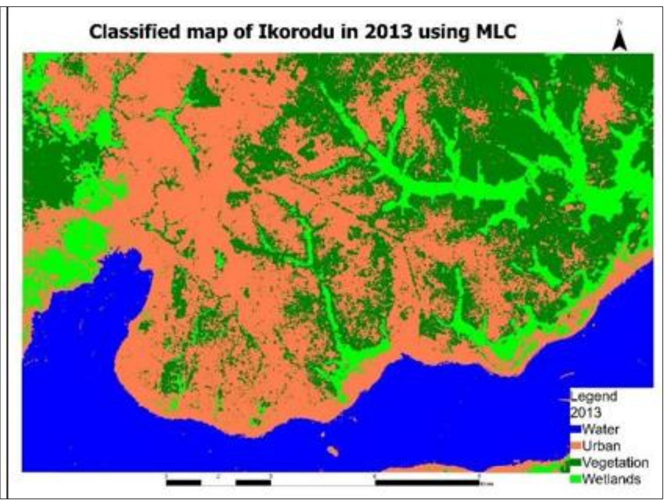
4. Results

4.1. Supervised classification

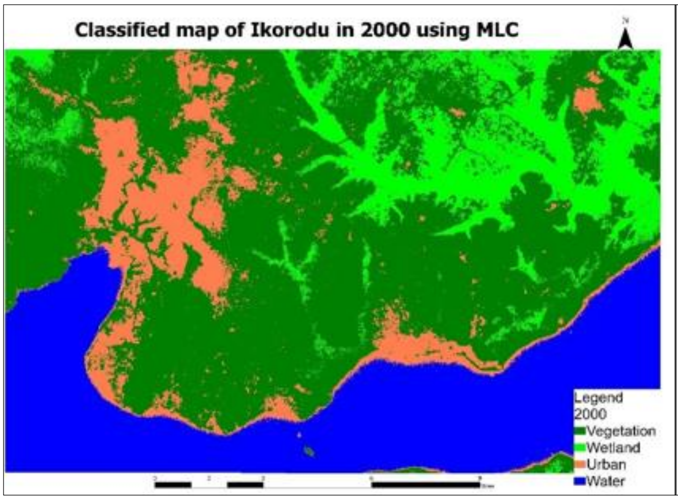
A supervised classification using the Maximum Likelihood Classifier (MLC) was performed in ENVI to categorize the study area into distinct land cover classes, including wetlands, vegetation, built-up areas, and water bodies. Regions of Interest (ROIs) were manually digitized based on expert knowledge and visual interpretation of the Landsat imagery. ROI separability was assessed using the Transformed Divergence (TD) metric, with all class pairs yielding values above 1.9 (Table 3), indicating excellent spectral separability and minimal overlap between land cover categories. However, the discrepancy in the hundredths place in the values in Table 3 stems from the manual digitization process. For example, the low values recorded (training and validation) in the hundredths place in 2000 were due to the imagery being more pixelated than others. Likewise, the low values in the validation dataset for both 2013 and 2024 were due to the inability to obtain additional fine pixels for ROIs, especially for wetlands and vegetation. Overall, this high separability (above 1.9) supported the reliability of the classification results. The output classified map provided a detailed spatial representation of land cover distribution and formed the basis for subsequent change detection and zonal statistical analysis.



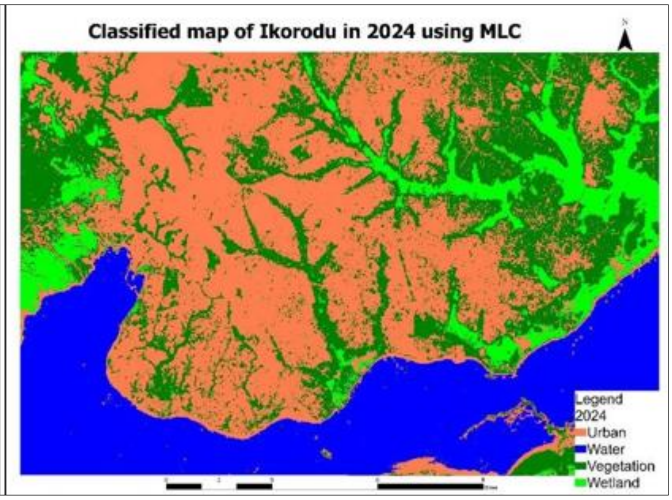
3(a): MLC classification result for Ikorodu in 1990



3(b): MLC classification result for Ikorodu in 2000



3(c): MLC classification result for Ikorodu in 2013



3(d): MLC classification result for Ikorodu in 2024

Fig 3: Showing the MLC classification result for Ikorodu from 1990 to 2024 (a-d). The four classes in the classification are identified with various colors in the legend

Table 3: Showing the ROI separability results for the training and validation datasets for the four years.

ROI Separability Result				
Classes	**1990**	**2000**	**2013**	**2024**
	Training Data	**Validation Data**	**Training Data**	**Validation Data**
Vegetation and Wetlands	1.999	1.999	1.970	1.940
Urban and Vegetation	1.997	1.993	1.997	1.996
Water and Urban	1.998	1.999	1.999	2
Urban and Wetlands	1.999	1.999	2	1.999
Water and Wetlands	2	2	2	2
Water and Vegetation	2	2	2	2

The classified maps for the four years were highlighted in Figure 3.
The panel signifies the Land Use Land Cover (LULC) dynamics over the 34-year interval. The four classes are Vegetation, Wetland, Urban, and Water. Panel (a) shows the distribution of the LULC across four classes in 1990. Panel (b) shows the distribution of the LULC across four classes in 2000. Panel (c) shows the distribution of the LULC across four classes in 2013, and Panel (d) shows the distribution of the LULC across four classes in 2024.

4.2 Accuracy assessment (confusion matrix)

Classification accuracy was further verified using a validation dataset and a confusion matrix, confirming that the method produced dependable thematic maps for temporal comparison and environmental analysis. The result is presented in Table 4(a–d) representing the years 1990, 2000, 2013, and 2024, respectively. The overall accuracy across the four years exceeded 88%, while the Kappa coefficient was 0.80, indicating strong agreement beyond chance. While most of the overall accuracy was above 90%, the lowest overall accuracy of 88.962% was recorded in 2000 (Table 4b) and is attributed to the pixelated image as explained by the ROI separability result (Table 3). Furthermore, the kappa coefficients in 1990 (Table 4a) and 2013 (Table 4c) was in there in the 0.90 range, but the kappa coefficients in 2000 (Table 4b) and 2024 (Table 4d) were 0.82 and 0.88, respectively. The producers' accuracy for Urban and Water was above 90% across the four years, but it wasn't the same for Wetland and Vegetation. In 2020, the producer accuracy for Wetlands was 56% while vegetation was 99%, which explains why about 44% of the Wetland pixels were classified as Vegetation. A similar trend was observed in 2013 (Table 4c), where Wetland pixels (81%) were classified as Vegetation (14.8%) and Urban (4%). Despite this, the classification results were deemed robust and suitable for spatiotemporal analysis through the overall accuracy and kappa coefficients.

Table 4 a-d: The confusion matrix table panel for the classified image from 1990 to 2024 (a-d).

4(a): 1990 confusion matrix

Overall Accuracy = 99.8248%
Kappa Coefficient = 0.9966

	Reference (Percent)				
Class	Water	Urban	Vegetation	Wetland	Total
Unclassified	0	0	0	0	0
Water	99.95	0	0	0	66.32
Urban	0.05	99.87	0.5	0.08	5.87
Vegetation	0	0.13	99.17	0.24	9.14
Wetland	0	0	0.33	99.67	18.67
Total	100	100	100	100	100

4(b): 2000 confusion matrix

Overall Accuracy = 88.9622%
Kappa Coefficient = 0.8249

	Reference (Percent)				
Class	Vegetation	Wetlands	Urban	Water	Total
Unclassified	0	0	0	0	0
Vegetation	99.19	43.18	0.59	0	22.95
Wetlands	0	56.82	0	0	14.29
Urban	0.81	0	99.41	0.06	8.06
Water	0	0	0	99.94	54.7
Total	100	100	100	100	100

4(c): 2013 confusion matrix

Overall Accuracy = 97.2709%
Kappa Coefficient = 0.9435

Class	Reference (Percent) Water	Urban	Vegetation	Wetlands	Total
Unclassified	0	0	0	0	0
Water	99.93	0	0	0	69.53
Urban	0.07	100	2.12	4.12	12.72
Vegetation	0	0	97.7	14.82	6.75
Wetlands	0	0	0.18	81.06	10.99
Total	100	100	100	100	100

4(d): 2024 confusion matrix

Overall Accuracy = 93.5652%
Kappa Coefficient = 0.8813

Class	Urban	Reference (Percent) Water	Vegetation	Wetlands	Total
Unclassified	0	0	0	0	0
Urban	99.8	0.23	6.79	0.13	9.31
Water	0	99.77	0	0	63.92
Vegetation	0.2	0	93	27.1	11.04
Wetlands	0	0	0.21	72.77	15.72
Total	100	100	100	100	100

4.3 Thematic change detection

Thematic change detection was carried out to evaluate land cover transitions, specifically focusing on the conversion of wetlands to other land cover classes. Using the post-classification comparison method in ENVI, classified maps for 1990 to 2024 were prepared (Figure 4). The process also generated a detailed change detection matrix indicating areas That were wetlands in the base year but changed to other classes in subsequent years. Overall, the 34-year change in Ikorodu (Table 5) revealed a consistent decline in wetland coverage across the decades, with notable 15.93% conversions to Vegetation (agricultural land) and 8.39% to Urban (built areas). It is also important to note that the Wetland conversion to vegetation was influenced by the aggressive conversion of the latter to Urban areas (Aigbokhan, 2019). Over 24% of Vegetation was turned into Urban between 1990 and 2024 (Table 5).

Table 5: Showing the overall thematic change result from 1990 to 2024. It highlights the area and percentage of each feature change.

1990	2024	Area (m^2)	Percent (%)
Urban	Urban	33,575,400	5.89
Urban	Water	3,141,900	0.55
Urban	Vegetation	13,386,600	2.35
Urban	Wetland	10,754,100	1.89
Vegetation	Urban	140,293,800	24.59
Vegetation	Water	0	0.00
Vegetation	Vegetation	43,420,500	7.61
Vegetation	Wetland	1,284,300	0.23
Water	Urban	8,091,000	1.42
Water	Water	134,564,400	23.59
Water	Vegetation	5,565,600	0.98
Water	Wetland	49,500	0.01
Wetland	Urban	47,861,100	8.39
Wetland	Water	111,600	0.02
Wetland	Vegetation	90,876,600	15.93
Wetland	Wetland	37,457,100	6.57

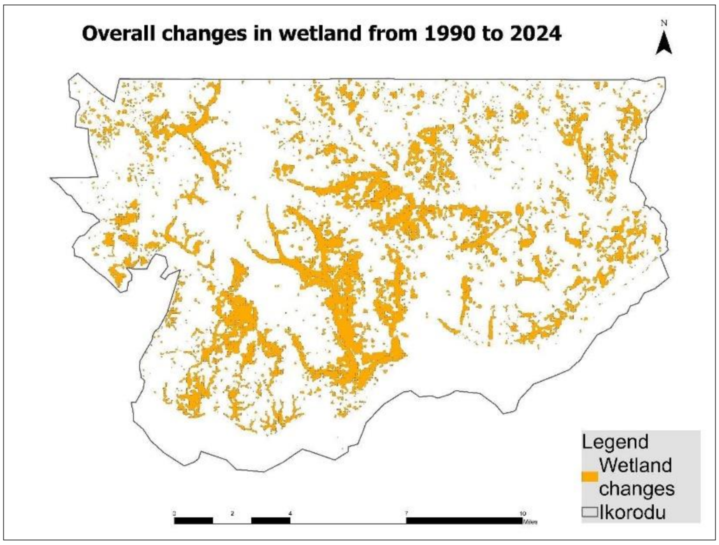


Fig 4: The overall wetland changes between 1990 and 2024. The extent reveals areas that were identified as wetlands in 1990 but are no more wetlands in 2024. This summarizes the changes across the entire 34-year interval.

4.4 Impact analysis

Zonal Statistics as a Table was employed in ArcGIS Pro to quantify the relationship between land cover classes and ancillary datasets, specifically DEM and population density.

The impact analysis in Table 6 reveals a consistent decline in the average elevation of wetland areas alongside a notable increase in population density from 2000 to 2013 (Oseni *et al*.,2020; Ju & Bohrer, 2022; Yager *et al*., 2024) [24, 12]. The mean DEM value for wetlands decreased from 18.5m in 2005 to 9,9m in 2012 and 10m in 2014. This suggests either a physical lowering of wetland terrain, potentially due to erosion, subsidence, or drainage, or a spatial shift of wetlands into slightly lower-lying areas over time. Simultaneously, population density rose from 387 to 912 people per square km, a 57.6% increase over a decade. Since the most recent data for DEM was from 2014, comparing it with the classified image of 2024 might be a bit of an overstretch, as shown by the 9.2m result (Table 6). Similarly, the most recent population density available was for 2020, and the reduction could be attributed to COVID. However, the impact analysis (Table 6) implies that the growing population pressure likely intensified the demand for land and resources, contributing to encroachment on wetland ecosystems.

Table 6: Showing the impact analysis between the classified images and the ancillary data. The impact analysis shows the relationship between the classified map each year and the corresponding ancillary data.

Year	Land Cover	Mean DEM (m)	Mean Population Density (people/km²)
2000	Wetlands	18.506 (2005)	387.151
2013	Wetlands	9.941 (2012), 10.067 (2014)	912.197
2024	Wetlands	9.228 (2014)	880.370 (2020)
2000	Vegetation	19.066 (2005)	1,179.576
2013	Vegetation	22.093 (2012), 21.537 (2014)	1,155.409
2024	Vegetation	16.462 (2014)	1,443.638 (2020)
2000	Urban	19.199 (2005)	2,358.845
2013	Urban	19.435 (2012), 19.294 (2014)	2,285.597
2024	Urban	22.144 (2014)	2,606.112 (2020)
2000	Water	0.005 (2005)	543.090
2013	Water	0.022 (2012), 0.004 (2014)	422.184
2024	Water	0.007 (2014)	616.808 (2020)

5. Discussion

The findings of this study align with several previous works highlighting wetland decline due to anthropogenic pressures (UN-Habitat, 2010; Seifolddini & Mansourian, 2014; Zhou *et al*., 2018; Ogunlade & Oluwole, 2022) [29, 22]. The classified land cover maps (Figure 3) revealed a clear reduction in wetland areas between 1990 and 2024, consistent with global trends reported by Davidson (2014) [5] and Seto *et al*. (2010) [30], who documented widespread wetland loss driven by urban expansion and agricultural encroachment. The confusion matrix results (Table 4) demonstrated high classification accuracy, with overall accuracies exceeding 85% and kappa coefficients indicating strong agreement (Foody, 2020) [9]. This validates the effectiveness of the MLC method applied in ENVI (Nv5, 2024; Richards & Jia, 1999) [28]. Thematic change detection analysis (Table 5) further confirmed that a significant proportion of wetlands were converted into built-up and farmland classes over time (Dekolo & Olayinka, 2015; Adedire & Adegbile, 2018; Aigbokhan, 2019; Oyedepo & Oluyege, 2024) [1, 25]. It seems that increasing demand from urbanization on wetlands led to the detour of vegetation (Aigbokhan, 2019) [1]. Furthermore, the Integration of DEM and population density (ancillary datasets), provided insight into the topographical and demographic drivers (Table 6) of these changes to wetland conservation (Oseni *et al*., 2020; Ju & Bohrer, 2022) [24, 12]. This was highlighted in the impact analysis from Zonal statistics, which revealed that wetland areas with lower elevation and increasing population densities experienced the highest rates of conversion (Table 12), corroborating findings by Asselen *et al*. (2013) [2] on wetland vulnerability in densely populated lowland areas. The vulnerability also presents natural disasters like flooding (Pricope & Shiver, 2022) [27]. This spatial correlation underscores the importance of incorporating both physical and socioeconomic variables when evaluating environmental change.

6. Limitations and Recommendations

This study faced several limitations, primarily stemming from data resolution and availability. The use of Landsat imagery with a 30-meter spatial resolution limited the ability to detect fine-scale wetland features, especially in heterogeneous landscapes. The 2000 image was particularly pixelated despite having a cloud cover of 7%. This impeded the accurate generation of ROIs and classification accuracy. Additionally, the absence of recent DEM and population density data constrained the analysis of topographic and demographic impacts. Future studies should incorporate higher-resolution satellite imagery, such as Sentinel-2 or commercial datasets, to improve classification detail. These improvements would support more effective wetland conservation strategies and monitoring frameworks for future studies.

7. Conclusion

Urbanization in Ikorodu (as in most parts of the world) is massive; this growing population pressure likely intensified the demand for land and resources, contributing to encroachment in wetland ecosystems. The inverse relationship between ancillary data implies that wetlands may be increasingly confined to more marginal, lower-elevation areas as urban and agricultural expansion takes precedence in more accessible zones. These insights underscore the need for integrated wetland management and policy interventions that balance land use with priority conservation.

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