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ORIGINAL ARTICLE

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## Spatio-Temporal Analysis and Prediction of Land Use and Land Cover Dynamics of Padma-Gorai River Estuary Using Landsat Satellite Images from 1987-2018.

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### ARTICLE INFO

#### Article history:

Received 15 April 2025

Received in revised form 4 January 2026

Accepted 5 January 2026

Available online 22 January 2026

#### Keywords:

Floods

LULCs

Landsat Satellite

Erosion and Accretion

Prediction

Estuary

### ABSTRACT

Land use and land cover (LULC) changes are significantly impacted by natural hazards, such as floods, often leading to alterations in vegetation, soil erosion, and the displacement of land resources. This study aims to analyze the spatio-temporal changes in LULCs from 1987 to 2018, including erosion and accretion, and predict the future trend of changes (2018-2030) in the Padma-Gorai Estuary, Bangladesh, in response to flood-induced natural disturbances. The present study has utilized Landsat satellite images from TM and OLI/TIRS sensors. Supervised classification and maximum likelihood methods were employed to categorize and create land use maps, including agricultural land, water bodies, char land, and fallow land. Additionally, this study employed the CA-Markov model to forecast the future trends of LULCs over the next twelve years. The results of LULCs show that massive changes occurred between agricultural land and char land. In 1987, agricultural land comprised approximately 140.94 (ha) of the total land, but it increased to 430.56 (ha) of the total land in 2018. However, the char land is gradually decreasing; in 1987, it accounted for 1058.85 (ha) of the total area, but by 2018, it only made up 272.43 (ha) of the study area. On the contrary, the study area experienced more accretion during the 1989–1997 time period, totaling 372.61 (ha), and experienced the lowest amount in 2016–2018, totaling 19.25 (ha). The maximum erosion that happened between 1989 and 1997 was 373.97 (ha), and the lowest was in 2008–2016, which was 59.45 (ha). However, the 2016–2018 period had the highest unchanged rate, with 492.3889 (ha) of land, and the period from 1989 to 1997 exhibited an increase in the lowest unchanged rate, totaling 89.06218 (ha) of land. The prediction map also reveals that agricultural land, char land, vegetation, fallow land, and water bodies will cover 131.98 (ha), 699.66 (ha), 169.02 (ha), 80.37 (ha), and 773.89 (ha), respectively, in 2030. The study concludes that natural processes and human activities significantly influenced LULCs in the Padma-Gorai Estuary over three decades, and the landscape will continue to undergo dynamic changes by 2030. The study's findings provide critical insights for sustainable land use planning, flood risk mitigation, and environmental management, underscoring the necessity for adaptive measures to address evolving estuarine dynamics in such a climate change context.

## 1 Introduction

Land cover includes both the real-world features of the Earth's surface, like the distribution of plants, soil, water, and other physical factors, as well as man-made features such as human settlements (Prasad et al., 2018). Land use

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refers to how people have utilized the land and the areas around it; it usually emphasizes the value of land for carrying out economic endeavors. Understanding the complexity, driving forces, and impacts of land use land cover (LULC) changes on environmental and human security is important for decision-making planning to manage natural resources (Garedew et al., 2009). Information regarding LULC change plays a significant role in local, regional, and macro-level planning. Insufficient data on the LULC change rates hinders planning and management efforts. The land-cover alterations take place naturally progressively and gradually; however, occasionally they may be abrupt and rapid due to anthropogenic deeds. On the spatiotemporal scale, the morphology of the river changes under varying environmental circumstances due to erosion and deposition of the riverbanks' inner and outer bends (Akhter et al., 2019; Ali et al., 2017; Annayat and Sil, 2020). Erosion of riverbanks and channel shifting, being a geomorphological phenomenon, has been studied by several researchers during the last few years (Das et al., 2007; Das and Saraf, 2007; Pati et al., 2008; Philip et al., 1989).

In recent years, several scholars of Bangladesh examined the spatiotemporal changes and dynamics of river morphology on the country's various river basins utilizing multi-temporal satellite imagery and Geographic Information System (GIS) techniques, e.g., evaluation of Jamuna River's mid-channel bar (Ashworth et al., 2000); Brahmaputra rivers' channel distribution and stability (Takagi et al., 2007); Jamuna rivers' migration rate and island dynamics (Baki and Gan, 2012); changes in morphology of lower Brahmaputra and Jamuna river (Bhuiyan et al., 2015; Sarker et al., 2014); Manu rivers' platform dynamics and associated hazards (Deb and Ferreira, 2015); Ganga-Padma river's platform dynamics (Islam et al., 2016); erosion-accretion and migration pattern of Dudhkumar rivers' bank (Pal et al., 2017), changes in Padma river's channel and bar evaluation (Nawfee et al., 2018) and prediction of Teesta rivers' spatiotemporal change (Akhter et al., 2019). They emphasized in their research works that the geospatial tools and techniques are useful for studying river morphology over different time and spatial scales. Regrettably, many studies have neglected to consider the seasonal fluctuations in river morphological changes. An in-depth understanding of the fluctuations in river morphology during different seasons is critical. The Ganges River system, spanning over 1.09 million km<sup>2</sup>, begins in the Gangotri glacier in the Himalayas and is among the world's greatest river systems. Stretching over 2526 km, this river traverses the countries of China, Nepal, India, and Bangladesh, thus establishing its status as a truly international waterway. India possesses the majority (79.1%) of the whole watershed; while, only a small portion (4.3%) is located within Bangladesh, which is comparable to 32% of the country's territory (Mirza, 2004). Several scholars have specifically discussed the characteristics of the Ganges River system (Abbas and Subramanian, 1984; Goodbred Jr, 2003; Islam and Akhter, 2005; Islam et al., 1999; Sahu et al., 2010; Singh et al., 2007; Sinha and Friend, 1994; Wasson, 2003). For instance, sediment mineralogy was explored by Datta and Subramanian (1997) and Tiwari et al. (2004). Sesoren

(1984), Umitsu (1993), Goodbred Jr and Kuehl (2000), Rudra (2010), and Rudra (2014) examined the evolutionary characteristics of the Ganga-Brahmaputra delta. Previous studies have found a correlation between the river and the human population, focusing on environmental problems, hydrology and water resources, erosion hazards, land loss, and social issues. The Gorai-Madhumati, a distributary of the Ganges River, has repeated changes in its channel location as a result of morphological evolution. Gorai Madhumati, being a part of Bangladesh's southwestern river system, has been subjected to massive man-made and natural changes (Banglapedia., 2021). Geospatial tools and techniques such as GIS and Remote Sensing (RS) are immensely useful in identifying river morphology and dynamics at different spatiotemporal scales, as they incorporate multifaceted aspects and effectively connect them (Batalla et al., 2018; Cui et al., 2019; Das and Saraf, 2007; Hou et al., 2019; Jiang and Wang, 2019; Rowland et al., 2016). GIS and RS simplify faster and cost-effective detection of the surface water bodies' temporal changes, by how those alterations affect river channels by applying open-source and inexpensive remotely sensed data and software (Durand et al., 2016; Yamazaki et al., 2014).

Previous research works conducted in Bangladesh have only focused on the man-made and seasonal variables that result in river channel alterations, LULC changes, and erosion of riverbanks. Hence, a comprehensive long-term spatiotemporal analysis of flood-induced LULC dynamics in the Padma-Gorai River estuary remains largely unexplored (Alam et al., 2023). Existing research has primarily focused on localized assessments of channel shifting and riverbank erosion (Arefin et al., 2021), often overlooking the longer-term, extensive impacts of flood incidents on estuarine landscapes. Notably, there is a lack of integration between flood events and their direct impacts on estuarine landscapes, productive land loss, and land cover transformation across multiple decades (Islam, 2016). Therefore, given the increasing frequency and severity of floods owing to climate change, addressing these dynamics is critical for sustainable land use planning as well as environmental management. The present study aims to fill this gap by providing a thorough analysis of LULC changes from 1987 to 2018, with an emphasis on major flood-influenced erosion and accretion processes, and forecasting LULC dynamics for 2018–2030 in the Padma-Gorai Estuary using Landsat satellite images. By explicitly linking floods over a longer period to the land cover transformations, along with landscape changes, this investigation offers new insights for future land-use planning to optimize sustainable land use and environmental management, advancing beyond the scope of prior Bangladeshi river morphology studies. The study's findings can also be shared with pertinent stakeholders and policymakers of various planning ministries, such as the Ministry of Water Resources (MoWR), to help with decision-making on matters like the identification of low-cost techniques for inland water transport (IWT).

## 2 Materials and methods

### 2.1 Study area

The Padma-Gorai estuary has been selected as the present study area in the Kushtia-Pabna districts of Bangladesh. It is located in the northwest region of Bangladesh, between 23.91° and 23.95° north latitudes, and 89.09° and 89.15° east longitudes. The Padma River is one of the three major river systems, namely the GBM (Ganges-Brahmaputra-Meghna River system, where the Ganges River is called the Padma River) (Arefin et al., 2021). The Gorai-Madhumati River, one of the oldest rivers in Bangladesh, is named Gorai in the higher reaches and Madhumati in the lower reaches (Banglapedia., 2021), and it is the main right-bank distribution point of the Ganges River. The river course is wide, long, and meandering (BWDB, 2011). This study area experienced significant changes in LULCs due to a combination of natural and anthropogenic factors. The study area is shown in Fig. 1.

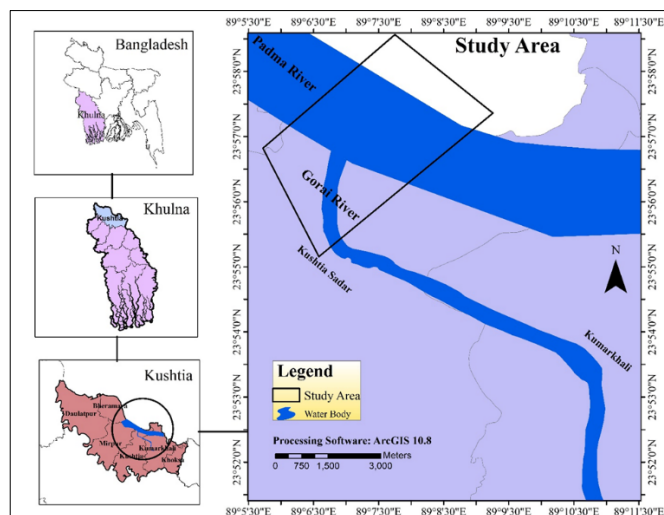


**Fig. 1:** Study Area - The Padma-Gorai estuary.

**Table 1:** User Queries adapted from.

| Satellite ID | Sensor ID | Path/Row | Spatial Resolution (m) | Image Quality | Image Acquisition Date |
|--------------|-----------|----------|------------------------|---------------|------------------------|
| Landsat 5    | TM        | 138/43   | 30                     | 9             | 24-12-1987             |
| Landsat 5    | TM        | 138/43   | 30                     | 9             | 11-01-1989             |
| Landsat 5    | TM        | 138/43   | 30                     | 9             | 25-01-1997             |
| Landsat 5    | TM        | 138/43   | 30                     | 9             | 23-01-1999             |
| Landsat 5    | TM        | 138/43   | 30                     | 9             | 26-11-2006             |
| Landsat 5    | TM        | 138/43   | 30                     | 9             | 17-01-2008             |
| Landsat 8    | OLI/TIRS  | 138/43   | 30                     | 9             | 13-11-2016             |
| Landsat 8    | OLI/TIRS  | 138/43   | 30                     | 9             | 28-01-2018             |

### 2.2 Data collection

This study posits that the notable LULC changes in the study region between 1987 and 2018 are responsible for major flood events. The 1988 flood, for instance, inundated around 60% of Bangladesh, affecting more than 45 million people and extensively damaging agriculture and infrastructure (Forewarn-Dashboard, 2024). Similarly, the 1998 flood, regarded as the most severe in recent times, submerged over two-thirds of the nation, causing widespread destruction and displacement (Del Ninno et al., 2001). Over 1,100 people were killed, and 14 million individuals were affected by the 2007 flood, which inundated 42% of the land area (World-Bank, 2011). The 2017 flood, one of the most severe river flooding occurrences, was attributed to both heavy rainfall and discharge, with a shift in risk ranging from 1 to 2 for both the meteorological and hydrological approaches (Philip et al., 2019). These events likely contributed to noticeable LULC changes in the study area, including erosion and accretion. To analyze the land use dynamics and erosion accretion of the study area, secondary data were collected from available Landsat satellite images of 1987, 1989, 1997, 1999, 2006, 2008, 2016, and 2018, using the official website of the United States Geological Survey (<https://earthexplorer.usgs.gov/>). Landsat TM and OLI/TIRS sensor data have been counted, considering the dry season in the satellite data (Table 1). The selection of these satellite images was not based on fixed annual or decadal intervals, but rather on the years preceding and following major flood events in the study area. As the Padma-Gorai Estuary is highly flood-prone, this strategy was adopted to better capture the influence of flooding on land use changes and erosion–accretion processes. The dynamic geomorphological reactions and LULC changes linked to major hydrological disturbances might be better understood by giving priority to images from flood-relevant years.

## 2.3 Data analysis

### 2.3.1 Image pre-processing

Pre-processing satellite images is crucial for establishing a direct relationship between biophysical processes and data (Abd El-Kawy et al., 2011; Coppin et al., 2004). Landsat data pre-processing techniques are modified to manage datasets and align with applications. Three primary preprocessing procedures were used in this study to calibrate Landsat images.

### 2.3.2 Geometric correction

The study used ERDAS Imagine software to perform geometric correction on satellite images, effectively removing distortion and providing accurate direction, distance, and polygon area information in a GIS.

### 2.3.3 Radiometric calibration

The primary objective of this stage was to transform the digitized numbers into units of Top of Atmosphere reflectance. The equations and parameters needed to convert calibrated Digital Numbers (DNs) to physical units, such as at-sensor radiance or Top-Of-Atmosphere (TOA) reflectance, have been provided in a "sensor-specific" manner in other sources. For example, MSS (Markham and Barker, 1987), TM (Chander et al., 2009), ETM+ (Handbook2), and ALI (Markham et al., 2004). These calibrations consist of two steps:

- I. DN to Radiance Conversion using Equations (1), (2), (3), and (4)

$$L_{\lambda} = \left( \frac{LMAX_{\lambda} - LMIN_{\lambda}}{Q_{calmax} - Q_{calmin}} \right) (Q_{cal} - Q_{calmin}) + LMIN_{\lambda} \quad (1)$$

or

$$L_{\lambda} = G_{rescale} \times Q_{cal} + B_{rescale} \quad (2)$$

where;

$$G_{rescale} = \frac{LMAX_{\lambda} - LMIN_{\lambda}}{Q_{calmax} - Q_{calmin}} \quad (3)$$

$$B_{rescale} = LMIN_{\lambda} - \left( \frac{LMAX_{\lambda} - LMIN_{\lambda}}{Q_{calmax} - Q_{calmin}} \right) Q_{calmin} \quad (4)$$

$L_{\lambda}$  = Spectral Radiance at the Sensor's Aperture [ $W/m^2$  sr  $\mu m$ ]

$Q_{cal}$  = Quantized Calibrated Pixel Value

$Q_{calmin}$  = Minimum Quantized Calibrated Pixel Value Corresponding to LMIN, [DN]

$Q_{calmax}$  = Maximum Quantized Calibrated Pixel Value Corresponding to LMAX, [DN]

$LMIN_{\lambda}$  = Spectral at-Sensor Radiance that is Scale to  $Q_{calmin}$

$LMAX_{\lambda}$  = Spectral at-sensor Radiance that is Scale to  $Q_{calmax}$

$G_{rescale}$  = Band-Specific Rescaling Gain Factor [ $W/m^2$  sr  $\mu m/DN$ ]

$B_{rescale}$  = Band-Specific Rescaling Bias Factor [ $W/m^2$  sr  $\mu m/DN$ ]

- II. Radiance to TOA Reflectance using Equation (5)

$$\rho_{\lambda} = \frac{\pi \cdot L_{\lambda} \cdot d^2}{ESUN_{\lambda} \cdot \cos \theta_s} \quad (5)$$

where;

$\rho_{\lambda}$  = Planetary TOA reflectance [unitless]

$\pi$  = Mathematical constant equal to 3.14159 [unitless]

$L_{\lambda}$  = Spectral radiance at the sensor's aperture [ $W/(m^2$  sr  $\mu m)$ ]

$d$  = Earth-Sun distance [astronomical units]

$ESUN_{\lambda}$  = Mean exoatmospheric solar irradiance [ $W/(m^2$   $\mu m)$ ]

$\theta_s$  = Solar zenith angle [degrees]

### 2.3.4 Atmospheric correction

Landsat satellite imagery converts DN into TOA reflectance, eliminating solar and sensor factors. However, it does not consider air phenomena like scattering and emission, and atmospheric correction is not considered in this study. Since this study primarily focuses on LULC changes concerning major flood events, thorough atmospheric correction is less critical for identifying major trends, because inter-annual variability in atmospheric effects is minor compared to the large-scale land cover transformations. In addition, previous studies in similar contexts have satisfactorily employed TOA reflectance for spectral indices such as Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), Modified Normalized Difference Water Index (MNDWI), and Soil Adjusted Vegetation Index (SAVI) for LULC classification as well as long-term change detection, with the minimal impact on overall trends (Hu et al., 2025; Saldarriaga et al., 2025; Xu, 2006). Classification accuracy was rigorously assessed utilizing approximately 250 reference points that were verified against Google Earth Pro's high-resolution imagery, indicating that minor atmospheric differences did not significantly affect the LULC classifications' reliability.

## 2.4 Image classification

LULC classification is a technique using satellite images, often using supervised and unsupervised methods (Lang et al., 2008; Naikoo et al., 2020). Supervised classifications categorize pixels into specific LULC classes, using methods like the maximum likelihood classifier (MLC), spectral mapping, K-Means, and ISODATA (Atkinson and Lewis, 2000; Chamling and Bera, 2020; Munoz-Mari et al., 2012; Zhang et al., 2014). In this study, we employed the (MLC) approach to perform supervised classification on each image individually. The aforementioned approach was favored due to its improved precision, extensive utilization, straightforward implementation, ease of application, and high performance (Dangulla et al., 2020). The detailed

classification scheme used for this study is presented in Table 2.

**Table 2:** A detailed classification scheme used for the supervised classification in this study.

| Code | Land Cover Types  | Description                                                    |
|------|-------------------|----------------------------------------------------------------|
| 1    | Fallow Land       | Settlements, Barren Field, Open Space, Bare Soils              |
| 2    | Vegetation        | Trees, Shrubs, and Marshy Land, Grassland, and Vegetable Lands |
| 3    | Water Body        | River water, Canals, Ponds, Lakes, and Reservoirs              |
| 4    | Agricultural Land | Croplands, Pastureland                                         |
| 5    | Char Land         | Sandy area                                                     |

## 2.5 Accuracy assessment

Accuracy assessment is a post-classification operation that validates the classification's efficacy by comparing the resulting LULC to actual ground land cover (Muriithi, 2016; Owajori and Xie, 2005). Different approaches assess the accuracy level of classified thematic maps, with the standard method being the error or confusion matrix (Congalton, 1991; Foody, 2002; Prasad and Ramesh, 2019; Smits et al., 1999). Accuracy is calculated using three scales: users' accuracy, producers' accuracy, and overall accuracy. The Kappa coefficient quantifies the required classification accuracy for all elements (Coppin and Bauer, 1996; Foody, 2010). In this study, approximately 250 reference points were randomly selected from each classified image independently and were verified using high-resolution imagery from Google Earth Pro. A stratified random sampling method was applied to ensure balanced representation across all LULC classes. The selected points were evenly distributed throughout the spatial extent of the study area to avoid spatial bias and to reflect the geographic variability of land cover types, and to calculate the user's accuracy, producer's accuracy, total or overall accuracy, and Kappa statistics, the following formulae were used as equations (6), (7), (8), and (9), respectively (Islami et al., 2022):

$$UA = \frac{\text{Number of correctly classified pixels in each category}}{\text{Total number of reference pixels in that category (The row total)}} \times 100 \quad (6)$$

$$PA = \frac{\text{Number of correctly classified pixels in each category}}{\text{Total number of reference pixels in that category (The column total)}} \times 100 \quad (7)$$

$$TA = \frac{\text{Total number of correctly classified pixels (Diagonal)}}{\text{Total number of reference pixels}} \times 100 \quad (8)$$

$$Kappa\ Coefficient(K) = \frac{(TSXTCS) - \sum (Column\ Total \times Row\ Total)}{(TSXTS) - \sum (Column\ Total - Row\ Total)} \quad (9)$$

Where, UA = User Accuracy, PA = Producer Accuracy, TA = Total Accuracy, TS = Total Sample and TCS = Total Corrected Sample

### 2.5.1 Change detection

The Post Classification Comparison (PCC) method accurately detects changes in research periods, reducing radiometric calibration issues between photos captured on different dates (Mallupattu and Sreenivasula Reddy, 2013; Wang, 2012). In this study, change detection was determined by utilizing categorized photos from the years 1987 and 2018.

### 2.5.2 Spectral indices

Spectral indices are pixel values from multiple spectral bands in a multispectral image, highlighting land-cover categories, with a range of -1 to +1 (Bashar et al., 2023). In this study, four remote sensing-based indices were used: NDVI, SAVI, NDWI, and MNDWI. This combination utilizes various spectral responses to different forms of land cover, and will also change land cover over the years. Table 3 presents detailed information on the analyzed spectral indices for this study.

### 2.5.3 Erosion and accretion rate

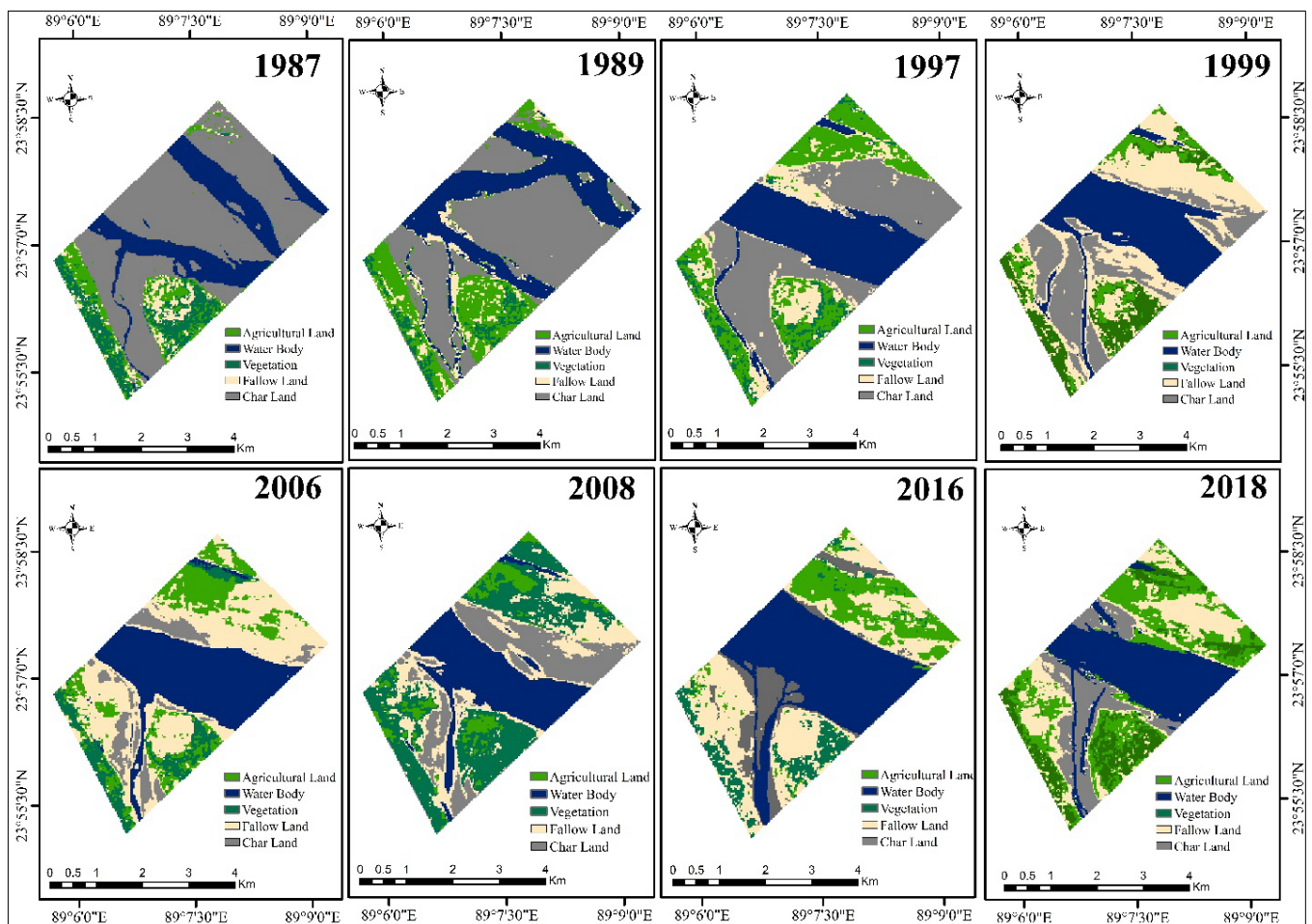
Bangladesh's geographical location exerts a substantial influence on its climate, hence contributing significantly to the country's frequent and devastating floods. The floods cause substantial erosion and accretion in several rivers (Rahman et al., 2015). The major morphological modifications can provide a definitive conclusion in the analysis process. For this investigation, ArcGIS 10.8.2 software was utilized to compute the erosion and accretion rates of the research region between the years 1987 and 2018.

### 2.5.4 Prediction of land use and land cover

To predict the future LULC pattern of the study area, integration of the Markov chain and cellular automata model (CA Markov) was used. Markov chain gives no information on the spatial 288 distribution of each land use category (Araya and Cabral, 2010; Koomen and Beurden, 2011). The CA-Markov model is extensively used in LULC modeling (Brown et al., 2000; Sang et al., 2011; Zhilong et al., 2017). The model can effectively predict the future change in LULC in space and time. Markov chain predicts future changes based on the previous state in each class and the transition probability (Behera et al., 2012; Houet and Hubert-Moy, 2006). The ability of the Markov model to be used intensively in modeling LULC changes not only to differentiate between LULC classes but also to measure the transition rate between them (Azizi et al., 2016). In this study, we utilized this method to analyze the prediction of land use and land cover changes for 2018-2030.

**Table 3:** Description of analyzed spectral indices.

| Image Index                                       | Short Form | Formula                                                                      | Description                                                                                                                                                                                                              | References         |
|---------------------------------------------------|------------|------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------|
| <b>Normalized Difference Vegetation Index</b>     | NDVI       | $NDVI = \frac{(NIR - R)}{(NIR + R)}$                                         | NDVI is valuable for environmental monitoring and management. NDVI is used in various applications, including forest health monitoring, crop yield estimation, land cover change detection, and water quality monitoring | (CropIn, 2021)     |
| <b>Normalized Difference Water Index</b>          | NDWI       | $NDWI = \frac{(Green - NIR)}{(Green + NIR)}$                                 | The NDWI is a spatial indicator that responds to changes in leaf moisture content.                                                                                                                                       | (Das et al., 2021) |
| <b>Modified Normalized Difference Water Index</b> | MNDWI      | $MNDWI = \frac{(Green - SWIR)}{(Green + SWIR)}$                              | MNDWI effectively differentiates between water and urban areas in satellite images. This method utilizes the visible green (GREEN) and short-wave infrared 1 (SWIR1) spectral bands.                                     | (Xu, 2006)         |
| <b>Soil-Adjusted Vegetation Index</b>             | SAVI       | $SAVI = \left( \frac{(NIR - Red)}{((NIR + Red + L))} \right) \times (1 + L)$ | SAVI is a vegetation index that attempts to minimize soil brightness influences using a soil brightness correction factor. This is often used in arid regions where vegetative cover is low.                             | (Huete, 1988)      |

**Fig. 2:** Land use and land cover map of the study area, left to right and top to bottom, from 1987 to 2018.

In our study, the validation process was primarily based on the built-in validate module of IDRISI Andes, which provides a visual and statistical comparison of simulated and actual LULC maps, with slight misallocations in dynamic classes, including water bodies and char lands, confirming the CA-Markov model's reliability for projecting LULC changes of the study area up to 2030. The Validate module in the IDRISI Andes software was used to check the accuracy of the model by comparing the simulated 2018 map with the actual classified 2018 LULC map, following a similar approach used by Ahmed et al. (2013) and Parsa and Salehi (2016).

### 3 Results

#### 3.1 Evaluation of land use and land cover

Fig. 2 presents the classified images of land use and land cover maps from 1987 to 2018, while Fig. 3 and Table S1 present the corresponding area results for each classed image.

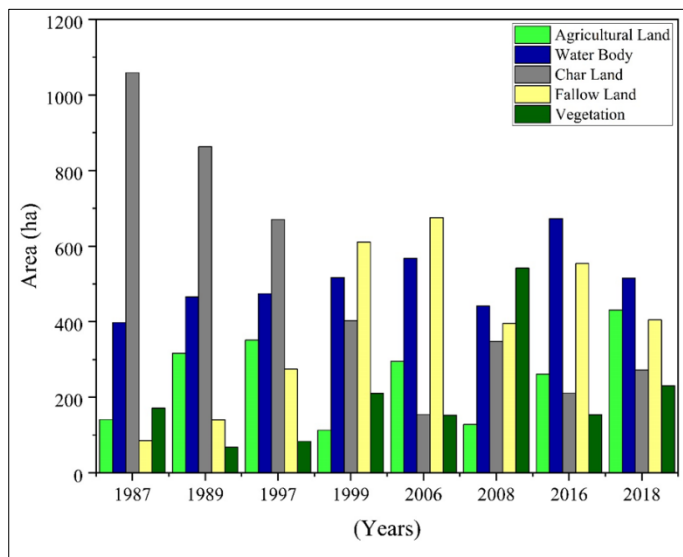


**Fig. 3:** Areal changes in land use and land cover of the study area from 1987 to 2018.

In 1987, char land dominated the total area, covering 1058 (ha), followed by water bodies at 397.89 (ha). The smallest land area was 84.78 (ha), while vegetation and agricultural land covered 171.09 (ha) and 140.94 (ha), respectively. The classification results (1989) showed that char land occupied a major chunk of the total area, covering 863.1 (ha), followed by water bodies at 465.93 ha. Fallow land was 140.4 (ha), while agricultural land covered 316.71 (ha). Vegetation covered only 67.41 (ha). In 1997, vegetation covered the least amount of the total area, with char land covering 670.41 (ha). The agricultural land covered 351.18 (ha), while the water body covered 474.3 (ha). This year, the total area of fallow land was 274.32 (ha). The land cover map of 1999 showed expansion of fallow land and vegetation in all directions, with 610.65 (ha) and 210.69 (ha). Only a small portion, 112.86 (ha) of agricultural land was occupied. Waterbody areas expanded, totaling 517.05

(ha), while diminishing char land represented 402.3 (ha). In 2006, fallow land covered 675.42 (ha), with the water body covering 567.54 (ha). Vegetation covered 152.73 (ha), while agricultural land covered 295.29 (ha). In 2008, agricultural land occupied the least amount of the total area, with 541.8 (ha) of vegetation and 347.04 (ha) of char land. In 2016, the land cover map showed expansion of fallow land and water bodies in all directions, with only 154.17 (ha) of vegetation remaining. The 2018 land use and land cover map revealed that 515.16 (ha) of the total area was under water bodies, with only 230.58 (ha) in the vegetation category.

#### 3.2 Accuracy Assessment of Classified Images

Table 4 provides a detailed accuracy report for the classified images from 1987 to 2018. In 1987, the overall accuracy of the classified images was 85.33%, and the Kappa statistics were 0.81. In 1989, the overall accuracy was 88%, and the Kappa accuracy was 0.85. Again, in 1997, the overall accuracy was 88%, and the Kappa statistics were 0.85. However, in 1999, the Kappa and overall accuracy were found to be 0.82 and 86%, respectively. The overall accuracy of the classified images was found 86% in 2006 and 86.67% in 2008. The Kappa statistics for these years were 0.82 and 0.83, respectively. The overall accuracy in 2016 and 2018 was 88% and 90.67%, respectively, with corresponding Kappa statistics of 0.85 and 0.88.

#### 3.3 Changes in land use and land cover

From the comprehensive analysis of the satellite images from 1987 to 2018, there have been significant changes in land use and land cover. A substantial portion of the study area was once occupied by char land, which accounted for 57% in 1987, 47% in 1989, and 36% in 1997, and steadily decreased to drop at a low of 22% (1999) and then at its minimal point of only 8% (2006). In 1987, the water body area accounted for 21% of the total area, rising to 25% in 1989 and then to 26% in 1997. In 2008, the water body experienced a decrease, covering only 24% of the total area. Vegetation was about 9% of the total area in 1987, which decreased to 4% in 1989 and remained unchanged at 4% in 1997. In 1999, it experienced a significant increase, reaching 11% of the total area. In 2006, the area of vegetation decreased further, accounting for only 8% of the total area. After a considerable change, it became 29% of the total area in 2008. It faced further destruction and turned into only 8% of the total area. Then, in 2018, it became 12% of the total area, but only after a slight increase. In 1987, agricultural land accounted for 8% of the total area, a slight increase to 17% in 1989, and a further increase to about 19% in 1997. In 1999, it decreased to 6% of the total area. Finally, in 1987, the fallow land area accounted for 5% of the total area, grew to 8% in 1989, and reached 15% in 1997. The area of fallow land continued to increase, reaching 33% in 1999 and 36% in 2006. In 2008, the water body experienced a decrease, covering only 24% of the total area. In 2016, the water body's coverage increased to 30%.

**Table 4:** Accuracy assessment report of the classified images.

| Year        | Classes     | Producer accuracy | User accuracy | Kappa  | Overall accuracy | Overall Kappa |
|-------------|-------------|-------------------|---------------|--------|------------------|---------------|
| <b>1987</b> | Fallow land | 87.50             | 70.00         | 0.8305 | <b>85.33%</b>    | <b>0.8167</b> |
|             | Vegetation  | 83.87             | 86.67         | 0.8319 |                  |               |
|             | Water body  | 87.88             | 96.67         | 0.9573 |                  |               |
|             | Agri land   | 81.25             | 86.67         | 0.8305 |                  |               |
|             | Char land   | 86.67             | 86.67         | 0.8750 |                  |               |
| <b>1989</b> | Fallow land | 77.78             | 93.33         | 0.9123 | <b>88.00%</b>    | <b>0.8502</b> |
|             | Vegetation  | 87.50             | 70.00         | 0.6429 |                  |               |
|             | Water body  | 100.00            | 100.00        | 1.00   |                  |               |
|             | Agri land   | 83.33             | 83.33         | 0.7917 |                  |               |
|             | Char land   | 96.55             | 93.33         | 0.9174 |                  |               |
| <b>1997</b> | Fallow land | 80.56             | 96.67         | 0.9561 | <b>88.00%</b>    | <b>0.8505</b> |
|             | Vegetation  | 92.59             | 83.33         | 0.7967 |                  |               |
|             | Water body  | 93.33             | 93.33         | 0.9167 |                  |               |
|             | Agri land   | 92.31             | 80.00         | 0.7581 |                  |               |
|             | Char land   | 89.66             | 86.67         | 0.8347 |                  |               |
| <b>1999</b> | Fallow land | 77.14             | 90.00         | 0.8276 | <b>86.00%</b>    | <b>0.8250</b> |
|             | Vegetation  | 95.65             | 73.33         | 0.6850 |                  |               |
|             | Water body  | 93.75             | 100.00        | 1.00   |                  |               |
|             | Agri land   | 80.00             | 80.00         | 0.8696 |                  |               |
|             | Char land   | 92.31             | 80.00         | 0.7581 |                  |               |
| <b>2006</b> | Fallow land | 77.88             | 93.33         | 0.7581 | <b>86.00%</b>    | <b>0.8253</b> |
|             | Vegetation  | 87.50             | 70.00         | 0.9123 |                  |               |
|             | Water body  | 96.43             | 90.00         | 0.8770 |                  |               |
|             | Agri land   | 78.13             | 83.33         | 0.7881 |                  |               |
|             | Char land   | 92.59             | 83.33         | 0.7967 |                  |               |

|             |             |        |        |        |               |               |
|-------------|-------------|--------|--------|--------|---------------|---------------|
| <b>2008</b> | Fallow land | 82.76  | 80.00  | 0.7521 | <b>86.67%</b> | <b>0.8333</b> |
|             | Vegetation  | 86.21  | 83.33  | 0.7934 |               |               |
|             | Water body  | 93.75  | 100.00 | 1.00   |               |               |
|             | Agri land   | 80.00  | 80.00  | 0.7500 |               |               |
|             | Char land   | 90.00  | 90.00  | 0.8750 |               |               |
| <b>2016</b> | Fallow land | 95.83  | 76.67  | 0.7222 | <b>88.00%</b> | <b>0.8502</b> |
|             | Vegetation  | 85.71  | 80.00  | 0.7541 |               |               |
|             | Water body  | 100.00 | 96.67  | 0.9587 |               |               |
|             | Agri land   | 72.97  | 90.00  | 0.8673 |               |               |
|             | Char land   | 93.55  | 96.67  | 0.9580 |               |               |
| <b>2018</b> | Fallow land | 87.50  | 93.33  | 0.9153 | <b>90.67%</b> | <b>0.8837</b> |
|             | Vegetation  | 87.50  | 93.33  | 0.9153 |               |               |
|             | Water body  | 93.33  | 93.33  | 0.9167 |               |               |
|             | Agri land   | 96.43  | 90.00  | 0.8770 |               |               |
|             | Char land   | 96.15  | 83.33  | 0.7984 |               |               |

**Table 5:** Land use and land cover changes of the study area from 1987- 2018 (area in hectares).

|                          | Year    |       |        |       |        |       |        |       |        |       |        |       |        |       |        |       |
|--------------------------|---------|-------|--------|-------|--------|-------|--------|-------|--------|-------|--------|-------|--------|-------|--------|-------|
|                          | 1987    |       | 1989   |       | 1997   |       | 1999   |       | 2006   |       | 2008   |       | 2016   |       | 2018   |       |
| Classes                  | Area    | P (%) | Area   | P (%) | Area   | P (%) | Area   | P (%) | Area   | P (%) | Area   | P (%) | Area   | P (%) | Area   | P (%) |
| <b>Agricultural land</b> | 140.94  | 8%    | 316.71 | 17%   | 351.18 | 19%   | 112.86 | 6%    | 295.29 | 16%   | 127.98 | 7%    | 261.81 | 14%   | 430.56 | 23%   |
| <b>Vegetation</b>        | 171.09  | 9%    | 67.41  | 4%    | 83.34  | 4%    | 210.69 | 11%   | 152.73 | 8%    | 541.8  | 29%   | 154.17 | 8%    | 230.58 | 12%   |
| <b>Water body</b>        | 397.89  | 21%   | 465.93 | 25%   | 474.3  | 26%   | 517.05 | 28%   | 567.54 | 31%   | 441.36 | 24%   | 672.66 | 36%   | 515.16 | 28%   |
| <b>Fallow land</b>       | 84.78   | 5%    | 140.4  | 8%    | 274.32 | 15%   | 610.65 | 33%   | 675.42 | 36%   | 395.37 | 21%   | 553.86 | 30%   | 404.82 | 22%   |
| <b>Char land</b>         | 1058.85 | 57%   | 863.1  | 47%   | 670.41 | 36%   | 402.3  | 22%   | 154.44 | 8%    | 347.04 | 19%   | 211.05 | 11%   | 272.43 | 15%   |

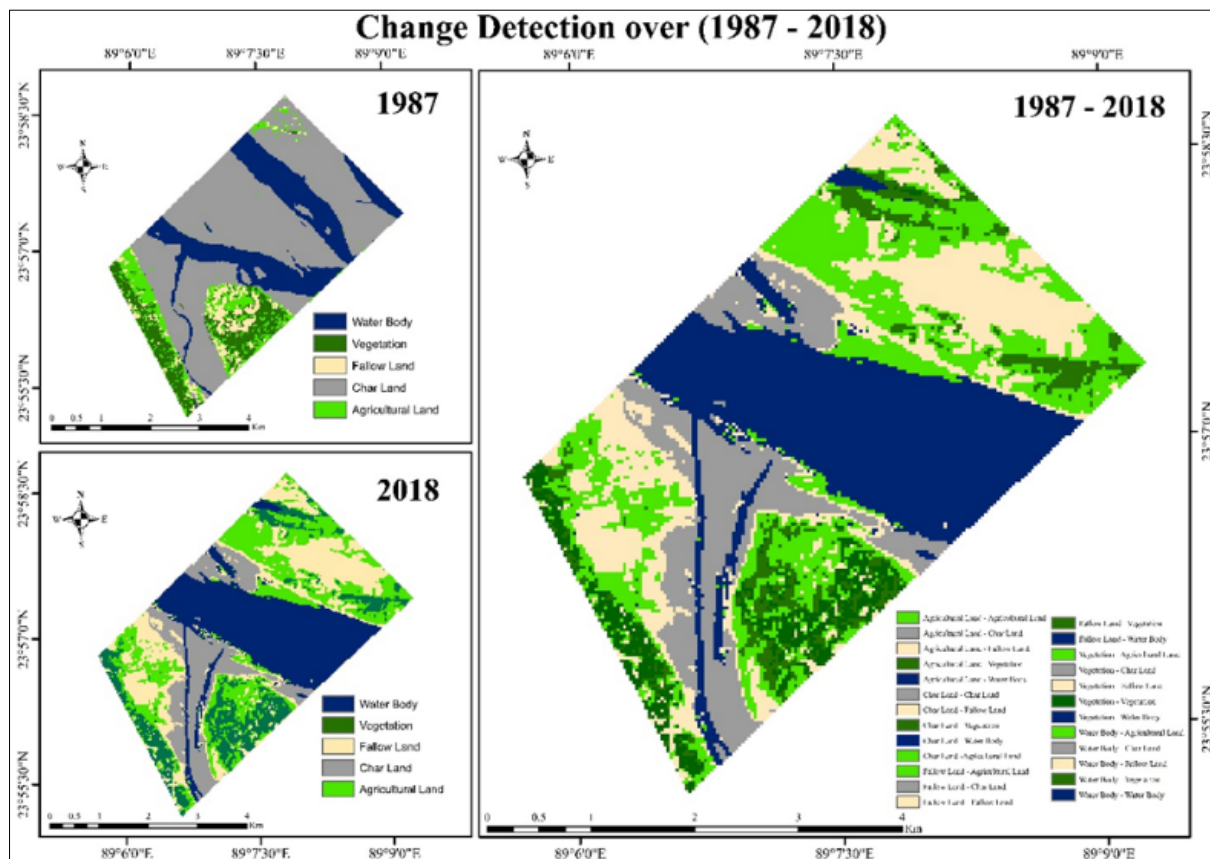


**Fig. 4:** Change detection calculation images from 1987 to 2018.

In 2018, it drastically decreased to 22% due to the challenges faced. Table 5 presents the results of the land use and land cover areas.

### 3.4 Change detection

To calculate the land use land cover changes, the classified images of 1987 and 2018 were used in this study, and the results are presented in Fig. 4 and Table 6. It can be seen that the total investigated area was determined to be 1847.7 ha. The highest changed area seen by char land to water bodies is 359.19 ha. The change also increased in char land to fallow land (246.06 ha), char land to char land (210.42 ha), and char land to agricultural land (191.88 ha). The lowest changes were vegetation to char land (1.53 ha) and vegetation to water bodies (2.07 ha).

**Table 6:** Resultant thematic changes statistics: from-to-change matrices (1987–2018).

| From (1987)       | To (2018)         | Changed Area (ha) |
|-------------------|-------------------|-------------------|
| Agricultural land | Agricultural land | 49.23             |
|                   | Char land         | 3.69              |
|                   | Fallow land       | 36.18             |
|                   | Vegetation        | 36.99             |
|                   | Water body        | 9.0               |

|             |                   |        |
|-------------|-------------------|--------|
| Char land   | Agricultural land | 191.88 |
|             | Char land         | 210.42 |
|             | Fallow land       | 246.06 |
|             | Vegetation        | 51.3   |
|             | Water body        | 359.19 |
| Fallow land | Agricultural land | 32.94  |
|             | Char land         | 2.88   |
|             | Fallow land       | 12.42  |
|             | Vegetation        | 32.13  |
|             | Water body        | 4.41   |
| Vegetation  | Agricultural land | 41.49  |
|             | Char land         | 1.53   |
|             | Fallow land       | 24.75  |
|             | Vegetation        | 101.25 |
|             | Water body        | 2.07   |
| Water body  | Agricultural land | 114.39 |
|             | Char land         | 53.91  |
|             | Fallow land       | 80.64  |
|             | Vegetation        | 8.46   |
|             | Water body        | 140.49 |

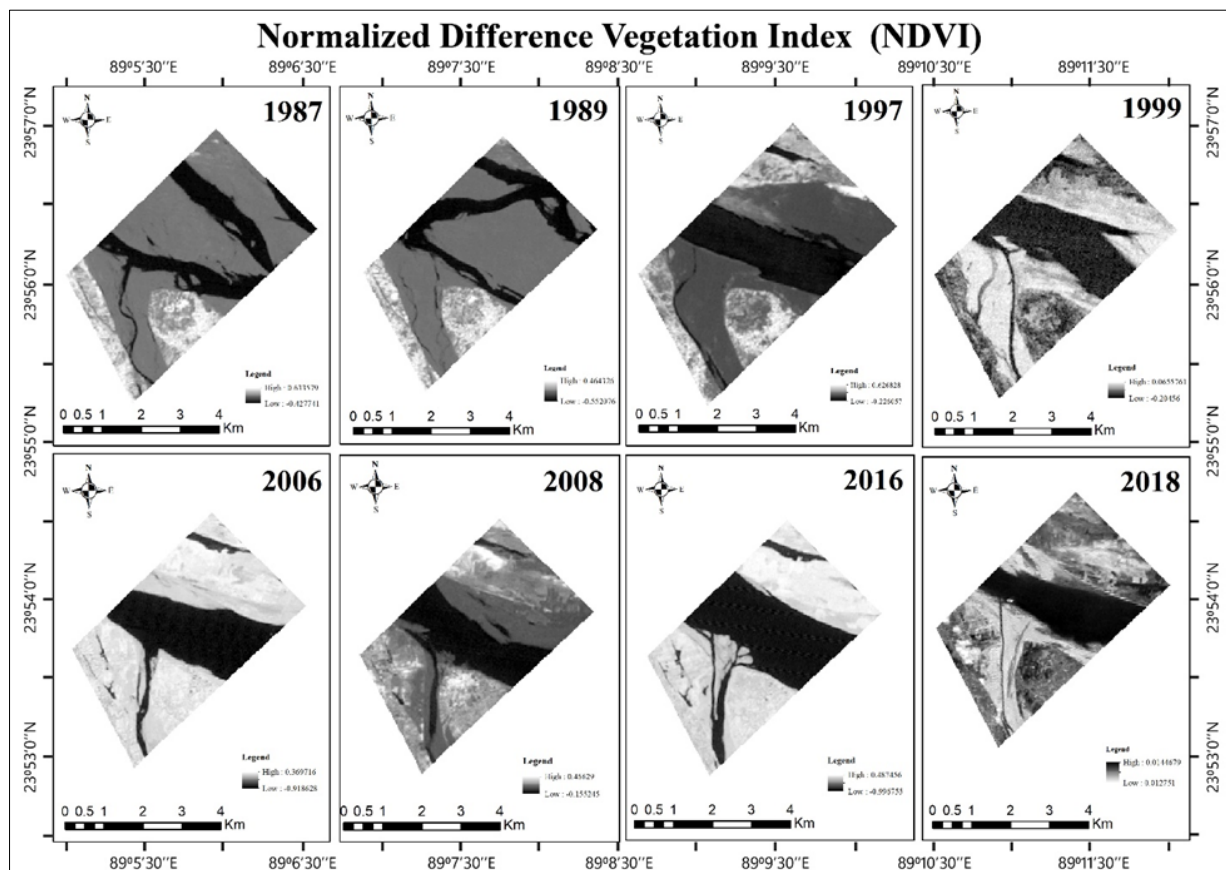


**Fig. 5:** Changes in the vegetation cover of the study area (1987-2018).

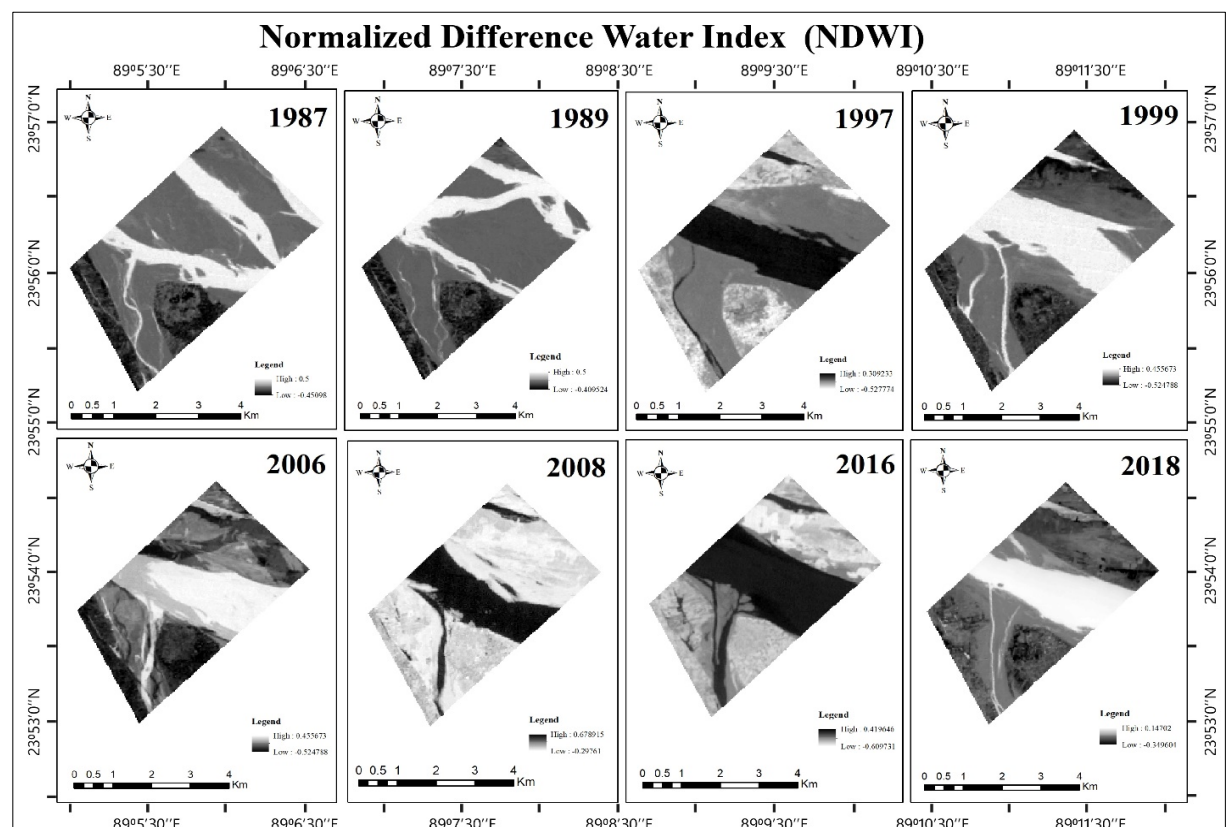


**Fig. 6:** Changes in the water bodies of the study area (1987-2018).

### 3.5 Spectral indices

The study area's vegetation coverage fluctuated from 1987 to 2018, with the highest peak in 1987 and the lowest in 2018. Variations were caused by riverbank erosion, deposition, and flood effects. The most significant change occurred between 2016 and 2018, with a value of 0.48 in 2016 and 0.01 in 2018, while the highest NDVI value was only 0.10 in 2006 and 2018. The least vegetation was evident during the 2016-2018 period, as presented in Fig. 5.

Fig. 6 depicts over the thirty years from 1987 to 2018; the analysis of NDWI values reveals significant insights into water trends. Throughout the studied areas, the highest NDWI values showed steady, healthy, and dense vegetation with very minor changes. The highest NDWI values for each year were as follows: 0.5 in 1987, 0.5 in 1989, 0.30 in 1997, 0.46 in 1999, 0.456 in 2006, 0.68 in 2008, 0.42 in 2016, and 0.15 in 2018. These fluctuations can be linked to small changes in land usage, seasonal variations, and meteorological circumstances. On the other hand, the lowest NDWI readings indicated areas with shallow water since they displayed greater variability. The low NDWI values for

each year were: -0.45 in 1987, -0.41 in 1989, -0.53 in 1999, -0.53 in 2006, -0.30 in 2008, -0.60 in 2016, and -0.35 in 2018.

Significant insights into the presence and status of water bodies are revealed by analyzing MNDWI values during the thirty years from 1987 to 2018. We obtain a notable alteration in the Gorai River Estuary Water Body from the MNDWI analysis. Variations in water cover are caused by hydrological events, climatic circumstances, and seasonal changes. The high values of MNDWI for each year were as follows: 0.77 in 1987, 0.74 in 1989, 0.56 in 1997, 0.45 in 1999, 0.45 in 2006, 0.74 in 2008, 0.99 in 2016, and 0.29 in 2018. The low values of MNDWI for each year were: -0.47 in 1987, -0.40 in 1989, -0.29 in 1997, -0.52 in 1999, -0.52 in 2006, -0.27 in 2008, -0.40 in 2016, and -0.23 in 2018. Fig. 7 portrays the results of MNDWI.

Over thirty years (1987-2018), analysis of SAVI values has yielded important insights regarding the health and coverage of vegetation. The high SAVI values were: 0.42 in 1987, 0.27 in 1989, 0.44 in 1997, 0.04 in 1999, 0.04 in 2006, 0.31 in 2008, 0.53 in 2006, and 0.0011 in 2018. The low SAVI values for each year were: -0.15 in 1987, -0.20 in 1989, -0.08 in 1997, -0.09 in 1999, -0.09 in 2006, -0.06 in 2008, -0.13 in 2016, and -0.0024 in 2018. Fig. 8 displays the results of SAVI.

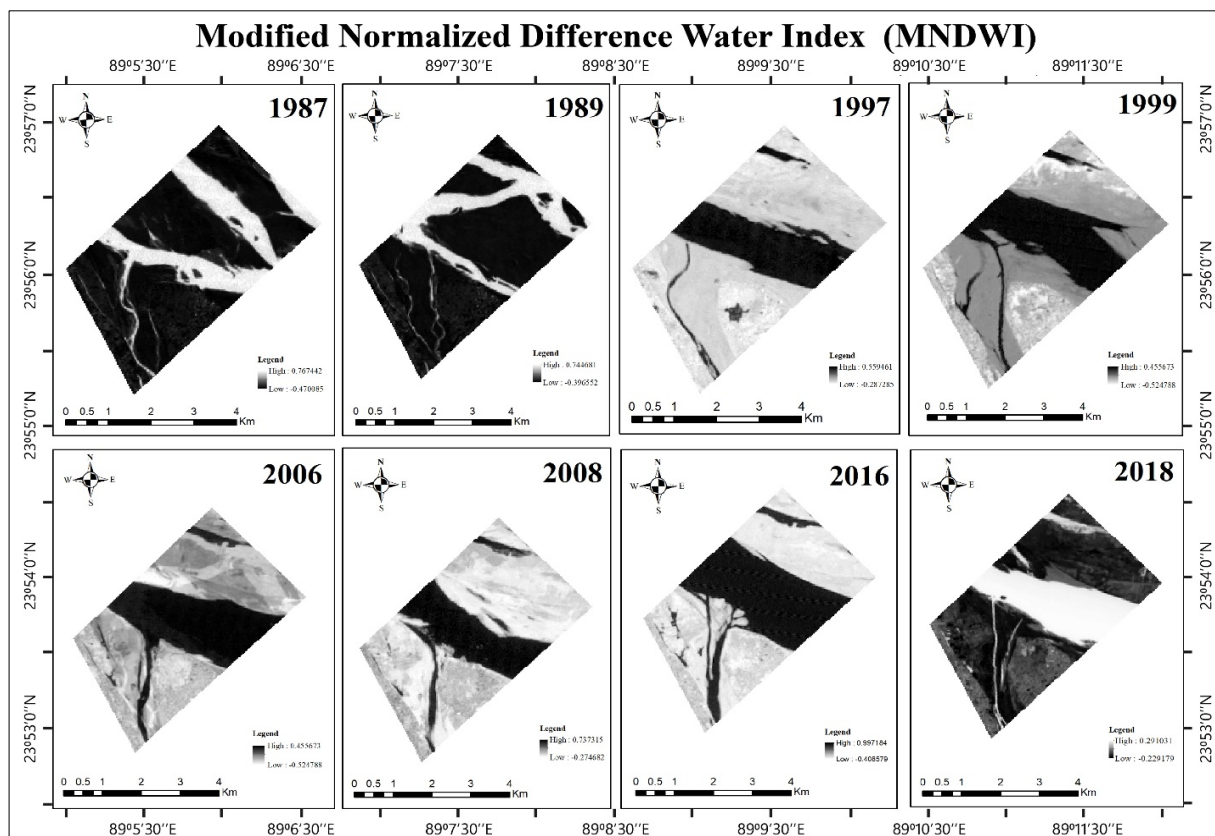


**Fig. 7:** Changes in the modified water bodies of the study area (1987-2018).

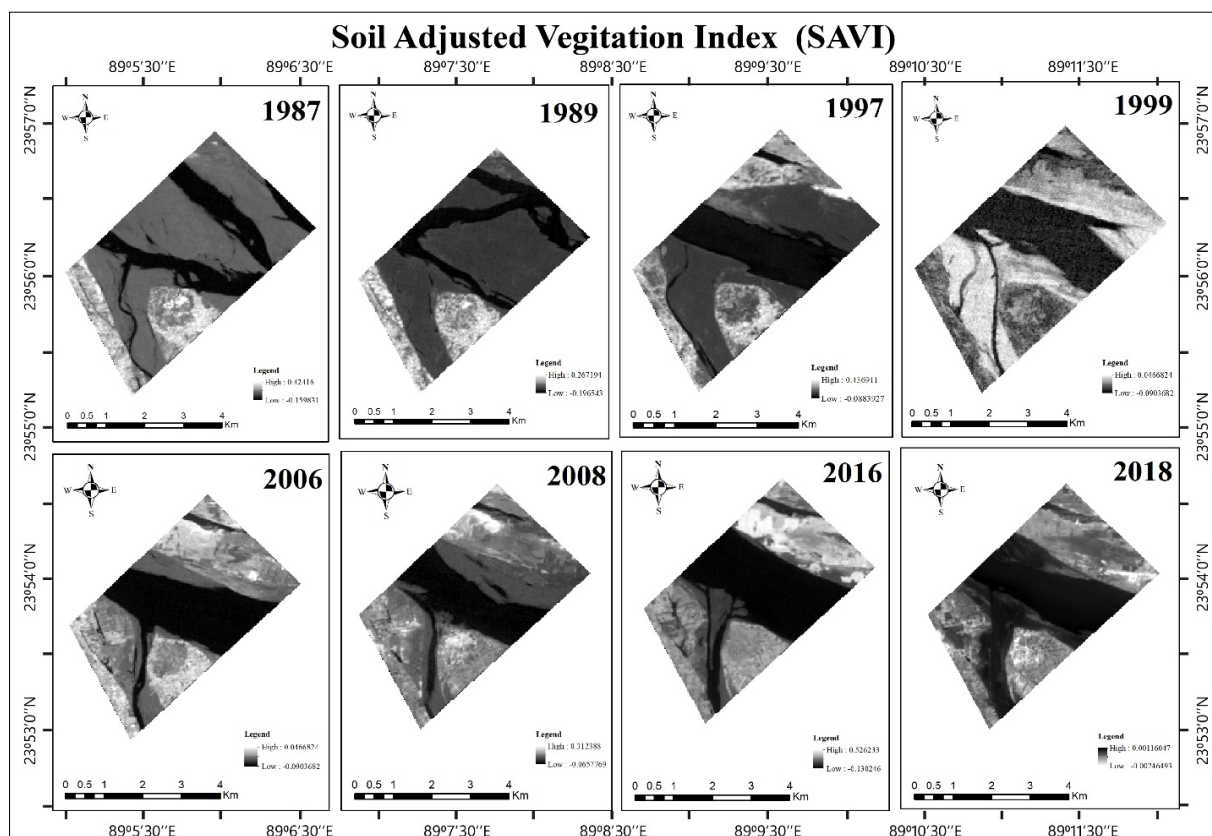


**Fig. 8:** Changes in the soil-adjusted vegetation cover of the study area (1987-2018).

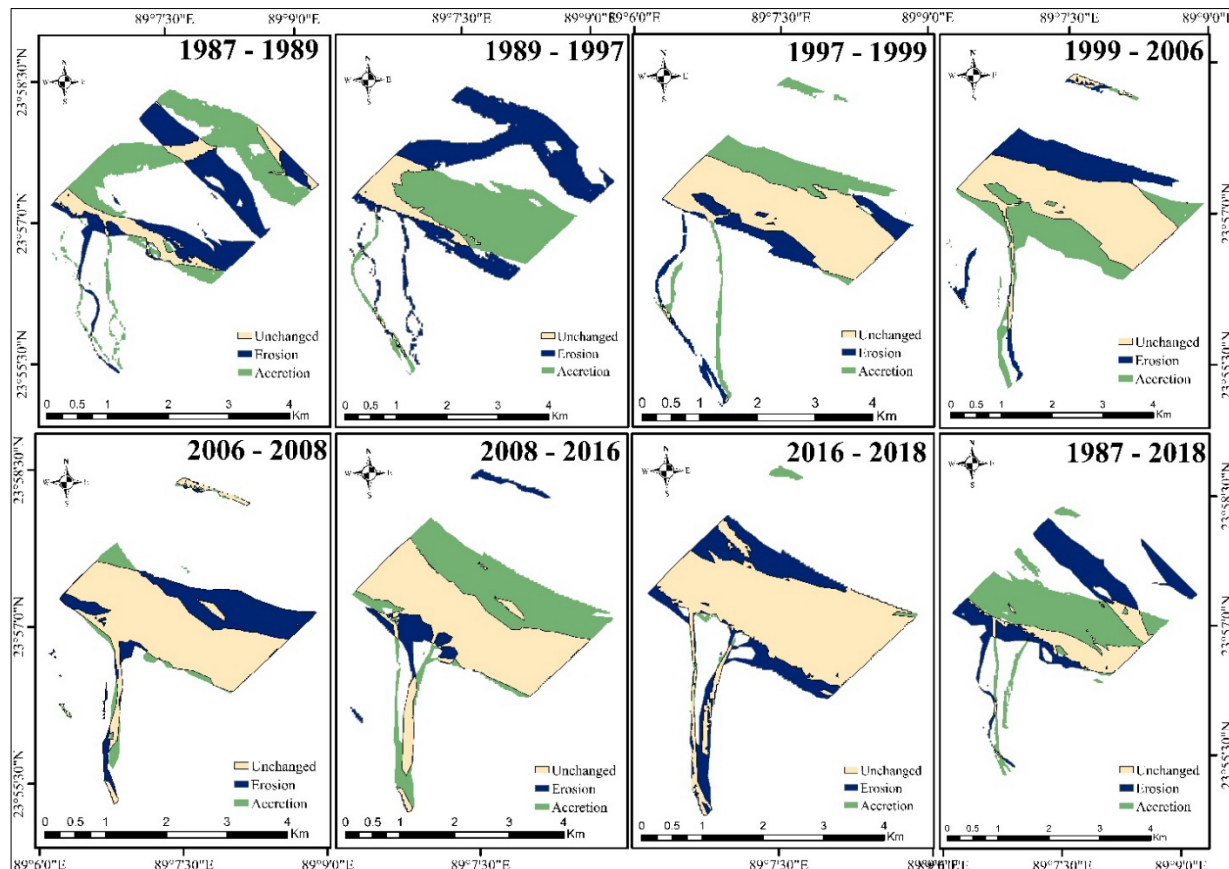


**Fig. 9:** Erosion and accretion scenario of the study area from 1987 to 2018.

### 3.6 Erosion and Accretion

Fig. 9 and Table S2 present the estimated erosion, accretion, and unchanged area for the 31 years from 1987 to 2018. Eight satellite images were used to calculate the eroded land area. The measurements were conducted during the following periods: 1987–1989, 1989–1997, 1997–1999, 1999–2006, 2006–2008, 2008–2016, 2016–2018, and 1987–2018. The 1989–1997 period had the highest erosion rate, resulting in the erosion of 373.9667 ha of land. The erosion rate was also higher in 1987–1989, with 287.4012 (ha) of land eroded. In the 1997–1999 period, the erosion rate decreased from 111.8398 (ha). Gradually, the erosion rate increased slightly from 1999 to 2006 and from 2006 to 2008, to 154.2516 (ha) and 174.4927 (ha), respectively. The period from 2008 to 2016 had the lowest erosion rate, measuring 59.45402 (ha). From 2016 to 2018, the erosion rate increased slightly, reaching 180.0769 (ha). Finally, the erosion rate increased from 1987 to 2018, resulting in 259.0678 (ha) of land erosion over 31 years. This 31-year period experienced a cumulative erosion of 1600.55072 (ha), resulting in the erosion of a total land area of 3918.6003 (ha). This high erosion rate caused a huge land loss in this area. The accretion rate varies significantly for 31 years from 1987 to 2018. The period from 1987 to 2018 saw the highest accretion rate, increasing to 373.4158 (ha) of land. The time interval from 2016 to 2018 saw the lowest accretion rate, with an increase of 19.25446 (ha) of land. The accretion rate was also higher in the years 1989–1997 and 1987–1989, during which 372.6194 (ha) and 353.1346 (ha) of land were deposited. From 1997 to 1999, the accretion rate dropped to 168.4619 (ha). But in the 1999–2006 time period, the accretion rate increased very little to 203.6068 (ha). In 2016–2018, the accretion rate increased to 291.0489 (ha). This 31-year period saw a cumulative accretion rate of 1829.24676 (ha), encompassing a total land area of 4147.2963 (ha). The Gorai Estuary changes its course very frequently. This study uses some historical years to illustrate the dynamic shifting of the Gorai Estuary. The Gain and Loss of each LULC of the study area are presented in Figures S1 and S2.

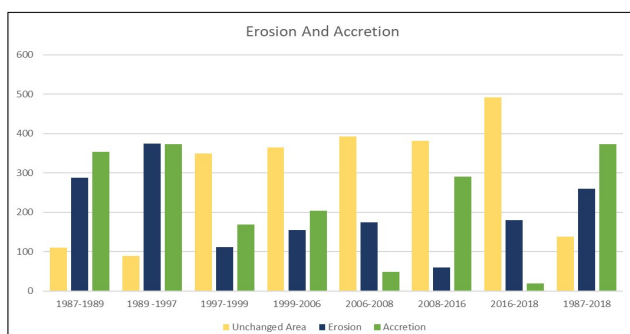


**Fig. 10:** Erosion and accretion rate of the study area (1987-2018).

The unchanged rate varies significantly from 1987 to 2018. The 2016–2018 period, with 492.3889 (ha) of land, had the highest unchanged rate. The period from 1989 to 1997 saw an increase in the lowest unchanged rate, measuring

89.06218 (ha) of land. The unchanged rate also increased in the years 2006–2008, 2008–2016, 1999–2006, and 1997–1999, encompassing land areas of 393.1661 (ha), 381.417 (ha), 364.052 (ha), and 349.8417 (ha). Between 1987 and 1989 and 1987–2018, the unchanged rate dropped to 109.8942 (ha) and 138.2276 (ha), respectively. The total unchanged land area was measured in these 31 years at 2318.049 (ha) (Fig. 10).

### 3.7 Prediction of land use and land cover of the study area (2018-2030)

Table 7 represents the prediction rate of each land class for the next 12 years. It indicates that the water body will dominate all land cover classes and cover approximately 41.75% of the study area. The table also shows that the fallow land will cover only 4.33% and 80.73 (ha) of the study area. Charland, agricultural land, and vegetation will cover 37.74%, 7.11%, and 9.11% of the study area. The prediction map of the study area is presented in Fig. 11. The accuracy level and Kappa statistics of the validation model are also presented in Tables S3 and S4.

**Table 7:** Prediction of land use and land cover of the study area (from 2018 to 2030).

| Land Classes      | Total Area (ha) | Percentages (%) |
|-------------------|-----------------|-----------------|
| Agricultural land | 131.94          | 7.11            |
| Char land         | 699.66          | 37.74           |
| Vegetation        | 169.02          | 9.11            |
| Water body        | 773.89          | 41.75           |
| Fallow land       | 80.37           | 4.33            |
| <b>Total</b>      | <b>1853.55</b>  | <b>100 %</b>    |

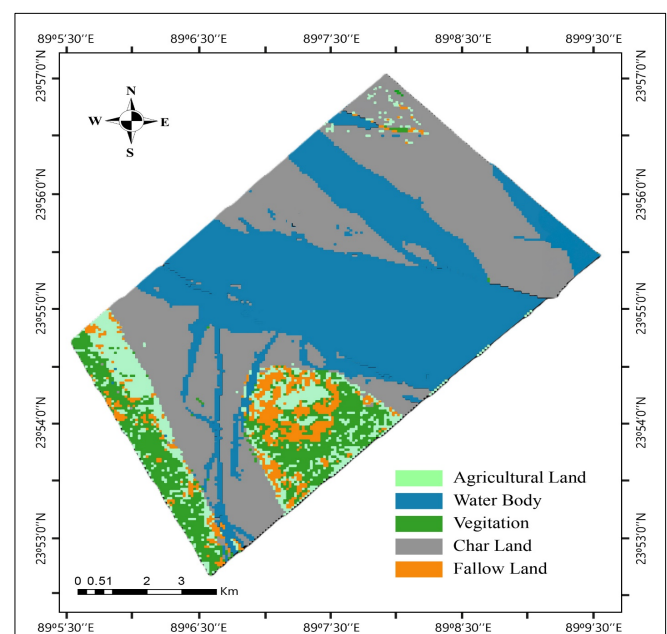


**Fig. 11:** Predicted land use and land cover map of the study area from 2018 to 2030.

## 4 Discussion

To observe the spatiotemporal changes of the Padma-Gorai estuary and its trend of changing land use and land cover patterns over the years, different compatible GIS and Remote Sensing-based analyses have been conducted in the present study. From the LULC change perception table, it has been found that agricultural land turned into char land, fallow land, vegetation, and water bodies over 30 years (1987-2018). At the same time, agricultural land has also benefited from other land uses. Char land has undergone significant transformations, acting as both a supplier and receiver of changes in land use. It has shifted from being used for agriculture, left fallow, and even used as a water body. Additionally, it has played a vital role in the growth of fallow land, vegetation, and water bodies, indicating important natural processes related to land and water systems. Fallow land has also transformed into agricultural land, char land, vegetation, and water bodies by the influence of shifts in land management practices and possibly the crop rotation cycles. The change of vegetation is quite shuffled. The changes in the landscape have been quite remarkable. Water bodies, especially, have changed a lot. They have shifted from agricultural land to char land, fallow land, and vegetation. The transformation of land cover features is affected by climate change, environmental issues like floods, and anthropogenic activities. Gazi et al. (2020) noted that in recent decades, global warming and climate change have altered rainfall schedules in river basin regions. This has led to several issues like flooding, shifts in water flow and discharge, and erosion and deposition along riverbanks. Because many riverbanks consist of clay and sand, they wear away with each monsoon season. Some of the momentous impacts were highlighted during the study. Mahmud et al. (2017) also stated that during the monsoon season, comparatively large discharge with high velocity leads to a high rate of sediment transport, eventually resulting in erosion, and reduced flow in the dry time causes sediment accumulation in the bed, resulting in the rising of the islands in the Padma River. The stark differences between various land types, such as vegetation and others, highlight how important it is to preserve the ecosystem and the diversity of plant and animal life. The significant alterations occurring with water bodies demonstrate how critical it is to effectively manage water resources to address issues, e.g., drought, flooding, and water scarcity. The transformations in areas like char land and fallow land reveal the ongoing natural changes and efforts to restore the land, calling for plans that smartly manage the land.

According to the NDVI analysis, although there were significant changes in the vegetation in 1987 (ranging from 0.63 to 0.43), it was more stable in 2018 (ranging from 0.01 to 0.01). In contrast, the greatest changes in water bodies were observed using NDWI in 2008 (ranging from 0.68 to -0.29), but by 2018, there had been some fluctuation (ranging from 0.15 to -0.35). Plant growth and water level behavior are heavily influenced by sediment build-up, erosion, and flood-prone areas. Garcia et al. (2008) mentioned that due to variations in water flow, sediment, and the surrounding environment, the rivers and streams in these regions shift and alter, affecting their shape and features. In the Gorai

Estuary in Bangladesh, there used to be a variety of plants and animals thriving along the riverbanks, supporting both farming and wildlife. The river's flow was steady, which was crucial for the local community's agriculture and way of life. Green spaces play a vital role in controlling drought, soil erosion, and temperature balance. Some researchers, Zoungrana et al. (2018) and Majumdar and Das (2014) mentioned that river erosion may depend on the velocity of water, slopes, and the sorts of materials making up the riverbank. Florsheim et al. (2008) demonstrated in their study that riverbank erosion is a dynamic and natural process that can occur due to the water flow and velocity of the water over time. Floods may also damage and destroy vegetation, which affects the variety of species in the region and agricultural production. Water quality can temporarily decline as silt and contaminants wash into water sources. Both people using the water and animals that live there may be harmed by this. Growing urbanization encroaches on green places, creating problems such as temperature fluctuations, dry periods, and increased evaporation (Li et al., 2011; Lu and Weng, 2006).

The erosion-accretion graphic displays the results of the study area's natural erosion and accretion rate during the previous 31 years. The way the land was used changed between 1987 and 1989. While some regions saw expansion and erosion, others remained unchanged. From 1989 to 1997, more land changed. The areas that remained constant decreased, but erosion and growth sharply increased. From 1997 to 1999, the unchanged area increased noticeably, which indicates that the land use pattern was stable over time. Erosion and accretion still played a significant role, indicating that natural forces were actively shaping the land. During the period of 1999 to 2006, the unchanged land area increased, and slight erosion and sedimentation were also found over the years. It is proof of good rotation of land use and versatile adjustment in land utilization. From 2006 to 2008, previously unchanged land decreased, erosion increased, and growth decreased markedly. From here, it can be said that the land was deteriorating and decreasing. But from 2008 to 2016, the exact opposite happened: the land development rate increased, but the rate of erosion decreased. And a large amount of land remains unconverted. This proves the improvement and stability of the land.

The amount of unused land was largely unchanged between 2016 and 2018. This indicates an upward trend in land use. As a result, the rate of erosion was high, and the growth rate was reduced. It can be said that many challenges in land management will make the erosion control system effective. Broadly speaking, complex interactions between natural processes and land use change are constantly evolving over time. Avoidance of this requires adaptation strategies that increase stability, erosion, and soil accumulation. Sustainable development should be ensured, which is necessary to cope with the changing nature. Floodwater is a powerful erosion agent that can remove the nutrient-rich topsoil, uproot vegetation, and reduce vegetation cover. As a result, we can see that the ability of the land to sustain vegetation is affected, and silt entering water sources can damage water quality. Halder and Mowla Chowdhury (2023) say that floods can cause massive and rapid changes

in river courses. Again, human activities and large-scale impacts such as overuse of land, changes in land use, river channelization, sand removal, vegetation damage or felling, and dam construction can accelerate erosion and sedimentation if not properly managed. Muzahid et al. (2024) found that the maximum extent of erosion observed between 2016 and 2019 was 4.6 km<sup>2</sup>, whereas the maximum extent of accretion observed between 2013 and 2016 was 7.12 km<sup>2</sup> in Gorai River, Kushtia.

The prediction of LULC changes in the Gorai River estuary from 2018 to 2030 reveals notable shifts across various land classes. The total study area spans 1,853.55 ha and will face significant land cover change over the years. The Gorai River estuary's transformation can happen due to both natural and human activities. Agricultural land will cover 7.11% of the area, with char land and vegetation accounting for 37.74% and 9.11%, respectively. Water bodies will be dominant, accounting for 41.75%, and fallow land will take up 4.33% of the area. Here, char land and water bodies are the dominating land cover features because of the continuous erosion accretion process, as the Padma brings a lot of sediment every year, and when it is deposited, it creates new char land in the river, and the erosion process continuously changes its bank area. Sarker et al. (2003) proved that at the preceding stage of flooding, the alteration in the riverbank line causing erosion occurs as excess sediment deposits as sand bars within the channel, resulting in the change of flow path and movement of sand bars thereupon, and also due to the silty materials from the banks' flow collapse. This follows Islam et al. (2025), who highlighted that the Ganges–Padma system has a massive sediment load that causes frequent bank line migration and the dynamic formation and disappearance of chars (vegetated islands). In the case of the River Padma, the cohesive substrate that contains consolidated and weathered Pleistocene-aged sediments (natural barrier) is immune to erosion and is available on the left bank, but on the right bank, they are scarce.

## 5 Conclusion and Limitations

This study focused on land use and land cover dynamics, including erosion and accretion, and predicted the land use and land cover of the Padma-Gorai River estuary. The LULC in this area fluctuated unpredictably, and it reached its maximum in char land, near the water body. The Study area experienced more accretion in the 1989–1997 time period, which is 372.6194 (ha), and the lowest in 2016–2018, which is 19.25 (ha). The maximum erosion that happened during the year 1989–1997 was 373.97 (ha), and the lowest was in 2008–2016, which was 59.45 (ha). River morphometric change, encompassing bank erosion, channel alteration, geomorphological features, and land cover changes, intensifies geohazards along river banks and floods in various years. This study also evaluates the future trend of LULC from 2018 to 2030, which shows char land (699.66 ha) and water bodies (773.89 ha) will be the most dominant land cover features. Thus, this study will help policymakers comprehend the river's space-time features and create an inclusive management and action plan to address river

dynamics issues. The study's findings will aid local land managers in implementing sustainable land use, erosion monitoring, and biodiversity conservation in the Padma–Gorai estuary, as well as help disaster planners highlight flood and erosion vulnerable zones, which will be beneficial for the early warning system and resettlement program. The water management authorities, in turn, would gain insights into changes in river flow, siltation, and irrigation demand, maintaining water quality and planning climate change adaptation strategies. Although this research provides evidence based on disaster, land, and water, future work should be conducted in this study area, considering socioeconomic status and loss of biodiversity under the aspects of climate change.

The possibility of inaccuracies in land use and land cover classification resulting from the moderate spatial resolution of Landsat images, which may not capture the finer details of the estuary's dynamic environment, is one of the primary limitations of this research. In addition, the temporal consistency of the data may be impacted by the limited availability of cloud-free imagery, particularly during the monsoon season, which further restricts the analysis. The study's dependence on historical satellite data also implies that any technological advancements or modifications in land cover classification methodologies since 1987 may affect the comparability of results over time. Finally, the prediction of future trends is fraught with inherent uncertainties, particularly in a region that is subject to intricate natural processes and human interventions.

## Acknowledgement

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

## Author Contributions

Conceptualization, methodology, data curation, visualization, formal analysis, writing - original draft, M.S.I., conceptualization, methodology, formal analysis, validation, visualization, writing - original draft, M.K.H., conceptualization, formal analysis, visualization, writing - original draft, S.K., conceptualization, formal analysis, validation, writing - original draft, M.S.K., conceptualization, formal analysis, writing - original draft, M.O.F.M., S.T., and M.J.P., and conceptualization, investigation, methodology, supervision, validation, and writing review & editing, M.A.K. All authors have read and agreed to the published version of the manuscript.

## Conflict of Interest

The authors declare no conflict of interest.

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## Supplementary Materials

**Table S1:** The areal extent (ha) of the LULCs over time (1987-2018).

| Classes           | 1987    | 1989   | 1997   | 1999   | 2006   | 2008   | 2016   | 2018   |
|-------------------|---------|--------|--------|--------|--------|--------|--------|--------|
| Agricultural Land | 140.94  | 316.71 | 351.18 | 112.86 | 295.29 | 127.98 | 261.81 | 430.56 |
| Vegetation        | 171.09  | 67.41  | 83.34  | 210.69 | 152.73 | 541.8  | 154.17 | 230.58 |
| Water Body        | 397.89  | 465.93 | 474.3  | 517.05 | 567.54 | 441.36 | 672.66 | 515.16 |
| Fallow land       | 84.78   | 140.4  | 274.32 | 610.65 | 675.42 | 395.37 | 553.86 | 404.82 |
| Char Land         | 1058.85 | 863.1  | 670.41 | 402.3  | 154.44 | 347.04 | 211.05 | 272.43 |

**Table S2:** Erosion and Accretion of the study area from 1987 to 2018.

| Year              | Previous Years | Next Years | Unchanged Area | Erosion  | Accretion |
|-------------------|----------------|------------|----------------|----------|-----------|
| <b>1987-1989</b>  | 397.2954       | 463.0288   | 109.8942       | 287.4012 | 353.1346  |
| <b>1989 -1997</b> | 463.0288       | 461.6815   | 89.06218       | 373.9667 | 372.6194  |
| <b>1997-1999</b>  | 461.6815       | 518.3036   | 349.8417       | 111.8398 | 168.4619  |
| <b>1999-2006</b>  | 518.3036       | 567.6588   | 364.052        | 154.2516 | 203.6068  |
| <b>2006-2008</b>  | 567.6588       | 440.871    | 393.1661       | 174.4927 | 47.7049   |
| <b>2008-2016</b>  | 440.871        | 672.4658   | 381.417        | 59.45402 | 291.0489  |
| <b>2016-2018</b>  | 672.4658       | 511.6434   | 492.3889       | 180.0769 | 19.25446  |
| <b>1987-2018</b>  | 397.2954       | 511.6434   | 138.2276       | 259.0678 | 373.4158  |

**Table S3:** Summary of Kappa statistics for the models on validation data.

| Kappa Indices                | CA Markov |
|------------------------------|-----------|
| K <sub>standard</sub>        | 0.48      |
| K <sub>no</sub>              | 0.66      |
| K <sub>location</sub>        | 0.72      |
| K <sub>location strata</sub> | 0.72      |

**Table S4:** Components of agreement and disagreement for model validation.

| Name of Component   | CA Markov |
|---------------------|-----------|
| Agreement Chance    | 0.1667    |
| Agreement Quantity  | 0.2803    |
| Agreement Strata    | 0.0000    |
| Agreement Grid cell | 0.2703    |
| Disagree Grid cell  | 0.1044    |

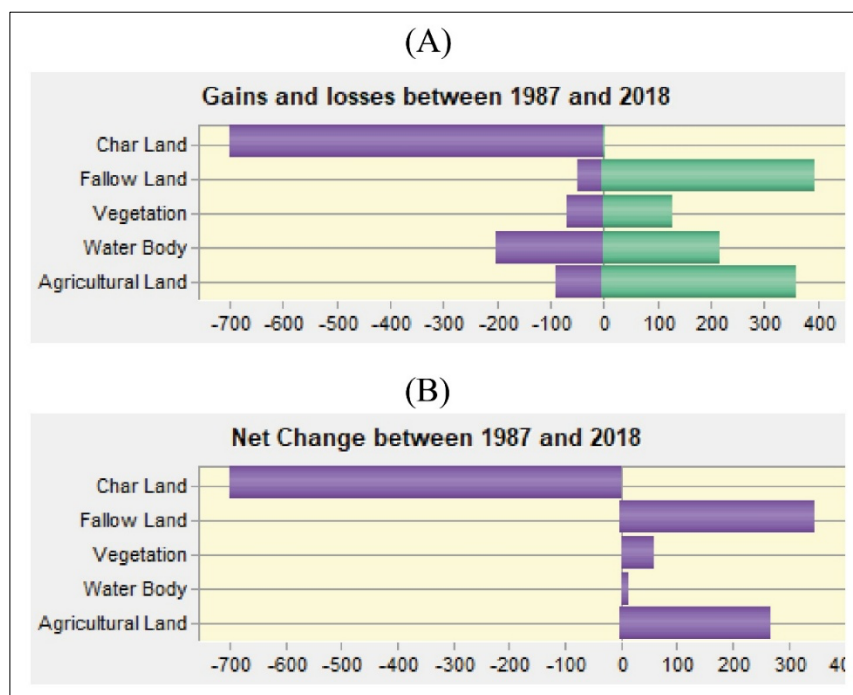


**Fig. S1:** Gain and Loss of LULCs of the study area (1987-2018).

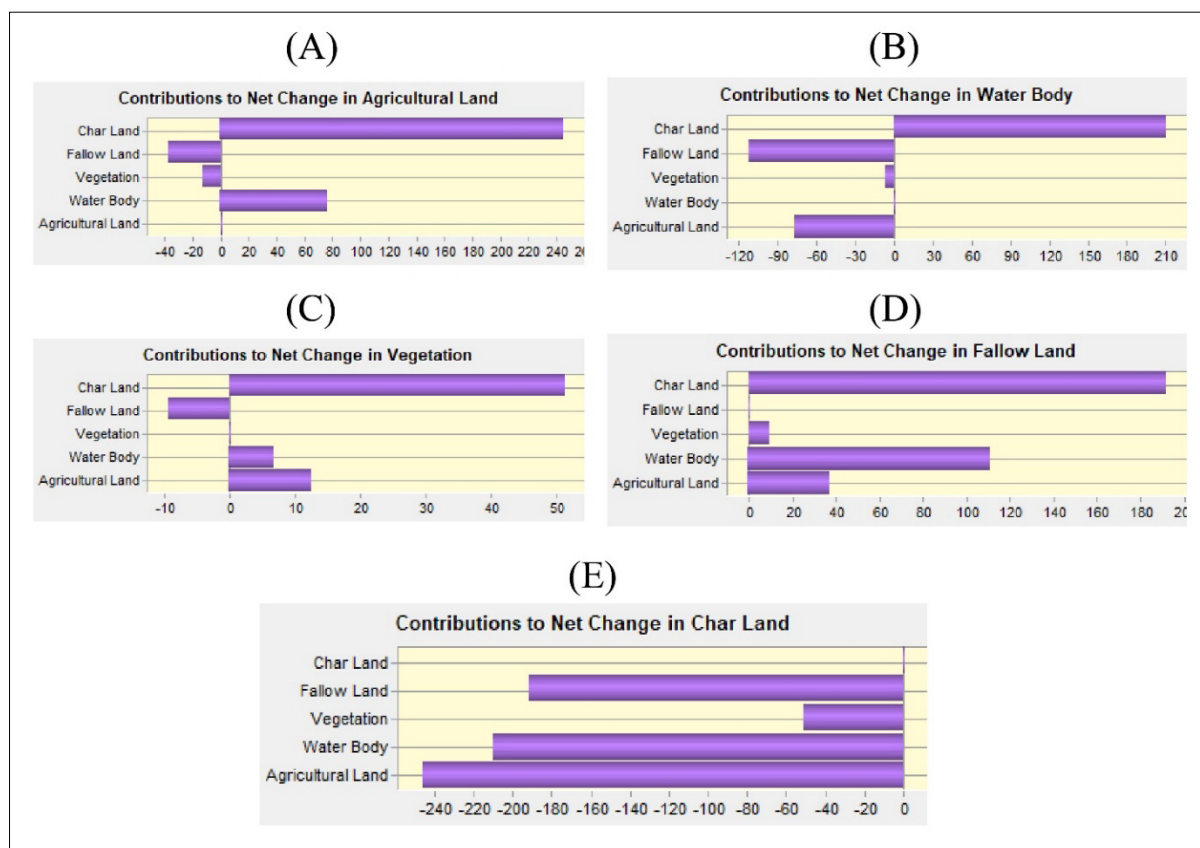


**Fig. S2:** Contribution of each class for the land use and land cover changes.