E-ISSN : xxxx-xxxxx
JOMAFISH: Journal of Marine and Fisheries Science
Vol 1 No 1 (2026)
Website: https://journal.emergingmdtrends.com/index.php/jomafish

Remote Sensing for Mangrove Mapping and Monitoring: Sensors, Indices, Algorithms, and Applications

Luhur Moekti Prayogo[1*], Perdana Ixbal Spanton M[2], Jumiati[3]

[123]Universitas PGRI Ronggolawe Tuban, Indonesia

*Correspondent email: luhurmoektiprayogo@gmail.com

Received: .12 Juni 2026 **Revised:** 5 Juli 2026 **Accepted:** 3 September 2026 **Published:** 10 November 2026

Abstract. Mangrove forests are spatially dynamic intertidal ecosystems whose monitoring is constrained by difficult field access, tidal variation, cloud cover, spectral similarity with terrestrial vegetation, and rapid land-use change. Remote sensing has therefore become a central tool for mapping mangrove extent, condition, species composition, structural attributes, and temporal change. This review synthesizes recent developments in optical, synthetic aperture radar (SAR), hyperspectral, unmanned aerial vehicle (UAV), and LiDAR approaches for mangrove mapping, with emphasis on freely available Landsat and Sentinel data and applications relevant to tropical coasts. Studies published mainly during 2016–2026 were examined across four analytical dimensions: sensor characteristics, spectral or structural features, classification algorithms, and accuracy assessment. The evidence shows that Landsat remains valuable for long-term change analysis, whereas Sentinel-2 improves detection of narrow and fragmented stands through 10-m observations. Combining Sentinel-1 SAR and Sentinel-2 optical time series generally improves robustness in persistently cloudy regions. Mangrove-specific indices such as the Mangrove Vegetation Index can simplify extent mapping, while hyperspectral imagery, UAV data, and LiDAR are increasingly important for species discrimination, canopy height, biomass, and restoration assessment. However, no sensor or index removes the need for representative training data and independent validation. Tidal stage, mixed pixels, seasonal compositing, class imbalance, and spatially non-independent validation remain major sources of uncertainty. For Indonesia, an operational strategy should integrate multi-temporal Sentinel-1/2 data, machine learning, field observations, and standardized accuracy reporting to support repeatable mapping for conservation, restoration, blue-carbon accounting, and coastal management.
Keywords: mangrove mapping; remote sensing; Sentinel-2; synthetic aperture radar; machine learning

Abstrak. Hutan mangrove merupakan ekosistem intertidal yang dinamis secara spasial dan pemantauannya sering terkendala akses lapangan, variasi pasang surut, tutupan awan, kemiripan spektral dengan vegetasi daratan, serta perubahan penggunaan lahan yang cepat. Oleh karena itu, penginderaan jauh telah menjadi perangkat utama untuk memetakan luasan, kondisi, komposisi jenis, atribut struktur, dan perubahan temporal mangrove. Artikel review ini mensintesis perkembangan

pemetaan mangrove menggunakan data optik, synthetic aperture radar (SAR), hiperspektral, unmanned aerial vehicle (UAV), dan LiDAR, dengan penekanan pada Landsat dan Sentinel yang tersedia secara bebas serta aplikasinya pada pesisir tropis. Literatur yang terutama diterbitkan pada 2016–2026 dianalisis berdasarkan karakteristik sensor, fitur spektral atau struktur, algoritma klasifikasi, dan penilaian akurasi. Landsat tetap unggul untuk analisis perubahan jangka panjang, sedangkan Sentinel-2 meningkatkan deteksi tegakan sempit dan terfragmentasi melalui resolusi 10 m. Integrasi deret waktu Sentinel-1 SAR dan Sentinel-2 optik umumnya meningkatkan ketahanan klasifikasi pada wilayah yang sering berawan. Indeks khusus mangrove seperti Mangrove Vegetation Index dapat menyederhanakan pemetaan luasan, sementara citra hiperspektral, UAV, dan LiDAR semakin penting untuk diskriminasi jenis, tinggi tajuk, biomassa, dan evaluasi rehabilitasi. Meskipun demikian, tidak ada sensor atau indeks yang dapat menggantikan kebutuhan data latih yang representatif dan validasi independen. Tahap pasang surut, mixed pixel, komposit musiman, ketidakseimbangan kelas, dan validasi yang tidak independen secara spasial tetap menjadi sumber ketidakpastian utama. Untuk Indonesia, strategi operasional sebaiknya mengintegrasikan data multitemporal Sentinel-1/2, machine learning, pengamatan lapangan, dan pelaporan akurasi terstandar untuk mendukung konservasi, rehabilitasi, akuntansi karbon biru, dan pengelolaan pesisir.
Kata kunci: pemetaan mangrove; penginderaan jauh; Sentinel-2; radar aperture sintetis; machine learning

1. Pendahuluan

Mangroves occupy the land–sea interface in tropical and subtropical coasts and form one of the most structurally complex and biogeochemically important coastal ecosystems. Their ecological functions include shoreline stabilization, nursery habitat for fisheries, nutrient transformation, biodiversity support, and long-term carbon storage. Indonesia is particularly important in this context. The Global Mangrove Watch 2010 baseline estimated approximately 26,890 km^2 of mangroves in Indonesia, equivalent to about 19.5% of mapped global mangrove extent (Bunting et al., 2018). Independent carbon assessments likewise emphasize the disproportionate contribution of Indonesian mangroves to global blue-carbon storage (Alongi et al., 2016). These ecological and climatic values make spatially explicit, repeatable, and accurate monitoring a management necessity rather than merely a cartographic exercise.

Mangrove mapping is technically difficult because the target class is not defined by vegetation alone. Mangroves occur within an intertidal geomorphic setting, are frequently narrow or fragmented, may be mixed with aquaculture ponds and terrestrial vegetation, and are periodically inundated. Tropical cloud cover can reduce the availability of optical images, while tidal stage can alter the apparent width, moisture signal, and spectral background of the forest edge. At medium spatial resolution, one pixel may contain canopy, mudflat, water, and aquaculture infrastructure simultaneously. These conditions explain why a classification model that performs well in one estuary may not transfer directly to another coastline.

Earth observation has nevertheless transformed mangrove research. Early global products demonstrated that Landsat could support standardized 30-m mapping across the tropics (Giri et al., 2011). Subsequent global and regional products exploited Landsat time series, Japanese L-band SAR, and increasingly cloud-computing infrastructure to monitor change at scales that field surveys cannot achieve (Hamilton & Casey, 2016; Thomas et al., 2017; Bunting et al., 2018, 2022). More recent Sentinel-1 and Sentinel-2 missions provide complementary C-band radar and multispectral observations at approximately 10-m scale, improving the representation of small patches and offering a practical basis for national or subnational operational monitoring (Hu et al., 2020; Ghorbanian et al., 2021; Pinkaew et al., 2024).

The scope of mangrove remote sensing has also expanded. Mapping is no longer limited to binary mangrove/non-mangrove extent. Optical red-edge and shortwave-infrared information, vegetation indices, texture measures, radar backscatter, hyperspectral signatures, and three-dimensional structural observations can be used to examine canopy condition, species, height, biomass, and restoration trajectories. Very-high-resolution WorldView imagery has been tested for species-level mapping in Karimunjawa, Indonesia (Rahmandhana et al., 2022), while recent studies have combined UAV hyperspectral imagery with LiDAR or integrated satellite predictors with UAV-LiDAR to improve structural and biomass estimation (Cao et al., 2021; Pradisty et al., 2025). ICESat-2 photon-counting LiDAR has further enabled global-scale canopy-height mapping when combined with multi-source imagery (Yu et al., 2024).

These developments create a methodological challenge: more data do not automatically produce more reliable maps. Increasing the number of bands, indices, temporal metrics, or machine-learning models can improve separability, but it can also increase model complexity, sampling bias, and overfitting. Mangrove-specific indices may be useful for rapid extraction but remain sensitive to local canopy density and background conditions. Likewise, high overall accuracy may conceal poor performance for narrow mangrove classes when non-mangrove pixels dominate the validation sample. A useful review therefore needs to connect sensor physics, ecological characteristics, algorithm choice, and accuracy assessment rather than ranking methods solely by reported overall accuracy.

This review aims to (1) summarize the strengths and limitations of major remote-sensing data sources for mangrove mapping; (2) evaluate spectral indices, multi-source features, and classification algorithms used for extent, health, species, and structural mapping; (3) synthesize representative global and Indonesian applications; (4) identify recurring sources of mapping uncertainty; and (5) propose a reproducible workflow suitable for mangrove monitoring in Indonesia and other tropical coastal environments.

2. Review Method

2.1 Literature identification and scope

A structured narrative review was adopted because mangrove remote-sensing studies differ substantially in spatial scale, target variable, sensor type, field design, classification system, and reported accuracy metric. Peer-reviewed literature was identified from journal publisher platforms and bibliographic records using combinations of the terms mangrove, mapping, remote sensing, Landsat, Sentinel-1, Sentinel-2, SAR, hyperspectral, UAV, LiDAR, vegetation index, Google Earth Engine, machine learning, species, canopy height, biomass, and health. The synthesis prioritised studies published mainly from 2016 through 2026, while retaining a small number of earlier global mapping papers that established the methodological baseline for current work.

Studies were retained when remote-sensing observations were directly used to delineate mangrove extent, detect temporal change, discriminate mangrove classes or species, estimate vegetation condition, or retrieve structural attributes relevant to management. Method papers were also included when they introduced an index or workflow subsequently applied to mangrove mapping. Studies focused only on ecological field measurements without a remote-sensing component were used sparingly for context. The review emphasizes primary research; review and methodology papers are used to organize concepts and identify persistent limitations.

2.2 Synthesis framework

Each study was interpreted through four linked components: (i) observation system, including spatial, spectral, temporal, and structural information; (ii) feature engineering, such as spectral bands, vegetation indices, radar metrics, textures, phenological summaries, topography, and tide-related masks; (iii) classification or regression approach; and (iv) validation strategy. This framework allows direct comparison between simple threshold-based mapping and increasingly complex machine-learning or data-fusion approaches.

Reported accuracy values were treated as context-dependent rather than directly interchangeable. Overall accuracy, Kappa, F1-score, producer's accuracy, user's accuracy, RMSE, correlation, and concordance quantify different aspects of performance. Differences in training sample size, validation independence, class prevalence, mapping unit, and geographic scope can produce large differences even when algorithms are similar. Consequently, the review emphasizes methodological interpretation and reproducibility rather than selecting a single 'best' algorithm.

3. Results and Discussion

3.1 Remote-sensing data sources for mangrove mapping

Mangrove monitoring has developed from single-date medium-resolution optical mapping toward multi-temporal and multi-sensor analysis. The choice of sensor should follow the mapping objective. Long-term historical change requires a consistent archive such as Landsat. Delineation of narrow stands benefits from Sentinel-2 or commercial very-high-resolution imagery. Persistent cloud cover creates a strong role for SAR. Species and canopy-condition studies benefit from red-edge or hyperspectral information, while structural variables such as canopy height and biomass require three-dimensional information or calibrated multi-source models.

Table 1. Major remote-sensing data sources and their roles in mangrove mapping.

Sensor/data source	Typical information	Best-suited objectives	Main strengths	Key limitations
Landsat TM/ETM+/OLI	30 m; multi-decadal archive	Extent, historical change, disturbance drivers	Long time series; free; globally consistent	Mixed pixels in narrow stands; clouds; 30-m edge uncertainty

Sensor/data source	Typical information	Best-suited objectives	Main strengths	Key limitations
Sentinel-2 MSI	10–20 m; visible, NIR, red-edge, SWIR	Extent, density/condition, species/community, change	10-m bands; red-edge; frequent revisit; free	Clouds and tidal inconsistency; some bands at 20 m
Sentinel-1 SAR	~10 m C-band radar	Extent, inundation context, cloud-prone monitoring	All-weather/day-night capability; temporal metrics	Speckle; backscatter ambiguity; sensitivity to geometry/moisture
JERS-1 / ALOS PALSAR / ALOS-2	L-band SAR	Global extent and long-term change	Canopy/woody-structure sensitivity; cloud independent	Coarser temporal availability; interpretation can be context dependent
WorldView / Pléiades and similar VHR	Sub-meter to few meters	Fine boundaries, species/community, validation	Detailed crown/patch representation	Cost, small coverage, shadows, large data volume
Hyperspectral satellite/airborne	Tens–hundreds of narrow bands	Species, biochemical and moisture differences	High spectral separability; SWIR information	Preprocessing complexity; cost/coverage; dimensionality
UAV multispectral/hyperspectral	cm–dm scale	Restoration plots, species, canopy gaps, training/validation	Very high detail; flexible acquisition	Limited area; regulation; geometric/radiometric consistency
LiDAR / ICESat-2	3-D structural observations	Canopy height, biomass support, structural condition	Direct vertical information; useful for calibration	Sparse sampling for spaceborne LiDAR; cost for airborne/UAV LiDAR

3.2 Landsat and the value of long-term consistency

Landsat remains foundational because few other satellite archives combine decadal continuity, global coverage, stable calibration, and open access. Giri et al. (2011) demonstrated a globally consistent mangrove assessment using approximately 1,000 Landsat scenes, establishing a 30-m baseline that supported later global change studies.

Hamilton and Casey (2016) combined global forest-cover information with mangrove masks to generate annual estimates for 2000–2012. These products provided an important transition from static inventories toward time-series monitoring.

The Landsat archive also enables attribution of change. Goldberg et al. (2020) used a Random Forest-based analysis of more than one million Landsat images to distinguish anthropogenic and natural drivers of mangrove loss from 2000 to 2016. They estimated that land-use change accounted for 62% of global mangrove loss during that period. In Southeast Asia, Richards and Friess (2016) documented more than 100,000 ha of mangrove deforestation during 2000–2012 and showed that the dominant replacement land use varied geographically. Such results illustrate the value of temporal depth: a short high-resolution image series may delineate current boundaries well, but cannot substitute for a consistent long-term archive when the research question concerns historical trajectories and drivers.

The main limitation is scale. A 30-m pixel represents 900 m^2, which is problematic where mangroves form thin shoreline strips, fragmented restoration patches, or mixed boundaries with water and ponds. This scale mismatch can cause both omission of small stands and commission along vegetated coastal margins. Therefore, Landsat is often best interpreted as the temporal backbone of a monitoring system rather than as the only source for contemporary fine-scale inventories.

3.3 Sentinel-2 and Sentinel-1: a practical operational combination

Sentinel-2 significantly improves operational mangrove mapping because its visible and near-infrared bands include 10-m observations and its red-edge and shortwave-infrared bands provide additional information about vegetation structure, chlorophyll, and canopy moisture. Wang et al. (2018) found that Sentinel-2 could accurately delineate mangrove extent and provided useful information for community-level discrimination, with red-edge features among the most informative variables. At national scale, Hu et al. (2020) reported F1-scores of 0.895 for Sentinel-2 and 0.88 for Sentinel-1, while combining the two sensor families increased the F1-score to 0.94. The 10-m product also detected small mangrove patches that were poorly represented by 30-m products.

The complementarity is particularly important in the tropics. Sentinel-2 is spectrally rich but cloud dependent. Sentinel-1 C-band SAR observes the surface through clouds and provides backscatter information related to canopy structure, moisture, and inundation geometry. In the Hara protected area, Ghorbanian et al. (2021) combined seasonal Sentinel-1 and Sentinel-2 features in Random Forest classification and reported an average overall accuracy of 93.23% with Kappa of 0.92. Pinkaew et al. (2024) expanded the idea to national-scale mapping in Thailand by combining Sentinel-1, Sentinel-2, and SRTM predictors in Google Earth Engine; Gradient Tree Boost achieved mean overall accuracy of 96.75 ± 0.63%, closely followed by Random Forest at 96.64 ± 0.72%.

These high accuracies should not lead to a mechanical rule that fusion is always superior. SAR backscatter can vary with incidence angle, canopy wetness, tidal condition, and speckle filtering. Optical reflectance can vary with cloud shadow, atmospheric correction, and sun-sensor geometry. The practical advantage of fusion is redundancy: when one data stream is degraded, the second may retain discriminatory information. A robust workflow therefore builds seasonal or percentile composites, harmonizes spatial resolution, and evaluates whether the added features improve class-specific accuracy rather than simply increasing predictor count.

3.4 Spectral indices: from NDVI to mangrove-specific formulations

Vegetation indices reduce multi-band reflectance into variables designed to emphasize greenness, moisture, or canopy condition. NDVI remains widely used because it is simple and interpretable, but NDVI alone does not distinguish mangroves from terrestrial vegetation with similar chlorophyll activity. Mangrove-specific indices therefore attempt to use the joint expression of high vegetation greenness and the wet intertidal environment. Baloloy et al. (2020) introduced the Mangrove Vegetation Index (MVI), formulated from green, NIR, and SWIR1 reflectance, and reported index accuracy of approximately 92% across diverse test sites. The method was designed for rapid mapping and was implemented in Google Earth Engine, making it attractive for operational screening.

Table 2. Common spectral or derived features used in mangrove remote sensing.

Feature	Typical formulation/input	Main information	Strength	Caution

Feature	Typical formulation/input	Main information	Strength	Caution
NDVI	(NIR − Red)/(NIR + Red)	Vegetation greenness/density	Simple; useful for canopy condition and temporal trend	Not mangrove-specific; saturates in dense canopy
EVI / red-edge indices	Visible, NIR and/or red-edge combinations	Dense vegetation, chlorophyll/structure	Can reduce some NDVI saturation; Sentinel-2 red edge is informative	Coefficient or band choices vary across studies
NDWI/MNDWI and moisture indices	Green/NIR/SWIR combinations	Water and wetness context	Useful for intertidal masks and water separation	Water adjacency and tides can change values strongly
MVI	|NIR − Green| / |SWIR1 − Green|	Mangrove greenness + canopy/environment moisture	Rapid mangrove-focused extraction; transferable concept	Threshold still depends on site, canopy density and background
EMVI	(Green − SWIR2)/(SWIR1 − Green)	Hyperspectral mangrove discrimination	Strong separation in tested hyperspectral datasets	Not universally transferable; reported unsuitable for Sentinel-2 in original test
SAR backscatter & ratios	VV, VH, HH/HV depending sensor	Structure, moisture and inundation response	Cloud independent; complementary to optical	Speckle and environmental sensitivity
Texture / temporal percentiles	GLCM or seasonal/time-series statistics	Canopy heterogeneity and phenology	Adds spatial/temporal context	Can overfit when training data are limited

Feature	Typical formulation/input	Main information	Strength	Caution
Topography/tidal constraints	DEM, slope, distance to coast, tidal masks	Ecological habitat restriction	Reduces confusion with inland vegetation	Requires careful thresholds and local geomorphic knowledge

Hyperspectral developments extend this logic. Yang et al. (2022) proposed an Enhanced Mangrove Vegetation Index (EMVI) using green and two SWIR bands to enhance differences in greenness and canopy moisture. The index performed strongly across several hyperspectral datasets but was not considered suitable for Sentinel-2 in the original evaluation. This is an important reminder that an index is tied to sensor spectral response functions. Transferring an equation between instruments without evaluating band placement and bandwidth can create false equivalence.

Health mapping creates an additional interpretive challenge. Akbar et al. (2020) used Sentinel-2 NDVI to describe temporal variation in mangrove vegetation condition in Segara Anakan. Hidayah et al. (2023) applied a Mangrove Health Index approach in the Madura Strait. More recently, As-syakur et al. (2026) directly validated Sentinel-2-based MHI estimates against field-derived MHI across 194 plots in Bali and East Java. The satellite estimate showed a moderate relationship with field observations ($r = 0.71$; $R^2 = 0.50$) but a positive bias of 20.6 and a low Lin's concordance correlation coefficient of 0.36. Therefore, satellite health indices are valuable for spatial screening and relative comparison, but they should not automatically be interpreted as unbiased substitutes for plot-level ecological measurement.

3.5 Machine learning and the importance of training design

Random Forest is currently one of the most common mangrove classifiers because it handles nonlinear relationships, mixed feature types, and large predictor sets with relatively little parameter tuning. It has been used with Landsat, Sentinel-1/2, spectral indices, texture, and topographic features from local to national scales. Support Vector Machines, CART, Gradient Tree Boost, Extremely Randomized Trees, object-based classifiers, and deep-learning approaches have also been applied. Recent work in the

Indus Delta integrated nine Sentinel-2 indices with Random Forest and achieved approximately 85% accuracy while detecting strong 2018–2024 dynamics (Yu et al., 2026).

Algorithm selection, however, is often less important than sample design. Training samples should represent the full environmental range of mangroves and the classes most likely to be confused with them: coastal terrestrial forest, nipa, aquaculture, mudflat, seagrass or marsh where relevant, water, and built-up coastal land. Randomly splitting neighboring pixels from the same polygon into training and testing datasets can inflate accuracy because the two sets are spatially autocorrelated. Spatially separated validation blocks or independent field sites provide a more realistic assessment of map transferability.

Class imbalance also matters. Mangroves may occupy only a small proportion of a coastal study region. A classifier that maps most pixels as non-mangrove can still achieve high overall accuracy. For this reason, F1-score, producer's accuracy, user's accuracy, precision, recall, and class-specific confusion matrices should accompany overall accuracy. Area-adjusted accuracy and uncertainty estimates are preferable when map area itself is a primary outcome.

3.6 Species-level mapping: opportunity and persistent difficulty

Species-level mapping is scientifically valuable because species composition influences habitat function, biomass, restoration performance, and ecosystem resilience. It is also substantially more difficult than extent mapping because mangrove species may have overlapping canopy spectra, vertically mixed crowns, and strong within-species variation caused by salinity, age, inundation, leaf angle, and phenology. Wang et al. (2018) demonstrated that Sentinel-2 can provide useful community discrimination, but emphasized caution when moving from extent to detailed species classes.

The Indonesian evidence illustrates both opportunity and difficulty. Rahmandhana et al. (2022) combined field spectroscopy and WorldView-2 imagery in Karimunjawa and Kemujan, Central Java. Mapping performance decreased sharply as taxonomic detail increased; the best single-species level result was very low, which the authors related to field heterogeneity, mixed pixels, sample limitations, and threshold selection. By contrast, Febrianto et al. (2025) used Sentinel-2 and machine-learning approaches to map dominant mangrove species distribution in Segara Anakan. These differing outcomes reinforce that species mapping is not determined by nominal spatial resolution alone; field reference quality, species arrangement, spectral separability, season, and model design are equally important.

Hyperspectral and structural information can improve discrimination. Lassalle et al. (2023) synthesized multispectral and hyperspectral approaches and demonstrated that high spectral resolution, particularly SWIR information, increases species separability. Cao et al. (2021) combined UAV hyperspectral and LiDAR data and reported overall accuracy above 95% for several classifiers, with Rotation Forest reaching 97.22%. LiDAR-derived canopy-height information was especially useful where species were spectrally similar. Wang et al. (2022) further showed that multispectral and hyperspectral imagery can be used to map spatial components of mangrove biodiversity without requiring every pixel to be assigned to a species, offering an alternative ecological use of spectral diversity.

3.7 Mapping structure, canopy height, biomass, and restoration

The next major frontier is structural mapping. Canopy height provides information on stand development, exposure, productivity, and biomass. Simard et al. (2019) produced a global analysis of mangrove canopy height and carbon stocks using remote sensing and field data, showing strong climatic controls on maximum canopy height. Spaceborne LiDAR now extends structural observations at global scale. Yu et al. (2024) integrated ICESat-2 photon-counting LiDAR with multi-source imagery to produce a global 30-m mangrove canopy-height product validated with extensive airborne LiDAR data.

For restoration monitoring, multi-source approaches are particularly promising because restored stands may have similar canopy greenness but different vertical structure and biomass. Pradisty et al. (2025) combined satellite predictors with UAV-LiDAR estimators in tropical mangrove restoration areas in Indonesia to estimate canopy height and aboveground biomass. Such workflows can bridge local high-detail measurements and regional satellite coverage. They also provide a more management-relevant outcome than extent alone: a restored polygon may remain mapped as 'mangrove' for years while structural development, biomass accumulation, and canopy complexity change substantially.

Structural products should nevertheless be interpreted at their support scale. A satellite pixel summarizes a horizontal area, while LiDAR observations sample vertical structure along discrete footprints or swaths. Calibration relationships can vary with species, stand age, crown shape, and saturation of optical or radar predictors. Field plots remain necessary for biomass conversion and for evaluating whether a structural model remains valid outside its original training domain.

3.8 Global change products and what they reveal

Global products have progressed from static Landsat baselines to radar-supported temporal series. Bunting et al. (2018) produced the Global Mangrove Watch 2010 baseline using ALOS PALSAR and Landsat, reporting overall accuracy of approximately 94%. The later GMW version 3.0 used JAXA L-band SAR mosaics across 11 epochs from 1996 to 2020 (Bunting et al., 2022). The dataset indicated a net global mangrove extent loss of about 3.4% during 1996–2020, while Southeast Asia accounted for the largest regional net loss.

Change products are especially useful when combined with driver attribution. Thomas et al. (2017) used JERS-1 and ALOS PALSAR time series to identify global patterns and drivers of change during 1996–2010 and showed that Southeast Asia contained the greatest concentration of anthropogenic disturbance. Goldberg et al. (2020) later separated commodities, settlement-related conversion, shoreline erosion, and extreme weather as distinct loss processes. Together, these studies show that a binary loss map is only the first step. Management requires interpretation of whether change is caused by aquaculture expansion, agriculture, erosion, extreme events, restoration, or natural sediment-driven colonization.

3.9 Representative evidence from recent mangrove-mapping studies

Table 3. Representative studies illustrating developments in mangrove remote sensing.

Study	Scale/location	Data	Objective	Key methodological finding
Bunting et al. (2018)	Global	ALOS PALSAR + Landsat	Global baseline extent	OA ~94%; globally consistent 2010 baseline

Study	Scale/location	Data	Objective	Key methodological finding
Hu et al. (2020)	China	Sentinel-1 + Sentinel-2	National 10-m extent	Fusion F1 = 0.94; small patches better represented
Baloloy et al. (2020)	Multi-region	Sentinel-2 / Landsat	Index-based extent	MVI index accuracy ~92%; rapid mapping concept
Yancho et al. (2020)	Multiple sites	GEE + Landsat/Sentinel workflow	Accessible mapping methodology	GEEMMM standardized practical workflow
Ghorbanian et al. (2021)	Iran	Sentinel-1 + Sentinel-2	Ecosystem classes	OA 93.23%; Kappa 0.92
Cao et al. (2021)	Local/UAV	UAV hyperspectral + LiDAR	Species	Rotation Forest OA 97.22%
Rahmandhana et al. (2022)	Karimunjawa, Indonesia	WorldView-2 + field spectra	Species	Accuracy declined strongly at detailed species level
Bunting et al. (2022)	Global	JAXA L-band SAR time series	Extent change 1996–2020	Net global loss ~3.4%
Hidayah et al. (2023)	Madura Strait, Indonesia	Sentinel-2	Mangrove health/condition	Demonstrated satellite MHI application
Pinkaew et al. (2024)	Thailand	Sentinel-1/2 + SRTM + GEE	National extent	GTB OA 96.75 ± 0.63%
Yu et al. (2024)	Global	ICESat-2 + multi-source images	Canopy height	Global 30-m structural mapping
Febrianto et al. (2025)	Segara Anakan, Indonesia	Sentinel-2 + ML	Species distribution	Demonstrated species-scale ML in complex natural mangrove
Pradisty et al. (2025)	Indonesia	Satellite + UAV-LiDAR	Canopy height & AGB	Supports restoration structure/biomass monitoring
As-syakur et al. (2026)	Bali & East Java, Indonesia	Sentinel-2 + 194 field plots	MHI validation	$r = 0.71$; $R^2 = 0.50$; positive bias 20.6
Yu et al. (2026)	Indus Delta	Sentinel-2 + 9 indices + RF	Mangrove dynamics	OA ~85%; mapped 2018–2024 regeneration/degradation

3.10 Major sources of uncertainty

Tidal stage is one of the most distinctive sources of uncertainty in mangrove remote sensing. A low-tide image exposes mudflat and tidal channels, whereas a high-tide image increases water adjacency and may inundate understory or fringe pixels. If images from different tidal stages are compared directly, apparent change may reflect water level rather than vegetation change. Tide filtering, seasonal compositing, or multi-date percentiles reduce this problem, but the acquisition strategy should be explicitly reported.

Cloud and cloud-shadow contamination remain critical for optical data. Median compositing is useful in tropical regions, but long compositing windows may mix phenological states and conceal abrupt disturbance. A short window may leave too few clear observations. Radar helps fill this gap but introduces speckle and geometric effects. Multi-sensor workflows therefore require a balance between temporal consistency and sufficient observations.

Mixed pixels and boundary placement strongly influence area estimates. Narrow mangrove strips, fragmented rehabilitation sites, and creek networks can be smaller than a 30-m Landsat pixel and sometimes smaller than a 10-m Sentinel-2 pixel. The resulting area bias is not necessarily random: it can systematically omit small patches or merge mangroves with adjacent terrestrial vegetation. Minimum mapping unit, post-classification filtering, and pixel resolution should therefore be reported together with mapped area.

Reference-data uncertainty is often underreported. GPS error, inaccessible swamp interiors, outdated reference imagery, and subjectivity in visual interpretation can introduce label noise. When field samples are collected along accessible edges, the training set may overrepresent fringe mangroves and underrepresent interior canopy conditions. High-resolution imagery and UAV observations can help, but their acquisition date should match the satellite period closely enough to avoid labelling real ecological change as classification error.

Finally, validation design can produce misleading confidence. Pixel-random validation within the same training polygons is not equivalent to independent validation. Spatially blocked cross-validation, independent field sites, or time-separated testing provides more realistic evidence of transferability. For change detection, both dates should be validated or the uncertainty of the transition map should be quantified.

3.11 Recommended workflow for Indonesian coastal studies

Table 4. Recommended workflow and minimum reporting standards for mangrove remote-sensing studies.

Stage	Recommended practice	Reason
Define mapping objective	Separate extent, condition, species, structure, and change objectives	Prevents choosing a sensor or index before the ecological question
Select spatial/temporal scale	Use Landsat for long history; Sentinel-2 for 10-m extent; add VHR/UAV for local detail	Match pixel size and archive length to target process
Control clouds and tides	Apply quality masks; report compositing window; consider tidal filtering	Reduces false temporal and edge changes
Build ecologically meaningful predictors	Optical bands + selected indices; SAR temporal metrics; DEM/coastal constraints where justified	Avoid uncontrolled feature proliferation
Design representative samples	Include confusing coastal classes; distribute samples across geomorphic and canopy conditions	Improves model transferability
Use robust classification	RF/GTB/SVM or index threshold chosen through validation	Algorithm complexity must be supported by data quantity
Validate independently	Spatially separated test samples; confusion matrix; F1/PA/UA; area uncertainty	Avoid inflated accuracy from spatial autocorrelation
Field-check condition products	Validate MHI/biomass/height against plot observations	Satellite indices should not substitute untested field equivalents
Document reproducibility	State sensor product, dates, bands, thresholds, code/platform, sample counts, and random seeds	Allows replication and future monitoring
Archive outputs	Store classified maps, probability layers, metadata, and validation tables	Supports long-term institutional monitoring and comparison

For many Indonesian studies, a practical default workflow is to use Sentinel-2 surface reflectance for optical spectral information, Sentinel-1 for cloud-independent structural and inundation-related information, and a DEM or coastal mask to restrict classification to plausible intertidal zones. A seasonal or percentile composite can reduce cloud and short-term noise. Predictor selection should begin with physically meaningful bands and a small set of indices rather than dozens of highly correlated variables. Random Forest or Gradient Tree Boost can then provide baseline classifications with probability outputs that identify uncertain zones for field checking.

The field component should be designed alongside the satellite analysis. Plots or validation points should cover dense, sparse, degraded, restored, and fringe mangroves as well as adjacent non-mangrove vegetation and aquaculture landscapes. For species studies, leaf or canopy spectra alone are insufficient if species are vertically mixed; crown position, stand composition, and structural information may be required. For health or biomass studies, the satellite date should be as close as feasible to field measurement.

Google Earth Engine can improve reproducibility by providing standardized access to Landsat and Sentinel archives and by enabling cloud-scale compositing and machine learning. Yancho et al. (2020) demonstrated a dedicated Google Earth Engine Mangrove Mapping Methodology, while national-scale examples in China and Thailand show that cloud platforms can support operational mapping (Hu et al., 2020; Pinkaew et al., 2024). Nevertheless, the platform does not remove the need to document preprocessing decisions, training labels, accuracy metrics, and export parameters.

3.12 Research gaps and future directions

Three research priorities stand out. First, mangrove mapping needs stronger integration of tidal information. Many studies mention tides but do not explicitly standardize image selection by water level. Combining satellite acquisition times with tidal models or deriving inundation frequency from radar and optical time series could reduce edge uncertainty and improve transferability between estuaries.

Second, future mapping should move from single categorical outputs toward uncertainty-aware products. Per-pixel mangrove probability, class confidence, ensemble variation, and area-adjusted uncertainty are more informative for management than a binary map without confidence information. Uncertainty is especially important for rehabilitation monitoring, where newly planted or sparse stands occupy the spectral transition between bare substrate and mature mangrove.

Third, structural and functional monitoring should increasingly complement extent. The availability of ICESat-2, UAV-LiDAR, hyperspectral satellites, and machine learning allows mangrove studies to evaluate whether forests are becoming taller, denser, more species-diverse, or more carbon-rich, not only whether green canopy remains present. In Indonesia, linking Sentinel-based national monitoring with strategically sampled UAV/LiDAR and field plots could create an efficient hierarchical system for blue-carbon verification and restoration assessment.

Deep learning and foundation-model approaches are likely to expand, but they should be evaluated against simpler baselines. A complex neural network is not automatically preferable when the study has limited field labels, high geographic heterogeneity, or a small target area. Future papers should therefore compare advanced models with transparent Random Forest or index-based baselines and test geographic transfer to independent coastlines.

4. Conclusion

Remote sensing has evolved from a tool for delineating mangrove extent into a multi-scale framework capable of monitoring change, condition, species composition, canopy structure, and biomass. Landsat remains indispensable for historical analysis, while Sentinel-2 provides a practical 10-m optical basis for contemporary mapping and Sentinel-1 increases robustness in persistently cloudy tropical regions. Multi-sensor Sentinel-1/2 approaches consistently show strong potential for operational mapping, particularly when seasonal or time-series features are combined with machine-learning classifiers. Mangrove-specific indices such as MVI can accelerate extent extraction, but thresholds remain environmentally dependent, and health indices require field validation before they are interpreted as absolute ecological measurements. Hyperspectral, UAV, and LiDAR observations extend mapping to species and three-dimensional structure, although these approaches require stronger field reference data and greater processing effort. The most important methodological lesson is that mapping accuracy is controlled not only by sensor resolution or classifier choice, but also by tidal consistency, sample representativeness, spatial independence of validation, class imbalance, and explicit treatment of uncertainty. For Indonesia, where mangrove extent and blue-carbon importance are globally significant, a reproducible monitoring system should combine long-term Landsat context, multi-temporal Sentinel-1/2 mapping, targeted field validation, and high-resolution structural observations. Such an integrated framework can provide defensible spatial evidence for conservation, restoration evaluation, fisheries-support habitat management, and blue-carbon accounting.

Acknowledgements

The author acknowledges the researchers and institutions whose peer-reviewed studies provide the evidence base for this review. No external funding was used in the preparation of this manuscript.

Conflict of Interest

The author declares no conflict of interest.

References

Akbar, M. R., Arisanto, P. A. A., Sukirno, B. A., Merdeka, P. H., Priadhi, M. M., & Zallesa, S. (2020). Mangrove vegetation health index analysis by implementing NDVI (normalized difference vegetation index) classification method on Sentinel-2 image data case study: Segara Anakan, Kabupaten Cilacap. IOP Conference Series: Earth and Environmental Science, 584(1), 012069. https://doi.org/10.1088/1755-1315/584/1/012069

Alongi, D. M., Murdiyarso, D., Fourqurean, J. W., Kauffman, J. B., Hutahaean, A., Crooks, S., Lovelock, C. E., Howard, J., Herr, D., Fortes, M., Pidgeon, E., & Wagey, T. (2016). Indonesia's blue carbon: A globally significant and vulnerable sink for seagrass and mangrove carbon. Wetlands Ecology and Management, 24(1), 3–13. https://doi.org/10.1007/s11273-015-9446-y

As-syakur, A. R., Novanda, I. G. A., Sugiana, I. P., Dewi, I. G. A. I. P., Andiani, A. A. E., Aryunisha, P. E. P., Riskianisya, A., & Wijana, I. M. S. (2026). Validasi Mangrove Health Index berbasis Sentinel-2 di Bali dan Jawa Timur, Indonesia. Jurnal Kelautan Tropis, 29(1), 59–69. https://doi.org/10.14710/jkt.v29i1.30565

Baloloy, A. B., Blanco, A. C., Sta. Ana, R. R. C., & Nadaoka, K. (2020). Development and application of a new mangrove vegetation index (MVI) for rapid and accurate mangrove mapping. ISPRS Journal of Photogrammetry and Remote Sensing, 166, 95–117. https://doi.org/10.1016/j.isprsjprs.2020.06.001

Bunting, P., Rosenqvist, A., Hilarides, L., Lucas, R. M., Thomas, N., Tadono, T., Worthington, T. A., Spalding, M., Murray, N. J., & Rebelo, L.-M. (2022). Global mangrove extent change 1996–2020: Global Mangrove Watch version 3.0. Remote Sensing, 14(15), 3657. https://doi.org/10.3390/rs14153657

Bunting, P., Rosenqvist, A., Lucas, R. M., Rebelo, L.-M., Hilarides, L., Thomas, N., Hardy, A., Itoh, T., Shimada, M., & Finlayson, C. M. (2018). The Global Mangrove Watch—A new 2010 global baseline of mangrove extent. Remote Sensing, 10(10), 1669. https://doi.org/10.3390/rs10101669

Cao, J., Liu, K., Zhuo, L., Liu, L., Zhu, Y., & Peng, L. (2021). Combining UAV-based hyperspectral and LiDAR data for mangrove species classification using the rotation forest algorithm. International Journal of Applied Earth Observation and Geoinformation, 102, 102414. https://doi.org/10.1016/j.jag.2021.102414

Diniz, C., Cortinhas, L., Nerino, G., Rodrigues, J., Sadeck, L., Adami, M., & Souza-Filho, P. W. M. (2019). Brazilian mangrove status: Three decades of satellite data analysis. Remote Sensing, 11(7), 808. https://doi.org/10.3390/rs11070808

Febrianto, S., Rahman, A., Jati, O. E., Wirasatriya, A., Muskananfola, M. R., & Latifah, N. (2025). Machine learning for mangrove species distribution using Sentinel 2 satellite image in Segara Anakan, Cilacap Region, Indonesia. Regional Studies in Marine Science, 81, 103984. https://doi.org/10.1016/j.rsma.2024.103984

Ghorbanian, A., Zaghian, S., Asiyabi, R. M., Amani, M., Mohammadzadeh, A., & Jamali, S. (2021). Mangrove ecosystem mapping using Sentinel-1 and Sentinel-2 satellite images and random forest algorithm in Google Earth Engine. Remote Sensing, 13(13), 2565. https://doi.org/10.3390/rs13132565

Giri, C., Ochieng, E., Tieszen, L. L., Zhu, Z., Singh, A., Loveland, T., Masek, J., & Duke, N. (2011). Status and distribution of mangrove forests of the world using earth observation satellite data. Global Ecology and Biogeography, 20(1), 154–159. https://doi.org/10.1111/j.1466-8238.2010.00584.x

Goldberg, L., Lagomasino, D., Thomas, N., & Fatoyinbo, T. (2020). Global declines in human-driven mangrove loss. Global Change Biology, 26(10), 5844–5855. https://doi.org/10.1111/gcb.15275

Hamilton, S. E., & Casey, D. (2016). Creation of a high spatio-temporal resolution global database of continuous mangrove forest cover for the 21st century (CGMFC-21).

Global Ecology and Biogeography, 25(6), 729–738. https://doi.org/10.1111/geb.12449

Hidayah, Z., Rachman, H. A., & As-Syakur, A. R. (2023). Pemetaan kondisi hutan mangrove di kawasan pesisir Selat Madura dengan pendekatan Mangrove Health Index memanfaatkan citra satelit Sentinel-2. Majalah Geografi Indonesia, 37(1), 84–91. https://doi.org/10.22146/mgi.78136

Hu, L., Xu, N., Liang, J., Li, Z., Chen, L., & Zhao, F. (2020). Advancing the mapping of mangrove forests at national-scale using Sentinel-1 and Sentinel-2 time-series data with Google Earth Engine: A case study in China. Remote Sensing, 12(19), 3120. https://doi.org/10.3390/rs12193120

Lassalle, G., Ferreira, M. P., Cué La Rosa, L. E., Del'Papa Moreira Scafutto, R., & de Souza Filho, C. R. (2023). Advances in multi- and hyperspectral remote sensing of mangrove species: A synthesis and study case on airborne and multisource spaceborne imagery. ISPRS Journal of Photogrammetry and Remote Sensing, 195, 298–312. https://doi.org/10.1016/j.isprsjprs.2022.12.003

Pinkaew, S., Boonrat, P., Koedsin, W., & Huete, A. (2024). Semi-automated mangrove mapping at national-scale using Sentinel-2, Sentinel-1, and SRTM data with Google Earth Engine: A case study in Thailand. The Egyptian Journal of Remote Sensing and Space Sciences, 27(3), 555–564. https://doi.org/10.1016/j.ejrs.2024.07.001

Pradisty, N. A., Schlund, M., Horstman, E. M., & Willemen, L. (2025). Estimating canopy height and aboveground biomass in tropical mangrove restoration areas through multisource remote sensing. Ecological Informatics, 92, 103522. https://doi.org/10.1016/j.ecoinf.2025.103522

Rahmandhana, A. D., Kamal, M., & Wicaksono, P. (2022). Spectral reflectance-based mangrove species mapping from WorldView-2 imagery of Karimunjawa and Kemujan Island, Central Java Province, Indonesia. Remote Sensing, 14(1), 183. https://doi.org/10.3390/rs14010183

Richards, D. R., & Friess, D. A. (2016). Rates and drivers of mangrove deforestation in Southeast Asia, 2000–2012. Proceedings of the National Academy of Sciences of the United States of America, 113(2), 344–349. https://doi.org/10.1073/pnas.1510272113

Sharifi, A., Felegari, S., & Tariq, A. (2022). Mangrove forests mapping using Sentinel-1 and Sentinel-2 satellite images. Arabian Journal of Geosciences, 15, 1593. https://doi.org/10.1007/s12517-022-10867-z

Simard, M., Fatoyinbo, L., Smetanka, C., Rivera-Monroy, V. H., Castañeda-Moya, E., Thomas, N., & Van der Stocken, T. (2019). Mangrove canopy height globally related to precipitation, temperature and cyclone frequency. Nature Geoscience, 12, 40–45. https://doi.org/10.1038/s41561-018-0279-1

Thomas, N., Lucas, R., Bunting, P., Hardy, A., Rosenqvist, A., & Simard, M. (2017). Distribution and drivers of global mangrove forest change, 1996–2010. PLOS ONE, 12(6), e0179302. https://doi.org/10.1371/journal.pone.0179302

Wang, D., Qiu, P., Wan, B., Cao, Z., & Zhang, Q. (2022). Mapping α- and β-diversity of mangrove forests with multispectral and hyperspectral images. Remote Sensing of Environment, 275, 113021. https://doi.org/10.1016/j.rse.2022.113021

Wang, D., Wan, B., Qiu, P., Su, Y., Guo, Q., Wang, R., Sun, F., & Wu, X. (2018). Evaluating the performance of Sentinel-2, Landsat 8 and Pléiades-1 in mapping mangrove extent and species. Remote Sensing, 10(9), 1468. https://doi.org/10.3390/rs10091468

Yancho, J. M. M., Jones, T. G., Gandhi, S. R., Ferster, C., Lin, A., & Glass, L. (2020). The Google Earth Engine Mangrove Mapping Methodology (GEEMMM). Remote Sensing, 12(22), 3758. https://doi.org/10.3390/rs12223758

Yang, G., Huang, K., Sun, W., Meng, X., Mao, D., & Ge, Y. (2022). Enhanced mangrove vegetation index based on hyperspectral images for mapping mangrove. ISPRS Journal of Photogrammetry and Remote Sensing, 189, 236–254. https://doi.org/10.1016/j.isprsjprs.2022.05.003

Yu, H., Wu, J., Aslam, R. W., Naz, I., Tariq, A., Ullah, S., Elmannai, H., & Said, Y. (2026). Integrating multi-index remote sensing and machine learning for mangrove dynamics assessment using Sentinel-2 imagery. iScience, 29(8), 116796. https://doi.org/10.1016/j.isci.2026.116796

Yu, J., Nie, S., Liu, W., Zhu, X., Sun, Z., Li, J., Wang, C., Xi, X., & Fan, H. (2024). Mapping global mangrove canopy height by integrating Ice, Cloud, and Land Elevation Satellite-2 photon-counting LiDAR data with multi-source images. Science of the Total Environment, 939, 173487. https://doi.org/10.1016/j.scitotenv.2024.173487