

# Geographical Data and Computational Tools for Determining Restoration Priorities in Mangrove Ecosystems

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## Abstract

In this review article

## Introduction

### Mangrove Forest Ecosystems

Mangrove forests are unique, highly productive coastal ecosystems characterised by salt-tolerant trees and shrubs that thrive in the harsh intertidal zones. These plant species are also known as mangroves, as they are the dominant species in their environments. The areas between land and sea, where conditions fluctuate widely in salinity and water level, create complex niches for the distinct species that can tap into the vast resources that these areas possess; these forests are vital for global ecological balance, providing critical biodiversity services and supporting complex food webs [1].

A primary function of mangroves is to mitigate global climate change. They possess an exceptional capacity for carbon sequestration, storing up four times more carbon than comparable terrestrial forests [2]. Also, mangroves serve as natural coastal defence barriers, providing protection against tidal erosion and storm surges, while functioning as habitats for numerous species of fish and birds; thus supporting coastal communities worldwide.

Despite these benefits, mangrove forests are facing rapid decline: deforestation is primarily driven by anthropogenic pressures such as urbanisation, aquaculture expansion, and agricultural development, leading to reported annual loss rates of 1 to 2 per cent of total area [2]. The development of effective preservation strategies has become increasingly complex due to the diversity of mangrove species and the vast range of global climate conditions, generating demand for globally available datasets and advanced analytical tools. Having access to sound ecological modelling of species distributions allows for more effective restoration efforts, I.E., planting the right mangrove species after logging or climate disasters.

Additionally, real-time updates on forest coverage can issue warnings to NGOs and local authorities, which lead to faster, more effective action [1].

To address the challenge of global mangrove monitoring, the Global Mangrove Watch (GMW) platform provides open access to remote sensing data and analytical tools. This platform delivers near real-time information on mangrove extent and global change dynamics Global Mangrove Watch. A key component of GMW is the mangrove loss alert system, which utilises Copernicus Sentinel-2 satellite data processed at a 20-meter resolution. While Sentinel-2 typically provides weekly image acquisitions, the alert process is subject to delays due to cloud cover and the need for multiple observations to confirm genuine ecosystem change. Consequently, an alert is typically transmitted approximately three months after a loss event occurs [1].

### Geological Survey Tools: how is remote sensing performed?

The main technologies employed to collect geographical data for remote sensing of ecological landscapes are: LiDAR, multispectral imagery and hyperspectral imagery; as seen in Li et al., Giri et al., Lassalle et al., and Ghorbanian et al.[3][4][5][6].

LiDAR remote sensing is performed by low altitude aircraft equipped with light lasers; as the aircraft flies at constant speed, the sensor emits light and measures the time it takes to rebound, creating a 3D model of the scanned surface. It may struggle to get accurate plant resolution with multilatered, dense, tall forests[7].

Satellite Aperture Radar (SAR) consists of satellite imagery obtained by using sensors capable of utilising other bands of the electromagnetic spectrum. Depending on the bandwidths used by said sensors the images may be classified as multispectral (about 3 to 10 wide bands within the range of 0.43  $\mu\text{m}$  to 12.51  $\mu\text{m}$ ) or hyperspectral (a couple hundred narrow bands in the range of 0.4 to 2.5  $\mu\text{m}$ ) [8]. The usage of these tools was evaluated by Kwon and collaborators, and yielded promising results[9].

Despite having modern technology and open data access, achieving global conservation goals for coastal ecosystems has been difficult because consistent, worldwide data on their past and present health is lacking. Now, access to resources such as the decades-old Landsat satellite archive and newer, higher-resolution satellites enables us to analyse changes over long periods. This high-resolution data helps us accurately map scattered or fragmented ecosystems, such as mangrove forests. This new data is combined with powerful computing systems and cloud platforms (e.g., Google Earth Engine), allowing us to quickly process satellite data for the entire planet. This combination has encouraged many global-scale studies that can help answer critical questions for mangrove conservation. Still, it is important to note that these datasets merge data from different countries and institutions, which is often patchy, has varying resolutions, and may be incomplete. As seen in the Global Mangrove Watch official documentation, data fusion is needed to some extent, depending on the analysis one wishes to run. It will become evident when the results of the referenced studies are discussed, which poses challenges for running machine learning algorithms and for interpreting results holistically and ecologically.

## Aim

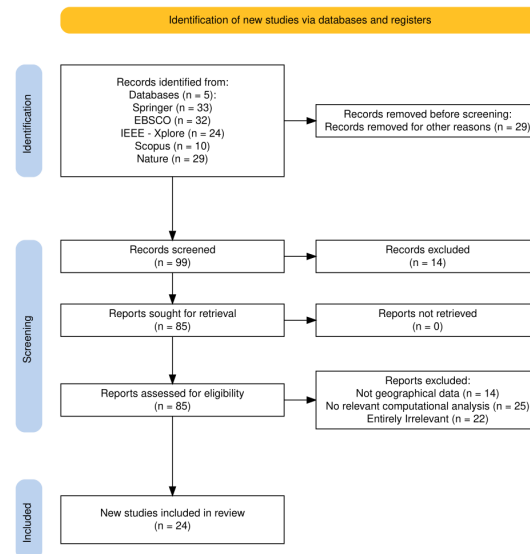
The aim of this paper is to assess the status of the technologies and analysis techniques used in determining the conservation status and restoration needs of mangrove forests; as well as identifying research gaps.

## Objectives

The five main objectives of this paper are:

1. To review and assess the current completeness and robustness of various available datasets. Several factors can affect data access and analysis, such as cloud cover and shadows when comparing satellite data. These limitations can hinder the consistency of images required for continuous change monitoring [10].
2. To identify the most common technologies used for mangrove identification and conservation, which implies understanding the benefits and limitations of each.
3. To identify the current computational models used to analyse these datasets and assess their performance metrics.
4. To outline the current challenges of measurement tools and computational analysis methods,

**Figure 1:** As shown, records were retrieved from different databases, relevant studies were screened in Nature as well; though these were excluded as the same papers are expected to show up from the other databases.



considering recent datasets and their analysis results [3].

5. To elaborate on the existing research gaps in order to address successfully identified shortcomings, which will be useful and relevant for future work in the subject.

## Methodology

### Article Selection Process

In the first stage of this scoping review, records from four major databases were retrieved. The initial search produced a combined set of studies, with the number of records obtained from each source presented in Figure 1.

During screening, we identified a number of non-English records and further duplicates. Because our institution offers full-text access to all searched databases, none of the records were excluded due to retrieval limitations.

The remaining studies were then divided among the research team, and each member screened titles and abstracts to assess their relevance to the research objectives. Studies were excluded if they did not involve geospatial data, if they relied solely on simple descriptive or statistical analyses, or if they did not use the modelling approaches central to our review, such as Random Forest or CNN-based methods, they fell outside the scope of this study.

## Findings

### Shortcomings of the Computational Analysis Techniques

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### Research Gaps

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Convolutional Neural Networks (CNNs) are the most widely used models in the field and form the foundation of most mangrove classification approaches; however, they struggle to detect small and fragmented mangroves resulting in incorrect classifications [11]. This limitation leads to three sub-challenges: the difficulty of distinguishing small patches of mangroves in complex backgrounds; the inefficiency of manual labelling in deep learning model training; and models developed or trained using data from one specific geographic region failing to perform well when applied to a different region with different characteristics [11].

Another limitation is encountered when analysing underwater scanning. Satellite data relies primarily on visible light and some wavelengths which are typically scattered by water resulting in poor accuracy for underwater mangroves. [10].

Furthermore, field validation and cross-referencing with local knowledge are necessary as some communities continue to explore methods for partial restoration. This can shape projects to maximise the benefits of identification and conservation of mangroves [1].

## Conclusions

## References

- [1] Maricé Leal and Mark D. Spalding. *The State of the World's Mangroves 2024*. Global Mangrove Alliance, July 2024. DOI: 10.5479/10088/119867. URL: <https://repository.si.edu/handle/10088/119867> (visited on 11/24/2025).
- [2] Thomas A. Worthington et al. "Harnessing Big Data to Support the Conservation and Rehabilitation of Mangrove Forests Globally". In: *One Earth* 2.5 (May 22, 2020), pp. 429–443. ISSN: 2590-3322. DOI: 10.1016/j.oneear.2020.04.018. URL: <https://www.sciencedirect.com/science/article/pii/S2590332220302050> (visited on 10/29/2025).
- [3] Qiaosi Li, Frankie Kwan Kit Wong, and Tung Fung. "Mapping multi-layered mangroves from multispectral, hyperspectral, and LiDAR data". In: *Remote Sensing of Environment* 258 (June 2021), p. 112403. ISSN: 00344257. DOI: 10.1016/j.rse.2021.112403. URL: <https://linkinghub.elsevier.com/retrieve/pii/S0034425721001218> (visited on 11/18/2025).
- [4] Chandra Giri et al. "Monitoring mangrove forest dynamics of the Sundarbans in Bangladesh and India using multi-temporal satellite data from 1973 to 2000". In: *Estuarine, Coastal and Shelf Science* 73.1 (June 1, 2007), pp. 91–100. ISSN: 0272-7714. DOI: 10.1016/j.ecss.2006.12.019. URL: <https://www.sciencedirect.com/science/article/pii/S0272771407000029> (visited on 11/25/2025).
- [5] Guillaume Lassalle et al. "Advances in multi- and hyperspectral remote sensing of mangrove species: A synthesis and study case on airborne and multisource spaceborne imagery". In: *ISPRS Journal of Photogrammetry and Remote Sensing* 195 (Jan. 2023), pp. 298–312. ISSN: 09242716. DOI: 10.1016/j.isprsjprs.2022.12.003. URL: <https://linkinghub.elsevier.com/retrieve/pii/S0924271622003185> (visited on 11/18/2025).
- [6] Arsalan Ghorbanian et al. "Weakly Supervised Semantic Segmentation of Mangrove Ecosystem Using Sentinel-1 SAR and Deep Convolutional Neural Networks". In: *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 18 (2025), pp. 17497–17512. ISSN: 2151-1535. DOI: 10.1109/JSTARS.2025.3586289. URL: <https://ieeexplore.ieee.org/document/11072052> (visited on 11/23/2025).
- [7] Liwei Deng et al. "Comparison of 2D and 3D vegetation species mapping in three natural scenarios using UAV-LiDAR point clouds and improved deep learning methods". In: *International Journal of Applied Earth Observation and Geoinformation* 125 (Dec. 2023), p. 103588. ISSN: 15698432. DOI: 10.1016/j.jag.2023.103588. URL: <https://linkinghub.elsevier.com/retrieve/pii/S1569843223004120> (visited on 11/18/2025).
- [8] GISGeography. *Multispectral vs Hyperspectral Imagery Explained*. GIS Geography. July 23, 2014. URL: <https://gisgeography.com/multispectral-vs-hyperspectral-imagery-explained/> (visited on 12/16/2025).

- [9] Soohyun Kwon, Hyeon Kwon Ahn, and Chul-Hee Lim. "Can Synthetic Aperture Radar Enhance the Quality of Satellite-Based Mangrove Detection? A Focus on the Denpasar Region of Indonesia". In: *Remote Sensing* 17.11 (Jan. 2025). Publisher: Multidisciplinary Digital Publishing Institute, p. 1812. ISSN: 2072-4292. DOI: 10.3390/rs17111812. URL: <https://www.mdpi.com/2072-4292/17/11/1812> (visited on 11/25/2025).
- [10] Uday Pimple et al. "Enhancing monitoring of mangrove spatiotemporal tree diversity and distribution patterns". In: *Land Degradation & Development* 34.5 (Mar. 1, 2023), pp. 1265–1282. ISSN: 1085-3278. DOI: 10.1002/ldr.4537. URL: <https://research.ebsco.com/linkprocessor/plink?id=1ac97efb-b02e-32b6-8ca3-f1f271c277bc> (visited on 11/25/2025).
- [11] Ruoxin Zhang et al. "FragMangro: A cross-domain zero-shot model for monitoring fragmented mangrove ecosystems". In: *Journal of King Saud University Computer and Information Sciences* 37.4 (May 20, 2025), p. 46. ISSN: 2213-1248. DOI: 10.1007/s44443-025-00053-y. URL: <https://doi.org/10.1007/s44443-025-00053-y> (visited on 11/18/2025).