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Forecast verification of a 3D model of the Mediterranean Sea. The use of discrete wavelet transforms and EOFs in the skill assessment of spatial forecasts

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Abstract

The quality assessment of a nested model system of the Mediterranean Sea is realised. The model has two zooms in the Provençal Basin and in the Ligurian Sea, realised with a two-way nesting approach. The experiment lasts for nine weeks, and at each week sea surface temperature (SST) and sea level anomaly are assimilated. The quality assessment of the surface temperature is done in a spatio-temporal approach, to take into account the high complexity of the SST distribution. We focus on the multi-scale nature of oceanic processes using two powerful tools for spatio-temporal analysis, wavelets and Empirical Orthogonal Functions (EOFs). We apply two-dimensional wavelets to decompose the high-resolution model and observed SST into different spatial scales. The Ligurian Sea model results are compared to observations at each of those spatial scales, with special attention on how the assimilation affects the model behaviour. We also use EOFs to assess the similarities between the Mediterranean Sea model and the observed SST. The results show that the assimilation mainly affects the model large-scale features, whereas the small scales show little or no improvement and sometimes, even a decrease in their skill. The multiresolution analysis reveals the connection between large- and small-scale errors, and how the choice of the maximum correlation length of the assimilation scheme affects the distribution of the model error among the different spatial scales.

Keywords: Forecast verification; Spatio-temporal analysis; Wavelets; EOFs; Mediterranean Sea

1. Introduction

The quality assessment of a three-dimensional model forecast is a difficult task, particularly when studying its spatio-temporal characteristics. For this kind of study we can use *in situ* data, but their coverage is usually limited in space and/or time, making difficult the comparison with a three-dimensional model. Another possibility is the use of satellite observations, which have very good coverage in space and time but are limited to the ocean surface. The comparison of the model even to such incomplete fields can however add valuable information to the understanding of the model behaviour.

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The comparison between these complex fields, model and observations, is not straightforward because two fields describing the distribution of a variable can differ in many ways (*e.g.* an overall bias, missing processes, bad positioning of a given feature, etc.). The first step to assess the quality of a forecast is thus to establish which processes are being studied. The definition of the spatio-temporal scales related to these processes will then fix the model characteristics that we need to study.

Forecast verification depends thus on what we want to verify, and at which spatio-temporal scales. The verification process must be designed to find the answers to the questions that may arise when dealing with forecast results. In field forecast verification, these questions are related to the accuracy of the model with respect to observations, but also to the spatial distribution of the studied variable and the temporal evolution of this distribution. The study of the spatial distribution of a variable can help us to see if there are missing processes in the model (such as a recurrent gyre or a front) and to learn about the capacity of the model to represent the reality at different physical spatial scales.

The study of such complex error fields cannot be done with a unique error measure. To answer questions related to the spatial distribution of a variable, its spatial distribution averaged over time can be studied. However, in field forecast verification special attention must be paid to the fact that the number of grid points in a model and the spatial correlation between them makes very difficult to study the skill distribution in space (Livezey and Chen, 1983). It is very unlikely that two adjacent points in a model grid are completely independent, so the interpretation of a spatial skill (temporal averaged) becomes ambiguous (Wilks, 1995; Briggs and Levine, 1997; Jolliffe and Stephenson, 2003).

Time error evolution is thus preferred to avoid the correlation problem, as long as the time between analyses is longer than the temporal correlation scale. An average over all points in a grid at a given time is thus commonly used in the verification process. The temporal evolution of the error is very useful to obtain a general idea about the quality of the model. It is often the only way an error measure is applied. However, to answer some of the questions specified above, one needs to keep the spatial distribution of the studied variable. Spatio-temporal techniques can help us to study the evolution of a variable in time, keeping the spatial distribution information, and avoiding the ambiguity of correlation between adjacent points. Multi-scale techniques allow us to study the behaviour of a model at different spatial scales (Daubechies, 1992; Mallat, 1998), or even to focus on a specific scale of interest. Nested models, as the one we are working with, can also be considered as a multi-scale approach. Each nested level is a refinement of the parent model, so the verification at those two model grids can also give us an idea about the model behaviour at different spatial and/or temporal scales (Denis et al., 2003).

Wavelet Transforms are widely used in multi-scale decomposition studies (Daubechies, 1992; Torrence and Compo, 1998). They overcome the localisation problem of Fourier Transforms. By using a variable window size that is translated and dilated over the studied domain, wavelets allow us to separate a signal into orthogonal components related to the position and scale of the signal (Mallat, 1989, 1998).

Several studies have applied a multi-scale approach to analyse the spatial behaviour of a variable. Liang and Robinson (2005) established a multi-scale Energy and Vorticity Analysis (MS-EVA), that uses wavelets for the multi-scale decomposition. Liang and Robinson (2004) used MS-EVA to study the energy and vorticity balances at different spatial and temporal scales of the Iceland-Faroe Front and considered the transfer and distribution of energy and vorticity between the large-scale, mesoscale and sub-mesoscale. A similar approach was used by Fournier (2002, 2003) for atmospheric fields. Yano et al. (2001) made a three-dimensional study of a convective cloud system, characterising preferred spatial orientations of the system. Briggs and Levine (1997) and Casati et al. (2004) worked with 500-hPa geopotential height fields and rain fields respectively.

Two-dimensional wavelets have been recently applied in the frame of forecast verification (Briggs and Levine, 1997; Casati et al., 2004). In these papers the authors decomposed a model into several spatial scales using wavelets, and assessed the quality of the model at each of these scales. As these scales have a physical meaning, we can identify the error with a physical process characteristic of each scale (Briggs and Levine, 1997).

This last approach is exploited in this work. Wavelets are a perfect tool for spatio-temporal analyses of two-dimensional fields. The aim is to decompose the model forecast sea surface temperature (SST) and the observations into different resolution levels or scales. Then, the comparison between model and observations can be done at each of these scales. This allows us to identify the scales that are mainly contributing to the global error, and thus to have a closer look into the behaviour of these fields.

Empirical Orthogonal Functions (EOFs) are also used in this work. They can decompose a matrix into orthogonal modes representing the major patterns of variability found in the data. EOFs are very useful in the comparison between a model and observations in a