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Seafloor classification using a multibeam echo sounder: A new rugosity index coupled with a pixel-based process to map Mediterranean marine habitats

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ABSTRACT

Multibeam echo sounders (MBES) have been commonly used over the last decades in hydrography to perform bathymetric measurements with high precision and provide backscatter imagery of the seafloor. Although seafloor classification techniques have been recently developed using MBES backscatter imagery, few semi-automated or completely automated methods joining acoustic imagery and bathymetric data to map marine habitats exist today. In order to fill this gap, a pixel-based data treatment process was designed to provide map of marine habitats coupling the rugosity computed from bathymetry and the backscattering data. In this way, a specific rugosity index, called Bathymetric Automated Treatment for the Classification of the Seafloor (BATCLAS), was developed by computing the least square fitting on the bathymetric soundings in order to obtain a metric value of the seascape unevenness. The whole process relies on a software suite specifically created to treat and edit acoustic data from MBES, using classification algorithms based on customisable decision trees. Tested on an acoustic data set acquired along the French Mediterranean coast with a R2Sonic 2022 MBES and validated with field observations, this method allowed to detect and map with accuracy marine habitats such as complex rocky substrates, *Posidonia oceanica* (L.) Delile seagrass meadows and artificial structures.

1. Introduction

Seafloor classification, i.e. the identification of the substrate nature (e.g. sand, rock, mud) and the habitat characterisation (e.g. seagrass meadows, algal cover, artificial structures), has been an important challenge since the end of World War II, at first for military purpose and navigation safety [24,26] , and later for natural resources' prospecting and environmental management [6,18]. The first seafloor classification techniques using acoustic data (Fig. 1) were based on the use of towed side scan sonar (SSS) for sedimentary classification [36] which provide the reflectivity, or the backscatter, of the sea bottom. Backscatter imagery from SSS was then coupled with the echo-integration methodology, or Acoustic Ground Discrimination Systems (AGDS), using the acoustic data of the water column provided by single beam echo sounders (SBES) [20] . Echo integration relies on the analysis of the first return echo (E1, hereafter called "rugosity") and the whole of the first multiple return echo (E2, hereafter called "hardness") [40] . This AGDS allows to detect and discriminate different types of sediments [7] as well as to identify the marine vegetation such as kelps [30] and seagrasses [37] . Although the echo integration has proved to be an interesting tool to identify the seafloor nature, the use of an SBES is an important drawback when considering the size of its swath and thus, the surface mapped per transect.

In parallel with research effort for classification techniques based on the use of SBES, the usage of multibeam echo sounders (MBES) for the mapping of the seafloor and its nature identification increased throughout the years 2000s [2,5] . Most of the classification methods developed for MBES rely on the analysis of the backscatter imagery of which quality has constantly improved, now matching the one of SSS [4] . The first analysis processes realised to identify the seafloor nature with MBES imagery were based on the backscattering intensity (BI) only [17] . Several approaches were later developed, such as the coupling of the backscatter intensity and the incidence angle [15] , and a pixel and object-based analysis [19] .

The most recent classification techniques with MBES combine both bathymetric and backscatter data. This is made possible by

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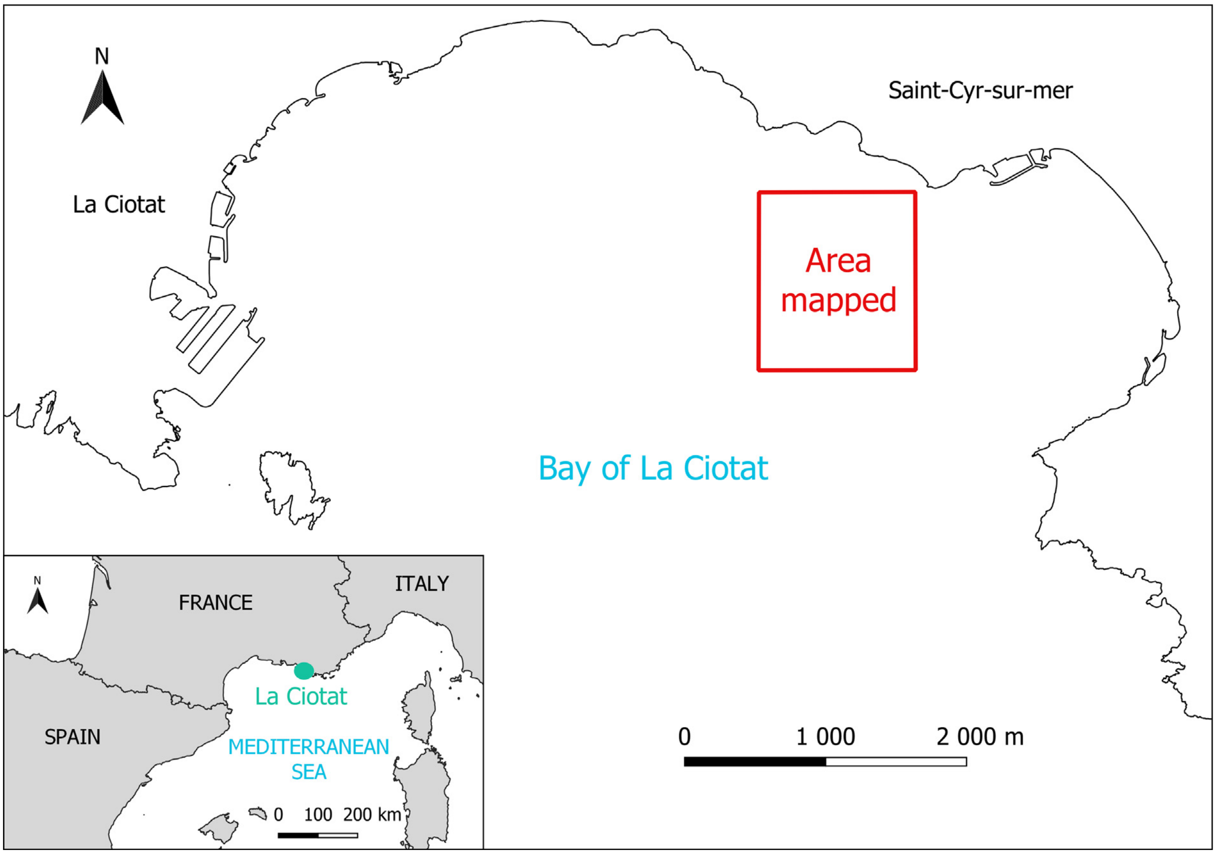

Fig. 1. Location of the study site (red square) on the French Mediterranean coast in the bay of La Ciotat selected for MBES acoustic data acquisition. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the emergence of new analysis processes like artificial neural network [28] . Other approaches rely on algorithms based on decision trees taking into account, besides backscatter data, the seafloor morphobathymetry under the shape of the Bathymetric Position Index (BPI) [16,29] . The BPI developed by Lundblad et al. [23] is an adaptation of the Topographic Position Index (TPI) used in land mapping of Weiss [39] .

All these classification methods find their use in a wide range of applications in the field of the seafloor exploration (e.g. natural resources, abyssal habitats, sedimentary structures) but also for the survey of key marine habitats in the framework of coastal management. In this line of thought, the European Marine Strategy Framework Directive aims to apply an ecosystems-based approach in the regulation and management of the marine environment, natural marine resources and marine ecological services [22] . Among the Mediterranean ecosystems concerned by this European directive, the extensive meadows formed by the seagrass *Posidonia oceanica* (L.) Delile and the coralligenous communities require accurate spatial data, and thus precise maps of marine habitats, for an effective ecosystem-based management [6] .

With the survey and conservation of the key Mediterranean marine habitats in mind, we aimed to accelerate the mapping process and to improve its objectivity through a pixel-based (PB) classification technique. In order to develop an automated seafloor classification method using data of a compact MBES for coastal surveys with small vessels, we chose a slightly different way to combine bathymetric and backscattering data. The first step consisted in an adaptation of the SBES AGDS to MBES characteristics by studying echo integration on each beam [1] . The limits of this technique, especially the induced limitation in the seafloor surface covered for classification – more specifically the difficulty to obtain exploitable data for closed angles on either side of the swath - led us to work on an index based on bathymetric data in a different way than the BPI. Thus, in the present research we targeted (1) to develop a new bathymetric index exploiting as much as possible the large swath capacity of the MBES to study the rugosity of the seafloor; (2) to include the backscattering imagery in the classification process; (3) to validate with field observations the habitats detected with BATCLAS; and (4) develop a PB process to generate maps of marine habitats.

2. Material and methods

2.1. Study area

The study site chosen is situated in the bay of La Ciotat (south of France; Fig. 1). It has a surface of 1.3 km^2 and mainly presents a sedimentary seafloor with the seagrass *P. oceanica* forming meadows on the north-eastern part, artificial reefs of various types (production, against illegal trawling), a World War II aircraft wreck and sparse rocky reefs.

2.2. Positioning and acoustic data acquisition

Acoustic data acquisition was performed in August 2017. A R2SONIC™ 2022 MBES was mounted on the hull of the *Seaviews One*, a small vessel (6 m long) especially designed for hydrographic surveys with a central shaft for the sounder, the navigation unit and the sound velocity probe. An inertial navigation system Applanix I2NS™ integrated with the MBES and encompassing a full Real Time Kinetic (RTK) Global Navigation Satellite System (GNSS) mod providing a positioning precision of 1.0 cm on XY axes and 1.5 cm vertically, a rolling and pitching precision of 0.015° and a precision for heading trajectories of 0.02° was operated. Two GPS antennas AeroAntenna Inc. AT1675-540 were used for satellite signal reception and navigation heading. Each offset of the whole system (sounder and positioning devices) was carefully measured at the vessel's conception phase and regularly checked to avoid constant accuracy errors.

The navigation during acquisition was operated by a Raymarine ACU 200 autopilot synchronised with the RTK GNSS using ViewMap, a Geographic Information System (GIS) and navigation software which allows to trace and follow precise trajectories during acoustic data acquisition. The whole navigation system has an accuracy of 0.5 m to follow trajectories.

Acoustic data were acquired at a frequency of 450 kHz with an individual beam width of 0.9° × 0.9° for a maximum swath sector of 160° and 1 024 soundings per swath. Underwater sound velocity was constantly checked using a Valeport Ltd miniSVS sound velocity sensor mounted on the MBES. Additional underwater sound velocity profiles were performed with another miniSVS to detect the possible presence of a thermocline or fresh water layers impacting the sound propagation.

2.3. Positioning accuracy

GNSS positioning data were post-treated with the open-source program package RTKLIB. By taking into account the accuracy of each sensor – i.e. the RTK GNSS, the inertial navigation system, the MBES, the sound velocity sensor and the sound velocity profiles – leading to horizontal and vertical errors, we obtained a XY accuracy of ±0.078 m, and a Z accuracy of 0,050 m.

2.4. Acoustic data processing

R2Sonic 2022 soundings were processed using the ViewSMF computer program for the visualisation and treatment (automatic or manual) of MBES acoustic data and metadata. False echoes were removed using filters to isolate one or several soundings. Each ping of the acoustic data acquired was accordingly "cleaned" using the filters manually adjusted combined with an automated swath scrolling to increase processing speed.

The angle of incidence of the reflected beam was corrected (Eq. (1)) using the sound velocity constant measurements and profiles according to the following formula:

$$\theta = \arcsin\left(\frac{SV}{SV_0}.\sin(\theta_0)\right) \tag{1}$$

with θ (°) the corrected value of the angle of incidence and SV (m.s^{-1}) the true sound velocity; θ_0 (°) the false value of the angle of incidence and SV_0 (m.s^{-1}) the erroneous sound velocity value. These corrections were automatically computed in ViewSMF.

2.5. Backscatter processing

Backscatter data were processed in ViewSMF too. First, a time-variable gain was run to soften the effect of sound propagation on the seafloor acoustic response and to offset the incidence angle that modify the target strength according to the Lambert's cosine law. Then, snippets, i.e. time series of data samples per beam, were computed too, in order to reduce the noise generated by the beam spreading on the bottom and thus, to increase the overall resolution of backscatter images.

2.6. The rugosity index BATCLAS

A rugosity index was developed to detect and quantify the seafloor variations corresponding to marine habitats (e.g. rocky reefs, seagrass meadows, artificial structures). The Bathymetric Automated Treatment for the Classification of the Seafloor (BATCLAS) was thus created by realising linear regressions with a least square fitting method on the bathymetric soundings in order to obtain a metric residual value of the seascape unevenness.

The residuals are evaluated for every good soundings in each ping of the whole dataset. Not all the soundings are usable, depending whether the sounding is considered as an outlier or it has a too much grazing angle. In fact, least square fitting methods are very sensitive to outliers and noises, so this could skew the expected values.

A linear regression is made on every validated soundings and their neighbourhood. The neighbourhood is adapted to the quantity of close soundings: the less soundings, the wider the neighbourhood and the lower the positioning accuracy. At least the ten nearest values are kept and, at best, all the soundings in the surrounding meter in the ping (only if they are not outliers).

This group of soundings in a ping are considered as a scatter plot of polar pair points, i.e. time of range R (s) and beam angle θ (°), in the vessel frame converted to Cartesian pair points, i.e. lateral distance Y (m) and depth Z (m). The conversion is helpful to have the same unit dimension into the pairs. Finally, the residuals of the least square fitting is computed based on the linear regression of Z on Y.

By considering a scatter plot of the n pairs $\{(y_1, z_1), (y_2, z_2), \ldots, (y_n, z_n)\}$, the center of gravity (Eq. (2)) is given by:

$$\left(\bar{y}, \bar{z}\right) = \left(\frac{1}{n}\sum_{i=1}^{n} y_i, \frac{1}{n}\sum_{i=1}^{n} z_i\right) \tag{2}$$

The linear function that fits at best the scatter plot is given by $\alpha.y_i + \beta$, where the parameters α and β are chosen to minimize the difference between z_i and $\alpha.y_i + \beta, \forall i \in [1, n]$. Hence, the residuals (equation (3)) are given by:

$$\begin{aligned} Res &= \sum_{i=1}^{n} (z_i - \alpha.y_i + \beta)^2 \\ &= n.\alpha + 2.\alpha.\beta.S_y + \beta^2.S_y^2 - 2.\beta.S_{yz} - 2.\alpha.S_y + S_z^2 \end{aligned} \tag{3}$$

where $S_y = \sum_{i=1}^{n} y_i$; $S_z = \sum_{i=1}^{n} z_i$; $S_{yz} = \sum_{i=1}^{n} y_i.z_i$; $\alpha = \frac{cov_{yz}}{\sigma_i^2}$ and $\beta = \bar{z} - \alpha.\bar{y}$ with the covariance between Y and Z, $cov_{yz} = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \bar{y}\right).\left(z_i - \bar{z}\right)$ and the variance of Y, $\sigma_y^2 = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \bar{y}\right)^2$.

The BATCLAS index is directly calculated on the processed MBES data in ViewSMF and its value is finally exported in a digital elevation model (DEM) also encompassing bathymetric and backscatter data.

2.7. Ground truth data

Ground truth campaigns were performed following acoustic data acquisition, after the first analyses of the MBES products – i.e. bathymetry, backscatter imagery, BATCLAS index – to validate the seafloor nature. The sampling strategy was built according to the value of the BATCLAS index. High values (e.g. rocks, seagrasses, artificial structures) as well as low results (e.g. dead matte, sediments) were thus investigated on the field with 39 punctual underwater observations by scuba diving as well as with a camera AEE S60 immersed from the surface. The position of each sampling point was carefully checked using the same RTK GNSS as for acoustic data acquisition. Finally, a ground truth catalogue is generated in the GIS ViewMap under the shape of a waypoint layer encompassing underwater pictures as well as a description of the observation (e.g. depth, coordinates, textual description, nature of the seafloor).

2.8. Pixel-based classification

Since the BI and BATCLAS provide different types of information on the seafloor nature, it is thus enlightening to classify the seafloor three times – once with the backscatter only, once with the BATCLAS index, once with the coupled data – to compare the results. In this line of though, a pixel-based classification was proceeded in ViewMap on (1) the backscatter data alone; (2) the BATCLAS data alone, (3) the combined BATCLAS and backscatter data using a decision tree as well as manual editing according to the ground truth data (Fig. 2). The decision tree consisted in the allocation of a minimum and a maximum values to the different parameters (i.e. depth, rugosity, backscatter) defining each habitat class. The minimum and maximum values were manually defined. Four habitat classes – i.e. hard substrate, *P. oceanica* seagrass meadows, coarse and fine sediments - were thus defined according to their rugosity and backscatter properties. The BATCLAS and/or BI value of each data pixel was then used to generate a map of marine habitats by following the classification order of the decision tree (Fig. 2).

In order to provide a map that can be exploitable for analysis by conservation agencies, this pixel-based map requires local modifications and cleaning due to acoustic noise as well as the manual identification of several specific habitats. These changes were made in a second time, still using ViewMap, by manually delimiting the areas to be excluded from the automated classification, or those requiring a specific classification. The classification of specific areas relies not only on the acoustic data acquired but also on the ground truth and the bibliographical knowledge of the zone. The amount of manual editing to produce the final map was about 25% and corresponded to 1 h of work. The last cleaning step was performed by removing pixel agglomerates with an area lower than 10 m^2. Finally, habitat polygons were generated from the pixel classification, thus allowing further spatial analysis of the seascape.

3. Results

3.1. MBES products

The depth in the area mapped ranged from 10 m to 49 m depth (Fig. 3a). The seafloor appeared flat with a single uneven ground area at the centre of the zone. The backscatter imagery showed variations in the BI in the south of the area that could correspond to heterogeneous sedimentary natures (Fig. 3b). The ground irregularity detected at the centre of the bathymetric data was detected on the acoustic imagery too. A contrasted BI is observed in the north-eastern part of zone and could reflect the edge of a seagrass meadow (Fig. 3b). The tracks of the vessel's nadir were visible on the backscatter mosaic under the shape of very high BI values (Fig. 3b). When looking at the BATCLAS map, two structures with a high rugosity value (BATCLAS > 1 m) were detected at the centre of the area (Fig. 3c). The possible presence of the edge of a seagrass meadow at the north-east, already distinguished on the backscatter imagery, was observed on the BATCLAS map. Moreover, a reduction of the BATCLAS value along a depth gradient at the level of the *P. oceanica* meadow was recognisable (Fig. 3c). The possible sedimentary pattern on the backscatter imagery (Fig. 3b) is not observed on the BATCLAS map (Fig. 3c). On the contrary, several rough shapes are localised in the south-east corner that did not appeared on the backscatter imagery.

3.2. Underwater observations

Ground truth data revealed various types of marine habitats, of which artificial reefs built for biomass production at the centre of the study area and anti-trawling reefs lined up in the south-west of the zone (Fig. 4). The presence of a *P. oceanica* seagrass meadow was confirmed on the northern part of the area (Fig. 4). A gradient in the meadow density was observed with a decrease from the lower to the deeper depths that was also seen in the value of the BATCLAS index (Fig. 3c). Where heterogeneous sediments were expected to be found according to the BI high value measured on the centre part of the backscatter imagery (Fig. 3b), an alternation between coarse sediments and a flat rocky seabed was observed (Fig. 4). This flat hard seabed seems to correspond to a hardened ancient sediment following an induration process.

3.3. Seafloor classification

The pixel-based seafloor classification using backscatter data alone did not allow to properly detect the limits of marine habitats (Fig. 5a) despite the good quality of the backscatter mosaic obtained (Fig. 3b). The sedimentary patterns observed on the mosaic were not detected by the algorithm, nor the rocks. However, the deeper limit of the *P. oceanica* seagrass meadow is well mapped while the shallow one is not (Fig. 5a). The BI high values of the vessel tracks resulted in an erroneous classification (oblique bands) and thus the incapacity to discriminate seagrass meadows from sediments and rocks.

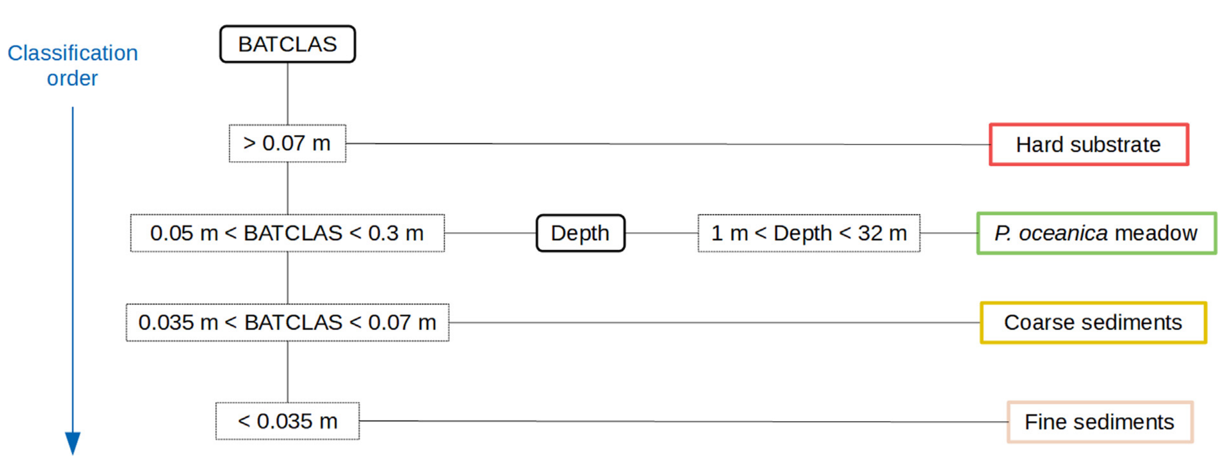

Fig. 2. Example of the decision tree combining BATCLAS and bathymetric data for the pixel-based classification.

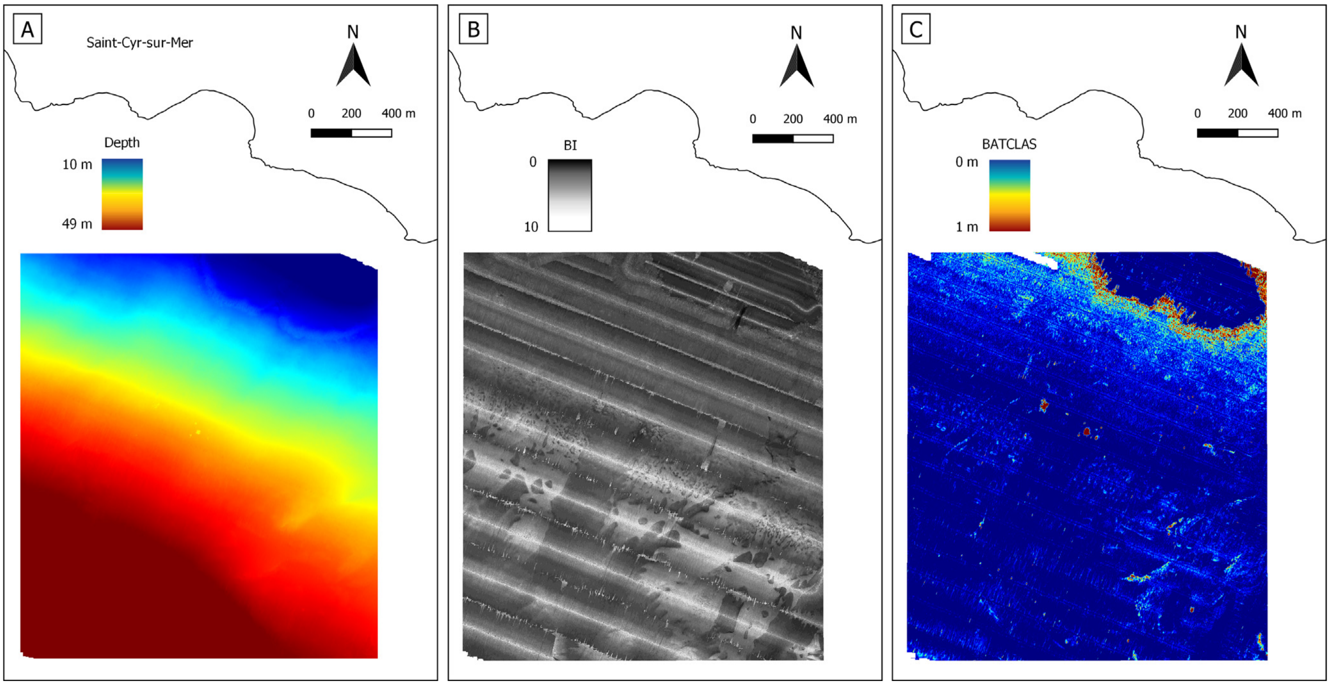

Fig. 3. Maps obtained from acoustic data of the MBES. (A) Bathymetric map; (B) Backscatter map; (C) BATCLAS (rugosity) map. BI: backscatter intensity (without units).

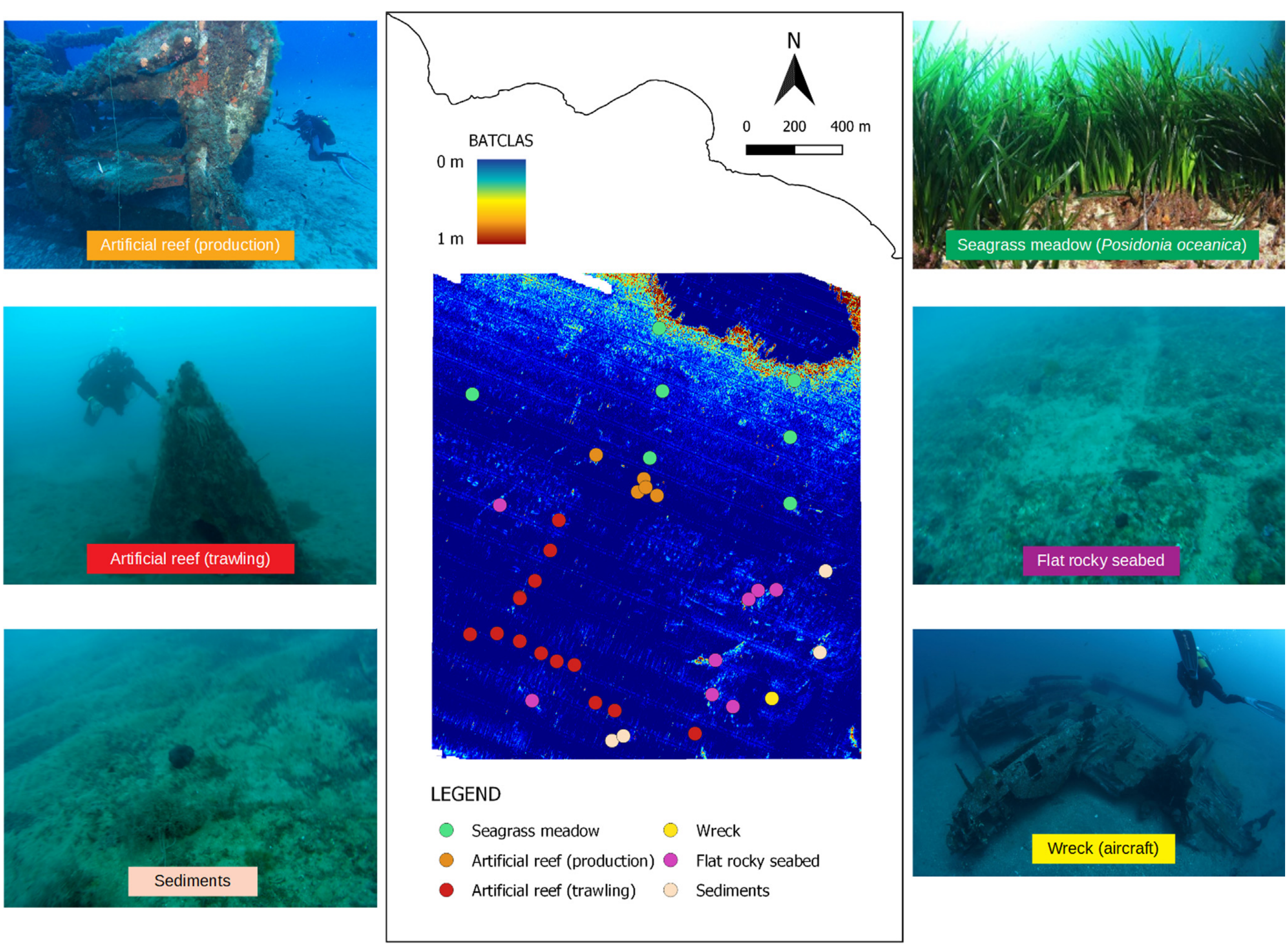

Fig. 4. Location of the punctual ground truth data over the BATCLAS map and underwater photographs of the marine habitats observed.

The classification based on the BATCLAS index values provides a map of marine habitats (Fig. 5b) consistent with the ground truth data (Fig. 4). The upper limit of the *P. oceanica* meadow is well delimited while the deep limit is not clearly depicted. The artificial reefs (anti-trawling and production) and the aircraft wreck are correctly mapped as "hard substrate" (Fig. 5b). Coarse sediments sporadically mapped and the patterns observed on the BATCLAS map (Fig. 3c) are not outlined. Once again, the vessel route is materialised by oblique tracks, particularly visible within the seagrass meadow.

The final map of marine habitats – using backscatter and BATCLAS values, manual editing and ground truth data – clearly showed the limit of the *P. oceanica* meadow as well as the artificial reefs nearby and the flat hard substrate (Fig. 6). The latter habitat surfaces were delineated using the backscatter data while rocky substrates and artificial structures, i.e. anti-trawling reefs, production reefs and the P38 Lightning wreck (a crashed aircraft from World War Two), were detected with the BATCLAS index and classified according to ground truth, just like the *P. oceanica* meadow. It is important to note that polygons of an area under 10 m^2 were erased to reduce acquisition noise and remove falsely classified pixels. In this process, several small anti-trawling reefs disappeared from the final map while being previously detected on ground truth and BATCLAS data.

4. Discussion

The BATCLAS index combined with backscatter data proved to be an efficient base to map Mediterranean marine habitats. Moreover, the pixel-based classification directed by a decision tree allows a fast treatment of acoustic data to produce a map of marine habitats. The new technique, however, can be improved at different steps of the process (acoustic data acquisition and treatment, automatisation of the PB classification). This first study also open new opportunities to obtain key data on the structure of marine habitats in terms of conservation and management of the coastal areas.

4.1. BATCLAS: advantages and operability

Indices similar to BATCLAS have been previously used to map marine habitats and substrates such as the Bathymetric Position Index (BPI) [13,15,29]. Although the BPI and BATCLAS both describe the elevation of the seafloor, several key disparities separate them in terms of calculation and interpretation. The first difference lies in the data format used for the computation. BATCLAS is calculated in the GIS ViewSMF using the raw bathymetric data (cleaned from false echoes) of the MBES, while the BPI is computed on the DEM [16,39]. From this divergence ensues a higher resolution of the rugosity maps generated with BATCLAS due to the high density of bathymetric soundings available on the raw acoustic data and so, the high density of rugosity index computed on each usable sounding. Thus, BATCLAS allows to detect smaller underwater structures than the BPI (e.g. rocky and artificial reefs, seagrass patches and wrecks). The second disparity is the unit of the two indices: the BPI has no unit and is dimensionless [13] while BATCLAS is expressed in metres [1]. This leads to

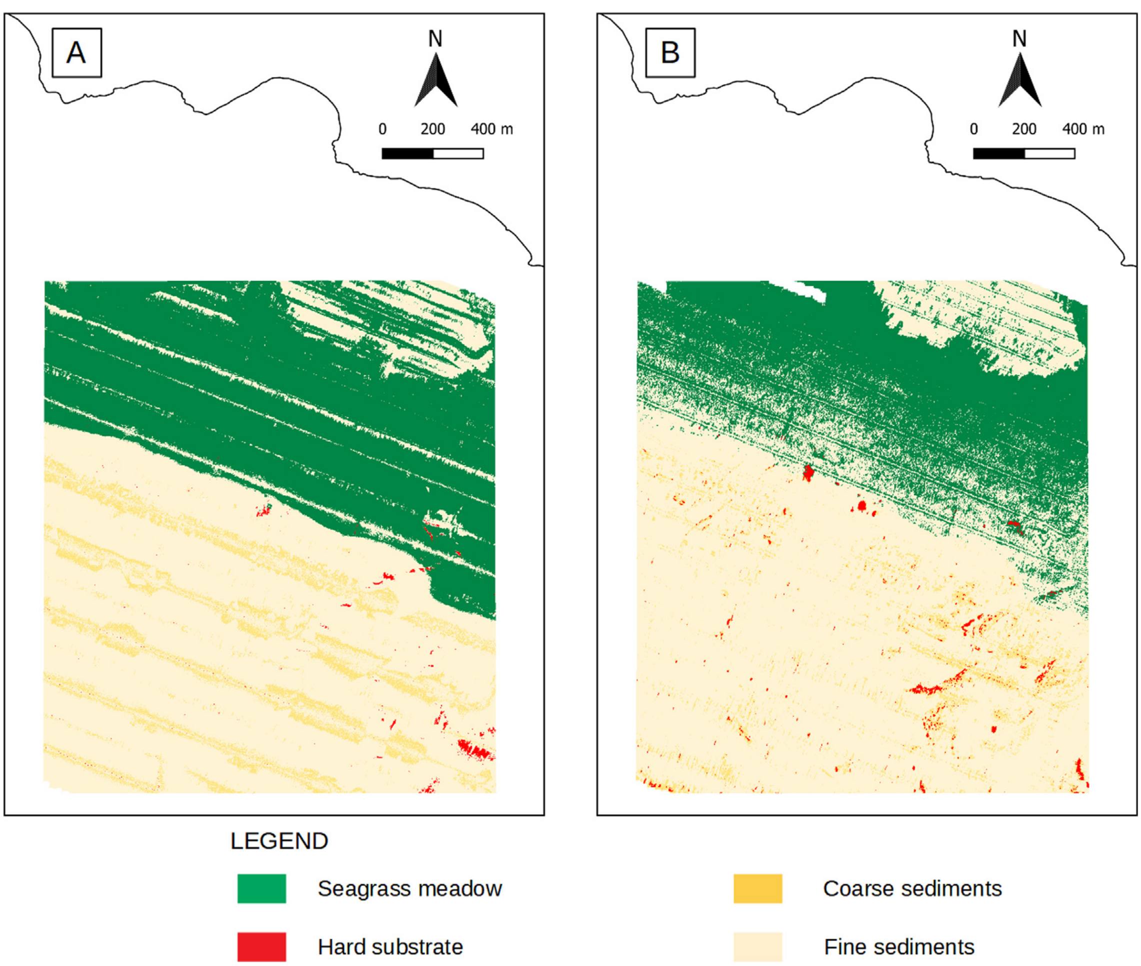

Fig. 5. Seafloor classification with a decision tree using: (A) Backscatter data alone; (B) BATCLAS index value alone.

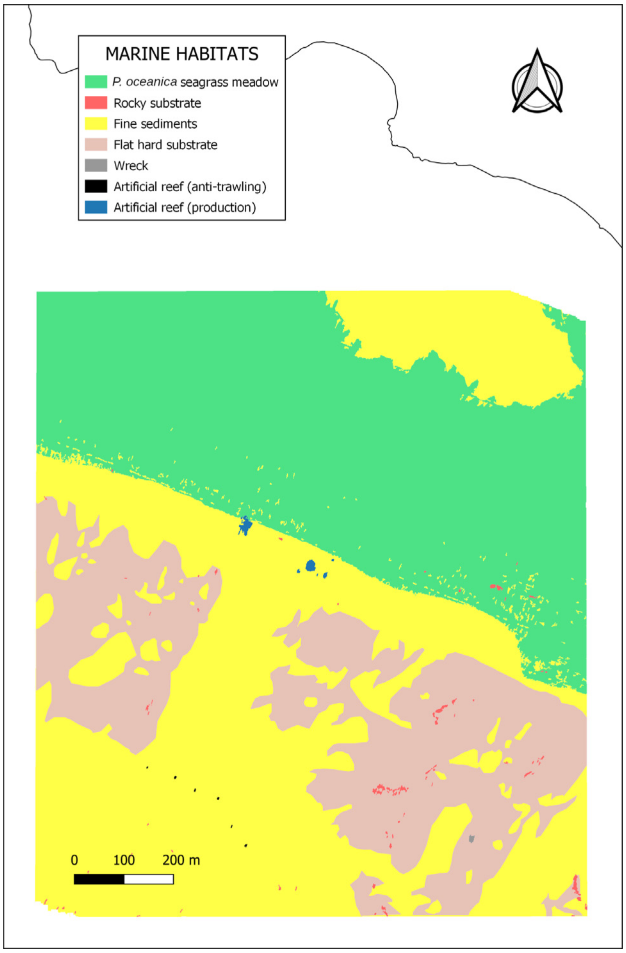

Fig. 6. Final map of marine habitats using both backscatter and BATCLAS values as well as manual editing and ground truth.

the difficulty to compare the BPI values between different datasets, whilst the values of BATCLAS can be used on different sites to map the seafloor with decision tree and can be confronted too. Furthermore, BATCLAS provides a more intuitive comprehension of the geomorphology of the seabed and can be understood by non-specialists in underwater mapping and bathymetric indices such as stakeholders.

As mentioned in the previous paragraph, BATCLAS is calculated directly with the cleaned raw data of the sounder. This data sorting has a high impact on the quality of the rugosity values. The quality of the rugosity maps generated is thus strongly linked with the one of the acquisition parameters, such as the width of the sector. Using regularly the same MBES let us accept that many outlier echoes appear at both extremities of the MBES swath when its sector is maximum (160°). Furthermore, it is well known that the bathymetric information is deteriorated in grazing angles, especially since the beam resolution is low [8] , enough for affecting the residuals in a way that the result could not reflect a known value anymore. That is why, we advise to use a lower swath sector of 120° max for future survey, or else to not compute the rugosity index beyond this angle. Although increasing the acquisition duration, it will consequently reduce the time of data treatment as well as improve the quality of the PB classification process. It is important to note that a proper refraction correction of the sounder's beams was performed using sound velocity profiles [41] . However, we observed in previous campaigns that a lack of correction of the sound refraction leads to noise at the extremities of the MBES swath on BATCLAS maps. This issue is obvious and easy to avoid since BATCLAS is directly computed from the bathymetric data.

In the method description, we use some hyper parameters like the max angle sector or the minimal number of neighbours or the with of neighbourhood. They were fix empirically according to our experience and to the MBES, but this does not eliminate the possibility to try other values and to adapt them to another MBES. Finally, we choose to apply a linear regression to each situation because considering the meter order neighbourhood and the application (marine habitats like seagrass). But perhaps, with a larger neighbour or application on sand ripples (for example), a parametric or quadratic regression would be more appreciate than a linear one.

In the present study the BATCLAS index showed its capacity to provide resolution maps of the seafloor rugosity up to 50 m depth. To this day we used this index to map coralligenous reefs up to 120 m depth in Corsica (unpublished data). Although the range of the MBES used in this study allows to obtain bathymetric data up to 400 m depth, the increase of depth goes along with a decrease of the resolution of the bathymetric data as well as the imaging data. It will lead to lower resolution rugosity maps using the BATCLAS index and thus a lower capacity to detect small "structures" at great depths. However, the number of soundings per ping (1024 for the R2SONIC 2022) and the high ping rate (60 Hz) allows to obtain a high density of soundings per square metre even at 100 m depth.

4.2. Classification process

The PB classification process requires "clean" data (i.e. bathymetry, backscatter, BATCLAS) to minimise at best manual editing and to ameliorate the generation efficiency of maps of marine habitats [10]) . We discussed earlier of several ways to improve the quality of the BATCLAS maps to use them in PB classification. However, backscatter data also requires a specific treatment to be rid of the noise band (Fig. 3b) resulting from the high angle of incidence of the beams at the nadir [17] . Although this noise band do not interfere for manual classification (Fig. 6), it produces erroneous detection of the seafloor nature when used in the PB classification (Fig. 5a) [19] . Two approaches are currently employed to tackle this issue: (1) erase the nadir artefact [10] , (2) correct the backscatter data using angle-varying gain [25] . The first solution results in a loss of information for the classification. The second one can be successfully applied for homogenous habitats such as sediments but may lead to erroneous classification for more complex assemblages like rocky bottom and patchy seagrass meadows. A third option, based on the first one, could be to define acquisition trajectories that cover the nadir, although this solution would increase the duration of data acquisition. With both BATCLAS and backscatter data "cleaned", it is then possible to use their values to build the decision tree and automatically generated maps of marine habitats with minimum errors and thus less manual editing.

Another lead to improve the PB classification would be to take into account other data sources such as aerial and satellite images. Indeed, the pixel information of panchromatic and multispectral photos are commonly used to map marine habitats in shallow marine areas with low turbidity [31,34] . The decision tree could thus integrate the information of pixel colours from panchromatic and multispectral aerial photos alongside the BI and BATCLAS for a better discrimination of shallow habitats.

4.3. The importance of precision in the study of marine habitats

Although the precision is a common source of inquiry in hydrographic and bathymetric measures, it is most of the time not a real source of concern for maps produced for biological and conservation purposes. It is especially verified in works dealing with *P. oceanica* seagrass meadows. It is important to have in mind that this plant, forming a key habitat of the Mediterranean Sea, has a very slow annual horizontal growth rate between 1 cm and 6 cm [27] . Thus, it is obvious the study of their spatial evolution through times requires a centimetre positioning precision. Such positioning accuracy can currently be reached by using a sensor with high coverage, mounted on the boat's hull – i.e. a MBES – coupled with a RTK GNSS. Over the past 15 years, several studies have mapped the coverage of seagrass meadows with a MBES, four of them being about *P. oceanica* meadows [14] . More works (13) over the last 45 years [14] were using towed SSS which – although having a high backscatter imaging resolution – have at best a metric positioning precision [3] . Currently, managers and stakeholders wish to use the data gathered along the past decades to compare the various maps of *P. oceanica* meadows to highlight the colonisation and regression of the plant [38] . However, it is evident that an accurate evaluation of these phenomena cannot be produced due to the precision disparities between the different studies.

A high positioning precision is also required to locate and study deep fragmented habitats such as small rocky blocks and artificial structures (just like the anti-trawling reefs of this study). More specifically, an accurate position of these substrates is mandatory for ground truthing and further underwater investigations [32] . In particular, precise ground truthing is the only way to discriminate the main habitat types and validate the presence of bio concretions in the study of coralligenous habitats [42] .

4.4. Contribution to the study of marine habitats

One of the main advantages of BATCLAS is its capacity to detect small sized underwater structures that are otherwise not taken into account by other mapping techniques. This is especially the case of small rocks that may be the substrate for a key habitat of the Mediterranean Sea supported by the coralligenous communities [11] . Nowadays, no direct acoustic method allows to detect coralligenous assemblages due to the hard consistency of the calcareous species at the base of these communities, which is indissociable from the rocks where they settle. Thus, the current mapping technique consists in the association of backscatter (from a MBES or a SSS), bathymetric data and ground truthing [32] . Although these three sources of information are suitable to detect large hard substrates, they are not able to highlight the presence of small rocky structures, some of them measuring few square metres. The use of BATCLAS to detect and map these small-scaled formations, possibly numerous, could lead to a revaluation of the area covered by coralligenous assemblages at the scale of the whole Mediterranean Basin.

The second potential contribution of BATCLAS in the study of marine habitats' structure concerns the evaluation of *P. oceanica* seagrass meadows' shoot density. *P. oceanica* shoot density decreases while the depth increases due to the lower light availability at the deepest extents of the meadows [9,12] . It is one of the bioindicators commonly used in management purpose to assess the ecological status of seagrass meadows [35] . As mention earlier a decrease of the BATCLAS index value was observed on a depth gradient at the level of the *P. oceanica* meadows (Fig. 3c). Although it is obvious that the rugosity index is not able to provide an account of the shoot number, it may provide a qualitative map of the variations of the meadow density (Fig. 7). Further investigation is required to link the value of the *P. oceanica* meadows shoot density with the one of the BATCLAS index. Eventually, after a calibration process, the meadow density will be available at a large spatial scale for management purpose and not only on discrete reference stations as it is currently measured.

5. Conclusion

The MBES is not solely used for bathymetric measurements any more. It is now commonly employed for the mapping of marine habitats due to the high precision and resolution of the data produced. The new automated processes of data treatment improve the effectiveness of the mapping operation and increase the objectivity the classification of the seafloor. The BATCLAS index demonstrated its capacity to provide spatial information on key Mediterranean habitats that are at the centre of managers and stakeholders concerns. It is thus able to detect hard substrates favourable for the development of coralligenous communities as well as to map the structure of *P. oceanica* meadows.

In parallel to the research effort on the seafloor classification, recent technical development on the MBES hardware and the software allows to provide both the map of marine habitats and the detection of fish schools in the water column [21,33] . This new three-dimensional way to display and analyse acoustic data is expected to bring to managers an intuitive way to use spatial data for the conservation of coastal areas and fishery stocks. It will also give means to perform an ecosystem-based evaluation of the marine environment with spatial data, in contrary to current approach that mainly relies on discrete measurements.

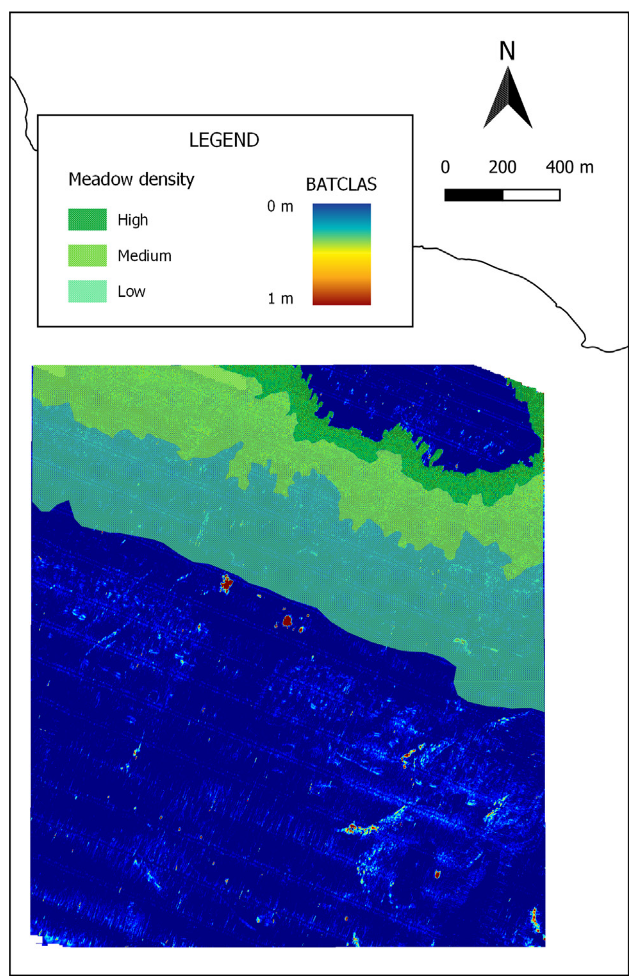

Fig. 7. Qualitative map of the *P. oceanica* meadow's density according to the value of the BATCLAS index.

CRediT authorship contribution statement

Christophe Viala: Conceptualization, Methodology, Software, Supervision. **Marie Lamouret:** Writing - original draft, Writing - review & editing. **Arnaud Abadie:** Data curation, Writing - original draft, 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.

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