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An expeditious low-cost method for the acoustic characterization of seabeds in a Mediterranean coastal protected area

N. Sánchez-Carnero [a,b,*], D. Rodríguez-Pérez [c], S. Llorens [d,e], V. Orenes-Salazar [f], A. Ortolano [f], J. A. García-Charton [f]

[a] Grupo de Oceanografía Física, Facultade de Ciencias do Mar, Universidade de Vigo, 36310 Vigo, Spain
[b] Centro para el Estudio de los Sistemas Marinos (CESIMAR-CONICET), Argentina
[c] Departamento de Física Matemática y de Fluidos, Facultad de Ciencias, Universidad Nacional de Educación a Distancia (UNED), c/ Esparta s/n, 28232, Las Rozas, Madrid, Spain
[d] Institut d'Investigació per a la Gestió Integrada de Zones Costaneres, Universitat Politècnica de València, C/Paranimf, 1, 46730, Valencia, Spain
[e] Instituto Español de Oceanografía (IEO), C.O. Murcia, C/el Varadero 1, Lo Pagan, 30740, Murcia, Spain
[f] Departamento de Ecología e Hidrología, Universidad de Murcia, Campus Espinardo, 30100, Murcia, Spain

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ABSTRACT

Posidonia oceanica meadows are ecosystem engineers which, despite their ecological relevance, are experiencing habitat fragmentation and area decrease. Cartography and information on the ecological status of these habitats is key to an effective maritime spatial planning and management for habitat conservation. In this work we apply an acoustic methodology to map benthic habitats (substrate and vegetation) in an archipelago of the Natura 2000 Network close to the coast of Murcia (SE Spain) where dense and sparse areas of *P. oceanica*, and patches of *Cymodocea nodosa* appear over a sandy and had bottom. The methodology uses dual frequency information (200 kHz and 38 kHz) acquired with a single-beam echosounder to develop a bathymetry, and performs sea bottom and vegetation supervised classifications, using video and scuba diver observations as groundtruthing data. Sea bottom was classified from acoustic features of the first and second 200 kHz echoes into 5 substrate classes using a random forest classifier: sand, fine sand, coarse sand, hard bottoms and hard bottoms with sandy patches. The vegetation was classified from features extracted from the "above-bottom" part of the echo (height and back-scattering intensity) in both frequencies, resulting also in a 5 class classification: *C. nodosa* meadows, dense *P. oceanica* meadows, dispersed *P. oceanica* meadows, dense *P. oceanica* with sand patches, and no-vegetation; according to the random-forest Gini index, 38 kHz features were the most informational variables for this classification. The validation accuracies of both classifications were 85% (substrates) and 70% (vegetation), close to accuracies reported in the literature when using a similar number of classes. The results of this article (including bathymetric, and substrate and vegetation thematic maps), together with the acoustic methodology described and used, are contributions that can improve the continuous monitoring of Mediterranean seagrasses.

1. Introduction

The Mediterranean Sea is well-known as a biodiversity and complexity hotspot, unique because of the number of habitats, level of endemism, and overall marine biodiversity it hosts. However, it is nowadays considered among the most impacted among the regional seas, facing increasing anthropogenic pressures as pollution and eutrophication (Coll et al., 2010; Sala et al., 2012), direct human pressures in coastal areas (Carreño and Lloret, 2021), microfibers release (Pedrotti et al., 2021), introduction of non-indigenous species (Sardain et al., 2019; Rotter et al., 2020), overexploited natural resources (FAO, 2020), or climate change trends (Sala et al., 2012; Tuel and Eltahir, 2020).

Alerted by this growing deterioration, several national and international environmental policies and initiatives have been implemented in the last three decades, designed to monitor and recover Mediterranean marine ecosystems: EU Marine Strategy Framework Directive (MSFD; 2008/56/EC), Mediterranean – Monitoring Forecasting Centre (MED MFC), EU Biodiversity Strategy for 2030 (European Commission, 2021), etc.

One of the most worrying dangers in the Mediterranean Sea is the

* Corresponding author. Grupo de Oceanografía Física, Universidad de Vigo, Spain.
E-mail address: nsanchez@uvigo.gal (N. Sánchez-Carnero).

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loss of habitats (Marbà et al., 2014), some of them of very high ecological value as the *Posidonia oceanica* meadows. These are complex ecosystem engineers (Personnic et al., 2014) that support fisheries, carbon sequestration and coastal protection (Carmen et al., 2019). Moreover, *P. oceanica* presents a high net primary and O_2 production together with large amounts of biomass (Boudouresque et al., 2006). However, despite their ecological relevance, they are experiencing habitat fragmentation (Montefalcone et al., 2010) and area decrease (Carmen et al., 2019).

Explicit cartography and information on the ecological status of marine habitats is key to an effective maritime spatial planning and management for habitat conservation, and one of the focus of previous initiatives. However, the state of knowledge about species and habitat distribution in the Mediterranean Sea is still limited (Romagnoli et al., 2021).

Benthic habitat mapping consists in the spatial representation of the distribution and extent of physically distinct areas of the seafloor that are associated with groups of species or communities that consistently occur together (Harris and Baker, 2020). This information can be generated using different techniques: scuba diving provides valuable detailed data but involves high economic and time investment and has limited geographical coverage. Towed video cameras and remotely operated vehicles have proven useful in obtaining information on the composition of biological communities, but data quality is limited by the water turbidity and their interpretation is time-consuming and likely to be subjective (Crawford et al., 2001). Remote sensing technologies based on satellite and aerial imagery have been used successfully to map benthic habitats in Mediterranean Sea (Borfecchia et al., 2013; Mannino et al., 2021), but despite recent advances (Kutser et al., 2020), they are limited by depth (less than 10 m for detection, around 5 m for discrimination), light absorption, clouds or sea surface roughness (sunglint) (Kenny et al., 2003).

Acoustic methods represent, since the mid 1980s, a methodological alternative less expensive in terms of time and costs per unit area (Hamilton et al., 1999; Blondel, 2002; Kenny et al., 2003) that allows coverage of large areas at high resolution in a cost effective way, providing information on seabed roughness, substrate type and granulometry as well as fine scale details on benthic habitats (Goff *et al.*, 2003; Anderson et al., 2008; Brown et al., 2011). Single-beam echosounders (SBES) have been for decades the standard tool for seabed mapping, (Rodríguez-Pérez et al., 2014; Fajaryanti and Kang, 2019), and remain the most used because of their affordable cost.

Regarding underwater vegetation, and particularly seagrass, a variety of scientific echosounders has been used for mapping these habitats (Gumusay et al., 2019), including SBES (Stevens et al., 2008). However, the standard acoustic system to map seagrass has been the Side Scan Sonar (SSS), a single-beam transducer with a broad athwartship and very narrow alongship angles that provides wide-area and high-resolution images of the seabed. SSS presents a great versatility and relatively low operational costs for mapping seagrass (Greene et al., 2018), but it does not confer a high precision in bottom detection and bathymetry, and it also reduces the scattering volume close to the first echo from the seabed, reducing the acoustic information for habitat mapping. In this sense SBES continues to be the best option (regarding cost/time relation) when the objective is habitat mapping in an area, including seagrass and other benthic habitats.

In this work we present a cost-affordable methodology for benthic habitat mapping using acoustic methods, including substrate and benthic vegetation characterization. As a case study, we apply this mapping methodology in an area with sandy and rocky bottoms, also harboring both dense and sparse areas of *P. oceanica* meadows, and patches of *Cymodocea nodosa*.

2. Material and methods

2.1. Study area

The study was performed in the coast of Murcia (SE Spain), in a small archipelago composed of two volcanic islands. Isla Grosa, the main island, covers a total area of ~17 ha and is situated 2.5 km from the coast. El Farallon, much smaller (~0.4 ha), is aligned towards the open sea in a northeasterly direction about 700 m away from Isla Grosa (Fig. 1).

The archipelago lies immediately north of the Cape of Palos, a transition zone where the profile of the continental shelf changes from rocky, narrow, and steep to the south of the cape, to sandy, wide, and gently sloped to the north.

The subtidal zone of both islands is composed of rocky reefs covered by photophilic algae interspersed with precoralligenous biocoenoses (in areas protected from light). Beyond rocky habitat, key habitat types include patches of sand, and extensive meadows of the seagrass *Cymodocea nodosa* and *Posidonia oceanica*, which adopt diverse morphological configurations. The deepest areas are occupied by detritic biocoenoses.

The archipelago belongs to the Natura 2000 Network under the European Habitats (92/43/EEC) and Birds (2009/147/EC) Directives, is included in the SPAMI (Specially Protected Area of Mediterranean Importance) "Mar Menor and Oriental Mediterranean zone of the Region of Murcia coast" under the Barcelona Convention, and has been recently designated a Wildlife Reserve Area (a national protection figure) including the two coastal areas of 80.68 and 35.01 ha, respectively.

2.2. Acoustic survey and groundtruthing

The acoustic survey was carried out from 10 to November 11, 2020 with general good weather conditions. A total of 49 acoustic transects with east-west orientation (with an average north-south separation of 50 m) and 8 cross-transects (with an average east-west separation of 300 m) were performed covering the total of the study area (Fig. 1).

Acoustic data were recorded with a split-beam echosounder (EK60 Simrad) working with a COMBI C 38/200 kHz transducer. It should be noted that the beams for both frequencies were simple, hence the equipment functioned as a SBES. This transducer was attached to the hull rail of a small boat (6.70 m). The 200 kHz and 38 kHz frequencies were operated with pulse lengths of 64 μs and 1024 μs, respectively. Both frequencies worked with emitting power of 800 W and a ping rate of 4 ping/s. The boat speed was kept between 4 and 4.5 knots. To perform continuous positioning simultaneously with the recording of acoustic information, a u-blox NEO-M8 GPS Card global positioning system (GPS) receiver was used, with 2.5 m theoretical horizontal resolution. The positions, in geographic coordinates, were referenced to Datum WGS84.

After an unsupervised classification of acoustic data (described below), video and scuba diving transects were defined in order to provide groundtruthing information in key areas and thus characterize acoustic diversity of the sea bottom. Thus, 14 transects 100 m long were drawn in the study area, distributed in such a way that they all crossed 2 acoustic transects and that, at least two of them, covered more or less homogeneous areas of each of the unsupervised acoustic classes (Fig. 1).

Of the 14 transects, 12 were made using a geo-referenced towed underwater camera system (Trobbiani et al., 2018) and other 2 by scuba diving equipped with underwater video camera recording continuously. Moreover, one of the video transects was repeated by scuba diving. In the scuba diving transects GPS location at the beginning and end of the transects was acquired in order to georeference transects. Each of these videos was visualized and every change in seabed was annotated regarding two characteristics: substrate and vegetation. Attending to substrate, rocky and sedimentary bottoms were identified, including *de visu* granulometric characterization of the sediment. Attending to vegetation, *Cymodocea nodosa* and *Posidonia oceanica* meadows were the only two seagrass species present as meadows in the area and were

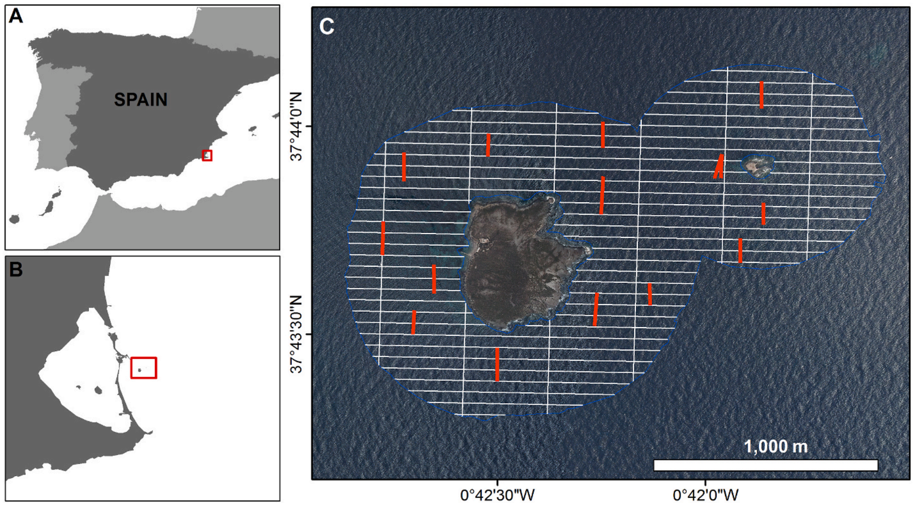

Fig. 1. Location maps (A and B) and study area (C). Study area is outlined in blue, acoustic transects (white) and video transects (red) are shown in the study area. Background image source: *Plan Nacional de Ortofotografía Aérea* of the Spanish National Geographic Institute (IGN). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

characterized by their density and distribution (patches). Thus, homogeneous georeferenced bottom segments were identified over the transects. This process was carried out three times, by three different researchers, in order to reduce interobserver biases. Finally consensus segments were established, and are the ones included in this work.

2.3. Acoustic processing

In order to carry out a statistical analysis of the acoustic data, it is necessary to perform a series of signal processing steps, which allows the characterization of each ping (each location that was insonified) by its acoustic characteristics. All the acoustic preprocessing steps have been performed with the open-source software ECOSONS (https://github.com/daniel-rperez/ecosons).

2.3.1. Bottom detection and ping average

There are different algorithms in the literature that have been used for background detection. In this case, the “threshold method” has been used (Hamilton, 2011; Sánchez-Carnero et al., 2012a). This method places the beginning of the echo (or bottom location) at the first bin (first energy value) that has a value at least 40 dB lower than the maximum value of the echo; this threshold, which is dependent on the transducer and ping characteristics, is selected for this study to be most conservative in detecting the top of sea bottom, and not including any structure (such as seagrass shoots) built on top of it, and also not causing false bottom detections. The end of the first echo is determined geometrically, at twice the distance between the beginning of the echo and the surface, since the transducer has worked vertically oriented and just below the sea surface.

In addition to this first echo, we have identified the second echo, that also provides information of interest in relation to the characteristics of the bottom (Orlowski, 1984; Siwabessy et al., 2000). To calculate the start of the second echo, the start time of the first is multiplied by two, and it is assumed that its length is the same as that of the former.

After bottom detection for each acoustic ping, an algorithm was applied to smooth the ripples observed in the bottom due to the joint movement of the transducer with the vessel. In this case, the smoothing (or error detection) algorithm consisted in taking the 10 echoes immediately before and the 10 immediately after every echo (first or second). These 21 echoes were then grouped according to their shape similarity (evaluated using Euclidean distances). When a group of similar neighboring echoes exceeded 50% of the total, their average (bin by bin) was considered the most homogeneous representative of the central echo.

2.3.2. Acoustic corrections

After the generation of the acoustic wave on the surface of the transducer, it travels towards the bottom, undergoing processes of energy reduction per unit area or attenuation, due to both the geometric spreading of the wave front and the viscous and chemical relaxation energy losses, parameterized by the attenuation coefficient. Because of this, there is a dependency relationship between the energy received from the bottom and its depth. In order to classify the seabed acoustically it is necessary to correct this dependency applying three correction processes: time adjustment, power adjustment, and echo convolution.

The *time adjustment* or time correction consists in the “stretching” of all the echoes to bring them to a certain given depth (close to the maximum working depth). In this way, the length of all the bottom echoes that will be analyzed will be the same and, therefore, independent of the depth. In our case, the depth used for the correction was 40 m. After time adjustment, the energy of the echoes already "stretched" is corrected to compensate for the losses that occur in the advance of the wave from the surface to the bottom (and its return), this is what is called *power adjustment*. For this, all the stretched echoes are brought to a reference depth by mathematically restoring the “lost” energy. In our case, the depth used for this correction was 5 m. Finally, after the two previous corrections we have echoes with comparable energies and lengths, despite the different depths at which they have been taken. However, the shape of the curve that describes each echo will be much more detailed when the echoes come from greater depths, since their lengths, compared to the pulse length of the emitted ping, are longer. To solve this last difference and thus obtain comparable echo shapes at different depths, a *“ping-length Pouliquen (PLP) correction”* was performed (Rodríguez-Pérez et al., 2014) that brings all the echoes to a form comparable to that of an echo received from the reference depth of 5 m, by convolution of the stretched echo with a depth-dependent smoothing window; this postprocessing method of the acoustic signal is a simulation of the original ping-length correction proposed by Pouliquen (2004), hence the name. Details of all these corrections can be found in Rodríguez-Pérez et al. (2014) and Sánchez-Carnero et al. (2018).

2.3.3. Bathymetry and topography characterization

In order to compute a bathymetry, surface the obtained depth values (corresponding to the bottom detection) were subjected to a Monte Carlo simulation process. This process, in addition to allowing the positioning uncertainty due to the error associated with the GPS to be included, allows smoothing the “transect effect” (very high data density in a single direction) that often generates artifacts in the bathymetries obtained. For this, an algorithm was applied simulating bathymetric measurements around the points to force a relative weighting in the interpolation algorithm. The simulated points are assumed to have a Gaussian distribution around the acquired points with a depth-dependent radius of variation (see details in Sánchez-Carnero et al., 2012a). Moreover, points corresponding to the coastline of the islands, sampled every 10 m, were added to the matrix of bathymetric values, to force the convergence on the coastline avoiding erroneous values by extrapolation over land.

The interpolation method used was a multi-resolution averaging method. This method seeks that the estimated depth value in "super-pixels" constructed by adding tiles of 2^n x 2^n pixels of the interpolation raster be equal to the average depth of the bathymetric points contained in those super-pixels (Rodríguez-Pérez and Sánchez-Carnero, 2022). After bathymetry computation, several topographic variables were calculated: slope, orientation and rugosity.

2.3.4. *Acoustic variables calculation*

Corrected echoes were used to calculate energetic variables in order to perform an acoustic seabed characterization. Each of the variables was defined as the energy accumulated in the echo tail (discarding the last 5% to avoid possible overlaps with the second echo) including a certain percentage of its length (discarding, in each case, bins from the beginning of the echo). In our case, 50%, 80% and 100% were used, when working with the 38 kHz frequency, and 50%, 70% and 100%, when working with the 200 kHz frequency (see details in Rodríguez-Pérez et al., 2014). These variables were calculated for both the first and second echo. Thus, every echo was characterized by six acoustic energy values: E1_100, E1_70, E1_50, E2_100, E2_70, E2_50.

In addition to these variables, the acoustic intensity contained in a window above the detected seabed and relative to the average water column intensity above it was calculated (mean, Im_v, and standard deviation, Is_v). The window height, H_v, was computed as the limit above the sea bottom where the acoustic intensity was above the water column level (Sánchez-Carnero et al., 2012b). That height was taken as the height of vegetation structures, thus obtaining for each echo three variables (Im_v, Is_v, H_v).

2.4. *Statistical analysis*

The statistical analysis consisted in two classifications made using the two pairs of matrices of acoustically derived variables: one of acoustic echo energy (E1_100, E1_70, E1_50, E2_100, E2_70, E2_50) and another one of vegetation structures (Im_v, Is_v, H_v) along with the depth. One matrix of each type was obtained for each frequency.

Firstly, the echoes in each of the energy matrices were classified using an unsupervised hierarchical classification. This type of procedure is very useful when the number of classes is not known beforehand or when some class can be expected to show greater intraclass variability than the variability presented between classes. Nevertheless, it is a useful tool for an initial analysis that shows the acoustic diversity and helps in the design of the groundtruthing, as has been done in this work (see 2.2 above).

Using groundtruthing data from transects, a second supervised classification was performed based on the observed bottom types. In this case, a Random forest (RF) classifier was used (Breiman, 2001). To generate a training data matrix, we located points separated every 10 m along the groundtruthing transects, associating each point with the bottom characteristics of the homogeneous segment. A buffer of 10 m was established around each of these points and then every acoustic point inside the buffer was associated with its bottom characteristics (see Appendix A for echo samples of these 10 m buffers measured along transects, and Appendix B for a descriptive statistics of the acoustic variables for the bottom and vegetation classes within). The random forest was adjusted using the 90% of the pairs of data (a set of acoustically derived variables, and the associated groundtruth bottom or vegetation type), keeping the remaining 10% of samples to validate the obtained classification. With the aim of assessing the performance of the classification, each classification was adjusted 1000 times with random partitions of the 90% training and 10% validation data points. A global accuracy was computed and the best classification data set, according to groundtruthing, was kept to obtain the final classification.

Seabed substrate classifications were carried out for both frequencies (38 kHz and 200 kHz) separately, including six energy variables in each classification. In accordance with (Sánchez-Carnero et al., 2012b) the 200 kHz data matrix provided a more accurate classification and, for brevity, will be the only one presented in the results. Vegetation structures, on the other hand, were classified using depth and the three vegetation variables (Im_v, Is_v, H_v), computed for both frequencies (38 kHz and 200 kHz), as input thus including 7 variables.

All the acoustic variable calculations were carried out with *ad hoc* scripts based and using the open-source software ECOSONS (https://github.com/daniel-rperez/ecosons), which implements some common acoustic processing and analysis methods in Octave. All statistical calculations were done using the statistical software R (R Core Team, 2021) and, in particular, the randomForest package (based on Breiman, 2001).

3. Results

3.1. *Groundtruthing data*

From the 14 underwater transects approximately 1 h of seabed recording was acquired, corresponding to just less than a nautical mile in length. Regarding seabed substrate, 5 bottom types where identified: fine sand, coarse sand or gravel, sand (no grain size distinction), rocky bottom, and rock with sand patches. In relation to the vegetation over the bottom, also 5 classes were identified: *Cymodocea nodosa* meadows, dense *Posidonia oceanica* meadows, dispersed *P. oceanica* meadows, dense *P. oceanica* with sand patches, and no-vegetation (Fig. 2). *Posidonia oceanica* meadows were classified as dense (Fig. 2-A) whenever the shoot density let observe the substrate and identify its type only in small patches of lesser density; meadows were classified as disperse, when the substrate was continuously observable through the vegetation (Fig. 2-E); finally, if areas of 1 m radius or larger showed no vegetation, meadows were classified as with patches (Fig. 2-B,C).

In total, 43 homogeneous segments were identified, two of which were discarded because visibility was not good enough to correctly identify the bottom vegetation type. Regarding substrates, 20 segments of rocky bottom were obtained, 4 of them presenting sand patches, in addition 21 segments of sand, being 7 of fine sand and 1 of coarse sand. In the other 2 segments, substrate could not be identified because of dense vegetation. The hard substrate bottoms corresponded to 784 m (118 of them in areas with sand patches), and the sandy bottoms to 633 m (being 229 m of fine sand and 100.10 m of coarse sand). In the case of vegetation, 34 of the 43 segments showed vegetation and 8 bottoms showed no vegetation (in one segment visibility was not good enough). The predominant vegetation was the dense *Posidonia oceanica* meadows observed in 23 segments, covering 926 m (with 305 m areas of dense *P. oceanica* in patches). Four segments of *Cymodocea nodosa* (112 m) and 7 segments of dispersed *Posidonia oceanica* (228 m) were also observed (Fig. 3).

Regarding scuba groundtruthing, 9 locations were identified as sandy bottom (being 3 fine sand, 5 coarse sand and 1 sand without grain size distinction), and 1 as rocky bottom. Regarding vegetation, 9 locations showed vegetation, being 1 *Cymodocea nodosa* meadow, and 8 *Posidonia oceanica* meadows (3 dense, 4 disperse, and 1 dense with sandy patches). There was one groundtruthing location where visibility conditions did not allow the identification of either bottom or vegetation.

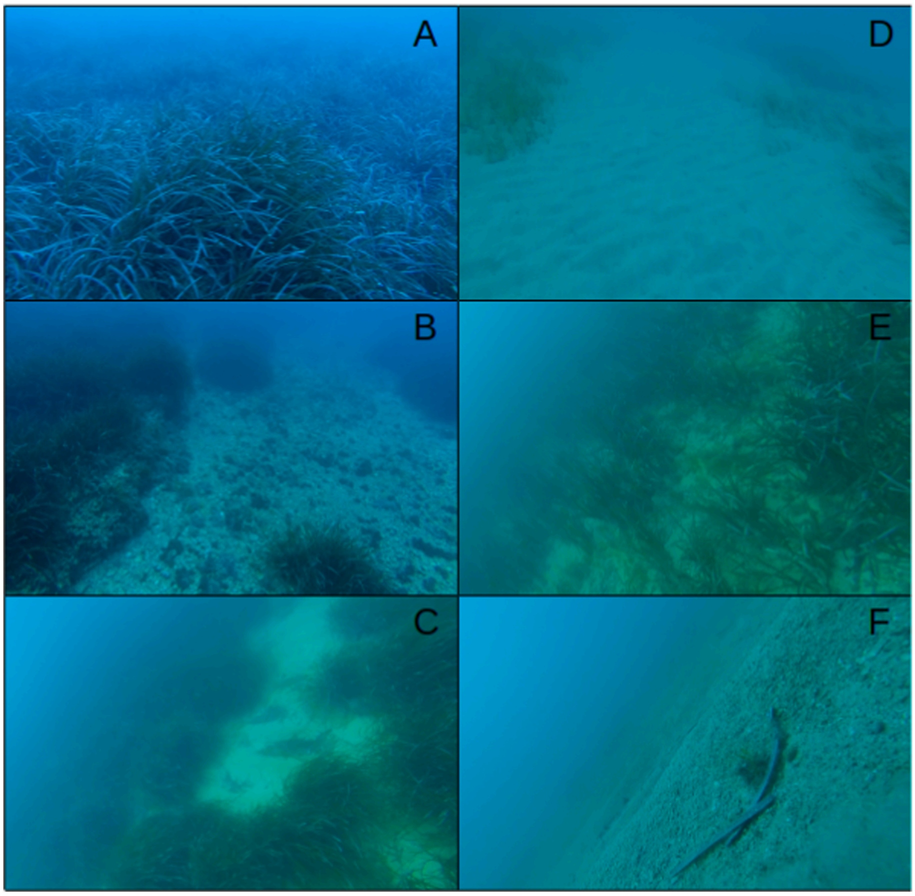

Fig. 2. Examples of substrate and vegetation type combinations: dense *Posidonia oceanica* meadows (A), patches of dense *P. oceanica* meadows on hard substrate (B), patches of dense *P. oceanica* meadows on fine sand (C), *Cymodocea nodosa* meadows on fine sand (D), scattered *P. oceanica* meadows on sand €, coarse sand with no vegetation (F).

3.2. Bathymetric and topographic surfaces

The interpolated bathymetric surface was obtained for a pixel size of 1 m. The bathymetric surface obtained allowed the calculation of derived topographic variables. In our case, these variables were slope, orientation, and roughness.

The study area showed depths of up to just over 30 m, with the deepest areas located on the southeast face of each of the two islands. In both cases there is an abrupt decrease in depth, with slopes of up to 20° near the coast that present South-Southeast orientation. The rest of the work area has soft slopes, no more than 5° in 93% of the study area, with variable orientations, typical of soft sloping bottoms. Regarding roughness, it presented low values (<0.3, that represents less than 30 cm of height differences in 3 × 3 m neighbors) in almost the entire study area (Fig. 4).

3.3. Seabed classification

A seabed cartography was obtained attending to two bottom characteristics: type of substrate and presence and density of vegetation. Supervised classification of 200 kHz acoustic energy data identified 5 substrate classes: hard or rocky bottoms, coarse sand, fine sand, sand (without specifying grain size, because it could not be identified in the images), and hard bottoms with sand patches. The 38 kHz results were only slightly different (and worse) so they are not included here.

Supervised classification of vegetation structures data identified 5 vegetation cover classes: dense *Posidonia oceanica* meadows, patches of dense *Posidonia oceanica* meadows on sandy bottom, scattered *Posidonia oceanica* meadows, *Cymodocea nodosa* meadows, and no vegetation.

Regarding substrate classification, mean global accuracy obtained after 1000 adjustments was 85.28%, being the mean accuracy of the best classification 100%. According to the Gini index, contribution from the first echo was more important than from the second, being E1_50 the most informative variable. In both echoes variables including complete echo backscattering (E1_100 and E2_100) were the least informative of all.

The classification obtained showed a predominance of sandy bottoms (~61% of acoustic points), located in the east and southeast of the islands, meanwhile rocky bottoms (~38%) are located mainly in the northwest side of the islands. Locations classified as rocky bottoms with sandy patches were scarce (~1%), always appearing close to the islands (Fig. 5).

Regarding vegetation analysis, mean global accuracy obtained after 1000 adjustments was 76.21%, being the accuracy of the final classification 70.59%. The 38 kHz vegetation variables (Isd_v and Im_v, in this order) as well as depth were the variables with more contribution in the classification process, according to the Gini index.

Most of the study area showed seagrass presence, only 17% of the acoustic points were classified as bottom without vegetation, all of them located in the southeast of the islands, being that the deepest area, and with sandy bottoms according to the substrate classification. Of the two seagrass species studied, *Posidonia oceanica* was the most widespread (76.5%) covering most of the study area, although it showed different density patterns: dense *P. oceanica* meadows (27.5%) were located mainly in the north and west of Isla Grosa, meanwhile disperse *P. oceanica* meadows (30.6%) were located mainly in the south and east of both islands, around sandy bottoms without vegetation. Finally, dense *P. oceanica* meadows with sandy patches (18.4%) are located in the

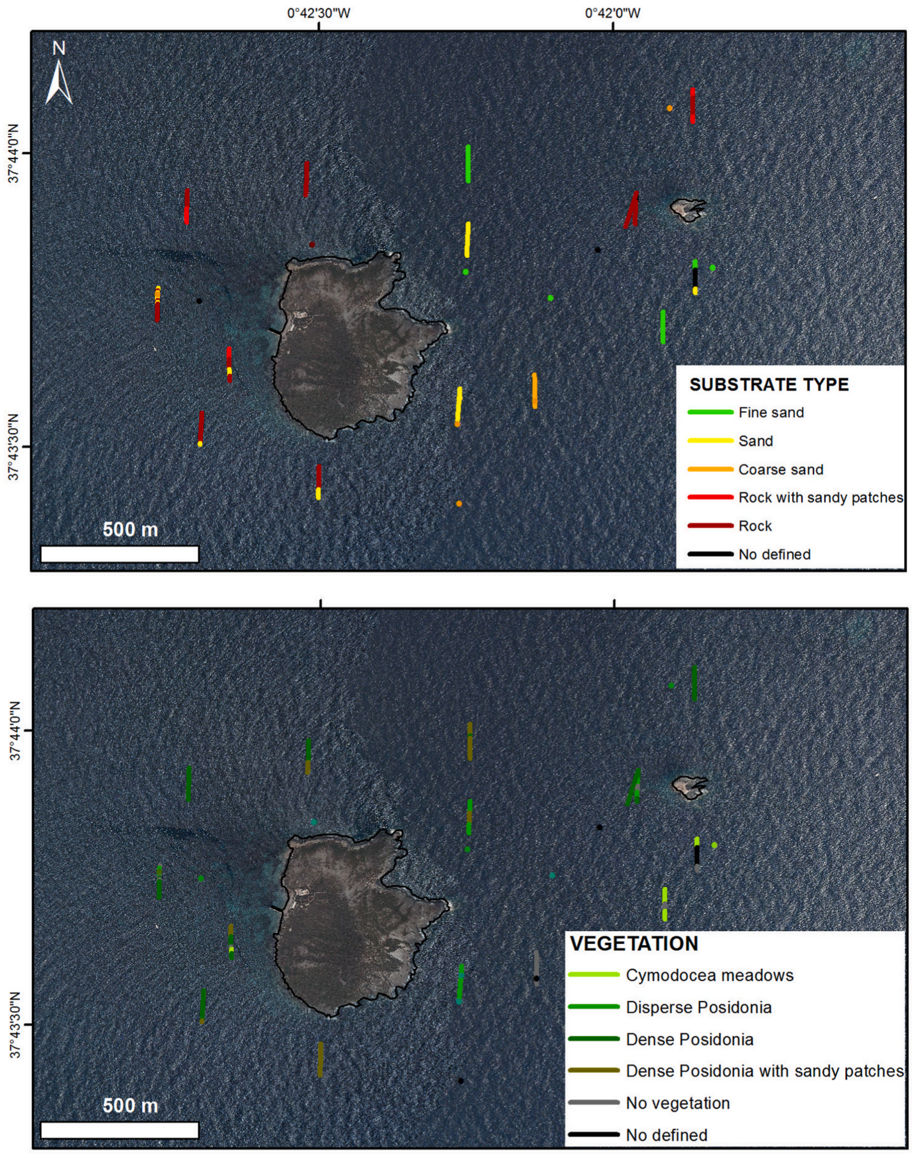

Fig. 3. Groundtruthing video-transects color-coded according to the substrate (up) and vegetation (down) identified by the observers' consensus. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

southwest of Isla Grosa as well as around Farallon island, mixed with spots of dense *P. oceanica* meadows (Fig. 5).

4. Discussion

In the previous sections we have presented an acoustic methodology to cartography the seabed in a coastal area of ecological relevance, attending to its substrate, vegetation, and topographic characteristics.

The Mediterranean Sea is a well-known biodiversity hotspot. However our current knowledge of species and their distribution is still limited to the most shallow and northern areas of the sea (Bevilacqua et al., 2020; Romagnoli et al., 2021). Habitat mapping and classifications are crucially important to habitat-based management, such as marine spatial planning and nature conservation (Sokołowski et al., 2021). Benthic habitat is a complex concept that is primarily determined by substrate type (sediment or rock), which reflects the physical processes in the near-bottom environment and has a profound effect on the communities developing on it (Kostylev et al., 2001). The effort of the present work has been focused in a comprehensive habitat mapping of a National Park composed by a small archipelago included in the protected areas "Islas e Islotes del Litoral Mediterráneo", a Site of Community Importance (LIC), and also a Special Protection Area for Birds (ZEPA).

As indicated in the introduction, underwater acoustics stands out among the different methodologies and tools used for habitat mapping. SBES are an optimal compromise between affordability, efficiency, and functionality to measure bathymetry and also characterize the acoustic properties of submerged objects. We have used a dual frequency (38 kHz and 200 kHz) SBES (EK60 Simrad) to measure the bathymetry and study both the substrate, and the underwater vegetation supported by it, taking into account their expected different acoustic responses. Although ping rate was the same at both frequencies, the vertical sampling at 200 kHz was sixteen times finer than at 38 kHz, providing a higher vertical resolution of 1.2 cm (for 38 kHz it was close to 19 cm). This better resolution of 200 kHz provides greater sensitivity to changes in the structural characteristics of vegetation and substrate roughness.

Although a long-standing idea (Pouliquen and Lurton, 1992), using different frequencies simultaneously for habitat mapping is still a developing one (Tęgowski et al., 2019; Mopin et al., 2022). We analyzed data in both frequencies, 38 and 200 kHz, obtaining the best results for

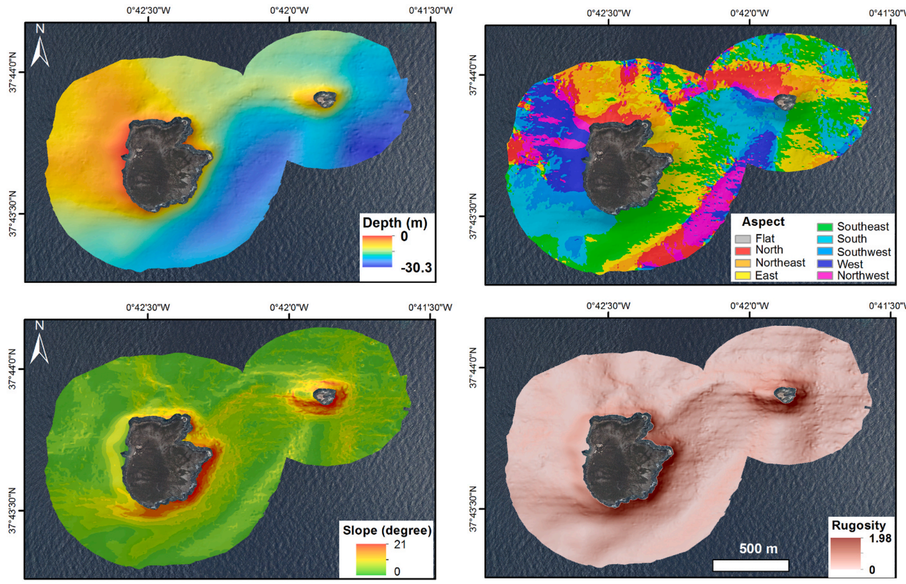

Fig. 4. Bathymetry, slope, aspect, and rugosity surfaces computed from bathymetric data. Aspect values: flat (−1), north (0–22.5 & 337.5–360), northeast (22.5–67.5), east (67.5–112.5), southeast (112.5–157.5), south (157.5–202.5), southwest (202.5–247.5), west (247.5–292.5), northwest (292.5–337.5).

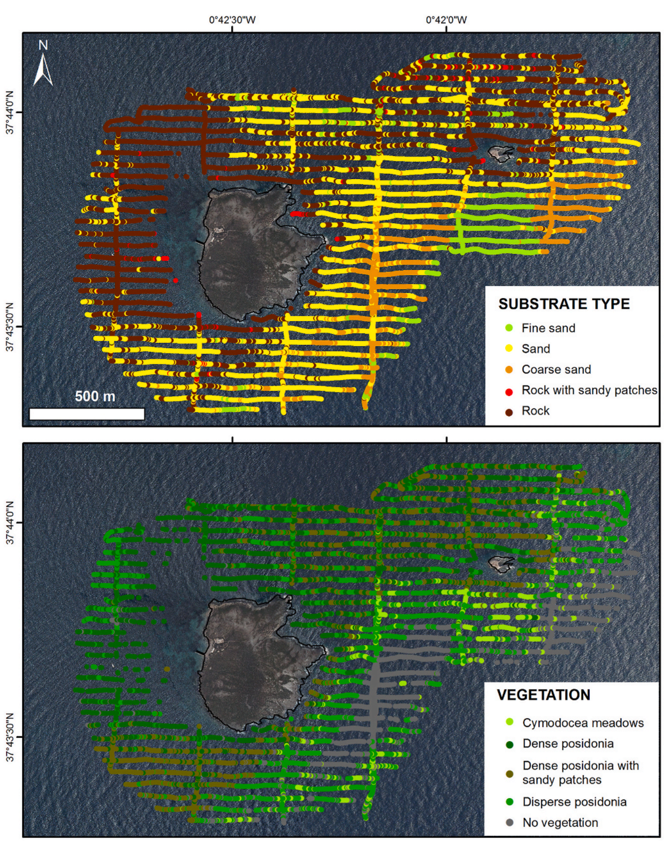

Fig. 5. Substrate (up) and vegetation (below) classification from acoustic data.

the highest frequency. However, other authors have found it otherwise; for example, Freitas et al. (2008) characterized sedimentary bottoms using 50 and 200 kHz, both with 300 μs pulse duration and 100 W power emission, and found the best agreement between the acoustic classification and sediment distribution using the lowest frequency, when applying the QTC-View system. Differences between methodologies can explain this situation. In our study, emission power of both frequencies was considerably higher, which could increase the penetration power of the 200 kHz signal. Besides, while QTC-View only examines the shape of the first echo, we have included in our analysis the first and second echoes, along the lines of other studies about seabottom classification (Rodríguez-Pérez et al., 2014; Ferretti et al., 2015; Yamasaki et al., 2017; Lee and Yik, 2018, among others), some of them using the classification system RoxAnn, the first commercial classification software using the two echoes methodology (Voulgaris and Collins, 1990).

After supervised substrate classification using energetic variables, Gini index computed from random forest pointed consistently to E1 having more weight than E2 in that classification. According to Orlowsky (1984), and authors following him, E1 informs mainly about roughness and E2 informs mainly about hardness. However, E2 is more susceptible to acquisition conditions (ship speed, depth or slope changes, sea surface conditions, etc.) (Hamilton, 2001). The higher importance of E1 could be linked both to the use of a frequency of 200 kHz and to the special distribution of submerged vegetation in our area. The acoustic hardness is related with the penetration depth of the acoustic wave, which is very low for high frequencies as 200 kHz, hence roughness will be more determinant of our measurements, and it is summarized by E1. However, even if acoustic hardness played a role, our results (confirmed by groundtruthing) show that most hard bottom areas are covered with dense *Posidonia oceanica* (see Fig. 5), which in turn increases the rugosity. Regarding used variables, E1_100 and E2_100 were the less informative ones about the substrate (as in Rodriguez-Pérez et al., 2014). This was an expected result since these variables include the complete first and second echoes (defined from bottom detection (in E2) or a ping length after it (in E1), and until the beginning of the next echo).

The acoustic analysis of vegetation comprised intensity and height values, to discriminate vegetation species and density patterns. The Gini index of the random forest supervised classification highlighted as most significant the 38 kHz variables. Most common approaches in the literature tend to use frequencies closer to 200 kHz. Many are just based on detection of the heights of plant leaves, hence the requirement of a better spatial resolution usually provided by higher frequency pulses. In particular, this height only approach has been adopted by Olguner and Mutlu (2020) using a SBES and commercial software (with post-processing or manual edition to correct false non-target species). It was also the approach of (Sánchez-Carnero et al., 2012b; Llorens-Escrich et al., 2021), employing a SSS vertical configuration to measure depths and heights above sea bottom, and also of Shao et al. (2021) who compare different more elaborate classification approaches, taking also into account the spatial and vertical accuracies of the mapping. Dual frequency studies (both below and above 100 kHz) have also been performed, although not addressed at the plant itself, but to the sediment beneath and classifying sediment plus vegetation as a different substrate class (Puhr et al., 2014). Our combination of plant height and backscattering overcomes some of the difficulties of *P. oceanica* having a low plant threshold value (around −80 dB) at 200 kHz, because its acoustic response attains a relative maximum around 40 kHz (Lyons and Pouliquen, 1998), so it is reasonable that 38 kHz data is finally the most significant for classification; as far as we know of, there is still no consensus as to whether this 40 kHz acoustic response is due to acoustic compliance of the shoot or to the formation of air bubbles attached to it. This relationship between photosynthetic activity generated bubbles and acoustic backscattering has, however, been confirmed both theoretically and experimentally in the range of 1–8 kHz (see Ballard et al., 2020, and references therein) and has been exploited in works using sub-bottom profilers (SBP) to detect near bottom vegetation (e.g. Fakiris et al., 2018; Dimas et al., 2022). Although recent works show the success of SSS, multibeam or satellite imagery or a combination thereof (Kenny et al., 2003; Rende et al., 2020, and references therein) to detect and classify *P. oceanica* meadows, single beam echosounder is still a more portable solution. It also provides bathymetric data, which is useful for vegetation cartography (given its dependency on light), something not provided by, for example, towed SSS, which only offers seabed images with a minimum distance between the transducer and the bottom (Greene et al., 2018) but cannot determine depth reliably (Gumusay et al., 2019). On the other hand, all of these methods based on occasional measurements of acoustic response share the limitation of being dependent on the plant growth and phenological stages, this is why ground-truthing is essential (Gumusay *et al.*, 2018); this concern has been raised by authors using acoustic methods to study underwater algae assemblages (e.g. Shao et al., 2021). Fortunately for our work, *P. oceanica* and *C. nodosa* have long lived shoots (over 4000 and 800 days, respectively) and are also among the seagrasses with slowest clonal growth (Marbà et al., 1996; 2004), thus being less affected by seasonality. This limitation could be reduced in optical remote sensing methods, using time series analysis; however, these methods are most limited by depth: up to 8–9 m for detection and 2–3 m for classification in clear water conditions (see e.g., the review by Kutser et al., 2020).

Our supervised substrate classification included 5 classes: 3 corresponding to sandy bottoms (fine, coarse and medium) and two to rocky bottoms (one of them with sand patches above the rocky substrate); this is a common division in areas without finer (mud or silt) or coarser (gravel or mollusk shell debris) sedimentary bottoms (Fauziyah et al., 2020; Viala et al., 2021). This substrate-only classification shows a remarkable spatial coherence, despite the classifier not including spatial constraints. As previously said other approaches have included vegetation as a different substrate arriving at different numbers of classes defined as substrate + vegetation (Puhr et al., 2014). The groundtruthing validation of our classification rendered an accuracy slightly above 85%, which is comparable to accuracies around 80% reported in the literature, either using SBES (Tęgowski, 2005), MB echosounders (Che Hasan et al., 2012; Diesing and Stephens, 2015; Trzcinska et al., 2020), or a combination of both (Tęgowski et al., 2019), all of them with comparable number of substrate classes (from 2 to 6, which in some cases included wrecks or artificial structures), and using many groundtruting points for training.

Regarding vegetation analysis, the classification accuracy was slightly higher than 70%, and quite close to some reported in the literature obtained by scuba dives groundtruth (Gumusay et al., 2019, 72%), with the advantage of a better survey efficiency. Better results were achieved by Puhr et al. (2014): they detected *C. nodosa* with 90% accuracy and *P. oceanica* with 84% (although this was acoustically indistinguishable from macroalgae when covering the same type of substrate); when complemented with aerial photography, the accuracy grew up to 94% for *P. oceanica* (in shallow areas up to 4 m deep). Stevens et al. (2008) also used a SBES to map seagrass and reached 92% and 74% of agreement in bare areas and areas with continuous seagrass, respectively. Manik and Apdillah (2020) and Shao et al. (2021) report similar accuracies (87% and over 90%, respectively) also working with single-beam to detect underwater vegetation (macropytes and algae, respectively). High accuracies are frequently reported in studies using multibeam echosounders, as the 83% of Hamana and Komatsu (2016), mapping seagrass from depth data, although other authors only obtained 53% of classification agreement between sand, dense and sparse vegetation (which improved to a 78%, after simplifying the classification to just sand and vegetation) (Tecchiato et al., 2015). Finally, concerning results obtained from SSS, considered the most suitable mapping tool for *P. oceanica* (Pasqualini et al., 2000), our accuracy is close to the 72% accuracy obtained with vertical SSS measurements (Sánchez-Carnero et al., 2012b), or accuracies ranging from 78% to 88% obtained using a traditional configuration (Bennett et al., 2020).

5. Conclusions

In this work we have presented a cost-affordable methodology for benthic habitat mapping using single-beam echosounders and classifying separately substrate and benthic vegetation. Our study area has been an area with sandy and rocky bottoms, that support both dense and sparse areas of *P. oceanica* meadows, and patches of *Cymodocea nodosa*, and also has areas with no vegetation. Our method was able to map all these habitat components with accuracies of 85%, for the substrates, and of 70%, for the vegetation (or lack thereof).

The substrate classification method is commonly based on the 200 kHz echo tail energy and uses first and second echo; the classifier highlights the first echo half-tail energy (E1_50) as the most informative variable. The vegetation classification method, on the other hand, adds to the successful approach of vegetation height the scarcely used vegetation backscattering intensity; in this case, bathymetry and 38 kHz variables resulted in the most informative ones.

The bathymetric and thematic maps included in this article (Figs. 4 and 5, respectively), together with the methodology presented, add to the existing ones aimed at the quantification of Mediterranean seagrasses habitat extent and condition, particularly of *P. oceanica* and *C. nodosa*, that are selected by the Water Framework Directive 2000/60/EC and the Marine Strategy Framework Directive (MFSD-2008/56/EC), as representative species for evaluating “Good Ecological Status” and “Good Environmental Status” in the Mediterranean marine environments.

CRediT authorship contribution statement

N. Sánchez-Carnero: Methodology, Formal analysis, Data curation, Conceptualization, Writing – original draft, Writing – review & editing. **D. Rodríguez-Pérez:** Software, Methodology, Formal analysis, Conceptualization, Writing – original draft, Writing – review & editing. **S. Llorens:** Investigation, Writing – original draft. **V. Orenes-Salazar:** Data curation, Investigation. **A. Ortolano:** Data curation, Investigation. **J.A. García-Charton:** Project administration, Funding acquisition, Investigation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Sample echograms

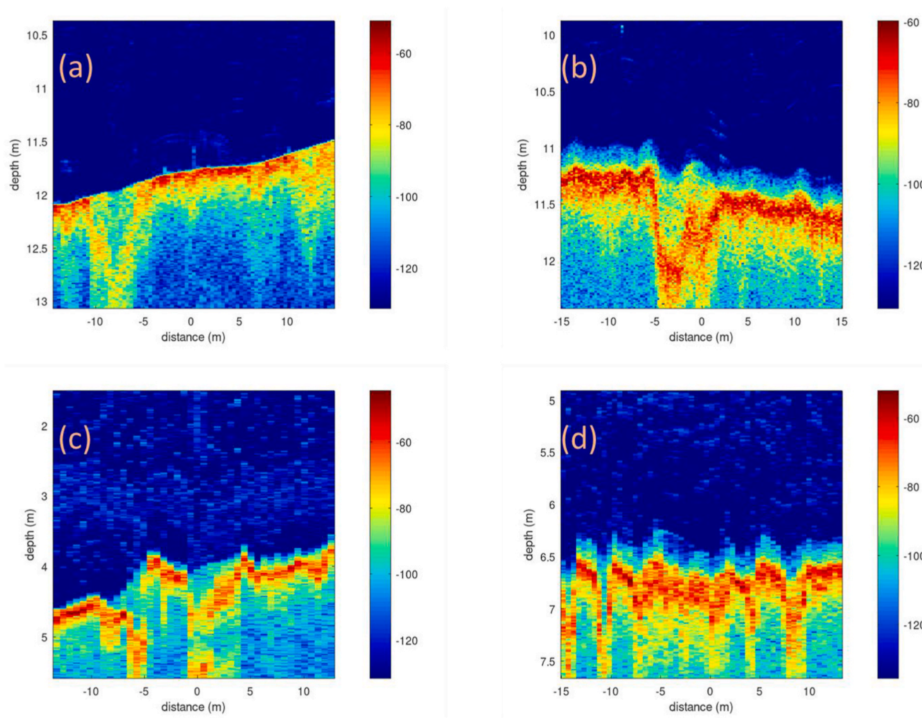

Fig. A.1. Near bottom echograms (200 kHz) acquired close to groundtruthing points with different sea bottom types: (a) fine sand, (b) sand-coarse sand, (c) rock with sandy patches, (d) rock.

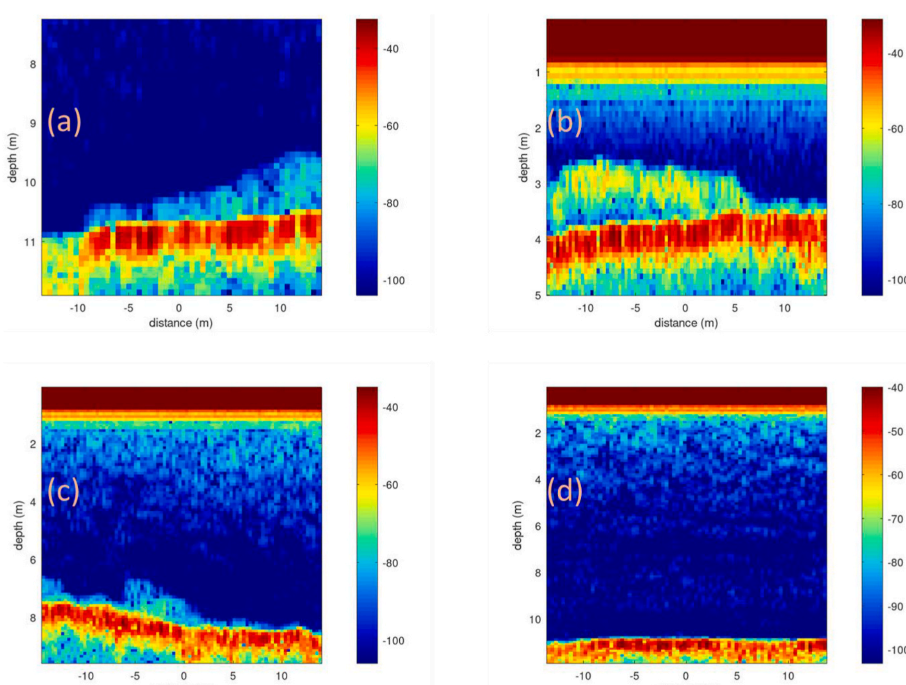

Fig. A.2. Near bottom echograms (38 kHz) acquired close to groundtruthing points with different vegetation types: (a) Cymodocea meadows, (b) dense *P. oceanica*, (c) dense *P. oceanica* with sandy patches, (d) no vegetation.

Appendix B. Descriptive statistics of acoustic variables used for classification

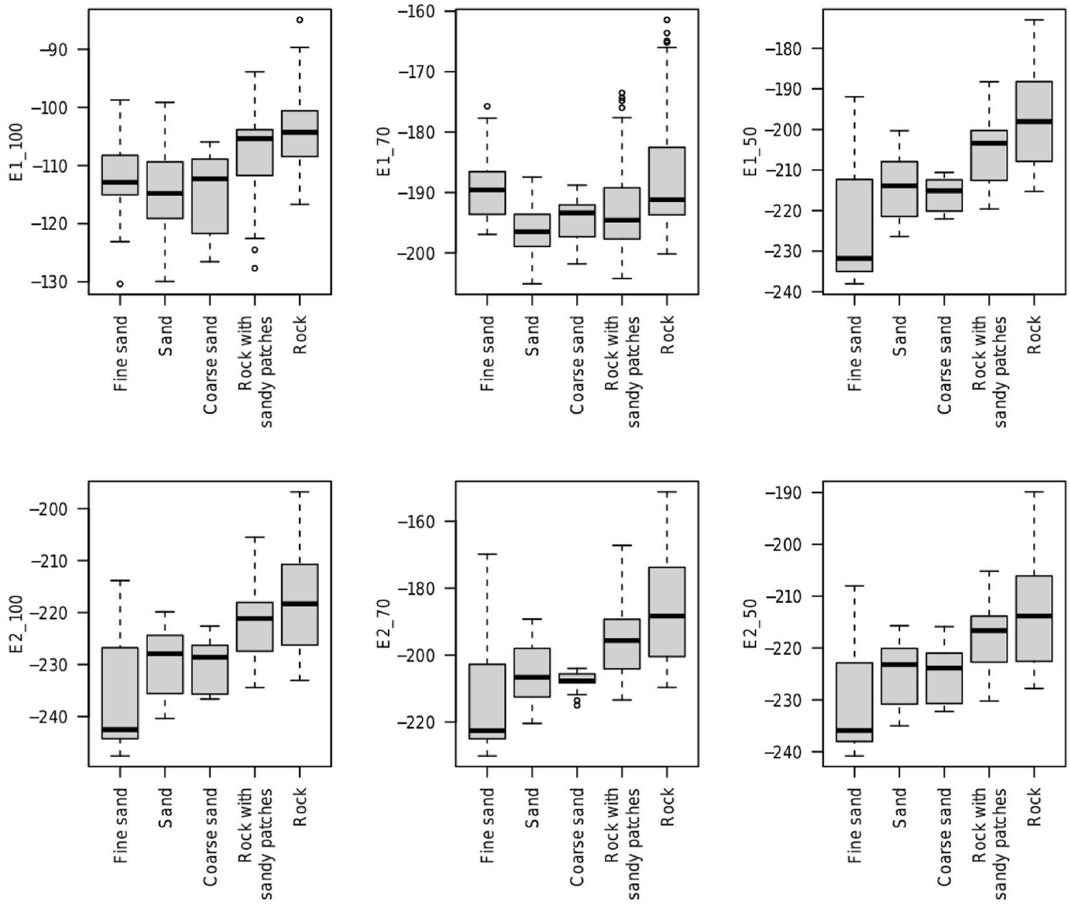

Fig. B.1. Box-plots of variables used for sea bottom classification using the 200 kHz signal. Upper row: E_100, E_70, E_50 for the first echo. Lower row: E_100, E_70, E_50 of the second echo.

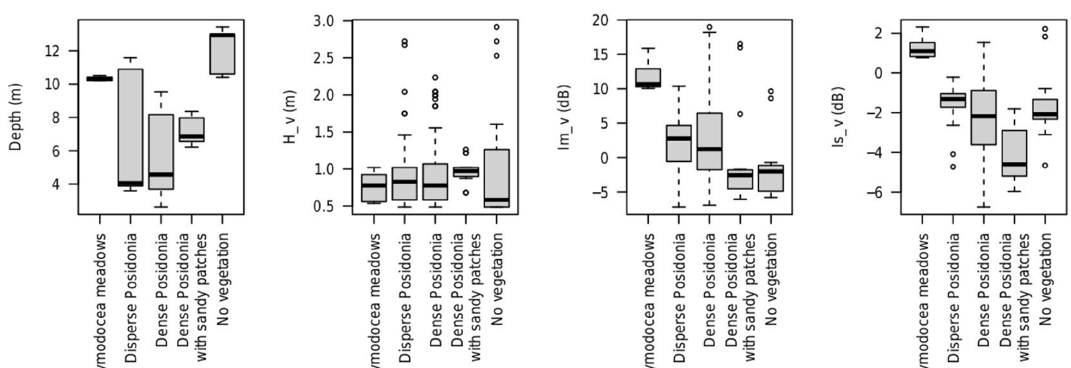

Fig. B.2. Box-plots of variables used for macrophyte classification using the 38 kHz signal: depth, H_v (estimated vegetation height), I_m (intensity above the water signal in dB), Is_v (intensity r.m.s. in dB).

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