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Objective automated classification technique for marine landscape mapping in submarine canyons

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ABSTRACT

This study proposes a fully automated and objective technique to map marine landscapes in submarine canyons. The method is suitable for broad and regional scale mapping derived from sonar data using multivariate statistical analysis. The method is divided into two main parts: the terrain analysis and the multivariate statistical analysis. The first part aims to optimise the sonar data and comprises three steps 1) data resampling, 2) determination of length scale, and 3) multiple scale analysis. The second part covers the actual marine landscape classification and consists of 1) principal component analysis (PCA), 2) K-means clustering, and 3) cluster determination. In addition, a confidence map is presented based on cluster membership derived from cluster distance in attribute space.

The technique was applied in the Lisbon–Setúbal and Cascais Canyons offshore Portugal. The area was classified into 6 marine landscapes that represent the geomorphological features present in submarine canyons. The main findings from the study are 1) the transferability of a tool from geomorphometric analysis – Estimation of Scale Parameter (ESP) – to detect the length scale of potential patterns in bathymetric grids; 2) multiple scale terrain analysis allows an appropriate discrimination of local and broad scale geomorphic features in marine landscape mapping; 3) the method not only delineates geomorphic seafloor features but also points out properties that might influence biodiversity in a complex terrain.

1. Introduction

Over the past decade, the ongoing effort to develop an efficient and reliable method to map and study benthic habitats in various environments has promoted the advancement of classification techniques in the habitat mapping community (Brown et al., 2011). Benthic habitats are physically distinct areas of seafloor that are associated with particular communities of plants and/or animals. Of those two components that structure a benthic habitat – the physical environment and the species community – it is often the detailed species information that is lacking during seafloor characterisation. General geophysical mapping is therefore commonly used as the basis for benthic habitat mapping. Advances in sonar technology now permit seafloor imaging with high resolution and wide coverage using a wide variety of instruments and systems of different frequencies and resolutions (Hayes and Gough, 2009; Hansen et al., 2011; Nakanishi and Hashimoto, 2011; Paull et al., 2013; Harris et al., 2014; Wynn et al., 2014). These data can be used to depict various seafloor geomorphic features and interpreted to provide potential habitats represented on a marine landscape map.

"Marine landscape" is a concept introduced originally by Roff and Taylor (2000), who developed a classification based on enduring geophysical features that reflect changes in biological community compositions. They emphasized the importance of identifying and conserving representative spaces or landscapes rather than preserving individual species. They produced a classification using geophysical features to identify representative and distinctive benthic habitats supporting different communities, which works as an ecological framework for marine conservation.

Based on this fundamental concept, the marine landscape in this study is defined as an environment distinguished by its abiotic characteristics with a potential to provide colonization ground for specific biological assemblages. This approach has been applied successfully in the marine realm, specifically in shallow water environments (Al-Hamdani et al., 2007; de Grosbois et al., 2008; Verfaillie et al., 2009; Kotilainen and Kaskela, 2011). On a global scale a similar approach was used to segment the ocean floor based on a multivariate analysis of biophysical data by Harris and Whiteway (2009).

Although the aim of the studies mentioned above is similar, i.e., to classify the seabed in relation to its biological association, either for managerial purposes or to predict biological occurrences, each study offers a different methodology. The methods vary from the conventional

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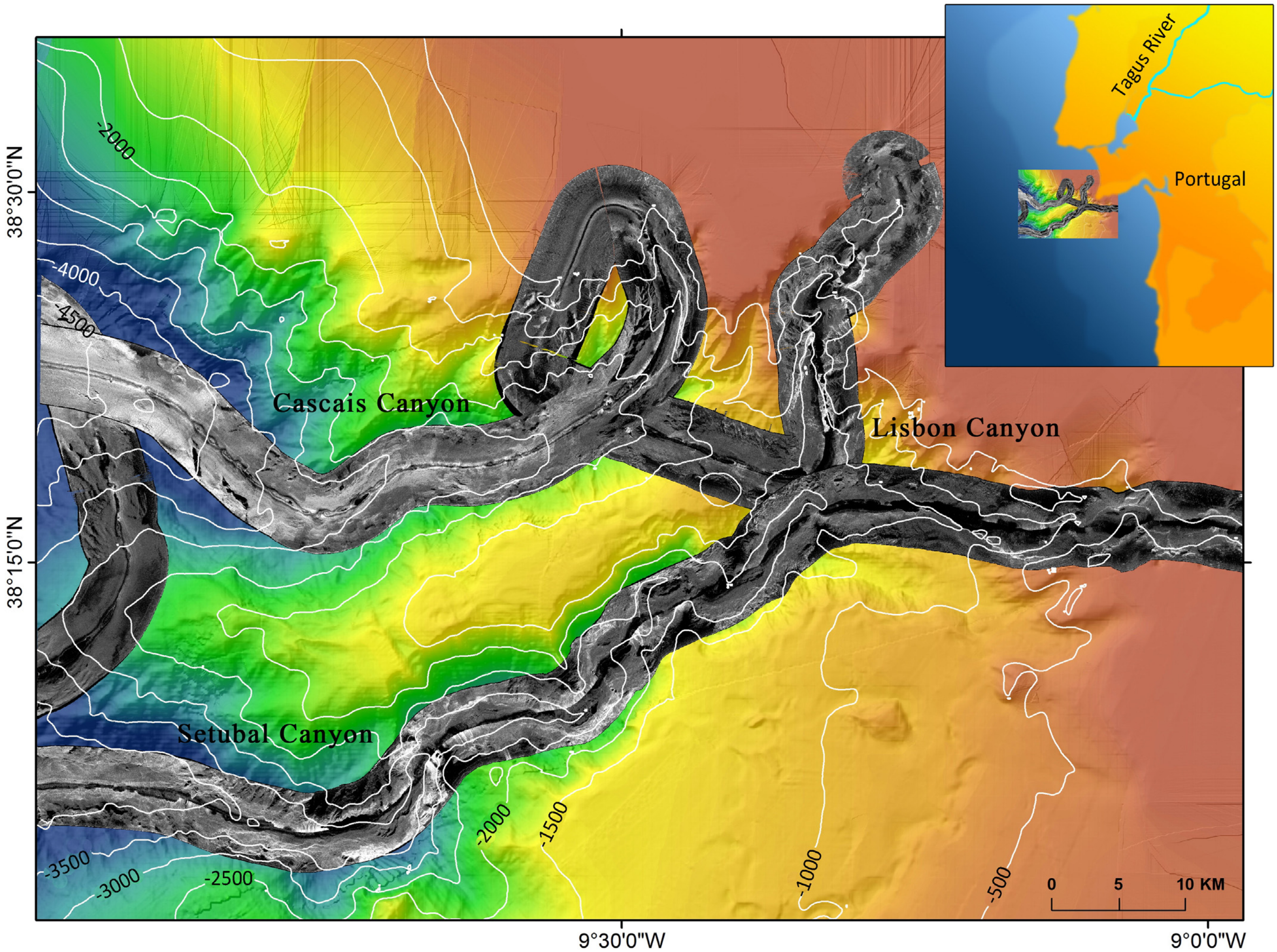


Fig. 1. Bathymetry map of Lisbon–Setúbal and Cascais Canyons offshore Portugal, overlain by TOBI sidescan sonar imagery coverage. Contour interval is 500 m. The inset map shows the location of the study area relative to the location of Portugal.

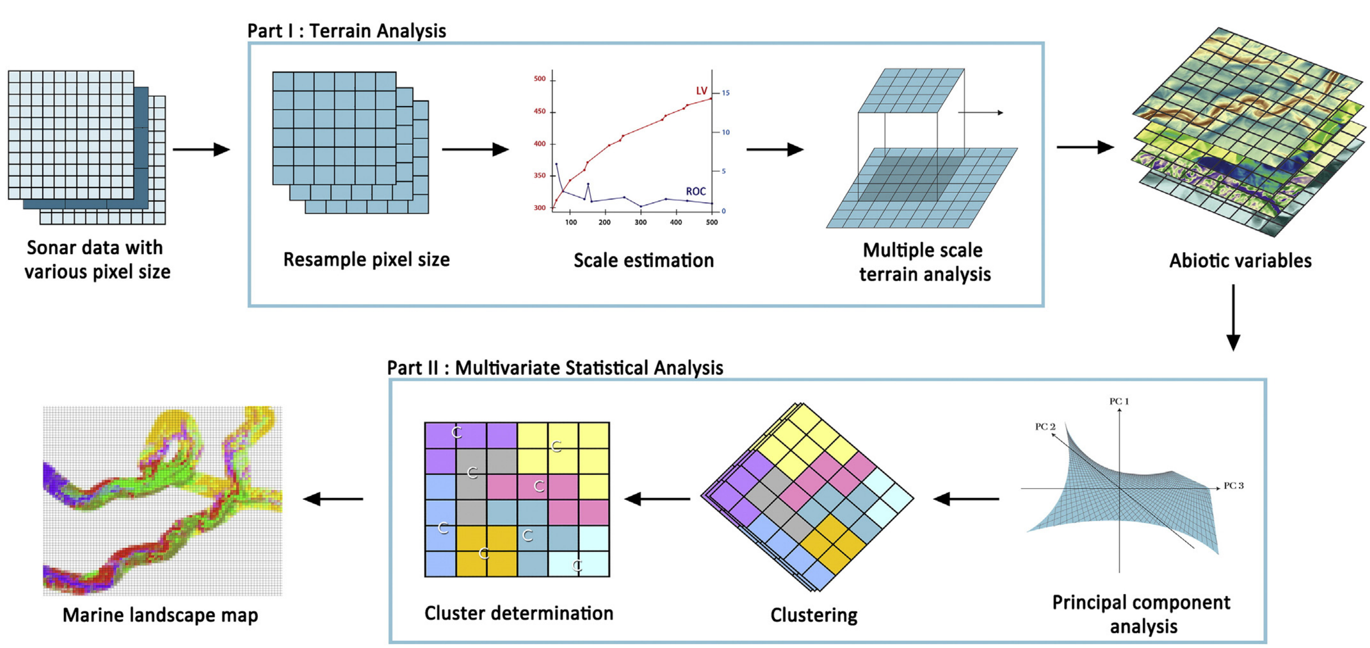


Fig. 2. A simplified flow chart of the automated and objective techniques used to produce marine landscape maps for submarine canyons. The method consists of two parts; terrain analysis and multivariate statistical analysis.

Table 1
List of abiotic variables included in the principal component analysis.

Abiotic variable	Descriptions	Length scale	
		25 m	225 m
Digital terrain model (DTM) of bathymetry	Obtained from multibeam bathymetry survey. Represent depths of the ocean floor.	☑	
Slope	First derivatives of DTM. Represents the maximum rate of change in value from a cell to its neighbour	☑	☑
Aspect	First derivatives of DTM.		
Eastness = sin(aspect)	Describes the orientation of slope. Indices for eastness and northness provide continuous measure (−1 to +1)	☑	☑
Northness = cos(aspect)		☑	☑
Bathymetric position index (BPI)	Measures the elevation of each cells compared to the mean elevation of neighbouring cells (Weiss, 2001)	☑	☑
Fractal dimension	A derivative from DTM. Indicates the spatial variation in roughness	☑	☑
Feature extract	A third derivative of DTM. Classified the surface into 6 categories (pit, channel, pass, ridges, peaks and planar) based on slope tolerance and curvature tolerance value	☑	☑
Plan curvature	A second derivative of DTM. Provides the rate of change of aspect	☑	☑
Profile curvature	A second derivative of DTM. Provides the rate of change of gradient	☑	☑
Rugosity	A measure of small scale variations of the surface area across the neighbourhood of the central pixel (Jenness, 2004)	☑	
Sidescan sonar imagery	Obtained from Towed Ocean Bottom Instrument (TOBI). Sonar images are acquired by emitting continuous sonar pulses whilst moving, this returns with the image of the seafloor.	☑	
Ratio of sidescan sonar to synthetic imagery	Synthetic sidescan sonar imagery was produced by simulating the TOBI vehicle movement over the canyon bathymetry, and represents the sidescan backscatter components produced by the sloping terrain (Ismail, 2011). Ratio represents the lithological attribute of the imagery.	☑	

Ticked boxes indicate the available scale for the variables.

approach of manual digitising over algorithm-assisted digitising to fully automated techniques, or use combinations thereof. Unfortunately, most methods developed so far have subjective aspects in several stages of their application (e.g., the parameters to use, the number of classes, the scale). The ideal methodology should offer robust statistical ways to make these choices objectively. Moreover, with the current state of the art in acoustic technology, large volumes of data are commonly available, therefore a time- and labour-saving approach is preferable. A robust approach that is objective, repeatable and can speed up the delineation of marine landscape from acoustic or other remotely-sensed full coverage data is much needed.

1.1. Scope and aims

Taking the above arguments into account, the aim of this study is to develop a fully automated marine landscape mapping technique that is robust, objective and repeatable, based on remotely sensed acoustic survey data, using multivariate statistical analysis. The method is developed in submarine canyons because of their complex characteristics defined by their spatial structure that contains true three-dimensional morphology and terrain variability often supporting increased biodiversity. However, submarine canyons are difficult to quantify as they often overwhelm conventional mapping techniques. This aim will be addressed through the following objectives:

1. Evaluate and compare the effect of a single scale vs. multiple scale approach
2. Test the transferability of a method used in Object Based Image Analysis (OBIA) to detect the scale that best represents real-world objects in multibeam bathymetry data.
3. Evaluate the advantages of the proposed method in comparison to manual delineation for marine landscape mapping.

2. Materials and methods

2.1. Study area

Submarine canyons are important geological features incised in most continental margins of the world's oceans (Harris and Whiteway, 2011). They serve as conduits for the transport of large amounts of sediment and organic matter from continental shelves to the deep abyssal plains (Hickey et al., 1986; Puig and Palanques, 1998;

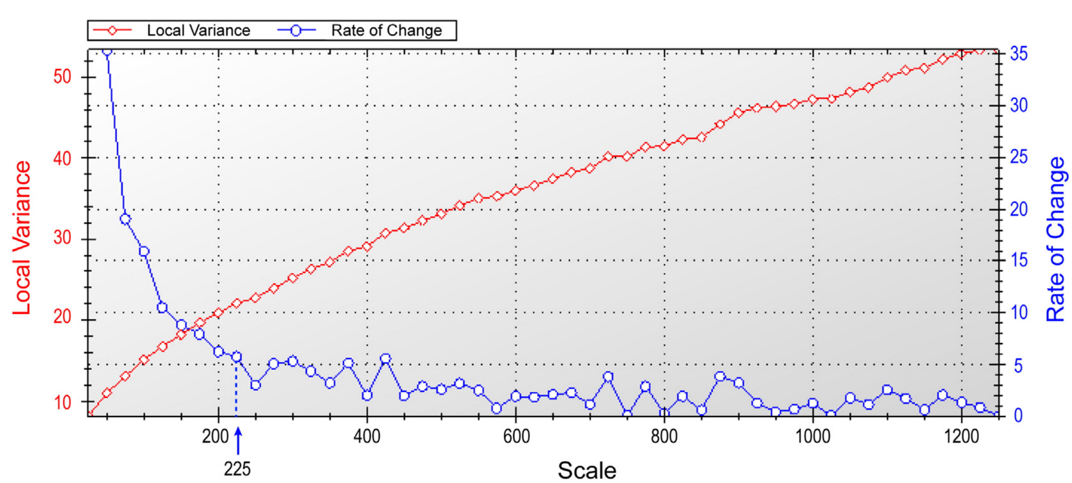


Fig. 3. ROC-LV graph obtained using the ESP tool to determine the most appropriate analysis window size for multiple scale terrain analysis. Blue arrow indicates the threshold at which the analysis window size best represents real-world objects. Dragut et al. (2010) defined the threshold as the first break in ROC-LV curve after continuous and abrupt decay. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

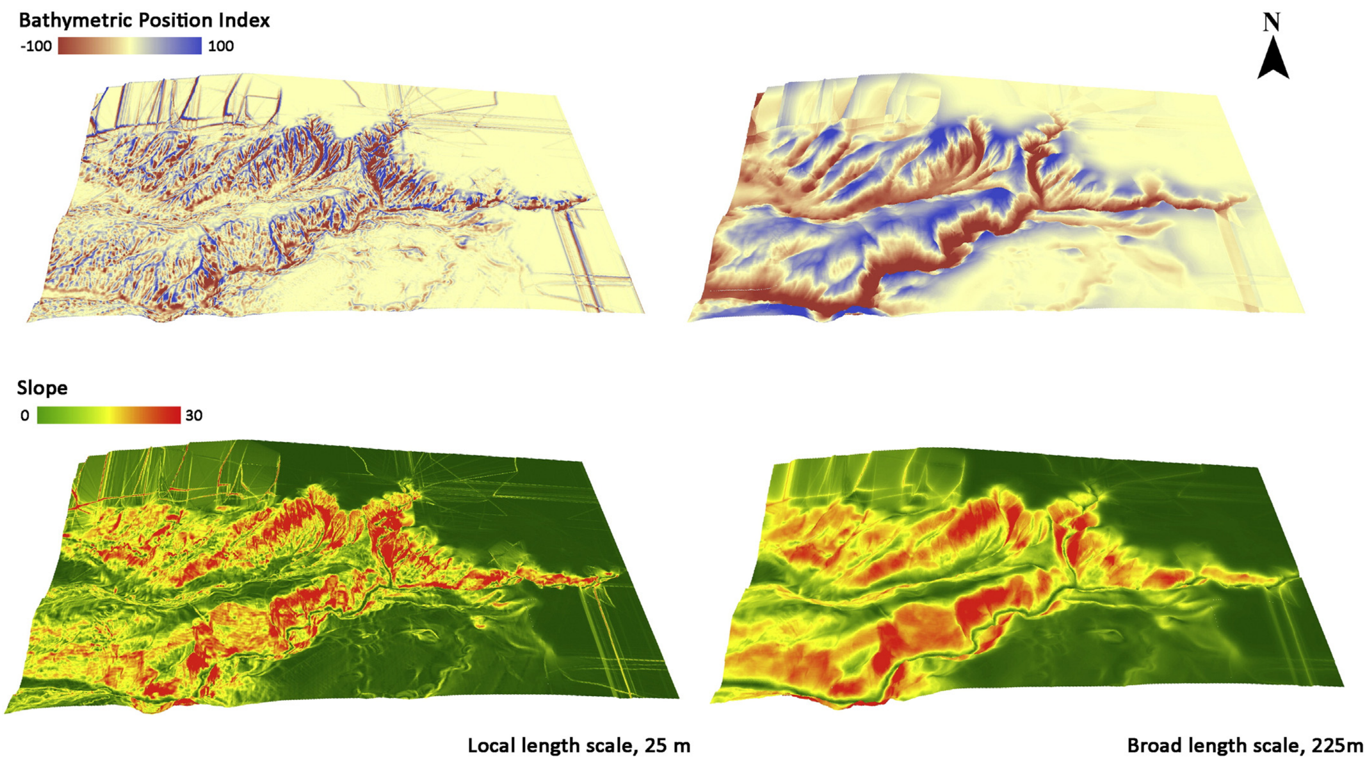


Fig. 4. 3D views of the Portuguese Canyons from south. The figure shows variations of bathymetric position index analysis (top) and slope analysis (bottom) resulting from using two different length scales. The local length scale is 25 m (initial pixel size) and broad length scale at 225 m. Note the different features delineated at the different analysis scales. Results from local length scale contained detail features but noisier whereas broader length scale shows the gross canyon morphology.

Monaco et al., 1999). The deep and complex topography, strong currents and occurrence of high turbidity promote a high variability of substrates and terrain, affecting the habitat heterogeneity and making submarine canyons a potential hotspot for biodiversity (Vetter and Dayton, 1998; Mortensen and Buhl-Mortensen, 2005; Tyler et al., 2009). Considerable interest in benthic habitats associated with submarine canyons (Tyler et al., 2009; Huvenne et al., 2012; Currie and Sorokin, 2014; De Leo et al., 2014), especially in vertical and overhanging terrains that occur at the heads of shelf-incising canyons, has been generated (Yoklavich et al., 2000; Brodeur, 2001; Huvenne et al., 2011; Johnson et al., 2013). Such terrains hold biologically diverse communities, but are especially difficult to map.

The Cascais and Lisbon–Setúbal Canyons that are the subject of this study, cut the western Portuguese continental margin between 38° and 38° 30′N (Fig. 1). Cascais Canyon begins at a water depth of 175 m at the shelf edge of the Portuguese margin. It is not connected directly to a river system but its head is situated 27 km southwest of the Tagus river mouth. It is the shortest canyon on the Central Portuguese

Table 2
Component matrix showing correlation between rotated PCs and the original variables.

Abiotic variables	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8
Bathymetry (B)	0.2218	−0.1743	0.3156	0.2163	−0.1114	0.2176	−0.0012	0.0869
Bathymetric position Index 225 m (BPI)	**0.4467**	0.0513	0.0196	0.0374	−0.0937	0.2715	−0.1152	−0.1453
Bathymetric position Index 25 m (BPIf)	**0.4079**	0.0469	−0.1128	−0.0831	0.1966	−0.1630	0.2895	0.1995
Eastness 225 m (E)	0.0868	−0.2879	0.1453	−0.3705	**−0.4482**	−0.1676	0.0802	−0.0489
Eastness 25 m (Es)	0.0525	−0.2767	0.1719	−0.3297	**−0.4627**	−0.2143	0.1629	−0.0231
Feature extraction 225 m (FE)	0.1841	0.1727	−0.0748	0.0168	−0.1006	−0.2428	**−0.5214**	−0.2453
Feature extraction 25 m (FEf)	0.0942	0.3065	0.0411	−0.0495	−0.0143	**−0.4097**	−0.0296	0.0742
Fractal dimension 225 m (FD)	0.0508	−0.1845	0.2898	**0.5001**	−0.0266	−0.2048	0.0960	−0.0141
Fractal dimension 25 m (FDf)	0.1115	−0.0496	0.2470	0.4893	−0.1057	−0.2876	0.0207	−0.1147
Northness 225 m (N)	−0.0224	0.1360	**−0.4576**	0.2526	**−0.4097**	0.0328	0.1057	0.1225
Northness 25 m (Ns)	−0.0230	0.1012	**−0.4407**	0.2664	**−0.4383**	0.0032	0.1222	0.1399
Plan curvature 225 m (PL)	−0.3543	0.0062	0.1552	0.0708	0.0298	0.0648	0.4444	0.1356
Plan curvature 25 m (PLs)	−0.2619	−0.0339	0.0973	0.0677	−0.1446	**0.4346**	0.0018	−0.2248
Profile curvature 225 m (PR)	**0.4112**	0.0578	0.0369	0.0226	−0.0319	0.3326	0.1372	−0.1252
Profile curvature 25 m (PRs)	0.3504	0.0324	−0.0901	−0.0651	0.1784	0.0045	0.4046	0.1624
Rugosity (RG)	0.0137	**−0.4141**	−0.1565	0.2073	0.1734	−0.1513	−0.0597	0.0213
Slope 225 m (S)	0.0570	**−0.4338**	−0.3251	−0.0802	0.0945	0.0876	−0.1340	−0.0128
Slope 25 m (Ss)	0.0153	**−0.4987**	−0.2488	0.0688	0.1465	−0.0392	−0.0767	0.0457
TOBI ratio (R)	−0.0872	0.0230	0.1165	−0.0435	0.0081	−0.0634	−0.2677	**0.6667**
TOBI sidescan sonar (T)	−0.1361	0.0443	−0.1790	−0.0388	0.1667	−0.2933	0.2870	−0.5069
Eigenvalues	3.5780	2.9221	2.3250	1.8047	1.4658	1.3373	1.1772	1.1644

Highest factor loads in each PC are highlighted in bold. A 3D representation for the first three principal components is illustrated in Fig. 5 with each variable plotted in abbreviation.

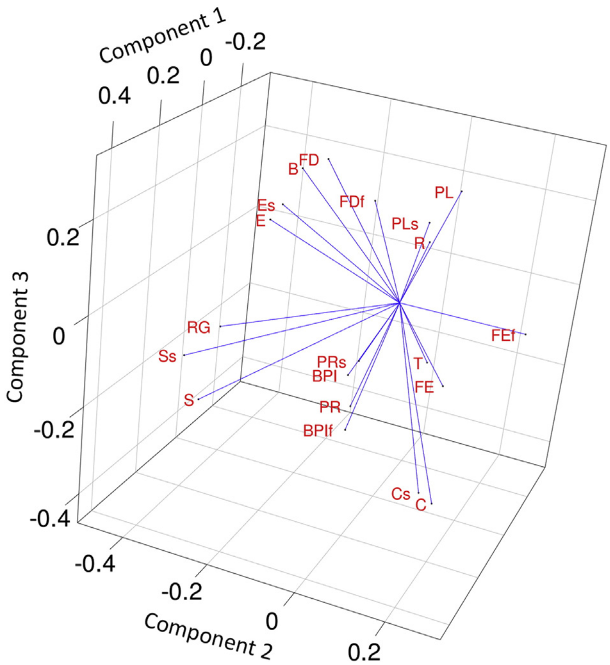


Fig. 5. 3D representation of the first three principal components and coefficients of each variable. The plot illustrates which variables are driving the PCs. The longest arrow in the plot represents the most prominent abiotic variable in the principal components. The distances between arrows describe their correlation, the closer the arrows, the more correlated they are.

continental margin. Although the average gradient of the whole axis is only about 3°, its slope gradients typically exceed 10°, making it the steepest canyon (Lastras et al., 2009) in the region. The upper Cascais Canyon first trends south-southwest then changes direction further down, to a westward and later north-westward trend.

The Lisbon Canyon head is situated 13 km southwest from the Tagus river mouth and 5 km west of the nearest coastline at an approximately 120 m water depth. It incises 28 km into the shelf with a total length of 37.5 km (Lastras et al., 2009). The canyon trends north–south towards the middle course of Setúbal Canyon and is almost perpendicular to the Setúbal branch at a 2010 m water depth, where these canyons join.

The Setúbal Canyon is east–west oriented and the canyon head is located at an approximately 90 m water depth, situated at about 20 km south-southwest of the Sado river mouth and 6 km west of the nearest coastline in Setúbal Bay. The branch cuts 41 km into the continental shelf (Arzola et al., 2008). Setúbal Canyon is amongst the submarine canyons that extend across the continental shelf and approach the coast. This type of canyon is known to intercept organic-matter-rich sediments; these cause organic rich material to be supplied downslope. For example, Gage et al. (1995) reported finding sea grass at a water depth of 3400 m in the middle canyon.

2.2. Data

The data and samples used in this study were collected during 5 different cruises in the area. Multibeam bathymetry data were compiled from RRS Charles Darwin cruises 157 (May/June 2004) and 179 (April/May 2006) and from ancillary data kindly provided by IFREMER (French Research Institute for Exploration of the Sea). The data were integrated during the HERMES project (Hotspot Ecosystem Research on the Margins of European Seas) (http://www.eu-hermes.net). The multibeam bathymetry was processed using SwathEd and results in an image with a pixel size of 100 m.

30 kHz TOBI (Towed Ocean Bottom Instrument) sidescan sonar imagery was collected during three cruises in 2003, 2005 and 2006: RV Pelagia 219, RSS Discovery 297 and RSS Charles Darwin 179. The sidescan sonar imagery, also published in Lastras et al. (2009), was pre-processed using the PRISM (v4.0) and Erdas Imagine (v8.5) software suites to produce imagery with improved geographical registration (Ismail, 2011). TOBI was towed at an altitude of approximately 400 m above the seafloor at about 2 kn, producing 6 km wide swath images with a horizontal resolution of 6 m (Le Bas et al., 1995).

The grids of multibeam bathymetry and sidescan sonar imagery used here had a different resolution of 100 m and 6 m, respectively. Therefore, the data was resampled to a common cell size of 25 m resolution. This is thought as a good compromise to keep the sidescan sonar detail, without over-interpolating the multibeam-derived datasets.

2.3. Research strategy

The technique to map the marine landscape in submarine canyons developed here, is divided into two parts: terrain analysis and multivariate statistical analysis. The first part focuses on optimising the usage of the acoustic dataset whilst the second part addresses the classification of the data into distinct physical areas and is partly based on the work of Verfaillie et al. (2009) in shallow waters. Both parts comprise 3 steps each, a simplified illustration of the research strategy is presented in Fig. 2.

The software used for each step in the first and second parts is listed as follows; the first part: 1) data were resampled in ArcMap 10.0 using bilinear algorithms, 2) determination of length scale for multiple scale analysis using the Estimation Scale Parameter tool in Ecognition and

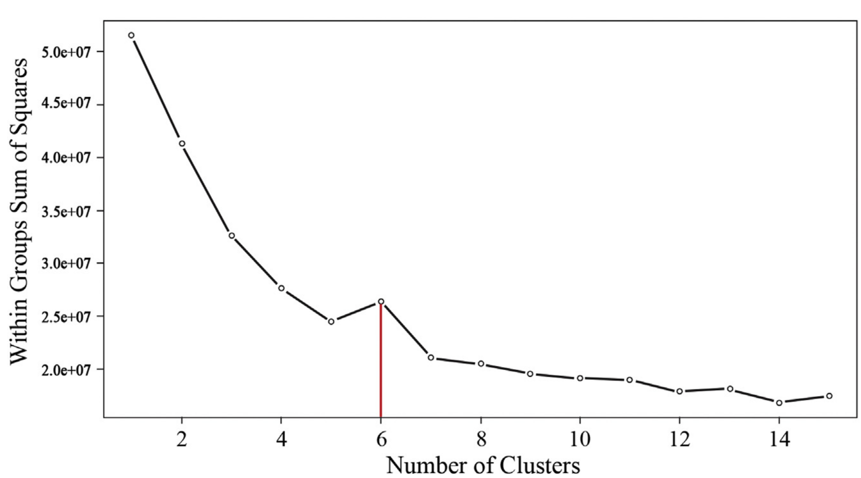
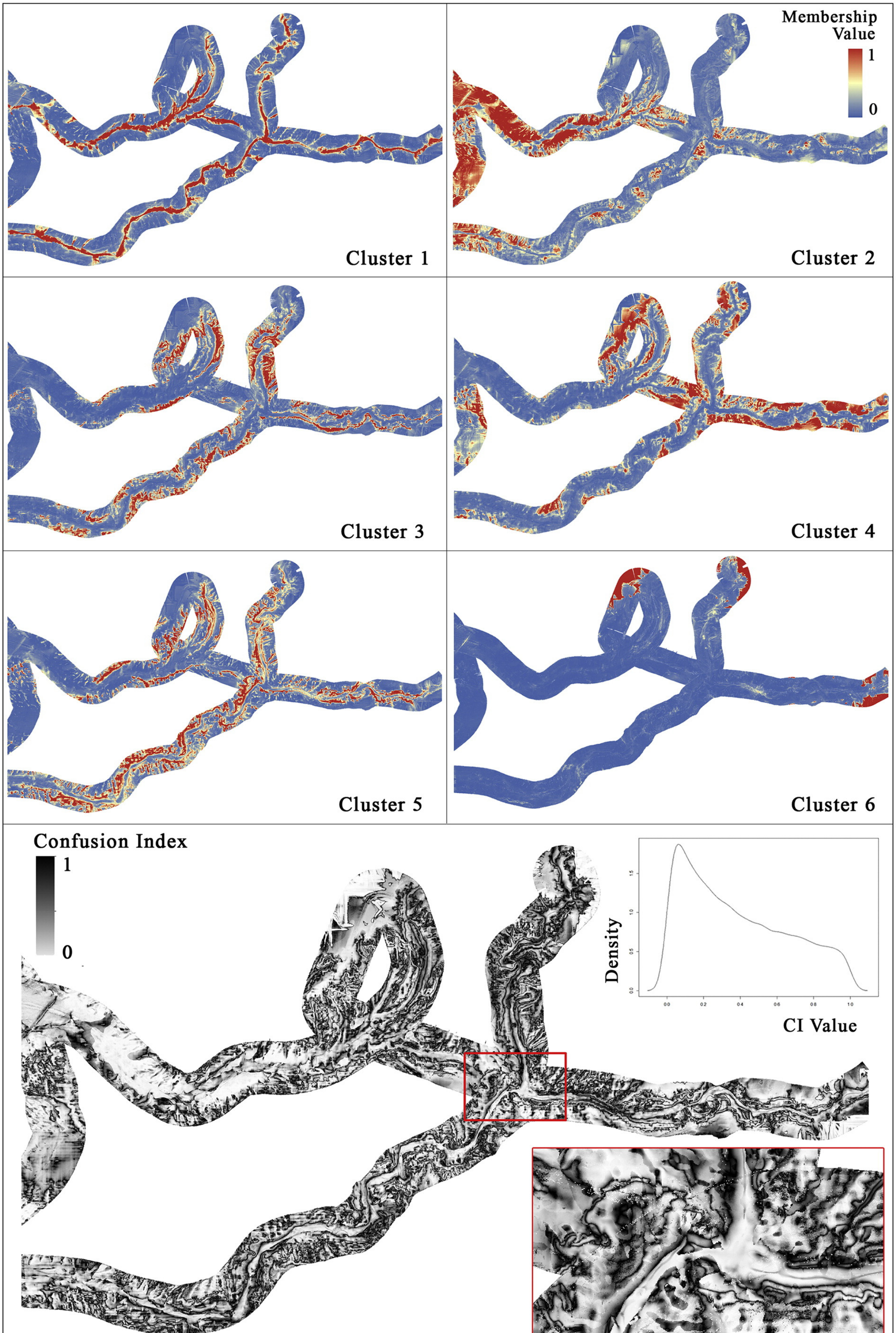


Fig. 6. Plot of number of clusters against within sum of squares. The bend (change in slope) marked in red and projected towards the x-axis indicates the optimum number of cluster is 6. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)


Membership Value
1
0
Cluster 1
Cluster 2
Cluster 3
Cluster 4
Cluster 5
Cluster 6
Confusion Index
1
0
Density
CI Value

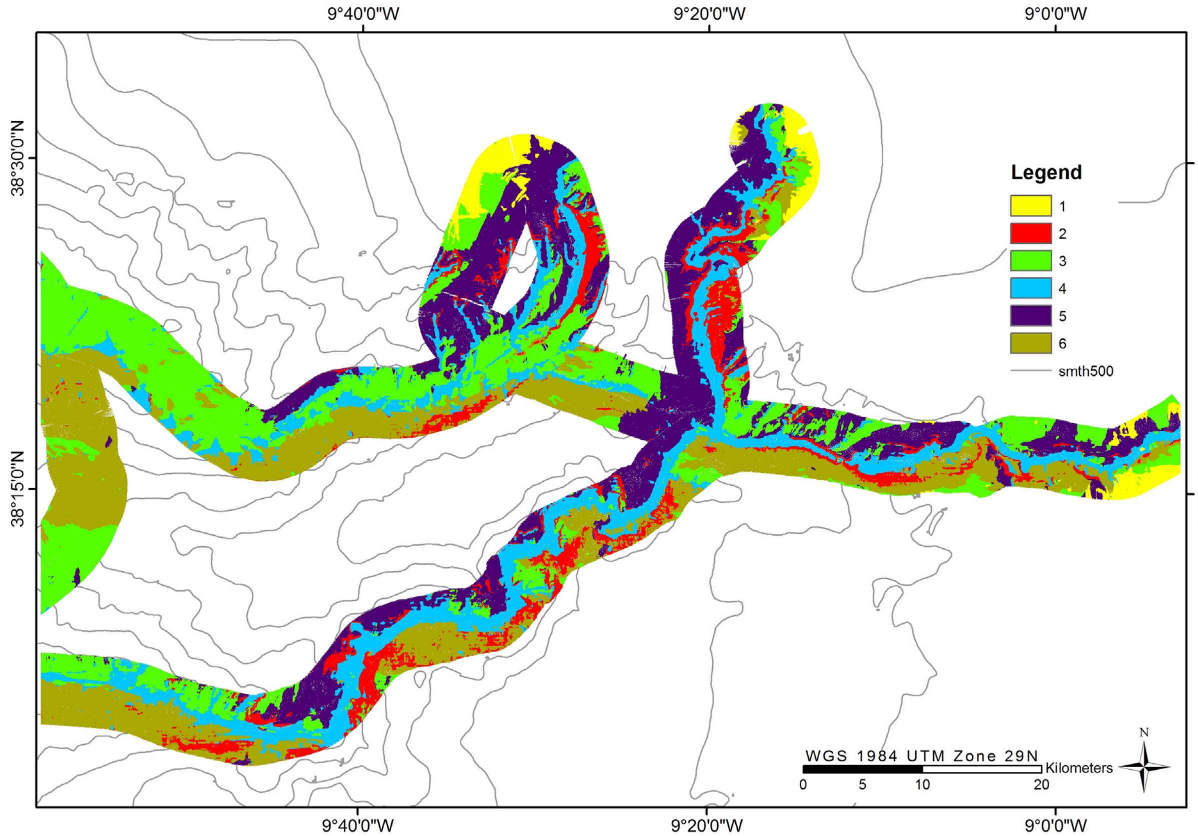


Fig. 8. Interpretation map showing Portuguese Canyon with 6 clusters solution using the fully automated technique summarised in Fig. 2. Characteristics and interpretation for each cluster are described in Table 3. Important geomorphological features of the canyon are clearly visible from the classification; Cluster 1 being the most shallowest and flat is the continental shelf, Cluster 2 as wall or cliff with highest ruggedness, Cluster 3, 5 and 6 are the flanks with different orientation and Cluster 4 with depression features is the channel floor.

3) production of terrain indices using multiple scale analysis in Landserf v2.3 (Wood, 2005). RStudio v0.98.484 was used in the second part of the method to carry out: 1) principal component analysis (PCA); 2) K-means clustering; and 3) cluster determination using within group sum of squares.

2.3.1. Single scale vs multiple scale terrain analysis

Multiple scale analysis refers to the incorporation of terrain indices produced at different scales to optimise the detection of details and features in bathymetric surfaces for marine landscape characterisation. Two length scales are used to represent local features and broad features, both of which are valued for habitat characterisation. The length scales represent $n \times n$ analysis window sizes to calculate terrain indices, where n is any odd integer value (Wilson et al., 2007). As suggested by Dolan and Lucieer (2014), using terrain indices obtained from multiple scale analysis in comparison to other approaches allows retaining the full detail of the bathymetric surface, whilst at the same time keeping the computation time reasonable. However, in their studies the length scales for the analysis were predetermined. An automated and objective procedure to select length scales for multiple scale analysis is proposed here and is adapted from a technique used for image segmentation in geomorphometry (Dragut et al., 2010). The Estimation Scale Parameter (ESP) tool is used for fast estimation of scale parameters for a multiresolution segmentation in Object Based Image Analysis (OBIA). The tool is based on the fundamental concept of the relationship between spatial structures of images and the size of objects in the real world. Hence both methods – multiple scale terrain analysis and segmentation – try to emulate real-world units by aggregating cells. The tool calculates the local variability or Local Variance (LV) in the segment or window, for increasing segment/window sizes. However, for multiple scale analysis, the LV graph does not show an obvious threshold for suitable scale, therefore the rate of change of local variance (ROC-LV) graph is used instead, as suggested by Dragut et al. (2010). ROC-LV measures the amount of change in LV from one scale level to another. Steps in the ROC-LV graph indicate the scale at which groups of real-world objects are more appropriately imaged.

Once the appropriate length scales are determined through the ROC-LV graph, terrain variables are calculated at those scales using Landserf. The resulting layers are then exported to R and are subjected to multivariate statistical analysis. A comparison between marine landscape maps created using single scale and multiple scale terrain indices is carried out to evaluate the significance of this step. A total of 20 abiotic terrain variables are used in the final multivariate statistical analysis. They include the multibeam bathymetry data and the TOBI sidescan sonar imagery, and their derivatives. The variables are listed in Table 1 with a brief explanation for each.

2.3.2. Principal component analysis

One of the most difficult tasks when automating a seabed classification technique is to ensure objectivity when selecting the variables that will form its basis. A commonly used method to condense a highly collinear dataset prior to clustering is Principal Component Analysis (PCA)

Fig. 7. Upper maps: membership value of K-means partitioning for each cluster ranging from 0.0–1.0, where 1.0 indicates the highest membership value. The bottom map is a confusion index map. It shows a quantification of clustering uncertainty ranging from 0.0 to 1.0, with 1.0 being the most uncertain. A zoomed area in red box shows the uncertain area as black and approaching white is much certain area. Inset plot is a density plot of confusion index value for the attributes. Narrow highly confused zones (black) in the confusion index map and a positive skewed density plot indicates a low conflicting clustering with good separation amongst the clusters. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 3
The characteristic of the 6 clusters and their interpretation based on the boxplot in Fig. 9.

Clusters	Characteristics	Interpretation
1	Shallowest, most homogeneous, flat, planar and linear surface	Continental shelf/slope
2	Most rugged and heterogeneous surface with steepest slope	Canyon wall or cliff (including cliff edge)
3	Mid depth SSW oriented canyon slope with linear surface	Canyon slope/rise (facing SSW)
4	Planar to depression, slight sidewardly and upwardly concave and diverge surface, valleys, channel-like features	Canyon floor
5	SSE oriented canyon slope	Canyon slope/rise (facing SSE)
6	NNW oriented canyon slope	Canyon slope/rise (facing NNW)

(Kabacoff, 2013). The abiotic variables in this study are highly collinear because they are derived from only two primary sources (i.e., multibeam bathymetry and sidescan sonar imagery). PCA is used to compute a set of new and linearly independent variables that are known as Principal Components (PC). Prior to PCA, all variables are standardised to have zero-mean and unit-variance in order to give them an equal weight in the PCA. The first PCs account for most of the variance in the original data, and can be chosen to form a smaller set of variables. The remaining variance, represented by the last PCs, is the error portion of the dataset.

A decision criterion based on the eigenvalues of the underlying correlation matrix is often used to determine how many PCs are to be retained in the analysis (Kabacoff, 2013). Following the Kaiser–Harris criterion, the analysis is limited to those PCs that have eigenvalues larger than 1, because they explain more variance than is contained in an original variable.

2.3.3. Clustering

The PCs resulting from the PCA are then used as attributes for clustering. The K-means algorithm is often used for data partitioning, also in the marine environment (Legendre et al., 2002; Verfaillie et al., 2009; Amiri-Simkooei et al., 2011; Ahmed and Demsar, 2013). K-means is an iterative procedure that starts with a random allocation of class centres. All data points are given the class of the closest class centre, calculated using the Euclidian distance in the N-dimensional space of the retained PCs (Hartigan and Wong, 1979). Once the clusters are formed, the class centres are updated to the location of the average for each cluster. Re-allocation of the centres proceeds by iteration until a stable solution is reached where the location of the centres no longer moves.

2.3.4. Cluster determination & confidence

An important step in achieving objectivity in automated classification is to determine the optimal number of clusters. There are many criteria that have been used to decide on the correct number of clusters for K-means partitioning (Dunn, 1973; Caliński and Harabasz, 1974; Davies and Bouldin, 1979). The method used here consists of a plot of within group sum of squares against number of clusters from the K-means clustering solution (ranging from 2 to 15). The change in gradient in the plot is used to determine the optimal number of clusters from the K-means solutions (Kabacoff, 2013).

Once the final clustering through K-means solution is achieved, a separate map of cluster membership is produced to show cluster dominance at each location. The membership value can be expressed as follows

$$\mu_{ik} = \frac{1}{(d_{ik}^2)} \times \frac{1}{\sum_{k=1}^{n} \frac{1}{(d_{ik}^2)}}$$

where μ_{ik} is the membership value of the ith data point to cluster k, d_{ik} is the distance between data point i and cluster centre k in attribute space and n is number of clusters. The above expression is modified from an expression used for fuzzy K-means classification for soil survey data (Burrough et al., 1997). The original expression was also used and reviewed in a study by Lucieer and Lucieer (2009) for seafloor sediment classification. Membership values are assigned to each cluster so that all values for each pixel sum to 1. Using this characteristic, clustering uncertainty can be quantified using the confusion index, CI

$$\mathrm{CI} = \frac{\mu_{(\max-1)_i}}{\mu_{\max_i}}$$

where $\mu_{\max_i}$ is the membership value of the cluster with maximum μ_{ik} at location i and $\mu_{(\max-1)_i}$ is the second largest membership value at the same i location. If the value of CI nears 0, then only one cluster k dominates the location and it has a low confusion (high maximum membership value of cluster k), however if the value of CI is near 1 there is high confusion between two or more clusters at location i.

2.4. Qualitative assessment

Expert visual interpretation based on sidescan sonar imagery from previous work in 2005 was used to evaluate the performance of the automated technique. The interpretation is independent from any input from the automated marine landscape map. Visual comparison was made between expert interpretations for Setúbal Canyon and the automated marine landscape map produced by overlaying both in ArcMap 10.0.

3. Results

3.1. Terrain analysis: ROC-LV graph

The ESP yields the ROC-LV graph as shown in Fig. 3. According to Dragut et al. (2010), the ROC-LV plot enhances the discrimination of the threshold at which the appropriate scale for real-world object representation is reached compared to an LV graph. The threshold is defined as the first break in the ROC-LV graph after the initial continuous and abrupt decay, and may appear as a step or small peak. In this case, it appears as a step in the ROC-LV curve. The next level after 25 m (initial pixel) that is recognised as the appropriate scale that represents real-world objects is 225 m. Meaningful objects refer to real world objects such as gullies, the channel floor and other geomorphological features that can be found in submarine canyons. The variation in slope and bathymetric position index using different length scales is shown in Fig. 4. The local scale (25 m) picks out fine-scale variability in the canyon such as gullies or small branches, whereas the broader scale (225 m) shows the overall pattern of the whole canyon system, highlighting major features and smoothing out details present in the local scale analysis.

3.2. Multivariate statistical analysis

3.2.1. PCA

The principal component analysis is conducted using the 20 abiotic variables listed in Table 1. Retaining only those PCs with eigenvalues larger than one, PCA results in eight PCs, explaining 79% of the total variance. The rotated component matrix (Table 2) shows the factor loads that explain the correlations between the rotated PCs and the original variables. The main variables that drive the PCA are bathymetric position index (BPI), profile curvature, slope, rugosity and northness (Fig. 5).

3.2.2. Clustering

A total of 2,316,746 pixels with eight PC variables were subjected to K-means clustering, in a cascade from two to fifteen clusters. The plot of

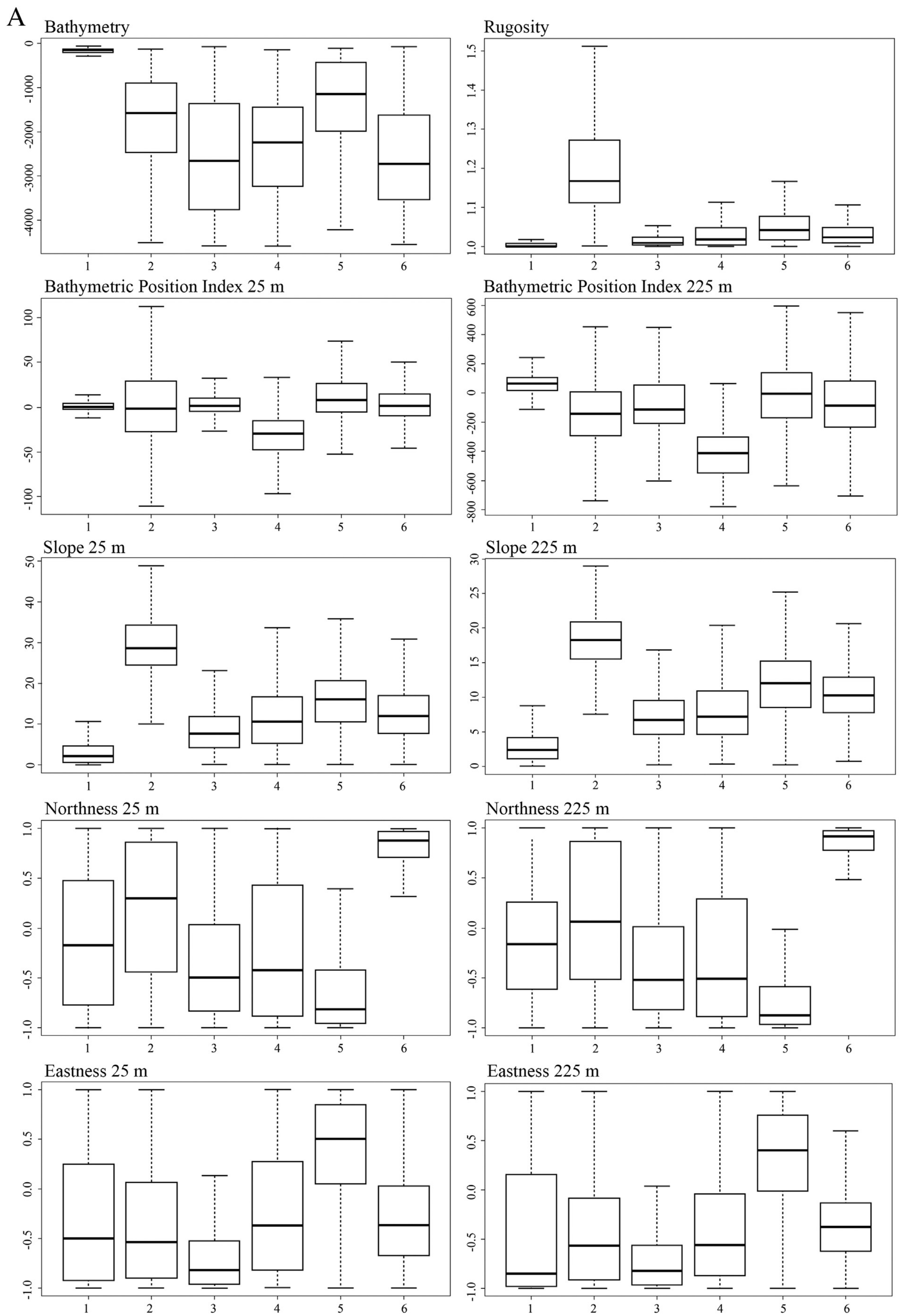


Fig. 9. a & b: Boxplot of clusters against original abiotic variables. Description of each abiotic variable is given in Table 1. In the boxplot, the middle line is the mean, the lower and the upper box boundaries are the first and third quartiles. The whiskers are the maximum and minimum observed values that are not statistical outliers.

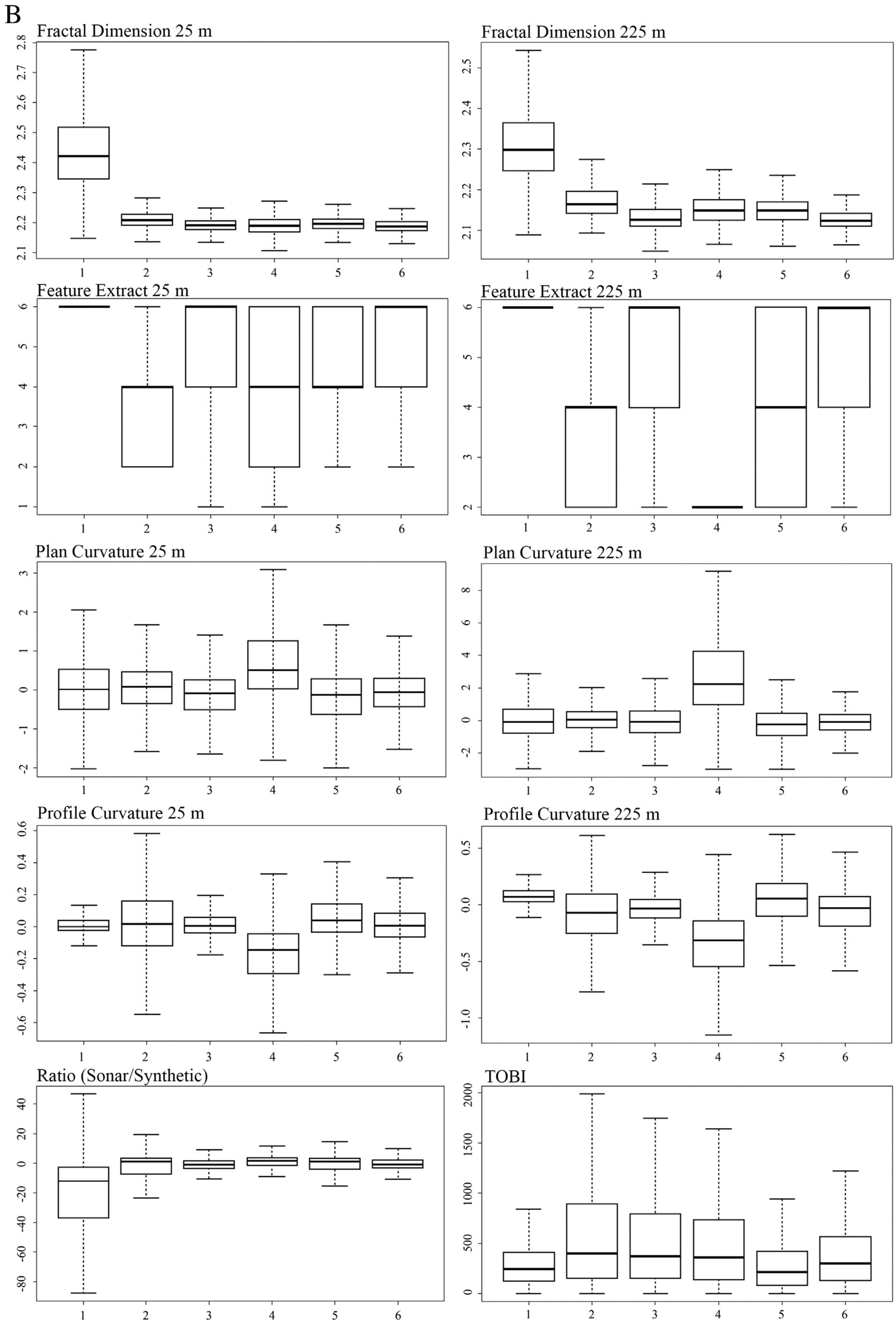


Fig. 9 (*continued*).

within group sum of squares against number of clusters is shown in Fig. 6, and indicates a distinct increase at six clusters. This change in slope suggests that a six cluster solution may be a good fit for the data. Hence, final clustering is carried out using the K-means algorithm with six clusters.

3.2.3. Membership value and confusion index

The concept of membership values originates from the technique of fuzzy classification, where it is used to show continuous spatial variation by creating overlapping classes (Lucieer and Lucieer, 2009). Through this, using the Euclidean distances of data points towards cluster centres from the K-means partitioning, the same calculations were used to show classification uncertainty (Fig. 7). High membership value means only one cluster is dominant for the data point; meaning at that location there is a high certainty of classification.

Based on the membership value for each cluster, a confusion index is produced (Fig. 7). The confusion index map has very narrow transition zones between clusters, with high confusion values only at the cluster boundaries. If spatial correlation in membership values is weak, broad zones of high confusion index values are observed, but they are not seen in the confusion index map. The density plot of confusion index values indicates a positively skewed distribution, with a high percentage of data points with confusion value approaching zero. A low value in confusion index (approaching zero) indicates a less conflicting classification.

3.3. Marine landscape map

The result of the six cluster solution is presented in Fig. 8 and Table 3. The six cluster solution represents the final marine landscape map produced for this area. The interpretation of each cluster is based on the boxplots of the original abiotic variables against the clusters (Fig. 9a & b). Through these boxplots, the characteristics of each cluster can be obtained based on the correlation with the original variables. Seventeen out of twenty abiotic variables show an obvious contribution to the classification.

For instance, rugosity, which represents the ruggedness of the terrain, shows a clear difference between the clusters. Cluster 2 is interpreted as a canyon wall, owing to its high values in slope and rugosity, and a wide range of distribution of rugosity and BPI. As canyon walls often consist of near vertical to vertical outcropping bedrock with the tendency to be covered by biological communities, such high value of slope and rugosity is expected. Its wide range of rugosity distribution is also explainable, because canyon walls have the most varied surface ruggedness. They can consist of just bare rocks, or be covered with sediments or fauna. Similarly, based on the boxplot (Fig. 9a), the BPI for Cluster 2 has the biggest range although the mean value is zero. Such a characteristic is observed because the Cluster 2 morphology is narrow and steep; therefore the value can change significantly from one neighbouring cell to another.

The rest of the clusters are also interpreted based on the criteria seen in the boxplots and the final interpretation is shown in Table 3. Each cluster has its own prominent variable that best shows its characteristics. Cluster 1 is mainly driven by the bathymetry and fractal dimensional variable, Cluster 2 is influenced by rugosity and slope, Cluster 4 has the lowest BPI and is channel-like based on the feature extract variable, whilst Clusters 3, 5 and 6 are dominated by the aspect variables.

3.4. Single scale vs multiple scale terrain analysis

An alternative marine landscape map was produced using only local scale terrain indices to evaluate the effect of using multiple scale analysis on the classification result (Fig. 10). The map produced was classified into 10 clusters. The main difference observed is that the clusters are more patchy and incoherent in the marine landscape map produced using single scale analysis. The map corresponds less well to features that can be seen in sidescan sonar imagery. Zoomed figures were made at three locations (Areas A, B, C) to highlight the differences between using single scale and multiple scales into the multivariate statistical analysis (Fig. 10). For example in Area A, the channel floor that appears in the sidescan sonar imagery was not delineated in the single scale marine landscape map. However, in the marine landscape map produced using multiple scale analysis, the channel floor is classified as a separate cluster (Cluster 4), distinguishing it from a canyon slope (Cluster 3). In Area B, the clusters from the single scale map can be seen as patchy and incoherent as mentioned above. Of the 10 clusters, one cluster (Cluster 5) is identified as a product of over-classification from Cluster 7 because they consistently appear next to each other and Class 5 almost forms an outline to Cluster 7. Meanwhile, Cluster 6 is identified as noise that has been picked out from TOBI sidescan sonar imagery. Area C shows an example of clusters that result from over-classification and noise. Another general difference between the two maps is that the single scale map has less-pronounced aspect influenced clusters. Cluster 1 is slope angled to the north whilst Cluster 8 to the south. However the patchiness of the clustering largely obscures the effect of the aspect variable.

3.5. Qualitative assessment

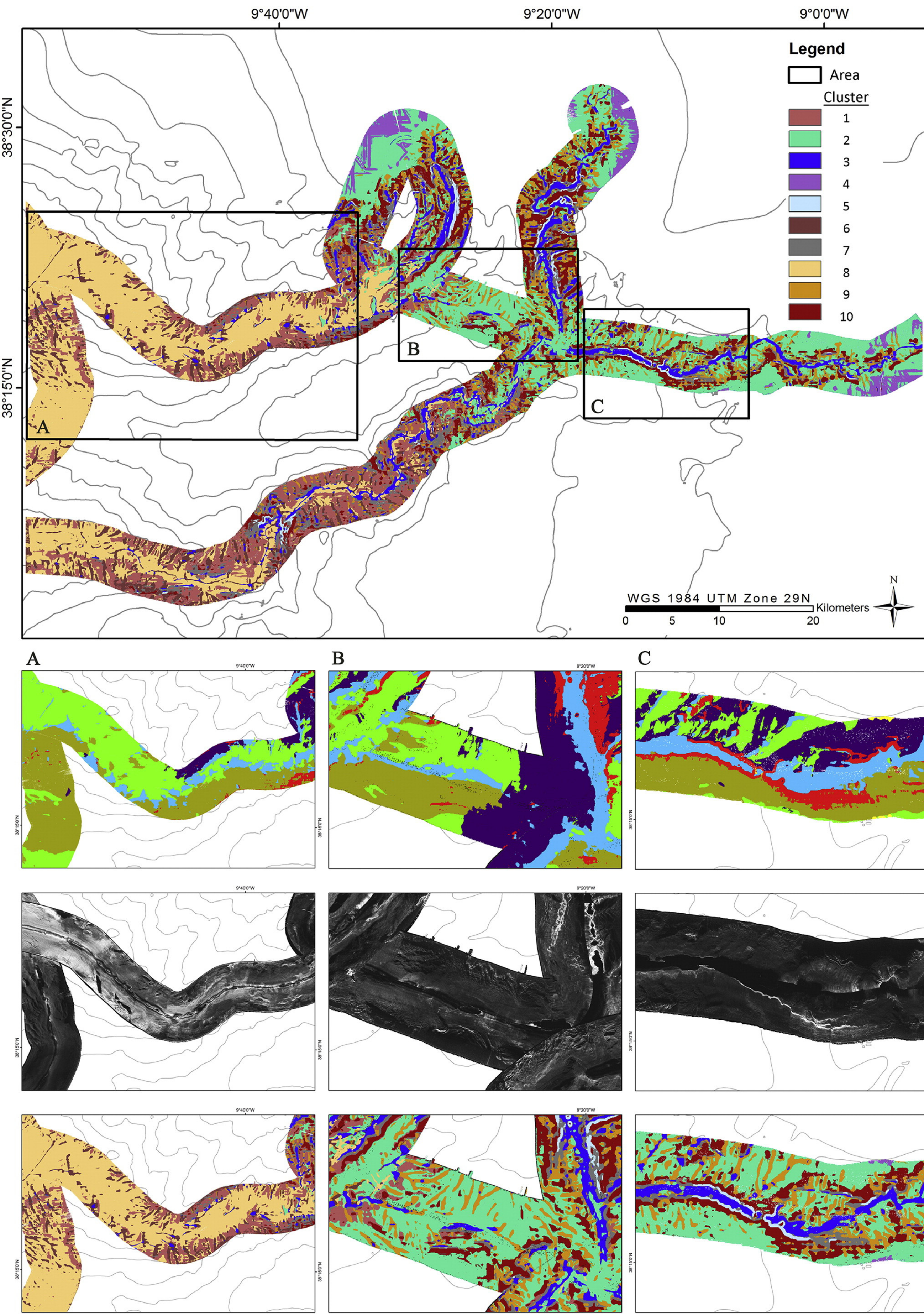
A visual interpretation (Fig. 11) was carried out for Setúbal Canyon based on the sidescan sonar imagery collected in 2005 (hence only covering Setúbal Canyon). A general comparison of the marine landscape map produced by the automated technique and the manual delineations shows that most clusters from the automated technique coincide with the features delineated manually by the expert. Misclassifications of features occur occasionally and most are within the navigational error. The sidescan sonar map used for this study was navigationally corrected by correlation with the bathymetry (Ismail, 2011), which was not the case for the data used for expert interpretation. Four sub-areas within the Setúbal Canyon were zoomed (Fig. 11) and clearly show that both maps correlate well. There are many features that can be identified visually by the human eye. These features can be very small and overwhelm the algorithm in the automated technique. However, often the algorithm will naturally group these features together into the same cluster. The automated approach is observed to be more consistent in picking out features and identifying homogeneity within features. The most obvious features that can be seen to coincide successfully between the two maps are the channel floor and canyon wall. However in manual delineation the channel floor seems narrower than that in the automated marine landscape map. This is because the expert tends to follow the axis of the channel floor (thalweg) closely and has difficulty deciding class boundaries. In particular, the area of transition between two features/clusters is often left unidentified in manual delineation, whereas the map from the automated technique gives a complete coverage.

4. Discussion

4.1. Multiple scale terrain analysis

The ESP tool technique was adopted from segmentation in Object Based Image Analysis (Dragut et al., 2010). It was used for fast estimation of the optimum length scales in an automated way. This tool gives an advantage over manual estimation, as it reduces the time spent on trial and error selection of the appropriate scale that best represents real-world objects in multibeam bathymetry data. It also provides an objective answer to the scale question. The ROC-LV graph indicates that at 225 m it recognises patterns that are suitable to represent a real-world object. Indeed, the terraces in the middle course of the Lisbon–Setúbal Canyon are reported to be approximately 200 m wide (Lastras et al., 2009).

The incorporation of terrain indices produced from local (25 m) and broad (225 m) scales allows an appropriate discrimination between features of potentially different ecological relevance. For instance, in a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9°0'0"W
38°30'0"N
38°15'0"N
Legend
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WGS 1984 UTM Zone 29N
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Kilometers
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single scale approach using only the local length scale, terrain indices may have similar slope values on the side of small geomorphic features such as gullies compared to slopes on the canyon wall. However, if broad scale terrain indices were to be used on their own, slopes over small features would effectively disappear since the analysis scale will be too large to capture the finer features available from the multibeam bathymetry data. Therefore, by including local and broad length scale terrain indices together, both fine scale and broad scale features are retained and stand out as distinct properties of the seabed which contribute as indicators of potential benthic habitats.

In addition to this, with the incorporation of broad length scale terrain indices, it is observed that the noise, compared to the local, single scale map was reduced, subsequently increasing the feature to noise ratio. Through this step, the automated technique is performed on meaningful objects that represent both fine and broad scale features that can be found in real-world canyons.

Apart from this, using multiple scale terrain analysis appears to reduce excessive clustering that result in meaningless clusters being delineated in the map. Since multivariate statistical analysis is affected by pixel size, having only single local scale terrain indices causes over-analysis, which contributes to clustering of artefacts into the classification. It became oversensitive towards slight changes in characteristics between pixels causing similar features to be clustered into separate clusters. However, by using multiple scale terrain indices, the multivariate statistical analysis operates on meaningful objects related to real features rather than just the pixel representation of the acoustic data.

4.2. Abiotic variables

One of the difficulties in maintaining objectivity in automated mapping is to justify the abiotic variables that are incorporated into the analysis without compromising the objectivity of the whole method. It is important to ensure that the method is as objective as possible with minimum input from the user. Every abiotic variable included will affect the automated classification, therefore all abiotic variables should contain relevant information about the canyon. Parameters yielded by the GIS software must be considered with care, and not simply included by default. For example, hillshade is often used to aid in the identification of seafloor features (Walker and Gilliam, 2013). Although it is a derivative of multibeam bathymetry, hillshade is not considered as an abiotic variable, even if it can be a good indicator for the correlation between the seabed and a (residual, unidirectional) current. However if there is no evidence of such interaction taking place, it would give false information because the azimuth used for hillshading would be arbitrary, rather than representing an actual characteristic of the terrain. Instead, directionality of the terrain and any potential interaction with oceanographic effects is simulated by the inclusion of aspect properties that are divided into northness and eastness to provide continuous variables (Hirzel et al., 2002; Wilson et al., 2007). Hence each abiotic variable included is relevant and has a useful input regarding the canyon and will contribute to the automated classification. In additional, by using PCA, there is no problem if more than one abiotic variable gives a similar input or representation of the canyon (i.e., if there is collinearity). The more abiotic variables with useful information are incorporated as input, the more potential habitats can be classified (Verfaillie et al., 2009). Once all the abiotic variables have been gathered, there are no subjective selections to be made. Instead they are subjected to PCA, which overcomes the problem that most conventional classification methods encounter, the selection of abiotic variables (Al-Hamdani and Reker, 2007). Also the selection of the relevant PCs (with eigenvalue >1) and the optimal number of clusters (based on the within group sum of squares) are fully objective.

4.3. Marine landscape map

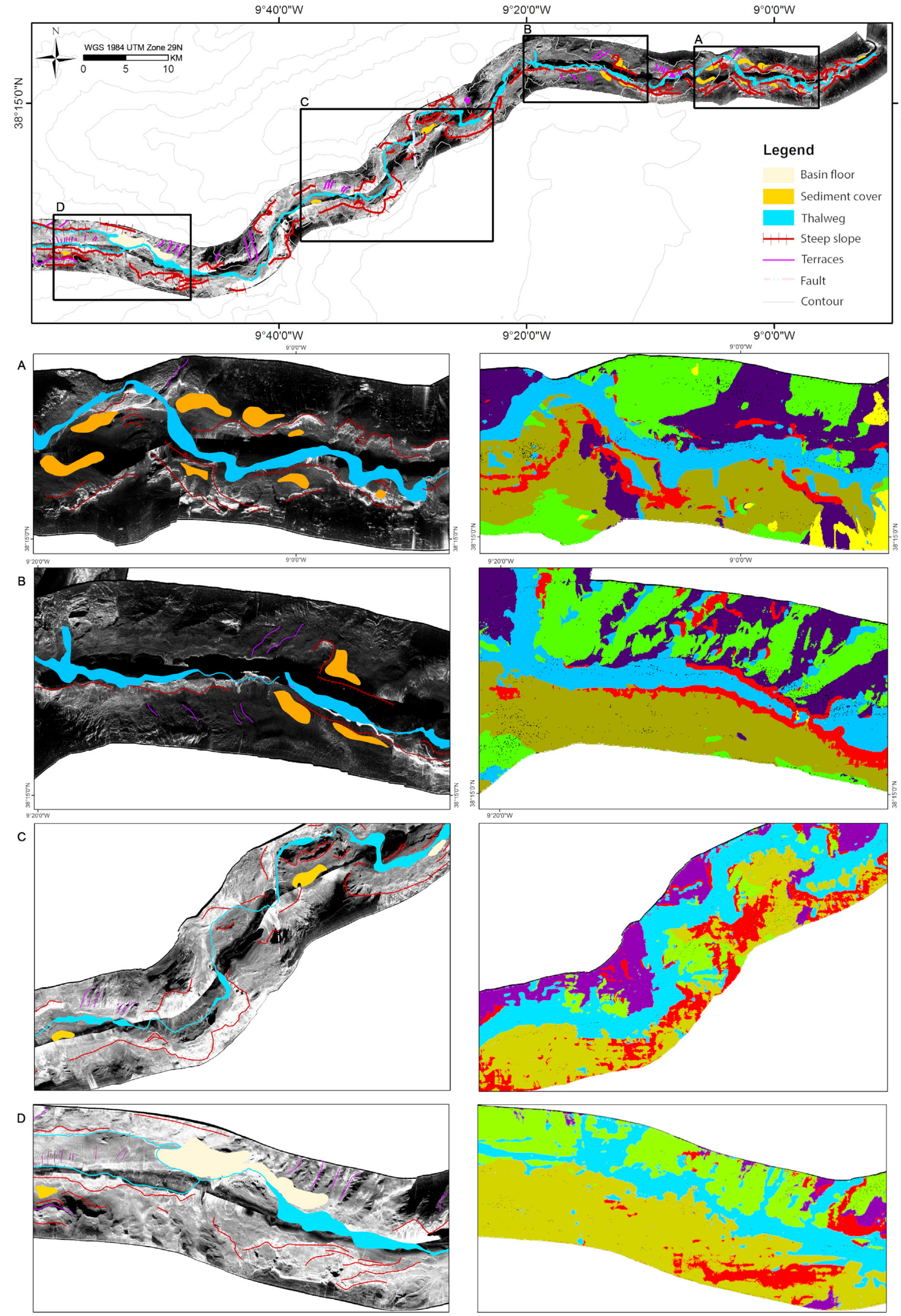
The resulting map for the Cascais and Lisbon–Setúbal Canyons has a total of 6 clusters that represent the marine landscapes of the area (Fig. 7). Each of these clusters is interpreted based on the correlation of the clusters with the original abiotic variables. The marine landscape map is largely based on the geomorphological features present in the multibeam bathymetry data, and hence corresponds to the first levels of typical hierarchical habitat classification systems (Davies et al., 2004), that are based on broad-scale geomorphological divisions of the marine realm. TOBI sidescan sonar data, and especially its ratio to synthetic imagery, was used to potentially represent sediment distribution and seafloor roughness, regardless of the orientation towards the sonar (Ismail, 2011), but that did not yield much contribution into the classification. The rotated component matrix (Table 2) shows that TOBI sidescan sonar imagery is not a high factor load in any of the PCs. In addition, based on the boxplot distributions (Fig. 9b), when correlated with TOBI data the 6 clusters are more or less congregated around similar values. Although it has the highest load in PC 8, the PC only explains 0.03% of the total variance. However, when visually compared to the TOBI sidescan sonar, the marine landscapes classified here can easily be related to the TOBI sidescan sonar features. It is already known that sedimentological distributions in canyons are strongly controlled by the geomorphological properties of the terrain (Arzola et al., 2008). This explains the correlation between the marine landscape map and TOBI sidescan imagery when compared visually.

Geomorphology is also recognised as a major control on biological communities and diversity in submarine canyons (Kenchington et al., 2014). Therefore, the marine landscape map can be useful to identify areas with ecological relevance. Although, the ultimate goal of habitat mapping is to identify ecologically relevant habitats that support different biological communities, this is not the case for marine landscape. The purpose of a marine landscape map is to identify areas that can give an indication about the biological community, but not to predict the biology. Therefore, the map produced in this study only acts as a proxy to aid biological predictions and focus future surveys. This is especially beneficial as an alternative when biological data are limited since it uses only abiotic variables to produce the marine landscape map.

Based on the marine landscape map produced from this study, three out of the six clusters are influenced by the aspect variable. Aspect is represented in continuous values by northness and eastness. Northness takes values close to 1 if the aspect is northward, −1 if southward and close to zero if aspect is either east or west. Eastness behaves similarly, except that values close to 1 show east-facing slope and −1 west-facing slope. However, is aspect an important feature to define marine landscape in submarine canyons? Naturally, aspect is a valuable variable for shallow water, where it provides information regarding the exposure to dominant swell or where sunlight is able to reach the seabed (Lucieer et al., 2013). However this is not the case for the deep sea environment, where it is known that light only penetrates approximately to no more than 1000 m (with significant light only penetrating to about 200 m) (Schrope, 2007). Nevertheless, slope orientation in the deep sea may still be meaningful if interaction between the current regime and differently orientated slope surfaces creates variable habitats.

Organisms inhabiting the deep sea environment are known to be subjected to regulating disturbances related to upper water-column processes (Gage and Tyler, 1992), which makes it possible to predict faunal response in homogeneous deep sea habitats, and identify the

Fig. 10. Marine landscape map produced using automated marine landscape classification with single scale in contrast to map in Fig. 8. The three selected areas A, B and C are compared to sidescan sonar imagery and marine landscape maps produced using multiple scale terrain analysis. The close-ups are shown in the nine smaller maps. First row: marine landscape map using multiple scale, second row: sidescan sonar imagery and third row: marine landscape map using single scale. The marine landscape map produced using single scale exhibit patchy and incoherent classes. There are products of over-classification since having fine details introduces noise and causes over-analysis.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Terraces
Fault
Contour

controlling factors that affect the presence of organisms. However, in a more complex and complicated environment this is not as straightforward. This is particularly true in submarine canyons, where the different regulating processes, heterogeneous environmental conditions and ecological functions are far from understood. Ongoing research in submarine canyons has shown that due to the terrain heterogeneity, the biological communities in submarine canyons vary compared to the adjacent continental slope (Soetaert et al., 1991; Grémare et al., 2002); even twin branches within the same canyon may exhibit a large difference in their community composition (Bianchelli et al., 2008) and flanks of the same branch can exhibit different biological coverage due to differences in substrate cover as a result of the orientation of the canyon with regard to the overall oceanographic regime in the area (Van Rooij et al., 2010; De Mol et al., 2011). This shows that submarine canyons are dynamic and varied from one another, which leads to a conclusion that no variables should be overlooked or neglected without solid reason. Amongst the potential factors that can be related to aspect, the current regime is the most prominent. It will affect the sediment, organic matter and food source pathways into submarine canyons. Although the community structures are influenced by food supply and food availability, which are strongly related to upper water column processes, in canyon communities, variability caused by habitat heterogeneity and water depth differences can easily override the effect of upper water column processes (Ramalho et al., 2014).

Unfortunately, the lack of detailed current information in most submarine canyons hinders the process of evaluating the influence of aspect towards the community structure. The marine landscape map produced here indicates the potential influence of the aspect variable. The next step now is to evaluate this against the community composition.

4.4. Qualitative assessment

A qualitative assessment was made based on visual comparison with sidescan sonar imagery expert interpretation. The comparison between the marine landscape map and visual interpretation of the sidescan sonar imagery supports that the automated method yields a useful and meaningful marine landscape map. Manual delineation in this study lacked in contiguity whereas the automated map provides a better coverage for a continuous classification. Other manual interpretations may have the same coverage as automated classification but they will be more time consuming to produce. The advantage of expert interpretation is the ability to pick out individual features in sidescan sonar that often overwhelm the automated method. Since the automated method is restricted to its pixel size for the ability to detect geomorphic features, it produces a more generalized map in comparison. On the other hand, with manual delineation there are still a percentage of features that are overlooked due to human error. Classification and boundaries between classes are more consistent throughout the whole automated process and this will be a useful contribution for further habitat quantification at later stages.

5. Conclusion

This study offers another step forward towards a better marine landscape mapping technique that stands out for being a fully automated approach. The philosophy behind this study is to ensure that the methodology is objective and suitable for broad and regional scale mapping based on seafloor geomorphic features that can be identified from different types of sonar data. Such information is often included as one of the attributes for actual habitat classification in one of the nested levels of hierarchal habitat mapping schemes. Additionally, the method utilizes bathymetric grid data that are the most common type of data obtained for most seafloor related studies. Therefore many habitat mappers will find this method useful, time and labour efficient. This method could also be advantageous to monitor seafloor changes through time. Dynamics of the marine environment changes seafloor conditions, however, the objective approach allows monitoring an area over a period of time with more confidence without bias from expert interpretations. Mapping marine landscape provides a surrogate for biodiversity and prospectively this method could contribute to design marine environmental management measures.

The following conclusions are drawn: 1) The ESP method that was designed to detect characteristic scales in geomorphometric analysis for OBIA is transferable, and can be used to detect potential patterns in bathymetric grids. The comparison of single scale and multiple scale maps reveals the delineation of seafloor features associated with patterns of real-world submarine canyon geomorphic features. 2) It is shown that using multiple scale terrain analysis, appropriate discrimination between features of different ecological relevance is achieved regardless of fine or broad scale features. Incorporation of both local and broad length scale terrain indices enables a production of a marine landscape map that contains fine and detailed canyon features without compromising the prominent and large scale geomorphic features. 3) Potentially this methodology is thought to be a useful guideline for complex deep sea habitat mapping because it does not only delineate seafloor geomorphic features for potential habitat but also points to properties that might influence biodiversity in a complex terrain as pointed out in the Discussion section on the importance of aspect as a driving parameter in submarine canyon marine landscape delineation.

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Fig. 11. An expert visual interpretation of Setúbal Canyon from sidescan sonar imagery collected in 2005 used for visual comparison with automated marine landscape map. A, B, C, and D are zoomed figures of the visual interpretation map from sidescan sonar imagery (left) in the selected area (outline in black) compared to automated marine landscape map (right). Refer to Fig. 8 for symbol legends in the automated marine landscape map. The expert interpretation in this area lacked contiguity and coverage, although manual delineation allows individual features to be picked out there is always a possibility of it being missed due to human error. In comparison, the automated technique produced a more consistent map but often too generalized (i.e.: small features are often grouped together).

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