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Patterns of chlorophyll interannual variability in Mediterranean biogeographical regions

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ABSTRACT

The Mediterranean Sea exhibits a strong basin and regional scale phytoplankton variability correlated to its semi-enclosed nature, complex orography and the variety of physical and chemical processes that regulate its productivity. Herein, using 17 years of ocean-color composites, we investigate differences in the regional patterns of interannual variability in satellite-derived chlorophyll (Chl), a proxy for phytoplankton biomass. A neural network classification, based on the Self-Organizing Maps (SOM) analysis in the time domain, is used to reveal regions of similar temporal variability of Chl in the Mediterranean Sea. Characteristic temporal patterns extracted by the SOM analysis show different scales of variation that can be related to already identified oceanographic features and biogeochemical variability in the Mediterranean Sea. Clear differences are noticed between regions located in the Western basin and Adriatic Sea, where rivers, winter mixing and winds are known to drive variations in primary production at regional scale and regions located in the Eastern basin, represented by a large and rather homogeneous region. Using the SOM-defined characteristic temporal patterns of Chl, we analyzed the regional influence of the North Atlantic Oscillation (NAO) and El Niño Southern Oscillation (ENSO) in the long-term (> 1 year) Chl variability. Our results indicate that NAO has more influence in the Chl variations occurring in regions located in the Western basin whereas ENSO exhibits higher impact on the central Mediterranean and Eastern basin during its positive phase. Both NAO and ENSO show non-stationary coherence with Mediterranean Chl. The analysis also reveals a sharp regime shift occurring in 2004-2007, when NAO changed from positive to negative values. This shift particularly affected the winter phytoplankton biomass and it is indicative of climate driven ecosystem-level changes in the Mediterranean Sea. Our results stablish a regional connection between interannual phytoplankton variability exhibited in different regions of the Mediterranean Sea and climate variations.

1. Introduction

A major challenge in the spatial analysis of oceanic systems is to classify and identify regions with common patterns since, unlike terrestrial ecosystems the sea is an intrinsically dynamical system often with diffuse boundaries and shallow gradients (Hinchey et al., 2008). Furthermore, numerous biological and environmental factors are nonlinearly involved in the two-way environment-organism relations in the sea (e.g. Kavanaugh et al., 2016). Despite these difficulties, the classification of marine areas into clear cut geographical units, displaying similar biogeochemical characteristics and/or dynamical behavior, has become essential in the understanding of the plankton community responses to present and future climate scenarios. These represent fundamental abstractions of the geographical organization of life in response to past or current physical and biological forces (Kreft and Jetz, 2010). Biogeographical regions not only facilitate the understanding of the functioning of marine ecosystems but they are also useful when trying to define indicators of the environmental state as well as when undertaking the management of resource and conservation decisions (Spalding et al., 2007). An example of this is the Marine Strategy Framework Directive (Directive 2008/56/EC; MSFD, 2008) that, in order to achieve its ecosystem conservation goals, establishes marine regions and sub-regions based on geographical and environmental criteria.

Biogeographical regionalization can be based on geographic or on ecologically relevant attributes of the abiotic (i.e., temperature, salinity, eddy kinetic energy, hydrodynamics, etc.) or the biotic environment (i.e., biomass, taxonomy, size structure, etc.) from measured

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records or from data obtained using various modeling approaches. Satellite ocean-color data provides synoptic and long-term time coverage, which is ideal when attempting this classification. Several approaches have been traditionally used to identify coherent areas of the sea using ocean color and other complementary information (see Ayata et al., 2017). Multivariate clustering methods, such as k-means analysis, principal component analysis (PCA) or empirical orthogonal functions (EOFs), have proven to be efficient at obtaining coherent patterns of variation that can be explained on the basis of the main oceanographic characteristics (D'Ortenzio and Ribera d'Alcala, 2009; Foukal and Thomas, 2014; Yoder and Kennelly, 2003). However, these methods are not capable of capturing the non-linear and turbulent character of the ocean dynamics. In addition, these approaches have drawbacks when managing datasets with missing values as they need some particular functional relationship or assumptions about the data such as distribution normality or preservation of the variance.

The Self-Organizing Maps (SOMs) developed in the last decades is a useful bioregionalization method since robustly clusters and identifies patterns in large datasets (Kohonen, 1982; Vesanto and Alhoniemi, 2000). The SOM is a neural network algorithm based on unsupervised learning that works as a nonlinear alternative to the above mentioned linear grouping methods. While the SOM may show performance limitations in some cases (Liu et al., 2006; Solidoro et al., 2007) an advantage of the algorithm is that it preserves topology, and the obtained patterns are topologically ordered. Similar patterns are arranged to be neighboring units on the neural network, while dissimilar patterns are located far away from each other. In the case of biological regionalization, this topological ordination permits the establishment of similarity relationships in the dynamical behavior of each region defined by the SOM classification. This method has been successfully used in diverse climate, atmospheric and oceanographic applications (e.g. Lachkar and Gruber, 2012; Leloup et al., 2007; Richardson et al., 2003; Uvo, 2003). In the case of satellite ocean-color data, SOM classification has been used for a variety of applications including the synthesis of spatial patterns of chlorophyll (Chl) variation, the optimization of image processing, the classification of spectral signals for subsequent inference of phytoplankton groups, or for linking of sea-surface with vertical profiles of chlorophyll (Ainsworth, 1999; Ben Mustapha et al., 2014; Charantonis et al., 2015; Farikou et al., 2015; Richardson et al., 2003; Yacoub et al., 2001). SOM classification can be applied to both space and time domains and provides a powerful tool for diagnosing ocean processes, as demonstrated by Liu et al. (2016).

Owing to its semi-enclosed nature in between two continents and to its intricate orography, the Mediterranean Sea exhibits regions of highly contrasting physical and chemical processes affecting their biological properties (e.g. Dubois et al., 2016; Reygondeau et al., 2017; Rossi et al., 2014). This seascape emerges from the three predominant and interacting spatial scales of the marine flow-basin scale, sub-basin scale, and mesoscale (Robinson et al., 2001), and from the differences in the geochemical inputs at these scales that determine phytoplankton productivity. The large scale factors, like the influx of nutrients by the Atlantic jet or the water-column stratification processes, result into a west-east oligotrophic gradient (e.g. Christaki et al., 2001; Dolan, 2000). This gradient is modulated by regional differences in terrestrial and atmospheric loads, dynamical features emerging from exchanges across straits and channels, as well as from mesoscale activity, frontal dynamics and local meteorology. Regional variations in the physical and chemical forcings generate a complex mosaic of biogeochemical environments, particularly in areas with river outflow and/or intricate topography. For example, enhanced Chl values along the northern coastal areas of the Mediterranean Sea have been associated with the impact of runoff from continental margins, vertical mixing due to the prevailing winds, or cooling and density mixing processes as well as persistent mesoscale dynamical features (Barale and Zin, 2000). Furthermore, the influence of the runoff can extend far from the deltas of major rivers such as the Rhone, Po or Nile, sustaining high phytoplankton production on the Mediterranean shelves that contrasts with the general oligotrophy prevailing in open waters (i.e. Antoine et al., 1995; Forget and André, 2007).

Even though the dynamics and pattern of seasonal phytoplankton variability in the Mediterranean Sea are well founded (e.g. Volpe et al., 2012), less is known about the longer timescale variability. At this scale, climate regulatory factors can be more important than direct anthropogenic influence in driving primary production and phytoplankton composition shifts (e.g. Dandonneau et al., 2004; Martinez et al., 2009; Rosseaux and Gregg, 2013). Several studies show that large-scale atmospheric circulation patterns described by climatic indices have an influence over ecological processes in the Mediterranean region (see Lionello et al., 2006). Being located at the southern limit of the North Atlantic storm tracks, the Mediterranean region is particularly sensitive to interannual shifts in the trajectories of mid-latitude cyclones that can lead to remarkable anomalies of precipitation and, to a lesser extent, of temperature (Trigo et al., 2006). The consequences of these climate scale changes in the dynamics of the marine ecosystem are different to those guiding seasonal ecological change and the response of phytoplankton to this type of variability may be spatially variable and depending on the main factors limiting production at each location. Indeed, the ecology-climate interaction is not always straightforward (Stenseth et al., 2003) and climate induced interannual variations and ecosystem shifts may depend on multi-scale processes with interactive variability giving rise to considerable uncertainties in the prediction of the responses of the marine ecosystems.

Previous studies have reported the influence of large-scale modes of atmospheric variability on Chl distributions and variability in the Mediterranean Sea (e.g. Katara et al., 2008). In the present study, we focus on the influence of climatic forcing on the long-term (> 1 year) regional variability of Chl in the Mediterranean Sea. Using satellitederived Chl datasets, we first classify the Mediterranean Sea into regions of different characteristic temporal variability revealed by the SOM analysis in the time domain. By this method, we are able to define coherent biogeographical regions that will form the basis of our interannual variability analysis. We then used cross-wavelets analysis of the characteristic temporal Chl patterns of each SOM-defined region to identify the coherent correlations with two of the most relevant largescale climate indices influencing the Mediterranean Sea, the North Atlantic Oscillation (NAO) and El Niño–Southern Oscillation (ENSO).

2. Materials and methods

2.1. Remotely sensed ocean-color and climate indices data

Our analysis is based on the sea surface Chl concentration (mg m $^{-3}$) data product developed by the European Space Agency Ocean-Color Climate Change Initiative Program (ESA OC_CCI) (Sathyendranath et al., 2017; Sathyendranath and Krasemann, 2014). This Chl data has been tailored to the Mediterranean region by reprocessing the ocean color CCI product with the specific regional algorithm MedOC4 (Mediterranean Ocean-Color 4 bands, Volpe et al., 2007). The resulting Level-4 product is distributed by the EU Copernicus Marine Environment Monitoring Service (CMEMS) and it can be downloaded from http://marine.copernicus.eu. This ocean-color data product is the result of merging MODIS-Aqua, SeaWiFS and MERIS sensors and it measures the average Chl content over the first optical depth. The analyzed Chl time-series covers the period 1998-2014 for the Mediterranean Sea (30 to 46°N and 6°W to 37°E) and gridded 8-day temporal resolution and 1km spatial resolution was downloaded. In order to reduce missing data, Chl values were first re-gridded to a 4 km regular grid and then the remaining gaps were filled in by applying spatial and temporal linear interpolation scheme (i.e., spanning three adjacent values).

NAO and Eastern Pacific and Central Pacific el Niño-3.4 (hereafter ENSO) indices were obtained from the National Oceanic and Atmospheric Administration (NOAA) Earth System Research Download English Version:

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