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ABSTRACT

A reduced-order Kalman filter is used to assimilate observed fields of the surface wind stress, sea surface temperature, and sea level into the coupled ocean–atmosphere model of Zebiak and Cane. The method projects the Kalman filter equations onto a subspace defined by the eigenvalue decomposition of the error forecast matrix, allowing its application to high-dimensional systems.

The Zebiak and Cane model couples a linear, reduced-gravity ocean model with a single, vertical-mode atmospheric model. The compatibility between the simplified physics of the model and each observed variable is studied separately and together. The results show the ability of the empirical orthogonal functions (EOFs) of the model to represent the simultaneous value of the wind stress, SST, and sea level, when the fields are limited to the latitude band 10°S–10°N, and when the number of EOFs is greater than the number of statistically significant modes.

In this first application of the Kalman filter to a coupled ocean–atmosphere prediction model, the sea level fields are assimilated in terms of the Kelvin and Rossby modes of the thermocline depth anomaly. An estimation of the error of these modes is derived from the projection of an estimation of the sea level error over such modes.

The ability of the method to reconstruct the state of the equatorial Pacific and to predict its time evolution is shown. The method is quite robust for predictions up to 6 months, and able to predict the onset of the 1997 warm event 15 months before its occurrence.

1. Introduction

The prediction of the El Niño–Southern Oscillation (ENSO), and its relation with global climate anomalies, is one of the major research efforts in short-term climate forecasting. Seasonal-to-interannual climate predictions are currently performed using statistical models (Graham et al. 1987; Barnett et al. 1988; Xu and von Storch, 1990); coupled ocean–atmospheric models (Zebiak and Cane 1987; Battisti 1988; Chen et al. 1995; Latif et al. 1993; Kirtman et al. 1997; Rosati et al. 1997); and hybrid models coupling a dynamical ocean model with a statistical atmosphere model (Latif and Flügel 1991; Barnett et al. 1993).

In the case of statistical prediction models, a set of inputs (predictors) is used to compute the temporal evolution of a given quantity (predictand). A different approach is allowed by coupled ocean–atmosphere models, for which deterministic predictions are associated with a given initial state. Dynamical predictions of ENSO have been supported by a large hierarchy of models, ranging from one-layer, reduced-gravity models (Zebiak and Cane 1987; Battisti 1988) to general circulation models (Latif et al. 1993; Kirtman et al. 1997; Rosati et al. 1997). The success of simple models is related with the spatial scales (roughly the whole equatorial Pacific Ocean), and temporal scales (3–4 yr) characteristics of ENSO. For such scales, the memory of the system lies in the ocean, which can be described as
a layer of warm water separated from a mass of cool, deep, nearly motionless water by a sharp pycnocline. It has been found that large-scale, low-frequency dynamics of such a configuration may be reproduced by reduced-gravity models (Neelin et al. 1994).

Although sophisticated coupled models have the potential to provide the most reliable interannual forecasts, their prediction skill during the period 1986–93 has been similar to the one of the other methods (Barnston et al. 1999). For that period, the correlation skill of 6-month predictions was around 0.6. Nonetheless, all prediction schemes failed to prognosticate the strength of the 1997–98 event (Barnston et al. 1999). Such a general failure has been related to the impact of intraseasonal oscillations, seen as a random noise in interannual prediction models (McPhaden 1999), changes in the climatology of the Pacific Ocean (Trenberth and Hoar 1997), errors in the initial state of coupled models (Chen et al. 1998, 1999), or the choice of predictors in statistical models (Xue et al. 2000).

The similarity in the performance between statistical and dynamical models indicates that dynamical predictions are far from reaching their full potential. One possible limitation of dynamical forecasts is the presence of errors in initial conditions (Latif et al. 1998). The presence of these errors may be related to the observational error, the compatibility between the model and the observations, and the data assimilation method used. An illustrative example of the impact of initialization on prediction skill is the case of the Zebiak and Cane model (Zebiak and Cane 1987, hereafter ZC), a nonlinear, coupled model of intermediate complexity, used in real-time ENSO forecasts (Latif et al. 1998).

In the first application of the ZC model for ENSO predictions (Cane et al. 1986), the ocean component was forced by observed wind stresses starting in January 1964 and ending at the time when the forecast began. Next, the resulting sea surface temperature (SST) was used to force the atmospheric component. Then, final ocean and atmosphere states were used as initial conditions for the coupled model. Using this method, the initial conditions of the SST and the winds are assumed to be in accord with the thermocline depth but not necessarily with their actual observed values (Cane et al. 1986).

A coupled initialization scheme was developed by Chen et al. (1995). In their procedure, hereafter called LDEO2, the wind stress of the coupled model is nudged toward The Florida State University (FSU) wind stress during the initialization of the model. This approach reduces both the error of the initial condition, and some of the small-scale, high-frequency modes appearing when the ocean component is forced by observed wind stress (Chen et al. 1995). As a result, the skill of the ENSO forecasts was increased, and this method has been used to perform operational ENSO forecasts. However, the method failed to predict the 1997–98 ENSO event, showing the need for further improvements.

As the LDEO2 initialization scheme relied only on wind observations, two alternative approaches to correct the 1997 failure were investigated. In one, the quality of the wind stress data was questioned by assimilating National Aeronautics and Space Administration (NASA) scatterometer winds (Chen et al. 1999). In the other, wind stresses were assimilated simultaneously with sea level (Chen et al. 1998), using a scheme known as LDEO3. Both approaches had a positive impact on the prediction of the 1997–98 event. Their successes have been explained as the correction of FSU wind errors in the eastern tropical Pacific. In that region, due to substantial data gaps, erroneously intense easterlies enhanced equatorial and coastal thermocline upwelling, and promoted an excessively cold SST field (Chen et al. 1999).

Following a similar vein, a new assimilation scheme is presented here. The method is based on the equations of the singular evolutive extended Kalman (SEEK) filter (Pham et al. 1998), a reduced-order simplification of the Kalman filter (Kalman and Bucy 1960). Similar to LDEO2 and LDEO3 approaches, this new approach is intended to transfer information from observations to all the components of the coupled system. On the other hand, the new scheme aims, as the LDEO3, to the simultaneous assimilation of different datasets in order to reduce the impact of data inaccuracies. However, there are various differences mainly related to fundamental differences between nudging and Kalman filter. For example, here we take advantage of the covariability between SST, surface wind stress, and sea level in the context of the coupled model. Moreover, with the Kalman filter, model equations are not modified, and assimilation is done in an intermittent way every time data is available. On the other hand Kalman filter allows a straightforward assimilation of any field related to a model solution by the observational operator H (which, for simplicity is considered linear through all this work). Finally, the relative weights between different observations may be directly expressed in terms of the respective observational error.

The paper is organized as follows. The data and estimated observational errors used in this study are presented in section 2. Section 3 presents a brief review of the ZC model and the multivariate EOF basis used to reduce the degrees of freedom of the assimilation method. The compatibility between the data and the model is presented in section 4. The assimilation method, and experiments are presented in sections 5 and 6, respectively. Finally, a summary and concluding discussion are given in section 7.

2. Data and error estimates

a. FSU winds

Wind fields used here come from the monthly pseudostress analysis from merchant ship observations pro-
vided by The Florida State University (Stricherz et al. 1992). Research quality pseudostresses are available until 1997. Pseudostresses for 1998 are obtained from the quick-look product. Following Stricherz et al. (1992), a drag coefficient $C_D = 1.6 \times 10^{-3}$ is used to compute the wind stresses. Long-term trend is removed, and anomalies are smoothed with a 1–2–1 filter in latitude, longitude, and time as in Zebiak (1989).

An estimate of the wind stress error is determined as follows. Mean wind speed over the tropical Pacific is approximately 7 m s$^{-1}$, or 49 m$^2$ s$^{-2}$ in pseudostress units (Shriver and O’Brien 1995). The error in moored-buoys anemometers is approximately 10%. The error associated with estimates of wind speed and direction is larger than that. Therefore, an optimistic measure of the error of wind pseudostress can be given as 10% of the mean value, that is, 4.9 m$^2$ s$^{-2}$ = 0.094 dyn cm$^{-2}$.

b. Reynolds SST

Maps of the SST from November 1981 to December 1998 are derived from the optimum interpolated SST analysis of Reynolds and Smith (1994). Anomaly fields are constructed from the monthly mean field of the Reynolds fields during November 1961 and December 1996. A 1–2–1 filter in latitude, longitude, and time is applied to the anomaly fields.

McPhaden et al. (1998) have verified the accuracy of the optimum interpolation SST analysis of Reynolds and Smith (1994) using independent data. They compute the root mean square (rms) between monthly analyzed fields and in situ Tropical Ocean and Global Atmosphere–Tropical Atmosphere–Ocean (TAO) moorings at the equator at three different locations (110°W, 140°W, and 165°E). The rms was computed from January 1982 to January 1993. The mean rms differences at each location are 0.38°C, 0.39°C, and 0.24°C, respectively. The SST anomaly error used here is obtained as the mean of these three values, that is, 0.34°C.

c. TOPEX/Poseidon altimetry

Monthly anomalies of the sea level are derived from the TOPEX/Poseidon (T/P) sea level fields (Busalacchi et al. 1994). The long-term surface topography anomaly maps are used to construct monthly mean maps from January 1993 to December 1996. Next, the reduced-gravity relation between thermocline depth and sea level is used to infer the thermocline depth.

As the ZC model projects dynamical equations onto the equatorial modes, the thermocline depth is also projected onto the equatorial Kelvin and Rossby modes using the method described in Boulanger and Menkes (1995). The Rossby component is constructed as a sum of different Rossby modes. This decomposition has the advantage of expressing sea level information in terms of prognostic variables of the model, diminishing the possible impact of the incompatibilities between the observations and the simplified physics of the model. This decomposition is also similar to the two-steps scheme associated with LDEO3 initialization: first, sea level is assimilated into the wind-driven ocean component of the model using a reduced-order Kalman filter (Cane et al. 1996); second, the coupled ocean–atmosphere model is relaxed toward wind stress observations, and Kelvin and Rossby solutions obtained in the first step.

Cross correlation between T/P altimeter data and dynamical topography fields from TAO data show rms differences of 4 cm in the equatorial region, but higher values off the equator (Busalacchi et al. 1994). Smaller error measures have been reported on monthly and longer timescales, but a value of 4 cm will be used here, corresponding to an error of 7 m for the thermocline depth. Equipartition of thermocline error into Kelvin and Rossby mode errors is done by assuming that the confidence of the decomposition algorithm is similar for both waves. This is not really true because of the fact that high Rossby modes have their maximum off the equator, where the reduced-gravity approximation is less accurate. Thus, our hypothesis is valid only as well as the reduced-gravity approximation is valid. Furthermore, assuming that errors of Kelvin and Rossby modes have zero mean and are uncorrelated, the error variance can be described as

$$\langle \varepsilon^2_n \rangle = \langle a_n^2 \psi^2_k (y) \rangle + \sum_n \langle a_n^2 \psi^2_n (y) \rangle$$

because of the following relations:

$$\langle a_n \rangle = \langle a_n \rangle = 0, \quad n = 1, \ldots$$

$$\langle a_n a_m \rangle = \langle a_n a_m \rangle = 0 \quad n \neq m,$$

where $\psi_k (y)$ is the meridional structure of the Kelvin wave, $\psi_n (y)$ the meridional structure of the $n$th Rossby wave, and $a_k$ and $a_n$ are the amplitudes of these modes.

The algorithm of Boulanger and Menkes (1995) is used to solve equation (1). The left-hand-side term is now a constant for all latitudes. A minimum of eight Rossby modes has to be used for a reasonable reconstruction of such a constant function over the latitude band of (10°S–10°N). The error associated with the Kelvin coefficient is obtained directly by this procedure. The error of the Rossby component is obtained by the longitudinal average of the second term on the right-hand side. Figure 1 shows the errors of the Kelvin amplitude coefficient (solid line), and the error of the Rossby field (dashed line). The error estimates converge as the number of Rossby modes increases. From the asymptotic limits, $\varepsilon_k = (\langle a_k^2 \rangle)^{1/2} = 12$ m, and $\varepsilon_n = 6$ m. Sensitivity to these values is examined later.

In this first application, the analysis period is limited to January 1993–December 1998, that is, the time period for which comprehensive and coincident fields of T/P sea level, wind stress, and SST observations are available for the model domain. The temporal evolution of the meridional average of the zonal wind stress, the
Kelvin amplitude, the first Rossby mode, and the SST anomalies are given in Fig. 2. Positive values of wind stress indicate westerly anomalies (weakening the Walker circulation in the equatorial Pacific). Positive values of the thermocline depth indicate downwelling, associated with an increase of SST in the east.

A cursory examination of plots in Fig. 2 reveals the basic characteristics of the equatorial Pacific dynamics, as the large-scale nature of the warm/cold oscillations. Also, the high correlation between SST and thermocline depth justifies the parameterization of vertical mixing in the SST equation of the ZC model. Finally, the correlation between westerly wind stress anomalies with the eastern sea surface temperature anomalies suggests how local SST changes are related to remote forcing.

During the period January 1993–May 1995, westerlies are present in the western Pacific extending periodically toward the central Pacific where the anomalous wind is easterly. These easterlies in the eastern side of the basin inhibit the propagation of the downwelling Kelvin waves generated by the central westerlies, limiting the warming of the eastern waters. After May 1995, easterlies are present over the entire equatorial Pacific,
indicating stronger trade winds. Under these conditions, an upwelling Kelvin wave excited in the central Pacific will be amplified during its eastward travel, causing a cooling of the equatorial SST. The maximum strength of the central trades is observed at the beginning of 1996. Then, the wind anomalies decrease and finally, reverse to westerlies. The amplitude of the westerlies increase rapidly and propagate eastward, amplifying the downwelling Kelvin waves during all of 1997, thereby warming the central and eastern Pacific water. As the downwelling Kelvin waves propagate into the eastern equatorial Pacific, an upwelling wave is present in the central Pacific since October 1997 preceding the termination of the warm event on December 1997. The origin of this upwelling Kelvin wave (generated by the reflection of Rossby waves at the western boundary and/or excited by the winds) is not provided by the plots in Fig. 2.

3. The model

The standard configuration of the ZC model is used here. The ocean domain is a rectangular basin limited by 30°S–30°N and 124°E–80°W. Details of the model equations can be found in Zebiak and Cane (1987) and Battisti (1988), so only a brief description of the model is given here.

The dynamical model is a single-layer, reduced-gravity, anomaly model on the equatorial β plane. The ocean model has been simplified to determine only a subclass of all the possible motions: the low-frequency, long zonal-scale equatorial Kelvin and Rossby waves forced by an anomalous surface wind stress (Cane and Patton 1984). The SST is calculated separately through a non-linear equation, including three-dimensional advection, and it does not have a direct feedback on the ocean dynamics. The atmospheric model is based on the steady-state, linear model of a thermally forced tropical atmosphere (limited to a single vertical mode) of Gill (1980). The forcing of the atmosphere is given by a local heating depending on the SST, and a second term dependent on the wind convergence (Zebiak 1986).

The time step of the ocean model is 10 days. As the atmospheric model gives the steady-state solution associated with each SST field, the atmosphere adjusts too rapidly to the ocean changes. To avoid this, the ZC model allows a time dependency of the moisture term of the atmospheric heating. However, this procedure allows the development of small-scale anomalies that may persist and become completely unrelated to subsequent SST fields (Zebiak and Cane 1987). It has been shown that the method used to filter out these unrealistic anomalies modify the behavior of the model. Zebiak and Cane (1987) recalculated the atmospheric anomalies when temperature anomalies (given by SST anomalies averaged over the eastern equatorial Pacific Niño-3 region—5°S–5°N, and 90°–150°W) were small. This procedure favored a period of the warm events close to 4 yr.

In spite of the success of the model to simulate and predict the evolution of the Niño-3 index, the prediction skill of the model can be seriously affected by its simplicity: the lack of any variability generated at the mid-latitudes, the absence of the 30–60-day waves (as said before, interseasonal variability plays a role of stochastic forcing on interannual variability), the coarse resolution of the model distorting the simulation of coastal upwelling processes in the eastern Pacific, and the simplified relation between the atmospheric heating and SST (Zebiak 1986; Dewitte and Perigaud 1996). Therefore, dynamical incompatibilities between the model and the observations can be important, particularly in the off-equatorial region. This has a direct effect on assimilation algorithms. For example, the nudging constant of Chen et al. (1995) has a meridional dependency to take account of the fact that the winds generated by the model are less accurate away from the equator. The process gives more weight to the observations in the off-equatorial regions, allowing the observations to modify the physics of the atmospheric model where the model is less accurate.

The multivariate EOFs

The statistical properties of the coupled model are studied in terms of multivariate EOFs of a set of states obtained from a control run of the model. The coupled model is integrated from rest, with an initial wind stress anomaly of 0.5 dyn cm⁻² added during the first four months in the region 5°S–5°N and 163°E–163°W. After this period of time, the model is integrated in a coupled mode for 200 yr.

To compute a set of multivariate empirical orthogonal functions (EOFs), a multivariate state vector is defined to express the state of the system:

\[ \mathbf{x} = (T, \tau_x, \tau_y, u, v, k, h, u_x, v_y, d_{sw}, q), \]  

(2)

where \( T \) represents the sea surface temperature, \( \tau_x \) and \( \tau_y \) are the zonal and meridional components of the wind stress, \( u_x \) and \( v_y \) are the zonal and meridional components of surface wind, \( k \) is the amplitude of the equatorial Kelvin wave, \( h \) is the Rossby component of the upper-layer depth, \( u \) and \( v \) are the zonal and meridional components of the depth-integrated current anomalies between the thermocline and surface, \( d_{sw} \) is the surface wind divergence, and \( q \) is the atmospheric heating. Atmospheric fields such as the surface wind divergence and heat fluxes are included in the state vector because of the particular time step of these variables in the model. All the variables are normalized by the mean standard deviation of each one for the 200 yr of simulation. The number of components of the state vector (2) is 35 457.

A set of 107 multivariate EOFs is constructed from the monthly mean states during the last 115 yr. Figure 3 shows the eigenvalue spectrum of the covariance matrix. The 95% confidence levels, indicated by the dashed line have been calculated from a Monte Carlo simulation.
Fig. 3. Eigenvalue spectrum of the multivariate EOFs of the coupled model of Zebiak and Cane. Also shown are the 95% confidence levels (dashed line) from a Monte Carlo simulation.

Fig. 4. First multivariate EOF: (a) SST anomaly, (b) surface wind stress anomaly, (c) zonal variability of the equatorial Kelvin wave, and (d) Rossby component of the upper-layer depth anomaly. Units are std dev.

Figures 4 and 5 show the SST, wind stress, Kelvin amplitude, and Rossby component associated with the first two multivariate EOFs. The first mode (when considered with positive sign) corresponds to a warming of the eastern equatorial Pacific. The associated wind stress corresponds to a weakening of the trades, that is, a weakening of the Walker circulation, while the Hadley cir-
Fig. 5. Second multivariate EOF: (a) sea surface temperature anomaly, (b) surface wind stress anomaly, (c) zonal variability of the equatorial Kelvin wave, and (d) Rossby component of the upper-layer depth anomaly. Units are std dev.

culation is increased in the eastern Pacific. Both effects tend to increase the wind convergence east of the date line. This convergence is maximum near 110°W. In this region, the Kelvin amplitude is maximum, corresponding to an increase of the thermocline depth. In this first multivariate mode, both Kelvin and Rossby components of the thermocline act together to increase the depth of the thermocline in the eastern Pacific and to decrease the depth of the thermocline in the western Pacific. The Kelvin wave associated with this mode represents a downwelling Kelvin wave reaching the eastern boundary. The Rossby wave corresponds to an upwelling wave off the western boundary. This pattern of circulation is characteristic of the warm phase of ENSO, the El Niño phenomenon (Battisti 1988).

The SST of the second multivariate EOF also corresponds to a warming of the surface waters east of the date line. The main differences with the SST pattern of the first EOF are the lower amplitude of the warming, and the weak zonal gradients near the equator, compared with the strong meridional gradients. This increase of the SST anomalies is not produced by an east–west tilting of the thermocline, but rather by a meridional structure corresponding to an increase of the thermocline depth near the equator and a decrease at higher latitudes. The zonal structure of the field is weak and concentrated mainly east of the date line.

4. Compatibility between data and model

The assimilation experiments presented below use multivariate EOFs of the model to extrapolate the information from the available observations $\mathbf{y}$ to each component of the state vector $\mathbf{x}$. However, as the observations do not provide information about the full state vector, and they can be incompatible with the simplified dynamics of the model, an a priori study of the compatibility between the observations and the dynamics of the model is necessary. In this section, this is done in terms of the multivariate EOFs of the system.

Let $\mathbf{x}'$ be the true state of the ocean, $\mathbf{x}$ be the mean state of the model, and $\mathbf{S}$ be the matrix whose columns are the EOFs of the model. If $n$ is the dimension of the state vector, and the first $r$ EOFs are retained, then
is an $n \times r$ matrix. The true state can always be expressed as
\[ x' = x + S\mu + e', \tag{3} \]
where $\mu$ is an $r$-dimensional vector with the amplitude of each column of $S$, and $e'$ is the residual error. The only knowledge about the true state comes from the observations
\[ y'' = Hx' + e'', \tag{4} \]
where, for simplicity, a linear relation is assumed between the observed value $y''$ and the components of the state vector. Generalization to a nonlinear observation operator is straightforward. The observational error is $e''$. The innovation vector around the mean state is defined by
\[ d = y'' - Hx, \tag{5} \]
which may be expressed as
\[ d = HS\mu + He^*, \tag{6} \]
where $He^* = He^* + e'^*$. Equation (6) can be considered as a parametric definition of the error not accounted by the subspace defined by $S$ at the observation locations, $He^*$, in terms of the coefficients $\mu$. If we require that the two terms of Eq. (6) have no common information, that is,
\[ (HS)^THe^* = 0, \tag{7} \]
it can be found that
\[ (HS)^Td = A\mu, \tag{8} \]
\[ He^* = [I - HSA^{-1}(HS)^T]d, \tag{9} \]
where $A = (HS)^THS$ is an $r \times r$ symmetric matrix.

Equation (8) is formally equivalent to the equation used by Smith et al. (1996) for the least square fitting of EOFs to observations. This is due to the fact that Eq. (7) minimizes the projection of the error onto the space defined by the EOFs. Therefore, this method has the same disadvantages as the method of Smith et al. (1996), that is, the projection fails when the number of observations is not large enough (Kaplan et al. 1997).

Kaplan et al. (1997) discuss an alternative EOF fitting by the minimization of
\[ l[\mu] = (d - HS\mu)^TR^{-1}(d - HS\mu), \tag{10} \]
where $R$ is the observational error covariance matrix. The set of principal components minimizing (10) is the solution of
\[ (HS)^TR^{-1}d = A'\mu, \tag{11} \]
where $A' = (HS)^TR^{-1}HS$ is also an $r \times r$ symmetric matrix. In this case, the innovation vector is split in two orthogonal terms with the inner product $\langle a, b \rangle = a^*b$. Comparison of Eqs. (8) and (11) shows that both methods only differ in the metric of the inner product.

The subspace $S$ is representative of observations if $HS\mu$ expresses the same information as $d$. Therefore, we can define the representativity of $S$ as the projection between the innovation vector and $HS\mu$:
\[ \text{Rep} = \cos(d, HS\mu), \tag{12} \]
where the cosine is computed with respect to the chosen inner product.

Because of its definition (12), a representativity value of $1/\sqrt{2} \approx 0.71$ means that the innovation vector is equally projected over the EOF subspace and over its complementary. That is, representativity values below 0.71 mean that the complementary space represents the observations better than the EOF basis.

Equations (8)–(12) are applied to the Reynolds SST, FSU wind stress, and the Kelvin and Rossby modes of the thermocline depth. Average representativities, from October 1992 to December 1998, as a function of the number of EOFs used are shown in Fig. 6. This figure shows the ability of the EOFs to represent each individual field as well as the combination of all of them. In each case, two datasets are considered. A set, referred to as near equatorial, restricted to the band $10^\circ$S–$10^\circ$N (solid lines), and a set, referred to as model grid, restricted to the band $19^\circ$S–$19^\circ$N (broken lines). Red lines correspond to FSU wind stress, blue lines to Reynolds SST, green lines to Kelvin and Rossby modes, and black lines to the combination of all the fields. For Rossby modes, the near-equatorial data are expressed in terms of the first two Rossby modes. It can be shown that in such a region, the combination of Kelvin and two Rossby modes describe the basic spatial and temporal variability of the thermocline depth.

As the representativity measures the ability of the EOFs to fit observations, higher values are obtained, in general, when the number of modes increases, or the number of observations decreases. Results of individual fields show high-representativity values when EOFs are fitted to observed SST and thermocline modes (Kelvin...
and Rossby). In that case, curves display a rapid saturation, in accord with the fact that only 12 modes of the model pass the statistical significance test. Lower values are obtained with the wind stress. In that case, more modes are needed to explain the spatial variability of the winds, specially at higher latitudes, where the model is known to be less accurate. Degradation of representativity to explain the covariability of all the fields is indicated by the lower values of black lines. This is especially true when the data are expanded to higher latitudes. When data are limited to the neighborhood of the equator, values higher than 0.71 are obtained when more than 30 EOFs are considered.

Robustness of the representativity is affected by the sensitivity of Eq. (8), or Eq. (11), to the observational error. A measure of such sensitivity is given by the condition number of matrix $A$. A matrix is singular if its condition number is infinite, and is ill conditioned if its condition number is too large. As the condition number increases, the sensitivity to the errors increases (Leon 1990). The condition number of matrix $A$ depends on $H$, and the number of EOFs, $r$. Figure 7 shows the condition number as a function of $r$. Results are shown for wind stress (red), SST (blue), and thermocline modes (green). As before, results are shown for both near-equatorial, and model-grid datasets. As the number of observations decreases, or as $r$ increases, the condition number increases. Note that the worse results are associated with the wind stress, and the SST. This indicates that the method is not well suited to infer the structure of the full state vector when these fields are assimilated alone. When all the observations are considered together, curves are slightly smaller than for the thermocline modes. Then, if all fields are considered near the equator, the condition number is 34.7, 98.5, and 180.2 for values of $r$ of 20, 40, 60, respectively. To see the relative smallness of these values, note that the maximum value plotted in Fig. 7 is 17 638.7, and that a matrix is ill conditioned when condition number is greater than $10^6$ (Press et al. 1992, p. 53).

In summary, when EOFs are used to represent the covariability of observations near the equator, the condition number is more robust when all the fields are combined simultaneously than when data is used individually (in particular for the wind stress and SST). On the other hand, for the range of $r$ providing representativity above 0.71, the condition number does not reach values that would invalidate the results. That is, despite the simplifications of the model and its well-known limitations to correctly locate some observed spatial features (Zebiak 1986; Cane et al. 1986; Dewitte and Perigaud 1996), the model is relatively adept at representing the covariability of the wind stress, the SST, and the thermocline data when observations are limited to low latitudes, and the number EOFs is higher than the number of statistically significant modes of the model.

Finally, Fig. 8 provides an example of the compatibility between observations of SST and oceanic equatorial waves with the physics of the model. Compared are the observed value of the Niño-3 index with the index associated with the SST anomaly field derived from projection of the Kelvin and Rossby modes via multivariate EOFs of the model. The strong similarities between both curves suggests that the ocean model captures the basic relationship between thermocline depth and SST in the eastern equatorial Pacific. This result also shows the significance of the Kelvin and first Rossby wave in determining the current state of the thermocline depth over that region.

5. The assimilation method

a. The reduced-order Kalman filter

The reduced-order Kalman filter (ROKF) used in this work is based on SEEK filter equations (Pham et al. 1998). The SEEK filter is a suboptimal version of the Kalman filter (Kalman and Bucy 1960) based on two hypotheses: the reduced rank of the error covariance matrices, and the conservation of the rank in time. Although these hypotheses cannot be justified for a nonlinear system, the SEEK filter has been used successfully to assimilate T/P sea level into a primitive equation tropical Pacific Ocean model (Verron et al. 1999), and to reconstruct the mesoscale circulation of the midlatitude western Atlantic circulation (Brasseur et al. 1999).

Analysis step equations of the SEEK filter are directly derived from the Kalman filter equations by expressing the error covariance matrix, $P'$, at time $t_k$, as
\[ P_1^k = S^k \Lambda^1 S_1^T. \]  

where subscript \( k \) refers to time \( t_k \), \( S_1 \) is the basis of the analysis subspace at time \( t_1 \), and \( \Lambda_1 \) is the error covariance restricted to the analysis subspace. If \( n \) is the number of components of the state vector (2), then matrices \( P_1^k \), \( S_1 \), and \( \Lambda_1 \) are of order \( n \). However, if the rank of \( P_1^k \) is \( r \), only \( r \) columns of matrices \( S_1 \) and \( \Lambda_1 \) need to be retained. Thus, the numerical cost of the analysis step is reduced if the Kalman filter equations are expressed in terms of the \( r \)-dimensional space defined by the columns of \( S_1 \).

Following the notation recommended by Ide et al. (1997), if \( y_1^T \) represents a set of observations at time \( t_1 \), and \( x_1^T \) is the current guess of the system state, the new estimate of the state of the system, \( x'_1 \), is obtained using equations (see Pham et al. 1998):

\[ \Lambda_{k+1} = [\Lambda_{k-1} + (H^T S T R_k^{-1} H S)]^{-1}; \]
\[ K_k = S_k \Lambda_{k+1} (H S)^T R_k^{-1}; \]
\[ x'_k = x_k + K_k [y_1^T - H x_k^T]; \]
\[ P'_k = S_k \Lambda_{k+1} S_k^T. \]

The relative weight of the first guess and the observations is given by the gain matrix \( K_k \), which depends on error covariance matrices \( P_k \) (estimation of the error of \( y_1^T \)) and \( R_k \) (estimation of the error of \( y_5^T \)). Equations (14)–(17) are valid in the measure that Eq. (13) is valid.

Under the hypothesis that the model is linear and exact, the rank of the error covariance matrix is constant in time, and the time evolution of the columns of \( S_1 \) (Pham et al. 1998). Then, if \( M \) is the transition matrix associated with the model, the forecast step of the Kalman filter can be rewritten as

\[ x_{k+1} = M x_k; \]
\[ S_{k+1} = MS_k; \]
\[ P_{k+1} = S_{k+1} \Lambda_{k+1} S_{k+1}^T. \]

The generalization of Eqs. (18)–(20) to a nonlinear, nonperfect model is not straightforward because the rank of the covariance matrices may not be conserved in time, because of the dynamical coupling between the space defined by \( S_1 \) and its null space, that is, Eq. (20) is no longer valid. Moreover, because of the nonlinearity of the model, Eq. (19) cannot be solved explicitly, and only an approximation of the time evolution of the subspace basis can be obtained.

These facts lead us to use an alternative method of equations (19)–(20). Let \( d_k \) be the innovation vector at time \( t_k \), about the current forecast of the state of the system:

\[ d_k = y_k^T - H x_k^T. \]

It can be shown that

\[ E(d_k d_k^T) = H P_k H^T + R_k; \]
\[ = H S \Lambda_k (H S)^T + R_k; \]

where \( R_k \) contains both the observational error covariance and the error covariance on the null space of \( S \) (Cane et al. 1996). Now, if Eqs. (6)–(8) are used, we obtain

\[ d_k d_k^T = H S \mu_k \mu_k^T (H S)^T + H e^T e^T H^T \]

because of the orthogonality of the decomposition of the innovation vector. Note that the residual vector \( e^T \) is a function of the observational error and the error not accounted by the subspace defined by \( S \).

Because of the similarity between Eqs. (23) and (24), we use \( \mu_k \mu_k^T \) as an ad hoc approximation of the error covariance on the analysis subspace, \( \Lambda_k \). Two relationships between \( \mu_k \) and \( \Lambda_k \) are used here:

\[ \Lambda_k = \text{diag}(\mu_k \mu_k^T); \]
\[ \Lambda_k = \frac{1}{k} \sum_{j=1}^{k} \mu_j \mu_j^T. \]

In any case, this methodology allows us to compute a nonstationary, nondiagonal estimate of the forecast error covariance matrix \( S \Lambda S^T \). By using Eqs. (25) or (26), the parameterization of the dynamical coupling between the subspace defined by \( S \) and its complement, and the error of the model, are not necessary because \( \Lambda_k \) comes directly from the current misfit between the observations and the current state of the system.

In summary, the ROKF algorithm uses Eq. (18) to obtain the current state of the system. Equations (6)–(8) and (21) are used to compute the set of principal components \( s_k \) for the estimation of the current forecast error covariance by Eqs. (25) or (26). Finally, Eqs. (14)–(16) are used to correct the state of the system.

b. Nudging the surface wind stress

The performance of the ROKF will be compared with the performance of the nudging of surface wind stress in the model equation for wind stresses. The method used here replicates the method proposed by Chen et al. (1995). That is, at each time step the anomalous model wind stress \( \tau = (\tau_u, \tau_v) \) is substituted by \( a \tau_u + (1 - a) \tau_v \), where \( \tau_v \) is the observed anomalous wind stress. Following Chen et al. (1995), \( a \) is a function of the latitude. In our experience of assimilation, \( a \) is a linear function of latitude, with a value of 0.25 near the equator, and increasing by 0.1 per grid point up to the latitude where it attains the value 0.55, which is then held constant. That is, the model winds are given more weight in the equatorial region and less weight in the higher latitudes.

Neither nudging nor Kalman filter use the hypothesis of a perfect model. In the case of nudging, a new term is introduced into the dynamical equations in order to correct the output of the model. As this term is linear,
the behavior of the model dynamics is linearized when the data model misfits are important. On the other hand, in the present application, the nudging of the wind stress does not modify the value of the prognostic fields (the Kelvin amplitude, and the Rossby component of the upper-layer depth anomaly), but its forcing term. That is, nudging does not modify the current state of the system, but its ulterior time evolution. This approach strongly reduces the possible dynamical imbalances between the prognostic fields. On the contrary, algorithms based on the Kalman filter compute the dynamical evolution of the system with no relaxation term, allowing the full development of nonlinearities of the dynamics. Account for the model error is done by computing an estimate about the error of the new system state. Therefore, uncertainties in the determination of such an error are allowed to propagate in a nonlinear way, contaminating all the dynamical scales of the system. On the other hand, all the components of the system are updated by Eq. (16). This allows a potential way for a faster extrapolation of the information from observations to all the variables of the model, but also increases the risk of dynamical imbalances, that is, initialization shocks may exist after each assimilation step.

6. Model initialization experiments

A set of assimilation experiments, using both nudging of the wind stress and the ROKF presented in the previous section, are performed in order to obtain the initial conditions to predict the time evolution of the Niño-3 index.

Since T/P data are available since October 1992, the prediction experiments are restricted to the period of January 1993–December 1998. Note that the goal of these experiments is to examine the potential of a ROKF to assimilate, directly and simultaneously, different types of data into the ZC model, but not to give an exhaustive comparison between different assimilation methods (this would require longer time series, including several warm and cold events).

Nudging and ROKF also differ in the temporal distribution of the observations used to identify the state of the system. In the case of nudging, the coupled model is integrated from January 1961 until the initial time of the forecast. During this period, the model wind stress is relaxed toward observations. Thus, the final state is used as the initial condition for the prediction of ENSO. This means that initial conditions for ENSO forecasts are a function of the state of the system from 1961 onward. On the contrary, the ROKF is initialized on October 1992 with the long-term mean anomaly of the model. Then, observations are used to give a first estimate of the state of the system at this time. Next, sequential assimilation cycles are done until reaching the initial time for the forecasts.

Initial states for 15-month ENSO forecasts are computed each month from January 1993 to December 1998. ENSO forecasts are compared with observations via the Niño-3 index. The correlation and the rms of the error between the predicted values and the observations, are used to assess the performance of the initialization.

a. Nudging the wind stress

The first experiment presented here uses the nudging method to retrieve the initial conditions for ENSO forecasts, and thereby establish a baseline for the ROKF experiments. Wind observations are considered on the model grid, that is between 19°S and 19°N, and are the only data assimilated.

Figure 9 displays Niño-3 index forecasts with these experiments. The thick solid line represents the hindcast of Niño-3 index, the thin solid lines show the 15-month forecasts, and the dashed line indicates the observed value. The curves show low correlation between hindcasts and observations during the whole period under consideration, indicating that nudging of the wind stress is not able to reproduce the temperature of the eastern Pacific. Pure forecasts (thin solid lines) evolve very close to the evolution with assimilation (thick solid line). This indicates small impact of new observations on the evolution of the system, that is, a strong inertia of the model. This fact helps to explain the delay in identifying the onset and the climax of the 1997 warm episode.

Figure 10 compares the correlation and rms error for different lead time predictions with the initialized model, and the Niño-3 persistence. Zero lead time represents the initialization time. The results show small correlation at short lead times, and errors are greater than persistence for lead times shorter than 8 months. For longer lead times, results show no correlation with observations.

b. Reduced-order Kalman filter

The ROKF is now used to assimilate simultaneously wind stress, SST, and the Kelvin and the first Rossby mode of the thermocline depth into the ZC model. As the assimilation procedure starts in October 1992, the
assimilation results might still be very sensitive to the initial conditions. As before, each analyzed field is saved to be used as initial conditions for a 15-month forecast.

Initialization experiments are performed with different values of $r$, that is, different number of multivariate EOFs. The correlation between the observations and predictions at several lead times is displayed in Fig. 11a. This plot shows the correlations for values of $r$ ranging from 1 to 70. The plot also displays the correlation obtained with the nudging initialization. The ROKF initialization is providing higher correlation at short time leads than nudging does. This is related to the fact that SST observations are being assimilated.

Analysis of these results show that only three EOFs are enough to provide a high correlation (above 0.9) between observations and the reconstructed (i.e., lead time equal to zero) Niño-3 index. The correlation at short lead times increases rapidly with the number of EOFs, and stabilizes since more than 8–10 modes are used. However, if the number of modes is lower than 22 modes, correlation degrades rapidly after five months, indicating a rapid growth of initial errors. Such a rapid amplification of the initial error may be related to the findings of Goswami and Shukla (1991), who found that the growth of small initial errors in the ZC coupled model is governed by processes with two well-separated timescales. The fast timescale process induces error-doubling timescales of about 5 months. The slow timescales induce error-doubling timescales of about 15 months. Therefore, even if the ROKF seems to be able to identify the current state of the system (high correlation at the initial time), the method is unable to capture the fast-growing error components, and the correlation between the prediction states and observations diminishes for lead times longer than the doubling timescales of such errors. A less spectacular drop of correlations is obtained when the SEEK filter incorporates more EOFs. This fact may indicate that to capture the time evolution for lead times larger than four to five months, higher-order EOFs may play a non-significant role.

Different initialization experiments, Fig. 11b, have been done by using a nondiagonal $A_k$ [Eq. (26)] instead of a diagonal matrix [Eq. (25)]; using the error metric, Eq. (11), instead of the identity metric, Eq. (8); and assimilating SST observations over the entire model grid instead of only within the band $10^\circ S$–$10^\circ N$. The forecasts are similar to the ones obtained previously, that is, high correlations at lead time 0 with only 3 EOFs, a rapid decrease of correlations when only a few modes are used, and a range of values of $r$ with a lower decrease of the correlation.

Common features of Figs. 11a,b seem to indicate that only a few EOFs of the model are necessary to reconstruct the temporal evolution of Niño-3 index, as well as for short-term predictions. This result is in agreement with the fact that the few statistically significant modes explain more than 88% of the variance of the full-state vector space. However, the most striking feature of these results is that these modes are not sufficient to capture the time evolution of the system. That is, initial fields of the coupled model contain errors that amplify rapidly. The potential impact of high modes may be related to the role of these modes in determining growing errors. This is explained by the fact that singular vectors of matrix $M^T M$, with $M$, the transition matrix of the model (see, e.g., Xue et al. 1997), have substantial projection onto high-order EOFs. That is, fast-growing errors may not be determined by the lead modes of the model.

The potential role of high modes is not only related to the structure of singular vectors, but also to the inherent data model incompatibilities discussed in section 4. Representativity measures have shown that a basis of functions extracting more information than its complement, must contain more modes than the model-significant modes. In other words, data-to-model misfits may have substantial projections over modes higher than the model-to-model misfits.

Figures 12 and 13 are an example of the impact of data model incompatibilities on initialization. Figure 12 shows ENSO predictions obtained by initialization experiments using 20 EOFs (Fig. 12a), and 47 EOFs (Fig.
Fig. 11. Forecast skill measured by the correlation between predicted and observed Niño-3 index from Jan 1993 to Dec 1998. The number of EOFs used with the ROKF ranges from 1 to 70. The ordinate axis represents the lead time (in months). (a) SST observations are limited to the band (10°S–10°N), and the identity metric is used to fit the EOFs to the data. (b) SST observations are assimilated over all the model grid, and the metric of the data EOF fitting is given by the inverse of the error covariance matrix.
Fig. 12. The 15-month forecast of the Niño-3 index. The thick solid line is associated to the initial conditions. Dashed line is the observed value. Thin solid lines show the evolution of forecasts starting every month. The ROKF with (a) 20 EOFs and (b) 47 EOFs are used. The metric is the identity matrix, $\Lambda_k = \text{diag}(s_k s'_k)$, and SST is assimilated over all the model grid.

In these experiments, Eqs. (8) and (25) are used, and SST observations are extended to the model grid. Hereafter these experiments are cited as r20 and r47. Comparing the thick solid line in Figs. 12a and 12b it can be noticed that the initial conditions of the prediction experiments become closer to the observed value as the number of modes increases.

The main shortcoming of the r20 initialization is the inability of the forecasts to identify the termination of warm events, specially at the end of 1993, or at the end of 1998. To determine the reason for this, we compare the initial conditions given by these initialization experiments. Figure 13 shows the difference between r20 and r47. Fields with differences larger than two standard deviations are the zonal wind stress and the Kelvin wave amplitude. The impact of these differences has been examined by resetting to zero the wind stress components or the Kelvin amplitude of the initial conditions provided by the experiment r47. The correlation and the rms error of these experiments are shown in Fig. 14. Note the small impact of resetting the wind stress to zero on the prediction skill of the solutions, and the larger impact of resetting the Kelvin amplitude. This behavior was expected because the oceanic Kelvin wave is one of the prognostic variables of the model, while the atmospheric model mainly depends on the current SST distribution. Examining the initial Kelvin and Rossby fields in experiment r20 (not shown), it was found that both fields were too weak near the western boundary (Fig. 13 shows that the differences of the Rossby waves are generally large there). Finally, as these weak waves propagate eastward, the temporal evolution of the system at the central and eastern equatorial Pacific is rapidly contaminated. Note that the failure of the lead multivariate EOFs to reconstruct the required wave amplitudes is directly related to one of the well-known...
properties of the model, that is, the weak variability in the coupled model west of the date line (Cane et al. 1986).

Initial conditions obtained with the r47 experiment are shown in Fig. 15. Kelvin and Rossby waves at the western boundary are derived from the statistical properties of the model, that is, the delayed oscillator mechanism. Comparison of the equatorial thermocline depth (sum of Kelvin and Rossby modes) averaged around the equator with hindcasts from a more elaborated ocean analysis system (Behringer et al. 1998) shows that the simple ZC model produces a correct alternation of equatorial upwellings and downwellings near the western and eastern boundaries through the considered period of time, and a correct timing for the heat-content buildup in the western equatorial Pacific since mid-1995. Nevertheless, note that analyses shown in Fig. 15 do not display, as discussed before, the observed variability at the western boundary. Forecasts from these initial conditions successfully predict the warm event of 1997–98 by identifying its onset, rapid increase of the temperature, amplitude of the event, and its duration. Forecasts since May 1996 predict a warm event for the 1997, indicating that preconditions of such an event may be present in the tropical Pacific at least 15 months prior to the event, in agreement with the remarks of McPhaden and Yu (1999). These experiments also indicate that a nonlinear, coupled model based on the delayed oscillator may generate the correct amplitude of the warm event starting from conditions before November 1996, the time when wind anomalies associated with the Madden–Julian oscillation begin to appear, even though such anomalies have been suggested as being important for the timing and amplitude of the event (McPhaden and Yu 1999).

SENSITIVITY TO WAVE ERRORS

Errors of the Kelvin and Rossby modes have been determined by assuming that the reduced-gravity approach is strictly valid over the band 10°S–10°N (see section 2). The sensitivity of the results to these values has also been examined with six additional experiments. In these new model initializations, the Kelvin and Rossby errors have been, separately or simultaneously, increased (or decreased) by 20% of the value given in section 2.

The results (not shown) show small impact to changes
in the error estimates for the Kelvin and Rossby modes. The results are almost insensitive to changes on Rossby error estimates because of the large number of observations, 2378, being assimilated. Results are slightly more sensitive to changes in the Kelvin error estimate. When the Kelvin error estimate is increased 20%, the skill of the forecasts diminishes for 6–8-month lead time predictions, but remain unchanged for higher lead times. However, when the Kelvin error estimate is reduced 20%, a more noticeable decrease of the skill of the predictions occurs for lead times larger than 12 months. Thus, the Kelvin error estimate is low enough to provide an estimate of the thermocline structure over the equator, but is large enough to avoid an overfitting that degrades the prediction for interannual timescales.

7. Summary

A simplified reduced-order Kalman filter has been applied to the coupled ocean–atmosphere nonlinear model of Zebiak and Cane. The multivariate EOFs of the coupled model are used to reduce the dimension of the problem. In the case of the state vector used in this work, the size of the covariance matrices $P$ used by the classic Kalman filter is 5 Gb. When the ROKF is used with $r = 100$, the size of the matrices $S_r$ and $L$ is 14 Mb and 40 Kb, respectively. The ROKF is used to assimilate fields of the SST, surface wind stresses, and thermocline depth (derived from the T/P sea level) into the coupled model every month.

Projecting the Kalman filter equations onto the multivariate EOFs of the model means that, although incomplete, the physics of the model is used to reduce the degrees of freedom of the KF algorithm. To ensure a relative compatibility with the model, observations are limited to $10^°S–10^°N$. A representativity study shows that the ability of the EOFs to account for the covariability of the observed fields that decreases at high latitudes. The study of the conditioning of the data EOF fitting used to infer the forecast error covariance matrix has shown that the method is not well suited when only SST or wind stress observations are assimilated with the ROKF.

The prediction skill of the forecasts initialized from the outputs of the filter has been compared to persistence and the nudging of surface wind stress. The forecasts obtained from the filter show higher correlations with observations than the results coming from the nudging experiment for all lead times. The method is shown to be robust for forecasts shorter than 4–5 months, with a sharp reduction of the correlation skill when only the lead modes are used. These facts indicate that the method is not able to identify the error associated with the fast error modes of the model, especially when only the lead modes of the model are retained. It has to be noted that such a result is related to the coupled nature of the model. For a tropical wind-driven ocean model, the impact of higher modes on the ROKF is less crucial (as, e.g., in the work of Cane et al. 1996). This is because part of the initial errors in the ocean are damped by the fixed wind forcing. Contrarily, in the case of coupled ocean–atmosphere models, such initial errors may be rapidly amplified. A natural extension of this work is the use of basis of functions accounting for the dynamical evolution of the coupled system as, for example, the singular vectors of the model.

Despite the fact that the filter has been shown to be robust for timescales shorter than 4–5 months, the filter has provided initial conditions of the tropical Pacific, predicting the onset of the 1997–98 warm event 15 months before its occurrence. These predictions start from states prior to the first westerly wind burst associated with the Madden–Julian oscillation, often suggested as a triggering mechanism for the onset of warm events. Such a result indicates the possibility that the delayed oscillator mechanism may itself be the origin of the correct amplitude of the 1997–98 El Niño event, consistent with the concept of an oscillation that does not need a trigger.

The numerical cost of the filter has been highly reduced by computing an estimate of the forecast co-
The variance matrix on the subspace defined by the multivariate EOFs, from the available observations. On the other hand, as the time evolution of $\Lambda_k$ comes from the observations instead of being computed by the time evolution of the error covariance matrix, the dynamical interaction between the EOF subspace and its null space has been avoided. A second extension of this work is related to the use of Eqs. (8) and (9) to infer the statistical properties of the residual subspace error. This information can then be used for the creation of error maps, as well as to provide the framework allowing the computation of the temporal evolution of the forecast error covariance matrices.

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