NEODAAS Ocean Indicator suite

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Context

Anthropogenic pressures on marine ecosystems have increased exponentially in the last century. Measuring and monitoring the resulting environmental change are challenging tasks. Remote sensing provides a tool for constant, consistent and coherent observation of the global oceans, with sensors and data streams being continuously developed for better resolution and accuracy.

To facilitate the exploitation of the wide range of remote sensing data available, the NERC Earth Observation Data Acquisition and Analysis Service (NEODAAS) has developed a suite of ocean indicators from key biogeochemical variables representative of the status of the marine ecosystem. These indicators can inform regional analysis, add context to short-term trends and specific events, and highlight potential correlations between biogeochemical and physical variables. While these products can be valuable to industry, governmental agencies, policymakers and the general public, our ocean indicators are targeted to researchers planning to incorporate remote sensing data in their studies to support models and/or *in situ* measurements, increasing the impact of their work.

The NEODAAS ocean indicator products can be derived from current and historical remote sensing records at temporal and spatial resolutions optimal for user requirements. Among others, we currently source data from the Copernicus Sentinel missions, the Copernicus Marine Environment Monitoring Service (CMEMS), and the ESA Climate Change Initiative (CCI). Our production systems are prepared to ingest any high-quality, climate-grade data stream. The ocean indicators suite is currently composed of:

- Time series

Time series can be assembled at different temporal and spatial resolutions that are suitable for different applications: while temporal aggregation increases the coverage, it has a smoothing effect which might lead to information loss on short-term and point events. Data can be extracted at specific locations or for extended regions. In this case, regional mean values are calculated by performing the average, weighted by pixel area if needed, over the region of interest. For variables that present a distinct seasonality, such as chlorophyll concentration, annual cycles can be extracted from the original signal. A deseasonalised time series can then be derived by subtracting the seasonal cycle from the original time series, and then fitted to a linear regression to obtain a linear trend.

- Anomalies

Anomalies are computed by subtracting a reference value from the observations. In the case of chlorophyll anomaly maps, this is done on a pixel-by-pixel basis and in $\log_{10}$ space, but a similar operation can be performed on time series and linear space. The reference value is typically extracted from a climatology: a temporal average over a certain period of time. Different temporal windows can be chosen depending on the application, for example, by computing an annual anomaly, we effectively remove the seasonal signal at each grid point, while retaining information on non-seasonal events during the year (Gregg and Rousseaux, 2014). Daily climatologies provide a measure of the typical annual cycle and can be used to derive daily anomaly time series that reveal changes in the timing and amplitude of seasonal peaks.

- Trends

The detection of long-term climate change trends and trend-change points relies on the existence of long, continuous records; these allow us to tease the footprint of climate change out from the seasonal and interannual components of the signal. It has been argued that the existing remote sensing records are already mature enough to detect the climate change signature in sea surface temperature, chlorophyll and primary productivity time series for some regions (Henson et al., 2016; et al., 2019). Our current trend detection method for chlorophyll concentration is based on the Census-I algorithm, where the time series is decomposed as a fixed seasonal cycle plus a linear trend component plus a residual component. Similarly, we have implemented a sea surface temperature trend detection algorithm based on ordinary least squares regressions corrected to account for serial autocorrelation, in accordance with IOCCP recommendations.

Applications

Phytoplankton phenology in the Western English Channel

Phytoplankton – and chlorophyll concentration as their proxy – respond rapidly to changes in their physical environment. In the North Atlantic, these changes present a distinct seasonality and are mostly determined by light and nutrient availability (González-Taboada et al., 2014). The following examples showcase chlorophyll concentration time series from late 1997 to the present for different locations within the Western English Channel. In particular, data was extracted from the OC-CCI v4 dataset for two Western English Channel Observatory stations, E1 (open-shelf) and L4 (coastal), located in the Plymouth Sound, and for a wider box located in the English Channel, as summarised in Figure 1.

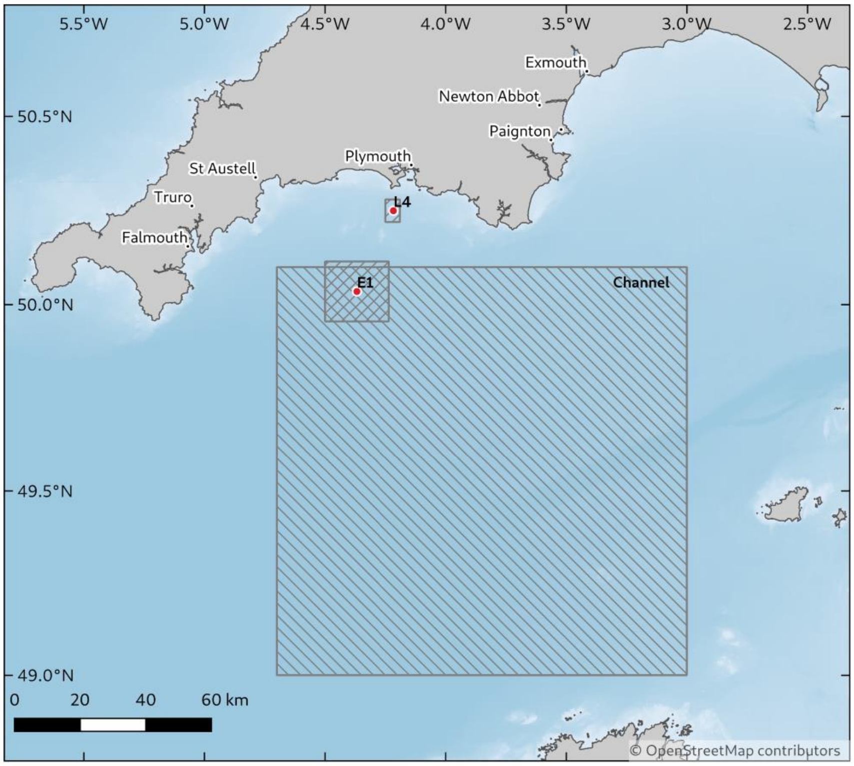

Figure 1: Geographical extent of the L4, E1 and Channel boxes.

The time series in Figure 2 provide a general view of the Western English Channel dynamics in the last 22 years. The cycle is dominated by the seasonal transition between mixing and stratification, with all three regions showcasing phytoplankton blooms in spring and autumn. The intensity of both blooms is broadly comparable at L4, while the autumn bloom tends to dominate at the open-shelf station E1. This can be connected to E1 developing the summer thermocline earlier than L4. L4 is influenced by river inputs, which can cause high nutrient events that compensate for the nutrient depletion after the spring bloom (Smyth et al., 2010). Both stations can be subject to strong mixing due to tidal currents and weather conditions. The second half of the 20th century has seen an overall 0.32°C/decade in sea surface temperature in the Western English Channel (L'Heveder et al., 2016), which can account for changes in the duration of the spring phytoplankton bloom.

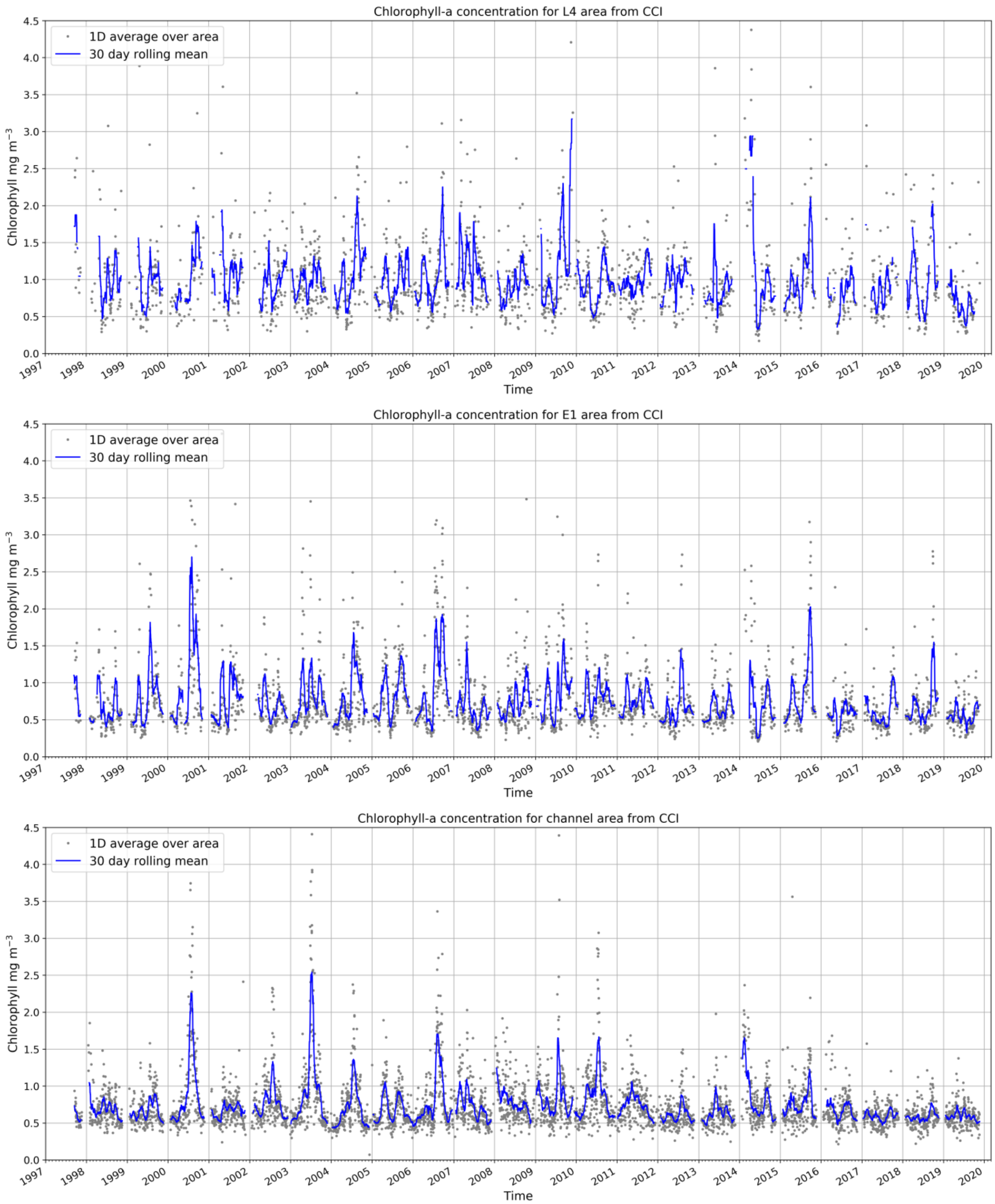

Figure 2: 1997-2020 chlorophyll-a time series of daily and 30-day rolling averages for the L4 (top), E1 (centre) and Channel (bottom) areas.

Chlorophyll correlation with climate indexes

Chlorophyll anomalies can be correlated to climate indexes in particular regions, such as the El Niño–Southern Oscillation (ENSO) index in the equatorial Pacific (Racault et al., 2012) and the Indian Ocean Dipole (IOD) index in the Indian Ocean (Brewin et al., 2012). The study of chlorophyll anomalies in consonance with sea surface temperature and sea level anomalies reveal decreases in SST decreases in SST and sea level anomalies are generally followed by an increase in mixing and vertical nutrient transport, resulting in positive chlorophyll anomalies.

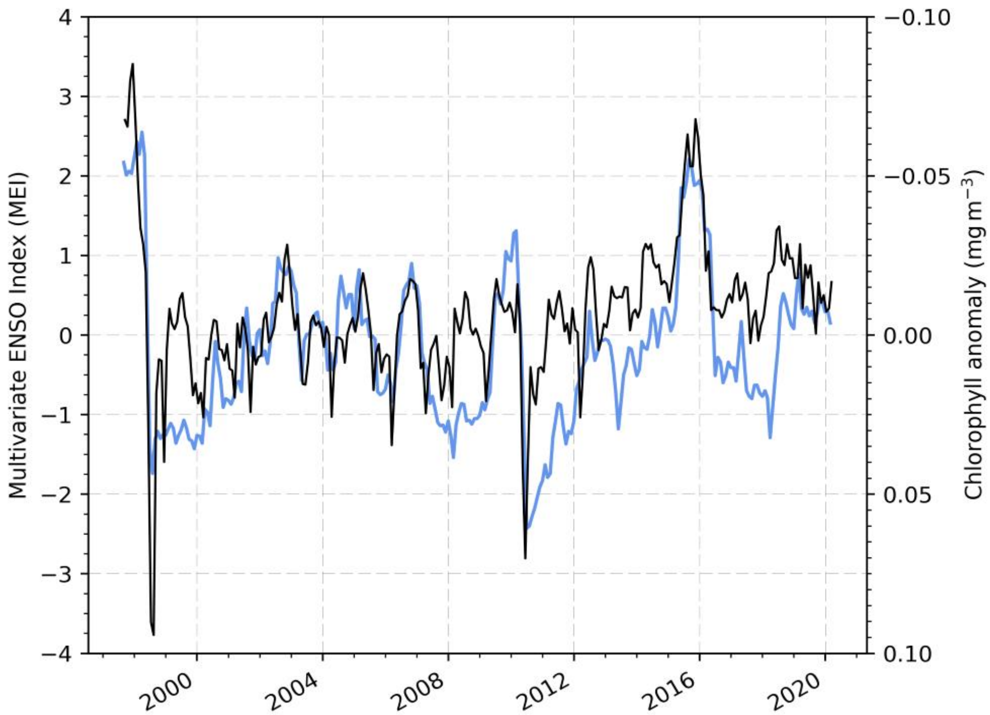

Figure 3: 1997-2020 time series of daily chlorophyll anomaly () and Multivariate ENSO Index (MEI, blue)

Figure 3 shows the 1997-2020 time series of monthly chlorophyll anomalies with respect to the 1997-201 climatology in the equatorial Pacific (ENSO 3.4 region), both computed using data from the OC-CCI v4 release. The monthly multivariate ENSO Index (MEI) was obtained from the NOAA PSL MEIv2 dataset (https://psl.noaa.gov/enso/mei).

Observations show that ocean chlorophyll is a precursor of sea surface temperature responses to ENSO in the equatorial Pacific. The correspondence between chlorophyll anomalies and the multivariate ENSO index is remarkable, with the strongest ENSO events of 1997 and 2016 inducing a considerable decrease in chlorophyll. Monitoring these chlorophyll interannual variability patterns associated with ENSO events can help us anticipate the effect that climate change will have in phytoplankton.

Arctic anomalies

Chlorophyll concentration is highly seasonal in the Arctic Ocean region due to a strong dependency on light and nutrient availability, which in turn are driven by seasonal sunlight and sea ice cover dynamics. The analysis of chlorophyll anomalies is critical in the context of Arctic amplification: negative anomalies are associated with a delay in ice breakup and, inversely, positive anomalies are detected in areas with early ice breakup event (Frey et al., 2017), although some studies have suggested increasing cloudiness over the region could dampen this effect (Bélanger et al., 2013).

Figure 4 shows the 2019 Arctic Sea annual chlorophyll anomaly with respect to the 1997-2019 climatology, both computed using the CMEMS 20-year reprocessed dataset based on the OC-CCI v4 release. Positive anomalies are shown in red, and negative anomalies are shown in blue.

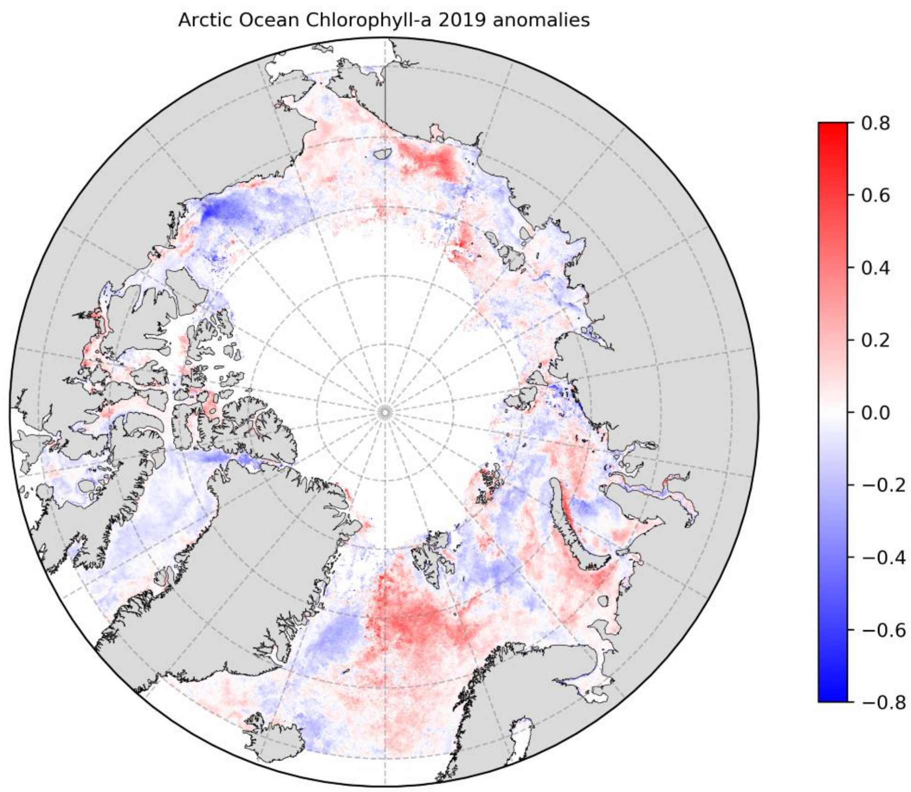

Figure 4: 2019 Arctic Ocean chlorophyll anomalies with respect to the 1997-2019 climatology. Positive anomalies are shown in red, and negative anomalies are shown in blue.

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