Deep Learning-Based Underwater Mapping of Posidonia Oceanica from Satellite Data for Coastal Habitat Monitoring

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Abstract

The POSEIDON project aims to develop scalable and repeatable approaches for monitoring Posidonia Oceanica (PO) meadows, a key Mediterranean habitat that supports coastal ecosystem services and long-term blue-carbon storage, yet they are increasingly threatened by warming waters and cumulative human pressures. This work presents a satellite-based workflow for benthic habitat mapping that combines Sentinel-2 multispectral imagery, ancillary bathymetry, and deep-learning semantic segmentation. Sentinel-2 Level-2A data and bathymetry were integrated into multi-band inputs on a common 10 m grid, with analysis restricted to water pixels. A wall-to-wall reference map was generated by harmonising existing habitat products into six benthic classes for supervised model training and evaluation. U-Net and DeepLabv3 architectures with a ResNet backbone were tested for a representative September 2015 scene. The workflow was first assessed in the Culuccia peninsula, where it achieved an overall accuracy of 0.830 and a Kappa coefficient of 0.786. It was then successfully transferred to the Capo Testa - Punta Falcone Marine Protected Area (MPA), where the best-performing configuration reached an overall accuracy of 0.882 and a Kappa coefficient of 0.843. These results show that open-access satellite data combined with robust semantic segmentation models can provide a reliable and non-destructive framework for seagrass mapping in complex coastal environments.

1. Introduction

1.1 General overview

Posidonia Oceanica (PO) meadows (Figure 1) are a priority habitat in the Mediterranean because they are closely linked to coastal ecosystem functioning and long-term carbon storage in shallow marine environments (Hemminga and Duarte, 2000; Waycott et al., 2009, Angelini et al., 2025, Gerla and Balletti, 2025, Spreafico et al., 2015). Their presence is also commonly used as an indicator of coastal environmental quality and ecosystem status (Montefalcone, 2009). Due to their ecological significance, these meadows are classified as 'Habitats of Community Interest' under the EU Habitats Directive (92/43/EEC) (European, 1992) and are monitored as a vital biological quality element under the Water Framework Directive (2000/60/EC) (European, 2000), benefiting from strict protection under multiple international maritime conventions.

Figure 1. Close-up view of a Posidonia Oceanica meadow in shallow coastal water.

At the same time, PO meadows are sensitive to cumulative pressures such as coastal development, pollution, anchoring, and increasing sea temperatures, and regressions have been reported in multiple Mediterranean settings over recent decades (Boudouresque et al., 2006; Marbà and Duarte, 2010; Telesca et al., 2015). From a monitoring perspective, the key requirement is practical: when meadow extent or condition changes, spatially explicit information is needed to quantify how much change occurs, where it is concentrated, and whether patterns are consistent through time.

Producing comparable spatial products at the scale of bays, islands, and Marine Protected Areas (MPAs), however, remains challenging. Field-based mapping using diving campaigns, underwater video, photography, and local sampling can be reliable, but it is costly and difficult to repeat frequently over long coastlines, especially when consistent multi-year updates are required (Phinn et al., 2008; Wabnitz et al., 2008). Satellite archives provide systematic observations over many years, and Artificial intelligence (AI) algorithms offer practical tools to convert these data into maps that can be compared across time.

Once a reproducible workflow is established, mapping can be repeated across multiple epochs and transferred to similar coastal settings with substantially lower effort than fully manual approaches.

1.2 State-of-the-art

Remote sensing approaches for seagrass mapping have evolved from early multispectral applications using Landsat to higher-resolution commercial imagery and, more recently, Sentinel-2, which has become a standard option due to open access and frequent revisit time (Traganos and Reinartz, 2018a; Borfecchia et al., 2021; Campillo-Tamarit et al., 2025). A persistent challenge in shallow coastal waters is that the recorded signal mixes seabed reflectance with water-column effects, and this relationship varies with depth, turbidity, and illumination. To reduce this variability, many workflows apply water-column corrections or depth-invariant transforms before classification

(Sagawa et al., 2010; Mederos-Barrera et al., 2022). Comparative evidence also indicates that, under certain conditions, machine learning applied to consistently preprocessed imagery can achieve competitive performance, particularly when ancillary variables such as bathymetry are incorporated (Mederos-Barrera et al., 2022).
Methodologically, both pixel-based classification and object-based image analysis (OBIA) have been used widely. OBIA is often effective for patchy habitats because it integrates spectral and spatial information, supporting the combination of heterogeneous inputs. For example, site-scale studies have integrated underwater photogrammetric products and acoustic bathymetry with satellite imagery to improve delineation and achieve very high accuracies where dense in-situ information is available (Rende et al., 2020). Other multi-sensor approaches rely on multibeam, side-scan sonar, airborne imaging, or UAV data to refine boundaries and support local validation, although consistent application over large regions remains challenging (Pasqualini et al., 2001; Veettil et al., 2020). In the Mediterranean context, higher spatial resolution generally improves boundary delineation and can extend mapping toward deeper limits in clear-water settings, especially when optical imagery is supported by ancillary information (Dattola et al., 2018; Poursanidis et al., 2018).

Deep learning has become central in environmental mapping because it can learn multiscale spatial features directly from data and supports semantic segmentation, which produces pixel-wise outputs while exploiting neighbourhood context (Ronneberger et al., 2015; Chen et al., 2017a). In seagrass monitoring, deep learning has been applied to both underwater imagery and satellite data, demonstrating the ability to detect Posidonia patches under challenging conditions and to produce coherent maps from Sentinel-2 with limited training data (Burguera, 2020; Scarpetta et al., 2022). Architectural variants and broader-scale frameworks suggest that generalisable products are achievable when training design, validation, and preprocessing are carefully controlled (Maurya et al., 2023; Peng et al., 2025; Chowdhury et al., 2024; Giménez-Romero et al., 2024).

Long-term monitoring remains a major direction. Landsat provides multi-decadal continuity, while Sentinel-2 time series enable higher-frequency mapping and can be implemented in scalable cloud environments such as Google Earth Engine (Cingano et al., 2024; Davies et al., 2024; Traganos et al., 2018b). Lessons from large-area land cover mapping also highlight the importance of scalable workflows, sampling design, and ancillary layers to support robust generalisation (Maxwell et al., 2019).

Within this context, the POSEIDON project (multitemPOral SEagrass mapping and monitoring of posIDONia meadows and banquettes for blue carbon conservation) provides a structured framework for multi-temporal and multi-scale monitoring of PO meadows and related coastal features, integrating satellite archives with UAV and acoustic surveys to support repeatable products and decision-making (Ceccherelli et al., 2024). Building on these advances, current research is increasingly focused on workflows that remain stable across time and that can be replicated across coastal sites with comparable conditions, supporting routine updates rather than one-off maps.

2. Methodology

2.1 Study areas

This work is developed within the POSEIDON framework for multi-temporal monitoring of PO and coastal seabed habitats in Sardinia, Italy. Sardinia is the second-largest island in the Mediterranean and lies immediately south of mainland Italy, between the Tyrrhenian Sea and the western Mediterranean Basin. Its long coastline and wide shallow-water shelves host extensive PO meadows, but these environments are also exposed to strong seasonal tourism, recreational boating and anchoring, and the growing influence of warming waters. These combined pressures make Sardinia an appropriate setting for repeatable coastal mapping and monitoring, and they have motivated the establishment of several Marine Protected Areas aimed at regulating activities while safeguarding sensitive habitats.

Within POSEIDON, five priority coastal areas (Figure 2) were selected to represent different management contexts and levels of human pressure:

- the Capo Testa - Punta Falcone MPA (about 5,000 ha) in the far north of the island,
- the Capo Carbonara MPA (about 14,360 ha) in the south-east,
- the Capo Caccia Isola Piana MPA,
- the port area of Porto Torres,
- the Culuccia peninsula, located about 12 km from Capo Testa - Punta Falcone,

In this paper, results are presented for the two northern Sardinia sites, the Culuccia peninsula and the Capo Testa - Punta Falcone MPA. Culuccia was selected as the starting case study because local investigations and prior observations were available. In addition, local researchers familiar with the area could support the interpretation of seabed conditions. This specific knowledge helped to constrain the class definitions and improve the reliability of the reference layer, providing a robust basis for model training and evaluation before applying the same workflow to the MPA site.

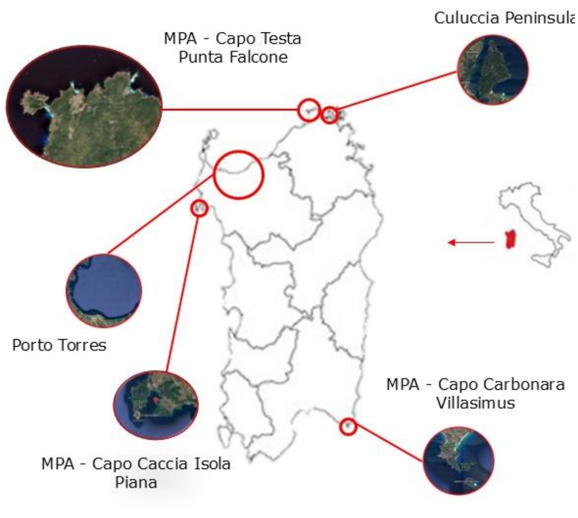
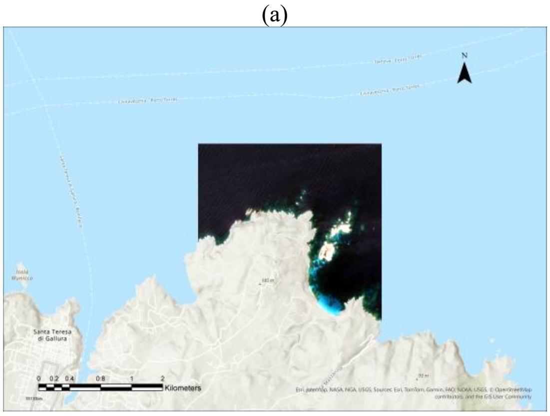


Figure 2. Location of case study areas.

2.2 Satellite data and sources

Sentinel-2 Multispectral Instrument (MSI) imagery from the Copernicus program was used as the primary satellite dataset. Level-2A products were selected because they provide bottom-of-atmosphere reflectance following atmospheric correction, thereby improving inter-scene comparability relative to Level-1C top-of-atmosphere products. This is particularly important in shallow coastal waters, where benthic classes may be distinguished only by subtle spectral differences. Sentinel-2 provides multispectral bands at 10 m, 20 m, and 60 m spatial resolution; all bands were used in this study except the cirrus band (B10). Figure 3 presents the composite band rasters used for training-sample extraction.

(a)



(b)

Figure 3. RGB representation of composite processed bands. Culuccia peninsula (a) and Capo Testa - Punta Falcone MPA (b).

September acquisitions were preferred because calmer sea conditions and higher post-summer water clarity generally provide more favourable conditions for optical mapping. In addition, PO canopies remain close to their seasonal maximum after summer growth, whereas stronger autumn senescence and leaf shedding have not yet substantially reduced meadow density or detectability. Candidate scenes were therefore screened to minimise cloud cover (typically below 10%) and to exclude acquisitions affected by strong turbidity or unfavourable illumination. All analyses and classification results presented in this paper are based on the September 2015 Sentinel-2 dataset for the two study areas.

3. Methodology

3.1 Preprocessing procedure

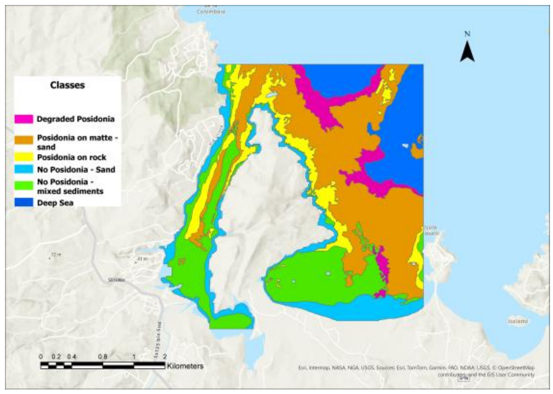
Underwater habitat mapping from multispectral satellite imagery is challenging because the sensor records a combined response from the seabed and the overlying water mass, and this response can vary between acquisitions. Preprocessing was therefore designed to standardise inputs across all epochs and improve the stability of multi-temporal classification.

The analysis domain was first restricted to marine pixels using the Sentinel-2 Scene Classification Layer (SCL) by retaining only water and masking land and cloud-affected areas. All Sentinel-2 bands were then harmonised to a common 10 m grid by resampling the 20 m and 60 m layers to 10 m using bilinear interpolation. A bathymetry layer from the Marine Geohazards along the Italian Coasts (MaGIC) dataset (Civil Protection Department, 2020) was added as ancillary information to support discrimination between classes that may show similar spectral signatures but occur in different depth zones. Finally, each epoch was clipped to the study-area boundaries and exported as a fixed-order multiband composite to ensure consistent inputs during training and inference.

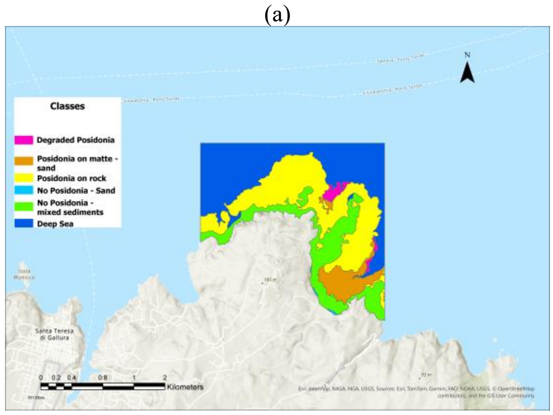
Water-column correction was not applied. Instead, depth information was provided explicitly through the bathymetry layer, allowing the segmentation models to learn depth-related gradients directly from the data within the adopted modelling framework.

3.2 Reference map construction

A wall-to-wall reference map was constructed to support supervised learning and ensure consistent class definitions across each study area. Rather than representing independent field-based ground truth, this thematic baseline was obtained by harmonising existing habitat products and thematic sources into a common six-class benthic scheme. Posidonia-related classes were derived from the EMODnet Seabed Habitats EUSeaMap 2023 dataset (EMODnet, 2023), while substrate classes were obtained from the CNR GeoNetwork portal (CNR, 2025) to complete the non-Posidonia portion of the map. A 20 m depth contour was used to delineate the likely outer extent of Posidonia presence; areas beyond this contour, where detailed habitat information was not consistently available, were assigned to the deep-water class.



(a)



(b)

Figure 4. The reference model of Culuccia peninsula (a) and Capo Testa - Punta Falcone MPA (b)

This consolidated reference database served as the source of training and validation labels for the present methodological assessment, forming a seamless categorical layer suitable for systematic sample extraction (Figure 4).

The reference layer was organised into six benthic classes:

- Class 1: Degraded Posidonia (dead matte);
- Class 2: Posidonia on matte - sand;
- Class 3: Posidonia on rock;
- Class 4: No Posidonia - sand;
- Class 5: No Posidonia - mixed sediments;
- Class 6: Deep water (deep sea).

Full spatial coverage was considered as a requirement because unmapped gaps can introduce ambiguous pixels during sample extraction and can bias both training and evaluation. For consistency and ease of interpretation, all reference datasets and classification maps were displayed using the same class symbology and colour coding, enabling direct visual comparison between predicted outputs and the established baseline.

3.3 Benthic habitat mapping via semantic segmentation

3.3.1 Training data preparation

The workflow began with the extraction of training and validation samples from pre-processed multiband Sentinel-2 and bathymetry composites. For each sampled pixel, class labels were assigned by spatially aligning the imagery with the reference layer under a consistent classification scheme. These labelled samples were subsequently partitioned into spatially independent, non-overlapping training and validation subsets. The validation subset was defined on geographically distinct areas, separated from the training subset to avoid spatial overlap and reduce local autocorrelation effects. This partitioning supports both the iterative model development phase and an independent assessment of the final classification performance.

3.3.2 Semantic segmentation framework

To map complex PO meadows, a semantic segmentation approach was adopted. Unlike conventional pixel-based classifiers that treat pixels as independent units, semantic segmentation assigns labels by simultaneously evaluating spectral signatures and surrounding spatial context. This is essential for benthic mapping in heterogeneous coastal scenes, where habitat boundaries are often gradual. By leveraging Convolutional Neural Networks (CNNs), the model captures local textures and broader spatial patterns, increasing robustness against environmental noise and small-scale spectral variability.

3.3.3 Candidate Deep Learning architectures

Two state-of-the-art architectures were evaluated to determine their effectiveness in underwater scene parsing: U-Net and DeepLabv3. U-Net is characterized by its symmetric encoder-decoder structure and skip connections, which are designed to preserve fine-scale spatial details (Ronneberger et al., 2015). In contrast, DeepLabv3 employs atrous (dilated) convolutions and an Atrous Spatial Pyramid Pooling (ASPP) module to capture multi-scale contextual information, making it robust against variations in seagrass patch size and density (Chen et al., 2017b). Both models were implemented using ResNet backbones and trained on the full spectral stack (excluding B10) to allow the networks to learn optimal feature combinations directly from the multi-band data.

3.3.4 Implementation and tuning

The proposed models were implemented using the *arcgis.learn* module within a Python environment, leveraging the PyTorch deep learning framework, which supported automated tiling strategies and batch processing. The training workflow consisted of iterative experiments to identify suitable hyperparameter settings, with the aim of improving model generalization and reducing the effects of class imbalance. This process contributed to pixel-level consistency across the study areas, resulting in spatially coherent habitat maps suitable for multi-temporal monitoring and quantitative change analysis.

3.4 Classification accuracy assessment

Thematic accuracy was evaluated using a confusion matrix generated by comparing predicted benthic classes against reference labels extracted from the spatially independent validation subset (Stehman, 1997).
To provide a comprehensive view of model reliability, three primary metrics were also calculated:

User’s Accuracy (UA): This represents the probability that a pixel classified on the map actually represents that category on the ground. It measures the error of commission (false positives).

$$UA_i = \frac{n_{ii}}{n_{i+}} \tag{1}$$

Producer’s Accuracy (PA): This represents how well the model identified real-world features. It measures the error of omission (false negatives).

$$PA_i = \frac{n_{ii}}{n_{+i}} \tag{2}$$

Overall accuracy (OA): This provides a global measure of classification success by calculating the proportion of all correctly classified pixels across the total sample.

$$OA = \frac{\sum_{i=1}^{k} n_{ii}}{N} \tag{3}$$

where k is the number of classes.

Cohen’s Kappa coefficient (κ) was also reported to account for agreement occurring by chance. While providing a standardized measure of success, kappa is interpreted with caution due to its sensitivity to class prevalence (Pontius Jr and Millones, 2011). It is computed as:

$$\kappa = \frac{N\sum_{i=1}^{k} n_{ii} - \sum_{i=1}^{k}(n_{i+}\,.\,n_{i+})}{N^2 - \sum_{i=1}^{k}(n_{i+}\,.\,n_{+i})} \tag{4}$$

4. Results and discussion

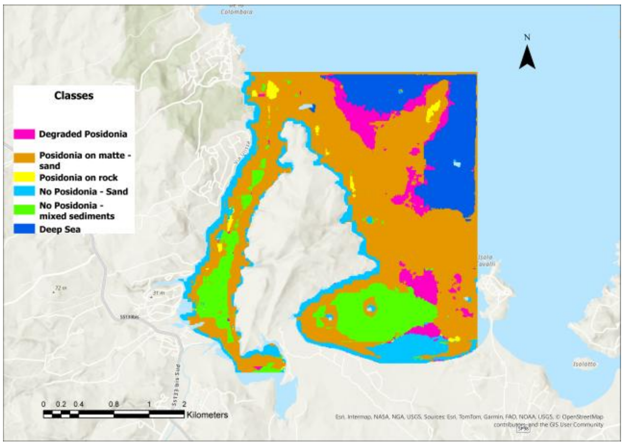
In this section, the results of the benthic habitat classification are presented for a single representative epoch over both study areas. The section first reports the classification outputs and summarises the model-selection process through the selected hyperparameter settings. Classification reliability is then quantified based on the independent validation samples.

4.1 Classification outputs and selected configurations

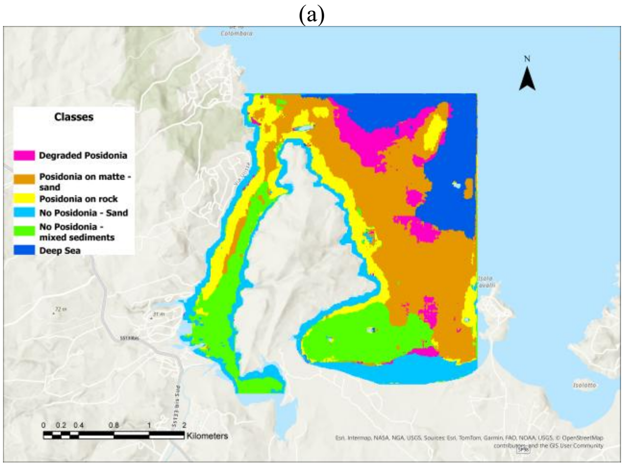
Initial comparative experiments indicated that DeepLabv3 consistently outperformed U-Net in capturing the multi-scale distribution of seagrass meadows and delineating complex benthic boundaries. Consequently, the following results and configurations are reported exclusively for the DeepLabv3 implementation. After the labelled samples had been prepared, model training required the selection and tuning of a set of hyperparameters influencing both learning behaviour and the spatial quality of the segmentation output. The main hyperparameters considered included the segmentation architecture and backbone, the tiling strategy used to generate training chips (tile size, stride, and padding), training settings such as batch size and learning-rate strategy, the validation split, and class-imbalance treatments including oversampling and class weighting. These choices affect convergence stability, minority-class performance, and the coherence of class boundaries in the final maps.

Parameter	Culuccia	Capo Testa
Architecture	DeepLabv3	DeepLabv3
Backbone	ResNet-34	ResNet-34
Tile size	30	30
Stride	15	15
Padding	7	4
Validation split	0.3	0.2
Oversampled classes	yes	yes
Class weight	yes	yes
Class balance	yes	yes
Learning rate scheduling	yes	yes

Table 1. Final hyperparameter settings for the Culuccia and Capo Testa - Punta Falcone study areas



(a)



(b)

Figure 5. Classification maps for the Culuccia study area. Initial classification (a) and final classification (b).

Hyperparameter tuning was carried out through iterative experiments. A baseline configuration was first adopted to produce an initial classification for the Culuccia testbed. The model settings were then progressively refined by adjusting parameters in a controlled manner in order to identify the most influential choices and improve overall model reliability. The final configurations selected for the September 2015 scene are reported in Table 1 for both study areas.

Figures 5 and 6 present the classification results for the two study areas. Figure 5 compares the initial and final classifications for Culuccia, highlighting a clear improvement in the representation of the Posidonia on rock class (yellow). In the initial classification (Figure 5a), this class is only sparsely predicted, possibly because of its more limited representation in the training data and the resulting difficulty in learning its spectral and spatial characteristics. In the final classification (Figure 5b), its distribution appears more coherent and extensive, suggesting improved model sensitivity after refinement of the model settings. Figure 6 shows the final classification for Capo Testa - Punta Falcone. Together, these outputs provide the basis for the quantitative validation presented in Section 4.2.

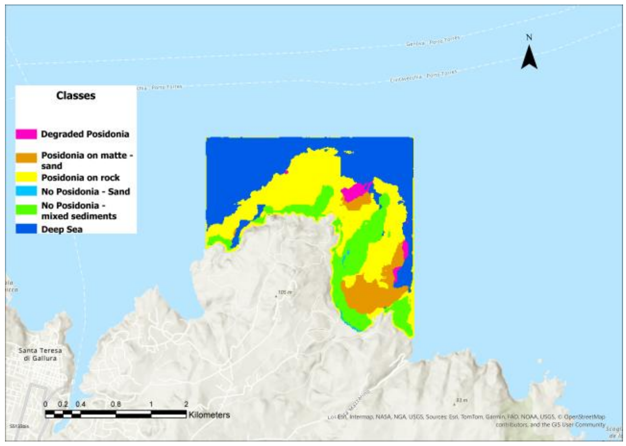


Figure 6. Final habitat classification map for the Capo Testa - Punta Falcone study area.

4.2 Evaluating the accuracy of classification

The reliability of the classified maps was evaluated through an accuracy assessment based on confusion matrices derived from a geographically separate validation subset. For each study area, predicted class labels were compared against the reference labels from the ground truth layer, and agreement was summarised using overall accuracy (OA) and Cohen's Kappa, together with class-level producers' and users' accuracies to characterise omission and commission tendencies.

For the Culuccia testbed, the final configuration achieved an overall accuracy of 0.831 with a Kappa coefficient of 0.786, indicating substantial agreement between the predicted map and the reference labels. For Capo Testa - Punta Falcone, the best-performing configuration achieved an overall accuracy of approximately 0.883, with Kappa about 0.843, confirming a high level of agreement in the MPA setting. Confusion matrices and the corresponding class-level accuracies for the two sites are reported in Tables 2 and 3.

C	C1	C2	C3	C4	C5	C6	UA
C1	23	8	1	1	1	0	0.68
C2	9	140	7	0	8	3	0.84
C3	0	9	42	1	13	1	0.64
C4	0	0	1	65	7	0	0.89
C5	0	3	0	1	76	0	0.95
C6	6	3	0	1	0	65	0.87
PA	0.61	0.86	0.82	0.94	0.72	0.94	0.83
κ							0.79

Table 2. Confusion matrix for the Culuccia study area.

C	C1	C2	C3	C4	C5	C6	UA
C1	10	0	0	0	0	1	0.91
C2	0	36	6	0	0	0	0.86
C3	0	3	91	1	8	6	0.83
C4	0	0	0	3	1	0	0.75
C5	0	0	2	0	65	0	0.97
C6	1	1	5	0	2	73	0.89
PA	0.91	0.90	0.88	0.75	0.86	0.91	0.88
κ							0.84

Table 3. Confusion matrix for the Capo Testa - Punta Falcone study area.

Beyond the overall indicators, the confusion matrices allow the most frequent misclassifications to be identified and interpreted in relation to the coastal setting. Misclassifications are expected to concentrate near class boundaries and in transition zones where mixed pixels and gradual changes in substrate or vegetation cover reduce separability. This information is important for interpreting the maps in an operational context because it indicates which classes and which spatial contexts should be prioritised for additional field verification.

5. Discussions

The achieved accuracy levels and the spatial coherence of the classification outputs indicate that the integration of Sentinel-2 data with ancillary bathymetry can support reliable discrimination between benthic classes, even in optically complex waters. In particular, the inclusion of depth information appears to play a key role in improving class separability, compensating for the absence of explicit water-column correction.

The comparison between architectures highlights the advantage of DeepLabv3 over U-Net in this context. The ability of DeepLabv3 to capture multi-scale spatial features through atrous convolutions and spatial pyramid pooling contributed to improved delineation of heterogeneous habitats and more consistent representation of patchy Posidonia distributions. This is particularly relevant in coastal settings where transitions between substrate types are gradual and mixed pixels are common.

The analysis of confusion matrices indicates that most classification errors occur at class boundaries and in transitional zones, where spectral similarity between classes and sub-pixel heterogeneity reduce separability. Misclassifications involving Posidonia on rock and mixed sediment classes suggest that these categories remain challenging, especially where training samples are limited or unevenly distributed. This highlights the importance of balanced sampling strategies and the potential benefit of integrating higher-resolution or complementary data sources for refining class definitions.

A key contribution of this work is the demonstrated transferability of the workflow. The successful application of the same preprocessing and modelling framework to two different study areas supports its robustness and potential for operational use. However, transferability is still dependent on the similarity of environmental conditions, including water clarity, depth range, and seabed composition. Extending the approach to more diverse coastal settings will require further evaluation.

Some limitations should be considered. The reference dataset was derived from harmonised existing habitat products rather than independent field surveys, which may introduce uncertainties in both training and validation. Consequently, the reported accuracy values should be interpreted as agreement with the reference layer rather than absolute thematic accuracy. Additionally, the use of a single temporal snapshot limits the assessment of temporal variability and seasonal effects.

6. Conclusions

This study presents a deep learning-based workflow for benthic habitat mapping using Sentinel-2 multispectral imagery integrated with bathymetric data. The results demonstrate that semantic segmentation approaches, particularly DeepLabv3 with a ResNet backbone, are effective in capturing the spatial distribution and structural complexity of PO meadows in shallow coastal environments. High levels of agreement with the reference dataset were achieved in both study areas, confirming the reliability of the proposed methodology.

The workflow was designed to ensure consistency in preprocessing, sample extraction, and model training, enabling reproducible mapping across different sites. Its successful transfer from the Culuccia test area to the Capo Testa - Punta Falcone MPA demonstrates its potential for scalability and application in comparable Mediterranean coastal settings with limited additional calibration.

Overall, the proposed approach provides a practical and scalable framework for generating consistent benthic habitat maps from open satellite data. This supports the development of operational monitoring strategies for Posidonia oceanica, contributing to coastal management, conservation planning, and long-term environmental assessment.

Future developments will focus on incorporating independent field-based validation datasets, refining class definitions, and extending the workflow to multi-temporal analyses to support change detection.

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