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Monitoring Alterations in Mangrove Forests Near Devi Estuary, Odisha Using Remote Sensing and GIS Techniques

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ABSTRACT

Mangrove forests are ecologically and economically significant coastal ecosystems that provide shoreline protection, carbon storage and habitat for diverse species. The Devi Estuary, a distributary of the Mahanadi River in Odisha, represents an ecologically sensitive zone and an important nesting ground for Olive Ridley turtles, yet remains vulnerable to increasing anthropogenic pressure. This study assesses spatio-temporal changes in mangrove cover from 2021 to 2025 using multi-temporal Landsat 8 and Landsat 9 surface reflectance imagery (30 m resolution) integrated with GIS-based techniques. Vegetation indices (NDVI, EVI), supervised classification and post-classification change detection were employed to evaluate alterations in canopy health and extent, supported by ground-truthing surveys for accuracy assessment. Results indicate a measurable decline in mangrove cover, with a net loss of 2.31% over the study period, primarily associated with aquaculture expansion and settlement encroachment. Simultaneously, localized regeneration led to a gain of 16.41% relative to degraded patches, reflecting partial recovery. NDVI analysis revealed notable fluctuations between 2023 and 2024, suggesting sensitivity to both natural and anthropogenic drivers. Increasing patch fragmentation and reduced canopy connectivity highlight growing ecosystem vulnerability. The study provides a valuable baseline for long-term ecological monitoring and supports evidence-based management strategies for conserving mangrove forest in the Mahanadi delta under changing climatic and anthropogenic conditions.

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1. Introduction

Mangrove forests constitute one of the most productive and ecologically significant coastal ecosystems, supporting rich biodiversity, stabilizing shorelines, and sustaining coastal livelihoods (Dixon, 1989; Lucy, 2006; Sahu et al., 2015; Nedumaran and Elamvaluthi, 2020). Globally, these halophytic plant communities occupy intertidal zones of tropical and subtropical regions with a maximum extent between 25°N and 25°S latitude (Berlyn, 1986; Roy et al., 2019), where they act as natural buffers against storms, erosion and saline intrusion. India, recognized as one of the 17 megadiverse countries, hosts approximately 4,99,168 ha of mangroves, although they constitute only 0.15% of the national geographical area as per Forest Survey of India (Forest Survey of India (FSI), 2024). Along the east coast, the state of Odisha contains extensive mangrove tracts, particularly within the Mahanadi delta. While considerable attention has been given to the mangroves of Bhitarkanika, smaller estuarine systems such as the Brahmani, Baitarani, Budhabalanga and Devi remain relatively understudied despite their historical ecological significance.

The Devi Estuary, located in Jagatsinghpur district, represents a dynamic and sensitive coastal environment influenced by tidal influx, sediment deposition and monsoonal hydrology. In recent decades, the region has experienced increasing anthropogenic pressures, including aquaculture expansion, land-use change and coastal development, potentially altering mangrove vegetation structure and extent. Understanding these changes is essential for effective conservation, especially under the Coastal Regulation Zone (CRZ) framework and the ecological signif-

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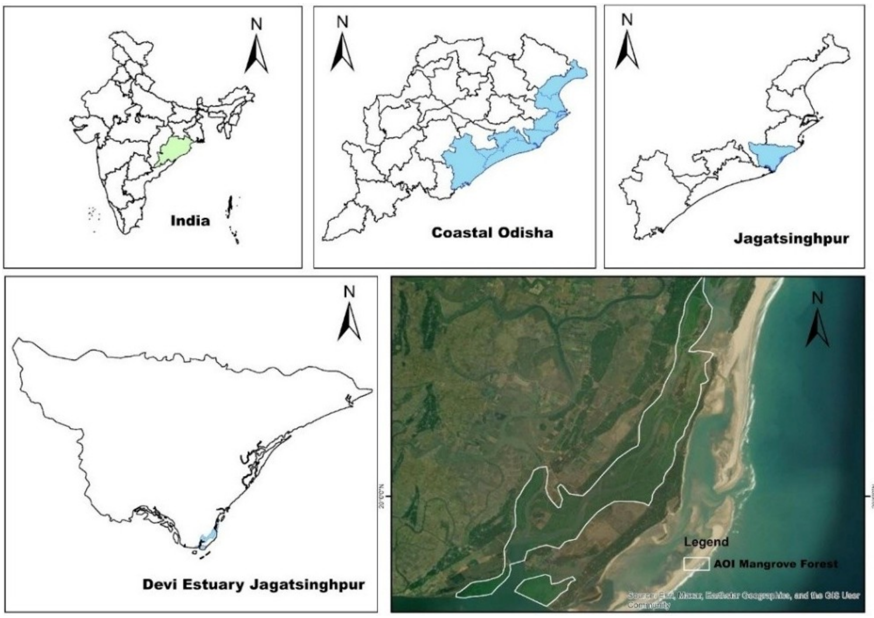

Fig. 1. Location Map of the Study Area.

icance of the estuary as an Olive Ridley turtle nesting zone.

Remote sensing and GIS offer efficient approaches for monitoring mangrove dynamics in areas with limited field accessibility (Dahdouh-Guebas et al., 2000; Nayak, 2002; Wang et al., 2003; Roy et al., 2019; Parida and Kumar, 2020; Anand et al., 2020; Maurya et al., 2021; Nayak and Mishra, 2023; Vasquez et al., 2024). Although several studies have examined mangroves along the Odisha coast, there remains a critical gap in high-resolution, short-term change detection specifically for the Devi Estuary. This study addresses this gap by analysing spatio-temporal changes in mangrove cover between 2021 and 2025 using multi-temporal satellite data and vegetation indices, providing insights essential for management and restoration planning.

2. Study Area

The State of Odisha in the east coast of India has a 575 km long coastline in 6 coastal districts (Balasore, Bhadrak, Kendrapara, Jagatsinghpur, Puri, and Ganjam) which has 257.51 km^2 of Mangrove cover (ISFR 2023) situated within the latitude 19º N–22º N and longitude 85º E–87º E (Mangrove Forest Division (Wildlife), 2015).The Mahanadi Delta alone occupies 120 sq kms of the state's entire mangrove area. However, the Mangrove ecosystems at the mouths of rivers like Brahmani, Baitarani, Budhabalanga and Devi were not taken into account, despite their historical abundance of lush mangrove forests. Devi river is a distributary of the Mahanadi river which forms an estuary named Devi estuary at Astaranga before draining into the Bay of Bengal and lies in between 19º 45'–19º 57' N latitude and 86º 04'–86º 20' E longitude in the Jagatsinghpur district of Odisha (Panda et al., 2010; Sahu et al., 2013; Sajina et al., 2025) (Fig. 1).

3. Methodology

The methodology combines multi-temporal satellite imagery, visual interpretation techniques and geospatial tools to analyze mangrove extent and transformation patterns at Devi Estuary, Odisha. Data from Google Earth Pro, Google Earth Engine (GEE), Arc Map 10.8.2 and Landsat-8 Satellite Imagery were used to identify, quantify and visualize changes in mangrove cover over the selected time periods i.e. 2021–25.

3.1. Satellite Data Acquisition

Multi-temporal satellite imagery was obtained to quantify annual vegetation dynamics in the study area for the periods 2021–2022, 2022–2023, 2023–2024 and 2024–2025 (Fig. 2). Landsat 8 OLI/TIRS and Landsat 9 OLI-2 surface reflectance products with the resolution of 30 meter were selected due to their radiometric stability, long-term temporal coverage and suitability for vegetation monitoring (Roy et al., 2014). Only imagery with less than 10% cloud

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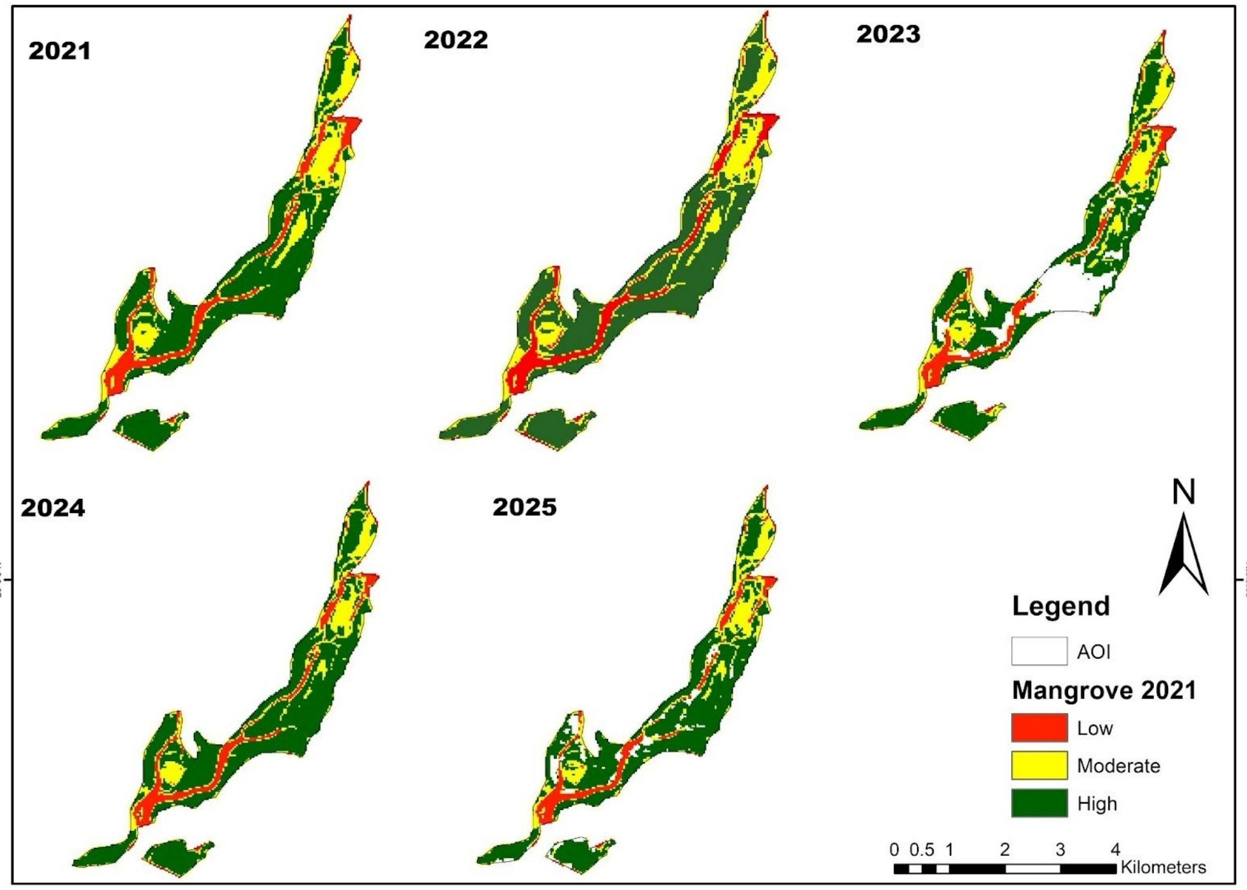

Fig. 2. Mangrove areas illustrated in Google Earth Pro in different years.

cover and captured within the same seasonal window each year was used to minimize phenological variation, following best practices recommended for ecological time-series analysis (Pettorelli et al., 2005). All imagery was sourced from the USGS Earth Explorer platform (Fig. 2).

3.2. Pre-processing of Satellite Images

The Landsat Level-2 products already include atmospheric correction using the Landsat Surface Reflectance Code (LaSRC), which removes atmospheric scattering and absorption effects based on aerosol and water-vapour models (Vermote et al., 2016). For conceptual clarity, surface reflectance (ρ) is expressed as:

$$\rho = \frac{\pi L_\lambda d^2}{ESUN_\lambda \cos\theta_s}$$

where,

L_λ= spectral radiance,

d = Earth–Sun distance,

$ESUN_\lambda$ = mean solar exo-atmospheric irradiance,

θ_s = solar zenith angle.

Clouds and shadows were removed using the Landsat QA band based on the Fmask rule-set (Zhu and Woodcock, 2012). All images were clipped to the study area boundary using the Area of Interest (AOI) shapefile to maintain spatial uniformity across years. These steps ensured that only atmospherically corrected and cloud-free reflectance values were used for spectral index computation, consistent with recommended preprocessing standards for change detection (Jensen, 2005).

3.3. Calculation of Area (km^2)

Since each Landsat pixel represents a 30 m × 30 m ground area, the area of vegetation change was estimated using:

$$Area_{pixel} = 30 \times 30 = 900 \text{ m}^2$$

Total area (m^2) within a given change class (C) was:

$$A_C = n_C \times 900$$

Where

n_C = number of pixels belonging to class C

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The converted area in square kilometres was obtained as:

$$A_{km^2} = \frac{A_C}{1,000,000}$$

All spatial analysis was performed in ArcGIS 10.8.2 and R using the packages **terra**, **raster**, **sf**, and **tidyverse**.

3.4. Supervised Classification Using Random Forest

To improve land cover discrimination and mangrove cover delineation, supervised classification was performed using the Random Forest (RF) algorithm, a widely used ensemble machine learning method known for its high classification accuracy and robustness to noise (Breiman, 2001). The RF classifier constructs multiple decision trees using bootstrap samples and aggregates their predictions through majority voting.

Training samples representing major land cover classes, including mangrove forest, water bodies, mudflats, other vegetation, and built-up areas, were collected through visual interpretation of high-resolution imagery and prior knowledge of the study area. Approximately 70% of the samples were used for training the model, while the remaining 30% were reserved for validation.

The RF model was implemented with 500 decision trees (ntree = 500), and the number of variables randomly selected at each split (mtry) was optimized automatically. These parameter settings are widely adopted in remote sensing classification studies to ensure model stability and accuracy. The key benefits of using random forest are efficient validation, reduction of variance well with moderate data size like satellite imagery. An accuracy assessment was done through confusion matrix.

The GIS generated map in the study area illustrating mangroves from 2021 serves as the baseline reference for the change detection analysis. Topology validation and ground truth mechanism are used to verify the data quality produced in ArcGIS. The change detection analysis has been conducted for five consecutive years i.e. 2021, 2022, 2023, 2024 & 2025. In case of inaccurate results, the above mentioned mechanism must be used to perform and validate the change detection analysis of the following years (Fig. 2).

3.5. Accuracy Assessment

Validation used a stratified random sampling approach with 70% training and 30% testing data. Main metrics derived from the confusion matrix and Kappa coefficient (k).

The Overall accuracy, Producer's Accuracy & User's Accuracy are identified by the following formula:

$$\text{Overall Accuracy (OA)} = \frac{\text{All Correct Classifications}}{\text{Total Samples}}$$

$$\text{Producer's Accuracy (PA)} = \frac{\text{Correctly Classified Mangroves}}{\text{Total Actual Mangroves}}$$

Measures how well real-world classes are correctly classified.

$$\text{User's Accuracy (UA)} = \frac{\text{Correctly Classified Mangroves}}{\text{Total Predicted Mangrove}}$$

It measures the reliability of classified pixels.

3.6. Kappa coefficient

In the Random Forest model, the Kappa coefficient measures how much better the model's predictions are than random guessing, after accounting for class imbalance.

The Kappa coefficient (κ) is calculated from the confusion (error) matrix using the following equation:

$$\kappa = \frac{P_o - P_e}{1 - P_e}$$

where P_o represents the observed agreement (Overall Accuracy) and is calculated as:

$$P_o = \frac{\sum_{i=1}^{r} n_{ii}}{N}$$

The expected agreement (P_e) is calculated as:

$$P_e = \frac{\sum_{i=1}^{r}(\ R_i \times C_i)}{N^2}$$

In these equations, n_{ii} is the number of correctly classified samples in class i (diagonal elements of the confusion matrix), R_i is the total number of reference samples in row i, C_i is the total number of classified samples in column i, N is the total number of validation samples, and r is the total number of land-cover classes.

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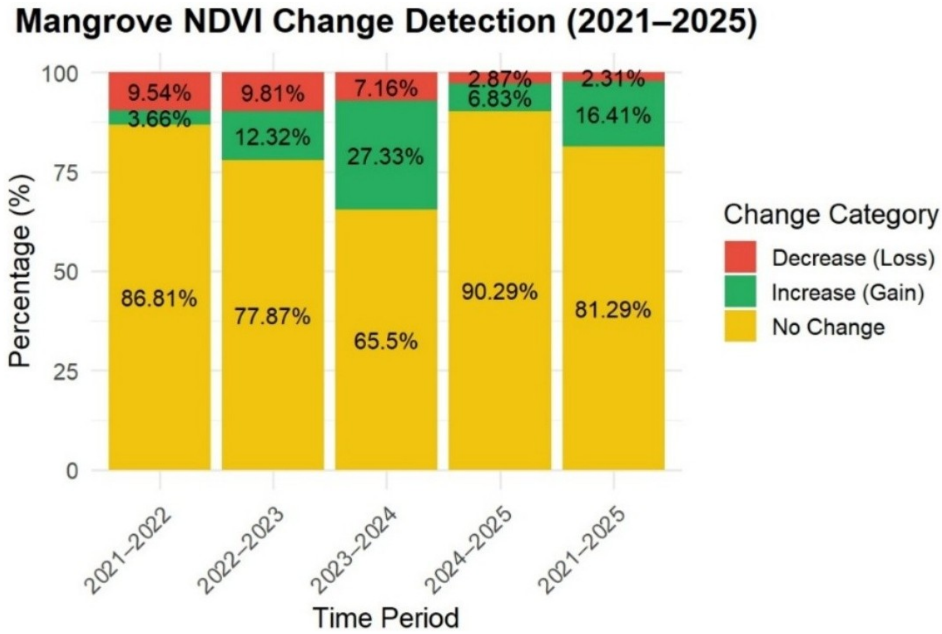

Fig. 3. NDVI Change Detection Analysis from 2021–2025.

4. Results

4.1. Spatio-Temporal Variations in Mangrove Cover Using Normalised Difference Vegetation Index (NDVI)

The Normalised Difference Vegetation Index (NDVI) was calculated from the Near-IR and Red bands of each scene as (NIR-Red) / (NIR+Red) and ranges in value from -1.0 to 1.0. This index has been used in various ecological studies to analyze the geographical trends of forest degradation and identify sudden shifts in ecosystems (Sakti et al., 2020; Vasquez et al., 2024). NDVI-based vegetation indices are used to identify changes in mangrove health and structure over time (Das and Dhorde, 2021).

From 2021 to 2025, mangrove vegetation exhibited noticeable temporal variations in growth and density, as indicated by the NDVI analysis shown in Fig. 3. High NDVI values greater than 0.6 indicate healthy and dense mangrove vegetation (Somani et al., 2024). The dominant type of vegetation during the whole study with high NDVI zones represents the stable and productive mangrove ecosystem. The NDVI data analysis results state that mangrove vegetation conditions are stable throughout the study period except the time period between 2023–2024 with significant change. Vegetation regeneration increased in 2023–2024 i.e. 27.33% and remarkable reduction in between 2022–2023 i.e. 9.81%.

The changes across the years might have been caused by various natural factors such as sediment deposition, sea level rise, hypersalinisation and acidification as well as anthropogenic factors like aquaculture, deforestation, human settlements etc. The mangrove forests show a strong adaptability to naturally recover these factors through regeneration and canopy growth.

4.2. Mangrove Classification Using the Random Forest Classifier

The total number of validation samples is $N = 500$ and the number of correctly classified samples is 462.

Overall Accuracy (OA)

$$\text{Overall Accuracy} = \frac{\text{Correctly classified pixels}}{\text{Total pixels}} \times 100 = \frac{462}{500} \times 100 = 92.4\%$$

Producer's Accuracy (PA)

Producer's accuracy measures how many actual mangrove pixels were correctly identified.

$$\text{PA} = \frac{228}{250} \times 100 = 91.2\%$$

User's Accuracy (UA)

User's accuracy measures how reliable the classified mangrove pixels are.

$$\text{UA} = \frac{228}{244} \times 100 = 93.4\%$$

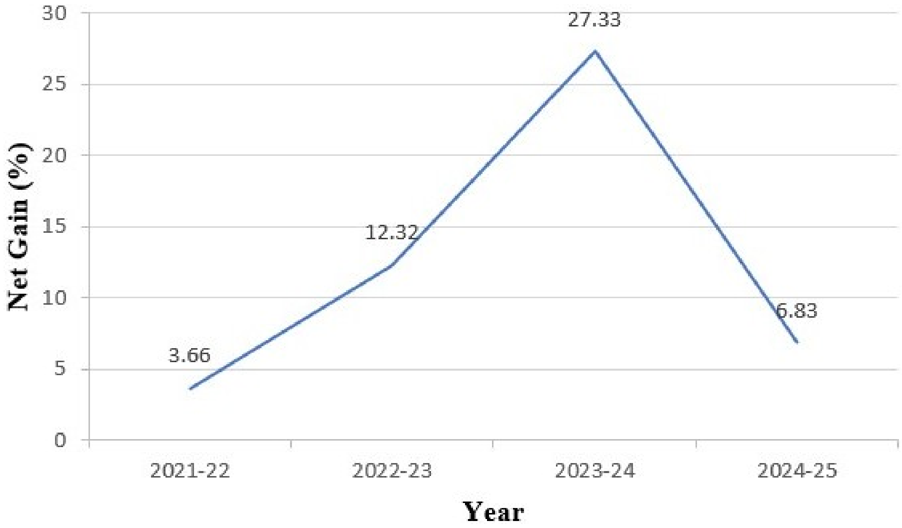

Fig. 4. Area of Increased Mangrove Cover along Devi Estuary, Odisha.

Kappa Coefficient (κ)

The Kappa coefficient is calculated as:

$$\kappa = \frac{0.924 - 0.309}{1 - 0.309} = \frac{0.615}{0.691} = 0.89$$

The classification accuracy of the Random Forest model was evaluated using a confusion matrix generated from independent validation samples. The classifier achieved an overall accuracy of 92.4% with a Kappa coefficient of 0.89, indicating excellent agreement between the classified map and the reference data. The producer's accuracy for the mangrove class was 91.2%, suggesting that most reference mangrove pixels were correctly classified, while the user's accuracy of 93.4% indicated a high reliability of the mapped mangrove class.

4.3. Mangrove Density Dynamics

The mangrove density was stable throughout the study period. However, there is a small change in 2023 that the medium density mangrove areas were slightly smaller. The mangrove areas with less dense cover between 2022–2023 increases significantly. The maps show that the central and southern regions of mangrove belt with high NDVI dominance where moderate and low NDVI zones marked near the northern and mudflat zones respectively.

4.4. Statistical Analysis

The sample area of mangroves located within and surrounding the mouth of Devi Estuary is illustrated in the above mentioned maps. NDVI change detection results were divided into 3 different classes: Increase, Loss and No change. These values represent the total mangrove area that comes under different classes with respect to time intervals. From the year 2021–2025, 16.41% of the study area exhibited an increase in mangrove cover, whereas 2.31% experienced a decrease and 81.29% remained unchanged overall the study period along the Devi Estuary as illustrated in Fig. 3. The temporal trend in increased mangrove cover is further illustrated using a line chart (Fig. 4).

5. Discussion

The analysis of multi-temporal remote sensing data demonstrates noticeable spatio-temporal shifts in mangrove cover along the Devi Estuary between 2021 and 2025. The integration of NDVI-based vegetation assessment, supervised classification, and machine learning approaches (Random Forest) provided reliable insights into mangrove dynamics. Random Forest (Breiman, 2001) was selected because it effectively handles high-dimensional and non-linear relationships common in environmental datasets, while being robust to noise and multicollinearity among predictor variables. In addition, it provides high classification accuracy with limited parameter tuning and offers variable importance measures, making it well suited for mapping and analyzing mangrove dynamics compared to many other classifiers.

The results show a marginal net decline (2.31%) in mangrove cover over the study period, largely attributable to anthropogenic drivers such as unregulated aquaculture expansion, conversion of tidal flats, and encroachment for settlements. These patterns are consistent with earlier findings from coastal

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regions of Odisha and other tropical estuaries, where expanding aquaculture and developmental pressures are key contributors to mangrove degradation (Roy et al., 2019; Parida and Kumar, 2020).

Despite this overall loss, the analysis also indicates clear signs of ecological recovery. Localized regeneration resulted in a 16.41% increase in vegetation cover in previously degraded areas, reflecting the inherent resilience and adaptive capacity of mangrove species when favourable hydrological and sedimentation conditions persist. The NDVI time-series analysis highlights fluctuating vegetation health trends, with the most significant decline observed between 2022 and 2023 (−9.81%), followed by a notable recovery between 2023 and 2024 (+27.33%). These temporal fluctuations may reflect climatic influences, hydrodynamic changes, and sediment redistribution processes in addition to human activity.

Fragmentation metrics reveal worsening patch connectivity and increasing isolation of mangrove stands an indicator of ecosystem vulnerability. Reduced canopy continuity may undermine ecological functions such as habitat provision, shoreline stabilization, and biogeochemical cycling. This trend aligns with global mangrove transformation patterns documented in similar deltaic systems.

The spatial distribution of NDVI values further indicates that dense and healthy mangrove patches remain concentrated in the central and southern estuarine belts, whereas northern and mudflat-adjacent zones continue to exhibit lower vegetation indices, suggesting ongoing disturbance or stalled regeneration.

The high Kappa coefficient indicates strong agreement between classified outputs and reference data. The high producer's and user's accuracies further confirm the robustness of the Random Forest algorithm in distinguishing mangroves from spectrally similar classes such as mudflats and other vegetation

Overall, the findings highlight both the sensitivity and resilience of the mangrove ecosystem at the Devi Estuary. While degradation pressures persist, the observed regeneration indicates that timely conservation actions such as restoration, hydrological rehabilitation, and regulation of aquaculture expansion could help stabilize and expand mangrove cover.

6. Conclusion

This study provides a comprehensive assessment of mangrove dynamics in the Devi Estuary, Odisha, using multi-temporal Landsat imagery and GIS-based analytical techniques. The findings indicate a modest but ecologically significant decline in mangrove extent between 2021 and 2025, driven primarily by aquaculture expansion and settlement encroachment. Despite this loss, evidence of regeneration in degraded patches highlights the inherent resilience of the system. NDVI based vegetation analysis revealed fluctuations in canopy health, particularly between 2023 and 2024, reflecting the combined influence of hydrological variability and local anthropogenic activities. Increasing fragmentation and reduced canopy connectivity suggest rising vulnerability, emphasizing the need for targeted restoration and stricter regulation of land-use practices under CRZ guidelines. Additionally, the Random Forest classifier demonstrated strong performance, achieving an overall accuracy of 92.4% and a high Kappa coefficient of 0.89.

The study's high classification accuracy (>90%) reinforces the reliability of remote sensing-based monitoring for coastal ecosystems. By establishing a baseline for short-term change detection, the results offer valuable insights for resource managers, policymakers and conservation practitioners. Future work should integrate higher-resolution datasets, species-level mapping and socio-ecological assessments to develop a more holistic understanding of mangrove resilience and long-term sustainability in the Mahanadi delta.

CRediT statement

LD: Investigation, Writing Original draft, Formal analysis, Editing; SKT: Data Analysis; ASM: Editing, Supervision

Declaration of competing interests

The authors declare that they have no known competing financial interests or personal relationships that could influence the work reported in this paper.

AI-use disclosure statement

During the preparation of this manuscript, the author used AI tools to improve the language and readability. After using this tool, the author reviewed the content and made changes wherever necessary. The author takes full responsibility for the contents of this publication.

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