Title (English): Comparison of supervised and unsupervised automatic classification methods for sediment types mapping using multibeam echosounder and grab sampling

Title (Italian):

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Abstract

Multibeam echosounder (MBES) systems are effective seabed mapping tools due to their simultaneous bathymetry and backscatter data acquisition. The acoustic response of the seafloor can be used to infer some of the physical characteristics of the sediment. However, further development and formalization of the methodology is still required. This investigation evaluates the ability to perform an automatic classification of sediment types with MBES data by using both unsupervised and supervised (with *in situ* sediment samples) digital image classification algorithms.

The case-study focussed on an area near the Basque coast, northern Spain (SE Bay of Biscay). The seafloor morphological aspects were calculated from a digital elevation model derived from datasets acquired with a SeaBat 7125 MBES, while the backscatter information was recorded with an EM3002D MBES. The parameters considered for the automatic classification were seabed rugosity, slope, backscatter amplitude mean level and backscatter variance. A total of 58 sediment grab samples were used for supervised automatic classification training and validation.

Results showed that supervised classification obtained higher precision than the unsupervised classification (76.9% and 30.8%, respectively) and higher reliability (0.7 and 0.2, respectively). According to these results, the unsupervised classification could be considered useful as a first estimate of the spatial distribution of seafloor types, but should only be used in studies where *in situ* samples are not available. In contrast, supervised classification demonstrated its ability to discriminate more sedimentary facies than the unsupervised classification and was especially effective in areas where the seabed displayed heterogeneous features and multiple sediment types. The result of this investigation confirms the potential of MBES and automatic classification algorithms for the production of classified maps of sedimentary types, with sufficient reliability for different applications, including management purposes.

Keywords: Multibeam echosounder, acoustic backscatter, automatic classification, sediment characteristics.

Riassunto and parole chiave

1. Introduction

During the last decades, the intensity and diversification of the exploitation of living and non-living resources in seas and oceans has increased significantly. For the management of these limited natural resources, the availability of thematic seabed maps is of high strategic interest. This need for detailed information regarding depth, seafloor features and seafloor types distribution, motivated the development of a wide range of techniques, with an emphasis on remote hydro-acoustic techniques. Nevertheless, the morphological distribution patterns and sedimentologic features of the seafloor is usually very complex. It is particularly difficult to achieve high reliability in the mapping of continuous variables (e.g. grain size distribution), and the conclusions derived solely based on *in situ* samples (i.e. grab and cores) can result in a misunderstanding of the spatial scales of the distribution of the characteristics of the seabed (Ellingsen, 2002). For this reason, the research on hydro-acoustic techniques focuses on the improvement of the accuracy and resolution of the obtained data, in order to achieve maximum detail and subsequently unravel the complexity of the seabed. In particular, the development of multibeam echosounder (MBES) systems allowed the collection simultaneously of detailed depth and reflectivity data with a comprehensive acoustic coverage (Hughes-Clarke *et alii*, 1996; Kenny, 2003). Therefore, MBES is an excellent seabed mapping tool (Brown & Blondel, 2009a).

Conventionally, the identification and interpretation of seafloor types and of morphological features using hydro-acoustic data, are accomplished with the input of expert human judgement. To facilitate the analysis of data from large areas, several methods for automatic classification of bottom types have been developed (Rooper & Zimmermann, 2007; Rzhanov *et alii*, 2012; Simons & Snellen, 2009; van Walree *et alii*, 2005). These techniques were designed to allow a faster and more objective processing. Several automatic classification algorithms have been applied to characterize the substrates based on seafloor bathymetry and backscatter data (Brown *et alii*, 2011; Che Hasan *et alii*, 2012; Fonseca & Mayer, 2007; Ierodiaconou *et alii*, 2011; Lamarche *et alii*, 2011; Stephens & Diesing, 2014). Moreover, these methods have also demonstrated great potential to predict benthic habitats and communities (Brown & Blondel, 2009b; Cutter Jr *et alii*, 2003; Herzfeld & Higginson, 1996; Lucieer & Lucieer, 2009; Lüdtke *et alii*, 2012). Although automatic methods have demonstrated high potential to segment the acoustic reflectivity in similar regions, they have not been fully accepted by the scientific community as a tool to produce systematic and reliable maps (Brown *et alii*, 2011). The numerous sources of error and uncertainty when using automatic classification algorithms affect the final classification accuracy. Among the most important sources of uncertainty, Ierodiaconou et alii. (2011) highlighted: the proper classification method employed; the quality of MBES records; the quality of the data used in defining classes of bottom types (or habitats); the adequacy of seafloor variables to define classes (e.g. slope, rugosity, reflectivity); the ability to integrate observations and hydro-acoustic data; and the complexity in setting the boundaries for defining classes to categorise the seafloor.

The objective set out in this research was to compare automatic methods of supervised and unsupervised classification, based on MBES records and sediment samples from an experimental area, and to establish which of both, unsupervised or supervised classification algorithms, provides the most reliable map of sediment type; in other words, analyse whether the incorporation of information from sediment samples in the process of automatic classification improves the accuracy and reliability of the resulting sediment type distribution map.

2. Material and methods

2.1. Regional setting

The study area was located in the SE Bay of Biscay (northern Spain) and covers an area of 0.32 km^2 (Figure 1). The seabed in this sector shows a high morphological diversity. The interaction of tectonic activity, basement topography and sea-level changes, together with processes of sediment supply and prevailing climatic conditions (Galparsoro *et alii*, 2010) have a critical influence on the configuration of the continental shelf seascapes and the distribution of seafloor material. In particular, strong NW swell waves dominate and are the most common sea state within the study area (González *et alii*, 2004). Under extreme offshore wave conditions, significant wave heights can exceed 5 m (several times a year) and, occasionally, 10 m (with return periods of 20 years) (Liria *et alii*, 2009). Thus, sediment dynamics are produced by wave dominated processes, which in turn, are responsible of the transport and shaping of the sandbanks.

In particular, the study area is characterised by a shallow rocky belt extending from the coastline up to 35-40 m depth and the presence of a paleo-channel. Sedimentary seabed extends from 35-40 m up to 80 m depth and it is characterised by the diversity of sediment types; from coarse sands up to fine mud (Figure 1). Several bedforms, such as sorted bedforms and mega-ripple fields, reflect the sediment dynamics produced by the action of currents and waves on the seafloor in this sector (Galparsoro *et alii*, 2010). The morphology of the seabed indicates that the influence of wave action reaches down to 50 m depth. In the southeast, the presence of marks of dredged material disposal was also identified.

2.2. Data sets

2.2.1. Bathymetry and backscatter information

Two surveys were conducted with two different MBES. Surveys were carried out in June 2011 within two weeks time in order to guarantee the same seafloor conditions. The morphological aspects were derived from a digital elevation model produced from SeaBat 7125 MBES records. This MBES operates at 400 kHz, producing 256 beams in a 128º angle swath and using up to 50 swaths per second. The beam width is 0.5º along-track and 1º across-track, producing very small footprints (for more details see Galparsoro, et alii., (2009)). The MBES was coupled with an Agp132 (TRIMBLE) global position system, receiving differential corrections. An OCTANS III (IXSEA) gyrocompass and motion sensor was utilised, to compensate for the movement of the vessel. Furthermore, a portable SVP 15 (RESON) was used, to measure sound velocity profiles throughout the entire water column every two hours during the survey. The software package PDS2000 was used to integrate the MBES data, with the information from all the auxiliary sensors during the surveys—data acquisition and synchronization. This software was used in real-time, as well as in the post-processing of the integrated data. Tidal correction was applied using records from a tide gauge located at Bilbao harbour and 1m resolution seafloor Digital Elevation Model (DEM) was produced in projected coordinate UTM, Zone 30 N (WGS84).

The backscatter data was recorded with a Kongsberg Simrad EM 3002D MBES. The system uses two angle mounted sonar heads, producing a total of 508 individual beams with a maximum swath width of 200º. The opening angle of each beam is 1.5º and the pulse length is 150µs. The sound frequency was set to 300 kHz. The MBES was interfaced with a Thales Aquarius GPS, receiving differential corrections. The data were corrected in real-time, for roll, pitch and heave, using a Seatex MRU5 motion sensor and, for heading, using an Anschütz Standard 20 gyrocompas. Two sound velocity profiles were measured with a "Sea-Bird" SBE19 (Seacat) STD system before and after the survey. A fixed Valeport mini SVS probe installed next to the starboard antenna was used to measure continuously the sound velocity values at the transducer. The acquisition software SIS from Kongsberg was used to integrate the MBES data, with the data from the auxiliary sensors. The data were post-processed with Kongsberg Neptune for the bathymetry. Tidal correction was applied using the nearest tide gauge. DEM and backscatter mosaic were computed at 1 m resolution in projected coordinate UTM, Zone 30 N (WGS84). Backscatter records were processed using the algorithm Geocoder, implemented in the Fledermaus software (Interactive Visualization Systems) (Fonseca & Mayer, 2007). Default processing parameters were chosen: adjusting (Tx/Rx power gain correction, beam pattern correction, no beam angle cut-off, use of the logged calibrated backscatter range) and filtering (flat Angle Varying Gain (AVG) correction with a window of 30).

2.2.2. Sediment samples

Sedimentologic characteristics were derived from 58 surficial grab samples corresponding to the period from 1994 up to 2011 (Galparsoro *et alii*, 2010) (see Figure 1 and Table 1). Sediment analysis was carried out using dry sieving method and Laser Diffraction Particle Size Analyser (LDPSA). In order to homogenise both data sets, a transformation was applied to the results obtained with LDPSA, to refer all data to the results obtained by dry sieving (Rodríguez & Uriarte, 2009).

2.2.3. Underwater images

Fourteen seafloor image recording locations were selected based on morphological features of the seabed derived from MBES data records and sedimentologic information derived from grab samples (see Figure 1). Images were recorded with a Kongsberg Simrad OE14-112 (PAL; Horizontal Resolution 460 TV Lines) installed in a still frame and georeferred with a DGPS. These were used for the subsequent visual interpretation of the classification of sedimentary types obtained by automatic classification.

2.3. Seafloor classification

2.3.1. Sediment classes definition

The definition of the sediment classes was based on sediment grain size (Blott & Pye (2001), Udden (1914) and Wentworth (1922)). The defined classes were: (1) Coarse and very coarse sand (CS and VCS) (-1-to 1phi; 500µm-2mm); (2) Medium sands (MS) (1-2phi, 250-500µm); (3) Fine sand (FS) (2-3phi, 125-250µm); and (4) Very fine sand (VFS) (3-4phi; 63 - 125µm). Coarse and very coarse sands classes were grouped into a one single class due to the limited number of samples for these classes. Thus, the total number of samples for each sedimentary class were: CS and VCS = 13; MS = 7; FS = 28; and VFS = 10.

On the other hand, the seabed morphological and backscatter variables (derived from MBES) considered for the automatic classification were : (1) depth; (2) backscatter amplitude; (3) slope; (4) texture (derived from the analysis of variance of backscatter); and (5) seabed rugosity. Rugosity was calculated as a measure of terrain complexity, defined as the ratio of surface area to planar area. It was calculated using ArcGIS extension Benthic Terrain Modeler (BTM), Version 1.0 (Wright *et alii*, 2005). Those information layers were standardized to a pixel size of 5 meters and the variables were re-scaled to values between 0 and 100. All outliers were removed by conditional expressions to avoid their participation in the classification process.

2.3.2. Automatic classifications

A non-supervised classification applying the Isodata method (Ball & Hall, 1965) was conducted using (ArcGIS 9.3). This is an iterative automatic classification algorithm based on the minimum spectral distance function (Iterative Self-Organizing Data Analysis Technique). This classification method does not require sediment samples, but is based on the definition of spectral classes present in the image. Classification of bottom types is based on the grouping of areas with similar characteristics (Chuvieco & Congalton, 1988). The maximum number of iterations for the process was set at 15 and a convergence threshold of 0.95 was established. This threshold defines the maximum percentage of pixels that are kept together in the same class and does not vary between iterations.

Secondly, Maximum Likelihood was used as the digital supervised classification algorithm (Chuvieco & Congalton, 1988) implemented in ArcGIS. This method requires some prior knowledge of the study area. For this research, reference sediment types (or classes of seabed) defined by the characteristics of grain size of the sediment samples, were used as observed data. Before the automatic classification, 80% of all sediment samples were reserved for the training and classification process (i.e. 46 samples) and the remaining 20% were reserved for validation (i.e. 12 samples); this division was conducted randomly. For each class of seabed, the statistical signature was calculated. This signature describes the seabed morphological characteristics and acoustic response of each class. The statistical signatures were used to apply the classification on the entire study area. Finally, the classified image obtained with the maximum likelihood algorithm was rendered applying a majority filter (in ArcGIS 9.3 software) to replace outlaying cells based on the majority of their eight contiguous neighbouring cells.

An accuracy assessment from each classification technique was established with the calculation of the producer accuracy (PA) and user accuracy (UA); for the total classification, and for each of the classes (Stehman, 1997). The values of producer and user accuracy were calculated as a percentage. In terms of overall accuracy, the average accuracy of the producer (the average of all the points of the producer) and the average accuracy of the user (the average of all the points of the user) were used. Furthermore, the validity of the overall classification and for each of the sedimentary types, was expressed with the Kappa statistic (*k*) (Stehman, 1997). The possible values for k range between 0 and 1, with the values closer to 1 reflecting the greater confidence in the classification.

3. Results

For each sediment type class considered in this study, the morphological and acoustic response extracted from the information layer used in the analysis is given in Table 2. Our results show that the backscatter amplitude values increased as grain size defining the sediment type increase, except for FS, which showed the lower value. In terms of slope, CS-VCS was collected on the steepest seafloor and the FS, the flattest. VFS and MS showed similar slope values. CS-VCS, MS and VFS showed the lower texture values; meanwhile the FS showed the highest. Finally, no differences were found on the rugosity of the seafloor.

The first run of the unsupervised classification, executed considering all information layers, resulted in a total classification accuracy of 15.38% and a validity (*k*) value of 0.16 (Figure 2). The resulting map did not reflect the spatial distribution of the characteristics of the seabed observed on the backscatter records (Figure 1), especially for the sorted bedform area where the coarser sediments were located. The bathymetry probably biased the classification because depth showed a higher percentage of the variance than the rest of the layers, and as a consequence impeded the input from other information. For this reason, the depth information was removed for subsequent analysis on unsupervised and supervised classifications. By doing that, the validation results obtained showed a significant improvement, with a total classification accuracy of 30.77% and 76.92% for unsupervised and supervised classifications, respectively (Table 3). Results obtained for each sediment class indicate that unsupervised classification was not able to classify VCS-CS and MS sediment classes, and most of the pixels were classified as being FS and VFS, which was incorrect. In contrast, supervised classification performed better for all sediment classes. For three of the sediment classes (i.e. VCS-CS, MS and VFS), all the ground-truthing samples were classified correctly. The classification performed worse when classifying CS-VCS pixels. Similar pattern was observed for the validity of the classification. Total validity values (*k*) resulted in 0.19 and 0.66, for unsupervised and supervised classifications, respectively (Table 4). For all sediment classes, supervised classification obtained better results, and only for FS, kappa value was similar for both classifications.

The sediment classes distribution maps (Figure 3) and areas (Table 5), derived from the unsupervised and supervised automatic classification methods, show a similar sediment classes distribution pattern and areas. Main difference was that supervised classification assigned higher areas for VCS-CS and FS; and lower areas for MS and VFS, than unsupervised classification. A sandy patch surrounded by fine sand was identified by the supervised classification while the unsupervised classification was not able to discriminate it (Figure 3). Thus, the supervised classification discriminated more facies in areas with more irregular morphology, and therefore, the capacity of identification of higher diversity of sediments deposits.

The results of both classifications were corroborated by the images of the seafloor obtained by underwater video (Figure 4). Differences in the content of biogenic material (i.e. composition of shells in different parts of the study area) in the surface of the sediment could be observed, which in turn, have determined the mean grain size of sediment samples, the acoustic response and the final classification of the map. In areas of FS and MS bioturbation marks could also be observed; meanwhile, in areas of VFS, which is distributed up to 50-55m depth, ripple marks produced by wave action are identifiable.

4. Discussion

The ongoing trend toward high resolution MBES has great potential for significant advances in mapping and characterization of bottom types to better improve our understanding about seafloor ecosystems (e.g. Brown et alli., (2011)). The present research has shown that the information obtained by MBES is especially useful in the process of classification of bottom types (Bellec *et alii*, 2009; Brown *et alii*, 2011; Che Hasan *et alii*, 2012; Rzhanov *et alii*, 2012). In general, our results are consistent with those studies, which concluded that the low reflectivity normally corresponds to the "soft" seabed (silt and fine sand) and high reflectivity with the "hard" sediments (gravel, stones or rock), while the sands and shells have average reflectivity values.

The first unsupervised classification (Figure 2) resulted in a very low accuracy and reliability of the sediment type distribution. The results indicated that the bathymetry produced interference during the process of automatic classification, due to the higher weight of the bathymetry layer in the overall variance that biased the result. The classification did not consider the input of the other characteristics of the seabed (i.e. backscatter, slope) and resulted in a simple representation of depth ranges. While it is generally accepted that grain size decreases and mud content increases with increasing depth, this assumption may only be valid at large scale and depth ranges. On a smaller spatial scale or in places with complex hydrodynamic processes, such as this case study, this pattern of distribution of sediment may not be valid (see Table 2). The resulting map of sediment type distribution was incompatible with structures that were previously identified from MBES interpretation and expert judgement. For this reason, the digital elevation model was omitted in subsequent classification processes.

The accuracy of the supervised digital classification (Maximum Likelihood algorithm) and reliability were both significantly better. The reliability value was the maximum for all the sediment types except for fine sand (Table 4) which lowered total value of kappa. Fine sand was the sediment type that presented the larger standard deviation for reflectivity and other parameters used for classification (Table 2). A discrepancy between the real distribution of sediment types and their representation in the samples, or an incorrect definition of the classes of sediment type could explain this pattern.

Another observation was the "noise" in the resulting map obtained from the supervised classification (Figure 3b). This noise is identifiable as parallel stripes and it is the result of errors (artefacts) caused by insufficient compensation of the vessel accelerations during acquisition of bathymetric data. Therefore, it is an artefact drawn by the lower quality of the original data used for the extraction of morphological characteristics of the seabed. This phenomenon, however, is less evident in the result of the unsupervised classification (Figure 3a).

In terms of the relation between sediment type and reflectivity, it was observed that the fine sand, contrary to what might be expected, had a lower value of reflectivity than the very fine sand. This could in turn affect the final result of the automatic classification and thus, the reliability of the map. The content of mud, could be the reason of the acoustic response of the very fine sand. The possible effect of infauna communities on the acoustic response of the sediment should also be considered. In this regard, it is recommended for future research to use other sediment physical characteristics such as porosity, compaction or lithological composition and characterization of benthic communities.

It could be assumed that automatic classification methods may not have the same reliability as the classification derived from human interpretation and expert judgment, but it could be stated that the sediment type distribution maps obtained from automatic classification methods, show an acceptable accuracy and reliability for many research and management purposes. The main advantage of these automatic algorithms is that they allow processing of a much higher volumes of information in less time and in an objective way. Moreover, the resulting maps could be validated and their accuracy and reliability could be calculated. The resulting maps could contribute towards a better understanding of the complexity and irregularity of the seabed, particularly in sedimentary substrates, which is of great importance in the interpretation of sedimentary processes and distribution of communities and benthic habitats.

5. Conclusions

Seafloor thematic maps (i.e. seafloor types, sediment distribution maps) are essential source of information to assist in the knowledge of the spatial distribution of the living and non-living resources. Moreover, they are an important source of information to understand ecosystem processes that could be used for estimating the environmental impact that could be produced by human activities and the adoption of new spatially-based management measures. The results obtained in this research support the idea that the image-based classification of the seabed (i.e. morphological characteristics and acoustic response) shows considerable promise for the use of MBES data for the production of thematic maps. Moreover, periodical surveys of coastal areas could also be useful to determine the changes and evolution of the seabed; especially in areas hosting intense human activities that can cause physical changes as dredging processes, dredged material disposal, underwater infrastructure or fishing activity.

This research has demonstrated the ability to produce reliable sediment type distribution maps based on multibeam echo sounding data, sediment samples and automatic classification algorithms. The results show that the incorporation of information from field samples in the classification process (supervised classification) significantly improved the accuracy and reliability of the resulting seabed sediment classification. We conclude that unsupervised classification is valid for an initial approximation of the spatial distribution of bottom types or studies in which there is no *in situ* sedimentologic information available, but the results should be considered with caution because of the high dependence on the choice of variables.

The extraction of information on the characteristics of the seabed from geophysical parameters has great potential but needs further development of techniques to process data and further progress in the understanding of the relation between the acoustic response of seafloor and its physical and biological characteristics.

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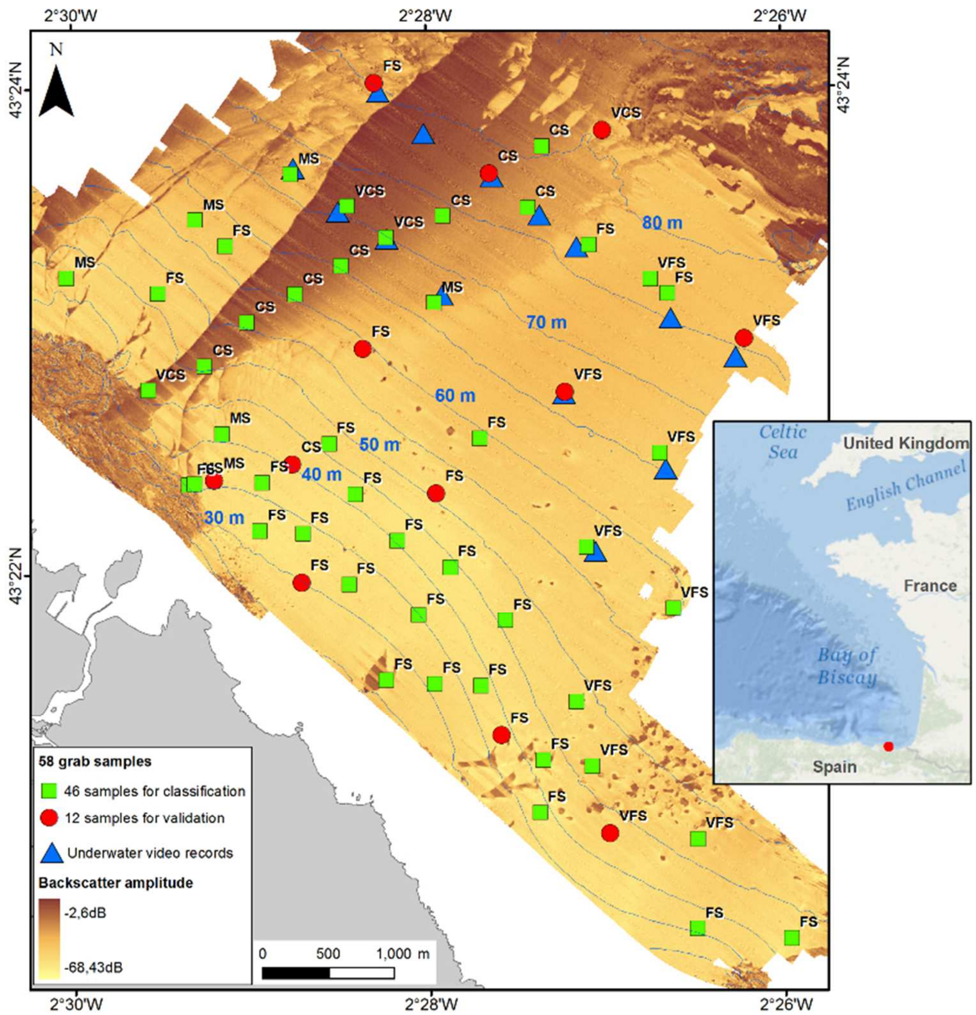

Figure 1. Study area location within the SE Bay of Biscay. Multibeam echosounder derived acoustic backscatter and the spatial distribution of sediment grab samples, classified into the ones used for the automatic classification process and the validation of the resulting classification, are shown (VCS: very coarse sand; CS: coarse sands; MS: medium sand; FS: fine sand; and VFS: very fine sand). Locations in which underwater videos where recorded are also represented.
71x73mm (300 x 300 DPI)

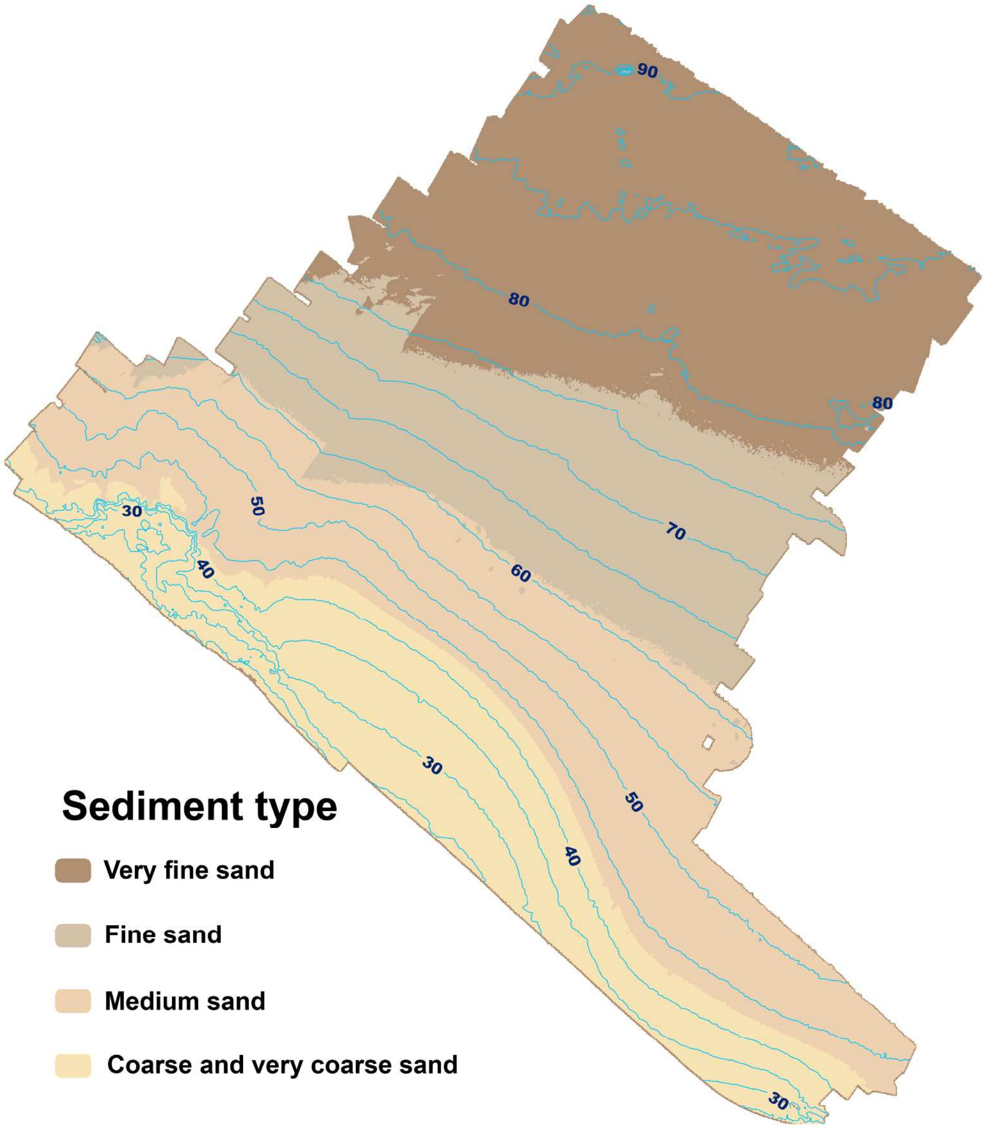

Figure 2. Sediment type distribution map resulting from the application of an unsupervised classification with bathymetry, backscatter amplitude, slope, texture and rugosity information layers. Total classification accuracy: 15.38% and a validity (k) value of 0.16. Interpretation of the result suggests a bathymetry biased classification.
414x476mm (220 x 220 DPI)

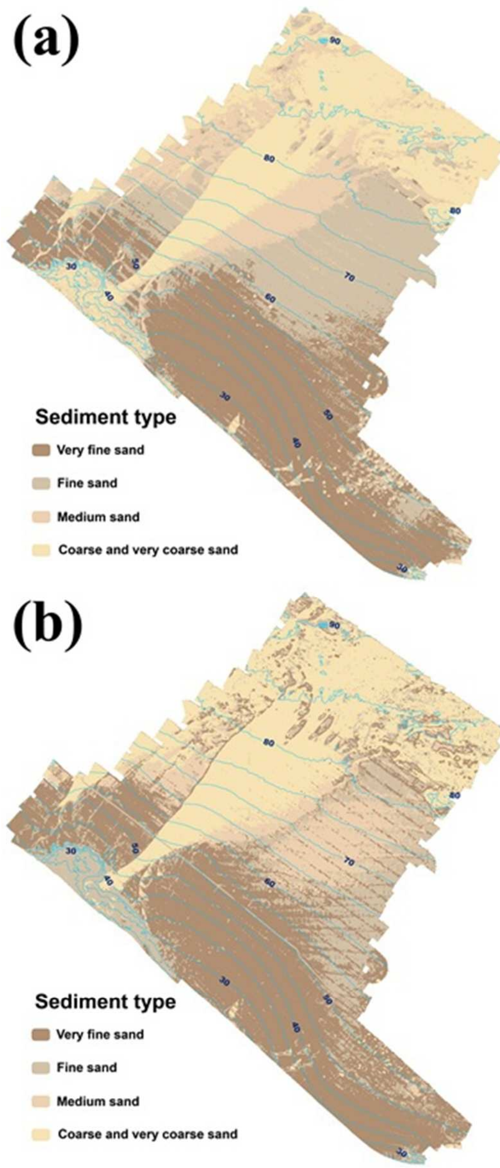

Figure 3. Sediment type distribution map resulting from the application of an unsupervised classification (a) and supervised classification (b) with backscatter amplitude, slope, texture and rugosity information layers.
30x71mm (300 x 300 DPI)

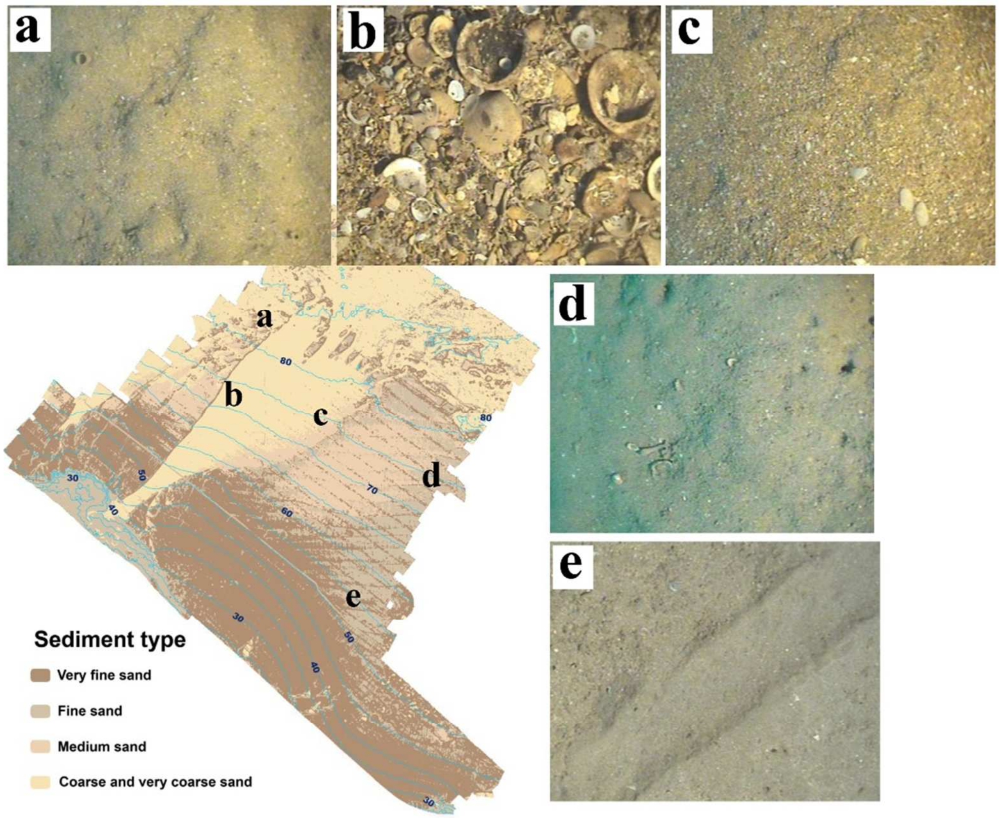

Figure 4. Sediment types distribution map obtained as a result of the supervised classification and underwater images of the surface of the seabed.
90x74mm (300 x 300 DPI)

Table 1. Sedimentologic characteristics of the grab samples. VCS: very coarse sand; CS: coarse sands; MS: medium sand; FS: fine sand; and VFS: very fine sand.

Sediment type	Nº of samples	Grain size (Phi)	Sorting	% gravel	% sand	% mud
VCS	4	-0,2±0,1	0,9±0,1	16,8±1,1	83,0±1,1	0,2±0,1
CS	9	0,3±0,3	0,8±0,1	7,6±2,7	92,1±2,8	0,4±0,4
MS	7	1,7±0,2	1,0±0,5	0,2±0,2	98,5±1,2	2,6±3,0
FS	28	2,6±0,3	0,8±0,3	0,9±1,1	92,1±4,8	7,0±4,7
VFS	10	3,3±0,3	0,8±0,1	0,9±0,6	79,2±12,7	19,9±12,0

Table 2. Number of samples, mean value and standard deviation for the variables and sediment classes considered in the classification process. CS-VCS: coarse and very coarse sand; MS: medium sand; FS: fine sand; and VFS: very fine sand.

Sediment class	Nº of samples	Depth (m)	Backscatter (dB)	Slope (%)	Texture	Rugosity
CS-VCS	13	-63,44±13,62	-22,82±3,92	39,24±7,58	3,72±4,35	1,00±0,00
MS	7	-49,49±15,31	-29,83±3,39	35,64±6,56	2,96±1,29	1,00±0,00
FS	28	-43,11±14,63	-32,05±2,29	31,71±10,46	4,66±4,38	1,00±0,00
VFS	10	-56,60±12,38	-30,07±2,93	34,78±9,49	3,03±3,10	1,00±0,00

Table 3. Validation results obtained for classified data using unsupervised and supervised classification methods. Total classification accuracies: 30.77% and 76.92%, respectively. PA: Producer Accuracy; UA: User Accuracy.

Class name (Sediment type)	Reference	Unsupervised classification				Supervised classification			
		Classified	Correctly classified	PA (%)	UA (%)	Classified	Correctly classified	PA (%)	UA (%)
VCS-CS	3	1	0	0.0	0.0	1	1	33.3	100
MS	1	0	0	-	-	1	2	100	100
FS	5	5	3	60.0	60.0	8	5	100	62.5
VFS	3	6	1	33.3	14.3	2	2	66.7	100
Total	**12**	**12**	**4**			**12**	**10**		

Table 4. Results obtained for the Kappa statistic (k) for unsupervised and supervised classifications.

Class name (Sediment type)	Unsupervised classification	Supervised classification
	Kappa	**Kappa**
VCS-CS	0.3	1.0
MS	0.0	1.0
FS	0.35	0.39
VFS	0.11	1.0
Total	**0.19**	**0.66**

Table 5. Number of pixels, % of assigned pixels and area assigned to each sediment type according to the unsupervised and supervised automatic classifications.

Class name (Sediment type)	Unsupevised classification			Supevised classification		
	Nº of pixels	% of assigned pixles	Area (km^2)	Nº of pixels	% of assigned pixles	Area (km^2)
VCS-CS	325579	25.3	8.1	362373	28.1	9.1
MS	205927	16.0	5.2	156890	12.2	3.9
FS	430859	33.5	10.8	513602	39.9	12.8
VFS	324907	25.2	8.1	254407	19.8	6.4
Total	**1287272**	**100**	**32.2**	**1287272**	**100**	**32.2**