Geographical Data and Computational Tools for Determining Restoration Priorities in Mangrove Ecosystems: A Scoping Review

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Abstract

Provide a structured summary that includes (as-applicable): background, objectives, eligibility criteria,sources of evidence, charting methods, results, and-conclusions that relate to the review questions andobjectives.

Introduction

Mangrove forests are among the most productive and valuable coastal ecosystems, providing essential ecosystem services such as shoreline stabilisation, storm surge attenuation, carbon sequestration, nutrient cycling, and biodiversity support. These services play a critical role in supporting coastal livelihoods and mitigating climate related risks. Despite their importance, mangrove ecosystems continue to experience widespread degradation driven by aquaculture expansion, coastal development, altered hydrological regimes, pollution, and climate induced stressors including sea level rise and increasing temperature extremes.

Over the past two decades, substantial progress has been made in monitoring mangrove ecosystems through advances in Earth observation technologies and computational analysis. Global and regional datasets derived from optical satellite imagery, synthetic aperture radar (SAR), LiDAR, hyperspectral sensors, and unmanned aerial vehicles have enabled increasingly detailed assessments of mangrove extent, structure, and temporal dynamics. In parallel, machine learning and deep learning methods have been widely adopted to improve classification accuracy, detect change, and estimate biophysical properties such as canopy height and biomass. Collectively, this body of work has significantly advanced the ability to observe mangrove forests at multiple spatial and temporal scales.

However, these advances have largely evolved in isolation. Existing studies typically focus on specific sensing modalities, geographic regions, or analytical tasks, with limited integration across data sources or modelling approaches. As a result, much of the literature remains oriented toward mapping and monitoring, rather than toward decision relevant assessment of restoration needs and long-term ecosystem resilience. In particular, the growing diversity of datasets and computational tools has not been systematically synthesised to evaluate how effectively current approaches support restoration prioritisation.

To address these challenges, this scoping review systematically synthesises existing research on mangrove ecosystem monitoring and restoration prioritisation. Specifically, the objectives of this review are to:

- Examine the completeness and robustness of existing geospatial datasets used for mangrove analysis.
- Identify the sensing technologies employed to acquire mangrove data, including optical, SAR, LiDAR, hyperspectral, and thermal modalities.
- Review the computational and machine learning techniques applied to these datasets, along with their reported performance metrics.
- Outline current limitations associated with data acquisition and computational analysis approaches.
- Identify key research gaps related to regional bias, data availability, and methodological limitations in current mangrove research.

A scoping review approach is appropriate for this study because the literature on mangrove restoration spans diverse datasets, sensing technologies, and computational methods, with heterogeneous objectives, study designs, and evaluation metrics that preclude narrow systematic synthesis. This approach enables comprehensive mapping of existing evidence, identification of methodological trends, and systematic detection of research gaps across disciplines.

Importantly, this review does not propose or evaluate a specific computational model. Rather, it synthesises existing evidence to identify limitations in current practice and to outline future research directions for mangrove ecosystem analysis. While the paper examines a broad range of methodological and practical issues, such as the availability and reliability of data, limitations in measurement technologies, the ways in which models are assessed, and the extent to which existing approaches support restoration decision making, these challenges ultimately converge around two overarching methodological gaps. The first is strong regional bias that limits model generalisation across diverse ecological contexts. The second is the absence of unified multimodal forest frameworks capable of integrating complementary geospatial data into holistic and decision relevant representations.

Methodology

This study adopts a scoping review methodology following the PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses - Scoping Reviews) guidelines. A scoping review approach was selected due to the interdisciplinary nature of the research topic, which spans geospatial data acquisition, remote sensing technologies, and computational analysis techniques applied to mangrove ecosystems. This approach enables comprehensive mapping of existing research, identification of methodological trends, and systematic detection of research gaps without restricting inclusion to narrowly defined outcome measures.

Literature Search Strategy

A structured literature search was conducted across five academic databases: *SpringerLink*, *IEEE Xplore*, *EBSCO*, *Scopus*, and *Nature*. These databases were selected to ensure broad coverage of environmental science, Earth observation, and machine learning literature.

Search queries were designed to capture studies related to mangrove ecosystems, geospatial data acquisition, and computational modelling. Keywords included combinations of terms such as *mangrove*, *remote sensing*, *satellite*, *SAR*, *LiDAR*, *hyperspectral*, *thermal*, *machine learning*, *deep learning*, and *convolutional neural networks*. The search strategy was intentionally broad to maximise recall, consistent with scoping review best practices.

Study Selection and Screening

All records retrieved from the database searches were aggregated and screened in multiple stages. Duplicate records were removed prior to screening. Non-English publications were excluded at this stage to ensure consistency in analysis.

The remaining records underwent title and abstract screening. Because the authors's institution provides

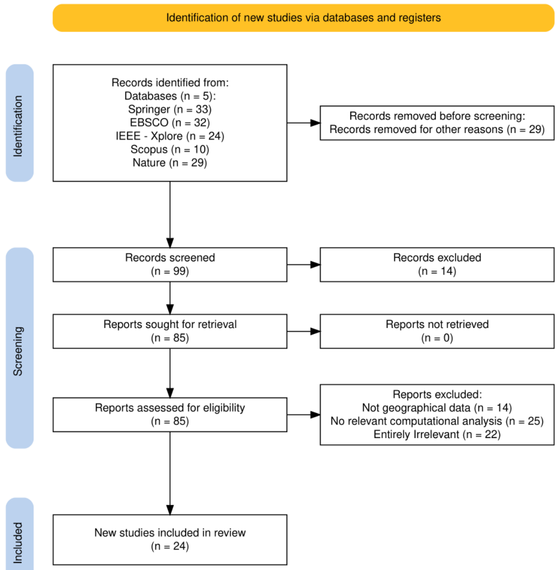

Figure 1: *PRISMA flow diagram illustrating the identification, screening, eligibility assessment, and inclusion of studies in this scoping review.*

full-text access to all searched databases, no studies were excluded due to retrieval limitations. The screened studies were then divided among members of the research team, and each reviewer independently assessed titles and abstracts for relevance to the research objectives.

Studies were excluded during screening if they:

- did not involve geospatial or remotely sensed data.
- relied solely on descriptive or basic statistical analyses without computational modelling.
- did not employ modelling approaches central to this review, such as machine learning or deep learning methods (e.g., Random Forest, convolutional neural networks).

Disagreements between reviewers were resolved through discussion to ensure consistency in study selection.

Eligibility Assessment and Inclusion

Following the screening stage, the remaining studies were assessed at the full-text level for eligibility. Studies were excluded if they lacked a clear spatial component, did not contribute substantively to understanding mangrove ecosystem monitoring or restoration, or fell outside the scope of computational and geospatial analysis considered in this review.

After applying the eligibility criteria, a final set of studies was retained for inclusion in the scoping review. These studies form the basis for the qualitative synthesis and quantitative analysis presented in subsequent sections.

Article Selection Process

The overall study selection process is summarised in the PRISMA flow diagram shown in Figure 1. The diagram illustrates the identification of records across databases, removal of duplicates, screening of titles and abstracts, assessment of full-text eligibility, and final inclusion of studies in the review.

Current Data Availability and Dataset Robustness

Evolution of Global Mangrove Datasets

Global mangrove datasets underpin large scale conservation assessments and policy initiatives. Early global products, such as the World Mangrove Atlas and the Landsat-based map by Giri et al. (2011), provided the first consistent estimates of global mangrove extent. While these datasets established critical baselines, they were static snapshots and did not capture temporal dynamics.

The introduction of time-series datasets marked a significant methodological shift. The Continuous Global Mangrove Forest Cover for the 21st Century (CGMFC-21) provided annual mangrove extent maps from 2000 to 2014 at 30 m resolution, enabling year-by-year analysis of loss and gain (Hamilton & Casey, 2016). However, CGMFC-21 employed conservative mangrove definitions, resulting in substantially lower area estimates than other products and potentially under-representing sparse or degraded stands.

The Global Mangrove Watch (GMW) initiative represents the most comprehensive effort hitherto, integrating optical and SAR data to produce multi-epoch and near-global time-series products. The latest release, GMW v4.0, established a 10 m resolution global baseline for 2020 with reported overall accuracy exceeding 95% (Bunting et al., 2022). This improvement significantly enhances the detection of narrow, fragmented, and small mangrove patches. Table 1 provides a comparative overview of major global mangrove datasets, summarising their release timelines, spatial resolution, temporal coverage, primary data sources, and the ecosystem attributes they capture.

Dataset Robustness and Uncertainty

Despite methodological advances, global mangrove datasets remain subject to several limitations. Differences in sensor selection, classification algorithms, training data, and mangrove definitions lead to discrepancies in mapped extent, particularly near latitudinal range limits and in transitional ecosystems (Leal & Spalding, 2024). Temporal gaps between dataset updates may obscure short-term disturbances or rapid regeneration events, while most global products prioritise extent over structural or functional attributes.

Furthermore, validation data are unevenly distributed geographically. Regions with limited field data often exhibit higher uncertainty, which can propagate into downstream analyses. These limitations highlight the need for complementary regional datasets, improved uncertainty quantification, and integration of structural and functional information for restoration planning.

Geological Survey Tools and Data Acquisition Technologies

Mangrove ecosystems are monitored using a diverse suite of geospatial sensing technologies, each capturing distinct and complementary attributes of forest condition. No single sensing modality provides a complete description of mangrove ecosystems, making multimodal integration essential for restoration-oriented analysis.

A holistic representation, in this context, refers to a joint latent encoding that simultaneously captures forest extent, vertical structure, physiological condition, hydrological dynamics, and temporal change, enabling restoration prioritisation based on both current state and long-term resilience.

Figure 2 provides an overview of the major sensing modalities used in mangrove studies and the ecological attributes they capture.

[Figure 2 placeholder: Sensing modalities and mangrove attributes captured]

Geospatial and Remote Sensing Tools Used in Mangrove Research

Table 1 summarises the aggregated frequency of major geospatial and sensing tools used in mangrove studies across the surveyed databases.

Several clear trends emerge from Table 1. First, satellite-based and airborne optical and radar systems dominate mangrove research, reflecting their scalability and long-term data availability. High-resolution aerial imagery and SAR-based platforms (particularly ALOS-PALSAR) appear most frequently, highlighting the community's reliance on sensors capable of capturing canopy structure and inundation dynamics.

Second, advanced sensing modalities such as LiDAR and hyperspectral imaging remain comparatively underrepresented, despite their demonstrated ability to capture three-dimensional structure, species composition, and biochemical traits (Li et al., 2021;

Table 1: *Major global mangrove datasets and their key characteristics*

Dataset	First Release	Spatial Resolution	Temporal Coverage	Primary Data Sources	Mangrove Attributes Captured
Global Mangrove Forests Distribution	2000	∼30 m	Circa 2000	Landsat	Extent
CGMFC-21	2014	∼30 m	2000–2012	Landsat-derived products	Annual extent and change
Global Mangrove Watch v2.0	2019	20–25 m	1996–2016	ALOS PALSAR, Landsat	Extent and loss
Global Mangrove Watch v3.0	2022	∼25 m	1996–2020	Multi-mission SAR and optical	Extent and temporal dynamics
Global Mangrove Canopy Height Maps	2020+	∼30 m	Multi-year	DEM and optical integration	Canopy height and structure
Global Mangrove Soil Carbon Stocks	2023	∼30 m	2020	Remote sensing and modelling	Soil organic carbon

Tool / Data Source	Number of Studies
High-Resolution Aerial Imagery	2431
ALOS-PALSAR (SAR)	2205
Thermal SAR (T-SAR)	1799
Thermal Infrared Sensors (TIRS)	1120
Hyperspectral Imaging (HSI)	812
SAR (general)	449
Satellite Platforms (general)	266
CubeSats	174
LiDAR	123
Landsat	28

Table 2: *Summary of tools and data sources used in mangrove studies*

Fu et al., 2025). This suggests that while high-fidelity structural and functional data are recognised as valuable, their integration into mainstream mangrove monitoring workflows remains limited, likely due to cost, availability, and analytical complexity.

Third, the relatively low representation of Landsat compared to SAR-based and aerial platforms reflects a gradual shift away from coarse optical imagery toward sensors better suited to cloud-prone, hydrologically dynamic coastal environments. Overall, these patterns indicate a strong dependence on a narrow subset of sensing technologies, reinforcing the need for multimodal integration to capture the full complexity of mangrove ecosystems.

Optical Multispectral Remote Sensing

Optical multispectral imagery from platforms such as Landsat and Sentinel-2 remains the most widely used data source for mangrove monitoring. These sensors support vegetation indices, phenological analysis, and land-cover classification (Bunting et al., 2022). Sentinel-2's red-edge bands enhance discrimination between mangrove vegetation and adjacent land covers but remain susceptible to cloud cover and atmospheric interference (Zhang et al., 2025).

Synthetic Aperture Radar (SAR)

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 um to 12 12.51 um) or hyperspectral (a couple hundred narrow bands in the range of 0.4 to 2.5 um) [8]. The usage of these tools was evaluated by Kwon and collaborators, and yielded promising results . SAR sensors provide cloud-independent observations and sensitivity to vegetation structure, moisture, and inundation dynamics. Sentinel-1 and ALOS PALSAR have proven effective for mangrove delineation in persistently cloudy regions and for detecting fragmented or narrow forest stands (Ghorbanian et al., 2025). SAR's ability to capture tidal and hydrological dynamics makes it particularly valuable for restoration suitability assessments.

LiDAR

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.

Hyperspectral and Thermal Infrared Sensors

Hyperspectral data support species-level discrimination and biochemical trait estimation, while thermal infrared data reveal physiological stress and hydrological anomalies (Farella et al., 2022; Fu et al., 2025). These modalities are underutilised in large-scale mangrove studies but offer significant potential for early stress detection and restoration monitoring.

UAV-Based Observations

UAV platforms provide ultra-high spatial resolution imagery for local-scale assessment and validation. While invaluable for monitoring restoration sites, UAV data lack scalability and require integration with satellite-based observations.

Computational Analysis Techniques

Computational and Analytical Techniques in Mangrove Research

Table 2 summarises the distribution of computational and analytical techniques applied in mangrove studies. The computational landscape revealed by Table 2 is notably methodologically conservative. Classical machine learning methods, particularly Random Forest and Support Vector Machines, dominate the literature. Their prevalence reflects advantages such as interpretability, robustness to noisy inputs, and suitability for moderate-sized datasets, which are common in ecological studies.

Computational Technique	Number of Studies
Spatiotemporal Models	634
Random Forest	556
Neural Networks (general)	419
Change Detection	350
Time-Series Models	305
Support Vector Machines	268
Decision Trees	192
Maximum Entropy (MaxEnt)	79
Gradient Boosting	70
XGBoost	70

Table 3: *Distribution of computational techniques used in mangrove-related studies*

Deep learning methods, while increasingly present, remain underrepresented relative to their potential, particularly for tasks requiring spatial context or multimodal integration. Neural networks are often applied in isolation to single-sensor data, typically optical imagery, limiting their ability to model complex ecosystem interactions.

Spatiotemporal and time-series models show growing adoption, reflecting increased access to long-term satellite archives. However, these approaches are typically restricted to single-modality temporal stacks, rather than fully integrated multimodal time-series analysis. Notably, advanced multimodal and attention-based architectures are almost entirely absent, despite their success in broader remote sensing and computer vision domains.

Classical Machine Learning Approaches

Random Forest, Support Vector Machines, and Maximum Entropy models remain widely used due to robustness and interpretability. These methods perform well for mangrove extent mapping and habitat suitability modelling but struggle with continuous structural variables such as canopy height and biomass (Li et al., 2021; Aparicio & Viodor, 2025).

Deep Learning for Mangrove Analysis

Convolutional Neural Networks have become dominant for high-resolution mangrove mapping, offering improved detection of fragmented and heterogeneous forests (Zhang et al., 2025; FragMangro, 2025). Temporal extensions, including ConvLSTM models, enable modelling of growth, disturbance, and recovery dynamics (Jamaluddin et al., 2024).

Multimodal and Attention-Based Models

Transformer-based architectures have emerged as powerful tools for multimodal remote sensing analysis. Cross-Attention Multimodal Transformers (CA-MMTs) fuse modalities at the channel level, enabling strong alignment and interaction across heterogeneous inputs (Bahaduri et al., 2024). This approach is particularly suited to mangrove ecosystems, where data availability varies spatially and temporally due to cloud cover, tidal state, and sensor coverage.

CA-MMT is highlighted here as a representative example of attention-based multimodal fusion rather than a prescriptive solution, and future work should empirically compare multiple fusion strategies under varying data availability and domain shift conditions.

While classification and regression metrics such as overall accuracy, AUC, and RMSE are widely reported, these metrics do not fully capture ecological or restoration relevance, highlighting the need for task-specific evaluation criteria aligned with resilience, suitability, and long-term viability.

[Figure 3 placeholder: Computational approaches and multimodal fusion strategies]

Implications for Mangrove Restoration Research

The quantitative patterns observed in Tables 1 and 2 provide strong empirical support for the research gaps identified in this review.

First, the dominance of satellite-centric tools combined with classical machine learning techniques indicates that most existing studies prioritise extent mapping and change detection, rather than holistic ecosystem assessment. While effective for monitoring loss and gain, such approaches are insufficient for restoration prioritisation, which requires integrating structural integrity, physiological stress, hydrological suitability, and long-term resilience.

Second, the limited adoption of LiDAR, hyperspectral, thermal, and UAV-based data—together with the scarcity of multimodal computational frameworks—highlights a disconnect between data richness and analytical capability. The sensing technologies required to characterise mangrove ecosystems comprehensively already exist, but are rarely combined within unified analytical pipelines.

Finally, the concentration of computational approaches around a small number of algorithms reinforces concerns regarding methodological inertia. Without systematic exploration of multimodal representation learning, domain adaptation, and generalisable architectures, mangrove research risks remaining fragmented and region-specific.

These findings quantitatively reinforce the need for unified multimodal forest frameworks, in which complementary sensing modalities are fused through flexible computational architectures to produce robust, transferable, and restoration-relevant representations of mangrove ecosystems.

Research Gaps

Regional Bias

When models trained within a single geographic context are applied to new regions, performance degradation is expected due to strong domain shift in spectral, structural, and environmental characteristics; however, such cross-region evaluations are rarely reported in the mangrove literature, with only isolated studies explicitly addressing transfer learning or domain adaptation (Li et al., 2021; Fu et al., 2025; Leal & Spalding, 2024; Wu et al., 2025).

[Figure 4 placeholder: Regional distribution of mangrove studies and data availability]

Mangrove ecosystems exhibit substantial regional heterogeneity in species composition, canopy architecture, sediment properties, tidal regimes, and anthropogenic pressure. These differences induce systematic variation in optical reflectance, SAR backscatter, thermal signatures, and structural metrics, resulting in significant covariate and concept shift across regions. As a result, models trained on data-rich regions—predominantly in Asia—may encode region-specific correlations rather than ecologically invariant representations.

This imbalance is not solely a data availability issue but has direct implications for model development, as algorithms trained predominantly on data-rich regions may encode region-specific correlations rather than ecologically invariant representations. Addressing regional bias is therefore essential for both scientific validity and operational scalability, requiring systematic cross-region evaluation, domain adaptation, and transfer learning strategies.

Lack of a Unified Multimodal Forest Framework

A second major research gap is the absence of a unified multimodal forest framework capable of integrating complementary geospatial data sources into a coherent and ecologically meaningful representation of mangrove ecosystems.

Each sensing modality captures a distinct and non-redundant component of forest condition:

- Optical multispectral imagery encodes extent, canopy cover, and phenology (Bunting et al., 2022).
- SAR captures structure, moisture, and inundation dynamics under all-weather conditions (Ghorbanian et al., 2025).
- LiDAR provides direct measurements of three-dimensional canopy architecture and biomass (Li et al., 2021).
- Thermal infrared data reveal physiological stress and hydrological anomalies (Farella et al., 2022).
- Hyperspectral data support biochemical and species-level trait estimation (Fu et al., 2025).

When analysed independently, these modalities provide only partial views of ecosystem condition. Optical imagery may indicate intact canopy cover even under physiological stress, while LiDAR-derived height may not reflect hydrological constraints or thermal extremes. Restoration decisions based on single-modality analyses therefore risk misidentifying resilient or suitable restoration sites.

Recent advances in multimodal representation learning provide a pathway toward addressing this limitation. Li et al. (2021) demonstrated that fusing multispectral, hyperspectral, and LiDAR data improves multilayer structural mapping, while Bahaduri et al. (2024) showed that channel-level cross-attention enables dynamic alignment between heterogeneous modalities. Channel-level fusion is particularly advantageous in mangrove ecosystems, where data relevance varies spatially and temporally due to cloud cover, tidal state, and sensor availability.

Figure 5 illustrates a conceptual unified multimodal framework designed to integrate spatiotemporal optical data, SAR, LiDAR, thermal infrared, and multispectral or hyperspectral inputs into a joint latent forest representation. [Figure 5 placeholder: Conceptual unified multimodal mangrove framework]

Importantly, this review does not advocate for a single architectural solution. Cross-attention transformers, multimodal CNNs, graph-based models, hybrid ConvLSTM–Transformer pipelines, and ensemble approaches all represent viable pathways depending on data availability and restoration objectives. The critical gap lies not in the absence of a specific model, but in the lack of end-to-end, restoration-oriented multimodal frameworks explicitly designed to support generalisable and decision-relevant mangrove ecosystem assessment.

Limitations of CNN-Centric Approaches in Fragmented Mangrove Landscapes

Convolutional neural networks (CNNs) form the foundation of most deep learning-based mangrove classification and mapping approaches. While effective for large, contiguous forest stands, CNN-based pipelines often struggle to accurately detect small, fragmented, or narrow mangrove patches embedded within complex coastal backgrounds. This limitation is particularly problematic in regions where mangroves are highly fragmented due to urbanisation, aquaculture, or partial degradation.

These challenges manifest in three interconnected ways: difficulty in distinguishing small mangrove patches from spectrally similar backgrounds; reliance on extensive manual labelling, which is inefficient and costly in ecologically diverse landscapes; and reduced model robustness when applied to regions with different spatial patterns or fragmentation characteristics. Addressing these issues requires exploration of alternative architectures, multiscale representations, and weakly supervised or semi-supervised learning strategies.

Inadequate Observation of Submerged and Underwater Mangrove Components

Another critical limitation in current mangrove monitoring approaches relates to the observation of submerged or underwater mangrove components. Most satellite-based remote sensing relies on visible and near-infrared wavelengths, which are strongly attenuated and scattered by water, resulting in limited penetration and reduced accuracy for submerged vegetation. As a result, below-water root structures and early-stage mangrove regeneration in shallow or turbid environments are often poorly characterised or entirely missed.

This sensing limitation constrains the ability to assess mangrove health and restoration potential in intertidal and subtidal zones. Addressing this gap will require integration of alternative sensing strategies, such as UAV-based surveys, acoustic or bathymetric data, and improved fusion of radar and optical observations under varying tidal conditions.

Limited Integration of Field Validation and Local Knowledge

Despite advances in geospatial analysis and machine learning, field validation and integration of local ecological knowledge remain insufficiently incorporated into many mangrove restoration studies. Ground-based observations and community-driven knowledge are essential for validating remotely sensed classifications, understanding site-specific constraints, and identifying feasible restoration pathways.

The absence of systematic field validation can result in restoration suitability maps that are technically accurate yet misaligned with local ecological, hydrological, or socio-economic realities. Future frameworks should therefore emphasise participatory validation, integration of in situ measurements, and collaboration with local stakeholders to ensure that computational outputs translate into effective and context-aware restoration decisions.

Future Work: Toward Unified Multimodal Frameworks for Mangrove Restoration Prioritisation

The research gaps identified in this review highlight the need for a paradigm shift in mangrove ecosystem analysis, from isolated, region-specific modelling pipelines toward unified, multimodal, and generalisable computational frameworks. Addressing these gaps requires coordinated advances in data integration, model design, evaluation methodology, and translational practice.

A primary direction for future work is the development of *unified multimodal forest frameworks* that integrate complementary sensing modalities, including spatiotemporal optical imagery, SAR, LiDAR, thermal infrared, and multispectral or hyperspectral data. Each modality captures distinct ecological attributes—such as canopy extent, vertical structure, physiological stress, inundation dynamics, and biochemical composition—that cannot be fully represented using any single data source. Multimodal integration enables the construction of holistic latent representations capable of supporting restoration prioritisation based on both current ecosystem condition and long-term resilience.

Recent advances in multimodal representation learning offer promising tools for achieving such integration. Attention-based architectures, including cross-attention multimodal transformers, allow heterogeneous data streams to interact at the feature or channel level, enabling dynamic weighting of modalities based on contextual relevance and data quality. This property is particularly valuable in mangrove environments, where sensor availability and informativeness vary spatially and temporally due to cloud cover, tidal state, and acquisition constraints. However, future research should remain architecture-agnostic, systematically comparing attention-based transformers, multimodal convolutional networks, graph-based models, and hybrid spatiotemporal pipelines under realistic data availability and domain shift conditions.

Addressing *regional bias and limited generalisation* represents another critical research direction. Future frameworks should explicitly incorporate cross-region validation, transfer learning, and domain adaptation strategies to assess and improve model robustness across diverse ecological contexts. Pre-training multimodal models on globally distributed datasets, followed by region-specific fine-tuning using limited local data, represents a promising pathway for reducing dependence on data-rich regions and improving scalability.

Future work must also move beyond CNN-centric pipelines that struggle in fragmented mangrove landscapes. Exploration of multi-scale representations, object-centric models, weakly supervised learning, and semi-supervised approaches may improve detection of small or degraded mangrove patches while reducing reliance on extensive manual labelling. Such approaches are particularly important in urbanised or partially restored coastal environments where fragmentation is pronounced.

The challenge of observing submerged and underwater mangrove components further motivates integration of alternative sensing strategies. Combining satellite observations with UAV-based surveys, bathymetric data, and tide-aware data fusion can improve characterisation of intertidal and subtidal zones. Developing models that explicitly account for tidal state and water-column effects will be essential for accurate assessment of early-stage regeneration and below-canopy structures.

Finally, future research should prioritise *restoration-oriented and participatory outputs*. Integrating field validation, in situ measurements, and local ecological knowledge into computational pipelines will be critical for ensuring that model outputs are actionable and context-aware. Restoration prioritisation frameworks should produce interpretable suitability indices, uncertainty estimates, and scenario-based projections that support decision-making by practitioners, policymakers, and local communities.

Conclusions

This scoping review synthesised the current state of geographical data, sensing technologies, and computational tools used to determine restoration priorities in mangrove ecosystems. By combining qualitative literature analysis with quantitative synthesis of tools and techniques across major academic databases, the review provides a comprehensive overview of methodological trends, strengths, and limitations in contemporary mangrove research.

The findings reveal that while satellite-based optical and SAR data dominate the literature and classical machine learning approaches remain prevalent, advanced sensing modalities such as LiDAR, hyperspectral, and thermal infrared data are comparatively underutilised. Similarly, despite growing interest in deep learning, most computational pipelines remain CNN-centric and single-modality, limiting their effectiveness in fragmented landscapes and complex ecological settings.

Five critical research gaps were identified. First, strong regional bias in data availability and model development constrains generalisation and scalability. Second, the absence of unified multimodal forest frameworks restricts the integration of complementary structural, functional, and temporal information. Third, CNN-based approaches struggle with small and fragmented mangrove patches and rely heavily on costly manual labelling. Fourth, current sensing strategies inadequately capture submerged and underwater mangrove components. Finally, limited integration of field validation and local ecological knowledge reduces the translational impact of computational outputs.

Addressing these gaps requires a shift toward unified, multimodal, and generalisable computational frameworks that integrate diverse sensing modalities, explicitly account for domain shift, and align model outputs with restoration decision-making needs. By framing mangrove restoration as a multimodal representation learning and generalisation challenge, this review positions future research at the intersection of remote sensing, ecology, and machine learning. Advancing in this direction is essential for translating technological progress into robust, scalable, and socially relevant strategies for mangrove conservation and restoration.

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