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# A novel method to retrieve oceanic phytoplankton phenology from satellite data in the presence of data gaps



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#### ARTICLE INFO

Article history: Received 30 May 2013 Received in revised form 2 October 2013 Accepted 8 October 2013

Keywords: Phytoplankton phenology Ocean colour Remote sensing Scale changing Ecological provinces

### ABSTRACT

Phytoplankton phenology is increasingly recognised as a key ecological indicator to characterise marine ecosystems. Existing methods to quantify phenology are often limited by gaps in the data record or by differences between the assumed and actual shapes of the seasonal cycle. A novel method to estimate phytoplankton phenology from satellite chlorophyll-a data is presented here, allowing us to determine the shape of the annual cycle from the data themselves, and to fill data gaps using data from the vicinity at a larger spatial scale. Up to two chlorophyll-a peaks (blooms) per annual cycle can be identified, and their timings and magnitudes estimated. The outputs are a set of time series with no data gaps at a succession of spatial scales, together with information at each scale about the climatological shape of the annual cycle, and the timing and magnitude of the principal and secondary blooms in each year. To illustrate the application of the Algarithm we present the results from a 12 year time series of SeaWiFS data from 1998 to 2009 in the North Atlantic; the timings and magnitudes of blooms show strong spatial patterns, and hence are suitable for incorporation into the definitions of ecological provinces. Due to its generic nature, the handling of data gaps and the lack of reliance on a pre-defined seasonal cycle, the method has a wide range of other potential applications including land-based phenology and the study of the timing of seasonal sea ice cover.

1. Introduction

Phenology, or the timing of changes in the annual biological cycle, is a key factor in the assessment of trends in ecosystems, and phenological methods are well established in studies of terrestrial ecosystems (see White et al. (2009) for an overview). Significant impacts of climate change on phenology have been documented in many terrestrial ecosystems (Badeck et al., 2004; Durant et al., 2007). Interest in marine phenology has grown more slowly until the last decade, during which time series of ocean colour (visible wavelength data over oceans) from satellite remote sensing have attained a sufficient length for elucidation of climatological and interannual variability in phenology (Racault et al., 2012; Sapiano et al., 2012). Chlorophyll-a concentration (Chl) is readily available from satellite ocean colour sensors such as SeaWiFS, MODIS and MERIS (O'Reilly et al., 2000) and is a good proxy for autotrophic biomass (Platt and Sathyendranath, 2008). Shifts in the timing of blooms can have effects at higher trophic levels, including fisheries (Cushing, 1990; Platt et al., 2003; Koeller et al., 2009), and can be an indicator of regime shifts in marine ecosystems (Edwards and Richardson, 2004; Ji et al., 2010).

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The quantification of a phenological measure such as the onset of a bloom is fraught with difficulties, given the often large interannual variations in the annual cycle of the property used (for example Chl in marine systems or Normalised Difference Vegetation Index in terrestrial systems). In temperate latitudes, the typical annual cycle of marine Chl consists of a spring bloom initiated by seasonallyrenewed light availability and terminated by nutrient depletion and predation, possibly followed by an autumn bloom, initiated by upwelled nutrients as stratification breaks down, and terminated by seasonally-reduced light availability. Other factors often complicate this simple description, for example terrestrial fertilisation in coastal waters or unusual weather patterns disrupting the cycle of mixing and stratification. Different considerations also apply in tropical waters where seasonal light variability is weak and bloom amplitude is typically much smaller, as well as in Arctic waters where light is strongly limiting and there is typically only a single (spring) bloom during the year (Cushing, 1959). Hence a key step in the description of the annual cycle is to determine whether one or two blooms per year occur in a given location. Platt et al. (2009) suggest that in some locations there may be a 2-year cycle with the principal peak alternating in amplitude between 1 year and the next.

White et al. (2009) describe four approaches used in characterisation of seasonality in terrestrial systems: a global threshold; a local threshold, defined in relation to the local maximum and minimum values; a conceptual–mathematical approach, in which

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either a functional form such as a Gaussian is fitted to the annual time series, or a subset of it, and the bloom onset defined as the time when the fitted function first exceeds a fraction (e.g. 20%) of its maximum amplitude, or the series is smoothed and a property of the smoothed series such as the peak rate of change is used to define bloom onset; and hybrid methods, in which a curve is fitted to the series and a global threshold applied to the fitted curve.

For marine systems, Ji et al. (2010) review several approaches to definition of bloom initiation: global and relative thresholds (Siegel et al., 2002; Platt and Sathyendranath, 2008); percentile of annual or seasonal cumulative biomass (Greve et al., 2005); and peak rate of change, as in the previous paragraph (Rolinski et al., 2007; Koeller et al., 2009). Other authors have used conceptual-mathematical methods such as shifted-Gaussian fitting (Platt et al., 2009; Song et al., 2010; Zhai et al., 2011) or sinusoid fitting (Sapiano et al., 2012), but these may not be robust to cases where the true shape of the seasonal cycle differs from the expected. Many authors focus on the more-easily-quantified peak position, using methods such as maximum Chl (Chiba et al., 2008; Kahru et al., 2011) or central tendency (Edwards and Richardson, 2004). This paper overcomes the shortfalls of assuming the distribution of the data. We describe an extension of conceptual-mathematical methods, in which the shape of the curve used to fit the series is derived from the Chl data themselves.

All methods of deriving phenology from intermittent measurements have to handle or be robust to the issue of data gaps. Gaps in remote sensing time-series can be discrete, due to cloud cover and atmospheric aerosol, or continuous over a period of time due to low sun angle in winter at high-latitude. When these gaps cover key phenological features such as a bloom peak or initiation, large errors in phenology estimation can result. In subpolar regions, Cole et al. (2012) quantified the impact of gaps on phenology estimates, finding typical errors of 30 days for the bloom initiation date and 15 days for the peak date. Some methods reduce the frequency of gaps by working at a lower spatial or temporal resolution, e.g. using monthly data instead of daily or weekly, or using one degree binned data. Others attempt to interpolate across gaps, either spatially (e.g. Beaugrand et al., 2008; Pottier et al., 2008) or temporally (e.g. Racault et al., 2012). We use the climatology of the annual cycle as a basis for interpolation across gaps in the time series for particular years. Where gaps appear in the climatology of the annual cycle at a particular spatial resolution, we use the climatology at a lower spatial resolution as a basis for interpolation across gaps at the higher resolution. This makes the algorithm robust even at high spatial and temporal resolution with respect to gaps in the data such as those caused by cloud cover, which might otherwise cause problems. This scale-changing approach is similar to that of Pottier et al. (2008), who use wavelets to reconstruct complex spatial patterns in Chl data with gaps. Our method is simpler and in theory should be more robust to data outliers.

In this work we demonstrate the use of the scale-changing technique to investigate *Chl* phenology in the North Atlantic. We show that the resulting phenological indicators show strong spatial coherence and can be used to classify the study area into regions (provinces) characterised by different phenologies.

#### 2. Materials and methods

#### 2.1. Datasets

Our study area is a region of the North Atlantic from  $35^{\circ}$ N to  $58^{\circ}1'19''$ N,  $75^{\circ}$ W to  $11^{\circ}0'29''$ E (Fig. 1), including the highly dynamic subpolar front and regions of coastal shelf sea. We use 12 years of *Chl* derived from the NASA SeaWiFS sensor between 1998 and 2009 (Feldman and McClain, 2010). The northern limit was chosen to



**Fig. 1.** The study area (shown as a white box). Limits are  $35^{\circ}$ N to  $58^{\circ}$ 1'19"N,  $75^{\circ}$ W to  $11^{\circ}$ 0'29"E. Biogeographical provinces from Longhurst et al. (1995) are shown in black.

exclude regions where a winter gap occurs in the SeaWiFS data due to low light levels during the northern hemisphere winter months. All available level 2 scenes intersecting the area were downloaded from NASA, and the OC5 Chl algorithm (Gohin et al., 2002) modified to include low Chl waters (Tilstone et al., 2011) was applied to all pixels with valid remote sensing reflectance  $(R_{RS})$ . The modified OC5 algorithm converges with the standard OC4 algorithm at low *Chl.* but has been shown to be more robust in optically-complex coastal waters with high Chl (Gohin et al., 2002; Tilstone et al., 2011). Hence the algorithm is applicable to both the open ocean where OC4 is valid, and coastal waters where OC4 often gives erroneously high Chl values. The resulting Chl values were mapped to an equidistant cylindrical projection with 4 km equatorial spatial resolution. Eight day composites were then generated by calculating the interguartile mean Chl and the number of valid Chl estimates at each pixel for each 8-day period (henceforth referred to as the Chl count). The resulting set of 8 day composites (46 per year) were used to estimate phenological parameters as described below.

#### 2.2. Methods

#### 2.2.1. Algorithm overview

The first step in the method is a scale-changing technique to fill data gaps by successively reducing the spatial resolution until all gaps are filled at low spatial resolution. Next, starting at the lowest spatial resolution (the entire scene treated as a single pixel) and successively increasing the resolution, the climatological shape of the annual cycle is determined using data from all years at that location. The climatology is then adjusted for each year to fit that year's *Chl* cycle. Bloom initiation is determined using a relative threshold. The algorithm is robust with respect to gaps in the data such as those caused by cloud cover, which might otherwise compromise fitting of the seasonal cycle. It uses information from a range of spatial scales to interpolate over time, filling all gaps in the data to provide an estimate of how the time series would look in the absence of such gaps. Fig. 2 shows a flowchart of the algorithm.

#### 2.2.2. Reduction in effect of outliers

Phenological indicators tend to be highly sensitive to outliers in the data; therefore we have taken a number of steps to minimise their occurrence:

- (1) We mask pixels affected by coccoliths using a comprehensive coccolith detection algorithm (Shutler et al., 2010);
- (2) We composite using the interquartile mean rather than the mean; and
- (3) We use the OC5 *Chl* algorithm (Gohin et al., 2002) modified to include low *Chl* waters (Tilstone et al., 2011).

These measures significantly reduce the number of anomalous *Chl* values appearing in the time series. Coccoliths cause the water to become uniformly brighter, with the result that the band ratio

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