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Subtidal seagrass and blue carbon mapping at the regional scale: a cloud-native multi-temporal Earth Observation approach

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ABSTRACT

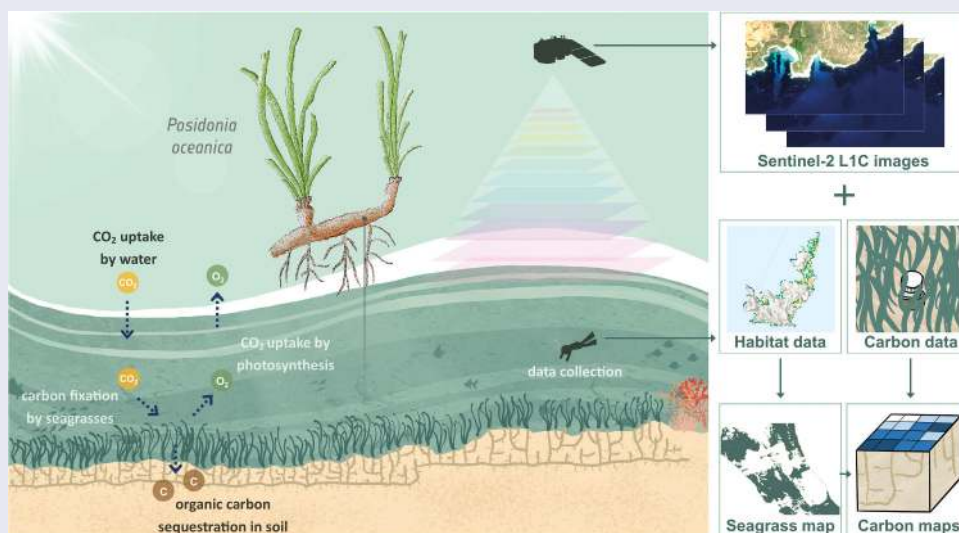
The seagrass ecosystems are among the most important organic carbon sinks on Earth, having a key role as climate change buffers. Among all seagrasses, *Posidonia oceanica*, an endemic seagrass species in the Mediterranean Sea, has been observed to feature the highest carbon stock and sequestration rate among all seagrasses. We developed a satellite-based workflow to complement *in situ* seagrass monitoring efforts in the Balearic Islands (Western Mediterranean), reducing field expenses while covering regional spatial scales. Our synoptic tool uses Sentinel-2 A/B satellite imagery at 10 m spatial resolution to generate a multi-temporal composite (2016–2022) of the Balearic Islands' coastal waters within the Google Earth Engine cloud computing platform, optimizing image processing and highlighting the importance of a high-resolution bathymetric dataset to increase seagrass mapping accuracies. Machine learning algorithms have been applied to perform seagrass detection, obtaining a seagrass cartography up to 30 m of depth, estimating 505.6 km² of seagrass habitat extent. Using existing *in situ* soil carbon stock (C_{stock}) data, we estimated a mean C_{stock} value of 12.27 ± 2.1 million megagram (Mg) C_{org} , while mapping a total annual C fixation (C_{fix}) and C sequestration (C_{seq}) rates of *P. oceanica* of 1,116.3 Mg C_{org} and 227 Mg C_{org} , according to depth. Our methodology highlights the key role of using a large image archive to generate the multi-temporal optical composite and an optimized bathymetry dataset to better map and account blue carbon in seagrass ecosystems across depth, showing the importance to integrate this Earth Observation approach to ensure a seagrass ecosystem monitoring at regional scales. This information aims to support the development of blue carbon strategies with synoptic time- and cost-efficient seagrass monitoring in the Mediterranean Sea.

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1. Introduction

Fifty percent of the Earth's carbon anthropogenic emissions are sequestered by the oceans, from which 15% is buried in coastal vegetated ecosystems (Duarte, Middelburg, and Caraco 2005), which includes seagrasses, mangroves and tidal flats. While occupying less than 1% of the Earth's surface and 0.2% of the ocean floor, these ecosystems play an outsized role by burying an estimated 10% (0.08–0.22 Pg C yr⁻¹) of the residual land sink (Duarte et al. 2013). The preservation, conservation, and restoration of these so-called “blue carbon” ecosystems due to their ability to sequester organic carbon (C_{org}) for a long-term period has been defined as an action to contribute to climate change mitigation (Belshe et al. 2019; Donato et al. 2011; Duarte et al. 2013; Fourqurean et al. 2012; Howard et al. 2014, 2017; Kennedy et al. 2010; Lavery et al. 2013; Macreadie et al. 2021; Rovai et al. 2018).

Seagrasses are one of the most productive global ecosystems due to their significant carbon storage capabilities (Duarte et al. 2010; Smith 1981). However, they are experiencing a global decline of about 5% yr⁻¹ after the 1980s due to overexploitation, physical modification, chemical pollution, introduction of non-native species and global climate change (Short 2003), even though there are information gaps (McKenzie et al. 2020). This has resulted in an estimated global loss of around 29% (Waycott et al. 2009), with initial records in 1879 and a 1/3 of the European seagrasses (de Los Santos et al. 2019), with the Mediterranean bioregion displaying the largest losses in subtidal seagrasses, estimated as 10–22% over the last century (Dunic et al. 2021). This fact has raised an interest in seagrass conservation in Europe as a priority policy (Nordlund et al. 2024), with expected dramatic losses in seagrass in the Mediterranean Sea under projected climate change scenarios (Chefaoui, Duarte, and Serrão 2018). Consistent with these data, *Posidonia oceanica*, an endemic Mediterranean seagrass species distributed down to 45 m of depth, has experienced a widespread decline in the past 60 years, losing over 40% of its coverage (Marbà, Díaz-Almela, and Duarte 2014; Telesca et al. 2015), where the 75% of its suitable habitat is threatened under the worst climate scenario by 2050 (Chefaoui, Duarte, and Serrão 2018). This decline of its extent may imply the loss of its C_{org} sink capacity (Marbà, Díaz-Almela, and Duarte 2014).

The Paris Climate Agreement of December 2015 (COP21) requires net neutral carbon emissions by 2100 outlining the National Determined Contributions (NDCs) to reduce emissions (UNFCCC 2015; Walsh et al. 2017), where Nature-based Solutions (NbS) have increasingly being adopted as the main strategy for their social benefits and innovative opportunities. Since net carbon sinks provide means of revaluing ecosystems and offsetting CO₂ emissions (Serrano et al. 2014), the ability to report and quantify the coastal vegetation's capacity to store and sequester carbon has increased interest in multiple fields.

P. oceanica has the highest sequestration rate among all seagrasses (Romero et al. 1994) and the highest median total biomass (2,013 g DW m⁻²) (Strydom et al. 2022), buffering particle resuspension while promoting particle trapping (Hendriks et al. 2008; Kennedy et al. 2010), resulting in high sedimentation rates and high burial capacity (M. Mateo et al. 2006). This leads to a massive C storage up to 410 kg C_{org} m⁻² which can persist for millennia (Lavery et al. 2013) due to anoxic conditions in the sediment (Gattuso et al. 2023), placing *P. oceanica* as an outlier among all seagrasses (Walker, Dennison, and Edgar 1999). However, *P. oceanica* has the lowest growth rates among marine angiosperms, both horizontally (1–6 cm yr⁻¹) and vertically (0.1–4 cm yr⁻¹) (Hemminga and Duarte 2000), creating reefs up to 6 m of thickness that would take around 60,000 years to create (Lo Iacono et al. 2008) and storing 98% of the sequestered C in the soil compartment (Serrano et al. 2019). Moreover, the carbonate-rich Mediterranean sediments below seagrasses are highly anoxic with relatively shallow oxygen penetration depths (<4.5 mm). This indicates minimal bacterial activity, leading to the long-term preservation of carbon stocks through the absence of C_{org} decomposition (Holmer, Duarte, and Marbà 2003). This makes its preservation even more critical in terms of avoided emissions (G. Roca et al. 2022) aiming at mitigating coastal deterioration (Marbà, Díaz-Almela, and Duarte 2014).

To monitor the seagrass extent, while scuba diving, Side Scan Sonar (SSS) methods and underwater cameras are widely used, they demand expensive resources and time (Del Valle Villalonga, Pons, and Bardolet 2023; Siljeström, Rey, and Moreno 1996). Nevertheless, this information remains crucial for

remote sensing applications to generate and validate derived models, where the distribution of this information in an open-hub still remains a priority to ensure accessibility and a real examination of seagrass distribution maps and global contribution of seagrass carbon stocks (C_{stocks}) (McKenzie et al. 2020). However, remote sensing techniques are being implemented not only in monitoring seagrass distribution at a regional and national scale together with *in situ* measurements (Barrell et al. 2015; Blume et al. 2023; Traganos, Lee, et al. 2022), but also to detect spatial heterogeneity and changes in C_{stocks} (Campbell et al. 2022). While multispectral cameras on-board Unmanned Aerial Vehicles (UAVs) can generate a higher resolution product for macrophyte mapping (Dekker et al. 2006; Nahirnick et al. 2018; Román et al. 2021), their extent is limited to the shallowest area and highly dependent on small field campaigns; whereas multispectral imagery on-board satellites generate a synoptic monitoring with periodic revisit times and improved spectral resolution covering broader geographical scales (Roca et al. 2022a).

To approach the seagrass mapping through Earth Observation (EO), multispectral satellite remote sensing has been used across multiple case studies using IKONOS, PlanetScope NICFI data, Landsat, Sentinel-2 (S2) and WorldView-2/3 imagery with two main approaches: utilizing single images and multi-temporal image composites (Blume et al. 2023; Coffey et al. 2023; Fornes et al. 2006; Lee et al. 2023; Lyons, Phinn, and Roelfsema 2012; Traganos, Pertiwi, et al. 2022; Zhao and Liu 2022; Zhou et al. 2022). While intertidal seagrass EO mapping require less image corrections (Davies et al. 2023, 2024; Zoffoli et al. 2020), subtidal seagrass detection remains more challenging not only due to light attenuation through the water column, but also due to increasing turbidity, sunglint and sea roughness (Caballero and Stumpf 2023). These challenges in optically complex waters mixed with other optical water types make the scalability of such mapping solutions challenging at regional and global scales due to radiometric heterogeneity (McKenzie, Langlois, and Roelfsema 2022). These differences can be optimized using a multi-temporal approach, widely used to obtain Satellite-Derived Bathymetry (SDB) (Caballero and Stumpf 2020), whose processing requires a high computing demand. Nevertheless, important improvements in

atmospheric and water column corrections, as well as the existence of cloud-computing environments, such as the Google Earth Engine (GEE) platform (Gorelick et al. 2017) for on-demand large computational image processing and storage, have paved the way to scale this multi-temporal approach, allowing spatial and temporal scalability.

Although carbon monitoring is heavily dependent on *in situ* measurements, remote sensing is being increasingly used to estimate carbon through space and time, especially for terrestrial applications (Campbell et al. 2022). In the case of subtidal seagrass ecosystems, the greater the depth, the lower the carbon storage and sequestration rate (Mazarrasa et al. 2017b; Serrano et al. 2014), which results in highest carbon storage in the shallowest waters, right where EO techniques perform best mainly due to higher light penetration.

The development of cost and time-efficient satellite-based synoptic techniques is crucial to monitor seagrass extent changes and to update C_{stocks} maps. This tool integrates limited *in situ* measurements, resulting in a faster update of seagrass cartography in optically shallow waters key for coastal managers. In this study, we present an EO approach using S2 data within the GEE platform to map *P. oceanica* seagrass meadows at 10-meter spatial resolution across the entire Balearic Islands (Spain), up to 30-meter depth. This approach aims to help update the *in situ* monitoring on seagrass distribution and spatially explicit blue carbon accounting to enhance blue carbon sequestration management practices.

2. Material and methods

2.1. Study area

The Balearic Islands (Spain) are located in the Western Mediterranean with 1,573 kilometers of coastline (79% rocky), characterized by shallow subtidal basins surrounded by deep platforms with seagrass ecosystems in a low-energy, oligotrophic, and clear water environment (Figure 1). The distribution of *P. oceanica* meadows in this area ranges between 1 and 45 m of depth (Larkum, Orth, and Duarte 2006), reaching higher depths in areas like the Cabrera Terrestrial-Maritime National Park (TMNP) archipelago (Orfila et al. 2005).

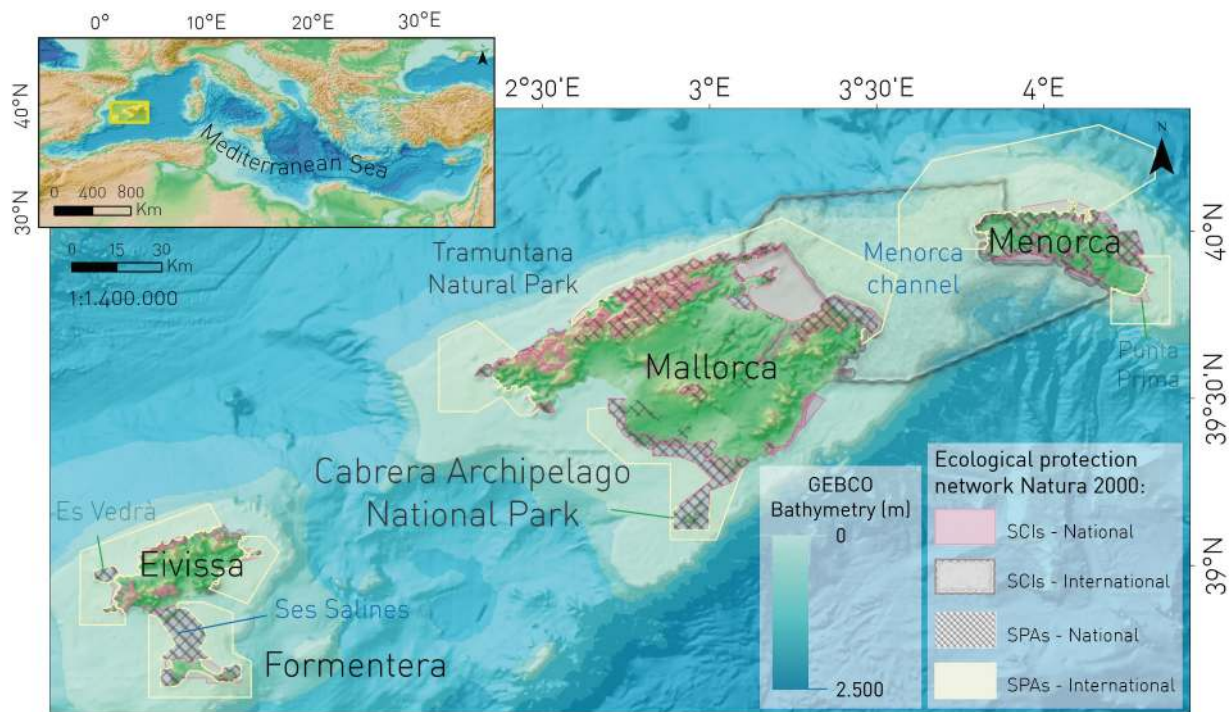


Figure 1. Overview of the study area (Balearic Islands, Spain; yellow rectangle in inset map) with Marine Protected Areas (MPAs), including Sites of Community Importance (SCIs) and Special Protected Areas (SPAs) (source: IDEIB); and GEBCO bathymetry.

These islands rank among the top tourist destinations across Europe (Hof and Schmitt 2011), threatening seagrass extent due to intensive coastal urbanization, massive seasonal nutrient water discharges, and anchoring events of recreational boating (Bockel et al. 2023; Deter et al. 2017; Pergent-Martini et al. 2022), causing a decline of 40% of *P. oceanica* extension in the last 60 years (Marbà, Díaz-Almela, and Duarte 2014). Moreover, on top of it, these ecosystems are ultimately threatened through persistent hotspots of Marine Heat Waves (MWHs) reaching the seabed (Fernández-Barba, Huertas, and Navarro 2024; Marbà and Duarte 2010).

Due to the relevance of the threatened *P. oceanica* and its ecosystem services, nowadays there is a regional law for its conservation and management (Decree 25/2018 of July 27, on the conservation of *Posidonia oceanica* in the Balearic Islands) (Blasco Hedo 2018) highlighting the continuous monitoring needs.

2.2. Data

2.2.1. Bathymetry

Bathymetric data from different vector sources were processed and harmonized in order to be used as

a valuable feature in the multi-temporal image composite and the machine learning algorithm following the workflow shown in Figure 2. The national coastline dataset from the National Geographic Institute (IGN) was considered as the 0 bathymetric value, featuring a better delineation of the shallow areas. All polylines were projected at the datum UTM ETRS89 31N (EPSG: 25831), and points were generated along lines every 5 meters. Depth values were transferred through a spatial join and values from 0 to 40 m were selected.

Subsequently, with the processed depth points ($n = 7,224,443$) (Table 1), using a boundary mask between 0 and 40 m of depth, interpolation was performed in ArcGIS Pro 3.0. Due to the capacity of using barriers and as a computable algorithm, we used the Inverse Distance Weighting (IDW) method, where the weight is a function of the distance of the input point and the cell location (Childs 2004). This interpolation generated a Digital Elevation Model (DEM) of the Balearic Islands bathymetry at 10 m spatial resolution whose grid was snapped at the S2 grid from 0 to 40 m of depth. The resulting bathymetry was validated

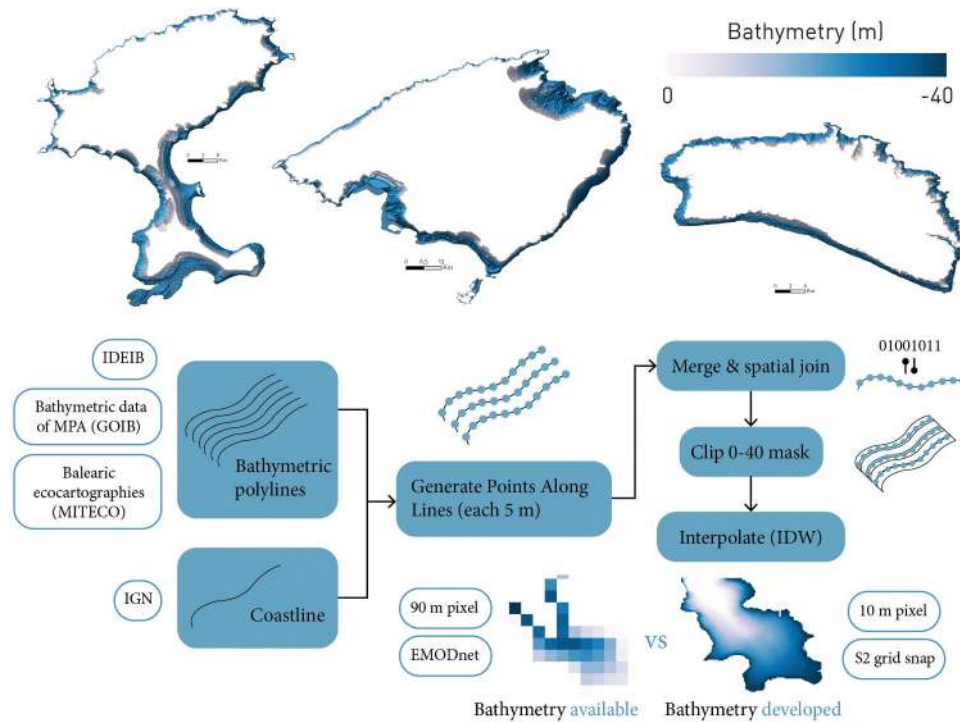


Figure 2. Workflow of the bathymetry developed using multiple vector datasets. Compared to the raster bathymetry available (EMODnet) at 90-meter pixel, the developed bathymetry at 10-meter pixel was essential in the improvement of the image composite and as a valuable feature in the seagrass habitat detection. IDEIB: “Infraestructura de Dades Espacials de les Illes Balears;” GOIB: “Govern de les Illes Balears;” MITECO: “Ministerio de Transición Ecológica y del Reto Demográfico;” IGN: “Instituto Geográfico Nacional;” S2: Sentinel-2; IDW: inverse distance weighted.

Table 1. Extracted points per island from existing data to generate a multi-source bathymetry at 10 m resolution.

	Eivissa-Formentera*	Mallorca	Cabrera	Menorca
Extracted points	2,755,917	2,400,224	353,744	1,714,558

*Eivissa and Formentera islands are always shown together due to the ecological continuity of the seagrass meadow along both islands.

with *in situ* measurements obtained through SSS, already transformed to 10 m S2 pixel information by Viaña-Borja et al. (2023) (see Supplementary Material S1).

2.2.2. Satellite imagery

For the regional-scale seagrass mapping in the Balearic Islands, we used images captured by the EU Copernicus programme S2-A/B twin satellites, at 10 m spatial

resolution with a 5-day revisit time due to its free access policy, its availability in the GEE data archive, and its suitable spectral resolution for coastal aquatic applications. To generate the multi-temporal composite, we used the Top of Atmosphere (TOA) Level 1C imagery acquired between January 2016 and December 2022, consisting of a total of 8,235 tiles (100×100-km per tile), from which 3,499 tiles were used for the multi-temporal composite after cloud cover filtering (Table 2).

Table 2. Tiles available and used from the S2A/B TOA imagery. Cloud-filtering performed using open-source GEE methodology developed for S2 imagery (Roca et al. 2022b).

	Eivissa-Formentera	Mallorca	Cabrera	Menorca	Total
Available tiles	960	3,881	1,927	1,467	8,235
Scenes used	430	1,634	822	613	3,499

2.2.3. Benthic habitat reference data

The mapping procedure uses published independent field-based measurements for benthic habitat mapping as validation data to assess the accuracy of our mapping results (extracted control points shown in [Figure 5](#)).

To validate the satellite-derived *P. oceanica* extent, LIFE Posidonia project seagrass cartography was used, available from the regional “Infraestructura de dades espacials de les Illes Balears” (IDEIB) data catalog and downloaded in June 2023 (<https://ideib.caib.es/posidonia/>). Sandy or rocky bottoms were retrieved for Menorca, Ibiza and Formentera from the ecocartographies published by the Spanish Ministry of Ecological Transition and Demographic Challenge (<https://www.miteco.gob.es/es/costas/temas/proteccion-costa/ecocartografias/ecocartografia-baleares.html>). Validation points for Cabrera TMNP archipelago were retrieved from the same ministry as a shared product developed by the TMNP (<https://www.miteco.gob.es/es/red-parques-nacionales/sig/medio-marino.aspx>). Benthic habitat data for Mallorca island were extracted from the marine cartography developed inside the protected areas (Sites of Community Importance (SCIs) and Special Protected Areas (SPAs)) by the *Conselleria de Medi Ambient i Territori de les Illes Balears*. See Supplementary Material 2 for reference map examples.

2.2.4. In situ carbon data

To collect carbon storage information, we conducted a systematic literature review of *P. oceanica* C_{stock} data in the Balearic Islands. [Table 3](#) shows the retrieved C_{stock}

data from 19 sampling sites (3 replicates per sampling point) in *P. oceanica* soils in the study area published in peer reviewed journals. Data were extrapolated to retrieve values in the 1-meter soil depth with the units of megagrams (Mg) $C_{org} \text{ km}^{-2}$ (1 Mg = 1 ton) for the samples with different depth cores. The average value of the 19 samples was used to transform the satellite-derived *P. oceanica* seagrass extent into a total mean C_{stock} estimation due to the lack of C_{stock} correlation across depth (see Supplementary Material 3).

2.3. Earth Observation workflow

We developed a cloud-based EO workflow within the GEE platform to process S2 imagery, implement training and validation datasets, perform the supervised machine learning classification, and assess the accuracy of the results ([Figure 3](#)).

2.3.1. Multi-temporal composites

Within the GEE platform, seven complete years (2016–2022) of S2 L1C imagery archive (COPERNICUS/S2_HARMONIZED) were processed for the Balearic Islands’ extent for seven bands (B1–B5, B8 and QA60). The S2 cloud probability dataset (COPERNICUS/S2_CLOUD_PROBABILITY) was first used for cloud masking of over 10% probability. Moreover, to enhance cloud-free tile selection, the previous Image Collection was masked between 0 and 30 m depth and cloud cover statistics per pixel were calculated according to Roca et al. (2022b), resulting in 3,499 scenes finally used (see [Table 2](#)). We statistically reduced all

Table 3. Literature review for in situ carbon stock data of *P. oceanica* soil in the Balearic Islands.

Scientific publication	Samples sites	Depth (m)	Locations	CAR* (g Corg m ⁻² yr ⁻¹) mean; range
 (Serrano et al. 2014)	3	2–32	Eivissa, Formentera	144; 89–185
 (Mazarrasa et al. 2017b)	11	15–37	Mallorca, Cabrera, Formentera	26; 9–52
 (Belshe et al. 2019)	5	5–25	Cabrera Archipelago	43; 20–103

(Continued)

Table 3. (Continued).

Scientific publication	Samples sites	Depth (m)	Locations	CAR* (g C _{org} m ⁻² yr ⁻¹) mean; range

*Mean C_{org} Accumulation Rate (CAR) in 1-meter soil.

pixels using the 20th percentile of each pixel stack to obtain a multi-temporal data synthesis in one single composite for all the Balearic Islands coastal waters within the depth of 30 m, using the bathymetry data previously developed at 10 m resolution. The statistical reduction minimizes the sunglint effects, waves, temporal turbidity, and other environmental noises which might have led to misclassification (Traganos, Lee, et al. 2022).

Furthermore, in order to avoid misclassification of mixed land-water pixels along the coast, we applied a water mask function following the Otsu method (Donchyts et al. 2016; Otsu 1979), consisting in maximizing interclass variance in B5 to obtain the best threshold in the Normalized Difference Water Index (NDWI), using B3 and B8 (McFeeters 1996). After obtaining the land masked composite, we obtained the water surface reflectance image (Bottom of Atmosphere, BOA) by applying the atmospheric correction following the Dark Pixel Subtraction (DPS) method (Chavez 1988; Traganos et al. 2018), subtracting the relative minimum pixel value for each band, and computing the Remote Sensing Reflectance (R_{rs}, sr⁻¹) of the composite.

Finally, we applied the Depth Invariant Index (DII) iterating bands B1/B2 and B2/B3 to minimize the light attenuation influence in the bottom and to help identify the different bottom types regardless the depth. Then we applied the water column correction empirical model created by Lyzenga (1981), creating a new feature minimizing the bias of the spectral values from surface R_{rs} and retrieving bottom reflectances

(Mederos-Barrera et al. 2022). The correction of the error is based on the correlation between depth and logged bands, reducing misclassification of deep sandy or rocky bottoms with similar spectral signatures to shallow seagrasses due to suspended materials and the absorption of light.

2.3.2. Training and validation data design

In order to guide the Machine Learning (ML) benthic habitat mapping in the cloud-native framework (Figure 3), we designed a training dataset for identifying three classes: seagrass, Optically Deep Waters (ODW), and sand/rock bottoms. Sandy and rocky bottoms were merged due to their similar spectral response observed in this case study (see Supplementary Material 4) and in the whole Mediterranean sea (Traganos, Lee, et al. 2022). The study area was labeled for training data through human-guided photointerpretation of the S2 multi-temporal mosaic and high-resolution imagery from MAXAR technologies and Airbus provided by GEE and an orthophotographs inside the 7-year range period provided by the IGN. This process was carried out within the GEE cloud environment to annotate points indicating the three mentioned classes.

We assume that our detected seagrass is *P. oceanica*, as the 95% of the seagrass extent in the Balearic Islands corresponds to this species and its spectral signature would be very similar to other neighboring seagrasses. Following this assumption at Tier 2 scale according to the Intergovernmental Panel on Climate Change

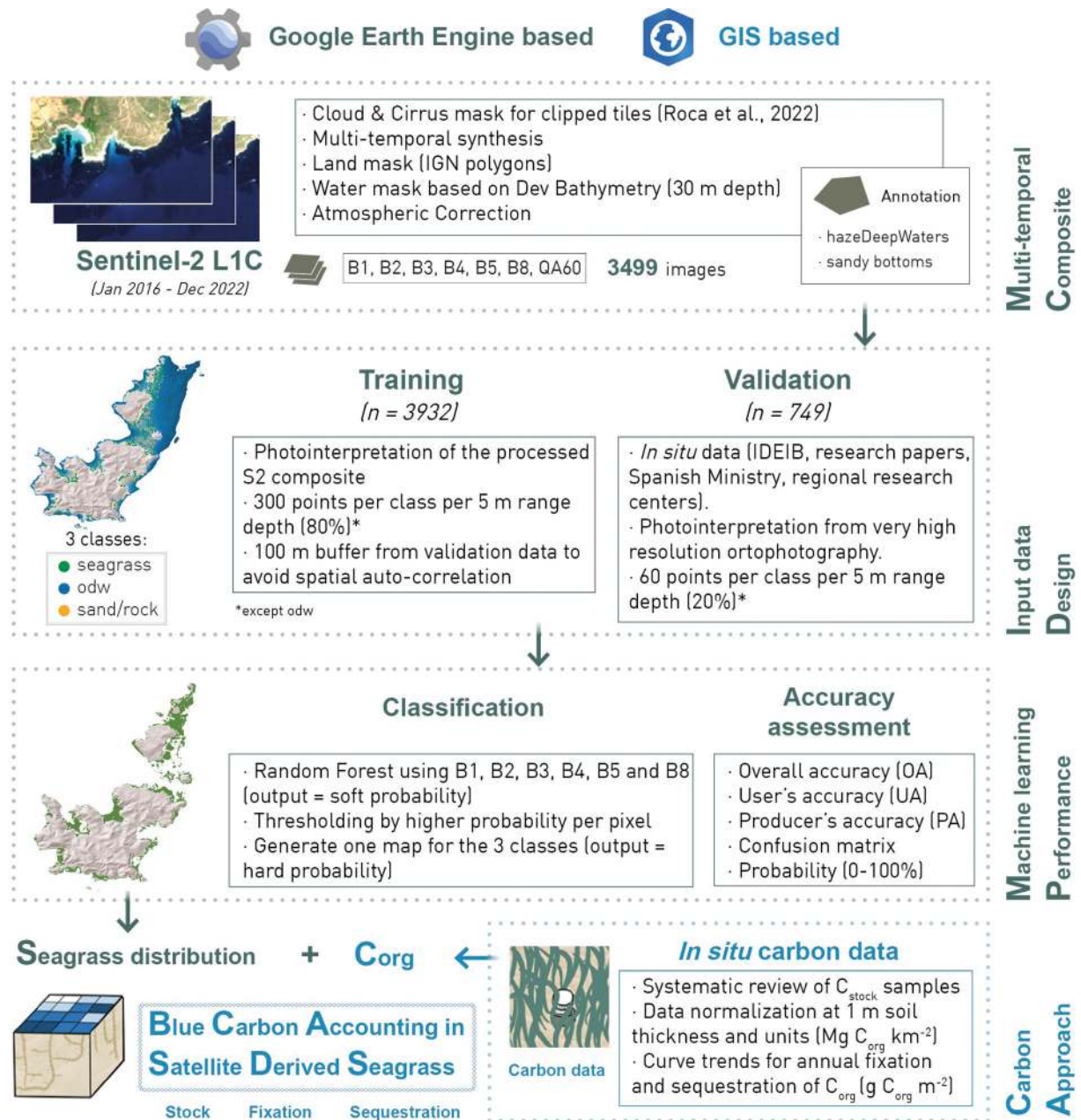


Figure 3. Google Earth Engine workflow for image processing, training and validation design and classification, and GIS workflow for carbon data processing. Optically Deep Waters (ODW).

(IPCC) methodological definition, the identification of the remaining 5% of sparse seagrass meadows of *Cymodocea nodosa* or *Zostera marina* would have generated a higher misclassification at 10 m spatial resolution provided by S2 imagery. Sandy and rocky bottoms were annotated following the photointerpretation of the bottoms with higher reflectance values in the Red-Green-Blue (RGB) composite, being spectrally different from seagrass bottoms (Figure 4). ODW labeling was performed using photointerpretation for both training and

validation, mostly to avoid misclassification of seagrasses in cliff shadows commonly observed in the north coast of Mallorca Island.

Validation points for seagrass and sand/rock were extracted randomly from the reference data (2.3.3) across the islands. In order to avoid spatial autocorrelation of training and validation samples, we buffered the validation data, excluding training points in a 100 m radius around the validation points.

Finally, to homogeneously extract training and validation points across the islands and depth, and to

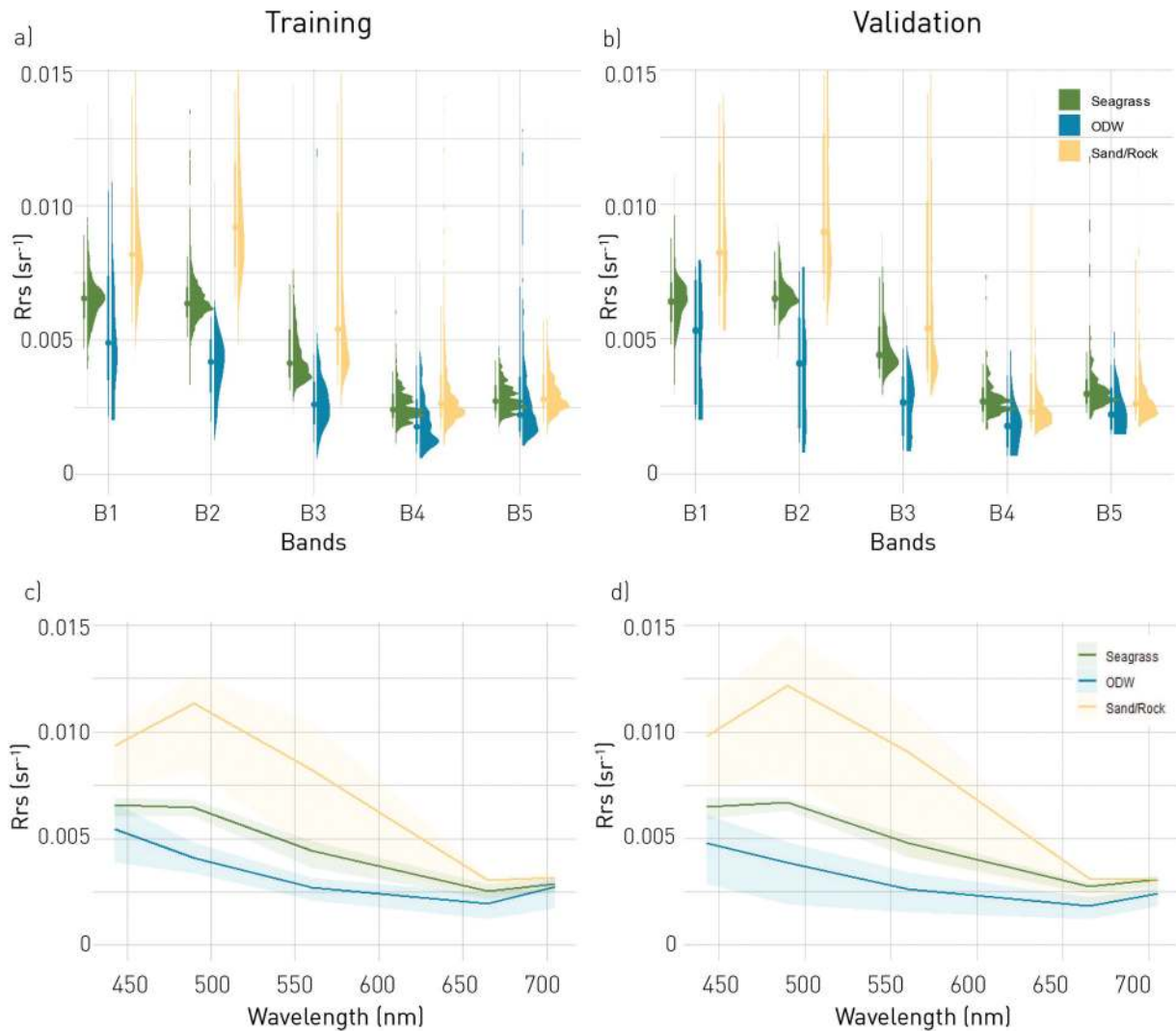


Figure 4. Halfeye plots of the remote sensing reflectance (R_{rs} , sr⁻¹) of the a) training and b) validation data from band 1 to band 5 of the Sentinel-2 multi-temporal composite. c) and d) show the spectral signatures for seagrass, optically deep waters (ODW) and sand/rock bottoms in the centered wavelength (nm) for the five bands, using the 25th and 75th percentile as the error range.

have a consistent 4:1 rate of training and validation data to be used in the Random Forest (RF) algorithm to avoid overfitting and to gauge the accuracy of the resulting model (Joseph 2022), we automatically and randomly sampled 300 (80%) and 60 (20%) features per depth per class for training and validation, respectively. This number could not be reached at all depths for the ODW class because of the lack of ODW at mid-depths, resulting in training and validation datasets consisting of a total of 3,932 and 749 features, respectively (Figure 5).

2.3.3. Supervised classification

To classify the multi-temporal S2 composite at 10 m spatial resolution, we used the developed training dataset to guide the RF algorithm, which is robust against overfitting

(Breiman 2001). We decided to use RF as an ensemble supervised machine learning classification algorithm because of its robustness against overtraining (Gislason, Benediktsson, and Sveinsson 2006), already tested for coastal habitat mapping at different scales (Goodwin et al. 2023; Hu et al. 2021; Traganos and Reinartz 2018; Traganos, Lee, et al. 2022). The RF algorithm incorporates ad-hoc self-learning decision trees, suitable to detect the non-linearity between classes and the collinearity border between *P. oceanica* and sedimentary bottoms, according to Traganos, Lee, et al. (2022).

In order to differentiate the threshold between classes, we used a probability mode within the GEE cloud-computing platform, generating an intermediate classification of 0-1 probability presence for each class. After running a qualitative analysis, we merged the

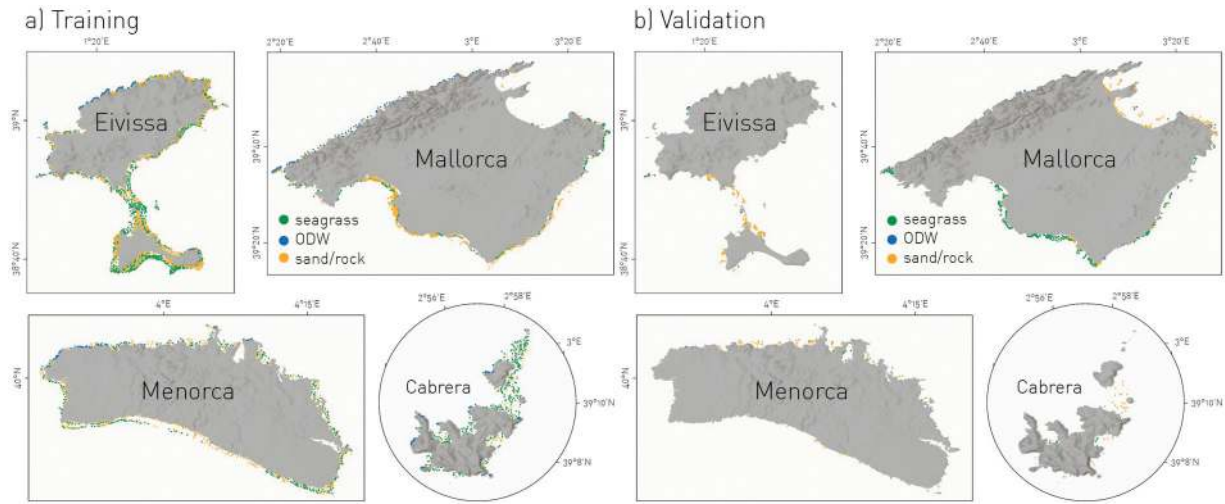


Figure 5. Map of points used to train the classifier (a), and validation points (b) extracted from reference data to perform the accuracy assessment of the generated classification.

probability layers and used a probability threshold of over 0.45 to enhance the seagrass classification (Traganos, Lee, et al. 2022).

2.3.4. Accuracy assessment and probability

To assess the accuracy of the regional benthic habitat mapping result, we used the validation data previously extracted to run standard quantitative metrics in remote sensing and classification image analysis, including the Overall Accuracy (OA), the Producer's Accuracy (PA) and the User's Accuracy (UA), as well as the confusion matrix to have insights in the misclassification between classes. Moreover, to check the spatial confidence of each class we used the soft classification expressed as pixel probability accuracy statistics with values ranging between 0 and 1.

2.4. Blue carbon estimation across space

In order to account for the blue carbon stored, fixed and sequestered by *P. oceanica* seagrass meadows in the study area, we used two different approaches. On the one hand, due to the impossibility to quantify the seagrass thickness through EO and knowing that *P. oceanica* mats can easily exceed 4 meters of thickness (Mateo et al. 1997), the C_{stock} under the meadows has been estimated assuming this average thickness in the Balearic Islands. Considering this, we performed an average mean of the *in situ* samples (Table 3) per km^2 to estimate C_{stock} at a regional scale (Mg

$C_{org} \text{ km}^{-2}$) by multiplying the mean value with the total satellite-derived seagrass extent.

On the other hand, to estimate annual fixed (a) and sequestered (b) carbon by the *P. oceanica* meadows, we used the already developed trend curves by Pergent-Martini et al. (2021) from 5 to 30 m of depth based on *in situ* measurements, applied in our study from 0 to 30 m of depth:

(a) Carbon fixation trend curve:

$$y = -202.5 * \ln(\text{depth}) + 724.6$$

(b) Carbon sequestration trend curve:

$$y = -40.5 * \ln(\text{depth}) + 145.5$$

The carbon values were retrieved by applying the (a) and (b) trend functions to the satellite-derived seagrass extent using the 10 m bathymetry developed in this study, obtaining a spatially explicit regional estimation of the fixed and sequestered blue carbon in the Balearic Islands. This process was developed using ArcGIS Pro 3.0 raster tools with the main scope of including the depth variable.

3. Results

3.1. Seagrass ecosystem extent detection

We estimated a seagrass extent of 505.6 km^2 spread along the depth of 0 to 30 m in the Balearic Islands with an OA of 92.5%. The PA for the model is 91.7%, while the UA is 94.8%, reflecting a slight

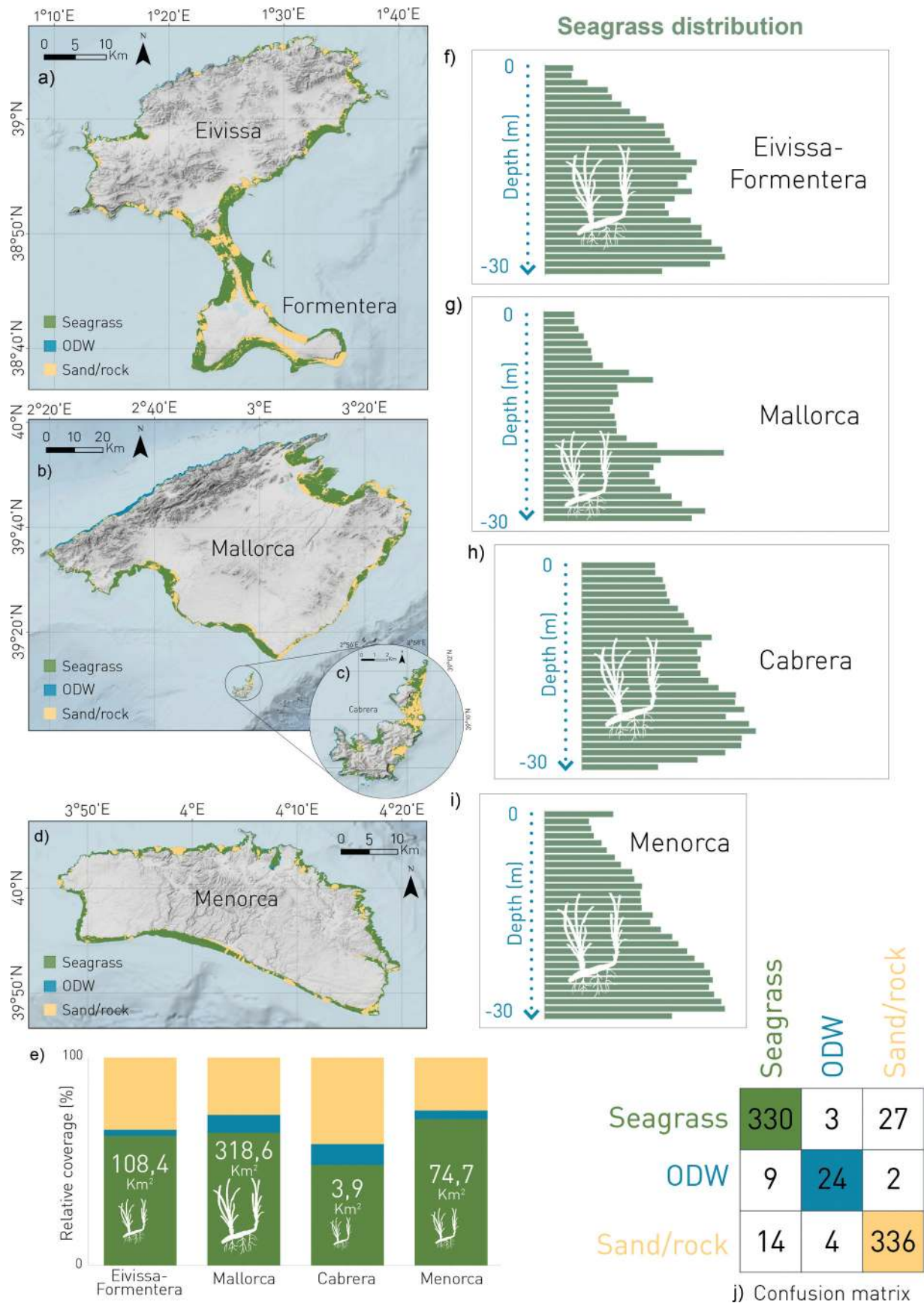


Figure 6. Satellite-derived benthic habitat mapping for the three classes: seagrass, ODW and sand/rock (a–d). Confusion matrix and relative coverage (%) of seagrass, ODW and sand/rock bottoms for each island is displayed in (j) and (e), respectively. Moreover, seagrass extent along depth for each island is shown in the individual green graphs (0–30 m of depth) (f–i).

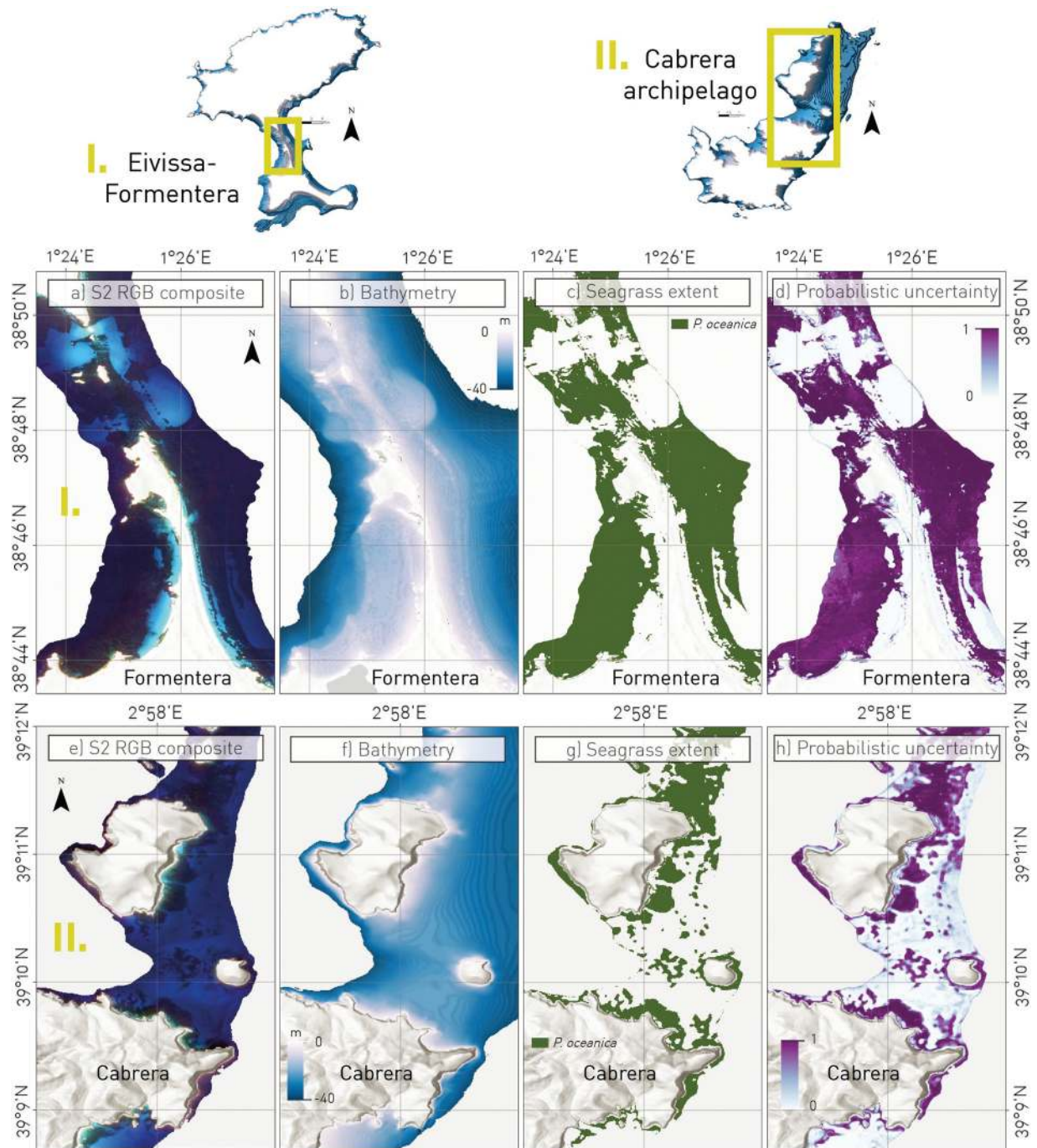


Figure 7. Sentinel-2 multi-temporal RGB composite (2016–2022) (a,e), developed bathymetry (b,f), satellite derived seagrass (c,g) and probability for seagrass presence (0–1) (d,h) using the cloud-computing based machine learning algorithm. Examples of (I.) Ses Salines (Eivissa-Formentera) and (II.) Cabrera archipelago.

underestimation trend in our mapping (Figure 6). Since UA is slightly higher than PA, the model may be conservative during the classification, probably due to spectral confusion and the imbalanced ODW class. The obtained bathymetry (or bathymetry dataset) was also validated with *in situ* data, and found to have a higher accuracy in less complex bottoms. The

bathymetric mean and standard deviation for the smooth slope bay of Alcúdia are both 0.6 m, while the bathymetric mean and standard deviation for the complex benthic beach/slope of Cala Millor beach with 5 m depth canyons are 2.93 m and 1.11 m, respectively (see Supplementary Material 1). Moreover, this bathymetric dataset was a key input

in the RF classification model to derive an accurate seagrass classification as demonstrated in the feature importance analysis in Supplementary Material 5. While EMODNET bathymetry was not relevant in the model, our bathymetric dataset featured as the 3rd most important variable.

Our seagrass coverage at Tier 2 level between 0 and 30 m depth in the Balearic Islands using a minimum 0.45 seagrass probability (Figure 7(d–h)), is 19.5% higher than the seagrass extent obtained at a Tier 1 scale by Traganos, Lee, et al. (2022) (407.1 km²), whereas it is 5% lower compared to the cartography from LIFE Posidonia project (532.5 km²) in the archipelago. The satellite-derived benthic habitat shown in Figure 6 corresponds to a seagrass extent of 108.4 km², 318.6 km², 3.9 km², and 74.4 km² for Eivissa-Formentera, Mallorca, Cabrera archipelago, and Menorca Island, respectively, adding up to a 64.3% of the total seabed to seagrass meadows. The island with more relative coverage of *P. oceanica* for each island according to the 30 m benthic seagrass extent is Menorca, followed by Mallorca and Eivissa-Formentera islands, successfully mapping an 8-km-large seagrass organism declared a World Heritage from the UNESCO (Figure 7(c)). However, the island with the highest total seagrass extent among all the islands is Mallorca, with 63% of the seabed corresponding to seagrass.

The confusion matrix shows the insights of the OA of the classification, mostly misclassifying sand as seagrass at deeper depths. While the spectral signatures for the three classes show differences (Figure 4), the spectral behavior across depth changes (Supplementary Material 6).

3.2. Blue carbon estimation in seagrass meadows

Based on the mean value of *in situ* carbon measurements, the estimated C_{stock} per unit in the Balearic Islands corresponds to $24,264 \pm 4,172 \text{ Mg } C_{org} \text{ km}^{-2}$. Based on the satellite-derived seagrass ecosystem extent, the total C_{stock} estimation for the seagrass meadows at the Balearic Islands' regional scale results in 12.27 ± 2.1 million $\text{Mg } C_{org}$ for all the islands between 0 and 30 m of depth. These uncertainties around the C_{stock} estimations rely on *in situ* measurements, but do not include the error of the seagrass extent measured.

Moreover, we estimated the overall annual C_{fix} rate for the Balearic Islands to be $1,116.3 \text{ Mg } C_{org} \text{ yr}^{-1}$, from which C is annually sequestered in the soil by $227 \text{ Mg } C_{org} \text{ yr}^{-1}$, corresponding to a 20.33% of the fixed C (see Table 4 for seagrass and carbon values per island). Therefore, *P. oceanica* has the ability to fix 0.05% of the annual CO₂ verified emissions of the Balearic Islands (2,396,184t CO₂ in 2022).

Thanks to the development of the 10 m pixel bathymetric product, as the main variable to contribute to the blue carbon accounting in *P. oceanica* soils, we obtained spatially explicit C_{fix} and C_{seq} maps up to 30 m depth for the Balearic Islands (Figure 8). According to the logarithmic curve trends for burial rates described by Pergent-Martini et al. (2021), the shallowest coastal areas present higher rates, as shown in the examples for Ses Salines (Eivissa-Formentera) and Cabrera archipelago (Supplementary Material 7).

All results can be accessed through the following interactive app (<https://ee-seagrass-mar.projects>).

Table 4. Seagrass coverage, carbon stock, annual carbon fixation and sequestration rates between 0 and 30 m of depth in the Balearic Islands (Mg = ton).

	Eivissa-Formentera	Mallorca	Cabrera	Menorca
Seagrass extent (km ²)	108.4	318.6	3.9	74.7
Relative seagrass coverage of total seabed mapped (%)	21.4	63	0.8	14.8
Seagrass inside MPAs* (km ²)	52.05	86.37	3.9**	15.67
Mean C_{stock} (Mg C_{org})	2,630,218	7,730,510	94,630	1,812,521
Mean C_{fix} (g $C_{org} \text{ yr}^{-1}$)	171.3	169.7	193	172.7
Total C_{fix} (g $C_{org} \text{ yr}^{-1}$)	237,680,294.2	701,105,124.7	9,645,447.8	167,875,226.7
Mean C_{seq} (g $C_{org} \text{ yr}^{-1}$)	34.8	34.5	39.2	35.1
Total C_{seq} (g $C_{org} \text{ yr}^{-1}$)	48,340,792.2	142,616,912.3	1,958,073	34,138,862.8

*40% of the MPAs of Spain are located in the Balearic Islands including 7 designations of marine protection: natural site, nature park, nature reserve, marine reserve, national park, Natura 2000 and biosphere reserve. These numbers are based on marine reserves only (service: https://ideib.caib.es/geoserveis/rest/services/public/GOIB_ReservesMarines/MapServer).

**Considering the extent of the Cabrera TMPN.

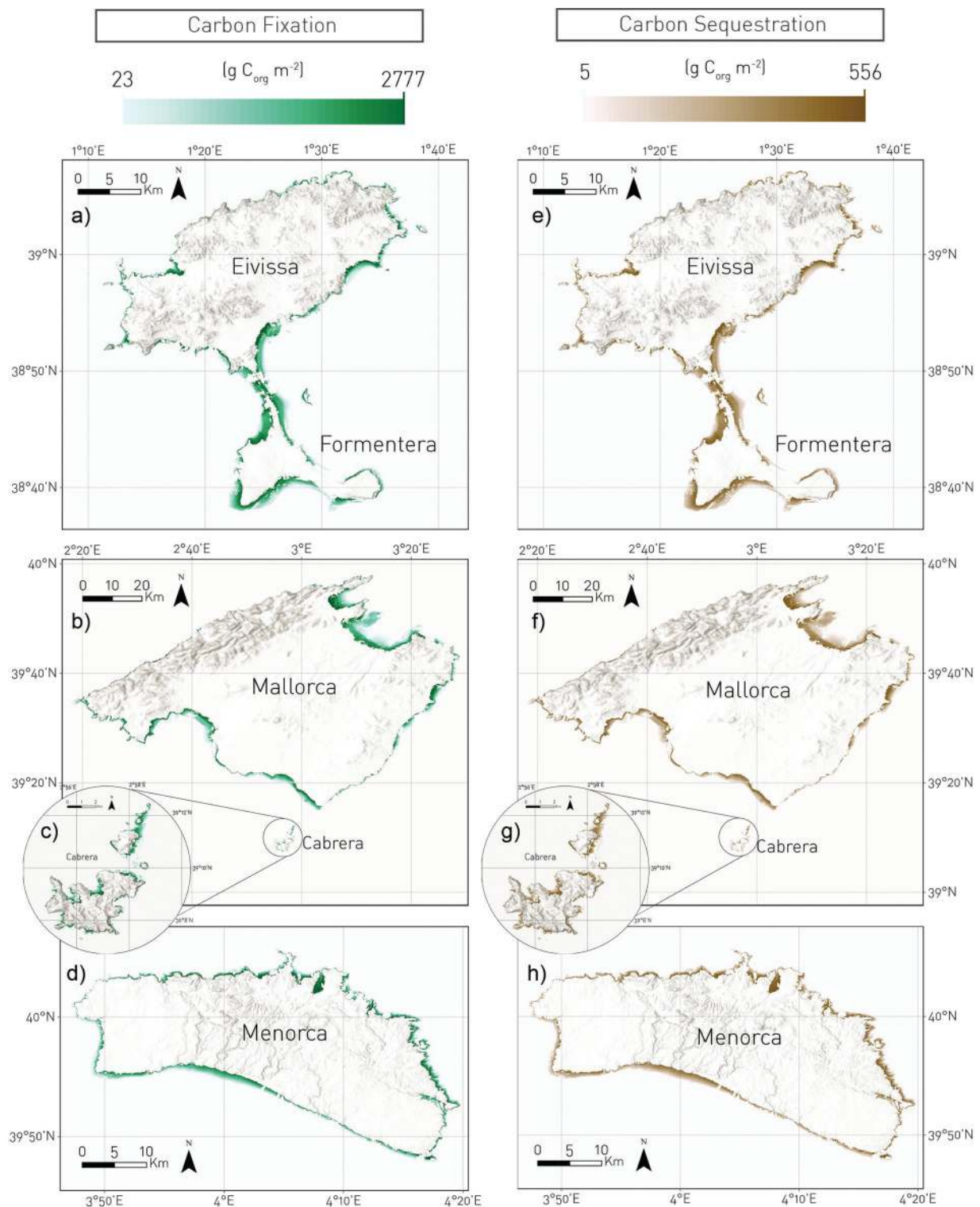


Figure 8. Annual carbon fixation (a–d) and sequestration rates (e–h) in *P. oceanica* soils for the Balearic Islands up to 30 m of depth.

earthengine.app/view/balearic-islands-seagrass), including the 7-year S2 multi-temporal RGB composite (2016–2022), developed bathymetry, seagrass extent, and both spatially explicit blue carbon fixation and sequestration annual rates.

4. Discussion

4.1. Cloud-native Earth Observation approach

The utilization of a unique scalable EO framework using S2 freely available imagery along with

in situ data enabled the spatially explicit quantification of *P. oceanica* seagrass and benthic habitat extent, as well as blue carbon fixation and sequestration rates across a bioregional scale. Featuring bathymetric and EO algorithms for multi-temporal satellite processing (2016–2022), machine learning and big data analytics within a GEE cloud-computing framework, we mapped 505.6 km² of *P. oceanica* seagrass meadows for the entire Balearic Islands, featuring a 5% underestimation according to the *LIFE Posidonia* regional cartography in the first 30 m of depth. While the most important effort remains in the acquisition of a unique multi-temporal enhanced satellite data composite, this processing within the GEE platform is fast, optimized and accessible without requiring additional resources. However, while the use of ML and cloud computing power features important benefits for large-scale seagrass ecosystem accounting, we highlight the feature importance of a preprocessed high-resolution bathymetric dataset as the most relevant input in the model to increase seagrass and blue carbon mapping accuracies, obtaining better accuracies as well as better mapping of shallow meadows close to the coastline. As demonstrated in this work (see Supplementary Material 5), global bathymetric datasets like GEBCO are less useful at the regional scale, resulting in an insignificant input in the model.

The key role of the GEE platform in this work remains in the cloud-native availability of satellite datasets and ML algorithms, which enabled the direct use of L1C S2 satellite data, avoiding the systematic download of almost 3,500 images and the local processing (with a computational time of around 3–4 minutes for the whole composite, estimated in more than 50 days in desktop), thus increasing time efficiency and avoiding the use of additional resources. However, while Sen2Cor and empirical DPS atmospheric corrections are available or can be applied nowadays in GEE, single image S2 studies highlight the potential of the ACOLITE processor for marine applications (Caballero and Stumpf 2020; Vanhellemont and Ruddick 2016, 2021), being its transfer and implementation within the GEE platform a high priority to seek a potential improvement. The combination of a high-confidence pre-processing workflow together with

a multi-temporal composite optimizes the reduction of natural optical interferences and artifacts, and above all eliminates the outliers by considering the reflectances of the whole time period and region rather than single images, which is widely accepted as the best approach for shallow mapping (Caballero and Stumpf 2023). While water quality derived variables can help in masking turbid areas, turbidity in the Balearic Islands is not a concern, as these waters are characterized by its high light penetration into the water column (Viaña-Borja et al. 2023). This is a key step integrated in GEE that led from single-image performance to regional and homogenous spectral behavior, avoiding differences in seagrass extent mapping due to inherent image properties, enabling a better reproducibility across the whole region. Moreover, the use of non-parametric threshold detection methods such as Otsu thresholding helped to overcome land-sea mixed pixels in a homogeneous histogram-based approach for all the Balearic Islands (Donchyts et al. 2016), optimizing the detection of the shallowest seagrass meadows.

As a Tier 2 case study, the design and exploitation of independent reference data sources was crucial to train and validate the seagrass mapping ML algorithm, whose open availability is a priority (McKenzie et al. 2020). While harmonizing both training and validation datasets using 90th and 80th percentiles worked in similar EO studies (Blume et al. 2023), their performance did not improve the habitat mapping classification, hence the random point sampling approach. To enable the stratified sampling of training and validation data across depth, accurate bathymetry remains key, ensuring the representability of the training and validation designed dataset. Additionally, the development and implementation of our EO approach in a well-studied regional area with extensive *in situ* datasets, like the Balearic Islands, enabled us to properly study the accuracy of our algorithm compared to field measurements. The 92.5% OA obtained for the seagrass ecosystem mapping is much higher than previous similar EO studies (Blume et al. 2023; Li et al. 2023; Traganos, Lee, et al. 2022), revealing the potential scalability of the algorithm across similar large-scale coastal areas and ecosystems.

Previous studies developed methodologies based on spectral vegetation indices for both intertidal and subtidal seagrasses at the local scale (Li et al. 2023; Zoffoli et al. 2020), whose performance is highly

dependent on the local environmental conditions. The use of ML within the GEE-native algorithmic pipeline reduces local-scale classifiers, enabling a better reproducibility in comparison to the majority of the current developed applications in the field of seagrass remote sensing (Li et al. 2023). This ensures reproducibility and further developments independent of desktop versions or licenses, as the upscaling of this processing within GEE free version under a nonprofit license has been shown to be viable when working at the regional scale. Moreover, further developments by combining the best performance of each ML classifier and the use of deep learning architectures could enable enhanced data-driven approaches for seagrass mapping (Perez et al. 2020). However, while EO can be used as a powerful tool to monitor seagrass extent, the spectral variability of optical waters has led to uncertainties at the global scale, mainly induced by misclassification, turbidity, ODW and change detection. Nevertheless, to assess the pixel-wise uncertainties at the high-resolution and regional scale of our results, the existent spatial-explicit uncertainty quantification methodologies would need to be optimized within GEE (Singh et al. 2024).

Regarding spectral misclassification, sandy and rocky bottoms featured a very similar spectral signature, and were thus unified in one class (Traganos, Lee, et al. 2022). Rocky bottoms might include algal bottoms, removing misclassification of seaweed in the seagrass class. However, other studies highlight the challenge of spectral separability between seaweed and seagrass in other regions (Bannari, Ali, and Abahussain 2022), but this problem is solved due to the high leaf density of *P. oceanica* seagrass and the sparse presence of seaweed in the Balearic Islands. Moreover, when analyzing the spectral signatures, other studies pointed out a reflection peak at the S2 Red-Edge band (B5, 705 nm) (Li et al. 2023), while we only noticed a slightly higher reflectance compared to the red band (B4, 665 nm), as can be observed in Figure 4. This correlation found between B4 and B5 was used by Li et al. (2023) to develop the Submerged Seagrass Identification Index (SSII), correlating the slope of the submerged seagrass spectral curve between both bands to density of seagrass distribution. However, the results showed in Supplementary Material 6 with a better correlation between the red

and Red-Edge bands at deepest depths (20–30 m) suggest a higher scattering signal, revealing higher uncertainties in subtidal seagrass detection from 20 meters' depth onwards. Finally, for the seagrass class, Chlorophyll-a and carotenoids have a strong spectral response in the blue window, corresponding to a better spectral differentiation in between classes for the blue band (B2, 490 nm). The inclusion of Photosynthetically Active Radiation (PAR) ocean color datasets would be potentially helpful to improve accuracies. However, the coarse spatial resolution of those datasets cannot be applied at the tested high-resolution scales.

On the other hand, the algorithm is not effective in ODW, those waters where the signal is not returned from the bottom due to increased light attenuation (Caballero and Stumpf 2023). In this case study, the unique area affected by turbidity in the shallow area was the semi-closed bay of Fornells (Menorca), misclassifying sand as seagrass, the only composite area (less than 0.2%) where the DII had a worse performance (Mederos-Barrera et al. 2022). Furthermore, ODW mostly appeared due to cliff shadows in the northwest coast of Mallorca, and the clipped multi-temporal composite at 0 or 30 m of depth generated a border effect which was mostly misclassified as seagrass. While we added it as a separate class in the classifier (Traganos, Lee, et al. 2022), other studies removed ODW by using optical indices like the NDWI (Blume et al. 2023), which were not effective in this area. Furthermore, the shift in Pearson's R correlation between the shallowest waters (0–20 m) and the deepest waters (20–30 m) (Supplementary Material 6) suggest a potential improvement of the classification by training two different models: one for shallow waters, with high positive correlations between B2 and B3; and another for deep waters, with high positive correlations between B4 and B5, which could lead to better accuracies. Alternatively, separate classes with deep spectral signatures could be designed in a unique ML model. Regarding seagrass change detection, as *P. oceanica* seagrass meadows have a very slow horizontal growth rate (1 cm yr^{-1}), corresponding to a potential 7 cm growth in our study period (2016–2022), the change detection at 10 m would include a considerable error, even across time windows of 5 years, not being able to potentially differentiate the error margin and the seagrass areal gain of

the slow growing rate organism, unless upon massive seagrass degradation areas, which in the study area occurred before the 1980s (Marbà, Díaz-Almela, and Duarte 2014). While other seagrass species like *Cymodocea nodosa* or *Caulerpa prolifera* seaweed change faster in time and space, which changes could be detected using this method in different time windows, due to the physiology of *P. oceanica*, the EO approach to detect changes in this species would require decadal temporal windows, not available yet in the S2 archive.

Although Landsat satellites can provide long-term monitoring of blue carbon ecosystems at 30 m spatial resolution (Ha et al. 2021), there is a lack of suitable historical satellite series at higher spatial and spectral resolution to make possible an accurate benthic habitat change detection of *P. oceanica* (Brewin et al. 2023), while being able to detect changes in other more dynamic species (Lyons, Phinn, and Roelfsema 2012). However, the S2 satellite constellation from ESA started in 2015, and can assist the generation of seagrass and blue carbon satellite products at 10 m, successfully supporting decision-making for climate mitigation initiatives (Traganos, Lee, et al. 2022), with ensured continuous monitoring by the launch of the next generation Sentinel-2C and Sentinel-2D. This fact should set the standard for the next decade, where advancements in hyperspectral and multispectral observations are opening new opportunities to generate better quality space-borne carbon products for mangroves, seagrasses and salt marshes (Brewin et al. 2023), enabling more accurate seagrass ecosystem change detection in the near future.

4.2. Blue carbon accounting in *P. oceanica*

The depth-induced gradients of light availability are crucial to assess the variability in sedimentary C_{stock} of seagrasses (Serrano et al. 2014), therefore high-quality bathymetric data is key for accurate blue carbon mapping. Recognizing the significance of precise bathymetric data in shallow coastal waters underscores the need for advanced remote sensing techniques in SDB (Caballero and Stumpf 2023).

The C_{stock} estimation associated to the 1-meter thickness deposits of *P. oceanica* meadows in the Balearic Islands (0–30 m depth) of this work corresponds to 24,264 Mg C_{org} , whereas the Tier 1 estimations by Traganos, Lee, et al. (2022) estimated

56,299,013 Mg C_{org} for Spain at the national level. Both estimations apply a single average value for C_{stock} from *in situ* measurements, showcasing the overestimations of Tier 1 studies and the need to move forward to the Tier 2 and Tier 3 scales. Despite C_{stock} measures are very variable, our estimates are more consistent with local scale studies performed by Serrano et al. (2014) and Monnier et al. (2022) estimating C_{stock} values of 10.8 kg $C_{org} m^{-2}$ and 25.8 kg $C_{org} m^{-2}$, respectively.

The Balearic Islands have a high availability of *in situ* carbon measurements compared to most other places globally, resulting in a more accurate regional blue carbon estimation when blending EO approaches. However, accurately estimating spatial probability and uncertainty becomes crucial when extrapolating C_{stocks} and fluxes from a limited number of *in situ* measurements (Campbell et al. 2022). The development of an uncertainty analysis to communicate the quality of EO predictions to end-users is still a discussed and under development topic with high computational demand (Singh et al. 2024). The C_{stock} estimation can be used in terms of avoided emissions to mitigate coastal degradation (Marbà, Díaz-Almela, and Duarte 2014; Roca et al. 2022). However, carbon fluxes measured as C_{fix} and C_{seq} in *P. oceanica* are the ones useful to quantify its role in climate change mitigation as new burial rate C removal from the system, estimated across depth in this study. Our Balearic-wide spatially explicit blue carbon maps obtained by applying Pergent-Martini et al. (2021) curve trends allow the identification of hotspot areas with high C_{seq} capacity to prioritize protection actions toward conservation. While the blue economy can help in conservation and management actions to mitigate climate change, the economic transfer value of these blue carbon estimates is still emerging in the coastal carbon markets and its implementation is still challenging. Additionally, the acquisition of carbon credits linked to emissions reductions may require pertinent verification by independent entities, even more complex in public areas as coastal waters, requiring cross-disciplinary involvement with economists and maritime lawyers. However, this tool could help improve the carbon trading, tracking avoided and potential emissions through monitoring, reporting and verification processes.

Moreover, we can identify additional variables that would enable enhanced carbon estimates. For example,

the consideration of seagrass matte thickness could generate more accurate regional C_{stock} estimations (Serrano et al. 2016). Additionally, since wave exposure significantly influences the remineralization of C_{org} (Roca et al. 2022), future studies should incorporate the hydrodynamic aspect in the spatially explicit blue carbon mapping combining numerical modeling. However, existing remote sensing datasets at 1 km spatial resolution may not provide added value due to their coarseness. Furthermore, some research has highlighted two more variables to consider: the impact of organic matter inputs through submarine emissaries during the high touristic season in the Balearic Islands and the consideration of sediment grain size to improve carbon estimations (Mazarrasa et al. 2017a). Therefore, it is crucial to avoid high complexity methodologies to make them usable by coastal managers, for which the selection of the most important variables is key. This is due to the complexity of the coastal environment, the high dependence on *in situ* measurements to estimate carbon values related to seagrasses, and the need of standardized information to develop blue carbon strategies across the countries.

Cloud-native scalable EO solutions can be a key tool in order to map seagrass extent and changes, processing massive S2 imagery and obtaining high-confidence seagrass and blue carbon maps. As carbon monitoring heavily depends on *in situ* measurements (Campbell et al. 2022), the acquisition of accurate bathymetric data is crucial to estimate spatially explicit blue carbon in seagrasses across depth. The gap between local carbon estimates and broader scales can be assessed by our replicable, scalable and time-effective EO tool, relying on quantified uncertainty per pixel. Such data can drive the quantification, evaluation, and variability of blue carbon in this undervalued yet highly significant emergent space, to support national carbon monitoring programs fulfilling the IPCC level 3 data requirements.

5. Conclusions

This study has demonstrated the importance of using a dense multi-temporal archive of Sentinel-2A/B satellite imagery within the cloud-native scalable EO approach, as well as the feature importance of a high-resolution bathymetric dataset to raise the accuracy of seagrass mapping and blue carbon estimates in coastal waters up

to 30 m of depth, especially enhancing the quantification of seagrass in shallow coastal waters. We successfully mapped up to 505.6 km² of *P. oceanica* seagrass extent with an OA of 92.5% in the Balearic Islands, resulting in 12.27 ± 2.1 million Mg C_{org} of C_{stock} , and 1,116.3 Mg C_{org} and 227 Mg C_{org} of annual carbon sequestration and fixation rates, respectively. However, our EO method is mainly limited by optically deep waters, cliff shadows, and turbidity. Moreover, its integration together with limited *in situ* measurements can optimize the seagrass cartography update time also in remote areas with less resources, as well as to improve carbon estimates at a Tier 2 and 3 level. This information is crucial to better manage and monitor *P. oceanica* seagrass ecosystems as the major climate change mitigator in the Mediterranean Sea, supporting the development of innovative blue carbon strategies.

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Disclosure statement

No potential conflict of interest was reported by the author(s).

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Author contributions

MR, CBL and DT designed the study. MR processed and analyzed the data, designed figures and wrote the original manuscript. APP designed the graphical abstract. AB helped in reference data analysis. All authors helped in proofreading reviews.

Data availability statement

The bathymetric dataset generated during this study is openly available in <https://doi.org/10.6084/m9.figshare.26898310.v1> as well as the original isobaths used to generate the product in <https://doi.org/10.6084/m9.figshare.27320685.v1>. Seagrass extent, carbon fixation and sequestration datasets can also be downloaded in <https://doi.org/10.6084/m9.figshare.27320766.v1>. GEE script for training and validation random sampling is available in <https://code.earthengine.google.com/a8db29543eedd9596ae647233d5629c7>. The authors report that, due to the proprietary commercially viable nature of code components, the multi-temporal composite and classification code cannot be made available as part of a legal spinout agreement.

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