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MARCO-BOLO
STRENGTHENING BIODIVERSITY OBSERVATION IN SUPPORT OF DECISION MAKING

Deliverable 5.3

Scientific document describing potential for satellite remote sensing to estimate blue carbon at regional scales within European coastal systems.

17 October 2025

Lead: Norwegian Research Centre (NORCE)

Natalya D. Gallo (NORCE), Silvia Chemello (CIIMAR), Richard Sanders (NORCE), Isabel Sousa Pinto (CIIMAR), Katalin Blix (NORCE), Jörg Haarpaintner (NORCE)

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Executive Summary

MARCO-BOLO Task 5.3 "Spatial mapping of blue carbon benefits" evaluates how satellite remote sensing can advance the mapping of blue carbon stocks across Europe, with a particular focus on seagrass meadows due to their importance for the European region. This work responds to the urgent need for robust, scalable approaches to quantify and monitor carbon stocks in European coastal habitats, supporting emerging policy and reporting requirements.

Our approach integrated five core activities:

1. **Synthesising the scientific literature** on remote sensing applications for seagrass carbon mapping.
2. **Collaborating with MPA-EUROPE** to compile and publish the EURO-CARBON database, the most comprehensive collection of organic carbon measurements for coastal habitats in Europe.
3. **Pairing large-scale environmental datasets** from NASA and Copernicus with *in situ* sediment carbon measurements, enabling spatially explicit modelling.
4. **Engaging stakeholders** through co-design sessions to ensure scientific outputs align with policy and management needs.
5. **Developing and testing predictive models** for seagrass carbon stocks using environmental variables.

Our models demonstrated high explanatory power ($R^2 > 0.8$), identifying bottom temperature, sea surface wave height, phosphate concentration, near-surface pH, and remote sensing reflectance at 443 nm as key predictors. Notably, using organic carbon density as the response variable improved model performance and policy relevance.

We conclude that satellite remote sensing and global oceanographic data products already provide substantial opportunities for evaluating and monitoring blue carbon services in seagrass beds. Anticipated advances—including new satellite missions and enhanced computational capabilities—will further increase these opportunities.

Currently, no countries in Europe have included seagrass beds in their emission inventories and climate plans, despite the prevalence of seagrasses along many coastlines. From 2026, reporting of wetlands under LULUCF may become mandatory for EU member states, but whether this will apply to seagrass beds depends on if member states consider them as "managed" marine ecosystems. Either way, policy needs for reporting carbon stocks are growing, and we show that remote sensing and global oceanographic data products can contribute substantially to mapping blue carbon benefits in Europe.

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1. Introduction

1.1 What is Blue Carbon?

The term “blue carbon” was first introduced by Nellemann et al. (2009), who defined it as the carbon captured and stored by coastal and marine ecosystems dominated by rooted vegetation. Over time, the definition of blue carbon has evolved. The Intergovernmental Panel on Climate Change (IPCC), in its Sixth Assessment Report (AR6), defines blue carbon more broadly as “biologically driven carbon fluxes and storage in marine systems that are amenable to management” (IPCC, 2022). For climate mitigation, however, “actionable” blue carbon ecosystems remain mangroves, seagrass meadows, and salt marshes (Schindler Murray et al. 2023).

1.2 Blue Carbon Ecosystems: What they are and why they matter

Mangroves, seagrass meadows, and salt marshes are vegetated coastal habitats recognized for their remarkable ability to sequester and store atmospheric carbon dioxide (CO_2) in both their biomass and underlying sediments. Despite covering a relatively small fraction of the Earth’s surface, these ecosystems account for disproportionately high rates of carbon burial, making them critical components in the global carbon cycle and highly relevant to climate change mitigation strategies. The inclusion of blue carbon ecosystems in national climate strategies is made possible through internationally recognized methodologies for carbon accounting, particularly those outlined in the 2013 IPCC Wetlands Supplement (IPCC, 2014). These methodologies enable countries to integrate coastal wetlands into their Nationally Determined Contributions (NDCs) under the Paris Agreement, report them in national greenhouse gas inventories, and potentially engage in voluntary carbon markets.

Despite the existence of guidelines, there is a recognized lack of technical capacity for including blue carbon into national greenhouse gas inventories. Currently, few countries are implementing the 2013 IPCC Wetlands Supplement and using it to inform their NDCs (Schindler Murray et al., 2023). A key barrier to realizing the full climate potential of blue carbon ecosystems lies in the limited capacity for measurement, reporting, and verification (MRV) and reliable assessments of carbon stocks and fluxes (Schindler Murray et al., 2023).

Beyond carbon storage capabilities, blue carbon ecosystems provide a range of multifunctional ecosystem services that support environmental integrity and human well-being, such as coastal protection from wave energy and erosion, water quality enhancement, fishery support through habitat provisioning, and biodiversity support (Valiela et al., 2002; Lee et al., 2014; Maxwell et al., 2017). Blue carbon ecosystems are embedded within multiple policy and conservation frameworks, representing a conservation priority within the European Union (EU). These ecosystems are also protected under several legal instruments, including the EU Habitats Directive (92/43/EEC), the Bern Convention (Annex I – habitat types of community interest and Annex II – Strictly Protected Flora Species), the Marine Strategy Framework Directive (2008/56/EC), and the Ramsar Convention on Wetlands. Integrating blue carbon strategies into broader marine and coastal zone management planning frameworks can help align biodiversity, climate, and development goals.

1.3 A focus on seagrass ecosystems: Structure, Functions, and Importance

We have decided to focus on seagrass meadows because less work has been done on valuation of carbon stocks in seagrasses compared to mangroves and they are more relevant for the European context.

Ecologically, seagrass meadows are considered one of the most productive and valuable marine ecosystems (Hemminga & Duarte, 2000). Seagrasses are submerged marine flowering plants that form extensive meadows in shallow coastal waters across temperate and tropical regions. They provide a broad range of ecosystem services (e.g., carbon sequestration, coastal protection through wave energy attenuation, water quality improvement, biodiversity support, fisheries enhancement) and contribute to food security for many coastal communities (Ondiviela et al., 2014). Seagrass meadows are found along many European coastlines and are limited to few species (Figure 1).

Figure 1. Map of seagrass meadows in Europe (data courtesy of UNEP World Conservation Monitoring Centre) and images of European seagrass species. Image credit: Bernat Garrigos for *C. nodosa*, Roberto Pillon for *P. oceanica*, Dan Mele for *H. stipulacea*, Dimitar Nikolov Berov for *Z. noltei*, and Erling Svensen for *Z. marina*.

Although seagrasses store less carbon in their above-ground biomass compared to mangroves or salt marshes, they are highly efficient at long-term carbon burial in sediments, often under anoxic conditions that slow decomposition and enhance carbon retention. Despite covering only 0.1% of the global seafloor, seagrass meadows are estimated to account for 10–18% of total oceanic carbon burial, highlighting their outsized contribution to the global carbon cycle (Duarte et al., 2013).

Despite their importance, seagrasses are experiencing global declines, largely driven by anthropogenic pressures (e.g., coastal development, pollution, boating and anchoring) as well as the wider impacts of climate change (Waycott et al., 2009). When these ecosystems are fragmented or destroyed, the previously stored carbon can be released back into the atmosphere, with implications for national carbon budgets. Globally these losses could amount to 299 Tg of carbon released per year if the rate of seagrass loss continued and organic carbon from the seagrass biomass and top metre of soil was remineralized (Fourqurean et al., 2012).

While 95 countries referenced blue carbon ecosystems in their most recent NDC submissions, only 8 made explicit mention of seagrasses, highlighting ongoing gaps in policy inclusion, technical capacity, and ecosystem valuation (Khan et al., 2022). The Blue Carbon Initiative, provides the following carbon stock values for the top 1 m of sediment in seagrass beds: global mean (108 Mg C_{org} ha^{-1}), and a range of 10-829 Mg C_{org} ha^{-1} (Howard et al. 2014), which can be used for Tier 1 estimation of blue carbon storage.

1.4 Study aims and scientific questions

The high costs and capacity limitations associated with monitoring and verification of blue carbon projects, as well as the lack or inaccessibility of belowground carbon estimation, weaken the ability of carbon markets to fund blue carbon ecosystem restoration and conservation and nations to report data from seagrass beds in their national climate commitments (Schindler Murray et al., 2023). To address this challenge, we examine how the growing availability of satellite data and oceanographic data products can contribute to seagrass blue carbon stock assessments in the European region.

We ask: ***which environmental variables have the most robust statistical relationships with carbon storage in seagrass beds and how well can this combination of environmental variables predict seagrass carbon storage for the European region?***

2. Methods

Five key activities were undertaken to accomplish T5.3: a literature review, a collaborative blue carbon database assembly, environmental data matching to pair carbon-relevant large-scale oceanographic data products with *in-situ* seagrass organic carbon measurements, co-production activities with relevant stakeholders, and model development and testing for estimating seagrass blue carbon stocks (Figure 2). We provide a brief narrative describing these activities and the task evolution.

Activity 1: Given the scientific developments in the blue carbon field between when the proposal was written and now, we undertook a literature review to determine the state of the art in remote sensing applications for seagrass mapping and blue carbon estimation. The review included the keywords: “seagrasses”, “remote sensing”, “blue carbon”, and “carbon proxies”. Over 80 scientific papers and reviews, encompassing more than 300 individual studies, were identified and examined. The types of publication ranged from remote sensing methodologies (used mainly to map seagrasses distribution) to different methods to assess carbon sequestration. These works detail a variety of remote sensing methodologies, ranging from satellite to unmanned aerial vehicles, used to map coastal vegetated habitats. A synthesis of the literature review is presented in section 3.1.

Activity 2: During the literature review, we identified that one of the key knowledge gaps was the lack of robust correlations between variables that can be remotely sensed and seagrass carbon storage. To address this knowledge gap, we initiated the development of a European dataset on blue carbon habitats, but then learned that a similar task had recently already been initiated by the MPA-Europe HEU project. To avoid duplication of efforts and ensure efficient use of MARCO-BOLO resources, a collaboration was established. T5.3 extracted over 16,000 relevant data points that contributed to the development and publication of the EURO-CARBON database (Graversen et al., 2025), which contains a total of 61,306 data entries for sediment organic carbon content measurements in Europe (expanded on in section 3.2).

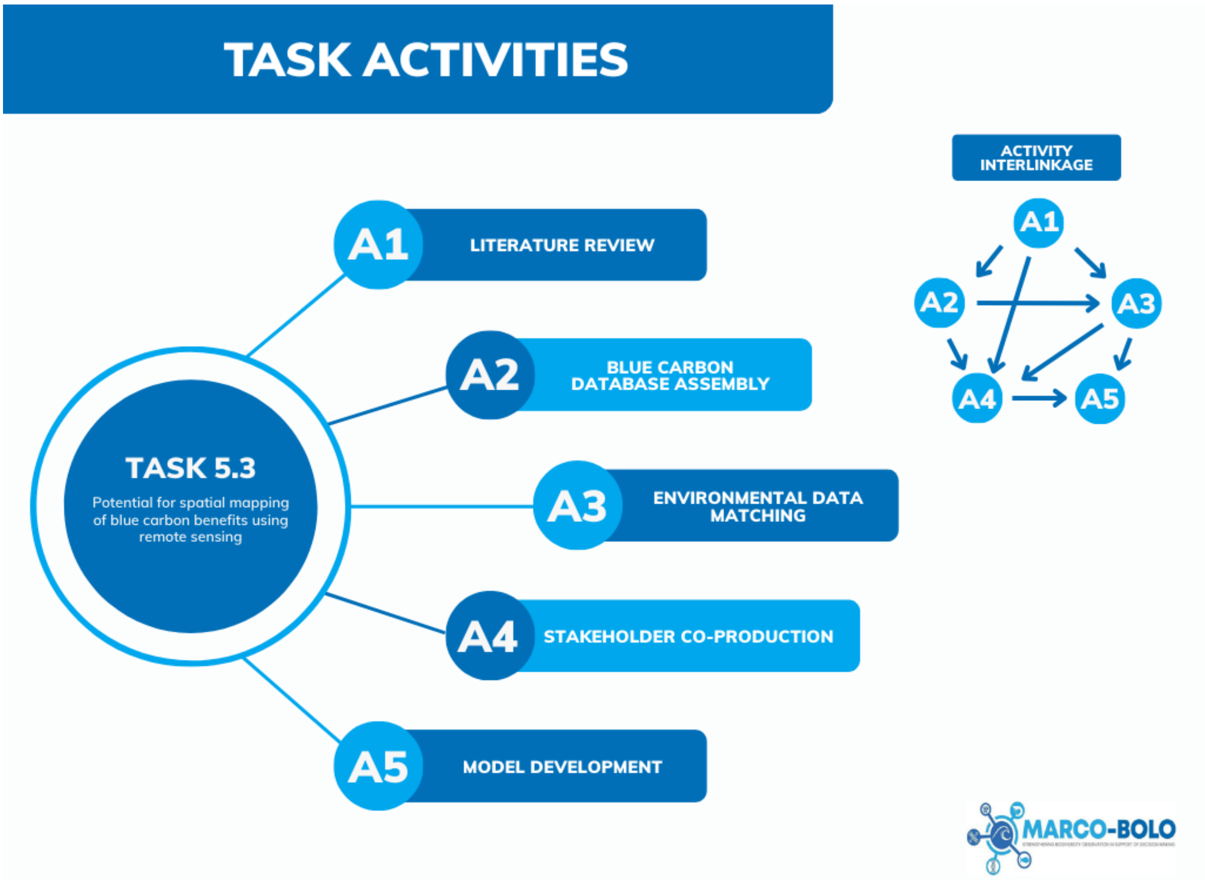

Figure 2. An overview of the five components that were undertaken as part of Task 5.3.

Activity 3: The results of the literature review (Activity 1) were used to assess which large-scale data products from NASA and Copernicus would contain relevant environmental variables to explain variation in seagrass sediment organic carbon content in Europe. Only data products that provided European-wide coverage were selected. Data were downloaded from the NASA Earth Data Level 3 & 4 Browser (https://oceandata.sci.gsfc.nasa.gov/l3/) and the Copernicus Marine Data Store (https://data.marine.copernicus.eu/products). We assume that seagrass carbon storage is a function of long-term processes, therefore the full multi-year dataset was extracted for each data product (expanded on in section 3.3). A representative value was extracted from each environmental dataset based on the location of the seagrass carbon samples in the EURO-CARBON database. Most commonly, the mean value was calculated, however, extreme values were also calculated (e.g., 5th, 10th, 90th, or 95th percentile) for certain variables. Each seagrass sample was also assigned to one of five regions (Baltic Sea, Black Sea, Mediterranean Sea, North European Atlantic, South European Atlantic). This resulted in a spatially matched dataset of 42 continuous environmental co-variates and a regional categorical variable for the 4,233 seagrass carbon samples in the EURO-CARBON database. This dataset was then used for model development in Activity 5.

Activity 4: In order to ensure that the scientific component of the work aligned with stakeholder needs, we presented our task to relevant stakeholders during two events as part of the MARCO-BOLO Community of Practice under WP6. A short presentation on the task activities was given during the 1st CoP event on making marine and coastal biodiversity observations policy relevant on May 23, 2024. A more in-depth stakeholder consultation was held during a co-creation session specific to Task 5.3 on June 27, 2025. Key points from these stakeholder consultations are expanded on in section 3.4. Stakeholder feedback directly affected decisions taken in Activity 5 regarding the response variable selected and sample depths considered.

Activity 5: Using the paired dataset of seagrass sediment carbon measurements and potential environmental predictor variables developed in Activity 3, we tested a suite of models to identify which environmental variables have the most robust statistical relationships with seagrass carbon storage. Both machine learning (Gaussian Process Regression, Decision Tree, and Neural Network) and non-machine learning methods (Random Forest and Generalised Additive Model) were tested. Non-machine learning models were implemented in the programming language R, and machine-learning models were developed and tested in the MATLAB Regression Learner R2024a toolkit. For each model, we examined model performance and variable importance in order to identify an appropriate reduced model that still offered high predictive ability for seagrass carbon density.

3. Results

3.1 Literature review

The literature review revealed a rapidly growing body of research on remote sensing applications for seagrass mapping and blue carbon estimation. Coverage, biomass, and density emerged as the most frequently used proxies for estimating blue carbon stocks. However, the literature synthesis highlighted a lack of robust, standardized relationships between remotely-sensed variables (e.g., above-ground biomass, canopy coverage) and actual carbon storage within seagrass meadows. Furthermore, methodologies for estimating blue carbon were often inconsistent across studies, complicating comparative analyses and model calibration.

3.1.1. What variables affect carbon storage in seagrass beds?

Seagrass ecosystems store organic carbon in both aboveground and belowground components. Aboveground biomass includes living and dead plant material such as leaves, while belowground carbon is primarily stored in roots, rhizomes, and sediments. Evaluating carbon storage is more challenging in seagrass beds than terrestrial forests because a large fraction of the organic carbon is stored in the organic-rich soils and not in the living plant biomass. Based on global data, only ~1.3% of the total carbon was stored in the living seagrass biomass compared to ~98.7% in the soil (Fourqurean et al., 2012).

The capacity of a seagrass bed to act as a carbon sink varies considerably across sites and is influenced by a range of biotic and abiotic variables. Mazarrasa et al. (2018) concluded that dominance of large-sized species, high canopy complexity, continuous meadow landscape, complex and stable biotic interactions, sheltered conditions, low turbidity, shallow water depth, and low but not limited nutrient availability positively affected long-term carbon storage in seagrass beds. In contrast, eutrophication, habitat fragmentation, altered biotic interactions, and climate change effects were threats to long-term carbon storage. In the Florida Gulf Coast, seagrass carbon storage was positively correlated with seagrass cover, proximity to oyster reefs, and distance from river outlets (McHenry et al., 2023). On the Turneffe Atoll in Belize, organic carbon stocks were highest in seagrass beds that were sheltered with low wind and wave energy, but seagrass canopy cover was not a significant predictor of carbon stocks (Felgate et al., 2024). Globally, coastal geomorphology and species identity is an influential driver of differences in seagrass organic carbon stocks, but only *Posidonia oceanica* is characterized by significantly higher carbon stocks whereas other species show very high intraspecific variation (Kennedy et al., 2022). An overview of key abiotic and biotic factors is provided below.

- **Biotic Factors**

Species composition: Different seagrass species exhibit varying growth forms, productivity, and root/rhizome structures, which influence both biomass accumulation and sediment trapping capacity.

Canopy complexity and biomass: Denser and more structurally complex meadows typically enhance sediment stabilization and organic matter retention, promoting greater carbon burial.

Primary productivity: Higher photosynthetic rates and net primary productivity increase organic input to sediments, boosting long-term carbon storage.

Associated biota: Faunal interactions, such as those with herbivores, epiphytes, or bioturbating organisms, can influence sediment dynamics, decomposition rates, and nutrient cycling.

- **Abiotic Factors**

Sediment characteristics: Grain size, organic matter content, porosity, and redox conditions strongly influence the potential for carbon accumulation and long-term burial.

Hydrodynamic energy: Water movement influences sediment deposition and erosion. Low-energy environments generally favor carbon retention, while high-energy areas may reduce burial efficiency through resuspension.

Water quality: Nutrient concentrations, turbidity, and dissolved oxygen levels impact seagrass growth and sediment chemistry, affecting both carbon input and stability.

Climate and geomorphology: Temperature, salinity, sea level changes, and geomorphological features (e.g., coastal slope, proximity to estuaries or reef systems) shape seagrass distribution and the physical processes governing carbon storage.

Landscape context: Seagrass beds adjacent to salt marshes, mangroves, or oyster reefs may benefit from synergistic effects, such as enhanced sediment trapping and nutrient cycling, which can increase their overall carbon sequestration potential.

Given the identified importance of certain abiotic and large-scale environmental drivers in explaining differences in seagrass organic carbon storage, these variables may be promising predictors for European seagrass organic carbon storage.

3.1.2. Remote sensing contributions to seagrass carbon stock mapping

Seagrass carbon storage is typically measured through field sampling of sediment cores, which provides accurate data but is costly, time-consuming, and destructive. Increasing access to open-source satellite imagery (e.g., Sentinel-2 and Landsat) and advances in cloud computing and machine learning (Traganos et al., 2022) now offer promising tools for assessing blue carbon stocks remotely.

Remote sensing includes data collected via drones, aircraft, and satellites—both from free and commercial sources. Over the past 50 years, methods for mapping seagrass beds have evolved from aerial photography to sophisticated satellite-based mapping (Dekker et al., 2006; Kutser et al., 2020). Tools like Landsat 8 and Sentinel-2 have been widely used to map seagrass beds, whereas medium-resolution sensors (e.g., MODIS, Sentinel-3) are less suitable due to the patchy nature of seagrass habitats. The seagrass species *Posidonia oceanica* has received most attention in remote sensing studies, mainly because of its high ecological importance as a priority Mediterranean habitat and the feasibility of mapping its extensive meadows cost-effectively using satellite imagery (e.g., Borfecchia et al., 2019; Cozza et al., 2019; Matarrese et al., 2008; Traganos and Reinartz, 2018; Fornes et al. 2006).

Mapping seagrass via satellite is challenging due to the optically complex properties of the coastal zone (Dekker et al., 2006). Factors like water turbidity and depth can limit the detection of seagrasses. In clear, calm waters, seagrass has been detected down to 40 m using Landsat-8 (Topouzelis et al., 2018), while combining aerial imagery and side-scan sonar has proven effective for mapping seagrass species in deeper areas (Pasqualini et al., 1998). Distinguishing between seagrass species using satellite data is also difficult. While some spectral bands (Coastal, Blue, Green, Red) can help (Traganos and Reinartz, 2018), they may not be sufficient in diverse or mixed beds (e.g., Knudby and Nordlund, 2011). Hyperspectral sensors and pigment-specific spectral features offer potential improvements (Traganos and Reinartz, 2018), and building a global spectral library for seagrass has been proposed to support this effort (Dekker et al., 2006).

Recent studies show high accuracy in using satellite data to map seagrass presence/absence (Traganos and Reinartz, 2018) and percent cover (Carpenter et al., 2022). For example, in Belize's Turneffe Atoll, a three-step approach using field data, UAV imagery, and Sentinel-2 produced a detailed map of seagrass cover, which is now accessible to coastal managers via Google Earth Engine (Carpenter et al., 2022). Advances in artificial intelligence machine learning models have also supported the development of more powerful models for mapping the extent of seagrass meadows. In the Mediterranean, deep learning models applied to Sentinel-2 data achieved 74–92% accuracy in mapping *P. oceanica* (Chowdhury et al., 2024).

While remote sensing is well-established for mapping seagrass extent, its use in estimating carbon stocks is still developing. One common method to estimate total carbon storage involves applying published carbon density values to seagrass extent maps. For example, Traganos et al. (2022) used Sentinel-2 data to map *P. oceanica* across the Mediterranean (19,020 km^2) and estimated 722 million MgC stored in shallow waters. Similarly, Felgate et al. (2024) applied this approach in Belize's Turneffe Atoll but noted that seagrass in turbid waters are missed by optical sensors, affecting subsequent carbon estimates. A recent review by Simpson et al. (2022) identified above-ground biomass, percent cover, Leaf Area Index (LAI), and Normalized Difference Vegetation Index (NDVI) for intertidal zones, as useful proxies that could support carbon stock estimation. However, this relies on the assumption that the proxies reflect below-ground carbon, which is not always valid. In Belize's Turneffe Atoll, no significant correlation was found between canopy cover and sediment carbon content (Felgate et al., 2024). Remote sensing can also help identify seagrass species and track seasonal growth patterns (Simpson et al., 2022). Yet, species identification alone has limited value for carbon estimates, as only *P. oceanica* consistently shows higher carbon storage (Kennedy et al., 2022). Simpson et al. (2022) also highlighted that spatial continuity and persistence of seagrass beds—both detectable via satellite—are linked to higher carbon stocks. Other key drivers of carbon burial like sediment grain size and sedimentation rate (Ricart et al., 2020) cannot be directly measured by satellites.

Given the abundant work already done on using remote sensing for seagrass mapping, our work focuses on how satellite and regional-scale environmental data can inform local conditions relevant to carbon storage and identify predictive relationships with seagrass carbon stocks.

3.2 Assembling, publishing, and analysing the EURO-CARBON Database

In the EURO-CARBON database v1 (Graversen et al., 2025, Lønborg et al. 2025), a total of 61,306 data entries for organic carbon content were included, with the following distribution: 76% from bare sediments, 18% from salt marshes, 7% from seagrass habitats, and 0.03% from macroalgal habitats. To compile this database, the data search was restricted to coastal and deep-sea settings within the main European Regional Seas, including the Baltic Sea, the Black Sea, the North-east Atlantic Ocean, and the Mediterranean Sea. The sediment data were obtained from three types of sources: directly from data contributors, from online databases, and from scientific papers and reports. Data collection began with a public call inviting researchers to contribute both published and unpublished data via a standardized submission template. Additional data were sourced from existing marine sediment databases and through a comprehensive literature search on Google Scholar, which initially yielded 17,700 entries and was refined to 1,112 potentially relevant studies. Further records were identified through reference lists, existing reviews, and academic theses. All samples underwent consistent post-collection processing.

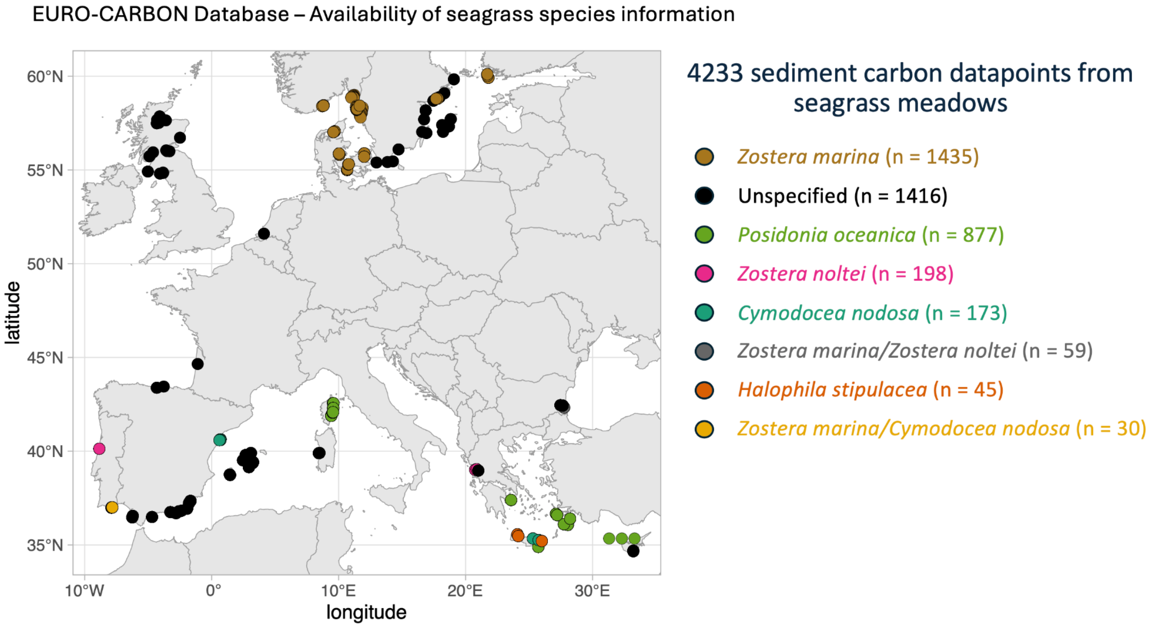

Figure 3. Overview of the spatial and species distribution of seagrass sediment organic carbon samples from the EURO-CARBON v1 database. “n=” refers to the number of samples of that type in the dataset.

The EURO-CARBON v1 database contains 4,233 sediment carbon datapoints from seagrass meadows collected between 1997-2023 in the European region. Samples were not evenly distributed across the European coastal region, with certain areas having much higher data availability (e.g., coastal areas in Sweden and Denmark) and other areas having very limited or no data (e.g., coastal areas in France and Italy). At the regional level, the highest number of samples came from the Mediterranean (n=2308), followed by the North European Atlantic (n=1348), South European Atlantic (n=317), Baltic Sea (n=171), and the Black Sea (n=89). Species information was available for two thirds of the samples (Figure 3). These include data from single-species meadows of *Zostera marina*, *Posidonia oceanica*, *Zostera noltei*, *Cymodocea nodosa*, and *Halophila stipulacea* (listed in order of sample frequency). A minor portion of the data (2%) came from mixed meadows of *Z. marina* and *Z. noltei*, and *Z. marina* and *C. nodosa*. The remaining third of samples did not have species information provided.

For all samples, data is provided on the % organic carbon content (dry weight), the sample start and end depth (i.e., compacted value), sample latitude and longitude, the data originator, sample collection details, and voluntary metadata. Organic carbon content (% dry weight) was available for all samples and ranged from 0.01-23.27%, with a mean of 2.36% and a median of 1.11% (Figure 4A). Data on carbon density (gC cm^{-3}) was available for 92% of samples and ranged from 0-0.31, with a mean of 0.014 and a median of 0.009 gC cm^{-3} (Figure 4B). Carbon density is the mass of organic carbon per unit volume of soil, and is determined by the product of the % organic carbon in the soil and the dry bulk density (DBD) of the soil. The data distribution for dry bulk density is shown in Figure 4C. Approximately 33% of samples did not have decompacted data provided and were corrected for compaction using a linear correction estimated from the 66% of samples with decompacted data available. Samples generally came from fine core slices (mean = 4.16 cm, median = 2.60 cm thickness) and sample decompacted mean depths range from 0.27-496.50 cm, with a mean of 29.83 cm, and a median of 16.75 cm (Figure 4D). Some of these very deep core samples likely come from *P. oceanica* meadows which can form "mattes" of high organic carbon content which can be 2.7 m or deeper (Fourqurean et al., 2012). These deep samples are rare and approximately 95% of samples are from shallower than 100 cm.

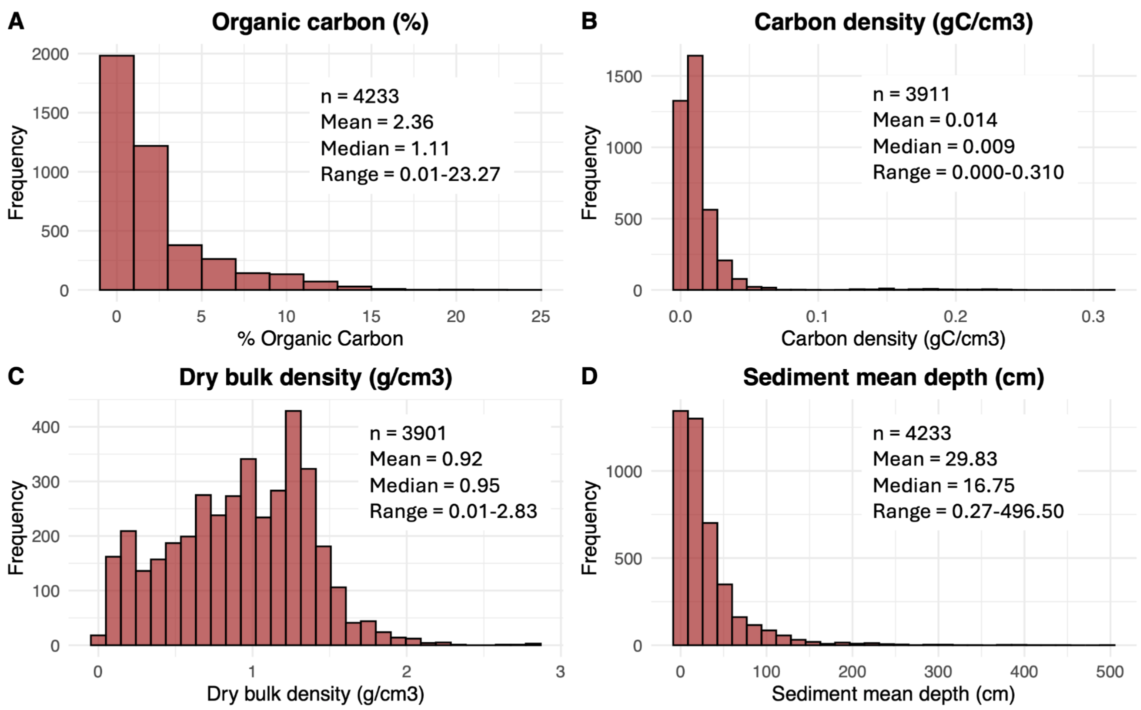

Figure 4. Data distribution of % organic carbon (A), carbon density (B), dry bulk density (C), and sediment mean depth (D) for the EURO-CARBON seagrass datapoints.

3.3 Environmental data matching and assembly

To support modeling of seagrass carbon stocks, we identified the following satellite and oceanographic data products that serve as proxies for key environmental drivers identified in the literature review.

Primary productivity: Higher photosynthetic rates and net primary productivity increase organic input to sediments, boosting long-term carbon storage. **Proxy variables:** RRS443, Chla, surface total phytoplankton concentration, total primary production of phytoplankton

Hydrodynamic energy: Water movement influences sediment deposition and erosion. Low-energy environments generally favor carbon retention, while high-energy areas may reduce burial efficiency through resuspension. **Proxy variables:** Eastward and northward seawater velocity, VHM0 (sea surface wave significant height), specific kinetic energy of seawater at the surface (eke), daily maximum, mean, and standard deviation of the significant wave height, daily number of significant wave height measurements

Water quality: Nutrient concentrations, turbidity, and dissolved oxygen levels impact seagrass growth and sediment chemistry, affecting both carbon input and stability. **Proxy variables:** KD490, RRS620, PBS443, CDOM, subsurface dissolved oxygen, nutrients (near-surface iron, nitrate, and phosphate concentrations)

Climate, geomorphology, and landscape context: Temperature, salinity, sea level changes, geomorphological features (e.g., coastal slope) and landscape context (e.g., proximity to estuaries, oyster reefs, wetlands, rivers) shape seagrass distribution, physical processes governing carbon storage, and nutrient cycling. **Proxy variables:** Salinity, bottom temperature, seafloor depth, foundation sea surface temperature, BBP443, CDOM, near-surface pH, surface pCO_2, surface total alkalinity, and surface downward flux of total CO_2 (fugacity)

From **NASA's Sentinel-3 satellite**, we selected six 4 km-resolution products. These included indicators of water quality (e.g., KD490 and RRS620 for suspended sediments), productivity (RRS443 and chlorophyll-a), and organic content (PBS443 and CDOM). These variables may influence carbon storage through effects on light availability, sedimentation, and organic matter input. We used composite data from the full mission period (2016–2025), assuming that long-term conditions shape sediment carbon accumulation.

From the **Copernicus Marine Data Store**, we selected seven products covering physical, biogeochemical, and carbon-related parameters (Table 1). These included bottom temperature, salinity, wave height, ocean currents, phytoplankton productivity, nutrient concentrations, and surface CO_2 fluxes. Copernicus data products differed in terms of their spatial resolution (ranging from 0.083 - 2 degrees) and the time period the data product was available for (Table 1). In all cases, we downloaded the full data product and calculated the mean value, and also in certain cases an extreme representative value (e.g. 5th, 90th, 95th percentiles).

Table 1. Overview of the Copernicus data products downloaded and used in the modelling analysis. The column "variable" indicates which composite value was used (e.g., mean, p90), and the "depth" column indicates which depth the composite value was calculated for.

Copernicus data product	Spatial resolution	Temporal resolution	Variable name	Variable description	Depth
Global Ocean Physics Reanalysis (1993-01-01-2021-06-01)	0.083deg	daily	bottomT (mean, p95)	Sea water potential temperature at sea floor bottomT [°C]	Seafloor
	0.083deg	monthly	uo (mean, p90)	Eastward seawater velocity (m s-1)	1.5m
	0.083deg	monthly	vo (mean, p90)	Northward seawater velocity (m s-1)	1.5m
	0.083deg	monthly	so (mean, p05)	Salinity	0.5m
	0.083deg	static	deptho	Bathymetry (m)	Seafloor
Global Ocean Biogeochemistry Hindcast (1993-01-01-2022-12-31)	0.25deg	daily	o2 (mean, p05)	Dissolved oxygen concentration (mmol m-3)	2.7m
	0.25deg	monthly	phyc (mean)	Total phytoplankton (mole concentration of phytoplankton expressed as carbon in sea water) (mmol m-3)	0.5m
	0.25deg	monthly	fe (mean)	Dissolved Iron (mmol m-3)	1.5m
	0.25deg	monthly	no3 (mean)	Nitrate (mmol m-3)	1.5m
	0.25deg	monthly	po4 (mean)	Phosphate (mmol m-3)	1.5m
	0.25deg	monthly	nppv (mean)	Total Primary Production of Phytoplankton (mg m-3 day-1)	0.5m
	0.25deg	monthly	ph (mean, p05)	pH	1.5m
	0.25deg	monthly	spco2 (mean, p95)	Surface CO2 (Pa)	Surface
Global Ocean Waves Reanalysis (1980-01-01-2023-04-30)	0.2deg	3-hour	VHM0 (mean, p95)	Sea surface wave significant height VHM0 [m] (1980-2023)	Surface
Global Ocean Gridded L 4 Sea Surface Heights And Derived Variables Reprocessed Copernicus Climate Service (1993-01-01-2024-06-01)	0.25deg	monthly	eke (mean, p95)	Specific kinetic energy of sea water eke [cm2/s2] (1993-2024)	Surface
Global Ocean OSTIA Sea Surface Temperature and Sea Ice Reprocessed (1981-10-01-2022-05-31)	0.05deg	daily	analysed_sst (mean, p95)	Foundation Sea Surface Temperature, which is the temperature free of diurnal variability (K)	Surface
Global Ocean L 4 Significant Wave Height From Nrt Satellite Measurements (2021-01-01-2025-05-13)	2deg	daily	VAVH_DAILY_MAX (mean)	Daily maximum significant wave height (m)	Surface
	2deg	daily	VAVH_DAILY_MEAN (mean)	Daily mean significant wave height (m)	Surface
	2deg	daily	VAVH_DAILY_STD (mean)	Daily standard deviation of significant wave height (m)	Surface
	2deg	daily	VAVH_DAILY_NBR (mean)	Daily number of significant wave height measurements (m)	Surface
Surface ocean carbon fields (1985-01-01-2023-12-01)	0.25deg	monthly	talk (mean, p95)	Total alkalinity in surface seawater (micro mol kg-1)	Surface
	0.25deg	monthly	spco2 (mean, p95)	Surface aqueous partial pressure of CO2 (uatm)	Surface
	0.25deg	monthly	fgco2 (mean, p95)	Surface downward flux of total CO2 (molC m-2 yr-1)	Surface

All environmental data were spatially matched to seagrass sediment carbon measurements using latitude and longitude. Due to the coarse resolution of some datasets, exact matches were not always possible—particularly in complex coastal zones. In such cases, we used the nearest available oceanographic value. For our dataset, 25–33% of sites required nearest-neighbour matching due to land masking in satellite grids (e.g., Figure 5).

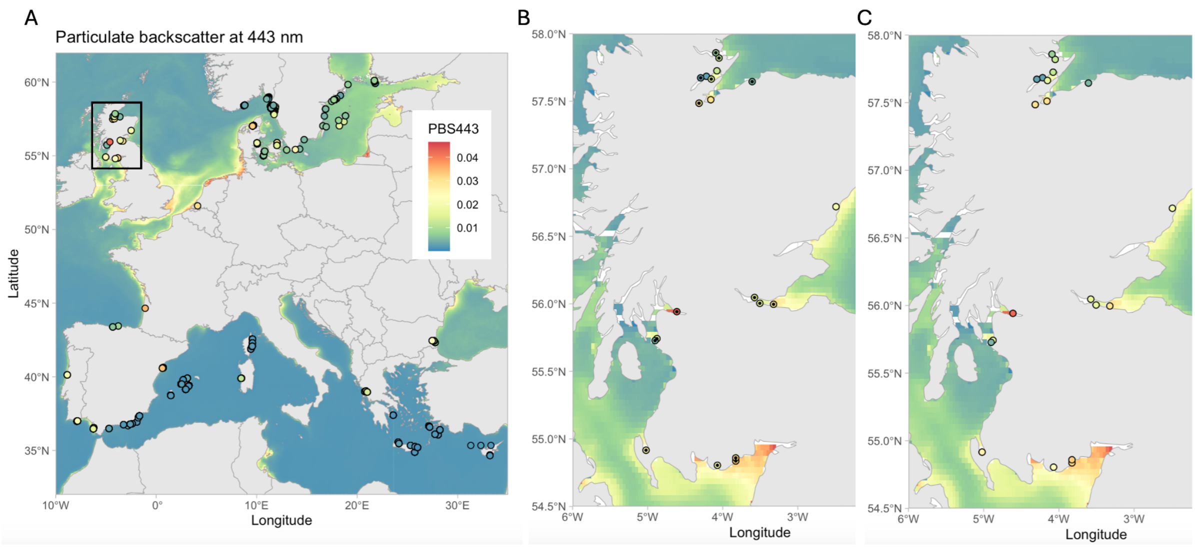

Figure 5. Satellite-derived composite particulate backscatter at 443 nm (PBS443) from Sentinel-3, overlaid with EURO-CARBON seagrass carbon measurement sites, color-filled with PBS443 values. Panel A provides a regional overview, while panels B and C zoom into a

topographically complex area where some sample sites lacked direct satellite data matches (black-dotted circles in B). These were assigned values from the nearest grid cell (shown in C).

The final dataset included 42 continuous environmental variables matched to the EURO-CARBON seagrass sediment dataset. These variables were used in modelling efforts (Activity 5) to explore relationships between environmental conditions and organic carbon storage in seagrass sediments.

3.4 Stakeholder feedback on modelling approach and output

In collaboration with WP6, we engaged with the Marco-Bolo Community of Practice (CoP) to maintain dialogue with potential users of our research. While data availability and model performance are critical for assessing remote sensing's role in blue carbon mapping, understanding user needs and limitations is equally important. Our participation in co-creation workshops aimed to explore how EU policymakers view opportunities to use seagrass blue carbon data in national inventories and climate plans and understand their requirements for data accuracy and MRV (monitoring, reporting, verification). Additionally, we wanted to identify who the more granular users would be of an analytical product that we could produce through Task 5.3 that could enable mapping and estimation of blue carbon stores in seagrass beds in Europe using global oceanographic data products.

We participated in two co-creation workshops. The first was more general to the MARCO-BOLO project as a whole but included a short presentation on our task and had EU Commission representatives from DG ENV, DG MARE, DG RTD, JRC and representatives from HELCOM and OSPAR (Benedetti et al., 2024). The second workshop was focused exclusively on co-creation of T5.3 and included representatives from DG ENV, DG MARE, DG RTD, CINEA, EMODNet, the GOOD BioEco Panel, and HEU sister projects OBAMA-NEXT, BioEcoOcean, and C-BLUES (Ashforth et al., 2025). Although we did not receive definitive answers to all our questions, the discussions provided valuable insights into stakeholder perspectives on needs and opportunities for seagrass mapping. Raising these questions also helped build relationships with stakeholders and initiate conversations. Notably, we learned that no EU countries currently include seagrass in their climate plans (despite their prevalence along many coastlines) highlighting gaps in perceived relevance and data availability.

A key benefit of the workshops was the opportunity to gather targeted feedback on our modelling approach and virtual research environment product. We discussed the parameters of the EURO-CARBON dataset to understand which response variable and depth horizon would be most relevant to stakeholders. Stakeholders indicated that carbon density was the most relevant response variable for estimating carbon stocks, and that depths beyond 100 cm were less useful for policy reporting. Based on this input, we limited our modelling dataset to samples with carbon density data and sediment depths shallower than 100 cm. Slides from the workshop that showed these questions are provided in Figure 6 and 7.

By sharing our preliminary modeling approach and results and how they would be incorporated into a LifeWatch ERIC Virtual Research Environment Interface, we were able to gauge community interest in using this product. Stakeholders expressed a preference for a simple tool that could estimate carbon stocks in the top 30 and 100 cm of soil based on seagrass bed coordinates. While researchers were identified as the primary users, there was also interest in a broader mapped product from non-academic stakeholders in the EU policy community. Early use by researchers is expected to focus on validating the tool with new sediment carbon data not included in the EURO-CARBON training dataset. This stakeholder feedback will guide the development of the virtual research environment for Task 5.3 as part of WP5.

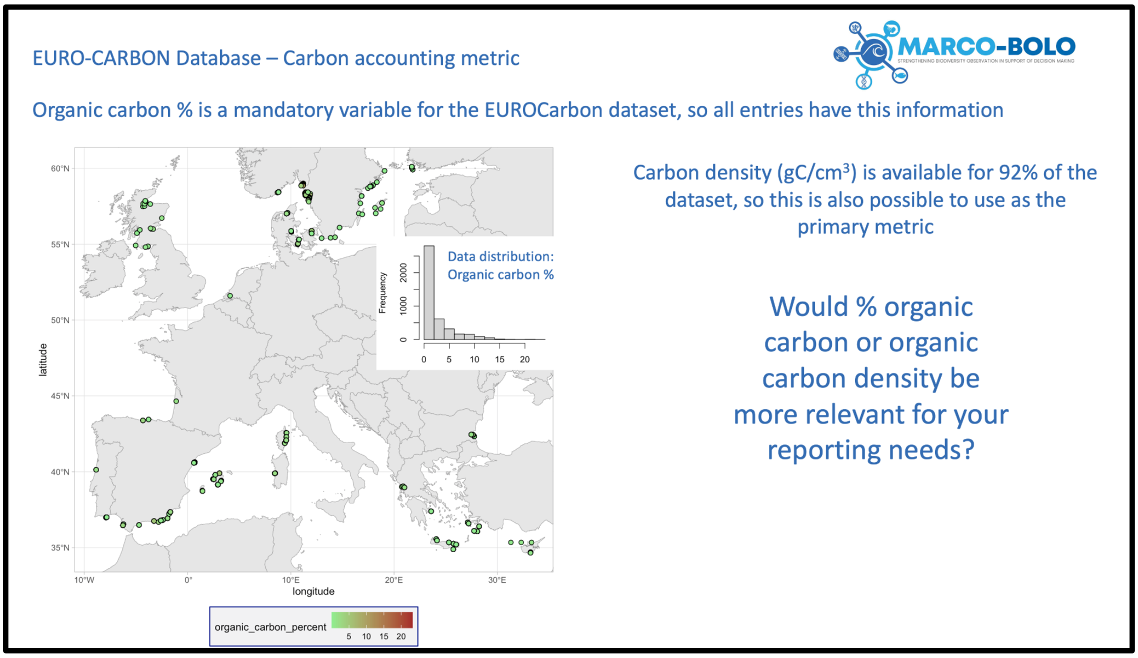

Figure 6. Slide from the co-creation workshop where stakeholders provided feedback on the most suitable response variable for their reporting needs.

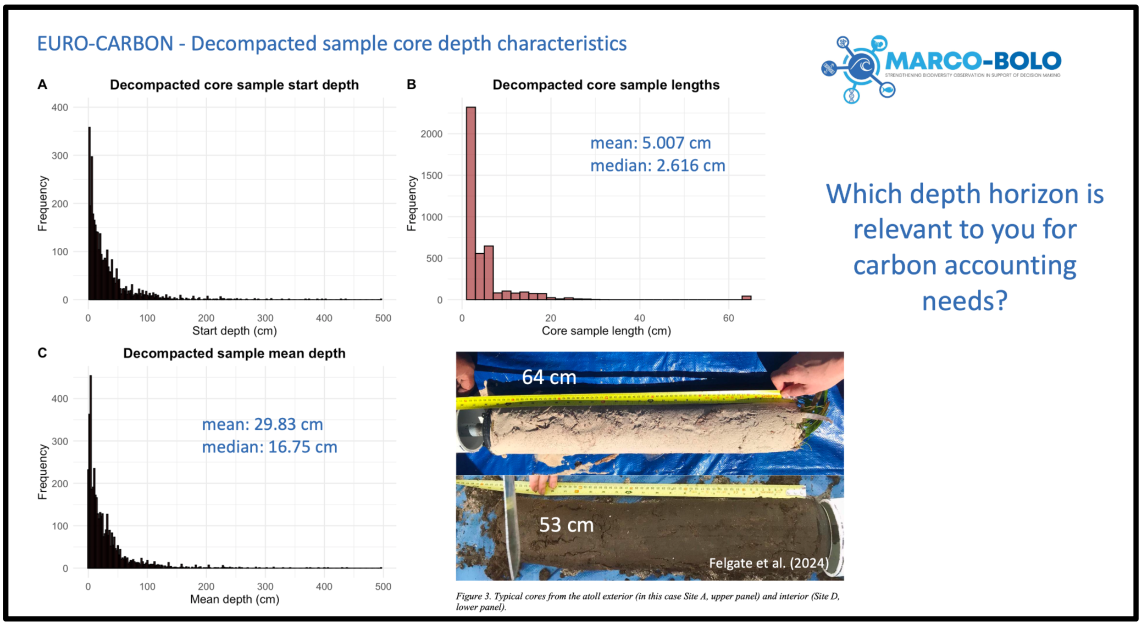

Figure 7. Slide from the co-creation workshop where stakeholders provided feedback on the most relevant depth horizon for their reporting needs.

In addition to the Marco-Bolo CoP workshops, we also participated in the "Wetlands and Blue Carbon" workshop (February 2025), organized by Trinomics, Ricardo, and Blue Carbon Lab under a CINEA study. In the breakout group on "Blueprint to Blue Carbon: Building an EU-wide Monitoring Roadmap," we shared information on Task 5.3 and gained further insight into policy needs. From this meeting, we learned that there was ongoing debate over whether allochthonous carbon should be included in seagrass carbon accounting. This has high implications for carbon accounting in seagrass beds, since a non-minor portion of the carbon can come from allochthonous sources. We also learned that from 2026, EU Member States will be required to include wetlands in their LULUCF emissions reporting (currently this is optional). However, only areas considered "managed" fall under this reporting requirement; it remains unclear whether seagrass beds will consistently meet this criterion. Participation in this workshop helped us better understand the evolving EU policy landscape specific to blue carbon reporting and build cross-EU grant connections with other blue carbon researchers. Further details on the workshop are available in the workshop report (Whiteoak et al. 2025).

3.5 Seagrass blue carbon model development and testing

The goal of Task 5.3 was to answer two key questions:

- **Q1:** Which remotely sensed environmental variables are most strongly linked to carbon storage in seagrass beds?
- **Q2:** How much variation in carbon stocks can be explained using these variables alongside other mapped environmental data?

To address these, we used a multi-model approach combining machine learning (Gaussian Process Regression, Decision Tree, Neural Network) and statistical methods (Random Forest, Generalised Additive Model). This allowed us to compare performance across techniques and identify robust patterns.

All models used a consistent structure:

Carbon density was modelled as a function of sediment depth, 42 environmental predictors (see Section 3.3), seagrass species, region, and core ID. Sediment mean depth was included in the model because carbon concentration is generally more concentrated near the sediment surface. Core ID was included as a random effect to account for the hierarchical nature of the data (i.e., even though the dataset is composed of 3680 observations, these only come from 382 unique sediment cores). Core ID was included as a random effect in all models except tree-based ones, which don't support random effects. Seagrass species and region were fixed categorical variables with eight and five categories, respectively (see Section 3.2). Although carbon density was selected as the main response variable based on stakeholder feedback, we also tested carbon percent, which had slightly more data (n = 4002 with data from 461 unique cores). Since the distribution of carbon density showed a strong right skew (Figure 4B), we applied appropriate transformations (e.g., log link with Gamma distribution for the generalized additive model).

To improve usability and reduce computational demands, we also tested simplified models using only the most influential variables. We evaluated model performance using cross-validation, leaving out subsets of data to test predictive accuracy and reduce overfitting.

3.5.1. Effects of selected response variable

For all tested models, organic carbon density had higher explanatory power than organic carbon percent. For example, in the Random Forest analysis, the model was able to explain 87% of the variation in carbon density, compared to 74% in organic carbon percent (Figure 8). This is encouraging, as carbon density was the preferred response variable for stakeholders and indicates that model performance is not worsened by using the slightly smaller dataset.

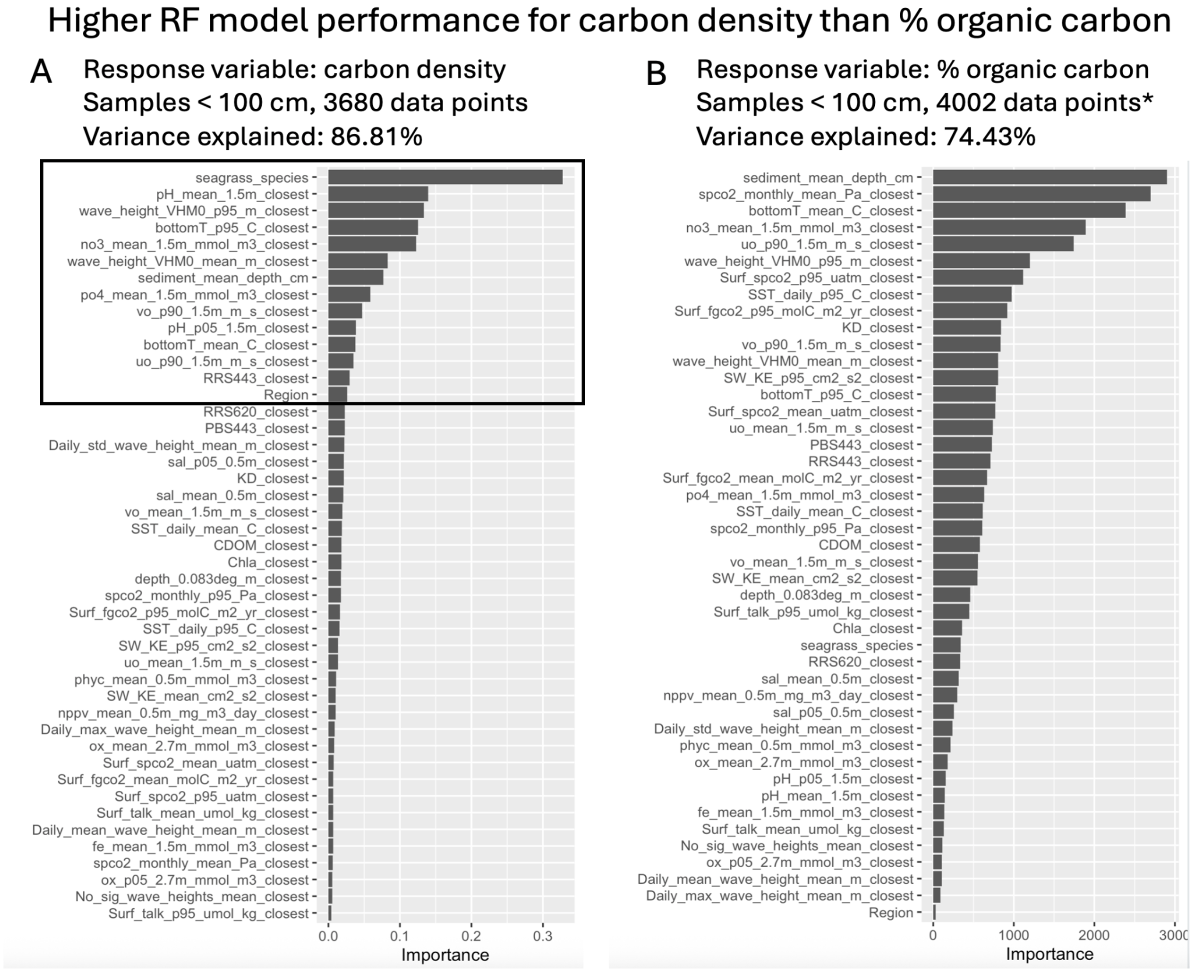

Figure 8. Comparison of variable importance for the full random forest models implemented in R, showing differences in variables importance and higher model explanatory power when carbon density (A) versus percent organic carbon (B) is used as the response variable. *Note that in B) a higher sample dataset is available for training the model, however the same reduced model performance was observed when using the smaller dataset. Thus we attribute this to the choice of response variable rather than data availability.

We found some differences in which environmental variables were most important depending on the response variable (Figure 8). Variables related to carbonate chemistry (e.g.

$spCO_2$, $fgCO_2$) and water clarity (KD490) were more relevant for explaining differences in organic carbon percent, while seagrass species had a higher importance in explaining differences in carbon density. This likely reflects the influence of dry bulk density, which affects carbon density but not carbon percent. These findings highlight the importance of measuring dry bulk density in seagrass carbon assessments, as it improves the usefulness of data for carbon accounting and policy applications.

3.5.2. Satellite remote sensing variables and seagrass carbon stocks

Across all models, two satellite-derived variables—remote sensing reflectance at 443 nm (RRS443) and diffuse attenuation coefficient (KD490)—consistently emerged as strong predictors of carbon density in seagrass beds. In contrast, chlorophyll concentration (Chla) and absorption due to gelbstoff and detritus (CDOM) were poor predictors, while RRS620 and PBS443 showed inconsistent results.

To assess the predictive power of remote sensing variables alone, we tested two generalized additive models using six satellite variables, sediment depth, core ID, and either seagrass species or region:

- **Model 1:** Included seagrass species
- **Model 2:** Included region

In both models, KD490 and RRS443 were highly significant ($p < 0.001$). Carbon density decreased with increasing RRS443, and higher carbon density was observed when values for KD490 exceeded 2, though patterns were less consistent at lower values. In Model 1, Chla showed weak significance ($p = 0.08$), while in Model 2, RRS620 was significant ($p = 0.002$). Sediment depth and core ID were also consistently important.

Model performance was similar whether using species or region, suggesting that users without species data can still apply the regional model effectively. However, since carbon density varies across species—e.g., higher in *P. oceanica*, lower in *Z. marina*, and lowest in mixed beds—we recommend using species data when available.

3.5.3. Can global oceanographic data products predict seagrass carbon stocks?

In short, our results show that yes, global oceanographic data products combined with satellite variables can effectively predict carbon density in seagrass beds. All tested models showed strong performance ($R^2 > 0.8$), with machine learning models outperforming traditional statistical approaches.

Since the results of the random forest analysis were already presented in 3.5.1, here we present the results of the machine learning models. The following machine learning models were evaluated: kernel machines: Gaussian Process Regression and Support Vector Machines (SVM) with different kernel functions (linear, exponential, Matern, isotropic and anisotropic squared exponential), decision trees (fine, medium, course, boosted and bagged) and Neural Networks (NN) (with different number of layers and neurons).

The three top-performing machine learning models were the Gaussian Process Regression (GPR), Decision Tree, and Neural Network. These models were first tested using all available predictors (42 environmental variables, sediment depth, species, region, and core ID), using re-substitution for validation. We then identified the 10 most influential variables using Shapley values and tested reduced models. The reduced GPR model improved performance, the decision tree remained stable, and the neural network declined—consistent with its need for more input data.

As a result, we prioritized the GPR and decision tree models. Because decision trees don't support random effects, we excluded core ID from that model to ensure it could be used for future predictions. Both reduced models were validated using 90% training and 10% testing data with 5-fold cross-validation. Performance was slightly reduced but remained high (Table 2). These results suggest that simplified models using global data can reliably estimate seagrass carbon stocks.

Table 2. Model performance metrics (root mean squared error (RMSE) and R^2) for the top candidate machine-learning models, showing model performance with all predictor variables included (top), performance of a reduced model with the top 10 influential predictors included (middle), and then the reduced model evaluated using an independent test dataset (bottom).

Full-model (all predictors included) with resubstitution for validation		
Model Type	RMSE	R^2
Decision Tree	0.00818	0.87365
Gaussian Process Regression	0.00465	0.95923
Neural Network	0.00573	0.93816
Reduced model (top 10 predictors included) with resubstitution for validation		
Model Type	RMSE	R^2
Decision Tree	0.00842	0.87133
Gaussian Process Regression	0.00919	0.84462
Reduced model (top 10 predictors included) with 10% independent test data for validation		
Model Type	RMSE	R^2
Decision Tree	0.00793	0.81989
Gaussian Process Regression	0.00707	0.88076

3.5.4. Key environmental predictors for seagrass carbon stocks

To balance model performance with ease of use, we aimed to identify a reduced set of high-impact environmental variables for predicting seagrass carbon density. We compared the top predictors across four candidate models to find those consistently ranked as most important (Figure 9). The following predictors commonly emerge as important:

- Sea surface wave significant height (95th percentile)
- Phosphate concentration
- Mean pH
- Remote sensing reflectance at 443 nm (RRS443)
- Diffuse attenuation coefficient (KD490)
- Bottom temperature (95th percentile)
- Eastward and northward seawater velocity (vo, uo)

In addition, seagrass species and sediment mean depth were consistently identified as significant predictors and should be included. While the model can still function without species data (e.g., using the “Unspecified” species category or including “Region” as a factor variable), species-specific data improves accuracy. Region alone was not a strong predictor when species data was available.

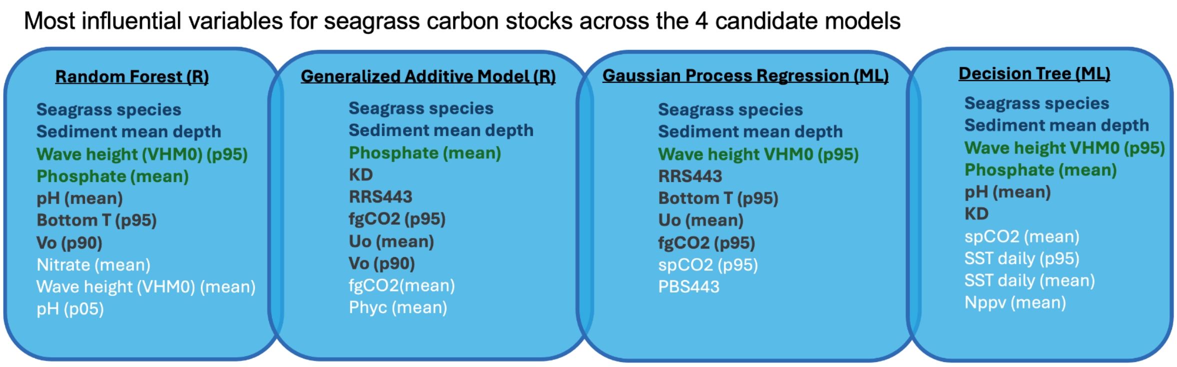

Figure 9. Top 10 most influential predictors identified by the four tested candidate models. Variables are ordered and color-coded based on which appear most frequently across multiple models (dark blue text, upper: variables that appear across all 4 models; dark green text, middle: variables that appear across 3 models; dark gray text, middle: variables that appear across 2 models; white text, bottom: variables that were only selected by 1 model).

Based on these findings, we recommend a simplified model using just 9 environmental predictors plus sediment depth and species:

Recommended model:
Carbon density (gC cm^{-3}) ~ KD490 + RRS443 + VHM0_p95 + Phosphate_mean + pH_mean + Bottom_T_p95 + Vo_p90 + Uo_mean + fgCO_2_p95 + Sediment depth + Seagrass species

This reduces the original 42 predictors to a manageable subset, while maintaining high model performance for practical use in policy and management tools.

4. Discussion

4.1 How can remote sensing contribute to European needs for blue carbon monitoring?

Remote sensing can make a significant contribution to European needs for blue carbon monitoring by providing scalable, cost-effective tools to map seagrass extent, estimate carbon storage, and supply environmental context across data-poor regions. While remote sensing cannot replace field observations, it can enable consistent EU-wide assessments, highlight priority areas for ground validation, and support the development of user-friendly products that make mapping seagrass carbon stocks more accessible to policymakers, managers, and researchers.

While our study suggests that remote sensing can contribute to mapping region-wide blue carbon stocks, it is unlikely that this approach would be appropriate for restoration efforts or mapping carbon accumulation rates. The approach we used is crude in that it assumes that carbon stocks in seagrass beds are due to long-term environmental processes and conditions. While this assumption appears robust for modelling at a whole-region level, these assumptions are likely not valid on the finer scale or when considering short time scales. Fine-scale variation and short-term changes require targeted field sampling.

Many organizations are working to help countries include blue carbon ecosystems in climate inventories. These include the Blue Carbon Initiative, International Partnership for Blue Carbon, Blue Carbon Accelerator Fund, Blue Natural Capital Financing Facility, and the Global Ocean Decade Programme for Blue Carbon. Resources such as the Blue Carbon Initiative's guide for Nationally Determined Contributions (Hamilton et al., 2023) and Northrop et al. (2020)'s overview of public data sources support this effort. As of 2022, the International Partnership for Blue Carbon identified about 40 actors working on blue carbon at the global and regional level. Despite growing support, challenges remain that prevent countries from including blue carbon ecosystems, and especially seagrass beds, in their climate pledges and national climate inventories (e.g., insufficient data and perceived relevance).

There is increasing interest in both market-based (e.g., carbon credits, payments for ecosystem services) and non-market approaches to valuing blue carbon. The Verra Standard is the most widely used for blue carbon credits, though most projects focus on mangroves (Friess et al., 2022). However, progress for seagrasses is emerging. France recently approved a methodology to generate blue carbon credits from protecting *Posidonia* meadows under its domestic offsetting Bas-Carbone label (Comte et al., 2024). The Verra Standard has also released a new methodology for quantifying greenhouse gas emissions and removals resulting from project activities for restoring wetlands, including seagrass beds (VM0033 v2.0; Emmer et al., 2023).

4.2 Study limitations and next steps

Now that we have identified key environmental predictors from satellite remote-sensing and oceanographic data products that can estimate carbon density in seagrass beds, the next step is to integrate this model into a Virtual Research Environment. This will be developed with LifeWatch ERIC as part of WP5 and the product shared with participants who attended the co-production workshop. This tool will allow users to estimate carbon stocks by simply entering the location and, if known, the seagrass species, of a seagrass bed of interest. The tool will automatically retrieve relevant environmental predictor variables and provide carbon stock estimates for the top 30 cm and 100 cm of sediment. In the future, it could be scaled to map carbon stocks across all European seagrass regions, similar to existing *P. oceanica* distribution maps in EMODNet (Figure 10).

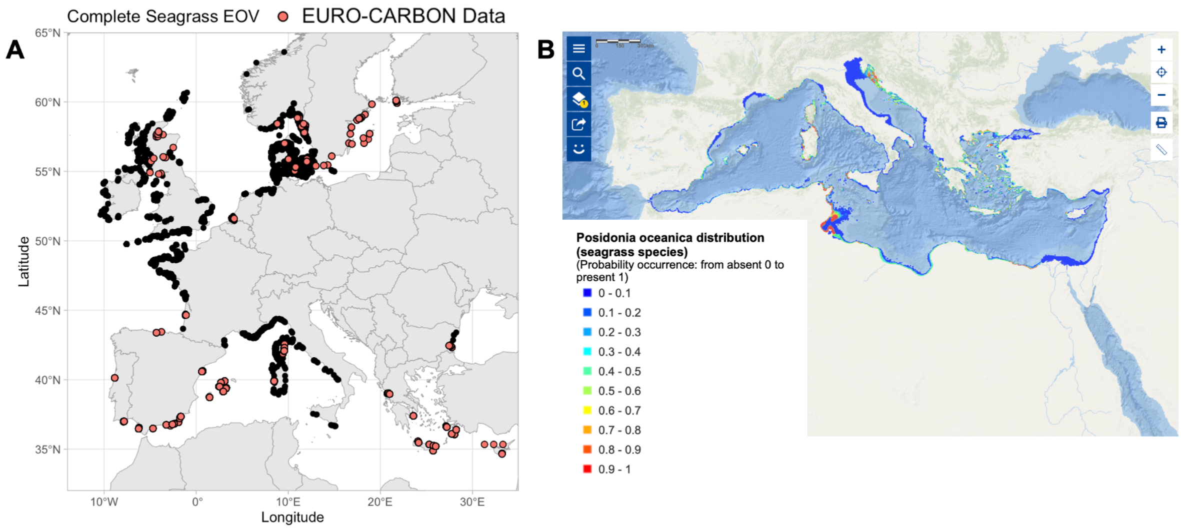

Figure 10. Seagrass essential ocean variable (EOV) data, available via EMODNet, provides comprehensive point and polygon records of seagrass beds across Europe. Panel A displays 132,233 seagrass observations (black points) and EURO-CARBON sediment sampling sites (pink circles). Seagrass location data from the EOV (A) or predicted seagrass distribution maps (B) could be used to create a map of carbon stocks through the virtual research environment.

Scientific research is a process of continuous improvement and thus we highlight these areas for future work. First, we emphasize that despite the high performance seen with the tested models, further testing is needed as additional *in situ* data become available. Even though the EURO-CARBON database presents the most comprehensive dataset of seagrass sediment carbon data for Europe, these 4,000+ samples only come from 461 unique cores, with large areas (e.g., France and Italy) still lacking data. More *in situ* sampling is needed to improve model accuracy and support national carbon stock assessments.

An additional area of improvement would be the incorporation of a data product that contains information on sediment type in the model, since mud content can be a predictor of seagrass soil organic carbon content (Serrano et al., 2016). Although we couldn't access region-wide sediment maps, future work could explore sources in EMODNet. Similarly, proximity to features like rivers, river deltas, oyster reefs, estuaries, and wetlands can affect allochthonous carbon deposition in seagrass beds but was not directly included in our model due to lack of spatial metrics. These could be added in the future using mapped datasets.

Our analysis focused on sediment depths up to 100 cm, based on stakeholder input. However, some seagrass beds, especially *P. oceanica*, store carbon much deeper (up to 2.7 m) (Fourqurean et al., 2012). Thus, predicted values from our model likely underestimate total carbon stocks.

4.3 Beyond carbon benefits in blue carbon ecosystems

While this study focused on carbon storage, seagrass beds provide many other valuable ecosystem services—that are equally or more important. Remote sensing can also contribute to monitoring these ecosystem services.

For example, seagrasses can improve water quality and support fisheries by functioning as nursery habitats. Sentinel-1 C-band synthetic aperture radar (SAR) satellite data can track marine vessel activity near seagrass beds, revealing areas of high recreational or fishing use (Chowdhury et al., 2024). Sentinel-2 and Sentinel-3 satellite data can be used to monitor turbidity, chlorophyll-a, and algal blooms in proximity to seagrass beds, thus providing information on water quality.

Coastal protection is another key benefit. Seagrasses reduce wave energy and storm impacts, helping prevent shoreline erosion. Satellite-borne SAR can offer fine-scale monitoring of coastal changes, sea level rise, and intertidal zones (e.g., Haarpaintner and Davids 2021; Di Paola et al., 2018; Meng et al., 2024). Unlike optical sensors, SAR can operate day and night and “see” through cloud cover, making it especially useful in coastal areas where clouds are common (Borfecchia et al., 2019). Although SAR cannot detect underwater vegetation, it can improve mapping and biomass estimates for intertidal seagrass beds (Simpson et al., 2022). Combining SAR with high-resolution optical imagery can enhance assessments of seagrass extent and erosion regulation and other ecosystem services—similar to approaches used for tropical forests (Reiche et al., 2016).

4.4 New satellite remote sensing tools for improved seagrass carbon stock monitoring and evaluation

Remote sensing is rapidly evolving, and upcoming satellite missions from NASA and the European Space Agency (ESA) will significantly enhance potential for blue carbon monitoring. New hyperspectral sensors will offer much finer detail on coastal biological processes by capturing a broader range of light wavelengths (Dierrssen et al., 2021). While hyperspectral data was previously available for certain regions, NASA and the ESA’s new missions will make it available on a global level.

NASA’s three new hyperspectral aquatic missions are the Plankton, Aerosol, Cloud, ocean Ecosystem (PACE) satellite (Werdell et al. 2019) which was launched in 2024, the Geostationary Littoral Imaging Radiometer (GLIMR) satellite which is planned to launch in 2026, and the Surface Biology and Geology (SBG) satellite (Cawse-Nicholson et al., 2021) which is planned to launch in 2028 (Dierssen et al., 2023). The ESA will launch the Copernicus

Hyperspectral Imaging Mission (CHIME) which is planned to launch in 2028, and will collect high-resolution hyperspectral observations of coastal waters as well as land.

These new satellite missions will enhance blue carbon monitoring in marine habitats by improving carbon monitoring, reporting, and verification. They will also provide detailed data on floating vegetation composition, benthic composition, phytoplankton community composition, and wetland composition. Hyperspectral sensors may further advance understanding of carbon storage in seagrass beds by better characterizing dissolved organic carbon from rivers and wetlands (Tzortziou et al., 2008). NASA's SBG mission is especially promising, offering global, high-resolution (30 m) data that can capture seagrass patchiness, distinguish species, and track seasonal and long-term changes (due to the 16-day revisit time)—including those driven by storms, sea-level rise, climate change, and restoration. ESA's CHIME mission will offer similar capabilities on a similar timeline. In contrast, the NASA GLIMR mission will only collect data from several specific regions, and none of these are in Europe, reducing the usefulness of this mission for European blue carbon monitoring.

Additionally, ESA's upcoming Copernicus CO_2M satellite mission will support spatial mapping of blue carbon benefits by enabling accurate measurements of CO_2, CH_4, and NO_2. The mission includes three satellites, with the first launching in late 2025. These data will help fill knowledge gaps on greenhouse gas fluxes in seagrass beds and other blue carbon ecosystems.

In conclusion, remote sensing and global oceanographic data can already contribute to evaluating blue carbon services in seagrass beds, but upcoming satellite missions will greatly expand these capabilities. However, with many tools available, it can be difficult for managers to know where to start. The Remote Sensing Toolkit helps bridge this gap by guiding users on how different satellites and aircraft can support mapping and monitoring needs (Figure 11). While some high-resolution products require payment, many datasets are freely accessible through the Copernicus Data Space Ecosystem for the European region (https://dataspace.copernicus.eu/).

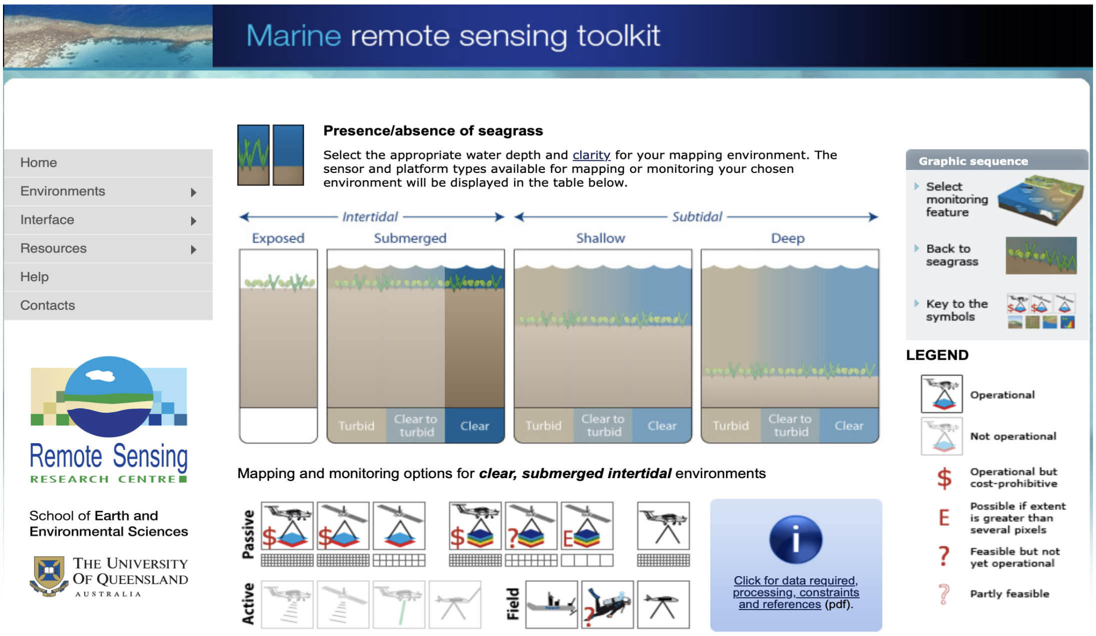

Figure 11. Interface for the marine remote sensing toolkit, showing different remote sensing technologies for mapping seagrass under different depth and turbidity conditions. The toolkit can be accessed: https://sees-rsrc.science.uq.edu.au/rstoolkit/.

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