WETLAND MAPPING, LAND MANAGEMENT

Wetland Conversion Dynamics in Port Harcourt Metropolis, Rivers State, Using Support Vector Machine Classification and Selected Spectral Indices

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Abstract

Wetland ecosystems provide essential ecological functions and natural services that contribute to biodiversity conservation, environmental sustainability, and socioeconomic well-being. However, rapid urbanisation and infrastructural development in Rivers State, Nigeria, have placed increasing pressure on wetland ecosystems, creating a need for reliable methods of wetland mapping and monitoring. This study assessed wetland extent across three temporal epochs, 1986, 2006, and 2026, using Support Vector Machine (SVM) classification and satellite-derived spectral indices. Landsat imagery obtained from the United States Geological Survey (USGS) archive, comprising Landsat 5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+), and Landsat 9 Operational Land Imager (OLI), was used to classify the study area into six land use/land cover classes: built-up area, bare earth, vegetation, water body, mangrove, and Nypa palm. The Enhanced Vegetation Index (EVI) and Automated Water Extraction Index (AWEI) were derived for the three epochs and compared with the Normalized Difference Vegetation Index (NDVI) and Normalized Difference Water Index (NDWI) to support wetland identification and assessment. Field observations and elevation data, using a threshold of ≤25 m above mean sea level, provided supplementary information for interpreting wetland distribution. The study area covered approximately 335.524 km^2, and the results indicated that wetland extent declined from 26.87 km^2 in 1986 to 7.75 km^2 in 2026, representing a reduction of approximately 19.11 km^2 (71.1%). The findings demonstrate substantial changes in wetland extent over the 40-year study period and highlight the value of integrating supervised classification, spectral indices, and supporting geographical information for multi-temporal wetland assessment. The study recommends continued satellite-based wetland monitoring to support conservation planning and sustainable environmental management in Rivers State, Nigeria.

Keywords: Wetland extent; Support Vector Machine; spectral indices; EVI; AWEI; NDVI; NDWI; Landsat imagery; Rivers State

1 Introduction

Wetland ecosystems provide essential ecological services that support biodiversity conservation, climate regulation, water quality maintenance, and socioeconomic well-being. They contribute to livelihoods through fisheries, agriculture, and other ecosystem-related resources, making their sustainable management critical to environmental protection and regional development [1]. However, the conversion and mismanagement of wetlands can increase environmental risks, including flooding and carbon emissions, thereby undermining sustainable development [2, 3]. The Ramsar Convention consequently promotes the conservation and wise use of wetlands as an integral component of sustainable development [4].

Port Harcourt Metropolis, comprising Port Harcourt and Obio-Akpor Local Government Areas in Rivers State, Nigeria, contains inland and coastal wetlands that are increasingly exposed to urbanisation, real estate development, and infrastructure expansion. These activities can transform wetlands into built-up areas and other land uses, potentially affecting ecological functions, environmental quality, and the livelihoods of surrounding communities [5]. Understanding the extent and patterns of wetland conversion is therefore necessary for effective land administration, environmental planning, and wetland conservation.

Remote sensing and Geographic Information Systems (GIS) provide valuable approaches for monitoring wetland changes over time. Satellite imagery enables the identification and mapping of land-cover features across different periods, while spectral indices help distinguish vegetation and water characteristics associated with wetland environments [3, 4]. The Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) are used to assess vegetation characteristics, whereas the Normalized Difference Water Index (NDWI) and Automated Water Extraction Index (AWEI) support the identification of water-related features. Their complementary information can assist wetland delineation and the interpretation of temporal changes in vegetation and surface-water conditions [6].

Support Vector Machine (SVM) classification offers a supervised approach for distinguishing land use/land cover classes from satellite imagery. When integrated with multi-temporal spectral indices, SVM classification can support the mapping of wetland extent and the assessment of changes across different periods. Comparing classified imagery and spectral indices for 1986, 2006, and 2026 provides a basis for quantifying wetland area changes and investigating the spatial patterns of conversion in Port Harcourt Metropolis.

Despite the ecological and socioeconomic importance of wetlands, reliable information on their long-term spatial dynamics remains essential for informed conservation and land-use decisions. This study therefore assesses wetland conversion dynamics in Port Harcourt Metropolis using multi-temporal satellite imagery, Support Vector Machine classification, and selected spectral indices. The findings are expected to provide geospatial evidence to support wetland monitoring, sustainable land administration, and environmental management in Rivers State, Nigeria.

2 Aim and objectives of the study

The aim of this study is to determine wetland size and conversion dynamics in Port Harcourt Metropolis, Rivers State, Nigeria, between 1986 and 2026 using Support Vector Machine (SVM) classification of multi-temporal satellite imagery and selected spectral indices. To achieve this aim, the study seeks to determine the spatial extent and distribution of wetlands for the years 1986, 2006, and 2026 using SVM classification; derive and analyze the Enhanced Vegetation Index (EVI) and Automated Water Extraction Index (AWEI) for the three epochs; and compare the performance of EVI and AWEI in relation to the Normalized Difference Vegetation Index (NDVI) and Normalized Difference Water Index (NDWI) for wetland identification and mapping. The findings are expected to provide geospatial information on changes in wetland extent and support improved wetland monitoring, conservation, and sustainable land-use planning in the study area.

3 Study area

The study area comprises Port Harcourt and Obio-Akpor Local Government Areas (LGAs) in Rivers State, located in the Niger Delta region of southern Nigeria. Rivers State was created on 27 May 1967 and now has 37 LGAs, with Port Harcourt serving as its capital. The state lies approximately between latitudes 4°35′N and 5°10′N and longitudes 6°55′E and 7°55′E. Port Harcourt LGA constitutes the urban core of the state and is an important commercial, administrative, port, and industrial center. Its development has historically been associated with maritime trade, railway transportation, and the petroleum industry [7]. On the other hand, Obio-Akpor LGA, established on 3 May 1989, covers approximately 260 km^2 and has experienced considerable urban and infrastructural development [8].

The physical environment is characterized by a network of rivers, creeks, and wetlands associated with the Niger Delta coastal ecosystem.

The population engages in diverse economic activities, including trading, civil service, fishing, and farming, alongside petroleum-related industries and other commercial enterprises. However, increasing urbanization, real estate development, and infrastructure expansion place pressure on the wetland ecosystems. These environmental characteristics and development pressures make Port Harcourt and Obio-Akpor LGAs suitable for investigating wetland extent and conversion dynamics using multi-temporal satellite imagery, Support Vector Machine classification, and selected spectral indices. The study area is shown in Figure 1.

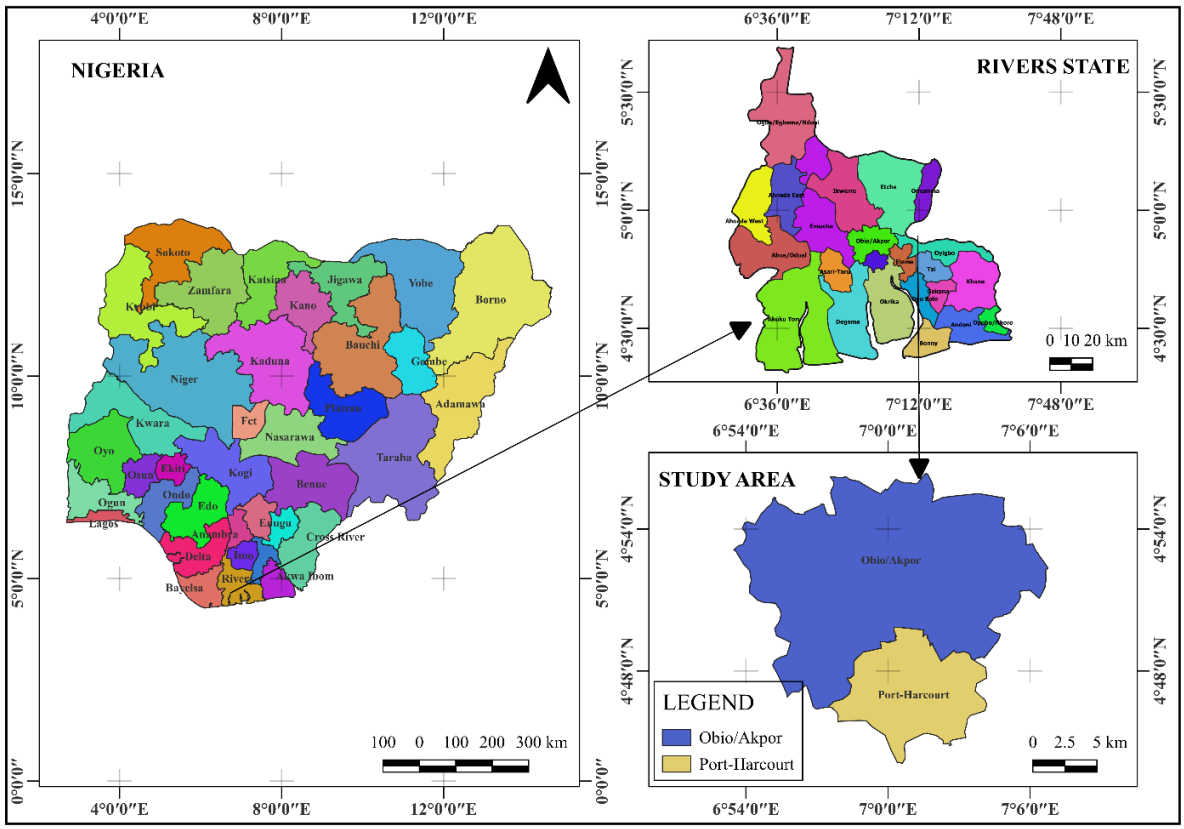


Figure 1. Map of the study area.

Figure 1: Map of Study Area

4 Materials and methods

4.1 System requirements

- ESRI ArcGIS 10.3 for clipping of the images and map compilation;
- QGIS 3.34.9 and Google Earth Engine (GEE) for image processing;
- a laptop computer with an Intel® Core™2 Duo P9700 processor, 4.00 GB RAM and a 64-bit operating system;
- Python for analysis of the results; and
- Microsoft Excel for data compilation and tabular presentation.

4.2 Data sources

Primary and secondary data sources were employed in this study. The data sets used were:

- Landsat 5 Thematic Mapper (TM);
- Landsat 7 Enhanced Thematic Mapper Plus (ETM+);
- Landsat 8/9 Operational Land Imager (OLI/TIRS) Level-2 surface reflectance (L2SP);
- ground coordinates of training sample locations and result validation; and
- qualitative data from observation.

4.3 Data manipulation and pre-processing

The blue, green, red, Near Infra-Red (NIR) and Shortwave Infrared (SWIR) bands were combined. In delineating wetland areas, it is important that the various bands of the acquired imagery are combined. This is simply because the objects in the environment have different spectral reflectance that are visible in either of the bands in the visible region of the electromagnetic spectrum [2]. The color composite of the study area was performed from the raster processing tool by adding the bands.

Radiometric correction was done to remove the distortions in satellite image pixel values (Digital Numbers, DN) caused by sensor characteristics, atmospheric conditions, and solar illumination. The raw brightness values were converted into more accurate surface reflectance measurements, ensuring consistency and comparability of satellite images across different dates, sensors, and locations.

The images were clipped to define the boundary that covers the Area of Interest (AoI). The image was added to the GIS software as a raster layer. A vector layer was then created that defined the clipped boundary, using the 'Clip Raster by Mask Layer tool'. This ensured that the image and layer were on the same spatial reference system (SRS), eliminating the introduction of unwanted data in the results [2].

4.4 Data processing

The data processing for this research was done in GEE platform where the various algorithms for the spectral indices were adopted to compute the values for NDVI, NDWI, EVI and AWEI combining multi-spectral sensors for the three epochs.

4.4.1 Normalized Difference Vegetation Index (NDVI)

This index is a measure of healthy, green vegetation. The combination of its normalised difference formulation and use of the highest absorption and reflectance regions of chlorophyll makes it robust

over a wide range of conditions. It can, however, saturate in dense vegetation conditions. The NDVI model used to validate EVI is given in Equation (1):

$$NDVI = \frac{NIR - Red}{NIR + Red} \quad (1)$$

where Red represents the value for Band 4 in Landsat 9 and Band 3 for Landsat 7, and

and NIR represents Band 5 in Landsat 9 and Band 4 in Landsat 7.

The value of this index ranges from −1 to 1. The common range for green vegetation is 0.2 to 0.8 [9, 10].

4.4.2 Normalized Difference Water Index (NDWI)

$$NDWI = \frac{Green - NIR}{Green + NIR} \quad (2)$$

where Green represents the value for Band 3 in Landsat 9 and Band 2 for Landsat 7, and

and NIR represents Band 5 in Landsat 9 and Band 4 in Landsat 7.

The value of this index ranges from −1 to 1. The common range for green vegetation is −0.1 to 0.4 [11].

4.4.3 Enhanced Vegetation Index (EVI)

The EVI was calculated using Equations (3)–(5). Mathematically, the EVI is expressed as:

$$EVI = G \cdot \frac{NIR - Red}{NIR + C_1 Red - C_2 Blue + L} \quad (3)$$

where G is the gain factor (2.5), NIR is the near-infrared reflectance value, R is the red band reflectance value, B is the blue band reflectance value, L is the canopy background adjustment (1) and C_1 and C_2 are the coefficients for atmospheric resistance (C_1 = 6 and C_2 = 7.5).

Therefore, for the satellite imagery used, the EVI for Landsat 8/9 is given by Equation (4), where Band 5 = NIR, Band 4 = Red and Band 2 = Blue:

$$EVI = 2.5 \times \frac{Band5 - Band4}{Band5 + 6 \times Band4 - 7.5 \times Band2 + 1} \quad (4)$$

For Landsat 4–7, the EVI is given by Equation (5), where Band 4 = NIR, Band 3 = Red and Band 2 = Blue:

$$EVI = 2.5 \times \frac{Band4 - Band3}{Band4 + 6 \times Band3 - 7.5 \times Band2 + 1} \quad (5)$$

4.4.4 Automated Water Extraction Index (AWEI)

The water extraction index was obtained using the formula of Mustafa et al. (2017) and Khalid et al. [6]:

$$AWEI = 4 \times (\rho_{Green} - \rho_{SWIR1}) - (0.25 \times \rho_{NIR} + 2.75 \times \rho_{SWIR2}) \quad (6)$$

The AWEI enhanced the land cover classification accuracy into binary water and non-water by utilizing multiple bands, blue, green, NIR, SWIR1 and SWIR2, and stabilizing the threshold from 0 while distinguishing water and non-water pixels. This ensured that the accuracy in classification was improved as shadow pixels were eliminated using Equation (6).

4.5 Analysis of the spectral indices

The values of the spectral indices EVI and AWEI were statistically analysed using the Pearson correlation model given by Equation (7):

$$r = \frac{\sum (EVI - \overline{EVI})(AWEI - \overline{AWEI})}{\sqrt{\sum (EVI - \overline{EVI})^2 \sum (AWEI - \overline{AWEI})^2}} \quad (7)$$

The values for the model were extracted for sample points within Port Harcourt Urban and substituted into the model to generate the correlation for the spectral indices using Python.

4.6 Wetland delineation criteria

Wetlands can be delineated where hydric soils, hydrophytic vegetation and low elevation are confirmed to be the characteristics in that area. In the delineation process, it is therefore required that at least three of the following criteria must be met:

- the NDWI or EVI values are high or moderate;
- a moderate vegetation index (MNDVI) relating to wetland vegetation;
- low elevation relating to the average data obtained from the SRTM Digital Elevation Model (DEM);
- field evidence of hydric soils and hydrophytic vegetation; and
- proximity to river networks.

Areas that satisfied three criteria were classified as wetland within the study area using the following threshold:

(("1986_LULC@1" = 3 OR "1986_LULC@1" = 5 OR "1986_LULC@1" = 6))

Wetland areas were delineated by integrating Land Use/Land Cover classes associated with wetland ecosystems with a digital elevation model (DEM) restricting wetland occurrence to areas ≤ 25m above mean sea level. This is because wetland ecosystems are not all water bodies or vegetation, but they are areas with low elevation, water and vegetation.

5 Results and discussion

5.1 Results of wetland size from SVM feature classification

Table 1, Table 2 and Table 3 show the classification results using the SVM for 1986, 2006 and 2026, and the classified maps are shown in Figure 2. Six classes were defined in this study, as shown in the tables. These show the results for the wetland area for the epochs.

Table 1. SVM distribution summary for 1986.

Class	Value	Pixel count	Area (m^2)	Area (km^2)	Area (%)	Area GEE (km^2)
Built-up	1	56,644	50,979,600	50.979	15.194	68.729
Bare earth	2	709	638,100	0.638	0.190	1.115
Vegetation	3	275,649	248,084,100	248.084	73.939	226.926
Water body	4	9,949	8,954,100	8.954	2.669	9.626
Mangrove	5	24,160	21,744,000	21.744	6.481	23.257

Class	Value	Pixel count	Area (m^2)	Area (km^2)	Area (%)	Area GEE (km^2)
Nypa palm	6	5,693	5,123,700	5.124	1.527	7.574
Total	–	372,804	335,523,600	335.524	100.00	337.227

Source: Author, 2026.

Table 2. SVM distribution summary for 2006.

Class	Value	Pixel count	Area (m^2)	Area (km^2)	Area (%)	Area GEE (km^2)
Built-up	1	158,774	142,896,600	142.897	42.589	101.399
Bare earth	2	1,637	1,473,300	1.473	0.439	3.194
Vegetation	3	187,762	168,985,800	168.986	50.365	109.169
Water body	4	9,765	8,788,500	8.789	2.619	7.065
Mangrove	5	9,563	8,606,700	8.607	2.565	5.218
Nypa palm	6	5,303	4,772,700	4.773	1.423	14.359
Total	–	372,804	335,523,600	335.524	100.00	240.404

Source: Author, 2026.

Table 3. SVM distribution summary for 2026.

Class	Value	Pixel count	Area (m^2)	Area (km^2)	Area (%)	Area GEE (km^2)
Built-up	1	250,385	225,346,500	225.347	67.163	225.347
Bare earth	2	1,603	1,442,700	1.443	0.430	1.443
Vegetation	3	93,251	83,925,900	83.926	25.013	83.926
Water body	4	18,949	17,054,100	17.054	5.083	17.054
Mangrove	5	2,930	2,637,000	2.637	0.786	2.637
Nypa palm	6	5,686	5,117,400	5.117	1.525	5.117
Total	–	372,804	335,523,600	335.524	100.00	335.524

Source: Author, 2026.

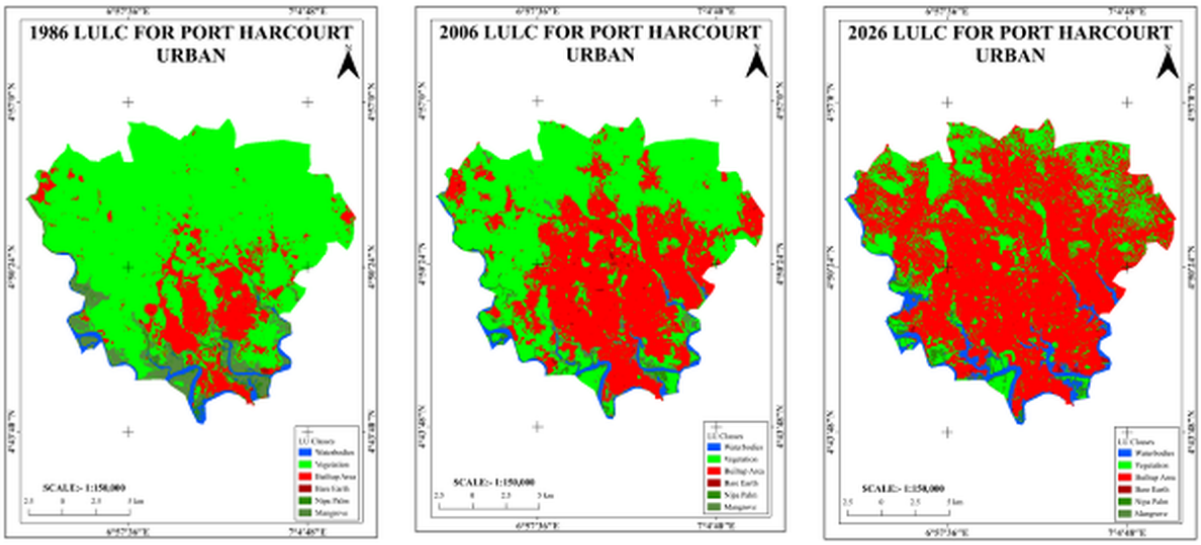


Figure 2. LU/LC maps for (a) 1986, (b) 2006 and (c) 2026.

5.2 Results of EVI and AWEI spectral indices

The EVI and AWEI maps for the three epochs are shown in Figures 3 and 4, and the resulting wetland and non-wetland maps in Figure 5.

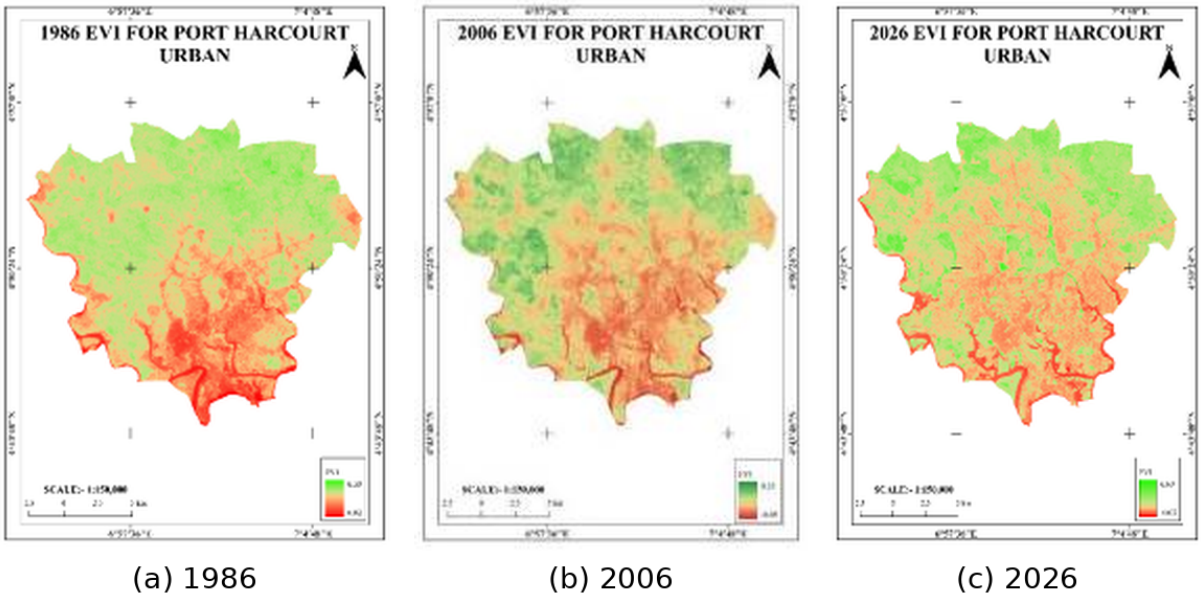
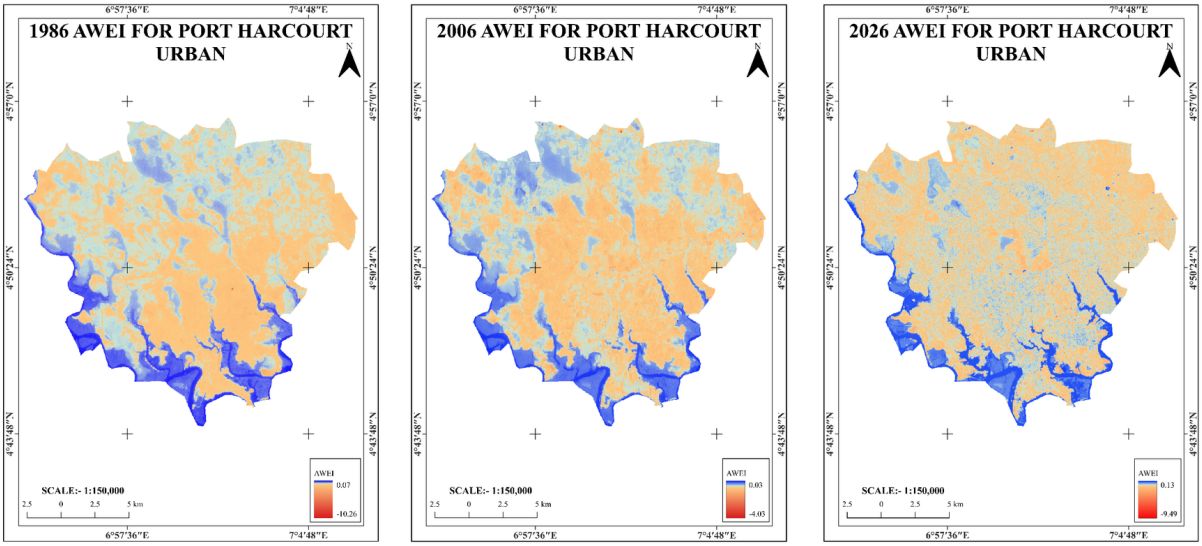
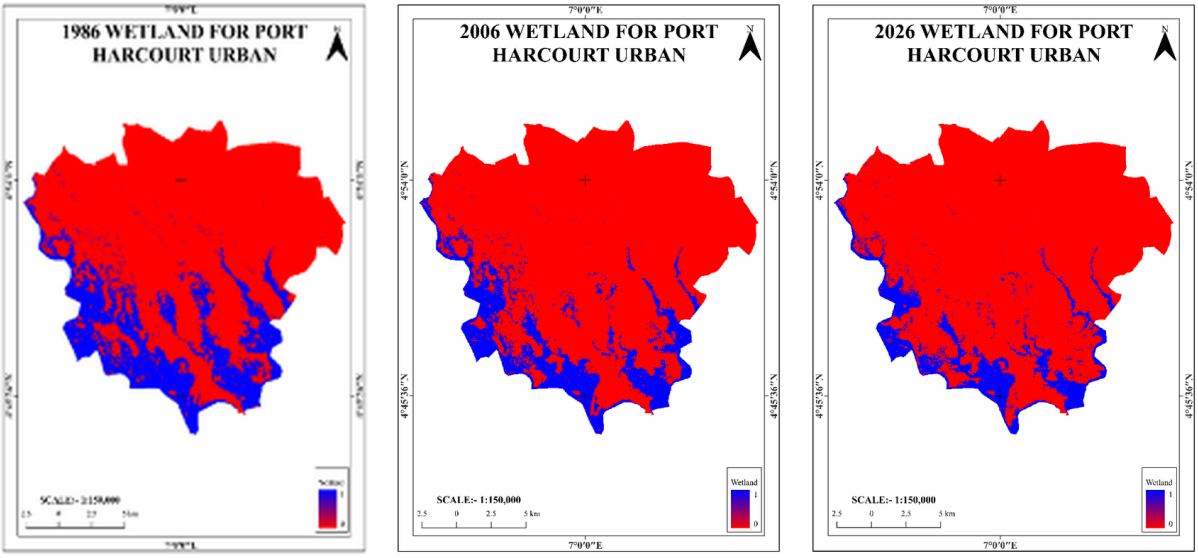


Figure 3. EVI maps for (a) 1986, (b) 2006 and (c) 2026.



(a) 1986 (b) 2006 (c) 2026

Figure 4. AWEI maps for (a) 1986, (b) 2006 and (c) 2026.



(a) 1986 (b) 2006 (c) 2026

Figure 5. Wetland and non-wetland maps for (a) 1986, (b) 2006 and (c) 2026.

Table 4 shows the size of the wetlands derived from the results of the EVI and AWEI using an SRTM elevation of ≤25 m above MSL for the three epochs, 1986, 2006 and 2026, for the study area. This demonstrates the effectiveness of EVI and AWEI in the delineation of wetlands in relation to the SVM LULC classification approach.

Table 4. Wetland areas per epoch from EVI and AWEI.

Year	Wetland area (m^2)	Non-wetland area (m^2)	Wetland pixels	Non-wetland pixels	Change in wetland vs previous epoch (%)
1986	72,035,100	262,999,800	80,039	292,222	–
2006	51,671,700	283,363,200	57,413	314,848	−28.27
2026	38,015,100	297,019,800	42,239	330,022	−26.43 (−47.23 vs 1986)

Source: Author, 2026.

5.3 Comparison of EVI and AWEI with NDVI and NDWI

Table 5, Table 6 and Table 7 show the spectral reflectance values for EVI and AWEI and their comparison with the NDVI and NDWI for the epochs under study.

Table 5. EVI and NDVI comparison, 1986–2026.

Epoch	NDVI (min.)	NDVI (max.)	EVI (min.)	EVI (max.)
1986	0.01	0.20	0.02	0.38
2006	−0.20	0.20	−0.05	0.23
2026	−0.04	0.45	−0.05	0.69

Source: Author, 2026.

Table 6. NDWI and AWEI comparison, 1986–2026.

Epoch	NDWI (min.)	NDWI (max.)	AWEI (min.)	AWEI (max.)
1986	−0.20	0.001	−10.26	0.07
2006	−0.30	0.20	−4.03	0.03
2026	−0.41	0.05	−9.49	0.13

Source: Author, 2026.

Table 7. Comparison of minimum spectral values, 1986–2026.

Epoch	EVI (min.)	NDVI (min.)	AWEI (min.)	NDWI (min.)
1986	0.02	0.01	−10.26	−0.20
2006	−0.05	−0.20	−4.03	−0.30
2026	−0.05	−0.04	−9.49	−0.41

Source: Author, 2026.

Figure 6 shows the spectral reflectance range curve, demonstrating the basis for validation of the spectral reflectance results obtained from EVI and AWEI. Using the green vegetation ranges for NDVI of 0.2–0.8 and the NDWI range of −0.1 to 0.4 [9] as control indices, the strength and the direction of the linear relationship were validated. The Pearson correlation results are presented in Table 8 and Figure 7.

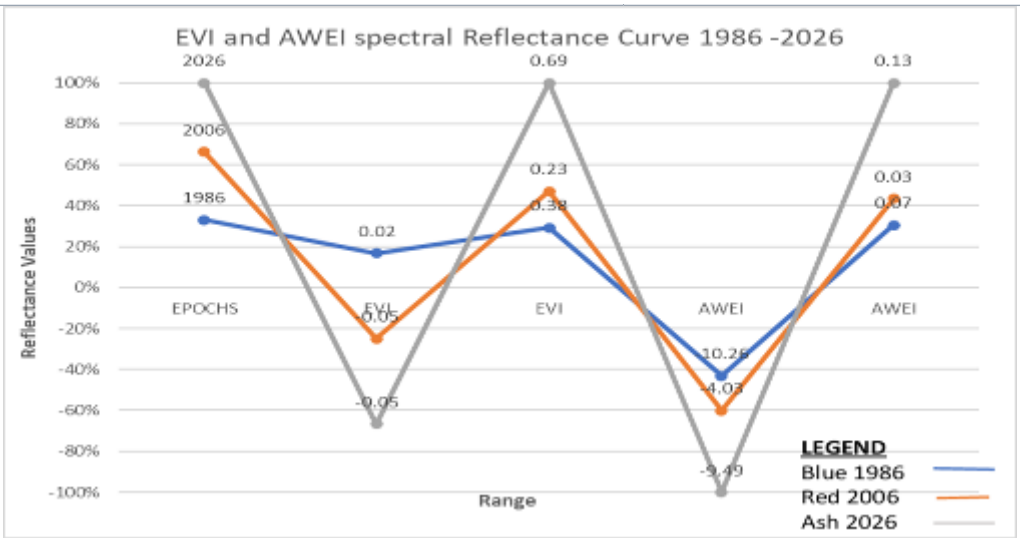


Figure 6. Spectral reflectance curve.

Table 8. Pearson correlation analysis results.

Epoch	Index 1	Index 2	*r*	R^2
1986	EVI	NDVI	0.9787	0.958
1986	NDWI	AWEI	0.6373	0.406
2006	EVI	NDVI	0.9929	0.986
2006	NDWI	AWEI	−0.076	0.006
2026	EVI	NDVI	0.9942	0.988
2026	NDWI	AWEI	0.544	0.296

Source: Author, 2026.

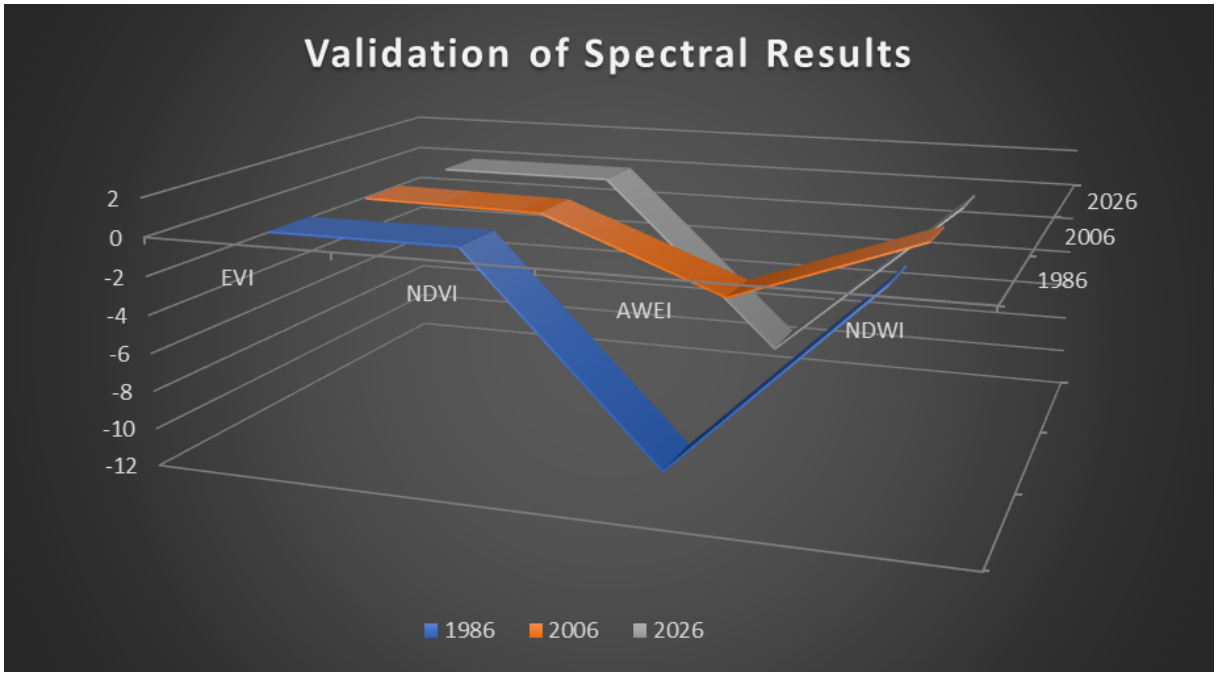


Figure 7. EVI and AWEI compared with NDVI and NDWI.

To further enhance the validation of the spectral indices, the Enhanced Vegetation Index (EVI) and Automated Water Extraction Index (AWEI) generated for each study epoch were validated using the Normalized Difference Vegetation Index (NDVI) and Normalized Difference Water Index (NDWI), respectively. All the indices were derived from the same cloud-masked Landsat imagery in Google Earth Engine (GEE) to ensure consistency in image acquisition, preprocessing, and spatial resolution. The validation comprised both qualitative and quantitative assessments.

The qualitative assessment involved visually comparing the spatial distribution, extent, and boundaries of vegetation and water bodies identified by EVI and AWEI with the corresponding NDVI and NDWI maps. This is shown in Figure 8, Figure 9, Figure 10 and Figure 11.

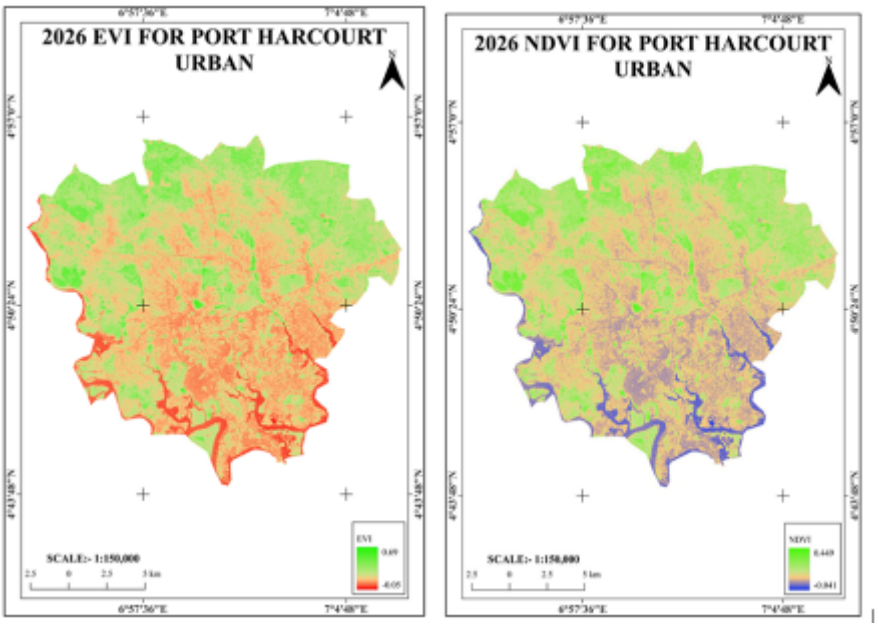


Figure 8. Visual comparison of 2026 vegetation indices.

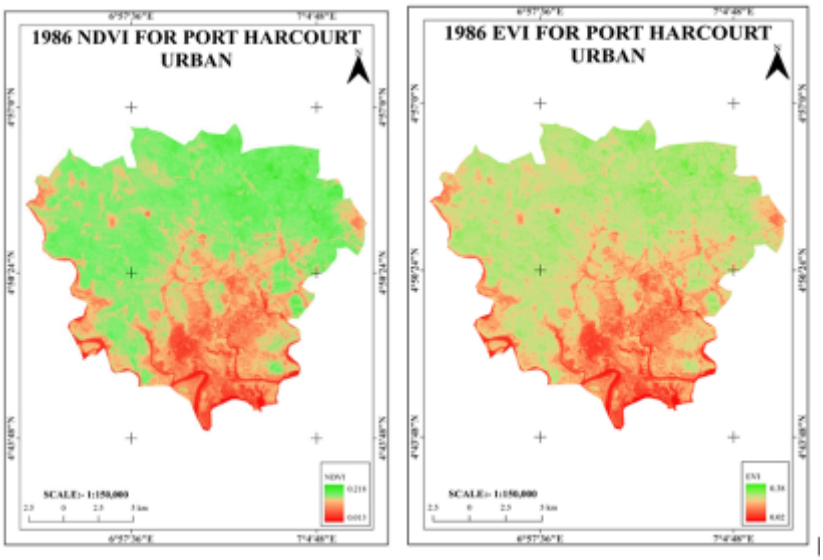


Figure 9. Visual comparison of 1986 vegetation indices.

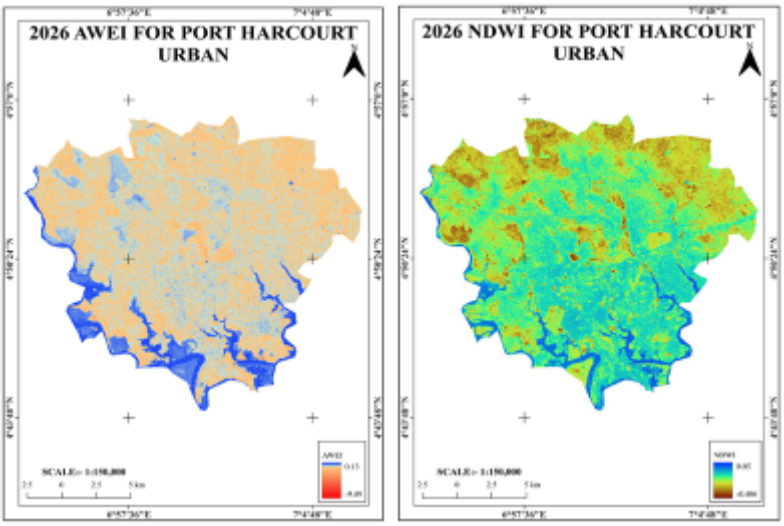


Figure 10. Visual comparison of 2026 water indices.

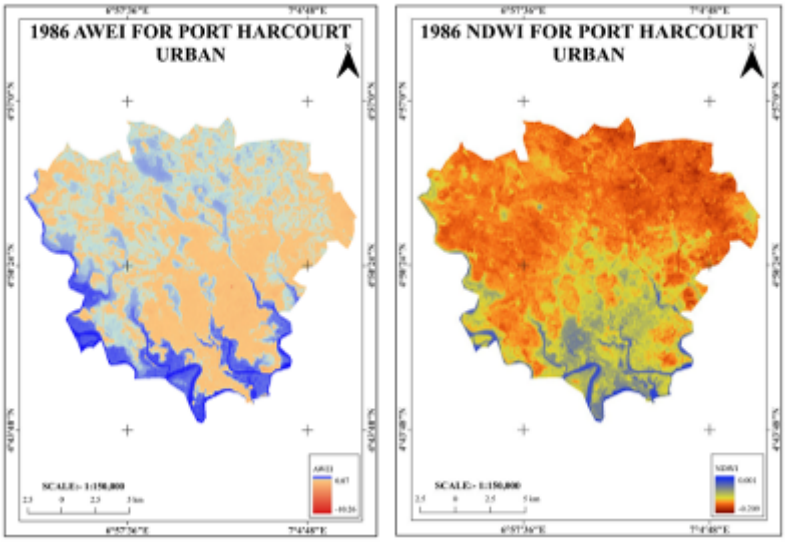


Figure 11. Visual comparison of 1986 water indices.

5.4 Discussion of the results

The wetland sizes as derived from the results of the SVM feature classification revealed the changes in wetland area due to the conversion of wetlands for other uses. From the SVM results for wetland size, the wetlands size has changed from 26.868 km^2 in 1986 to 7.754 km^2 in 2026.

In order to clearly define the features in wetland locations, this research classified Nypa palm and mangrove as wetlands. The values obtained for Nypa palm and mangrove together make up the size of wetlands in the study area.

The results reveal a huge conversion rate, pointing to the built-up feature classes having increasing values as shown in Figure 12. This means that the wetlands are converted for buildings. The management of land in the study area is critical because considering the rate of changes from wetland to built-up, it raises the signals that approvals for conversion are not being monitored, especially around natural ecosystems, in this case, wetlands.

This outcome corroborates the opinion of [5], who declared that despite the critical values of wetland ecosystems in enhancing ground water quality and controlling erosion, the wetlands were still depreciating in size. The results show that there is a continued decline in the size of wetlands and buttresses the need for immediate conservation efforts in order to resolve future challenges associated with wetland management.

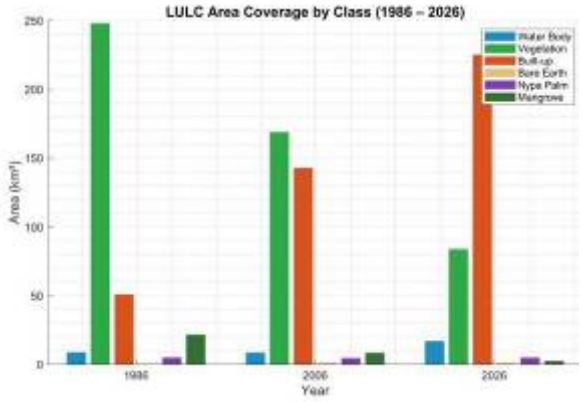


Figure 12. LULC area by class.

The spectral reflectance values obtained for the epochs under study resulted in the maps depicting wetland and non-wetland areas in the study area. The classified features were grouped into two major categories, wetland and non-wetland areas, using the binary coding 0 – non-wetland and 1 – wetland, as shown in Figure 5.

The generated spectral indices map at scale 1:50,000 revealed the spectral reflectance of vegetation and water throughout the study area; EVI showing the reflectance indices of the vegetation, and AWEI showing the reflectance of water. The values for EVI ranged from 0.02 to 0.38 in 1986; −0.05 to 0.23 in 2006 and −0.05 to 0.69 in 2026. The AWEI ranged from −10.26 to 0.07 in 1986; −4.03 to 0.03 in 2006 and −9.49 to 0.13 in 2026.

These values obtained from the process showed that EVI is at its minimum in 2026 compared to previous epochs studied, indicating a reduction in reflectance of vegetation. This therefore affirms that the vegetation health is declining as revealed in the LU/LC classification results.

The spectral indices results were also validated with known values of NDVI and NDWI for the same sample locations in Port Harcourt Urban, as graphically presented in Figures 8–11. The spectral reflectance correlation model adopting the Pearson correlation coefficient was generated. This statistical analysis model provided insights to the relationship of the spectral indices for vegetation and water within Port Harcourt Urban. The results established that there is a very strong relationship between the EVI and the NDVI as well as the AWEI and NDWI.

The EVI having strong correlation with the NDVI [12] and having ascertained from the correlation analyses done in this research makes it possible to use them interchangeably [12], even though NDVI is the most widely used vegetation index in mangrove research with 82% reviews already done as opined by Jin et al. (2018).

This approach demonstrated the dynamics of EVI, AWEI, NDVI and NDWI in quantifying wetland conversion dynamics and further builds on the necessity to obtain quick approvals, reduced costs, and curb further loss of valuable ecosystems by improving the mapping accuracies and optimizing restoration efforts [13].

6 Conclusion

This study assessed the spatial and temporal changes in wetland extent within the study area over a 40-year period (1986–2026), using Landsat 5 (TM), Landsat 7 (ETM+), and Landsat 9 (OLI) imagery. The Support Vector Machine (SVM) classification algorithm in Google Earth Engine (GEE) was employed to classify six land-cover categories: built-up areas, bare earth, vegetation, water bodies, mangroves, and Nypa palms.

The results demonstrated the effectiveness of EVI and AWEI in delineating wetlands and non-wetland areas, with patterns consistent with NDVI and NDWI results. The study revealed that wetlands covered 7.75 km^2 of the total study area of 335.52 km^2 in 2026. The findings provide essential baseline information for wetland monitoring, conservation, and sustainable management. Furthermore, they support the enforcement of environmental protection policies in line with SDGs 6, 11, 13, and 15, promoting natural resource sustainability, ecological preservation, and the protection of human livelihoods.

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References

[1] Waleed M, Sajjad M, Shazil MS, Tariq M, Alam MT. Machine learning-based spatial-temporal assessment and change transition analysis of wetlands: An application of Google Earth Engine in Sylhet, Bangladesh (1985–2022). *Ecol Inform*. 2023;75:102075. https://doi.org/10.1016/j.ecoinf.2023.102075

[2] Dienye A, Dagogo F, Pepple G. Monitoring wetland depletion (in Port Harcourt, Nigeria) using satellite remote sensing. In: *Proceedings of the Commonwealth Association of Surveying and Land Economy (CASLE) Conference*; 2018; Lusaka, Zambia. p. 173–186.

[3] Huang J, Hartemink AE. Soil and environmental issues in sandy soils. *Earth Sci Rev*. 2020;208:103295. https://doi.org/10.1016/j.earscirev.2020.103295

[4] Ramsar Convention. Wetlands and future change: Implications and opportunities with the Ramsar Convention. In: *Ramsar wetlands: Values, assessment, management.* 2018. p. 555–561. Available from: https://www.ramsar.org

[5] Tran TV, Reef R, Zhu X. A review of spectral indices for mangrove remote sensing. *Remote Sens*. 2022;14(19):4868. https://doi.org/10.3390/rs14194868

[6] Khalid HW, Khalil RMZ, Qureshi MA. Evaluating spectral indices for water bodies extraction in western Tibetan Plateau. *Egypt J Remote Sens Space Sci*. 2021;24(3):619–634. https://doi.org/10.1016/j.ejrs.2021.09.003

[7] Nnadozie V. *The establishment of Port Harcourt: A planned colonial city and its displaced inhabitants* [Internet]. My History Blog; 2025. Available from: www.myhistory.com.ng

[8] Amaefuna RO, Gobo AE, Ayotamuno A, Iyama W. Environmental impact of urbanization on land use compatibility and environmental quality in Port Harcourt, Rivers State. *Int J Agric Environ Bioresearch*. 2024;9(5):10–25. https://doi.org/10.35410/IJAEB.2024.5930

[9] Pettorelli N, Vik JO, Mysterud A, Gaillard JM, Tucker CJ, Stenseth NC. Using the satellite-derived NDVI to assess ecological responses to environmental change. *Trends Ecol Evol*. 2005;20(9):503–510. https://doi.org/10.1016/j.tree.2005.05.011

[10] Rouse JW, Haas RH, Schell JA, Deering DW. Monitoring vegetation systems in the Great Plains with ERTS. In: Third Earth Resources Technology Satellite-1 Symposium. Washington (DC): NASA; 1973. p. 309–317.

[11] Jackson TJ, Chen D, Cosh M, Li F, Anderson M, Walthall C, et al. Vegetation water content mapping using Landsat data derived normalized difference water index for corn and soybeans. *Remote Sens Environ*. 2004;92(4):475–482. https://doi.org/10.1016/j.rse.2003.10.021

[12] Lykhovyd P, Averchev O, Fedorchuk M, Fedorchuk V. The relationship between spatial vegetation indices: A case study for the south of Ukraine. *Environ Ecol Res*. 2023;11(5):740–746. https://doi.org/10.13189/eer.2023.110504

[13] Kayusi F, Chavula P. Enhancing wetland restoration through machine learning-based decision support systems. *LatIA*. 2023;1:81. https://doi.org/10.62486/latia202581

[14] Wali E, Kika HA, Gbuvboro AE, Daniel DN. Change detection on land use and land cover changes in the wetland ecosystem of the Niger Delta region. *J Res Environ Earth Sci*. 2025;11(7):81–92. https://doi.org/10.35629/2532-11078192

[15] Zedler JB, Kercher S. Wetland resources: Status, trends, ecosystem services, and restorability. *Annu Rev Environ Resour*. 2005;30:39–74. https://doi.org/10.1146/annurev.energy.30.050504.144248