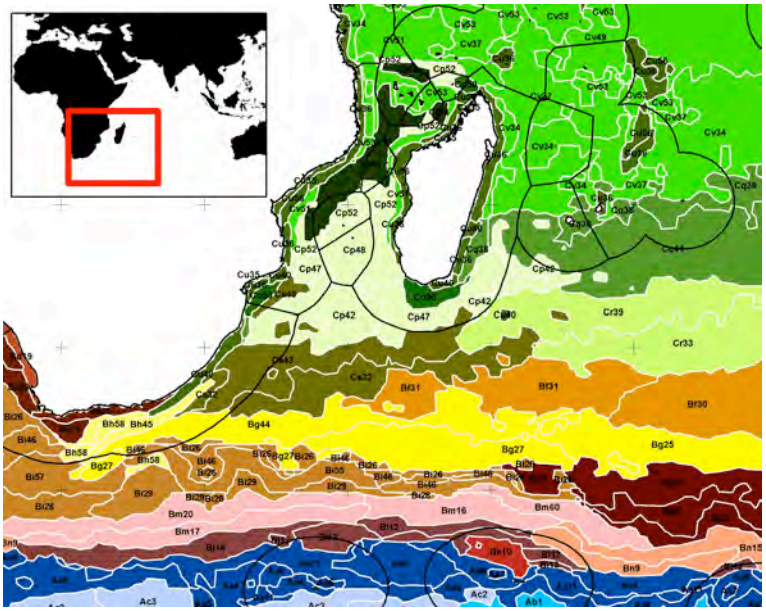
Assembling data for coastal and marine spatial planning in the Western Indian Ocean

Section I: Pelagic bioregionalisation



Author: Dr Erwann Lagabrielle[1]
[1] University of La Réunion/IRD
UMR ESPACE-DEV, BP 50172, 97492 Sainte-Clotilde Cedex, France

Prepared for:
A.S.C.L.M.E./Agulhas Somali Current Large Marine Ecosystem
GEF/UNDP/UNOPS Project 00047255
ICA 2011/LICA-SP/25683

SUMMARY

LIST OF FIGURES

LIST OF TABLES

Report citation:
Lagabrielle, E. 2012. Assembling data for coastal and marine spatial planning in the Western Indian Ocean - Section I: Pelagic bioregionalisation. Prepared for the A.S.C.L.M.E./Agulhas Somali Current Large Marine Ecosystem project, GEF/UNDP/UNOPS. 20 p.

1. INTRODUCTION

Restoring, maintaining and conserving the ecological integrity of the Agulhas Somali Current Large Marine Ecosystem (Figure 1) while ensuring optimal and sustainable utilization of the resources has been identified as a priority (Obura et al., 2012), especially with regard to the development of policy for the establishment of transboundary Marine Protected Areas (MPAs). This task requires knowledge of the spatial distribution of the physical and biological patterns and processes than sustain marine biodiversity in the region (Lombard *et al.* 2007; Sink and Attwood 2008). Understanding the spatial characteristics of the large and complex pelagic realm is the foundation for assessing pelagic biodiversity and further planning and implementing a representative system of MPAs in the Western Indian Ocean region. Therefore, the aim of this study was to map and describe the pelagic bioregions of the ASCLME area of interest. The intended outcome was a set of pelagic bioregions that will underpin a spatial framework to support future coastal and marine spatial planning. Bioregionalisation is a process that aims to classify a geographic area into broad scale, biologically meaningful units, based on a set of physical and biological variables. For example, variations in depth, temperature or nutrient availability across space and time define different habitat types. In turn, these habitats are assumed to be correlated with different biological communities. In this report, we identify a spatially nested system of bioregions grouped into 3 agregative levels.

2. A BRIEF OVERVIEW OF THE AGULHAS-SOMALI CURRENT

The oceanic region of the Western Indian Ocean links the Indian Ocean, the Southern Ocean and the Atlantic Ocean (Figure 1). In this region, the global South Equatorial current is combined with two major coastal currents flowing Northward: The Agulhas Current and the Somali Current. The Agulhas Current is the Western Boundary Current of the southwest Indian Ocean. It flows down the east coast of Africa from 27°S to 40°S. It is narrow, swift and strong. It includes upwelling zones associated with the strong tropical Agulhas current flowing in a south-westerly direction along the East coast, toward its inflection zone at 40° South (Lutjeharms, 2006). The Somali Current runs along the coast of Somalia and Oman. This current is heavily influenced by the monsoons and is the only major upwelling system that occurs on a western boundary of an ocean. The water upwelled by the Somali current creates one of the most productive ecosystems in the ocean (Mann and Lazier, 2006).

Figure 1. Some of the major currents in the western Indian Ocean indicated schematically (adapted from Lutjeharms and Bornman, 2010)

3. REVIEW OF EXISTING BIOREGIONALISATION METHODS AND APPROACHES

Ever increasing threats to marine biodiversity have led international policy to focus on the protection of coastal and pelagic regions (Convention on Biological Diversity, CBD). The 10th CBD Conference of the Parties held in Nagoya in 2010 agreed to a 10% conservation target for all oceanic regions by 2020. The objective of this policy is to conserve a representative sample of all marine habitats, including pelagic habitats, within MPA networks. Consequently, international and national initiatives have been undertaken to support the achievement of these conservation objectives for oceanic regions. Several projects are underway to map marine bioregions and habitats. A complete review of those projects and approaches to biogeographic classification of the world's oceans has been proposed by Spalding et al. (2007) and Vierros (2007). The main applications of these bioregionalisation initiatives are conservation related but some also integrate fishery management considerations (Hewitt and Linen 2000).

Since the introduction of the Large Marine Ecosystem approach (Sherman and Duda 1999) several projects have undertaken a bioregionalisation of the world oceans. Spalding et al. (2007) published a map of the marine coastal and shelf ecoregions of the world (Figure 2). This classification includes 229 coastal and shelf ecoregions. UNESCO (2009) recently published a world map of pelagic bioregions (Figure 2). These products have been undertaken at very broad scales to produce global expert-based conceptual maps rather than data-driven products suitable for management purposes at a regional and national scale.

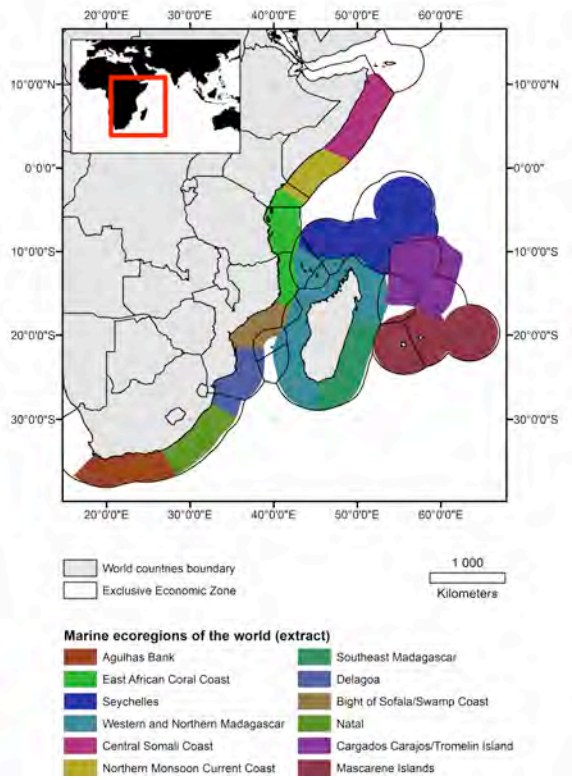


Figure 2. Extract from the map of the marine ecoregions of the world (Spalding et al., 2007) in the Western Indian Ocean.

National classifications of oceans into biologically meaningful units have been undertaken in Australia (Lyne and Hayes 2005) and New Zealand (Snelder et al. 2006) based on biophysical parameters derived from remote sensing and oceanographic models. In 2007, a group of 27 experts working on issues related to the Convention on the Conservation of Antarctic Marine Living Resources (CCAMLR) developed a bioregional habitat mapping protocol and a map for the Southern Ocean (Grant et al. 2006) using a similar approach.

Marine biological data for pelagic ecoregions are generally scarce and their spatial and temporal coverage is often incomplete or biased. Consequently, remote sensing data are often used to develop bioregional habitat maps (Grant et al. 2006). Remote sensing data offer a seamless temporal and spatial coverage of the ocean. In addition, most satellite-derived products are freely accessible on-line. The measured parameters that are generally used in classifying pelagic ecoregions are sea surface temperature, chlorophyll and sea surface height anomalies.

Data derived from oceanographic models (e.g. HYCOM, ROMS, MICOM) are currently being used to complement satellite data. These types of modelled data allow three-dimensional bioregional habitat mapping across the water column (Lyne and Hayes 2005). Physical oceanographic models can also be coupled to biological models (Fennel and Neumann 2001) to derive biological parameters that can further be integrated into the marine habitat mapping process. Other models use satellite imagery as inputs to model biological processes. For example, Behrenfeld and Falkowski (1997) developed algorithms to derive primary productivity from MODIS data (data used in this bioregionalisation study).

The parameters measured by satellite or generate by models are used as surrogates to characterise the environment and classify marine habitats. These habitats are theoretically associated with distinct species assemblages. However, most studies that test relationships

between habitats, communities and physical surrogates have been conducted at finer scales than those required for broad scale marine habitat mapping purposes (Post 2008). Most associations have not been explicitly tested and very few data sets are available to test classifications. Nevertheless, Grant et al. (2006) consider that a bioregionalisation analysis "may not require much ecological detail in a first instance since physical and environmental data can provide an understanding of environmental heterogeneity which will inevitably affect the ecology of a region". Literature reviews associated with expert workshops are generally undertaken to identify habitat-community associations and the most biologically meaningful variables that can be used to map their distribution.

The ocean is three-dimensional with horizontal and vertical connectivity. The extent of the links between pelagic and benthic habitats is debated although consensus has been reached that benthic and pelagic ecosystems should be considered separately in bioregional analyses. Spalding et al. (2007) and UNESCO (2009) consider "the development of parallel biogeographic systems, particularly in deep water areas, for the sea floor and overlying water column layers" necessary. This idea was applied for the bioregionalisation analysis of Australian waters by Lyne and Hayes (2005) which has two distinct components; pelagic and benthic. Most studies also separate the coastal (fine scale) and the offshore environment (broad scale) (Beck et al. 2003).

As biodiversity patterns and processes are scale-dependant, a hierarchical approach is often used to identify spatially nested habitats, from broad scale bioregions to fine scale habitats. For example, the Australian pelagic habitat classification is composed of four subsequent levels from the oceanic scale toward a finer scale that reflects more local processes (circulation regimes associated with gyres) (Lyne and Hayes 2005).

The integration of temporal variability and seasonality of the ocean environment is another challenge for the classification of the pelagic environment. Similar to the spatial approach, a hierarchical systematic approach is often developed to identify and capture this temporal variability and link it to the distribution of biological patterns and processes (Lyne and Hayes 2005). In practice, most bioregionalisation projects use annual or seasonal climatology data (complete time series) derived from satellite images (Grant et al. 2006).

Data derived from remote sensing, direct observations or models have different dimensions that require integration. Generally, a linear normalisation is applied to project the data in a comparable dimension. Other transformations include the application of non-linear functions (for example log or exponential) and the application of thresholds.

The bioregionalisation analysis aims to select and group data pixels (grid cells) into régions exhibiting similar ecosystem characteristics. This can be done by applying simple thresholds to key ecosystem parameters (e.g. to depth contours). When adding other parameters, the process becomes more complex as the potential number of combination of classes increases dramatically (Beck et al. 2003). To cope with such complexity, clustering algorithms are used to segment the geographic space into regions sharing similar properties and differing from other regions (Grant et al. 2006). In the context of a bioregionalisation analysis, the geographic space is partitioned into grid cells. Each cell contains the information on the environmental parameters (biotic or abiotic) that are used to identify cluster

The clusters identified by the bioregionalisation process must be compatible with planning and management applications. This means that the shape of those clusters on the map must be compact and each individual spatial feature must have a minimum area determined by the scale of application. In most applications, the total number of habitat types does not exceed 30.

4. METHODS AND DATA

4.1. Overview of the method

The purpose of a bioregionalisation is to classify an oceanic region into different sub-regions exhibiting similar bio-physical profiles. As biological data on marine ecosystem are generally scarce and fragmented, our method for the bioregionalisation analysis uses surrogate variables extracted from remote sensing data. Those variables (and related parameters) are integrated in a cluster analysis.

The whole analysis is based on the assumption of a multi-scale spatio-temporal organization of the ocean. Indeed, the ocean exhibit patterns and processes observed at the broadest scale (such as latitudinal temperature gradients) and simultanously at mesoscale (mesoscale eddies, for example) and fine scale (waves for instance). Those patterns and processes are spatio-temporally nested. This method is a synthesis of the approaches developed by Grant et al. (2006), Lyne and Hayes (2005) and Post (2008).

The pelagic bioregionalisation of the Western Indian Ocean involved the following steps (Figure 3) (adapted from Grant et al. 2006):

I. Identification of the key bio-physical and ecological patterns and processes
II. Identification of the relevant variables and parameters describing those patterns and processes, or their drivers.
III. Collection of relevant data sets and pre-processing of the data (e.g. normalisation, transformation, resampling, etc.).
IV. Application of clustering procedures
V. Post-analysis of clusters with experts
VI. Assessment and validation with experts

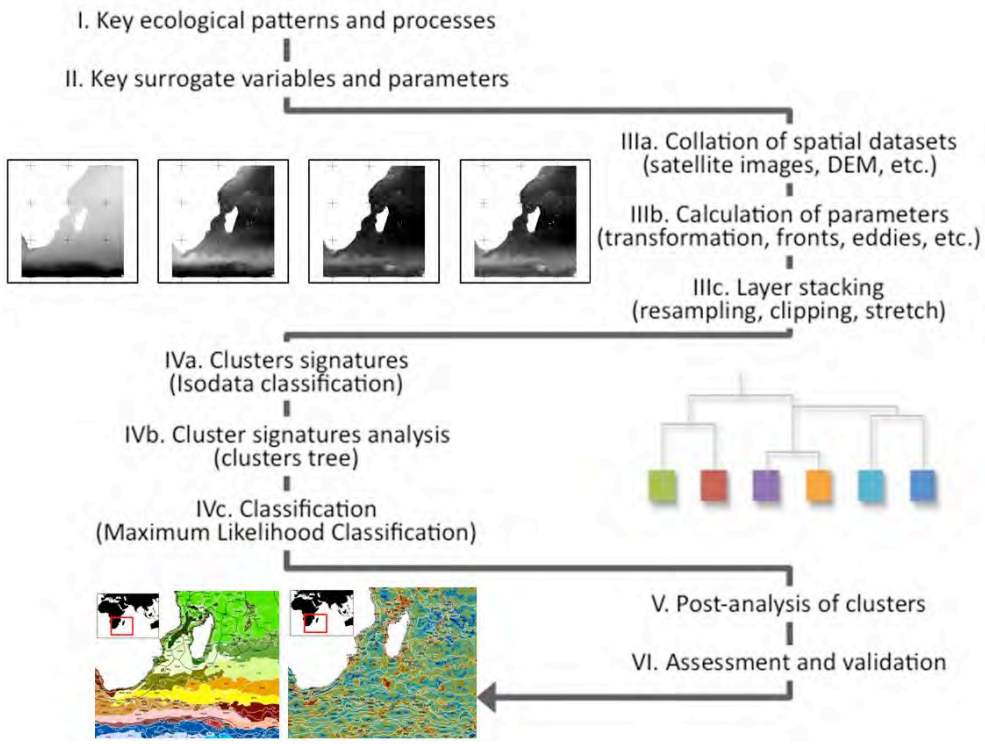


Figure 3. Overview of the bioregionalisation process.

4.2. Step I and II: Identification of the key ecological patterns and processes, and relevant variables and parameters

The table 2 summarizes the relevant variables and parameters associated to key ecological patterns and processes. Two scalar levels of organisation of the ocean ecosystem have been distinguished: broad and mesoscale. The map of variables and associated parameters are shown in Figure 4. Variables and parameters were selected based on a previous study in the Benguela Current System.

Table 1. Key ecological patterns and processes, and variables and parameters used for the bioregionalisation. The following acronyms are used to name the variables: sea surface temperature (SST), chlorophyll-a (CHLO), net primary productivity (NPP) and turbidity (K490). *cv* represents the coefficient of variation and *std* the standard deviation.

Key ecological patterns and processes	**Variables and parameters**
Bio-physical variables and parameters describing the average state of the ocean surface	
The distribution of marine biota exhibits global patterns associated with latitudinal gradients of temperature, net primary productivity and turbidity. At the scale of oceanic basins, this distribution is also influenced by global westward geostrophic currents and upwelling. The key parameter to detect those gradients is the mean of those variables and the maximum temperature.	SST mean
	SST max
	K490 mean
	NPP mean
Bio-physical variables and parameters describing the mesoscale variability of the ocean surface	
Alongside with broad scale patterns, the distribution of marine biota exhibits mesoscale patterns (sub-regions of high primary productivity for instance, associated with fronts of chlorophyl-a, sea surface temperature and turbidity) driven by mesoscale oceanographic processes (eddies, upwelling for instance). Those mesoscale patterns can be detected by extracting the coefficient of variation on time series of temperature, net primary productivity and turbidity. Mesoscale oceanographic features, such as eddies, are detected using altimetry data. The depth also affects the distribution of biota at this scale (height of the water column, also correlated to the distance to the coast).	SST std
	K490 cv
	NPP cv
	Eddies frequency
	Depth (Log (|Depth|+1))
	SST fronts
	CHLO fronts
	K490 fronts

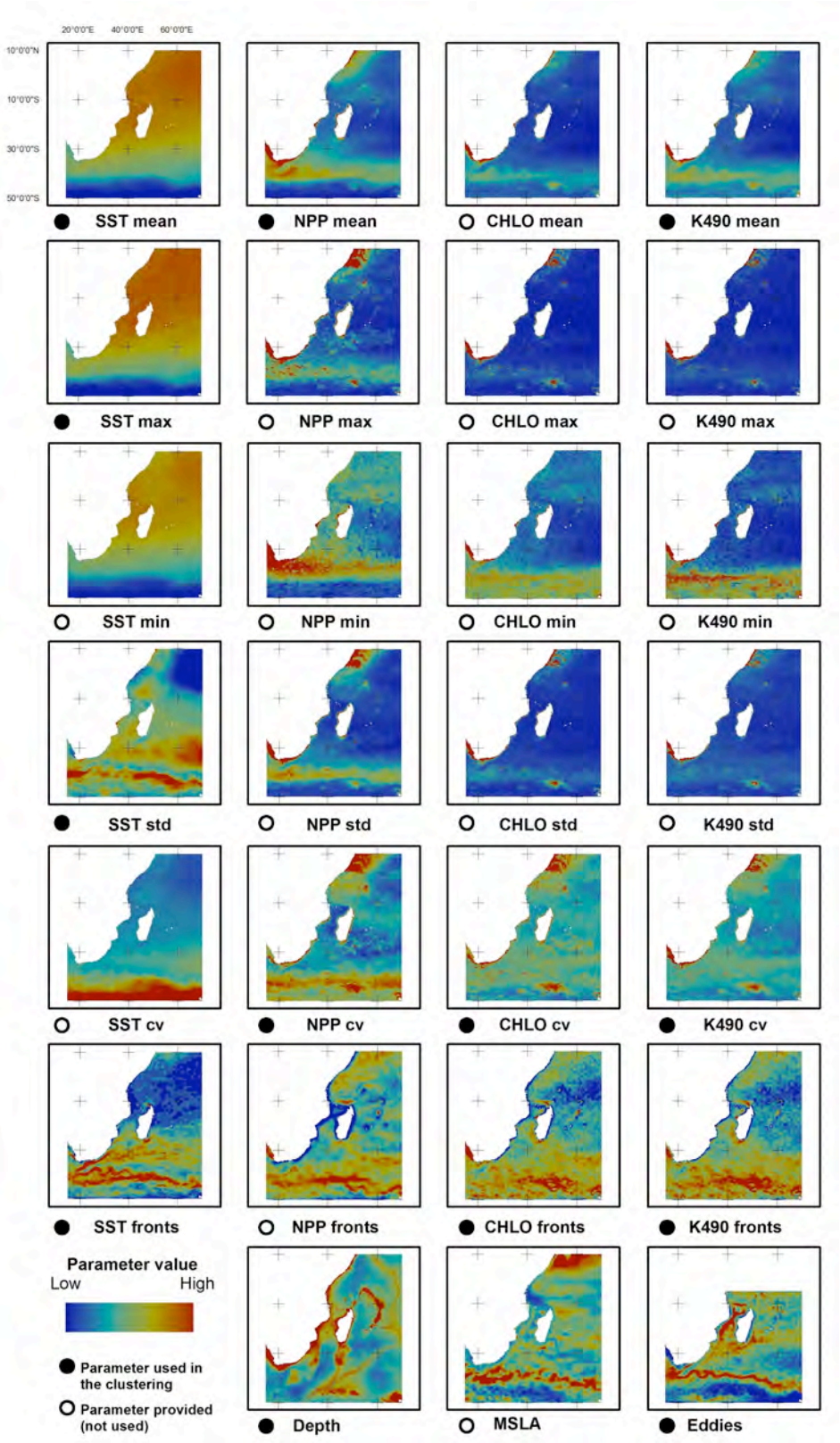


Figure 4. Overview of variables and parameters: sea surface temperature (SST), chlorophyll-a (CHLO), net primary productivity (NPP), turbidity (K490) and MSLA (mean sea level anomalies). *cv* is the coefficient of variation and *std* is the standard deviation. For eddies, the parameter calculated is the frequency. For depth, the parameter is Log ($|X|+1$). Note that all values are displayed with a standard deviation (n=2) stretch. Variables and parameters used in the bioregionalisation are indicated with a black dot.

4.3. Step III: Collection of relevant data sets and pre-processing

The data sets listed in Table 1 and shown in Figure 4 were collated to develop the pelagic bioregionalisation analysis (IIIa on Figure 3). The table 3 lists the variables, source of data, spatial resolution, parameters calculated and units (Table 2). More details about access to these data sets is available in Appendix 1.

Table 2. Spatial data sets collated for the pelagic bioregionalisation.

Variable	Source	Resol. (km)	Parameters	Units
Sea Surface Temperature	MODIS SST 4 2003-2011 l3 mapped 8 days	4	**mean**, min, **max**, **std**	°C
			cv	-
			fronts frequency	%
Chlorophyll-a	MODIS Chlorophyll-a 2003-2011 l3 mapped 8 days	4	mean, min, max, std	$mg.m^{-3}$
			cv	-
			fronts frequency	%
Turbidity	MODIS K490 2003-2011 l3 mapped 8 days	4	**mean**, min, max, std	m^{-1}
			cv	-
			fronts frequency	%
Net Primary Productivity	NPP MODIS 2003-2011 l4 8 days Oregon University	9	**mean**, min, max, std	$mgC\ m^{-2}\ day^{-1}$
			cv	-
			Fronts frequency	%
Mesoscale eddies	AVISO Delayed Time Mean Sea Level Anomalies 8 days 1992-2011 South of 5° South	30	**eddies frequency**	%
Mean sea level anomalies (MSLA)	AVISO Delayed Time Mean Sea Level Anomalies 8 days 1992-2011	30	absolute mean sea level anomaly	cm
Depth	DEM DEM SRTM V7 Plus	0.9	**log (|Depth| +1)**	-

* Dataset used for the clustering are indicated in bold.

In IIIb (Figure 3), all datasets were projected in a geographic projection (datum WGS 1984) using ArcGIS 10. In step IIIc, SST MODIS data were transformed to derive their physical values based on the formula provided in the header of each image. Fronts were detected using the Cayula and Cornillon (1992) algorithm implemented in the Arctool Box MGET (Roberts *et al., 2010*). The fronts were extracted from MODIS Level 3 mapped images with stretched value to ease the detection of fronts (linear stretching on 16 bits). Eddies features were detected on MSLA data using the Okubo-Weiss algorithm, also implemented in MGET with default algorithm parameters (the algorithm is not valid between at the equator between 5°N and 5°S). We used the DEM SRTM 30 PLUS Version 5 developed by Becker *et al.* (2009). Depth values were log (|X|+1) transformed to « flat » extreme values. All statistical parameters were calculated for each cell across time series (mean, min, max, standard deviation and coefficent of variation).

In IIIc (Figure 3), we clipped all images to a similar rectangular extent (5S, 40S, 10W, 30E). We applied a land-sea mask and normalised all parameter values from 0 to 1 using a fuzzy linear function in ArcGis. Finally, all datasets were re-sampled to 9 km (mean function).

4.4. Step IV: Clustering

In IVa (Figure 3) we used the clustering method “iso-cluster” in ArcGIS 10 Spatial Analyst Extension (ESRI) to identify clusters of cells exhibiting similar bio-physical profiles. This iterative algorithm allocates each cell to a cluster according to its profile in a multidimensional space defined by the variables and related parameters listed in Table 1. The number of clusters is specified by the user. The algorithm aims to minimize Euclidian distance among cells within each cluster. If clusters are too similar, the algorithm merges them. We limited the initial number of clusters to 60 and ran the clustering algorithm with 10 000 iterations and a sampling value of 1 to produce robust clusters.

In IVb, a dendrogram (or cluster-tree) was derived to visually analyse distance among clusters. The most distant clusters are the ones that are the most clearly differentiated. We cut the classification tree to a distance threshold of five, resulting in merging clusters with a distance inferior to this treshold. We then recalculated the final cluster tree with the merged clusters (Figure 5).

In IVc (Figure 3), we used the clusters from IVb as signatures to perform a Maximum Likelihood classification (MLC). The MLC allocates each cell of the image to a cluster and, at the same time, produces an image of the probability that each cell belongs to the given cluster. This uncertainty map is very useful for management as it informs the users about the spatial distribution of uncertainty across the planning domain (Figure 10).

The map of cluster was generalized using the following protocol in ArcGis : a) identify patches of area inferior to 50 neighbor pixels (neighbor of 4), b) remove those small patches (resulting in holes), c) expand the remaining patches, d) fill the holes with expanded patches, e) apply the « boundary clean » function, f) apply a majority filter, g) re-apply the « boundary clean » function, h) re-apply a majority filter, i) raster to vector transformation .

4.5. Steps V and VI: Post-analysis of clusters and validation

The uncertainty map provides a quality assessment indicator. The validation of the final classification of habitats should be undertaken through expert consultation with oceanographers, marine ecologists and fisheries biologists.

5. RESULTS

The final pelagic bioregions map contains 60 bioregions level 3 (Figure 8), hierarchically grouped into three bioregions level 1 (Figures 5 and 6) and 22 bioregions level 2 (Figure 7).

An analysis of the cluster-tree (Figure 5), cluster maps (Figures 6, 7 and 8) and cluster profiles (Figure 9) reveals that bioregions level 1 are organized along latitudinal gradients :
- South of 45°S, in the cold Southern Ocean, the bioregion A is clearly differentiated from other bioregions. Its mean temperature is 4,9°C, the productivity is low and the environmental conditions are stable (low variations of temperature, productivity and turbidity, low frequency of fronts and eddies).
- Between 45°S and 30°S, in the temperate Southern Ocean, the bioregion B is caracterised an average temperature of 16°C, an average productivity. Its environmental conditions are less stable with an average frequency of eddies 20,2 % and a higher frequency of fronts of sea surface temperature and chlorophyll.
- Located North of 30°S, the bioregion C is caracterised by sub-tropical water (mean temperature of 25,6°C), frequent eddies (22%) and a moderate frequency of fronts.

Among the 22 bioregions level 2, the bioregions Bi (Agulhas current retroflection zone) and Ct (Mozambique channel) exhibit high frequency of eddies (34,7 % and 44,5 % respectively). The bioregions Bd and Be in the Benguela Current are caracterised by very high level of primary productivity, cold water and stable environmental conditions indicative of an upwelling. The bioregion Cu is the Aghulas Current caracterised by sub-tropical temperatures and a very low frequency of eddies.

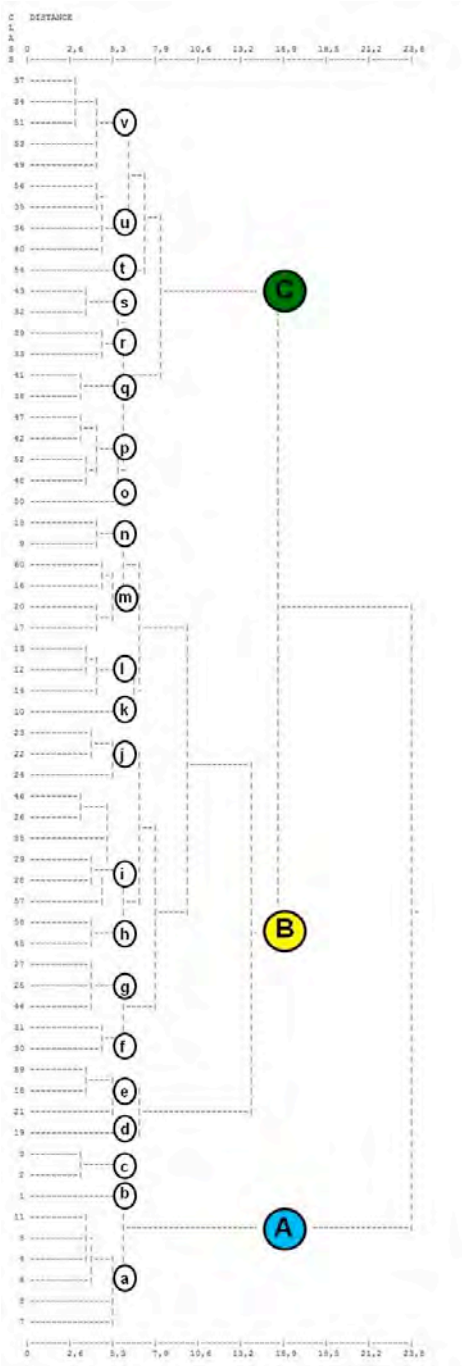


Figure 5. Cluster tree showing the hierarchical organisation of the 3 bioregions level 1, 22 bioregions level 2 and 60 bioregions level 3.

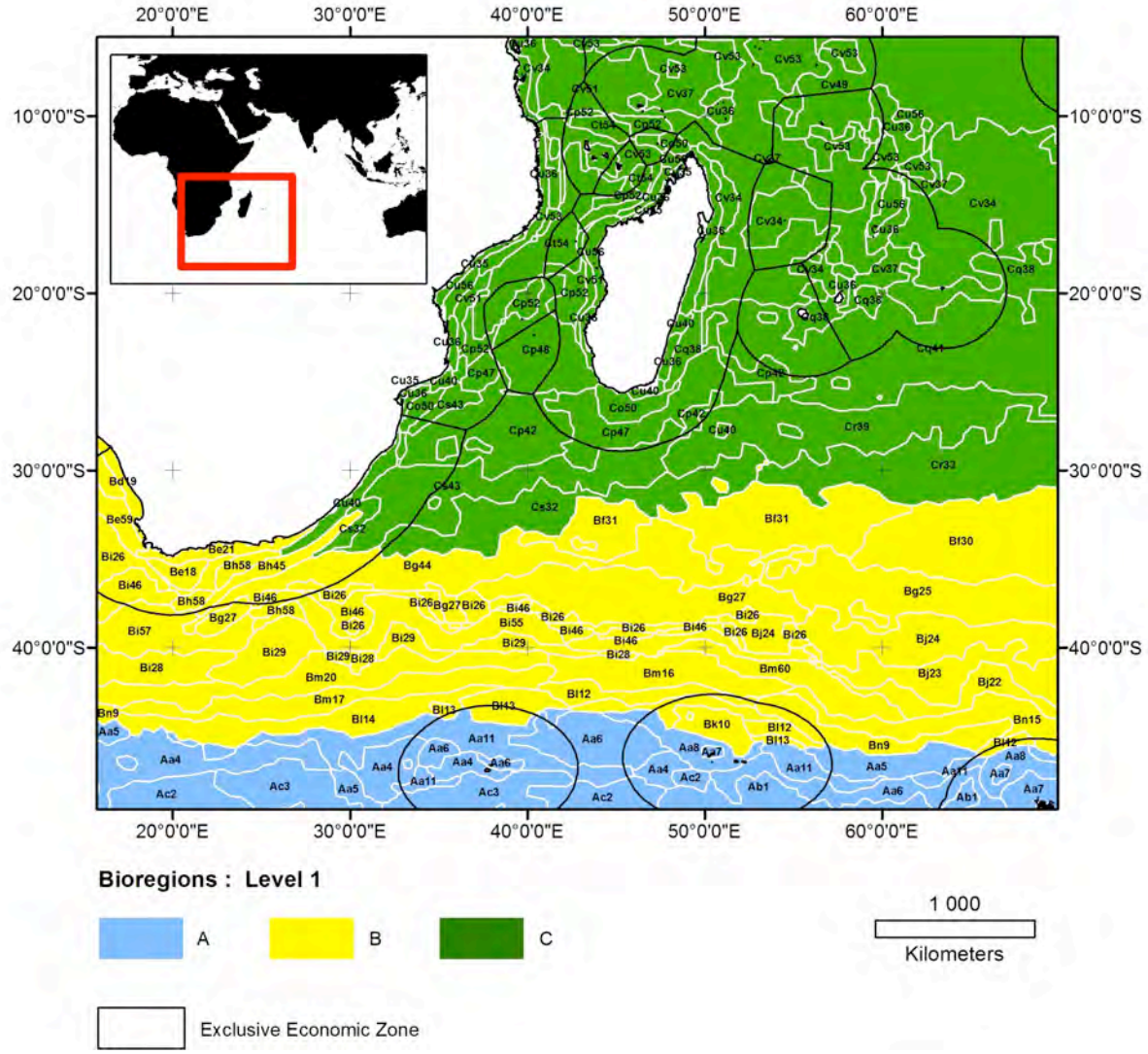


Figure 6. The bioregions level 1.

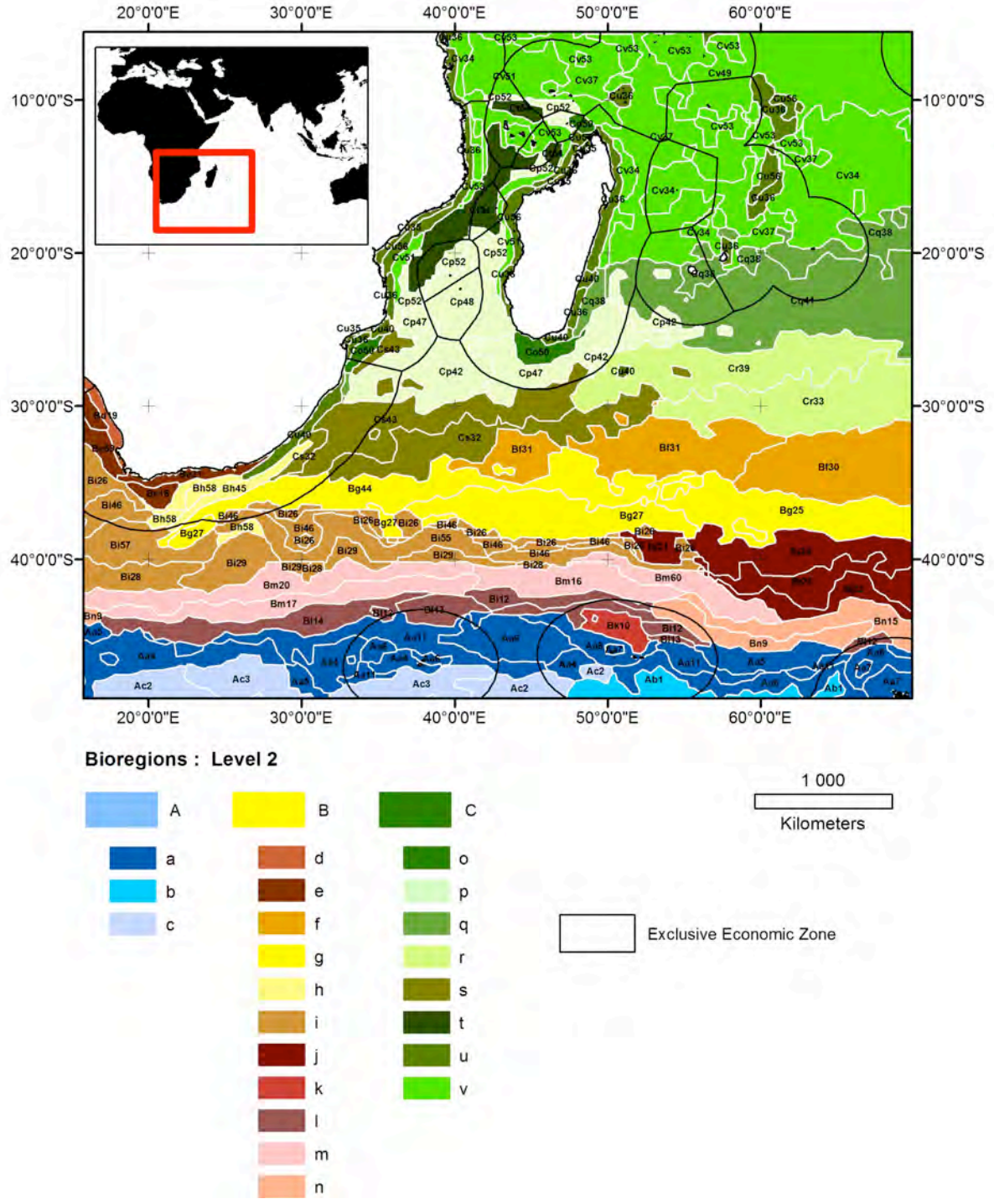


Figure 7. The bioregions level 2.

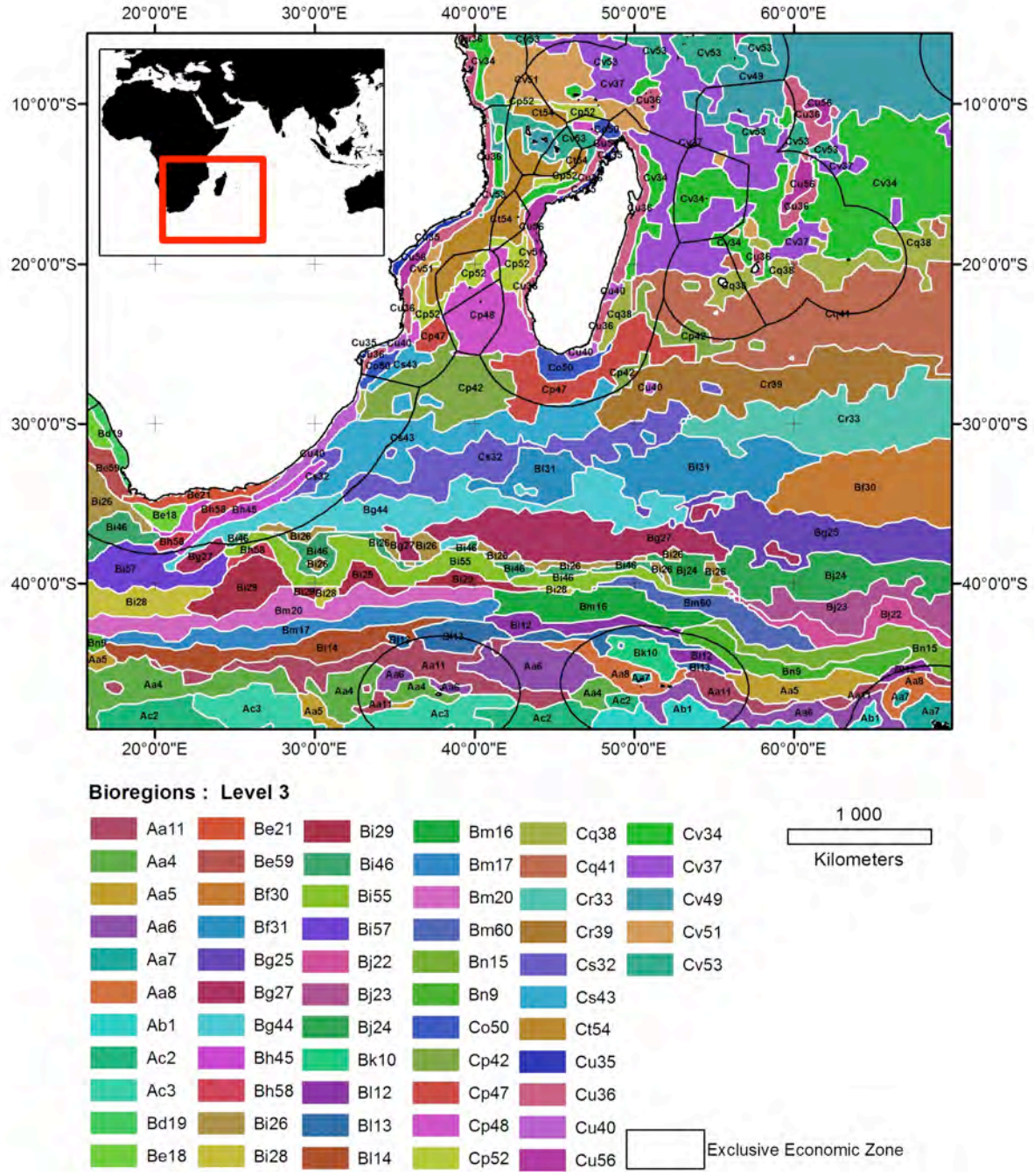


Figure 8. The bioregions level 3.

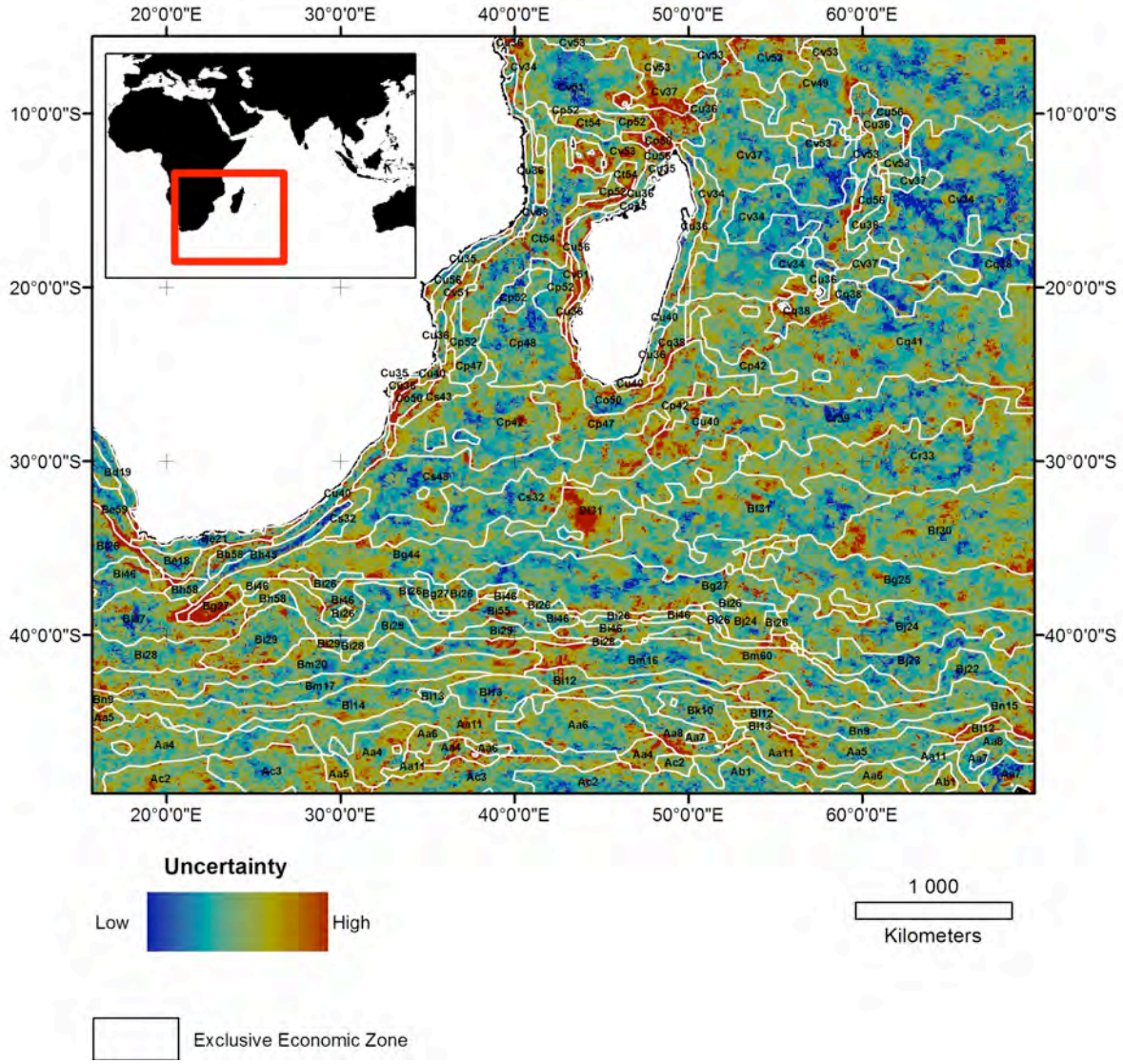


Figure 9. Map of the classification uncertainty.

Table 3. Mean parameter values per variables lumped per bioregions level 1 and 2.

Bioregion	Area (1000 km²)	Depth (m)	Bio-physical variables and parameters describing the average state of the ocean surface				Bio-physical variables and parameters describing the mesoscale variability of the ocean surface						
			SST mean (°C)	SST max (°C)	NPP mean (mgC m-2 day-1)	K490 mean (m-1)	Eddies (%)	SST std (°C)	NPP cv	K490 cv	SST front (%)	CHLO front (%)	K490 front (%)
A	**5135**	**-3726**	**4,9**	**10,2**	**221**	**0,04**	**8,4**	**1,8**	**0,5**	**0,2**	**2,3**	**11,8**	**11,7**
a	*3014*	*-3316*	*5,8*	*11,2*	*247*	*0,05*	*5,3*	*1,9*	*0,5*	*0,2*	*2,5*	*12,0*	*12,0*
b	*795*	*-4070*	*3,3*	*8,4*	*176*	*0,04*	*2,9*	*1,6*	*0,5*	*0,2*	*0,6*	*9,5*	*9,4*
c	*1326*	*-4453*	*3,8*	*8,9*	*187*	*0,04*	*18,7*	*1,7*	*0,5*	*0,2*	*2,6*	*12,5*	*12,1*
B	**10749**	**-4044**	**16,0**	**21,4**	**568**	**0,06**	**20,2**	**2,1**	**0,5**	**0,3**	**4,9**	**12,2**	**12,0**
d	*56*	*-118*	*15,2*	*19,9*	*4080*	*0,53*	*1,6*	*1,5*	*0,5*	*1,1*	*2,2*	*16,4*	*10,3*
e	*272*	*-314*	*18,2*	*22,7*	*1688*	*0,13*	*8,3*	*1,8*	*0,6*	*0,9*	*3,6*	*14,3*	*11,8*
f	*1456*	*-4107*	*19,6*	*25,3*	*354*	*0,03*	*10,4*	*2,3*	*0,3*	*0,3*	*4,7*	*11,9*	*11,2*
g	*2212*	*-4183*	*18,6*	*23,5*	*501*	*0,04*	*16,3*	*1,9*	*0,4*	*0,3*	*3,6*	*11,3*	*11,0*
h	*239*	*-2816*	*21,2*	*25,9*	*772*	*0,06*	*27,0*	*2,0*	*0,5*	*0,4*	*9,2*	*11,1*	*10,9*
i	*2152*	*-4138*	*17,8*	*23,1*	*691*	*0,06*	*34,7*	*2,1*	*0,5*	*0,3*	*5,4*	*11,7*	*11,6*
j	*1133*	*-4687*	*15,2*	*19,8*	*536*	*0,05*	*23,5*	*1,8*	*0,6*	*0,3*	*3,3*	*11,6*	*11,6*
k	*125*	*-2910*	*6,5*	*12,8*	*373*	*0,07*	*2,7*	*2,1*	*0,9*	*1,0*	*3,4*	*14,0*	*14,1*
l	*957*	*-3857*	*9,0*	*14,8*	*367*	*0,05*	*6,7*	*2,1*	*0,6*	*0,3*	*5,4*	*13,7*	*14,1*
m	*1531*	*-4222*	*13,2*	*19,3*	*576*	*0,06*	*21,3*	*2,3*	*0,6*	*0,3*	*7,0*	*13,2*	*13,4*
n	*616*	*-4435*	*9,9*	*16,2*	*387*	*0,05*	*25,9*	*2,4*	*0,6*	*0,2*	*5,4*	*12,8*	*13,1*
C	**11397**	**-1556**	**25,6**	**30,2**	**111**	**0,03**	**22,0**	**1,9**	**0,3**	**0,2**	**2,5**	**9,0**	**8,5**
o	*133*	*-1769*	*25,4*	*29,6*	*458*	*0,04*	*24,5*	*1,8*	*0,4*	*0,3*	*4,9*	*12,1*	*12,3*
p	*1500*	*-3630*	*25,4*	*30,0*	*338*	*0,03*	*30,9*	*2,0*	*0,3*	*0,2*	*3,7*	*10,5*	*10,2*
q	*1601*	*-3950*	*25,1*	*29,6*	*224*	*0,03*	*22,8*	*1,9*	*0,3*	*0,2*	*2,5*	*8,9*	*8,0*
r	*1469*	*-4517*	*22,6*	*27,8*	*253*	*0,03*	*16,2*	*2,2*	*0,3*	*0,2*	*4,1*	*9,9*	*9,1*
s	*1282*	*-3558*	*22,5*	*27,4*	*421*	*0,04*	*23,8*	*2,1*	*0,3*	*0,3*	*5,6*	*10,3*	*10,0*
t	*359*	*-2847*	*27,7*	*32,2*	*296*	*0,03*	*44,5*	*1,8*	*0,3*	*0,2*	*1,4*	*9,5*	*9,5*
u	*784*	*-977*	*26,8*	*31,1*	*548*	*0,05*	*12,9*	*1,8*	*0,5*	*0,4*	*1,1*	*6,4*	*6,5*
v	*4270*	*-3641*	*27,4*	*31,8*	*281*	*0,03*	*19,6*	*1,7*	*0,4*	*0,2*	*0,8*	*8,0*	*7,6*
Mean	***27281***	***-3780***	***17,9***	***22,9***	***396***	***0,04***	***18,7***	***2,0***	***0,4***	***0,3***	***3,4***	***10,8***	***10,5***

Table 4. Mean parameter values per variable per bioregion. Higher values are highlighted in red while lower values are highlighted in blue. Top 10 % highest and lowest values for each parameter are shown in bold underlined.

IDCode	Bioregion level 1	Bioregion level 2	Bioregion level 3	Area (1000 km²)	Depth (m)	Bio-physical variables and parameters describing the average state of the ocean surface				Bio-physical variables and parameters describing the mesoscale variability of the ocean surface						
						SST mean (°C)	SST max (°C)	NPP mean (mgC m-2 day-1)	K490 mean (m-1)	Eddies (%)	SST std (°C)	NPP cv	K490 cv	SST front (%)	CHLO front (%)	K490 front (%)
Ab1	*A*	*b*	*1*	795	-4070	3,3	8,4	176	0,04	2,9	1,6	0,5	0,2	0,6	9,5	9,4
Ac2	*A*	*c*	*2*	697	-4145	3,5	8,6	185	0,04	13,5	1,6	0,5	0,2	2,2	12,5	12,1
Ac3	*A*	*c*	*3*	629	-4568	4,1	9,2	189	0,04	24,6	1,7	0,5	0,2	3,1	12,5	12,2
Aa4	*A*	*a*	*4*	761	-4165	5,9	10,9	201	0,04	8,3	1,8	0,5	0,2	2,7	11,2	11,1
Aa5	*A*	*a*	*5*	339	-4444	6,5	12,4	274	0,05	13,0	2,2	0,5	0,2	3,4	12,1	12,2
Aa6	*A*	*a*	*6*	744	-2618	5,8	10,9	223	0,04	1,9	1,8	0,5	0,2	1,8	11,5	11,4
Aa7	*A*	*a*	*7*	169	-793	4,0	9,0	270	0,06	0,1	1,6	0,6	0,3	0,7	10,2	10,0
Aa8	*A*	*a*	*8*	279	-1684	5,3	11,2	280	0,05	1,7	1,8	0,6	0,4	2,4	14,6	14,6
Bn9	*B*	*n*	*9*	300	-4449	9,0	15,5	356	0,05	20,7	2,4	0,5	0,3	4,5	12,8	13,1
Bk10	*B*	*k*	*10*	125	-2910	6,5	12,8	373	0,07	2,7	2,1	0,9	1,0	3,4	14,0	14,1
Aa11	*A*	*a*	*11*	722	-3737	6,5	11,8	261	0,05	4,8	1,9	0,5	0,2	3,2	12,9	13,0
Bl12	*B*	*l*	*12*	242	-3249	8,4	15,2	364	0,05	7,5	2,3	0,6	0,3	6,3	14,9	15,2
Bl13	*B*	*l*	*13*	304	-2892	8,4	14,3	353	0,05	3,3	2,1	0,6	0,3	4,2	14,2	14,5
Bl14	*B*	*l*	*14*	412	-4925	9,7	14,9	378	0,05	8,7	1,9	0,6	0,2	5,7	12,7	13,2
Bn15	*B*	*n*	*15*	316	-4422	10,8	16,8	416	0,06	30,8	2,5	0,6	0,2	6,3	12,9	13,2
Bm16	*B*	*m*	*16*	347	-3202	12,6	19,3	550	0,06	21,0	2,7	0,6	0,3	7,8	14,3	14,6
Bm17	*B*	*m*	*17*	418	-4658	12,1	17,7	539	0,06	14,4	2,1	0,6	0,3	7,6	12,9	13,3
Be18	*B*	*e*	*18*	108	-205	17,9	22,4	1521	0,11	5,0	1,8	0,5	0,7	2,9	15,5	13,3
Bd19	*B*	*d*	*19*	56	-118	15,2	15,9	4080	0,53	1,6	1,5	0,5	1,1	2,2	16,4	10,3
Bm20	*B*	*m*	*20*	504	-4488	14,2	20,3	646	0,06	17,8	2,2	0,6	0,3	5,9	12,2	12,3
Be21	*B*	*e*	*21*	83	-124	19,0	23,8	2051	0,17	11,5	2,0	0,7	1,3	2,2	10,5	7,6
Bj22	*B*	*j*	*22*	205	-4680	13,8	18,3	517	0,06	33,1	2,0	0,6	0,3	5,2	12,2	12,2
Bj23	*B*	*j*	*23*	351	-4694	14,7	19,1	536	0,06	26,3	1,7	0,6	0,3	3,5	11,3	11,4
Bj24	*B*	*j*	*24*	577	-4693	15,9	20,8	542	0,05	18,5	1,8	0,5	0,3	2,6	11,5	11,4
Bg25	*B*	*g*	*25*	658	-4569	17,0	22,5	482	0,04	13,4	2,1	0,4	0,3	3,5	11,5	11,2
Bi26	*B*	*i*	*26*	373	-3886	18,7	23,1	637	0,05	28,7	1,8	0,4	0,3	3,4	11,8	11,7
Bg27	*B*	*g*	*27*	736	-3809	18,5	23,1	520	0,04	17,0	1,8	0,4	0,3	2,7	11,2	11,0
Bi28	*B*	*i*	*28*	260	-4848	15,7	23,0	724	0,07	28,0	2,6	0,6	0,3	6,2	11,0	10,6
Bi29	*B*	*i*	*29*	379	-3641	16,5	22,2	745	0,06	26,1	2,2	0,5	0,3	5,8	11,8	12,0
Bf30	*B*	*f*	*30*	694	-4625	18,8	25,2	345	0,03	7,7	2,4	0,4	0,3	4,3	12,3	11,5
Bf31	*B*	*f*	*31*	762	-3635	20,2	25,5	363	0,03	12,8	2,2	0,4	0,3	5,1	11,5	11,0
Cs32	*C*	*s*	*32*	615	-4085	21,8	26,9	419	0,04	19,8	2,1	0,3	0,3	5,8	10,6	10,3
Cr33	*C*	*r*	*33*	720	-4354	21,7	27,3	234	0,03	12,6	2,3	0,3	0,2	4,2	9,5	8,9
Cv34	*C*	*v*	*34*	1223	-3441	26,8	31,3	244	0,03	14,8	1,8	0,4	0,2	0,8	8,6	8,0
Cu35	*C*	*u*	*35*	51	-45	27,2	31,7	1328	0,12	11,3	2,1	0,4	0,5	0,7	3,8	2,7
Cu36	*C*	*u*	*36*	436	-1161	27,2	31,5	381	0,04	11,3	1,8	0,5	0,3	0,5	5,4	5,7
Cv37	*C*	*v*	*37*	1131	-4271	27,1	31,7	274	0,03	21,3	1,8	0,4	0,2	0,8	8,1	7,7
Cq38	*C*	*q*	*38*	394	-3331	25,7	30,2	218	0,03	17,2	1,8	0,3	0,2	2,2	8,4	7,7
Cr39	*C*	*r*	*39*	749	-4674	23,4	28,3	271	0,03	19,7	2,1	0,3	0,2	4,1	10,2	9,3
Cu40	*C*	*u*	*40*	133	-1711	24,3	28,6	686	0,06	16,7	1,9	0,2	0,6	2,9	5,8	6,0
Cq41	*C*	*q*	*41*	1207	-4152	24,9	29,4	225	0,03	24,7	1,9	0,3	0,2	2,5	9,1	8,1
Cp42	*C*	*p*	*42*	570	-4034	24,6	29,2	351	0,03	30,2	2,0	0,3	0,2	3,4	9,6	9,3
Cs43	*C*	*s*	*43*	667	-3672	23,1	27,9	424	0,04	27,5	2,1	0,4	0,3	5,4	10,0	9,8
Bg44	*B*	*g*	*44*	819	-4209	20,0	24,6	499	0,04	18,1	1,9	0,4	0,3	4,4	11,2	10,9
Bh45	*B*	*h*	*45*	136	-3002	21,6	26,1	701	0,06	18,3	1,9	0,4	0,4	8,9	10,5	10,4
Bi46	*B*	*i*	*46*	340	-3980	18,9	23,6	672	0,05	30,6	1,9	0,4	0,3	4,6	11,8	11,6
Cp47	*C*	*p*	*47*	387	-3837	24,7	28,9	341	0,03	35,1	1,9	0,3	0,2	4,8	11,0	10,6
Cp48	*C*	*p*	*48*	326	-3195	26,4	31,1	332	0,03	25,6	2,1	0,3	0,2	4,0	11,1	11,0
Cv49	*C*	*v*	*49*	973	-3458	28,3	32,2	295	0,03	19,3	1,5	0,3	0,2	0,7	6,5	6,2
Co50	*C*	*o*	*50*	133	-1769	25,4	29,6	458	0,04	24,5	1,8	0,4	0,3	4,9	12,1	12,3
Cv51	*C*	*v*	*51*	438	-3370	27,6	32,2	317	0,04	19,6	1,9	0,4	0,3	0,9	9,5	9,3
Cp52	*C*	*p*	*52*	217	-2853	27,4	32,1	308	0,03	33,5	1,9	0,3	0,2	2,2	11,2	11,0
Cv53	*C*	*v*	*53*	484	-3295	27,9	32,1	324	0,04	28,5	1,7	0,4	0,2	0,9	7,7	7,4
Ct54	*C*	*t*	*54*	359	-2847	27,7	32,2	296	0,03	44,5	1,8	0,3	0,2	1,4	9,5	9,5
Bl55	*B*	*l*	*55*	507	-4006	17,8	22,5	660	0,06	43,1	2,1	0,5	0,3	6,5	12,6	12,5
Cu56	*C*	*u*	*56*	164	-184	27,6	31,9	636	0,06	14,5	1,9	0,4	0,3	1,1	10,6	10,0
Bi57	*B*	*i*	*57*	293	-3908	19,1	24,6	734	0,06	42,4	2,4	0,5	0,3	6,2	10,3	10,3
Bh58	*B*	*h*	*58*	104	-2573	20,7	25,7	865	0,07	38,5	2,0	0,5	0,5	9,5	11,9	11,6
Be59	*B*	*e*	*59*	81	-654	17,6	21,8	1539	0,12	9,4	1,6	0,6	1,0	6,1	16,7	14,8
Bm60	*B*	*m*	*60*	261	-4366	14,0	19,7	535	0,06	39,6	2,6	0,6	0,3	7,2	14,0	13,9

6. DISCUSSION AND CONCLUSIONS

6.1. Synthesis of results and application

This study focuses on pelagic ecosystems. Three pelagic main bioregions are identified (bioregions. Those bioregions are divided into 22 bioregions level 1 and 41 clusters.

This analysis represents a step forward in the assessment and conservation of pelagic biodiversity in the Benguela Current System. The mapping method is based on a hierarchical approach. Our classification approach is similar to the one developed by Post (2008). It includes a clustering step followed by a cluster tree analysis and a Maximum Likelihood Classification. The production of a membership probability is very useful to inform management about the robustness of the map at different locations.

Several data sets have been collated, mainly on physical processes and patterns. Biological patterns and processes were integrated in the analysis through the use of surrogates. Parameters for such surrogates were measured from remote sensing data. The Net Primary Productivity layer was the most “biology-related” dataset.

6.2. Limitations and improvements

We assumed that water surface parameters reflect the properties of the water column although we recognise that this is not always appropriate. We did not integrated three-dimensional oceanographic models or validation data sets but the bioregionalisation process could be improved using such models and data sets.

The use of data sets extracted from three-dimensional oceanographic models should allow the distinction of depth layers and the production of bioregional maps in different depth zones. Such products will be more complex to analyse but a similar approach has already been implemented for the bioregionalisation of the Australian EEZ (Lyne and Hayes 2005).

The surrogacy of habitats for marine biodiversity as a whole should be tested using species distribution data. In addition, each habitat should be associated with key bibliographic references.

Further improvements of the pelagic bioregionalisation map require the collection, collation and integration of *in situ* biological data sets. The collation of such validation data sets is a challenge since most data sets are only available at local scales for few locations and are not easily accessible.

The bioregions, biozones and clusters identified during the bioregionalisation process should be used with caution because they only reflect areas of similarities based on a set of defined variables. They are not necessarily habitats with distinct biological assemblages (although we use this terminology for ease of reference) and the user should be aware of their definitions in terms of parameter values.

7. REFERENCES

Beck, M.W., Z. Ferdaña and K. Karr. 2003. Marine ecoregional planning advice. Marine Initiative Project Report.

Becker, J.J., D.T. Sandwell, W.H.F. Smith, J. Braud, B. Binder, J. Depner, D. Fabre, J. Factor, S. Ingalls, S-H. Kim, R. Ladner, K. Marks, S. Nelson, A. Pharaoh, R. Trimmer, J. Von Rosenberg, G. Wallace and P. Weatherall. 2009. Global bathymetry and elevation data at 30 arc seconds resolution: SRTM30_PLUS. Marine Geodesy 32(4):355-371.

Behrenfeld, M.J. and P.G. Falkowski. 1997. Photosynthetic rates derived from satellite based chlorophyll concentration. Limnology and Oceanography 42: 1-20.

Cayula, J.F. and P. Cornillon. 1992. Edge detection algorithm for SST images. Journal of Atmospheric and Oceanic Technology 9: 67–80.

Fennel, W. and T. Neumann. 2001. Coupling biology and oceanography in models. AMBIO: A Journal of the Human Environment 30(4): 232-236.

Grant, S., A. Constable, B. Raymond and S. Doust. 2006. Bioregionalisation of the Southern Ocean: Report of Experts Workshop, Hobart. WWF-Australia and ACE CRC.

Hewitt, R.P. and L.E.H. Linen. 2000. The fishery on Antarctic krill: defining an ecosystem approach to management. Reviews in Fisheries Science 8(3): 235-298.

Lombard, A.T., B. Reyers, L.Y. Schonegevel, J. Cooper, L.B. Smith-Adao, D.C. Nel, P.W. Froneman, I.J. Ansorge, M.N. Bester, C.A. Tosh, T. Strauss, T. Akkers, O. Gon, R.W. Leslie and S.L. Chown. 2007. Conserving pattern and process in the Southern Ocean: 21 designing a Marine Protected Area for the Prince Edward Islands. Antarctic Science 19(1): 39-54.

Lutjeharms, J.R.E. 2006. The Agulhas current. Springer-Verlag.

Lutjeharms, J.R.E., Bornman, T.G.. 2010. The importance of the greater Agulhas Current is increasingly being recognised. South Africa Journal of Science 106(3/4), Art. #160.

Lyne, V. and D. Hayes. 2005. Pelagic regionalisation: National bioregionalisation Integration Project. Australian Government National Oceans Office and CSIRO Marine Research.

Mann, K.H., Lazier, J.R.N. 2006. Dynamics of marine ecosystems: biological-physical interactions in the oceans. Oxford: Blackwell Publishing Ltd.

Obura, D.O., Church, J.E. and Gabrié, C. 2012. Assessing Marine World Heritage from an Ecosystem Perspective: The Western Indian Ocean. World Heritage Centre, United Nations Education, Science and Cultural Organization (UNESCO). 124 pp.

Post, A.L. 2008. The application of physical surrogates to predict the distribution of marine benthic organisms. Ocean and Coastal Management 51(2): 161-179.

Roberts JJ, Best BD, Dunn DC, Treml EA, Halpin PN. Marine Geospatial Ecology Tools : An integrated framework for ecological geoprocessing with ArcGIS, Python, R, MATLAB, and C++. Environmental Modelling & Software 2010; 1197:1207-25.

Sherman, K. and A. Duda. 1999. Large Marine Ecosystems: An Emerging Paradigm for Fishery Sustainability. Fisheries 24: 15-26

Sink, K. and C. Attwood. 2008. Guidelines for Offshore Marine Protected Areas in South Africa. SANBI Biodiversity Series 9. South African National Biodiversity Institute, Pretoria.

Snelder, T.H., J.R. Leathwick, K.L. Dey, A.A Rowden, M.A. Weatherhead, G.G. Fenwick, M.P. Francis, R.M. Gorman, J.M. Grieve, M.G. Hadfield, J.E. Hewitt, K.M. Richardson, M.J. Uddstrom and J.R. Zeldis. 2006. Development of an ecologic marine classification in the New Zealand region. Journal of Environmental Management 39(1): 12-29.

Spalding, M.D., H.E. Fox, G.R. Allen, N. Davidson, Z.A. Ferdaña, M. Finlayson, B.S. Halpern, M.A. Jorge, A. Lombana, S.A. Lourie, K.D. Martin, E. McManus, J. Molnar, C.A.

Recchia and J. Robertson. 2007. Marine Ecoregions of the World: a bioregionalization of coast and shelf areas. BioScience 57(7): 573-583.

UNESCO. 2009. Global Open Oceans and Deep Seabed (GOODS) – biogeographic classification. Paris, UNESCO-IOC. (IOC Technical Series, 84.)

Vierros, M. 2007. Approaches to biogeographic classification of the world's oceans. Background document, CCAMLR Biroegionalisation Workshop (Brussels, Belgium, 13-17 August 2007), United Nations University Institute of Advanced Studies.

Zahn, R., Lutjeharms, J., Biastoch, A., et al. 2010. GATEWAYS: Investigating the Agulhas Current off southern Africa and its global impacts. Eos Transactions, American Geophysical Union 91:109−110.