

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 characterized by salt-tolerant trees and shrubs that thrive in the harsh intertidal zones. These plant species are also named mangroves, given that they are the dominant species of their environment. The areas between land and sea where conditions fluctuate widely in salinity and water level, which creates 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 their significant role in global climate change mitigation. They possess an exceptional capacity for carbon sequestration, storing up four times more carbon than comparable terrestrial forests [2]. Furthermore, ecologically, mangroves serve as natural coastal defense barriers, providing protection against tidal erosion and storm surges, while also functioning as critical nurseries and habitats for numerous species of fish, crustaceans, 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 urbanization, aquaculture expansion, and agricultural development, leading to reported loss rates of 1 to 2 percent of the total area per annum [2]. The complexity of developing effective preservation strategies is amplified by the diversity of mangrove species and the vast range of global climate conditions they inhabit, necessitating comprehensive, globally available datasets and advanced analytical tools to determine where particular species may or may not thrive. 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 instruments. 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 utilizes 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 caused by cloud cover and the requirement for multiple observations to confirm genuine ecosystem change. Consequently, an alert is typically transmitted approximately three months after a loss event occurs [1].

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 like the decades-old Landsat satellite archive and newer, higher-resolution satellites allows us to analyze changes over long periods. This high-resolution data helps us accurately map scattered or fragmented ecosystems like 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 data sets notably merge data from different countries and institutions, which is often patchy, has different resolutions, and may be incomplete. As seen in the Global Mangrove Watch official documentation, data fusion is needed to some extent, depending on the

kind of analysis one may wish to run. It will become evident when the results of the referenced studies are discussed, this poses challenges when running machine learning algorithms, and when interpreting the results from a holistic and ecological perspective.

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.[3]
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, considering recent datasets and their analysis results. [4]
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.

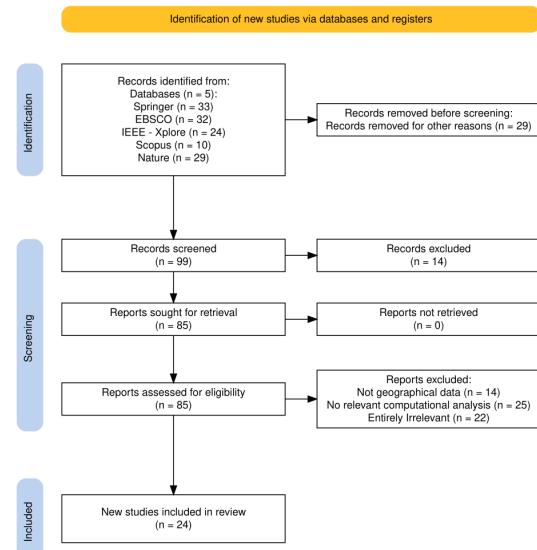
Methodology

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.

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.



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

This is the section for findings

Geological Survey Tools

This is the section for geological survey tools

Computational Analysis Techniques

This is the section for computational analysis techniques

Research Gaps

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Convolutional Neural Networks (CNNs) are the most widely used models in the field and are the foundation of most mangrove classification approaches. However, they struggle to detect small and fragmented mangroves resulting in incorrect classifications. [5] This gap in specific leads to the three sub-challenges, the first one is the difficulty of distinguish

small patches of mangroves in complex backgrounds. Secondly, manual labeling in deep learning model training results inefficient. And lastly, models used for analyzing mangroves (e.g., using satellite imagery or other data) that were developed or trained using data from one specific geographic region do not perform well when applied to a different region with different characteristics.

Another limitation encountered was when analysing underwater scanning. Given that satellite data relies mainly on visible light and some wavelengths, which are typically scattered by water, making accuracy poor for underwater mangroves. [3]

<https://doi.org/10.s44443-025-00053-y> (visited on 11/18/2025).

Conclusion

References

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