Sea Level Anomaly and Dynamic Ocean Topography Analytical Covariance Functions in the Mediterranean Sea from Envisat data

GOCESeaComb

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Introduction

Fluctuations in the level of the sea pose an issue of emerging importance, since latest scientific research shows a clear trend in the rise of the sea level.

TG station data, the multitude of unprecedented in accuracy and resolution observations of satellite altimetry in combination with the realization of GRACE and GOCE missions offer new opportunities for the estimation of sea level and dynamic ocean topography trends.

During heterogeneous data combination, error propagation through analytical data variance-covariance matrices is of great importance since it can provide reliable estimates of the output signal grid error.

The optimal combination operator for such studies used in physical geodesy is Least Squares Collocation (LSC).

Given that no analytical models are available for sea level anomalies (SLA) their incorporation in LSC-based combination schemes is problematic.

Open Problems and Objectives

This work presents some news ideas and results on the determination of analytical covariance functions and subsequently full variance-covariance matrices for the SLAs in the Mediterranean Sea.

Along track records of the SLA have been used both to derive linear trends of the SLA variation in the area under study and come to some conclusions on the Mediterranean variability at short scales.

The developed covariance functions are used in order to investigate any possible correlations with climate change indices over the Mediterranean Sea.

The signal and error characteristics of the sea level anomalies have been used at monthly, seasonal and annual scales.

The estimation of the analytical covariance functions is performed using 2^{nd} and 3^{rd} order Markov models as well as a kernel similar to that of the disturbing potential a.k.a dependent on a series of Legendre polynomials.

The same analysis has been carried out for the RioMed (Rio et al. 2007) dynamic ocean topography (DOT) model available for the entire Mediterranean.

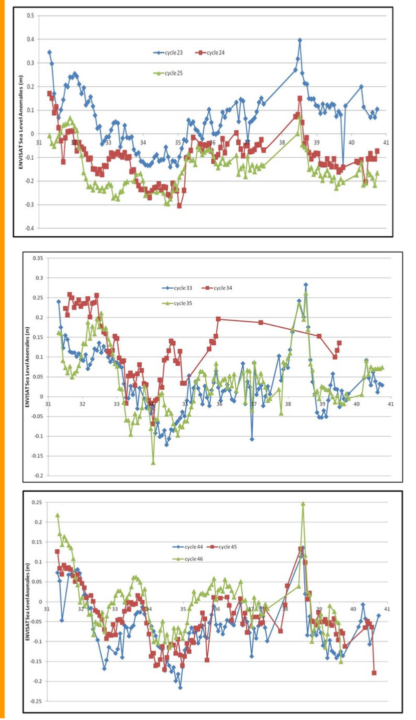
The goal is to come to some conclusions on the SLA and DOT spectral characteristics based on the empirically derived properties such as the variance and correlation length and determine analytical models to be used later for prediction with LSC.

SLA Variations in the Mediterranean Sea

The first part of this work refers to the identification of sea level variations within the ENVISAT satellite repeat period for time intervals as short as 35 days. The Table below summarizes the statistics of the annual ENVISAT SLAs phase B (cycles 6 to 94) after the application of all geophysical corrections except that of the global and local IB ones.

Statistics of annual ENVISAT SLAs (m)

YEAR	period	cycles	min	max	mean	std
2002	*14-5-02 to 13-1-03*	6-12	-0.552	1.044	0.073	±0.134
2003	*13-1-03 to 2-2-04*	13-23	-0.773	1.015	0.007	±0.140
2004	*2-2-04 to 17-1-05*	24-33	-0.802	1.061	0.025	±0.156
2005	*17-1-05 to 2-1-06*	34-43	-1.142	1.179	0.029	±0.153
2006	*2-1-06 to 22-1-07*	44-54	-1.391	0.893	0.036	±0.146
2007	*22-1-07 to 7-1-08*	55-64	-2.781	0.805	0.030	±0.128
2008	*7-1-08 to 24-1-09*	65-75	-0.727	0.798	0.026	±0.136
2009	*26-1-09 to 11-1-10*	76-85	-0.761	0.725	0.046	±0.136
2010	*11-1-10 to 22-10-10*	86-94	-0.523	0.897	0.056	±0.167



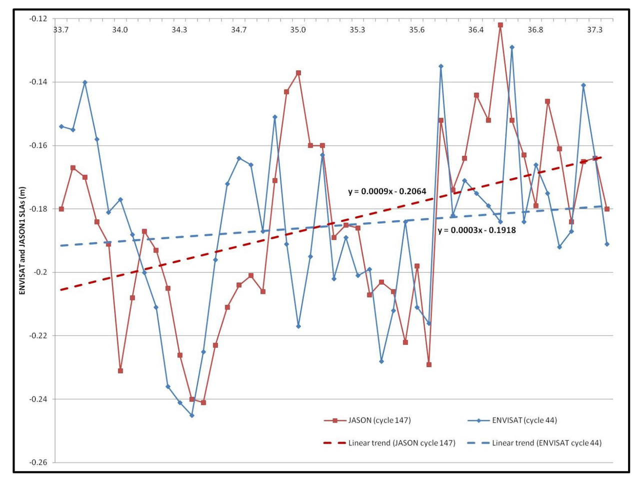


Figure 2(a) ENVISAT pass 399 SLAs for cycles 23, 24 and 25 (left top), cycles 33, 34 and 35 (left middle) and cycles 43, 45 and 46 (left bottom)

Figure 2(b) : SLAs from ENVISAT cycle 44 along pass 399 and JASON1 cycle 147 along pass 109 (right top).

Data used and corrections

The focus is based on single mission altimetry data from ENVISAT for the entire duration of the satellite mission (2002-2011), both in the along track direction (see Figure 1 top) and in 2D cases (see Figure 1 middle).

ENVISAT pass 444 was selected for the along track study while pass 399 was selected in order to derive linear trends of the SLA variation (Figure 1, bottom).

Pass 444 consists of ~120-130 observations for each cycle and the study covers the period between 2002-2010. For pass 399 three consecutive cycles, comprising more than three months (105 days) of data, are studied.

For the 2D case the entire Mediterranean basin was selected (30° ≤ φ ≤ 50° and -10° ≤ λ ≤ 40°) for the same period as pass 444. The total record consists of ~690k observations.

The data have been downloaded from the RADS server (DEOS Radar Altimetry Data System) in the form of SLAs relative to EGM2008, after applying all the necessary geophysical and instrumental corrections.

IB corrections have not been applied as they have little effect to the "global" SLA statistics

The last step in the analysis of the SLAs is to investigate for any possible correlations with global and regional climatic phenomena that influence the ocean state as well.

Three such indexes have been investigated, namely SOI (Southern Oscillation Index), NAO (North Atlantic Oscillation Index) and MOI (Mediterranean Oscillation Index) in order to investigate the correlation between SLA variations and climate indexes at the global (SOI), regional (NAO) and basin (MOI) scales.

Primarily, variations in the climate as depicted by oscillation indexes should also have a "signature" on the state of oceans, therefore triggering variability in the level of the sea.

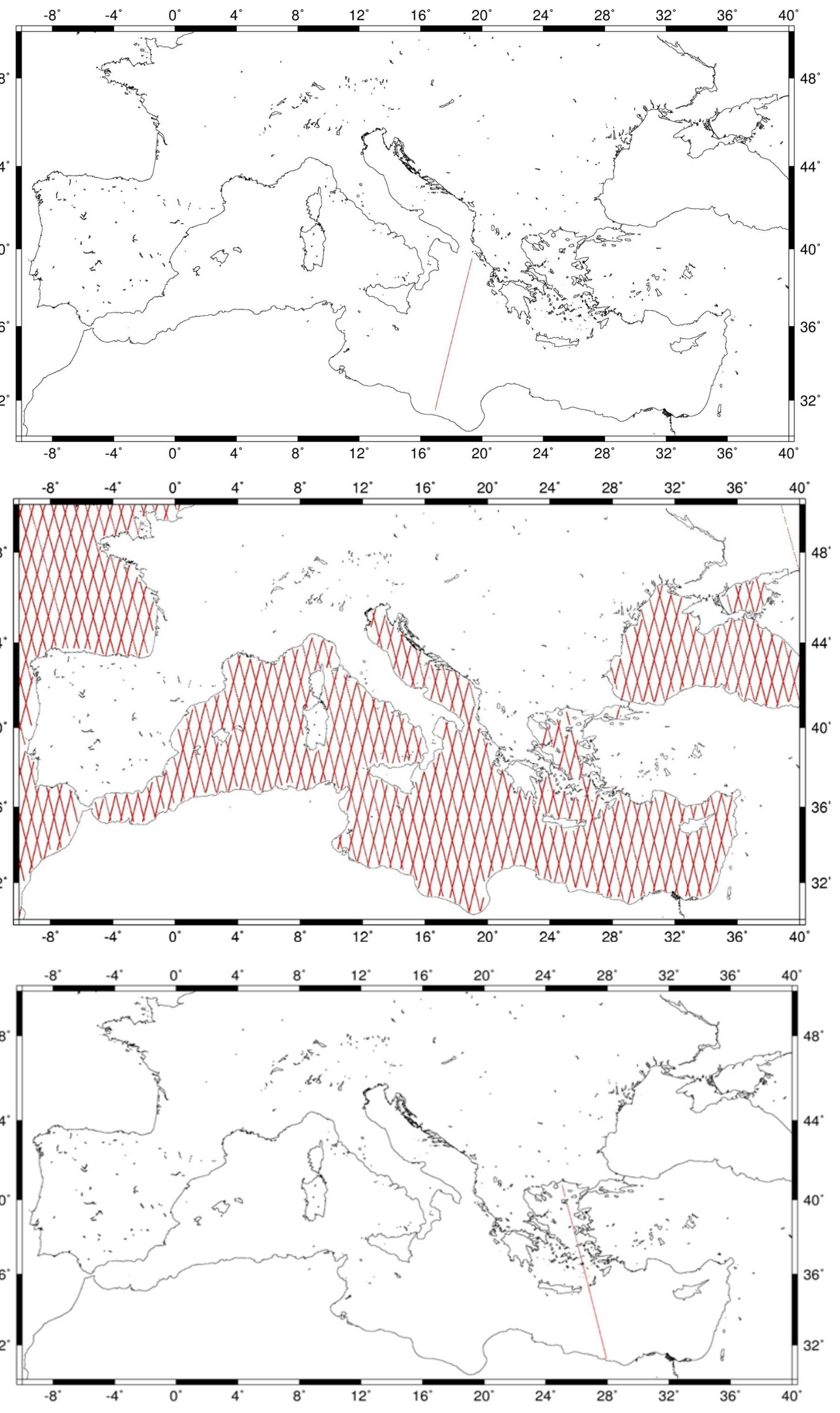


Figure 1: ENVISAT pass 444 used for the along track (1D) SLA covariance function study (top), distribution of ENVISAT passes in the Mediterranean Sea (2D case) and pass 399 used for studying linear trends.

Mathematical models and Covariance estimation

First, the empirical covariance functions have been determined for the period under study. For the 1D case along track 444, the empirical covariance function has been estimated and the variance *Co* and correlation length ξ for each 35 period day pass was determined. The aim is to investigate whether a cyclo-stationarity exists in the SLA data along the same pass for the period 2002-2010.

Then, various analytical covariance function models have been investigated in order to determine the one that provides the overall best fit to the empirical model, as well as the optimal results in terms of prediction accuracy. To this extend, various order exponential models have been studied, along with second and third order Gauss- Markov ones. Apart from planar models, a spherical one based on Legendre polynomial expansion, simulating the Tscherning & Rapp model, used to model the analytical covariance function of the disturbing potential, was used.

Empirical Covariance Functions

For pass 444, empirical covariance functions have been estimated for each satellite cycle between 2002-2010. Given the 35 day period each year consists of 10-11 cycles. An example of the estimated empirical covariance functions is shown below for 2007 and 2009.

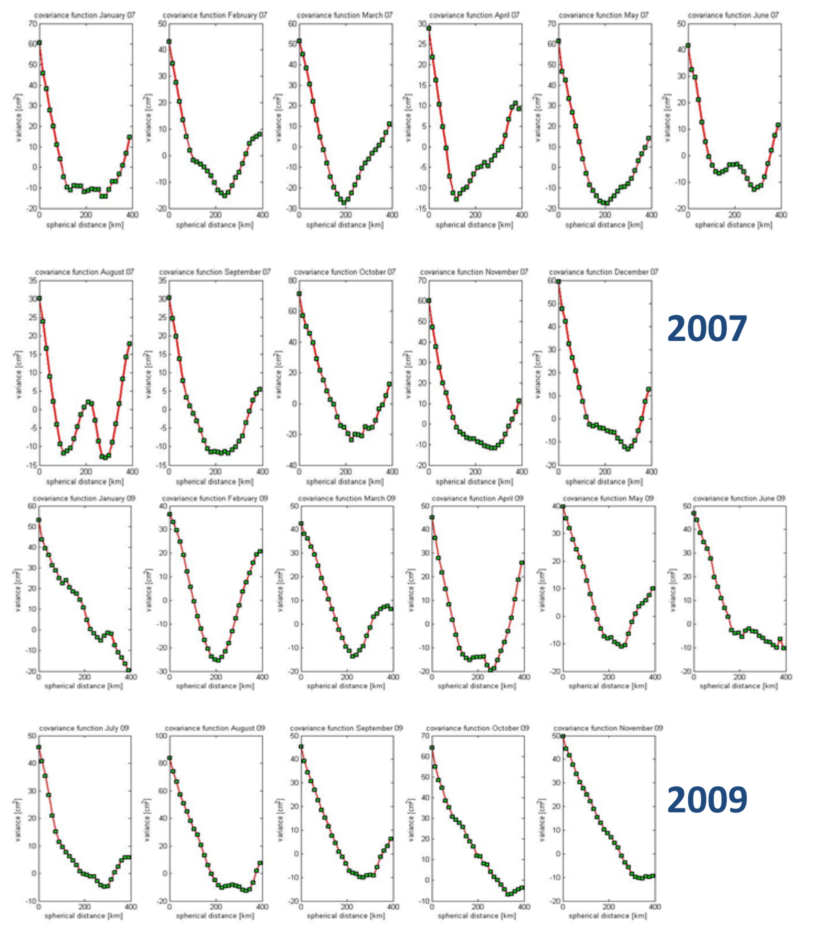


Figure 3: ENVISAT pass 444 empirical covariance functions through 2007 and 2009

It is interesting to notice how the SLA variance varies through the epochs of each year, with high values in January, lower values in Spring due to reduced rainfall, increasing values as summer progress due to snow melt and the thermal expansion in July-August. Finally, the variance values decrease again in Fall and start increasing in November due to higher level of precipitation.

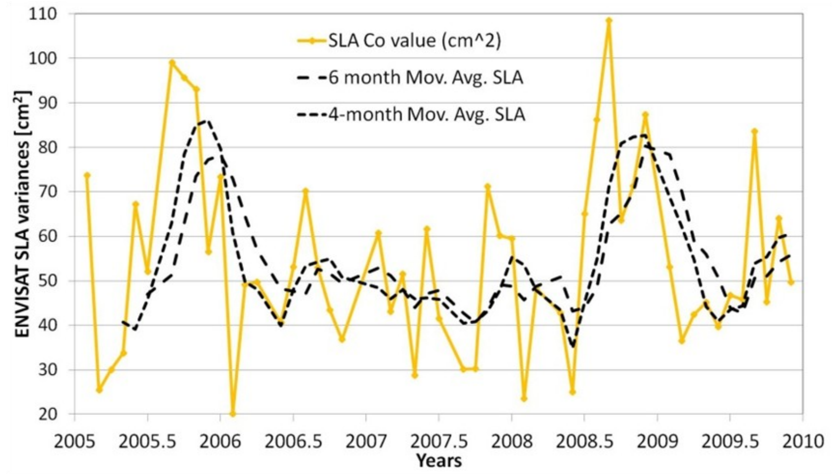


Figure 4: ENVISAT pass 444 variance variability for the period under study

A mean separation of the order of ~10 cm between the repeated ENVISAT cycles 23-24-25 is evidenced. For the cycles 33-34-35 it is interesting to notice that cycle 34 misses a significant number of records compared to the other. For the cycles 44, 45 and 46 covering the first three months of 2006, an interesting agreement is found between the consecutive records of the satellite .

Exponential Models

$$C(\psi)=\alpha e^{b\psi} \qquad \textbf{Model A}$$

$$C(\psi)=\alpha e^{b\psi}+ce^{d\psi} \qquad \textbf{Model B}$$

$$C(\psi)=\alpha e^{-\left(\frac{\psi-b}{c}\right)^2} \qquad \textbf{Model C}$$

$$C(\psi)=\alpha e^{-b\psi^2} \qquad \textbf{Model D}$$

$$C(\psi)=\alpha e^{-b\psi}\cos(\omega\psi) \qquad \textbf{Model E}$$

$$C(\psi)=\alpha(1+b\psi)e^{-b\psi} \qquad \textbf{Model F}$$

Gauss-Markov Models

$$C(r)=\sigma(\bullet)^2\left(1+\frac{r}{D}\right)e^{\left(\frac{-r}{D}\right)} \qquad \textbf{Model G}$$

$$C(r)=\sigma(\bullet)^2\left(1+\frac{r}{D}+\frac{r^2}{3D^2}\right)e^{\left(\frac{-r}{D}\right)} \qquad \textbf{Model H}$$

Spherical model based on Legendre polynomial expansion

$$C_{(\bullet,\bullet)}(\psi)=\sum_{n=0}^{\infty}\sigma(\bullet)_n^2 P_n(\cos\psi) \qquad \sigma(\bullet)_n^2=b\left(\frac{k_2^3}{k_2^3+n_3}+\frac{k_1^3}{k_1^3+n^3}\right)s^{n+1} \qquad \textbf{Model I}$$

In the above models, ***ψ*** denotes the spherical distance, ***ξ*** the correlation length, ***D*** the characteristic distance, ***r*** the planar distance and ***σ(•)²*** the variance of quantity ***(•)*** under investigation (SLA or DOT). The rest are parameters to be determined, so that the analytical model will fit the empirical one. It is noticed, that for all models a mixed equations adjustment scheme was used in order to determine the necessary parameters for each model, based on the empirical values.

Analytical Covariance function models for pass 444

An example of the analysis carried out is given in the sequel for pass 444 in August 2005. Figure 5 depicts the SLA as derived from pass 444, where a variation between -30 cm and +30 cm can be seen. For that pass, analytical covariance functions from all aforementioned models were derived and predictions using LSC have been carried out. Three tests have been performed. One, by omitting the first 20 points in the track and using the rest to estimate the SLA in these locations (TEST A in the sequel). The second, by omitting the last 20 points and using the rest to estimate the SLA in these locations (TEST B in the sequel). The third, by omitting every second point and using the rest to estimate the SLA in these locations (TEST C in the sequel).

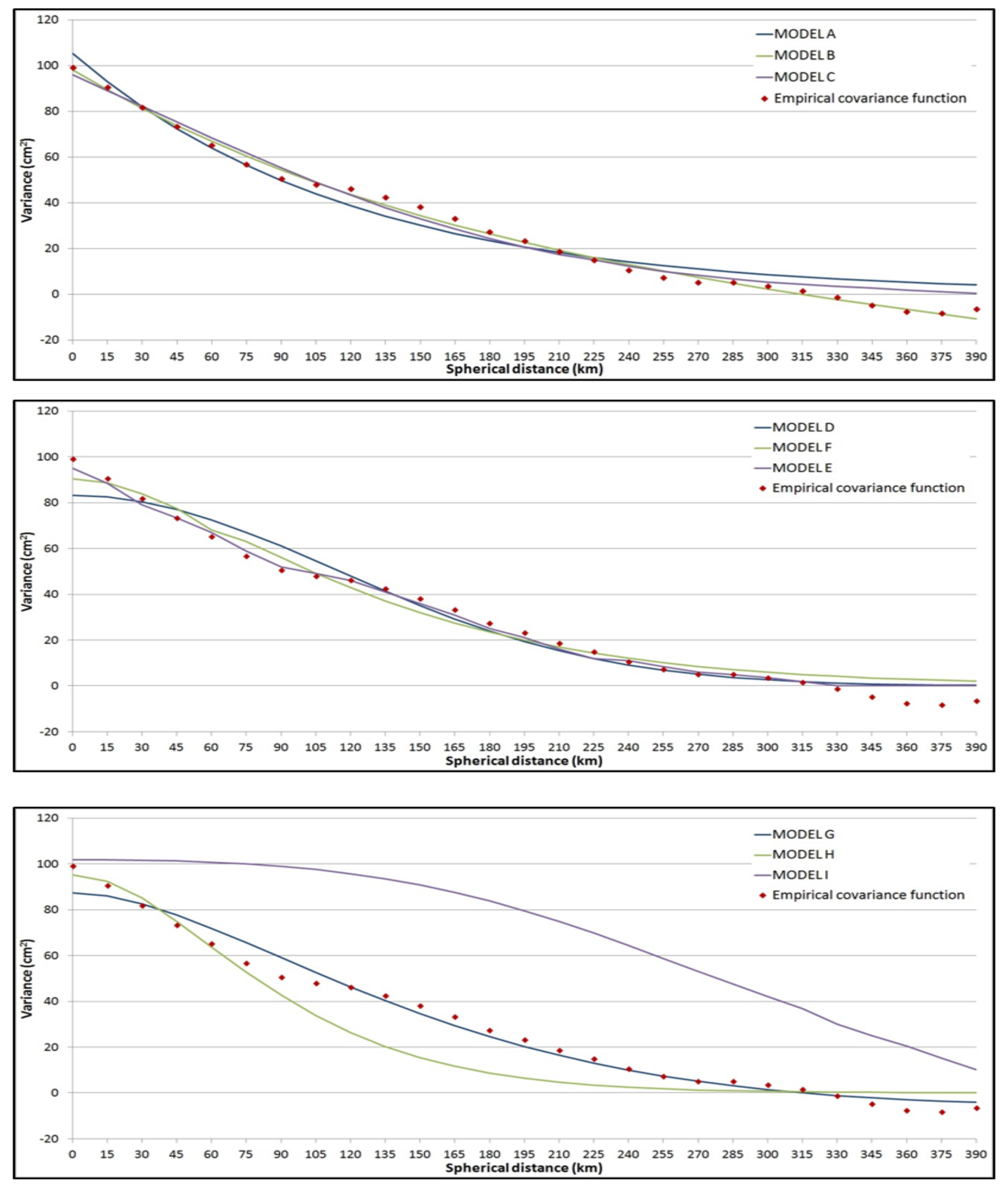


Figure 5: ENVISAT SLA along pass 444 analytical model covariance functions (model A, B, C top, model D, F, E middle, model G, H,I bottom).

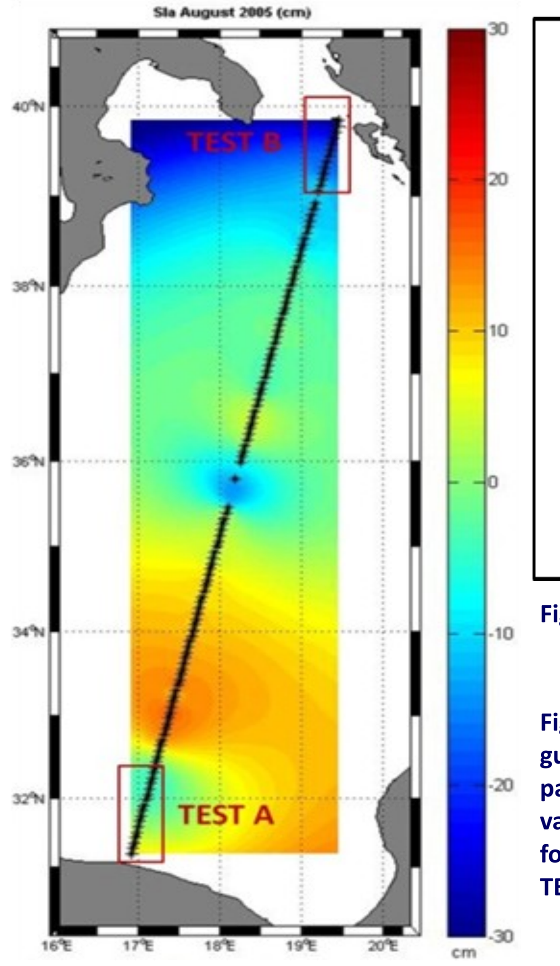


Figure 6: SLA in August 2005 along pass 444 and the various TESTs performed (TEST A, TEST B and TEST C)

Statistics of ENVISAT pass 444 August 2005 (cm)

	min	max	mean	std
SLA	-19.9	23.5	7.4	±8.5
TEST A				
Prediction errors with LSC for the various covariance models (cm)				
MODEL A	-29.07	3.74	-10.06	±8.87
MODEL B	-18.60	5.07	-4.02	±6.10
MODEL C	-27.75	4.46	-8.53	±8.75
MODEL E	-27.66	4.53	-8.63	±8.67
MODEL F	-22.22	9.53	-0.84	±9.39
MODEL G	-18.97	11.47	1.69	±8.70
MODEL H	-20.76	22.48	7.27	±12.88
MODEL I	-91.3	-2.70	-35.65	±32.5
TEST B				
Prediction errors with LSC for the various covariance models (cm)				
MODEL A	-13.39	5.95	-6.13	±5.54
MODEL B	-128.22	-10.89	-78.97	±35.41
MODEL C	-13.55	6.57	-5.99	±5.78
MODEL E	-13.74	6.38	-6.23	±5.78
MODEL F	-10.57	8.86	-3.15	±5.54
MODEL G	-10.19	10.42	-2.24	±5.94
MODEL H	-15.40	5.79	-7.73	±6.31
MODEL I	22.36	79.54	30.72	±28.59
TEST C				
Prediction errors with LSC for the various covariance models (cm)				
MODEL A	-7.61	5.08	-0.11	±1.99
MODEL B	-7.57	5.10	-0.06	±1.88
MODEL C	-7.52	5.09	-0.10	±1.95
MODEL D	-86.59	17.39	-1.43	±12.47
MODEL E	-7.55	5.09	-0.10	±1.95
MODEL F	-8.98	5.27	-0.08	±2.07
MODEL G	-9.00	5.27	-0.07	±2.07
MODEL H	-9.94	5.29	-0.08	±2.18
MODEL I	-11.58	10.37	-0.08	±4.57

Analytical covariance function models for 2D case

As far as the 2D case is concerned, two tests have been carried out. One using a complete cycle of the ENVISAT data for the entire Mediterranean Sea (all passes included, see Figure 1 bottom).

This consisted of a total number of 11870 SLA observations, for which analytical covariance functions were determined and predictions were made by omitting every second point and using the rest to estimate the SLA in these locations (TEST D in the sequel).

The second test refers to using the entire set of ENVISAT data, to predict SLA at an inner window where no observations are available. The inner window was selected for the area bounded between (32° ≤ φ ≤ 36° and 15° ≤ λ ≤ 20°. This resembles the case when no information is available in a specific area and LSC is used for the prediction. The validation is performed through comparisons with the available observations (TEST E in the sequel).

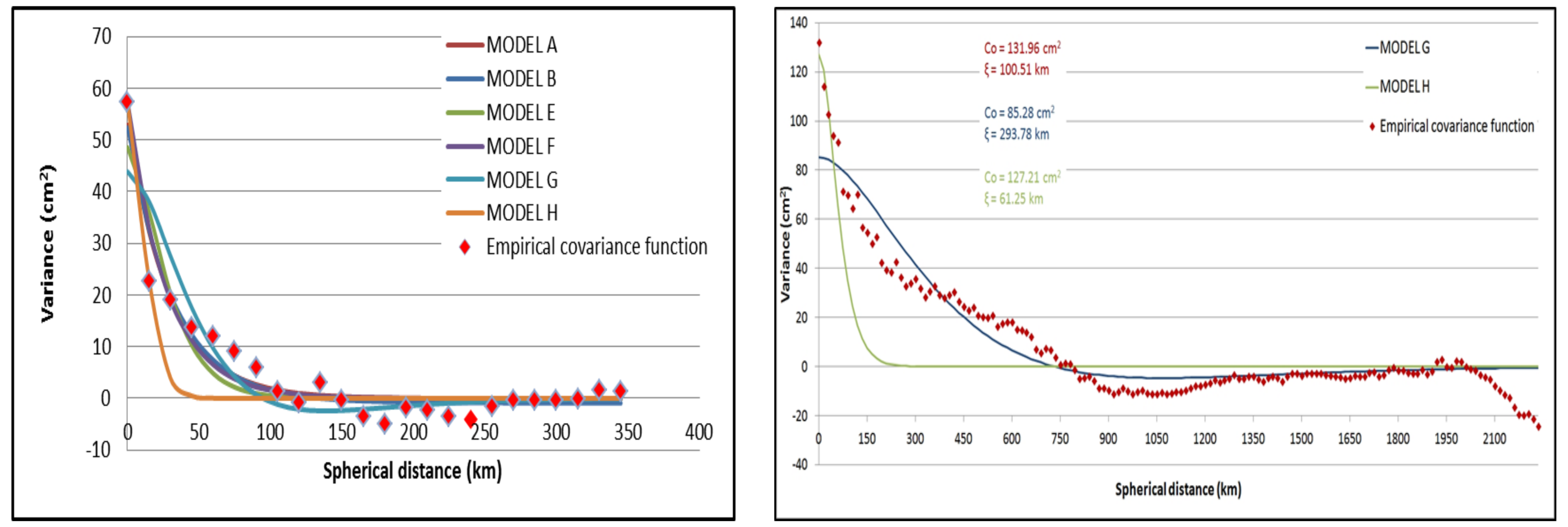
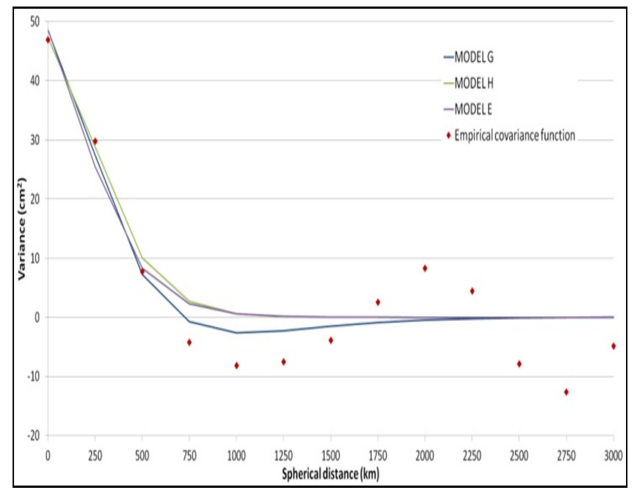
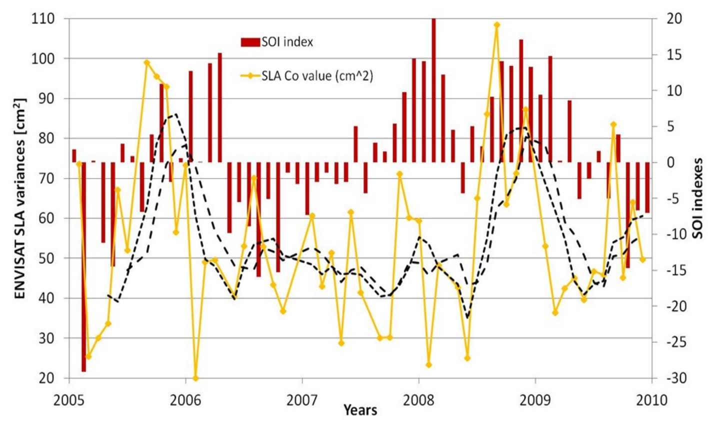


Figure 7: Window data analytical model covariance function (left) cycle 74 (right) and RIO_MED (bottom)



	min	max	mean	std
TEST D				
Prediction errors with LSC for the various covariance models (cm)				
SLA	-50.90	55.40	7.33	±11.49
MODEL A	-34.88	29.31	-0.03	±3.65
MODEL B	-34.88	29.37	-0.03	±3.65
MODEL E	-34.89	29.39	-0.03	±3.65
MODEL F	-47.95	55.15	-0.02	±4.57
MODEL G	-47.97	55.18	-0.02	±4.57
MODEL H	-80.37	89.49	-0.02	±5.77
TEST E				
Prediction errors with LSC for the various covariance models (cm)				
SLA	-44.80	19.80	0.04	±7.50
MODEL A	-30.91	29.50	0.19	±7.40
MODEL E	-30.91	29.50	0.19	±7.39
MODEL G	-403.55	234.2	1.03	±34.63



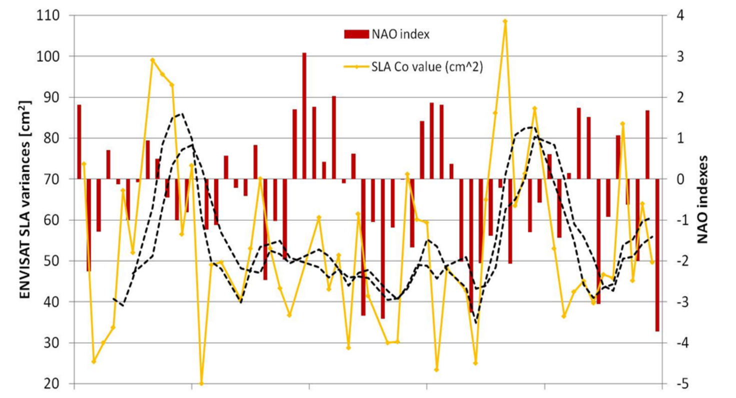
Correlation with climate indexes

The last step in the analysis of the SLAs is to investigate for any possible correlations with global and regional climatic phenomena that influence the ocean state as well.

Three such indexes have been investigated. The first one is the well-known Southern Oscillation Index (SOI) corresponding to the ocean response to El Niño/La Niña-Southern Oscillation (ENSO) events.

The next index investigated is the North Atlantic Oscillation (NAO) index, which corresponds to the fluctuations in the difference of atmospheric pressure at sea level between the Icelandic low and the Azores high.

The last index investigated is the Mediterranean Oscillation Index (MOI) which refers to the fluctuations in the difference of atmospheric pressure at sea level between Algeires and Cairo. For the present study, SOI data have been acquired from the Australian Government Bureau of Meteorology and NAO and MOI data have been acquired from the Climate Research Unit of the University of East Anglia.



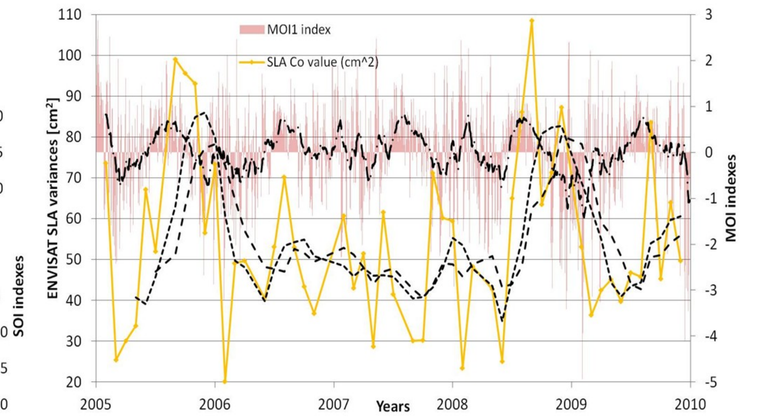


Figure 8: ENVISAT SLA variance fluctuations from 2005 to 2009 and correlation with SOI (left), NAO (top) and MOI (bottom)

Conclusions

- Cyclo-stationarity in the SLA can be evidenced from the empirical covariance functions. The statistical characteristics of the SLA follow a regular annual pattern with the change of the epochs. Extremes from that is due to the Ocean response to ENSO events and atmospheric forcing.
- In the along-track case, the prediction using the exponential analytical covariance function models provide the overall best results, with MODEL E giving the smallest prediction errors.
- The Gauss-Markov models give comparable results in the along-track case and in the 2D case during TEST D, but have one order of magnitude larger errors during TEST E.
- In all cases, the Legendre polynomial expansion for the covariance function give disappointing results since the analytical model does not manage to resemble the pattern of the empirical covariance function.

Reference

Rio, M.H., Poulain, P.M., Pascual, A., Mauri, E., Larnicol, G., Santoleri, R. A Mean Dynamic Topography of the Mediterranean Sea computed from altimetric data, in-situ measurements and a general circulation model. J. of Mar. Syst. 65, 484-508, 2007.

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