STUDYING DILUTION PROCESSES IN THE AMAZON PLUME USING SMOS AND MODIS DATA

Anton Korosov, Johnny Johannessen

Nansen Environmental and Remote Sensing Center, Thormohlensgate 47, Bergen 5096, Norway, anton.korosov@nersc.no

Nansen Environmental and Remote Sensing Center, Thormohlensgate 47, Bergen 5096, Norway, johnny.johannessen@nersc.no

1. ABSTRACT

A robust relationship between spectral normalized water leaving reflectance (Rrs) measured by MODIS and sea surface salinity (SSS) measured by SMOS in the Amazon river plume was established using neural network approach. The relationship is valid for range of SSS from 29 to 35 psu, for period of the highest rates of Amazon discharge into the ocean (July – October). Error of SSS retrieval from optical data comprises c.a. 1.5 psu. The neural network and linear correction was applied to MODIS L2 data from the period 2002 – 2012 and monthly fields of SSS for August, September and October were reconstructed at 10 km resolution.

2. INTRODUCTION

The objectives of our study were the following:

- To establish robust seasonal relationship between optical signal from MODIS and sea surface salinity (SSS) from SMOS
- To reconstruct spatial distributions of SSS in the Amazon plume from optical data for period 2002 – 2012
- To assess seasonal dynamics of DOC/SSS spatial distributions derived from MODIS data

3. DATA

SMOS L3 data was provided by Ifremer (Brest, France) as Matlab files with gridded global SSS fields at 1 day / 0.25 deg resolution for 2010, 2011, 2012 [1].

MODIS L2 data (version 6.5.8) for August, September and October of years from 2002 to 2012 was downloaded from NASA OBPG website [2].

Reanalyzed data from the TOPAZ hydro-dynamical modeling, assimilation and forecasting system comprised of daily fields of seas surface temperature, sea surface salinity and sea surface current at 12 km resolution for the Midatlantic area for summer months for the period 2002 – 2008 [3].

4. METHODOLOGY

4.1 Neural network approach

A neural network [4] capable of retrieving SSS from spectral values of Normalized water leaving reflectance (Rrs) has been trained on MODIS and SMOS data. It is, of course, not salinity which affects the optical signal detected by MODIS but colored fraction of dissolved organic carbon (DOC) which is contained in riverine waters. We assume that DOC is a conservative admixture in the process of mixing of fresh and colored riverine waters with saline and clean marine waters [5]. Hence the relation between salinity and DOC is linear. Since we don't have enough in situ measurements of DOC (or absorption of colored DOM, a_{CDOM}) we decided to train a neural network on SMOS data.

Normalized water leaving reflectance (Rrs) values at 7 wavelengths (412, 443, 488, 531, 555, 667 and 678 nm) were extracted from pixels of L2 MODIS data. Clouded pixels and pixels with L2 flags (4, 5, 6, 9, 10, 15, 20, 21, 23, 30) were omitted. Corresponding SSS values were taken from 5-day averaged SMOS data. Only pixels with SSS values between 27 and 37 psu were selected.

9 datasets consisting of Rrs and SSS values from three months (August, September and October) of three years (2010, 2011 and 2012) were built. Scatterplots of Rrs vs. SSS were plotted and 2 months with least scatter (08.2010 and 08.2012) and with similar Amazon discharge rates were selected for generating the training dataset. Datasets from August 2010 and 2012 were merged into one dataset consisting of c.a. 15000 pairs of Rrs and SSS and then randomly split in two datasets for training (10000 pairs) and for testing (5000 pairs).

A neural network with 7 input neurons (for 7 spectral values of Rrs), 15 neurons on the first hidden layer, 5 neurons on the second hidden layer and one output neuron (SSS) was built. The network was trained using SNNS v4.3 software in 750 epochs until the error of the test dataset stopped to decrease. Further training was stopped in order to prevent over-training.

4.2 Application of the neural network and comparison of SSS from SMOS and from MODIS

Coefficient of linear dependence of DOC on SSS (inclination of the line on a DOS vs. SSS plot) depends on concentrations of end-members: salinity in open ocean and concentration of DOC in riverine waters. Rates of Amazon river discharge into the ocean significantly vary in July, August, September and October, therefore linear dependence of DOC on SSS should be different. Therefore our relation between Rrs and SSS based solely on August data should be tested on data from other months (or other discharge rates).

Proc. 'ESA Living Planet Symposium 2013', Edinburgh, UK
9–13 September 2013 (ESA SP-722, December 2013)

The neural network was applied to MODIS data from three years (2010 – 2012) and four months (July – October) of the highest Amazon discharge. Pixels with SSS were extracted from MOIDS L2 images and from corresponding SMOS mapped 10-days averaged products and compared separately for each month. For comparison MODIS pixels were split into groups each corresponding to 1 psu intervals of SSS from SMOS. Values within each group were averaged and standard deviation assessed. Averaged values of SSS_{MODIS} were compared to centers of the intervals of SSS_{SMOS}

Averaged values of SSS derived from SMOS data vs. SSS derived from MODIS data were plotted and linear regression between these data was estimated. Correcting coefficients for fitting SSS_{MODIS} to SSS_{SMOS} were found.

4.3 Validation on in situ data

In situ measurements of SSS collected in the Amazon plume were extracted from the profiles (but not the gridded) CORIOLIS database from surface (depth = 0 m) measurements only for the period of MODIS observations (2002 – 2012) for summer/autumn months (July – October) [6]. In situ values were compared with values from one pixel exactly coinciding with the position of the measurement if satellite image was acquired +/- 4 hours relative to the observation.

5. RESULTS

5.1 Performance of the trained neural network on test dataset

A neural network was trained on training data and tested on a separate dataset. Comparison of the SSS_{SMOS} with SSS derived by neural network from optical data shows (Fig. 1) very good performance of the network with r^2=0.98 (n=3821) when applied to testing data from August 2010 and 2012.

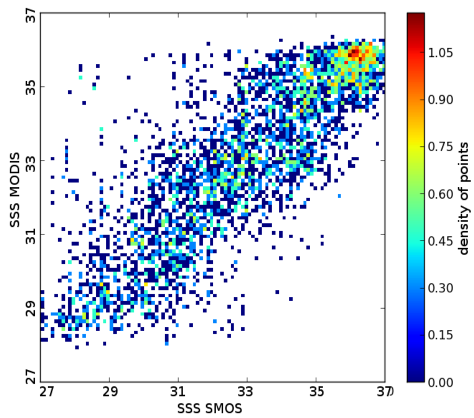

Figure 1. Comparison of SSS from SMOS and SSS reconstructed from testing dataset by the trained neural network. Color of the bins indicate number of points in log-scale.

5.2 Relation between SSS_{SMOS} and SSS_{MODIS}

The neural network was applied to MOIDS data from three years and four months and results were compared with SMOS data. Comparison shows that the most linear relation between SSS_{SMOS} and SSS_{MODIS} is observed in months August (Figs. 2, 3, 4). In July and September we can observe nonlinear dependence with logarithm-like (with bend of the curve being above the linear line) or exponent-like (with bend of the curve being above the linear line) shape. In October number of observations with low salinities is limited. Standard deviations of averaged SSS_{MODIS} are also least in August and comprise c.a. 1 psu while in other months data is noisier and errorbar height may reach 2 psu. Although the network was trained on August data the relation between SSS_{MODIS} and SSS_{SMOS} is not 1:1 but is slightly overestimated for low values (by c.a. 1.5 psu).

It takes about one months for Amazon river waters to travel from the point of discharge rates measurements (in Obidos) into the open ocean and about one more month to reach the outer edge of the plume. Measured maximum of discharge occurs in May – June therefore the August is the month when the plume is constantly filled with fresh water at the same rate. And the same rate of discharge assures that the concentration of DOC end-member in riverine waters is the same. That explains why we see accurate linear relation between SSS_{SMOS} and SSS_{MODIS} with the latter being a proxy for DOC signal.

Before the month of maximum discharge rate or after it the relation between SSS_{MODIS} and SSS_{SMOS} is not linear. Probably one of the reasons is that the discharge rate changes significantly (by 20% or 40%) and therefore the concentration of endmember DOC is also considerably different. Hence before the maximum discharge or after it the plume is filled with waters which initially (in the river bed) had significantly different amount of endmember DOC. It is difficult to find a robust non-linear fit for months before or after the maximum discharge due to several other problems:

- SMOS has lower sensitivity in low salinity range;
- MODIS data suffers from inaccurate atmospheric correction more in coastal waters than offshore;
- Interannual variations of maximum discharge rates are less than variations of lower discharge rates;
- Riverine waters with rather low salinity may reside in the plume for longer than two months and for the periods before or after max. discharge that cause a change of endmember DOC concentration by 50%.
- Surface salinity of ocean waters may be changed due to other factors than river inflow: advection, vertical mixing, evaporation, etc

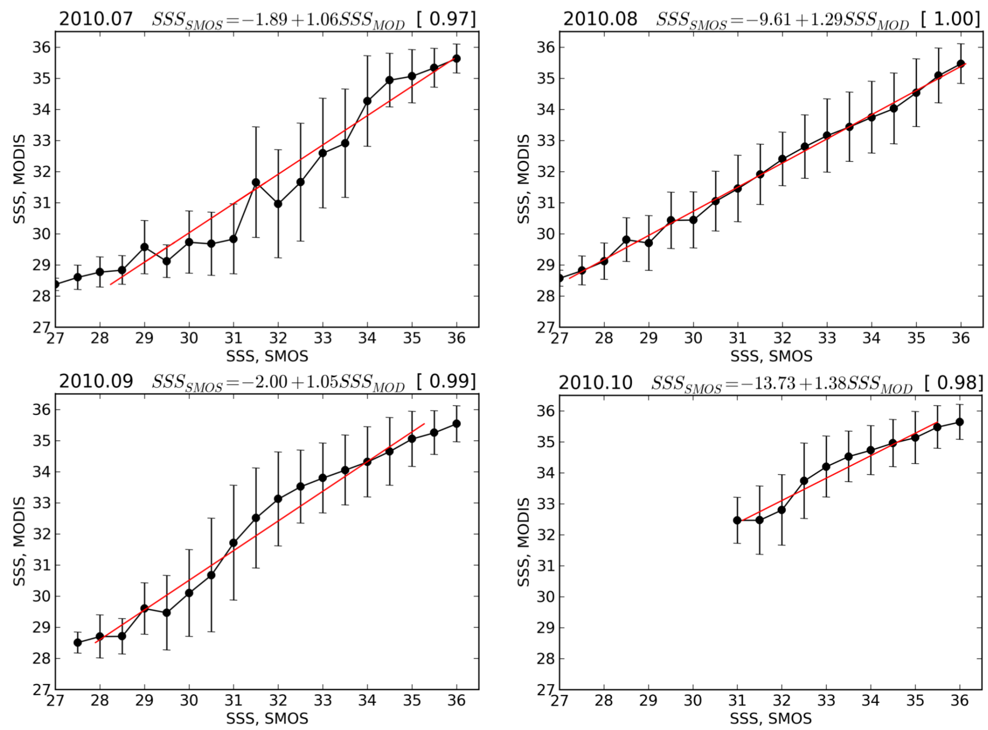

Figure 2. Comparison of SSS from SMOS and derived with the trained neural network from MODIS data taken in 2010. Red line shows linear approximation which equation is given in the title. Errorbars stand for standard deviation of averaging of MODIS data corresponding to SMOS data with 1 psu step. The equation above a figure shows the relation of SSS from SMOS and MODIS, the number in brackets – correlation of values.

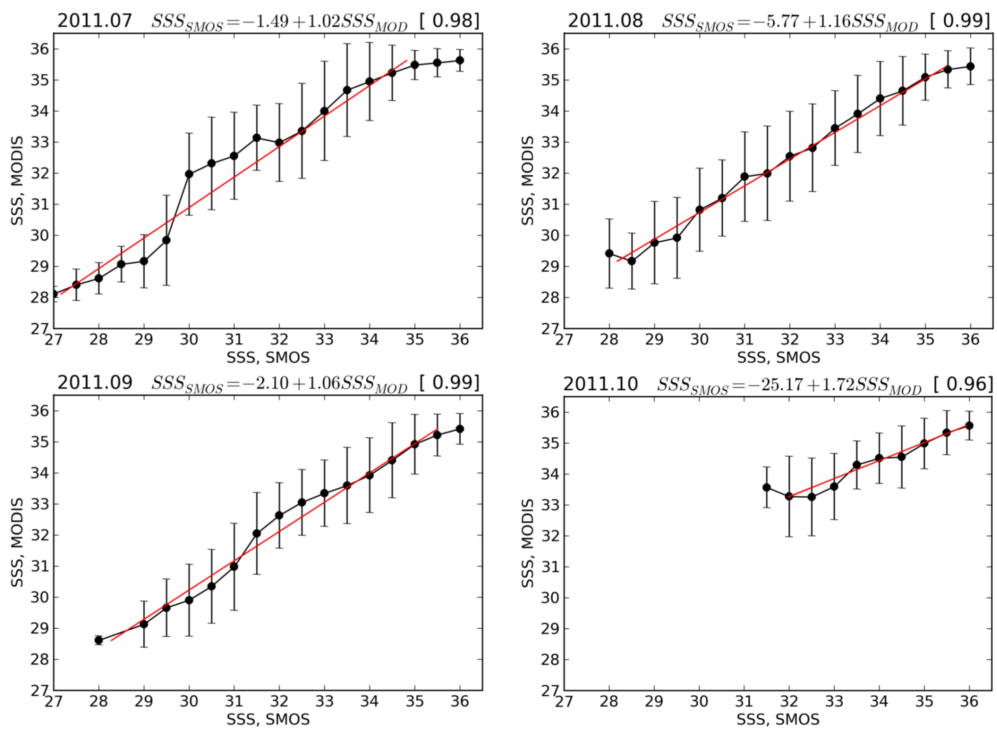

Figure 3. Comparison of SSS from SMOS and derived with the trained neural network from MODIS data taken in 2011. Other notations as in Fig. 2.

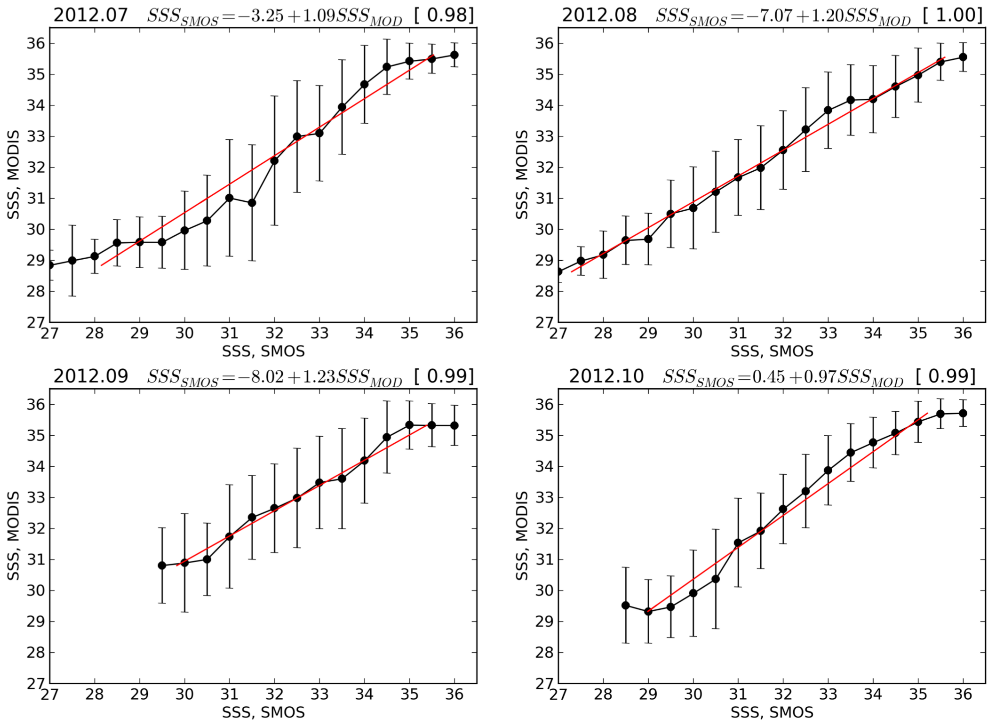

Figure 4. Comparison of SSS from SMOS and derived with the trained neural network from MODIS data taken in 2012. Red line and error bars as in Fig. 2.

We calculated the averaged over three years relation between SSS from MODIS and SMOS for August data:

$$SSS_{SMOS} = SSS_{MODIS} * 1.21 - 7.4 \quad (1)$$

With accuracy of ±1 psu within range 28 – 36 psu it can be applied to MODIS data taken after two months of measured maximum Amazon discharge. With accuracy of ±2.5 psu within range 29 – 35 psu it can be applied to MODIS data taken before or after the maximum.

5.3 Accuracy of SSS retrieval

Comparison of SSS fields derived from MODIS by the neural network with in situ measurements poerformed in the surface layer show high correlation (0.81) and low RMSE (0.79 PSU) between SSS_{MODIS} and SSS_{INSITU} (Fig. 5)

Comparison of MODIS and SMOS fields of SSS reveal high degree of coherence (Fig. 6) but with much higher spatial resolution of the MODIS data.

5.3 Seasonal dynamics of the Amazon plume as revealed from MODIS and TOPAZ data

Comparison of $MODIS_{SSS}$ field and daily averaged fields of sea surface currents simulated by the TOPAZ model revealed matching of these two datasets with unprecedented accuracy (Fig. 7). Contours of fresh water plume visible on SSS map from MODIS are followed by vectors of surface currents from TOPAZ. Series of overlaid images reveal impact of mesoscale eddies shedding from the North Brasillian Current and advecting the Amazon waters thousands kilometers offshore into the North Equatorial Counter Current. The hovmoller diagram (Fig. 8) built from data collected along the eddy propagation route shows that phase and speed of eddy propagation detected on MODIS data and on TOPAZ data coincide. Spatio-temporal matching of SMOS/MODIS and TOPAZ data allows to conclude that satellite data can be relatively easily assimilated into the model for increasing accuracy of SSS prediction.

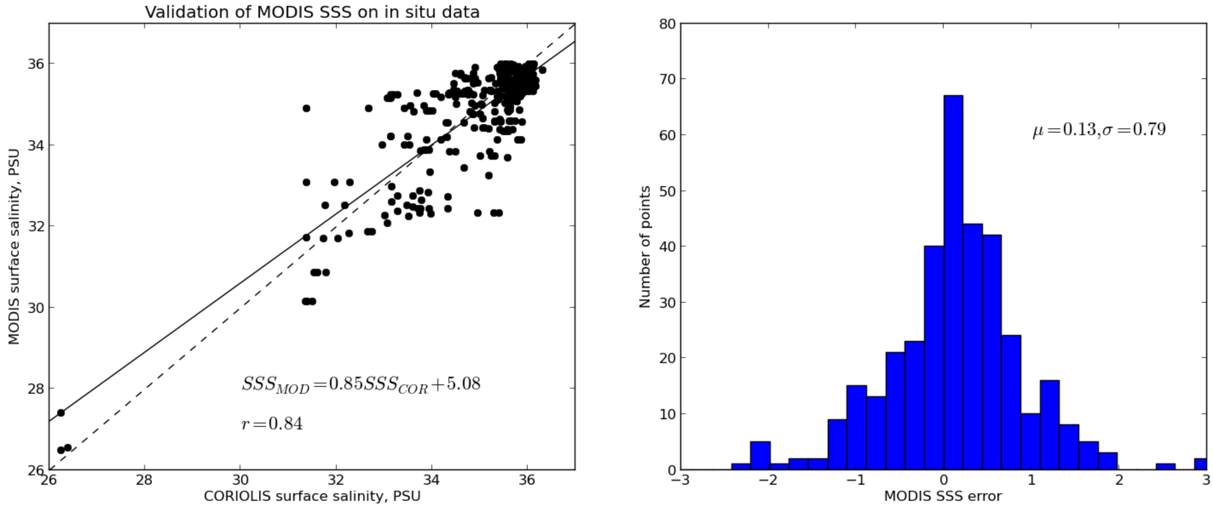

Figure 5. Validation of MODISSSS on independent in situ data. Correlation is 0.84, deviation – 0.79 psu.

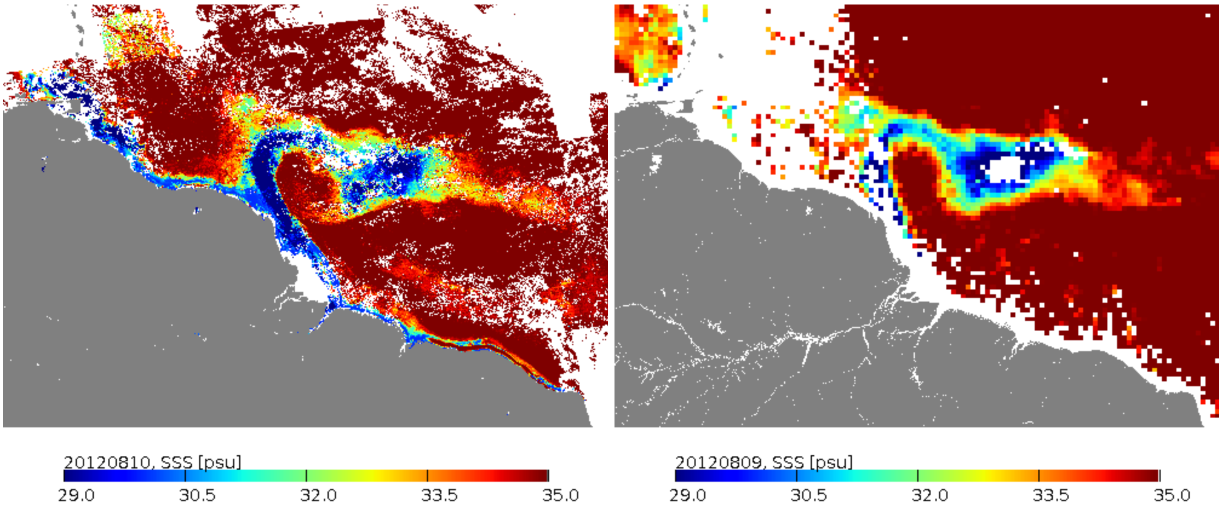

Figure 6. Comparison of SSS field derived from MODIS (left) and from SMOS (right) on 20 August 2012.

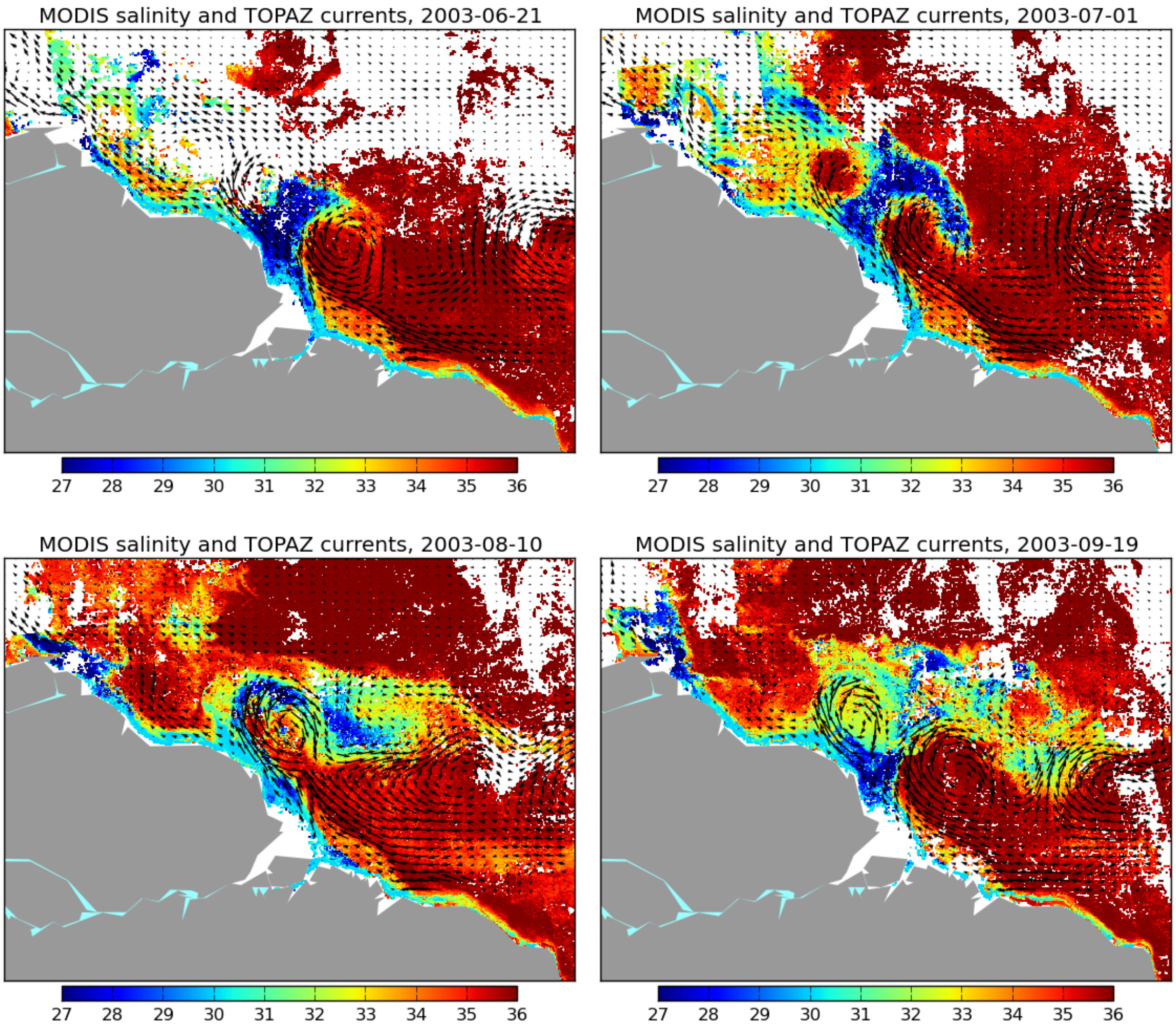

Figure 7. Weekly averages of $MODIS_{SSS}$ (color) and TOPAZ currents (vectors) for June, July, August and September.

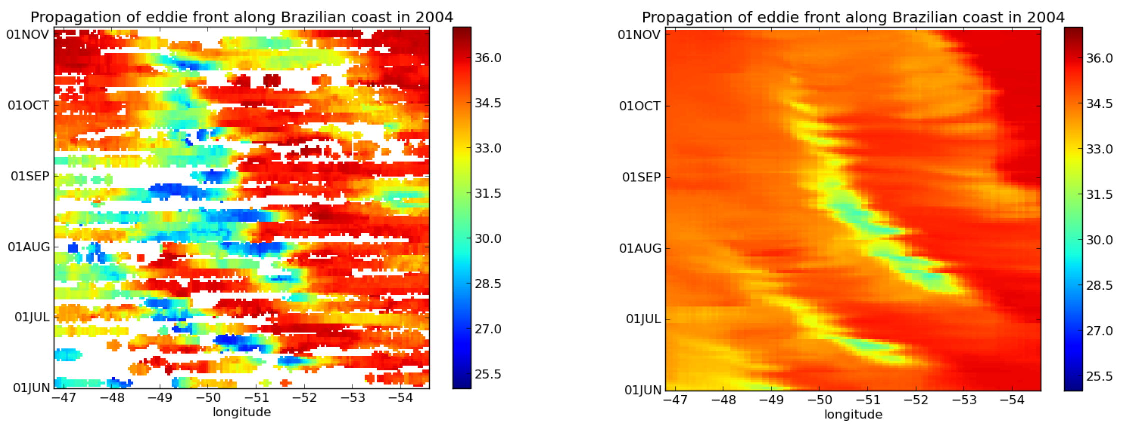

Figure 8. Hovmoller diagram built from data collected along track of westward propagating mesoscale eddies from MODIS SSS (left) and TOPAZ SSS (right).

6. ACKNOWLEDGEMENTS

Partly this work was supported by the PRODEX Project 90378 "SIOS – Study of the Impact of Ocean Salinity for ocean circulation", partly this work was performed under the STSM grant from the COST action 'SMOS-MODE' (ref. # COST-STSM-ECOST-STSM-ES1001-101212-024069). I greatly appreciate help and fruitful discussions with my colleagues in France: Severine Fournier and Nicolas Reul!

7. REFERENCES

1. http://cersat.ifremer.fr/
2. http://oceancolor.gsfc.nasa.gov/
3. Sakov, P., Counillon, F., Bertino, L., Lisæter, K. A., Oke, P. R., & Korablev, A. (2012). TOPAZ4: an ocean-sea ice data assimilation system for the North Atlantic and Arctic. *Ocean Sci.*, *8*(4), 633–656. doi:10.5194/os-8-633-2012
4. Haykin S., Neural Networks - A Comprehensive Foundation, Pearson Education, Singapore, 2005
5. Pozdnyakov D. V.,Korosov A.A., et. al, MODIS evidences the river run-off impact on the Kara Sea trophy, International Journal of Remote Sensing , Vol. 26, No. 17, 10 September 2005, 3641–3648
6. CORIOLIS DATABASE, INSITU_GLO_TS_REP_OBSERVATIONS_013_001_b, http://myocean.eu