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A global approach to hierarchical classification of coastal waters at different spatial scales: the NEA case

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Ecological classification of coastal waters has become increasingly important as one of the basic issues in the biology of conservation. Management and protection of coastal areas take place at different spatial scales. Thus, proper classification schemes should integrate equivalent information at various levels of definition in order to show its feasibility as a useful tool for assessment of coastal environments at the required scales. In this work, a global approach applied to the classification of the NE Atlantic coast is analysed in order to discuss pros and cons regarding different conceptual and technical issues for effective implementation of such a management tool. Using the hierarchical system applied at three different geographic scales: Biogeographic (NE Atlantic coast), Regional (Bay of Biscay) and Local (Cantabria region), five different topics were considered for debating strengths and weaknesses of the methodological alternatives at those spatial scales, using for validation the rocky shore macroalgae as a representative biological element of benthic communities. These included: (i) the spatial scales; (ii) the physical variables and indicators; (iii) the classification methodologies; (iv) the biological information; and (v) the validation procedure. Based on that analysis, the hierarchical support system summarized in this paper provides a management framework for classification of coastal systems at the most appropriate resolution, applicable to a wide range of coastal areas. Further applications of the physical classification for management of biodiversity in different environmental scenarios are also analysed.

Keywords: coastal classification, hierarchical, scales, physical variables, intertidal macroalgae, NE Atlantic, coastal management, ecological regions

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INTRODUCTION

One of the requirements associated with the ecosystem-based management approach in coastal areas is the characterization of marine assemblages and species distribution, in order to preserve and maintain the integrity and services of ecosystems through the conservation of marine diversity (Douvere & Ehler, 2009). For achieving that goal, delineation of ecologically meaningful regions and zoning categories is a basic objective (Gilliland & Laffoley, 2008). For instance, a general problem in the implementation process of the European Water Framework Directive (WFD, 2000/60/EC) was the need to find a balance between water body typologies being too specific (too many types) and being too general (types that do not adequately reflect natural variability) (Hering *et al.*, 2010). So, it was necessary to establish suitable ‘common types’ in order to accomplish the intercalibration exercise (IC) at certain biogeographic regions (European Commission, 2009).

Thus, from both conservation and planning perspectives, one of the first steps is to establish ecologically homogeneous types that can be ultimately comparable. But the problem arises in the difficulty of establishing clear borders in a natural and continuous environment. If standardized and extensive biological cartographies were available, the first classification option would be directly based on species information. However, there is a general lack of homogeneous, systematic and standardized species databases, especially along large areas. Besides, these kinds of classifications will characterize just a certain moment, being static. Hence, ecological models based on abiotic characteristics are emerging as a useful predictive tool for a variety of related assessment purposes, which facilitates the quantification of the responses of biological patterns and processes to human uses within a region. These models are dynamic, they have the capacity of evolving over time and can be periodically re-validated. Furthermore, they may also be useful for the development of conservation strategies to preserve species in degraded or fragmented areas, as well as in the analysis of shifting habitats due to climate change (Rice *et al.*, 2011).

Taking into account that the management of coastal areas takes place from broad to fine areas, the availability of classifications at different scales represents an essential element for an appropriate protection of a zone according to different specific objectives (Bianchi *et al.*, 2012; Swaney *et al.*, 2012). It will allow implementing action plans at levels of detail that are both ecologically meaningful and appropriate to the integrated management needs. This feature is particularly important for many policies and management initiatives which are characterized by a range of scales, with goals set at national or regional domains but implemented at a more local

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domain (Rice *et al.*, 2011). For instance, many efforts at managing environmental resources in coastal waters attempt to conserve species and to preserve the structure and processes of habitats in medium or large areas (e.g. Zacharias & Roff, 2000; Gregr & Bodtker, 2007). Biogeographic approaches are typically useful for understanding species distribution patterns and dynamics. This need of global studies can be handled through ecological classifications that permit the collation, unification and synthesis of data from large areas, providing an objective basis for analyses (Snelder *et al.*, 2007).

On the other hand, studies of marine ecosystems need also to be addressed on a case by case basis, since each area is unique in terms of locally specific environmental, social and economic characteristics (Reis, 2014). Therefore, classifications at a finer level of resolution may be useful for conservation planning and for the implementation of effective biomonitoring programmes in a particular region (Briceño *et al.*, 2013).

In this context, different methods have been applied to classify coastal waters at regional and larger scales all over the world (e.g. Sherman, 1986; Roff & Taylor, 2000; Mount *et al.*, 2007; Madden *et al.*, 2009). Specifically, several classification systems have been developed along the NE Atlantic region, including: the European Palaearctic Habitat Classification (Devilliers & Devilliers-Terschuren, 1996), the CORINE-Biotopes (Commission of the European Communities, 1991) or the Biogeographic regions for the Habitats Directive (1992/43/EEC), all of them based on species or communities distribution; the OSPAR regions (Dinter, 2001); the EUNIS Habitat classification (Davies *et al.*, 2004) or the WFD ecoregions for coastal and transitional waters (WFD, 2000/60/EC), which are both based on abiotic attributes; or the Baltic HELCOM and the BioMar project (Connor *et al.*, 1997), that encompass and complement all of them. Nowadays, the most harmonized and standardized classification approach adopted for management and conservation purposes along the European coasts is the EUNIS system. However, this broad-scale approach (i.e. all terrestrial and aquatic systems) is very static, lacking an adaptive capacity to detect changes over time or predict future scenarios in specific communities or species assemblages. On the other hand, thresholds of abiotic indicators are not very precisely defined and distinction between categories may be misleading.

Along the coast, the interaction between physical and biotic factors has been frequently analysed and it is well known that species vary due to natural abiotic influences and biological interactions (Lüning, 1990). Several abiotic and biotic factors determine the distribution and structure of coastal benthic communities, depending on the main drivers of ecological processes and patterns at the spatial scale of interest (Levin, 1992; Burrows *et al.*, 2009). For example, at a global scale, temperature and solar radiation are mainly responsible for biogeographic differences (Van den Hoek, 1982; Lüning, 1990). At higher scales (e.g. at a Regional scale) factors such as exposure to wave action, tidal range, salinity and nutrients may play a major role in the distribution and structure of communities (Kautsky & van der Maarel, 1990). However, at a local scale some of these variables do not vary significantly; therefore, other factors, such as geomorphological characteristics and bathymetry, seem to affect species distribution (Schoch & Dethier, 1996; Díez *et al.*, 2003; Chappuis *et al.*, 2014; Ramos *et al.*, in press). The successful protection of marine diversity, the assessment of anthropogenic impacts and the restoration of altered ecosystems rely largely on the understanding of processes and factors that structure biological assemblages (Chapman, 1999). Therefore, it is important to establish the significance of physical variables at different scales of analysis, as well as the interaction between them as a decisive element in the distribution of organisms.

Thus, given the influence of physical factors on the distribution of species, it could be advantageous to use these variables in coastal classifications, especially in the large-scale ones, due to the possibility of continuous data acquisition against the lack of homogeneous reliable biological information across large coastal areas. Based on such an assumption, it is possible to consider that more easily measured and standardized physical or chemical variables, which rely increasingly on remote sensing (Allee *et al.*, 2014) and models (e.g. Verfaillie *et al.*, 2009), could be used to develop specific methodologies for prediction of the potential distribution of species.

In the last decade, the ability of some variables (e.g. wave exposure, substrate composition, topography, current speed, temperature, etc.) as potential predictors of physical habitats for different communities has been applied to coastal system classifications (e.g. Roff & Taylor, 2000; Connor *et al.*, 2004; Mount *et al.*, 2007; Madden *et al.*, 2009). However, these classifications greatly vary depending on the region where they were developed, on the physical and biological heterogeneity and on the availability of data (Valentine *et al.*, 2005). In addition, the main results of these classifications are represented as habitat polygons instead of continuous coastal areas, as necessary for the various management purposes.

Regarding the biological element, intertidal macroalgae communities seem to be an optimum component. These communities are very relevant from an ecological and scientific point of view. From an ecological perspective, it has been shown that despite their small relative representation, they are vital for the ecological functioning of coastal zones (Lubchenco *et al.*, 1991). Scientifically, the composition and distribution of these assemblages have been widely studied, as they are the basis of rocky substrate reefs.

Therefore, in order to solve existing gaps, Ramos (2015a) developed a standardized hierarchical classification system along the NE Atlantic Region, at three different scales: Biogeographic (Ramos *et al.*, 2012, 2014), Regional (Ramos *et al.*, 2016) and Local (Ramos *et al.*, in press). This system takes into account both the physical characteristics of the coastal zones and those related to biological communities that colonize this environment at different scales. However, some questions arise from scientific and technical debates regarding the general suitability of such a type of classification system concerning, among others, the following issues: (i) the decision on scales and the definition of the spatial domain, (ii) the selection of the most representative physical variables, the required number of indicators and their type, (iii) the classification methodologies (statistical tools), (iv) the kind of biological information to test the ecological meaning of the classification and (v) the biological validation procedure.

So, based on the experience of those previous studies, the main objective of the present work is to discuss pros and cons regarding different conceptual and technical issues for effective implementation of such a hierarchical management tool. For this purpose, this paper is organized taking into account the five previously established topics (i–v), using the NE Atlantic case study as a reference point for discussion.

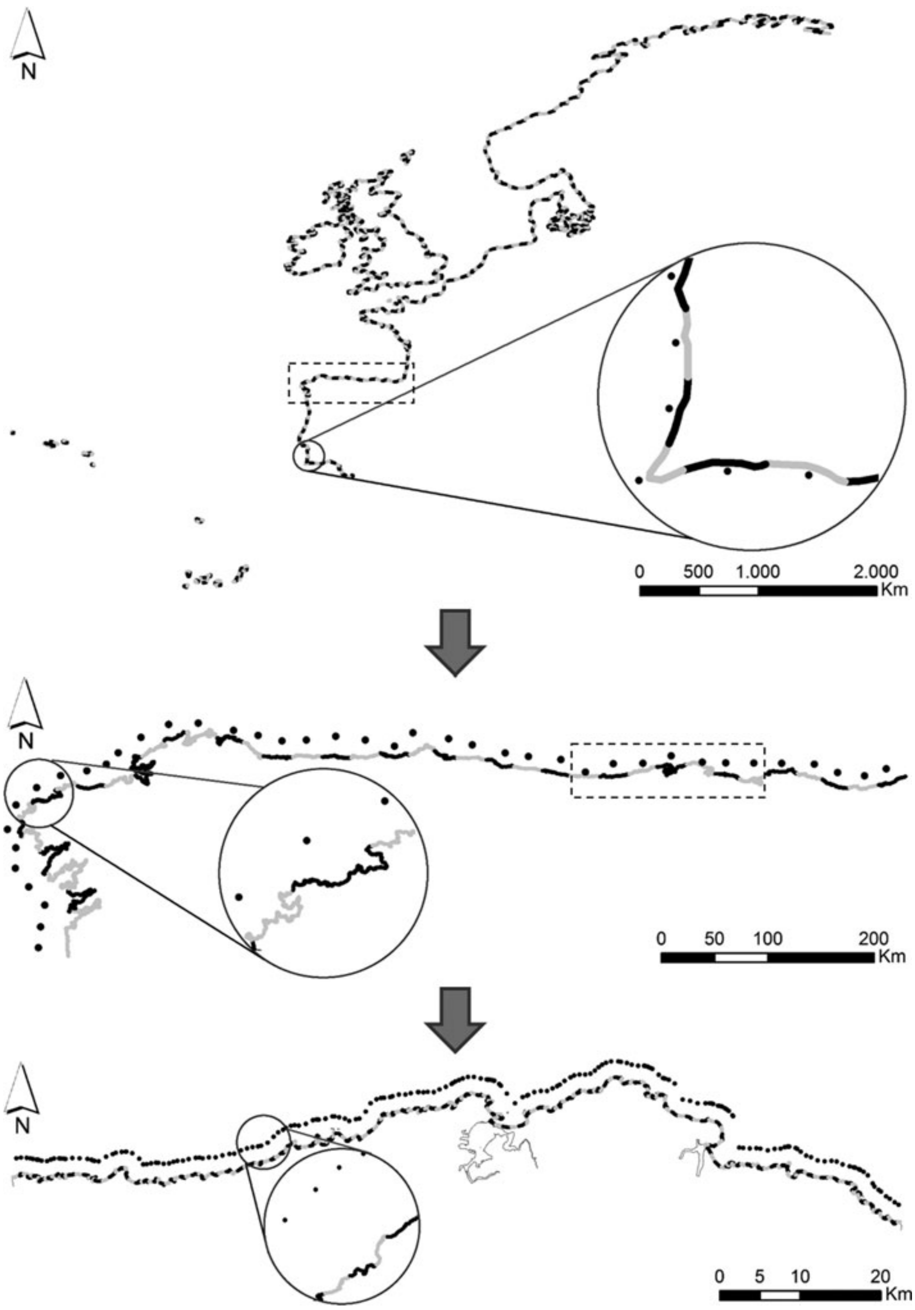

Fig. 1. Detailed representation of the technical procedure followed for division in stretches along the three scales, from top: NE Atlantic (Biogeographic scale), NW and N Iberian Peninsula (Regional scale) and Cantabria coast (Local scale). Black circles indicate reference points for quantification of physical variables.

NE ATLANTIC CASE STUDY

Decisions on spatial domains and scales

At least three main elements must be considered for analysis of this topic: the spatial domains, the size of the assessment units and the definition of the coastlines required at different working scales. The establishment of the most suitable spatial domain according to ecological features and management purposes is the first step to develop a hierarchical classification system at different scales. Once the study scales are selected, the specific spatial domains must be delimited to ensure that the physical data series properly describe the main processes within the study area. The scales could be Global (e.g. Europe), Biogeographic (e.g. NE Atlantic), Regional (e.g. North Sea) or Local (e.g. the North coast of Brittany). According to the objectives established by Ramos (2015a), three different scales integrate the reference case study: 'Biogeographic', that encompasses the NE Atlantic coast (NEA), from Norway to the Canary Islands, including all the regional seas integrated in that 'Geographic Intercalibration Region' (European Commission, 2013); 'Regional', that encompasses the North-west and North Iberian Peninsula coast, all along the important environmental gradients associated to the southern Gulf of Biscay; and 'Local' that corresponds to the coast of the administrative region of Cantabria (Figure 1).

In a second step, a uniform procedure for the division of the entire coasts in sections or assessment units of identical

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length has to be established. The size of these basic units has to be in accordance to the level of detail required in each case. Thus, the choice was based on a balance between an appropriate characterization of the environmental heterogeneity and a realistic number of segments that facilitate database management. After several experiences, a general pattern may be outlined, approximately, as follows: greater than 50 km at Global scale, between 25 and 50 km at Biogeographic scale, between 10 and 25 km at Regional scale, and smaller than 5 km at Local scale. Assuming those guidelines, different partitioning schemes were employed in the NEA case study: at the Biogeographic level (~22,000 km) the coast was subdivided each 40 km (550 stretches), at the Regional level (~2350 km) each 20 km (41 stretches) and, finally, at the local scale (~200 km) each 1 km (209 stretches).

For accomplishing this task, a third element should be preliminarily considered: the definition of the coastline at each scale, since a smooth line can be used at Global and Biogeographic scales (~1:500,000) (ESRI, 2002) and a more intricate one at Local scales (~1:5000) (National Center for Geographic Information by the National Geographic Institute; Spanish Government). A detail of the coastline drawn at different scales is shown in the zoom areas within Figure 1.

In summary, the methodological approach used to characterize a certain coastal area has to use a spatial resolution that recognizes the variability of environmental conditions at the level of detail required in each case.

Physical variables and indicators

The selection of the most representative physical variables is a crucial factor, since it is the basis for the whole classification. Some variables may only have ecological meaning at a certain scale and, what is most important, the use of unspecific variables may significantly affect the correct recognition of clear classification categories. For example, following the different selection of variables carried out by Ramos (2015a), the sea surface temperature is a very versatile variable, critical for all organisms because of its effect on physiological activities and molecular properties. Accordingly, the role of temperature is therefore recognized as one of the most important environmental factors directly responsible for differences in the distributions of marine organisms resulting in the delimitation of large biogeographic regions (e.g. Van den Hoek, 1982; Breeman, 1988). Another variable that determines the structure of communities along the coast at the whole range of scales is the intensity of wave action (Sousa, 1984; Burrows, 2012). Salinity also determines species distribution along Global or Biogeographic scales, while it varies over a short range along coastal waters at Regional or Local scales except in the proximity of large river discharges and ecotones between some regional seas (e.g. Baltic Sea – North Sea) (Lüning, 1990). Coastal morphology affects species distribution at Local scale (Ramos *et al.*, 2015b), while tidal range does not vary significantly along a limited area (Bermejo *et al.*, 2015; Ramos *et al.*, 2015b), but influences communities at larger scales (Lewis, 1964). Also, other factors as turbidity, topographic features or rockpools influence at each specific point causing local modifications (e.g. Díaz-Tapia *et al.*, 2013; Martín-García *et al.*, 2013). As the aim of this classification system is to describe macroalgae distribution patterns along Biogeographic, Regional and Local scales, specific factors such as those mentioned above have not been included.

In a second step, these variables have to be quantified in a standardized way and with the level of precision required. For this purpose, the great advance produced in generating oceanographic and meteorological data from satellite sensors and numerical modelling provides a suitable tool for the development of ecological classifications, which allows easy quantitative measurements of physical variables and provides continuous and uniform information along the coast. The type of information needed and, consequently, the specific source employed to obtain it depends on the required accuracy and precision at each scale. These sources could be satellite sensors, numerical reanalysis, numerical modelling and *in situ* sampling.

Coming back to the NEA case study, the sources for obtaining environmental information for the selected variables vary among the three spatial scales (Table 1). *In situ* salinity values were used at a European scale due to the lack of long temporal series of remotely sensed data. Vertical profiles of water salinity measurements were provided by the *World Ocean Database 2009* (WOD) of the National Oceanic and Atmospheric Administration (NOAA)-NESDIS National Oceanographic Data Center (NODC) (Boyer *et al.*, 2006). The tidal range was calculated from harmonic analysis computed using sea level observations of the TOPEX/Poseidon satellite altimetry. At a regional level, estimates of Photosynthetically Active Radiation (PAR), derived from 9.3 km Sea-viewing Wide Field-of-view Sensor (SeaWIFS) Level 3 data, were provided by the NASA Goddard Space Flight Center, Distributed Active Archive Center. The data used are integrated daily, which takes into account the number of daylight hours and cloud coverage. On the other hand, at local scale MyOcean (MODIS-Aqua and SeaWIFS sensors) products were employed due to their higher temporal resolution. To estimate the variations of sea surface temperature (SST) at the largest scales, remotely sensed Advanced Very High Resolution Radiometer (AVHRR) data from the Jet Propulsion Laboratory Physical Oceanography Distributed Active Archive Center (JPL PODAAC) were used. These data were processed in JPL within the NASA/NOAA AVHRR Oceans Pathfinder 5 project. Data from the Group for high Resolution Sea Surface Temperature (GHRSST) L4 products were used for the local scale. This sensor has the necessary accuracy to properly describe the coast of Cantabria, where extremely high temperatures seem to cause the distribution shifts in species (Fernández, 2011; Díez *et al.*, 2012; Duarte *et al.*, 2013; Voerman *et al.*, 2013).

Regarding coastal morphology, this variable was obtained by analysis of Geological Maps of Spain (Geological and Mining Institute of Spain, IGME) and by fieldwork in some cases (Ramos *et al.*, 2015b). Finally, in the case of the exposure to wave action, the information provided by the satellite missions TOPEX, TOPEX 2, Jason, Envisat and Geosat Follow-On GFO along a mesh of $1 \times 1.5^{\circ}$ was accurate enough at the Biogeographic scale. However, the inclusion of a numerical reanalysis (Global Ocean Wave, GOW) improved the temporal and spatial coverage of the wave height record (spatial resolution of 0.1°) at the Regional scale (Reguero *et al.*, 2012). At the Local scale a database with even higher resolution was used (200 m), the reanalysis Downscaled Ocean Waves (DOW) (Camus *et al.*, 2013). This wave reanalysis to coastal areas uses a hybrid methodology which combines numerical models (dynamic downscaling) and mathematical tools (statistical downscaling). The

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Table 1. Physical variables employed at each scale. Type of data sources in brackets: *in situ*, satellite sensor (sat. sensor) or numerical modelling (num. modelling).

Variable	Scales		
	Biogeographic	**Regional**	**Local**
Salinity	NODC (*in situ*)	X	X
Tidal range	TOPEX/Poseidon Mission (sat. sensor)		X
Wave height	TOPEX, Jason … (sat. sensors)	GOW (num. modelling)	DOW (num. modelling)
PAR	SeaWiFS (sat. sensor)		MyOcean (sat. sensors)
SST	AVHRR (sat. sensor)		GHRSST (sat. sensors)
Coastal morphology	X	X	Geological map + fieldwork

PAR, Photosynthetically Active Radiation; SST, Sea Surface Temperature; NODC, National Oceanographic Data Center (NOAA Data Center); GOW, Global Ocean Wave; DOW, Downscaled Ocean Waves; SeaWiFS, Sea-viewing Wide Field-of-view; AVHRR, Advanced Very High Resolution Radiometer; GHRSST, Group for high Resolution Sea Surface Temperature.

methodology has been tested and validated, confirming a good reproduction of the hourly time series structure and the different statistical parameters. Besides, it was calculated along the depth of closure (the most landward depth seaward of which there is no significant change in bottom elevation and no significant net sediment exchange between the nearshore and the offshore), more appropriate to characterize the intertidal area with the high level of detail required in this case study.

The third relevant decision regarding this topic is about selection of the 'virtual sampling points'. As most information relies on standardized, interpolated and validated databases associated to different grids (i.e. spatial resolution), we must establish the specific location of the representative sampling points at different scales. An important debate arose at this point regarding the representativeness of those stations at the three working domains of the NE Atlantic study. In the end, variables were calculated at points 5 km off the coast at the Biogeographic scale (Ramos *et al*., 2012), distance necessary to obtain homogeneous and reliable data from satellite sensors along regional seas with very distinct physical and oceanographic singularities (e.g. Canary Island, Biscay Gulf, Irish Sea, North Sea). A different criterion, based on average depth (~150 m deep), was established at the Regional scale (Ramos *et al*., 2016), since it is an area with a more similar continental shelf, where depth could be used as an appropriate reference; finally, a fixed distance of 2 km was the selected threshold at the Local scale (Ramos *et al*., in press), so these data need to be more accurate (cf. black dots in Figure 1). The suitability of these procedures has been demonstrated because of the similarity of the simulated patterns versus those obtained from *in situ* measurements at the three scales (cf. Ramos *et al*., 2012, 2016, in press). As stated by Ramos *et al.* (2012), this similarity confirms that the variability of the main coastal physical features was analysed appropriately. Besides, if the location of the reference points had been situated closer to the coastline, it would not have been possible to obtain continuous information throughout the coast.

A final element that must be established is the number of indicators for each variable, their type and how to ensure the absence of redundancies amongst them. An 'indicator' is a specific driver of a physical variable (e.g. 99th percentile, maximum, monthly average) associated to the spatio-temporal distribution of natural components (species, communities, habitats). As previously established, this constitutes a key point for classification because of the predictability capacity of each selected indicator. Different approaches previously developed in other regions agree on the use of some physical descriptors, although there are differences in how to express them (e.g. Mount *et al*., 2007; Madden *et al*., 2009). In general, it can be possible to consider several indicators for each variable, as average, maximum and minimum values and standard deviation, since data series with high temporal resolution were available. This way, normal and extreme conditions were considered. Then, one of the most suitable methodologies to avoid redundancy among indicators is to remove those that show mutual influence (i.e. intercorrelation coefficient higher than 0.9 or 0.95).

In any case, further studies on physical indicators should be carried out, in order to find out those that more accurately reflect the specific ecological responses of different biological communities. For example, related with SST, the number of days in summer that a certain temperature is exceeded (Voerman *et al*., 2013); or, related with exposure to wave action, the bottom shear stress or the frequency of extreme events, which have greater explanatory potential for the important interactions between wave energy and organisms (Gaylord, 1999). In the case of soft bottoms, it would also be very important to include some homogeneous indicator related to the grain size of sediments (Ysebaert *et al*., 2002) or a physical surrogate related to this variable.

Classification approaches (statistical tools)

Once all the information is available, a different problem arises: the interpretation of results by means of statistical tools. Despite uncertainties related to the introduction of mathematical artefacts for these types of combined analyses, they may provide an objective way to detect general trends in the distribution of areas with similar characteristics. Between the different statistical possibilities, two approaches are frequently applied: hierarchical agglomerative clustering (Legendre & Legendre, 1998) or a combination of self-organizing map (SOM; Kohonen, 2001) and the k-means algorithm (Hastie *et al*., 2001). Both approaches can be applied at different spatial scales, but the advantages and disadvantages summarized in Table 2 should be taken into consideration, as explained through their application in the NE Atlantic case study.

In this study, the hierarchical agglomerative clustering was applied at the Biogeographic scale (Ramos *et al*., 2012), with complete linkage as amalgamation rule, as a suitable method to look for discontinuities in data (Legendre & Legendre,

Table 2. Pros and cons of two different approaches (statistical tools) to classify coastal waters.

Statistical tool	Advantages	Disadvantages
Cluster	Different divisions according to the specific objective	Subjective decision on linkage distance
	Hierarchical visualization	Independent visualization of physical and biological variables
	Groups integrated in a continuous environment	
SOM + k-means	Preservation of neighbouring relationships	K-means establishes a rigid border in a continuous environment
	Patterns of data intuitively visualized	
	Visualization of physical variables, groups and biological information together	
	Objective decision rules	

1998). This procedure reflects different divisions of a region depending on the significance level (linkage distance) applied to the cluster analysis. This iterative procedure for the selection of a classification scheme also generates a sufficient variety of results that may accomplish the different requirements needed in each study (Figure 2A). This is one of the main strengths of this statistical methodology, since the identified groups are integrated in a continuous environment, whose limits must be better considered as gradient zones.

On the other hand, the procedure applied at Regional (Ramos *et al.*, 2016) and Local (Ramos *et al.*, in press) scales combined two techniques: (i) self-organizing map (SOM; Kohonen, 2001), an artificial neural network (ANN) technique; and (ii) the k-means algorithm (Hastie *et al.*, 2001) (Figure 2B). The SOM is a classification method that detects patterns or classes in a set of data, preserving the neighbouring relationships. This means that similar clusters in the multidimensional space are located together on a 2D grid that allows the data to be intuitively visualized. This allows distinguishing the environmental variability of even limited areas. However, the number of groups obtained with the application of the SOM was too high in order to create a simple and manageable classification. Thus, as the second step, a k-means algorithm was applied to cluster the trained map. One of the strengths of this protocol is the reduction of the level of subjectivity in the final classification, since several decision rules have been provided. First, the optimum map size of the SOM (number of units) was chosen based on the heuristic formula proposed by Vesanto *et al.* (2000). Besides, the number of units chosen was also supported as an optimum solution based on the minimum values for quantization and topographic errors by training with different map sizes. Second, the number of k-means group was justified according to the minimum Davies–Bouldin index (DBI) for a solution with low variance within clusters and high variance between them (Negnevitsky, 2002).

In addition, qualitative variables can be added hierarchically to the statistical classification, as a second level of the classification (Ramos *et al.*, in press). This approach may be very

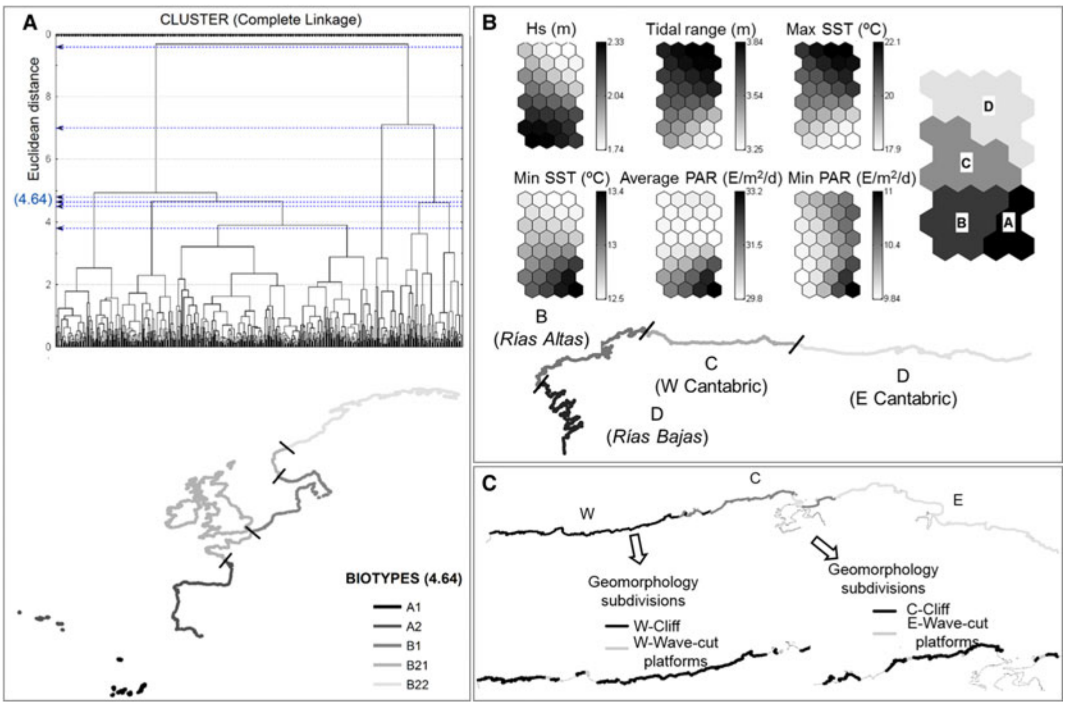

Fig. 2. Classification methodologies applied at different scales. (A) Cluster analysis throughout the NEA region (thresholds refer to cut-off Euclidean distances used for segregation of groups). Bottom: Groups obtained (biotypes) for a threshold of 4.64. (B) SOM analysis along NW and N Iberian Peninsula. Top left: gradient analysis of each physical variable on the trained SOM. Top right: k-means result on the SOM plane. Bottom: Map of the typologies obtained. (C) Map of the typologies obtained after SOM and k-means analysis along the coast of Cantabria and their hierarchical subdivision according to the variable 'coastal morphology'. Modified from Ramos *et al.* (2012, 2016, in press).

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useful to include the type of substratum (soft bottom or rocky), given the high influence of this characteristic in the distribution of benthic communities.

In our case study, the above-mentioned second level of the classification is accomplished at the Local scale. The units obtained by the application of SOM and k-means were subdivided by the addition of the categorical variable coastal morphology (Figure 2C). The addition of this variable provides a more detailed environmental characterization and a better explanation of the distribution of macroalgae species (Bermejo *et al.*, 2015). Thus, this hierarchical approach gives the option of including this variable or not, deciding in each case according to the purpose.

Biological information

In the end, the most important point is that our statistical classification has a real ecological meaning in terms of agreement with the specific objective and the study scale. It is therefore necessary to know the actual distribution of communities at the level of detail required in each case, in order to establish their relationship with the physical groups. The lack of standardized information of biological elements along the spatial domain, mainly for studies over large areas (e.g. NE Atlantic, Bay of Biscay), is one of the most frequent problems in this kind of work.

Two main questions arise in regard to this topic: What kind of data do we need? How can we obtain them? In general, at Regional and Local scales, quantitative or semi-quantitative information could be obtained from specific local studies. However, at Global and Biogeographic scales a homogeneous approach is required. In this sense, international initiatives aimed to palliate these problems by installing permanent international networks of observation stations, such as the COST Action ES1003 EMBOS (Development and implementation of a pan-European Marine Biodiversity Observatory System). In this network specific protocols were proposed in order to ensure standardized and homogeneous long-term monitoring for soft bottoms, hard substrata and pelagic communities in several pilot sites throughout Europe. This kind of work is of great importance, allowing assessment of long-term changes in marine biodiversity and their possible causes, taking into account natural and anthropogenic gradients along a large area.

In practice, two different approaches were applied to acquire the biological data depending on the requirements of each scale in the analysed case study. In this case, intertidal macroalgae communities are the biological element used at the three scales, although other organisms could also be employed. At the Biogeographic level (Ramos *et al.*, 2014), the generation of quantitative standardized data all along the NEA region was a very difficult task. The cost of carrying out homogeneous sampling to obtain data that could be directly comparable is very high. Because of this, a collaborative work among experts from EU member states involved in the intercalibration of metrics for assessment of macroalgae along the NEA space facilitates the generation of a standardized biological database, including the most suitable macroalgae species that may represent the NEA intertidal rocky shore all around the NE Atlantic area. Then, semi-quantitative abundance data of those macroalgae taxa were compiled using three levels: common (2), rare (1) or absent (0). The experts of each country determined these ranges taking into account the original quantitative data obtained by field surveys in the different regions. In this case, the compilation of data using the same species matrix and the same procedure ensured that there were no differences in taxonomic identification within working groups.

However, at smaller spatial scales, more detailed biological information is required, including quantitative macroalgae cover data along the altitudinal gradient on the shore (Ramos *et al.*, 2016, in press). In contrast to the biogeographic gradients, at these scales the macroalgae distributions at different bathymetric levels along the shore can help to explain certain patterns of longitudinal variability. Therefore, along the NW and N coast of the Iberian Peninsula quantitative data, standardized by both time and space, were obtained. For this purpose, field surveys were carried out during the same low spring tide cycle. At each site, three transects, perpendicular to the coast with a characteristic zonation pattern were selected. Then, a stratified and systematic sampling procedure was applied, dividing each transect into four areas (lower intertidal, middle intertidal, upper intertidal and supralittoral). Algae were identified *in situ* and taxa cover was obtained by photographic analysis in ARCGIS. This combined technique presents three main advantages. First, the identification of taxa through direct observation in the field allows the recognition of organisms partially hidden by canopy species, which would be more difficult at a later stage from photographs. Secondly, the automatic digital picture analysis provided objectivity to coverage data versus traditional observer estimation. Finally, photographs provide the added benefit of permanent visual records, which can later be revisited for additional information in the images (Parravicini *et al.*, 2009). The resolution obtained by this procedure is good enough for the application of some of the biotic indices developed for the assessment of macroalgae in application of the European WFD, such as the CFR index (Juanes *et al.*, 2008; Guinda *et al.*, 2014).

Biological validation (statistical tools)

The final question to be answered along this technical debate is related to the specific statistical tools for testing the suitability of the physical groups related to the distribution of communities and for characterizing these groups according to their species composition. To accomplish these goals, several statistical methods, with different degrees of objectivity, are currently available.

In general, standard analyses, such as cluster, SIMPER, MDS or PERMANOVA, are very often used in benthic ecology to test the statistical relationship between biological data and physical groups from different points of view. In short, the cluster analysis is mainly a screening tool, which allows identifying groups according to species distribution that may be later related with the physical groups (i.e. biotypes). Complementarily, MDS is a technique useful for gradient analyses, showing a clear advantage to see patterns of distribution of elements (e.g. sampling stations, cluster groups, etc.) in a continuous environment. In addition, SIMPER, PERMANOVA and ANOSIM tests provide a way to check differences in taxa composition between the physical groups previously defined.

Beyond this traditional scheme, alternative statistical procedures applied in the NEA case study, ratified their suitability for fitting biological-physical interactions. As demonstrated by Ramos *et al.* (2016, in press), the SOM analysis is not just a useful tool for the classification of environmental variables (cf. Section on Classification approaches), but a technique that allows (i) to visualize, in a very intuitive way, the patterns in macroalgae communities distribution and (ii) to identify their relation to environmental data and physical typologies by visualization of the gradient distribution in the same figure. In addition, the weight (i.e. connection intensity) of each species in each cell of the SOM can be interpreted as its occurrence probability in a given area, even in areas in which they did not occur during the sampling (Céréghino *et al.*, 2005). In fact, different studies have proved the benefit of SOM in processing of ecological and environmental data compared with conventional statistical methods (Céréghino *et al.*, 2005; Solidoro *et al.*, 2007).

Furthermore, new techniques related with the SOM analysis, such as the *component planes* (Vesanto, 1999), integrates the graphical representation of the physical variables that were previously included in the SOM and the macroalgae data. The simultaneous inspection of multiple component planes allows for the visualization of correlated variables, both physical and biological, because closely placed planes are indicative of similar behaviour or correlation between respective variables. An example of this technique is available from the Local scale (Ramos *et al.*, in press) of the NEA case study (Figure 3), applied to the interpretation of macroalgae distribution for the lower intertidal along the coast of Cantabria according to the physical classification of that coastal zone (SOM and k-means). Thus, environmental conditions, species distribution and physical groups can be analysed and compared as a whole. Those variables with a strong correlation appear as component planes that are closest together. For instance, in the top of the graph (Figure 3), the average SST was correlated with higher abundances of *Corallina officinalis/Ellisolandia elongata, Gelidium corneum* and *Pterosiphonia complanata* species where the temperature presented high values (group E) and with higher abundance of *Bifurcaria bifurcata* and *Halopteris scoparia* where the temperature is low (group W and C).

At this point, it is not possible to ignore the power of logistic regression models as another very useful statistical tool available to relate the environmental conditions and community assemblages, mainly for the case of using categorical variables (Ysebaert *et al.*, 2002; Guanche *et al.*, 2013). This method measures the fitting quality by comparing the deviance ratio (Δdev) and the chi-square distribution (χ^2). Assuming a confidence level $\alpha = 95\%$, if $\Delta\text{dev} > \chi^2_{0.95\%}$, Δdev, the fitting quality of the parameter was significant. Once the parameters estimated for the models are known, the predicted probabilities *p* of the significant fittings could be represented according to different categories. Thereby, the graphical representation allowed visualizing the probability of occurrence of each species, according to the analysed physical variable. For example, in Ramos *et al.* (2015b) it was used to relate

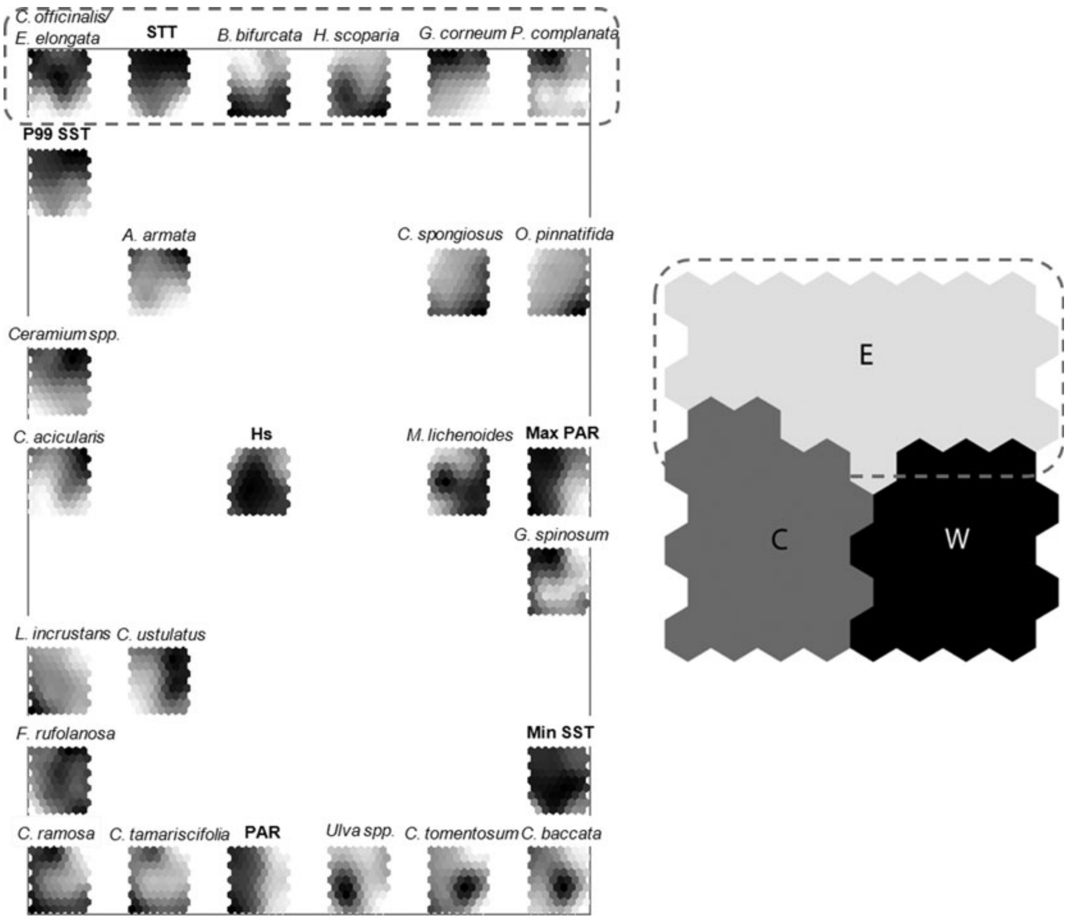

Fig. 3. Component planes ordering the physical variables and taxa in the lower intertidal. Visualization of variables in a shading scale on the previously trained SOM. Right: visualization of physical classification in the same trained SOM. Modified from Ramos *et al.* (in press).

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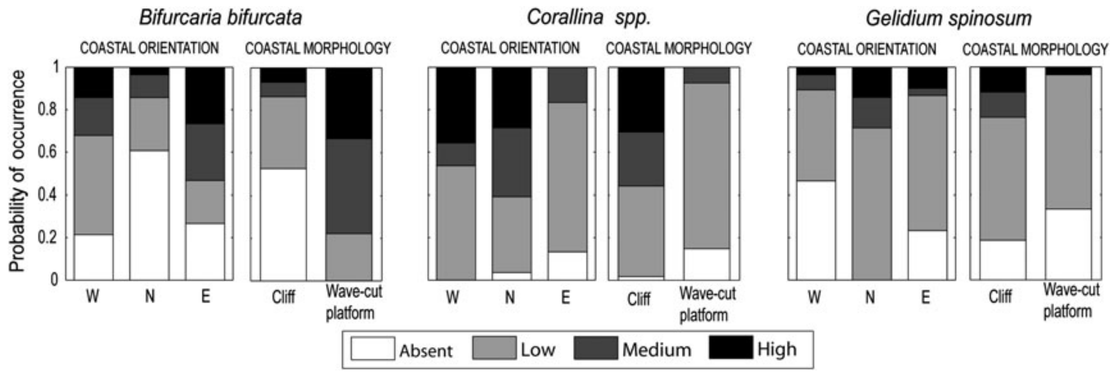

Fig. 4. Graphical results of logistic regression models: probability of occurrence of three macroalgae species conditioned by geomorphological variables (coastal orientation and coastal morphology).

geomorphological variables to macroalgae distribution. In this case, species probability of occurrence was represented as absent, low (0–33%), medium (33–66%) or high (99–100%) (Figure 4). Among other relations, it can be observed, at the lower intertidal, how *C. officinalis/E. elongata* has a great probability of occurrence in steep slopes that faced N and W. On the contrary, *Bifurcaria bifurcata* appeared mostly in wave-cut platforms facing W or E. Thus, the regression logistic models define and characterize the spatial patterns of species along environmental gradients, an important result supporting the suitability of those factors (i.e. coastal orientation and coastal morphology) in the classification approach at Local scale.

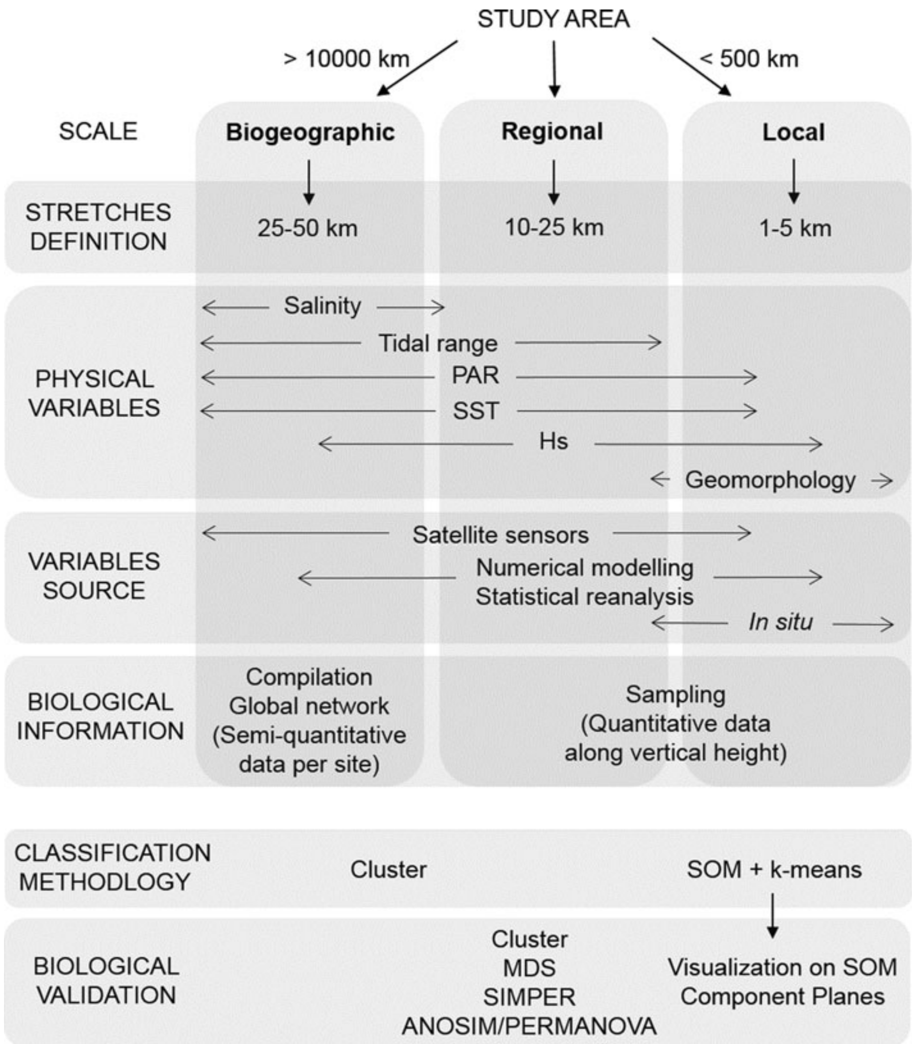

Fig. 5. Hierarchical support system used as management framework for classification of coastal areas at different spatial scales.

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APPLICATIONS

The hierarchical classification approach presented in this paper offers alternative procedures for the definition of ecologically relevant regions, a basic requirement for coastal environmental protection and management. This classification system would support the application of ecological-based approaches for diagnostics and assessments of health status of marine systems (e.g. ecological status, *sensu* WFD; state of conservation, *sensu* Habitats Directive, etc.), which ultimately will allow for their sustainable management at the required level of definition (i.e. geographic scales). Among others, such a hierarchical classification could be useful for works linked to maritime spatial planning, environmental impact assessment, analysis of climate change effects, rehabilitation and restoration projects, establishment of reference conditions, integrated coastal management, implementation of environmental legislation, etc. (e.g. Laruelle *et al.*, 2010; Pittman *et al.*, 2011).

A good example of some of those applications was the use of the Biogeographic classification carried out at the NE Atlantic scale (Ramos *et al.*, 2012) as technical justification for the establishment of physically harmonized coastal zones for the potential distribution of macroalgae. Thereby, new 'biotypes' (physical-based groups) were adopted for the Intercalibration of assessment metrics for macroalgae carried out at this geographic region (IC NEA GIG), splitting off the common IC type NEA 1/26 (from Canary islands to the Arctic Sea) into three more homogeneous subtypes: (1) NEA '1/26 A1' (Canary Island and Azores); (2) NEA '1/26 A2' (Iberian Peninsula and Southern France) and 'NEA 1/26 B21' (Northern France, Ireland, Norway and UK) (European Commission, 2013).

Further applications of these procedures may focus on the temporal scales of variability. In that complementary framework, some applications to predict future changes in macroalgae communities and the related consequences on their current ecological status were proposed by Sales & Ballesteros (2009). The physical information compiled with high spatial and temporal resolution (i.e. meteo-oceanographic data series) allows studying historical shifts in species distribution. The understanding of these changes is very important to determine the specific indicators (environmental conditions) that may cause the disappearance, reduction, increase or appearance of a specific species or population. Therefore, based on physical surrogates and information on actual patterns of distribution it may be possible to retrospectively estimate the degree of stress in a specific area (McArthur *et al.*, 2010).

In a prospective way, the availability of accurate information on current physical characteristics and communities distribution provides an important base for assessment of habitat suitability of different species. This information allows developing species distribution models (SDMs) that could be applied for prediction of their future spatial distribution in different projected climate scenarios (e.g. Intergovernmental Panel on Climate Change). Climatic conditions in future could be introduced in SDMs and predict the distribution of target species and marine biodiversity (e.g. Cheung *et al.*, 2009; Jordà *et al.*, 2012).

CONCLUSIONS

The methodological framework proposed in this paper allows the establishment of a classification system of the coastal environment and to recognize the physical and biological variability associated within and between groups at different scales. This is based on the analysis of specific abiotic characteristics that determine the distribution of different benthic communities, adapting the methodologies to specific spatial requirements. For this purpose, the hierarchical support system, summarized in Figure 5, provides a management framework for classification of coastal systems at the most appropriate resolution, applicable to a wide range of coastal areas.

This classification system offers an objective statistical tool for the definition of ecologically relevant regions, which may be useful for environmental protection and for the assessment of anthropogenic effects and climate change in coastal ecosystems. In addition, the knowledge obtained about the relationships of species with environmental factors will be helpful for decision-making on the management and conservation of natural resources, offering a procedure to predict the composition and structure of sustainable systems over space and time.

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