Biophysical regions identification using an artificial neuronal network: A case study in the South Western Atlantic

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Abstract

A classification method based on an artificial neuronal network is used to identify biophysical regions in the South Western Atlantic (SWA). The method comprises a probabilistic version of the Kohonen’s self-organizing map and a Hierarchical Ascending Clustering algorithm. It objectively defines the optimal number of classes and the class boundaries. The method is applied to ocean surface data provided by satellite: chlorophyll-a, sea surface temperature and sea surface temperature gradient, first to means and then, in an attempt to examine seasonal variations, to monthly climatologies. Both results reflect the presence of the major circulation patterns and frontal positions in the SWA. The provinces retrieved using mean fields are compared to previous results and show a more accurate description of the SWA. The classification obtained with monthly climatologies offers the flexibility to include the time dimension; the boundaries of biophysical regions established are not fixed, but vary in time. Perspectives and limitations of the methodology are discussed.

Keywords: Biophysical regions; South Western Atlantic; Self-organizing map

1. Introduction

Oceanic provinces provide a useful framework for describing the mechanisms controlling biological, physical and chemical processes and their interaction. The use of provinces for assessing marine primary production was saliently exemplified by Longhurst (1995). The South Western Atlantic (SWA) presents a wide variety of biomes, which makes this part of the ocean prone for the regional classification. Several attempts have been made to develop objective methodologies to define oceanic biophysical provinces.

Longhurst (1998, hereafter L98)determines provinces in the world ocean considering several databases: chlorophyll fields obtained from the Coastal Zone Color Scanner sensor, global climatologies of mixed layer depth, Brunt-Väisälä frequency, Rossby internal radius of deformation, photic depth, and surface nutrient concentrations. In the SWA, L98 classification leads to five regions (Fig. 1). The Southwest Atlantic Shelves Province (FKLD) and Brazil Current Coastal Province (BRAZ) are limited by the 2000 m isobath to the east and are separated by the confluence between the Brazil and Malvinas currents; the South Atlantic Gyral Province (SATL) comprises the South Atlantic anticyclonic circulation; the Subantarctic Water Ring Province (SANT) is only partly represented in the southern part of the SWA, and the South Subtropical Convergence (SSTC) Province represents the region with the largest area in the SWA.

L98 regional partitioning is made on a global scale with global criteria and therefore leads to a large-scale smoothing. An investigator interested in a specific basin or region...
Saraceno et al. (2006, hereafter S05) applied a simple classification methodology based on histograms mean fields of satellite-retrieved sea surface temperature (SST), SST gradient and chlorophyll-a (chl-a). Local minima in the histogram of each field provide the thresholds used to define the boundaries between provinces (S05). S05 find a good correspondence with L98 Provinces and identified three new regions in the SWA: the Patagonian Shelf Break (PSB), Zapiola Rise and Overshoot regions (Fig. 1). However, the methodology used by S05 lacks objectivity at the stage of summarizing the information from the various histograms to establish the biophysical regions.

We propose here to use a method based on an artificial neuronal network to classify biophysical regions using satellite data. The use of artificial neuronal networks in geosciences has been increasing over the past 10 years. Neuronal networks are used in applications that include cloud identification (Lee et al., 1990), biomass estimation from microwave imagery (Jin and Liu, 1997) or climate variability (Cavazos, 1999, 2000) among others. In particular, the self-organizing map (SOM) is a useful neuronal network tool for classification and pattern recognition, also known as Kohonen map (Kohonen, 1990, 1995). SOM achieves a non-linear mapping of the feature space (Kraaijveld et al., 1995) to be used to reduce the dimension of the data input. The SOM non-linear mapping has advantages over linear methodologies like principal component analysis (PCA). If the data distribution on a two-dimensional space has a correlation close to zero, one may find difficulty in using PCA to perform a suitable data mapping. Instead, by using a SOM, the resulting weights will be adjusted in such a way as to match the shape of the data distribution. Kohonen (1995) shows that the SOM algorithm represents most faithfully those dimensions of the input variables along which the variance in the sequence of inputs is most pronounced. This will often correspond to the most important features of the input variables. The method used here is a probabilistic version of the Kohonen’s self-organizing map (PR SOM, Anouar et al., 1998) combined with a hierarchical ascending classification (HAC, Jain and Dubes, 1988). The method is applied to satellite SST, SST gradient and color images in the SWA. It provides an unsupervised classification of the input data. The number of classes and the boundaries of the classes are objectively defined. After illustrating its potential on the mean fields of the data, the method is applied to monthly climatologies in an attempt to describe seasonal variations of the classes.

The article is organized as follows: the prominent features of the SWA, the data, and a brief description of the neuronal network used are presented in Section 2. The classifications obtained using mean values and monthly climatologies are presented and compared with biophysical regions described in previous works in Section 3. Results are summarized and discussed in Section 4.
2. South Western Atlantic, data, and methods

2.1. South Western Atlantic

The SWA most prominent feature is the Brazil-Malvinas (hereafter B/M) Current Confluence, one of the most energetic eddy regions of the world ocean (Chelton et al., 1990) (Fig. 1). The confluence is formed by the collision between the Malvinas Current (MC) and the Brazil Current (BC) approximately at 38°S. The MC is part of the northern branch of the Antarctic Circumpolar Current that carries cold, high nutrient and relatively fresh Subantarctic waters equatorward along the western edge of the Argentine Basin. The BC flows poleward along the continental margin of South America. The BC carries warm, low nutrient and salty water. The BC and MC are bounded by the Brazil Current Front (BCF) and the Subantarctic Front (SAF), respectively (Fig. 1). The position of the fronts is strongly controlled by the bottom topography (Saraceno et al., 2004). The BCF and the western branch of the SAF in the SWA are located along the 300 m isobath. The eastern part of the SAF, when it separates from the continental margin at the Confluence region, closely follows the 3000 m isobath. After its collision with the MC, the BC flows southward and, at about 44°S, returns to the NE. This path is commonly referred to as the overshoot of the Brazil Current.

2.2. Satellite data

We use 6 years (January 1998–December 2003) of Sea-viewing Wide Field of View Sensor (SeaWiFS) images and ten years (January 1986–December 1995) of SST derived from advanced very high resolution radiometer (AVHRR) to objectively establish the biophysical provinces in the SWA. An SST gradient image is calculated for each SST image, preserving the SST spatial resolution (about 4 km). SST gradient magnitude fields are produced using a Prewitt operator (Russ, 2002) using a window of 7 × 7 pixels (30 × 30 km). This box size retains the large and mesoscale frontal features with an acceptable amount of noise (Saraceno et al., 2004). Monthly climatologies and means of the SST, SST gradient, and chl-a datasets are then produced.

Phytoplankton pigment concentrations are obtained from eight-day composite SeaWiFS products of level 3 binned data, generated and distributed by the NASA Goddard Space Flight Center (GSFC) Distributed Active Archive Center (DAAC) with reprocessing 4 (http://daac.gsfc.nasa.gov/data/dataset/SEAWIFS/). The bins correspond to approximately 9 × 9 km grid cells.

Satellite-derived SST observations are obtained from the AVHRR onboard NOAA-N polar orbital satellites (NOAA-7 to NOAA-13 in the present case). Each image is a 5-day composite with approximately a 4 × 4 km resolution. The data processing, including cloud detection and 5-day compositing, was performed at the Rosenstiel School of Marine and Atmospheric Science, University of Miami (RSMAS) and is described in Olson et al. (1988). The 5-day compositing reduces the effect of cloud coverage and the likelihood of negative biases due to cloud contamination (Podestà et al., 1991).

The SST and chl-a data bases used span different sets of years. A second AVHRR database produced by the Jet Propulsion Laboratory (JPL, version 4.1), time-coincident with the chl-a database, has been considered. The RSMAS and JPL SST climatologies show very similar patterns, indicating that interannual variability is not an issue. However, the SST gradient climatologies show important differences in the B/M collision region and in general in the regions where the strongest SST gradients are present (not shown). This is due to the excessive cloud coverage assigned to regions with strong thermal gradients in the JPL dataset (Vazquez et al., 1998). Thus, we have preferred to use a SST dataset with adequate cloud masking in critical frontal regions and non-synoptic with chl-a.

2.3. Classification method

The objective of the classification method is to synthesize the most important features of the three fields (SST, SST gradient, and chl-a) in a two-dimensional matrix. Pixels in the resulting matrix are clustered as pertaining to a few classes. The following steps can summarize the methodology (see also Fig. 2):

![Fig. 2. Diagram flow of the different steps considered for the classification method used. Top: the three variables considered are normalized separately and ranged in a single input matrix; middle: the input matrix is used by PRSOM to obtain a map of N classes of the dataset; bottom: HAC is used to reduce the number of classes and the interclass inertia is considered to choose the number of classes retained (Q).](image-url)
2.3.1. Input matrix

Each field considered is independently normalized and spatially averaged onto a $35 \times 35$ km grid. The three normalized fields are organized in a single input matrix to form the learning database. In the present application, we consider a dataset composed of three variables. So each datum $z$ is a three-dimensional vector ($z \in \mathbb{R}^3$, SST, SST gradient, and chlorophyll-a).

2.3.2. SOM and PRSOM

The SOM introduced by Kohonen (1995) has been used for visualization and clustering high-dimensional patterns. Visualization as proposed in SOM methods uses deformable discrete lattice to translate data similarities into special relationships. A large variety of related algorithms have been derived from the first SOM model (Kohonen, 1995) which share the same idea of introducing topological order between the different clusters. In the following we introduce the PRSOM, which uses a probabilistic formalism (Anouar et al., 1998). This algorithm approximates the density distribution of the data with a mixture of normal distributions. Artificial neuronal networks as SOM or PRSOM are divided in two phases: learning and validation. At the end of the learning phase, the probability density of data estimated by PRSOM can be used as an accurate classifier. The validation phase is not used in the present application.

As the standard SOM, PRSOM consists of discrete topology defined by an undirected graph noted $C$ (Fig. 3). Usually this graph is a regular grid in one or two dimensions with $N_c$ cells. For each pair of cells $(c,r)$ on the grid, the distance $\delta(c,r)$ is defined as being the shortest path between $c$ and $r$ on the graph. This discrete distance defines a neighborhood with positive kernel function $K^T(\delta)$ parameterized by $T$ defined as:

$$K^T(\delta) = \exp(-0.5\delta^2/T),$$

where the parameter $T$ controls the neighborhood size of each cell $c$.

Let $A = \{z_i, \ldots i = 1 \ldots N\}$ the learning dataset where $z_i \in \mathbb{R}^d (z_i = (z_{i1}, \ldots, z_{id}))$. As for standard SOM algorithm, PRSOM defines a mapping from $C$ to $A$, where a cell $c$ is associated with its referent vector $w_c = (w_{c1}, \ldots, w_{cd})$ in $\mathbb{R}^d$ which represents a subset of the learning dataset $A$. At the end of the learning phase, two neighboring cells on the map have close referent vectors in the Euclidian space $\mathbb{R}^d$.

In contrast to SOM, which provides a referent vector to each cell $c$, PRSOM is a probabilistic model which associates a spherical Gaussian density function $f_c$ with each cell $c$. The density function is defined by its mean (referent vector) and its covariance matrix, defined by $\Sigma = \sigma^2 I$, where $\sigma$ is the standard deviation and $I$ is the identity matrix. PRSOM allows us to approximate the density distribution of the dataset using a mixture of normal densities. As in the Kohonen algorithm for SOM, PRSOM makes use of a neighborhood system whose size, controlled by $T$, is decreased from an initial value $T_{\text{max}}$ to $T_{\text{min}}$. At the end of the learning phase, the map provides the topological order. The partitions provided by PRSOM are different from those provided by SOM which uses Euclidian distance. The estimation of the density function gives an extra information. At the end of the learning phase, the dataset $A$ is divided in $N_c$ subsets: each cell $c$ of the map represents a particular subset.

The selection of the number of cells is arbitrary and can be determined by experimentation with the data and knowledge of the phenomena analyzed. Here, the PRSOM map was trained using the global database and a 2-D map of $10 \times 10$ cells ($N_c = 100$) with values for $T_{\text{max}}$ and $T_{\text{min}}$ of 3 and 1, respectively. The results obtained, as will be described in the next section, provide an accurate representation of the main characteristics of the input dataset. The dataset is then partitioned into 100 subsets (classes) which correspond to the $10 \times 10$ cells.

2.3.3. Hierarchical ascending classification

We choose the widely used Hierarchical ascending classification (HAC) to cluster the cells of the map. The HAC proceeds by successive aggregations of cells reducing the number of cells by one each time. It is based on the following steps:

1. Find the two closest clusters according to a measure of dissimilarity.
2. Agglomerate them to form a new cluster.

The routine is repeated until the number of clusters desired is obtained. In our case, the first iteration considers the partition resulted from PRSOM (one hundred classes). The following iterations require defining a measure of dissimilarity between the merged clusters and all other clusters. There are many ways to do so. The most widely considered rule for merging clusters is the method proposed by Ward and as described by Ripley (1996). The method uses two measures: the intraclass inertia and the interclass inertia. The intraclass inertia is the sum over all classes of the observation within each class and the interclass inertia is a measure of class dispersion, as estimated by the mean of the squared distances of the class centres to the global gravity centre (Saporta, 1990). The Ward algorithm merges at each iteration the two classes which will give the smallest increase to the interclass inertia. This operation is repeated until obtaining the desired number of
classes. At each iteration, it is possible to measure the inter-class inertia increase, which makes it possible to set a stopping criterion for the algorithm.

2.3.4. Selection of the number of classes to be retained

To choose the number of classes to be retained during the HAC, we consider the interclass inertia. The Ward criterion used in the HAC implies that a lower class number corresponds to a lower interclass inertia. Similarly, the lower is the difference in the interclass inertia between consecutive levels (e.g., between class 5 and class 6), the smaller is the difference between classes (i.e., classes are not significantly different). Thus, after each aggregation in the HAC, we compute the difference in the interclass inertia between consecutive levels and select the lowest number of classes for which differences in the interclass inertia are almost zero.

3. Results

3.1. Classification of mean fields

The main patterns of the SWA summarized above (Section 2.1) and other important characteristics are visible in the mean chl-a, SST, and SST gradient fields (Fig. 4). The mean chl-a field (Fig. 4a) exhibits a strong contrast between the shelf and the open ocean. The highest values...
of chl-a are localized in the estuary of the La Plata river and along the coast of Uruguay and south of Brazil (Figs. 1 and 4a). The PSB region is characterized by very high chl-a values, higher than the values over the shelf (Fig. 4a). High chl-a values are distributed along the overshoot region, partly coinciding with high SST gradients (Fig. 4a). The MC is identified by a local minimum in chl-a while the lowest chl-a values correspond to the SATL Province (Figs. 1 and 4a). The SST mean field (Fig. 4b) shows in general decreasing values with increasing latitude; exceptions correspond to the presence of the southward flowing BC and the northward flowing MC (Fig. 1). The cold tongue between the PSB front and the Malvinas Return front (Saraceno et al., 2004) reveals the MC. The BC is identified by warmer temperatures along the Brazilian shelf-break. The SST gradient mean field (Fig. 4c) shows the average paths of the main fronts in the SWA: SAF and BCF (see Fig. 1). The amplitude of the SST gradient is not homogeneous along the fronts, reflecting the high spatial and temporal variability of the thermal fronts in the region. For example, an instantaneous image (not shown) exhibits the highest SST gradient values in the B/M collision region (at about 38°S) while the highest values are present at the Brazilian shelf-break in the mean image: this reflects the important spatio-temporal variability of the confluence region. The Zapiola Rise region corresponds to relative low SST gradients values year round (Saraceno et al., 2004).

The results obtained considering the three mean input fields and retaining four and five classes in the HAC are shown in Fig. 5. Each class corresponds to a homogeneous region. Pixels belonging to the same class are not randomly distributed, but are well organized and contiguous. Considering four classes in the HAC (Fig. 5a), a basic fundamental division is obtained that nearly coincides with L98 Provinces. The continental shelf is separated from the open ocean, corresponding to the FKLD and BRAZ L98 Provinces. The open ocean is divided meridionally into 3 regions that basically correspond, respectively from north to south, to (i) SATL, (ii) northern part of SSTC, and (iii) southern part of SSTC and SANT L98 Provinces in the SWA.

Fig. 6. Comparison of the mean (red bar) and standard deviation (blue bar) values affected by each class when four (left column) and five (right column) classes are retained in the HAC. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this paper.)
Means and standard deviations of the pixels corresponding to each class of the three input variables when four and five classes are retained in the HAC are presented in Fig. 6. In four and five class cases, mean values for the three variables are different for each class and higher than the standard deviations, indicating that each class represents a different and homogeneous region. Regions corresponding to classes one to three are the same on both classifications. The region associated with the fourth class (dark blue values, Fig. 5a) splits into two different regions (blue and dark blue values, Fig. 5b) when five classes are retained in the HAC. Classes four and five of Fig. 5b and class four of Fig. 5a have very different SST mean gradient values, whereas chl-a and SST mean values are similar. Classes four and five in the five class classification are more homogeneous (i.e., present lower standard deviation values) than class four in the four class classification. Thus, as more classes are retained during the hierarchical classification, more details and more homogeneous classes are obtained. However, the risk of losing the common characteristics that allow a simple interpretation by synthesizing the dataset also increases with the number of classes.

To choose the number of classes we consider the interclass inertia (Section 2.3). Fig. 7 shows that the interclass inertia converges to 0.4 when more than 50 classes are considered. This limit explains 100% of the interclass inertia dispersion between classes. Considering 12 classes, 90.4% of the dispersion is explained and the interclass inertia difference between consecutive levels is nearly zero (Fig. 7). Considering 6 classes, the interclass inertia difference is also very low, but the interclass inertia dispersion explains only 80% of the dispersion. Thus, in the following we retain 12 classes during the HAC and compare the 12 class classification to previous results.

Fig. 8 presents the 12 class classification superimposed onto the biophysical regions established with the same data using a completely different and independent (histogram based) methodology (S05). The 12 classes are compact regions and summarize the main characteristics of the three mean input fields considered. Table 1 presents the correspondence between the regions established in this study and by S05. In general, there is a good agreement.

Class 1 corresponds to the northern part of the SSTC region (S05). The southern limit of the region is at about 42°S, matching the northern limit of the Zapiola Rise and Overshoot regions (Fig. 8). Class 1 presents intermediate chl-a and high SST and SST gradient values (Fig. 9, Table 2). The variability of the BCF is probably responsible for the observed chl-a values.

Class 2 corresponds to an intermediate region between SSTC and SATL regions. It presents high SST and SST gradient values and low chl-a values (Fig. 9, Table 2).

Class 3 roughly coincides with the SATL region (S05). The southern limit is about 1° to the north relative to the boundary established by S05 (Fig. 8). The class has the lowest chl-a concentrations and the highest SST of the 12 classes (Fig. 9, Table 2).

Class 4 corresponds to the BRAZ region (S05). The class presents the highest mean values in chl-a (3.78 mg/m^3). They are associated with the outflow of the Rio de la Plata. Mean SST values are high while mean SST gradients are low.

Class 5 corresponds to the SANT (L98) Province. The class exhibits low chl-a and SST values and is characterized by high SST gradient values (Fig. 9, Table 2) which are associated with the strong eddy activity present in the region (S05). On average, the region extends two degrees to the north in comparison to the northern limit established by S05 for the same region (Fig. 8).

Class 6 corresponds to the eastern part of the Overshoot region (S05). The region has high SST gradient and intermediate SST and chl-a values (Fig. 9, Table 2). The intermediate chl-a values are probably due to the advection of chl-a by eddies. In the region, eddies are shed by the BC with a frequency of approximately eight per year (Lentini et al., 2002).

Class 7 is divided into two geographically separated regions characterized by low SST gradient means and intermediate SST and chl-a means (Fig. 9, Table 2). The western part (region 7b) corresponds to the western part of the Overshoot region of S05. S05 noticed that the area corresponding to region 7b has common characteristics with the Zapiola Rise (low SST gradient values) although they could not separate the region from the Overshoot region with their methodology. The eastern part (region 7a) corresponds to the Zapiola Rise region (S05). Region 7a extends more to the east than in S05.

Class 8 corresponds to the area where the Malvinas and Brazil currents collide. The strong thermal front is responsible for the high SST gradient values (Fig. 9, Table 2). Chl-a presents intermediate values (Fig. 9, Table 2). Using simultaneous high resolution MODIS SST and color data, Barre et al. (2006) suggest that most of the high values present during the year are entrained from the shelf. The class presents high SST values.

Class 9 corresponds to the Patagonian Shelf, without considering the PSB region. The class is characterized by high chl-a values and low SST gradient values.

Class 10 corresponds to the entrance of the MC in the SWA. The class is characterized by the lowest SST values among the 12 classes. The region presents also low SST gradient and chl-a concentrations. Even if the MC is rich in nutrients, it corresponds to a zonal minimum in chl-a throughout the year. One possible explanation (which does not apply in summer) could be that the water column does not offer the necessary stability conditions to the development of the chl-a: basically there is no stratification. In summer, a sharp seasonal thermocline develops in the upper 20 m (Provost et al., 1996) and other factors (not
known to our knowledge) should limit the chlorophyll concentration.

Class 11 corresponds to the northern part of the PSB region (S05). The high chl-a and SST gradient values correspond to the shelf-break front and its rich biological activity. SST mean values are intermediate.

Class 12 corresponds to the southern part of the PSB, where lower SST, SST gradient, and chl-a values in comparison to the northern part of the PSB are present.

In summary, the present classification distinguishes four more regions than S05: a transition region between SATL and SSTC (class 2), the B/M collision region (class 8), the southern part of the PSB region (class 12) and the entrance of the MC in the SWA (class 10). S05 had noticed more heterogeneity in some of their regions but could not objectively decide neither the number of classes to retain nor the precise location of the boundaries between the regions. The method applied here determines objectively the number of classes to be retained (interclass inertia criterion) and the location of the physical boundaries between classes.
Table 2
Mean and standard deviation of chl-a, SST, and SST gradient pixels associated with each of the 12 classes obtained considering the three means fields presented in Fig. 4

<table>
<thead>
<tr>
<th>Class</th>
<th>Chl-a (mg/m³) Mean</th>
<th>Chl-a (mg/m³) Std</th>
<th>SST (°C) Mean</th>
<th>SST (°C) Std</th>
<th>SST gradient (°C/km) Mean</th>
<th>SST gradient (°C/km) Std</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class 1</td>
<td>0.41</td>
<td>0.07</td>
<td>15.79</td>
<td>1.26</td>
<td>0.10</td>
<td>0.01</td>
</tr>
<tr>
<td>Class 2</td>
<td>0.31</td>
<td>0.07</td>
<td>18.75</td>
<td>1.04</td>
<td>0.09</td>
<td>0.01</td>
</tr>
<tr>
<td>Class 3</td>
<td>0.18</td>
<td>0.05</td>
<td>21.18</td>
<td>1.29</td>
<td>0.07</td>
<td>0.01</td>
</tr>
<tr>
<td>Class 4</td>
<td>3.78</td>
<td>1.21</td>
<td>18.85</td>
<td>1.06</td>
<td>0.07</td>
<td>0.01</td>
</tr>
<tr>
<td>Class 5</td>
<td>0.37</td>
<td>0.06</td>
<td>6.96</td>
<td>1.48</td>
<td>0.13</td>
<td>0.01</td>
</tr>
<tr>
<td>Class 6</td>
<td>0.55</td>
<td>0.07</td>
<td>12.37</td>
<td>1.54</td>
<td>0.10</td>
<td>0.01</td>
</tr>
<tr>
<td>Class 7</td>
<td>0.46</td>
<td>0.07</td>
<td>9.94</td>
<td>1.35</td>
<td>0.08</td>
<td>0.01</td>
</tr>
<tr>
<td>Class 8</td>
<td>0.67</td>
<td>0.20</td>
<td>16.45</td>
<td>2.16</td>
<td>0.15</td>
<td>0.02</td>
</tr>
<tr>
<td>Class 9</td>
<td>1.27</td>
<td>0.28</td>
<td>14.62</td>
<td>2.64</td>
<td>0.07</td>
<td>0.02</td>
</tr>
<tr>
<td>Class 10</td>
<td>0.34</td>
<td>0.08</td>
<td>5.53</td>
<td>1.42</td>
<td>0.08</td>
<td>0.02</td>
</tr>
<tr>
<td>Class 11</td>
<td>1.63</td>
<td>0.27</td>
<td>10.93</td>
<td>1.44</td>
<td>0.10</td>
<td>0.02</td>
</tr>
<tr>
<td>Class 12</td>
<td>1.07</td>
<td>0.39</td>
<td>7.83</td>
<td>1.08</td>
<td>0.06</td>
<td>0.01</td>
</tr>
</tbody>
</table>

Fig. 9. Mean (red bar) and standard deviation (blue bar) of chl-a (top), SST (middle), and SST gradient (bottom) values of the pixels associated with the 12 classes presented in Fig. 8. Precise values are detailed in Table 2. Horizontal lines indicate threshold used to describe values as high, intermediate or low. Data are described as low when, respectively, SST, chl-a or SST gradient values are lower than 8 °C, 0.4 mg/m³ or 0.08 °C/km; intermediate when, respectively, chl-a is between 0.4 and 1 mg/m³ or SST is between 8 and 15 °C; and high when, respectively, SST, chl-a or SST gradient correspond to values higher than 15 °C, 1 mg/m³ and 0.08 °C/km. Region 4 presents mean chl-a values as high as 3.78 mg/m³.

Fig. 10. Interclass inertia (black line) and difference between consecutive interclass inertia levels (red line) for 1 to 60 HAC levels obtained considering the time average of SST, SST gradient, and chl-a. Horizontal line is the convergence limit of the interclass inertia (0.28) minus 10% of its value. Considering 8 classes, 85.9% of the interclass inertia variability relative to the convergence limit is explained and differences between adjacent levels are lower than 0.003.
3.2. Classification with monthly climatologies

We apply the PRSOM and HAC algorithms to the ensemble of monthly climatologies of SST, SST gradient, and chl-a in an attempt to describe seasonal variations of the provinces. The 36 monthly climatologies were organized in a single input matrix. We use the same criterion applied to the mean fields to choose the number of classes, i.e., the lower number of classes from which differences between consecutive interclass levels are almost zero. Eight classes are thus retained, which explain 85.9% of the interclass inertia dispersion between classes (Fig. 10). Monthly climatologies every other month and the corresponding classes are reported in Table 3 and Fig. 12. The eight classes are thus retained, which explain 85.9% of the interclass inertia dispersion between classes (Fig. 10). Monthly climatologies every other month and the corresponding classification are shown in Fig. 11.

The mean and standard values for each of the 8 classes are reported in Table 3 and Fig. 12. The eight classes present a high degree of homogeneity in SST and SST gradient. Classes 1–6 are also homogeneous in chl-a concentrations with values no higher than 0.6 mg/m³. Chl-a concentrations for classes 7 and 8 are not homogeneous and have mean values of 2 and 2.8 mg/m³ respectively, representing the regions with the highest chl-a values. As described below, classes 7 and 8 mostly occupy coastal shelf regions where chl-a values present a high degree of spatial variability.

The classification has been realized considering all the monthly climatologies together, thus it provides information on which areas of the SWA have common properties in SST, SST gradient and chl-a for each month of the year. Thus, it is possible to observe which classes are present each month. A description of the space-time distribution of the eight classes through the year (Fig. 11) is given below.

Class 1 has the lowest chl-a and SST gradient values and the highest SST among the eight regions considered. The respective values are typical of the SATL region. Class 1 is present in the northern part of the SWA from December to May.

Classes 2 and 3 occupy meridional regions just to the south of class 1. Because they approach the BCF and extend southward, they have respectively higher SST gradient and chl-a values and lower SST magnitudes. From October to May, class 3 mostly occupies the Overshoot region. From January to March class 3 occupies a region corresponding to the PSB front and the MRF. From June to September, class 2 remains between the northern part of the SANT region and the southern part of the SATL region.

Class 4 has high chl-a values and intermediate SST and SST gradient values. From November to May class 4 occupies the Overshoot region. From January to May it fills the region corresponding to the Zapiola Rise and in December, April and May, to the Patagonian shelf. From June to October, class 4 occupies small areas pertaining to the northern part of the SSTC region.

Class 5 is characterized by the lowest SST values (among the 8 classes) and relatively low SST gradient and chl-a values. From January to March it occupies the southern part of the domain, thus corresponding to the SANT region (that is south of the SAF). From April to December, class 5 corresponds to the MC and the Zapiola Rise region. In austral winter months (from July to September) it is the class that covers the largest area in the SWA.

Class 6 has low chl-a and SST values but high SST gradient amplitudes. These values are present year round in the south of the domain, corresponding to the northern part of the SANT region (or to region 5 in the description given in Section 3.1). From March to May, class 6 represents the Malvinas Return Front and the B/M collision region; from May to October it corresponds mostly to the B/M collision and Overshoot regions.

The near-shore continental shelf coincides with class 7 from December to April and with class 8 from May to October. In November, classes 4, 7, and 8 share the near-shore region. Class 7 does not represent homogeneous regions of the input variables, in particular for chl-a: its standard deviation is larger than the mean for class 7 (Fig. 12). The largest values of chl-a are concentrated in the estuary of the La Plata river. Considering more classes (up to 14, not shown) this problem is not solved: a unique class includes the estuary of the La Plata river and the nearest near-shore continental shelf between December and April.

Mean values corresponding to class 8 (Table 3) represent the MC from December to March and shelf waters during the rest of the year.

In several regions it has been argued that the mean chl-a values may be a response of advection by mesoscale features such as eddies or filaments. This is not the only mechanism important to the development of chl-a blooms in the region: the mixture of subantarctic waters with subtropical waters through cross frontal mixing creates small scale thermohaline structures (Bianchi et al., 1993, 2002) which may enhance the vertical stratification of subantarctic waters, and also lead to small-scale nutrient exchange (Brandini et al., 2000).

The eight classes suggested by the interclass criterion are not present year round (Fig. 11). In austral winter months (July–September), only five classes are present (Fig. 11). This corresponds to the fact that spatial patterns in austral winter are more homogeneous than during the other months of the year. Further, the monthly classification shows that not all areas corresponding to the biophysical regions as defined using the mean fields are present year round. It is then possible to estimate how representative are the regions found with the mean fields compared to regions established with monthly climatologies. In fact, only the Zapiola Rise and the PSB regions are not present all year round: Zapiola Rise is present from June to December and PSB from December to March. The other regions are always present, although their shapes (border limits) and characteristics (as represented by the different classes) vary throughout the year.
Fig. 11. Monthly climatologies of January, March, May, July, September, and November of chlorophyll-a (first column), SST (second column), and SST gradient (third column). The colorbar applies for the three first columns, which values are normalized between $-1$ and $1$. The fourth column is the result obtained by the application of the methodology presented (Section 2.3) to the ensemble of the 12 monthly climatologies and eight classes are retained in the HAC.
4. Summary and discussion

We have applied a method based on artificial neuronal network to classify biophysical regions using satellite data. The method provides an unsupervised classification which is fully objective and quite easy to apply. The number of classes and the boundaries of the classes are objectively determined. Further, the results do not present regions left unclassified and allow the use of high-resolution data.

Results on means reflect the major characteristics of the SWA, i.e., circulation patterns and frontal positions. Retaining twelve classes provides a precise representation of the biophysical regions in the SWA. The eight regions recognized by S05 are identified, as well as four new regions which provide a more accurate description of the SWA. All classes are homogeneous (i.e., present a low ratio between standard deviation and mean).

Results on monthly means define eight classes. The classification obtained shows a realistic representation of the monthly climatologies for most of the regions (Fig. 11). The near-shore regions and the La Plata river region are identified by a unique class in austral summer, presenting large heterogeneities for the input variables. This observation shows a limitation of the methodology to identify shelf regions. A possibility would be to apply the methodology only to the shelf regions where chl-a distribution is very heterogeneous. The eight classes are not present each month; in austral winter, input patterns are more homogeneous than in other seasons and only five classes are sufficient to represent surface winter structures in the SWA.

So far, we have used only surface data with two sources of satellite data (SST and color). Results could be improved considering more input fields, provided that the new input fields are relevant to establish biophysical regions. We have considered the root mean square (rms) of sea level anomaly as an additional input for the average case and for the monthly climatologies case. The rms of the sea level anomaly is a good indicator of the mesoscale activity in the ocean. The additional input field further evidences the Zapiola Rise region but does not significantly modify the classification obtained (not shown). In the monthly mean case, the Zapiola Rise region is present all the year round. Data from in situ observations provide information on the vertical structure of the ocean and can also be introduced using the same method. For example, the mixed layer depth provides useful information on the stratification; its inclusion could be considered to improve the classification.

Although the methodology presented here can certainly be improved, it offers the flexibility to include the time dimension; the boundaries of the biophysical regions are not fixed, rather they are variable in time.
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