SOFT project: a new forecasting system based on satellite data

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ABSTRACT

The aim of the SOFT project is to develop a new ocean forecasting system by using a combination of satellite data, evolutionary programming and numerical ocean models. To achieve this objective two steps are proposed: (1) to obtain an accurate ocean forecasting system using genetic algorithms based on satellite data; and (2) to integrate the above new system into existing deterministic numerical models. Evolutionary programming will be employed to build "intelligent" systems that, learning from the past ocean variability (provided by satellite data) and considering the present ocean state, will be able to infer near future ocean conditions. Validation of the forecast skill will be carried out by comparing the forecasts fields with satellite and in situ observations. Validation with satellite observations will provide the expected errors in the forecasting system. Validation with in situ data will indicate the capabilities of the satellite based forecast information to improve the performance of the numerical ocean models. This later validation will be accomplished considering in situ measurements in a specific oceanographic area at two different periods of time. The first set of observations will be employed to feed the hybrid systems while the second set will be used to validate the hybrid and traditional numerical model results.

Keywords: forecasting, satellite data, empirical orthogonal functions, numerical models, genetic algorithms, neural networks, Mediterranean Sea.

1. INTRODUCTION

Numerical ocean models are the most common tools for ocean prediction. The numerical approach attempts to forecast oceanic evolution by integrating forward in time the equations of ocean dynamics, providing a comprehensive understanding of the complex physical ocean evolution. In general, numerical ocean models require a continuous updating with real data in order to correct the deviations between model results and reality that appears due to the ocean nonlinear nature. This data requirement is rarely available. Unlike the atmosphere case, a continuous observation of the three dimensional structure of the ocean is not possible. Research ships allow reasonable spatial coverage but are limited by the relatively low frequency with which they can be employed. On the other hand, measurements from coastal stations and buoys have high temporal resolutions but often no spatial dimensions. In consequence, numerical models employ expected ocean states as computational starting points of the computation resulting in inaccurate forecasts.

Satellite imagery constitutes the only way to continuously monitor the space-time variability of the ocean at both high spatial and temporal resolutions simultaneously. Sea surface height, temperature, and ocean color can be measured in real time (e.g. *Mediterranean Forecasting System Pilot Project*: http://www.cineca.it/~mfspp000/). The nowcasting utilities of satellite data could be extrapolated forward in time by an adequate forecast of the satellite information. This goal could be achieved by developing ocean forecasting systems based on physical and mathematical approaches different to those used in traditional ocean modeling. One of these approaches consists on forecasting satellite-observed data by extracting dynamical information of the space-time ocean variability directly from time series of satellite observations. The information extracted about the past of the observed ocean fields could be used to predict their future evolution. In this way, the problem of ocean forecasting is reduced to find the dynamical model that best explains the behavior of a given time series of satellite observations. This is a less complex task than forecasting the detailed processes of ocean dynamics.

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2. OBJECTIVES OF THE SOFT PROJECT

The main objectives of the SOFT project are:

- To develop a new operational ocean forecasting system reliable and manageable using evolutionary programming and based on satellite imagery.

- To integrate de above new system into existing deterministic numerical ocean models creating therefore a new hybrid forecasting system that will improve the today existing models forecasts.

The background on which the first objective is based is that time series of satellite images contain, not just information suitable for nowcasting, but also dynamical information that can be extracted to forecast future states of the ocean: in other words, the information extracted from observed past ocean fields can be used to predict their future evolution. For the second objective, the background is that three-dimensional structures, vertical and small-scale velocities, heat fluxes and many other features are not directly sensed from space and therefore, detailed prediction of these cannot be done just from satellite data. Numerical ocean models have an enormous predictive potential on these variables, potential that is continuously growing as computer power and knowledge on marine processes develop.

3. METHODOLOGY

Forecasts of satellite data are obtained in three major phases (see fig. 1): Encoding satellite observed data, noise reduction and prediction of time variability.

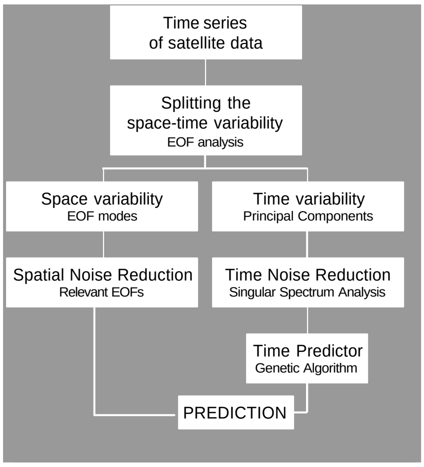


Figure 1: Flow chart of the SOFT system.

3.1 Encoding satellite observed data

In principle, prediction of the satellite observed fields would imply determination of the time evolution of each pixel. This task becomes unrealistic due to the large data set. In consequence, an encoding procedure is required in order to reduce the complexity of the problem. A convenient way to encode satellite images into a small set of numbers is the use of the Empirical Orthogonal Function (EOF) technique[1,2,3,4,5]. Briefly, the EOF technique decomposes space- and time-distributed satellite data into modes ranked by their temporal variance. As a result, a set of spatial modes and associated temporal amplitude functions are obtained. The spatial modes provide information of the spatial structures while the temporal amplitude functions describe their dynamics. The complete state of the system (i.e., the original sequence of satellite images) can be well approximated by simple linear combination of the most relevant spatial modes multiplied by their corresponding temporal amplitudes[6].

The problem of forecasting the dynamics of a two-dimensional field has thus been reduced to predicting the temporal amplitudes, a small set of time-series, corresponding to the most relevant EOFs. The decomposition in modes involves a diagonalization of the temporal covariance matrix. For satellite purposes, with a great many pixels, this problems becomes computationally intractable resulting more convenient using the snapshot technique. In such analysis the space and time axes are reversed relative to the EOF decomposition of temporal variance: the amplitude functions become spatial image patterns and the eigenvectors become dimensionless time series describing the time histories of the modes[2,3].

3.2 Noise reduction

In principle, each one-variable time-series corresponding to the EOF amplitude functions (or EOF modes in the case of decomposing the space-time variability accordingly to its spatial variance), will be contaminated by noise from the measurement process. In addition to the measurement noise, the EOFs of small variance (which are neglected in the previously described processes) introduce a stochastic component into the data. Noisy data affect prediction performance as the predictor attempts to predict noise (i.e., find a dynamical law of a random effect) at the expense of predicting the true underlying dependence. Therefore, filtering to isolate the deterministic signal in the data from stochastic noise, should be applied[7].

An adequate approach to remove noise without loosing a significant portion of the deterministic signal is the Singular Spectrum Analysis (SSA) or data adaptive approach [8,9]. Briefly, for the j-EOF we form a trajectory matrix X the row of which contain w-dimensional vectors of the form (A_j(t-Δt), A_j(t-2Δt), …, A_j(t-wΔt)), (A_j(t-3Δt), A_j(t-3Δt), …, A_j(t-(w+1)Δt)), being Δt the time step between observations and w the window of the filter. The covariance matrix, X^TX is computed and diagonalized to obtain a set of eigenvectors which are the orthogonal singular vectors. The corresponding eigenvalues are the average root-mean-square projection of the w-dimensional vectors that constitutes the trajectory matrix. This procedure can be useful in the presence of noise; discarding eigenvalues the magnitude of which is below the noise level can reduce noise; thus distinguishing the deterministic part of the signal from noise. A new noise-free time series can be reconstructed considering only the eigenvectors with eigenvalues above the noise level.

3.3 Prediction of time variability

The aim is now to obtain a dynamical model for each representative EOF, that using values of the time series predicts the future ones. Explicitly, given a deterministic time series {x(t_i)}, t_i=1…N, Takens' theorem[10] establishes the existence of a smooth map P: R^m ? R satisfying:

$$x(t) = P(x(t-t), x(t-2t),...., x(t-mt)) \quad (1)$$

where *m* is called the embedding dimension obtained from a state-space reconstruction of the time series and τ is a time lag unit[9]. During the past decade, various techniques have been developed to accomplish that task of approximating the mapping P(·). In SOFT project, the genetic algorithm developed by Alvarez et al.[11] will be employed to accomplish the task of approximating the mapping P(·). The algorithm proceeds as follows (see Figure 2): first, for the filtered j-EOF $\{\tilde{A}_j(t_i)\}, t_i = 1 \cdots N$ a set of candidate equations (the population) for P is randomly generated. These equations (individuals) are of the form of equation (1) and their right hand sides are stored in the computer as sets of character strings that contain random sequences of the state variables $(\tilde{A}_j(t-\Delta t), \tilde{A}_j(t-2\Delta t), \cdots, \tilde{A}_j(t-m\Delta t))$, real numbers, and the four basic arithmetic symbols $(+,-,\times,/)$. A criterion that measures how well the equation strings perform on a training set of the data is defined as:

$$\Delta_i^2 = \sum_{t=L+1}^{T} \left(\tilde{A}_j(t) - P^i(\tilde{A}_j(t-\Delta t), \tilde{A}_j(t-2\Delta t), \cdots, \tilde{A}_j(t-m\Delta t)\right)^2 \quad (2)$$

where P^i represents the *i*-equation string of the population, *L=mDt,* and *T* is the total length of the *j*-EOF $\tilde{A}_j(t)$. This criterion, the fitness to the data, establishes the strength of each individual. The strongest individuals, equation strings with best fits, are then selected to exchange parts of the character strings between them (reproduction and crossover). The individuals less fitted to the data are discarded. Finally a small percentage of the equation strings' most basic elements, single operators and variables, are mutated at random. As a result of this process a new set of equations (generation) with better fitness properties is obtained. The process is repeated a large number of times, to improve the fitness of the evolving population. At the end, the strongest individual represents the best dynamical functional relation found for the given amplitude function. Future values of the amplitude function can be easily obtained from these functional relations. Very little data are sufficient to use this approach and as a byproduct, the genetic algorithm can indicate the functional form that underlies the data [11].

Prediction of the satellite observed field is then achieved by adding the most relevant spatial modes previously multiplied by their corresponding forecast EOFs.

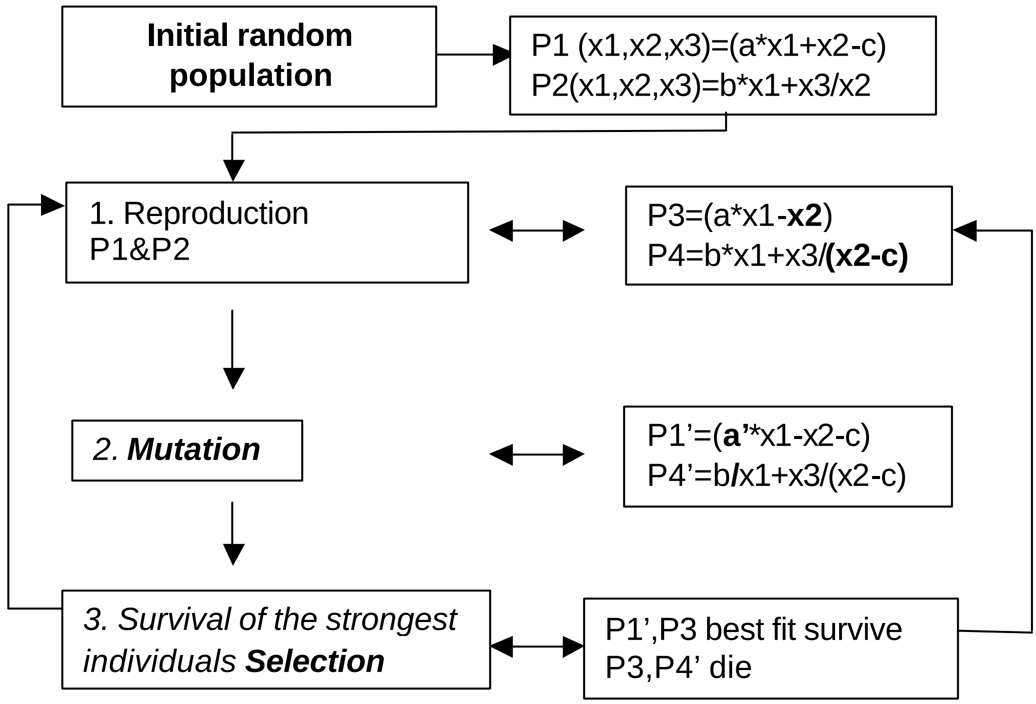


Figure 2. Genetic algorithm flow chart.

4. PRELIMINARY TESTS

Previous to the application of the SOFT system to predict satellite data, the genetic algorithm described by [11] was tested to forecast the 'El Niño' one dimensional time series [12]. After this success, the SOFT system was applied then for a two-dimensional problem with real satellite data. More specifically the test was carried out for the Alboran Sea with AVHRR images[13]. The data set considered was a time series of 68 monthly averaged SST images, ranging from March-93 to October-1998.

Figure 3 shows the mean, 1st, 2nd and 3rd spatial modes respectively obtained from the EOF analysis, while the solid lines in Figure 4 represent the temporal amplitude functions associated with each spatial mode. Basically, the 1st EOF mode captures the variability associated with the seasonal changes in the surface temperature of Atlantic and Mediterranean waters. The 2nd spatial mode appears to be related to the variability in the intensity of the two gyres. Finally, the 3rd mode essentially describes the spatial variability related to the Almeria-Oran Front[14]. These three modes account for 98.64% of the total variance of the data. A complex EOF decomposition of satellite altimetry data in the same area was performed by[15].

The temporal amplitudes of the 2nd and 3rd EOFs show a time dependence much more complex than the simple seasonal variation displayed by the 1st one. This could be an indication either of complex deterministic evolution or of contamination from random noise. To disentangle both components, the signals were filtered using the SSA method. Then, the genetic algorithm is employed to find the equation that best fits the data in one part of the dataset, the training set, ranging from March-1993 to June-1998. The predictability skill of the solution equation is then validated with data ranging from July-1998 to October-1998, the validation set, previously unknown for the algorithm. If the forecast performance of the solution equation is high in the validation set (more than 80% of agreement between data and forecast) the rebuilt signal is considered to be mainly deterministic. A new time series is then rebuilt from the original one considering a larger number of eigenvalues and the previous process is repeated. The procedure is stopped when the inclusion of new eigenvalues deteriorates the forecasting skills, since then it can be argued that the variability represented by the new eigenvalues has a strong noisy component. The final filtered signal is thus rebuilt with the maximum number of eigenvalues that provide a good forecast skill in the validation set.

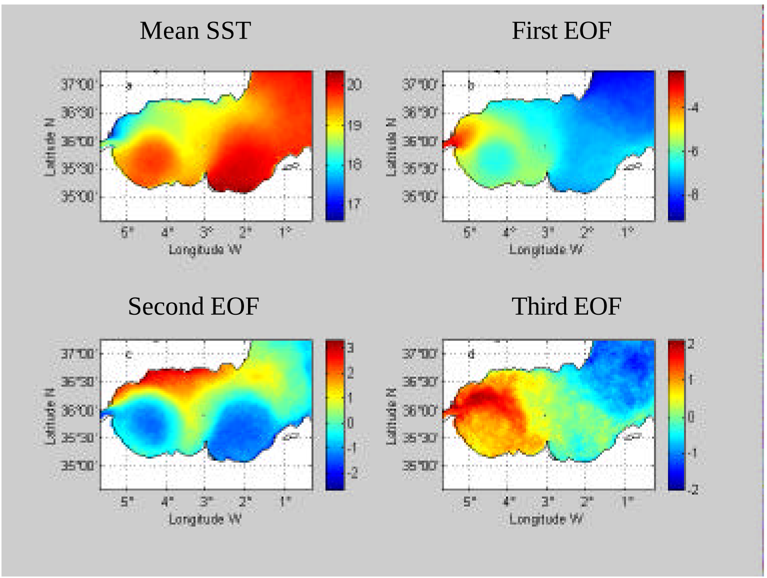


Figure 3: Mean SST, 1st, 2nd and 3rd EOFs of the Alboran Sea.

Figure 4 shows the results of applying the genetic algorithm solution equations. The agreement is goof, thus indicating that the time variability of each EOF is deterministic and, therefore, the genetic algorithm has been able to capture the main time variability of each EOF. It is remarkable that this has been achieved without the use of any explicit knowledge of the ocean dynamics, and using data just from the upper layer of the sea.

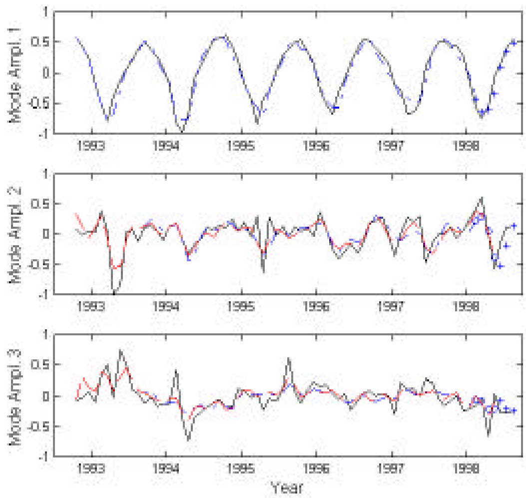


Figure 4: Temporal amplitudes corresponding to the 1st, 2nd and 3rd modes (solid black line). The red dashed line represents the SSA-filtered amplitude. The dash-dotted line represents the fitting with GA in the training set. Symbols show one-month-ahead forecasts.

It remains, to close the procedure, to obtain the total forecasted SST spatial field. This is accomplished by adding to the mean SST the three EOFs multiplied by their predicted amplitudes. This has been done for the forecasting set. Figure 5 shows the monthly averaged SST field for November-1998, December-1998, January-1999, and the corresponding one-month-ahead forecast. The result correctly reproduces the main SST structure of the gyres in particular and the Alboran Sea in general.

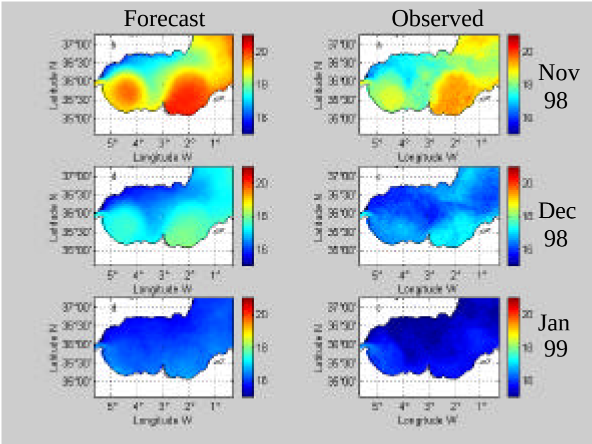


Figure 5: Results of SOFTforecasts.

5. PRESENT STATE OF THE PROJECT

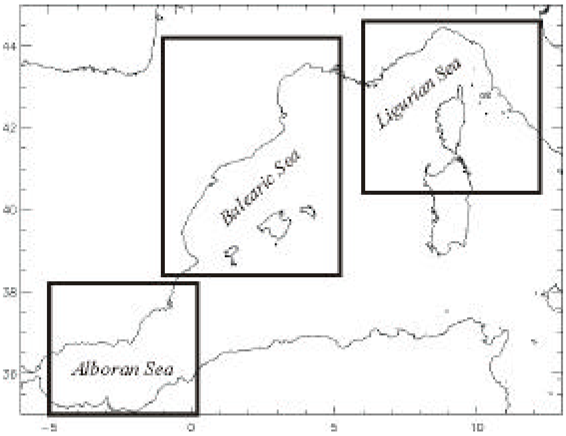
SOFT started in January 2001. Presently (September 2001), after nine months of the beginning of the project, the following tasks are underway:

- Data acquisition and processing
- EOFs computation
- Development of non linear time series predictors:
    - Improvement of genetic algorithm for time series prediction.
    - Development of a Neural Network for time series prediction.
    - Development of a Neuro-Fuzzy algorithm for time series prediction
- Implementation of the 3D PE model: nesting in the Liguro-Provençal region. Double nesting down to 1 km resolution in progress.

In the following subsections we provide details of the data acquis ition and EOFs computation.

5.1 Data acquisition and processing

The satellite data for the project consists in: Sea Level Anomaly (hereafter SLA; from combined Topex/Poseidon and ERS-1/2), Sea Surface Temperature (hereafter SST; from AVHRR and ATSR) and color (SeaWifs). For every sensor 3 regions have been selected (Figure 6): Alboran Sea, Balearic Sea (including Gulf of Lions) and Ligurian Sea. The temporal coverage for each particular data set is shown in table 1. Data from the Azores area are also being obtained.



SENSOR	DATA	ZONES	PERIOD
T/P-ERS1/2	SLA	Alboran Ligur Balear	Oct-92/Oct-99 Oct-92/Oct-99 Oct-92/Oct-99
AVHRR	SST	Alboran Ligur Balear	Mar-93/Mar-00 Mar-93/Mar-00 Mar-93/Mar-00
ATSR	SST	Alboran Ligur Balear Lions	Oct-98/Dec-00 Dec-96/Jul-98 Dec-96/Jul-98 Dec-96/Jul-98
SEA-WIFS	Color	Alboran Ligur Balear	Jan-98/Jun-01 Jan-98/Jun-01 Jan-98/Jun-01

Figure 6: Study regions of the SOFT project

Table 1: Temporal coverage of the data.

SLA data were produced by CLS (Toulouse, France; http://www.cls.fr/mater/). The spatial resolution is 0.2^ox0.2^o and a map every ten days is generated. The height is given in mm and the anomaly is built by removing a temporal mean of 4 years (1993-1996).

AVHRR data were acquired and processed by the German Aerospace Research Center-DLR (http://isis.dlr.de/). Geometrical resolution at the center of each image is 1.1132 km. The images were declouded and monthly means were computed.

ATSR and SeaWIFS data were provided by SOC (Southampton, England; http://www.soc.soton.ac.uk/). The processing state of the provided data corresponded to a level 2 product, *i.e.*, temperature and chlorophyll-a were obtained from the radiance of the different channels and were given on the non rectangular grid with axis parallel and perpendicular to the satellite track. Thus, it was necessary to process the data and it was achieved by GHER&IMEDEA [16]. Basically, the processing included spatial interpolation onto a regular grid, declouding procedure and computation of temporal means (every 10 days for ATSR and every 7 days for SeaWIFS).

5.2 EOFs results

The EOFs have been computed following standard steps for satellite applications[1,2,3,5] :

1. Construction of the anomaly data-set: From the original data set a mean has to be subtracted to build afterwards the covariance matrix. Following[17] the kind of mean used (temporal or spatial) yields to different results. On the one hand, removing a spatial mean allows to highlight structures of strong gradient, such as fronts. On the other hand, removing a temporal mean reveals features that vary in time. In this case we have subtracted a temporal mean (same criterion adopted in the preliminary tests[13]), *i.e* for a given variable T (temperature for instance).:

$$T^{'}(x_i,t_j)=T(x_i,t_j)-\frac{1}{N}\sum_{k=1}^{N}T(x_i,t_k) \qquad (3)$$

where N is the number of time steps.

2. Construction of the covariance matrix: As it has been indicated previously, for satellite studies, with a huge spatial dimension, results more convenient to diagonalize the spatial covariance rather than the temporal covariance (method of *snapshots*). The two methods are completely equivalent[3]. Therefore we have diagonalized the spatial covariance matrix.

3. Diagonalization of the covariance matrix: EISPACK routines have been used to diagonalize the covariance matrix. The output of the subroutines consists on the set of eigenvalues (in increasing order) and the corresponding temporal eigenvectors.

4. Computation of the spatial amplitudes: The spatial amplitudes have been computed by projecting the temporal modes onto the original data set.

Figures 7-12 reproduce the EOF results of the different regions and for SLA and SST (from AVHRR) data. Before entering into details some 'technical' comments are needed. First, for SLA the temporal mean is not shown since it is almost zero (SLA is obtained by definition by removing a temporal mean (of 4 years, in our case). Second, for SLA the three leading modes are shown while for SST we present only the two first modes because the second mode explained less than 1% of the total variance, being not relevant further modes. Finally, the geographical limits of the Alboran Sea do not coincide exactly for both kinds of data, since the western boundary of SLA maps produced by CLS do not capture Gibraltar.

A general observation valid for all the regions and data sets is the predominance of the first EOF. It clearly represents the basin-wide seasonal mode; warming and cooling for SST with the corresponding stretching and squeezing for SLA due to the steric effect. However, the maximum in SLA occurs in October while in SST it takes place in August. This lag between SST and SLA maximum can be seen as a phase shift. This puts in evidence the fact that sea level is an integrated variable and needs a heating not only of the surface but for a column of water of a few tenths of meters until sea level increases. The first spatial amplitude is positive everywhere for all the basins, which indicates different rates of warming/stretching or cooling/squeezing[2].

As stated by [2] the fraction of variance explained by the first EOF tends to decrease with the increase in the number of temporal degrees of freedom as one would expect. This is what we find by comparing SST-EOFs and SLA-EOFs. In the latter the temporal dimension was 258 while in the former was 94. Also, the fraction of variance explained by the first EOF is much higher for semienclosed regions as the Mediterranean sea. However, this clear predominance of the first mode would change if we had removed the spatial mean instead of the temporal mean[17].

More specifically, in the Alboran Sea, the main feature revealed by the first spatial amplitude of SLA is the seasonality of the eastern gyre which is intensified in October. The second mode seems to have also a seasonal periodicity (but not so clear), and corresponds to the variability of the western gyre, being intensified around June-August. These results are in good agreement with those obtained by [18]. Concerning SST-EOFs no significant features are found different from [13].

In the Balearic Sea, the first SLA-EOF manifests the seasonality of the Northern Current, of decreasing intensity in summer. This is a well-known result, see for example [19]. The second mode displays a seasonal variability overimposed with an interannual variability. The associated spatial amplitude has a strong signal in the Gulf of Lions yielding to modifications of the Northern current's position (due to its traveling wave character[19]). In the middle of the Balearic Sea an anticyclonic eddy of about 150 km is also present in EOF 2. This structure was intensified during 1998 according EOF 3 (see [20] for more details confirming these results). Regarding SST-EOFs, equivalent comments to those for the first SLA mode can be done. The second EOF does not have a clean time periodicity but the outstanding feature is again the presence in 1998 of a structure with high temperature over the Balearic Islands and reaching the Catalan coast; at the same time the Northern current seems to be deviated by the presence of this warm water mass. Again this is coherent with [20].

Finally, related to the Ligurian Sea it can be seen, from the first EOFs (both SLA and SST), the beginning of the 'Liguro-Provençal-Northern' current related to the seasonal variability with maximum fluxes in winter. The cyclonic circulation usually observed in the Channel of Corsica is also depicted in the second EOF of both data sets[21].

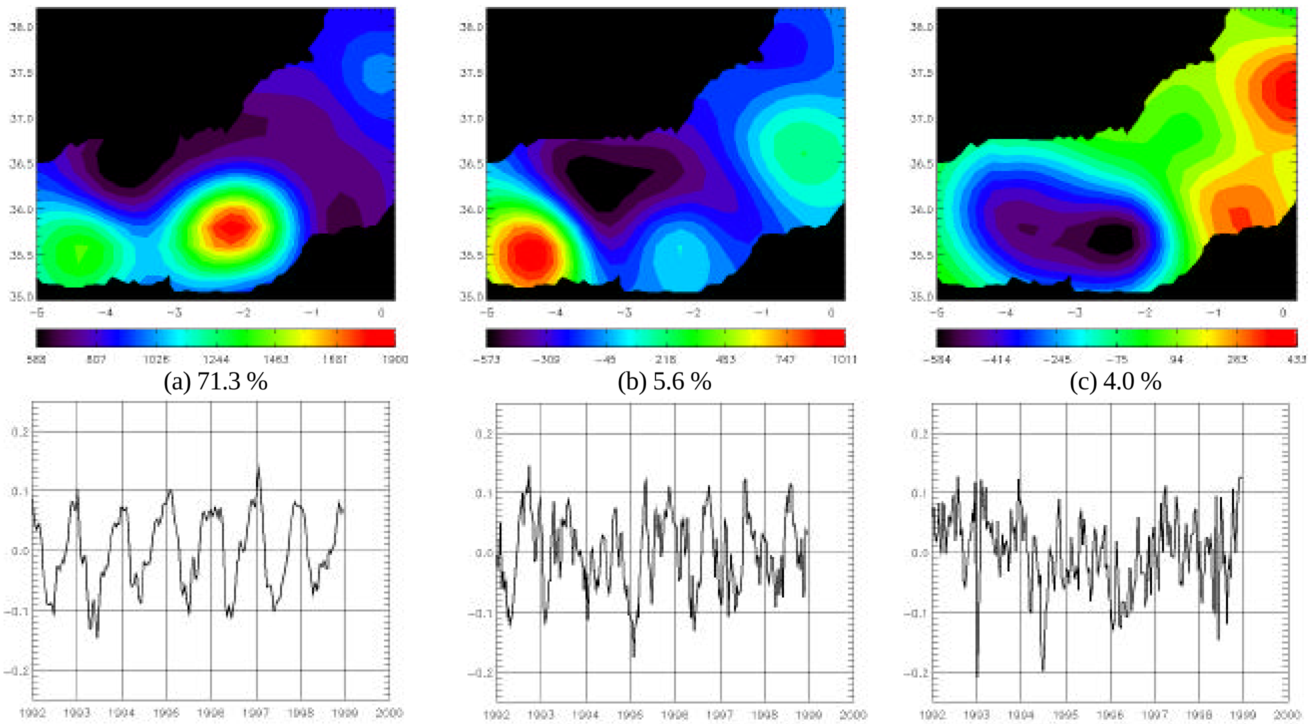


Figure 7: EOF decomposition of SLA series in the Alboran Sea: (a) 1st spatial amplitude and temporal mode; (b) 2nd spatial amplitude and temporal mode; (c) 3rd spatial amplitude and temporal mode. Divisions of the x axis in the temporal modes correspond to Oct-15-year.

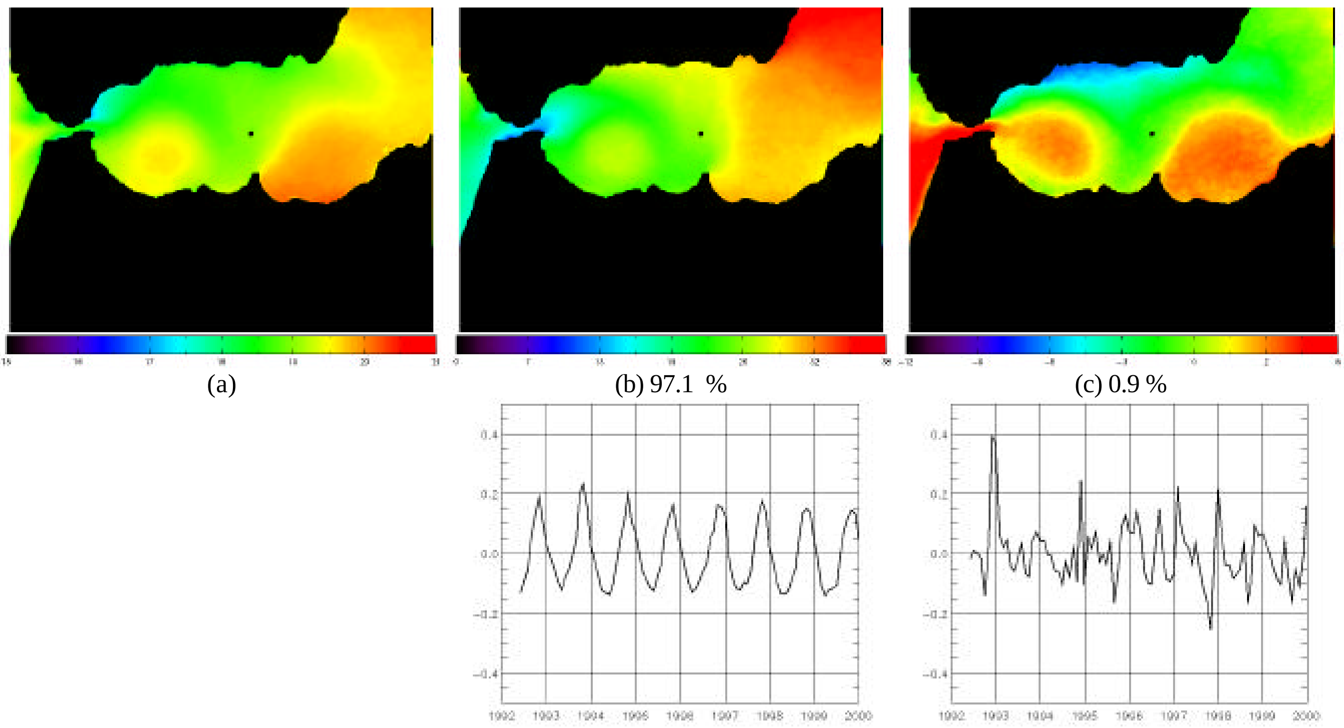


Figure 8: EOF decomposition of SST series in the Alboran Sea: (a) temporal mean; (b) 1st spatial amplitude and temporal mode; (c) 2nd spatial amplitude and temporal mode. Divisions of the x axis in the temporal modes correspond to Oct-15-year.

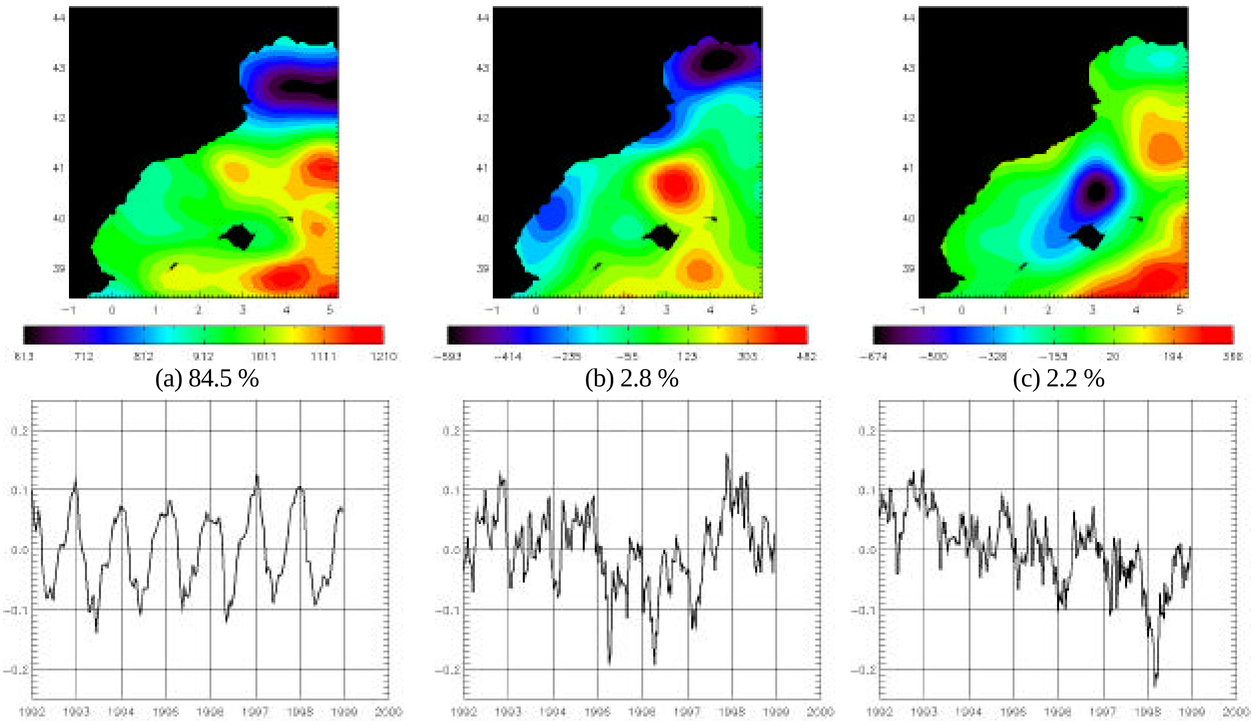


Figure 9: EOF decomposition of SLA series in the Balearic Sea: (a) 1st spatial amplitude and temporal mode; (b) 2nd spatial amplitude and temporal mode; (c) 3rd spatial amplitude and temporal mode. Divisions of the x axis in the temporal modes correspond to Oct-15-year.

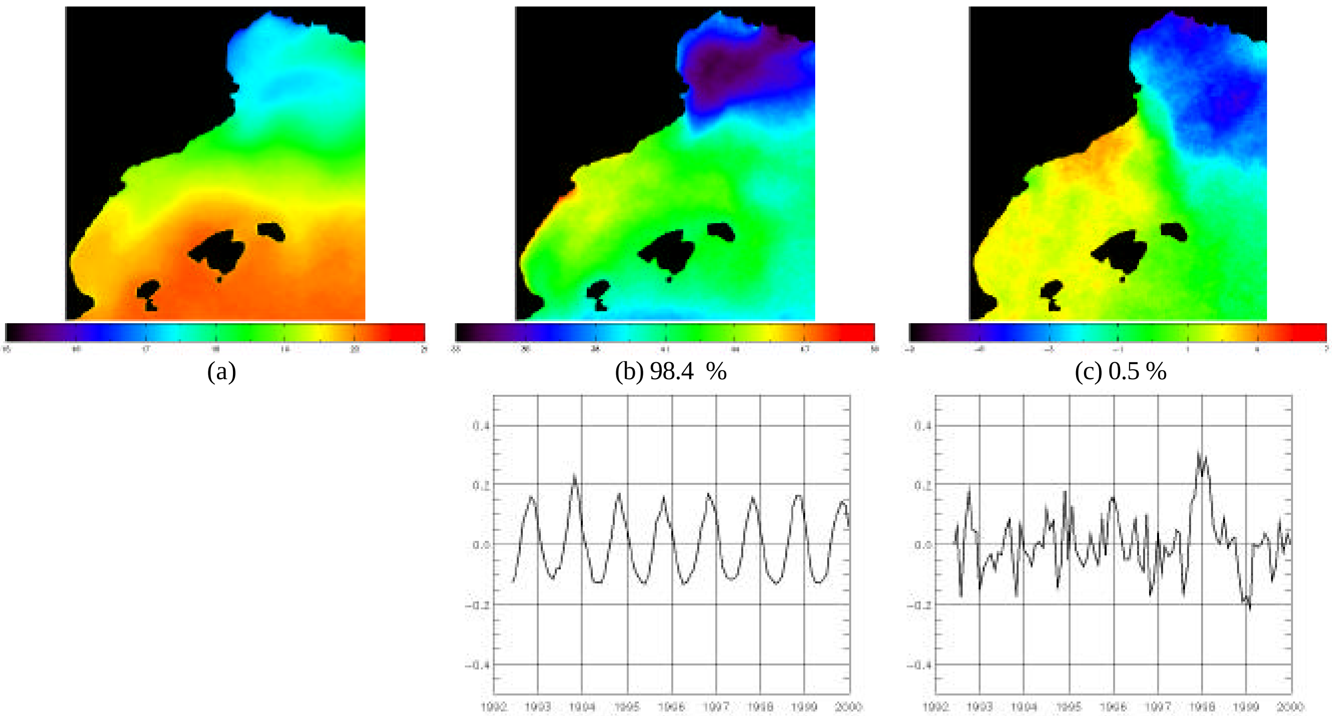


Figure 10: EOF decomposition of SST series in the Ligurian Sea: (a) temporal mean; (b) 1st spatial amplitude and temporal mode; (c) 2nd spatial amplitude and temporal mode. Divisions of the x axis in the temporal modes correspond to Oct-15-year.

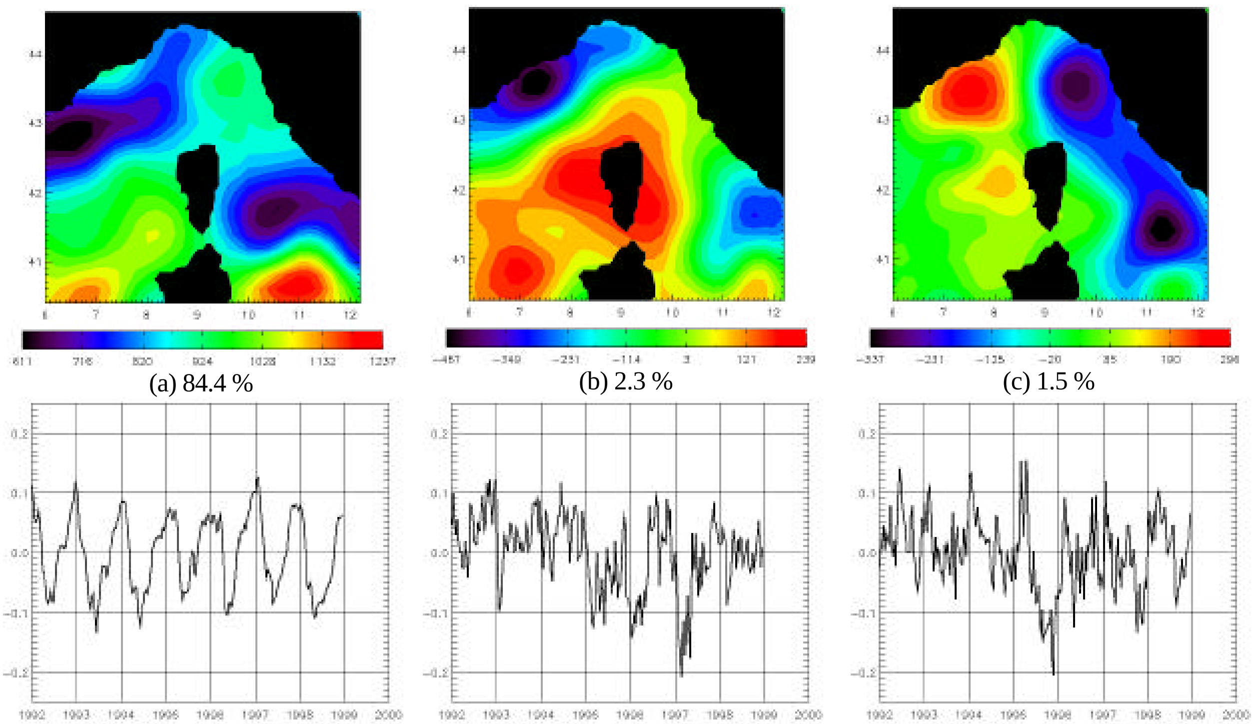


Figure 11: EOF decomposition of SLA series in the Ligurian Sea: (a) 1st spatial amplitude and temporal mode; (b) 2nd spatial amplitude and temporal mode; (c) 3rd spatial amplitude and temporal mode. Divisions of the x axis in the modes correspond to Oct-15-year.

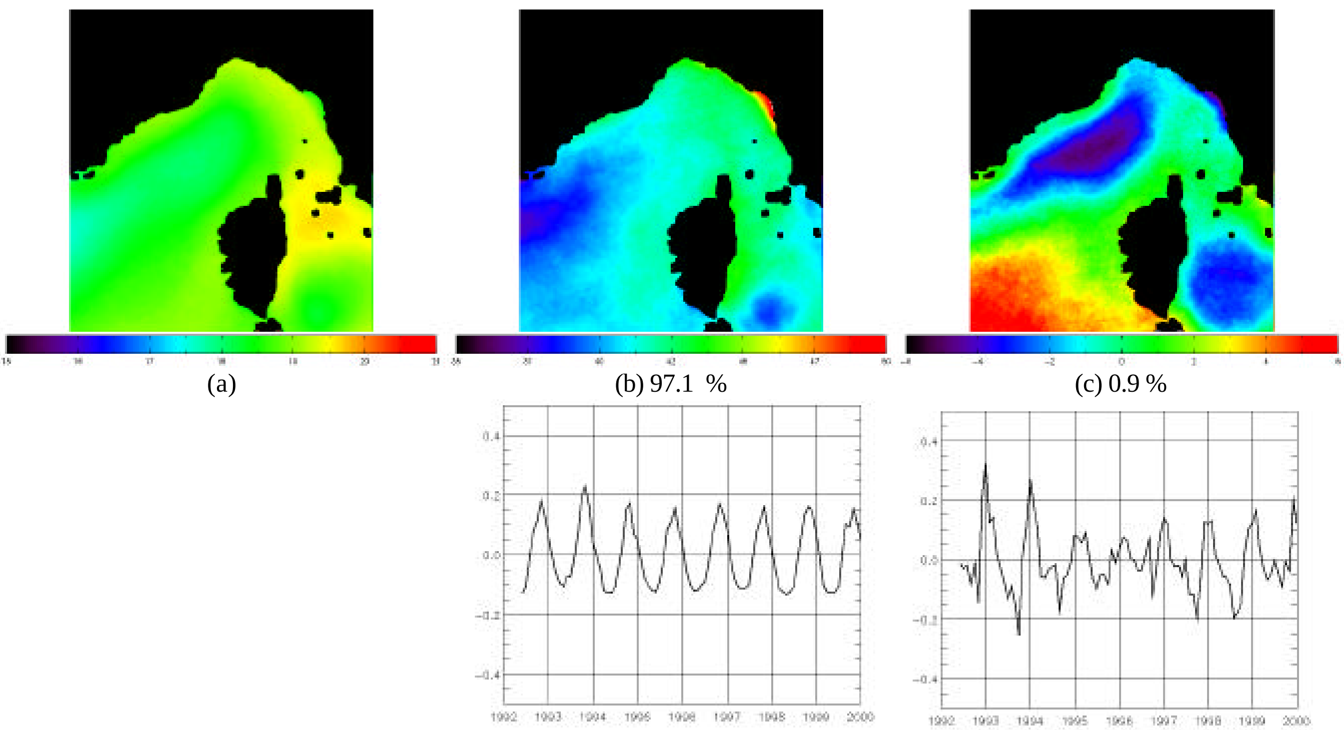


Figure 12: EOF decomposition of SST series in the Ligurian Sea: (a) temporal mean; (b) 1stspatial amplitude and temporal mode; (c) 2nd spatial amplitude and temporal mode. Divisions of the x axis in the modes correspond to Oct-15-year.

6. SUMMARY AND EXPECTED IMPACTS

Preliminary results from SOFT project show that satellite data combined with genetic algorithms provide a valuable tool to complement ocean modeling forecasting. Satellite Ocean Forecasting SysTem is expected to improve ocean modeling predictions in situations where the dominant EOFs contain a strong deterministic-evolution component as compared to the stochastic one.

Satellite observations are becoming an essential part of the daily work of oceanographers, engineers, managers, fishery companies, navies and authorities to plan their offshore activities and to gain understanding of the processes occurring in the seas. New satellites and sensors provide almost continuously increasing capability in sampling the temporal and spatial variability of the ocean. Sophisticated calibration and validation procedures now also allow quantitative measurement of physical and biological quantities. Recent advances in image analysis allow researchers and managers to identify and track faint structures in noisy backgrounds. In summary, all these technologies allow satellite data users to obtain nowcast of ocean conditions relevant to their activities. The success of the present project will imply the capability to extrapolate, in time, the present benefits of satellite information. It is expected that the satellite based ocean forecast system will strongly impact the planning of offshore activities of fisheries and marine commerce, the activities related to environmental control and sustainability and the present knowledge about ocean predictability.

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