EUROPEAN COMMISSION
DIRECTORATE-GENERAL
Joint Research Centre

Assessing the Dynamics of Ecological Provinces in the European Seas

NICOLAS HOEPFFNER
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MARK D. DOWELL

2005 EUR 21514 EN

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MARK D. DOWELL

European Commission – Joint Research Centre
Institute for Environment and Sustainability
Inland & Marine Waters Unit
TP 272, I-21020 Ispra (VA) – Italy

2005 **EUR 21514 EN**

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Printed in Italy

Abstract

The concept of oceanographic provinces has existed for almost a century, providing a useful framework for understanding the mechanisms controlling biological, physical and chemical processes in the ocean and their interactions. This work is an attempt to identify and map marine provinces using satellite observations related to biological processes such as phytoplankton primary production. The approach is based on fuzzy logic as a means of classifying the European Seas into objectively defined areas. The analysis has identified nine domains based on three important variables, surface chlorophyll concentration, sea surface temperature, and available radiation for photosynthesis. These domains were subsequently mapped over the European geographical window using satellite ocean colour and temperature data. The method displays correctly most important productive and unproductive zones, as well as captures the dynamic nature of the marine systems.
This study has been conducted in the frame of the institutional project ECOMAR (Monitoring and Assessment of Marine Ecosystems, Action # 2121) within the Inland and Marine Unit of the Institute for Environment & Security.

INTRODUCTION

The global configuration of the Earth system with respect to land and water has lead, in the ancient time, to a quasi natural division of the global ocean into five different oceans, and a plethora of marginal seas recognized from the shape of the coastlines as having unique characteristics due to more or less restricted connections with open oceanic waters. From this, further delineation of provinces/regions in the oceanic and coastal environment has been undertaken on various occasions and based on different criteria. Although some degree of success and consensus has been reached to classify benthic ecosystems and habitats along a narrow fringe of the coastal system, pattern recognition within the pelagic realm ran into a lot of frustration mainly because of the dynamic nature of the oceans and seas, and the difficulty to conduct regular surveys at an adequate time scale, using traditional ship campaigns.

At the same time by mid-twentieth century, a sudden socio-economic interest on the commercial value of marine resources due, partly, to new technological development for their exploitation call into question the concept of freedom-of-the-seas, pleading instead for an extension of nations' rights over, notably, offshore lucrative fisheries. As a result, the coastal ocean was further divided into the so-called Exclusive Economic Zones (EEZ, see UNCLOS 1982) setting maritime (rather than marine or oceanic) boundaries at 200 nautical miles from each nation's coastlines. Together with such geo-political decision, other partition schemes of the marine environment were rapidly developed to face urgent requirements to monitor, control and eventually manage the invaluable richness of marine ecosystems, being under continuous threats from both human activities and climate change. In most cases, however, the technical challenge to perceive tangible structures over large oceanic areas has inclined people to draw arbitrary lines on the basis of arguments reflecting human convenience rather true physical and biological discontinuities. As an example, 27 major fishing areas have been established globally as early as the late 50's (FAO, 1956) for statistical purposes. Even though it is claimed that these areas have been identified accounting for distribution of aquatic species and environmental conditions, much stronger weight was given to pre-existing conventions with managerial fisheries, national boundaries and fishing practices. In the same way, the International Council for the Exploration of the Sea (ICES) has agreed since the early 20th century on the division and sub-division of the North Atlantic. This partition has evolved through time at few occasions to accommodate for more political requirements regarding fishing statistics.

Another common property of most existing provinces in the ocean is the immutability of their boundaries in time and space. While this may be useful for many administrative purposes (management reporting, socio-economic statistics), fixed boundaries obviously fail to capture the highly dynamic nature of ocean systems. Unlike the terrestrial domain, the interactions between a given community of marine organisms with the chemical and physical factors making up their environment, i.e. an ecosystem, vary at all time scale from less than a day up to multiple decades. Therefore any *ecosystem-based* studies or management practices aiming at the conservation and protection of the marine environment require the identification of spatial units or provinces, with boundaries reflecting the dynamic changes of the major processes involved.

One way to fulfill that condition is to select environmental (or others) criteria that can be measured remotely, e.g. with Earth Observation satellites. The advantage of satellite data is to produce synoptic field of a wide range of bio-physical parameters at regional and global scales. Even if a set of parameters defining a particular province are not amenable to remote sensing (e.g. nutrient concentration, trophic complexity), satellite observations (e.g., ocean colour, temperature, wind) can still be instrumental to guide a classification system, where other attributes of that province or class may have to be inferred from other database or statistical associations with an incumbent degree of uncertainty. For example, multi-annual time series of chlorophyll maps from satellite-based optical sensors inspired Longhurst (1995) to partition the global ocean into 57 provinces based on the actual knowledge of relevant physical features and of the typical responses of the pelagic organisms (i.e. indexed from chlorophyll values) to physical forcing. In spite of being associated with fixed boundaries, the distribution of the global ocean into provinces was used successfully to estimate marine productivity accounting for a real regional diversity in ocean ecology (Longhurst et al. 1995). The fantastic potential of satellite data was then further exploited to reproduce the dynamic dimension of marine provinces, using sequential images of bio-physical variables collected by multiple sensors to construct decision-trees for a classification system (Brock et al. 1998; Watts et al. 1999).

An alternative approach, based on fuzzy logic, has been implemented in this study to identify and map oceanic provinces using satellite observations of various properties over the European Seas. The method takes into account the uncertainty associated with incomplete information and produces a set of maps depicting the distribution of provinces in terms of a probability-like membership function. The membership maps, with values ranging from 0 to 1, indicate the likelihood that a pixel (location and time) belongs to a particular province. Fuzzy logic has already been used to classify ocean satellite pixels and to blend different algorithms to retrieve chlorophyll concentration from space (Moore et al. 2001). In this latter case, the assignment of partial or graded class memberships to different water types, hence, different algorithms, has the overall effect to accommodate pixels with mixture of different water types and to smooth out the transitions between water types in the output image. Simpson and Keller (1995) used fuzzy logic to classify sea ice, clouds, and water pixels from AVHRR data, allowing for situations with mixed ice-water signals.

The properties used in this work for zonal classification are the surface chlorophyll concentration (*CHL*), sea surface temperature (*SST*), and the above-water incident photosynthetic available radiation (*PAR*). These are important determinants controlling primary production in marine waters. The chlorophyll level stands as an index of the trophic state of the water (Herbland et al. 1983, Morel and Berthon, 1989), but would account for about 30% of the variability in productivity (Campbell and O'Reilly, 1988). In light-limited environments, the instantaneous rate of production (P) is proportional to *PAR*, up to a light-saturated value, P_{max}. Finally, the maximum rate of photosynthesis (P_{max}) is also influenced, in part, by the temperature. However, the response of phytoplankton to changes in these variables cannot be easily quantified using a single universally reliable model, as it depends on the community species, their physiological state and capacity to adapt. On the other hand, a partition of the marine environment into provinces, each of them calibrated against a satellite-derived combination of *CHL*, *PAR*, and *SST*, would improve the computational scheme of the photosynthesis rate in these distinct environmental domains.

THEORETICAL METHOD: FUZZY LOGIC

Fuzzy logic was first introduced by Zadeh (1965) as a mathematical way to represent vagueness and imprecision inherent in the data. Within conventional set theory, every element/object/property of a system (i.e. data) is either a member or a non-member of a given set of that system. This concept is clearly restrictive when applied to the natural systems and the environment, where properties and populations evolve also through ambiguous and unresolved continuous functions from one state to another, or one condition to another, reflecting processes of adaptation and/or bio-geographical change along physical and chemical gradients. As a result, natural systems are organized into patches or fragmented features, connected through boundaries of which the extension depends on the capacity of the property / population under study to progress or not from one patch characteristics to another. To account for that unclear transitional situation, a classification scheme based on fuzzy logic simply states that an object/data can have partial *membership* to more than one set. Note that a full membership to exclusively one set is still permitted, representing a particular case within the entire probability field of the system.

In more formal terms, let **U** denote a system-ensemble containing x elements, (**U** = $\{x\}$). In conventional set theory, given a subset **A** of **U**, each element x would either belong or not belong to **A**. Accordingly, membership of x in **A** is defined by the simple step function:

$$f_A(x) = \begin{cases} 1\,(\text{if } x \in A) \\ 0\,(\text{if } x \notin A) \end{cases} \qquad (1)$$

where f_A is called the *membership function*.

Under fuzzy set theory, the membership function is altered to allow for graded memberships such that:

$$0 \leq f_A(x) \leq 1 \qquad (2)$$

It expresses the degree of natural imprecision in associating x to a particular subset **A,** or the probability that x belongs partly (partial membership) to the subset **A**.

According to Bensaid et al. (1996), a system of c fuzzy sets is *constrained* if:

$$\sum_{i=1}^{c} f_i(x) = 1 \qquad (3)$$

In some situations, the *c* sets may not represent all possible ranges of variability in the system, and thus a given observation might have low probability of belonging to any of the sets, and the sum of f_i's would be less than 1. The system becomes then *unconstrained* as it is the case with satellite data (Moore et al. 2001).

APPLICATION SCHEME

The overall application scheme is partitioned into two main steps (Fig. 1): one involving in-situ data and the other satellite data. In the first step, applied strictly to in-situ data, distinct classes in the oceanic realm are defined on the basis of sea surface temperature (*SST*), photosynthetically active radiation (*PAR*), and surface chlorophyll concentration (*CHL*). The choice of these variables (Prod_Var thereafter) is dictated by their direct influence on the productivity of marine waters. Most of the productivity algorithms to be applied with satellite data (Campbell et al. 2002) are combining at least two of these variables in addition to other information related to the efficiency of phytoplankton to conduct photosynthesis.

In a second step, membership functions are given to satellite data with respect to each of these distinct classes.

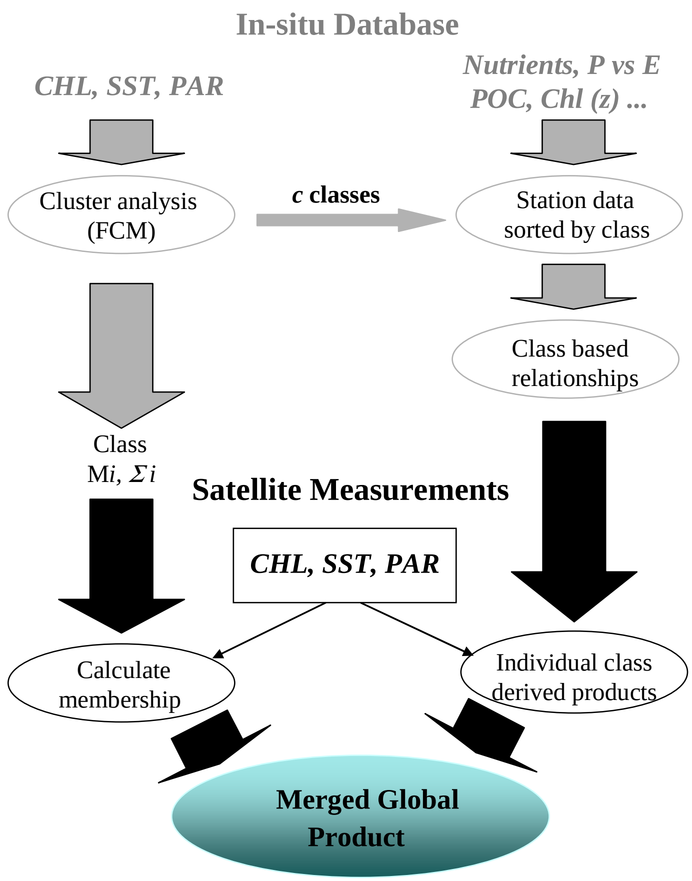

Figure 1: Schematic representation of the fuzzy logic procedure adopted. Top half of the flow chart shows analysis related to in-situ data and the bottom half shows that related to satellite data (adapted from Moore et al. 2001)

Fuzzy c-means clustering algorithm

The field measurements were collected from existing database representing a wide range of environmental marine conditions. Surface chlorophyll values, sea surface temperature and photosynthetic radiation were extracted from three different databases:

- A large database assembled by Behrenfeld and Falkowski (1997) to develop and test their light-dependent, depth-resolved model for phytoplankton carbon fixation. It includes measurement from both case 1 and case 2 waters, from oligotrophic gyres to highly productive upwelling regions.
- A dataset collected in the Southern Baltic (ULISSE, Dowell et al. 1997) as the result of a collaborative work between the Institute of Oceanology of the Polish Academy of Science (IO-PAS) and the Joint Research Centre of the European Commission (EC-JRC). Four cruises were conducted on board r/v Oceania in 1993 and 1994 to investigate bio-optical and biogeochemical processes in the Gulf of Gdansk, along the Polish coast as far west as the Pomeranian Bay, and the southern part of the Baltic Proper.
- Finally, another dataset from the Coastal Ocean Processes Experiment of the East China Sea (COPEX-ECS, see http://copex.kordi.re.kr/) project was used as representative of a turbid coastal environment. The project was launched in 1993 for a 10-years period to collect physical and biological data in the East China Sea and Yellow Sea.

A total of 1153 stations were blended (Fig. 2) and analyzed in terms of ecological grouping through an unsupervised cluster analysis (FCM, Bezdek 1981).

The FCM algorithm produces a fuzzy clustering of the data into a specified number of clusters or classes (herein denoted as *c*). The basic function of this algorithm is to choose clusters that minimize the distance between the data points and the prototype cluster centers (or cluster means). Cluster centers are iteratively adjusted until optimization criteria are met (e.g., maximum number of iterations or minimum change residual). The clustering routine then returns the mean Prod_Var vectors for the *c* classes, and a matrix containing the memberships of each point to each class.

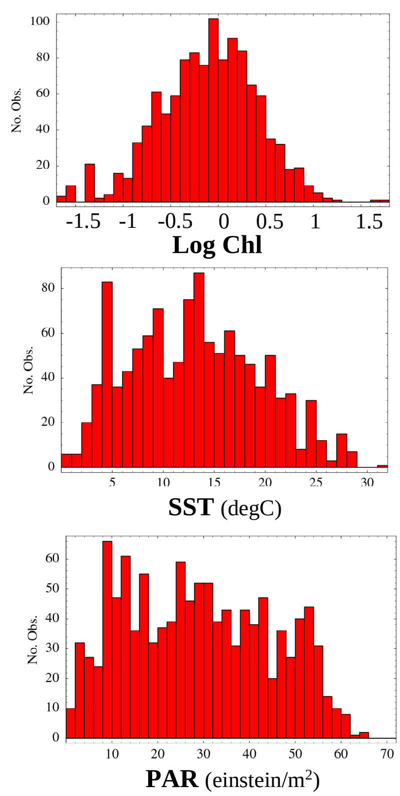

Figure 2: Statistical diagram showing the distribution of each of the three variables(Prod_Var) used for the cluster analysis: surface chlorophyll, sea surface temperature, and photosynthetically active radiation

An intitial guess number of clusters, *c*, ranging from 3 to 25 was first given to the FCM clustering routine, and the results were evaluated using so-called *cluster validity measures* (Bezdek *et al*. 1997). Four validity measures used to objectively assess the optimal number of clusters were used: the *partition coefficient* and *partition entropy* (Bezdek, 1981), the *compactness and separation index* (Xie and Beni, 1991), and the *Davies-Bouldin index* (Davies and Bouldin, 1979). All of them converged to yield an optimum number of clusters, $c = 9$ classes, each represented by a given range of *CHL*, *SST*, and *PAR* (Table 1).

Table 1. Characteristic tendencies for SST, PAR, and CHL within each class, and description of the associated provinces.

	SST	PAR	CHL	Province
Class 1	high	high	very low	Oligotrophic Tropical
Class 2	high	high	low	Temperate shallow MLD
Class 3	medium	low	low	Temperate Deep MLD

Class 4	medium	high	medium	Temperate Stratified
Class 5	low	medium	medium	Polar Stratified
Class 6	medium	very low	medium	High Lat, Low Light
Class 7	medium	low	high	Mid-,High Lat. Overturning
Class 8	medium	high	high	Mid-, High Lat. High Nutrient
Class 9	low	medium	very high	High Lat. Spring Blooms

Once the clusters were identified, the individual stations were sorted according to the cluster (class) with the highest membership value, and the mean Prod_Var vector, $\mathbf{M}_i$, and covariance matrix, $\boldsymbol{\Sigma}_i$, were calculated for each class *i*. The statistical properties (Fig. 3) of these three variables for each class then become the basis for defining membership to each class found in the satellite data.

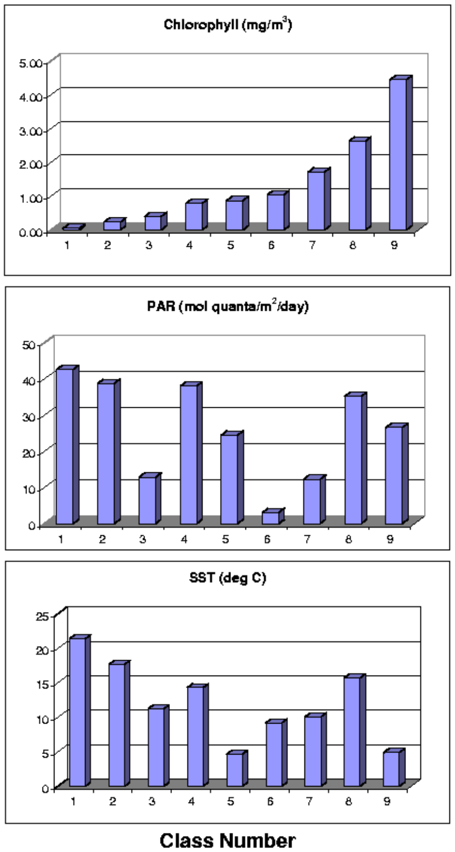

Figure 3: Plots showing the mean values of the three variables in each of the nine classes. The classes themselves have been ordered such that chlorophyll values increase from class 1 to class 9.

Fuzzy membership function

The second step, depicted in the lower box in Figure 1, illustrates the application of the method to satellite data. At each ocean pixel $\boldsymbol{x}$, we have satellite observations of CHL, SST, and PAR. A membership function, $f_i(\boldsymbol{x})$, is computed for each $\boldsymbol{x}$ to each class i (i = 1, 2,...c). The membership function (ranging from 0 to 1) expresses the likelihood that the vector of observations $\boldsymbol{V}$ = (Prod_Var) at pixel $\boldsymbol{x}$ was "sampled" from the distribution of class i. Membership values are then used to weight variables derived from the corresponding class-specific models. In practice, only those classes with membership values above a certain threshold are plausible.

For any measured $\boldsymbol{V}$ = (Prod_Var), the fuzzy membership is defined in terms of the squared distance between $\boldsymbol{V}$ and the ith class mean $\mathbf{M}_i$. For this, we use the squared Mahalanobis distance given by:

$$Z_{\boldsymbol{i}}^{\boldsymbol{2}} = (\mathbf{V} - \mathbf{M}_i)^t \boldsymbol{\Sigma}_i^{-1} (\mathbf{V} - \mathbf{M}_i) \qquad (4)$$

where t indicates the matrix transpose. The Mahalanobis distance is a generalized distance from $\boldsymbol{V}$ to $\mathbf{M}_i$ in units of standard deviations adjusted for covariance.

If the $\boldsymbol{V}$ vectors belonging to class i are multivariate normal, and if the observation was "sampled" from class i, then $Z_{\boldsymbol{i}}^{\boldsymbol{2}}$ has a χ^2 distribution with n degrees of freedom (where n is the dimension of the set). Thus, we define the membership function to be:

$$f_{\boldsymbol{i}} = 1 - \mathrm{F_n}(\mathrm{Z}_i^2) \qquad (5)$$

where $F_n(Z^2)$ is the cumulative χ^2 distribution function with n degrees of freedom. When $\boldsymbol{V} = \mathbf{M}_i$, then $Z_i^2 = 0$, and $f_i = 1$. In that particular case, the pixel has full or 'crisp' membership in class i. As $\boldsymbol{V}$ becomes more distant from $\mathbf{M}_i$, $f_{\boldsymbol{i}}$ decreased from 1 to 0, indicating a reduced likelihood that the pixel belongs to class i.

RESULTS: EUROPEAN MARINE ECOLOGICAL PROVINCES

Using the class statistics defined from the field dataset, fuzzy memberships to each class are calculated for all valid pixels included in monthly composite satellite images of CHL, PAR, and SST. All satellite data used to generate the space and time dynamic in the distribution of the eco-provinces in European Seas are obtained from publicly available data bases, and selected so as to guarantee the long-term potential for generating province distributions. Chlorophyll concentration (CHL) and Photosynthetically Available Radiation (PAR) data are both accessible from the SeaWiFS project web site at the NASA/DAAC (http://daac.gsfc.nasa.gov/oceancolor/panorama.shtml). On the other hand, Sea Surface Temperature (SST) data are obtained from the Pathfinder project at the following web site (http://podaac.jpl.nasa.gov/sst/). Details on the algorithms and processing of these data are available through the websites provided above. The datasets were obtained for global coverage with the spatial resolution of 9 km and a monthly temporal increment. The 9-km spatial resolution was chosen as it is compatible for all datasets, and also because it limited the size (and therefore data volume) required for this investigation. The data were all available in identical mapped projections and no remapping was required. An ancillary dataset, day length, was also used in the analysis, and calculated using standard geometrical sun-earth equations (e.g. Iqbal 1983). A European subset was extracted from the global dataset to fit a region of 1000 by 700 pixels centered on European Regional Seas and other marine waters of European interest.

The geographical window includes a large portion of the Eastern North Atlantic so as to cover the entire region defined by the OSPAR Marine Convention.

Europe is surrounded by a large number of seas, all differing with respect to their physical structure and water content. Typical morphologies range from quasi-enclosed basins (Mediterranean Sea, Black Sea, Baltic Sea) to water masses widely open to the deep ocean (Celtic Sea, Gulf of Biscay). Such a variety is also reflected in the ecological status of the marine waters and the distribution of provinces (Figs. 4) showing all nine classes represented during most of the year. Oligotrophic situations (class 1 and 2) are concentrated in the lower half of the window, i.e. up to 40° N of latitude, with an significant shift of the very low chlorophyll region (class 1) toward the African coast and Mediterranean Sea during spring and summer. In that part of the geographical window, seasonal variations of the provinces are also restricted to change between class 1 and 2 only. An exception is the northwest African upwelling system, which is adequately represented by class 8 (High nutrient) characterized by lower mean temperature (~ 15°C) than the surrounding waters (~21°C and ~17°C for class 1 and 2 respectively, see fig. 3) and high chlorophyll concentration (~2.5 $mg.m^{-3}$) along the coast line. This province extends further offshore from January to May with maximum coverage in April and May, in agreement with maximum strength of upwelling events in this area (Nykjaer and Van Camp 1994). A narrow class-4 province (Temperate stratified) acts for some months as transitional water between the productive coastal upwelling system and the open oligotrophic ocean.

The Mediterranean Sea is dominated by a bi-province system during most of the year, varying between class 1 and 2 during summer months (April- October) and between class 2 and 3 from November to February. The boundary between these two provinces is, however, highly dynamic in space and time. The border line extends either east-west as shown from September to January, thus dividing the basin into a northern and a southern part along a line stretching from the northern tip of Tunisia to the Syrian coast. During summer months, the transition is rather meridional, thus dividing the basin into a western and eastern part along a line connecting the Sicily Channel, the Strait of Messina and the Strait of Otranto. The Adriatic Sea and northern region of the Aegean Sea have northern or western Med Sea characteristics rather than southern or eastern ones. The Mediterranean Sea is known to be one of the most oligotrophic seas. In summer, relatively nutrient-poor Atlantic water flows into the Mediterranean basin, becoming even more impoverished as it reaches the eastern part of the basin (Berland et al. 1988). The oligotrophy in the eastern part is even more accentuated by the lack of nutrient supply from rivers. The completion of the Aswan Dam in 1965 has considerably reduced the supply of biogenic material in the eastern Med, with large impact in the upper trophic levels and fisheries (Dowidar 1984).

Such marked difference between eastern and western part of the Med has been already evidenced from satellite-derived chlorophyll analyses, either using the Coastal Zone Color Scanner time series (Barale and Zin 2000) or the operating SeaWIFS sensor (Bosc et al. 2004).

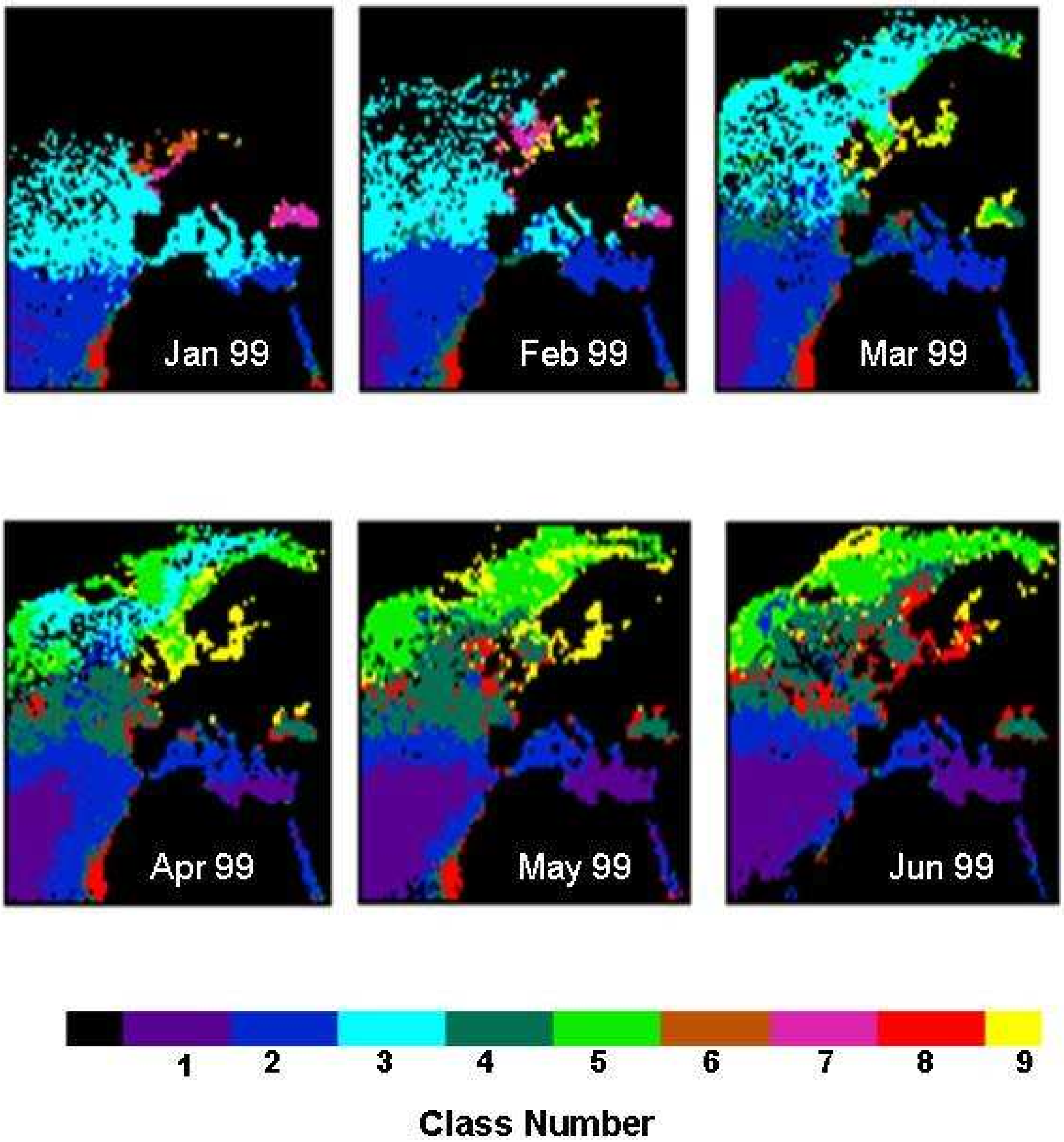

Figure 4A: Spatial and temporal variations of the ecological provinces in European waters for January to June 1999, as resulting from unsupervised classification based on chlorophyll biomass, temperature and photosynthetic irradiance.

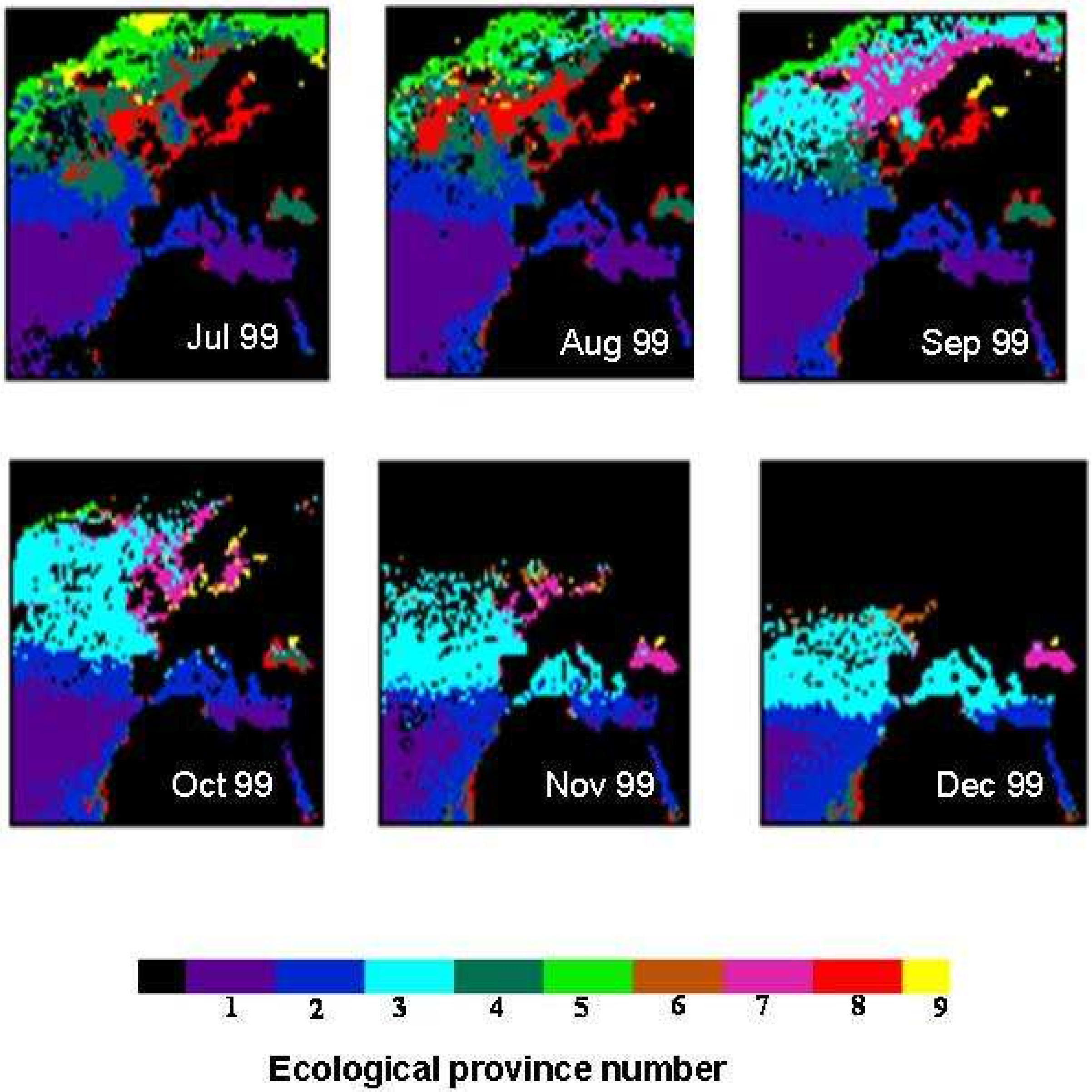

Figure 4B: Spatial and temporal variations of the ecological provinces in European waters for July to December1999 , as resulting from unsupervised classification based on chlorophyll biomass, temperature and photosynthetic irradiance.

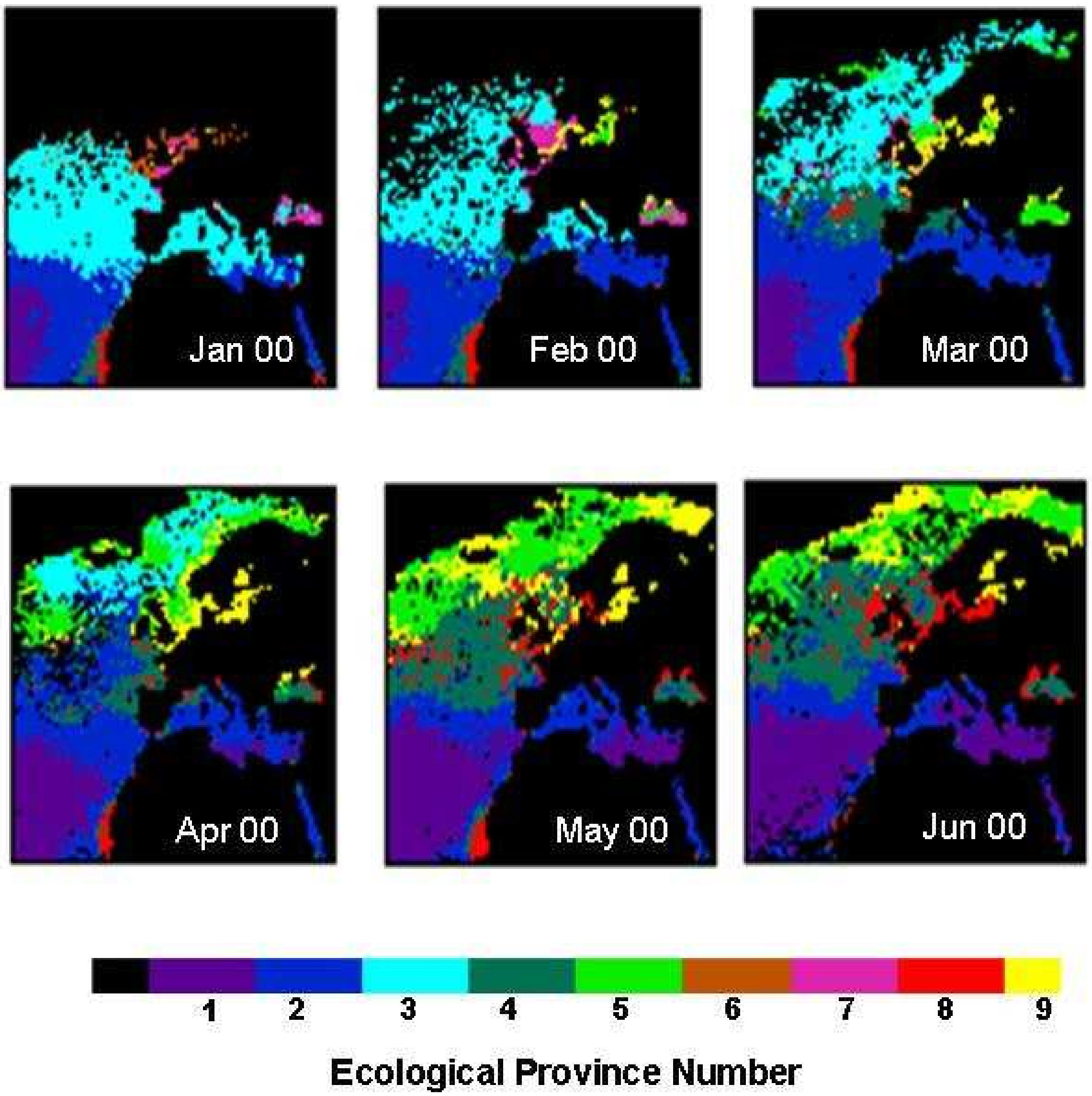

Figure 4C: Spatial and temporal variations of the ecological provinces in European waters for January to June 2000 , as resulting from unsupervised classification based on chlorophyll biomass, temperature and photosynthetic irradiance.

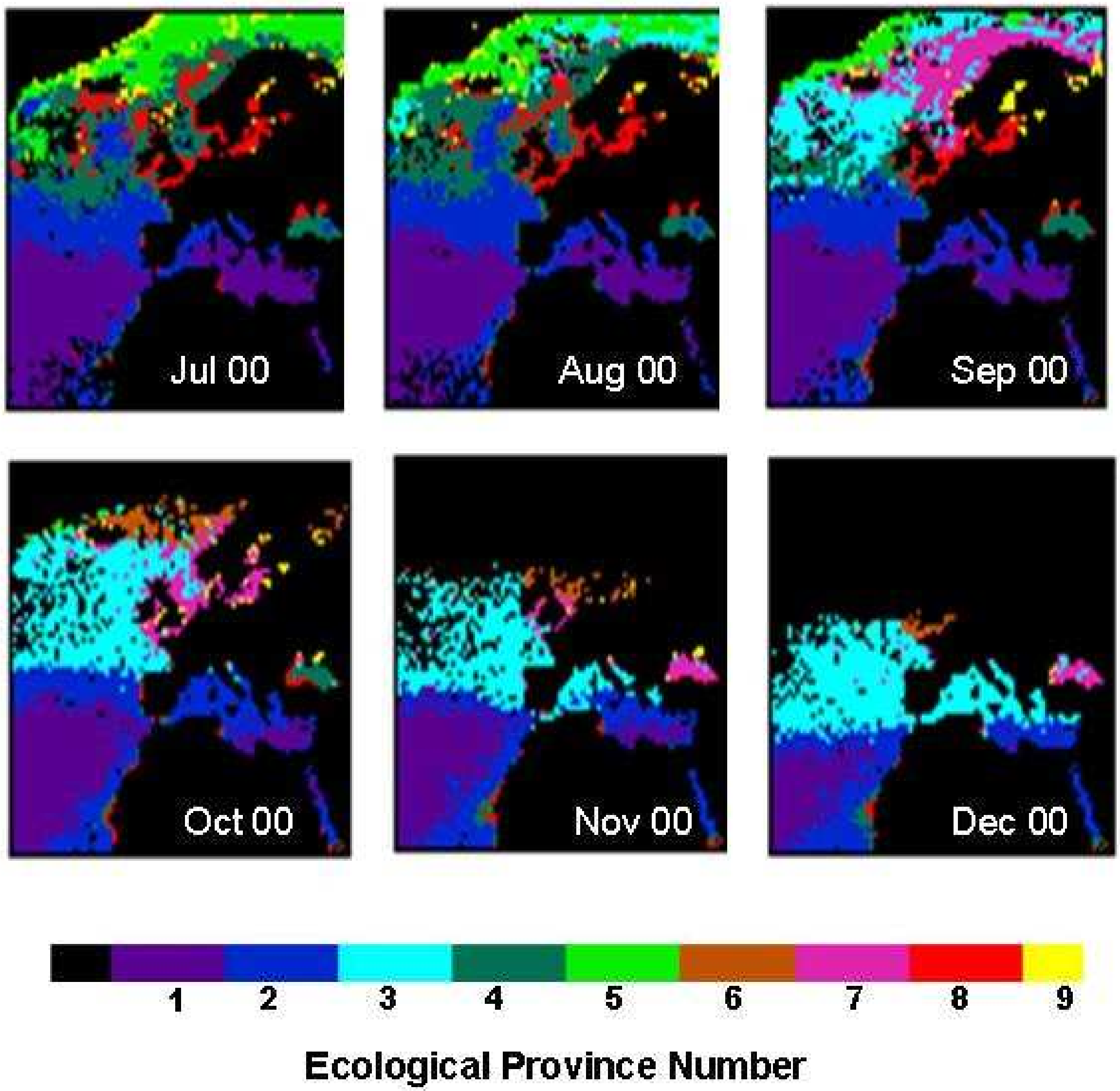

Figure 4D: Spatial and temporal variations of the ecological provinces in European waters for July to December 2000, as resulting from unsupervised classification based on chlorophyll biomass, temperature and photosynthetic irradiance.

On the other hand, monthly SST maps as derived from AVHRR analyses tend to display a north-south division of the basin, except for the summer months (June to October) where the thermal structure at the surface tends to become homogenous over the entire Mediterranean basin (Barale and Zin 2000).

The cluster analysis has also generated two other classes (4 and 8, Temperate stratified and High Nutrient, respectively) in the northwest Mediterranean Sea, corresponding to the Liguro-Provencal basin and the Gulf of Lions, and to a lesser extent the Alboran sea. These are short-lived provinces with strong signature in March and April corresponding to the phytoplankton spring bloom. In this area, intense vertical convections usually occur during winter carrying nutrients in the upper layer, but maintaining phytoplankton cells in unsuitable light conditions for photosynthesis. With increasing seasonal air temperature and stratification of the water column, phytoplankton and nutrients are trapped in the upper lighted zone, thus optimizing phytoplankton growth.

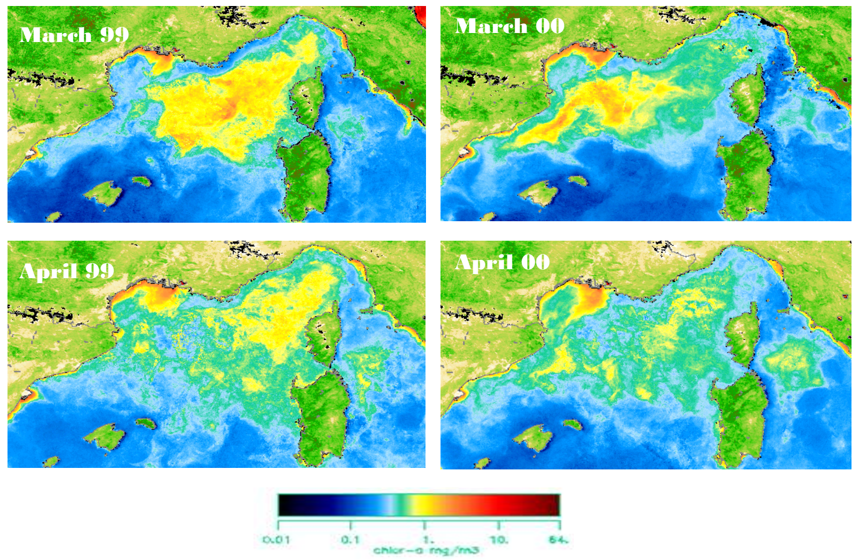

Figure 6: Monthly composite of surface chlorophyll concentrations as derived from SeaWiFS images for the northwestern Mediterranean Sea in March and April 99 and 2000 (data source: http://marine.jrc.cec.eu.int/)

Note that the fuzzy method to select eco-provinces accounts accurately for the inter-annual variability of the various input fields. In this particular case, for example, highly productive province (e.g. class 8) in the northwest Mediterranean Sea in spring 2000 is shifted westward compared to its position in 1999. This reflects a major change in the phytoplankton community and biomass occurring at the same periods, as observed from satellite images (fig.6).

North of 40°N of latitude, the marine provinces are more diversified with a strong seasonal variability in all seas, including the Black Sea (see fig. 4 and 5). The temperate open North Atlantic is dominated by a class-3 province (Deep mixed layer depth) during all winter and autumn seasons, with typical characteristics of low productive waters mostly due to low irradiance input (fig.3), whereas the temperature remains within a medium range value of 11°C. Starting in March, a bloom situation is progressively occurring as the water column becomes startified from the southern limit of the area. The 'Stratified' province spreads all over the North Atlantic in April and May (fig. 4), with patches of really high productive regions (class 8, High Nutrient) in June and August. Substitution back to low productive temperate waters can be observed in July through October. Note that the identification of provinces in high latitude regions during winter and autumn is significantly affected by the lack of satellite optical data during these low solar radiation periods.

During summer time, another province is identified along the Greenland coast with productivity similar to surrounding North Atlantic waters, but with characteristics of a cold water community. This province extends up to the Barents Sea where, occasionally, coccolithophores have been particularly abundant in the recent years (Vance et al. 1998, Napp and Hunt 2001) during summer, and recognized with a very clear milky signature on satellite true color images (Brown and Yoder 1994). The presence of coccolithophore blooms can be associated with patches of higher productive waters differentiated in figures 4 as class-9 (High Lat. Spring bloom) provinces. This phytoplankton community has an important biogeochemical impact in the greenhouse gases cycling, acting as a sink for atmospheric CO_2 on the one hand, and releasing dimethylsulphide to the atmosphere on the other hand.

In the eastern North Atlantic, along the north European coast, class-9 and class-8 provinces are dominating in figures 4. March, April and May are the most productive-low-temperature coastal waters spreading all around the British Isles, northern Europe, the Norwegian coast, and in the entire Baltic. Starting in May, however, slightly less productive waters with medium range temperature (typically class-8 province) are observed along the eastern coast of France and England to propagate quickly the next month to the southern North Sea, the Baltic and along the Scandinavian coast. The extension of class-8 province is even more drastic in July and August. Note that with respect to forcing factors for productivity, such class- 8 provinces in the north seas are equivalent to the province identified in the northwest African upwelling system, suggesting that this combination of light, temperature and phytoplankton biomass could represent an ideal situation for the production of organic carbon. In September and October, class-8 province is progressively substituted by a class-7 type of province, which is half-less productive in term of phytoplankton biomass in response to a significant reduction in solar radiation at that time of the year and deepening of the mixed layer.

The situation in the North Sea deserves special attention. The water budget and circulation in the North Sea is driven by a combination of tides, wind, and density gradients, leading to a cyclonic circulation with Atlantic salt water entering from the north (Norwegian Sea) along the British coast, and warmer waters from the Channel flowing along the French/Dutch/Belgian coasts. This description is well depicted in the distribution of the provinces during March to June, with the penetration into the North

Sea of the water type identified along the Norwegian coast. In July, August and September, the central part of the North Sea becomes however, completely isolated from the northern Atlantic provinces. During that period, the classification scheme includes a central class-2 unproductive province (Temperate shallow MLD) surrounded by a mesotrophic class-4 water type, itself bounded by a very productive class-8 province extending along the coastline, the northern entrance of the North Sea, and in the English Channel. In that case, the cluster is undoubtedly dominated by the input variable of chlorophyll biomass, as similar pattern can be observed with SeaWiFS images for the North Sea (fig.7). Class-2 and class-4 provinces are characterized by similar amount of solar radiation and not so much difference with respect to SST. On the other hand, the phytoplankton biomass ranges from 0.1 mg Chl.m^{-3} in the central North Sea up to 5-10 mgChl.m^{-3} along the coast of England and Belgium (fig.7).

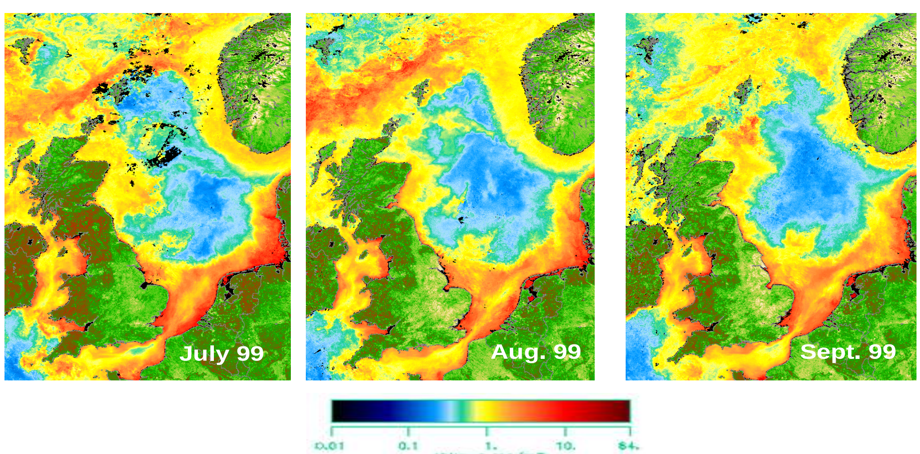

Figure 7: Monthly composite of surface chlorophyll concentrations as derived from SeaWiFS images for the North Sea in July, August and September 1999 (data source: http://marine.jrc .cec.eu.int/).

In the Baltic during most of the year, membership functions for valid pixels of all three variables evolve within two closely-related provinces, a typical 'High Lat. Spring bloom' from March to May changing to a 'High Nutrient' conditions (class-8) from June to September. Most of the variation between both provinces results from a drastic change in temperature, averaging 5°C or less in one case to 15°C in class 8 (fig.3). The difference in temperature is such that the associated change in the mean chlorophyll biomass observed between class-8 and class-9 provinces would also be combined with a shift in the phytoplankton species community. The spring phytoplankton bloom, which usually occurs around April in the Baltic when the temperature of surface waters exceeds 3°C, is dominated by Diatoms assemblage. A second peak of chlorophyll, and to a lesser extent primary production, is observed in summer associated with the growth of nitrogen-fixing cyanobacteria, mainly *Nodularia spumigena* but also other species such as *Aphanizomenon* spp. and *Anabaena* spp. These 'anomalous' [by contrast with naturally-occuring spring bloom] and often toxic blooms are recurrent phenomena in the Baltic Sea since the late 60s, in response to an increasing nutrient loads in coastal waters from human activities on land (Finni et al 2000).

Note that a seasonal transition between class-9 and class-8 provinces is not specific to the Baltic. It is also observed along the coast of northern Europe and western Black Sea, in close relation with changes in the phytoplankton community structure for most of the cases. In the Southern Bight of the North Sea, the temperature ranges from 0°C in winter to 22°C in summer and controls the phytoplankton species succession from small diatoms in spring to dinoflagellates in summer (Peperzak 2003).

Within the Black Sea, the classification scheme and membership functions tend to discriminate between the North and Western coastal areas from the rest of the basin. The northwestern ecological region includes the Azov Sea, the Golf of Odessa and the area influenced by the Danube inflow. It is also a province characterized by a wide and shallow continental margin limited off shore by the 200m isobathic line. As for the Baltic Sea, this province varies annually from a class-9 blooming situation starting in February and extending through April-May, to a class- 8 summer ecosystem affected by heavy nutrient load from the adjacent river basins. On the contrary, the central and eastern part of the Black Sea shows less variations, remaining from April to October as class-4 province with typical characteristics of temperate and stratified waters. A patch of class-2 unproductive stratified water is even noticeable in the eastern Black Sea during July and August. During late autumn and winter, most of the Black Sea remains at a High- and Mid-latitude Overturning (class 7) situation with some differences, however, in the central part of both the western and eastern areas. Analyzing CZCS data, Nezlin(1997) also observed a quasi-homogenous chlorophyll concentration in most of the Black Sea during December and January.

Considering the water circulation at the surface, the properties of water masses in the Black Sea and the bathymetry would tend to divide the basin into three systems: a coastal region bounded offshore by a steep slope and characterized by a cyclonic water current, so-called the Rim current following the margin all around the basin. In addition, the Crimea peninsula is affecting the water circulation in the central part of the basin, dividing the western and eastern area into two distinct gyres. Except for a month or two in winter, this physical structure does not correspond to the present classification based on factors controlling the productivity where both eastern and western gyres are identified as a unique ecological region, suggesting similar community structure for these waters.

DISCUSSION AND CONCLUSION

The method implemented in this work enables the differentiation of 9 'eco-regions' varying in time and space over all European Seas and beyond. Each of the provinces is associated with a common set of variable, i.e. temperature, light, and biomass concentration, but with different combination with respect to their magnitude. In turn, these variables are major factors controlling the primary production and carbon cycle in the upper layer, as well as the community structure at the base of the food chain. In addition, the variables are accessible from satellite remote sensing, allowing the province boundaries to be defined in a functional and dynamic manner.

In general, open oligotrophic ocean is dominated by very small organisms, ranging from picoplankton (0.2-2µm in diameter) to nanoplankton (2-20µm) size category. They likely constitute most of the algal community in class 1, 2 and 3, very much adapted to low light and low nutrient conditions. As a result, they are also efficient producers, accounting for a major part of the photoautotrophic carbon reduction in the world's ocean. Small sized cells are capable of higher photon absorption rate per unit cell volume than similar cells but with larger diameter. That property allows them to take full benefit of local nutrient burst occurring at depth under low light conditions. The microbial food chain predominates in that system where microbes are regenerating dissolved organic matter into the system via small autotrophs production and consumption by flagellates and ciliate organisms.

Upon seasonal stratification of the water column in response to an increase in solar irradiance and temperature, large amount of nutrient get trapped within the mixed layer favoring the growth of larger cells typically represented by Diatoms assemblage. This process is represented in our study through seasonal substitution of class 3 by classes 4, 5 and 6, taking over most of the northern Europe in April , May and June. Such a change in the phytoplankton biomass and species composition is accompanied by changes in the physiological state and in the combination of factors regulating growth and biomass. Although Diatoms have a lower photosynthetic efficiency and lesser turnover rate compared with small picoplankton cells, they can produce a large amount of biomass, proportional to the amount of nutrient, specifically silica entering the composition of the organism frustules. The capacity to increase 100 fold the biomass concentration rapidly is an asset to re-shape the marine food pyramid into a more traditional system, where micro-phytoplankton is grazed by macro-zooplankton, themselves consumed by small pelagic fishes and larger predators.

As the availability of nutrient in the upper productive layer decreases, a new community of phytoplankton is taking place with smaller sized diatoms and prymnesiophytes with higher turnover rates, more adapted to highly stratified summer conditions and to a background amount of nutrient regenerated within the top mixed layer. Under some circumstances (high temperature, low wind, appropriate elemental stochiometry), this situation could drive to anomalous blooms, monospecific, and potentially toxic for the rest of the organisms, including humans (so-called Harmful Algal Booms). Cyanobacterial blooms are, for example, recurrent in the Baltic during summer time, whereas *phaeocystis* cells tend to develop large colonies in the Channel and the North Sea. The proposed classification accounts for these particular situations with the classes 7, 8 and 9 which also include regions of high production due to permanent, or quasi permanent, upwelling of nutrient –rich deep waters (e.g. along the coast of West Africa in fig.4).

The distribution of the provinces in 1999 and 2000 are not significantly different, suggesting that the oceanographic factors that have been chosen for this classification are sufficiently recurrent on some time scale (monthly) to characterize typical regions at some distinct spatial scales. It also gives confidence in the method, with the possibility to investigate inter-annual changes in the distribution of these eco-regions and shifts from an ecosystem to another in response to, e.g., climate change.

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