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Remote Sensing for Seagrass Mapping and Monitoring: Methods, Sensors, and Applications

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Abstract. Seagrass meadows are highly productive coastal ecosystems, yet their submerged position, patchy distribution, seasonal variability, and exposure to turbidity make consistent mapping difficult. Remote sensing provides a practical means to extend field observations across space and time, but mapping performance depends strongly on sensor characteristics, water-column conditions, image preprocessing, classification design, and validation quality. This review synthesizes recent progress in remote sensing for seagrass mapping and monitoring, emphasizing studies published from 2017 to August 2026 and applications relevant to tropical and Indonesian waters. The literature was evaluated according to sensor type, preprocessing strategy, classification or regression method, ecological variable, and accuracy assessment. Landsat remains important for multi-decadal change detection, while Sentinel-2 has become the principal freely available sensor for contemporary mapping because its 10-m visible bands and frequent revisit provide a useful compromise between spatial detail and temporal coverage. PlanetScope and WorldView imagery improve delineation of small or fragmented meadows, whereas UAV and hyperspectral systems enable centimetre-scale mapping, species discrimination, and detailed biomass assessment. Machine-learning approaches, particularly Random Forest, Support Vector Machine, and gradient-boosting methods, are increasingly used, but classifier choice cannot compensate for poor atmospheric correction, sun-glint contamination, depth effects, mixed pixels, or weak reference data. Recent Indonesian studies demonstrate applications ranging from seagrass extent and benthic habitat mapping to aboveground carbon estimation. A robust operational workflow should therefore combine aquatic atmospheric correction, tidal and cloud screening, representative field data, depth-aware feature engineering, independent spatial validation, and explicit uncertainty reporting. Such standardization is essential for reproducible monitoring, restoration assessment, fisheries habitat management, and blue-carbon accounting.
Keywords: seagrass mapping; remote sensing; Sentinel-2; machine learning; coastal monitoring

Abstrak. Padang lamun merupakan ekosistem pesisir yang sangat produktif, tetapi posisinya yang terendam, distribusi yang terfragmentasi, variasi musiman, dan pengaruh kekeruhan menyebabkan pemetaan secara konsisten menjadi sulit. Penginderaan jauh memungkinkan pengamatan lapangan diperluas secara spasial dan temporal, namun kinerja pemetaan sangat dipengaruhi karakteristik sensor, kondisi kolom air, prapengolahan citra, desain klasifikasi, dan kualitas validasi. Artikel review ini mensintesis perkembangan terbaru penginderaan jauh untuk pemetaan dan pemantauan lamun, terutama publikasi 2017 sampai Agustus 2026 serta aplikasi yang relevan bagi perairan tropis dan Indonesia. Literatur dianalisis berdasarkan jenis sensor, strategi prapengolahan, metode klasifikasi atau regresi, variabel ekologis, dan penilaian akurasi. Landsat tetap penting untuk analisis perubahan

multidekade, sedangkan Sentinel-2 menjadi sensor bebas akses utama untuk pemetaan modern karena band tampak beresolusi 10 m dan frekuensi perekaman yang tinggi. PlanetScope dan WorldView meningkatkan kemampuan delineasi padang lamun yang sempit atau terfragmentasi, sementara UAV dan sistem hiperspektral mendukung pemetaan skala sentimeter, diskriminasi spesies, dan estimasi biomassa yang lebih rinci. Metode machine learning, khususnya Random Forest, Support Vector Machine, dan gradient boosting, semakin banyak digunakan, tetapi pemilihan algoritma tidak dapat menggantikan koreksi atmosfer yang baik, penanganan sun glint, efek kedalaman, mixed pixel, dan data referensi yang memadai. Studi terbaru di Indonesia menunjukkan aplikasi mulai dari pemetaan luasan dan habitat bentik hingga estimasi karbon atas permukaan. Workflow operasional yang kuat perlu menggabungkan koreksi atmosfer khusus perairan, penyaringan pasang dan awan, data lapangan representatif, rekayasa fitur yang mempertimbangkan kedalaman, validasi spasial independen, serta pelaporan ketidakpastian secara eksplisit. Standardisasi tersebut penting untuk monitoring yang dapat direplikasi, evaluasi rehabilitasi, pengelolaan habitat perikanan, dan akuntansi karbon biru.
Kata kunci: pemetaan lamun; penginderaan jauh; Sentinel-2; machine learning; pemantauan pesisir

1. Pendahuluan

Seagrasses are marine angiosperms that form intertidal and subtidal meadows in shallow coastal waters. Their ecological functions extend well beyond primary production: they provide nursery and feeding habitat for fish and invertebrates, stabilize sediments, attenuate hydrodynamic energy, improve water quality, and store substantial quantities of organic carbon. These services make seagrass meadows closely linked to fisheries productivity, coastal protection, biodiversity conservation, and climate-change mitigation. Yet they remain among the least consistently mapped coastal habitats, particularly in tropical developing regions where monitoring resources are limited (Unsworth et al., 2018, 2019).

The global conservation problem is not simply that seagrasses are declining, but that changes in extent and condition are often poorly documented. A synthesis of long-term records identified net losses across all major seagrass bioregions, while also showing that recovery can occur where pressures are reduced (Dunic et al., 2021). Indonesia illustrates this tension particularly well. It contains globally significant seagrass resources and high species diversity, but many meadows are exposed to coastal development, destructive activities, declining water quality, sedimentation, and other local pressures (Unsworth et al., 2018). Management therefore requires spatially explicit information that can be updated more frequently than conventional field mapping alone permits.

Remote sensing has progressively filled this information gap. Historical Landsat archives enable multi-decadal assessment of large seagrass areas, while contemporary Sentinel-2 imagery improves discrimination of smaller benthic features because visible bands are available at 10-m spatial resolution. Commercial constellations such as PlanetScope and WorldView increase spatial detail further, and unmanned aerial vehicles (UAVs), imaging spectroscopy, and uncrewed surface systems now provide very-high-resolution information for local ecological characterization. Cloud-computing platforms, including Google Earth Engine (GEE), have additionally shifted seagrass mapping from single-scene desktop analyses toward reproducible multi-temporal and regional workflows (Traganos et al., 2018; Deeks et al., 2024; Floyd et al., 2026).

However, underwater remote sensing is fundamentally different from terrestrial vegetation mapping. The signal recorded by an optical sensor is influenced not only by the seagrass canopy but also by the atmosphere, air-water interface, water depth, suspended matter, colored dissolved organic matter, phytoplankton, bottom substrate, illumination geometry, and sea-surface roughness. Consequently, a visually clear image is not necessarily an analytically reliable image. Sun glint, depth-dependent attenuation, tidal state, and spatially variable water clarity can generate spectral differences that are unrelated to seagrass condition. This explains why algorithms that perform well in clear tropical lagoons may transfer poorly to turbid estuaries or temperate coastal waters (Wilson et al., 2020; Kuhwald et al., 2022).

The purpose of this review is to synthesize recent methods, sensors, algorithms, and applications for seagrass remote sensing, with particular attention to mapping workflows that are transferable to tropical marine research. The review addresses five questions: (1) which remote-sensing platforms are most suitable for different spatial and ecological objectives; (2) which preprocessing steps are essential for optically shallow waters; (3) how classification and regression methods are being used for extent, percent cover, biomass, and carbon-related variables; (4) which uncertainty and validation problems most strongly affect reported accuracy; and (5) how these lessons can be translated into a practical monitoring framework for Indonesian coastal waters.

2. Methods

2.1 Review design and literature selection

A structured narrative review was conducted to synthesize peer-reviewed studies on seagrass mapping and monitoring using satellite, airborne, UAV, and aquatic remote-sensing platforms. The principal time window was 2017 to August 2026 so that the synthesis reflects the operational Sentinel-2 era and recent advances in cloud computing, machine learning, high-resolution commercial imagery, and hyperspectral platforms. Older concepts were discussed only when required to explain established correction principles. Searches used combinations of the terms seagrass, remote sensing, mapping, monitoring, Sentinel-2, Landsat, PlanetScope, WorldView, UAV, hyperspectral, Google Earth Engine, machine learning, water column correction, percent cover, biomass, and blue carbon.

Priority was given to original research articles with explicit information on imagery, preprocessing, ecological target variables, training or reference data, and validation. Major recent review articles were retained to contextualize methodological development. Studies were considered especially informative when they evaluated alternative sensors or classifiers, reported independent accuracy statistics, analysed temporal change, or demonstrated operational workflows at regional to national scales. Indonesian case studies were deliberately included to ensure that the synthesis addresses tropical shallow-water conditions, where high biodiversity, complex benthic mosaics, tides, turbidity, and fragmented reef-island settings are common.

This article is a methodological review rather than a formal meta-analysis. Accuracy values therefore are not pooled statistically because the reviewed studies differ in class definitions, field reference design, depth range, water clarity, sensor resolution, spatial scale, and accuracy metric. Instead, published performance values are used comparatively to identify recurring methodological patterns and limitations.

2.2 Analytical framework

Each study was interpreted through five linked components: (1) sensor and platform characteristics; (2) preprocessing and correction of atmospheric, surface, and water-column effects; (3) feature construction, including spectral bands, ratios, indices, texture, bathymetry, and time-series statistics; (4) classification or regression algorithms; and (5) validation design and uncertainty reporting. This framework is important because apparent differences between algorithms are frequently caused by differences in image quality or reference data rather than by the classifier itself. The final synthesis therefore emphasizes complete workflows instead of ranking individual algorithms in isolation.

3. Results and Discussion

3.1 Why seagrass mapping is an optically difficult problem

Seagrass reflectance reaching a satellite sensor is a composite signal. In shallow water, photons interact with the atmosphere, water surface, water column, vegetation canopy, sediment, and adjacent bottom types before reaching the detector. As depth increases, red and near-infrared energy attenuates rapidly, leaving the blue and green spectral regions as the most useful bands for many submerged-habitat applications. The result is a strong depth effect: identical seagrass can appear spectrally different at 1 m and 5 m depth, while dense seagrass over bright carbonate sand can differ from sparse seagrass over dark sediment even at the same depth.

Water clarity further modifies detectability. Wilson et al. (2020) mapped submerged vegetation in optically complex Atlantic Canadian waters with Sentinel-2 and reported an overall accuracy of 79%, but the depth at which bottom habitat remained detectable varied substantially across the image. Kuhwald et al. (2022) found that Sentinel-2 could map five benthic habitat classes in turbid Baltic waters with balanced overall accuracies around 0.92 in optically shallow areas, while performance declined toward the transition to optically deep water. These studies demonstrate that a universal maximum mapping depth should not be assumed; it depends on bottom contrast, water constituents, image quality, and sensor signal-to-noise characteristics.

Season and tide must also be treated as components of the observation model. Intertidal meadows may be exposed or submerged depending on acquisition time, and tropical meadows can exhibit seasonal changes in leaf area, biomass, epiphytes, and water quality. Zoffoli et al. (2020) used Sentinel-2 to retrieve intertidal seagrass percent cover with approximately 14% uncertainty and demonstrated that the revisit frequency can resolve seasonal dynamics. For monitoring, this means that choosing an image only because it has low cloud cover can introduce temporal inconsistency if tidal or phenological conditions differ among years.

3.2 Sensors and platforms

Table 1. Principal remote-sensing platforms used for seagrass mapping and their most appropriate roles.

Platform	Typical characteristics	Strongest applications	Main limitations
Landsat 5/7/8/9	30 m multispectral; decades-long archive	Long-term change, regional baseline, trend analysis	Mixed pixels in narrow/patchy meadows; limited fine benthic detail
Sentinel-2 MSI	10–20 m visible/red-edge; frequent revisit	Current extent, percent cover, regional monitoring, GEE workflows	Depth/turbidity effects; only a few water-penetrating bands at 10 m
PlanetScope/SuperDove	~3 m; high revisit; up to 8 bands in newer products	Small patches, fine habitat boundaries, biophysical mapping	Commercial access; cross-generation radiometric consistency
WorldView-2/3	Very high spatial resolution; coastal/visible bands	Detailed benthic classes, small meadows, local validation	Cost, smaller swath, preprocessing and calibration demands
UAV RGB/multispectral	Centimetre-scale, user-controlled timing	Local extent, species zonation, training/validation, restoration	Limited coverage, flight logistics, water-surface effects
UAV/USV hyperspectral	Centimetre-scale; dense spectral sampling	Species/macroalgae discrimination, spectral libraries	Data volume, cost, calibration, scale-dependent spectral mixing
Cloud computing (e.g., GEE)	Access to large archives and scalable processing	Regional/national compositing, ML, repeatable monitoring	Does not remove sensor physics or reference-data limitations

3.2.1 Landsat for historical change detection

The Landsat archive remains indispensable where the research question concerns historical change rather than fine contemporary habitat detail. Its principal strength is temporal continuity: multiple Landsat missions allow consistent reconstruction of coastal habitat dynamics over several decades. The 30-m pixel size, however, is a substantial constraint in narrow intertidal strips, small reef flats, and fragmented meadows where one pixel may contain seagrass, sand, coral rubble, and water simultaneously.

For long-term monitoring, the most defensible Landsat applications are therefore broad extent classes, change trajectories, or large homogeneous meadows. Fine species-level mapping should not be expected from 30-m multispectral imagery in complex tropical seascapes. Sentinel-2 and higher-resolution imagery increasingly complement Landsat by providing contemporary spatial detail while Landsat anchors the historical baseline. This multi-sensor logic is more informative than treating one sensor as universally superior.

3.2.2 Sentinel-2 as the contemporary workhorse

Sentinel-2 has become the most widely transferable free sensor for seagrass mapping because its 10-m blue, green, red, and near-infrared observations, additional red-edge bands, broad swath, and frequent revisit provide a practical balance between spatial resolution and temporal availability. Traganos and Reinartz (2018) demonstrated its suitability for Mediterranean seagrasses and showed that atmospheric and water-column corrections could support discrimination of Posidonia oceanica and Cymodocea nodosa. Traganos et al. (2018) then extended the concept to a cloud-based workflow across the Aegean and Ionian Seas, mapping more than 2,500 km^2 of P. oceanica with Support Vector Machines and independent validation.

The sensor is equally useful outside clear Mediterranean conditions, but workflow choices become more important. Wilson et al. (2020) used a branching approach with thresholds and Random Forest in optically complex Atlantic Canada; Kuhwald et al. (2022) combined ACOLITE atmospheric correction, water-column analysis, video transects, and aerial imagery in the Baltic Sea. These studies show that Sentinel-2 should be treated as an adaptable observation system rather than a fixed recipe. The same bands can support very different models depending on water optical properties and class definitions.

Large-scale applications now demonstrate that Sentinel-2 can support operational monitoring. Deeks et al. (2024) processed 507 Sentinel-2 images in GEE along 9,452 km^2 of north-eastern Brazilian coastal waters, mapped 328 km^2 of seagrass with classification accuracies exceeding 79%, and identified local declines over a five-year period. Floyd et al. (2026) compared Landsat 8, Planet NICFI, and Sentinel-2 for national-scale mapping in the Maldives and found that sensor choice had a stronger effect on accuracy than classifier choice; Sentinel-2 produced the most accurate binary seagrass map among the tested datasets.

3.2.3 High-resolution commercial imagery

Commercial imagery becomes valuable when the management unit is smaller than the Sentinel-2 pixel grid or when patch structure is itself an ecological indicator. Coffer et al. (2020) developed a reproducible processing regime for WorldView-2 and RapidEye and found up to 97% agreement with aerial photointerpretation, demonstrating that fine spatial resolution can substantially improve mapping of heterogeneous meadows. Wilson et al. (2022) directly compared WorldView-3 and Sentinel-2 in Atlantic Canada and emphasized the trade-off between spatial detail, cost, scale, and processing demands.

PlanetScope provides a particularly useful intermediate scale between Sentinel-2 and very-high-resolution WorldView imagery. The newest SuperDove generation adds spectral information while retaining metre-scale spatial detail. In Teluk Pandan, Lampung, Harahap et al. (2026) compared Sentinel-2 and PlanetScope imagery and found that higher spatial resolution improved mapping detail, while increased spectral resolution enhanced object differentiation. Their PlanetScope eight-band configuration identified more benthic habitat classes than three-band inputs, illustrating that spatial and spectral resolution influence different dimensions of mapping performance.

3.2.4 UAV, hyperspectral, and multi-platform observations

UAVs bridge the scale gap between quadrat or transect surveys and satellite imagery. They permit centimetre-scale observations, flexible acquisition near low tide or under clear-sky windows, and direct mapping of meadow boundaries, patchiness, and species zonation. Amone-Mabuto et al. (2024) integrated Sentinel-2 and UAV imagery with machine learning in Maputo Bay. Sentinel-2 supported long-term extent assessment, while UAV observations provided finer species-level and biomass information, illustrating how nested platforms can separate regional monitoring from local ecological characterization.

Hyperspectral imaging provides dense spectral information capable of distinguishing subtle differences between seagrass, macroalgae, and other benthic materials. Smart et al. (2026) concluded that hyperspectral approaches offer strong potential for composition and extent mapping but remain constrained by spectral mixing, platform access, and lack of standardized workflows. Nevstad et al. (2026) demonstrated multi-scale hyperspectral mapping with UAV and uncrewed surface vehicle observations at approximately 10-cm and 1-cm spatial scales. Their results emphasize that classification performance is scale-dependent: the same spectral classes can behave differently as spatial support changes.

3.3 Preprocessing: the decisive stage before classification

Table 2. Major preprocessing challenges in optical seagrass remote sensing.

Issue	Why it matters	Recommended response
Atmospheric path signal	Changes apparent water-leaving reflectance	Aquatic atmospheric correction (e.g., ACOLITE/DSF); report processor/version
Cloud and haze	Removes or distorts usable coastal pixels	Cloud masking plus manual/quality review; multi-date compositing
Sun glint	Adds surface reflection unrelated to benthos	Image-based glint correction; select low-glint scenes; mask severe areas
Tidal variation	Changes exposure, water depth, and shoreline position	Use tidal metadata; select comparable tidal windows; analyse intertidal/subtidal separately
Water-column attenuation	Same bottom appears different with depth	Depth-invariant features, empirical/analytical correction, or depth-aware classification
Spatially varying turbidity	Alters spectral response and mapping depth	Scene selection, water-quality masks/features, local models, multi-temporal composites
Mixed pixels	Combines seagrass with sand/coral/algae/water	Higher resolution, fractional cover/regression, object-based or sensor-specific class schemes

Atmospheric correction over water deserves more attention than it often receives in seagrass studies. Standard terrestrial correction assumptions can be inappropriate because water-leaving reflectance is low and aerosol errors can be large relative to the benthic signal. Vanhellemont (2019) adapted the dark spectrum fitting approach for Landsat and Sentinel-2 aquatic applications and included optional image-based glint correction. ACOLITE-based processing has subsequently been used in multiple seagrass studies, including Wilson et al. (2020) and Kuhwald et al. (2022). Reporting the correction processor, version, settings, and output reflectance definition is essential for reproducibility.

Sun glint is another frequent source of error. A bright specular reflection from the sea surface can overwhelm differences between benthic classes. Glint correction can improve imagery, but it should not be treated as a guarantee; heavily glinted pixels may remain unreliable. Scene selection is therefore the first control. Multi-date compositing can reduce isolated artifacts, although compositing can also mix seasonal or tidal states if the acquisition window is too broad.

Water-column correction remains one of the most debated steps. Traganos and Reinartz (2018) found analytical corrections useful in clear Mediterranean waters, whereas Kuhwald et al. (2022) reported that water-column correction did not significantly improve classification compared with atmospherically corrected data alone in their Baltic study. The correct conclusion is not that water-column correction is either always necessary or unnecessary. Its benefit is context-dependent and should be tested against an independent validation set. A depth layer can also be included directly as a predictor or used to stratify classification into depth zones.

The water-depth problem also implies that red-edge and near-infrared information should be interpreted cautiously for submerged canopies. These bands are valuable for exposed intertidal vegetation and for discriminating land/water boundaries, but they attenuate rapidly underwater. Blue and green bands commonly carry the most useful benthic signal at depth. The optimal feature set is therefore a function of tidal exposure, depth, water transparency, and sensor resolution rather than a fixed vegetation-index formula.

3.4 Feature engineering and spectral information

Early benthic mapping frequently relied on transformed band ratios or depth-invariant indices designed to reduce the effect of water depth. Contemporary machine-learning workflows can ingest raw or corrected spectral bands, band ratios, bathymetry, texture, seasonal composites, and statistical summaries simultaneously. This flexibility is advantageous but also creates a risk of using large predictor sets without ecological interpretation. Predictors should be chosen based on whether they represent bottom brightness, pigment absorption, water depth, substrate texture, or seasonal behavior.

Sentinel-2 time series are especially useful because repeated observations provide temporal features that a single image cannot. A percentile, median, minimum, seasonal amplitude, or multi-date spectral trajectory can help distinguish persistent seagrass from transient turbidity or exposed sediment. Blume et al. (2023) used multi-temporal Sentinel-2 data and extensive feature engineering within GEE to support national seagrass and blue-carbon accounting in The Bahamas. Traganos et al. (2022) similarly demonstrated the scalability of multi-temporal Earth Observation for Mediterranean-wide seagrass extent mapping.

High-resolution sensors introduce another principle: classification schemes should be sensor-aware. Harahap et al. (2026) showed that a sensor with more spectral bands can distinguish a greater number of benthic classes, whereas a coarser or spectrally limited configuration may require broader classes. Forcing every sensor to reproduce an ecologically detailed scheme can reduce accuracy and create unstable classes. A defensible map therefore defines classes that are both ecologically meaningful and spectrally separable at the resolution of the chosen sensor.

3.5 Classification and regression algorithms

Random Forest (RF) is now one of the most common classifiers in seagrass remote sensing because it handles nonlinear relationships, interactions among predictors, mixed variable types, and moderate training datasets with limited parameter tuning. Turissa et al. (2024) used Sentinel-2A and RF in GEE to map five shallow-water classes in Bintan, Indonesia, obtaining an overall classification accuracy of 76%. Wilson et al. (2020) also used RF as the principal classifier after threshold-based separation of spectrally obvious classes.

Support Vector Machine (SVM) remains competitive, particularly where sample sizes are moderate and class boundaries are nonlinear. Traganos et al. (2018) used SVM for large-scale Mediterranean mapping, while Traganos and Reinartz (2018) found SVM superior to RF and maximum likelihood in their Mediterranean case. Floyd et al. (2026), however, observed relatively small overall differences among SVM, RF, and CART compared with the larger influence of sensor choice. These findings caution against presenting one classifier as universally best.

Gradient-boosting methods are increasingly used for complex benthic problems. Harahap et al. (2026) compared RF and XGBoost for benthic habitat composition, seagrass percent cover, and above-ground carbon. Their results were broadly comparable, with XGBoost showing slightly improved regression performance in some tasks. A 2026 Manado study combined recursive feature elimination with LightGBM to monitor seagrass distribution from Sentinel-2 and reported stable overall seagrass area from 2020 to 2025 despite year-to-year fluctuations. The key advance is therefore not merely a new classifier, but integration of feature selection, temporal information, and independent validation.

Regression should be preferred when the ecological target is continuous. Percent cover, biomass, leaf area index, or carbon stock are not inherently categorical variables. Converting 23% and 49% cover into the same 'sparse' class discards information. RF regression, XGBoost regression, partial least squares, or other continuous models can retain ecological gradients when reference data are sufficiently dense. Classification remains appropriate when management requires habitat classes or when field labels are categorical.

3.6 From extent to condition: percent cover, biomass, and blue carbon

The most basic remote-sensing product is presence/absence extent, but management increasingly requires information on condition. Seagrass percent cover is a logical intermediate variable because it can describe gradual degradation before complete meadow loss. Zoffoli et al. (2020) demonstrated Sentinel-2 retrieval of percent cover in intertidal Zostera noltei, while recent high-resolution training approaches show that reference data derived from finer imagery can support Sentinel-2 regression when field quadrats are sparse.

Biomass and carbon-related variables are more demanding because a similar surface reflectance can represent different canopy heights, species, epiphyte loads, or leaf densities. Wicaksono et al. (2022) developed multitemporal Sentinel-2 models for seagrass aboveground carbon stock and carbon assimilation in Labuan Bajo, Indonesia. The study demonstrates how repeated imagery can move monitoring beyond static extent into temporally explicit ecosystem-function indicators. Hafizt et al. (2024) mapped benthic habitats in the Takabonerate Islands with Sentinel-2 and achieved an overall accuracy of 80.5%; the mapped seagrass extent was subsequently used for carbon-stock estimation.

Earth Observation is also being scaled to national blue-carbon accounting. Blume et al. (2023) combined more than 18,000 Sentinel-2 images, multi-temporal feature engineering, RF classification, and nationwide reference data to estimate seagrass extent across the shallow waters of The Bahamas. Such approaches are promising, but carbon accounting must preserve the distinction between mapped extent and carbon density. A highly accurate extent map does not automatically imply an equally accurate carbon stock estimate; uncertainty in biomass or sediment-carbon coefficients must be propagated separately.

3.7 Evidence from representative recent studies

Table 3. Representative studies in recent seagrass remote sensing.

Study	Location	Data	Method/target	Main contribution
Traganos & Reinartz (2018)	Mediterranean	Sentinel-2	SVM/RF/ML; water-column correction	Mapped P. oceanica and C. nodosa; SVM strongest among tested classifiers
Traganos et al. (2018)	Aegean & Ionian Seas	Sentinel-2 + GEE	Multi-scene compositing + SVM	Large-scale mapping of ~2,510 km^2 P. oceanica
Coffer et al. (2020)	United States sites	WorldView-2, RapidEye	Reproducible processing/classification	Up to 97% agreement with aerial interpretation
Wilson et al. (2020)	Atlantic Canada	Sentinel-2	Thresholds + RF	OA 79%; mapping depth varied spatially
Zoffoli et al. (2020)	European Atlantic intertidal	Sentinel-2	Percent-cover retrieval/time series	SPC uncertainty ~14%; seasonal dynamics resolved
Kuhwald et al. (2022)	Western Baltic Sea	Sentinel-2 + video/aerial data	RF; tested water-column correction	Balanced OA ~0.92 in optically shallow zone
Wicaksono et al. (2022)	Labuan Bajo, Indonesia	Sentinel-2	Multitemporal carbon models	Mapped aboveground carbon and assimilation

				dynamics
Blume et al. (2023)	The Bahamas	Sentinel-2 + GEE	RF + multi-temporal features	National-scale extent and blue-carbon accounting
Turissa et al. (2024)	Bintan, Indonesia	Sentinel-2A + GEE	RF; photo-transect reference	Five benthic classes; OA 76%
Hafizt et al. (2024)	Takabonerate, Indonesia	Sentinel-2A	NNC after atmospheric/glint/water corrections	Eight benthic classes; OA 80.5%
Amone-Mabuto et al. (2024)	Maputo Bay	Sentinel-2 + UAV	Machine learning	Satellite extent + UAV species/biomass information
Deeks et al. (2024)	NE Brazil	Sentinel-2 + GEE	Regional classification/time change	>79% accuracy; mapped 328 km^2 seagrass
Floyd et al. (2026)	Maldives	Landsat 8, Planet NICFI, Sentinel-2	SVM, RF, CART comparison	Sensor choice influenced OA more than classifier; S2 best of tested sources
Harahap et al. (2026)	Teluk Pandan, Indonesia	Sentinel-2 + PlanetScope	RF and XGBoost	Higher spatial detail vs spectral separability quantified
Nevstad et al. (2026)	Coastal habitat site	UAV + USV hyperspectral	Spectral Angle Mapper	Scale-dependent classification at cm resolutions

3.8 Accuracy assessment and uncertainty

Accuracy assessment is the point at which a visually attractive seagrass map becomes a defensible scientific product. Overall accuracy alone is insufficient because it can be dominated by large classes such as water or sand. Producer's accuracy, user's accuracy, precision, recall, F1-score, and a confusion matrix should be reported for the seagrass class. For continuous variables, R^2 should be accompanied by RMSE or MAE and, where possible, bias. Reference data should describe how percent cover or class labels were determined and whether observation dates were close to the satellite acquisition.

Spatial independence is a frequent weakness. If adjacent pixels from the same field polygon are randomly divided between training and testing data, the test set is not truly independent. The model is effectively evaluated on near-duplicates of its training environment. Spatially separated validation polygons, blocked cross-validation, or independent field campaigns provide a more realistic estimate of transferability. Roelfsema et al. (2021) emphasized expert-derived, standardized training and validation data as a critical component of global-scale benthic habitat mapping.

Reference data should also match the satellite pixel support. A 0.5-m quadrat is not necessarily representative of a 10 × 10 m Sentinel-2 pixel, especially in patchy habitats. One solution is to aggregate high-resolution UAV or aerial classification to the satellite grid. This creates reference labels that represent the same spatial support as the model target. Recent work evaluating compressed high-resolution imagery for Sentinel-2 percent-cover training similarly highlights the value of scale-matched reference data.

Uncertainty should be mapped where possible rather than represented by a single global percentage. Accuracy can decline with depth, turbidity, distance from field samples, or patch fragmentation. A probability surface, classification entropy, ensemble disagreement, or spatially explicit uncertainty layer can help managers identify where the map is reliable and where new field sampling is needed. This is especially important when remote-sensing products are used to calculate habitat area or blue-carbon stocks.

3.9 Implications for Indonesia

Indonesia is an ideal but challenging setting for remote-sensing-based seagrass monitoring. The country contains extensive island coastlines, high seagrass diversity, mixed coral-sand-seagrass mosaics, strong monsoonal seasonality, and many areas where field surveys are logistically expensive. At the same time, clear shallow reef flats in some regions offer excellent optical conditions. A national strategy should therefore not impose one universal model; it should establish a standardized framework with locally calibrated components.

Recent Indonesian studies already demonstrate a useful progression of scale and ecological complexity. Wicaksono et al. (2022) mapped temporal carbon-related properties in Labuan Bajo; Turissa et al. (2024) used Sentinel-2 and GEE to map seagrass and other benthic classes in Bintan; Hafizt et al. (2024) linked Sentinel-2 benthic mapping to seagrass carbon estimation in Takabonerate; Harahap et al. (2026)

quantified how spatial and spectral resolution affect biophysical mapping in Lampung; and Chen et al. (2026) used Sentinel-2 temporal features and LightGBM to monitor Manado seagrass distribution. Together, these studies show that Indonesia has moved beyond simple presence/absence mapping toward percent cover, carbon, machine learning, and time-series monitoring.

For routine monitoring, Sentinel-2 is likely to provide the most practical national backbone because it is free, frequently acquired, and compatible with GEE. However, PlanetScope, UAV, or other high-resolution imagery should be used strategically in priority sites for calibration, validation, restoration monitoring, and complex patch mosaics. Long-term Landsat observations remain useful when historical trajectories are required. A multi-resolution sampling design can therefore be more cost-effective than attempting to map every site using the highest-resolution imagery available.

3.10 Recommended workflow for repeatable seagrass mapping

Table 4. Recommended minimum workflow and reporting standards for seagrass remote sensing.

Stage	Recommended practice	Minimum information to report
1. Define objective	Specify extent, percent cover, species, biomass/carbon, or change	Objective, target classes/variable, spatial scale
2. Field/reference design	Sample all major habitats, depths, turbidity zones, and meadow densities	Sampling date, coordinates, class rule, cover method, number of samples
3. Image selection	Match field season and tidal state; minimize cloud, haze, and glint	Sensor/product, dates, tide, cloud/glint criteria
4. Aquatic preprocessing	Atmospheric correction, land/cloud/glint masking; test depth correction	Processor/version, output reflectance, correction equations/settings
5. Feature construction	Use bands, ratios, depth/bathymetry, temporal and texture features as justified	Full predictor list and feature-selection method
6. Model training	Compare interpretable baseline and ML model; avoid leakage	Algorithm, parameters, class balance, training design
7. Independent validation	Use spatially independent, scale-matched data	Confusion matrix or R^2/RMSE/MAE; class-specific accuracy
8. Uncertainty	Assess depth/turbidity/patch-size	Error sources,

analysis	effects and map probability where possible	confidence/probability layer, area uncertainty
9. Change analysis	Use comparable seasons/tides/sensors and consistent class definitions	Temporal normalization, change threshold, uncertainty propagation
10. Reproducibility	Archive code, metadata, training rules, and map legend	Software/platform, code availability, CRS, resolution, export settings

The workflow begins with the ecological question rather than the satellite. A study designed to detect meadow loss can use broader classes and longer time series, whereas species discrimination or percent-cover mapping requires substantially denser reference data and finer spatial or spectral resolution. Selecting a sensor before defining the target variable often leads to an overly detailed classification scheme that the imagery cannot support.

Preprocessing alternatives should be evaluated empirically. For example, a study may compare atmospherically corrected imagery with and without water-column correction, or single-scene mapping with a seasonal composite. The preferred version should be selected using independent validation rather than visual appearance. Similarly, RF, SVM, and gradient-boosting models should be compared under the same training and validation split; otherwise differences in accuracy cannot be attributed to the algorithm.

Finally, repeatability should be treated as a scientific result. Cloud platforms make it possible to store scripts, standardized composites, and classifiers that can be rerun annually. A management-oriented seagrass product should therefore include not only the final map but also acquisition rules, preprocessing steps, class definitions, validation data structure, and uncertainty. This enables future users to determine whether an apparent change reflects ecological dynamics or a change in methodology.

3.11 Research gaps and future directions

First, species-level mapping remains a major frontier. Multispectral sensors can separate some species assemblages where canopies are extensive and spectrally distinct, but high-diversity tropical meadows frequently contain several species within one pixel. Hyperspectral imagery, centimetre-scale UAV data, and combined structural observations may improve discrimination, but standardized spectral libraries and multi-season field data are still limited (Smart et al., 2026; Nevstad et al., 2026).

Second, temporal monitoring should move from occasional map comparison toward explicit time-series models. Frequent Sentinel-2 acquisitions make it possible to distinguish seasonal cycles from persistent degradation, but this requires consistent tidal and water-quality controls. The problem is particularly important in tropical environments where monsoon-driven turbidity and cloud cover can produce apparent trends if the annual composites are not seasonally comparable.

Third, uncertainty needs to be propagated into ecosystem-service products. Percent cover, biomass, and blue-carbon estimates inherit uncertainty from the habitat map, regression model, field measurements, and carbon conversion factors. Reporting only a final carbon value creates false precision. Future studies should provide confidence intervals or Monte Carlo-style propagation where data permit.

Fourth, integration of remote sensing with ecological and fisheries observations offers strong potential for JOMAFISH-relevant research. Spatially explicit seagrass maps can be combined with fish abundance, juvenile nursery use, water quality, coastal development, and fishing-pressure data to evaluate habitat function rather than extent alone. In this sense, remote sensing should be viewed as an ecological observation layer that supports marine management, not as an end product in isolation.

4. Conclusion

Remote sensing has transformed seagrass mapping from localized, infrequent surveys into repeatable observations across regional to national scales. Landsat remains essential for historical trajectories, Sentinel-2 provides the most practical freely available platform for current mapping, and high-resolution commercial imagery, UAVs, and hyperspectral systems add detail for fragmented meadows, species, percent cover, and biomass. The literature does not support a single universally best sensor or classifier. Performance is controlled by the interaction among spatial and spectral resolution, water clarity, depth, tide, preprocessing, class definition, training data, and validation design. Aquatic atmospheric correction, glint control, and explicit treatment of the water column are therefore as important as machine-learning selection. For Indonesia, a hierarchical monitoring strategy is recommended in which Sentinel-2 and cloud computing form the operational backbone, Landsat provides historical context, and high-resolution imagery or UAV surveys supply calibration and detailed ecological information at priority sites. Future research should emphasize standardized reference data, spatially independent validation, time-series analysis, uncertainty propagation, and integration of seagrass maps with fisheries, restoration, and blue-carbon applications. These practices will make remotely sensed seagrass information more scientifically defensible, reproducible, and useful for coastal decision-making.

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