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Advancements in remote sensing and GIS for assessing mangrove vulnerability: A comprehensive review

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Abstract

Mangroves are crucial coastal ecosystems that buffer against natural disasters, support biodiversity and provide essential services to human communities. However, they face increasing threat from human activities and natural pressures. This review explores the application of remote sensing and Geographical Information Systems (GIS) in assessing the vulnerability of mangrove ecosystems. Remote sensing offers a large-scale, observational capacity, while GIS facilitates in-depth spatial analysis, together enhancing the accuracy and efficiency of vulnerability assessments. This review paper details the methodologies employed in these assessments, including the Multi-decadal Land Cover Change Analysis, the Mangrove Vulnerability Index Method and Hot Spot G_i^* Model method. Each method utilizes a combination of satellite imagery, spatial data processing and vulnerability indexing to monitor mangrove health and risks. The integration of these technologies allows for a nuanced understanding of mangrove dynamics and supports effective conservation strategies. The review underscores the advancements in Remote Sensing and GIS technologies that promote community involvement and foster international cooperation to ensure the sustainable management and resilience of mangrove ecosystems worldwide.

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Introduction

The Marine ecosystem includes various habitats, each making distinct contributions to the overall ecological balance. The mangrove ecosystem is particularly notable and crucial as a coastal biome. Mangroves are forests along coastlines in tropical and subtropical regions worldwide, situated between land and sea (Judith, 2022). Mangrove forests are made up of trees and shrubs that are well-suited to thrive in dynamic ecological environments characterized by changing levels of soil salinity, oxygen and the presence of water influx (Friess *et al.*, 2019; Chowdhury and Hafsa, 2022; Huntley, 2023). Mangroves are called the “Rainforests of the seas” due to their biological diversity (Law *et al.*, 2019). Mangrove areas are popular tourist destinations because of their unique geographic positioning (Asy’Ari and Putra, 2021). They are considered as keystone species and are a habitat for indigenous plants, migratory fishes and birds (Ma *et al.*, 2021) These areas provide vital resources like food through aquaculture and agriculture, as well as fuel wood, construction materials and traditional medicinal plants (Akram *et al.*, 2023).

They also offer a wide range of ecological and economic benefits, such as safeguarding against coastal environment from natural disasters, purifying water, creating habitats for fish and shrimp breeding, supplying construction materials and medicinal resources and attracting tourists, among other advantages (Beck *et al.*, 2022). The major livelihood that depends upon mangroves is fishing, which contributes significantly to the economy. According to Achim Steiner, the head of the UN Environment program, it is observed that $57,000 per hectare of economic contribution can be acquired by mangroves annually (Van Lavieren, 2012).

Simultaneously, mangroves stand among the most endangered and fragile ecosystems globally, undergoing a significant decrease over the past fifty years. Global initiatives like the Ramsar Convention on Wetlands or the Kyoto Protocol emphasize the urgency of implementing protective measures and conservation efforts promptly to halt the ongoing decline of mangrove forests (Kuenzer *et al.*, 2011).

Global distribution of mangroves

Mangroves are present in over 120 tropical and subtropical countries and territories, but they are relatively rare, constituting less than 1% of all tropical forests globally. According to a recent assessment, the global mangrove coverage was 14.8 million in 2020 (FAO, 2020; Jia *et al.*, 2023). The largest mangrove regions are in South and Southeast Asia, followed by South America, Western and Central Africa, North and Central America, Western and Central America, and Oceania. Five countries- Indonesia, Brazil, Nigeria, Mexico, and Australia hold 47% of the world’s mangrove areas, and 63% of the total mangrove area is concentrated in just ten countries (FAO, 2023). About 90% of the entire global mangrove areas were hosted by developing countries, establishing a fragile equilibrium between the sustenance of communities and the conservation of mangroves (Van Lavieren, 2012).

Scope of mangrove vulnerability assessment

Major threats to mangrove ecosystem

Mangrove forests, which serve as a habitat for some of the rarest plant species on earth (Buot Jr, 2022), are facing significant destruction due to land utilization for several anthropogenic activities such as agriculture, aquaculture and urban development along coastlines (Bhowmik *et al.*, 2022). Despite forming a rare and unique ecosystem, mangroves face a severe threat, being destroyed at a rate five times faster than tropical forests (Yeo, 2016). The North and Central American mangroves are at great risk due to the development, hurricanes and aquaculture introducing challenges. In Southeast Asia, aquaculture, particularly the cultivation of shrimps, mud crabs and oysters, significantly contributes to people's livelihoods. Even though, it is represented as a significant threat to mangroves (Van Lavieren, 2012).

In the past half- century, there has been a loss of about 35% of mangrove areas worldwide (Gouvêa *et* *al*., 2022), with Asia contributing to over a third of this reduction (Arifanti *et al*., 2021). Indonesia has experienced the greatest reduction in mangrove areas, with Myanmar and Australia also seeing significant losses (Akram *et al*., 2023). The global rate of mangrove decline over the past ten years has been about 0.4% annually (Friess *et al*., 2020), a rate that exceeds the loss rates of both tropical rainforests and coral reefs, which are among the most endangered ecosystems (Yousefi and Naderloo, 2022). The Global Mangrove Watch reports that between 1996 and 2020, the world lost 5,245.24 square kilometres of mangrove forests (Ramli, 2022; Bunting *et al*., 2022). Among the 64 species of mangrove plants globally, the International Union for Conservation of Nature (IUCN) Red List has identified 12 species as being at risk or endangered (Rahim, 2023).

Besides this several natural calamities such as storms and cyclones, Tsunamis, sea level rise and temperature also affect the effective functioning of the mangrove ecosystem. In recent decades, the mangrove forests along India's intertidal coastal regions have suffered extensive harm due to a series of environmental challenges, including cyclones making landfall, earthquakes triggering tsunamis, increased salinity and the ongoing rise in sea levels (Paul *et al*., 2018).

Role of remote Sensing and geographic information systems techniques in mangrove conservation

Remote sensing involves observing and analyzing objects from a distant area without making physical contact, typically through the use of satellites (Lillesand, 2015). This process involves analyzing the physical attributes of a region by detecting the radiation that is reflected and emitted, usually via satellites. Different methods exist to quantify the amount of energy that is reflected or absorbed, alongside capturing images that offer the right balance of spatial and spectral detail. Additionally, various techniques are available for extracting spectral information, which can vary based on the type of data and its intended use (Maurya *et al*., 2021). Spectral information is essential in remote sensing as it provides valuable insights into the earth's surface attributes, such as water quality, vegetation health, and land use and cover. These attributes are crucial for a wide range of environmental monitoring and management applications. Objects on the Earth's surface absorb or reflect different wavelengths of light, and these variations in emitted wavelength allow for the detection and analysis of surface attributes.

The extensive and often inaccessible mangrove forests can be evaluated using RS techniques, avoiding the need for direct field surveys. By utilizing satellite imagery combined with Geographic Information Systems (GIS), it is possible to efficiently keep track of changes within the mangrove ecosystem. Additionally, applying diverse classification techniques to the remotely sensed data gathered by various sensors enables the detailed analysis of numerous aspects of the mangrove ecosystem. These aspects include measuring the height of trees, the density of the canopy, the biomass above ground, the variety and types of species, the overall health of the mangroves, as well as the Leaf Area Index (LAI) and the chlorophyll content in the leaves (Maurya *et al*., 2021).

This review comprehensively explores the integration of RS and GIS techniques to assess mangrove vulnerability. By analyzing existing methodologies, case studies and future prospects, the review aims to offer valuable insights into effective methods for mapping and monitoring mangrove ecosystems. It specifically evaluates various classification approaches, satellite imagery and sensor utilization in mangrove research. Furthermore, the review identifies an appropriate vulnerability assessment approach, emphasizing gaps in current research and guiding future efforts toward comprehensive mangrove conservation strategies.

Remote sensing data

In the context of assessing the vulnerability of mangroves, the use of Remote Sensing (RS) methods significantly contributes by offering valuable insights into the behaviour and changes within these ecosystems (Vasquez *et al.*, 2024). Over the years, researchers have devised various methods to study mangrove ecosystems by leveraging remote data collection. These approaches have evolved from traditional to more advanced techniques. In the earlier, conventional method, two primary techniques were commonly employed (Heenkenda *et al.*, 2014).

1. Aerial photography (AF): This method involves taking photographs from aircraft flying at relatively low altitudes above the Earth's surface. AF captures high-resolution images, particularly effective for studying small areas. It provides detailed information essential for accurate classification procedures.
2. Visual interpretation (VI): This technique enables researchers and professionals to analyze and comprehend mangrove ecosystems by carefully observing and analyzing captured aerial images. VI relies on human expertise to identify features and classify elements within the images.

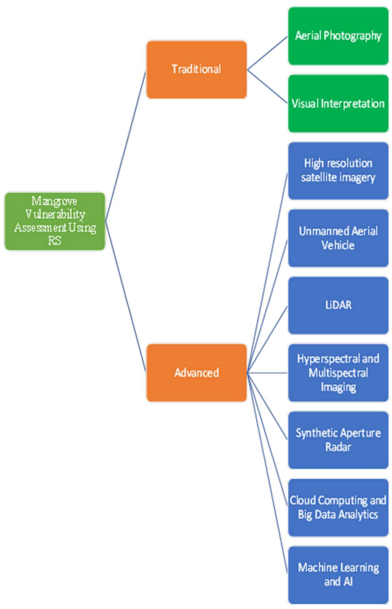

Fig. 1. Traditional and advanced techniques employed in remote sensing

Recent advancements in remote sensing play a vital role in characterizing mangroves. By utilizing satellite imagery including Landsat ETM+, Landsat- OLI, Landsat OLI-2, Sentinel-2, Unmanned Aerial Vehicles, LiDAR Technology, Hyperspectral and Multi spectral Imaging employing, Synthetic Aperture Radar (SAR), Cloud computing and Big Data Analytics and image processing using machine learning and AI algorithms, AI algorithms, a more precise understanding of mangrove ecosystems. These modern techniques enhance traditional methods like aerial photography and visual interpretation, allowing for a comprehensive analysis of mangroves and their evolution over time (Vasquez *et al.*, 2024). The widely used traditional and advanced techniques have been depicted in Fig. 1.

Types of satellite imageries

Landsat, operating since 1972, plays a vital role by providing high-quality imagery without charge. Its continuous availability and global accessibility make it indispensable for researchers, planners and decision-makers. The extensive Landsat data archive offers unique insights into Earth's changes over time, supporting research and natural resource management. Notably, Landsat's spectral and spatial resolution further enhances its versatility for various Earth observation applications (Pasquarella *et al.*, 2018).

Landsat images are becoming increasingly valuable tools for mapping these ecosystems (Islam *et al.*, 2021). These data are often utilized for classifying land use characteristics within a designated area. This is due to their accessibility for free download and their optimal spatiotemporal resolution, which provides a range of options for conducting such studies (Purwanto *et al.*, 2021). Various techniques are used to detect or extract mangrove forests from Landsat imagery. These methods include vegetation indices, supervised and unsupervised classification, neutral network classification, spectral indices and object-based approaches (Roy *et al.*, 2019). Numerous studies conducted across different latitudes globally employ diverse techniques (Findi, 2022), which indicates the appropriateness of utilizing satellite imagery and their spectral indices. However, there is a limited number of review articles specifically dedicated to assessing mangrove cover using Landsat satellite imagery (Budi *et al.*, 2022).

Landsat-9, which was successfully launched on October 27, 2021, is the latest addition to the Landsat satellite series. Along with Landsat-8, it represents the first Sustainable Land Imaging (SLI) mission of the Landsat programme, initiated in 2015 in collaboration with NASA and the USGS (Masek *et al.*, 2020). Landsat-9 is equipped with two sensors: the Operational Land Imager (OLI-2) and the Thermal Infrared Sensor (TIRS-2). The sensors on Landsat- 9 are designed for a mission lifespan of five years, even though the spacecraft itself can function for more than ten years. While Landsat-9 is largely similar to Landsat-8, it has several enhancements over its predecessor. These improvements include stray light correction, a higher observation capacity of approximately 1,400 scenes per day, increased radiometric resolution, and a shorter revisit time of 8 days. Recent researches is carried out by utilizing these satellite imageries (Saralioglu and Vatandaslar, 2022)

The SPOT satellite, operational since 1986, has significantly contributed to Earth observation. With its excellent spatial and spectral resolution, it serves diverse applications (Almeida, 2015). Unlike Landsat, SPOT imagery is not accessible for free on public platforms, which may pose challenges for users requiring widespread access to satellite data. The ASTER satellite, launched in 1999, has become a valuable asset for Earth observation. Its availability at no cost since 2016 has expanded its utility for researchers and professionals across various domains (Abrams and Yamaguchi, 2019).

The Moderate Resolution Imaging Spectroradiometer (MODIS) instruments, launched on NASA's Terra and Aqua satellites in 1999 and 2002, have been essential for Earth Observation. MODIS delivers detailed data with a high frequency, capturing images of the entire Earth every 1 to 2 days. This regular coverage is crucial for observing dynamic processes like vegetation changes, land cover variations, and atmospheric conditions. Unlike SPOT, MODIS data is freely available, making it a favoured option for researchers and professionals. MODIS satellite images were used by several researchers (Younes *et al.*, 2020; Samanta *et al.*, 2021).

Table 1. Application of GIS-based software used in mangrove vulnerability assessment

Software	Description	Usage in studies
Arc GIS	Developed by ESRI, Arc GIS offers tools and services for mapping and spatial analysis	Widely used by researchers (Hussain and Islam, 2020; Sagala *et al.*, 2024; Mondal *et al.*, 2024)
Q GIS	Quantum GIS is a open- source software for spatial analyses, data visualization and mapping.	Used in Some studies (Charrua *et al.*, 2020)
TerrSet (Idrisi)	TerrSet is a combined GIS and remote sensing software created by Clark Labs at Clark University. It is intended for analyzing and visualizing digital geospatial data.	Used for land use and landcover change detection by several researchers (Shrestha *et al.*, 2019; Abijith and Saravanan, 2022)
Google Earth Engine	Google Earth Engine is a cloud- based platform for geospatial analysis that allows users to visualize and analyze satellite imagery of the Earth.	Utilized by several researchers for mangrove forest cover analysis (Bajaj *et al.*, 2024; Kotikot *et al.*, 2024).

Sentinel, which was launched in 2014, is another important contributor to Earth observation (Eoportal Directory, (Hu *et al.*, 2020), providing similar sensor capabilities. It's worth noting that data from Sentinel is only accessible starting from that year. Similar to ASTER, this highlights the importance of carefully ensuring data consistency when utilizing Sentinel images within study periods. Apart from the satellite missions noted, there are additional alternatives accessible; Nevertheless, the majority of these choices necessitate payment for data access, although their costs have decreased over time (Zhao *et al.*, 2022). The decision among these various sources of satellite imagery should be determined by specific project needs, data accessibility, financial resources and time constraints.

Table 2. Functions of various tools used in GIS software in mangrove vulnerability assessment

Tool category	Tool name	Function
Geoprocessing Tools	Buffer	Generates polygonal shapes around features at a set distance.
	Clip	Selects features that intersect with or are within the boundaries of the clipping features.
Spatial Analyst Tools	Extraction by Mask	Retrieves cells from a raster that match regions specified by a mask.
	Reclassify	Modifies or updates values within a raster dataset.
	Raster Calculator	Constructs and runs Map Algebra expressions using a calculator-like interface.
Image Classification Tools	Maximum Likelihood Classification	Places pixels into categories based on how likely they are to belong to each category based on the interpretation keys.
Machine Learning Algorithms	Iso Cluster unsupervised Classification	Automatically groups pixels together based on their colour or other properties without needing any intial training information.
	Neural Networks	Integrates spectral data with other types of information to improve classification accuracy and predictive analysis
	Random Forest	Uses an ensemble of decision trees to analyze complex data, enhancing classification and prediction, particularly in evaluating mangrove ecosystems.
Time series Analysis tool	Time series Clustering	Groups time series data based on similar patterns over time, aiding in the analysis of temporal changes in mangrove environments.
Vegetation Indices	NDVI (Normalized Difference Vegetation Index)	Measures vegetation health by comparing the difference between near-infrared and red light, useful for monitoring the health and density of mangrove areas.
	EVI (Enhanced Vegetation Index)	Similar to NDVI, but more effective in densely vegetated areas, providing more accurate monitoring of regions like mangroves.

Application of GIS software and tools

Software used

The researchers primarily utilized two types of software, as indicated in the Table 1.

From the Table 1, it is found that both Arc GIS, QGIS, TerrSet, Google Earth Engine is widely used in assessing mangrove vulnerability, and researchers choose between them based on their specific needs and preferences.

Tools used

Various kinds of Tools used in GIS Software are listed in Table 2.

Integration of remote sensing and GIS

RS Technology offers significant advantages particularly in monitoring forests, especially when estimating mangrove vulnerability (Islam, 2014; Kamal *et al.*, 2015; Hussain and Islam, 2020). GIS are also utilized for forest monitoring, predicting wildfire occurrences and detecting changes in forested areas (Harris *et al.*, 2017; Qayum *et al.*, 2020; Talukdar *et al.*, 2024). Several studies were conducted using RS data to assess forest loss and socioeconomic conditions (Mia *et al.*, 2016; Lucas *et al.*, 2020; Farzanmanesh *et al.*, 2024). The Forest Discrimination Index (FDI) based on remote sensing is important for monitoring forests by classifying vegetation density levels (Modica *et al.*, 2015; Shah *et al.*, 2022; Halder and Pereira, 2024).

Examples for successful integration

The integration of RS and GIS for mangrove vulnerability has been found successful by several researchers (Li *et al.*, 2015; Hussain and Islam, 2020; Mondal *et al.*, 2024). In a study conducted by (Hussain and Islam, 2020), mangrove vulnerability assessment is carried out based on geo-statistical hotspots (G_i^*) model. Another study was conducted based on mangrove vulnerability concerning the sea level rise (Mondal *et al.*, 2024). Additionally, researchers have successfully integrated remote sensing data with GIS models to evaluate mangrove health, carbon stock assessment and forest management (Bindu *et al.*, 2020; Numbere, 2022; Saoum and Sarkar, 2024).

Benefits and challenges

The combination of RS and GIS offers a robust method for assessing mangrove vulnerability. It provides a holistic view of mangrove health, dynamics and threats. By merging RS's ability to deliver large-scale, frequent observations with GIS's spatial analysis and modelling capabilities, we can precisely monitor and manage mangroves. For example, evaluating vulnerability to sea level rise or estimating carbon stocks becomes more accurate and efficient. However, challenges exist, such as technical complexities in integrating data from diverse sources and the high costs associated with advanced remote sensing. Despite these obstacles, the benefits of RS and GIS integration are crucial for effective environmental conservation efforts.

Case studies

The integration of RS and GIS technologies has significantly advanced our understanding and management of mangrove vulnerabilities, as evidenced by several noteworthy case studies spanning different regions. These real-world examples highlight the effective use of spatial analysis and remote observations in monitoring mangrove ecosystems and informing conservation efforts. From assessing mangrove health using satellite imagery to employing GIS for spatial planning and vulnerability mapping, these studies offer valuable insights into methodologies, outcomes, and lessons learned in global mangrove conservation. A comprehensive summary table consolidating key information from various case studies, including the region, references, study area, main findings, methodology employed and key challenges and insights is given in Table 3.

Table 3. Case studies in mangrove vulnerability assessment

Region	References	Study area	Main findings	Critical evaluation of methodology	Key challenges and insights
Africa	(Sunkur *et al.*, 2024)	Mauritius (Le Morne, Ferney)	Significant growth in mangrove cover, aiding climate adaptation strategies	The use of Sentinel-2A and SPOT-5 imagery offers high resolution data, but the reliance on just two time may overlook seasonal variations and short term changes.	Effective in monitoring ecosystem changes and enhancing coastal resilience.
	(Negm, 2024)	Hamatta and Safaga, Egypt	Low vulnerability due to factors like mangrove height and canopy density	Mangrove vulnerability Index (MVI) with field measurements and Elision ranking provides localized insights but may lack generalizability across diverse regions.	Highlights the importance of local environmental conditions in assessing resilience.
Asia	(Sagala *et al.*, 2024)	Northern Coast of Java, Indonesia	significant impacts from sea level rise to mangroves is observed.	Coastal and Mangrove vulnerability method uses physical factors effectively but might underestimate socioeconomic and human-induced factors.	Stresses the need for focused conservation efforts in densely populated and at-risk regions
	(Halder and Pereira, 2024)	Sunderbans, Bangladesh	Loss of 11.57 km² of mangroves due to cyclones and sea level rise.	Remote sensing and GIS combined with vegetation indices, effectively highlight degradation but may not fully capture the complexity of ecosystem responses to multi-hazard scenarios.	Points to severe impacts in species areas, emphasizing targeted management.
	(Mafi-Gholami *et al.*, 2021)	Mangrove forests of Iran (Nayband, Khamir, Tiab, Jask, Gwadar)	Varied vulnerability levels; need for targeted conservation strategies	Fuzzy-based approach with hierarchical analysis for vulnerability indexing, but the validation with ground truth data is limited in spatial coverage.	Validates the approach with ground truth measurements, effective in habitat-scale vulnerability identification.
	(Zhang *et al.*, 2023)	Coastal regions of china	Significant reduction in vegetation due to Sea level Rise; need for integrated conservation	Sea Level Affecting Model (SLAMM) across socioeconomic scenarios demonstrates the complex interaction of factors, but it	Demonstrates the interaction of tidal variations and sedimentation rates on mangrove

				might oversimplify the ecological responses to sea level rise.	distribution.
	(Chowdhury and Hafsa, 2022)	Sunderbans, Bangladesh	Significant landcover changes due to shrimp cultivation is observed	LULC mapping with change detection analysis provide clear evidence of changes but may overlook finer ecological impacts beyond the land cover transitions.	Urges effective management strategies to safeguard vulnerable ecosystems and guide decision-making.
	(Mondal *et al.*, 2024)	Andaman and Nicobar Islands, India	Effects of 2004 Earthquake analyzed, climate impacts on coastalines studied.	CVI and MVI using high resolution satellite images provide detailed insights, but the study might benefit from integrating temporal analyses of post-earthquake recovery.	Emphasizes updated management practices needed for earthquake-prone areas.
	(Sardar and Samadder, 2023)	Sunderbans, India	Climate change impacts showing high vulnerability in western sunderbans	Fuzzy-based AHP approach effectively identifies vulnerable areas, but the model's complexity may limit its replicability in other regions.	Aids in identifying areas requiring improved climate adaptation strategies
	(Majumdar, 2021)	Sunderbans, India	Identified areas of high and low vulnerability based on climate change impacts	Bio-physical vulnerability assessment utilizing IPCC AR IV framework is robust, but the study may underestimate socioeconomic factors affecting resilience.	Highlights areas with favourable conditions for mangrove resilience and effective management.
Marshall Islands	(Crameri and Ellison, 2022)	Jaluit Atoll	Expansion of mangrove areas noted; future risks from sea level rise identified.	Historical data analysis provides valuable long-term trends, yet the study might benefit from more detailed future projections using current climate models.	Although mangroves are showing growth, persistent challenges from future SLR and sediment availability remain concerns.

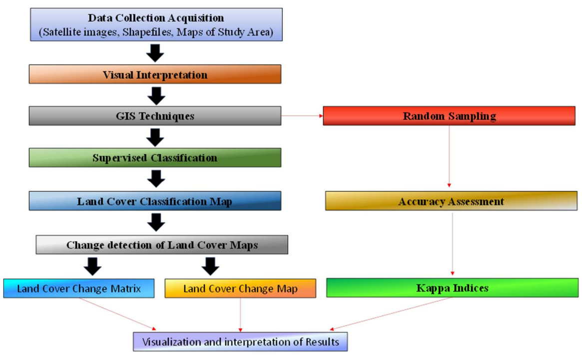

Fig. 2. Steps involved in assessing mangrove vulnerability via multi-decadal land cover change analysis

Key methodologies used

Based on the literatures, three widely used methodologies are outlined as follows:

1) Multi-decadal land cover change analysis method
2) Mangrove Vulnerability Index Method
3) Hot G_i^* model method

Multi-decadal land covers change analysis

(Chowdhury and Hafsa, 2022) conducted a multi-decadal landcover change analysis over the mangrove forest of Bangladesh. The overall methodology has been illustrated in Fig. 2.

Data and data source

The data for the study area was collected from multispectral and multi-temporal Landsat satellite data spanning four years: 1980,1990,2000,2010 and 2020. These data were sourced from the USGS server, where historical and contemporary satellite data are freely available. Specifically, the satellite image from 1980 was obtained from Landsat 1-5 Multispectral Scanner (MSS) Level-1, with a spatial resolution of 60m. The 1990, 2000 and 2010, 2020 satellite images were from Landsat 4-7 Thematic Mapper™. To ensure clarity and accuracy in the landcover mapping process, only cloud-free images were selected for the study area. Typically, cloud-free images were selected over the study area during the winter season in Bangladesh, particularly from December to February, ensuring optimal conditions for data collection.

Data preparation and processing

Lansat images underwent processing, analysis and visualization using ArcMap 10 software. Additionally, Microsoft Excel is employed for specific calculations. To comprehensively cover the designated study area, four satellite images of Landsat images were used. These images were combined into a single composite using the mosaicking process within ArcMap 10. Subsequently, the study area's shapefile was used to extract the specific region of interest for detailed examination. Geometric correction and referencing were applied to each image in ArcMap to ensure spatial accuracy. Finally, the imagery was classified into distinct classes using a predefined scheme, with the Maximum Likelihood Classification method employed for systematic categorization of the Landsat data (Islam *et al.*, 2019; Thakur *et al.*, 2021; Kumar *et al.*, 2021).

As per the specified criteria, training samples were meticulously chosen for vegetation. This selection process involved analyzing both true-colour and various false-color combinations to identify the most representative samples. These samples were then utilized for applying the Maximum Likelihood Classification technique to categorize the Landsat images.

Following classification, a change detection analysis was conducted to identify alterations across images from different years. The extent of land cover for each category in every year, along with the changes occurring over each period, was calculated using the "Calculate Geometry" feature in ArcMap 10.5 software was utilized to determine the geometric properties of the features. Furthermore, a change detection matrix was created in Microsoft Excel using the GIS-processed image data.

To assess the accuracy of the image classification, validation points were generated using a random sampling tool in ArcGIS software- a method validated by (Congalton, 1988). The actual landcover categories were determined through visual analysis of the Landsat images, considering both true and false colour imagery. This cross-validation process ensured the reliability of the classified imagery.

Accuracy assessment

Accuracy assessment is vital for evaluating the dependability of remote sensing image classification. Kappa-based indices, alongside overall accuracy, are widely used measures to evaluate the accuracy and reliability of classification algorithms. These metrics are derived from a confusion matrix, which displays the accuracy of land cover mapping. In the study conducted by (Chowdhury and Hafsa, 2022), the Kappa-based indices utilized include Producer Accuracy, User Accuracy, Overall Accuracy and Kappa Coefficient. Producer Accuracy gauges the true positive values of a class, while User Accuracy computes the false negative values of that class. Overall Accuracy evaluates the true positive values of the entire thematic map. These indices, including the Kappa Coefficient, are computed using specific formulas used by certain researchers (Petropoulos *et al.*, 2015; Verma *et al.*, 2020; Das *et al.*, 2021):

$$K = \frac{N \sum_{i=1}^{n} O_{ii} - \sum_{i=1}^{n} (RP_i * CP_i)}{N^2 - \sum_{i=1}^{n} R_i C_i} \quad (1)$$

Where,

K= Kappa- Coefficient.

N= Total number of pixels observed.

O_{ii}= Number of pixels observed in row I and column i

N= Total number of rows/columns (Classes) in the confusion matrix

RP_i= Total Number of pixels in row i

Cp_i= Total number of pixels in column i

The locations for the assessment are randomly sampled and Accuracy is calculated with the help of Arc GIS software.

Overall accuracy is obtained using specific formula as follows:

$$OA=\frac{\sum CP_{ii}}{N} \quad (2)$$

Where,

OA= Overall accuracy

$\sum CP_{ii}$=total observed pixels classified correctly.

N= Total number of pixels observed.

Producer's accuracy is obtained using following formula:

$$PA=\frac{\sum RP_{ii}}{R_i} \quad (3)$$

Where,

PA = Producer's accuracy.

RP_{ii}= accurately classified observation in specific row i.

R_i= total observation in the same row i.

User's accuracy is determined with the help of following formula:

$$UA=\frac{\sum CP_{ii}}{C_j} \quad (4)$$

Where,

UA= User's accuracy

CP_{jj}= accurately classified observation in a specific column j.

C_j = total observation in the same column j.

Mangrove vulnerability index

Database and analysis

Mondal *et al.*, 2024 examined coastal vulnerability in the northern coast of Java, Indonesia, considering eight critical factors. These factors included geomorphology, sea level rise, shoreline change rate, coastal slope, regional elevation, bathymetry, mean tidal range and various mangrove area coverage. To compile comprehensive data, various sources were utilized: geomorphology data from Bhuvan thematic map service, shoreline change data from Landsat via US Geological Survey, sea level trends from the Permanent Service for Mean Sea Level and regional elevation and coastal slope data from Shuttle Radar Topography Mission via USGS. Additionally, bathymetry data were processed using ArcGIS, while mean tidal range data came from the Survey of India and (Sangmanee, 2021). Surface elevation change data for upliftment and subsidence analysis were derived from (Acharyya, 2006). These datasets formed the foundation for assessing coastal and mangrove vulnerability in the study area. The overall methodology is depicted in Fig. 3.

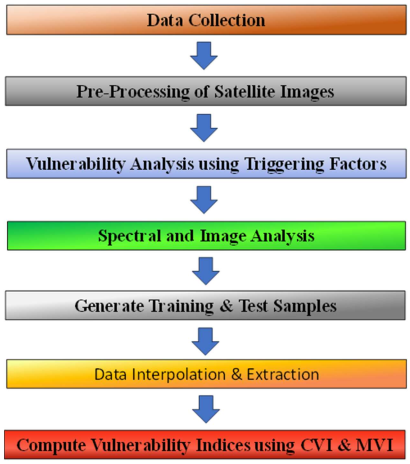

Fig. 3. Steps involved in assessing mangrove vulnerability via MV

Pre-processing of satellite images

The research carried out by (Mondal *et al.*, 2024) on delineating mangrove forests utilized imagery from three satellites: GEO-1, Worldview-2 and WorldView-3, each with an 11-bit radiometric resolution. The digital number (DN) values from these images were converted into Top of Atmosphere (TOA) reflectance using a standard formula, as detailed by (Chavez, 1988) and (Mahiny and Turner, 2007). This preprocessing approach was also applied to Landsat-5 and 7 images. For Landsat-8 OLI data, DN values were transformed to at-sensor reflectance following the guidelines in the Landsat-8 user handbook (2019). Additionally, Landsat imagery was employed to assess shoreline changes across six designated study zones.

Vulnerability analysis

The vulnerability analysis was carried out by (Mondal *et al.*, 2024) is in 10 m×10 m grids, considering the spatial resolution of 2m. The research considered following factors:

Geomorphology

The geomorphological map was digitized to delineate zones based on vulnerability, with structural origins such as dissected hills and valleys deemed less vulnerable (rank 1), and coastal origins and offshore islands as more vulnerable (rank 5) (Ashraful Islam *et al*., 2016; Mondal *et al*., 2022).

Shoreline change

Utilizing cloud-free Landsat data from 2004 to 2022, shoreline changes were analyzed using the NDVI- Tasselled-Cap Transformation technique. The Digital Shoreline Analysis System (DSAS) in ArcGIS was used to calculate the Linear Regression Rate (LRR) of shoreline movement, categorizing erosion rates into five vulnerability ranks (Kumar *et al*., 2010; Mondal *et al*., 2022).

Sea-level rise

The trend of sea level rise was analyzed using data from 15 Bay of Bengal stations, interpolating for the Andaman region due to a lack of local data. Higher sea level rise was linked to higher vulnerability (Sarwar, 2013; Ashraful Islam *et al*., 2016).

Regional elevation

Using SRTM data, areas with low elevation were classified as highly vulnerable due to their susceptibility to sea-level rise.

Slope

Coastal areas with gentle slopes were considered more vulnerable to coastal risks. Slope data was classified into five vulnerability ranks based on the natural breaks method (Hoque *et al*., 2018).

Bathymetry

Depth data from GEBCO indicated that shallower waters and gentle shores allow for more widespread damage (Ashraful Islam *et al*., 2016).

Mean tidal range

Data from the Survey of India and (Sangmanee, 2021) has been used in this case and it suggested that areas with a low tidal range are highly vulnerable due to constant water flow during the study period (Dwarakish, 2008; Gorokhovich, 2013).

Mangrove area coverage

The area of mangroves was assessed using imagery from GEO-1, Worldview-2 and World view-3 satellites, with higher mangrove coverage areas ranked as more exposed to vulnerability factors such as erosion and wave action. Supervised image classification and spectral indices extraction were used for mangrove analysis.

The study utilized ARC 10.2.2 for data analysis, employing various methodologies for each parameter to assess the vulnerability of different zones in the Andaman region to coastal and mangrove degradation.

Determining spectral indices

In the Andaman region, studying mangrove habitats is challenging due to difficult access and harsh conditions. Mangroves typically grow at elevations below 30 m. To identify mangrove areas, this study did not rely solely on spectral properties but also explored the use of multiple indices combined with high-resolution satellite imagery from WorldView-2, WorldView-3 and Geo-1. Five spectral indices were utilized: three vegetation indices (NDVI, SAVI and RVI), one specifically designed for mangrove recognition (CMRI) and two additional indices (NDSSI and NDWI) derived from the satellite four spectral bands. The inclusion of the CMRI was particularly noted for its effectiveness in distinguishing mangroves from non-mangrove vegetation and other land types, showing satisfactory results in previous research (Gupta *et al*., 2018; Mondal *et al*., 2022).

Classification technique

The study identified seven major land use and landcover classes in the study area using Google Earth Engine images and field surveys. These classes include water, terrestrial vegetation, settlements, sand, mangroves, fallow land and agriculture. Differentiating between mangroves and other mixed forests was crucial due to minor spectral differences. The study utilized a standard visual image interpretation method to characterize these classes.

For classifying these areas, the maximum likelihood classification technique was applied, ensuring accurate identification of various land types using the same training samples across all layers. This methodology aligns with established practices in remote sensing and land use classification (Saha *et al.*, 2005; Mondal *et al.*, 2019, 2022).

Training /test sample generation and accuracy assessment

In assessing the accuracy of digital image classification for the study area, Mondal *et al.*, 2024 prepared test samples using data from Google Earth and field surveys to evaluate the effectiveness of the classification process. The study involved a collaborative field survey by the Centre for International Forestry Research (CIFOR), Indonesia and The Wildlife Institute of India (WII), along with the use of high spatial resolution imagery from Google Earth for areas that were difficult to access. A total of 9541 training pixels were selected randomly across seven identified classes, based on the visual interpretation of satellite images. For accuracy assessment, an equal number of 200 pixels per class were used, ensuring a fair evaluation. The most accurate result were obtained with layer combination 9, which showed an overall accuracy of 91.44%, significantly higher than other combinations that relied solely on spectral bands and indices. This high level of accuracy underscores the effectiveness of the methodology employed in distinguishing between different land use and land cover classes in the study area.

Index computation

Using a semi-quantitative approach based on eight criteria, we computed both the Coastal Vulnerability Index (CVI) and the Mangrove Vulnerability Index (MVI) (Ashraful Islam *et al.*, 2016; Mahmood *et al.*, 2020; Mondal *et al.*, 2022). To calculate the CVI and MVI, the entire 2022 shoreline in each zone was divided into 10 m × 10 m grids, as outlined methodology section. Each grid's vulnerability level was then ranked on a scale from 1 to 5, where 1 represents very low vulnerability and 5 represents very high vulnerability.

After assessing the vulnerability ranking of each grid, CVI and MVI were calculated using equations, following the method proposed by (Gornitz, 1991).

$$CVI=\sqrt{(a \times b \times c \times d \times e \times f \times g)/7} \quad (5)$$

$$MVI=\sqrt{(a \times b \times c \times d \times e \times f \times g \times h)/8} \quad (6)$$

Where,

a= geomorphology, b= rate of shoreline change, c= sea level rise, d= regional elevation, e= coastal slope, f= bathymetry, g= mean tidal range, h= mangrove area coverage.

Using the natural breaks classification method in ArcGIS software, the Coastal Vulnerability method in ArcGIS software, the coastal Vulnerability Index (CVI) and Mangrove Vulnerability Index (MVI) scores were categorized into five vulnerability categories: very low, low, moderate, high and very high vulnerability. Additionally, 30 location data points were collected from the Andaman and Nicobar Islands to analyze subsidence and upliftment (Acharyya, 2006). Subsequently, data for other regions were generated using interpolation techniques in Arc GIS software, utilizing location data (X and Y coordinates) and upliftment/ subsidence (Z) data. The interpolation image was then used to extract data at the grid level for all zones 1 to 6, employing the zonal statistics tool. This grid data was converted into point data and exported to .dbf format. Finally, the average value of upliftment/ subsidence data for all zones was calculated using Microsoft Excel spreadsheet.

Hot spot G_i^* model

(Hussain and Islam, 2020) have conducted Hot spot G_i^* model for mangrove forest vulnerability assessment: a remote sensing- based geo-statistical investigation of the Sundarbans mangrove forest, Bangladesh. The entire methodology is outlined in the Fig. 4.

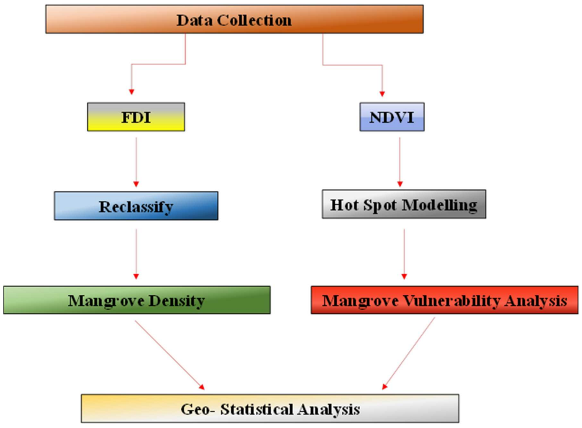

Fig. 4. Steps involved in Assessing Mangrove Vulnerability via Hot spot G_i^* model

Data

In this study, researchers utilized Landsat-5 and Landsat-8 satellite data to analyze mangrove forests from a geo-statistical and geospatial perspective. They employed ArcGIS 10.7 software to conduct various analyses, including the Forest Density Index (FDI), Normalized Difference Vegetation Index (NDVI) and G_i^* analysis. The study covered Landsat-5 data for the years 2001 to 2011 and Landsat-8 data for 2013 and 2015, aligning data collection with the seasonal patterns of the mangrove forests. By assessing both short-term and long-term changes, the researchers applied FDI to distinguish forested from non-forested areas. They further classified the results to examine forest cover and density. NDVI was used to assess the forest's status and the NDVI data were integrated into G_i^* analysis to identify vulnerable forest areas.

Mangrove density

The Forest Density Index (FDI) was used to map the density of mangrove land cover. This was done by analyzing Landsat-5 and Landsat-8 satellite data based on their spectral characteristics. The FDI helped distinguish between vegetated and non-vegetated areas, as well as different forest density classes. Waterbodies were identified using negative FDI values. The mangrove forest was divided into two density categories: high density and low density. High density areas had values more than one standard deviation above the mean FDI output, while low-density areas had values below this threshold. The process involved adjusting the FDI using following equation to achieve these classifications.

FDI= NIR- (Red+ Green) (7)

Where, NIR represents the near-infrared band of Landsat-5 (0.76-0.90 µm), Red denotes the visible red band of Landsat-5 (0.63-0.69 µm) and Landsat-8 (0.630-0.680 µm) and Green represents the visible green bands of Landsat-5 (0.52-0.60 µm) and Landsat-8 (0.525-0.600 µm).

Health status of mangroves

The Normalized Difference Vegetation Index is a commonly used metric for assessing the health and vigor of vegetation. In this case, NDVI was utilized to evaluate the well-being of mangroves. The calculation involves analyzing data from Landsat-5 and Landsat-8 satellites. NDVI relies on the spectral properties of vegetation, with the visible red band absorbing light and the near-infrared band reflecting more light from green vegetation. The NDVI value is obtained using the following formula:

$$NDVI = \frac{NIR-Red}{NIR+Red} \quad (8)$$

Where,

NDVI represents the normalized difference vegetation index. NIR refers to near-infrared band four (0.76-0.90 µm) of Landsat-5 and band five (0.845-0.885 µm) of Landsat-8. Red represents visible red band three (0.63-0.69 µm) of Landsat-5 and band four (0.630-0.680 µm) of Landsat-8.

Hot spot G_i^* model and mangrove vulnerability assessment

In this case, the hotspot (G_i^*) model was employed to assess spatial autocorrection. By analysing neighbouring data, the model identified areas with either high or low values of clustered objects. The primary focus was on mangrove forests and the concentration of the Normalized Difference Vegetation Index (NDVI) served as the input parameter. Geospatial distribution of NDVI was visualized, leading to the delineation of seven distinct zones within forested areas. These zones were categorized based on specified percentage confidence levels (Gi Bins). For instance, the 99% cold confidence level represented the extreme vulnerable zone, while the 95% cold confidence level indicated the very vulnerable zone. Conversely, the 99% hot confidence level denoted the extreme safe zone and the 95% hot confidence level corresponded to the very safe zone. Clusters without statistical significance were classified as stable zones. Overall, this approach provided valuable insights into mangrove vulnerability using following geostatistical equations:

$$(G_i^*)=\frac{\sum_{j=1}^{n} W_{ij}x_j - \bar{X}\sum_{j=1}^{n} W_{ij}}{S\sqrt{\frac{(n\sum_{j=1}^{n} W_{ij}^2 - (\sum_{j=1}^{n} W_{ij})^2}{n-1}}} \tag{9}$$

$$\bar{X}=\frac{\sum_{j=1}^{n} x_j}{n} \tag{10}$$

$$S=\sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n}} - (\bar{X})^2 \tag{11}$$

Where,

the (G_i^*) calculates the hotspots and cold spots of spatial autocorrection statistics. X_j represents the attribute value of feature j, W_{ij} denotes the spatial weight between the feature I and j and n is the total number of features.

Table 4. Limitations and challenges

Methodology	Challenges	Inherent limitation
Multi- Decadal land cover change analysis	Seasonal and phenological shifts in vegetation may lead to misinterpretation of land cover changes. Atmospheric conditions like haze or shadow can obscure true changes.	Limited temporal data may miss episodic or abrupts events such as cyclones or floods, which significantly alter landscapes but go undetected.
Mangrove vulnerability index (MVI)	Inaccuracies in elevation data and geomorphological mapping due to dynamic terrain in mangrove regions.	Reliance on datasets like SRTM can introduce errors, particularly in areas with dense vegetation, and may not fully capture local-scale processes.
Hot Spot G_i^* Model and NDVI use in mangrove studies	NDVI may not effectively differentiate between mangrove species or detect stress conditions specific to mangroves. Atmospheric condition can affect accuracy.	NDVI's limitations may lead to misclassification of mangrove health. The Hot Spot G_i^* Model might not fully account for spatial autocorrelation in continuous environments.

Limitations and challenges of methodologies discussed

Each methodology used in mangrove vulnerability assessments, with its effectiveness in certain aspects, also presents several challenges for researchers. The widely used methodologies in this field also come with inherent limitations. These challenges and limitations are summarized in the Table 4.

Necessity of community participation and sustainable management in mangrove conservation

Community involvement and sustainable management are crucial for successful mangrove conservation. Including local communities in conservation projects not only improve the effectiveness of these causes but also builds a strong sense of responsibility and care for mangrove ecosystems. When communities participate, they provide valuable insights and support, making conservation efforts more practical and widely embraced. Equally important are sustainable management practices, which ensure that conservation strategies effectively balance environmental protection with local economic needs, making them both functional and lasting. By combining community engagement with sustainable methods, conservation strategies become more robust and capable of delivering long-term benefits for both the environment and local people. This integrated approach leads to healthier mangrove ecosystems and supports a more sustainable future.

Future direction and challenges

In the realm of mangrove vulnerability assessment using remote sensing and GIS, addressing challenges requires a multifaceted approach.

Collaboration among stakeholders, investment in capacity building programmes, and advancements in technology play pivotal roles. Initiatives promoting data sharing and open access to satellite imagery enhance data availability, while capacity building programmes improve skills of practioners. Continued research and development in remote sensing technologies, such as higher resolution imagery and hyperspectral sensors, enable more precise monitoring. Integration of artificial intelligence and automation streamlines data analysis processes, while exploring cost- effective solutions, including public- private partnerships, ensures efficient and sustainable monitoring effects.

Looking ahead, advancements in remote sensing technology and Artificial Intelligence integration hold promise for precise and comprehensive mangrove ecosystem monitoring. However, challenges related to data availability, processing complexities, and cost- effectiveness remain. Addressing these obstacles will require collaborative efforts and innovative solutions to achieve accurate vulnerability assessments and ensure long-term mangrove conservation.

Conclusion

In conclusion, mangrove hold immense ecological significance, acting as vital buffers between marine and terrestrial environments, safeguarding shorelines, improving water quality, and providing crucial habitats for diverse species. However, these ecosystems face threats such as urbanization, aquaculture expansion, and climate change, which necessitate robust vulnerability assessments. Remote sensing and GIS technologies emerge as invaluable tools in this regard, facilitating the identification of high-risk areas and understanding degradation factors. Platforms like Arc GIS and QGIS, TerrSet (Idrisi), Google Earth Engine alongside geoprocessing tools, image classification techniques, Machine Learning Algorithms and so on within these softwares, enable the preparation of study area maps and comprehensive vulnerability analysis. Through case studies and methodologies multi-decadal land cover change analysis, mangrove vulnerability index, and hot spot G_i^* model, remote sensing and GIS prove effective in managing mangrove vulnerabilities across different regions and their challenges and limitations were carefully reviewed.

Considering factors like exposure to stressors, sensitivity to changes, and adaptive capacity, interdisciplinary collaboration and community involvement emerge as essential components in mangrove conservation efforts. By prioritizing conservation efforts and leveraging technology, we can ensure the resilience and longevity of mangrove ecosystems for future generations. Overall, remote sensing and GIS play a critical role in assessing mangrove vulnerability and guiding conservation initiatives, highlighting the importance of interdisciplinary approaches and community engagement in preserving these invaluable ecosystems.

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