Preparing Levels 3 and 4 for the SMOS mission

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***Abstract**: The Soil Moisture and Ocean Salinity mission (SMOS) from the European Space Agency, scheduled for launch in November 2009, will initiate the era of satellite salinity observations. Because of the numerous geophysical contamination sources and the instrument complexity, the salinity products will have a low signal-to-noise ratio at Level 2. Averaging data in space and time is expected to allow a reduction of the observational error down to mission requirements (0.1 psu) at Level 3 (global maps with regular distribution). Geostatistical methods such as Optimal Interpolation are being implemented at Level 3 to operate this noise reduction. The methodologies require auxiliary information about a priori SSS statistics that, under Gaussian assumption, consist in the mean field and the covariance of the departures from it. The present study is a contribution to the definition of the best estimates for mean field and covariances to be used in the near-future SMOS Level 3 products. At Level 4, the spatial-temporal structure of the salinity errors is investigated in a numerical ocean model to prepare for the assimilation of this new stream of observations.*

Keywords: Sea Surface Salinity, SMOS, Optimal Interpolation, correlation scales.

I. INTRODUCTION

The European Space Agency has designed the Soil Moisture and Ocean Salinity (SMOS) mission [1] to overcome one of the main remaining deficiencies in ocean observation: salinity. The SMOS satellite is scheduled for launch in November 2009. It uses a L-band interferometric radiometer called Microwave Interferometric Radiometer by Aperture Synthesis (MIRAS) [2] to retrieve both soil moisture over land and salinity over the oceans. The radiometer measures brightness temperature, which is linked to salinity through the dielectric constant of seawater.

The sensitivity of brightness temperature to sea surface salinity (SSS) is relatively low. The range of sensitivities is on the order of 0.8 K to 0.2 K per psu, depending on the incidence angle of the radiometer, its polarization and the temperature of the ocean in the area [3]. Another critical factor is the roughness of the surface, which is controlled by wind/wave direction, foam, rain, and predominantly wind speed. The resulting effect is high measurement noise (i.e., low signal-to-noise ratio) for salinity at the SMOS pixel level (Level 2, 30x30 km^2). In order to satisfy the mission objectives, focusing on large-scale oceanography, data averaging will be conducted in space and time. The resulting global maps with regular distribution (Level 3) are expected to have accuracies of 0.2 (0.1) psu over 100x100 (200x200) km^2 in 10-30-day averages [4]. The selected method for data averaging is Optimal Interpolation. This method requires basic *a priori* information of the magnitude to be averaged: the mean field and the covariance of the departures from the mean.

Nowadays, operational model simulations of the ocean circulation assimilate satellite-measured sea surface temperature (SST) and elevation, as well as available in situ measurements, but salinity is left unconstrained or forced to be relaxed to climatological values (which can significantly differ from current values even on average, [5]). When SMOS products become available, data assimilation (DA) of SSS will be conducted using different methodologies but in general knowledge of the spatial and temporal structure of the errors associated with the SSS fields will be necessary.

Therefore, the goal of this study is two-fold: 1) to define the appropriate parameters needed for Optimal Interpolation, and 2) to analyze the structure of the salinity errors in preparation for data assimilation.

II. OPTIMAL INTERPOLATION REQUIREMENTS:

Statistical interpolation of oceanic data using the Optimal Interpolation (OI) method has been extensively described in the literature [6, 7]. The advantage of OI is its simplicity of implementation and its relatively small cost if the right assumptions can be made (e.g., the fields are Gaussian, no bias is present, random observational error). The basic idea behind the method is that the optimally interpolated field is equal to a background field plus an innovation weighted by optimal weights, which are determined so as to minimize the analysis error variance. One of the limitations of the method is that it requires auxiliary statistical information that sometimes can be difficult to obtain. Both the mean or background field and a covariance matrix of the departures from the mean are needed.

The input data to the OI algorithm are anomalies respect to a background field and both observations and background field should contain no bias for the algorithm to properly work. In the case of surface salinity, an appropriate background field needs to be chosen. One possible approach is to use climatological fields that were estimated as long-term means of the available in situ observations [8, 9]. The problem with choosing these long-term means is that bias may be introduced caused by temporal trends [5]. These trends can be significant [10, 11] and therefore a more recent averaged field may be more appropriate.

The SSS field chosen as background for the Optimal Interpolation method is an average of the recent observations (2001-2008) collected by the ARGO (Array for Real-time Geostrophic Oceanography) Program. The ARGO program has been conducting continuous sampling of the hydrographic structure of the ocean since 2001, providing temperature and salinity profiles (near-surface to 1000-2000 meters). Currently, there are over 3000 profilers deployed in the ocean, providing extended coverage of the different water masses in every basin. The procedure followed to create the background field is the successive correction methodology used by [11] to produce the World Ocean Database.

Another requirement of the OI method is an estimate of the covariance of the anomaly. Under the common assumption that the variance of the anomaly is spatially homogeneous, the covariance matrix is proportional to the correlation matrix. At the regional scale, some specific datasets have already allowed to derive information about spatial decorrelation scales for the near surface salinity field [12]. However, at the scale of the global ocean, the proper evaluation of the correlations from observations is still unattainable with the currently available spatial and temporal data distribution. At global scale, even the characterization of the mean field is a challenge. The correlation model is further simplified to be an elliptical Gaussian function reproducing some of the real inhomogeneities and anisotropies

$$r_{ij} = e^{-(Ax_{ij}^2 + By_{ij}^2 + Cx_{ij}y_{ij})}e^{-t/T}$$

where x_{ij}, y_{ij} are the components of the distance vector between the two points and A, B, C are the spatially varying parameters of the elliptical Gaussian model. The time dependence of the correlations is considered through the exponential decay function where T is the decay period.

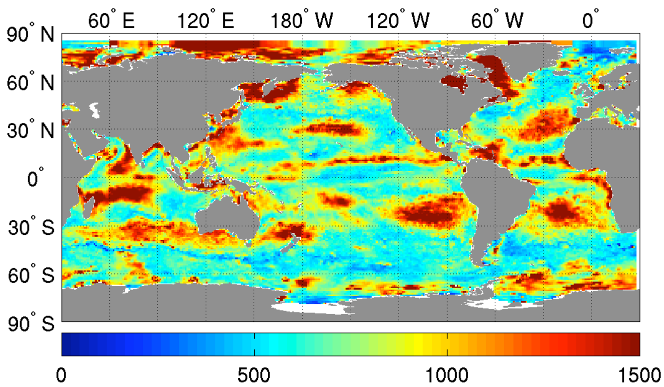

Fig. 1: major axis length of the elliptical Gaussian model adjusted to the spatial correlation function. The correlation function is derived from HYCOM model time series spatially averaged over 1/3-degree boxes and filtered at 10 days (Butterworth). The scales are given in km.

In order to obtain the parameters of the correlation model, the solutions from a global ocean model are used. The available archived hindcast (2003-2008) from HYCOM (HYbrid Coordinate Ocean Model, [13, 14] is used. The ocean model solutions have a horizontal resolution of 1/12-degree and, in order to produce correlation estimates at the appropriate resolution, they are averaged into 1/3-degree boxes. The major axis of the elliptical correlation from the ocean model solution is shown in Figure 1.

III. ERROR COVARIANCE FOR DATA ASSIMILATION

One of the proposed long-term goals for SMOS Level 4 product (combination of SMOS data and additional information) is the use of data assimilative techniques to imbed SSS observations into ocean circulation models. In order to achieve this goal, preliminary research is underway to properly tune the necessary tools with the currently available information. Knowledge of model SSS error covariances is needed to properly implement SSS data assimilation schemes.

An ensemble approach is used to generate the covariances due to external forcing uncertainties. The model is a regional 1/3-deg implementation of the NEMO-OPA9.0 model [15] over the eastern subtropical North-Atlantic Ocean. As a previous step, the investigation of model SSS sensitivity to various forcings and parameters showed that the wind stress was the most impacting parameter on the regional SSS [16]. Based on this finding, one hundred simulations are generated using perturbations of the wind stress forcing. The perturbations are generated by linearly combining randomly selected leading EOFs of the forcing fields. The initial conditions and other forcings are maintained unchanged for all experiments. Therefore, the obtained ensemble covariances represent model error covariances induced by wind stress forcing errors. The surface salinity ensemble spread, which is inhomogeneously distributed over the modeling domain due to the influence of local ocean dynamics, has an average value of 0.1 psu. The horizontal error correlation distances are globally larger than 100 km.

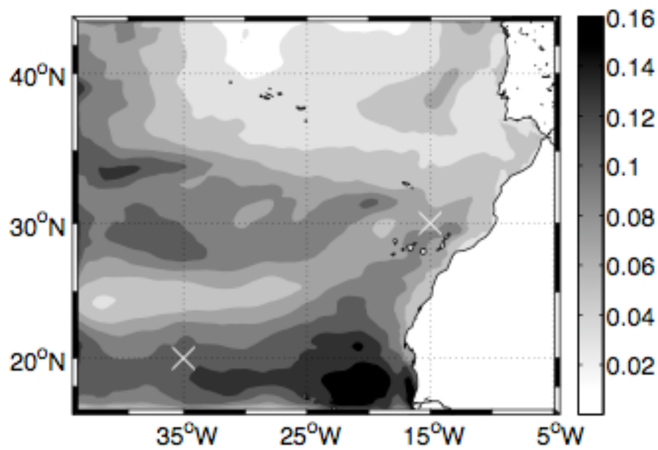

Fig. 2: SSS ensemble standard deviation (psu): average over the last year of the simulation.

They are anisotropic, with extended correlations in the direction of the main surface currents. Along the vertical, SSS model error at the surface is significantly correlated with the salinity error at 100-m depth in the main part of the domain, reflecting the significant error correlation between the surface and the upper thermocline. Deeper in the ocean, the correlation vanishes, except in subduction and upwelling areas, where significant correlations can be found deeper than 500 meters. These scales indicate the potential vertical penetration of the surface information provided by satellite observations into the ocean model. Further details about this study can be found in [17].

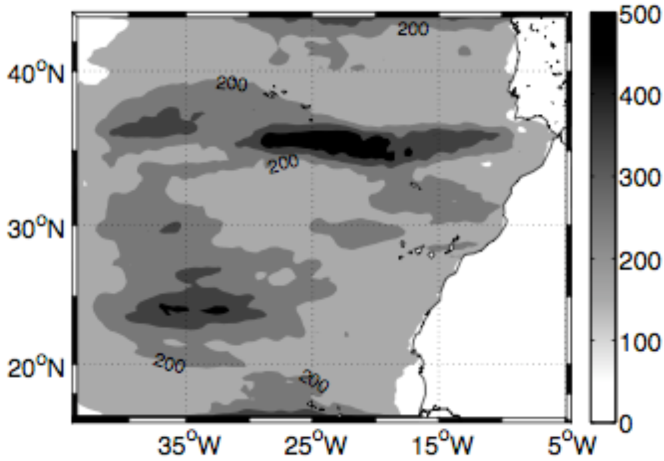

Fig. 3: zonal scale of SSS ensemble error correlation (km): average over the last year of the simulation. The e-folding criterion is used to determine the correlation scale.

IV. FUTURE DIRECTIONS

In a short to middle term, level 3 SMOS products will be derived for bias detection and for level 1 and 2 product validation purposes using simple averaging algorithms. In a longer term, once surface salinity data reach reasonable validation level, the several days to interanual scale SSS variability will be investigated, both from SMOS-only data and various instruments combination (lagrangian drifters, moorings, thermosalinographs onboard vessels, Aquarius/SAC-D mission). The Optimal Interpolation approach will be used to combine the various sources of information with adequate weights [18]. The SMOS time series might be used to provide an alternative to the model-derived covariance description. Improvement of various inferred fields (SSS, water fluxes, SST,…) at regional scale will combine data from different sensors using data fusion [19] and data assimilation [20] techniques.

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