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Simple heterogeneity parametrization for sea surface temperature and chlorophyll

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ABSTRACT

Using satellite maps this paper offers a complex analysis of chlorophyll & SST heterogeneity in the shelf seas around the southwest of the UK. The heterogeneity scaling follows a simple power law and is consequently parametrized by two parameters. It is shown that in most cases these two parameters vary only relatively little with time. The paper offers a detailed comparison of field heterogeneity between different regions. How much heterogeneity is in each region preserved in the annual median data is also determined. The paper explicitly demonstrates how one can use these results to calculate representative measurement area for *in situ* networks.

1. Introduction

It is well known that oceanographic fields (such as sea surface temperature & chlorophyll) form spatially patchy structures. Understanding field patchiness is an important factor in understanding ecosystem dynamics, or stability (Martin, 2003). Various processes act to increase or decrease heterogeneity of oceanographic fields. The characteristic spatial scales at which these processes happen then determine the field patchiness. These are processes like wind-driven upwelling, mixing by currents, solar radiation, air–sea surface processes at the sea level such as evaporation, heat exchange, biological processes, etc. (Abraham, 1998; Currie and Roff, 2006; Gower et al., 1980; Mahadevan and Campbell, 2002; Mahadevan and Campbell, 2003; Mahadevan, 2004; Martin, 2003; Strass, 1992). It has been also established (Mahadevan and Campbell, 2002; Mahadevan and Campbell, 2003; Mahadevan, 2004) that spatial field patchiness can be understood in terms of characteristic response times to the processes altering the field.

The spatial/temporal heterogeneity can be described at some fixed scale, but also scale invariant formalisms can be employed. For instance, one can try to determine how a characteristic heterogeneity parameter (like variance) changes with the scale ℓ (Mahadevan and Campbell, 2002; Mahadevan and Campbell, 2003; Mahadevan, 2004), or quite often one can statistically describe the field scaling properties by a simple model, such as a multifractal (Lovejoy et al., 2001; Mandelbrot, 1982; de Montera et al., 2011; Nieves et al., 2007; Seuront et al., 1996a; Seuront et al., 1996b; Seuront and Lagadeuc, 1997; Seuront et al., 1999; Skakala and Smyth, 2015).

One of the very important practical questions in oceanography is to evaluate the suitability of *in situ* measurement networks. Complicated dynamical and statistical methods are often employed to achieve the task (Fu et al., 2011; Langland, 2005; McIntosh, 1987; She et al., 2007). These methods are typically dependent on large amount of data produced by numerical oceanographic models. One of the key problems is to determine suitable spacing between observational stations, or what is called "the representative measurement area". This is often achieved by statistical methods such as "effective coverage" (Fu et al., 2011). A simple method of parametrizing field heterogeneity through its scaling properties could under suitable circumstances provide an alternative simple and straightforward approach to answer this problem. This is because the representative scale of measurement can be defined as a scale at which the heterogeneity parameter, such as standard deviation, reaches its desired value.

2. Methods

2.1. Theory

It has been observed before (Mahadevan and Campbell, 2002; Mahadevan and Campbell, 2003; Mahadevan, 2004) that variance of many oceanographic tracer (ϕ) distributions scales as a power law:

$$\langle Var(\phi_\ell)\rangle = C' \cdot \ell^{H'}, \tag{1}$$

where $\langle Var(\phi_\ell)\rangle$ is a regional average of field variance within the boxes with area ℓ^2 and C', H' are two scaling parameters. Mahadevan and Campbell (2003) and Mahadevan (2004) considered the H' parameter to be the main indicator of patchiness. Since variance is by definition

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non-negative and (generically) it grows with scale, one has $C' > 0$ and $H' > 0$. The scaling relation (1) can often be seen as a consequence of a more specific multifractal scaling. Stochastic multifractal scaling results from a symmetry of scale-invariance, which is present whenever one can neglect dimensional constants used in phenomenological theories. It is perhaps not surprising that the symmetry can be frequently observed in the nature (Mandelbrot, 1982).

In this paper the data scaling will be fitted by a small modification of Eq. (1):

$$\sigma_\ell \equiv \frac{\langle \sigma(\phi_\ell) \rangle}{\langle \phi \rangle} = C \cdot \ell^H. \tag{2}$$

The power law (2) defines σ_ℓ as a regionally averaged standard deviation σ of normalized field ϕ within boxes with area ℓ^2. The field ϕ is normalized by its regional mean value $\langle \phi \rangle$ and scale ℓ is measured in kilometers. H, C are again two free parameters that are assumed to fit the scaling of ϕ. The C parameter determines the characteristic size of the fluctuations and the H parameter determines how much the fluctuations can be reduced by "zooming into" smaller spatial regions. Alternatively, H tells us what proportion of heterogeneity appears at which scale and the C parameter tells us about what is the overall size of the heterogeneity. The C, H fit of the scaling law is obtained from standard linear interpolation of the $Log(\sigma_\ell)$–$Log(\ell)$ plot. The accuracy of the fit can then be estimated through the parameter called standard coefficient of determination, R^2. The coefficient of determination can be defined as:

$$R^2 = 1 - \frac{\left\langle (f - v)^2 \right\rangle}{Var\ (v)}, \tag{3}$$

where f is the value of the fit and v is the value to be fitted. It is clear that the closer R^2 is to 1, means a better linear fit for the data.

To characterize the "overall" patchiness in the region it is suggested to use the (up-to-L) scale-averaged heterogeneity σ_ℓ:

$$\langle \sigma_\ell \rangle_\ell = \frac{\int_0^L C \ell^H d\ell}{L} = \frac{C \cdot L^H}{H + 1}. \tag{4}$$

Another important used quantity will be fluctuations (in %) of a value K:

$$\Delta K \equiv 100 \cdot \left\langle \left| 1 - \frac{K}{\langle K \rangle} \right| \right\rangle. \tag{5}$$

The ΔK parameter is used as a best estimate of both inter- and intra-annual variability in K; for example if law (2) is used with C, H estimated by their mean values, $\Delta C, \Delta H$ tell us what is the degree of time-representativity of the characteristic spatial fluctuation size C, as well as of the scaling profile exponent H.

2.2. Data and analysis

The key purpose of the present analysis is to determine whether spatial scaling of sea surface temperature (SST) and chlorophyll can be described by the power law (Eq. (2)). This means one analyzes scaling of statistically significant sample of single overpass imagery data. If the model defined by the power law fits the data well, the data heterogeneity is described by the C and H parameters. One can then ask if, and how, these two parameters change inter- and intra-seasonally.

The sea surface temperature (SST) and chlorophyll heterogeneity were analyzed in the shelf sea region near the south-west of UK. It is bounded by longitudes between −10 and −2; and latitudes between 48 and 53. The region is displayed in Fig. 1. The analysis was based only on satellite data: for SST the NOAA Advanced Very High Resolution Radiometer (AVHRR), for chlorophyll Sea-Viewing Wide-Field-of-View Sensor (SeaWiFS) and Moderate Resolution Imaging Spectroradiometer (MODIS) satellite measured data were used. The single overpass satellite data are represented by images such as Fig. 1. The data were obtained from NERC Earth Observation Data Acquisition and Analysis Service (NEODAAS). They were taken from the period between 1998 and 2009 and NEODAAS also provided annual medians for the same period.

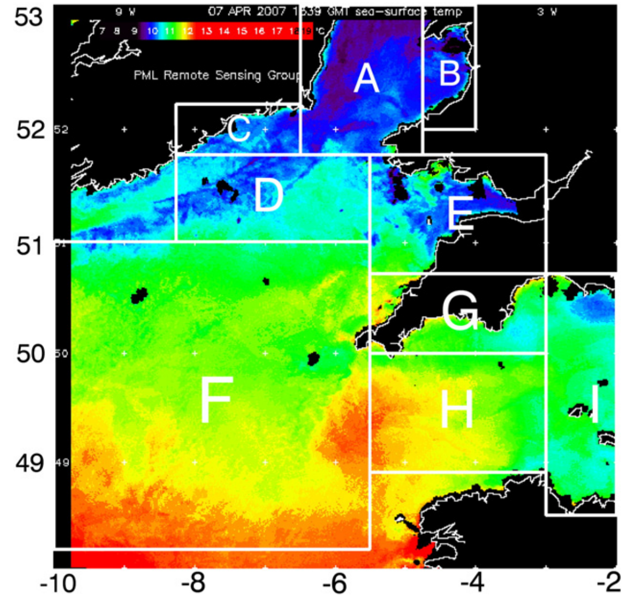

Fig. 1. The SST AVHRR satellite single overpass image from 7/4/2007. The regions analyzed are marked: (A) Irish Sea I, (B) Irish Sea II, (C) Irish Coast, (D) Celtic Sea I, (E) Bristol Channel, (F) Celtic Sea II, (G) Cornwall region, (H) English Channel II, (I) English Channel I.

To start the analysis, one needs to divide the region into suitable sub-regions with similar intra-regional heterogeneity patterns. This means that the inter-regional variation in heterogeneity is supposed to be significantly larger than intra-regional. The annual heterogeneity patterns were explored and 9 characteristic sub-regions were chosen as shown in Fig. 1. The regions displayed in Fig. 1 were named as (A) Irish Sea I, (B) Irish Sea II, (C) Irish Coast, (D) Celtic Sea I, (E) Bristol Channel region, (F) Celtic Sea II, (G) Cornwall region, (H) English Channel I and (I) English Channel II region. The Bristol Channel region was excluded from the chlorophyll data analysis as large concentrations of sediment in this region are known to invalidate the remote sensing chlorophyll algorithm (O'Reilly et al., 1998). For the purpose of the analysis two types of data-sets were considered: satellite single overpass imagery and annual median data.

2.2.1. Satellite single overpass imagery

Selecting satellite single overpass imagery is always a difficult task for this region due to the large amount of cloud cover in the images that leads to data sparsity. This is one of the reasons why one often resorts in obtaining data via numerical models. From the 1998–2009 period it was possible to collect approximately 120 sufficiently clear scenes for each, SST & chlorophyll. From these images most of the scenes were suitable for the analysis of only some specific selected regions. For each region the number of suitable images was between 40 and 110. The focus was also on seasonal heterogeneity patterns, since within the selected regions the seasonal harmonics were expected to dominate the inter-annual changes (Vantrepotte and Melin, 2009).