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REVIEW ARTICLE

Latent concepts for area enhancement of mangrove forest: A novel approach through geospatial studies

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Abstract

Despite their vital roles in carbon sequestration, biodiversity conservation and coastal protection, mangrove ecosystems have historically faced degradation from pollution, deforestation and human activity. Mangrove restoration faces several challenges, including deforestation due to unsustainable logging for timber and fuelwood, as well as habitat loss from coastal development projects such as ports and resorts. The expansion of aquaculture, particularly shrimp farming, has led to the large-scale conversion of mangrove areas into degraded or unproductive land. Huge restoration projects have been started all over the world to deal with these issues. Geospatial technologies such as GIS (Geographic Information System), GPS (Global Positioning System), remote sensing and satellite imagery have made it easier to find suitable sites for restoration, which was a challenging task in the past. These technologies also enable the acquisition of large amounts of data. Topography, soil quality, land use and biodiversity are some of the factors that influence the process of identifying possible restoration sites. Although obstacles like ecosystem complexity, lack of data and methodological constraints still exist, developments in machine learning and radar remote sensing provide promising paths to obtaining vital information. Conservation efforts are being bolstered by data integration and predictive modeling-driven evidence-based rehabilitation strategies. This review examines the cutting-edge geospatial technologies and their critical role in surmounting obstacles and promoting the rehabilitation and re-establishment of mangrove habitats.

Keywords

geospatial techniques; mangrove; modelling; potential areas

Introduction

Mangroves and their importance

Mangroves are significant ecosystems that have several benefits, including preserving biodiversity, safeguarding the shore, sequestering carbon contributing to the global carbon cycle (Fig. 1) and providing essential goods and services to coastal communities which are also essential for maintaining the stability of the coast and halting erosion (1). Economically, mangroves support fisheries, aquaculture and coastal livelihoods by serving as nurseries for commercially important fish species and providing raw materials such as timber and honey. Ecologically, they act as natural barriers against storm surges and coastal erosion, protect biodiversity by hosting unique and endangered species and improve water quality by filtering pollutants. Culturally, many coastal communities regard mangroves as integral to their heritage and traditions, using them for medicinal

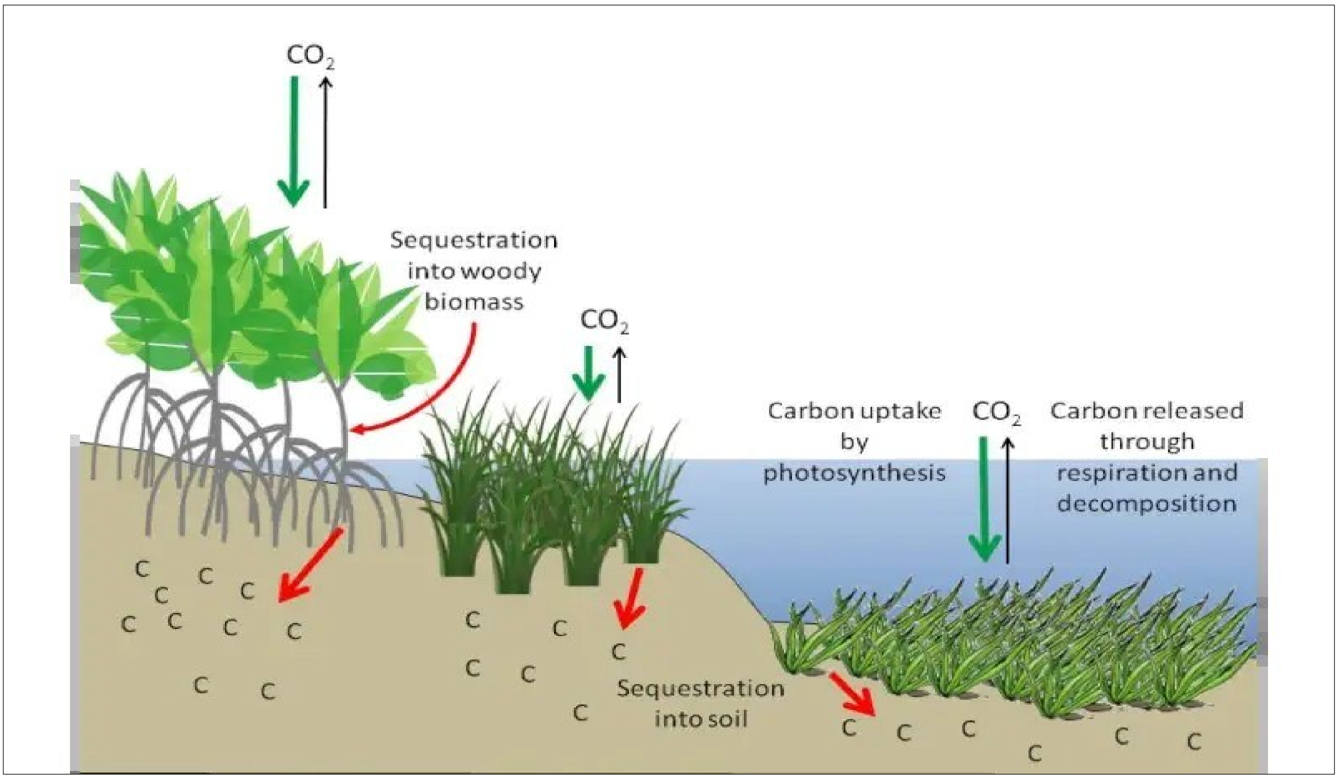

Fig. 1. The efficiency of (L-R) mangrove forests, salt marshes and seagrass beds as reservoirs for carbon. More carbon dioxide is taken up from the atmosphere (green arrows) than is re-released (black arrows), while a substantial amount is stored in soils (red arrows) for hundreds to thousands of years if left undisturbed.

purposes, spiritual practices and sustenance. Moreover, mangroves are among the planet's most efficient ecosystems for carbon sequestration, capturing and storing large amounts of carbon in their biomass and soils, making them indispensable in the fight against climate change. According to Alongi (2), Mangrove forests are tropical forests with substantial ecological and commercial value. As they can sequester carbon and enhance coastline stability, they are crucial for sustainable development and climate change adaptation (3). Non-native mangroves, such as Rhizophora mangle, have been found to facilitate carbon storage, carbon burial in sediment and the accretion of coastal ecosystems, highlighting their importance in mitigating climate change (4).

Constraints and development in mangrove re-establishment

Mangrove ecosystems have historically suffered greatly from human activities like deforestation, coastal development and the growth of aquaculture. These important habitats were frequently cleared for infrastructure and agriculture prior to the 20th century because they were thought to be barriers to development (5). However as scientific knowledge increased, mangroves' critical roles in carbon sequestration, biodiversity conservation and coastal protection became apparent in the late 20th century (6). Mangrove restoration has become a top priority globally thanks to global initiatives led by agencies like the FAO and UNEP, as well as local movements and community involvement (7).

In the twenty-first century, physical disturbances and human activities like deforestation and heavy metal poisoning pose a serious threat to mangrove habitats, despite technological advancements and conservation efforts (8). On the other hand, mangrove monitoring and management have been transformed by technological advancements like LiDAR and satellite photography, which allow for precise tracking of changes in extent, health and biodiversity (9). Mangrove ecosystems have been protected by laws and regulations enacted by governments and international organizations and integrated coastal management strategies work to strike a balance between conservation and societal needs (10).

The objective of this review is to explore the novel contributions of geospatial technologies in overcoming the challenges associated with mangrove restoration and conservation. It emphasizes how advancements in tools such as Geographic Information Systems (GIS), Global Positioning Systems (GPS), remote sensing and satellite imagery have revolutionized the identification of suitable restoration sites, which has traditionally been a complex and resource-intensive task. By integrating data on topography, soil quality, land use and biodiversity, these technologies facilitate evidence-based strategies for effective mangrove rehabilitation.

Geospatial technique's role in mangrove re-establishment areas identification

Geospatial techniques are vital for identifying suitable areas for mangrove reestablishment. Integrating historical data and expert consultation aids in site selection, while participatory mapping and field surveys provide valuable insights (11). Integrating diverse datasets, such as climate, topography, soil characteristics, hydrology and land use patterns, significantly enhances the accuracy and efficiency of mangrove restoration efforts by providing a holistic understanding of ecosystem dynamics. For instance, combining climate data with hydrological models enables the identification of areas with suitable tidal regimes, essential for mangrove growth and regeneration. Similarly, integrating topographical information with soil salinity and pH data helps pinpoint locations with optimal substrate conditions for mangrove saplings.

A notable example of successful dataset integration is the restoration project in the Mekong Delta, Vietnam, where geospatial analysis combined satellite imagery with climate and hydrological data to identify degraded mangrove zones and prioritize them for replantation. This approach improved the success rate of replantation efforts by aligning interventions with natural tidal patterns.

Remote sensing, GIS and GPS technologies enable accurate mapping and monitoring of mangrove ecosystems, supported by high-resolution imaging (12). Global remote sensing datasets facilitate efficient data collection and processing, reducing survey time and resource requirements (13). Interdisciplinary approaches, such as Multi-Criteria Decision Making, enhance restoration efforts by producing suitability maps (14). Multi-Criteria Decision Making (MCDM) refers to a set of analytical techniques and methodologies used to evaluate and prioritize options based on multiple, often conflicting criteria. It integrates diverse datasets-such as ecological, socio-economic and environmental parameters-to identify and rank potential restoration sites based on their suitability and alignment with restoration goals. Geospatial techniques enable efficient restoration site selection, progress monitoring and evaluation of ecosystem services, fostering greater conservation efforts in mangrove rehabilitation (15).

Required data sets

Abd-El Monsef (16) gave a multidisciplinary approach to environment, geography, climate and socioeconomic status to be incorporated into this strategy for locating possible locations for mangrove reestablishment. Shrestha (14) demonstrated the utilization of multi-sensor data, including satellite data, can also assist in the identification and forecasting of possible biophysical suitable regions within a tropical mangrove ecosystem. Some of the required data sets are summarized in Table 1.

Data sets and resolution

Having extensive coverage and historical records, satellite data is useful for long-term, large-scale mangrove monitoring. Conversely, drones are suited for small-area monitoring since they provide greater resolution and temporal resolution (17). High spatial and spectral resolution is made possible by aerial multispectral sensors, including the Compact Airborne Spectrographic Imager, which enables precise and thorough evaluation of mangrove areas. Xia (18) provided more evidence that mapping mangrove species was successful when using a combination of remote-sensing datasets, such as Sentinel-2 and Gaofen-3. Many forms of datasets useful for the specified purpose are available, of which some are listed in Table 2.

Preprocessing

In remote sensing, preprocessing is essential since it can greatly enhance the usefulness and quality of the data. Zheng (19) emphasized the significance of this stage by putting forth an adaptive spatial preprocessing technique that improves edges and smoothens noise in remote sensing images at the same time. Sowmya (20) divided the processing of remote sensing images into four steps, the first being preprocessing, which fixes geometric, atmospheric and radiometric aberrations. This can increase the precision of automatic feature recognition processing.

Indices for mangrove area mapping

Numerous studies have contrasted various mangrove mapping indices and the greatest accuracy was discovered by Kongwongjan (21) when THEOS spectral bands and indices like NDVI, SR and SAVI were combined. Muhsoni (22) found that the most accurate methods for mapping mangrove density using Sentinel-2 imagery were NDVI with exponential regression, RVI (Ratio Vegetation indices) with exponential approach and NDVI with polynomial approach. Kasawani (23) suggested the use of soil-line-based vegetation indices, such as SAVI. The

Table 1. Data types, its format and accessibility

Data Type	Format	Data Sources	Data Access	Relevance to Restoration
Land Use and Land Cover	Raster data, vector data	Satellite imagery (Landsat, Sentinel), aerial photography	USGS EarthExplorer, ESA Copernicus Open Access Hub, ISRO Homepage, Bhuvan Portal	Identifies degraded lands and suitable zones for mangrove replantation while avoiding land-use conflicts.
Soil Type and Quality	Vector data, raster data	Soil maps, satellite/aerial imagery, soil samples	ISRIC SoilGrids, FAO Soil Portal, ICAR Website, Impact Observatory	Ensures site conditions support mangrove growth by analyzing soil salinity, pH and organic matter.
Topography and Elevation	Raster data	Satellite imagery (SRTM, ASTER), aerial photogrammetry	USGS EarthExplorer, AWS Public Dataset Program, Survey of India Website, Impact Observatory	Identifies low-lying coastal areas suited for intertidal mangroves and evaluates flood and erosion risks.
Temperature and Precipitation	Gridded data, time series	Climate station data, satellite imagery	NOAA NCDC, WorldClim, IMD Website	Assesses climate suitability and predicts the impact of climate change on restoration areas.
Tidal Data	Time series	Tide gauges, satellite altimetry	NOAA Tides & Currents, EMODnet Physics, NCCR Website	Ensures appropriate tidal regimes for nutrient exchange and site drainage.
River Discharges	Time series	Stream gauges, hydrologic modeling	USGS NWIS, EMODnet Hydrography, CWC Website, India Water Portal	Evaluates sediment supply and freshwater availability critical for mangrove establishment.
Ocean Currents and Salinity	Vector data, gridded data	Satellite altimetry, ARGO floats	NOAA ERDDAP, IOOS Glider DAC, NIO Website, IMD Website	Assesses nutrient transport and salinity levels essential for site suitability.
Biodiversity Assessment	Vector data, raster data	Field surveys, aerial/ satellite imagery	GBIF, Map of Life, MoEFCC Website, Climate Data Guide	Identifies key species for replantation and highlights potential to create habitats for endangered species.

Source: Zheng (19) and Ellison (6)

Table 2. Satellite sensors used for mangrove mapping

Satellite	Sensor	Resolution	Accuracy Metrics	Data Source
OPTICAL				
Landsat 8	OLI	30 m	Overall accuracy is 92%, Kappa 0.91 for species mapping	USGS EarthExplorer
Sentinel-2	MSI	10-60 m	Overall accuracy is 85%, Kappa 0.82 for extent mapping	ESA Copernicus Open Access Hub
PlanetScope	PlanetScope	3-5 m	Overall accuracy is 88%, Kappa 0.86 for habitat mapping	Planet Explorer
Pleiades	PHR	0.5-2 m	Overall accuracy is 82%, Kappa 0.78 for species classification	Airbus Defense & Space
Quickbird	QuickBird	0.6-2.4 m	Overall accuracy is 84%, Kappa 0.81 for extent mapping	Maxar
IKONOS	PAN, Multi	0.8-4 m	Overall accuracy is 79%, Kappa 0.75 for habitat mapping	Maxar
WorldView-2	WV110	0.5-2 m	Overall accuracy 86%, Kappa 0.83 for species mapping	Maxar
S A R				
RADARSAT-2	SAR	1-100 m	Overall accuracy 83%, Kappa 0.81 for mangrove classification	MDA Geospatial Services
ALSO PALSAR	PALSAR	10-100 m	Kappa 0.89 for mangrove classification	JAXA
UAVSAR	L-band SAR	1-5 m	Overall accuracy is 86%, Kappa 0.84 for species mapping	NASA/JPL UAVSAR
LIDAR				
GEDI	Lidar	25 m spots	R^2 = 0.61 vs field biomass data	NASA Earthdata
ICESat-2	Lidar	10 m spots	RMSE 11.2m vs airborne lidar	NSIDC

Generalized Composite Mangrove Index (GCMI), unveiled by Xue (24), performed better than previous indices in differentiating mangroves from other land covers. Principal polar spectral (PPS) indices were employed to distinguish between mangrove species, with encouraging outcomes (25). Table 3 provides various related indies for mapping mangroves and their Data requirements.

Image analysis technique

It has been discovered that pixel-based classification models, like support vector machines and maximum likelihood classification, work well for classifying individual pixels according to their spectral properties. Many of such analysis techniques have been compared in Table 4 with their accuracy. When compared to the Support Vector Machine method, the Maximum Likelihood Classification technique yielded noticeably higher user, producer and overall accuracies (26). It has been demonstrated that object-based classification models, which classify nearby pixels as objects, increase mapping accuracy for mangroves (27). In a comparison of four supervised classification algorithms for tracking changes in mangrove cover, Random Forest (RF) was found to perform the best (28).

Geospatial modelling

To comprehend and work with spatial data, geospatial modeling-a fundamental aspect of GIS-must use statistical techniques and spatial algorithms (29). The creation of a Statistical Analysis Module (SAM) that operates inside the GIS operating environment (30) further improves this integration and enables the finding of hidden patterns (31). Imbalanced data and prediction errors are two issues (32) that geospatial modeling must deal with, but with the advent of cloud computing and high-resolution statistical data, it has changed dramatically. For efficient management and workflow facilitation, GIS modeling is essential, especially in decision-making. Here are a few Geospatial models:

Habitat suitability models

• ***Statistical models****:* Hu (33) mapped the restoration potential of mangrove forests in China using the Maximum Entropy (MaxEnt) model and the Genetic Algorithm for Rule-set Prediction (GARP), with the MaxEnt model outperforming GARP. Suhardiman (34) mapped site suitability for 14 mangrove species in the Indonesian Mahakam delta using a geostatistical approach that combined salinity, tidal inundation, clay and sand variables. For Kandelia obovata trees in northern Taiwan, Shih (35) created spatial habitat

Table 3. Various indices and their accuracy levels

Index	Formula	Outcomes	Uses
NDVI	$NDVI = \frac{NIR - RED}{NIR + RED}$	Mapped mangrove extended with 83% accuracy using NDVI threshold analysis of Landsat imagery.	Measures vegetation health and density, monitor crop growth, assesses drought conditions and maps deforestation.
Soil adjusted vegetation index (SAVI)	$SAVI = \frac{(1+L) * NIR - RED}{NIR+RED+L}$ Where L is a soil adjustment factor.	Integrated SAVI and other indices from hyperspectral data to map 5 mangrove species with 83% overall accuracy.	Minimize soil brightness influences on vegetation indices, useful in areas with high soil exposure.
Ratio vegetation index (RVI)	$RVI = NIR / RED$	Used RVI for mangrove species discrimination achieving classification accuracy classification accuracy of up to 94%.	Estimate biomass, distinguish vegetation from the soil and monitor vegetation vigor and density.
Generalized composite mangrove index (GCMI)	$\eta * \frac{(1-0.25) * (NIR - 0.25)}{NIR}$ $= \frac{2.(NIR^2 - RED^2) + 1.5.NIR + 0.5.RED}{NIR+RED+0.5}$	Derived GCMI to estimate mangrove sub canopy inundation levels with RMSE - 0.12m.	Map and monitor mangrove ecosystems and discriminate mangroves from other vegetation types.
Principal Polar spectral (PPS)	It involves calculating the first derivative of the reflectance spectrum and identifying its principal components.	Captured spectra difference between 5 mangrove.	Identify vegetation stress and estimate biophysical.

Table 4. Image analysis techniques in mangroves

Technique	Accuracy	Training Data Needs	Uses	Software
Pixel-based classification	Overall accuracy of 89.5% for land cover classification using SVM. Kappa coefficient: 0.88	Representative samples from each class	Land cover mapping, change detection	ENVI, ERDAS Imagine
Deep learning	Overall accuracy of 91.4% for land cover classification using CNN	Large diverse training set	Object detection, scene understanding	TensorFlow, Keras
Textural analysis	Overall accuracy of 83.7% for land use classification using GLCM textural features. A Kappa coefficient of 0.81 was reported.	Representative textural samples	Habitat mapping, geology	ENVI, ORFEO Toolbox
Spectral mixture analysis	R^2 of 0.91 for estimation of mineral abundances	Pure spectral endmembers	Mineral mapping, soil characterization	ENVI, RStoolbox
Object-based image analysis	The overall accuracy of 85.3% for land cover classification using an object-based approach. Kappa coefficient of 0.82.	Representative segmented objects	Urban mapping, precision agriculture	eCognition, ERDAS Imagine
Random Forest	Overall accuracy: 87.3%, Kappa coefficient: 0.84 for land cover classification using random forest with hyperspectral data	Representative training samples	Land cover mapping, forest mapping	ENVI, ERDAS Imagine, sci-kit-learn
Support Vector Machine	Overall accuracy of 89.5% for land cover mapping using SVM. Kappa coefficient of 0.88. Class-specific accuracies ranging from 82-96%.	Representative training samples	Land cover mapping, land use classification	ENVI, SAGA GIS, scikit-learn
Maximum Likelihood	An overall accuracy of 82.1% was reported for land cover mapping using maximum likelihood classification. Kappa coefficient of 0.79. Class-specific accuracies from 75-91%.	Representative training statistics	Land cover mapping, geology	ENVI, ERDAS Imagine, QGIS
Data fusion	Overall accuracy improvement of 5-10% compared to single sensor classification. Fusion increased Kappa coefficient by 0.1-0.2.	Aligned training data	Multi-sensor integration, comprehensiveness	ERDAS Imagine, ENVI

NB: High overall accuracy and Kappa coefficients are essential for ensuring reliable mangrove identification across varied landscapes. R^2 values from spectral analysis can help assess environmental variables like soil salinity or water content crucial for mangrove growth.

suitability index (HSI) models that included salinity of the water, soil sorting coefficient and frequency of flooding as important environmental variables whose output is shown in Fig. 2.

- ***Machine Learning models***: Liu (36) employed machine learning ensembles to map mangrove extent at high resolutions, with Liu specifically focusing on West Africa and Ambarwari reviewing the use of machine learning methods in mapping and monitoring mangroves. Maung (37) demonstrated the application of cutting-edge technology in this field by evaluating natural mangrove recovery in Myanmar using an artificial neural network.

Species Distribution Models (SDMs)

- ***Correlative models***: Twilley (38) enhanced this by adapting an ecological model to simulate restoration trajectories, providing a practical tool for restoration project design. However, Rovai (39) cautioned that single-species plantings in restoration sites may compromise secondary succession, emphasizing the need for careful site selection and management using a correlative model.

- ***Mechanistic models***: Hu (33) and Worthington (15) both used mechanistic models to identify potential restoration sites for mangrove afforestation. Hu employed species distribution models to assess mangrove suitability in China, while Worthington developed a global typology of mangroves to calculate the potential benefits of restoration.

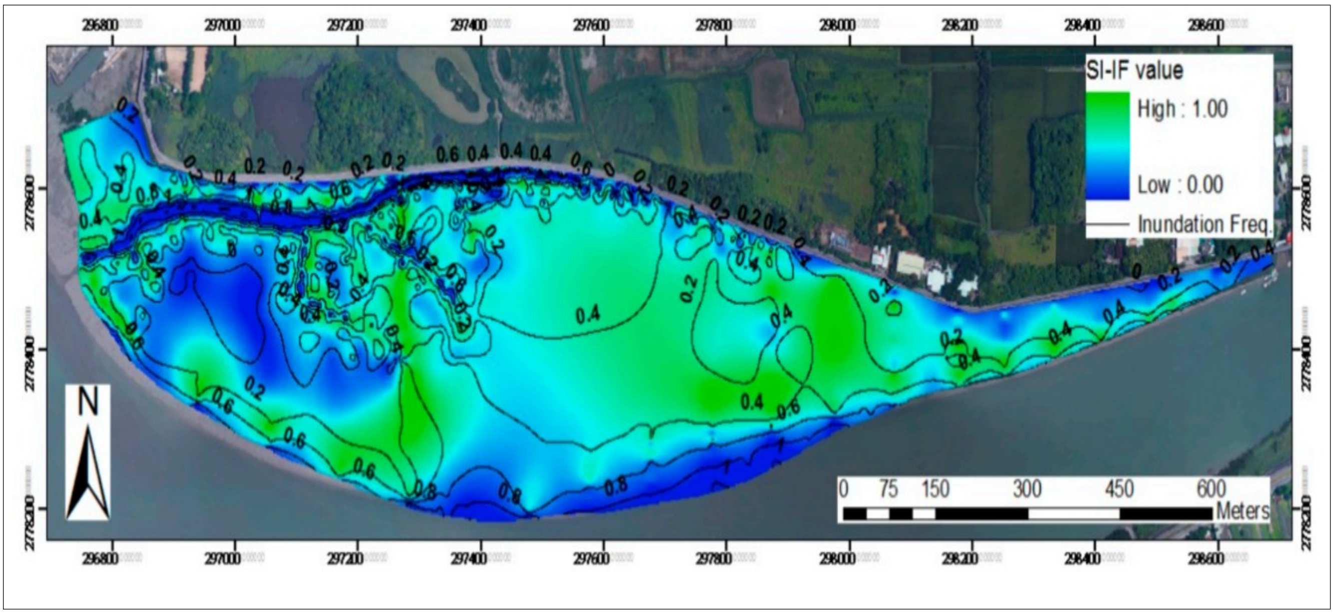

Fig. 2. The improved HSI map of the model prediction. A high value indicates the mangrove areas, while a low value indicates areas of mudflats and tidal creeks (35).

Remote Sensing and GIS-based models

• ***Land cover change models***: Kura (40) employed land cover change models to forecast future changes in mangrove areas; Kura focuses on southern Ethiopia, while Etemadi focuses on Iran. Rising sea levels are expected to cause a loss of mangrove area to open water, according to Etemadi's study in Iran and an increase in agroforestry and agricultural land at the expense of natural vegetation, according to Kura's study in Ethiopia. Both studies emphasize that to address these changes, precise mitigation and adaptation strategies are required. In the SRB, Ethiopia, Entahabu (41) used Land Change Modeler (LCM) (Fig. 3) to model and predict changes in land use and land cover from 1990 to 2048. He discovered that in 2028 and 2048, bar land, built-up land and cultivated land will increase at the expense of water bodies, forests, shrubs and plantation land.

• ***Spatial analysis models***: Syahid (42) used an analytical hierarchy process to determine the importance of various parameters in predicting suitable areas for mangrove planting in Southeast Asia. By combining expert judgment with analytical methods, such as putting weights from expert assessments and criterion preferences into a mathematical model called the Best Worst Method (Fig 4), a relatively new Multi Criteria Decision Making technique, the study was able to identify potential locations for mangrove plantations in southern Iran (43).

Hydrodynamic models

Numerous studies have shown how important it is to take hydrodynamic and hydrological parameters into account when restoring mangroves. The necessity to restore natural hydrological regimes is emphasized by Pérez-Ceballos (44) particularly arguing for the identification of hydrological flow pathways. Van Loon (45) demonstrated how to use a hydrological classification based on the length of inundation and a hydrological classification based on observed water levels over at least 30 days during a lunar tidal cycle. Understanding and controlling the natural processes and environmental features of mangroves is crucial, as stressed by Mazda (46) which is especially true in light of the changing hydrological and sedimentary circumstances.

Factors to consider when choosing a geospatial technique for mangrove plantation Identification

The specific objectives of the research should guide the application of a model to identify potential mangrove restoration locations. For instance, a model like the MaxEnt model, which can accurately predict future mangrove distributions, would be suitable if the goal is to rank the restoration sites in order of priority (33). However, it's imperative to consider the underlying causes of damage and deterioration and to develop a decision tree to guide the restoration process (47). Pôças (48) presented a methodological framework that is necessary to assess the suitability of spatial data sets for ecological and environmental applications while taking user needs and quality indicators into account. The selection of a model for mangrove restoration should be based on the specific objectives of the study and the availability of data (38).

Limitations of geospatial techniques

The intricacy of mangrove ecosystems poses difficulties in precisely identifying appropriate plantation regions, requiring a thorough examination of geographic data (49). Obstacles like tidal variations and atmospheric pollution can still make precise species discrimination difficult (50). Given the ever-changing nature of mangrove forests and their significance in mitigating and adapting to climate change, this is at most important (51). However, obstacles like cloud cover, sensor limitations and budgetary constraints might make it more difficult to obtain high -quality data, particularly in isolated or inaccessible areas. Innovative techniques for data collecting and analysis are required to overcome these issues, such as the use of machine learning algorithms and the integration of various imaging types

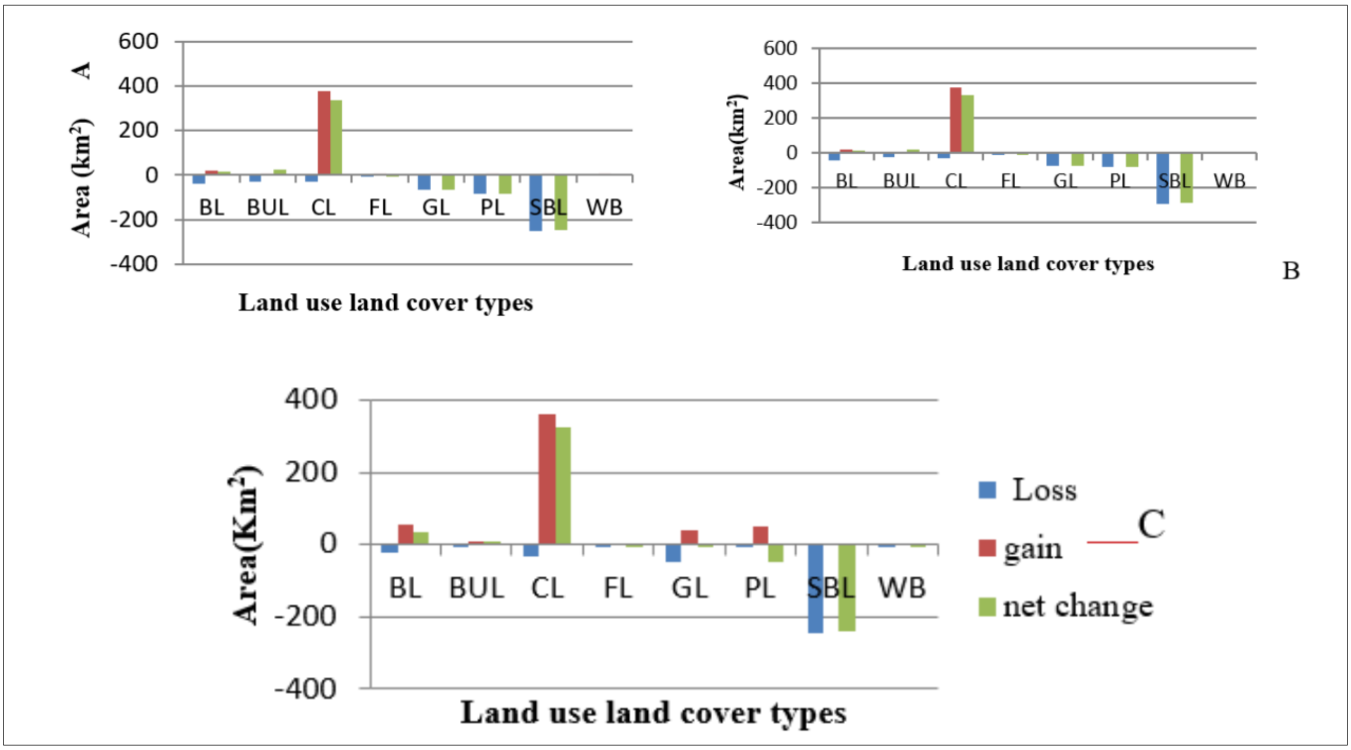

Fig. 3. The gains and losses of LULC types identified of SRB in 1990 (A), 2002 (B) and 2018 (C) with each keyword indicating different lulc classes (41).

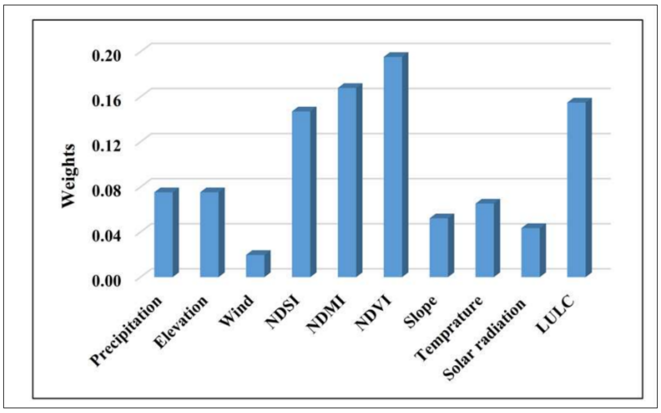

Fig. 4. Weights of the considered criteria calculated based on the Best Worst Method (BWM) for mangrove plantation suitability mapping (43).

(52). Furthermore, the use of Synthetic Aperture Radar (SAR) has been shown to provide cloud-free observations, making it a valuable tool for mapping and monitoring mangrove ecosystems (53). The choice of mangrove rehabilitation should be based on conservation, landscaping, sustainable production and coastal protection and should consider factors such as site degradation, site selection and source of seedlings (54). Notwithstanding these drawbacks, mangrove habitats have been successfully mapped and monitored using remote sensing, yielding important data for management and conservation (55).

Future prospects

Recent advancements in remote sensing, such as hyperspectral data and radar imagery recommended by Prasad (56), along with Synthetic Aperture Radar (SAR) systems noted by Thakur (49), are revolutionizing mangrove management. Drones and UAVs (Unmanned Aerial Vehicle), also emphasized by Prasad (56), offer cost-effective solutions for precise small-area analysis. Integrating machine learning algorithms for classification and predictive modeling, enhances mapping accuracy (57). Furthermore, leveraging geospatial big data analytics and cloud computing enables effective large-scale processing for comprehensive ecosystem monitoring. Kumar (58) envisions automated workflows and mobile apps to streamline mangrove monitoring, supporting informed decision-making. These advancements collectively improve mangrove mapping precision, deepen understanding of ecosystem dynamics and facilitate efficient restoration site identification.

Conclusion

Important functions like carbon sequestration, biodiversity preservation and coastal protection are provided by mangrove ecosystems. Nonetheless, over time, human activity has caused them to deteriorate. Recognizing their significance, extensive restoration projects have been started all over the world. Finding appropriate locations is difficult but essential. Mangrove mapping and monitoring have been revolutionized by geospatial techniques such as GIS, remote sensing and satellite imagery, which allow for the efficient collection of data over vast areas. In conclusion, Geospatial technologies revolutionize mangrove restoration ecology, enabling efficient habitat assessments and changing predictions. Challenges persist due to ecosystem complexity, but innovations like machine learning offer solutions. To enhance mangrove restoration efforts, stakeholders should integrate machine learning with geospatial techniques to improve predictive modeling for site selection, monitoring and planning. Community involvement should be prioritized through participatory mapping, education and livelihood-aligned incentives to foster long-term stewardship. Employing Multi-Criteria Decision Making (MCDM) frameworks can balance ecological, economic and social considerations, ensuring optimal site selection. Investments in high-resolution satellite imagery and UAV data acquisition will improve the precision of mapping and monitoring. Additionally, training programs and knowledge-sharing platforms can build local capacity and facilitate the adoption of advanced tools. Quantifying the economic benefits of mangroves, such as carbon sequestration and coastal protection, can strengthen funding and support policy. Governments should implement supportive policies, allocate dedicated funding and link restoration to global climate goals and carbon credit schemes. Lastly, incorporating climate change adaptation measures and using geospatial technologies for progress tracking will ensure the resilience and sustainability of mangrove restoration projects. Success depends on a harmonious blend of techno-social philosophies, continuous methodological improvements and robust policies, aiming to reinstate ecosystem structures for nature and society's long-term enrichment.

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Authors' contributions

SRG contributed to the design of the study, data analysis, and drafting of the manuscript. SP supervised the research, coordinated the study, and critically revised the manuscript. RK assisted with drone operations and data acquisition. MR participated in data interpretation and manuscript preparation. PCP contributed to the literature review and provided input on the introduction. SRG was involved in data collection and statistical analysis. All authors read and approved the final manuscript.

Compliance with ethical standards

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During the preparation of this work the authors used QuillBot to improve language and readability, with caution. After using this tool, the authors reviewed and edited the content as needed and takes full responsibility for the content of the publication.

References

1. Kathiresan K. Importance of mangrove ecosystem. Int J Mar Sci. 2012;2(10). https://doi.org/10.5376/ijms.2012.02.0010
2. Alongi DM. Carbon cycling and storage in mangrove forests. Annu Rev Mar Sci. 2014;6(1):195– 219. https://doi.org/10.1146/annurev-marine-010213-135020
3. Chow J. Mangrove management for climate change adaptation and sustainable development in coastal zones. J Sustain For. 2018;37 (2):139–56. https://doi.org/10.1080/10549811.2017.1339615
4. Soper FM, MacKenzie RA, Sharma S, Cole TG, Litton CM, Sparks JP. Non-native mangroves support carbon storage, sediment carbon burial and accretion of coastal ecosystems. Glob Change Biol. 2019;25(12):4315–26. https://doi.org/10.1111/gcb.14813
5. Duke NC. Mangrove floristics and biogeography. Trop Mangrove Ecosyst. 1992;41:63–100. https://doi.org/10.1029/CE041
6. Ellison JC. Long-term retrospection on mangrove development using sediment cores and pollen analysis: a review. Aquat Bot. 2008;89(2):93–104. https://doi.org/10.1016/j.aquabot.2008.02.007
7. Primavera J, Rollon R, Samson M. 10.10 The pressing challenges of mangrove rehabilitation: pond reversion and coastal protection. Biologica (Santiago). 2011;50:232.
8. Feller IC, Friess DA, Krauss KW, Lewis III RR. The state of the world's mangroves in the 21st century under climate change. Hydrobiologia. 2017;803(1):1–12.
9. Hamilton SE, Casey D. Creation of a high spatio-temporal resolution global database of continuous mangrove forest cover for the 21st century (CGMFC-21). Glob Ecol Biogeogr. 2016;25 (6):729–38. https://doi.org/10.1111/geb.12449
10. Friess DA, Webb EL. Variability in mangrove change estimates and implications for the assessment of ecosystem service provision. Glob Ecol Biogeogr. 2014;23(7):715–25. https://doi.org/10.1111/geb.12140
11. Hashim J. Human resource management practices on organisational commitment: The Islamic perspective. Pers Rev. 2010;39(6):785–99.
12. Green EP, Clark C, Mumby P, Edwards A, Ellis A. Remote sensing techniques for mangrove mapping. Int J Remote Sens. 1998;19 (5):935–56. https://doi.org/10.1080/014311698215801
13. Justice C, Townshend J. Data sets for global remote sensing: lessons learnt. Int J Remote Sens. 1994;15(17):3621–39. https://doi.org/10.1080/01431169408954347
14. Shrestha S, Miranda I, Kumar A, Pardo MLE, Dahal S, Rashid T, et al. Identifying and forecasting potential biophysical risk areas within a tropical mangrove ecosystem using multi-sensor data. Int J Appl Earth Obs Geoinformation. 2019;74:281-94. https://doi.org/10.1016/j.jag.2018.09.017
15. Worthington T, Spalding M. Mangrove Restoration Potential: A global map highlighting a critical opportunity. 201. https://doi.org/10.17863/CAM.39153
16. Abd-El Monsef H, Hassan MA, Shata S. Using spatial data analysis for delineating existing mangroves stands and siting suitable locations for mangroves plantation. Comput Electron Agric. 2017;141:310–26. https://doi.org/10.1016/j.compag.2017.08.002
17. Ruwaimana M, Satyanarayana B, Otero V, M. Muslim A, Syafiq A M, Ibrahim S, et al. The advantages of using drones over space-borne imagery in the mapping of mangrove forests. PloS One. 2018;13 (7):e0200288. https://doi.org/10.1371/journal.pone.0200288
18. Xia Q, Qin CZ, Li H, Huang C, Su FZ. Mapping mangrove forests based on multi-tidal high-resolution satellite imagery. Remote Sens. 2018;10(9):1343. https://doi.org/10.3390/rs10091343
19. Zheng L, Xu W. An improved adaptive spatial preprocessing method for remote sensing images. Sensors. 2021;21(17):5684. https://doi.org/10.3390/s21175684
20. Sowmya D, Shenoy PD, Venugopal K. Remote sensing satellite image processing techniques for image classification: a comprehensive survey. Int J Comput Appl. 2017;161(11):24–37.
21. Kongwongjan J, Suwanprasit C, Thongchumnum P. Comparison of vegetation indices for mangrove mapping using THEOS data. Proc Asia-Pac Adv Netw. 2012;33:56–64. http://doi.org/10.7125/APAN.33.6
22. Muhsoni FF, Sambah A, Mahmudi M, Wiadnya D. Comparison of different vegetation indices for assessing mangrove density using sentinel-2 imagery. Int J Geomate. 2018;14:42–51. https://doi.org/10.21660/2018.45.7177
23. Kasawani I, Norsaliza U, Mohdhasmadi I. Analysis of spectral vegetation indices related to soil-line for mapping mangrove forests using satellite imagery. 2010.
24. Xue Z, Qian S. Generalized composite mangrove index for mapping mangroves using Sentinel-2 time series data. IEEE J Sel Top Appl Earth Obs Remote Sens. 2022;15:5131–46. https://doi.org/10.1109/JSTARS.2022.3185078
25. Ramdani F, Rahman S, Giri C. Principal polar spectral indices for mapping mangroves forest in South East Asia: study case Indonesia. Int J Digit Earth. 2019. https://doi.org/10.1080/17538947.2018.1454516
26. Kanniah KD, Sheikhi A, Cracknell AP, Goh HC, Tan KP, Ho CS, et al. Satellite images for monitoring mangrove cover changes in a fast growing economic region in southern Peninsular Malaysia. Remote Sens. 2015;7(11):14360–85. https://doi.org/10.3390/rs71114360
27. Lee TM, Yeh HC. Applying remote sensing techniques to monitor shifting wetland vegetation: A case study of Danshui River estuary mangrove communities, Taiwan. Ecol Eng. 2009;35(4):487–96. https://doi.org/10.1016/j.ecoleng.2008.01.007
28. Toosi NB, Soffianian AR, Fakheran S, Pourmanafi S, Ginzler C, Waser LT. Comparing different classification algorithms for monitoring mangrove cover changes in southern Iran. Glob Ecol Conserv. 2019;19:e00662. https://doi.org/10.1016/j.gecco.2019.e00662
29. Burrough P. GIS and geostatistics: Essential partners for spatial analysis. Environ Ecol Stat. 2001;8:361–77.
30. Ding Y, Fotheringham AS. The integration of spatial analysis and GIS. Comput Environ Urban Syst. 1992;16(1):3–19. https://doi.org/10.1016/0198-9715(92)90050-2
31. Krivoruchko K, Gotay C. Using spatial statistics in GIS. In: International congress on modelling and simulation. 2003. p. 713–36.
32. Koldasbayeva D, Tregubova P, Gasanov M, Zaytsev A, Petrovskaia A, Burnaev E. Challenges in data-based geospatial modeling for environmental research and practice. ArXiv Prepr ArXiv231111057. 2023. https://doi.org/10.48550/arXiv.2311.11057
33. Hu L, Li W, Xu B. The role of remote sensing on studying mangrove forest extent change. Int J Remote Sens. 2018;39(19):6440–62. https://doi.org/10.1007/978-3-319-62206-4_10
34. Suhardiman A, Tsuyuki S, Sumaryono M, Sulistioadi YB. Geostatistical approach for site suitability mapping of degraded mangrove forest in the Mahakam Delta, Indonesia. J Geogr Inf Syst. 2013.
35. Shih SS. Spatial habitat suitability models of mangroves with Kandelia obovata. Forests. 2020;11(4):477. https://doi.org/10.3390/f11040477
36. Liu X, Fatoyinbo TE, Thomas NM, Guan WW, Zhan Y, Mondal P, et al. Large-scale high-resolution coastal mangrove forests mapping across West Africa with machine learning ensemble and satellite big data. Front Earth Sci. 2021;8:560933. https://doi.org/10.3389/feart.2020.560933
37. Maung WS, Sasaki J. Assessing the natural recovery of mangroves after human disturbance using neural network classification and

Sentinel-2 imagery in Wunbaik Mangrove Forest, Myanmar. Remote Sens. 2020;13(1):52. https://doi.org/10.3390/rs13010052

38. Twilley RR, Rivera-Monroy VH, Chen R, Botero L. Adapting an ecological mangrove model to simulate trajectories in restoration ecology. Mar Pollut Bull. 1999;37(8–12):404–19. https://doi.org/10.1016/S0025-326X(99)00137-X
39. Rovai AS, Soriano-Sierra EJ, Pagliosa PR, Cintrón G, Schaeffer-Novelli Y, Menghini RP, et al. Secondary succession impairment in restored mangroves. Wetl Ecol Manag. 2012;20:447–59.
40. Kura AL, Beyene DL. Cellular automata Markov chain model based deforestation modelling in the pastoral and agro-pastoral areas of southern Ethiopia. Remote Sens Appl Soc Environ. 2020;18:100321. https://doi.org/10.1016/j.rsase.2020.100321
41. Entahabu HH, Minale AS, Birhane E. Modeling and predicting land use/land cover change using the land change modeler in the suluh river basin, northern highlands of Ethiopia. Sustainability. 2023;15(10):8202. https://doi.org/10.3390/su15108202
42. Syahid LN, Sakti AD, Virtriana R, Wikantika K, Windupranata W, Tsuyuki S, et al. Determining optimal location for mangrove planting using remote sensing and climate model projection in southeast asia. Remote Sens. 2020;12(22):3734. https://doi.org/10.3390/rs12223734
43. Sahraei R, Ghorbanian A, Kanani-Sadat Y, Jamali S, Homayouni S. Identifying suitable locations for mangrove plantation using geospatial information system and remote sensing. ISPRS Ann Photogramm Remote Sens Spat Inf Sci. 2023;10:669–75. https://doi.org/10.5194/isprs-annals-X-4-W1-2022-669-2023
44. Pérez-Ceballos R, Zaldívar-Jiménez A, Canales-Delgadillo J, López -Adame H, López-Portillo J, Merino-Ibarra M. Determining hydrological flow paths to enhance restoration in impaired mangrove wetlands. PloS One.2020;15(1):e0227665. https://doi.org/10.1371/journal.pone.0227665
45. Van Loon AF, Te Brake B, Van Huijgevoort MH, Dijksma R. Hydrological classification, a practical tool for mangrove restoration. PloS One. 2016;11(3):e0150302. https://doi.org/10.1371/journal.pone.0150302
46. Mazda Y, Wolanski E. Hydrodynamics and modeling of water flow in mangrove areas. Coast Wetl Integr Ecosyst Approach. 2009;8:231–62.
47. López-Portillo J, Lewis RR, Saenger P, Rovai A, Koedam N, Dahdouh-Guebas F, et al. Mangrove forest restoration and rehabilitation. Mangrove Ecosyst Glob Biogeogr Perspect Struct Funct Serv. 2017;301–45.
48. Pôças I, Gonçalves J, Marcos B, Alonso J, Castro P, Honrado JP. Evaluating the fitness for use of spatial data sets to promote quality in ecological assessment and monitoring. Int J Geogr Inf Sci. 2014;28 (11):2356–71. https://doi.org/10.1080/13658816.2014.924627
49. Thakur S, Mondal I, Ghosh P, Das P, De T. A review of the application of multispectral remote sensing in the study of mangrove ecosystems with special emphasis on image processing techniques. Spat Inf Res. 2020;28(1):39–51.
50. Pimple U, Simonetti D, Peters R, Berger U, Podest E, Gond V. Enhancing monitoring of mangrove spatiotemporal tree diversity and distribution patterns. Land Degrad Dev. 2023;34(5):1265–82. https://doi.org/10.1002/ldr.4537
51. Giri C. Observation and monitoring of mangrove forests using remote sensing: Opportunities and challenges. Remote Sens. 2016;8(9):783. https://doi.org/10.3390/rs8090783
52. Heumann BW. Satellite remote sensing of mangrove forests: Recent advances and future opportunities. Prog Phys Geogr. 2011;35(1):87–108. https://doi.org/10.1177/0309133310385371
53. Nascimento Jr WR, Souza-Filho PWM, Proisy C, Lucas RM, Rosenqvist A. Mapping changes in the largest continuous Amazonian mangrove belt using object-based classification of multisensor satellite imagery. Estuar Coast Shelf Sci. 2013;117:83–93. https://doi.org/10.1016/j.ecss.2012.10.005
54. Field CD. Rehabilitation of mangrove ecosystems: an overview. Mar Pollut Bull. 1999;37(8-12):383–92. https://doi.org/10.1016/S0025-326X(99)00106-X
55. Rasolofoharinoro M, Blasco F, Bellan M, Aizpuru M, Gauquelin T, Denis J. A remote sensing based methodology for mangrove studies in Madagascar. Int J Remote Sens. 1998;19(10):1873–86. https://doi.org/10.1080/014311698215036
56. Prasad S, Bruce LM, Chanussot J. Optical remote sensing. Adv Signal Process Exploit Tech. 2011.
57. Ray RD, Douglas BC. Experiments in reconstructing twentieth-century sea levels. Prog Oceanogr. 2011;91(4):496–515. https://doi.org/10.1016/j.pocean.2011.07.021
58. Kumar A, Stupp P, Dahal S, Remillard C, Bledsoe R, Stone A, et al. A multi-sensor approach for assessing mangrove biophysical characteristics in coastal Odisha, India. Proc Natl Acad Sci India Sect Phys Sci. 2017;87:679–700.