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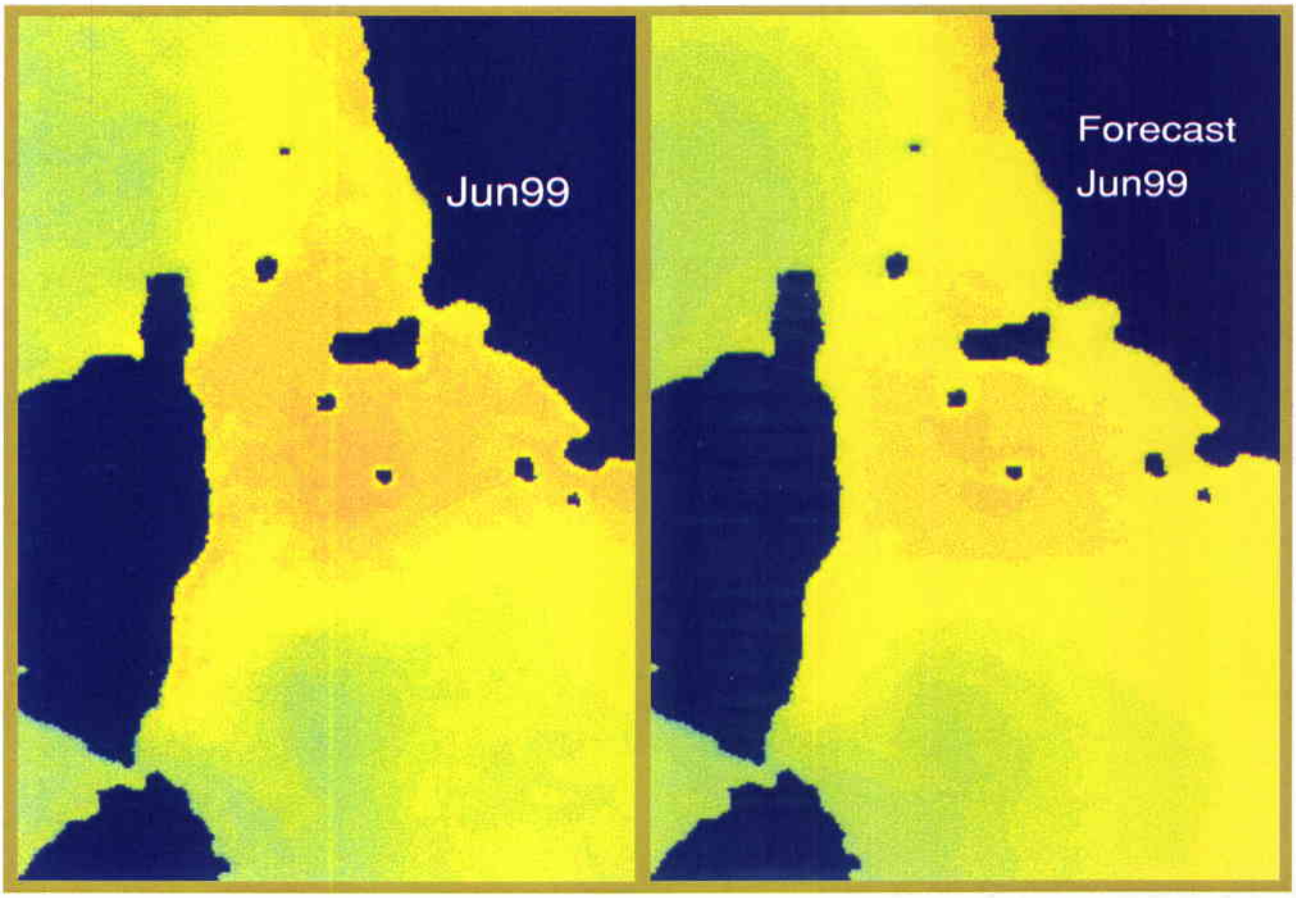
A satellite based ocean forecasting system to support naval operations in crisis situations



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May 2000

NORTH ATLANTIC TREATY ORGANIZATION ORGANISATION DU TRAITE DE L'ATLANTIQUE NORD

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A satellite based ocean forecasting system to support naval operations in crisis situations

Alberto Alvarez, Alejandro Orfila, Jurgen Sellschopp

Executive Summary:

The *MC Guidance for the Military Implementation of Alliance Strategy*, MC-400, requires NATO naval forces to have the capability to operate in a wide range of different geographical locations, each of them characterized by particular oceanic environmental conditions. Military missions, such as antisubmarine warfare (ASW) and mine warfare (MIW), can be strongly affected by some ocean factors. Thus, a Rapid Environmental Assessment (REA) of the oceanic parameters with military relevance is needed to improve operational and tactical decisions. During crisis situations, restrictions on Exclusive Economic Zones and territorial waters limit the use of conventional methods for environmental assessment. In such circumstances, satellites constitute a very important tool to Rapid Environmental Assessment (REA), providing discreet and secure environmental information. The possibility to carry out forecasts of the ocean environment exclusively based on satellite remote sensing would provide a great advantage in the future dominance and shaping of the ocean battlefield.

This report describes a satellite based ocean forecasting system (SOFT) working on operational time scales to estimate, several months in advance, mean sea surface temperature and surface current conditions. These fields are already relevant to improve, respectively, atmospheric boundary layer descriptions necessary for radar performance and drift estimates. Present research is devoted to obtain satellite based forecasts of volumetric sound speed conditions, relevant to predict range-dependent acoustic sensing performances, as well as to expand the capabilities of the system to achieve satellite based forecasts on tactical time scales, of the order of days.

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A satellite based ocean forecasting system to support naval operations in crisis situations

Alberto Alvarez, Alejandro Orfila, Jurgen Sellschopp

Abstract:

We employ a nonlinear ocean forecasting technique based on a combination of genetic algorithms and empirical orthogonal function (EOF) analysis. The method is used to forecast the space-time variability of the sea surface temperature (SST) of the ocean area around the Island of Elba. The genetic algorithm identifies the equations that best describe the behaviour of the different temporal amplitude functions in the EOF decomposition and therefore, enables global forecasting of future time-variability.

Keywords: Satellite remote sensing ○ satellite based ocean forecasting ○ genetic algorithms.

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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. As an operational tool, it possesses certain limitations. Numerical forecasts of the ocean require the derivation of the dynamical laws controlling the ocean processes as well as the detailed knowledge of the initial conditions. Restrictions are inevitable due to the intrinsic dependence of numerical ocean models on initial data. Unlike the atmosphere case, a continous observation of the three dimensional structure of the ocean is not possible. In consequence, numerical models employ expected ocean states as computational starting points of the computation resulting in inaccurate forecasts. The level of knowledge required by numerical ocean models is rarely available although the surfacing of new ocean observing platforms, like Autonomous Underwater Vehicles (AUV), will greatly improve the accuracy of numerical ocean model predictions by introducing reliable data [1, 2, 3, 4, 5].

Satellite imagery constitutes the only way to continously monitor the space-time variability of the ocean. Sea surface temperature, colour, sea surface level winds, waves and, to a certain extend, currents can be measured in real time [6, 7]. Satellite techniques yield information on shallow water conditions for amphibious landing forces, optical clarity of the water to predict the effectiveness of optical minehunting systems, sea surface temperature and surface roughness to feed atmospheric models.

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 modelling. One of these approaches could consist 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 behaviour of a given time series of satellite observations. This is a less complex task than forecasting the detailed processes of ocean dynamics.

This report describes the development of a satellite based ocean forecasting system (SOFT). The scientific core of SOFT merges different techniques and methods from statistics, non-linear physics and artificial intelligence [8, 9]. The forecast satellite data is obtained in three major phases. In the first phase, the space-time variability in the time series of satellite data is divided into space and time components, resulting in a set of spatial patterns and amplitude functions, which describe the time evolution of the spatial patterns. In general, the space-time variability contained in the time series of satellite data can be well explained as a combination of a small number of spatial patterns and their respective time dependent amplitudes. This feature allows reduction of the initial complexity of the problem. In a second phase, each amplitude function of the most relevant patterns, a time series, is analyzed to determine and extract the deterministic part of its variability. Then, each amplitude function is forecast using a nonlinear time series predictor based on artificial intelligence resulting in forecast values of each amplitude function corresponding to the most representative spatial patterns. The total forecast is obtained by adding the dominant spatial patterns previously multiplied by their predicted amplitudes. SOFT provides not only forecasts of future ocean states but also identifies and extracts that part of the ocean variability that can be predicted. Although at an early stage of development, SOFT is able to provide reliable SST predictions and rough mean surface currents estimations months in advance. It is hoped that further development can convert the SOFT prediction system into an important tool in the Rapid Environmental Assessment (REA) framework.

The report is organized as follows: the scientific core of SOFT is reviewed in Section II. It is not the aim of this section to provide an in-depth description of the different techniques constituting the SOFT prediction system, but to describe the key physical concepts underlying the method. Section III shows an application of the SOFT system to the region where the experiment GOATS2000 will be carried out. Section IV discusses the applications of the SOFT system to different areas of naval warfare. Future work is described in Section V.

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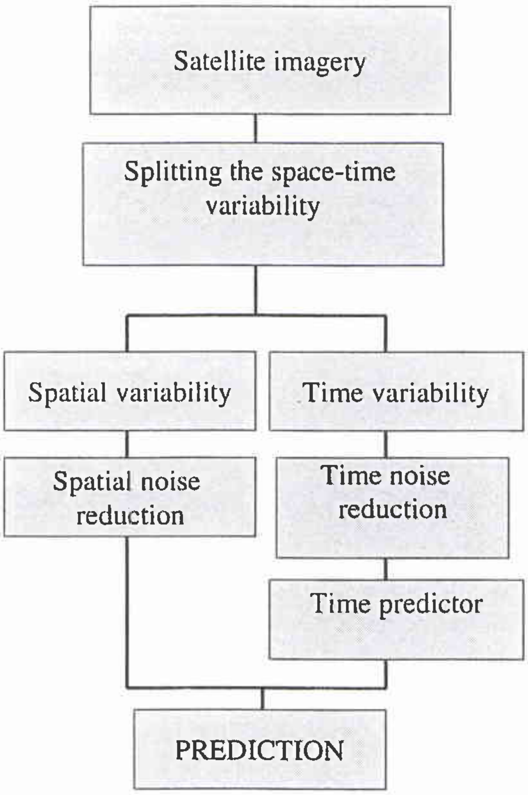
The satellite based ocean forecasting system (SOFT)

2.1 *Flow chart of the SOFT system*



2.2 *Splitting the satellite observed space-time variability*

Satellite images describing the state of the sea consist of thousands to millions of pixels representing the two-dimensional patterns observed. In principle, prediction of the observed fields would imply determination of the time evolution of each point. 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 [10]. This technique has been widely used in the analysis of advanced very high resolution radiometer (AVHRR) SST images to study the space-time variability associated with frontal, eddy, and jet structures in the ocean [11]. Essentially, 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 mode amplitude functions are obtained. The spatial modes provide information of the spatial structures while the amplitude functions describe their dynamics. If the dynamical laws governing the part of the ocean subject of study are known or modelled, one can obtain the evolution of each amplitude function. Conversely, the complete state of the system (i.e., the original sequence of satellite images) can be reconstructed by simple linear combination of the spatial modes multiplied by the amplitude functions. If only the N EOFs containing the highest temporal variances are used in the reconstruction process, the set of images resulting from the EOF procedure is still the best approximation one can obtain by linearly combining N arbitrary spatial patterns multiplied by N arbitrary amplitude functions.

Alternatively, EOF modes can be computed ranked by their spatial variance. In such an 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. This approach is more suitable to the extraction of small scale features [11].

2.3 *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 affects prediction performance as the predictor attempts to predict the noise (i.e., find a dynamical law of a random effect) at the expense of predicting the true underlying dependence. Filtering to isolate the deterministic signal in the data from stochastic noise, should be applied to the amplitude functions before attempting to predict future values of the amplitude functions. An adequate approach to remove noise without loosing a significant portion of the deterministic signal is the Singular Spectral Analysis (SSA) or data adaptive approach [12]. Briefly, for the j- amplitude function we form a trajectory matrix X the rows of which contain m-dimensional vectors of the form $(A_j(t-\Delta t), A_j(t-2\Delta t), ..., A_j(t-m\Delta t))$, $(A_j(t-2\Delta t), A_j(t-3\Delta t), ..., A_j(t-(m+1)\Delta t))$. The covariance matrix, $X^T X$ 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 m-dimensional vectors that constitutes the trajectory matrix. Ordering them according to size, the first eigenvector has the maximum possible projection, the second has the largest possible projection for any fixed vector orthogonal to the first and so on. 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 the noise. A new noise-free time series can be reconstructed considering only the eigenvectors eigenvalues of which are above the noise level.

2.4 The genetic algorithm for time series prediction

Once the EOF decomposition has been obtained and the deterministic part of the evolution of the amplitude functions isolated, the aim is to obtain the dynamical model that best represents the deterministic part of each mode amplitude function of the most representative EOFs and use them to predict the future state of the system.

Traditionally, the problem of finding a dynamical model from a time series of observations has been solved assuming that the time series is produced by a linear system excited by white Gaussian noise [13]. The variability observed in the time series is then assigned to the stochastic nature of the excitation, which can not be modelled. More recently, a new perspective to resolve this problem has been described [14]. Essentially, the time series is considered as the output of a deterministic, autonomous (i.e. without forcing) dynamical system. The complex variability of the time series is assigned to the nonlinear structure of the underlying dynamical system and not to the exogenous random excitation, as in the linear case. The potential usefulness of this approach to forecast the ocean is significant because many aspects of ocean evolution show a nonlinear nature.

The works of Takens [15], Casdagli [16], and others have established the methodology for forecasting time series from the evolution of nonlinear systems. Explicitly, Takens' theorem [15] establishes that given a deterministic time series $\{x(t_i)\}, t_i = 1 \cdots N$ there exists a smooth map $P : R^m \to R$ satisfying:

$$x(t) = P(x(t-\tau), x(t-2\tau), \cdots, x(t-m\tau)). \tag{1}$$

where m is called the embedding dimension obtained from a state-space reconstruction of the time series and τ is a time lag unit. During the past decade, various techniques have been developed to accomplish the task of approximating the mapping $P(\cdot)$ defined in Eq. (1). Examples of these techniques are methods based on polynomial fitting, neural networks and radial basis functions [14]. More recently, another functional search procedure based on Darwinian theories of natural selection and survival is surfacing [17]. The main advantages of these procedures, called evolutionary algorithms, is that very little data are sufficient to utilize this approach and as a byproduct, these algorithms can indicate the functional form that underlies the data [18]. These advantages make evolutionary algorithms excellent tools to attempt to forecast ocean evolution where relatively short time series are available. That the final result is given as an analytical functional expression gives this method of an interesting operational character.

In this study, we have adapted the approach developed in [18] for single-variable dynamical systems to spatially extended system [8]. The algorithm proceeds as follows, Figure 1: First, for the j- amplitude function a set of candidate equations (the population) for P is randomly generated. These equations (individuals) are of the form of Eq.(1) and their right hand sides are stored in the computer as sets of character strings that contain random sequences of the state variables $(A_j(t-\Delta t), A_j(t-2\Delta t), ..., A_j(t-m\Delta t))$, real numbers, and the four basic arithmetic symbols $(+,-,\times,$ and $/)$. A criterion that measures how well the equation strings perform on a training set of the data is defined as:

$$\Delta_i^2 = \sum_{t=L+1}^{T} \left(A_j(t) - P^i\left(A_j(t-\Delta t), A_j(t-2\Delta t), ..., A_j(t-m\Delta t)\right)\right)^2 \qquad (2)$$

where P^i represents de i-equation string of the population, $L = m\Delta t$ and T is the total length of the time series $A_j(t)$. 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. The prediction of the two-dimensional field is then achieved by adding the most relevant spatial EOFs previously multiplied by their corresponding forecasted amplitudes.

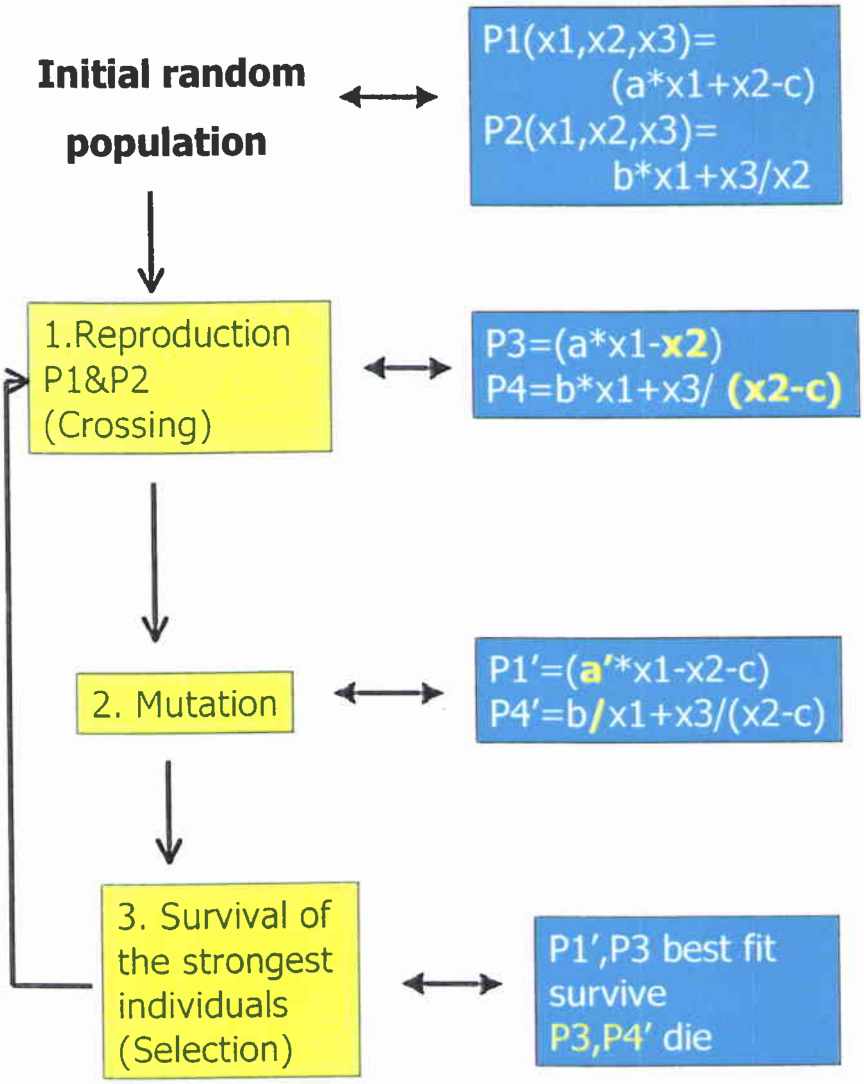


Figure 1 *Genetic algorithm flow chart*

3

SOFT applications

3.1 The GOATS 2000 experiment

The scope of the REA component GOATS 2000 experiment is to demonstrate the capabilities of AUVs as REA platforms for MCM in very shallow water. The experiment will take place in the Procchio Bay off the Island of Elba. A number of AUVs with REA sensors will be launched from R/V *Alliance*, from shore or from T-boat *Manning*. In order to support the different AUVs missions, a nested modeling and assimilation capability is added in a collaborative effort between Harvard University, University of Colorado and SACLANTCEN. A local circulation model will be nested whithin a model covering the Ligurian Sea and this within the NAVOCEANO Mediterranean Sea model. At all scales, the physical models will be coupled with biological and sediment models as appropriate.

As an example of current SOFT capabilities, we have applied the satellite based prediction system to study predictability at operational time scales of the oceanographic area involved in the GOATS 2000 experiment, in order to improve operational planning.

3.2 Review of the oceanographic conditions of the area of interest

The Island of Elba is located on the NW continental shelf of Italy. At this point, the continental shelf is relatively wide compared with its southern and northern profiles (65 km wide offshore the italian coast extending along 80 km in the NW direction). The boundaries of this oceanographic region are defined by the Tyrrhenian Sea to the south, the mainland to the east, the island of Corsica to the west and the Ligurian Sea to the north. Each of these boundary areas is characterized by well defined oceanographic and atmospheric processes that influence the oceanographic conditions and circulation patterns. It is of key relevance to determine the main forcing mechanisms acting on the surrounding seas and their degree of influence on the oceanographic area around the island of Elba. The importance of this information arises on establishing the oceanographic links of the region of interest with the circulation structures existing in the nearby ocean basins. The strength of these links would determine the role of the forcings associated with basin and local-scale phenomena on the circulation. Thus, the oceanographic conditions in the coastal waters surronding the island of Elba could be dependent on the large-scale circulations on the Ligurian and Tyrrhenian seas.

The Tyrrhenian Sea is surrounded by land masses resulting a shape of a triangle with the west coast of Italy as the hypotenuse and the right angle provided by the north-south line of the coasts of Corsica-Sardinia and the eastward extent of the northern Sicilian coast. The mountainous topographies of the surrounding land prevent the input of meteorological events that strongly influence conditions in other basins of the Western Mediterranean. These characteristics make the Tyrrhenian Sea the most isolated basin in the Western Mediterranean. The sea's openings to the outer Mediterranean occur at the Corsica Channel in the north, with a sill depth of 450 m and a broad south opening between Sardinia and Sicily. Two other small connections are the straits of Messina and Bonifacio which do not contribute significantly to the general basin circulation due to their limited cross-sections.

The basin scale circulation of the Tyrrhenian Sea is driven principally by the relationships of this sea with the neighbouring basins, principally with the Ligurian-Provencale basin. Of all the basins of the Western Mediterranean, the Tyrrhenian Sea is the region where the heat and water-vapour exchanges between the sea and atmosphere have the least intensity. However, the maximum air-sea interaction occurs at the neighbouring Ligurian-Provencale basin. This feature induces strong buoyancy fluxes between both basins. Specifically, an outflow of Tyrrhenian waters through the Corsica Channel is observed in the winter season when strong air-sea interaction processes occur in the Ligurian-Provenzal basin. This outflow involves the whole eastern boundary of the Tyrrenian Sea, and it is capable of driving seasonal intrusions of Modified Atlantic Water (MAW) from the Algerian current into the basin. This basin-scale circulation pattern is seasonally modulated, with a maximum signal in winter which is almost absent in summer.

Besides this large-scale circulation pattern induced by air-sea interactions, quasi-permanent mesoscale structures are present in the northern Tyrrhenian Sea. The most remarkable feature in the area is the existence of a cyclonic eddy off the Strait of Bonifacio [19]. This cyclonic gyre is associated with an anticyclonic one to the south. Most studies indicate that the origin of these two gyres is a direct consequence of the year-round jet of wind blowing eastward through the Bonifacio strait [20, 21, 22]. Both gyres undergo significant seasonal changes [23]. In summer, the cyclonic gyre is zonally oriented with possible intrusions on the corresponding shelf of the Italian and Corsican coasts. In winter, the gyre is streched in a meridian line in the western part of the basin. These variations are linked to the seasonal variability of the northward surface current flowing along the eastern boundary of the Tyrrhenian Sea.

The major large scale hydrodynamical feature in the Ligurian-Provencale basin is a well defined cyclonic circulation involving the surface layer of the MAW and the

Levantine Intermediate Water (LIW) below. It is fed by two principal currents, flowing northward along each side of northern Corsica: the Tyrrhenian current, which intrudes into the Ligurian-Provencale basin through the Corsica Channel, and the West Corsican Current. North of the Island, the two currents join together and flow westward along the coastal Ligurian-Provenzal region as far as the Gulf of Lion and the Catalan Sea.

The physical processes occurring at the location where both currents, the outflow of Tyrrhenian waters and the Western Corsican Current, converge are of special interest due to the geographical proximity to the Island of Elba. Observations [24] indicate that north of the Island of Corsica, the warmer water from the Tyrrhenian tends to flow onto the Tyrrhenian shelf off Livorno, whereas the West Corsican Current remains to the west, with the result that a thermal front separates them. The front is associated with meanders and small eddies, mainly anticyclonic, which induce smaller scaled parcels and frontal intrusion in the area. It seems that these eddy activities reside in this region throughout the year.

3.3 SOFT application to GOATS 2000: Results

In order to apply SOFT as a REA tool in the GOATS 2000 experiment, we have considered a time series of 82 monthly averaged SST images of the area of interest, from March 1993 to December 1999. Each monthly image is composed based on the daily maximum images using the average for every single pixel's position. The monthly composition normally consists of approximately 160 AVHRR passes. Several tests ensure that SST values are derived only for cloud free water surfaces. All pixels flagged as cloud are excluded from further processing. The data set is an AVHRR MCSST product from the German Aerospace Research Center-DLR. The monthly satellite images from March 1993 to December 1997, called training set, has been employed by SOFT to determine the dynamical laws governing this oceanographic area and the prediction functions. Validation of the SOFT prediction system has been carried out using the satellite data from January 1998 to December 1999, the validation set. Specifically, the predictive relations found by SOFT in the training set (March 1993-December 1997) are employed to obtain one-month ahead predictions of the mean SST and surface current fields in the validation set (January 1998-December 1999). During this period, predictions are validated with the corresponding real observations.

3.3.1 Forecast SST

One-month ahead predictions were validated during the years 1998 and 1999. It is important to notice that the satellite data collected during these two years was not

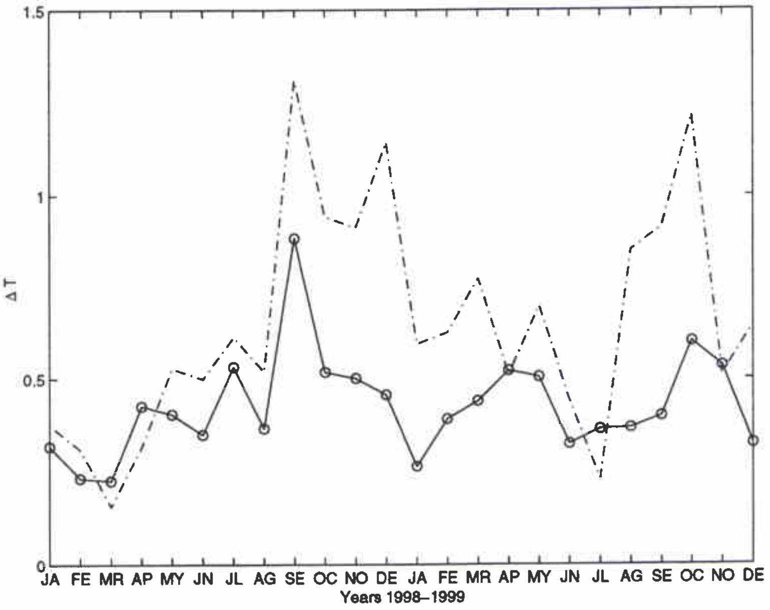


Figure 2 *Forecast skill on one month ahead predictions obtained with SOFT (solid line with circles) and climatology (dashed-dotted line) during 1998-1999.*

used with the SOFT system to extract the dynamical laws employed to carry out the predictions. A measure of the accuracy of the forecasts is given by:

$$\Delta T = \sqrt{\frac{\sum_i \sum_j (\psi_O(i,j) - \psi_F(i,j))^2}{N}} \tag{3}$$

where N is the number of sea pixels and $\psi_O(i,j)$ and $\psi_F(i,j)$ are the observed and predicted SST fields, respectively. Figure 2 shows the monthly values of ΔT obtained in the validation data set. For comparison, the deviation of the observed field from the monthly climatology, obtained by time-averaging the monthly fields of different years, is also plotted in Figure 2. Results indicate that during the validation period, SOFT provides in general better estimations of the surface temperature than those obtained by the climatological fields. The performance of the system is better during late summer and autumn where the area shows maximum variability. The forecast skill of SOFT shows a seasonal cycle. This feature is confirmed in Figure 3 where the mean forecast skill of each month obtained from averaging the different monthly predictions in the training and validation sets is shown. Autumn is the season showing more time-space variability. This variability is induced by the oceanographic transition caracter of this season, where dynamical links between the Ligurian and Tyrrhenian seas start to develop. This is translated into a lower predictability of SOFT if compared with other seasons. However, it should be noticed that during

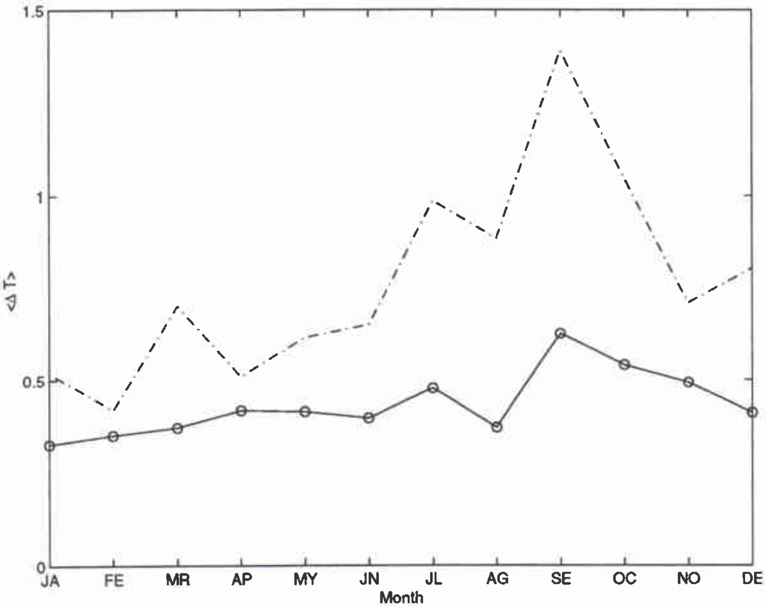


Figure 3 *Monthly average forecast skills obtained with SOFT (solid line with circles) and climatology (dashed-dotted line)*

summer and autumn SOFT highly improves the estimations obtained by climatology. At this point it is important to stress that the system is not only predicting seasonal changes, which account for a substantial amount of the time variability, but also spatial oceanographic features having more complex time variability than the purely seasonal cycle represented by the climatoligical fields. This has also been verified by the fact that up to five spatial EOFs and respective amplitude functions have been considered to obtain such accurate results. In this way, while seasonal variability is represented by the first EOF, the remainder describes different aspects of the space-time variability of the area. Figures 4-7 show the comparison between the satellite observed SST and the predicted fields obtained by the SOFT system during the year 1999. It can be inferred from these results that the prediction system not only addresses the seasonal temperature changes, which are dominant, but also includes oceanographic features characteristic of the area. In this way, the space-time variability coming from the Strait of Bonifacio as well as changes in the current front north of Corsica are well represented on the predictions.

3.3.2 Forecast geostrophic surface currents

Images of sea-surface temperature, derived from space-borne infrared sensors, have been used by several authors to obtain information on ocean circulation [25, 26, 27, 28]. One possible approach uses a simple model, based on the thermal wind equation, to quantitatively estimate the geostrophic current from the temperature gradients. If a linear surface T-S relationship together with a linear decreasing of the horizontal density gradient with depth are assumed, the geostrophic current at the sea surface is given by [27]:

$$[u, v] = \frac{g\,h}{2\,\rho\,f}\,(a + b\,\beta)\left[\frac{\partial T}{\partial y}, -\frac{\partial T}{\partial x}\right] \tag{4}$$

where g is the gravitational acceleration, $h = h(x, y)$ is the water depth, which may vary horizontally, f is the Coriolis parameter, ρ is the density of water, $a = -0.10\,\frac{Kg}{m^3\,C}$, $b = 0.79\,\frac{Kg}{m^3\,psu}$ and β $(\frac{psu}{C})$ is an empirical parameter obtained from an assumed linear T-S relationship. Notice that a linear approximation of the equation of state has been employed in Eq. (4). The geostrophic model Eq. (4) obviously oversimplifies the oceanographic conditions [29]. In addition, the model requires assumptions on parameters related to the temperature salinity relationship and the depth dependence of the density gradient. These assumptions are not justified unless proved by *in situ* measurements. Finally, it should also be pointed out that barotropic motions are not contained in Eq. (4). Despite all these model uncertainties, experimental findings suggest that with some *a priori* knowledge of the oceanographic area, SST data can supply quantitative information on the horizontal variability of surface currents in areas where geostrophically-balanced currents account for important portions of the mesoscale variability.

We proceed now to exemplify how ocean diagnostic methods based on satellite imagery can be employed to obtain information about future ocean states when applied to predicted satellite data. The diagnostic model Eq. (4) has been implemented into the SOFT prediction system to include predictions of the geostrophic surface currents. This task has been carried out by estimating for each month the parameter β, depending on the specific oceanographic conditions of each ocean area, by means of a robust linear fitting of the monthly averaged surface temperature and salinity obtained from the historical dataset MEDATLAS. Our results indicate that linear trends between surface temperature and salinity can be found in the northern Tyrrhenian sea except during spring and begining of autumn. Conversely, the simplified assumed depth-dependence of horizontal density gradients could not be validated with *in situ* data. This feature should be kept as a warning in the analysis of inferred surface velocities. Figures 10 to 12 shows the geostrophic currents predicted one month in advance by SOFT during the validation year 1999. Although current predictions can not be validated due to the absence of *in situ data*, results agree qualitatively and quantitantively with expected geostrophic circulations in the different seasons obtained from historical data [19].

3.3.3 *Concluding remarks for GOATS 2000*

Several remarks should be pointed out based on the results obtained by SOFT concerning the predictability of the coastal area of the island of Elba and surrounding oceanographic regions:

a) The predictability of the oceanographic conditions of the area is strongly influenced by the dynamical links between the Ligurian and Tyrrhenian seas. Specifically, the lowest predictability is found in September corresponding to the highest space-time variability. At this month, SOFT provides a substantially better SST estimation than that obtained from climatology.

b) Satellite data indicates that the shelf area of Elba behaves like a semienclosed sea with no influence of open sea processes. This is in agreement with historical studies. In consequence, the circulation on the shelf is mostly determined by rather local processes.

c) The northern boundary of the shelf where the Tyrrhenian outflow converges with the Western Corsican Current is characterized by complicated eddy fields and ageostrophic motions. Satellite based estimations of surface speeds are not accurate in this area.

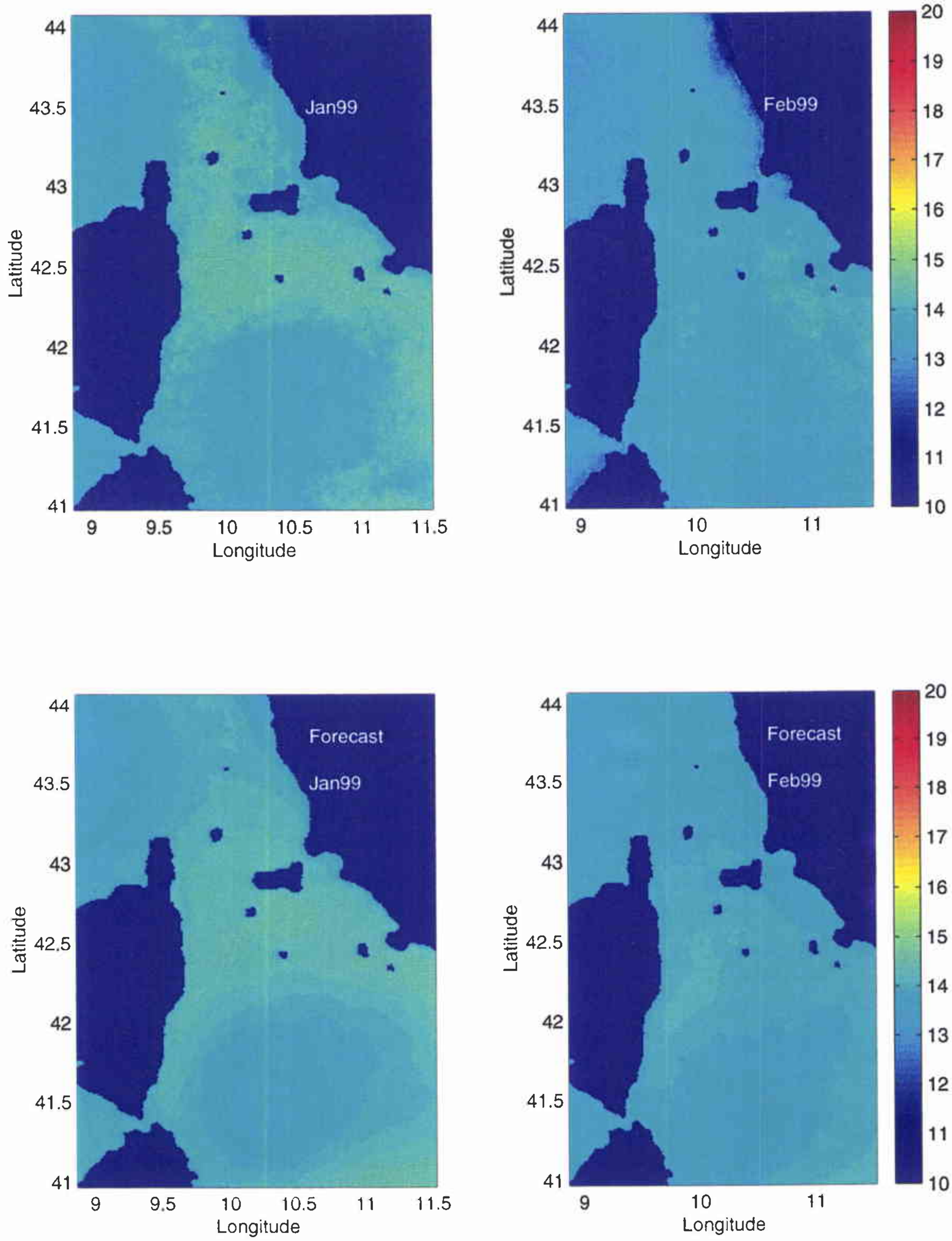


Figure 4 *SST observed fields versus one month ahead predictions for January and February 1999*

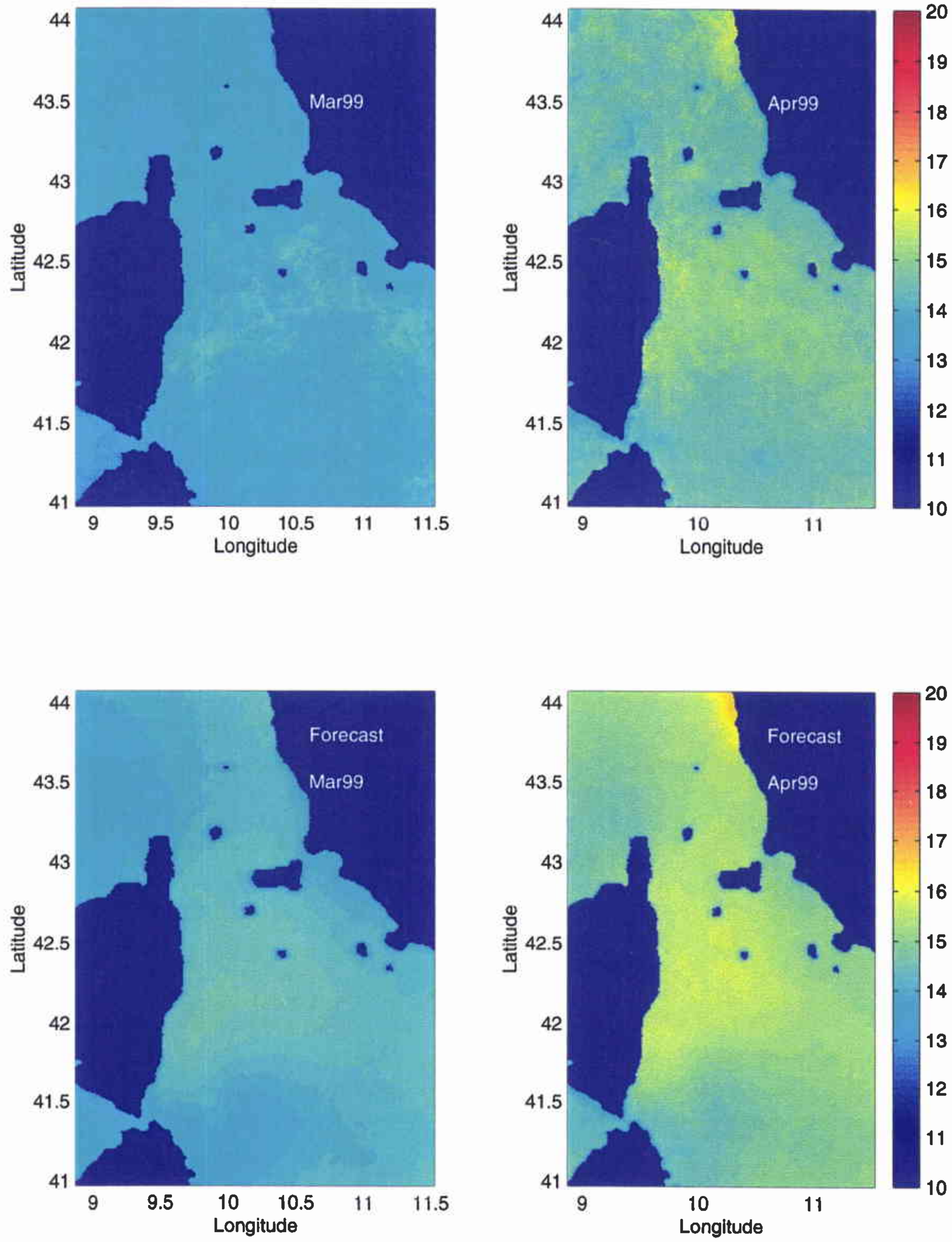


Figure 5 *SST observed fields versus one month ahead predictions for March and April 1999*

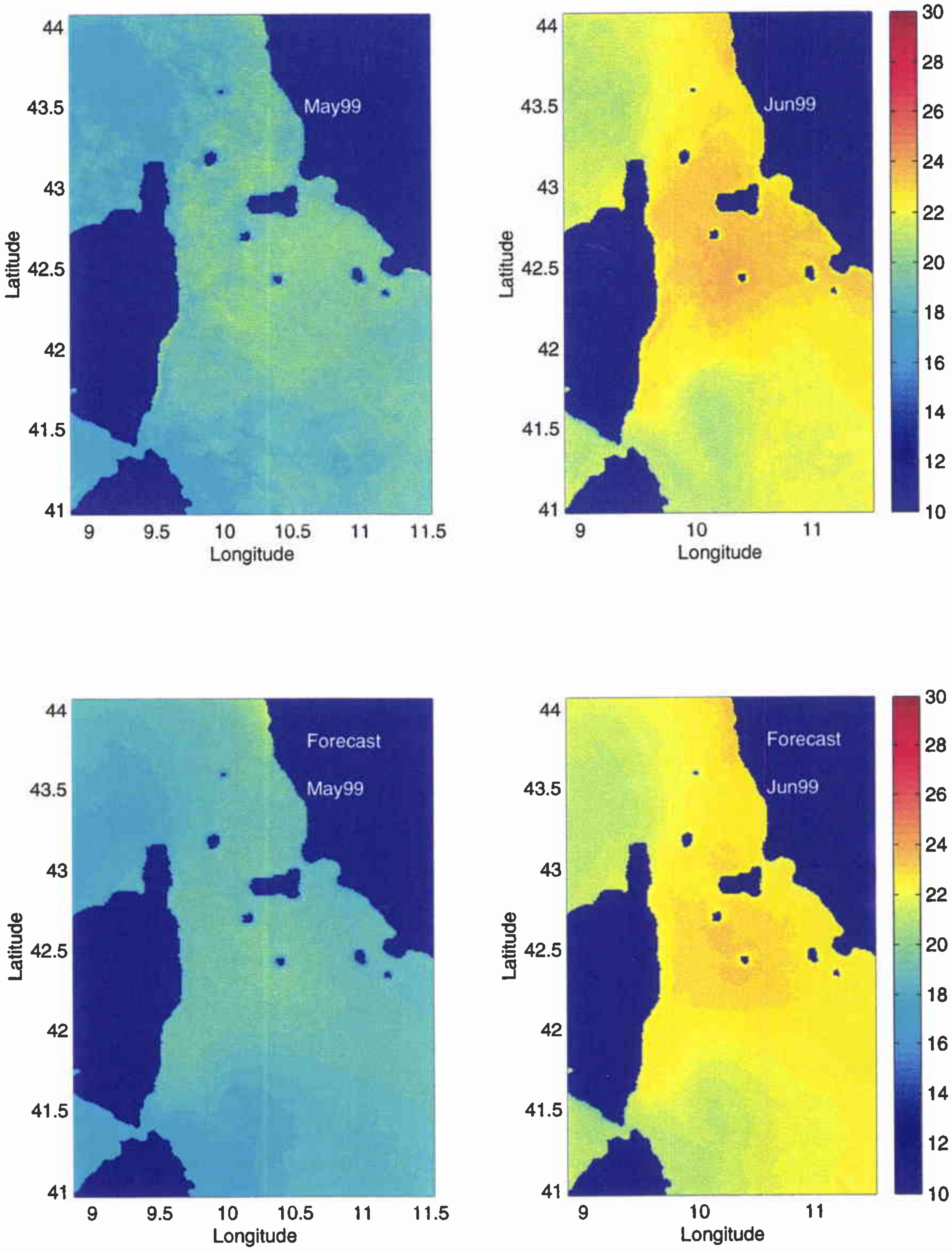


Figure 6 *SST observed fields versus one month ahead predictions for May and June 1999*

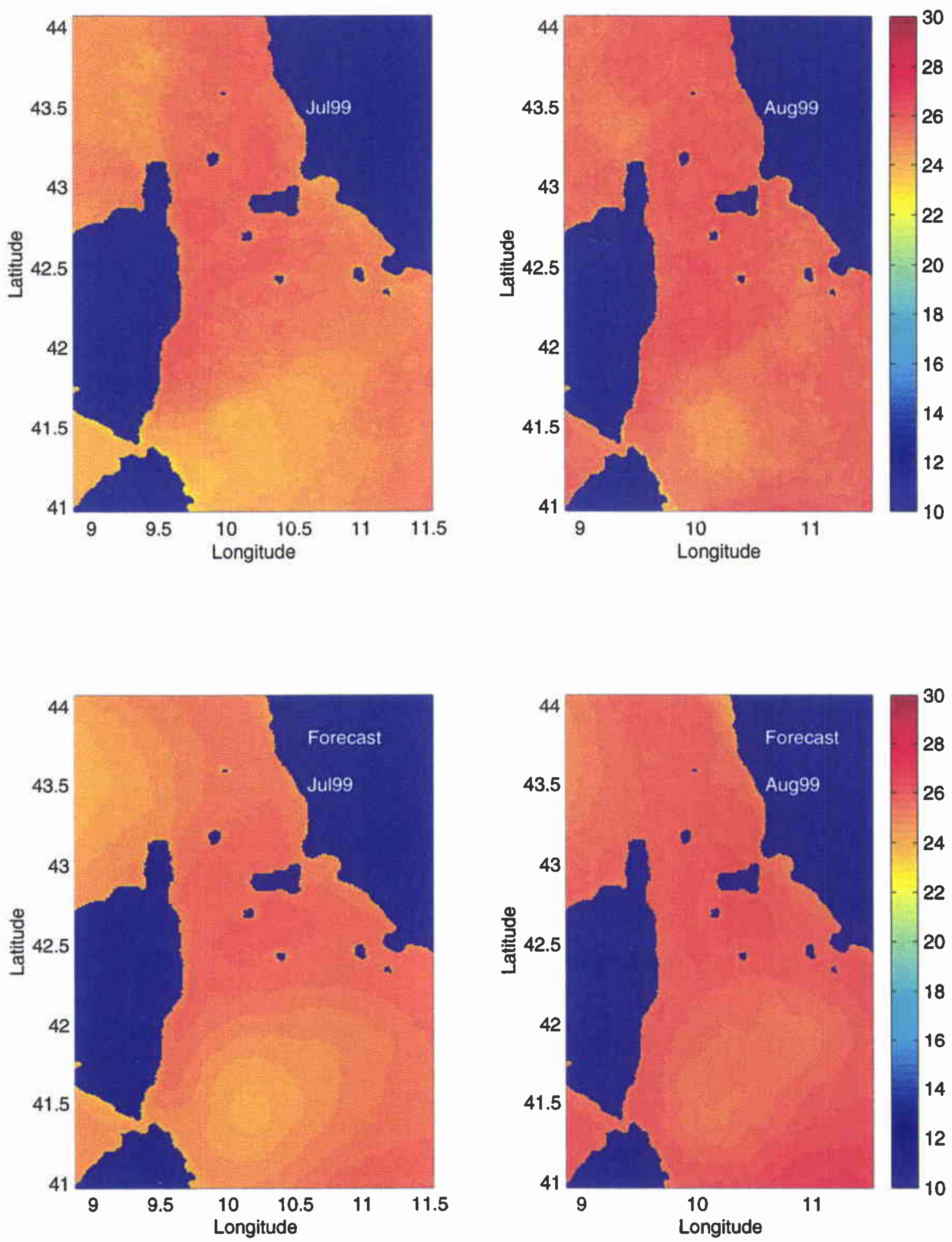


Figure 7 *SST observed fields versus one month ahead predictions for July and August 1999*

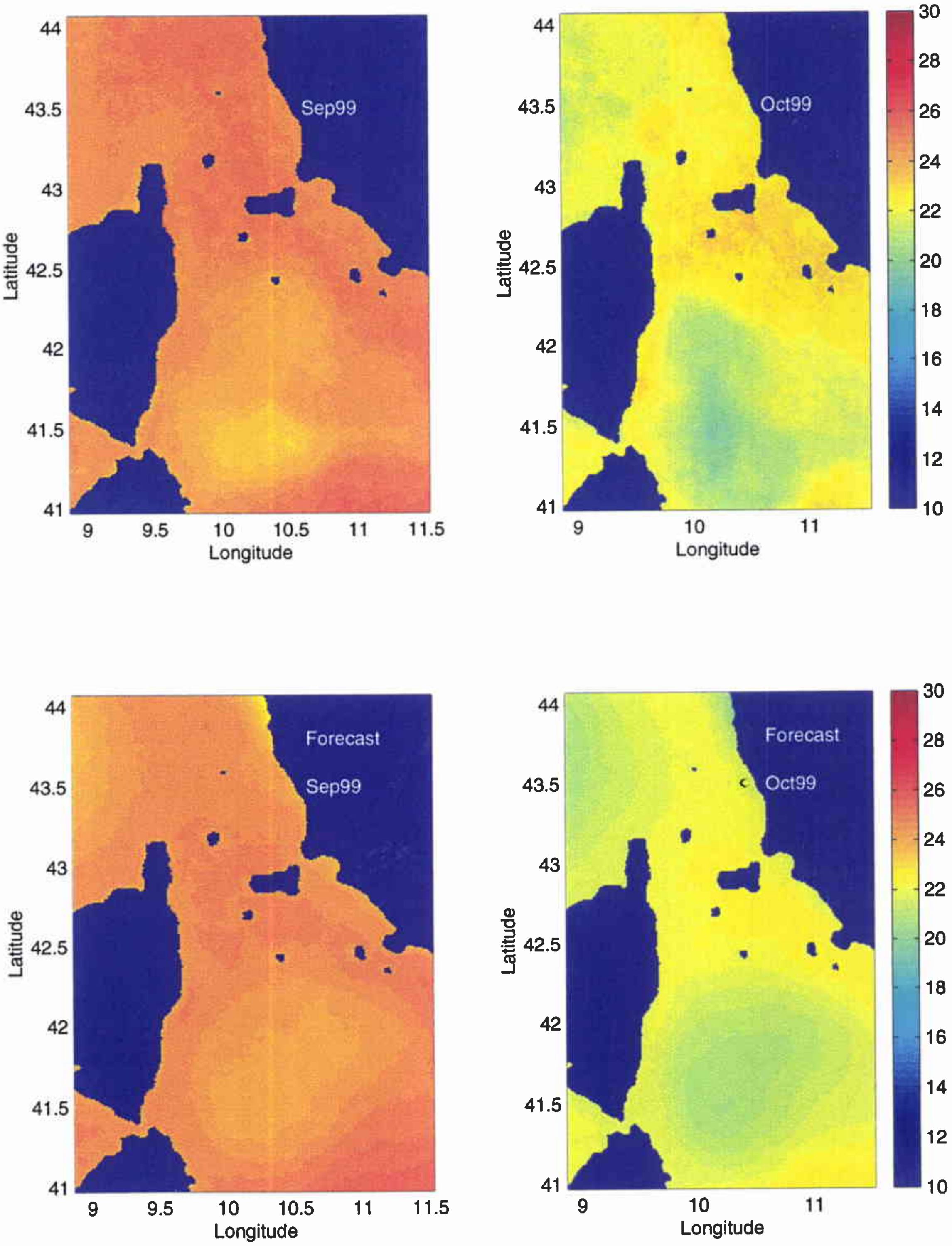


Figure 8 *SST observed fields versus one month ahead predictions for September and October 1999*

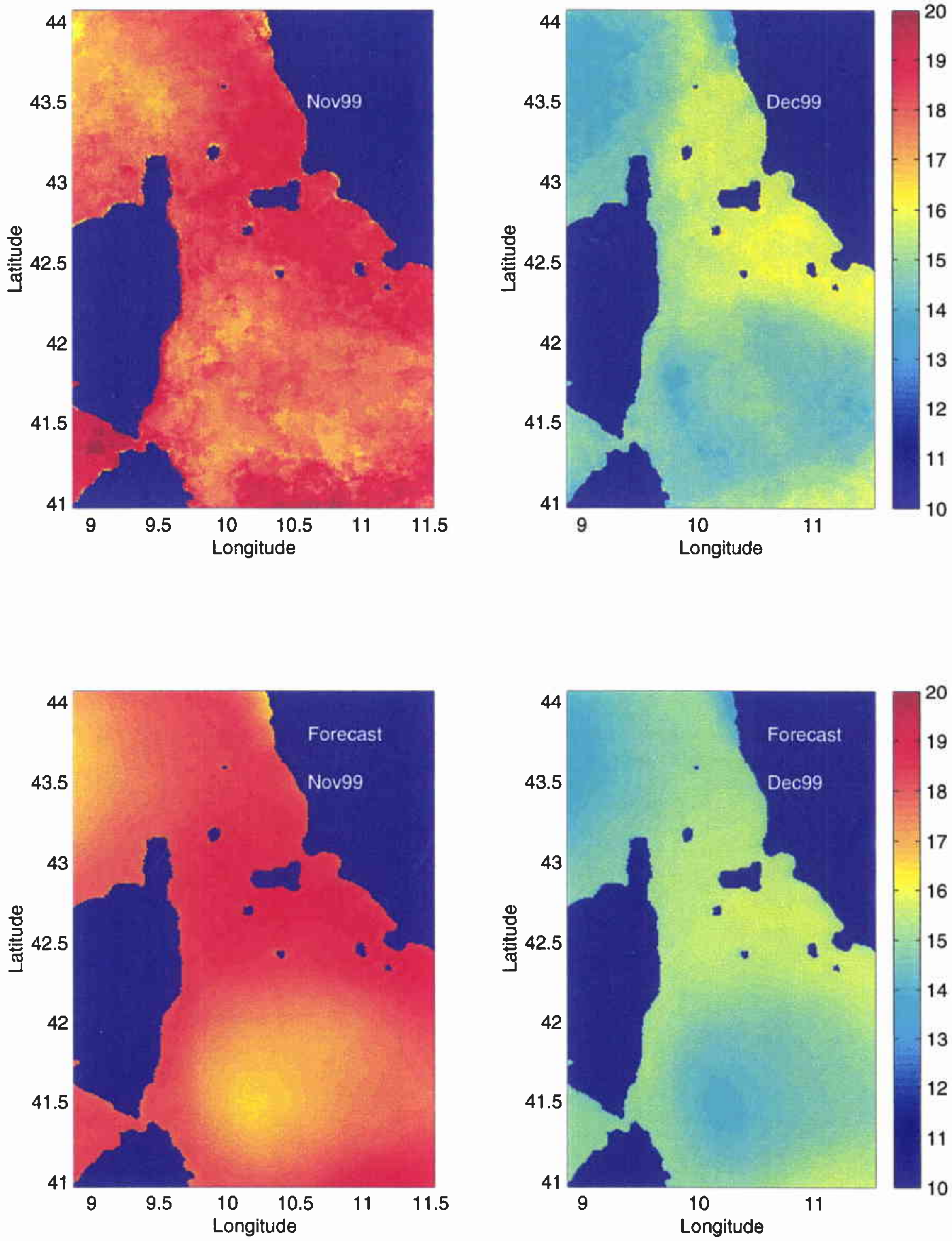


Figure 9 *SST observed fields versus one month ahead predictions for November and December 1999*

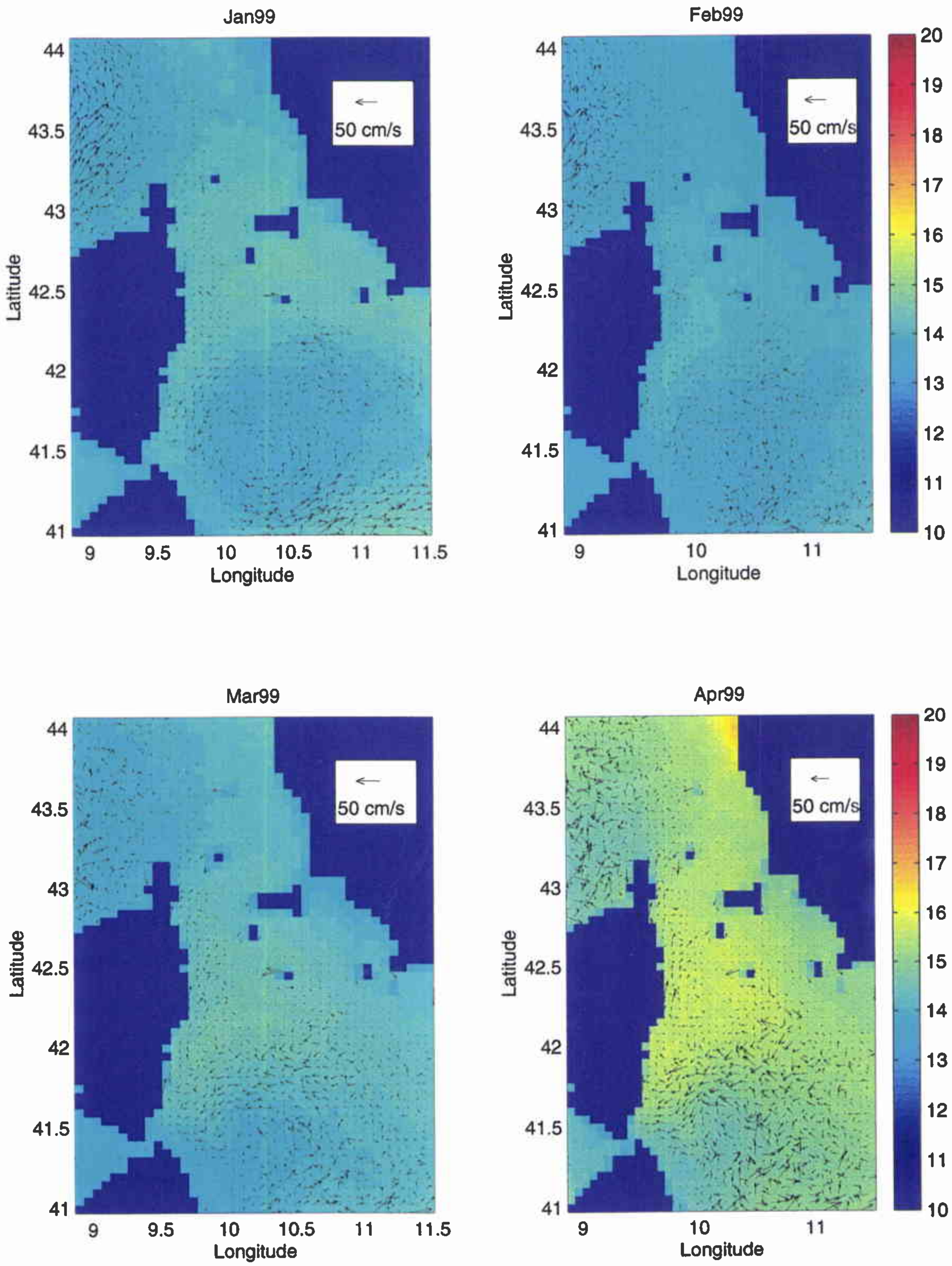


Figure 10 *One month ahead predictions of surface geostrophic velocity fields at surface for January, February, March and April 1999 superimposed on predicted SST*

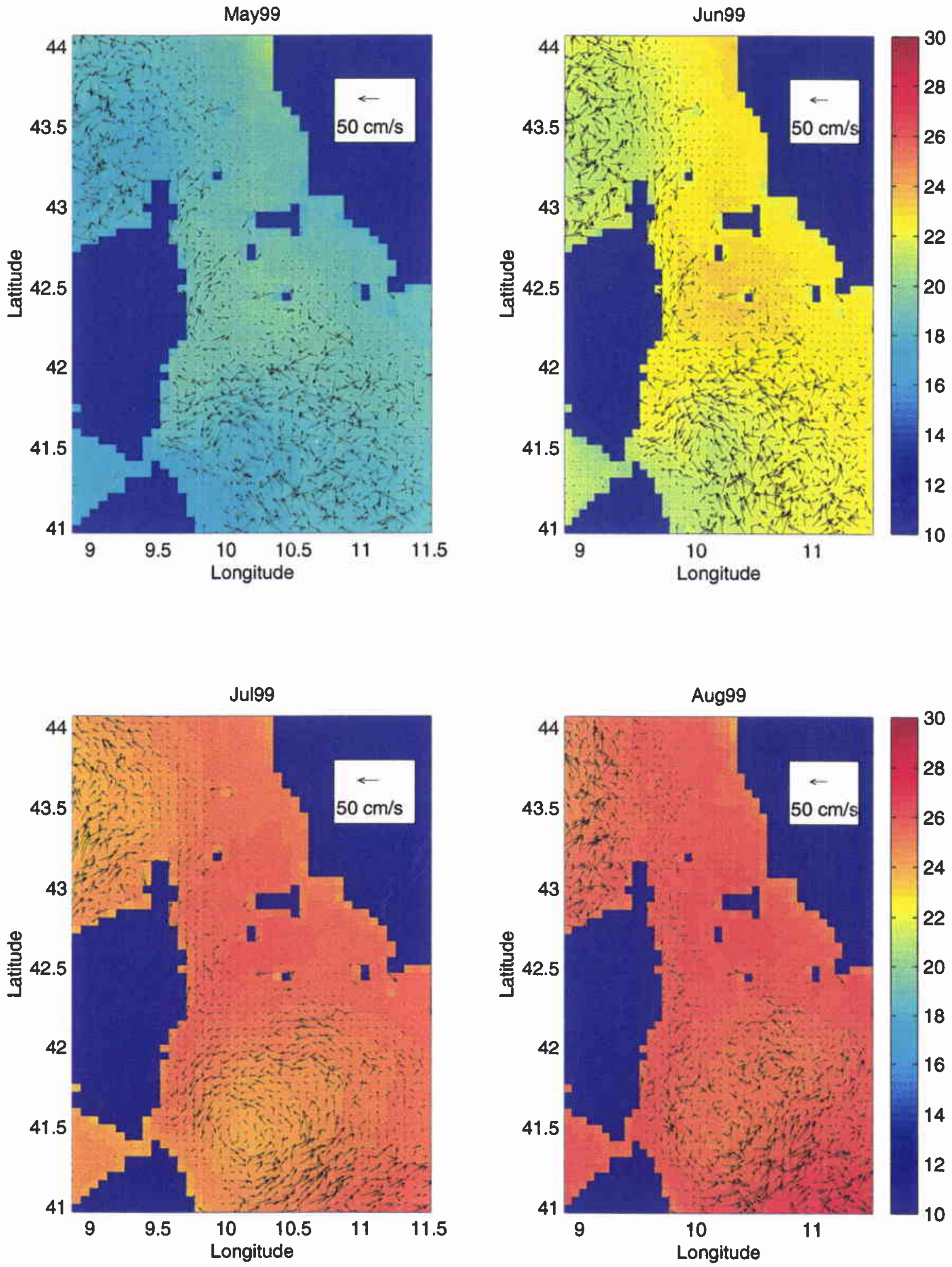


Figure 11 *One month ahead predictions of surface geostrophic velocity fields at surface for May, June, July and August 1999 superimposed on predicted SST*

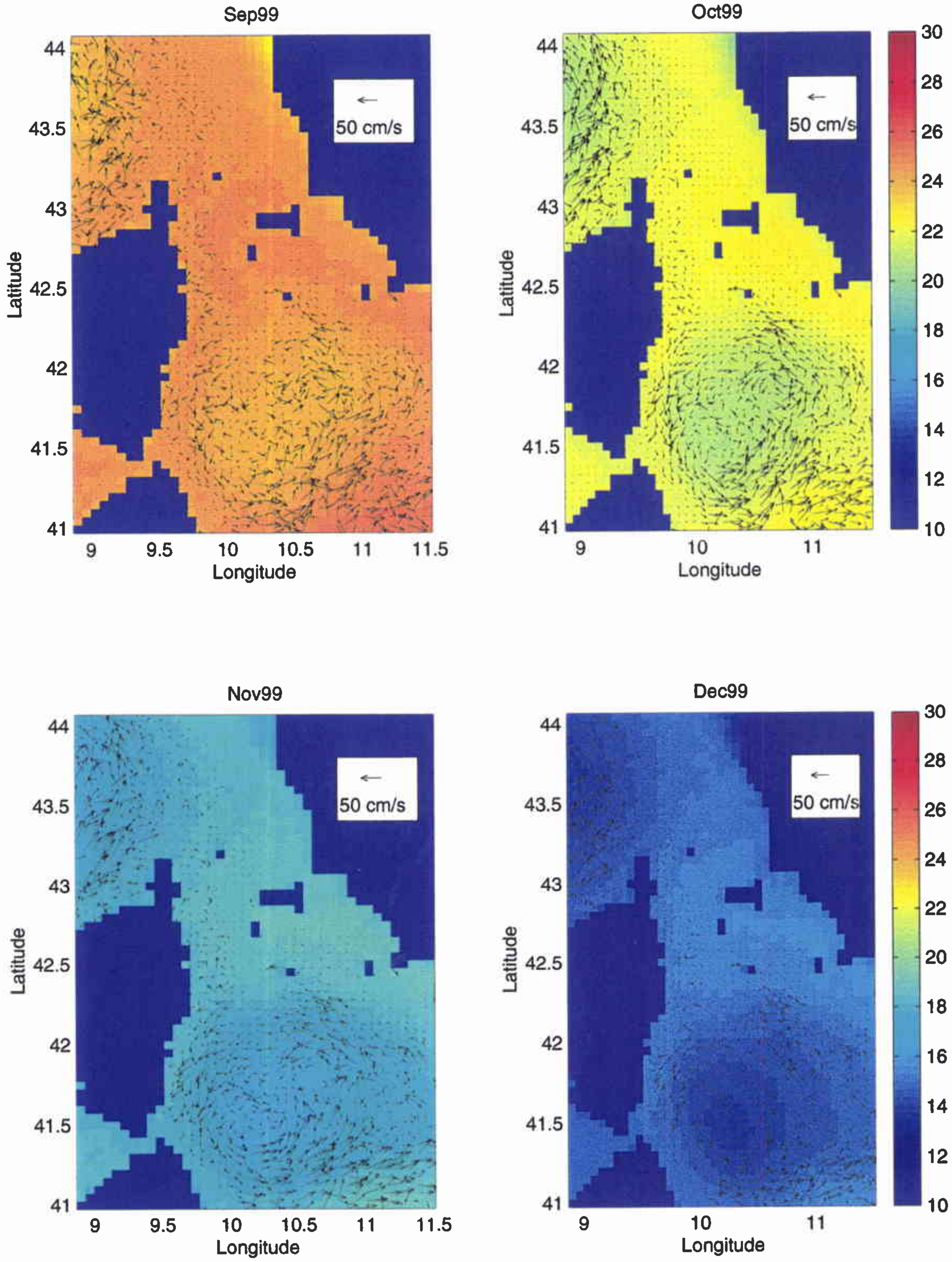


Figure 12 *One month ahead predictions of surface geostrophic velocity fields at surface for September, October, November and December 1999 superimposed on predicted SST*

4

Analysis of current and future operational applications of the SOFT system

The fact that the environment can strongly determine the dominance and shaping of the naval battlespace has resulted in increasing attention towards different methodologies and systems to obtain reliable diagnostics and prognostics of oceanographic conditions in order to plan or execute a naval operations. Efforts have been recently devoted to the generation of intelligent ocean observing platforms able to provide quietly the required oceanographic information. Satellites have become an important tool to diagnose environmental conditions during a crisis situation, as such systems are relatively inexpensive, cover a large area and certainly represent a discreet and secure observing system.

A substantial improvement of military satellite support would be possible if oceanographic conditions could be forecast from satellite information. This task can be accomplished by considering recent developments in different scientific areas. In the previous sections, a methodology to achieve such satellite based ocean forecasts, SOFT, has been proposed and examples of its applicability provided. It remains, to analyse the potential of this prediction system as a REA element in a crisis situation.

As SOFT is undergoing development, the range of applicability to naval support is limited. Predicted information is restricted to SST fields and derived magnitudes. These forecasts have already a basic application to military purposes. For example, the predicted SST field can be employed to resolve the ocean-atmosphere boundary layer in atmospheric ocean models, while velocity estimations can provide an indication of convergence areas of drifting mines in MCM warfare. As a first step to expand present capabilities, research is foccussing on developing a SOFT module to predict volumetric sound speed conditions for some areas of the Mediterranean Sea with strategic interest. If successful, SOFT will be able to provide satellite based forecasts of the horizontal and vertical structure of the sound speed providing estimations of sonar performance and submarine detection risk in the selected areas.

While the space-time scale variability involved in open sea ASW is well resolved by the actual forecasting system, satellite based prediction of litoral ocean conditions would require the employment of novel predicting techniques. Specifically, coastal areas are characterized by strong time variability. The possibility to carry out satellite based mean daily predictions is under study. The application of SOFT to coastal areas would help to estimate future values of the oceanographic conditions influencing mine warfare operations. These oceanographic factors are the temperature/salinity profile, water clarity, tides, currents, sea state, upwelling and biological conditions. It is not realistic to think that all the above mentioned conditions can be forecasted on the basis of satellite information. Among them, temperature/salinity profile, sea state, upwelling and biologist could be forecasted from satellite information. However, the development of hybrid prediction systems composed of ocean numerical models that include information forecast by the SOFT system has distinct potential which will be the subject of future reports.

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Title

A satellite based ocean forecasting system to support naval operations in crisis situations.

Abstract

We employ a nonlinear ocean forecasting technique based on a combination of genetic algorithms and empirical orthogonal function (EOF) analysis. The method is used to forecast the space-time variability of the sea surface temperature (SST) of the ocean area around the Island of Elba. The genetic algorithm identifies the equations that best describe the behaviour of the different temporal amplitude functions in the EOF decomposition and therefore, enables global forecasting of future time-variability.

Keywords

Satellite remote sensing – satellite based ocean forecasting – genetic algorithms

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