Report for Short Term Scientific Mission: Improvement of the Sea Surface Salinity Data from SMOS in Mediterranean Sea

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INTRODUCTION

The sea surface salinity (SSS) is being measured globally by the Soil Moisture and Ocean Salinity (SMOS) satellite mission, allowing to obtain an unprecedented spatial and temporal coverage in the measurement of this variable. SSS is derived through the relation between brightness temperature (BT) and sea surface temperature (SST). This relation is more reliable for high values of BT and SST, so the precision of the salinity estimates decreases at high latitudes. Other sources of error for remotely-sensed SSS are sea roughness, astronomical radiation sources (e.g. galactic glint and cosmic background), atmosphere attenuation of the emitted signal, presence of heavy rain, and proximity to land and ice (Lagerloef et al., 2010; Boutin et al., 2012). In addition, illegal man-made radio emissions (radio-frequency interference, RFI) in the protected L-band frequency result in permanently or intermittently contaminated zones of the ocean, such as the European seas and Asia (Boutin et al., 2012). These sources of error result in noise and biases that need to be corrected, and gaps in the satellite SSS fields. The aim of this project is to work on the improvement of the SSS data from the ***SMOS*** in the Mediterranean Sea.

DATA AND METHOD

Satellite data

SMOS L2 from BEC

Three years (2011, 2012 and 2013) of the brightness temperatures measured by SMOS and provided by the European Space Agency (ESA) has been processed in order to generate the salinity maps. The brightness temperatures, that are given in antenna reference frame, are geolocalized in a Lambert Azimutal grid at 25km and they are downloaded to Bottom of Atmosphere reference frame.
To do that, the dielectric constant model proposed in Klein et al.,1977 is used and galactic (Tenerelli et al., 2008), sun glint (Reul et al.,2007) and roughness (Guimbard et al., 2012) contributions are corrected.
The resulting brightness temperatures have been processed following the methodology explained in Olmedo et al.,2016.

The idea of this method is the following: a single value of sea surface salinity is retrieved for each brightness temperature. Then, salinities greater than 0 but lower than 50 practical salinity unities are classified as function of the coordinates of the geographical position in the earth (latitude and longitude), the coordinates of the pixel in the antenna of the instrument and the orbit direction of the satellite when the measurement was taken (ascending or descending satellite pass).
After that, all the salinities (in 2011, 2012 and 2013) that belong to the same class, form a statistical distribution.
Filtering criteria are defined based on the number of salinities in each class, its standard deviation, kurtosi and skewness.
When a class is discarded, all the salinities of the class are also discarded. Otherwise, a representative value is defined (the mode).

SMOS SSS L3 maps from BEC

All the salinities of a given class are corrected with its corresponding representative value of salinity, before being used to generate the L3 maps. Thus, the systematic biases of the salinities are removed, producing relative values of salinities, not absolute ones. In order to obtain absolute values of salinities an annual climatological value (WOA13, 2013) is added.

SMOS SSS L3 maps at 0.25X0.25° resolution have been generated by means of a classical scheme of objective analysis applied over time periods of 9-days, with the three influence radii (321km, 267km and 175km) proposed in (WOA13, 2013).

SMOS L2

Level 2 Ocean Salinity User Data Product (UDP) version 5.50, provided by ESA, are used in this study. Daily data for 2012 and 2013 consisting of the ascending orbits have been selected, and the SSS data calculated using Roughness Model 1 (Yin et al., 2012) have been retained for this study. Data located farther than ± 300 km of the centre of the track are subject to higher errors (Zine et al., 2008; Yin et al., 2014), and are therefore typically removed (i.e. Boutin et al., 2014). In this work, however, we have retained the full swath in order to assess if these errors at the edges of the swath can be discarded through the DINEOF analysis.

Several quality flags, provided with the data, are used in order to remove data suspected of low quality. These are the flag for poor geophysical retrieval (which detects sun glint, galactic glint, wind speed and suspected ice), the flag for poor retrieval (bad convergence of the algorithm calculating SSS) and a quality flag specific for the roughness model used (Dg quality SSS1). A pixel with these three flags activated is removed from the dataset. Two additional steps are performed in order to remove data with low quality. The first one consists of a range check in which pixels with a value too high or too low with respect to a monthly climatology calculated using the data described in section 2.2. This test is performed on a pixel basis, and the difference threshold is set to 2. The final dataset has an average amount of missing data of 75.45%, and the average percentage of missing data in space and time is shown in figure 1. The highest amount of missing data (more than 90%) is found in the eastern part of the North Atlantic Ocean and the Mediterranean Sea. Part of the eastern Mediterranean Sea does not contain any data (white areas in figure 1), and therefore these zones are not used in the rest of this work. The percentage of missing data is the lowest in September, although there is no clear trend over time.

Thermosalinograph data

In order to validate the corrected SMOS SSS products with independent SSS data, high resolution near-surface (5 m depth of intake) global salinity data provided by thermosalinographs (TSG) mounted on merchant vessels are used. Stephane Marchand from the LOCEAN provided all the TSG data set and the matlab program to read and sort the all data set. The nominal horizontal resolution is around 2.5 km. For the purpose of the SMOS SSS validation, TSG data have been averaged over 1°. The data are systematically post-calibrated with collocated CTD, Argo data and water samples, when they are available, and provided with flags by the french Service d'Observation of SSS (*Alory et al.*, 2015, *in revision for Deep Sea Research*; http://www.legos.obs-mip.fr/observations/sss), thus, the error is on the order of 0.02-0.08 pss. Only data with "Adjusted" and "Good" or "Probably Good" flags data are used in this study. The 9 days (18 days) SMOS DEBIASed SSS and TSG SSS data have been colocated choosing TSG data located within a SMOS pixel at ±4 days (±9 days).

Method

DINEOF

DINEOF (Data Empirical Orthogonal Functions, Beckers and Rixen (2003); Alvera-Azcárate et al. (2005)) has been used in this study in order to calculate daily SSS fields with low noise and reduced error. DINEOF consists of an EOF-based reconstruction of the missing data in a geophysical dataset, extracting the main patterns of variability from the data. It uses a truncated EOF basis to infer the missing data, and therefore noise can be effectively reduced in the reconstructed dataset, as noise is typically found in the higher order EOFs. Some transient information, however, can be also removed from the final result as these might be also found in the higher order EOFs. In order to calculate the EOF basis from a dataset that has missing data, the following steps are performed: first the average value of the data is removed and the missing values are set to zero (i.e. the mean of the dataset). A first EOF decomposition using only the first EOF is performed, and this reduced EOF basis is used to infer an improved estimation of the missing data. Once convergence has been reached for the estimation of the missing data using the first EOF, the whole procedure is repeated using 2 EOFs. Then 3, 4... n EOFs are calculated. The total number of EOFs to be calculated, n, is deter- mined by cross-validation: a set of initially valid data (about 3% of the total data) is set aside at the beginning and treated as missing data. At each step, a cross-validation error is calculated. The number of EOFs that minimises this error is used as the optimal for the dataset reconstruction.

Method BEC data

Results: validation and comparison

Comparison of the two products

Before to work on the improvement of the two products, the idea is to understand which one is better and if we have used the two products to construct a better one of SSS in the Mediterranean. The time and space resolution of SMOS L2 ESA was changed to be compare with the SMOS L2 and L3 BEC data. The difference between the three products is ranged between -3.6 and 3 with higher difference along the coast (Figure 1). The mean bias is 0.15 with the L2 BEC and L3 BEC. The root mean square difference (RMSD) is 0.6 with the L2 BEC and 0.7 with the L3 BEC. The standard deviation difference (STDD) is around 0.5 for the L2 BEC and 0.6 for the L3 BEC. The correlation with the L2 BEC is 0.9 and 0.8 with the L3 BEC. The L2 BEC are clearly closer from the L2 ESA. The product use are not the final one.

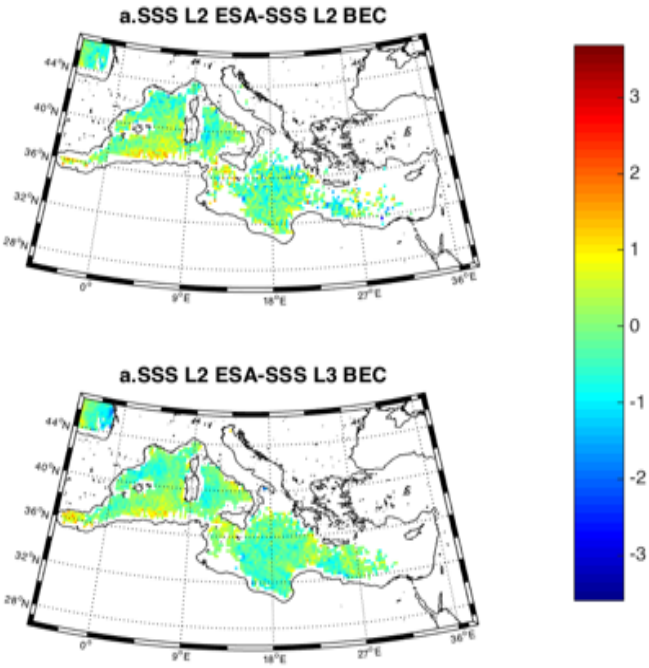

Figure 1: Bias between SMOS DINEOF and SMOS DEBIAS.

The two products are quite different, in particularly around the coast. In general, the SMOS DINEOF product are lower than the SMOS DEBIAS.

Comparison with in-situ data

The products SMOS L2, L3 BEC and SMOS L2 ESA, the gaps are filled by DINEOF and the three product are compared with the in situ data.

The three products are compared with the in situ data, in space and time (figure 2). The variability is higer with the reference product of ESA use in our lab (figure 2,a). The best results are observed with the L3 product (figure 2,c). The SMOS L2 from BEC are noisy and the comparison with the in-situ data show this variability. So it seems that the objective will be to improve the SMOS L2 BEC in order to improve the product.

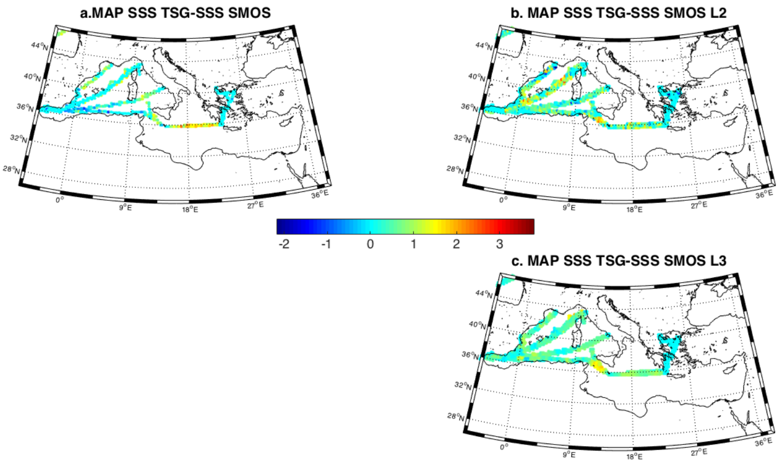

Figure 2 : Map with the difference between the SSS TSG and a. SMOS ESA, b. SMOS L2 BEC and c. SMOS L3 BEC.

The comparison with the SMOS L3 BEC an L2 BEC give a better comparison with bias of 0.4 compare to the SMOS L2 which give a bias of 0.6 with the in-situ data. The number of comparison for the SMOS L3 and L2 BEC is lower due to the space resolution which is lower than the SMOS L2. The root mean square difference (RMSE) is lower for the SMOS L3 BEC (0.63) and the standard deviation on the difference (STDD) (0.51) compare to the SMOS L2 BEC where RMSE is 0.7 and STDD is 0.6 and the SMOS L2 where RMSE is 0.8 and STDD is 0.6.

The comparison with the in situ is present in the figure 3, we observed that the figure 3 c show a better comparison between the in situ data and the SMOS L3 BEC. The longitude represents by the colorbar show a strong variability around 10° in the two BEC products, it is the region around Corsica so maybe is due to the presence of coast. The study in details of the value in SMOS L2 and L3 BEC product and the in situ data would be interesting in the future. The SMOS L2 ESA product are less good that the two other (figure 3,a).

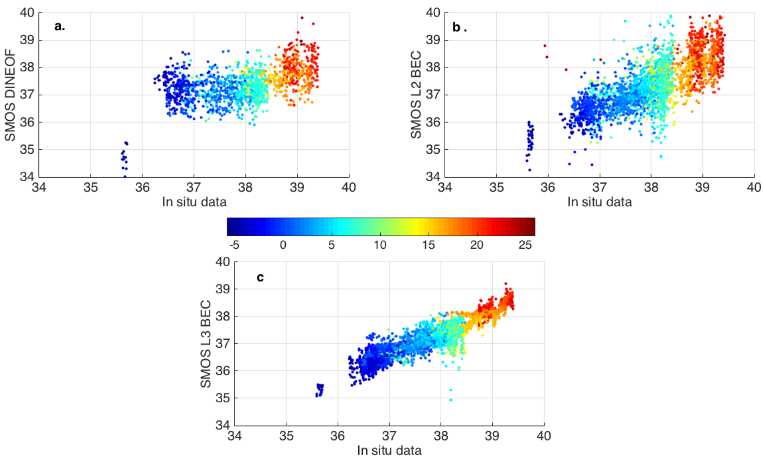

Figure 3 : Comparison in time and space in 2012 with a.) SMOS L2 ESA and thermosalinograph, b.) SMOS L2 BEC and data from thermosalinograph and c.) SMOS L3 BEC and data from thermosalinograph.

Conclusions and future work

The three products SMOS L2 BEC, L3 BEC and L2 ESA give quite good result for the first product in Mediterranean. Actually, the variability on the two L2 products seems lower than the L2 BEC products so we need to work on this part and try to correct the filter inside DINEOF to improve the results.

The method used in BEC give two products one L2 and L3 at lower space resolution than the SMOS L2 ESA, but this can be correct in the future verion. The first comparison is promising and the idea is to continue this work to used the correction of the L2 BEC and apply the DINEOF method in order to improve the SMOS product in the Mediterranean Sea . In the future, we will continue to work with the BEC and the SMOS L2 BEC product. The goal is to construct a method which used the two method to construct a daily SMOS product.

The improvement of the SMOS L2 data are really important to improve the assimilation of the data in the reanalysis data and the model simulation. Indeed, the data analysis is the process by which observations of the actual system are incorporated into the model state of a numerical model of that system. Actually the in situ data of SSS available for assimilation are not so large and in some area the quality are limited.

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