

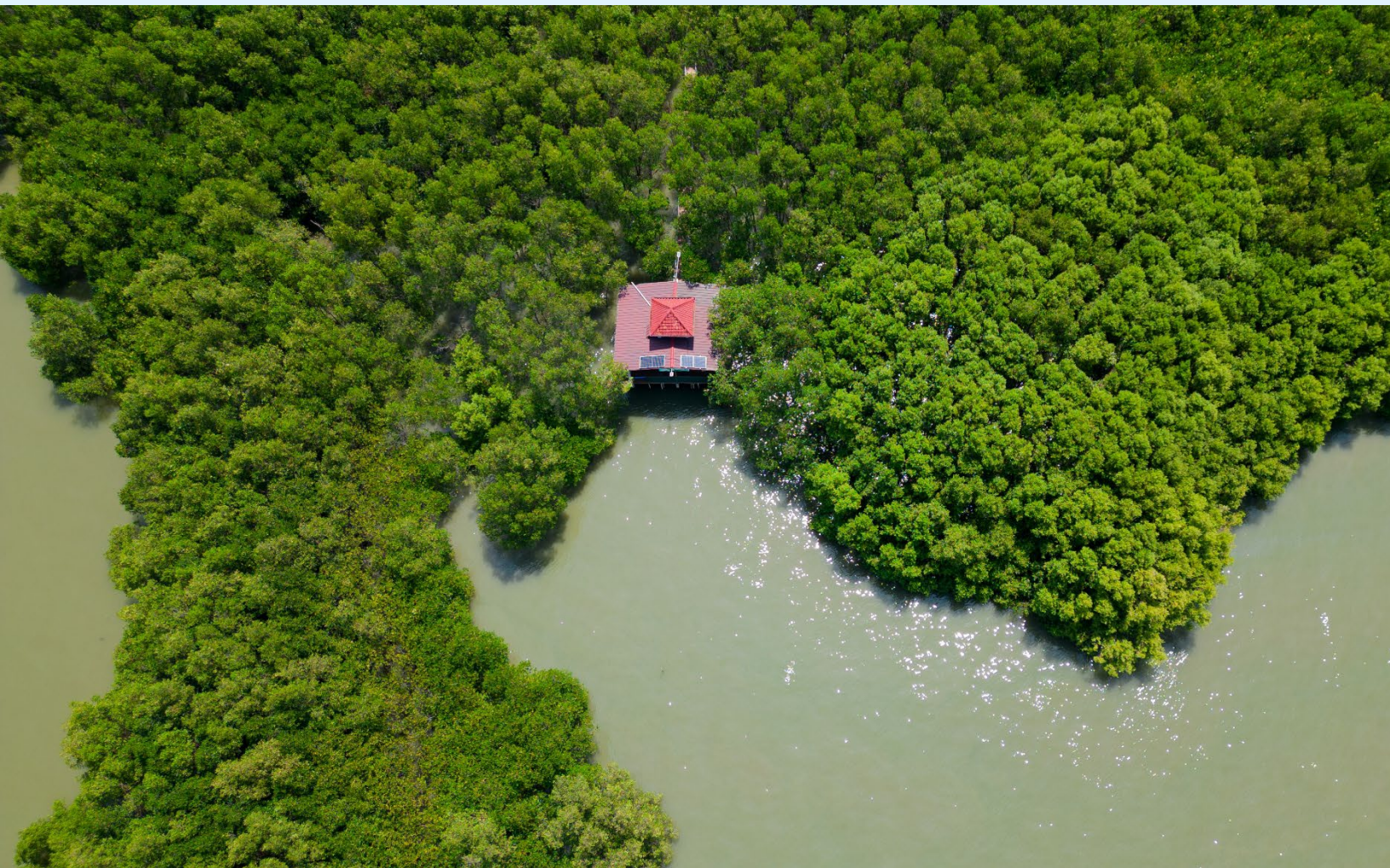


PEMSEA Regional Methodology for Blue Carbon Project Accounting

A Harmonized Guide for Estimating Carbon Stocks, Sequestration, and GHG Reductions in Coastal Ecosystems

Annex D

Mapping Blue Carbon Ecosystem



This annex is part of the publication entitled “PEMSEA Regional Methodology for Blue Carbon Project Accounting: A Harmonized Guide for Estimating Carbon Stocks, Sequestration, and GHG Reductions in Coastal Ecosystems. It benefitted from intensive consultations, discussions, and inputs from PEMSEA Country, Non-Country Partners and the PEMSEA Resource Facility supported by Kristina Di Ticman, Blue Carbon consultant. However, the contents of this publication do not necessarily reflect the views or policies of PEMSEA Country and Non-Country Partners and its other participating organizations. The designation employed and the presentation do not imply expression of opinion, whatsoever on the part of PEMSEA concerning the legal status of any country or territory, or its authority or concerning the delimitation of its boundaries.

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D.1 Introduction

Blue carbon ecosystems (BCEs)—primarily mangroves, seagrasses, and salt marshes—are coastal vegetated habitats that absorb, sequester, and store substantial quantities of carbon in both living biomass and underlying sediments. Although they occupy a relatively small proportion of the Earth’s surface compared with terrestrial forests, these ecosystems are among the most carbon-dense natural systems and contribute disproportionately to long-term carbon sequestration.

Mapping BCEs—delineating where they occur, quantifying their spatial extent, and tracking changes over time—is a foundational component of blue carbon accounting, monitoring, and management. Spatially explicit information is required to establish baselines, support monitoring and reporting, and link field-based carbon measurements to ecosystem extent in a transparent and reproducible manner.

D1.1 Why Mapping is Necessary

Mapping is necessary because blue carbon accounting relies fundamentally on accurate information about the location, extent, and dynamics of BCEs. Carbon stocks, sequestration rates, and greenhouse gas emissions are all expressed per unit area; without reliable maps, these estimates cannot be scaled beyond individual plots or sites. Spatial data therefore provide the activity data required to translate field measurements into ecosystem- or project-scale carbon estimates.

Globally, BCEs are subject to ongoing loss and degradation due to land-use change, coastal development, pollution, and climate-related pressures. Conversion or degradation of these ecosystems not only reduces future sequestration potential but may also result in the release of previously stored carbon. Mapping enables quantification of ecosystem extent and change, supporting assessment of gains, losses, and degradation relevant to carbon accounting and mitigation planning (Araya-Lopez et al., 2023).

Field-based measurements remain essential for quantifying carbon stocks and processes, but BCEs often occur in remote, tidally influenced, or logistically challenging environments. Conducting comprehensive ground surveys across entire coastal regions is therefore rarely feasible. Remote sensing and spatial analysis provide a scalable means of characterizing BCE distribution across broad areas, while also guiding the design of field sampling and supporting extrapolation of site-level measurements to larger spatial units.

D1.2 Application of Mapping Outputs

Spatial outputs derived from BCE mapping serve multiple, interrelated functions in blue carbon projects and programs. At the core, maps establish the spatial extent and distribution of BCEs, forming the basis for baseline carbon inventories and for tracking changes in ecosystem area through time. These spatial datasets support national and subnational reporting, coastal planning, and integration of blue carbon into climate mitigation strategies.

For project-level applications, mapping defines project boundaries, informs stratification, and supports the calculation and verification of activity data required for carbon accounting and, where applicable, participation in voluntary carbon markets or payment for ecosystem services schemes. Mapping outputs also guide conservation and restoration planning by identifying areas of ecosystem loss, degradation, or recovery, and by enabling monitoring of intervention outcomes. In operational terms, maps support field survey planning by helping practitioners design efficient sampling schemes that capture spatial variability while accounting for accessibility, tidal conditions, and logistical constraints.

Maps of initial or historical conditions provide evidence for baseline assessment but do not, by themselves, establish the counterfactual baseline. Apply the baseline requirements of main Chapter 8 when using mapping outputs in project accounting.

D1.3 Technologies That Enable Mapping

Mapping of BCEs is enabled through the combined use of remote sensing and Geographic Information Systems (GIS). Remote sensing provides spatial observations from satellite, airborne, unmanned aerial, and acoustic platforms, allowing consistent detection of ecosystem extent, structure, and change across large and often inaccessible coastal areas. GIS provides the analytical framework for managing, integrating, and interpreting these spatial datasets alongside field measurements and ancillary information.

Together, these technologies allow mapping outputs to be generated in a manner that is transparent, repeatable, and scalable, forming a critical foundation for blue carbon accounting, monitoring, and reporting.

D.2 Remote Sensing for Mapping Blue Carbon Ecosystems

Remote sensing (RS) is the primary technology used for mapping blue carbon ecosystems because it enables consistent, repeatable, and cost-effective observation of large and often inaccessible coastal areas. Compared with field-based surveys alone, remote sensing provides broader spatial coverage, supports standardized mapping across sites and countries, and enables analysis of historical ecosystem change using archived imagery.

In blue carbon applications, remote sensing does not replace field measurements. Instead, it complements field data by providing spatial context, informing sampling design, and enabling extrapolation of site-level measurements to ecosystem, project, or national scales.

D2.1 What Is Remote Sensing and How It Works

Remote sensing is the acquisition of information about the Earth's surface without direct physical contact, using sensors mounted on satellites, aircraft, unmanned aerial vehicles (UAVs), or other platforms. These sensors measure energy reflected or emitted from land and water surfaces and record it as digital data that can be processed into images or spatial layers.

For BCE mapping, remote sensing is used to identify the presence and extent of mangroves, seagrasses, and salt marshes; to distinguish vegetated areas from water, bare sediment, or built environments; and to detect changes in ecosystem extent or condition through time. The type of information that can be extracted depends on how different surfaces interact with incoming or emitted energy, particularly across visible, infrared, microwave, and acoustic wavelengths.

D2.2 Types of Remote Sensing Sensors

Remote sensing sensors are commonly classified as passive or active, based on their source of energy.

Passive sensors record energy that is naturally reflected or emitted from the Earth's surface, most commonly sunlight reflected in the visible and infrared portions of the spectrum. Multispectral sensors, such as those onboard the Landsat and Sentinel-2 satellites, record reflectance in a limited number of broad spectral bands and are widely used for mapping BCE extent and monitoring change at local to national scales. Hyperspectral sensors record reflectance across hundreds of narrow, contiguous bands, allowing finer discrimination of vegetation properties and,

in some cases, species composition, although these data are typically more complex and less widely available. The utility of passive optical data can be constrained by cloud cover, atmospheric conditions, and water properties.

Active sensors emit their own energy and measure the returned signal, making them independent of sunlight. Synthetic Aperture Radar (SAR) uses microwave energy that can penetrate clouds and is largely unaffected by atmospheric conditions, making it particularly valuable in tropical regions with persistent cloud cover and for detecting structural properties of mangrove forests. Light Detection and Ranging (LiDAR) uses laser pulses to measure distances to the Earth's surface, providing highly accurate information on terrain elevation and vegetation structure, including canopy height, which can support biomass estimation and stratification.

D2.3 Platforms for Data Acquisition

Remote sensing sensors are deployed on a range of platforms depending on the spatial scale, resolution, and objectives of the mapping effort.

- Satellite platforms provide consistent and repeatable coverage over large areas and are widely used for regional and national mapping due to their global availability and long-term data continuity.
- Airborne platforms, including piloted aircraft and UAVs, support targeted mapping at very high spatial resolution and are increasingly applied in blue carbon projects for detailed site assessments and validation.
- For submerged ecosystems such as seagrass meadows, acoustic and marine platforms—including sonar systems and underwater imaging—are used where optical sensors are limited by water depth or turbidity.

D2.4 Resolution and Its Importance in Blue Carbon Mapping

The suitability of remote sensing data for BCE mapping is strongly influenced by resolution, which determines the level of spatial and thematic detail that can be achieved.

- Spatial resolution refers to the ground area represented by a single pixel; coarser-resolution data are appropriate for regional assessments, while finer-resolution imagery is required to delineate narrow coastal features or small restoration sites. Figure 1 illustrates how differences in spatial resolution influence the representation of mangrove extent and boundary detail, with implications for activity data and uncertainty in blue carbon mapping.

- Spectral resolution describes the number and width of wavelength bands recorded, with higher spectral resolution improving the ability to distinguish vegetation types and conditions.
- Radiometric resolution reflects the sensitivity of the sensor to differences in brightness and affects the detection of subtle changes in reflectance.

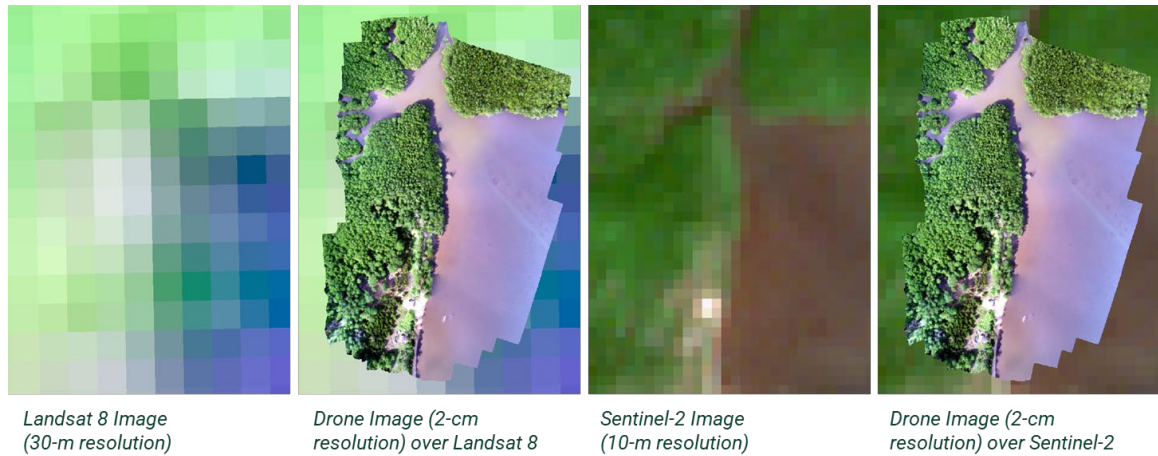


Figure 1: Comparison of mangrove representation at different spatial resolutions. From left to right: Landsat 8 imagery (30 m resolution), drone imagery (≈ 2 cm resolution) overlaid on Landsat 8, Sentinel-2 imagery (10 m resolution), and drone imagery (≈ 2 cm resolution) overlaid on Sentinel-2. This shows how increasing spatial resolution improves delineation of mangrove boundaries and fine-scale features, with implications for ecosystem extent estimation, stratification, and uncertainty in blue carbon mapping.

Source: Landsat 8 imagery (U.S. Geological Survey/NASA); Sentinel-2 imagery (Copernicus Programme/European Space Agency); drone imagery acquired by the authors.

Selection of appropriate resolution involves balancing detail, spatial coverage, data availability, and processing requirements, and should be aligned with the intended application, such as national inventory development versus project-level monitoring.

D2.5 Analytical Approaches Used in Blue Carbon Mapping

Once remote sensing data are acquired and pre-processed, analytical techniques are applied to convert spectral or structural information into meaningful map outputs. Ecosystem extent is commonly derived using image classification approaches, including supervised methods that rely on reference data and unsupervised methods that group pixels based on statistical similarity.

Object-based image analysis (OBIA), which groups neighboring pixels into spatial objects, is often used with high-resolution imagery to incorporate shape, texture, and contextual information.

More advanced analytical approaches, including machine learning and deep learning methods, are increasingly used to improve classification performance and capture complex spatial patterns, particularly when integrating data from multiple sensors. Cloud-based processing platforms enable large-area and time-series analyses using open satellite archives and high-performance computing resources, supporting consistent application of methods across space and time.

D2.6 Advantages of Remote Sensing for Blue Carbon Ecosystems

Remote sensing offers several advantages for BCE mapping, including efficient coverage of large areas, access to remote or hazardous environments, and consistent, repeatable observations suitable for long-term monitoring. The availability of historical satellite archives further enables retrospective analysis of ecosystem change, which is essential for baseline reconstruction and trend assessment in blue carbon accounting.

D2.7 Limitations and Challenges

Despite its strengths, remote sensing has important limitations that must be recognized in BCE applications. Optical imagery can be constrained by cloud cover, particularly in tropical regions, while water-column effects such as depth and turbidity complicate mapping of submerged seagrass ecosystems. Higher-resolution and advanced sensors increase data volume and analytical complexity, and species-level discrimination remains challenging in many mixed or sparse vegetation systems.

These limitations underscore the importance of combining remote sensing with field-based validation, careful interpretation of results, and transparent reporting of uncertainty in blue carbon mapping and accounting.

D.3 General Mapping Framework for Blue Carbon Ecosystems

Mapping blue carbon ecosystems follows a structured sequence of steps that transforms raw spatial data into validated map products suitable for carbon accounting, monitoring, and management. While specific tools, sensors, and algorithms may vary depending on data availability and technical capacity, the underlying workflow is consistent across ecosystems and project contexts. This section outlines a general mapping framework applicable to mangroves, seagrasses, and salt marshes, providing a common reference for subsequent ecosystem-specific approaches.

D3.1 Data Acquisition

The mapping process begins with the selection of appropriate spatial data sources. Data selection should be driven by the mapping objective (e.g., baseline extent, change detection, project-scale monitoring), the spatial scale of analysis, and the environmental characteristics of the site.

Data inputs typically include optical satellite imagery, Synthetic Aperture Radar (SAR), LiDAR, and relevant ancillary datasets. Spaceborne platforms are commonly used for regional and national assessments due to their repeat coverage and open data availability, while airborne platforms and UAVs support higher-resolution mapping for local-scale assessments and validation.

Spatial resolution requirements should be defined at this stage. Medium-resolution imagery (approximately 10–30 m) is generally sufficient for mapping overall ecosystem extent, whereas finer-resolution data may be required for narrow coastal features, fragmented habitats, or small restoration sites. Selection of data sources should balance spatial detail, temporal coverage, consistency through time, and processing requirements.

D3.2 Pre-processing and Data Preparation

Raw remote sensing data must be pre-processed to ensure spatial consistency and physical interpretability prior to analysis. Pre-processing does not introduce new information but reduces sources of error that would otherwise propagate into classification and area estimates.

Typical preparation steps include radiometric correction to account for sensor characteristics and atmospheric effects, and geometric correction to align imagery accurately with geographic coordinates. For submerged ecosystems such as seagrass meadows, additional water-column

correction may be required to reduce the influence of depth, turbidity, and surface reflectance on the recorded signal.

For multi-temporal analyses, use a common coordinate reference system and analysis grid, co-register images, apply consistent radiometric and atmospheric processing, and document any cross-sensor normalization. Use comparable tidal and seasonal conditions where practicable, and maintain consistent class definitions and classification procedures. Document remaining differences and assess their effects on change detection and area estimates; see D7.4.

D3.3 Image Processing and Classification

Following pre-processing, spatial data are analyzed to delineate BCE classes and generate thematic maps of ecosystem extent. This step converts continuous spectral or structural information into discrete map categories (e.g., mangrove, seagrass, salt marsh, water, bare substrate).

Classification approaches may include pixel-based methods, object-based image analysis, or hybrid approaches that integrate spectral, spatial, and contextual information. Supervised classification is commonly used for BCE mapping, relying on reference data derived from field observations or high-resolution imagery to train classification models. Simpler, transparent approaches are often preferred for baseline mapping and MRV applications, while more complex methods may be justified for detailed monitoring or research-oriented analyses.

Regardless of the method used, classification outputs should be clearly defined, internally consistent, and aligned with the intended use of the map as activity data for carbon accounting.

D3.4 Validation and Accuracy Assessment

Validation is a critical step that evaluates how well the classified map represents real-world conditions. This involves comparison of mapped classes against independent reference data, such as field observations, UAV imagery, or very high-resolution satellite data.

Validation should be conducted using a statistically defensible sampling design and reference data that are independent from any data used to train the classification. Accuracy assessment typically includes construction of an error matrix and calculation of class-level and overall accuracy metrics.

Validation does not eliminate uncertainty but makes it explicit. Quantifying classification accuracy is essential for determining whether mapping outputs are fit for purpose and for

supporting subsequent estimation of area uncertainty used in carbon stock and emission calculations.

D3.5 Integration and Use of Mapping Outputs

Validated mapping outputs form a core spatial input to blue carbon workflows. Ecosystem extent maps are used to estimate activity data, support stratification of field sampling designs, and provide the spatial basis for carbon stock, sequestration, and emission calculations.

Mapping outputs are also used for monitoring ecosystem change over time, supporting adaptive management, restoration planning, and reporting under national inventories or project-level MRV frameworks. At this stage, spatial datasets should be integrated within a GIS environment, accompanied by appropriate metadata, and archived in a manner that supports transparency, reproducibility, and future re-analysis.

D.4 Data Sources and Inputs

Mapping blue carbon ecosystems requires the integration of multiple data sources that provide complementary spatial, structural, and contextual information. No single dataset is sufficient on its own. Reliable mapping outputs depend on the combined use of remote sensing imagery, ancillary geospatial data, field-based measurements, and, where appropriate, community and local knowledge. Together, these inputs support ecosystem delineation, calibration of classification approaches, validation of map outputs, and interpretation of spatial uncertainty.

The descriptions of basic and advanced technologies in this annex do not assign a methodological level to an accounting estimate. Determine the applicable level from data suitability, representativeness, calibration, validation and uncertainty, in accordance with main Chapter 7.

D4.1 Basic Optical Remote Sensing Data

Optical satellite imagery forms the primary data source for mapping the extent and spatial distribution of BCEs. Freely available medium-resolution datasets, such as those from the Landsat series and Sentinel-2, are widely used for national and regional assessments, baseline mapping, and long-term change analysis due to their global coverage and multi-decadal continuity.

Higher spatial resolution optical imagery, including commercial satellite data and aerial photography, is commonly used for project-scale applications, mapping narrow coastal features,

or supporting training and validation. From optical imagery, practitioners typically derive land- or habitat-cover layers that describe ecosystem presence and condition. These spatial layers constitute the activity data required for area-based blue carbon accounting.

D4.2 Advanced Remote Sensing Inputs

Advanced remote sensing datasets are used to address limitations of basic optical imagery or to capture ecosystem characteristics not readily observable in two-dimensional optical data.

Synthetic Aperture Radar (SAR) imagery is particularly valuable in regions with persistent cloud cover and is widely applied in mangrove mapping to improve detection of forest extent and structure. LiDAR provides three-dimensional information on terrain and vegetation structure, including canopy height, and is especially useful for stratification and biomass-related analyses in forested BCEs. Hyperspectral data enable finer discrimination of vegetation properties and benthic substrates, but their use is typically limited to research or targeted applications due to data availability and processing requirements.

Unmanned platforms, including UAVs and marine-based acoustic systems, are increasingly used to support high-resolution mapping, targeted assessments, and validation, particularly in complex or submerged environments such as seagrass meadows.

D4.3 Ancillary and Geospatial Data

Ancillary geospatial datasets provide contextual information that constrains and refines interpretation of remote sensing outputs. These include existing land-use and habitat maps, shoreline and tidal boundary datasets, digital elevation models (DEMs), and bathymetric data.

Elevation and depth information are particularly important for BCE mapping, as ecosystem distribution is strongly influenced by tidal inundation and water depth. Ancillary datasets do not replace remote sensing imagery, but they improve classification performance, support stratification, and reduce misclassification by limiting analyses to ecologically plausible zones.

D4.4 Field and Ground-Based Data

Field data play a critical role in BCE mapping by supporting both calibration and validation of spatial analyses. While detailed field methods are described elsewhere in this methodology, their role

within the mapping workflow is to link spatial patterns to measured ecosystem properties and to provide independent reference data for accuracy assessment.

Field-based inputs may include vegetation measurements, soil observations, in situ spectral data, and georeferenced photographs. These data are used to train or interpret classification outputs and, critically, to validate final maps and quantify classification accuracy and spatial uncertainty. Field data are therefore essential for ensuring that mapping outputs are suitable for use in carbon accounting and MRV applications.

D4.5 Community and Local Knowledge

Community and local knowledge can provide valuable contextual information for BCE mapping, particularly in areas with limited historical data or rapidly changing coastal conditions. Local understanding of ecosystem boundaries, species distribution, geomorphology, and land-use history can support stratification, guide selection of training and validation sites, and assist in interpretation of ambiguous mapping results.

When systematically documented and combined with remote sensing and field measurements, community-based inputs can enhance both the technical robustness and practical relevance of mapping outputs, while also supporting stakeholder engagement and transparency.

D4.6 Data Integration

Credible BCE mapping depends on the effective integration of multiple data sources within a consistent analytical framework. Optical and advanced remote sensing data provide spatial coverage, ancillary datasets constrain interpretation, and field and community inputs support calibration and validation. Integrating these inputs improves classification accuracy, strengthens uncertainty assessment, and ensures that mapping outputs are fit for purpose in blue carbon accounting, monitoring, and reporting.

All data sources and integration steps should be clearly documented to support reproducibility, quality assurance, and independent review.

D.5 Ecosystem-Specific Mapping Approaches

While the general mapping framework described in Section D.3 applies to all blue carbon ecosystems, ecosystem-specific characteristics influence the choice of data sources, processing approaches, and interpretation of mapping outputs. Mangroves, seagrass meadows, and salt marshes differ in vegetation structure, position along the land–sea gradient, and interaction with tidal and water-column processes. These differences affect how ecosystems are detected and delineated using remote sensing.

This section outlines commonly used mapping approaches for each ecosystem type. The methods described are illustrative and are not intended to prescribe specific algorithms or sensors. Projects should select approaches that are appropriate to their objectives, data availability, and technical capacity, provided that resulting maps are validated and suitable for use as activity data in blue carbon accounting.

D5.1 Mangrove Mapping Methods

Mangroves are intertidal, woody vegetation communities that occur at the interface between land and sea. Mapping mangroves focuses primarily on delineating horizontal extent, with additional structural information used where available to support stratification or biomass-related analyses.

Baseline mangrove mapping is commonly conducted using multispectral optical imagery, such as Landsat or Sentinel-2, combined with supervised classification or vegetation indices. These approaches are widely used because they rely on freely available data, are relatively transparent, and can be applied consistently across large spatial extents. Index-based approaches and supervised classifiers are effective for distinguishing mangroves from water, bare sediment, and most non-mangrove vegetation when supported by appropriate reference data.

In areas with persistent cloud cover or spectral confusion with terrestrial forests, Synthetic Aperture Radar (SAR) imagery is frequently integrated to improve detection of mangrove extent and canopy structure. Where available, LiDAR data provide additional information on canopy height and terrain elevation, supporting stratification and more detailed spatial analyses.

Advanced analytical approaches, including object-based image analysis and machine learning classifiers, may further improve mapping accuracy, particularly in heterogeneous landscapes or fragmented mangrove systems. However, increased methodological complexity should be justified by improved performance and accompanied by robust validation.

For blue carbon applications, mangrove mapping outputs are primarily used to define ecosystem extent, support stratification of field sampling, and track gains and losses over time. Structural

metrics derived from remote sensing may inform stratification but do not replace field-based biomass measurements.

D5.2 Seagrass Mapping Methods

Seagrasses are marine flowering plants that occur in intertidal and subtidal coastal environments. Intertidal meadows may be exposed at low tide, while submerged meadows present additional mapping challenges because water depth, turbidity and surface conditions affect the optical signal. Select imagery and survey methods appropriate to the meadow's tidal position, water clarity and seasonal conditions.

Baseline seagrass mapping is commonly conducted using high-quality optical imagery combined with water-column correction and supervised classification. These approaches are most effective in shallow, relatively clear waters and are widely used for establishing seagrass extent as activity data. Ancillary information on bathymetry and water clarity is often required to constrain analyses to areas where optical mapping is feasible.

In turbid or deeper environments, single-date optical imagery may be insufficient. Multi-temporal approaches that integrate imagery acquired under varying tidal and environmental conditions can improve detection by enhancing persistent seagrass signals relative to transient noise. Where optical limitations remain significant, acoustic methods such as side-scan sonar and multibeam echo sounders provide an alternative means of mapping seagrass presence and extent.

Advanced approaches, including hyperspectral imagery and data-fusion techniques that combine optical, acoustic, and field data, may support species discrimination or fine-scale structural assessment. These methods are typically applied in targeted studies rather than routine project implementation.

For blue carbon accounting, seagrass mapping outputs are primarily used to delineate spatial extent and monitor changes through time. Species composition and density information, where available, may support interpretation but are not required unless explicitly linked to carbon stock estimation methods.

D5.3 Salt Marsh Mapping

Salt marshes are intertidal wetlands dominated by salt-tolerant grasses, sedges, rushes or shrubs. Mapping approaches shall accommodate their natural geographic distribution, including higher-latitude and subarctic settings. Mapping focuses on ecosystem extent and vegetation distribution

along elevation and inundation gradients, using observations appropriate to local tidal, seasonal and phenological conditions.

Baseline salt marsh mapping commonly relies on multispectral optical imagery combined with vegetation indices and supervised classification. Medium-resolution satellite data are often sufficient to delineate broad marsh extent and detect long-term changes when applied consistently through time. Seasonal and phenological variability can be leveraged through multi-temporal analysis to improve class separability from mudflats and other intertidal surfaces.

Elevation data play a particularly important role in salt marsh mapping, as vegetation distribution is closely linked to tidal inundation thresholds. Integration of digital elevation models, especially those derived from LiDAR, improves classification performance and supports assessment of vulnerability to sea-level rise.

More advanced approaches may integrate SAR data or multi-sensor data fusion to capture moisture-related or structural differences across marsh zones. Machine learning classifiers are often applied in these contexts, particularly for regional-scale monitoring. As with other BCEs, increased analytical complexity should be accompanied by appropriate validation.

Salt marsh mapping outputs support estimation of ecosystem extent, monitoring of expansion or loss, and interpretation of spatial patterns relevant to carbon stock and sequestration assessments.

Where remotely sensed vegetation characteristics are used to estimate biomass, the relationships shall be supported by appropriate field calibration and validation. Belowground biomass estimates derived from remotely sensed or aboveground characteristics shall use locally appropriate relationships supported by field measurements. Account for seasonal variability where relevant, following Annex C.

D.6 Validation and Accuracy Assessment

Validation and accuracy assessment are required steps in blue carbon ecosystem mapping to ensure that spatial outputs are reliable and fit for use in carbon accounting, monitoring, and reporting. Because maps derived from remote sensing are interpretations of surface conditions, their accuracy must be independently evaluated before mapped ecosystem extent is used as activity data or incorporated into MRV frameworks.

In this annex, validation refers to the assessment of classified mapping outputs using reference data that are independent from any data used to train or calibrate the mapping approach. This

distinction is critical, as internal classifier performance alone does not indicate how well a map represents real-world conditions.

D6.1 Purpose of Validation in Blue Carbon Mapping

The primary purpose of validation is to quantify how accurately mapped classes represent BCEs on the ground or seafloor. For blue carbon applications, this assessment serves two closely linked functions: first, to determine whether mapped ecosystem classes (e.g., mangrove, seagrass, salt marsh) are reliable enough to be used as activity data; and second, to provide the basis for estimating spatial uncertainty associated with mapped ecosystem area.

Only maps that have undergone formal validation and accuracy assessment should be used for reporting ecosystem extent, monitoring change, or supporting carbon stock and emission calculations.

D6.2 Independence of Validation Data

Validation must be conducted using reference data that are independent of the data used to train or develop the classification. Using the same data for both training and validation leads to biased accuracy estimates and overconfidence in mapping results.

Acceptable sources of independent reference data include field survey observations, georeferenced photographs, UAV or aerial imagery, very high-resolution satellite imagery, and existing authoritative maps where methods and acquisition dates are appropriate. Training and validation datasets should be documented separately to ensure transparency and reproducibility.

D6.3 Sampling Design for Validation Points

Validation samples should be selected using a statistically defensible sampling design that supports unbiased accuracy estimation. Common approaches include simple random sampling and stratified random sampling.

For BCE mapping, stratified random sampling is generally recommended because it ensures adequate representation of less extensive or spatially fragmented ecosystem classes, such as

narrow mangrove fringes or patchy seagrass meadows. The sampling design should be documented, including the rationale for stratification and allocation of samples among classes.

D6.4 Determination of Sample Size

The number of validation samples should be sufficient to estimate accuracy metrics with acceptable confidence and precision. Sample size depends on the number of mapped classes, expected classification accuracy, and acceptable error bounds.

While no single sample size is universally applicable, validation datasets typically include tens to hundreds of reference points distributed across the mapped area, with sufficient samples assigned to each BCE class to support stable estimation of omission and commission errors. The rationale for selected sample sizes should be clearly reported.

D6.5 Error Matrix and Classification Errors

An error matrix (also referred to as a confusion matrix) is the primary tool for evaluating map accuracy. It compares mapped class labels with reference class labels at each validation location.

From the error matrix, two key types of classification error are quantified: errors of omission, where a real BCE class is not captured on the map, and errors of commission, where a map class is assigned incorrectly. Both error types directly affect estimates of ecosystem extent and must be considered when interpreting mapping outputs for carbon accounting.

D6.6 Accuracy Metrics

Report overall accuracy, producer's accuracy and user's accuracy using estimators consistent with the validation sampling design. Where sampling fractions differ among strata, apply the appropriate sampling weights; the unweighted proportion of correctly classified validation samples shall not be treated as an estimate of overall map accuracy. Document the sampling design, sample allocation, weights and uncertainty of the reported estimates.

Class-level accuracy metrics are particularly important for BCE applications, as errors in specific ecosystem classes can disproportionately influence area-based carbon stock and emission estimates. Where appropriate, additional metrics may be reported to support interpretation, provided their meaning and relevance are clearly explained.

		reference data classes			
thematic map classes		A	B	C	sum
	A	35	2	2	39
	B	10	37	3	50
	C	5	1	41	47
	sum	50	40	46	136

$$\text{overall accuracy} = (35+37+41)/136 \approx 83.1\%$$

producer's accuracies

$$A \quad 35/50 \approx 70.0\%$$

$$B \quad 37/40 \approx 92.5\%$$

$$C \quad 41/46 \approx 89.1\%$$

user's accuracies

$$A \quad 35/39 \approx 89.7\%$$

$$B \quad 37/50 \approx 74.0\%$$

$$C \quad 41/47 \approx 87.2\%$$

Figure 2: A sample error matrix that summarizes classifier (Richards, 2022)

D6.7 Linking Accuracy Assessment to Area Uncertainty

Areas calculated directly from mapped pixel counts may be affected by classification error. Estimate ecosystem-class or stratum areas and their uncertainty using independent validation data and a documented, statistically appropriate estimator consistent with the sampling design.

Report the mapped area and error-adjusted area in hectares, together with the standard error and a confidence interval at a stated confidence level. Document the reference data, sample allocation, sampling weights and estimation procedure. Standard error shall not be presented as a confidence interval without the appropriate conversion.

Carry area uncertainty into the carbon-accounting uncertainty assessment under main Chapter 6. Where several carbon pools occupy the same mapped stratum, use the same stratum area and account for the shared area uncertainty when combining pool estimates.

D6.8 Quality Assurance and Quality Control (QA/QC)

Validation and accuracy assessment should be supported by basic quality assurance and quality control procedures. These include verification of reference data completeness and consistency,

independent review of validation datasets, and clear documentation of assumptions, limitations, and sources of uncertainty.

Applying QA/QC procedures strengthens transparency and supports independent review and verification of mapping outputs used in blue carbon accounting.

D6.9 Role of Validation in Blue Carbon Accounting

Validated maps provide the spatial foundation for estimating BCE extent, deriving activity data, tracking ecosystem change, and propagating spatial uncertainty into carbon stock and emission calculations. Without formal validation and accuracy assessment, mapping outputs should be considered exploratory and should not be used for reporting or accounting purposes.

D.7 Monitoring and Change Detection

Monitoring and change detection extend baseline mapping by tracking how the spatial extent and condition of blue carbon ecosystems (BCEs) evolve through time. In blue carbon accounting, monitoring supports the identification of ecosystem gains, losses, degradation, and recovery, and provides updated activity data required for carbon stock, sequestration, and emission assessments.

Monitoring outputs must be interpreted in a manner consistent with the objectives of the assessment and the temporal dynamics of different carbon pools. Changes detected through spatial analysis should be validated and reported together with associated uncertainty, following the principles outlined in Section D.6.

D7.1 Approaches to Monitoring

Remote sensing–based monitoring of BCEs generally follows two complementary approaches.

Map-to-map comparison involves generating classified ecosystem maps for two or more time periods and comparing them to identify changes in ecosystem extent or class transitions (e.g., mangrove to aquaculture, seagrass to bare substrate). This approach is widely used in baseline updating and periodic reassessment.

Time-series analysis uses sequences of satellite observations to detect trends, seasonal patterns, or abrupt changes in ecosystem condition or extent. Rather than relying on a small number of

discrete maps, time-series approaches analyze temporal trajectories to distinguish persistent change from short-term variability.

Both approaches require consistent data processing and classification logic through time to ensure that detected changes reflect real ecosystem dynamics rather than methodological artefacts.

D7.2 Basic Monitoring Procedures

Basic monitoring approaches are commonly applied in national inventories and project-level assessments because they rely on open satellite archives and relatively simple analytical workflows.

Moderate-resolution satellite datasets, particularly from the Landsat series, are widely used due to their long temporal coverage and consistent global availability. Change detection may be conducted through visual interpretation, post-classification comparison of ecosystem maps from different years, or analysis of vegetation indices to identify sustained declines or increases in vegetation cover.

These approaches are effective for detecting large-scale and persistent changes in ecosystem extent, but they are sensitive to differences in image quality, tidal conditions, and classification consistency across time periods.

D7.3 Advanced Monitoring Approaches

Advanced monitoring approaches integrate multi-sensor data, automated classification methods, and higher temporal resolution to improve detection of subtle or gradual change.

Machine learning classifiers are commonly applied to multi-temporal datasets to enhance robustness to noise and variability, while cloud-based processing platforms enable consistent analysis of long image archives across large spatial extents. Integration of active sensors, such as Synthetic Aperture Radar (SAR), improves monitoring in persistently cloudy regions, while LiDAR data provide additional information on vertical structure and elevation change where available.

In some contexts, remote sensing-based monitoring may be complemented by field-based structural or process measurements, such as surface elevation monitoring or biomass re-measurement, to support interpretation of observed spatial changes.

D7.4 Key Technical Considerations

Several technical considerations are critical for reliable change detection. Imagery from different dates must be precisely co-registered so that each pixel represents the same ground location across time; misregistration can produce false change signals. Temporal resolution and monitoring frequency should be selected based on the expected rate of ecosystem change and the objectives of the assessment.

Mapping updates shall follow the applicable ecosystem-annex monitoring schedule and the project monitoring plan. Additional assessments shall be undertaken where disturbances or other evidence indicate potentially material changes in ecosystem extent or condition. Use comparable tidal and seasonal conditions where practicable, and document differences in imagery, resolution, methods and reference-data availability between monitoring periods.

D7.5 Interpretation of Change for Blue Carbon Accounting

Not all detected spatial changes have equivalent implications for carbon accounting. Monitoring outputs should be interpreted in terms of the type of change (loss, gain, degradation, or recovery), its persistence through time, and its relevance to carbon pools and emission pathways.

Temporary disturbances, seasonal variability, or short-term fluctuations should be distinguished from permanent ecosystem conversion. Where spatial change is used to update activity data, associated uncertainty should be quantified and reported in accordance with the accuracy assessment framework described in Section D.6.

Where mapped change is used in carbon accounting, assess the accuracy and uncertainty of the change categories using reference information appropriate to the dates compared. Accuracy estimates for individual maps shall not be assumed to represent the accuracy of the resulting change map.

D7.6 Role of Monitoring in MRV and Adaptive Management

Monitoring and change detection provide the empirical basis for updating activity data, verifying permanence, identifying potential leakage risks, and supporting adaptive management decisions. Consistent monitoring supports transparent reporting under MRV systems and enables evaluation of conservation or restoration interventions over time.

By integrating repeatable remote sensing observations with appropriate validation and uncertainty assessment, monitoring outputs contribute to both the scientific robustness and policy relevance of blue carbon accounting frameworks.

D.8 Data Management and Archiving

Effective data management and archiving are essential to ensure that blue carbon ecosystem mapping and monitoring outputs remain transparent, traceable, and usable for carbon accounting, monitoring, reporting, and verification (MRV). Spatial datasets, field observations, and analytical outputs underpin estimates of ecosystem extent, change, and associated carbon stocks. Without consistent organization and documentation, these data cannot be reliably interpreted, reproduced, or independently reviewed.

D8.1 Purpose of Data Management

Data management practices for BCE mapping are designed to ensure that spatial outputs and supporting datasets are accurate, internally consistent, and fit for reporting and verification. Because blue carbon assessments integrate remote sensing data, field measurements, and ancillary information collected at different scales and times, clear data structures are required to prevent loss of context, misinterpretation, or duplication.

Well-managed datasets support comparison across time and sites, facilitate re-analysis as methods evolve, and enable independent review of mapping outputs used in carbon accounting and MRV frameworks.

D8.2 Data Types and Metadata Requirements

All datasets used in BCE mapping and monitoring should be accompanied by complete and consistent metadata. Metadata describe how, when, where, and by whom data were collected and processed, and are essential for reproducibility and quality assurance.

Key metadata elements include information on data source, acquisition date, spatial resolution, processing steps, classification methods, and any indices or derived variables. For field-based reference data, metadata should include geographic coordinates, ecosystem type, observation date, and data collection method. Where laboratory analyses are linked to mapping outputs, sample identifiers and analytical methods should be clearly documented.

Record the coordinate reference system and relevant horizontal and vertical datums, acquisition season and tidal conditions, class definitions, minimum mapping unit, and areas that could not be reliably observed. Retain identifiers separating training and validation data, the validation sampling design and weights, and versions of datasets and processing methods.

Metadata should be sufficient to allow a third party to understand and reproduce the mapping workflow without requiring additional clarification.

D8.3 Data Organization and Archiving

Mapping and monitoring data should be organized and archived in formats that are non-proprietary, well-documented, and accessible over time. Recommended practices include consistent file naming conventions that indicate location, ecosystem type, and date; storage of spatial outputs in standard geospatial formats; and retention of both raw and processed datasets together with documentation of processing steps.

Archiving both inputs and outputs allows mapping results to be re-evaluated as new data, methods, or verification requirements emerge. Where possible, datasets should be stored in institutional or shared repositories that support long-term access and version control.

At the regional and global levels, centralized data archives and standardized data structures facilitate synthesis and comparison across projects and jurisdictions. Alignment with established coastal carbon data repositories or compatible data structures is encouraged, where feasible.

Retain mapping inputs, outputs and supporting records in accordance with the main methodology's monitoring-record retention requirements.

D8.4 Quality Assurance and Quality Control (QA/QC)

Basic quality assurance and quality control procedures should be applied prior to archiving mapping-related datasets. These procedures include verification of data completeness and consistency, review of classification outputs and reference datasets, and documentation of assumptions and known limitations.

QA/QC procedures for data management are complementary to, but distinct from, validation and accuracy assessment described in Section D.6. While validation quantifies map accuracy, QA/QC ensures that datasets are internally coherent, properly documented, and free from avoidable errors prior to use in reporting or verification.

D8.5 Role of Data Management in Blue Carbon Accounting

Well-managed and archived datasets underpin all subsequent stages of blue carbon assessment, including accuracy assessment, monitoring and change detection, uncertainty analysis, and reporting under MRV frameworks. Transparent data management supports traceability of results, facilitates independent verification, and enhances confidence in spatial outputs used for carbon accounting.

By ensuring that mapping data are organized, documented, and accessible over time, data management and archiving contribute directly to the long-term credibility and usability of blue carbon ecosystem mapping outputs.

D8.6 Reporting templates

Use these supporting records with the ecosystem reporting templates in Annexes A–C. Use identical project, stratum and reporting-period identifiers. Reference existing datasets and reports instead of duplicating them. Repeat rows or tables as needed; use “not applicable” with a reason where appropriate. Blank cells are for project records, not worked examples.

These templates organize the mapping and validation requirements in this annex, drawing on the mapping accuracy guidance listed in its references and the data-management guidance in Howard et al. (2014). They do not replace the selected mapping method or its validation requirements.

Template R1: Mapping inputs and methods

Field	Record
Project ID and name; reporting period	
Map ID, version, production date and responsible organization	
Ecosystem, geographic coverage and stratum IDs; linked A–C report IDs	
Map purpose and observation dates; distinguish observed maps from any counterfactual baseline model	
Coordinate reference system, horizontal datum and vertical datum where applicable	
Classification legend and definitions; minimum mapping unit; spatial resolution	
Image or survey acquisition dates; season, tide, water level and visibility conditions	

Field	Record
Processing and classification method; software/model version; training-data IDs	
Unobservable areas and data gaps; treatment of clouds, deep water or other limitations	

Input dataset / ID	Source and access reference	Acquisition date / coverage	Resolution / scale

Template R2: Validation, accuracy and area estimates

Field	Record
Validation dataset ID, dates and reference-label method	
Sampling population and design; sampling strata and allocation	
Sample inclusion probabilities or weights; reference to sampling records	
Independence from training data; handling of uncertain reference labels	
Area-weighted error matrix reference; accuracy estimator and uncertainty method	
Confidence level and interval method; area units (ha)	
Overall accuracy and uncertainty; validation limitations	

Report class-level accuracy separately from area estimates. Identify an unavailable estimate and its reason; do not substitute mapped pixel area for an error-adjusted estimate without explanation. User's and producer's accuracy describe classification performance, not the confidence interval of area.

Map class / stratum ID	Validation sample count	User's accuracy (%)	Producer's accuracy (%)	Uncertainty / results reference

Map class / stratum ID	Mapped area (ha)	Error-adjusted area (ha)	Area SE (ha)	CI lower–upper (ha)

Template R3: Change detection and interpretation

Field	Record
Earlier and later map IDs, versions and observation dates	
Comparability of legends, resolution, registration, season and tidal conditions	
Change-validation design and reference-data IDs; change-area estimation method	
Treatment of unobservable areas and unresolved change	
Confidence level and uncertainty method; interpretation and field-check reference	

Record the from-class and to-class for each transition, including unchanged classes where required for complete area accounting. Distinguish observed change from a classification or observation artifact. Cross-reference the resulting area inputs in the relevant A–C report.

Stratum / transition ID	From-class → to-class	Estimated area (ha)	SE / CI (ha)	Evidence / linked A–C record

Template R4: Spatial metadata, QA/QC and handover

Field	Record
Final spatial dataset, legend and metadata file IDs / locations	
Validation records, error matrix and area-estimation files / locations	
Version history and description of boundary or classification revisions	
Area and uncertainty values transferred to A–C; receiving report / table IDs	
Treatment of shared area uncertainty across pools or reporting calculations	
Archive custodian, access controls and retention basis under the main methodology	
Prepared by / date; reviewed by / date; approval status	

Check / record ID	Finding or limitation	Correction / disposition	Reviewer / date

Record unresolved limitations explicitly. Archive the inputs, processing history and validation evidence needed to reproduce the map and its reported areas.

D.9 Case Studies

The following case studies illustrate selected applications of the mapping approaches described in Sections D.3–D.7 and are provided for reference only.

D9.1 Rapid Mangrove Mapping Using the Mangrove Vegetation Index (MVI)

Overview

The Mangrove Vegetation Index (MVI) is a mangrove-specific spectral index developed to enable rapid, accurate, and repeatable mapping of mangrove extent using freely available multispectral satellite imagery. Unlike general vegetation indices (e.g., NDVI), which often struggle to separate mangroves from dense terrestrial forests, MVI was designed to explicitly capture the unique greenness and moisture characteristics of mangrove canopies.

Conceptual Basis

Mangroves exhibit two key spectral properties that distinguish them from most terrestrial vegetation:

1. High vegetation greenness, expressed by strong reflectance in the near-infrared (NIR) relative to visible wavelengths.
2. High canopy and substrate moisture, reflected by lower short-wave infrared (SWIR) reflectance due to leaf water content and frequent tidal inundation.

MVI combines these properties by comparing reflectance differences between the green, NIR, and SWIR1 bands, producing values that increase with the likelihood that a pixel represents mangrove vegetation.

Data Requirements

- Primary input: Multispectral satellite imagery (Sentinel-2 MSI or Landsat 8/9 OLI).
- Ancillary data (recommended): Coastline layers or tidal zone masks to constrain analysis to plausible mangrove areas.
- Validation data: Field inventory points and/or high-resolution drone orthophotos.

Because MVI relies only on standard multispectral bands, it can be implemented using open satellite data and cloud-based platforms, making it suitable for national- and regional-scale mapping.

Mapping Approach

Rather than relying on complex classifiers or extensive training datasets, MVI enables index-based mangrove delineation using a threshold value derived from representative mangrove and non-mangrove samples. This simplifies the workflow and reduces user-dependent bias often associated with supervised classification.

The approach is particularly effective for:

- Separating mangroves from dense inland forests
- Mapping small or fragmented mangrove patches
- Producing consistent maps across large geographic extents

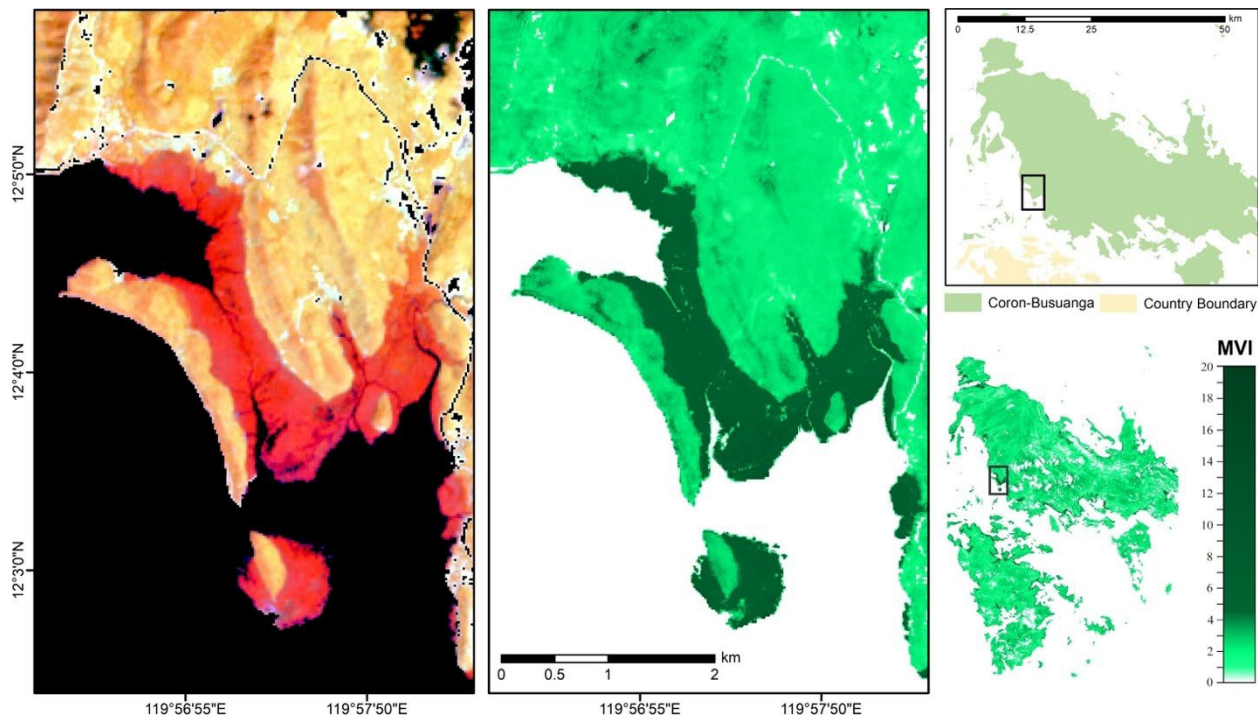


Figure 3: Comparison of the false color (RGB B11-B8-B4) visualization of the atmospherically corrected Sentinel-2 image (leftmost) and the output MVI image (center) in Busuanga, Philippines. The mangroves are dark green in color while the non-mangroves are in white to lighter green. The MVI clearly delineated both the nearshore and upstream mangroves by a threshold of 4.5. (Baloloy et. al. 2020)

Accuracy and Performance

The MVI was tested across multiple mangrove sites in the Philippines and Japan, and further applied in other regions of Southeast Asia, South America, Africa, and Australia. Validation using field inventory data and drone orthophotos demonstrated:

- Overall classification accuracy of approximately 92%
- Consistent discrimination of mangroves from terrestrial vegetation, water, bare soil, and built-up areas
- Comparable performance when applied to both Sentinel-2 and Landsat imagery, supporting cross-sensor consistency

These results illustrate the performance achieved in the published study. Each project shall independently validate its mapping outputs and demonstrate their suitability for the intended accounting use.

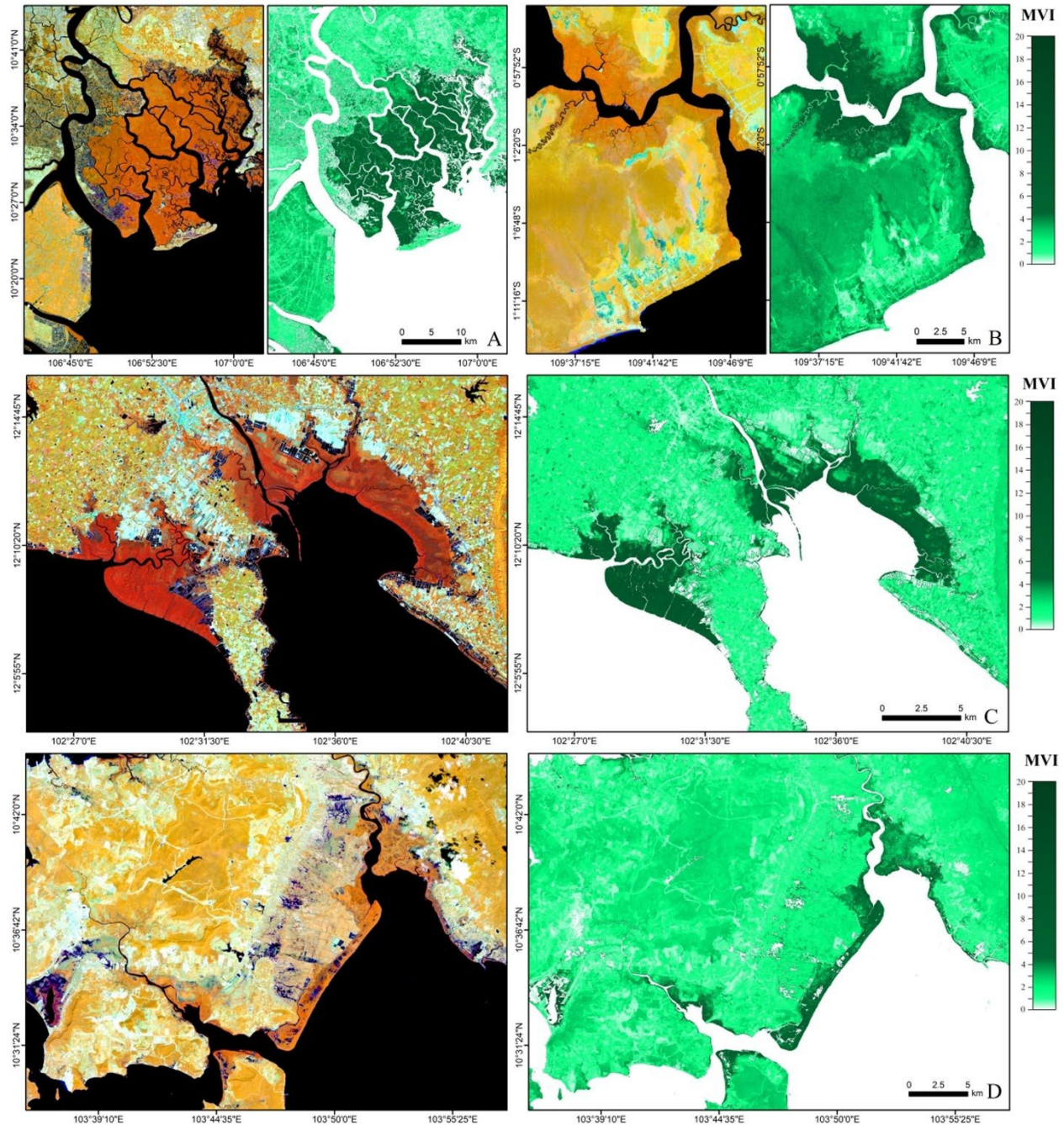


Figure 4: False color composite visualization and MVI images of generated from Sentinel-2 covering (A) Can Gio Mangrove Forest, Ho Chi Minh City, Vietnam, (B) Muara Kubu and Batu Ampar, West Kalimantan, Indonesia, (C) Mueang Trat District, Trat, Thailand, and (D) Prey Nob, Cambodia. A different threshold was selected for each study site due to the unique coastal environment. (Baloloy et. al., 2020)

Relevance for Blue Carbon Mapping

For blue carbon projects, MVI offers a practical entry-level method for generating mangrove activity data that is:

- Transparent and reproducible
- Suitable for baseline establishment and change detection
- Compatible with national greenhouse gas inventories and project-level assessments

While MVI does not directly estimate biomass or carbon stocks, it provides a robust spatial foundation upon which field-based biomass measurements and emission factors can be applied.

Limitations and Considerations

- Select and validate MVI thresholds using representative local reference data. Thresholds reported for other sites shall not be assumed to apply without assessment.
- MVI focuses on extent mapping, not species composition or forest structure.
- As with all remote sensing products, independent field validation remains essential.

Source Paper: 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.

D9.2 Mapping Intertidal Seagrass in Turbid Coastal Waters Using Multi-temporal Sentinel-2 Imagery

Overview

This case study demonstrates an approach for mapping intertidal seagrass meadows in highly turbid tropical waters, where conventional single-image optical methods often fail. The method integrates multi-temporal Sentinel-2 imagery, water-column correction, and supervised classification, producing accurate seagrass extent maps suitable for blue carbon baseline assessment and monitoring.

The example is based on Trinh et al. (2023), which mapped seagrass meadows in the Bai Bon intertidal flat, Phu Quoc Island, Vietnam, an area characterized by strong tidal dynamics and persistent turbidity.

Methodological Basis

Seagrass mapping in shallow coastal waters is complicated by:

- water depth and turbidity,
- changing tidal exposure,
- and seasonal variability in seagrass cover.

This approach is based on the premise that seagrass spectral signals become more distinguishable when information from multiple tidal stages and acquisition dates is combined. By aggregating many images over time, the method reduces noise from individual scenes and enhances the persistent signal associated with seagrass presence.

Data Inputs

Primary satellite data

- Sentinel-2 MSI imagery (10–20 m), selected for its high revisit frequency and suitable spectral bands for shallow-water applications.

Supporting reference data

- UAV (drone) imagery, classified using object-based image analysis, to provide high-resolution ground truth for training and validation.
- Field observations of seagrass species, density, and water depth collected during low-tide conditions.

Derived variables

- Visible, NIR, and SWIR reflectance bands.
- Vegetation and water-related indices commonly used in shallow-water mapping (e.g., NDVI, EVI, NDWI-type indices).

Mapping Approach

1. Multi-temporal compositing

A large set of Sentinel-2 images acquired under varying tidal and turbidity conditions is combined into a composite representation, reducing scene-specific noise.

2. Water-column correction

Water-column effects are explicitly addressed to minimize depth- and turbidity-related attenuation of the seagrass signal.

3. Supervised classification

A Random Forest classifier is trained using reference data derived from UAV imagery and field observations, allowing seagrass to be distinguished from sand, mudflat, and open water classes.

4. Consistent application across space

The same classification framework is applied across the entire study area, ensuring spatial consistency suitable for area estimation and monitoring.

Accuracy and Performance

In this study, water-column correction alone changed mean classification accuracy only slightly, from 80.4% to 80.6%. The multi-temporal composite approach reached 88.6%. UAV-derived reference mapping supported training and validation.

Relevance for Blue Carbon Mapping

This case study is highly relevant for Blue Carbon Ecosystem mapping because it:

- addresses one of the most challenging BCE environments—turbid intertidal seagrass meadows;
- provides a repeatable framework for deriving seagrass extent as activity data;
- reduces uncertainty in seagrass area estimates used for carbon stock and sequestration calculations; and
- demonstrates the value of combining remote sensing and field-based reference data in MRV-oriented mapping.

The approach is particularly applicable in deltaic and estuarine systems common across Southeast Asia.

Limitations and Considerations

- The method relies on a sufficient number of cloud-free images; areas with limited archive coverage may not benefit fully from multi-temporal compositing.
- Water-column correction improves results but may offer diminishing returns relative to multi-temporal approaches.
- Species-level discrimination remains challenging at Sentinel-2 resolution, especially in mixed seagrass beds.
- UAV and field data substantially improve accuracy but may not always be available.

Source Paper: Trinh, X. T., Nguyen, L. D., & Takeuchi, W. (2023). Sentinel-2 mapping of a turbid intertidal seagrass meadow in Southern Vietnam. *Geocarto International*, 38(1). <https://doi.org/10.1080/10106049.2023.2186490>

D9.3 Multi-temporal Salt Marsh Mapping Using Optical Time-Series and Supervised Classification

Overview

This case study illustrates a scalable approach for mapping salt marsh extent and species composition over multiple decades using freely available satellite imagery and cloud-based processing. The method demonstrates how consistent classification of intertidal salt marshes can be achieved across large spatial and temporal scales, supporting long-term monitoring and change detection for blue carbon assessments.

The example is based on the work of Chen et al. (2022), which mapped salt marshes in China's intertidal zone from 1985 to 2019 using Landsat and Sentinel-2 imagery processed in Google Earth Engine (GEE).

Methodological Basis

Salt marshes occupy narrow elevation bands within the intertidal zone and exhibit strong seasonal and spectral variability. The approach builds on the principle that:

- salt marsh vegetation can be distinguished from mudflats, open water, and upland vegetation using spectral reflectance patterns, and
- long satellite archives allow consistent observation of change when classification rules are applied uniformly through time.

Supervised classification is used to assign pixels to salt marsh and non-salt-marsh classes, and—where data allow—to dominant salt marsh vegetation types.

Data Inputs

Primary remote sensing data

- Landsat series (Landsat 5 and 8; 30 m) for historical and long-term monitoring.
- Sentinel-2 MSI (10–20 m) to support more recent and higher-detail mapping.

Supporting reference data

- Field observations and photographs.
- UAV (drone) imagery for local validation and interpretation of vegetation types.

Derived variables

- Reflectance bands in the visible, near-infrared (NIR), and shortwave infrared (SWIR).
- Common vegetation and wetness indices, including NDVI, EVI, NDWI-type indices, used as classification features.

Mapping Approach

1. Image preparation and compositing

Multi-year image composites are generated to reduce cloud contamination and seasonal noise, focusing on comparable tidal and phenological conditions.

2. Feature extraction

Spectral bands and indices sensitive to vegetation vigor and moisture conditions are combined to enhance separability between salt marsh vegetation and other intertidal surfaces.

3. Supervised classification

A Support Vector Machine (SVM) classifier is trained using known reference samples and applied consistently across multiple time steps.

4. Multi-temporal application

The same classification logic is used for multiple target years, enabling direct comparison of salt marsh extent and distribution through time.

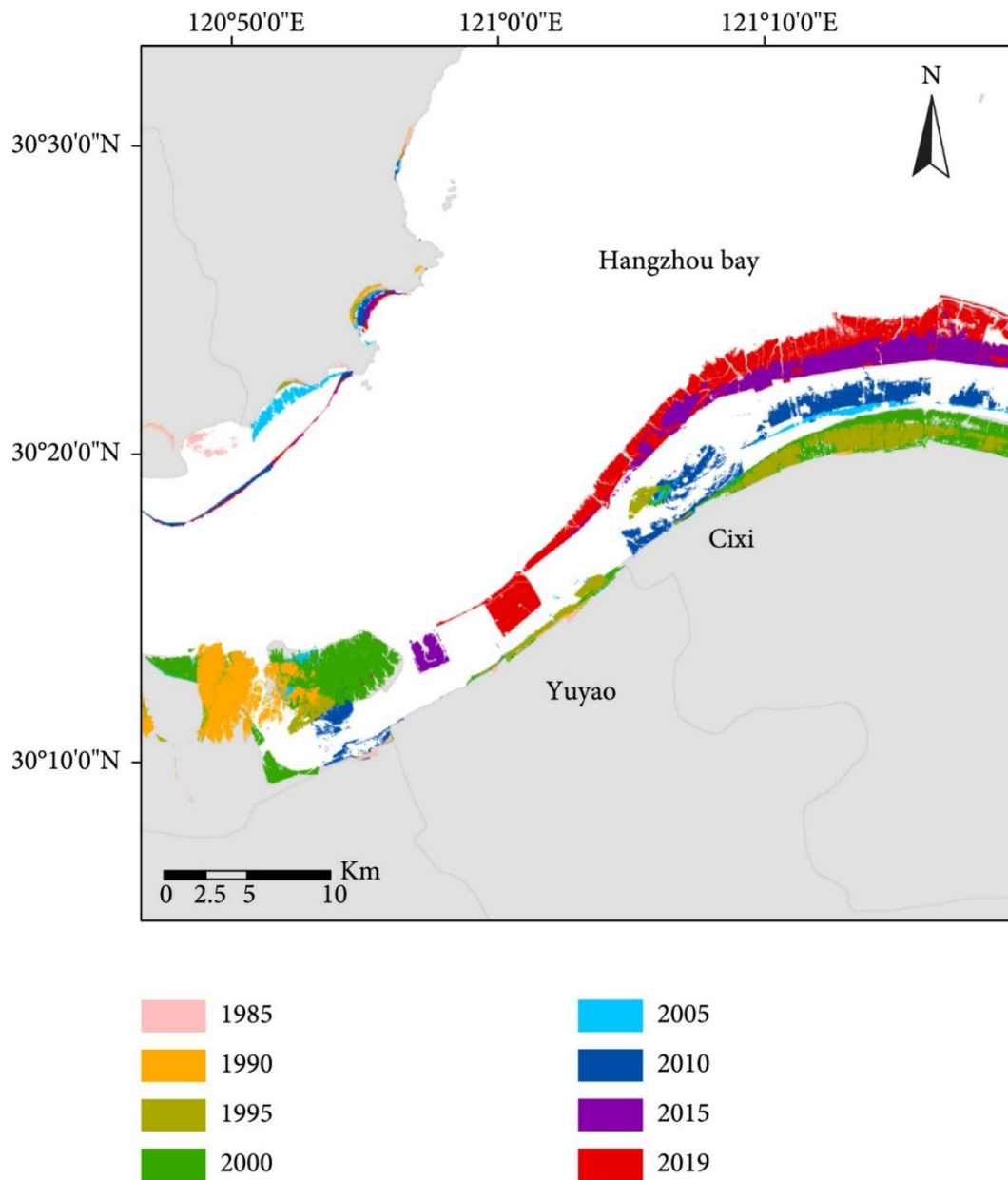


Figure 5: Salt marsh distribution in Hangzhou Bay from 1985 to 2019 (the different color indicates the year when the salt marshes were appeared for the first time) (Chen et al., 2022)

Accuracy and Performance

Classification accuracy is evaluated using independent reference data derived from field surveys, UAV imagery, and high-resolution observations where available. The study reports high overall accuracy for salt marsh extent mapping across most periods, demonstrating that supervised classification combined with long satellite archives can reliably capture both spatial patterns and long-term trends.

Accuracy assessment follows standard good practice using error matrices and class-specific accuracy metrics, providing confidence in reported area estimates and detected changes.

Relevance for Blue Carbon Mapping

This case study is directly relevant to Blue Carbon Ecosystem mapping because it:

- demonstrates consistent, repeatable monitoring of salt marsh extent over decades;
- supports derivation of activity data (area change) required for carbon stock and emission estimates;
- illustrates how open satellite archives and cloud platforms can be used for national or regional-scale MRV; and
- provides a framework adaptable to other coastal regions with similar intertidal settings.

The approach is suitable for both baseline mapping and periodic reassessment under blue carbon programs.

Limitations and Considerations

- Tidal stage and seasonal effects can influence classification results; careful selection of imagery windows is critical.
- Species-level discrimination requires stronger validation and may not be feasible everywhere using medium-resolution imagery alone.
- Historical validation data are often limited, increasing uncertainty in early-period maps.
- Optical methods may be constrained in persistently cloudy regions, where SAR integration may be required.

Source paper: Chen et al. (2022) *Spatiotemporal Mapping of Salt Marshes in the Intertidal Zone of China during 1985–2019* (DOI: 10.34133/2022/9793626).

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