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, andconclusions that relate to the review questions andobjectives.

Introduction

Mangrove forests are among the most productive and valuable coastal ecosystems, perfoming ecological functions such as shoreline stabilisation, storm surge attenuation, carbon sequestration, nutrient cycling, and biodiversity support [1].

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 and fishing enterprise globally [1].

Despite the former, as shown in the The State of the World's Mangroves 2024, these 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[1].

Over the past two decades, substantial progress has been made in monitoring mangrove ecosystems through advances in Earth observation technologies and computational analysis[2]. 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 [3], [4], [5], [6], [7], [8], [9], [2], [10], [11], [12], [13], [14], [15], [16] [17], [18], [19].

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. 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 the computational analysis of the resulting data. 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. Thus, this paper aims identify methodological trends and detect research gaps in the current ecological framework used in mangrove ecosystems.

This review does not propose or evaluate a specific computational model: it synthesises existing evidence to identify limitations in current practice and to outline future research directions for mangrove ecosystem analysis.

As will become evident later, strong regional bias limits model generalisation across diverse ecological contexts, and the absence of unified multimodal forest frameworks capable of integrating complementary geospatial data into holistic and decision relevant representations are the main hindrances to streamling the process. This leads to many events such as floods, fires, and human intervention not being addressed in time by local NGOs or local authorities. It also make the implementation of this techniques in new enviroments costly in time and resources.

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.

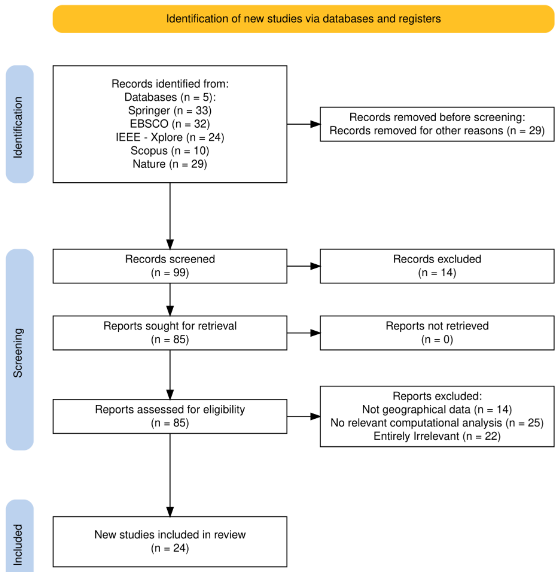

Figure 1: *PRISMA flow diagram illustrating the identification, screening, eligibility assessment, and inclusion of studies in this scoping review.*

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 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.

Geospatial and Remote Sensing Tools Used in Mangrove Research

Table 2 summarises the aggregated frequency of major geospatial and sensing tools used in mangrove studies across the surveyed databases.

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

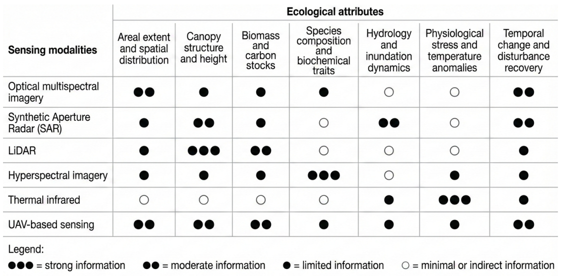

Figure 2: *Conceptual modality attribute matrix illustrating the relative strength of ecological information captured by different sensing modalities in mangrove ecosystem studies*

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*

Several clear trends emerge from Table 2. 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; 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

Machine learning and deep learning methods are increasingly used to analyse mangrove-related geospatial datasets for both regression and classification tasks, driven by the growing availability of multi-source remote sensing data and the need to infer biophysical properties at scale (Adam et al., 2010; Giri et al., 2011; Hamilton & Casey, 2016). Regression tasks typically aim to estimate continuous variables such as above-ground biomass, carbon stocks, or canopy height, whereas classification tasks focus on mangrove extent delineation, species discrimination, and change detection (Lucas et al., 2007; Bunting et al., 2018). Across these applications, ensemble-based methods, kernel-based learners, and deep neural networks have emerged as dominant computational approaches.

Regression-based modelling

Regression-based machine learning models are widely applied to estimate mangrove biomass and structural attributes from remotely sensed inputs. Commonly used algorithms include Random Forest (RF), Support Vector Machine (SVM), and gradient boosting methods such as Extreme Gradient Boosting (XGBoost), owing to their ability to model non-linear relationships between spectral, textural, and structural features (Breiman, 2001; Cortes & Vapnik, 1995; Friedman, 2001). Model performance is most often evaluated using the coefficient of determination (R^2) and root mean square error (RMSE), which together capture explanatory power and absolute prediction error (Li et al., 2021; Maung et al., 2025).

Empirical results reported in the mangrove literature indicate moderate to strong predictive performance for biomass estimation, though with substantial variability across regions and forest types. For example, Maung et al. (2025) evaluated RF, SVM, and XGBoost models for above-ground biomass estimation in Myanmar mangroves using multispectral and SAR inputs and reported that RF achieved the best performance (R^2 = 0.48, RMSE = 28.12 Mg ha^{-1}) after feature selection, while alternative models exhibited markedly lower explanatory power. In a contrasting subtropical plantation setting, Peng et al. (2025) reported higher accuracy using XGBoost applied to Sentinel-2 data, achieving an R^2 of approximately 0.68 with an RMSE of 6.85 Mg ha^{-1}, reflecting the reduced structural complexity and biomass range of managed stands. In structurally complex old-growth mangroves, Selvaraj et al. (2023) reported an R^2 of 0.78 but a substantially higher RMSE of 38.24 Mg ha^{-1}, highlighting the influence of biomass heterogeneity and signal saturation effects.

Across studies, reported R^2 values for mangrove biomass estimation commonly fall within the range of 0.5–0.8, with RMSE values strongly dependent on forest maturity, biomass distribution, and sensor configuration (Simard et al., 2019; Xie et al., 2025). Multiple studies demonstrate that regression performance improves when complementary structural information is incorporated. In particular, the integration of canopy height metrics derived from airborne or spaceborne LiDAR with optical and SAR features has been shown to mitigate saturation effects and improve predictive accuracy (Asner et al., 2012; Simard et al., 2019; Xie et al., 2025). These findings consistently support the value of multimodal data fusion for robust estimation of mangrove biophysical properties.

Classification-based modelling

Classification approaches are extensively used for mangrove extent mapping, species classification, and land cover change detection. Traditional machine learning models such as Random Forest and SVM remain widely adopted due to their robustness to noisy inputs and limited training data requirements (Belgiu & Drăguţ, 2016; Giri et al., 2011). More recently, convolutional neural networks (CNNs) and other deep learning architectures have been applied for pixel-level segmentation and fine-scale species mapping, particularly where high-resolution optical or hyperspectral imagery is available (Li et al., 2022; Lassalle et al., 2023).

Reported classification performance is typically quantified using overall accuracy, Cohen's Kappa, F1-score, or area under the receiver operating characteristic curve (AUC), depending on task formulation (Congalton & Green, 2019). Representative studies indicate that high classification accuracy is achievable under favourable conditions. For instance, Aparicio and Viodor (2025) demonstrated strong performance of a lightweight CNN architecture (MobileNetV3) for mangrove species identification from smartphone imagery, illustrating the potential of deep learning for in situ and participatory monitoring applications. In remote sensing–based studies, Random Forest classifiers frequently achieve overall accuracies exceeding 90% when trained on high-resolution multispectral or hyperspectral data, while SVM performance is more sensitive to kernel selection and training sample composition (Adam et al., 2010; Fu et al., 2025).

Across the literature, overall classification accuracies for mangrove mapping commonly range between 80% and 95%, with higher values often reported in studies covering limited spatial extents or a small number of species classes (Lassalle et al., 2023; Fu et al., 2025). However, several studies caution that high overall accuracy can obscure systematic misclassification of rare species or fragmented mangrove patches, emphasising the importance of reporting class-level metrics and confusion matrices (Congalton & Green, 2019; Belgiu & Drăguţ, 2016).

Evaluation practices and limitations

Despite advances in computational modelling, evaluation practices across mangrove studies remain heterogeneous. Most studies rely on random cross-validation or hold-out test sets drawn from the same geographic region used for model training, while cross-region or cross-site validation is rarely conducted (Maung et al., 2025; Fu et al., 2025). As a result, reported performance metrics may overestimate model generalisability, particularly in geographically heterogeneous mangrove systems where spectral, structural, and environmental conditions vary substantially (Lucas et al., 2007; Simard et al., 2019).

Differences in target variables, sensor combinations, spatial resolution, and validation protocols further limit direct comparison of reported metrics across studies (Congalton & Green, 2019). Recent work has therefore highlighted the need for standardised benchmarking datasets, spatially explicit validation strategies, and transparent reporting of uncertainty (Belgiu & Drăguţ, 2016; Li et al., 2021). Ensemble approaches and multimodal learning frameworks have been proposed as promising directions to improve robustness and reduce sensitivity to site-specific biases, although their application in mangrove research remains limited and largely region-specific (Li et al., 2021; Bahaduri et al., 2024).

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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