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Spatiotemporal dynamics of coastal wetland vegetation under large-scaled disturbances

(大規模攪乱下における沿岸湿原植生の時空間ダイナミクス)

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Abstract

Coastal wetlands, particularly mangrove forests, are one of the most carbon-rich ecosystems globally. However, mangroves have been deteriorated by natural and anthropogenic disturbances. To clarify the effects of these disturbances on the spatiotemporal dynamics of mangrove forests, it is crucial to distinguish mangroves from other land use types, identify predictors of forest disturbances and recovery patterns and assess species-specific characteristics and responses to environmental cues.

This study focuses on the Sundarbans mangrove forest in Bangladesh, a region characterized by high biodiversity and influenced by various disturbances, making it suitable for assessing coastal wetland vegetation dynamics. By integrating ground truth data with remote sensing, I examined the long-term impacts of these disturbances. I hypothesized that satellite imageries with a spectral resolution of 10 to 30 m detect land use and land cover (LULC) classes by analyzing spectral reflectance using multiple vegetation indices (VIs), i.e., normalized difference vegetation index (NDVI), green NDVI (GNDVI), soil-adjusted VI (SAVI), green-red VI (GRVI) and enhanced VI (EVI). A random forest (RF) algorithm was applied in conjunction with VIs to distinguish dense mangrove from other land cover classes (Chapter 1). One of the primary natural disturbances affecting this region is tropical cyclones (TCs), which, in the context of global climate change, have become intense and frequent. To quantify the impacts of TCs on mangroves, I compared EVIs in pre- and post-TCs (Chapter 2). In addition, I employed structural equation modeling (SEM) to examine the relationships among forest disturbance, TC wind speeds and track distances, temperature, precipitation and elevation. The ecological dynamics of mangrove forest types were assessed by interpreting species-specific phenological traits and their responses to disturbances at landscape level (Chapter 3).

To evaluate the effects of disturbances on mangroves with increase in high accuracy, spatiotemporal changes in LULC were analyzed over a few decades. Using remote sensing, various vegetation classes were integrated into a RF classifier (Chapter 1). This method effectively distinguished dense mangrove forest from other land cover types, revealing significant declines in mangrove areas while human-modified landscapes expanded. Natural disturbances, such as TCs, contributed to degradation in inaccessible regions, while anthropogenic activities, i.e., aquacultural land, altered areas near forest boundaries. These findings highlighted the importance of continuous monitoring of LULC, restoration of

habitat quality, sustainable aquaculture practices and mangrove afforestation for sustainable management strategies to mitigate further loss and enhance mangrove ecosystem resilience.

To clarify the long-term effects of TCs on the mangrove forest at large scale, temporal changes in mangroves were monitored by EVI from 1988 to 2024 (Chapter 2). Interannual changes in EVI indicated that TCs declined 0.2% to 22% of the total 5,980 km² mangroves. Although the damaged mangroves started to revegetate soon after TC strikes, strong and frequent TCs delayed the regeneration. SEM revealed wind speed as the highest predictor of forest disturbances, with TC track distance and precipitation also contributing to mangrove decline. These findings suggested that the predictable effects of TCs on mangroves will be amplified by stronger wind speeds at landfall and increasing precipitation. Therefore, mangrove restoration should prioritize protecting propagule sources, replanting site-specific native and wind-susceptible species along forest edges to promote natural regeneration, shield inner mangroves and stabilize coastal areas.

Mangrove forest phenology is crucial for assessing ecosystem health and sustainability. However, landscape-level interactions between mangrove species, their phenology and climatic factors remain insufficiently studied. This study analyzed a 21-year time-series of NDVI and EVI from MODIS surface reflectance across four dominant mangrove forest types (Chapter 3). Using Savitsky-Golay smoothing and discrete Fourier transform, key phenological metrics, i.e., start of the season, peak greenness and end of the season, were extracted. Seasonal patterns varied among the forest types, with fluctuations in canopy greenness. EVI-based metrics captured phenological variations well. Mixed forests showed an earlier phenological response in relation to precipitation, whereas native dominant species required more stable ecological conditions. Furthermore, *H. fomes* correlated negatively to TC-induced wind speed and showed delayed recovery, indicating climatic influences on mangroves. These findings suggest that species-specific mangrove phenology and responses to climatic factors, as detected by spectral reflectance of EVI, enable to be used for monitoring future species-specific changes under disturbances at landscape scale.

In conclusion, the utilization of optical sensors and the integration of optimal VIs detected the interactive effects of natural (e.g., TC) and anthropogenic (i.e., aquacultural land) disturbances on mangrove vegetation. SEM modeled that strong TC making landfall with increased precipitation near the forest edges caused evident disturbances to the

mangrove vegetation. While mangroves revegetated within a few years following TCs, the increasing intensity and frequency of these events impeded recovery processes. To ensure the conservation of vulnerable mangrove species and ecosystems, it is imperative to quantify changes in species characteristics in response to climatic factors. Mangrove replantation should be carried out following improvements in habitat quality to support natural seedling establishment and selection of site-specific native species instead of invasive species, thereby enhancing forest dynamics and promoting sustainable recovery after large-scale disturbances.

General introduction

Large-scale disturbances shape habitat structure and dynamics. Understanding habitat response to disturbances is vital in the context of global climate change (Macamo et al., 2016; Peereman et al., 2022). Mangroves are of key concern, considering mangroves role in providing ecosystem services, such as carbon sequestration and coastal protection; however, mangroves are vulnerable to disturbances of diverse intrinsic characteristics (Alongi, 2008). On a global scale, approximately two-thirds of mangrove habitats have undergone degradation to date (Spalding et al., 2010). Diverse mangrove species, which adapt to saline and hypoxic environments by morphological and physiological evolution, deteriorate immediately after disturbances when species stress thresholds are exceeded (Kathiresan and Bingham, 2001; Mo et al., 2023). Mangrove regeneration and species diversity also vary depending on species characteristics to climatic factors (Krauss and Osland, 2020). Detecting mangrove dynamics and species-specific responses to disturbances is crucial for clarifying conservation and restoration strategies for protecting coastal ecosystems (Hossain et al., 2022). This dissertation examined the long-term land use and land cover (LULC) changes in a mangrove region in Bangladesh, the largest continuous mangrove forest worldwide, with assessing forest disturbances and recovery patterns, and species responses to environmental cues.

Mangroves are distributed at the interface between land and sea in tropical, subtropical and warm temperate areas, covering ca 137,760 km² with distinct ecological traits (Long et al., 2024). South and Southeast Asia and latitudes between 5°N and 5°S have the highest spatial coverage and species diversity, and only 15 countries are home to almost 75% of the mangrove species (Aslan et al., 2016). However, this region is facing a loss due to the conversion of forests to aquaculture and rice plantations, making it a global hotspot for mangrove degradation (Brown et al., 2020; Goldberg et al., 2020). Meanwhile, mangrove ecosystems receive intense disturbances by tropical cyclones (TCs) than terrestrial forest due to their coastal location, resulting in a 45% naturally induced mortality among mangrove trees (Baldwin et al., 1995; Halder et al., 2021). The Sundarbans mangrove forest in Bangladesh comprises diverse plant species and provides ecological values over a million livelihoods (Azad et al., 2021a; Thakur et al., 2021a). The mangroves of Bangladesh have received considerable attention (Khan et al., 2021; Mahmood et al., 2021), but frequent TCs strikes have disrupted the ecosystem and dynamics (Rashid et al.,

2009; Quader et al., 2017). A long-term database is required to detect the changes induced by such disturbances, contributing to the understanding of mangrove recovery and informing improved conservation and management strategies for protecting coastal ecosystems (Hossain et al., 2022).

Satellite-based remote sensing data are widely used to detect land covers (Saoum and Sarkar, 2024) using the spectral reflectance across the electromagnetic spectrum (Végh and Tsuyuzaki, 2021). In addition, optical multi-spectral imagery offers detailed spatial information on LULC changes, particularly in a complex environment of mangroves where ground surveys have spatial and temporal limitations (Zhao et al., 2024). Since the spectral signature of mangrove vegetation is influenced by underlying soil properties and tidal fluctuations (Aji et al., 2023), vegetation indices (VIs) serve as a reliable basis for accurate monitoring of vegetation (Zhu et al., 2021).

In Chapter 1, I used multiple VIs that provide additional spectral signatures, precise and reliable classification (Maryantika and Lin, 2017; Shishir and Tsuyuzaki, 2018). Each VI showed unique characteristics in detecting LULC classes and the optimal VIs for each class were combined with a random forest (RF) classifier to reduce the classification errors. By the VI-integrated RF algorithm, I separated mangrove vegetation from other LULC classes and analyzed the spatial pattern of LULC changes. The developed LULC map was applied to quantify the spatiotemporal dynamics of coastal wetlands with high precision in relation to disturbance scale.

By applying thresholding to time-series of spectral VIs, it is possible to quantify disturbances linked to TCs (Zhang et al., 2016). This approach offers critical spatial information that supports policymakers in advancing forest management and restoration efforts (Primavera et al., 2006; Wang and Xu, 2009). Sporadic TC-induced strong winds, intense rainfall and storm surges directly disturb mangrove forests and forested landscapes by defoliation, breaking or uprooting trees (Fibich et al., 2023), yet mangrove vegetation often recovers rapidly following such disturbances (Krauss and Osland, 2020). Mangrove may therefore represent ecologically stable ecosystems; however, intense and frequent TCs driven by climate change make mangrove recovery uncertain and spatial extent of forest disturbances also varies. Accurately separated mangroves were used to estimate the extent of forest disturbances related to TCs and environmental factors by structural equation modeling (SEM) in Chapter 2. The path diagram of SEM shows causal relationships, depicting direct and indirect effects of each independent variable on the dependent variable

through regression analysis (Feng et al., 2021). To measure TCs derived forest disturbances, I considered environmental factors such as precipitation, temperature, elevation and slope, because disturbance levels are affected not only by wind speed and track distance of TCs but also by the characteristics of coastal environment (Mo et al., 2023). Modeling the magnitude of interaction of each factor on forest disturbances by SEM, Chapter 2 aimed to clarify the effects of TC-induced disturbances on the mangrove forest to promote natural regeneration and restoration of degraded mangroves.

Accurate estimation of mangrove phenology is important for interpreting plant photosynthetic activity and carbon uptake under ongoing climate change (Wu et al., 2017). While mangrove phenology traditionally relies on *in situ* measurements of growth stages such as leaf flush, flowering, and leaf shedding, MODIS-derived spectral VIs have shown increasing potential to characterize phenological patterns by capturing seasonal changes in canopy greenness over large landscape scales (Guzman et al., 2018; Mandal et al., 2020; Zeng et al., 2020). The spectral reflectance of VIs correlates with the mangrove species and their phenological traits (Aji et al., 2023). Furthermore, seasonal variations in precipitation have influenced the phenology of mangrove species (Cleland et al., 2007). Species-specific responses to natural disturbances such as TC also varied and influenced reproductive mangrove phenology (Aung et al., 2013; Azad et al., 2019). Therefore, Chapter 3 expected to examine the phenological traits of mangrove forest types at landscape level to assess species-specific characteristics and their responses to climatic factors. Species-specific phenological characteristics and responses to disturbances can be used for conserving vulnerable mangrove species.

The major objectives of this study were: 1) to detect spatiotemporal changes in and around mangroves by characterizing VIs for LULC classification; 2) to evaluate mangrove forest disturbances driven by the complex interactions between TCs and environmental indicators; and 3) to elucidate mangrove species characteristics by spectral VIs at landscape scales. Throughout this study, I aim to clarify the applicability of satellite data for assessing large-scale forest disturbances. The integrated approach should contribute to the sustainable conservation and restoration strategies of mangrove ecosystems, which are increasingly threatened by climate-induced disturbances.

Study sites

The Sundarbans, the largest continuous mangrove forest worldwide, develops in the delta of the Ganga-Brahmaputra Rivers and comprises a complex ecosystem of tidal and riverine waterway, mudflats and innumerable islands (Kumar et al., 2021). Mangroves cover ca 10,000 km², of which 60% lies in Bangladesh (21°30'N to 22°30'N and 89°00'E to 89°55'E), distributed along the southwestern coast of the Bay of Bengal, at less than 2 m a.s.l. (Fig. S-1). Sundarbans faces to south towards the Bay of Bengal with gentle slope (0.002°) (Chaffey, 1985). The mangrove forest is monitored within four administrative ranges, namely Sathkhira, Khulna, Chandpai and Sharankhula, extending from west to east, and 55 compartments (smaller operational blocks) (Halder et al., 2021). Two rivers are distributed along the east and west sides of the mangrove.

The diverse mangrove forest provides habitat for over 300 vascular plant species representing 245 genera, more than 1760 animal species, including 49 mammals, 35 reptiles, and 355 bird species (Mandal and Hosaka, 2020). The natural mangrove forest is composed of halophytic tree species and over 27 mangrove tree species, *Heritiera fomes* Buch.-Ham. (Malvaceae), *Excoecaria agallocha* (Euphorbiaceae) and *Ceriops decandra* (Griff.) Ding Hou (Rhizophoraceae) are the predominant, occupying ca 95% of the vegetated area (Iftekhar and Saenger, 2008). Others include *Sonneratia apetala* Buch.-Ham. (Lythraceae), *Avicennia officinalis* L. (Acanthaceae), *Xylocarpus mekongensis* Pierre (Meliaceae), *Bruguiera gymnorhiza* (L.) Lamk. (Rhizophoraceae), *Xylocarpus granatum* Koenig (Meliaceae) and *Nypa fruticans* Wurmb (Arecaceae) (Giri et al., 2007). Ecological zonation of mangrove species was defined depending on salinity (Table S-1). The mangrove forest in the northern and eastern oligohaline zone of Bangladesh supports high species diversity compared to those in the southern and western regions, due to consistent freshwater inflow that reduces salinity level. The mangrove in Bangladesh has been designated as a reservoir in 1875 and UNESCO World Heritage site in 1997 (Khan et al., 2021).

The mangrove has a tropical monsoonal climate with an annual precipitation ranges from 1,640 mm in the west to 2,000 mm in the east (Rogers and Goodbred, 2014). Approximately 80% precipitation occurs during the monsoon, i.e., June to September. Minimum and maximum temperatures are between 12°C to 35°C in the mangrove region (Kanan et al., 2023). The annual relative humidity is 70-80% throughout the year. In the monsoon season, this area is often affected by tropical cyclones that induce tidal waves, flooding and

saltwater infiltration (Mandal and Hosaka, 2020). Mangroves are crucial for protecting coast from strong winds, tidal waves, coastal erosion and saltwater intrusion (Rahman and Asaduzzaman, 2013).

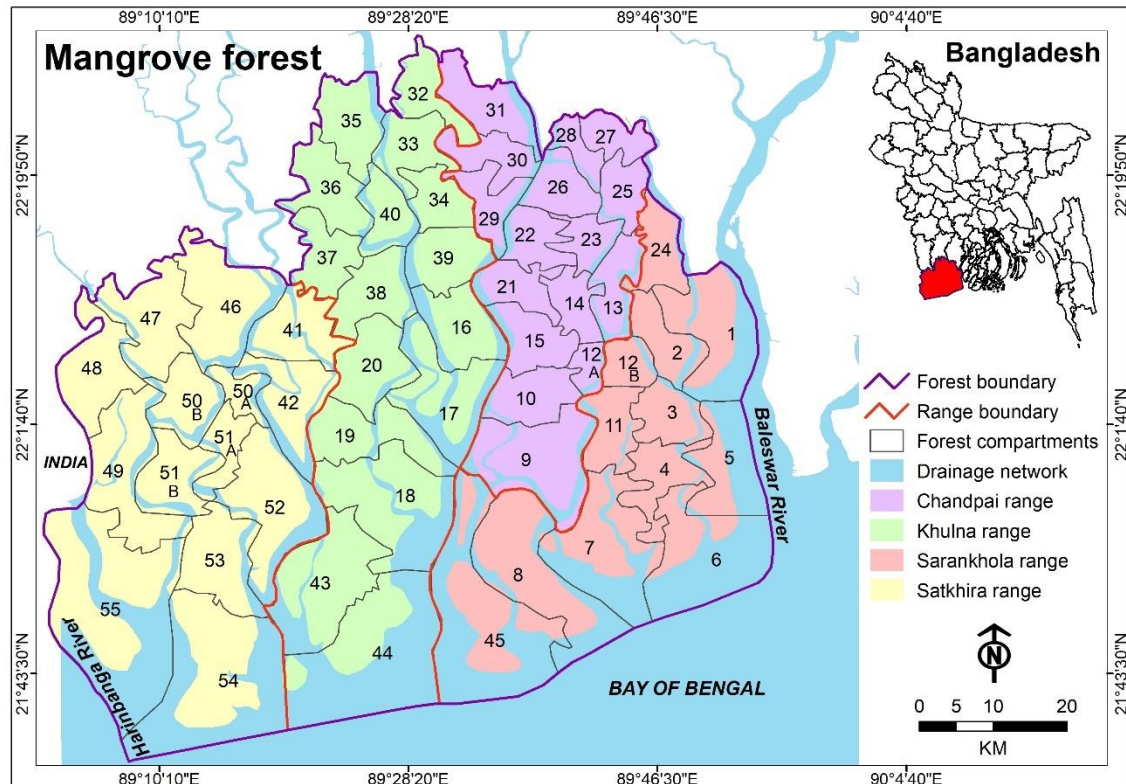


Fig. S-1. Spatial extent of the Sundarbans mangrove forest. The inset map highlights the geographical position of the mangrove forest in Bangladesh.

Table S-1. The ecological characteristics of the dominant mangrove tree species.

Characteristics	<i>H. fomes</i>	<i>E. agallocha</i>	<i>C. decandra</i>
Leaf habits	Evergreen tree species	Deciduous tree species	Evergreen mangrove shrub
Ecological zonation	Oligohaline, freshwater	Mesohaline, moderate saltwater	Polyhaline, saltwater
Salinity level	< 2 dS/m	2-4 dS/m	> 4 dS/m
Average height	> 20 m	< 15 m	2 m
Forest Area coverage	73%	16%	-
Root adaptations	Pneumatophores	Surface roots	Stilt roots
Leaf phenology	Leaf flush	March-May	-
	Leaf shedding	February to April	-
	Flowering	July	-
	Fruiting	July-September	April-May

(Source: Rahman and Islam, 2015; Siddique et al., 2021; Hossain et al., 2012)

Chapter 1: Effects of disturbances on the spatiotemporal patterns and dynamics of coastal wetland vegetation

1.1. Introduction

Disturbance is defined as an event that removes biomass and thereby causes changes in ecosystem structures and functions (Keddy, 2017). Mangroves are unique inter-tidal forested wetlands in tropical and subtropical regions (Giri et al., 2011). Because mangrove habitats are characterized by high salinity, high tidal fluctuations, strong winds, high temperatures and hydric muds, salt-tolerant plants establish there by developing aerial roots (Keddy, 2010; Sandilyan and Kathiresan, 2012). Because mangrove ecosystems are diverse and productive, the ecosystems provide various ecological services, such as shoreline alleviation, biodiversity, carbon sink, storm surge protection, water purification, agriculture and fishery and timbers (Mo et al., 2023). However, mangroves have decreased globally by 0.2% to 0.4% per annum (Hamilton and Casey, 2016). Sundarbans located in Bangladesh and India develops the largest mangrove worldwide (Erwin, 2009). The mangroves in Sundarbans expose to tropical cyclones, storm surges, coastal flooding, sea-level-rise, etc., which are enhanced by climate change (Thakur et al., 2021b). The mangrove is enclosed by embanked islands, where farmlands and aquaculture ponds are constructed, experiences increased anthropogenic pressure (Mondal et al., 2021a). Therefore, the combined effects of natural and anthropogenic disturbances on mangrove should be observed in details (Giri et al., 2007), by land use and land cover (LULC) changes (Hu et al., 2020).

Mangrove forests in Bangladesh covers 3.2% of the mangrove areas in the world (Giri et al., 2011). The mangroves encompass ca 10,000 km² at less than 2 m a.s.l. in tropical moist forests and 60% lay in Bangladesh (Iftekhar and Saenger, 2008). The mangroves are subjected to tidal incursions twice daily (Payo et al., 2016). The gentle slope of Sundarbans faces to south towards the Bay of Bengal (Chaffey, 1985). The mangroves provide coastal bio-protection and support over a million livelihoods through the ecosystem services (Thakur et al., 2021a). Therefore, this area is often affected by cyclones. Increased human intervention, i.e., aquaculture expansion, has triggered the mangrove depletion (Erwin, 2009). However, little is known about the dynamics of mangroves due to inaccessibility and scale (Mandal and Hosaka, 2020).

Satellite remote sensing provides comprehensive and cost-effective mapping, monitoring and assessing of ecosystems at large scale (Thomas et al., 2017). Furthermore, image classification using multi-spectral imagery and digital image processing algorithms monitors spatiotemporal changes in LULC (Thakur et al., 2021a). LULC changes are capable of characterizing mangrove ecosystem, which is a prerequisite for decision-making in ecosystem management policies (Ahmad et al., 2023). Evaluating LULC accuracy with error matrix and κ coefficient is the standard for evaluating remotely sensed image classification (Mondal et al., 2021b). Nevertheless, the effectiveness of these datasets for LULC changes in mangroves are controversial in separating and classifying mangroves from others (Quader et al., 2017; Hossain et al., 2022). Therefore, this study aims to assess the applicability of satellite data for detecting the spatiotemporal dynamics of coastal wetland vegetation in relation to disturbances.

Vegetation index (VI) provides a radiometric assessment of spatial and temporal variations in photosynthetic activity in vegetation using specific spectra (Rhyma et al., 2020). VIs assess vegetation activities as their values are proportional to biophysical parameters, i.e., leaf area index (LAI) (Arshad et al., 2020). VIs are widely used in disturbance ecology, particularly to detect forest canopy dynamics (Taillie et al., 2020) and land-cover changes (Silva et al., 2020). Decadal changes in LULC examined by VIs evaluate mangrove health (Thakur et al., 2021b). The classification of mangroves and non-mangrove areas are evaluated by five VIs, normalized difference VI (NDVI), green normalized difference VI (GNDVI), green-red VI (GRVI), soil-adjusted VI (SAVI) and enhanced VI (EVI) (Aji et al., 2023), because each VI has certain characteristics that are relevant for estimating greenness. Multiple VIs allow additional signatures, accurate and reliable classification, and LULC monitoring, particularly in complex ecosystems represented by mangrove forests (Maryantika and Lin, 2017).

NDVI has been used for detecting the dynamics of LULC but decreases the accuracy with increasing surface greenness, owing to the saturation of VI (Kushida et al., 2015). GNDVI, SAVI, GRVI and EVI improve the problems of NDVI. GNDVI exhibits lower saturation in high vegetation cover by the introduction of green spectrum into NDVI (Maryantika and Lin, 2017). GRVI is sensitive to changes in leaf green color at the canopy surface and assesses forest degradation and phenology (Shishir and Tsuyuzaki, 2018). SAVI reduces hyper-reflection of soil by the addition of a term, soil brightness correction factor (Huete, 1988). EVI reduces soil and atmospheric effects by blue band (Zhu et al., 2021).

LULC changes have been investigated by VIs in various mangrove regions (Baloloy et al., 2020; Rodrigues et al., 2023). So far, studies on mangroves have focused mostly on LULC classification (Islam et al., 2019; Kundu et al., 2021). Because VI-based LULC classification at medium resolution has not been validated, the effectiveness of multiples VIs was evaluated in this study. Random forest (RF) is a machine-learning algorithm for supervised classification using multiple decision trees (Belgiu and Drăguț, 2016). RF is suitable for analyzing plant classification (Breiman, 2001), forest phenology (Aji et al., 2023), vegetation changes (Wang et al., 2022) and land cover changes (Purwanto et al., 2023), independent of the number of variables (Toosi et al., 2019). RF classifier was used with VI-based LULC classes to decrease classification error. The cloud-based Google Earth Engine (GEE) platform was used for analyzing large multitemporal geospatial data. The high accuracy of classifying and monitoring changes in LULC is crucial for conserving the vulnerable mangrove forests.

The three major objectives were: 1) evaluating the advantages and disadvantages of each VI for detecting mangroves; 2) characterizing the VIs on each LULC class and constructing an integrated RF classifier utilizing the VIs; and 3) assessing the dynamics of LULC induced by natural and anthropogenic disturbances. Detecting spatiotemporal patterns and dynamics of LULC using RF classifier provides a valuable tool for mangrove monitoring and helps policymakers improve conservation and restoration strategies.

1.2. Materials and methods

1.2.1. Study area

The study was conducted in the Sundarbans mangrove forest, Bangladesh (Fig. 1-1a). The forests are distributed in estuarine formed by the convergence of rivers. The study area is 8,360 km² in the mangrove regions by creating a 5 km buffer zone of exposed and part of interior coast around the mangrove forest (21°61'N to 22°68'N and 88°97'E to 89°93'E) (Fig. 1-1b). The exposed coast and lower estuaries face high cyclone risks, soil salinity (>15 dS/m), and tidal movement (range: 0.3 to > 2 m), leading to intensive interaction with the marine environment (Mondal et al., 2022). Tidal water fluctuations and soil salinities are above threshold levels, i.e., 0.3 m and 4 dS/m, respectively, in the selected interior coast. Two rivers, the Baleswar River and Harinbanga River, are distributed along the east and

west sides of the mangrove. The monthly average temperature, precipitation and relative humidity in the mangrove region range from 12°C to 35°C, 1,600-2,000 mm, and 70-80%, respectively (Kanan et al., 2023).

The study area included mangrove, grass-land, bare land, waterbody, etc. (Forest Department of Bangladesh, 2020). The coastal periphery is characterized by aquacultural land for shrimp culture and salt production and homestead vegetation. Although the reserved mangrove has managed by conversion from agriculture to integrated management since 1879 (Mahmood et al., 2021), the mangroves have been degraded and reduced by both natural and anthropogenic activities (Hossain et al., 2022).

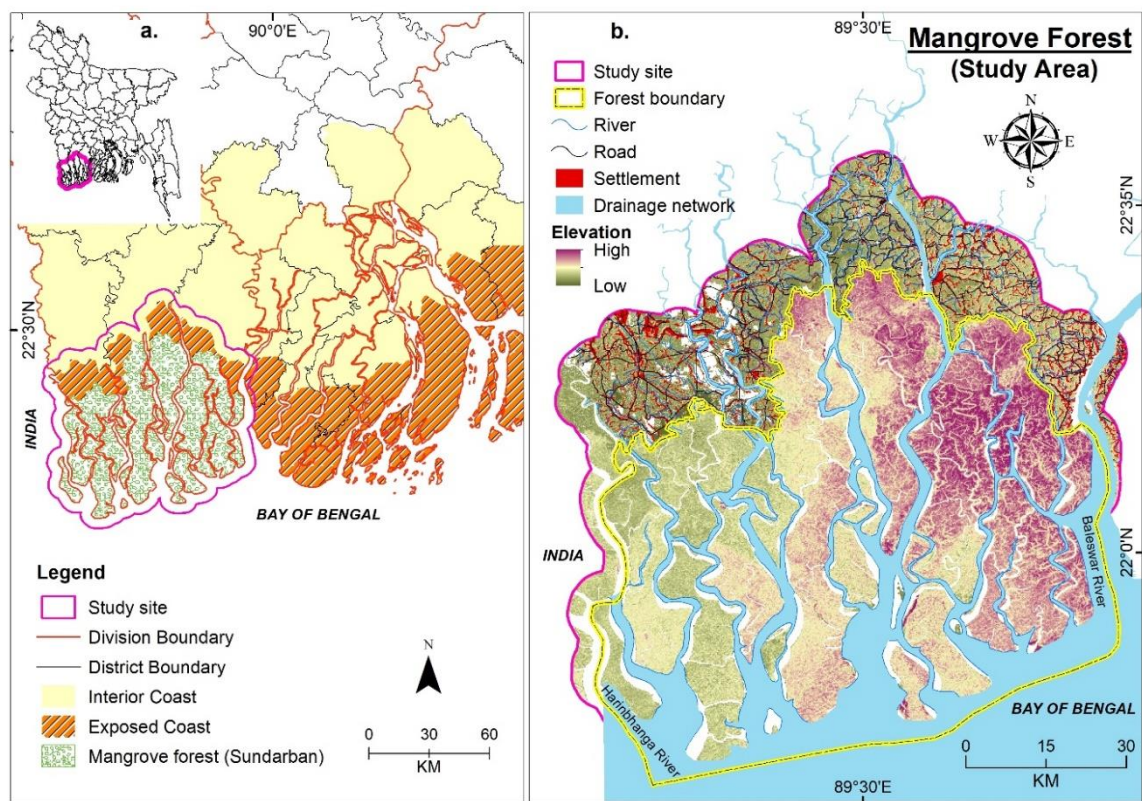


Fig. 1-1. a. The distribution of mangrove forest and their adjacent areas in the buffer zone. **b.** Study area.

LULC classes in the study area were interpreted by high-resolution (< 1 m) Google Earth Pro and false color composites (FCC; R = near-infrared, G = red, B = green) of multispectral data. Eight LULC categories were determined. Of those, high density mangrove forests and a smooth texture in FCC with no exposed soil (Quader et al., 2017) is classified as dense mangrove. Dense mangrove indicates tall trees with well-health status of mangroves and homogeneous distribution (Sari and Rosalina, 2016), and provides the highest biodiversity, disaster mitigation and livelihood (Uddin et al., 2013). Sparse

mangrove was recognized by a coarse texture in FCC with exposed soil in-between trees (Quader et al., 2017). Sparse mangrove reflects lower canopy cover and reduced tree density, typically found in salt-water zone, fringe and riverbank, indicating the expansion of salt-resilient species and a degraded vegetation condition (Kanjin and Alam 2024). Detecting the coverage of both dense and sparse mangrove forest emerged as a key concern in this study. The remainders were water bodies, aquacultural land, mudflats near estuary, homestead vegetation consisting of trees, shrubs and herbs on and around rural settlements and roads, bare land including sand bar and cropland. Natural disturbances, such as cyclone, storm surge and salinity intrusion, affect the structure and function of mangroves, while anthropogenic disturbances, e.g., overexploitation of forest resources, expansion of agriculture and fishery, urban development, cause changes in and around mangroves (Kumar et al., 2021; Kanan et al., 2023). Moreover, soil salinity and disturbance are increased by the conversion from rice field to aquaculture (Islam et al., 2018).

1.2.2. Satellite imageries for LULC classification

Landsat datasets were used, because of long-term data > 50 years (Table 1-1). The data obtained by Sentinel-2A (10 m resolution) were also used for the comparison of VIs (Drusch et al., 2012) and shuttle radar topography mission (SRTM) was used for obtaining elevation. The data were obtained from GEE surface reflectance tier 1 data archive within five years interval from 1988 to 2020. To avoid the interference of cloud, images were selected during the dry seasons (January to March) when cloud cover was less than 10%. The data in 2010 was not obtained for the absence of quality images.

Table 1-1. The ranges of spectral bands and resolution of the collected satellite imageries.

Year	Platform*	Sensor	No. of Bands	Wavelength (nm)	Resolution (m)	Earth Engine Snippet
1988 1991 1995 2000 2006	Landsat 5	Thematic Mapper (TM)	07	Blue: 441-514 Green: 519-601 Red: 631-692 NIR: 772-898	30	("LANDSAT/LT05/C02/T1_L2")
2016	Landsat 8	Operational Land Imager (OLI)	11	Blue: 452-512 Green: 533-590 Red: 636-673 NIR: 851-879		("LANDSAT/LC08/C02/T1_L2")
2020	Sentinel-2A	Multispectral Instrument (MSI)	13	Blue: 458-523 Green: 543-578 Red: 650-680 NIR: 785-900	10	("COPERNICUS/S2_SR_HARMONIZED")

* Data sources: Landsat 5 and 8: <https://earthexplorer.usgs.gov/>. Sentinel-2A: <https://scihub.copernicus.eu/>. SRTM (version 4): <https://srtm.csi.cgiar.org/>. based on GEE, 2024.

1.2.3. Image pre-processing

GEE cloud platform was used for image processing (Gorelick et al., 2017). Landsat (TM and OLI) products are devoid of radiometric and geometric distortion (Kafy et al., 2020) and the GEE contains atmospherically corrected surface reflectance (SR) data (Tamiminia et al., 2020). I applied scaling factors for Landsat Level 2 SR (0.0000275 ± 0.2 per pixel), filtered functions reduced an image collection to a single image and masked cloud of Sentinel-2 using the QA (pixel_qa) band bit mask technique. The visible (red-green-blue) and near-infrared (NIR) bands were composite for VIs. To avoid geometric distortion, a consistent coordinate system was used under the default of WGS84 (EPSG: 4326).

1.2.4. Vegetation indices

A total of eleven VIs, NDVI, GNDVI, SAVI, GRVI, EVI, simple ratio index (SR), mangrove vegetation index (MVI), normalized difference moisture index (NDMI), atmospherically resistant vegetation index (ARVI), red-edge chlorophyll vegetation index (RECI) and green chlorophyll vegetation index (GCI) were used to examine the variations in surface greenness. These VIs were selected based on their respective sensitivity to monitor vegetation cover in the tropical environments, that were characterized by water, soil background effects and mangroves. The effectiveness of the VIs for LULC classification were examined by the multiple comparison and error matrix between the VIs and the reference data prior to the RF classification. The examined five of the eleven VIs showed higher than 75% overall accuracy and were used to extract LULC categories. The other six VIs showed less than 60% accuracy. The five verified VIs were:

$$NDVI = (NIR - Red) / (NIR + Red) \quad [1]$$

$$GNDVI = (NIR - Green) / (NIR + Green) \quad [2]$$

$$SAVI = ((NIR - Red) / (NIR + Red + L)) \times (1 + L) \quad [3]$$

$$GRVI = (Green - Red) / (Green + Red) \quad [4]$$

$$EVI = G \times ((NIR - Red) / (NIR + C_1 \times Red - C_2 \times Blue + L)) \quad [5],$$

where the blue, green, red, and NIR express reflectance from blue, green, red, and near-infrared spectrum. G is a gain factor, L incorporates a soil-adjustment factor, and C₁ and C₂ are coefficients to correct aerosol scattering in red band by the blue band (Jiang et al., 2008). Here, G = 2.5, C₁ = 6.0, C₂ = 7.5, and L = 1 for EVI and 0.5 for SAVI (Huete et al., 2002; Maryantika and Lin, 2017).

NDVI, GNDVI, SAVI, GRVI and EVI range from -1.0 to +1.0. NDVI has a disadvantage that water influences NDVI, making it less effective in distinguishing changes in vegetation density (Miura et al., 2001). Thus, several VIs modified from the NDVI have been developed for the extraction of vegetation (Rokni and Musa, 2019).

GNDVI improves the estimation of intercepted photosynthetic active radiation, water, and nitrogen uptake into plants and is less influenced by the background and atmospheric factors (Gitelson et al., 1996). GNDVI is more responsive to chlorophyll concentration than NDVI (Trong et al., 2020).

SAVI includes a correction factor L (Eq. 3) to reduce the effects of soil reflectance and the saturation at the high end of vegetation density (Huete, 1988). SAVI often detects bare soil and sparse vegetation from the others (Vani and Mandla, 2017), and demonstrating high accuracy in delineating mangrove and non-mangrove areas (Rhyma et al., 2020).

GRVI can effectively extract dense vegetation from other land cover types using the ratio of green and red wavelengths (Shishir et al., 2020).

The parameters were adopted in EVI (Eq. 5) improves sensitivity in high biomass regions and the accurate identification and mapping of mangroves that is often saturated by NDVI by minimizing background signals and atmosphere influences (Huete et al., 2002). EVI is spectrally sensitive to the NIR and contains information from multiple canopy leaf layers (Huete, 2012). Therefore, NDVI, GNDVI, SAVI, GRVI and EVI derived from Landsat TM and Sentinel-2A imageries were compared for detecting mangrove LULC classes and changes.

1.2.5. Evaluation of VIs on LULC classification

The effectiveness of VIs from Landsat and Sentinel-2A were evaluated in detecting disturbance-induced changes in LULC, by comparing VI change maps with a reference map derived from ground truth, aerial photographs or satellite images (Jensen, 2015). The

land cover types were aligned with the reserved forest map (Forest Department of Bangladesh, 2020), and the adjacent area cross-referenced with the indicative coastal land use zone map (Mia and Islam, 2005). The land cover patterns of mangroves were subdivided into sparse and dense mangroves through image interpretation and verified VIs. Coastal land use patterns were adjusted by incorporating aquacultural land, bare land and cropland. Historical maps were used as reference data for LULC classifications. By overlaying the reference data on Google Earth Pro, a total of 320 ground truth points were created. For each point, the spectral reflectance of VIs for LULC types was extracted from both Landsat and Sentinel-2A images.

Correlations between VIs for LULC classes were evaluated using Pearson's correlation coefficients (r). One-way analysis of variance (ANOVA) was used to identify differences in VIs among the LULC classes. When ANOVA was significant at $p < 0.01$, Tukey's multiple comparison tests were conducted between the LULC classes. All statistical analyses were conducted in R (R 4.2.2) with libraries tidyverse and corrplot (R Core Team, 2024).

1.2.6. VI-integrated RF classification

RF is a non-parametric method combining multiple classification methods and regression trees by a random subset of samples from the training data (Breiman, 2001). The RF algorithm was constructed within GEE to extract the LULC by spectral spectrums and VIs. Each VI was calculated at each pixel. Each pixel was classified into the respective LULC classes by VIs.

To reduce the identification error on VI-based LULC maps, the VIs was added as bands with the processed satellite imageries for RF classifier. The optimal VIs for each LULC class were used in stratification and assembling of sample points for VI-integrated RF classification. The optimal VI for each class were determined through the Tukey (HSD) cross-validation test (p -value < 0.05). More than 50 sample points were randomly selected for each LULC class, whereas 70% of the reference samples were used as a training set. Multiple decision trees were generated using the training samples, where each tree made a classification decision. The RF classifier predicts the final LULC map through majority voting from each tree for mangrove classification (Toosi et al., 2019). The number of decision trees and variables at each node was set at 100 and equal to the square root of the number of variables, respectively.

1.2.7. Accuracy assessment of LULC classification

The classification accuracies were examined by an error matrix of κ coefficients in the GEE platform using 30% of validation datasets and Google Earth image as the reference (Fig. 1-2). The confusion matrix was generated to calculate the overall accuracy (OA) and κ coefficient index from the VIs and RF integrated LULC classification (Foody, 2002). OA is expressed by $\frac{\sum_{i=1}^r X_{ii}}{N} \times 100$, where $\sum_{i=1}^r X_{ii}$ is total observed pixels classified correctly, and N is total number of pixels observed. κ is expressed by $\frac{N \sum_{i=1}^r X_{ii} - \sum_{i=1}^r x_{i+} x_{+i}}{N^2 - \sum_{i=1}^r x_{i+} x_{+i}}$, where x_{ii} is number of pixels observed in row i and column i, r is total number of rows/columns (classes) in confusion matrix, x_{+i} is total number of pixels in row i and x_{i+} is total number of pixels in column i. κ ranges from 0 to 1. When $\kappa > 0.80$, the result of classification is reliable. The classification procedure was repeated 10 times with different training and test sets, using cross-validation to reduce the classification errors.

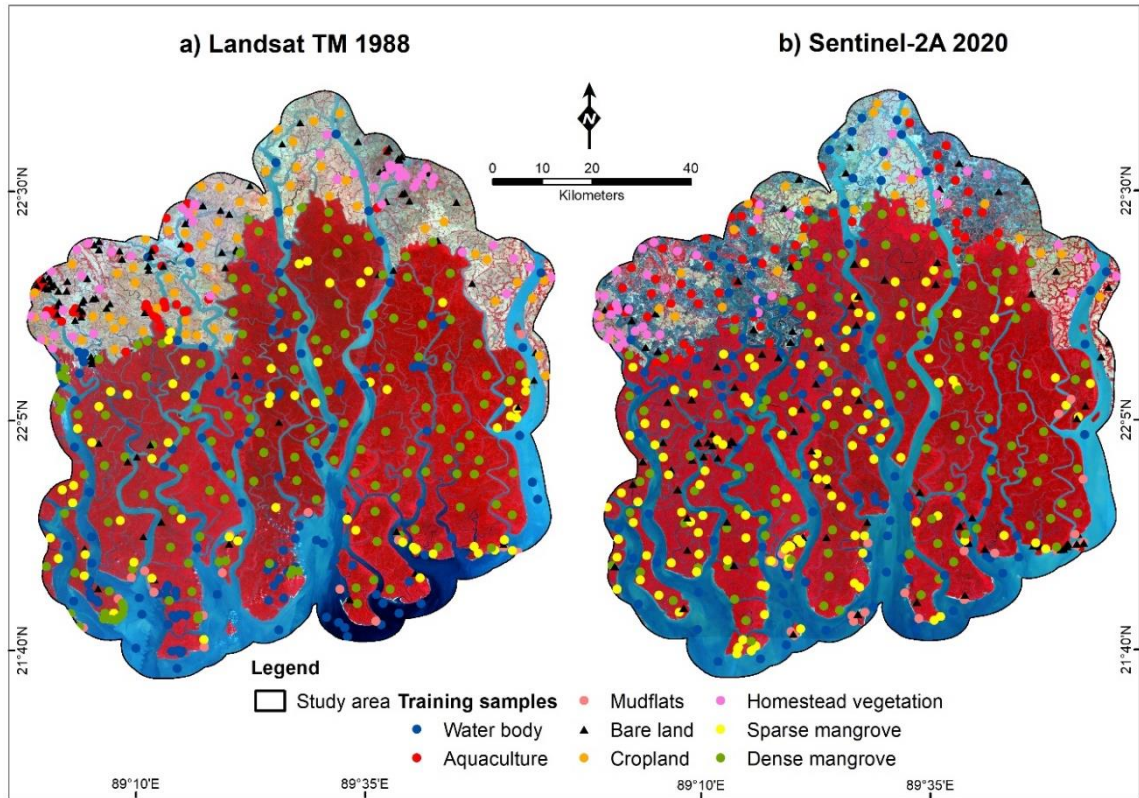


Fig. 1-2. Spatial distribution of training and testing samples for LULC classes in the study area. 605 points were generated using the stratified random sampling method, with 182 assigned for validation. **(a)** Samples for 1988; **(b)** Samples for 2020. (Image source: Landsat TM and Sentinel-2A in false color composites (FCC) downloaded from GEE, 2024).

The spatial autocorrelation of LULC samples was examined by the Global Moran's Index (Moran's I) with the coordinates of training samples in ArcGIS version 10.3. The Moran's I calculated by $I = \frac{n \sum_{i=1}^n \sum_{j=1}^n \omega_{ij} (x_i - \bar{x})(x_j - \bar{x})}{S_0 \sum_{i=1}^n (x_i - \bar{x})^2}$, where, n is the number of points, x is the variable of interest, $\bar{x}$ is the mean and ω_{ij} is the spatial weight describing the distance between i and j and S_0 is the aggregate of all the spatial weight (i.e., $S_0 = \sum_{i=1}^n \sum_{j=1}^n \omega_{ij}$). The value of Moran's I range from -1 to 1 , where $I > 0$, < 0 , and $= 0$ indicate the clustered, dispersed and random pattern of the selected samples (Wang et al., 2021). The inverse distance and Euclidean distance were used to analyze the distribution pattern of LULC samples within the study area (Rhyma et al., 2020).

1.2.8. Quantification of spatiotemporal dynamics of LULC

The post-classification change detection algorithm, i.e., the annual rate of change (ARC) for each class, was calculated to analyze the spatiotemporal dynamics in the LULC (Jensen, 2015), as well as gains and loss of LULC classes, particularly in dense and sparse mangroves more precisely to evaluate the effects of disturbances on mangroves. ARC (%) is $(A_2 - A_1) / A_1 \times 100 / (T_2 - T_1)$, where, A_1 characterizes spatial coverage of LULC classes at the previous year (T_1), A_2 denotes coverage of LULC classes at the proceeding year (T_2), and $(T_2 - T_1)$ is the time interval. A pixel-based transition matrix using “from-to” information was applied to quantify the conversion rate from a specific land use types to others of the exact geo-location, and their respective coverage in relation to mangroves during surveyed periods to investigate the spatial pattern of LULC changes (Pimple et al., 2018) (Appendices, Table A-1).

1.3. Results

1.3.1. VI-based distribution of surface greenness

The correlation matrix showed high correlations between the VIs constructed by land cover types in satellite images, with r ranging from 0.95 to 1, except for the GRVI ($r < 0.61$) in both 1988 and 2020 (Appendices, Fig. A-4). GRVI showed moderate correlations between VIs, influenced by the spectral behavior of the green band. EVI and SAVI were strongly correlated with the highest r of 0.99.

Surface greenness fluctuated on all the VIs from 1988 to 2020, although the fluctuation patterns differed across VIs (Fig. 1-3). The spectral reflectance overlapped among vegetated land, i.e., homestead vegetation, sparse and dense mangrove with NDVI, GNDVI, SAVI, and cropland with GRVI; meanwhile, non-vegetated land, i.e., water body, aquaculture, and bare land showed dispersion for all the verified VIs except GRVI.

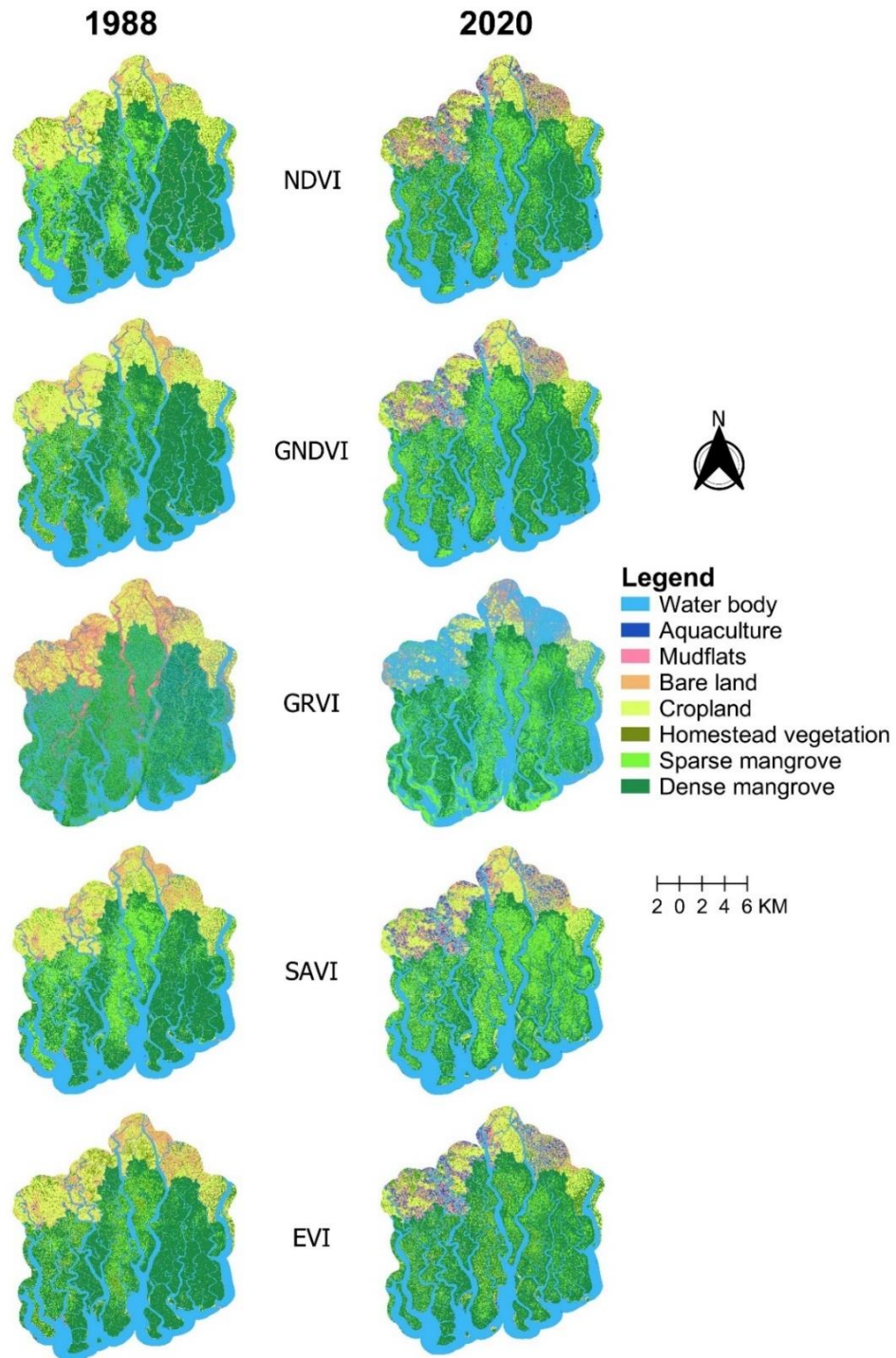


Fig. 1-3. Spatial distribution patterns of five VIs derived from the Landsat TM and Sentinel-2A surface reflectance images in 1988 and 2020, respectively.

The water body showed the lowest NDVI of -0.51 (Fig. 1-4). Aquaculture ranged from -0.21 to 0 of NDVI. Dense mangrove had a higher NDVI, 0.55 to 0.85, and overlapped with sparse mangroves, of which NDVI ranged 0.5 to 0.75, while the other land cover types showed less than 0.5 of NDVI. NDVI did not separate homestead vegetation and mangroves vegetation, i.e., homestead vegetation ranged from 0.37 to 0.6 of NDVI and mangroves did 0.5 to 0.8. NDVI detected cropland within the range of 0.2 to 0.39. Mudflats showed an NDVI below 0.15, overlapping with bare land (0.08 to 0.22 of NDVI).

GNDVI of homestead vegetation averaged 0.44 with a range of 0.37 to 0.5, which fell between cropland (0.21 to 0.36) and sparse mangroves (0.5 to 0.61). Dense mangrove showed GNDVI of 0.53 to 0.74 that overlapped with sparse mangroves. GNDVI of -0.52 to -0.1 separated water bodies from aquaculture, of which GNDVI ranged -0.23 to -0.09. Bare land displayed GNDVI of 0.12 to 0.28, which overlapped between mudflats (0.05 to 0.14) and cropland.

Dense mangrove showed the highest GRVI, ranging from 0.08 to 0.3 but overlapped with sparse mangrove (0.07 to 0.19), homestead vegetation (0 to 0.13) and water body (0.01 to 0.14). Cropland displayed the lowest GRVI with a range of -0.16 to -0.04 that had a high overlap with -0.1 to -0.03 of bare land. Non-vegetated land, i.e., water body, aquaculture, mudflat, and bare land showed GRVI less than 0.14. Non-vegetated land was mostly classified as water bodies in 2020, likely due to soil interference. Mudflat, ranging from -0.03 to 0.01, were distinguishable from the other non-vegetated surfaces.

Since SAVI overlapped with water body (-0.16 to -0.05) and aquaculture (-0.08 to -0.03), these two land use types were not separated by SAVI. SAVI on bare land averaged 0.1 and separated it from mudflats (0.05) and cropland (0.17). Cropland (0.1 to 0.23), homestead vegetation (0.18 to 0.33), sparse mangrove (0.25 to 0.41) and dense mangrove (0.3 to 0.45) were not identified well by SAVI, because of high overlaps of SAVI. SAVI separated the homestead vegetation and dense mangrove but did not from the sparse mangrove.

Because sparse mangrove showed 0.3 to 0.4 of EVI and dense mangrove did 0.4 to 0.7, these two LULC types were separated by EVI. However, EVI did not separate homestead vegetation (range: 0.2 to 0.37) from cropland (0.11 to 0.23) and sparse mangrove due to overlaps between them. EVI did not discriminate aquaculture, mudflats and bare land, either. Water bodies displayed the lowest EVI, -0.18. EVI distinguished well between dense and sparse vegetation more than other LULC types.

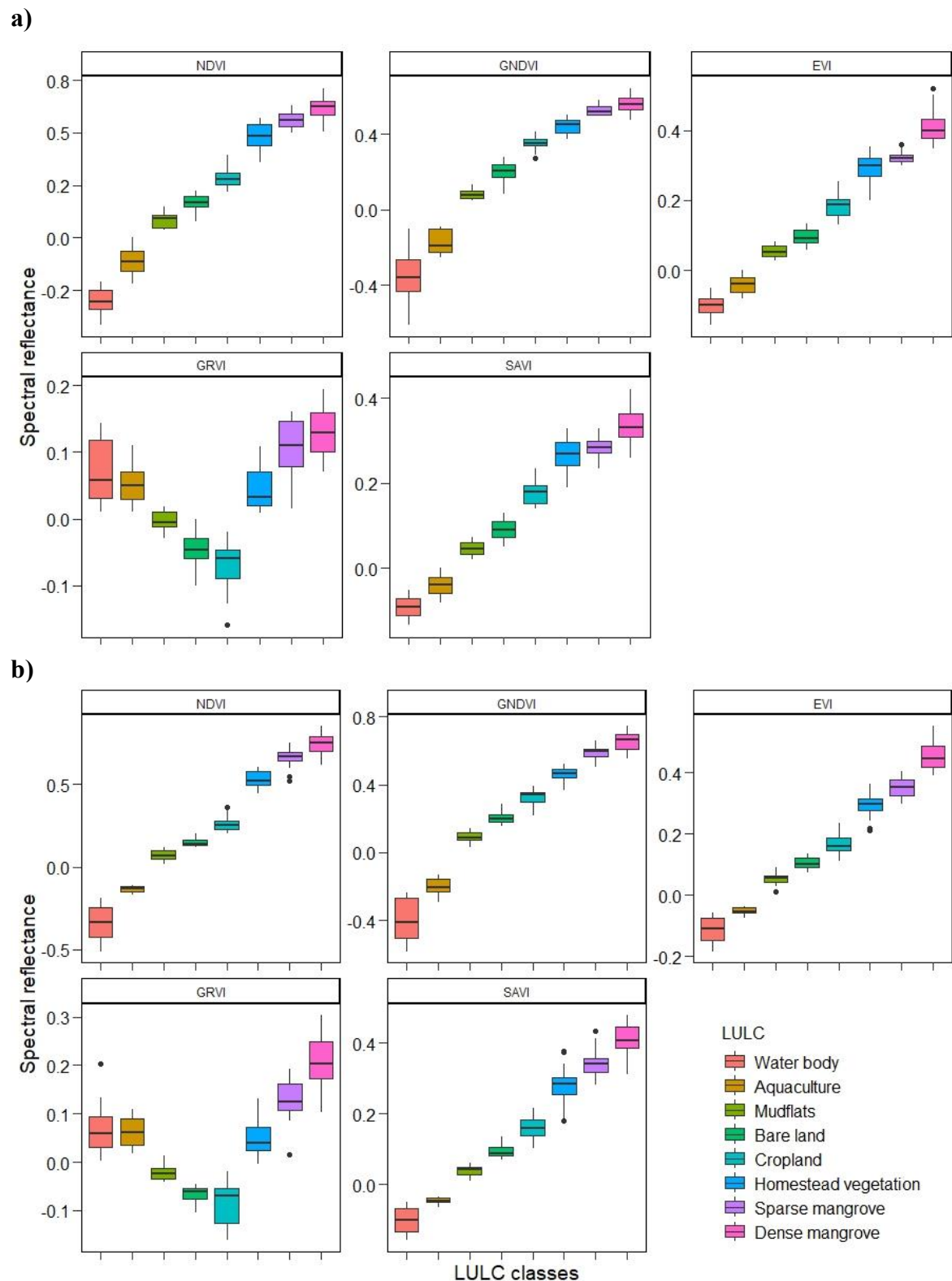


Fig. 1-4. Designated spectral reflectance overlaps and separations were observed in the five VIs for 320 reference points from Google Earth of the categorized LULC. **(a)** shows the range of VIs for LULC classes by Landsat TM of 1988 and **(b)** shows the VI values for LULC of 2020 by Sentinel-2A.

For all the VIs in 1988 and 2020, the VIs between LULCs were different (ANOVA, significant at $p < 0.01$). The NDVI revealed distinct LULC pairs, excluding sparse mangrove and homestead vegetation, dense and sparse mangrove, and tidal flats and bare land (Tukey test, $p < 0.05$) (Table 1-2). The pairs of sparse mangrove-dense mangrove, aquaculture-mudflats, and bare land-cropland were not significantly different in GNDVI ($p > 0.05$), while GNDVI distinguished the other pairs. SAVI was different for the pairs of water bodies-dense mangrove, aquaculture-bare land, and homestead vegetation-dense mangrove. GRVI did not distinguish between mangrove and non-mangrove vegetation, except for vegetated and non-vegetated land use types. EVI distinguished between dense mangrove and homestead vegetation and between dense and sparse mangroves (adjusted $p = 0.0002$ and 0.003 , respectively).

NDVI separated aquacultural land at spectral reflectance of -0.12 ± 0.08 (mean $\pm$ SD) in 1988 and -0.13 ± 0.02 in 2020; cropland at 0.29 ± 0.04 in 1988 and 0.26 ± 0.04 in 2020. GNDVI differentiated water bodies at -0.30 ± 0.12 in 1988 and -0.45 ± 0.1 in 2020, homestead vegetation at 0.44 ± 0.06 in 1988 and 0.46 ± 0.06 in 2020. SAVI and GRVI detected bare land (0.09 ± 0.02 in 1988 and 2020) and mudflats (-0.01 ± 0.02 in 1988 and -0.02 ± 0.02 in 2020) respectively. However, NDVI, GNDVI, SAVI and GRVI showed poor separability between sparse mangrove and dense mangrove (Tukey test, $p > 0.05$). EVI proved the robustness to separate sparse mangrove (0.32 ± 0.02 in 1988 and 0.35 ± 0.03 in 2020) from dense mangrove (0.41 ± 0.04 in 1988 and 0.45 ± 0.04 in 2020) as well from all other classes ($p < 0.05$). Of the five VIs, only the spectral range of EVI was employed for the detection of sparse and dense mangroves. Thus, lower p -values (rejection of the null hypothesis) were used to confirm the optimal VI to separate LULC classes.

Table 1-2. Mean and standard deviation (SD) of VIs in LULC categories in 1988 and 2020. The same letters on the upper-right of the mean $\pm$ SD indicate VIs not different between LULC classes (Tukey's HSD test, $p < 0.05$).

Year	VIs	Water body	Aquaculture	Mudflats	Bare land	Cropland	Homestead vegetation	Sparse mangrove	Dense mangrove
1988	NDVI	-.25 $\pm$.09 ^a	-.12 $\pm$.08 ^{ab}	.09 $\pm$.04 ^{bc}	.17 $\pm$.04 ^{cd}	.29 $\pm$.04 ^d	.47 $\pm$.07 ^{de}	.59 $\pm$.03 ^{ef}	.66 $\pm$.04 ^f
	GNDVI	-.30 $\pm$.12 ^a	-.17 $\pm$.07 ^{ab}	.08 $\pm$.02 ^{ab}	.22 $\pm$.05 ^{bc}	.35 $\pm$.04 ^{cd}	.44 $\pm$.06 ^d	.50 $\pm$.03 ^e	.58 $\pm$.04 ^e
	GRVI	.07 $\pm$.05 ^a	.05 $\pm$.03 ^{ab}	-.01 $\pm$.02 ^{bc}	-.05 $\pm$.02 ^{bc}	-.07 $\pm$.03 ^{bc}	.04 $\pm$.03 ^{cd}	.11 $\pm$.04 ^d	.13 $\pm$.04 ^d
	SAVI	-.09 $\pm$.02 ^a	-.04 $\pm$.02 ^{ab}	.05 $\pm$.02 ^b	.09 $\pm$.02 ^c	.18 $\pm$.03 ^d	.26 $\pm$.04 ^{de}	.29 $\pm$.02 ^{ef}	.34 $\pm$.04 ^f
	EVI	-.10 $\pm$.03 ^a	-.04 $\pm$.02 ^b	.06 $\pm$.02 ^b	.10 $\pm$.02 ^c	.19 $\pm$.03 ^d	.29 $\pm$.04 ^d	.32 $\pm$.02 ^e	.41 $\pm$.04 ^f
2020	NDVI	-.40 $\pm$.09 ^a	-.13 $\pm$.02 ^{ab}	.06 $\pm$.03 ^{bc}	.14 $\pm$.02 ^{cd}	.26 $\pm$.04 ^d	.49 $\pm$.05 ^{de}	.67 $\pm$.02 ^{ef}	.80 $\pm$.03 ^f
	GNDVI	-.45 $\pm$.11 ^a	-.19 $\pm$.04 ^{ab}	.08 $\pm$.03 ^{ab}	.19 $\pm$.03 ^{bc}	.33 $\pm$.05 ^{cd}	.46 $\pm$.06 ^d	.59 $\pm$.02 ^e	.70 $\pm$.03 ^e
	GRVI	.07 $\pm$.05 ^a	.06 $\pm$.03 ^{ab}	-.02 $\pm$.02 ^{bc}	-.07 $\pm$.02 ^{bc}	-.09 $\pm$.04 ^{bc}	.05 $\pm$.03 ^{cd}	.13 $\pm$.04 ^d	.21 $\pm$.05 ^d
	SAVI	-.10 $\pm$.03 ^a	-.05 $\pm$.01 ^{ab}	.04 $\pm$.01 ^b	.09 $\pm$.02 ^c	.16 $\pm$.03 ^d	.28 $\pm$.04 ^{de}	.34 $\pm$.03 ^{ef}	.41 $\pm$.04 ^f
	EVI	-.12 $\pm$.04 ^a	-.05 $\pm$.01 ^b	.05 $\pm$.02 ^b	.10 $\pm$.02 ^c	.17 $\pm$.03 ^d	.29 $\pm$.03 ^d	.35 $\pm$.03 ^e	.45 $\pm$.04 ^f

1.3.2. VI-integrated RF classification

The integrated LULC classification was developed with the optimal spectral range of VIs as variables for the RF classifier (Fig. 1-5). The training samples of LULC classes for VI-integrated RF classification showed random spatial patterns in 1988 and 2020 ($I = 0.11$, $z = 0.94$, $p = 0.35$ and $I = 0.04$, $z = 0.57$, $p = 0.56$), indicating the independence of the training and validation datasets from each other (Appendices, Fig. A-5).

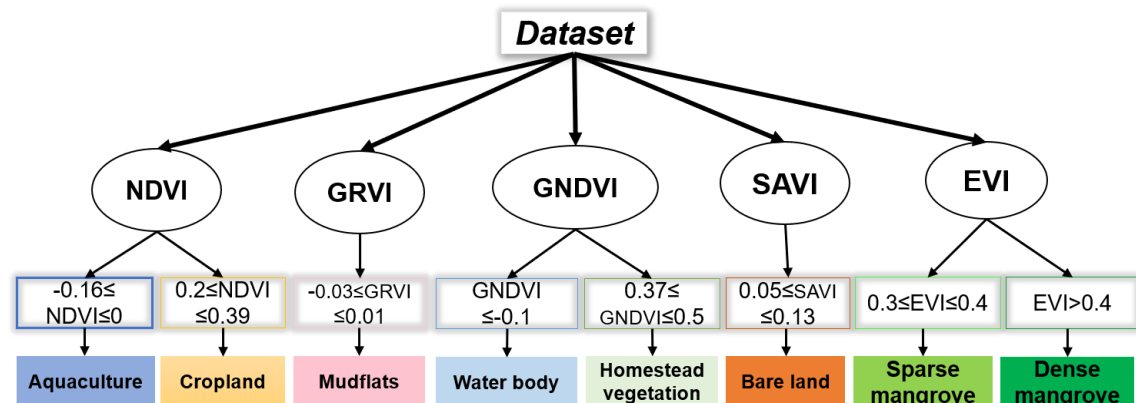


Fig. 1-5. The training sample sets for the RF classifier include selected spectral reflectance of the VIs. Numerals marked with inequality signs indicate threshold VI values for each class in the training data.

The VIs with RF classified LULC types with the highest overall accuracy rates (96% in 1988 and 97% in 2020). These were supported by κ , 0.96 in 1988 and 0.97 in 2020. GRVI exhibited the lowest overall accuracy and κ (77% and 0.77, respectively). GNDVI showed 89% accuracy with a κ of 0.88, signifying the enhancement in LULC classification scheme through the VIs integrated RF approach (Table 1-3). Therefore, the RF classifier with all five VIs proved most effective in predicting LULC classes.

Table 1-3. Classification accuracies of VIs, evaluated by error matrix with κ coefficient.

	1988		2020	
	Overall accuracy (%)	κ	Overall accuracy (%)	κ
NDVI	87	0.85	88	0.87
GNDVI	88	0.86	89	0.88
GRVI	77	0.77	79	0.78
SAVI	81	0.79	82	0.80
EVI	85	0.84	86	0.85
RF+VIs	96	0.96	97	0.97

1.3.3. Spatial pattern of LULC changes

The VI-integrated RF classifier distinguished four vegetated land types, viz., dense mangrove, sparse mangrove, homestead vegetation and cropland; and four non-vegetated types (bare land, mudflats, aquaculture and water body) (Fig. 1-6). The area was covered mostly with the mangrove forest (Table 1-4). Dense mangrove explained 2/3 of the areas. The dense mangrove decreased from 3,517 km² in 1988 to 2,871 km² in 2020. Dense mangrove changed the total area less from 1988 to 2016 and then decreased largely, ca 621 km², with increase in sparse mangrove (553 km²) and bare land (295 km²) from 2016 to 2020. Sparse mangrove in the southwest expanded from 621 km² in 1988 to 1,125 km² in 2020 but declined from 2000 to 2016. On artificial land use, croplands accounted for 12% in 1988 but decreased thereafter, replaced by aquacultural land and bare land along the northern edge of the mangrove forest (Fig. 1-6g). In aquaculture, ARC increased by 13.8% between 1988 and 2020, with a sharp increase from 2016 to 2020. Tidal flats along mangrove coasts expanded five-fold (21 km² in 1988 to 114 km² in 2020). Water bodies and homestead vegetation showed less changes compared to other classes.

Table 1-4. Temporal changes in LULC examined by satellite imagery from 1988 to 2020.

LULC classes	1988		1991		1995		2000		2006		2016		2020		*ARC
	km ²	%	km ²	%	km ²	%	km ²	%	km ²	%	km ²	%	km ²	%	1988-2020 %
Water body	2167	26	2133	26	2046	24	2139	26	2114	25	2217	27	2171	26	0.01
Aquaculture	42	0	155	2	133	2	169	2	348	4	504	6	516	6	36
Mudflats	21	0	29	0	100	1	187	2	6.3	0	89	1	114	1	13.8
Bare land	590	7	635	8	580	7	725	9	366	4	435	5	730	9	0.7
Cropland	980	12	823	10	864	10	673	8	960	11	620	7	404	5	-1.8
Homestead vegetation	423	5	453	5	358	4	413	5	547	7	431	5	430	5	0.05
Sparse mangrove	621	7	996	12	1152	14	619	7	732	9	572	7	1125	14	2.5
Dense mangrove	3517	42	3135	38	3125	38	3435	41	3286	39	3492	42	2871	34	-0.6
Total area	8360														
Overall accuracy%	96		96		95		96		95		97		97		
κ statistics	0.96		0.96		0.96		0.96		0.94		0.96		0.97		

* ARC is an abbreviation of annual rate of change.

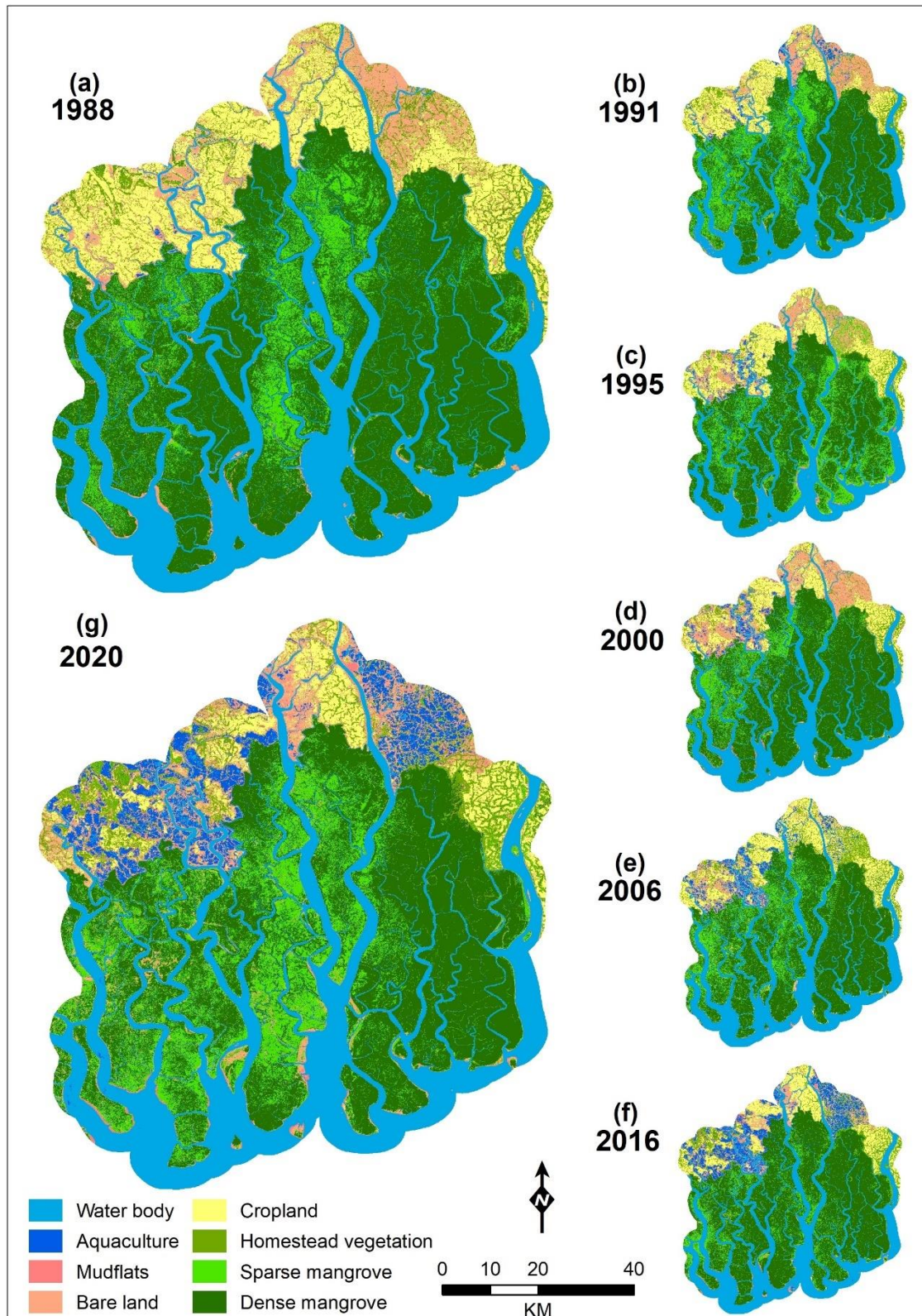


Fig. 1-6. LULC maps during surveyed years from 1988 to 2020, determined by VI-integrated RF algorithm. **a-e:** Landsat TM sensor detected LULC for 1988 (**a**), 1991 (**b**), 1995 (**c**), 2000 (**d**) and 2006 (**e**). **f.** LULC in 2016 detected by Landsat sensor OLI. **g.** LULC of 2020 by Sentinel-2A multi-spectral image.

Between 1980 and 2020, there was a major conversion of dense to sparse mangrove (709 km²), sparse to dense mangrove (242 km²), cropland to bare land (228 km²) and aquaculture (222 km²) and bare land to aquaculture (165 km²) (Table 1-5). The dense mangrove of 960 km² changed to sparse mangrove, bare land and others, while those of 314 km² regenerated to sparse mangrove and others. The total loss of dense mangrove was 646 km², indicating the effects of disturbances on the structure and spatial distribution of mangrove vegetation. In particular, tall trees of dense mangrove such as *H. fomes* are mostly concentrated in the eastern freshwater zone and gradually decline. Sparse mangrove increased by 504 km² due to dense mangrove, water body and bare land, suggesting the landward expansion of dwarf species characterized by lowered canopy cover and tree density, mostly in the south and southwestern saltwater zone during the study period.

Table 1-5. LULC change matrix between 1988 and 2020 (km²).

LULC classes	Aquaculture	Bare land	Cropland	Dense mangrove	Homestead vegetation	Mudflats	Sparse mangrove	Water body	Total area in 1988
Aquaculture	14	5	1	0	2	1	1	17	41
Bare land	165	208	42	7	53	41	12	62	590
Cropland	222	228	329	0.9	124	32	8	36	980
Dense mangrove	18	93	2	2557	51	11	709	76	3517
Homestead vegetation	30	93	25	0.2	170	0	0.4	13	423
Mudflats	3	4	1	1	0	2	1	10	21
Sparse mangrove	2	37	0.3	242	7	10	322	9	621
Water body	62	61	4	20	23	16	32	1950	2167
Total area in 2020	516	730	404	2871	430	114	1125	2172	8360

1.4. Discussion

1.4.1. The evaluation of the optimal VI and RF method

Using multiple VIs in RF showed an accuracy of over 95%, showing that the protocol used here is applicable for LULC analyses. Although the RF algorithm has a high accuracy in land cover mapping, it misclassifies mangroves as others (Campomanes et al., 2016) and adding VIs as variables reduces classification errors (Jhonnerie et al., 2015). VIs have the respective advantages and disadvantages in detecting surface attributes, such as water and

phytomass, through reflectance (Shishir and Tsuyuzaki, 2018). Water body interferes with red reflectance and a few VIs become saturated even when the phytomass is low (Vescovo et al., 2012). Although NDVI increased with increase in surface greenness, NDVI did not detect homestead vegetation and sparse mangrove well due to distortion from background reflectance (Landeros et al., 2021). GNDVI showed the highest accuracy but did not detect dense and sparse mangroves well due to its high sensitivity to dense forest canopies (Razali et al., 2020). To reduce these erroneous estimates, the use of multiple VIs allows for a comprehensive assessment of vegetation characteristics, such as phytomass, vegetation health, water content and stress (Huete, 2012), which are used as indicators of ecosystem functioning. However, a high correlation does not indicate the validity of both indices for LULC classes (Silva et al., 2020). GNDVI separated the vegetated and non-vegetated land and EVI separated dense and sparse mangroves, because EVI correlated more for depicting changes in canopy greenness (Mandal et al., 2020). Because EVI overcomes saturation and shows higher sensitivity to dense vegetation (Zhu et al., 2021), EVI is a prerequisite for mangrove vegetation classification.

1.4.2. Effects of natural and anthropogenic disturbances

The spatiotemporal dynamics of LULC changes were investigated by LULC map, because of high accuracy for long term at large scale. To understand the dynamics, the effects of natural and anthropogenic disturbances should be examined. The accessibility to the study area was least so that the large-scaled mangrove decline was mostly induced by natural disturbances, not by human disturbances. One of the major natural disturbances is tropical cyclone in this region (Mandal and Hosaka, 2020). Cyclones struck in the studied area before and after the study period. Since cyclones do not often destroy mangrove ecosystems completely (Krauss and Osland, 2020; Quader et al., 2017), the land cover seemed to change from dense to sparse mangroves after cyclone attacks. Mangrove forests across Bangladesh declined by 1.2% (Giri et al., 2007). During the study period, dense mangrove decreased by 0.6%/yr and sparse mangrove increased by 2.5%/yr. Dense mangrove gradually increased between 2000 and 2016, suggesting that spontaneous regeneration occurred soon after cyclone strikes. These also suggest that the separation of sparse and dense mangroves is useful to evaluate ecosystem damages. Storm surges derived by cyclones often increase salinity on land, thereby affecting the mangroves (Dasgupta et al., 2017). Increase in salinity causes the leaf senescence and defoliation of *H. fomes*, causing

a decline in the mangrove forest (Kumar et al., 2021). The expansion of sparse mangroves along the southwestern part and forest edges indicates increased soil salinity, which has favored salt-tolerant species such as *C. decandra* and *E. agallocha*, thereby contributing to the alternation of forest structures (Rashid et al., 2009; Kanjin and Alam 2024). Anthropogenic disturbance is characterized by a substantial reduction in agricultural land and the expansion of aquaculture near the interface between forest and human habitat, limiting the development of vegetation, including mangroves (Sardar and Samadder, 2021). Mangrove in southeastern Bangladesh has been degraded due mostly to anthropogenic activities, e.g., shrimp and salt farms (Hasan et al., 2024). Changes in mangroves from dense to sparse and from sparse to bare land indicate the impacts of natural and anthropogenic disturbances on the mangrove forest (Hossain et al., 2022), as detected using multiple VI-integrated RF classifier in this study.

The use of multiple sensors induces errors in LULC classification with varying spatial resolution (Shishir and Tsuyuzaki, 2018). However, defining the range of each VI for various LULC classes may partially rectify classification errors of multi-temporal Landsat and Sentinel-2A data through multiple decision trees in RF. The combination of EVI with RF extracted dense and sparse mangroves from other vegetation types well. The rate of change in sparse mangroves was an indicator of changes in habitat quality and ecological processes. The constructed VI-integrated RF classifier mapped spatial patterns and detected temporal changes in mangrove vegetation, suggesting immediate implementation of ecologically appropriate mangrove conservation and restoration. Because the northern and southwestern parts of the mangroves changed faster than the eastern parts, these mangroves should be prioritized in the management policy. The quality of mangrove habitat deserves attention, as it is a key to promoting regeneration (Zhu et al., 2021). The mangrove reforestation program along the coast of Bangladesh have proven successful in protecting and stabilizing coastal areas (Saenger and Siddiqi, 1993). Conservation policy should consider limiting users of forest resources, ensuring sustainable aquaculture practices, restoring water bodies and protecting them from encroachment.

1.5. Conclusion

Mangroves are ecologically important coastal wetlands. Evaluation of VIs for mangrove detection using optical sensors and the integration of the optimal VI and RF for each LULC

class improved the accuracy of LULC classification. EVI is advantageous in distinguishing between sparse and dense mangroves and provides a reliable indicator for mangrove ecosystem health and distribution. Analysis of LULC maps during 1988 and 2020 quantified an increase in sparse mangroves and a decrease in dense mangroves, suggesting that natural disturbances have largely distorted the mangrove forest. The transition matrix of LULC classes revealed the change from dense to sparse mangroves and *vice versa*, indicating the effect of disturbances on mangroves. Therefore, natural disturbances have a greater impact on mangroves than anthropogenic disturbances. Accurate identification of sparse mangroves, dense mangroves and non-mangroves indicate changes in mangrove ecosystems under disturbances and allow restoration and conservation measures to be implemented. The VI-integrated RF classification can be used as an indicator for habitat quality restoration, mangrove afforestation and sustainable aquaculture practices in the region.

Chapter 2: The effects of disturbances derived by tropical cyclones on mangrove forests in Bangladesh

2.1. Introduction

Tropical cyclones (TCs) are the most destructive natural disturbances in mangrove regions (Lugo, 2008). Mangroves, as diverse and productive coastal ecosystems, provide numerous ecosystem services (Brander et al., 2012; Das et al., 2022). The unique structure and density of mangroves make them as the effective nature-based solution for coastal protection against disturbances (Amaral et al., 2023). However, mangrove forests are vulnerable to TCs due to their geographical positions in terrestrial-marine ecotone (Peereman et al., 2022). TCs have become increasingly intense and frequent, due to global climate change (Michener et al., 1997; Alongi, 2015). The recovery of mangroves varies with the disturbance intensities (Azad et al., 2019), although the relationships between disturbance intensity and recovery patterns have been unclear.

The Sundarbans mangrove forest of Bangladesh is exposed to strong winds and is vulnerable to TC disturbances (Halder et al., 2021). Over the past four decades, 255 TCs stroke the Bay of Bengal in the Northern Indian Ocean (Sahoo and Bhaskaran, 2018). Mangrove tree species are considered to be resilient to TC disturbances (Alongi, 2008). A few tree species re-sprout immediately after TC strike (Krauss and Osland, 2020). However, intense and frequent TCs strike disrupt mangrove regeneration (Taillie et al., 2020). Furthermore, disturbances caused by TCs wreak havoc on endangered mangrove forests (Mishra et al., 2021). So far, studies on the impacts of disturbance on mangroves have focused mostly on recent or major TC events (Dutta et al., 2015). Still, a long-term database is required to detect the changes induced by such disturbances, contributing to the understanding of mangrove recovery and informing sustainable mangrove management strategies (Hossain et al., 2022). Therefore, the effects of TCs on mangroves were assessed to map forest disturbances.

TCs, characterized by sustained high winds, intense rainfall and storm surges, cause large-scale disturbances to mangrove forests via defoliation, broken or uprooted trees and stagnant canopies, while modifying the environments by sedimentation and hypersalinization (Peereman et al., 2022). TC disturbances extend from a few kilometers

to several hundred kilometers (Fibich et al., 2023). Disturbance levels are affected not only by the characteristics of TC and distance from the TC track but also by mangrove ecosystem tree density and coastal environment (temperature, precipitation, elevation and slope) (Mo et al., 2023). The disturbances in forests driven by the complex interactions between TCs and environmental indicators are rarely studied on a large spatial scale, particularly in remote mangrove areas.

Remotely sensed images offer comprehensive methods in disturbance ecology (Shishir and Tsuyuzaki, 2018) to project large-scale mangrove forest disturbances (Giri et al., 2007; Peereman et al., 2022). Time series analyses using pixel-based VIs allow for accurate monitoring of vegetation and reveal spatial trends (Zhu et al., 2021), with thresholding to detect affected forest areas (Zhang et al., 2016; Taillie et al., 2020) before and after the events (Wang and Xu, 2009). This study aims to assess forest disturbance patterns related to TCs and environmental factors over a 36-year period.

The mangrove forest show spatiotemporal variations in response to disturbances (Akhtar and Tsuyuzaki, 2024) and the resultant forest disturbances are directly or indirectly affected by TCs and the environmental factors (Fibich et al., 2023). Therefore, the effects of disturbances derived by TCs on the mangrove forest were evaluated based on three questions: 1) how does EVI detect long-term changes in mangrove vegetation in response to TC disturbances? 2) what extent do TCs cause forest disturbances? and 3) which TC and environmental factors have the effects on mangrove forest disturbances?

2.2. Materials and methods

2.2.1. Study area

The mangrove forest of Bangladesh is distributed in the southwestern coast between 21°30'N to 22°30'N and 89°00'E to 89°55'E (Fig. 2-1). The mangrove forest develops in the delta of the Ganga-Brahmaputra Rivers, covers ca 5,980 km² (60% of total area) and comprises a complex ecosystem of tidal and riverine waterway, mudflats and innumerable islands (Kumar et al., 2021). The elevation of the mangrove deltaic swamp forest is essentially flat, with a gentle slope of 0.03 m/km towards the Bay of Bengal and experiences twice-daily tidal incursions (Payo et al., 2016). The natural mangrove forest composed of halophytic tree species (Iftekhar and Saenger, 2008).

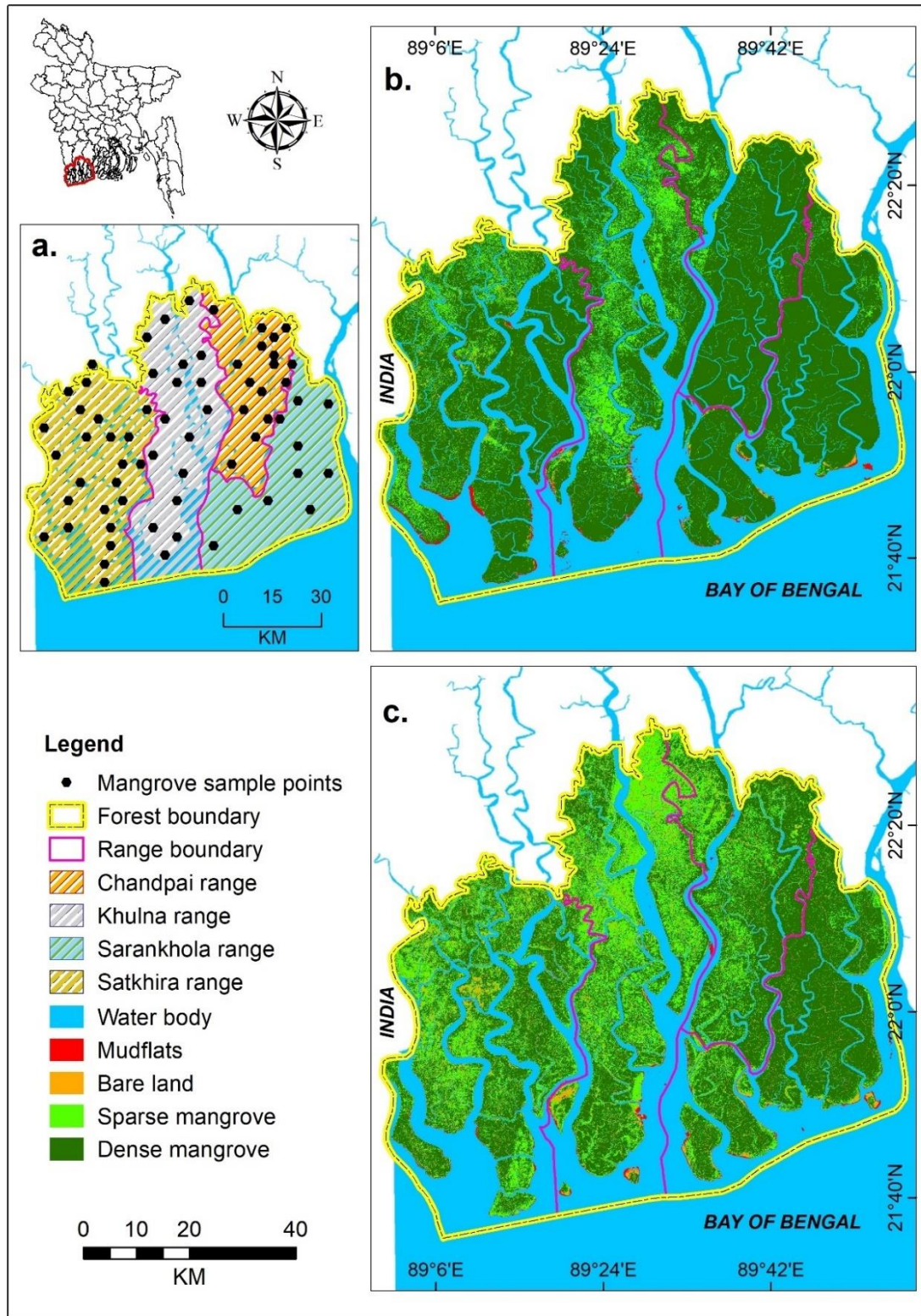


Fig. 2-1. Spatial extent of mangrove vegetation among all land cover classes in mangrove forest, Bangladesh, as estimated by VI-integrated RF classification. **a.** The mangrove forest area is monitored under four administrative ranges. Mangrove vegetation **b.** in 1988 and **c.** 2024 (at 30 m resolution). Land cover classes comprise all natural features specified in the legend. (Data source: Landsat 5 and 8: <https://earthexplorer.usgs.gov/> based on GEE, 2025 and Forest Department of Bangladesh, 2020)

The mangrove has a tropical monsoonal climate with an average annual precipitation of 1,800 mm (range: 1,640 to 2,000 mm) and average annual minimum and maximum temperatures are between 21°C to 30°C. This area is often affected by TCs during the monsoon and post-monsoon (Fig. 2-2) when wind velocities occasionally exceed 120 km/h, inducing tidal waves, flooding and saltwater infiltration (Mandal and Hosaka, 2020; Dutta et al., 2015). The northernmost forest area dominated by *H. fomes* is more vulnerable to TC and disturbances increase with increasing height (> 20 m) and mean dbh (< 10 cm) (Halder et al., 2021).

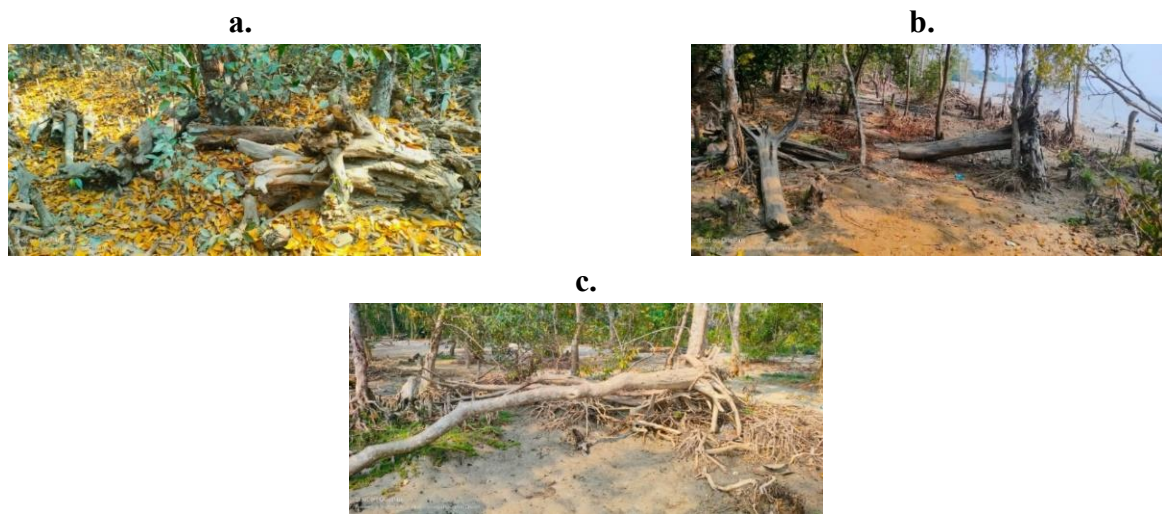


Fig. 2-2. Mangrove forest disturbances, captured in November 2022, following the cyclone in October 2022: (a) defoliation of trees; (b-c) broken stems and uprooted trees.

2.2.2. Tropical cyclones

The open-source data platform ‘International Best Track Archive for Climate Stewardship (IBTrACS V4)’ by the National Oceanic and Atmospheric Administration (NOAA), USA (Knapp et al., 2010), provides high-resolution TC track data, thereby offering comprehensive information to explore the impact of TCs on mangrove forest disturbances. TCs over the Northern Indian basin from 1988 to 2024 for 36 years were sourced from the IBTrACS V4, and the Bangladesh Meteorological Department (Fig. 2-3a). A total of 32 TCs (Appendices, Table A-2), which made landfall within a spatial range of 200 nautical miles (3.3°) of the centroid ($22^\circ 02'N$, $89^\circ 47'E$), were selected (Fig. 2-3b). TCs were categorized by wind intensity using the Saffir-Simpson Hurricane Wind Scale (SSHWS): TD, tropical depression ($\leq 61 \text{ km h}^{-1}$), TS, tropical storm ($63\text{--}117 \text{ km h}^{-1}$), H1-H5, hurricanes of category 1 ($119\text{--}153 \text{ km h}^{-1}$), category 2 ($154\text{--}177 \text{ km h}^{-1}$), category 3 ($178\text{--}208 \text{ km h}^{-1}$), category 4 ($209\text{--}251 \text{ km h}^{-1}$), and category 5 ($> 251 \text{ km h}^{-1}$) (Mo et al., 2023).

The TC, with the highest wind speed affecting the study area each year was analyzed, with adjustments for image quality. For each TC, the maximum 1-minute sustained wind speed (km h^{-1} ; hereafter, wind speed) and the minimum distance between the TC track and the centroid (km ; track distance) were calculated to assess mangrove forest disturbances.

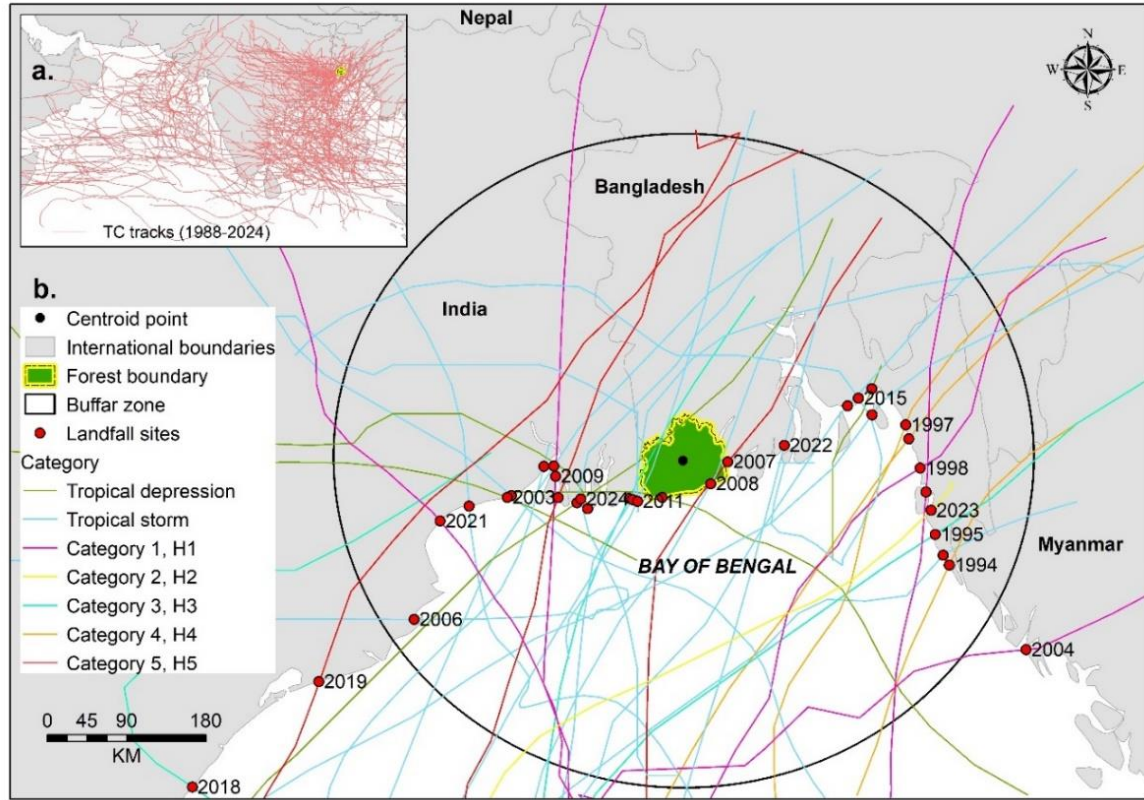


Fig. 2-3. **a.** TCs over the Northern Indian basin since 1988. **b.** Major TCs have struck the mangrove forest within buffer zone, with TC tracks (solid line) and landfall sites (red points). The distance between the mangrove forest and the TC track was calculated from the centroid point by proximity near tool in ArcGIS. Base map: UIA World Countries Boundaries.

2.2.3. Satellite images and preprocessing

To investigate the effects of TC disturbances on mangroves, Landsat datasets from 1988 to 2024 were processed in GEE (<https://code.earthengine.google.com/>). The satellite images (GEE ID: LANDSAT/LT05/C02/T1_L2, LANDSAT/LE07/C02/T1_L2, LANDSAT/LC08/C02/T1_L2, and LANDSAT/LC09/C02/T1_L2) were GEE level 2, tire 1 surface reflectance (SR) ortho-rectified images, corrected for radiometric and geometric distortion, and filtered for cloud and shadow masking using the pixel_qa band bit mask. Landsat 7 ETM+ scan-line-off strips were considered (Chen et al., 2017). Slope and elevation data (30 m resolution) was obtained from NASA SRTM Digital Elevation

(USGS/SRTMGL1_003) for 1988 to 2005 and ALOS DSM (JAXA/ALOS/AW3D30/V3_2) for 2006 to 2024. The mean annual temperature (°C; hereafter, temperature), mean annual precipitation (mm; precipitation) datasets were extracted from the TerraClimate (IDAHO_EPSCOR/TERRACLIMATE) to characterize large-scale and long-term environmental changes (Abatzoglou et al., 2018).

2.2.4. *EVI extraction*

EVI was used to detect mangrove vegetation, using data from Landsat datasets via GEE. Because EVI improves sensitivity in high biomass regions and the accurate identification and mapping of mangroves that is often saturated by NDVI by minimizing background signals and atmosphere influences (Huete, 2012).

$$EVI = G \times ((NIR - Red) / (NIR + C_1 \times Red - C_2 \times Blue + L)), \text{ range: } -1 \text{ to } +1 \quad [1],$$

where the blue, green, red, and NIR express atmospherically corrected surface reflectance from blue, green, red, and near-infrared spectra. G is a gain factor, L is the canopy background adjustment that addresses nonlinear, differential NIR and red radiant transfer through a canopy, and C_1 and C_2 are coefficients to correct aerosol scattering in red band by the blue band (Jiang et al., 2008). Here, $G = 2.5$, $C_1 = 6.0$, $C_2 = 7.5$, and $L = 1$ (Huete et al., 2002). $EVI > 0.3$ distinguished mangroves from other land cover classes (Akhtar and Tsuyuzaki, 2024). The spatial dynamics and extent of mangroves before and after TCs were analyzed using EVI under GEE to evaluate forest disturbances and recovery by geospatial techniques.

2.2.5. *Spatiotemporal trend analysis*

Mangrove vegetation changes were categorized into three phases (1988-1999, 2000-2010 and 2011-2024) based on the mean of EVI of the same season from 1988-2024 and three major TCs: TC91, TC07, and TC20. The fluctuations of EVI of the mangrove forest were assessed using Theil-Sen median trend and Mann-Kendall test (Zhu et al., 2021). Theil-Sen median is a robust non-parametric statistical method for trend calculation in time series data, reducing the influence of data outliers (Theil, 1992). Sen's slope, S is calculated by $S_{EVI} = \text{Median}((EVI_i - EVI_j) / (i - j))$, where EVI_i and EVI_j denote EVI of year i and j (time, $i > j$), respectively. $S_{EVI} > 0$ indicates an increasing trend of the series and vice versa. Mann-Kendall test is combined with Theil-Sen slope to explore spatiotemporal trends for long

time series of mangrove vegetation (Zhao et al., 2023).

2.2.6. Quantification of mangrove forest disturbances

Changes in EVI were used to examine TC-induced forest disturbances during 1988 and 2024. To compare the mangrove vegetation before and after TCs strikes, EVI before the TC and in the subsequent years were identified as pre- and post-disturbance situations, respectively. Since the TCs arose between April and November, the pre-and post-disturbances were designed using images between January and March, when cloud cover was less than 10% (Mandal and Hosaka, 2020). For TC91, TC07 and TC20, soon after TC images were collected from 01 May 1991 to 30 May 1991, 01 December 2007 to 31 January 2008, and 01 June 2020 to 30 June 2020, respectively.

The effects of TCs on forest disturbance often show nonlinear behavior, with minimal impact below a certain threshold of TC characteristics, beyond which disturbance intensity increases markedly (Imbert 2018). To assess the effects of major TCs on EVI for three large TC events (TC91, TC07 and TC20), the best model was selected from three developed generalized linear mixed-effects models (GLMMs): linear, quadratic and cubic regressions by Akaike's information criteria (AIC) (Tsuyuzaki, 2023). All relationships were used to evaluate EVI response and recovery to TC. For each TC event, the model was specified as: $EVI \sim \text{poly}(\text{TC}, 3, \text{raw} = \text{TRUE}) + (1 \mid \text{year})$, where EVI was the response variable, TC wind data for 6 years (1 year before to 5 years after TC) were used as fixed effects, and year as a random effect with a gaussian distribution and identity-link function. EVI from the 12 months preceding a TC event (i.e., May 2019-April 2020, if the TC occurred in May 2020) were averaged and used as baseline conditions (Mo et al., 2023). The assumption was that EVI of mangrove showed a rapid decline by major TC disturbance, followed by a gradual, nonlinear recovery under stable conditions.

The subtraction method was used to calculate the differences in pre-and post-TC EVI (ΔEVI) across 32 pairs of images. ΔEVI is expressed by $\Delta EVI = EVI_{i+1} - EVI_i$, where EVI_i and EVI_{i+1} refer to the EVI calculated from the pre- and post-TC images, respectively. A total of 70 mangrove vegetation ground-truth points, identified by the forest department of Bangladesh, were used to establish threshold values for EVI. ΔEVI was categorized using a threshold based on the mean ($\mu_{\Delta EVI}$) of the difference image and standard deviation ($\sigma_{\Delta EVI}$) (Zhang et al., 2016; Taillie et al., 2020). The threshold is $\mu_{\Delta EVI} \pm n\sigma_{\Delta EVI}$, where n is an empirical value, which was set to be: $\pm 1\sigma$ (thus, $n = 1$); $\pm 2\sigma$ (thus, $n = 2$); and $\pm 3\sigma$ (thus, n

= 3), verified with literature (Mandal and Hosaka, 2020). Pixel values less than the thresholds of 0.1 were classified as negative changes or forest disturbance, values greater than the threshold as positive changes or forest recovery and pixels with no changes as stable forest. The classified area per pixel was converted into area in km². Here, forest disturbance refers to a decrease in mangrove greenness signal (EVI) and spatial extent following a TC effect that falls below a certain threshold compared to the baselines. In contrast, forest recovery is defined as an increase in the spatial extent of canopy greenness observed in post-TC EVI levels (Dutta et al., 2015). ΔEVI less than $\mu_{\Delta EVI} \pm n\sigma_{\Delta EVI}$ probably reflect natural forest dynamics rather than TC-induced disturbances.

Random samples for disturbed, recovered and stable forest were created through visual interpretation of high-resolution imagery in Google Earth Pro (Fig. 2-4) and evaluated by a confusion matrix and κ coefficient. The threshold-based ΔEVI approach showed over 90% overall accuracy with κ of 0.89% in classifying forest disturbances.

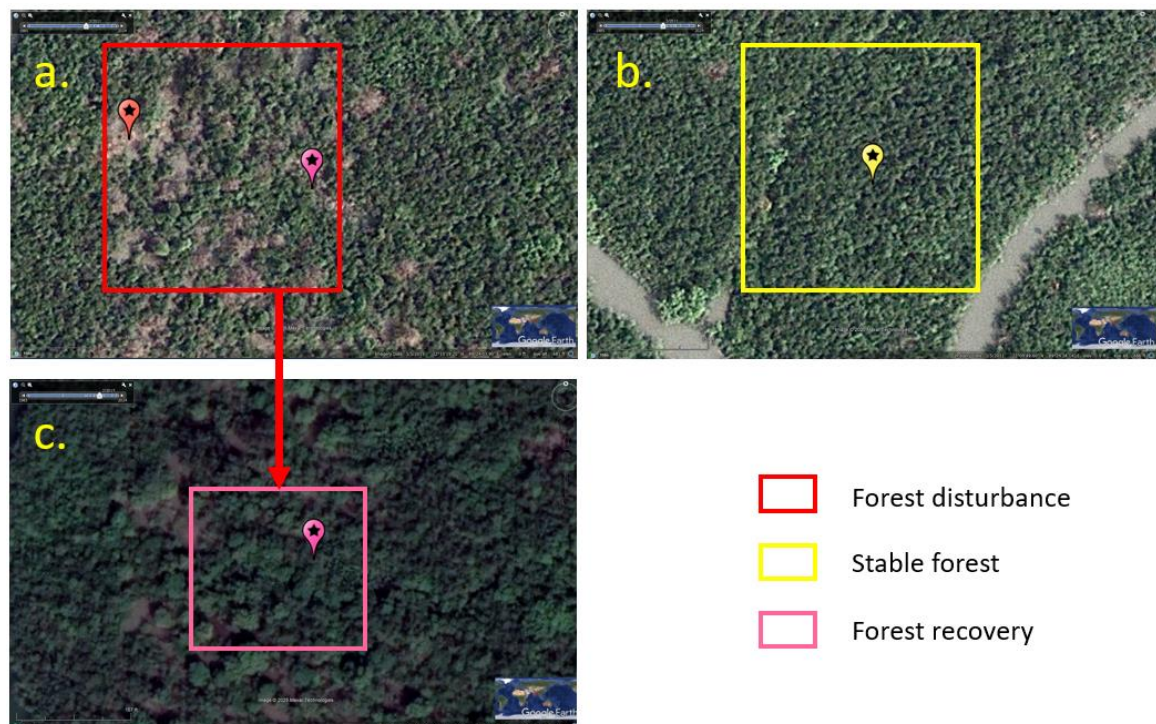


Fig. 2-4. Interpretation of **a.** forest disturbance (22°10'20"N and 89°24'1"E) **b.** stable forest (22°9'50"N and 89°24'28"E) and **c.** forest recovery (22°10'19"N and 89°24'4"E) after the TC07 strike (16 November 2007) to extract reference points of forest changes using Maxar imagery in Google Earth Pro. A total of 50 disturbed, 50 stable and 32 recovered pixel reflectance data points were selected randomly within the study area.

2.2.7. Evaluation of the effects of TCs on mangrove

The effects of TCs and environmental factors on the mangrove forest across 32 TCs were analyzed by a structural equation modeling (SEM) (Grace, 2006; Feng et al., 2021). A hypothetical causal model was formulated based on the individual effects of TC and environmental factors on mangrove forest disturbances (Appendices, Fig. A-6). TC variables were represented by two indicators: direct effects, i.e., wind speed and track distance. Environmental variables included temperature, precipitation, elevation, and slope. Precipitation and temperature reflected the climatic variations and were linked, as TCs bring extreme precipitation and lead to coastal flooding (Taillie et al., 2020), while temperature is related to precipitation and TCs (Fibich et al., 2023; Mo et al., 2023). Elevation and slope were included, assuming that higher elevations and steeper slopes are exposed more to wind forces. Model fit was assessed by standardized root mean square residual (SRMR) and comparative fit index (CFI) (Fan et al., 2016). Pearson's correlation coefficients (r) were used to examine multicollinearity concerning the TCs and environmental variables (Shishir et al., 2020). $r \geq 0.90$ between elevation and slope indicated multicollinearity between these variables. Highly correlated explanatory variables cause unstable coefficient estimates in the model (Graham, 2003). Slope was discarded to avoid collinearity with elevation and due to its insignificant effects on the mangrove forest disturbances ($r = 0.15$) (Appendices, Fig. A-7).

Before identifying the potential multivariate relationships using SEM, correlations between the forest disturbance (response variable) and factors (explanatory variables) were examined by a generalized linear model (GLM) with a Gaussian distribution (Appendices, Table A-3). All statistical analyses were conducted in R (version 4.2.2) (R Core Team, 2024), with libraries tidyverse, kendall, trend, lavaan, semplot, glmmTMB, lme4 and lmerTest.

2.3. Results

2.3.1. EVI-based spatiotemporal trends of the mangrove forest

In total, 5,980 km² were examined. Of them, 2/3 were occupied by dense mangrove (Fig. 2-1). The dense mangrove decreased from 3,517 km² (59%) in 1988 to 2,510 km² (42%) in 2024. Meanwhile, sparse mangrove increased from 621 km² (10%) in 1988 to 1,330 km²

(22%) in 2024.

EVI fluctuated interannually from 1988 to 2024 (MK test, $p < 0.01$) (Fig. 2-5). From 1988 to 1999, EVI increased (MK test: $\tau = 0.09$ and $p < 0.001$; Sen's slope: $S = < 0.001$ and $Z = 3.97$). Between 2000 and 2010, EVI sharply decreased ($\tau = -0.38$ and $p < 0.001$; $S = -0.0002$ and $Z = -13.77$), indicating the effects of major TC of 2007. EVI showed an increasing trend ($\tau = 0.11$ and $p < 0.001$; $S = < 0.001$ and $Z = 5.05$) again from 2011-2024. These results suggested that EVIs were influenced by the major TCs strike.

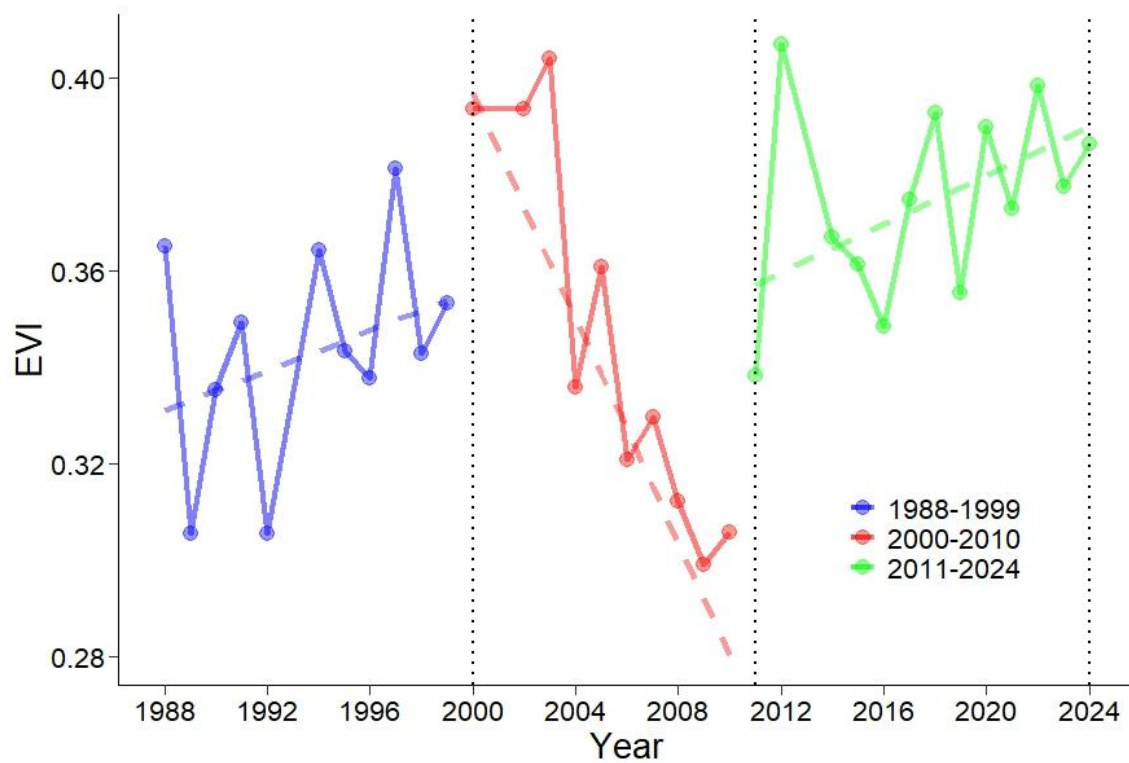


Fig. 2-5. Spatiotemporal trends of EVI from 1988 to 2024. Changes in mangrove vegetation are represented in three phases: blue color for 1988-1999, red for 2000-2010 and green for 2011-2024, considering three major TCs: TC91, TC07, and TC20. All data were collected from dry seasons in the same month and contiguous years to minimize seasonal effects on the EVI. Trend lines correspond to Sen's slope.

2.3.2. Changes in EVI before and after TC strikes

EVI decreased soon after the three TCs but increased afterward (Fig. 2-6). EVI was 0.35 ± 0.07 before the TC of 1991, decreased soon after the TC strike, and the lowest EVI recorded in 1992 (0.31 ± 0.04), one year after the TC. Within five years, the highest EVI 0.36 ± 0.07 was recorded in 1994, two years after the TC and decreased again in 1996 (0.33 ± 0.06), showing the effect of TC95. Before the TC strike of 2007, EVI was 0.32 ± 0.05 , and

decreased soon after as 0.31 ± 0.05 in 2008. EVI (0.3 ± 0.05) was lowest within one year after landfall in 2009, meanwhile increased subsequently with the highest EVI (0.41 ± 0.07) in 2012 and declined as 0.37 ± 0.06 in 2014. EVI fluctuated after the TC of 2020. In 2020, before the TC, EVI was high at 0.39 ± 0.05 and dropped soon after the TC (0.36 ± 0.09). The highest EVI (0.4 ± 0.06) was recorded in 2022, followed by a decline in 2023 (0.38 ± 0.06) due to TC22. These results indicated that frequent TCs affected mangrove vegetation, as shown by decreased EVIs.

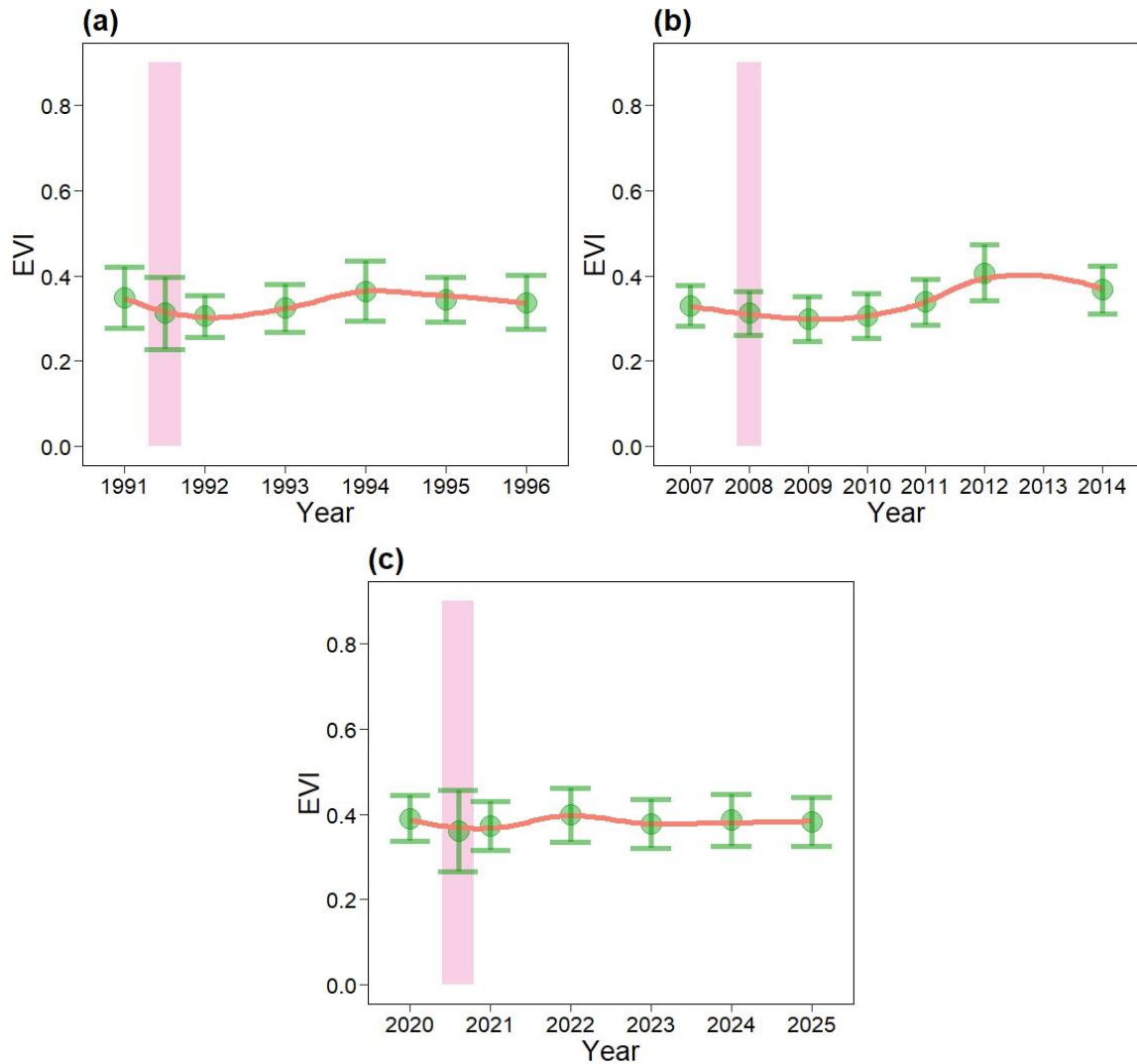


Fig. 2-6. Annual changes in the EVI of mangrove vegetation before and after TCs during three periods **(a)** from 1991-1996: TC91, **(b)** 2007-2014: TC07 and **(c)** 2020-2025: TC20. Mean (solid circles) is shown with SD (error bars). The mean EVI value reflects mangrove health, while SD indicates EVIs variability over the studied period. The shaded area indicates the year of TC landfall.

AICs on the three models were: TC91, Linear effect = -1197 , quadratic effect = -1200 and cubic effect = -1209 ; TC07, Linear effect = -1374 , quadratic effect = -1374 and cubic effect = -1377 ; and TC20, Linear effect = -1217 , quadratic effect = -1217 and cubic effect

= -1219.

AIC selected the cubic effects of TC as the best model for TC91 (GLMM, $p < 0.001$), TC07 (GLMM, $p < 0.01$) and TC20 (GLMM, $p < 0.05$) (Fig. 2-7), showing that EVI declined soon after the TC strikes, subsequently increased and thereafter decreased again. These results indicated immediate mangrove disturbance following TC, with recovery through regeneration occurring within 2 years. Meanwhile, another decline showed the effects of successive TC strikes. In particular, the selected area was affected by TCs every year, with major TCs resulting in substantial vegetation damage. Moreover, the effects of TCs on mangrove vegetation were unpredictable, and their impact varied (Table 2-1).

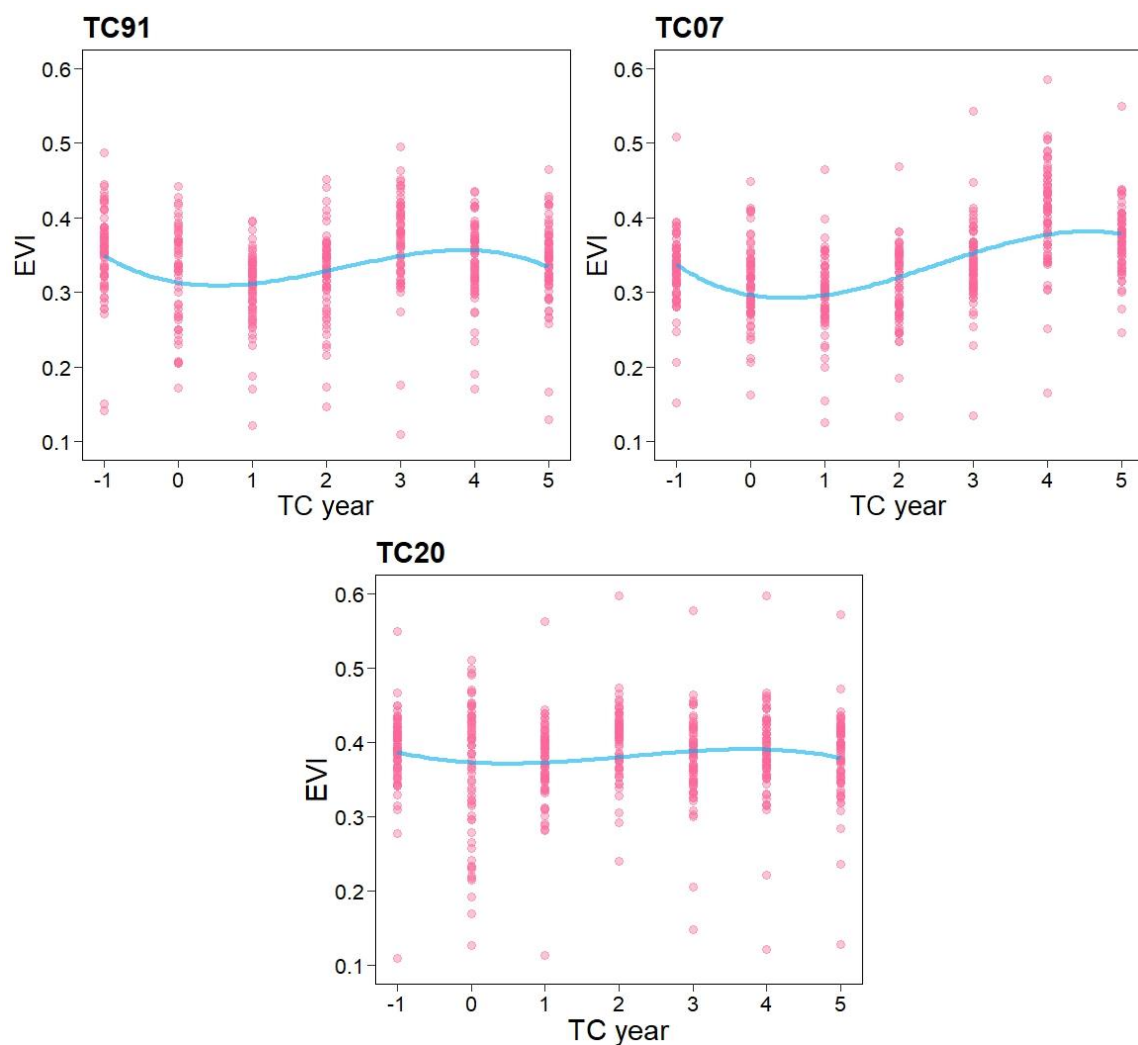


Fig. 2-7. Effects of TC91, TC07 and TC20 in the respective years on EVI were investigated by GLMM. The predicted lines are significant at $p < 0.01$. The best-fitting lines selected by AIC for TC91, TC07 and TC20 are $y = -0.003x^3 + 0.02x^2 + -0.02x + 0.31$ with TC91, $y = -0.003x^3 + 0.02x^2 + -0.02x + 0.3$ with TC07 and $y = -0.001x^3 + 0.01x^2 + -0.01x + 0.31$ with TC20 shown by closed circles and solid lines. Before TC: -1; during/soon after cyclone: 0, after cyclone: 1 to 5.

Table 2-1. Effects of TCs on EVIs, examined by GLMMs.

	TC91	TC07	TC20
EVI	0.33 ± 0.06	0.33 ± 0.06	0.38 ± 0.06
GLMM	0.003*	0.003*	0.001*

Each numeral on EVI shows mean with standard deviation. The slope is indicated in the cell of GLMM when it is significant at $*p < 0.05$.

2.3.3. *Changes in mangrove forest spatial extent*

The effect of TCs on the spatial extent of the mangrove forest varied between 1988 and 2024 (Fig. 2-8). Of the 32 TCs, 21 negatively affected and decreased < 5% of the mangrove forest (marked as forest disturbance); 6 decreased 5-10%; 3 decreased 11-20% and 1 TC decreased > 20% (Table 2-2). The TC of 2007 (category H5), with a maximum sustained wind speed of 260 km h⁻¹ that made landfall 38 km from the centroid of the study area, caused the highest disturbance by decreasing 22% (1,296 km²) of the forest area (Fig. 2-8). Mangrove vegetation recovered 819 km² after TC07 in 2011. The second most damaging TC occurred in 1988 (H3), disturbing 19% (1,146 km²) of the mangrove forest, passing through the mangrove forest with a wind speed of 205 km h⁻¹. The third was a 1995 TC (H3), which modified 15% (879 km²) of forest area, with a wind speed of 195 km h⁻¹. TC20 (H5) was the strongest TC studied, disturbing 14% of mangrove vegetation along the western part, less than previous TCs over the past three decades, with a considerable distance (111 km) between TC track and centroid point. Forest disturbances were recorded within 38 km for TC categories H3-H5, except for TC95. The spatial extent of forest disturbance increased with proximity to the riverbank or forest edges. The highest recovery of mangrove vegetation was recorded after TC89, resulting in a positive change of 871 km² in 1990. Mangrove vegetation mostly remained stable after the TC of 2018.

Table 2-2. The effects of wind speed and track distance on mangrove forest vegetation for each TC.

TC code	Wind speed (km h ⁻¹)	Track distance (km)	Stable forest (km ²)	Forest recovery (km ²)	Forest disturbance (km ²)	Forest disturbance (%)
TC88	205	32	2987	8	1146	19
TC89	100	231	3241	871	29	0.5
TC90	85	212	4071	61	10	0.2
TC91	260	185	3790	8	343	6
TC92	55	47	3399	666	77	1
TC94	230	306	3719	21	401	7
TC95	195	225	2682	580	879	15
TC96	85	28	3583	545	12	0.2
TC97	215	203	3808	10	322	5
TC98	130	186	3238	790	113	2
TC99	65	138	3573	563	5	0.1
TC00	83	46	3802	23	317	5
TC02	102	107	4022	4	27	0.5
TC04	120	309	2805	762	32	1
TC05	74	143	2333	6	398	7
TC06	65	158	2275	389	74	1
TC07	260	38	2740	104	1296	22
TC08	85	38	2171	15	430	7
TC09	120	134	3432	436	273	5
TC10	45	31	3311	819	11	0.2
TC11	65	49	3458	681	2	0.04
TC12	55	158	3980	1	160	3
TC14	55	112	4035	34	73	1
TC15	85	100	3974	25	143	2
TC16	110	108	3672	430	40	1
TC17	150	259	3170	912	59	1
TC18	195	204	4110	1	31	1
TC19	260	159	3591	532	19	0.3
TC20	270	111	3563	130	810	14
TC21	120	252	3420	690	32	1
TC22	85	100	4014	35	93	2
TC23	155	204	3980	60	102	2

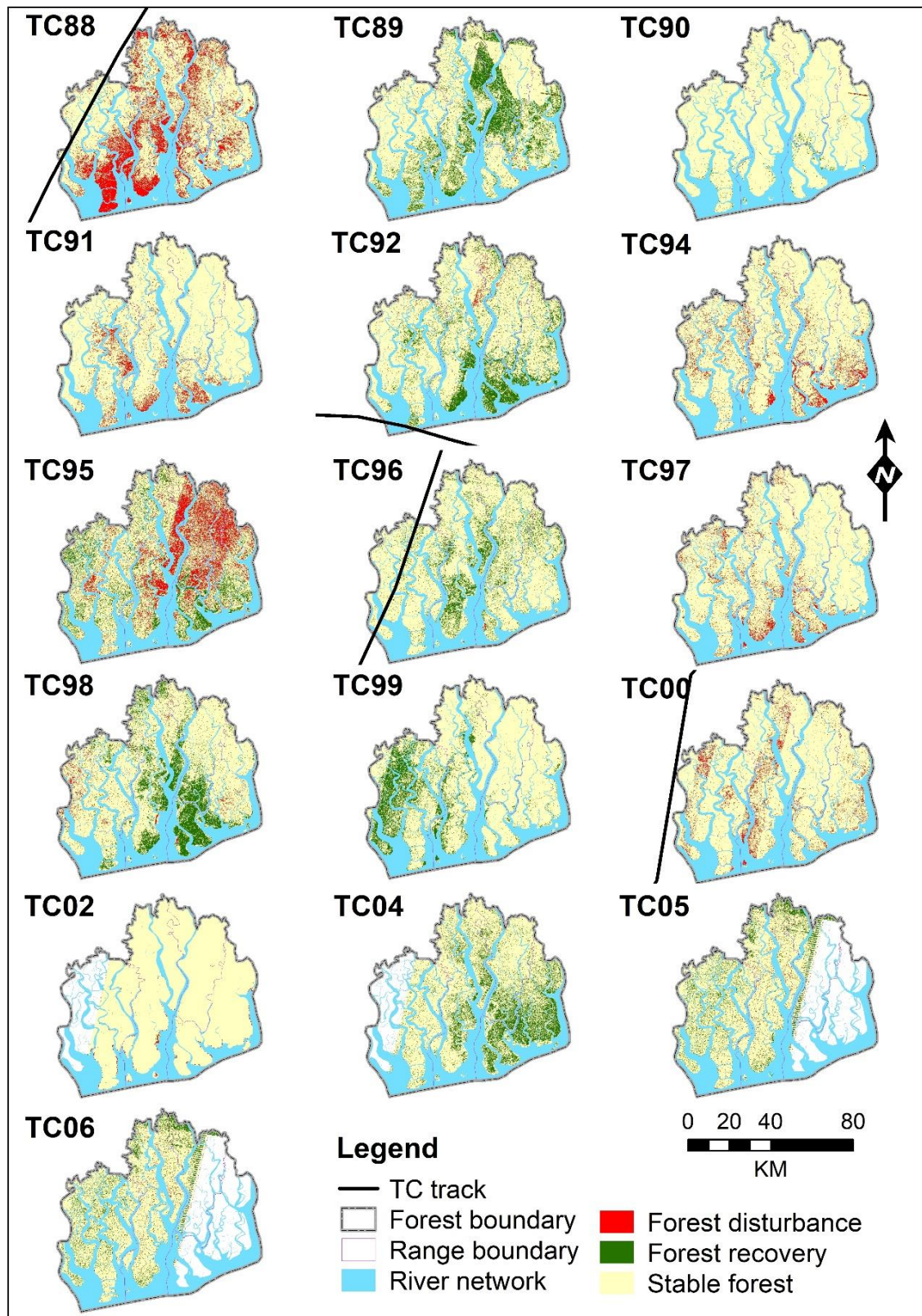


Fig. 2-8. Mangrove forest disturbances by each TC. Discrete colors (red, green and yellow) show the TC-induced forest disturbance, recovery and stable forest, respectively. The TC track is shown as a solid line, indicating landfall near the forest boundary.

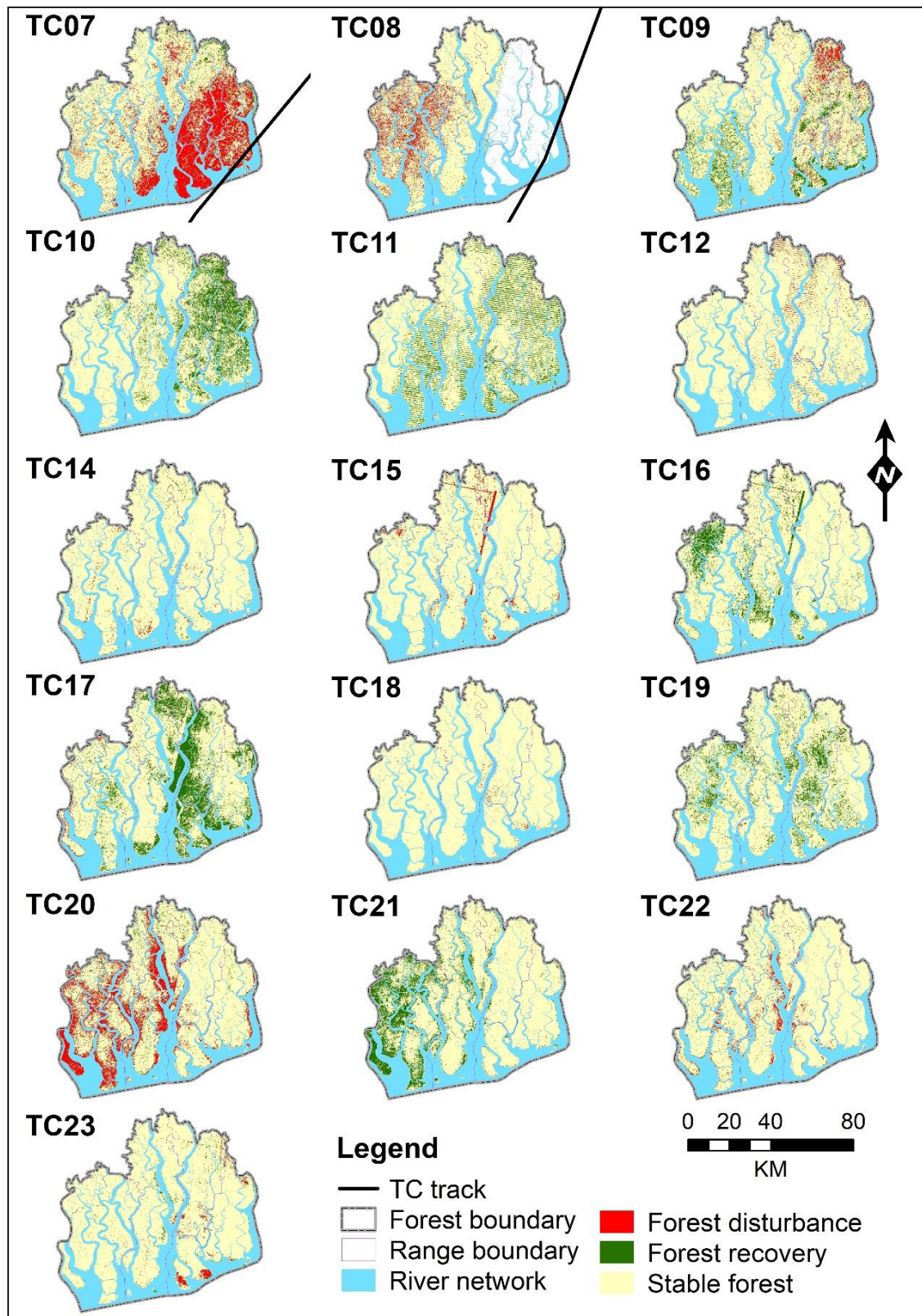


Fig. 2-8. Continued.

2.3.4. Relationships between TC, environmental factors and mangrove forest disturbances

Wind speed had a statistically significant positive effect on mangrove forest disturbance (GLM, $p < 0.001$), while distance from the TC track was negatively correlated with disturbed forest area ($p < 0.05$) (Fig. 2-9). Temperature, precipitation and elevation did not show any significant effects on forest disturbances.

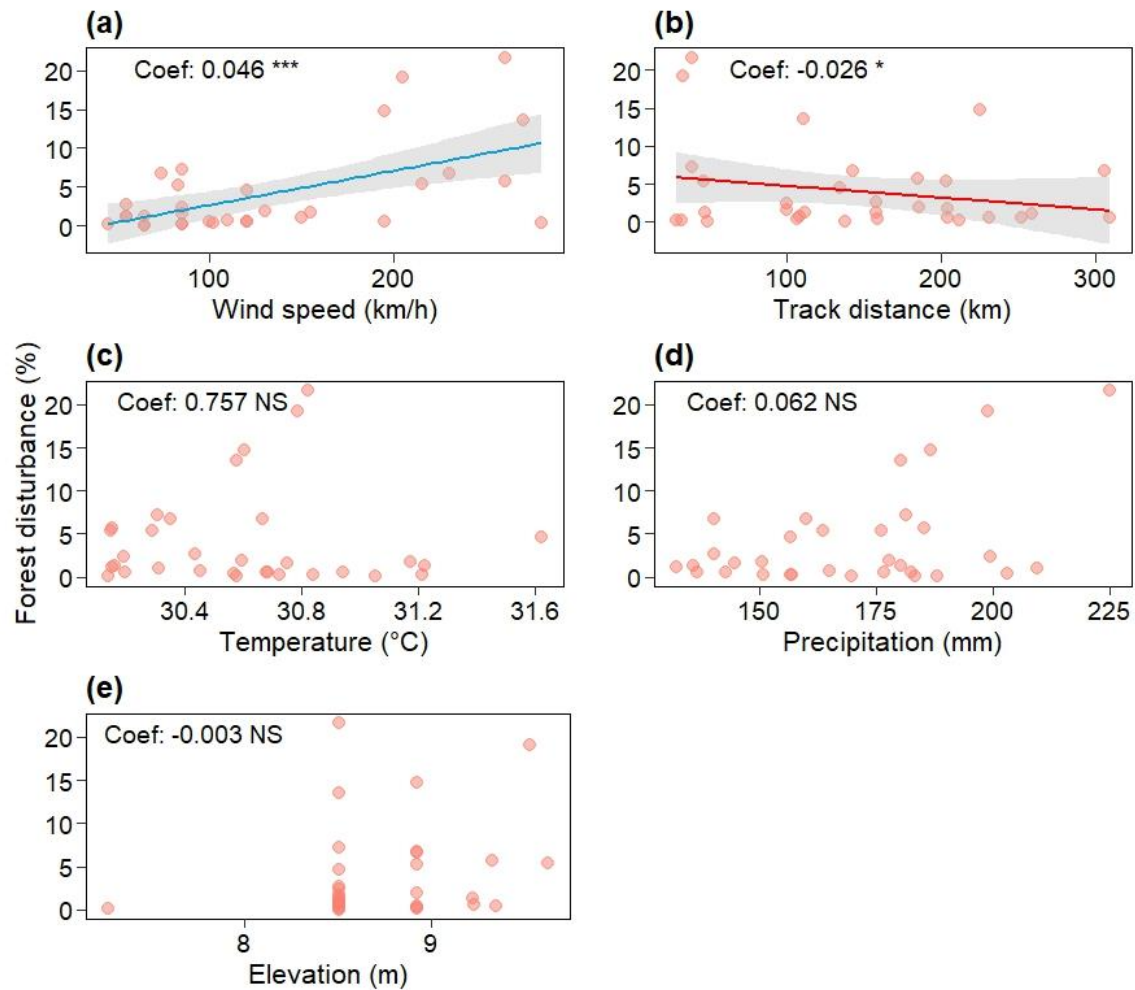


Fig. 2-9. Mangrove forest disturbances in relation to (a) wind speed (b) track distance (c) temperature (d) precipitation and, (e) elevation, as predicted by GLM for each TC ($n = 32$). Closed symbols denote the observed data. Correlation coefficients are shown by trend lines, indicating significant relationships at * $p < 0.05$ and ** $p < 0.001$ (blue and red solid line for positive and negative correlations, respectively), with 95% confidence intervals indicated by shaded areas (grey). No trend line for a non-significant relationship (NS, $p > 0.05$).

The characteristics of TCs, such as wind speed, directly and positively correlated to the forest disturbance (std. estimate: 0.59, $p < 0.001$) (Fig. 2-10), increasing disturbances

through defoliation, breakage and uprooting of trees. Meanwhile, track distance had a direct negative effect on forest disturbances (std. estimate: -0.37 , $p < 0.01$). The magnitude of the forest disturbance increased with increasing wind speed and decreased with increasing TC track distance from the centroid. Precipitation showed a direct positive correlation with the forest disturbance (std. estimate: 0.26 , $p < 0.05$) through an indirect positive correlation with wind speed (std. estimate: 0.28). These findings indicated that TC with higher wind speed and precipitation making landfall nearer the study area increased the forest disturbances. Elevation (std. estimate: 0.07 , $p = 0.54$) and temperature (std. estimate: 0.05 , $p = 0.68$) did not have significant effects on the mangrove forest disturbances; instead, they had mostly negative indirect correlations (std estimate: -0.06). Therefore, the SEM model effectively estimated the effects of each factor on mangrove forest vegetation (Appendices, Table A-4).

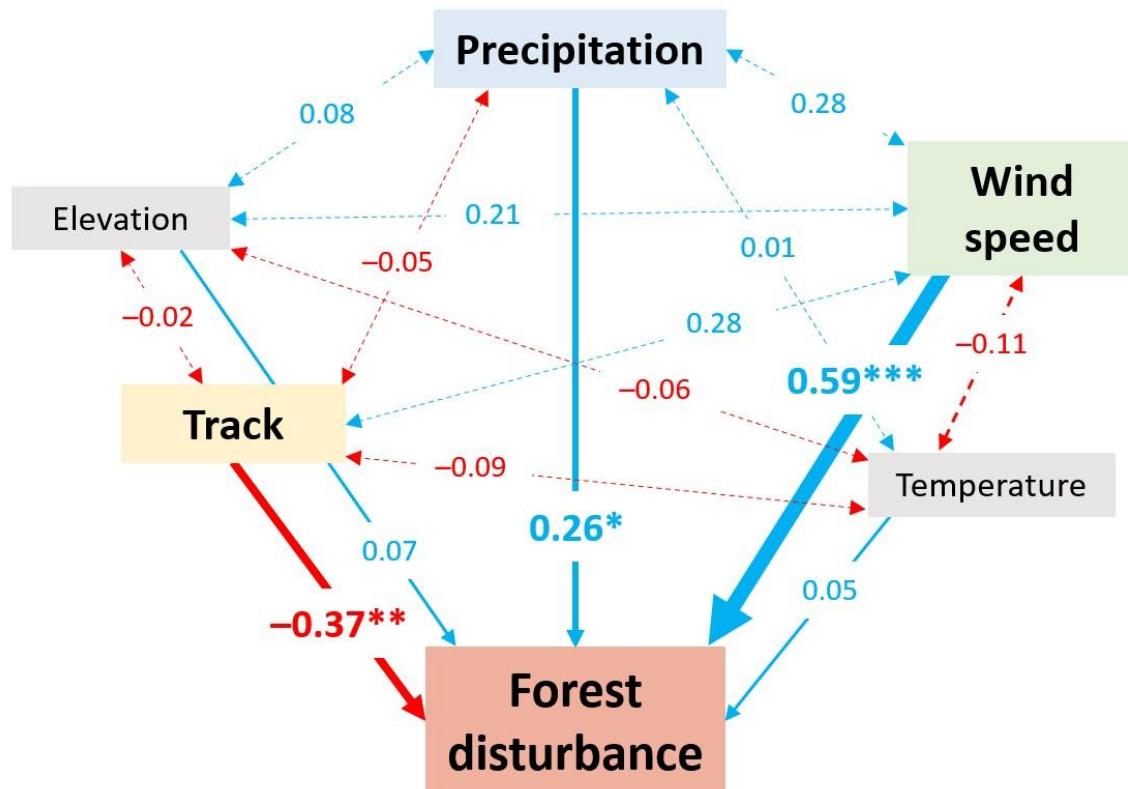


Fig. 2-10. Standardized SEM coefficient for detecting the relationships among TC and environmental factors on mangrove forest disturbances. The model fits the data well: SRMR < 0.05 and CFI > 0.95 . In the SEM model, single-headed arrows signify positive (in blue) and negative (in red) effects, where the tail variable directly affects the head variable (solid lines); meanwhile double-headed arrows show an indirect correlation between two explanatory variables (dashed lines). Each numeral represents the standardized path coefficients. Significant at $*p < 0.05$, $**p < 0.01$ and $***p < 0.001$.

2.4. Discussion

2.4.1. *Spatiotemporal changes of mangroves*

Spatiotemporal changes examined by EVI detected the interannual changes of mangrove vegetation well. Most changes are the conversion of dense mangroves to sparse mangroves, and *vice versa* (Akhtar and Tsuyuzaki, 2024). Historical data showed the susceptibility of the study area to TC disturbances. The abrupt decrease in mangrove cover suggests that the effects of TCs appeared shortly after the disturbances, whereas the increase indicates recovery through the regeneration (Krauss and Osland, 2020; Peereman et al., 2022). To protect and stabilize the coastal areas from TC, ca 1200 km² of mangroves have been planted by fast-growing species such as *S. apetala*, *A. officinalis*, *E. agallocha*, *C. decandra* and *X. mekongensis* along the coast of Bangladesh (Saenger and Siddiqi, 1993); these plantation areas were excluded from the analysis. In the selected forest area, restoration involves enrichment planting and assisted natural regeneration through the replanting of mangroves in degraded areas (Forest Department of Bangladesh, 2020). Following the major TCs, banning human intervention inside the forest to assist natural regeneration and enrichment planting in degraded areas is likely to be advantageous for forest recovery (Quader et al., 2017). Thus, the effect of TC disturbances is evident in the long-term spatiotemporal changes in mangrove vegetation.

2.4.2. *Effects of TC and environmental factors on mangrove forest disturbances*

Mangrove forest disturbances were disproportionally influenced by the extent and spatial distribution of TC-affected areas, depending on the wind speed and track distance of TCs along with precipitation. The present results suggested that major TC within shorter track distance to centroid caused substantial mangrove forest disturbances. TC track with the maximum wind speed of TC07 over the mangroves, induced the highest forest disturbances.

Wind speed was the most direct factor in clarifying the greater extent of mangrove forest disturbances. TC-induced forest disturbances increase when the maximum wind speed exceeds 100 km h⁻¹ in mangrove regions, whereas disturbance remains low at wind speeds of < 75 km h⁻¹ (Taillie et al., 2020; Mo et al., 2023). This study indicated that major TCs with maximum sustained wind speeds of > 200 km h⁻¹ cause forest disturbances at large-scale. Wind during the TC strike affected forest areas, probably by defoliation,

instantaneous litterfall, stem breakage and uprooting of trees (Everham and Brokaw, 1996; Lugo, 2008). Tall trees in dense mangroves, which are directly exposed to the force of TC winds (Zhang et al., 2016; Fibich et al., 2023), should be disturbed more than the shorter trees in sparse mangroves. In the study area, mangrove tree species form a mostly open canopy around 10 m high, with sporadic emergent trees up to 20 m (Azad et al., 2021a). Therefore, higher wind speed resulted in mangrove canopy loss and appeared to be a major factor affecting mangrove forest disturbances induced by TCs. Track distance was another factor, directly related to forest disturbance. Negative relationships between track distance and forest disturbance were reported and severity of forest disturbance decreases with increasing TC track distance (Silva and Twumasi, 2004; Peereman et al., 2022). TCs track close to the mangrove forest caused greater canopy loss, likely due to stronger sustained winds. The greatest disturbance typically occurred at scales within 40 km of the TCs landfall (Feng et al., 2020). The direct positive effect of precipitation is crucial, as erratic rainfall may lead to extensive coastal flooding, storm-surge and sedimentation, which reduce soil oxygen and photosynthesis in mangroves, eventually triggering mortality (Macamo et al., 2016; Taillie et al., 2020). Moreover, increased precipitation lowers soil salinity, thereby affecting the growth and productivity of salt-tolerant mangrove species (Siddique et al., 2021). The low elevation of shoreline mangrove with shorter canopies and submergence during storm surges seemed to reduce TC disturbance (Krauss and Osland, 2020); however, strong TC wind caused substantial mangrove damage. Therefore, the strong intercorrelated effects of wind speed, track distance and precipitation may have led to long-term mangrove forest disturbances.

2.4.3. Implications for mangrove recovery

Although TC disturbances decreased EVI, EVI fluctuated and increased for a few years after the disturbances. The increase in EVI after TCs indicates the recovery of mangrove canopies through re-foliation, re-sprouting and sapling and seedling growth (Peereman et al., 2022). Mangrove EVI returned to pre-disturbance levels, suggesting that mangrove recovery, as mangrove vegetation, has higher EVI than other land cover types (Akhtar and Tsuyuzaki, 2024). EVI showed the mangrove recovery began within two years after the major TCs. The durations of mangrove recovery are constrained by the intensity and scale of TC disturbances, species characteristics and interaction with other environmental cues (Taillie et al., 2020). Mangrove forests in Puerto Rico damaged by TCs recover 72% of

their canopy cover within eleven months (Branoff, 2020); in Myanmar, 60% of the mangrove areas experience recovery and remain undamaged for four years (Aung et al., 2013). However, mangroves in Mozambique did not recover even after 14 years (Macamo et al., 2016). The Sundarbans mangrove forest showed rapid recovery, indicating that the availability of propagules promoted natural regeneration after TC struck (Halder et al., 2021). *Rhizophora* species are viviparous, producing photosynthetic propagules that develop on the parent tree and rapidly establish as seedlings after being released (Chaffey, 1985). Tidal fluctuations in the low-elevation mangrove forests protect rooted seedlings and saplings from TC disturbances (Krauss and Osland, 2020). The observed 2-years mangrove recovery period aligns with seedlings to juveniles growth, suggesting that regeneration likely occurred through early-stage growth processes (Mo et al., 2023). Non-viviparous species like *H. fomes* produce large, nutrient-rich seeds that settle easily and support rapid seedling growth (Chaffey, 1985). In TC-affected mangrove areas, canopy gaps facilitates regeneration, thereby increasing the stand density of total individuals and seedlings (Rashid et al., 2009; Azad et al., 2019). Recovery following TC disturbances may contribute to the transition from dense to sparse mangrove stands (Hossain et al., 2022). In addition, EVI declines caused by defoliation recover more rapidly than those caused by broken stems or uprooted trees (Peereman et al., 2022). Mangrove species, such as *E. agallocha*, and *S. apetala*, recover by sprouting from damaged stems (Primavera et al., 2016); however, recovery through coppiced stems sprouts after TC disturbances is particularly slow (Saenger, 2002). Since mangrove EVI reflected canopy greenness, canopy recovery served as an indicator of overall mangrove recovery.

Mangrove forest disturbances identified 2-3 months after major TCs, with the most severe effects detected after 7-12 months, indicate that delayed mortality and dieback are likely driven by TC-induced hydrological fluctuations such as oxygen depletion, phytotoxin accumulation and increased salinity (Krauss and Osland, 2020; Mo et al., 2023). Moreover, repetitive and intense TC strikes lead to large disturbances in mangroves, reduce success in regeneration, and slow down the recovery process (Lugo, 2008; Macamo et al., 2016). In summary, mangrove canopy greenness recovers quickly after a TC strike, but the re-establishment of structural damage may take decades without further natural (e.g., TCs) or anthropogenic disturbances (e.g., logging) that could alter the recovery trajectory. Restoration intervention should include the evaluation of forest disturbance before and after a TC landfall, assessment of natural seedling establishment, and site-specific replanting of

native species in degraded forest areas. Enrichment planting of mangrove and mesophytic non-mangroves species in the degraded habitats about 1,363 ha have been failed for the unsuitability of the sites (Mahmood et al., 2021), indicating the implementation of site-specific replanting of native species in degraded forest areas. Thus, TCs will strike mangrove forests more frequently, suggesting probable changes in mangrove structure and ecosystem functions, whereas recovery dynamics help predict future mangrove stability by protecting propagule sources and restoring disturbed forest areas.

2.5. Conclusion

The findings projected that mangrove forest vegetation was vulnerable to strong winds. Major TCs that made landfall near forest edges with increased precipitation, caused evident effects on mangrove vegetation. The most severe forest disturbance (> 20% of the total forest area) was caused by a category 5 TC in 2007. Defoliation, trunk and stem breakage, uprooted trees and stagnant canopies caused by high wind speeds and increased exposure contributed to a decrease in EVI after a TC strike. While mangrove forest vegetation revegetated within a few years after a TC, frequent TCs decreased the recovery. Offshore mangrove replantation programs should be implemented to protect inner mangrove forests and stabilize the coastal areas. By satellite-based, long-term assessment of spatial patterns, the effects of each TC and environmental factors on forest disturbances and recovery after major TCs are crucial for formulating sustainable conservation and restoration strategies for mangrove forests globally, which are often affected by TCs under a changing climate.

Chapter 3: Spectral vegetation indices (VIs)-based phenological characterization of the mangrove forest

3.1. Introduction

Vegetation phenology studies the biological events in plant life cycle, such as leaf growth and development, flowering, leaf senescence, and leaf shedding (Njoku, 2014; Zeng et al., 2020), effects photosynthesis and carbon uptake in plants (Richardson et al., 2012). It indicates the response of biosphere to seasonal and interannual changes in environmental cues (Gong et al., 2024). Mangrove phenology shows the seasonal variations in biophysical characteristics that provide measurable and robust relationships between mangroves and climatic events, i.e., precipitation and temperature (Cleland et al., 2007; Guzman et al., 2018). However, few research has been conducted to clarify the interaction of mangrove species with phenological events and climatic factors.

Each plant species exhibits distinct spectral reflectance patterns influenced by leaf and stem structure and morphology, including growth form, leaf trait and phenology to adapt to the environments (Tsuyuzaki and Moral, 1995). Mangrove species differ in mesophyll reflectance, with near-infrared reflectance increasing with more cell layers and intercellular spaces (Aji et al., 2023). Mangroves exhibit green foliage year-around, however species-specific distinct phenological peaks are also observed (Mehlig, 2006). Studies of mangrove phenology predominantly rely on ground-based phenological information viz., budburst, leaf unfolding and senescence via field records or litterfall collection (Kamruzzaman et al., 2019; Nagai et al., 2016), however, *in situ* measurements experience spatial and temporal limitation due to inaccessibility and scale, particularly in complex ecosystems represented by mangrove forests. Therefore, accurate estimation of long-term and large-scale mangrove phenology is required to assess species-specific responses to climate change.

Satellite sensor-based multi-temporal imagery provides a systematic method to monitor large-scale temporal variations in surface greenness linked to mangrove phenology (Hanes et al., 2014; Cao et al., 2023). Mangrove phenology is likely to be characterized by vegetation index (VI)-based spectral reflectance patterns, viz., normalized difference VI (NDVI) and enhanced VI (EVI), because of their ability to epitomize photosynthesis, leaf greenness and vegetation density (Cao et al., 2015; Wu et al., 2017; Zeng et al., 2020). The Moderate Resolution Imaging Spectroradiometer (MODIS) provides multitemporal

imagery at a finer spatial resolution and MODIS-derived VIs have enabled accurate assessment of vegetation phenology at large landscape scales (Zhang et al., 2006). Thus, the study aims to detect the mangrove forest phenology using time-series VIs derived from MODIS data.

The Sundarbans mangrove forest of Bangladesh is characterized by mixed-evergreen tree species and phenological variation in leaf flush, flowering, leaf shedding and fruiting have been reported (Mandal et al., 2020), that is driven by the complex interaction of species composition, climatic factors (e.g., precipitation, temperature, radiance and water availability) and natural disturbances such as tropical cyclone (TC). However, detailed spatiotemporal information on mangrove phenology is crucial for understanding mangrove forest dynamics at a large landscape level.

I hypothesized that the mangrove forest showed an annual cycle of seasonal variation in canopy greenness, and forest types varied and were interactively related to phenological events and climatic conditions. Therefore, the spectral VIs-based phenological analysis of mangrove forest types and their relationship with climatic factors were examined by: 1) estimating the seasonal variation of mangrove forest types using a time-series of MODIS spectral VIs; 2) characterizing the phenological signatures of different mangrove forest types; and 3) assessing the species-specific characteristics and responses to environmental cues.

3.2. Materials and methods

3.2.1. Study area and climate

The Sundarbans mangrove forest, Bangladesh (21°30'N to 22°30'N and 89°00'E to 89°55'E) was selected as the study area (Fig. 3-1a). Mangroves in Bangladesh covers ca 5,980 km² (60% of total area), spanning marine and terrestrial interfaces and offering critical ecosystem functions (Dutta et al., 2015). A total of 70 samples per plot represented the most dominant tree species in number across 55 compartments (Fig. 3-1b). Mangrove phenology was analyzed based on four major forest types, classified according to the dominant trees species composition in each plot: i) *H. fomes*, ii) *E. agallocha*, iii) *C. decandra* and iv) mixed forests of *A. officinalis*, *B. sexangular*, *S. apetala* and BOLA (shrubs) (Appendices, Table A-5).

The eastern region supports the highest abundance of *H. fomes*, indicating the proximity to the freshwater sources from adjacent rivers (Sarker et al., 2016). *H. fomes* thrives in the both top canopy and in full shaded understory conditions (Khan et al., 2020). The fast-growing and light-tolerant *E. agallocha* is distributed across the entire area, suggesting the ability to colonize degraded mangrove areas (Chowdhury et al., 2019). The leafless period of *E. agallocha* is brief, with patchy and non-synchronous leaf shedding (Siddique et al., 2021). *C. decandra* is predominantly found in the south and south-western high-salinity zones. Mixed forests consist of both mangrove and non-mangrove tree species, where the spread of invasive species is notably high (Biswas et al., 2007).

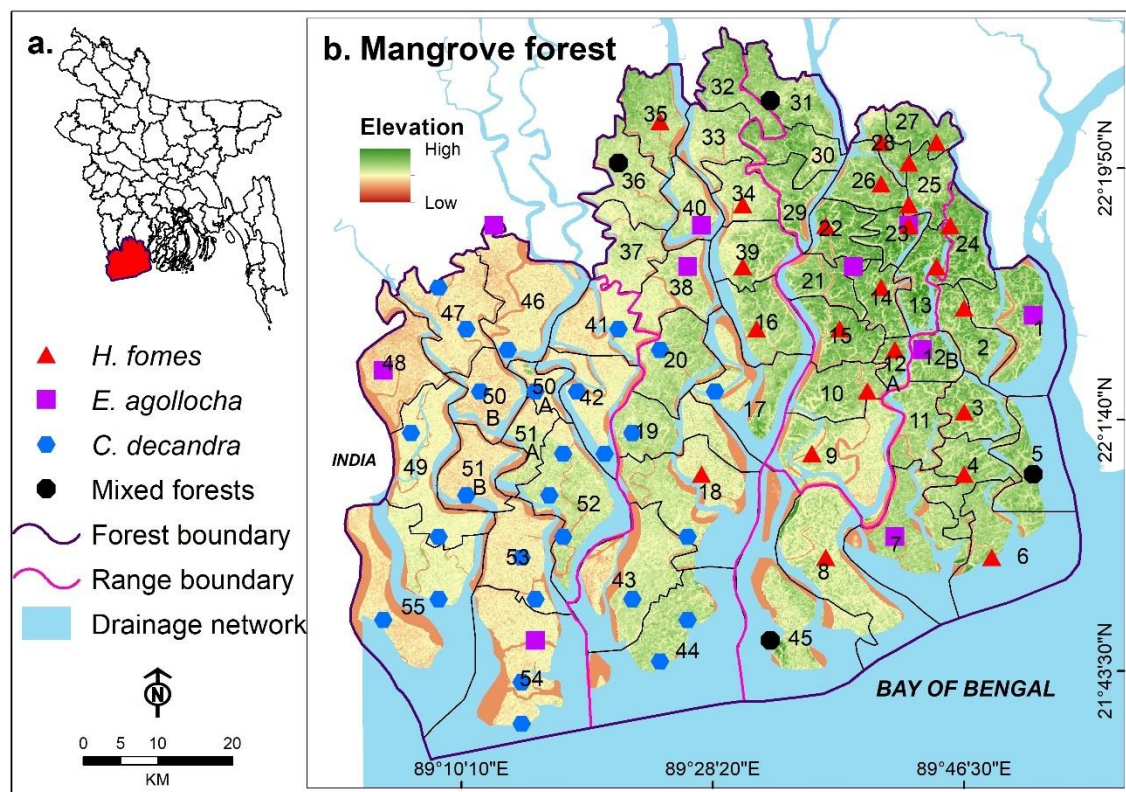


Fig. 3-1. a. Location of mangrove forest in Bangladesh and **b.** Spatial extent of mangrove forest and mangrove species sample points for phenological analysis collected from the Forest Department of Bangladesh. Numerals (1-55) indicated the compartments of the mangrove forest. Elevation extracted from the SRTM (version 4): <https://srtm.csi.cgiar.org/>. based on GEE, 2025.

The mean annual precipitation varies from 1,640 mm to 2,000 mm and the mean relative humidity throughout the year ranges between 70-80%. About 80-85% of total precipitation occurs during the monsoon, i.e., June to September between 2000 and 2024 (Fig. 3-2). A hot and humid pre-monsoon (March-May) with intermittent precipitation precedes the

monsoon which is followed by a post-monsoon period (October-November) and a dry winter (December-February) (Mandal et al., 2020). The average minimum and maximum temperature in pre-monsoon, monsoon, post-monsoon and dry winter is 29, 30, 26 and 20 °C, respectively (Fig. 3-2).

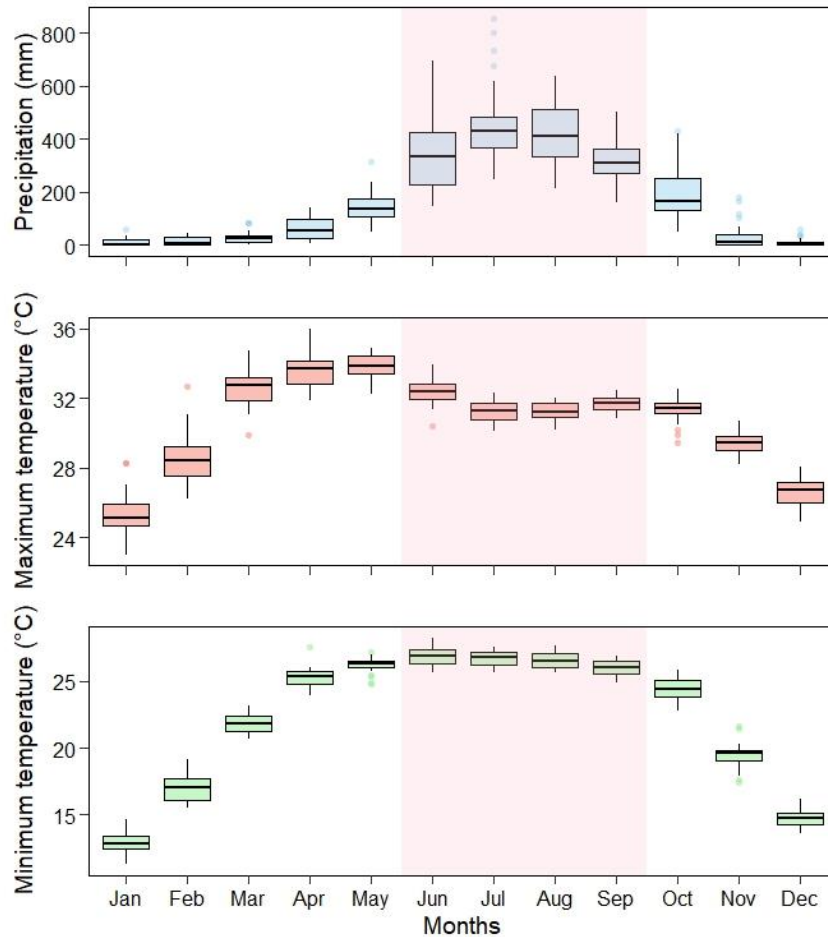


Fig. 3-2. Seasonal variations of monthly total precipitation (blue box) and maximum (red) and minimum (green) temperature of the mangrove forest area of Bangladesh from 2000-2024. The shaded area indicates the monsoon period. (Data source: TerraClimate IDAHO_EPSCOR/TERRACLIMATE based on GEE, 2025)

3.2.2. MODIS-Terra MOD13Q1 VIs

To investigate the mangrove phenology, MODIS-Terra 16-day composite MOD13Q1 at 250 m spatial resolution from January 2001 to December 2022 were processed by quality assessment (QA band) in google earth engine (GEE ID: MODIS/061/MOD13Q1) (LP DAAC: <https://lpdaac.usgs.gov>). Since seasonal vegetation dynamics may be influenced by the atmospheric conditions but MODIS QA band used only pixels with the highest quality. MODIS products provide VI value on a per pixel basis. MODIS-derived NDVI and

EVI are computed from atmospherically corrected bi-directional surface reflectance that have been masked for water, clouds, heavy aerosols, and cloud shadows.

$$NDVI = (NIR - Red) / (NIR + Red) \quad [1]$$

$$EVI = G \times ((NIR - Red) / (NIR + C_1 \times Red - C_2 \times Blue + L)) \quad [2],$$

where the blue, red, and NIR express atmospherically corrected surface reflectance from blue (469 nm), red (645 nm), and near-infrared (858 nm) spectra. G is a gain factor ($G = 2.5$), L is the canopy background adjustment ($L = 1$) that addresses nonlinear, differential NIR and red radiant transfer through a canopy, and C_1 and C_2 are coefficients to correct aerosol scattering ($C_1 = 6.0$, $C_2 = 7.5$) in red band by the blue band (Huete et al., 2002). NDVI, the most widely used VI, has a disadvantage that soil background and atmosphere influences NDVI, saturated at high biomass mangrove region (Rhyma et al., 2020). In contrast, EVI enhances sensitivity in high biomass regions and reduces residual atmosphere contamination from smoke and thin sub-pixel cloud clouds (Huete, 2012).

3.2.3. Time-series smoothing

To reduce the noise and reflection error of the raw time-series of MODIS-derived NDVI and EVI, a Savitsky-Golay (SG) smoothing filter was applied (Chen et al., 2004). The smoothing procedure was repeated with different filter order and filter length and fixed at 3rd-degree polynomial with the length of 5 for both NDVI and EVI ($p = 3$, $n = 5$).

Seasonal patterns in NDVI and EVI time-series data were detected using the discrete Fourier transform (DFT), which decomposes the mangroves signal into a series of sinusoids of different frequencies and a constant (Jeganathan et al., 2010). The sinusoids with their frequencies were summed using the inverse Fourier transformation to reconstruct a smooth wave resembling the original signal, with high frequency noise removed (Guzman et al., 2018). A 3 x 3 Daniell kernel moving average smoother was applied to smooth all estimated spectra for identifying dominant peaks in the periodogram (Bush et al., 2017). The shortest cycle was 1 month (twice the observation interval), and the longest cycle span was the full length of the 21-years.

3.2.4. Phenological metrics extraction

Phenology can be extracted from smoothed satellite image pixels by threshold-based, trend

derivative, and inflection-point methods (Zeng et al., 2020). Threshold-based phenology retrieving method was used, which is expressed by $VI_{ratio} = (VI - VI_{min}) / (VI_{max} - VI_{min})$, where $VI_{ratio} \leq 0.2$ and $VI_{ratio} \geq 0.2$ distinct as off-season and on-season, respectively (Cao et al., 2023). The 21-years SG filtered and DFT-reconstructed NDVI and EVI time-series was divided into 23 seasons to estimate three phenological metrics: start of the season (SOS), defined as the point where the VIs value exceeds threshold; end of the season (EOS), point where VIs value remained above threshold between the post-season minimum and peak EVI level; and time of maximum greenness (MaxGreen) denoted to the point of highest NDVI and EVI (Fig. 3-3). Phenological patterns were characterized by calculating the median values for all forest types from 2001-2022.

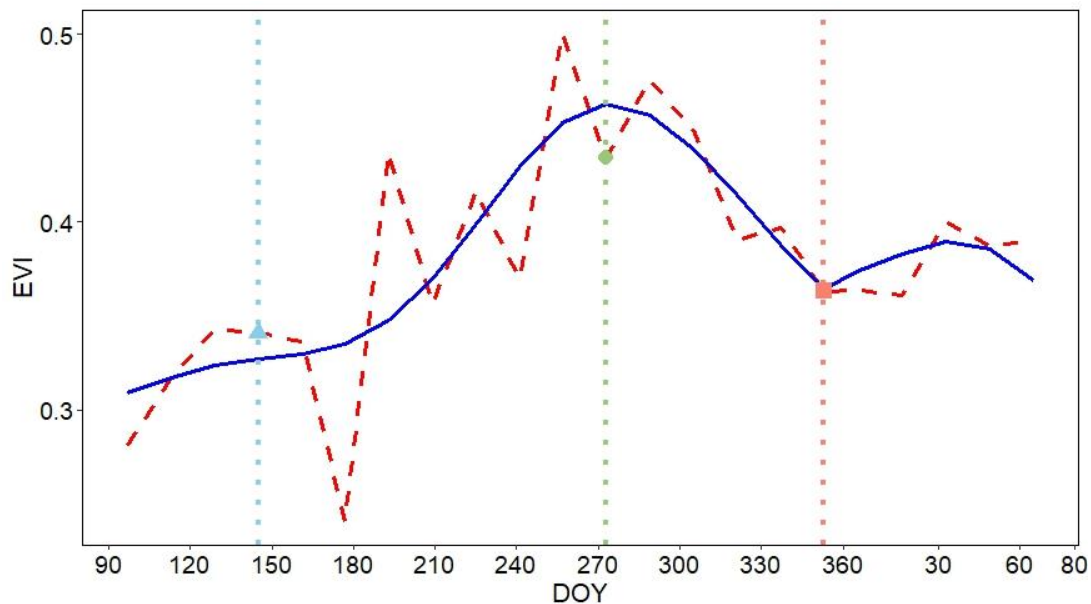


Fig. 3-3. Phenological metrics estimation using SG-filtered and DFT-reconstructed EVI time series for the 2019-2020 season for *H. fomes*. Discrete points indicate the inflection points for the SOS (triangle in blue), MaxGreen (circle in green) and EOS (square in salmon). The interrupted red line and solid blue line show the original EVI time series and the Fourier-smoothed series, respectively. DOY stands for day of the year (DOY 1 = 1st January).

3.2.5. Statistical analysis

SG-smoothing, DFT and threshold-based phenological metrics were estimated in R (version 4.2.2) (R Core Team, 2024), with libraries tidyverse and lubridate.

Generalized linear mixed models (GLMM) were employed to detect the variation of NDVI and EVI (as response variables) across mangrove forest types and phenological stages, which were included as fixed effects. A 21-year period was modeled as a random effect

(year) to account for interannual variability. The models assumed a Gaussian distribution with an identity link function. The interaction between mangrove forest types and phenological stages was included to assess whether phenological responses varied among species.

The relationship between species characteristics and climatic factors such as monthly mean precipitation, minimum and maximum temperatures and TC-induced wind speed explored by generalized linear models (GLM) with a Gaussian distribution.

3.3. Results

3.3.1. Seasonal variation in VIs

NDVI and EVI showed annual fluctuations across all four forest types (e.g., *H. fomes*, *E. agallocha*, *C. decandra* and mixed forests) (Fig. 3-4). The smoothed periodogram of NDVI and EVI revealed the same peak corresponding to one cycle per year (with 23 observations per year) (Fig. 3-5).

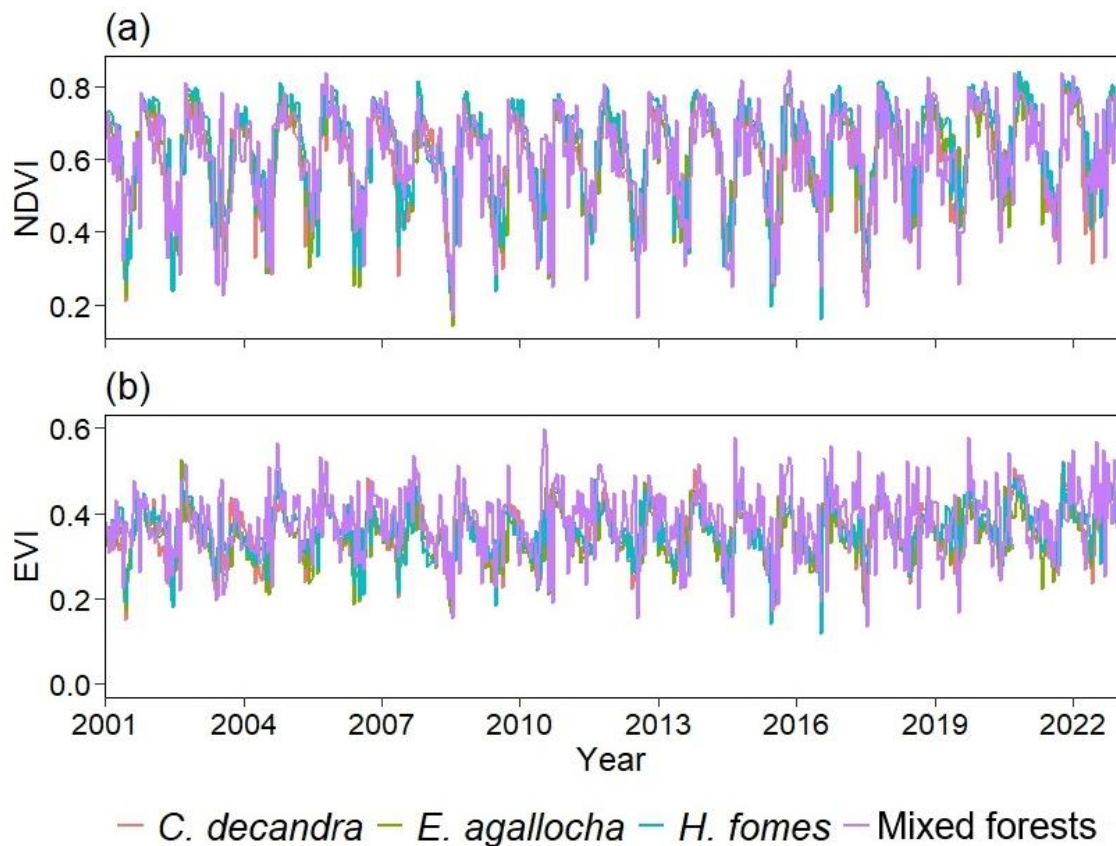


Fig. 3-4. SG-filtered (a) NDVI and (b) EVI time-series of four mangrove forest types over 21 years (2001-2022).

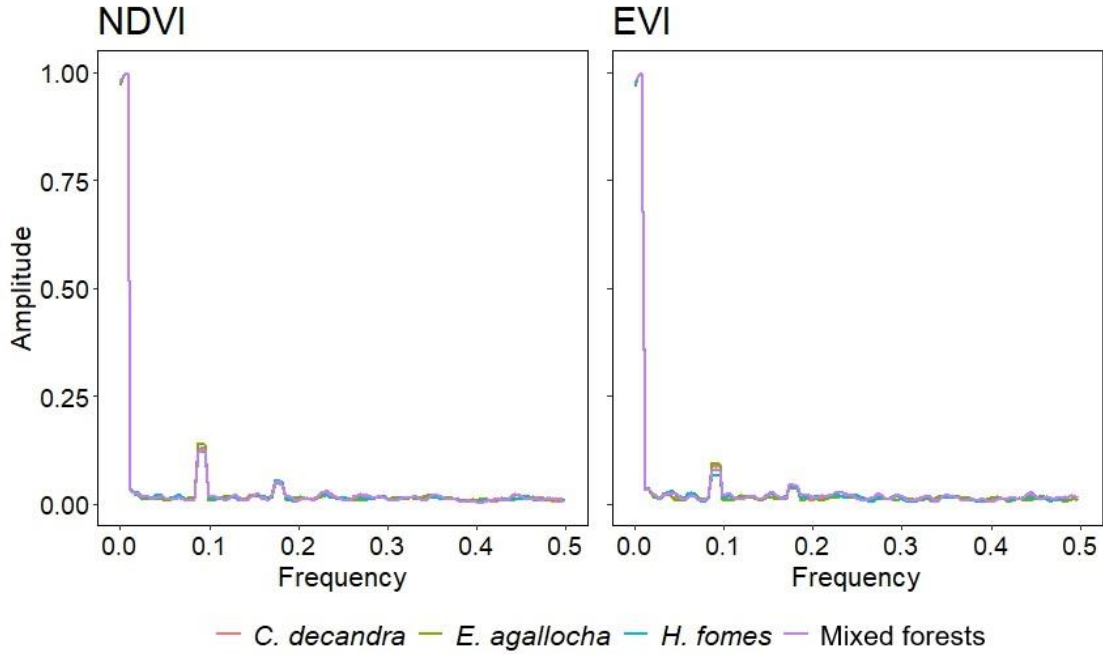


Fig. 3-5. Periodogram of NDVI and EVI shows the smoothed spectral estimates derived from DFT analysis for the four mangrove forest types. The x -axis shows all possible cycle frequencies (from one cycle every 1 month to the full length of the 21-years). The y -axis shows the amplitude of each cycle. The highest peak in each spectrum occurs at a frequency of 0.005 cycles per month.

3.3.2. VIs among mangrove forest types

NDVI and EVI differed across mangrove forest types (Fig. 3-6), with a significant peak at the MaxGreen stage (GLMM, $p < 0.001$). NDVI differentiated *H. fomes* and mixed forests from others, while EVI detected *E. agallocha* and mixed forests well (GLMM, $p < 0.05$).

H. fomes depicted overall higher NDVI than others, at SOS (mean $\pm$ SD: 0.72 ± 0.06) and EOS (0.74 ± 0.04). Mixed forests showed a distinct increase in NDVI during MaxGreen stage (0.79 ± 0.03 , $p < 0.01$). The lowest SOS and EOS were detected for mixed forests 0.67 ± 0.09 and 0.68 ± 0.08 , respectively. In contrast, *E. agallocha* and *C. decandra* did not significantly differ in seasonal NDVI behavior (Tukey test, $p > 0.05$) (Table 3-1). In particular, MaxGreen of *H. fomes* (0.79 ± 0.02) and mixed forests (0.79 ± 0.03) were greater than *E. agallocha* and *C. decandra* (Tukey test, $p < 0.05$).

E. agallocha (0.45 ± 0.04) and mixed forests (0.53 ± 0.04) showed a statistically significant increase in EVI during the MaxGreen phase (GLMM, $p < 0.001$). *C. decandra* and *H. fomes* did not differ significantly in seasonal EVI responses (Tukey test, $p > 0.05$). EVI of *C. decandra* was higher at SOS (0.38 ± 0.03) and EOS (0.39 ± 0.03). *H. fomes* and *E.*

agallocha had lower EVI at SOS, MaxGreen and EOS than *C. decandra* and mixed forests.

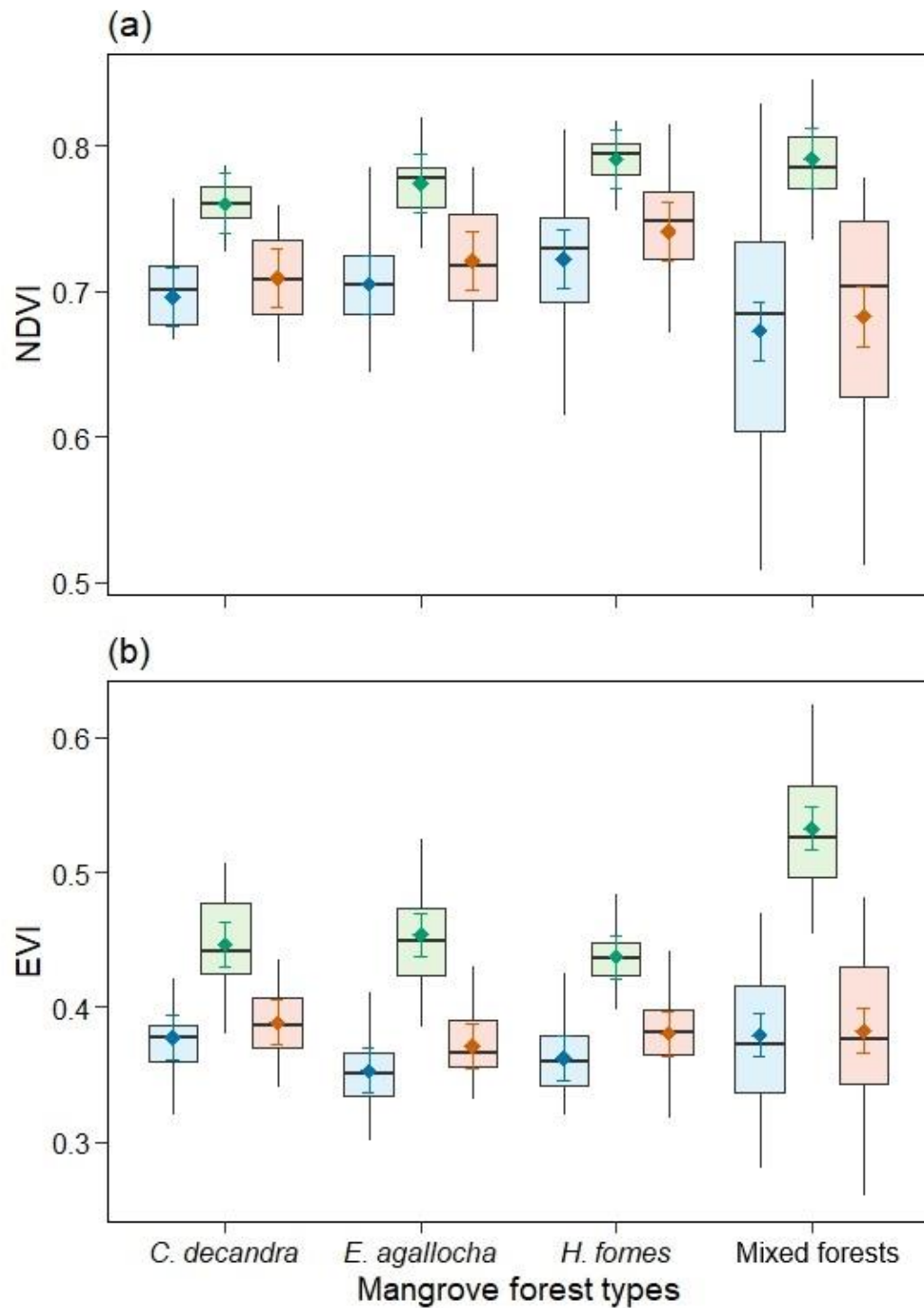


Fig. 3-6. Box-whisker plots showing (a) NDVI and (b) EVI for four mangrove forest types across three phenological phases: blue color for SOS, green for MaxGreen and salmon for EOS. The boxes illustrate the interquartile range, and the middle line indicates the median. Least-square means (solid circles) is shown confidence intervals (error bars, CI: 95%) of NDVI and EVI for mangrove forest types and phenology stages, as estimated by the GLMM.

Table 3-1. NDVI and EVI for 20 seasons (2001-2022) of four mangrove forest types at SOS, MaxGreen and EOS. The same letters on the upper-right of the mean $\pm$ SD indicate VIs not different between forest types within each phenology stage (Tukey's HSD test, $p < 0.05$).

VIs	Phenological metrics	<i>C. decandra</i>	<i>E. agallocha</i>	<i>H. fomes</i>	Mixed forests
NDVI	SOS ^{NS}	0.70 $\pm$ 0.05 ^{ab}	0.71 $\pm$ 0.05 ^{ab}	0.72 $\pm$ 0.06 ^b	0.67 $\pm$ 0.09 ^a
	Max Green*	0.76 $\pm$ 0.02 ^a	0.77 $\pm$ 0.02 ^a	0.79 $\pm$ 0.02 ^b	0.79 $\pm$ 0.03 ^b
	EOS ^{NS}	0.71 $\pm$ 0.03 ^{ab}	0.72 $\pm$ 0.04 ^b	0.74 $\pm$ 0.04 ^b	0.68 $\pm$ 0.08 ^a
EVI	SOS ^{NS}	0.38 $\pm$ 0.03 ^a	0.35 $\pm$ 0.03 ^a	0.36 $\pm$ 0.04 ^a	0.37 $\pm$ 0.06 ^a
	Max Green*	0.45 $\pm$ 0.04 ^a	0.45 $\pm$ 0.04 ^a	0.44 $\pm$ 0.03 ^a	0.53 $\pm$ 0.04 ^b
	EOS ^{NS}	0.39 $\pm$ 0.03 ^a	0.37 $\pm$ 0.03 ^a	0.38 $\pm$ 0.03 ^a	0.38 $\pm$ 0.06 ^a

Each numeral shows mean with standard deviation. GLMMs examine MaxGreen differs across mangrove forest types for both NDVI and EVI. *Significant at $p < 0.01$. NS: not significantly different.

3.3.3. Phenological variation among mangrove forest types

SOS was simultaneous on NDVI (day of the year: DOY 161; June 10) for all forest types, while EVI varied, ranging from DOY 129 (May 8) for *H. fomes* and mixed forests, DOY 177 (June 25) for *E. agallocha* to 185 (July 3) for *C. decandra* (Fig. 3-7). These results indicated that *H. fomes* and mixed forests were more sensitive to early precipitation, while *C. decandra* required more sustained environments before initiating growth. The MaxGreen metrics varied among species and spectral VIs during monsoon to post-monsoon. NDVI-based median DOY of MaxGreen for mixed forests was earlier (DOY 305; November 01) compared to *H. fomes* and *C. decandra* (DOY 313; November 09), with *E. agallocha* peaking later at DOY 321 (November 19). In contrast, EVI detected earlier MaxGreen dates, ranging from DOY 273 (September 30) for mixed forests, to DOY 289 (October 15) for others. Both VIs showed similar EOS (DOY 353; December 19) for all forest types, indicating leaf senescence due to seasonal stressors during the dry winter.

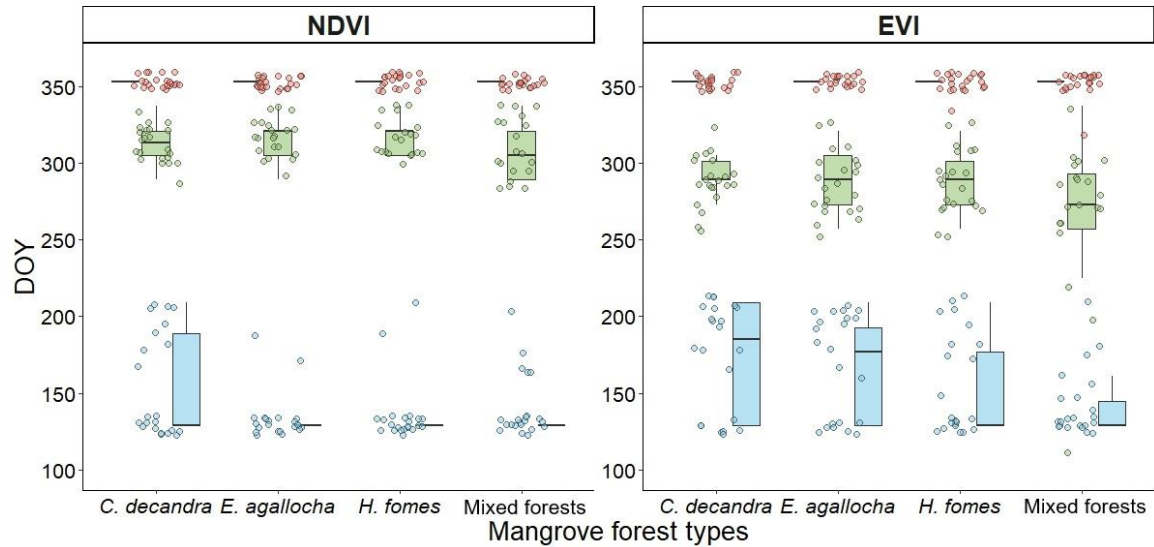


Fig. 3-7. DOY for SOS, MaxGreen and EOS in blue, green and salmon colors, respectively estimated from NDVI and EVI across four mangrove forest types. Boxes show interquartile ranges with median in thick black lines. Closed symbols denote the observed data for mangrove forest types.

3.3.4. Relationship between mangrove phenology and climatic factors

EVI of mangrove forest types were correlated with climatic factors, however, interactions were limited only for precipitation of mixed forests (GLM, $p < 0.05$), indicating species-specific responses to climatic variability (Fig. 3-8). Mixed forests during SOS was negatively correlated to precipitation, supporting an earlier phenological response to monsoon onset ($p < 0.05$). In particular, mangrove species showed a delayed response to precipitation, with vegetation greenness lagging behind the precipitation. *H. fomes*, *E. agallocha* and *C. decandra* did not have a significant impact in climatic response ($p > 0.05$), suggesting more stable or delayed phenological response. Minimum and maximum temperature were correlated with EVI of mangrove forest types; however, there was no significant species-specific response. Correlations were not significant with the timing of EVI MaxGreen and EOS for climatic factors (results not shown).

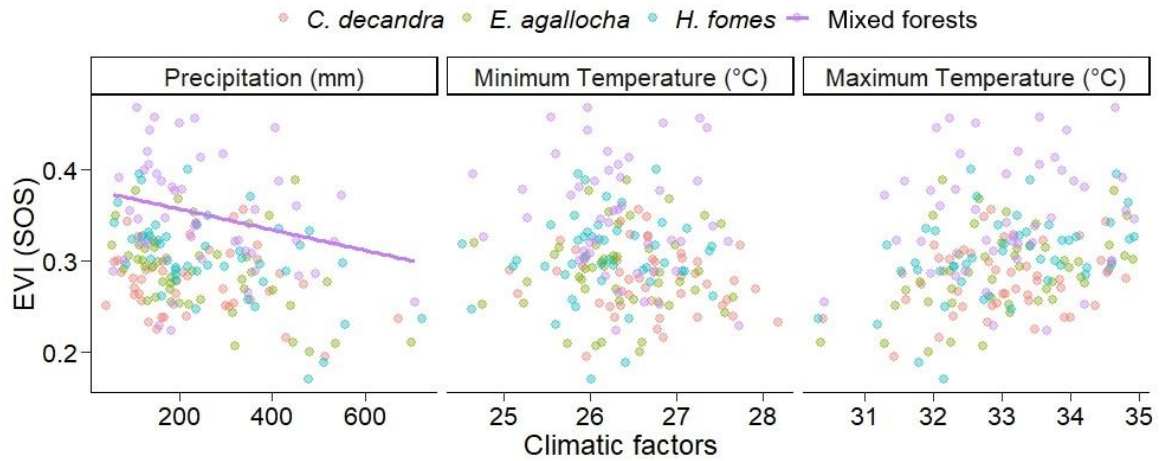


Fig. 3-8. Scatterplots illustrate the species-specific interaction between monthly EVI for SOS and climatic factors: precipitation, minimum and maximum temperature from January 2001 to December 2022, as predicted by GLM for all forest types ($n = 184$). Closed symbols denote the observed data. Correlation coefficients are shown by trend lines, indicating significant relationships at $p < 0.05$. No trend line for a non-significant relationship ($p > 0.05$).

3.3.5. Relationship between mangrove forest types and TC disturbance

EVI dropped sharply between 2008 and 2009 for all mangrove forest types, indicating a loss of biomass (e.g., leaves, branches) and suppressed photosynthetic activity immediately after the TC of 2007 (Fig. 3-9). EVI recovery for *E. agallocha*, *C. decandra* and mixed forests began one year after the TC landfall, indicating vegetation regeneration through resprouting and leaf regrowth. Mixed forests exhibited the fastest recovery and highest EVI (0.41 ± 0.05) in 2012, signifying higher ecological resilience. *H. fomes* showed the lowest post-TC EVI (0.28 ± 0.03) in 2010 and a delayed recovery even after two years compared to *E. agallocha*, *C. decandra* and mixed forests, suggesting greater sensitivity to TC-induced canopy damage and slower leaf regrowth. In particular, *H. fomes* was negatively correlated with TC wind (GLM, $p < 0.01$) (Table 3-2). These results indicated that mangrove forest types varied in response to TC.

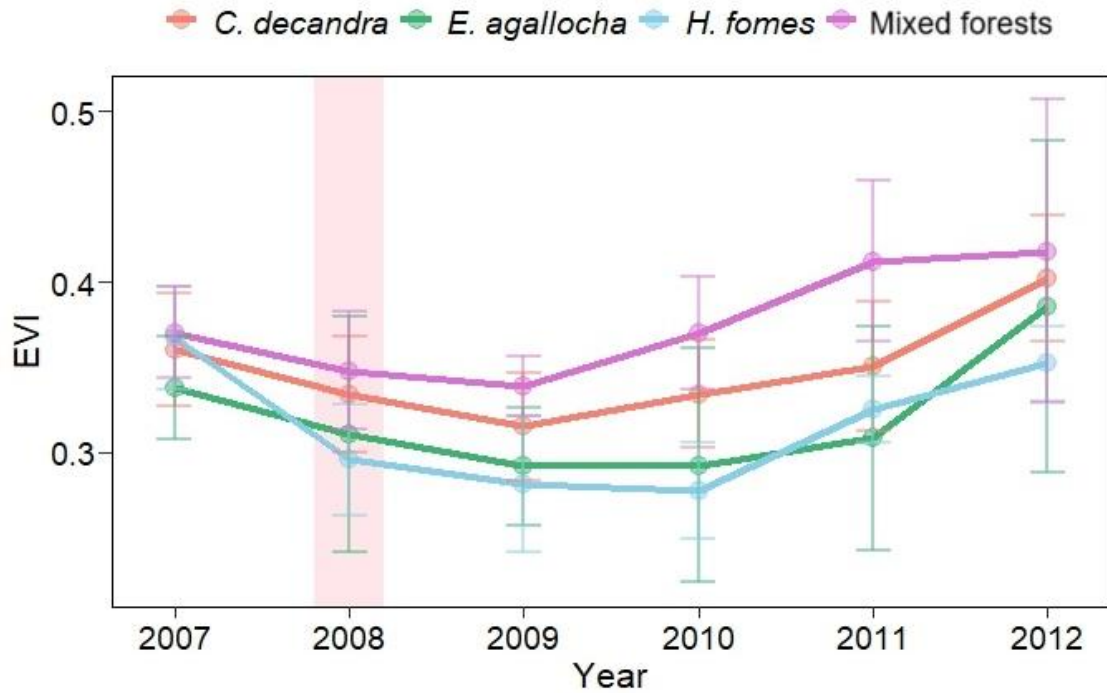


Fig. 3-9. Changes in EVI among four mangrove forest types before (2007) and after (2008-2012) a major TC of 2007, derived from the Landsat TM (30 m resolution). Mean is shown with SD (vertical lines). The shaded area denotes the aftermath of the TC landfall.

Table 3-2. Effects of TC-induced wind speed (km h^{-1}) on four mangrove forest types, estimated by GLM.

Mangrove forest types	Estimate	SE	t value	p value
Intercept	0.36	0.01	49.19	< 0.001
<i>C. decandra</i>	-0.00003	0.0001	-0.50	0.62
<i>E. agallocha</i>	-0.0001	0.0001	-0.75	0.45
<i>H. fomes</i>	-0.0002	0.0001	-2.12	<0.01
Mixed forests	-0.0002	0.0002	-1.28	0.20

3.4. Discussion

Seasonal variation and phenological pattern of the mangrove forest was depicted by MODIS-derived NDVI and EVI. The findings suggested that tropical moist broadleaf mangrove forest exhibited the seasonal variation of vegetation greenness with unimodal leafing pattern at large spatial scale (Rahman and Islam, 2015). MODIS-derived seasonal patterns of the mangrove forest showed a persistent annual cycle during the study period.

VI has distinct characteristics in detecting phenological metrics for different types of mangrove forests (Cao et al., 2023). While NDVI-based SOS was the same for all forest

types, EVI-based SOS varied among species, suggesting the sensitivity of VIs to phenological metrics (Guzman et al., 2018). NDVI and EVI differentiated *H. fomes* and mixed forests using the MaxGreen of the phenological metrics well. MaxGreen from spectral VIs likely has an advantage in differentiating mangrove species (Aji et al., 2023). The EOS was consistent across forest types, indicating that the threshold of off-season was similar throughout the year. EVI correlated more for depicting changes in canopy structural properties, viz., LAI, canopy greenness and leaf structure (Akhtar and Tsuyuzaki, 2024). EVI-based estimation of phenological metrics is likely to be more reliable, as major tree species i.e., *H. fomes*, *E. agallocha* and *C. decandra* shed leaves in winter (November-January), flush in pre-monsoon (March-May) and reach peak greenness in monsoon (July-September) (Rahman and Islam, 2015; Kamruzzaman et al., 2019).

Mangrove phenology among species showed seasonal variation, likely driven by the seasonal variation in precipitation and temperature of the study area (Azad et al., 2021b). Seasonal precipitation regulates canopy dynamics in tropical mangrove forests (Cleland et al., 2007). Monsoonal precipitation delivers a substantial influx of freshwater, which enhances foliage and chlorophyll, thereby boosting photosynthesis (Chowdhury et al., 2016; Aji et al., 2023). However, mangrove species did not respond immediately to precipitation, which is likely driven by delayed physiological responses to freshwater availability after high salinity of dry winters (Guzman et al., 2018). This study supports the idea that *H. fomes*, *E. agallocha* and *C. decandra* start flowering and reproduction with the onset of the monsoon, that is accompanied by relatively high temperature and produces litter including leaves and branches during dry period (Mandal et al., 2020). Therefore, precipitation plays a significant role in mangrove forest phenology.

Since tropical cyclones often strike the study area, seasonal greenness is influenced by forest disturbances and changes vegetation density immediately after a strong event. A major TC in 2007, with a maximum sustained wind speed of 260 km h^{-1} , lowered the EVI across mangrove forest types. Species-specific susceptibility to TC disturbances and recovery abilities varied. EVI lessened soon after the TC struck, particularly for the dominant *H. fomes*, indicating that taller mangrove species showed greater vulnerability to TC and delayed recovery, probably by TC-induced canopy damage (defoliation and branch breakage) and salinity stress (Azad et al., 2021a; Kumar et al., 2021). Major tree species along the TC07 track of southeastern part of the mangrove forest i.e., *H. fomes*, *S. apetala*, *E. agallocha* and *X. moluccensis* (Forest Department of Bangladesh, 2020), are severely

affected by trunk and stem breakage and uprooting (GOB, 2008), including the uprooting of at least one tree per 100 m², mostly tall trees (Hossain and Begum, 2011; Villamayor et al., 2016). *E. agalloch* and *C. decandra* are suggested to be the first pioneers soon after the felling of native *H. fomes* by sprouting (Rahman and Asaduzzaman, 2013). Wind-resilient *Rhizophora* species contributed to the lower impact of TC on mixed forests, while faster recovery and increased EVI are likely driven by the resprouting ability of *A. officinalis* and *S. apetala* in the mangrove forest (Halder et al., 2021). TCs during the off-fruiting seasons, as seen in the TC in 2007, remove mangrove propagules, allowing invasive species to sprout vigorously (Rashid et al., 2009). The earlier phenological response to monsoon onset and the rapid recovery of mixed forests are likely to facilitate the invasion of non-mangrove species after frequent disturbances (Biswas et al., 2007). Changes in canopy greenness detected using EVI after TC struck indicated the species-specific canopy damage, likely caused by defoliation, crown breakage or tree uprooting. However, EVI changes do not provide a precise estimate of damage type, which in turn influences species-specific recovery patterns (Peereaman et al., 2022).

Fast-growing and wind-resilient *E. agallocha* and *Rhizophora* species along the shorelines and forest edges would therefore be required to protect the vulnerable *H. fomes* in the inner mangrove. Further research should incorporate ground-level information such as leaf flushing, shedding, stand characteristics and biomass to validate the satellite-based phenology estimations. Moreover, unmanned aerial vehicles-based LiDAR with high-resolution multispectral or hyperspectral offers valuable tools for evaluating species composition and species-specific responses to disturbances (Li et al., 2023). Thus, species-specific phenological characterization and vulnerability to disturbances serves as a reference for future long-term phenological changes in the mangrove forest at the landscape scale.

3.5. Conclusion

The seasonal behavior in canopy greenness among mangrove species varied that were estimated by the 21-years MODIS SG-filtered NDVI and EVI. DFT-reconstructed NDVI and EVI time-series was used for phenological characterization of the mangrove forest, which discerned *E. agallocha*, *H. fomes* and mixed forests by MaxGreen. However, EVI-based phenological estimation of MaxGreen, SOS and EOS align more with ground

information. Results revealed the potential of MODIS 250 m resolution imagery to monitor mangrove phenology: SOS ranged from DOY 113 (pre-monsoon season) to DOY 177 (monsoon), MaxGreen varied between DOY 273 (late monsoon) and DOY 321 (post-monsoon), and EOS occurred around DOY 353 (dry winter). EVI detected Changes in climatic factors are likely to have an impact on photosynthetic activity and affect carbon uptake by the forest ecosystem. Selected forest areas received a greater amount of precipitation during the monsoon period; however, mangrove species were delayed in response to precipitation. Dominant *H. fomes* showed greater vulnerability to TC disturbances. Therefore, the estimated phenological signatures and potential interaction of mangrove species with climatic factors can be used to map species-specific mangrove forests at the landscape level and predict their phenological changes in response to climate change.

General discussion

To implement sustainable conservation and restoration strategies for mangrove forests, understanding the effects of large-scale disturbances is crucial. This study synthesized remote sensing with ground-truth data to examine changes in the spatial extent of mangrove forests vegetation at a large landscape scale. Disturbance-induced changes on mangrove regions were extracted through satellite imagery based LULC classification (Chapter 1); modeling the spatial extent of forest disturbances and recovery patterns in relation to TC characteristics and environmental factors (Chapter 2); and evaluating the relationship between species characteristics and climatic factors (Chapter 3). The rate of decline in dense mangrove areas was estimated by VI-integrated RF algorithms. SEM predicted wind speed as the highest predictor of forest disturbances. Species characteristics were examined by detecting variations in the spectral estimates of different mangrove forest types.

Chapter 1 proposed a new VI-integrated RF method to classify LULC. Multi-spectral satellite imagery is used to assess LULC changes for characterizing mangrove ecosystem (Giri et.al., 2007; Rodrigues et al., 2023). However, detection and separation of mangroves from other LULC classes are not clear as they concentrate on pixel-based changes (Hossain et al., 2022). The spectral reflectance of multiple VIs detected the variation of surface greenness among LULC classes. By using the designated spectral signatures range of each VI for various land cover types reduced error of LULC classification through multiple decision trees in RF. EVI showed the effectiveness in distinguishing between sparse and dense mangrove. Spatial pattern revealed anthropogenic disturbances such as aquacultural land expanded near forest edges, restricting the growth of vegetation, including mangroves (Hasan et al., 2024). The alteration from dense to sparse mangroves, indicating mangrove degradation should result from natural disturbances, i.e., TCs (Mandal and Hosaka, 2020). Accurate detection of mangroves by VI-integrated RF classifier indicates that sustainable aquaculture practices, restoring water bodies and habitat quality and mangrove afforestation should improve the mangrove ecosystems.

Mangroves are vulnerable to TC-induced sustained high winds and landfall (Taillie et al., 2020) and cause large-scale disturbances to mangrove ecosystems (Halder et al., 2021; Fibich et al., 2023); however, the relationships between disturbance intensity and recovery patterns should be studied. Chapter 2 revealed that the recovery of mangroves varied with the disturbance intensities. Mangroves revegetated within a few years soon

after the TC strike, indicating canopy recovery by stem sprouting, seedling to juvenile growth and/or canopy recovery (Peereman et al., 2022; Mo et al., 2023). However, intense and frequent TCs slowed down mangrove regeneration. SEM projected that strong TC winds making landfalls near the forests with increased precipitation caused the highest forest disturbances, are likely by defoliation, stem breakage and uprooting of trees (Lugo, 2008) and by modifying soil condition (Macamo et al., 2016). However, the frequency of TCs has declined in the past decade, their increasing intensity and rising sea level are expected to inundate coastal areas of Bangladesh, including mangroves (Paul and Rashid, 2016). Lower-intensity TCs impacted limited forest areas, while higher-intensity TCs caused more severe forest disturbances. Globally, TCs are predicted to become more intense with a 2°C increase in global mean temperature and rising sea surface temperature, increasing the future risk to mangrove forests and potentially leading to substantial losses (Zhang et al., 2019; Knutson et al., 2020). Therefore, the projected interaction between TCs and environmental factors and forest recovery indicated continuous monitoring of mangroves before and after TCs would help to evaluate and modify restoration efforts by establishing natural seedling and site-specific replanting of native species in degraded areas.

Vegetation phenology characterizes the spatiotemporal variability of ecosystem functions by influencing carbon cycling, terrestrial carbon sequestration, and mitigation of anthropogenic CO₂ emissions (Richardson et al., 2012). Although mangrove is an evergreen forest, time-series of NDVI and EVI-derived from MODIS-Terra showed seasonal variation in mangrove species greenness, indicating mangrove forests respond to the seasonality of environmental cues (Zhang et al., 2006; Rahman and Islam, 2015). Chapter 3 estimated mangrove phenology by analyzing spectral VIs of species-specific mangrove forest types, suggesting the EVI-based phenological metrics (SOS, MaxGreen and EOS) serve as indicators of photosynthetic activity (Guzman et al., 2018). Results concluded that lower greenness was associated with the dry season, while months with maximum precipitation were associated with peak greenness. Mixed forests displayed earlier phenology in relation to precipitation and rapid recovery after TC than dominant species like *H. fomes*, *E. agallocha* and *C. decandra*. Furthermore, the dominant mangrove species *H. fomes* showed high susceptibility to TC winds and delayed recovery after disturbance compared to other species are likely characterized by a higher wood density and diameter at breast height than others (Halder et al., 2021). TC-induced mechanical stress transfers energy through the crown-trunk-root system of the tree, causing full or

partial damage (Drouineau et al., 2000). Among species, large trees are more sensitive to wind damage than smaller trees (Baldwin et al., 2001). The observed delayed recovery of salt-intolerant *H. fomes* suggest that TC-induced storm surges increase salinity and thereby impede regrowth (Ahmed et al., 2022). Moreover, increased TC intensity under global warming highlights the ecological significance of species-specific sensitivity, such as landward expansion of salt-tolerant species and greater damage to *H. fomes* may alter species composition (Sarker et al., 2016), weaken ecosystem functions and thereby indicate the cryptic ecological deterioration in mangrove ecosystems.

This study identified the land cover types in and around mangroves and predicted potential forest disturbance by an integrated RF classifier with multiple VIs and SEM model with the complex interaction between TCs and environmental factors. Forest recovery following disturbances was also detected in relation to TC intensities. In addition, mangrove phenology characterized the species photosynthetic activity of mangrove forests in relation to climatic factors. Site-specific mangrove species and habitats can be conserved by interpreting phenological characteristics. Multiple VIs in RF accurately separated sparse and dense mangrove; however, the developed method was limited in distinguishing highly overlapping mixed evergreen mangrove species, particularly in cloudy and patchy mangrove regions (Miraki et al., 2023). The VI-integrated RF algorithm should be improved using ground truth data and more species-sensitive VIs derived from high-resolution multispectral or hyperspectral imagery to enable the classification of species-specific mangrove forest types. However, further research using additional ground-level environmental cues such as, salinity, litterfall, leaf area index (LAI) and anthropogenic impacts (i.e., logging) with the developed remote sensing methods may enhance monitoring of species-specific mangrove dynamics under disturbances, supporting better environmental management. The findings of the study can be applicable to other tropical forest regions with high TCs activity for predicting TC-induced forest disturbances and conserving degraded areas. The results may also be extended to temperate forests, where vegetation greenness depends on temperature, and shifts in temperature and precipitation could disrupt the seasonal cycle of forest ecosystems. For a generalization of evidence-based conservation, restoration and sustainable management of mangroves, accurate detection of forest cover, evaluation of forest disturbances and recovery patterns, and species-specific phenological characterization and responses to disturbances at large landscape scales under a changing climate are required.

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Appendices

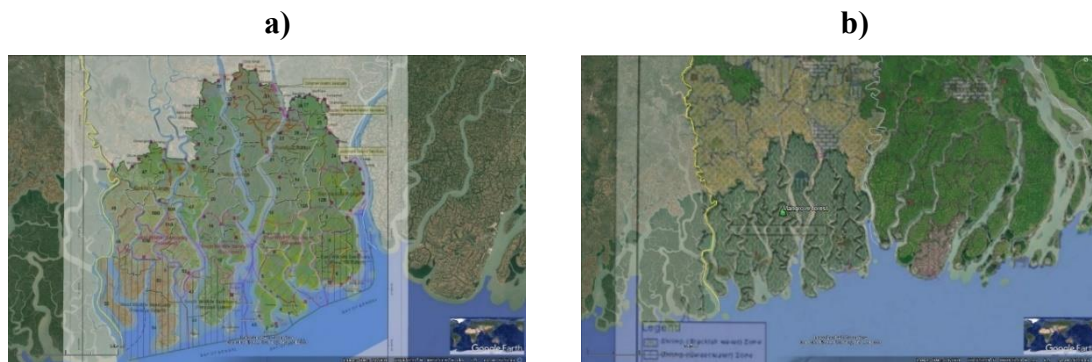


Fig. A-1. The land cover types were aligned with **a)** the reserved forest map and **b)** the indicative coastal land use zone map, interpreted using high-resolution (< 1 m) imagery from Google Earth Pro.

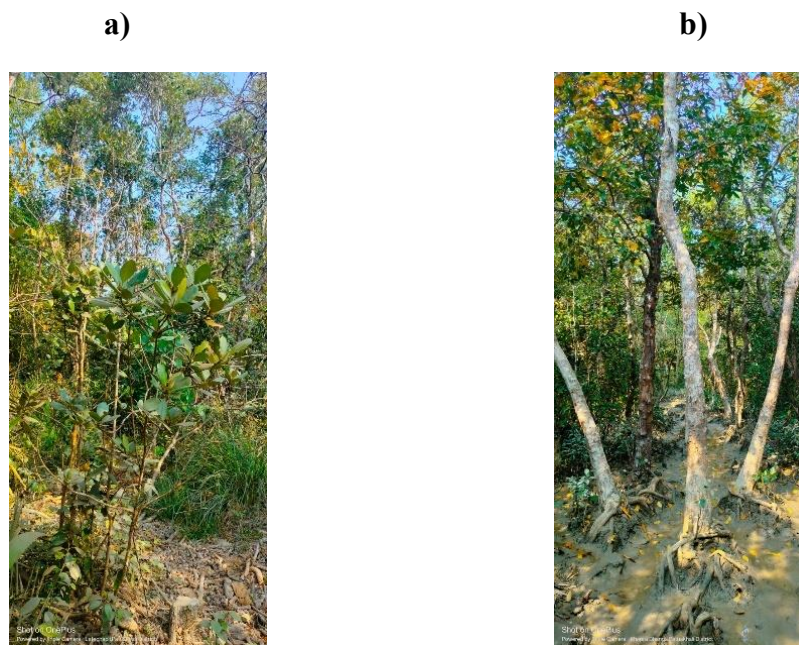


Fig. A-2. Selected mangrove forests area with **a)** sparse and **b)** dense vegetation cover.

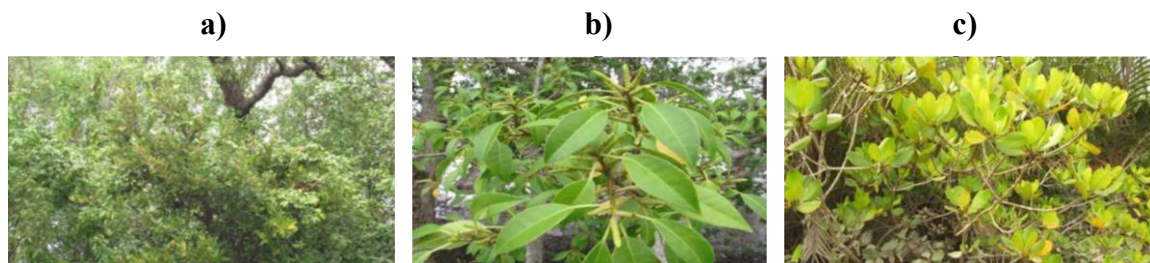


Fig. A-3. Three dominant mangrove tree species **a)** *H. fomes*, **b)** *E. agallocha* and **c)** *C. decandra*.

(Source: Barik et al., 2018)

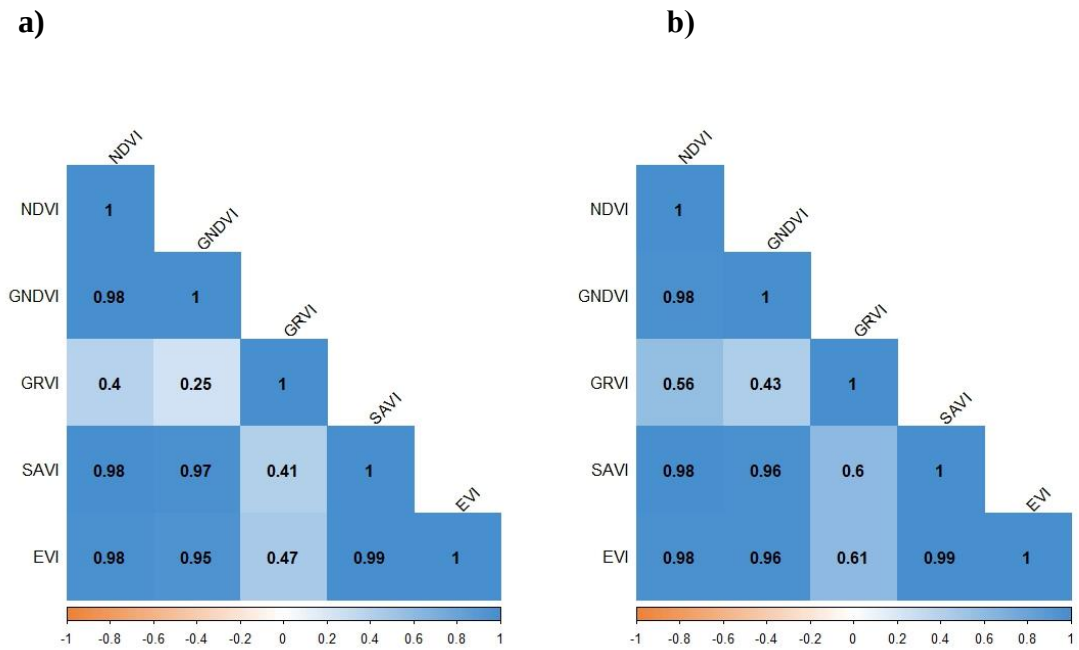


Fig. A-4. Correlation matrix between vegetation indices for detecting LULC classes of **a)** 1988 and **b)** 2020, value corresponds to Pearson's correlation coefficient (r).

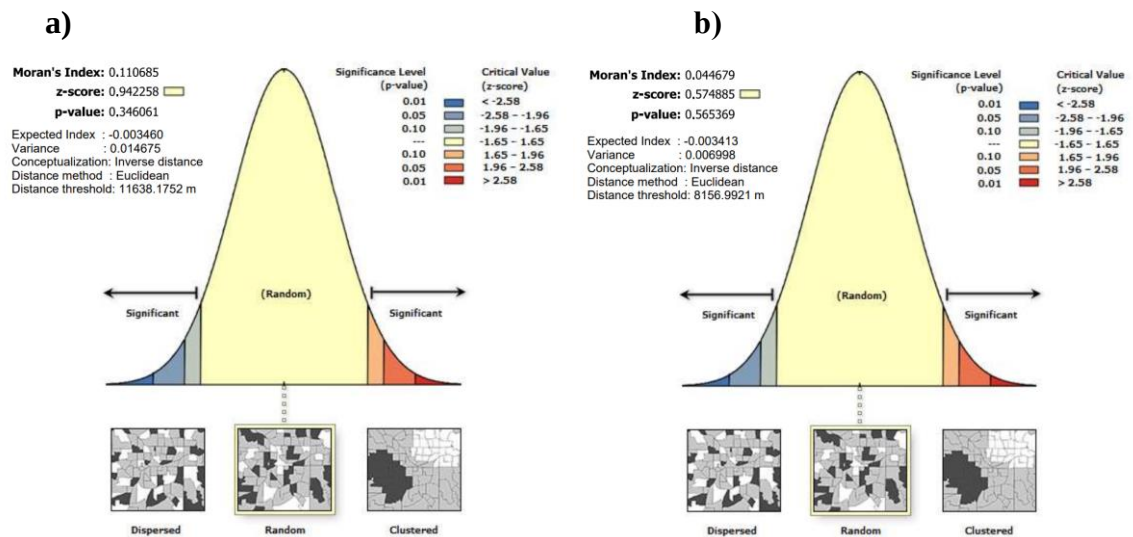


Fig. A-5. The spatial-auto correlation report from the Moran's I of training sample points for both **a)** 1988 and **b)** 2020.

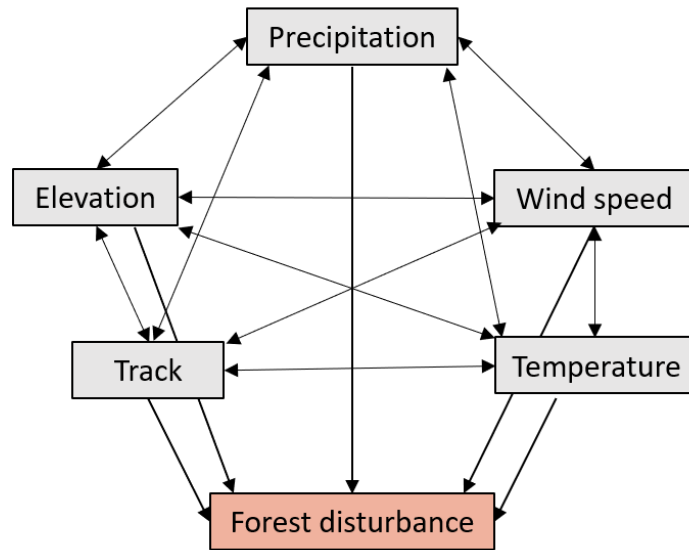


Fig. A-6. A hypothetical causal model with paths (lines) illustrates how TC and environmental factors (vertices) affect the mangrove forest disturbances in structural equation modeling. Single-headed arrows signify the direct effects of tail variable to the head variable and double-headed arrows show an indirect correlation between two explanatory variables.

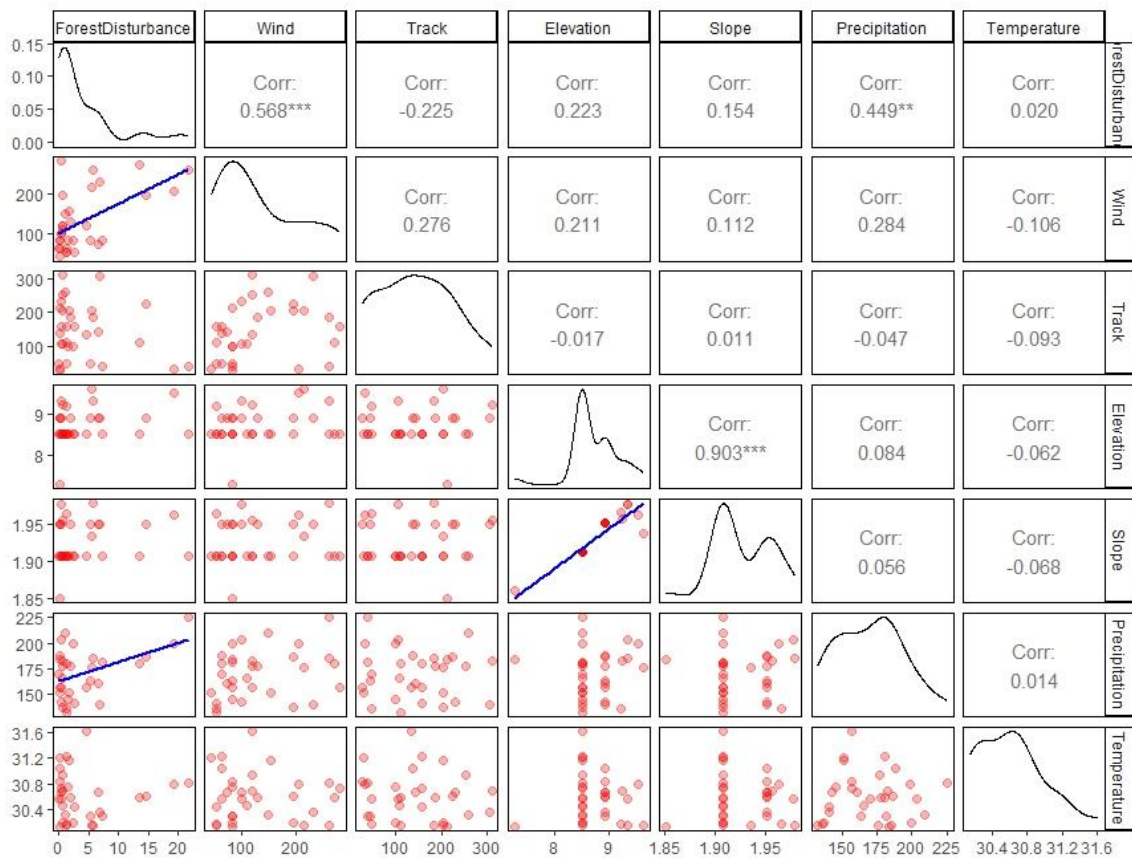


Fig. A-7. Scatter plot shows the correlations among TC and environmental factors. Values correspond to Pearson's correlation coefficient (r). Trend lines correspond to linear models (lm). *Significant correlations at $p < 0.05$.

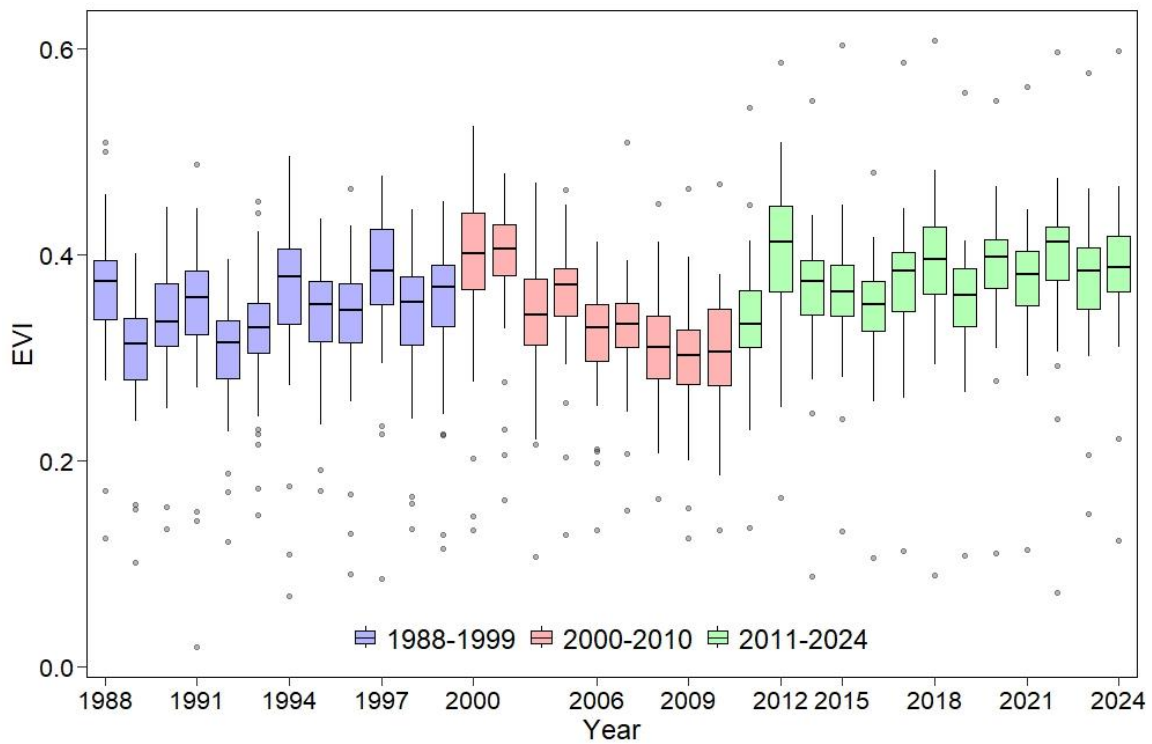


Fig. A-8. Spatiotemporal trends of EVI from 1988 to 2024, shown by a box-whisker plot. Changes in mangrove vegetation are represented in three phases: blue color for 1988-1999, red for 2000-2010 and green for 2011-2024, considering three major TCs: TC91, TC07 and TC20. The boxes illustrate the interquartile range, and the middle line indicates the median. All data were collected from dry seasons in the same month and contiguous years to minimize seasonal effects on the EVI.

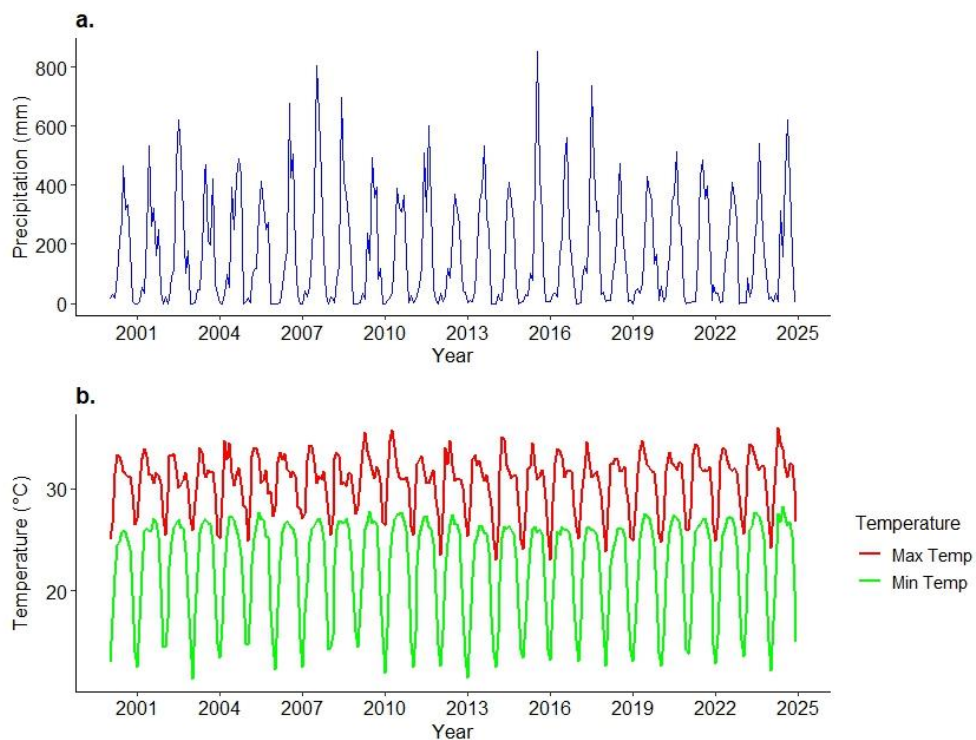


Fig. A-9. Line graphs show the monthly **a.** precipitation and **b.** temperature (maximum and minimum) between 2001 and 2022 in mangrove regions.

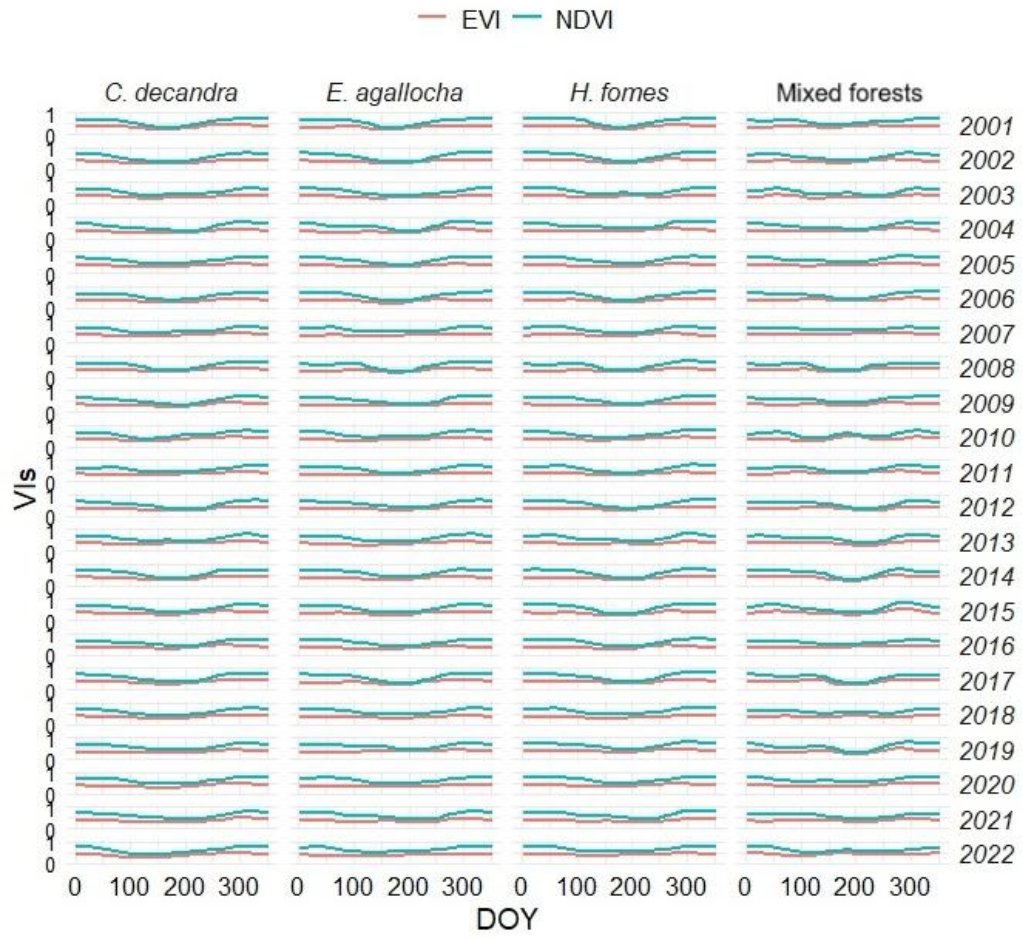


Fig. A-10. Smoothed time-series of NDVI (green color) and EVI (red) for four forest types in relation to DOY between 2001 and 2022.

Table A-1. Dynamic changes in and around mangrove regions from 1980 to 2020.

a) Changes between LULC classes in 1988–1991 (km ²)									
LULC classes	Aquaculture	Bare land	Cropland	Dense mangrove	Homestead vegetation	Mudflats	Sparse mangrove	Water body	Total 1988
Aquaculture	16	3	3	0	1	0	1	17	41
Bare land	54	354	55	3	63	13	19	28	590
Cropland	19	202	692	1	61	3	1	3	980
Dense mangrove	5	9	2	2872	75	0	544	10	3517
Homestead vegetation	4	55	70	33	240	1	19	1	423
Mudflats	3	5	0	0	1	3	1	9	21
Sparse mangrove	0	0	0	223	12	0	385	0	621
Water body	55	7	0	5	1	9	26	2064	2167
Total area in 1991	155	635	823	3135	453	29	996	2133	8360
b) Changes between LULC classes in 1991–1995 (km ²)									
LULC classes	Aquaculture	Bare land	Cropland	Dense mangrove	Homestead vegetation	Mudflats	Sparse mangrove	Water body	Total 1991
Aquaculture	32	84	1	2	1	3	11	22	155
Bare land	23	311	142	1	22	30	95	11	635
Cropland	30	98	620	0	31	33	9	4	823
Dense mangrove	0	3	0	2493	57	0	580	1	3135
Homestead vegetation	2	22	97	29	226	3	73	1	453
Mudflats	2	10	1	0	0	5	1	11	29
Sparse mangrove	1	10	2	596	20	0	366	2	996
Water body	44	44	0	4	1	27	17	1996	2133
Total 1995	133	580	864	3125	358	101	1152	2047	8360
c) Changes between LULC classes in 1995-2000 (km ²)									
LULC classes	Aquaculture	Bare land	Cropland	Dense mangrove	Homestead vegetation	Mudflats	Sparse mangrove	Water body	Total 1995
Aquaculture	49	17	1	0	0	16	0	50	133
Bare land	43	350	40	1	6	76	4	61	580
Cropland	15	173	584	0	70	17	0	5	864
Dense mangrove	1	2	0	2748	51	6	309	8	3125
Homestead vegetation	1	29	26	69	207	7	18	1	358
Mudflats	5	44	13	0	1	12	0	26	101
Sparse mangrove	3	103	11	616	78	33	287	20	1152
Water body	52	7	0	0	0	20	1	1968	2047

Total 2000	169	725	674	3435	413	187	619	2139	8360
d) Changes between LULC classes in 2000-2006 (km ²)									
LULC classes	Aquaculture	Bare land	Cropland	Dense mangrove	Homestead vegetation	Mudflats	Sparse mangrove	Water body	Total 2000
Aquaculture	81	19	3	0	1	0	0	66	169
Bare land	95	202	269	2	135	1	7	15	725
Cropland	25	53	515	7	69	1	1	3	674
Dense mangrove	2	2	6	3060	31	0	333	2	3435
Homestead vegetation	3	8	90	52	227	0	31	3	413
Mudflats	47	54	37	1	15	1	3	27	187
Sparse mangrove	3	3	26	162	65	0	355	4	619
Water body	93	26	15	1	6	3	3	1993	2139
Total 2006	348	366	960	3286	547	6	732	2114	8360
e) Changes between LULC classes in 2006-2016 (km ²)									
LULC classes	Aquaculture	Bare land	Cropland	Dense mangrove	Homestead vegetation	Mudflats	Sparse mangrove	Water body	Total 2006
Aquaculture	188	26	3	1	3	19	3	106	348
Bare land	117	105	36	3	17	35	5	49	366
Cropland	86	185	498	5	105	14	37	31	960
Dense mangrove	1	3	8	3058	49	1	163	3	3286
Homestead vegetation	42	93	72	35	211	3	78	12	547
Mudflats	0	1	1		0	1	0	2	6
Sparse mangrove	5	6	1	390	43	1	282	5	732
Water body	65	15	1	1	3	15	5	2009	2114
Total 2016	504	435	620	3492	431	89	572	2217	8360
f) Changes between LULC classes in 2016-2020 (km ²)									
LULC classes	Aquaculture	Bare land	Cropland	Dense mangrove	Homestead vegetation	Mudflats	Sparse mangrove	Water body	Total 2016
Aquaculture	331	55	6	1	7	19	1	84	504
Bare land	59	247	30	1	37	48	4	9	435
Cropland	2	148	353	0	108	4	4	1	620
Dense mangrove	1	16	0	2693	17	1	764	1	3492
Homestead vegetation	5	101	9	39	205	3	67	2	431
Mudflats	21	32	1	0	1	23	0	12	89
Sparse mangrove	4	92	3	137	50	1	283	3	572
Water body	94	39	2	1	4	14	3	2060	2217
Total 2020	516	730	404	2871	430	114	1125	2171	8360

Table A-2. Observed TC events in the study area and scenes derived from Landsat datasets.

TC code	Date	Name	Category*	Landfall area	Satellite Images
TC88	28-29 Nov 1988	04B	H3	Khulna, Bangladesh	Landsat 5 TM
TC89	23-27 May 1989	Unnamed	TS	Sundarban coast, Bangladesh	
TC90	17-18 Dec 1990	BOB 09/04B	TS	Cox's Bazar, Bangladesh	
TC91	29-30 April 91	Gorky	H4	Chattogram, Bangladesh	Landsat 7 ETM+
TC92	22-24 Sep 1992	Unnamed	TD	Sundarban coast, Bangladesh	
TC94	2-May	Unnamed	H4	Cox's Bazar, Bangladesh	
TC95	24-25 Nov 1995	Unnamed	H3	Cox's Bazar, Bangladesh	
TC96	28-29 Oct 1996	Unnamed	TS	Sundarban coast, Bangladesh	
TC97	18-19 May 1997	Unnamed	H4	Shitakunda, Bangladesh	
TC98	18-20 May 1998	Unnamed	H1	Shitakunda, Bangladesh	
TC99	08-11 June 1999	Unnamed	TS	Cox's Bazar, Bangladesh	
TC00	27-28 Oct 2000	Unnamed	TS	Sundarban coast, Bangladesh	
TC02	12-Nov	Unnamed	TS	Sundarban coast, Bangladesh	
TC04	15-19 May 2004	Unnamed	H1	Teknaf, Bangladesh	Landsat 7 ETM+
TC05	01-03 Oct 2005	Unnamed	TS	West Bengal, India	
TC06	30 June- 04 July 2006	Unnamed	TS	West Bengal, India	
TC07	15-16 Nov 2007	Sidr	H5	Khulna-Barisal coast, Bangladesh	
TC08	24-27 Oct 2008	Rashmi	TS	Khulna-Barisal coast, Bangladesh	
TC09	22-26 May 2009	Aila	H1	West Bengal, India	
TC10	07-08 Oct 2010	Unnamed	TD	Odisha, India	
TC11	16-19 June 2011	Unnamed	TS	West Bengal, India	
TC12	10-11 Oct 2012	Unnamed	TD	West Bengal, India	
TC14	03-06 Aug 2014	Unnamed	TD	Odisha, India	
TC15	26 July- 02 Aug 2015	Komen	TS	Chattogram-Cox's Bazar coast, Bangladesh	Landsat 8 OLI
TC16	20-21 May 2016	Roanu	TS	Barisal-Chattogram coast, Bangladesh	
TC17	28-30 May 2017	Mora	H1	Chattogram-Cox's Bazar coast, Bangladesh	Landsat 9 OLI
TC18	08-12 Oct 2018	Titli	H3	Andhra Pradesh, India	
TC19	26 April- 04 May 2019	Fani	H5	Odisha, India	
TC20	16-21 May 2020	Amphan	H5	West Bengal, India	
TC21	23-27 May 2021	Yaas	H1	Odisha, India	
TC22	23-24 Oct 2022	Sitrang	TS	Barisal, Bangladesh	
TC23	23-24 Oct 2023	Hamoon	H2	Cox's Bazar, Bangladesh	

* TD, tropical depression ($\leq 61 \text{ km h}^{-1}$), TS, tropical storm ($63\text{-}117 \text{ km h}^{-1}$), H1-H5, hurricanes of category 1 ($119\text{-}153 \text{ km h}^{-1}$), category 2 ($154\text{-}177 \text{ km h}^{-1}$), category 3 ($178\text{-}208 \text{ km h}^{-1}$), category 4 ($209\text{-}251 \text{ km h}^{-1}$), and category 5 ($> 251 \text{ km h}^{-1}$) based on SSHWS.

Table A-3. Threshold value for each TC based on mean (μ) and SD (σ) of ΔEVI and values for response variable (forest disturbance) and explanatory variables (wind speed, track distance, temperature, precipitation, and elevation) included in the structural equation modeling.

TC code	$\mu_{\Delta EVI}$	$\sigma_{\Delta EVI}$	$\pm n\sigma$	Threshold value	Forest disturbance (km ²)	Wind speed (km h ⁻¹)	Track distance (km)	Temperature (°C)	Precipitation (mm)	Elevation (m)
TC88	-0.06	0.04	3 $\pm\sigma$	0.07	19.16	205	32.46	31.85	198.78	9.54
TC89	0.03	0.03	1 $\pm\sigma$	0.06	0.49	100	230.95	31.77	142.77	8.93
TC90	0.02	0.04	2 $\pm\sigma$	0.10	0.17	85	212.05	30.13	183.29	7.26
TC91	-0.05	0.04	3 $\pm\sigma$	0.06	5.74	260	184.90	30.15	185.38	9.33
TC92	0.02	0.03	1 $\pm\sigma$	0.05	1.28	55	46.63	30.61	135.86	9.23
TC94	-0.02	0.05	2 $\pm\sigma$	0.07	6.71	230	306.12	30.41	140.20	8.93
TC95	0.00	0.04	1 $\pm\sigma$	0.03	14.71	195	224.89	31.02	186.57	8.93
TC96	0.04	0.03	1 $\pm\sigma$	0.07	0.21	85	28.40	31.40	156.63	8.93
TC97	-0.04	0.04	3 $\pm\sigma$	0.09	5.39	215	203.22	30.15	176.12	9.63
TC98	0.01	0.03	1 $\pm\sigma$	0.04	1.90	130	185.86	30.59	177.78	8.93
TC99	0.04	0.04	1 $\pm\sigma$	0.08	0.09	65	137.90	31.05	188.03	8.93
TC00	-0.02	0.03	3 $\pm\sigma$	0.07	5.30	83	45.83	30.28	163.58	8.93
TC02	0.01	0.03	3 $\pm\sigma$	0.13	0.45	102	106.69	30.56	203.05	9.35
TC04	0.03	0.03	1 $\pm\sigma$	0.06	0.54	120	309.45	30.68	182.51	9.23
TC05	-0.07	0.03	3 $\pm\sigma$	0.09	6.65	74	143.10	30.66	160.01	8.93
TC06	0.02	0.03	1 $\pm\sigma$	0.05	1.24	65	157.97	31.22	180.21	8.51
TC07	-0.03	0.04	2 $\pm\sigma$	0.06	21.67	260	38.15	30.82	225.10	8.51
TC08	-0.04	0.03	3 $\pm\sigma$	0.07	7.19	85	38.17	30.31	181.49	8.51
TC09	0.01	0.04	1 $\pm\sigma$	0.05	4.57	120	134.05	31.62	156.67	8.51
TC10	0.03	0.03	1 $\pm\sigma$	0.07	0.19	45	31.35	31.21	150.68	8.51
TC11	0.07	0.04	1 $\pm\sigma$	0.11	0.04	65	48.66	30.57	169.75	8.51
TC12	-0.04	0.04	3 $\pm\sigma$	0.11	2.68	55	158.03	30.43	140.27	8.51
TC14	-0.01	0.02	3 $\pm\sigma$	0.06	1.22	55	111.74	30.15	132.24	8.51
TC15	-0.01	0.03	3 $\pm\sigma$	0.06	2.40	85	100.06	30.19	199.42	8.51
TC16	0.03	0.02	1 $\pm\sigma$	0.05	0.67	110	108.10	30.45	164.94	8.51
TC17	0.02	0.02	1 $\pm\sigma$	0.04	0.99	150	258.61	30.31	209.55	8.51
TC18	-0.04	0.03	3 $\pm\sigma$	0.10	0.51	195	204.07	30.19	136.51	8.51
TC19	0.03	0.02	1 $\pm\sigma$	0.05	0.31	280	158.74	30.72	156.85	8.51
TC20	-0.01	0.03	2 $\pm\sigma$	0.05	13.54	270	110.98	30.57	180.23	8.51
TC21	0.02	0.03	1 $\pm\sigma$	0.06	0.54	120	251.76	30.93	176.80	8.51
TC22	-0.02	0.04	2 $\pm\sigma$	0.05	1.55	85	99.86	30.75	144.77	8.51
TC23	0.01	0.03	2 $\pm\sigma$	0.07	1.70	155	203.89	31.17	150.65	8.51

Table A-4. SEM results for each path in the final model. Std = standardized path coefficient estimates, SE = standard error, p = test of significance of path estimate, ~: regression and ~: variance.

Path	Std	SE	Z-value	p
Forest disturbance ~ Wind	0.585	0.133	4.395	< 0.001
Forest disturbance ~ Track	-0.368	0.125	-2.939	0.003
Forest disturbance ~ Precipitation	0.259	0.125	2.074	0.038
Forest disturbance ~ Temperature	0.049	0.120	0.408	0.683
Forest disturbance ~ Elevation	0.074	0.122	0.610	0.542
Forest disturbance ~ Forest disturbance	0.437	0.109	4.000	< 0.001
Wind ~ Wind	0.969			

Wind ~ Track	0.267
Wind ~ Rainfall	0.275
Wind ~ Temperature	-0.103
Wind ~ Elevation	0.204
Track ~ Track	0.969
Track ~ Precipitation	-0.045
Track ~ Temperature	-0.090
Track ~ Elevation	-0.016
Rainfall ~ Precipitation	0.969
Rainfall ~ Temperature	0.014
Rainfall ~ Elevation	0.082
Temperature ~ Temperature	0.969
Temperature ~ Elevation	-0.060
Elevation ~ Elevation	0.969

Table A-5. Plot-level mangrove species inventory for 55 compartments.

Com partm ent	Plot	Latitude	Longitude	Dominant species in number	Second most	Third most
1	66	22.1	89.85863	<i>E. agallocha</i>	<i>Hibiscus tiliaceus</i>	<i>H. fomes</i>
2	67	22.161678	89.775296	<i>H. fomes</i>	<i>E. agallocha</i>	NA
3	60	22.036678	89.775296	<i>H. fomes</i>	<i>E. agallocha</i>	NA
4	54	21.961678	89.775296	<i>H. fomes</i>	<i>E. agallocha</i>	NA
5	55	21.961678	89.85863	BOLA (Shrubs)	<i>H. fomes</i>	<i>E. agallocha</i>
6	49	21.861678	89.80863	<i>H. fomes</i>	<i>E. agallocha</i>	NA
7	12	21.886678	89.691963	<i>E. agallocha</i>	<i>C. decandra</i>	<i>H. fomes</i>
8	10	21.861678	89.60863	<i>H. fomes</i>	<i>E. agallocha</i>	<i>C. decandra</i>
9	16	21.986678	89.591963	<i>H. fomes</i>	<i>E. agallocha</i>	<i>C. decandra</i>
10	18	22.061678	89.65863	<i>H. fomes</i>	<i>E. agallocha</i>	NA
12A	22	22.111678	89.691963	<i>H. fomes</i>	<i>E. agallocha</i>	NA
12B	23	22.111678	89.725296	<i>E. agallocha</i>	<i>H. fomes</i>	<i>C. decandra</i>
13	31	22.211678	89.741963	<i>H. fomes</i>	<i>E. agallocha</i>	<i>Aglaia cucullata</i>
14	28	22.186678	89.675296	<i>H. fomes</i>	<i>E. agallocha</i>	NA
15	24	22.136678	89.625296	<i>H. fomes</i>	NA	NA
16	476	22.136678	89.525296	<i>H. fomes</i>	<i>E. agallocha</i>	NA
17	522	22.061678	89.475296	<i>C. decandra</i>	<i>E. agallocha</i>	<i>H. fomes</i>
18	515	21.961678	89.45863	<i>H. fomes</i>	<i>E. agallocha</i>	<i>C. decandra</i>
	511	21.886678	89.441963	<i>C. decandra</i>	<i>H. fomes</i>	<i>E. agallocha</i>
19	517	22.011678	89.375296	<i>C. decandra</i>	<i>H. fomes</i>	NA
20	526	22.111678	89.40863	<i>C. decandra</i>	<i>E. agallocha</i>	<i>A. officinalis</i>
21	29	22.211678	89.641963	<i>E. agallocha</i>	<i>H. fomes</i>	NA
22	34	22.261678	89.60863	<i>H. fomes</i>	<i>E. agallocha</i>	<i>A. officinalis</i>
23	35	22.261678	89.70863	<i>E. agallocha</i>	<i>H. fomes</i>	NA
24	70	22.261678	89.75863	<i>H. fomes</i>	<i>E. agallocha</i>	NA
25	36	22.286678	89.70863	<i>H. fomes</i>	<i>E. agallocha</i>	NA
	40	22.336678	89.70863	<i>H. fomes</i>	NA	NA
26	38	22.311678	89.675296	<i>H. fomes</i>	<i>E. agallocha</i>	<i>B. sexangula</i>
27	43	22.361678	89.741963	<i>H. fomes</i>	<i>C. ramiflora</i>	<i>Intsia bijuga</i>
28	42	22.361678	89.675296	<i>H. fomes</i>	<i>E. agallocha</i>	<i>A. officinalis</i>

29	482	22.261678	89.70863	<i>H. fomes</i>	<i>E. agallocha</i>	<i>C. ramiflora</i>
30	488	22.336678	89.70863	<i>H. fomes</i>	<i>E. agallocha</i>	NA
31	489	22.411678	89.541963	<i>B. sexangula</i>	NA	NA
32	491	22.436678	89.475296	<i>X. mekongensis</i>	<i>H. fomes</i>	NA
34	483	22.286678	89.50863	<i>H. fomes</i>	<i>E. agallocha</i>	NA
35	542	22.386678	89.40863	<i>H. fomes</i>	<i>E. agallocha</i>	NA
36	540	22.336678	89.35863	<i>A. officinalis</i>	<i>X. mekongensis</i>	<i>B. sexangula</i>
37	535	22.236678	89.375296	<i>H. fomes</i>	<i>E. agallocha</i>	<i>X. mekongensis</i>
38	534	22.211678	89.441963	<i>E. agallocha</i>	<i>A. cucullata</i>	<i>X. granatum</i>
39	479	22.211678	89.50863	<i>H. fomes</i>	<i>X. mekongensis</i>	<i>A. cucullata</i>
40	538	22.261678	89.45863	<i>E. agallocha</i>	<i>H. fomes</i>	NA
41	528	22.136678	89.35863	<i>C. decandra</i>	<i>A. officinalis</i>	<i>H. fomes</i>
42	520	22.061678	89.30863	<i>C. decandra</i>	<i>E. agallocha</i>	NA
42	516	21.986678	89.341963	<i>C. decandra</i>	<i>E. agallocha</i>	<i>X. mekongensis</i>
43	507	21.811678	89.375296	<i>C. decandra</i>	<i>H. fomes</i>	NA
44	506	21.786678	89.441963	<i>C. decandra</i>	<i>E. agallocha</i>	NA
44	502	21.736678	89.40863	<i>C. decandra</i>	<i>E. agallocha</i>	NA
45	475	21.761678	89.541963	<i>S. apetala</i>	NA	NA
46	852	22.261678	89.20863	<i>E. agallocha</i>	<i>X. granatum</i>	NA
46	843	22.111678	89.225296	<i>C. decandra</i>	<i>H. fomes</i>	<i>E. agallocha</i>
47	850	22.211678	89.191963	<i>H. fomes</i>	<i>B. gymnorhiza</i>	<i>A. officinalis</i>
47	845	22.136678	89.175296	<i>C. decandra</i>	<i>E. agallocha</i>	<i>H. fomes</i>
47	847	22.186678	89.141963	<i>C. decandra</i>	<i>E. agallocha</i>	NA
48	838	22.086678	89.075296	<i>E. agallocha</i>	<i>C. decandra</i>	NA
49	831	22.011678	89.10863	<i>C. decandra</i>	<i>E. agallocha</i>	NA
49	818	21.886678	89.141963	<i>C. decandra</i>	<i>E. agallocha</i>	NA
50A	837	22.061678	89.25863	<i>C. decandra</i>	<i>E. agallocha</i>	NA
50B	836	22.061678	89.191963	<i>C. decandra</i>	<i>E. agallocha</i>	NA
51B	824	21.936678	89.175296	<i>C. decandra</i>	<i>E. agallocha</i>	<i>Phoenix sp</i>
52	829	21.986678	89.291963	<i>C. decandra</i>	<i>E. agallocha</i>	NA
52	826	21.936678	89.275296	<i>C. decandra</i>	<i>E. agallocha</i>	<i>H. fomes</i>
52	820	21.886678	89.291963	<i>C. decandra</i>	<i>E. agallocha</i>	NA
53	814	21.861678	89.241963	<i>C. decandra</i>	<i>E. agallocha</i>	NA
53	810	21.811678	89.25863	<i>C. decandra</i>	<i>E. agallocha</i>	NA
54	805	21.761678	89.25863	<i>E. agallocha</i>	<i>C. decandra</i>	NA
54	801	21.661678	89.241963	<i>C. decandra</i>	<i>H. fomes</i>	NA
54	803	21.711678	89.241963	<i>C. decandra</i>	<i>H. fomes</i>	<i>E. agallocha</i>
55	806	21.786678	89.075296	<i>C. decandra</i>	<i>E. agallocha</i>	NA
55	807	21.811678	89.141963	<i>C. decandra</i>	<i>Phoenix sp</i>	<i>E. agallocha</i>