

Ocean Data Assimilation for Seasonal Forecasts

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ABSTRACT

The relative merits of ocean data assimilation are discussed in the context of state estimation and creation of ocean initial conditions for seasonal forecasts. The discussion is based on results from the ocean analysis components used in the different ECMWF seasonal forecast systems.

Uncertainty in time evolution of the wind stress results in a large uncertainty in the interannual variability of the upper ocean. It is shown that data assimilation is effective in reducing the level of uncertainty, and that the initialization of ocean by means of ocean data assimilation has beneficial impacts on the skill of seasonal forecasts.

Results show that data assimilation mainly corrects for systematic error, even though the assimilation method is not designed to do so. The presence of systematic error can be damaging for the representation of interannual variability in data-sparse areas. Univariate assimilation of temperature data can have a detrimental effect on the equatorial currents and salinity. These considerations have been taken into account when designing the ocean data assimilation procedure for the seasonal forecast system currently operational at ECMWF (System 2).

1 Introduction

From the atmospheric point of view, seasonal forecasting can be considered a boundary condition problem, which is associated to the predictability of the second kind: the forcing provided by the lower boundary conditions (sea surface temperature (SST), soil moisture) changes the population of the atmospheric attractor, and therefore the probability of occurrence of weather events (Palmer 1993, Corti 1994).

The prediction of the boundary conditions (SST, soil moisture) at seasonal timescales can be considered an initial value problem. The potential predictability arises from the longer memory associated with the higher heat capacity of water, and from the degree of predictability of ocean dynamics. The dynamic memory is particularly important in the tropical oceans, where the correct initialization of the upper thermal structure is considered instrumental in the prediction of the tropical SST at seasonal timescales with dynamical models (Palmer and Anderson, 1994).

The seasonal forecasting system at ECWFMF is based on a coupled ocean-atmosphere general circulation model that predicts both the lower boundary conditions (namely SSTs) and their impact on the atmospheric circulation. This approach is often called a one-tier approach. The probabilistic nature of seasonal forecasting is addressed by performing an ensemble of integrations with the aim of sampling the atmospheric probability density function (PDF). Because of deficiencies in the oceanic and atmospheric models the state of the coupled model drifts with forecast lead time. No flux correction is applied to correct the drift during the coupled model integrations. Instead, a set of historical hindcasts is performed to provide an estimate of the model climatological PDF, which is used for a-posteriori calibration of the model results (Stockdale 1998). In a one-tier approach, forecasting the SST using a fully-coupled model is essentially an initial value problem since predictability largely resides in information contained in the initial state of the ocean. This is especially true in the tropical Pacific.

The quality of seasonal forecasts is determined by the the various components of the system (the ocean initialization, the coupled model, the ensemble generation and the calibration strategy), which are closely interrelated.

The interdependence of the different components becomes clear when considering the calibration procedure. The a-posteriori calibration of model output requires an estimate of the model climatology, which is obtained by performing a series of coupled hindcasts during some historical period (typically 10-15 years). A historical record of hindcasts is also needed for skill assessment. Ocean initial conditions spanning the chosen calibration period are then required, which is equivalent to a historical ocean "reanalysis". The interannual variability represented by ocean reanalysis will have an impact on both the calibration and on the assessment of the skill. Because of the large impact on the forecast, the uncertainty in the ocean initial conditions should be considered in the ensemble generation (Vialard *et al.* 2003).

The skill of the seasonal forecasts is often used to gauge the goodness of the ocean initial conditions. The quality of the coupled model will determine the precision of the assessment (i.e., a bad coupled model would make a blunt measurement tool). If the major source of forecast error comes from the coupled model, changes to the ocean initial conditions would have little impact on the forecast skill. This is something to bear in mind when interpreting results of the impact of the ocean data assimilation on seasonal forecasts.

Alves *et al.* 2003 found that data assimilation improved the skill of the seasonal forecasts using a version of the ECMWF coupled model. Since the impact of data assimilation is likely to be model dependent, the same question is revisited in this paper using the results from the latest seasonal forecasting system at ECMWF, that became operational in 2002, and that will be referred to as System 2 (S2) hereafter (Anderson *et al.* 2003).

Although ocean data assimilation is now a common practice in generating ocean initial conditions for seasonal forecasts, the procedure itself is not without problems. In some cases the estimation of the ocean state can be degraded by the assimilation. This paper discusses the problems induced by ocean data assimilation, mainly due to the existence of systematic error and lack of appropriate multivariate formulations (which can be closely related, as will be shown). The problems are illustrated with examples from the previous ECMWF seasonal forecast system (System 1 or S1 hereafter), although they are common to other systems (Weaver *et al.* 2003, Vialard *et al.* 2003, Huddleston *et al.* 2003, Chepurin *et al.* 2003). Some of the strategies proposed to deal with these problems have been explored in the design of the new configuration of the data assimilation in S2.

This paper is organized as follows: in section 2 we describe the basic features of the ocean initialization in the ECMWF seasonal forecast systems, common to S1 and S2. The presence of systematic error and the lack of multivariate relationships create problems in the estimation of the salinity field (section 3) and equatorial currents (section 4). Some of strategies to deal with these problems have been incorporated in S2, whose performance is briefly discussed in section 5. In section 6 a summary of results is provided. The appendix provides a detailed comparison of S1 and S2.

2 The ocean initialization

Seasonal forecasts with dynamical coupled models require a good initialization of the thermal structure of the upper tropical oceans. Different techniques have been used to initialize the ocean models. The simplest technique to provide ocean initial conditions is to run an ocean model forced with observed wind stress and with a strong relaxation of the model SST, usually the top level temperature, to observations. Such stand-alone integrations are referred to as control runs (*CNTL*) in what follows. The forcing fields used to drive the ocean model in the operational environment come from ERA15 for the period before 1993 and from Operations from 1994 onwards (ERA/OPS in what follows)^{1 2}.

This technique would be satisfactory if errors in the forcing fields and ocean model were small. Unfortunately, wind stress products as well as ocean models are known to have significant errors. The uncertainty induced in the ocean can be measured by using a different wind product to force the same ocean model. A different

¹Note that when S2 was made operational, ERA40 had not yet finished. Hence the use of the earlier reanalysis ERA15

²As forcing fields we use daily fluxes of momentum, heat and fresh water, but it is the momentum fluxes that influence the most the thermal structure of the subsurface.

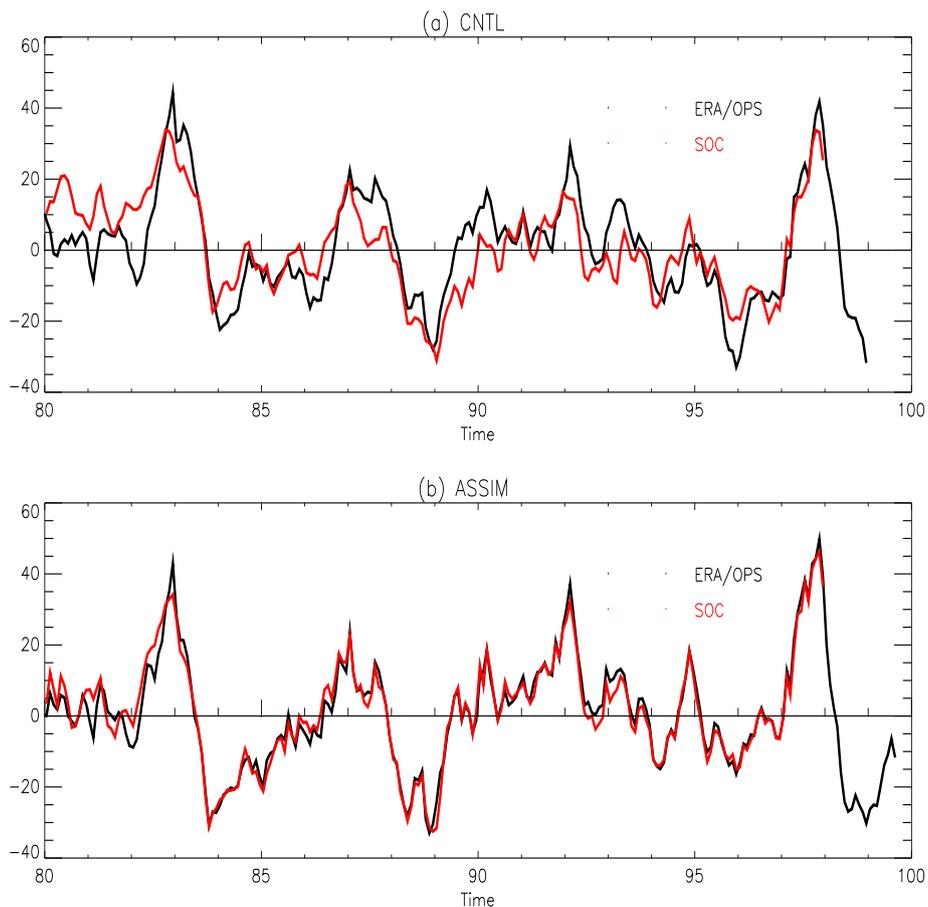


Figure 1: Time evolution of the interannual thermocline-anomalies from *CNTL* (a) and *ASSIM* (b) integrations, when *ERA/OPS* winds (black line) and *SOC* winds (red line) are used.

wind data set has been created by combining the global monthly mean wind stress from the Southampton Oceanography Centre (*SOC*) (Josey *et al.* 2002) with the daily variability from the *ERA/OPS* product. Figure 1a shows the evolution of the thermocline anomalies³ in the equatorial region *NIÑO3* (150W-90W, 5N-5S) from two different *CNTL* integrations. The black line shows the results from the run forced by *ERA/OPS* winds, while the red line shows results from the run that uses *SOC* winds. The differences in thermocline depth are of the same order as the interannual variability. Figure 1b shows the same diagnostics when data assimilation is included (*ASSIM* integrations hereafter). In order to constrain the interannual variability of the ocean it is therefore necessary to use some data assimilation.

³as measured by the depth of the 20 degree isotherm (D20)

2.1 The ocean data assimilation system

The background state for the data assimilation is produced by an ocean model forced by analyzed surface fluxes of momentum, heat and fresh water. The ocean model is based on HOPE (Hamburg Ocean Primitive Equation model) version 2 (Latif *et al.* 1994, Wolff *et al.* 1997). Horizontal discretization is on an Arakawa E grid with equatorial refinement. See the appendix for information on the resolution used for S1 and S2.

The ocean data assimilation scheme is essentially univariate temperature Optimum Interpolation (OI) carried out on overlapping sub-domains of the model horizontal grid. The Optimum Interpolation equations are solved on each level of the model independently, except for the top level where a strong relaxation to analyzed SSTs is applied (Reynolds and Smith 1994, Reynolds *et al.* 2002). Only subsurface temperature is assimilated in both S1 and S2, but in S2 balance relationships between salinity, velocity and temperature have been introduced (see appendix).

The model background errors are represented by Gaussian functions which are anisotropic and inhomogeneous, especially at the equator. The formulation follows Smith *et al.* (1991), though some parameter values are different. Details of the de-correlation scales and differences between S1 and S2 are given in the appendix. Observation errors are assumed to be correlated in time with a correlation scale of 3 days, and in space with a spatial correlation function of 2 degrees. The weight given to the data relative to the weight given to the background field varies with depth to account for the increase in uncertainty associated with the large temperature gradients near the thermocline.

The observations are from the GTSP (Global Temperature Salinity Profiling Project) at NODC (National Oceanographic Data Center). These include data from XBTs and TAO moorings in the equatorial Pacific. More recently the observing system has been expanded by drifting ARGO floats and the extension of TAO-type moorings into the tropical Atlantic (PIRATA) and the west Pacific (TRITON).

The temperature observations are assimilated into the oceanic model as follows. Every 10 days the model state is used as the background for an OI analysis using observations which span a window five days either side of the model background. An increment to the background is calculated. To avoid exciting gravity waves, and to allow the model dynamics to adjust gradually to the changes in the density field, this increment is added slowly over the subsequent 10 days, after which a new background field is available, and the cycle repeated. There is no temperature assimilation in the top model level; instead the model SST is relaxed to analyzed SST fields with a relaxation time-scale of 3 days.

Figure 2 shows the 1991-1998 average of a longitude-depth section of the assimilation increments along the equator from a typical ocean analysis. The mean increment has a large scale dipolar structure, as if the data assimilation were correcting the slope of the thermocline, making it deeper in the western Pacific and shallower in the eastern Pacific. This kind of error could appear if the equatorial winds were too weak, although it may be due to other mechanisms.

Regardless of the source of error, figure 2 shows that the data assimilation is correcting the system bias, whereas the scheme assumes the first guess given by the model background is unbiased. From the mathematical point of view, the presence of systematic error poses the problem of increased variance in the analysis (Dee and Da Silva 1998). In practice, the presence of systematic error may introduce spurious temporal variability in regions where the observation coverage is not uniform in time, which may be a serious problem when the ocean analysis is used to predict interannual variability. Systematic error could also be a serious problem if inadequate multivariate relationships are put in place: systematically changing the value of temperature may generate imbalances in the ocean state that damage the "unconstrained" variables, such as salinity and velocities, which in turn can feed-back into the systematic error in temperature.

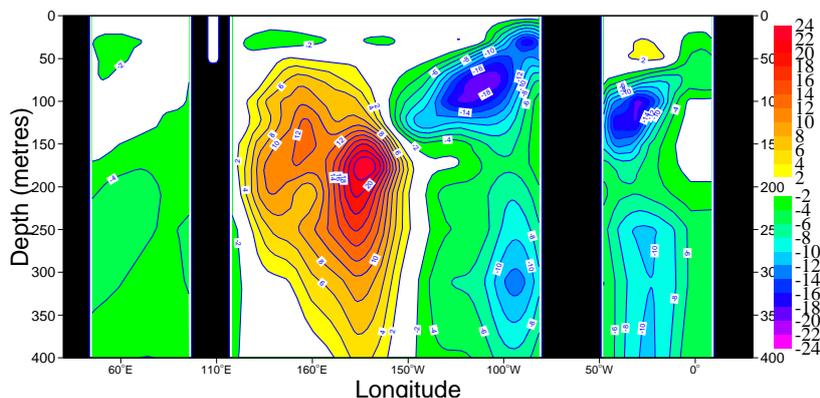


Figure 2: Equatorial longitude-depth section of mean assimilation temperature increment. Contours every $2^{\circ}\text{C}/\text{year}$. The mean corresponds to the time-average during the period 1991-1998.

3 Systematic error and Interannual Variability

In a previous section it was shown that data assimilation constrained the level of interannual variability in areas with sufficient data coverage, such as the equatorial Pacific. In other areas, where data are sparse, the impact of data assimilation on the representation of the interannual variability is not always beneficial.

Figure 3a shows the time evolution of the sea level in the equatorial Atlantic (70°W - 30°E , 5°N - 5°S) as represented by the *CNTL* – *S1* (red line) and *ASSIM* – *S1* (black line) ocean analyses from the previous system (*S1*). The most striking feature is the sudden decrease in the sea level of the *ASSIM* – *S1* integration at around 1985. The *CNTL* – *S1* does not exhibit any particular anomaly during that time. An inspection of the observation coverage (figure 3b) reveals a sudden increase in the number of observations around January 1995, possibly associated with a research cruise (see figure 4). Other (smaller) sea level changes apparent in the *ASSIM* – *S1* run occur when the observation coverage changed: both the increase in the number of observations at around 1992 and the appearance of PIRATA moorings around 1998 are associated with a decrease in the sea level of the equatorial Atlantic. The latter was reported by Segsneider *et al.* 2000.

The spurious sea level variability in the *ASSIM* – *S1* run of figure 3a is caused by the data assimilation trying to correct for systematic error in temperature (too diffuse thermocline), by means of applying a large negative increment to the temperature field without updating the salinity field. The process upsets the water mass characteristics, disrupts the hydrostatic balance and induces spurious convection. Figure 5 shows a meridional section across the equator of the temperature field before and after assimilation. Before the assimilation the profile is stably stratified. The univariate assimilation of temperature triggers convection and the stratification is broken.

Convection could be prevented if the water mass properties were preserved, which would imply updating the salinity field at the same time as the temperature following some kind of conservation principle. This is the basis of the scheme put forward by Troccoli and Haines 1999. The salinity increments are derived from the analyzed temperature by using the model temperature (T) and salinity (S) vertical profiles, assuming that the assimilation is correcting for vertical displacement of the water column and imposing preservation of the T - S relationship in the model profiles ($S(T)$ scheme). The conservation of water mass properties establishes a relation between temperature and salinity, in the same way as the geostrophic balance relates the density and the velocity fields. This scheme has been formulated for an OI framework (Troccoli *et al.* 2001) and it is one of the ingredients of data assimilation in *S2*. Figure 6 shows the sea level evolution after applying the T - S constraint (green line). For comparison, the sea level from *ASSIM* – *S1* is also shown. The problem with discontinuities in sea level is alleviated by the inclusion of the balance relationship. There is still an obvious discontinuity in the sea level at around 1985, which could be due to the $S(T)$ scheme not being fully effective (since it will not work if the

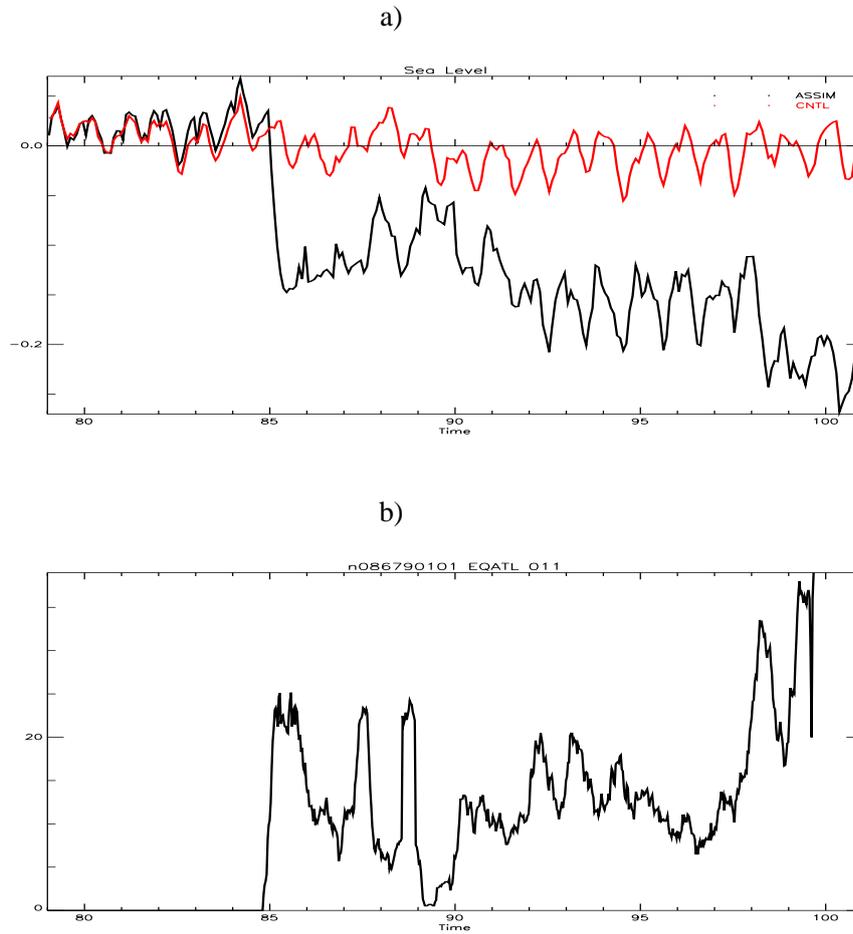


Figure 3: Time evolution of a) the sea level averaged over the equatorial Atlantic (5S-5N), as represented by the CNTL – S1 (red line) and ASSIM – S1 (black line) from S1, and b) number of observations per assimilation cycle in the area. The assimilation cycle is 10 days.

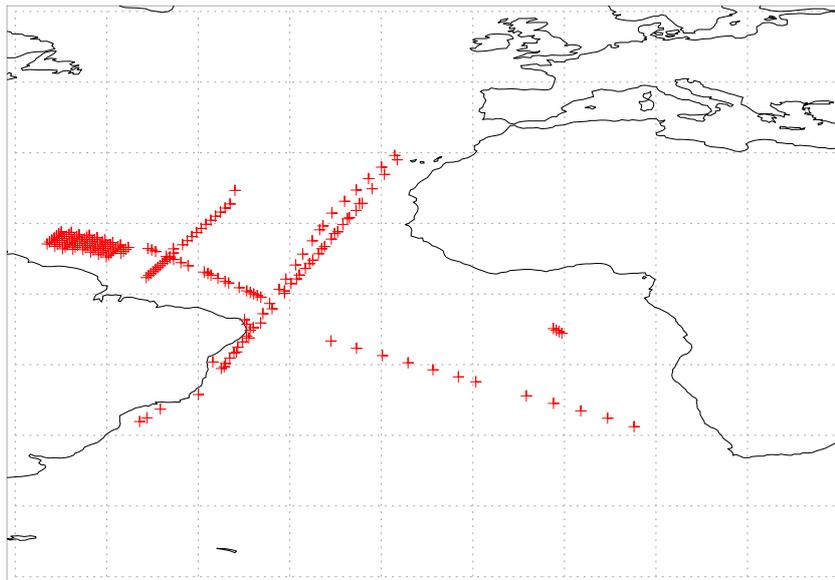


Figure 4: Observation coverage over the Atlantic for January-February 1985.

source of temperature error is due to horizontal advection), and/or to the fact that sporadic data is correcting the model mean state.

The preservation of the T-S relationship is a nonlinear constraint, but can be linearized and implemented in a variational formulation (Ricci *et al.* 2003). This is a step forward for the inclusion of flow dependent properties in the background error covariance matrix (Weaver, this issue).

4 Systematic error and the velocity field

Figure 7 shows a horizontal map of the zonal currents within the tropics from a) the observed climatology from Reverdin *et al.* 1994, for b) *CNTL* and c) *ASSIM*. Away from the equator, the zonal current is improved with the data assimilation, as a direct consequence of improved horizontal density gradients: for example, the North Equatorial Counter Current (NECC) is stronger in the data assimilation run than in the control run. However, near the equator, the data assimilation has a detrimental effect on the velocity field, especially in the eastern Pacific, where the eastward component becomes too strong, causing the undercurrent to surface.

In the East Pacific, the degradation of the currents is visible not only at the surface, but also at depth. Figure 8 shows the zonal velocity along the equator as a function of depth in the first 300 m for both *CNTL* and *ASSIM*. In the Eastern Pacific, the structure of the undercurrent in *ASSIM* is too broad when compared with observed current data. This error may be related to the unrealistic vertical circulation near the South American coast, characterized by very strong downwelling (see figure 4 later). The degradation of the surface velocity and the spurious vertical circulations appear also in other univariate systems (Vialard *et al.* 2003, Huddleston *et al.* 2003)

The spurious circulation induced by the data assimilation may cause additional errors in the temperature fields. There could be a positive feedback between errors induced by the data assimilation and errors in the model, that could lead to the existence of bias in the system. For instance, a temperature increment that is not dynamically balanced could be responsible for spurious circulations, which in turn could create further errors in the first guess for successive data assimilation cycles. Burgers *et al.* 2002 proposed a scheme to prevent the disruption of the geostrophic balance by imposing constraints between the density and velocity increments.

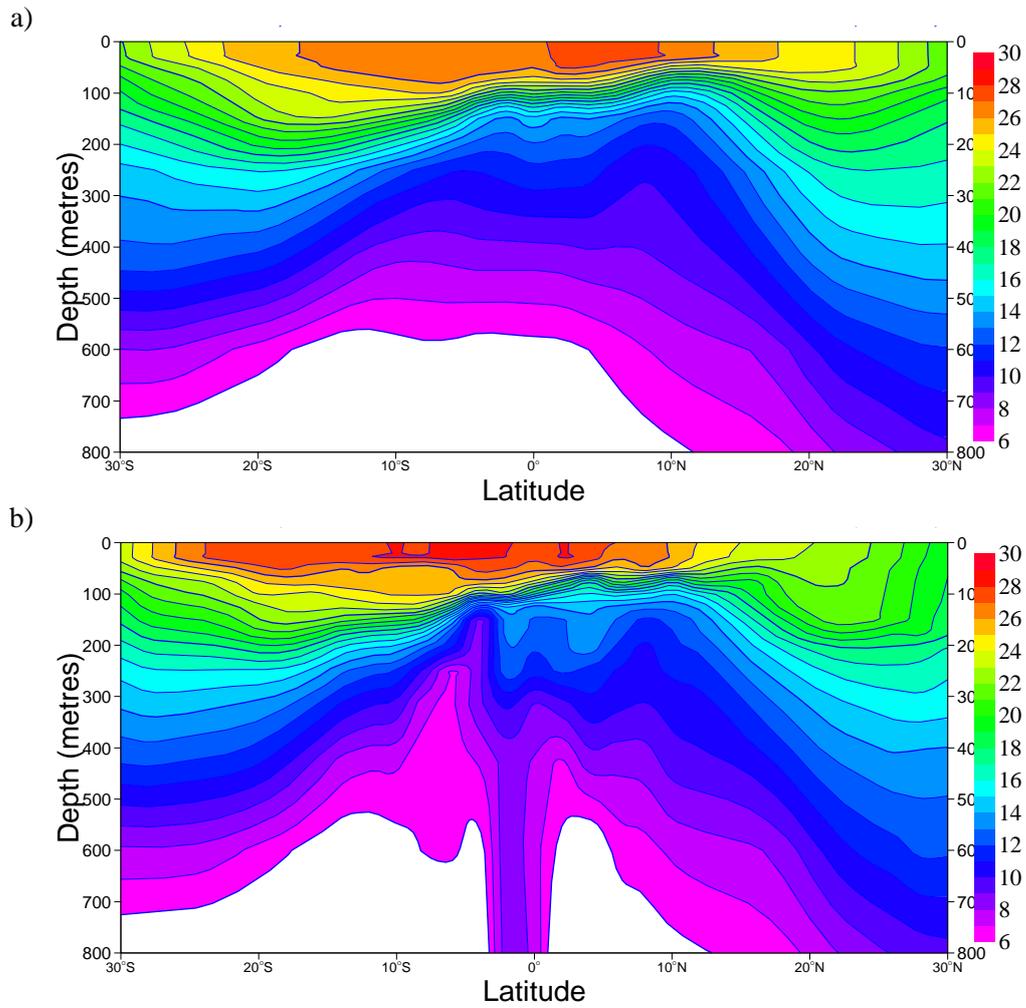


Figure 5: Latitude-Depth sections of temperature across the Atlantic (30°W) before (a) and after (b) univariate assimilation of temperature data. From Troccoli et al. 2002

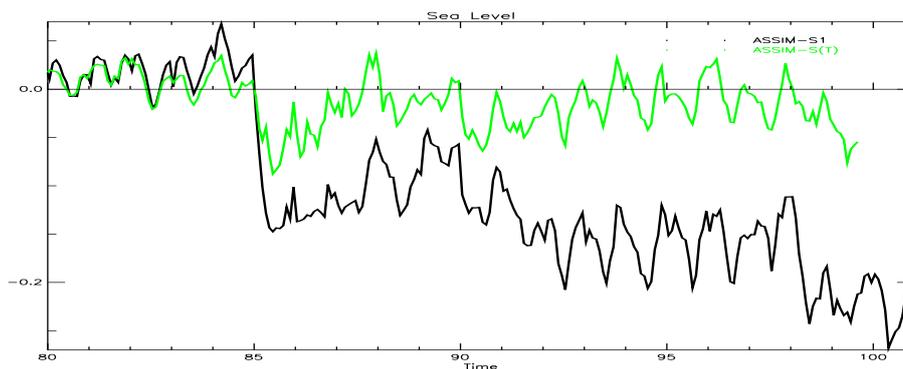


Figure 6: Time evolution of a) the sea level averaged over the equatorial Atlantic, as represented by the ASSIM with $S(T)$ scheme (green line) and ASSIM - S1 (black line)

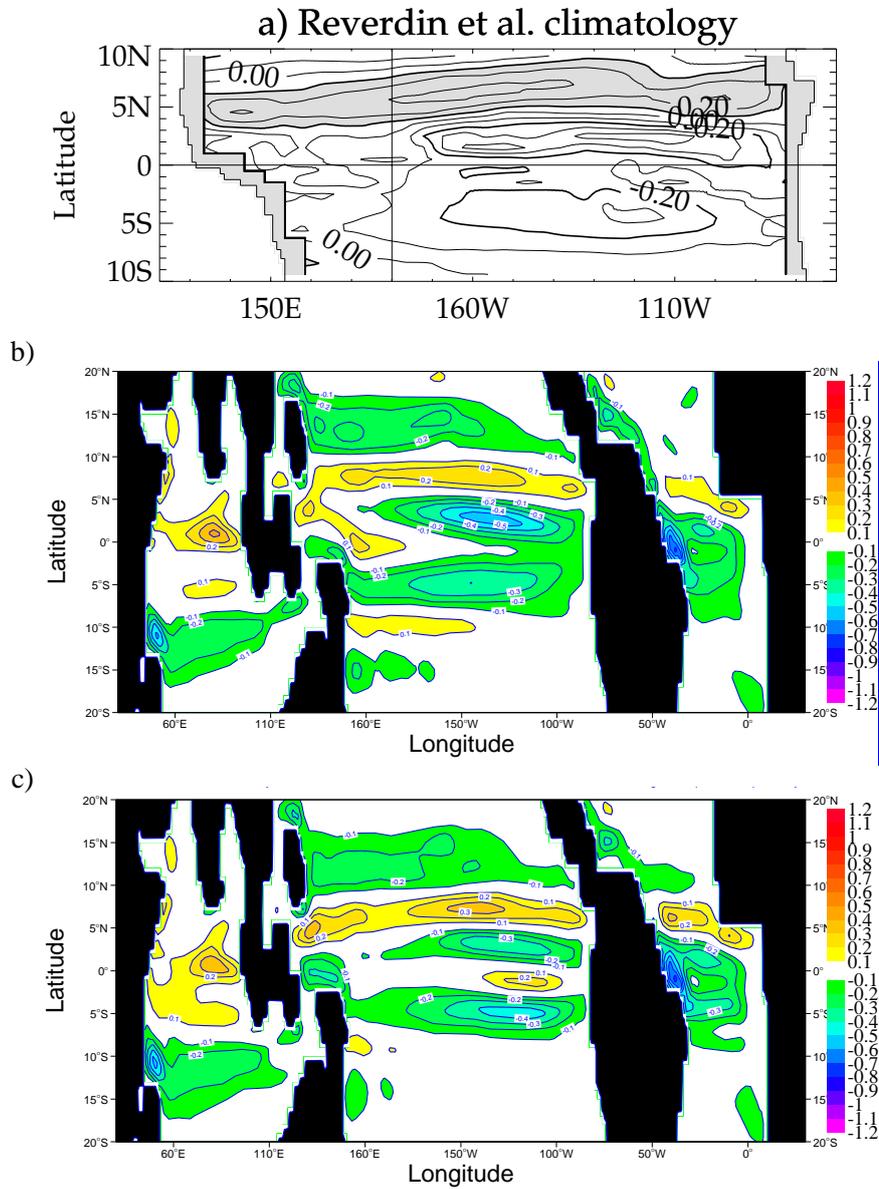


Figure 7: Mean zonal surface currents in the tropical oceans, the Reverdin climatology (a), from CNTL (b), and from ASSIM (c). The contour interval is 0.1 m/s.

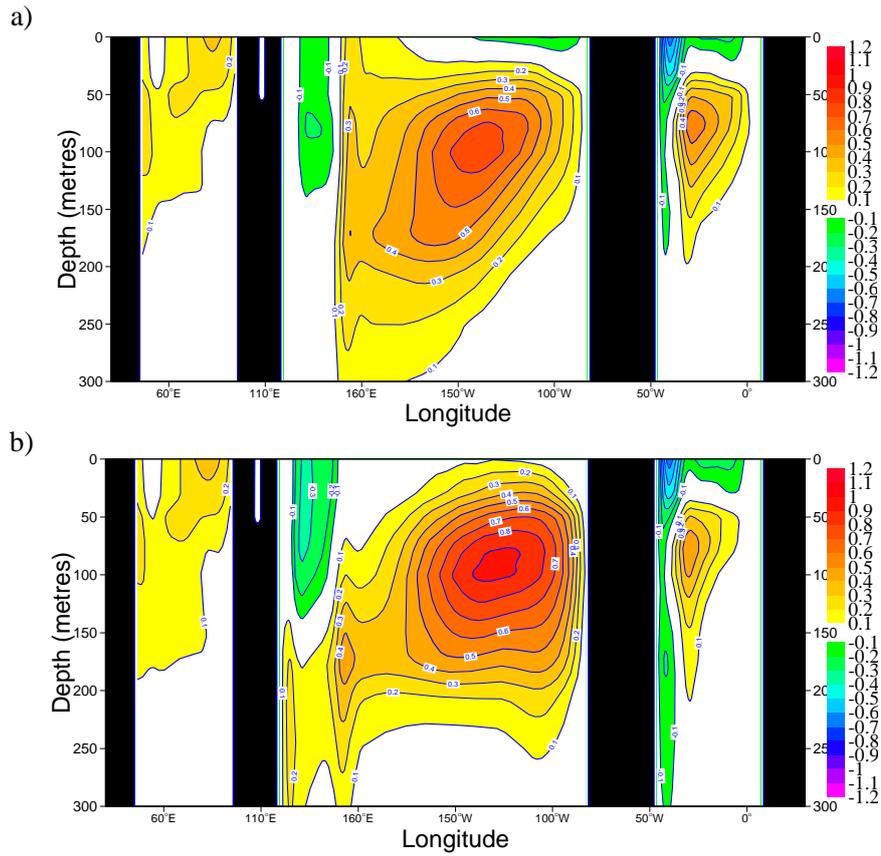


Figure 8: Equatorial depth-longitude section of the zonal velocity, from CNTL (a), from ASSIM (b) (1991-1998 time average). The contour interval is 0.1 m/s

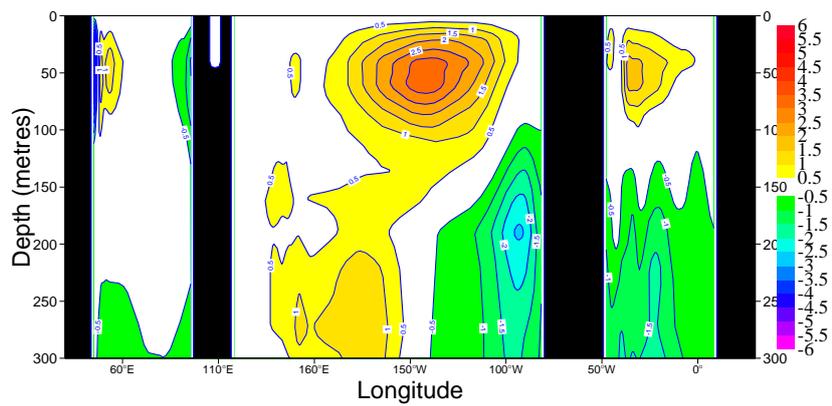


Figure 9: Equatorial longitude-depth section of the vertical velocity in the ASSIM run (1991-1998 average). Contour interval is 0.5m/day

The systematic error may have its origins in the momentum equation (resulting from inaccuracies in the wind field and in the vertical mixing of momentum among others). The errors in the momentum equations may even stem from the data assimilation procedure itself, which can introduce errors in the velocity field when disrupting the geostrophic balance between density and velocity. The scheme of Bell *et al.* 2003 for estimation and correction of the bias provides another approach for correction of the errors in the momentum equation, assuming that the error arises entirely from an incorrect value in the pressure gradient terms. There is a third category of methods, not discussed here, in which the error is estimated using adjoint methods (Bonekamp *et al.* 2001, Vidard *et al.* 2003).

4.1 Velocity adjustments

Imposing a geostrophic constraint between density and velocity increments is straightforward except near the equator where the geostrophic relationship breaks down. However, even at the equator it is possible to apply some kind of constraint (using scaling, symmetry, or continuity arguments), to come out with a local solution. That would produce two sets of solutions (one for the equator and another for outside the equator) that can be blended together. The equatorial solution constraint is important since it is at the equator that the currents are degraded most in the presence of data assimilation.

Here, the equatorial solution is obtained from the y -derivative of the geostrophic relation in a β -plane. Using the example of the shallow water equations, if Δh is the assimilation increment in surface elevation (equivalent to a density increment in a GCM), the corresponding velocity increments $(\Delta u, \Delta v)$ at the equator are given by 1:

$$\begin{aligned}\Delta v_{eq} &= 0 \\ \Delta u_{eq} &= -\frac{g'}{\beta} \frac{\partial^2 \Delta h}{\partial y^2}\end{aligned}\quad (1)$$

where the updates to the meridional velocity are neglected. Outside the equator, the geostrophic balance is given by 2:

$$\begin{aligned}\Delta v_{neq} &= \frac{g'}{f} \frac{\partial \Delta h}{\partial x} \\ \Delta u_{neq} &= -\frac{g'}{f} \frac{\partial \Delta h}{\partial y}\end{aligned}\quad (2)$$

The two solutions are blended by means of Gaussian weights, assuming that the equatorial solution holds for latitudes inside the Rossby radius of deformation y_0 (taken to be 2°). The Gaussian weights ensure that the blended solution also satisfies the geostrophic balance.

$$\begin{aligned}\Delta u &= \gamma \left((1 - e^{-(y/y_0)^2}) \Delta u_{neq} + e^{-(y/y_0)^2} \Delta u_{eq} \right) \\ \Delta v &= \gamma \left((1 - e^{-(y/y_0)^2}) \Delta v_{neq} \right)\end{aligned}\quad (3)$$

The balance constraint can be generalized by allowing only a fraction γ of the density increment to contribute to the geostrophic balance. In a generic case, γ could vary geographically, and also be a function of depth.

Figure 10 shows the surface currents in the experiment $ASSIM_G$ where the geostrophic balance has been applied. Unlike the experiment $ASSIM$, the undercurrent does not surface. The mean value of the zonal current is more

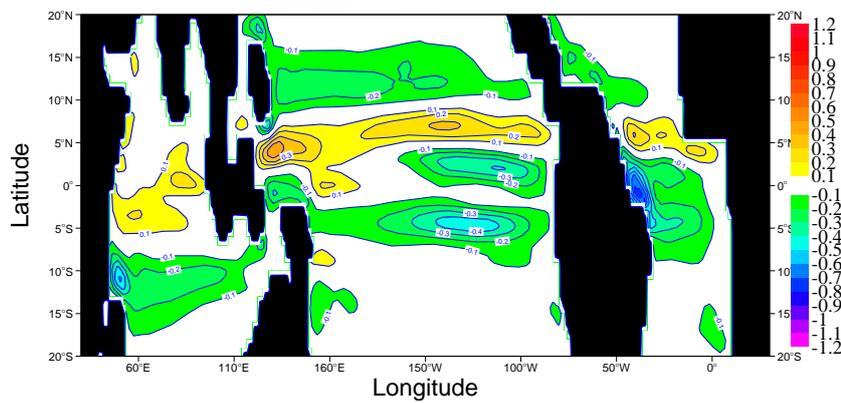


Figure 10: Mean zonal surface currents in the tropical oceans, from a data assimilation experiment where balanced updates to the velocity field are added (experiment $ASSIM_G$). For comparison see figure 7.

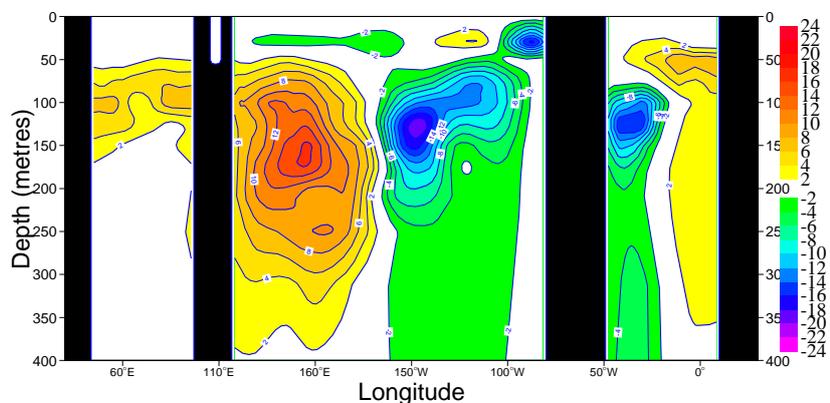


Figure 11: As figure 2, but from a data assimilation experiment where balanced updates to the velocity field are added (experiment $ASSIM_G$). Notice the reduction in the mean assimilation increment.

in agreement with the Reverdin climatology. The main effect of the geostrophic updates to velocity happens near the equator. Comparison with TAO currents indicates that the velocity updates also correct the velocity fields at depth, in particular in the eastern Pacific (not shown).

Given that the velocity increments improve the errors in the velocity field, it can be questioned if the erroneous circulations induced by the data assimilation in experiment $ASSIM$ did feedback on the errors in the temperature field. If so, smaller temperature increments in experiment $ASSIM_G$ would be expected. Figure 11 shows that this is indeed the case. The mean temperature increments in experiment $ASSIM_G$ in the upper Equatorial Pacific are about 20% smaller than in experiment $ASSIM$ (figure 2).

The geostrophic balance scheme to update the velocity field has been implemented in the data assimilation of S2. The operational implementation uses a depth dependent value of γ . The geostrophic balance has also been implemented successfully in a multivariate variational environment in the OPA ocean model (Weaver 2003, this issue).

4.2 Bias correction method

The standard procedure to deal with systematic error in a data assimilation system is to augment the model state with a set of systematic error variables (Dee and Da Silva, 1998). Specific assumptions about the nature and time evolution of the systematic error are needed. This approach is followed by the Bell *et al.* 2003 scheme for bias correction in a sequential data assimilation. Their scheme assumes that the systematic error comes from errors in the formulation of the pressure gradient, i.e., the error has a purely divergent component, and hence can be inferred using density information. In the shallow water equation example, this would be achieved by adding a correction term $(\frac{\partial h_b}{\partial x}, \frac{\partial h_b}{\partial y})$ to the pressure gradient:

$$\begin{aligned} \frac{\partial u}{\partial t} - fv + ru &= -g' \frac{\partial(h+h_b)}{\partial x} + X \\ \frac{\partial v}{\partial t} + fu + rv &= -g' \frac{\partial(h+h_b)}{\partial y} + Y \\ \frac{\partial h}{\partial t} + H \left(\frac{\partial u}{\partial x} + \frac{\partial v}{\partial y} \right) &= Q \end{aligned} \quad (4)$$

If the source of the error came from the wind forcing, this method could correct for error in the divergence of the wind, but it would not correct for errors in the curl.

The bias term can be estimated using information from assimilation increments of density (or temperature and salinity). The time evolution for the bias term is proportional to the time integral of the density increments (Δh):

$$h_b(t) = h_b(t - \Delta t) - \alpha \Delta h(t) \quad (5)$$

where α is a constant larger than zero but smaller than 1, and Δt is the assimilation interval (10 days in our case). If the estimation is correct, after a certain time, $\Delta h(t)$ would be zero, and the correction term would reach a constant value.

The above method has been applied to the data assimilation system described in section 2, prior to the inclusion of any balance constraints. The inclusion of the pressure gradient correction avoids degradation of the equatorial circulation, even when no geostrophic velocity increments are applied. Figure 12 shows the zonal velocity in the bias correction experiment ($ASSIM_{B1}$), which is better than that from experiment $ASSIM$ shown in figure 7c.

As expected from its design, the bias correction method also reduces the value of the average analysis increment. A more stringent test would be to check if the bias reaches a constant value, which can be easily done by looking at the evolution of the time-integrated assimilation increments. Figure 13 shows the time evolution of the accumulated assimilation increment at two depths in region EQ1 (130W-90W, 5N-5S) from 3 experiments with different values of parameter α . In experiment $ASSIM_{B1}$ (black curve) $\alpha = 0.1$, whilst $\alpha = 0.3$ in experiment $ASSIM_{B3}$ (in red). The standard data assimilation $ASSIM$ is also shown as a reference (green curve) The 2 panels of figure 13 are for depths 30m and 175m. If the bias were constant and the correction scheme were correct, the accumulated increment would tend to an asymptotic value. This criterion can be used to tune the value of α . The first feature to notice is the sensitivity of the scheme to the value chosen for α . At 30m depth (13a) the evolution of the accumulated increment stabilizes when the bias correction scheme is switched on for $\alpha = 0.1$ Even for the lower value of α there is a hint of overcorrection (the accumulated increments of $ASSIM_{B1}$ (black line) and $ASSIM_{B3}$ (red line) have different sign to those of experiment $ASSIM$ (green line)). At deeper layers, where the bias in the uncorrected cases ($ASSIM$) is smaller, the evolution of the bias is far from constant; at 175m, the integrated increment shows large fluctuations in time, which are correlated with

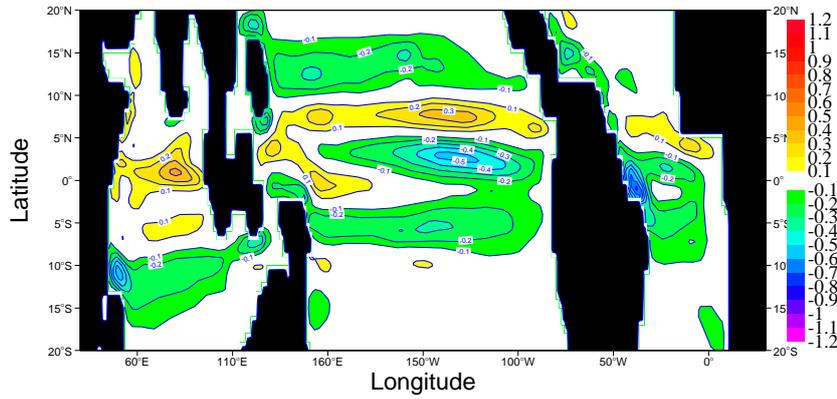


Figure 12: Mean zonal surface currents over the tropical oceans, from the data assimilation experiment where the bias is corrected (experiment $ASSIM_{B1}$). For comparison with figure 7.

the interannual variability. The El Niño of 1997-1998 is clearly visible in figure 13b, for instance. In this case the smaller increments are those from the standard experiment $ASSIM$. This is a clear example of the error of the system being flow-dependent, for which the bias correction scheme is not designed. It could be possible to allow for slow time fluctuations in the error, by introducing a memory term β in the bias estimation equation:

$$h_b(t) = \beta h_b(t - \Delta t) - \alpha \Delta h(t) \quad (6)$$

with β a number between 0 and 1. The relative values of α and β would determine the response of the estimated bias to changes in the flow, or other sources of non stationary systematic errors. A more comprehensive scheme for bias treatment is proposed by Dee, this issue.

5 Ocean Data Assimilation in System 2: Performance

Since January 2002 S2 has been the operational seasonal forecast system at ECMWF. Anderson *et al.* 2003 offers a comprehensive description of the system and the performance of the coupled forecasts. Details of the ocean model and ocean data assimilation are outlined in the appendix. The performance of the ocean analysis is briefly discussed here.

The main changes in the ocean data assimilation of S2 are the introduction of salinity and velocity updates when assimilating subsurface temperature. The salinity updates are derived using the $S(T)$ scheme discussed in section 3, which is active below the mixed layer. To calculate the velocity increments a depth dependent geostrophic constraint is used ($\gamma(z)$ in equation 3).

An adequate treatment of the systematic error would have been desirable. At the time of the operational implementation, the only scheme available was the bias correction scheme represented by equation 5. As the systematic error was likely to change with time, this version was not considered suitable for operational use. Instead, a more conservative and traditional approach was implemented: in order to control the systematic error, subsurface temperature and salinity are weakly relaxed to the WOA98 climatology (Levitus *et al.* 1998). The suitability of this choice is discussed below.

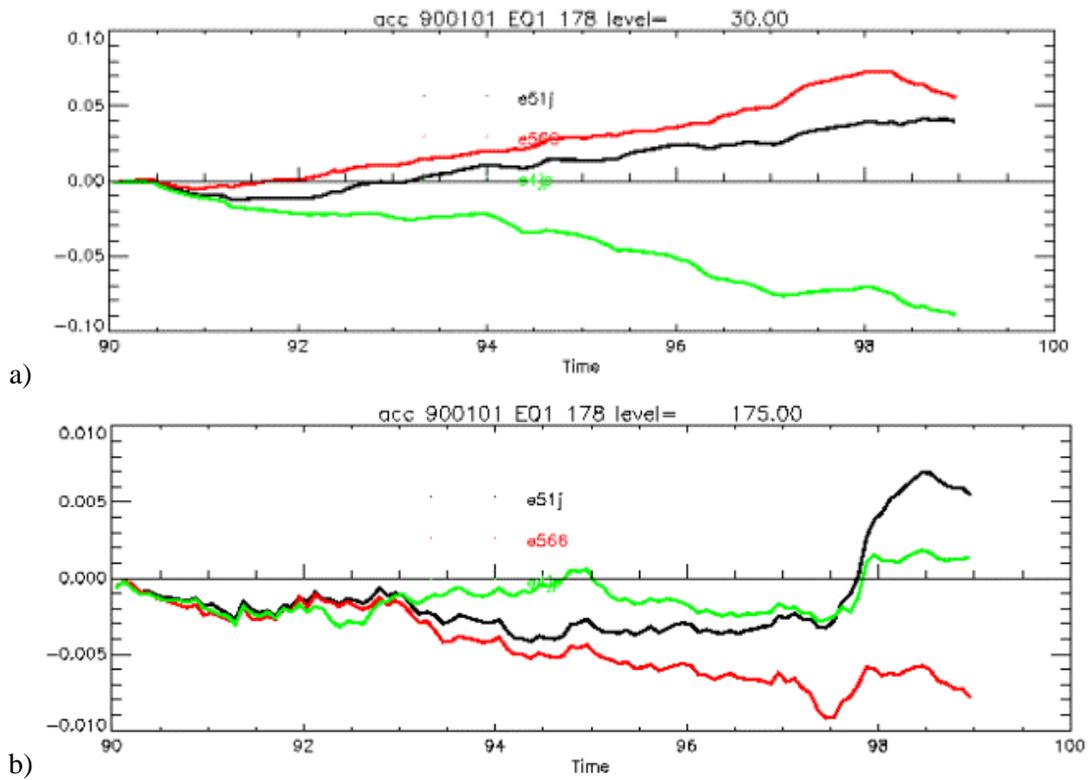


Figure 13: Time series of the accumulated assimilation increment in region EQ1 (130W-90W, 5N-5S), at 30 m (panel a) and 175m (panel b). Green is for experiment ASSIM, black is for ASSIM_{B1}, and red is for ASSIM_{B3}.

5.1 Impact of data assimilation on the state estimation

Figure 14 shows the mean difference between independent observations (Johnson *et al.* 2000, Johnson *et al.* 2002) and the analyses from S2. The two curves in each panel correspond to the *CNTL* – S2 (blue) and *ASSIM* – S2 (red). The data assimilation reduces the mean bias in temperature (upper panels), especially in the western equatorial Pacific (160E-150W, 5N-5S). In the eastern equatorial Pacific (150W-90W, 5N-5S) the bias in *ASSIM* – S2 is also reduced, but has the opposite sign to the bias in *CNTL* – S2: in the upper 200m the *ASSIM* – S2 analysis is biased warm with respect to the observations, whereas the *CNTL* – S2 analysis is biased cold. This indicates that the data assimilation is a source of systematic error itself. The error may stem from the inadequacy of the multivariate formulation (problems with velocities or salinity) and/or from the relaxation to WOA98 climatology. The relaxation to climatology can be a source of error if there are trends in the climate system. The relaxation technique may also be flawed if only temperature and salinity are changed without imposing any constraint on the velocity, especially at the equator (following the same arguments discussed in the previous section). Finally, the values at the equator of the gridded climatology may be contaminated by interpolation errors. Further work is in progress to understand the problem.

The lower panels in 14 show the mean differences (observations minus analysis) in the salinity field. The data assimilation is very effective in reducing the bias in salinity, even though salinity data were not directly assimilated. This is likely to come from the $S(T)$ scheme, since the salinity is better constrained where the scheme is active, i.e., below the mixed layer. The bias in the surface salinity is also reduced in the *ASSIM* – S2 analysis, even when no direct salinity correction is applied in the upper 50 m

Figure 15 shows profiles of the time averaged zonal velocity from the *ASSIM* – S1 (red line) and *CNTL* – S2 (blue line) analyses, together with the currents from TAO observations at selected moorings. In all the locations the currents from *ASSIM* – S2 are better than those from *CNTL* – S2. There is no sign of the undercurrent surfacing in the eastern Pacific. At 110W, the undercurrent in the *ASSIM* – S2 run is stronger than in the *CNTL* – S2 run, with its maximum closer to the observed value, but the shape is still too broad. This suggests that in S2 the value of parameter γ (in equation 3) below 150m may be too small.

The effect of data assimilation on the estimation of the interannual variability can be measured by comparison with altimeter data. Figure 16 shows the correlation of the sea level from the *ASSIM* runs of S1 and S2 with the altimeter data in different equatorial regions. Over the East Pacific (150W-90W, 5N-5S), both S1 and S2 are very well correlated with the altimeter data. The correlation is also good over the western-central Pacific (160E-150W, 5N- 5S), with S2 being slightly better than S1, probably due to the beneficial impact of the $S(T)$ scheme. The correlation in the other oceans is not so good. Overall S2 is better than S1, especially over the equatorial Atlantic, where the effect of the $S(T)$ scheme is more noticeable. However, this is still the area where the representation of interannual variability is poor, as the low values of the correlation with the altimeter data indicate.

5.2 Impact of data assimilation on ocean initialization

The ultimate test of the data assimilation in a seasonal forecasting system is whether it improves the forecast skill. SST is the variable traditionally used for skill assessment. Alves *et al.* 2003 addressed this question using results from a forecast system similar to S1 (S1A in what follows). Their results are presented here for comparison with those of S2. Figure 17 shows a bar diagram representing the errors in predicting SST of S1A and S2, for both the *ASSIM* and *CNTL* initialization. The results are shown for 2 areas in the equatorial Pacific which are more affected by ENSO variability: NIÑO3 (150W-90W, 5N-5S) and NIÑO4 (160E-150W, 5N-5S). S2 (blue bars) exhibits lower errors than S1A (pink bars). In both systems, the errors are reduced when data assimilation is used to initialize the ocean - the errors from the *ASSIM* initialization (dashed bars) are smaller than the errors from the *CNTL* initialization (solid bars).

In both systems the impact of assimilation is larger in NIÑO3 than in NIÑO4. NIÑO3 is a dynamically active area, where a large part of the interannual variability is related to the vertical advection of heat (weak upwelling

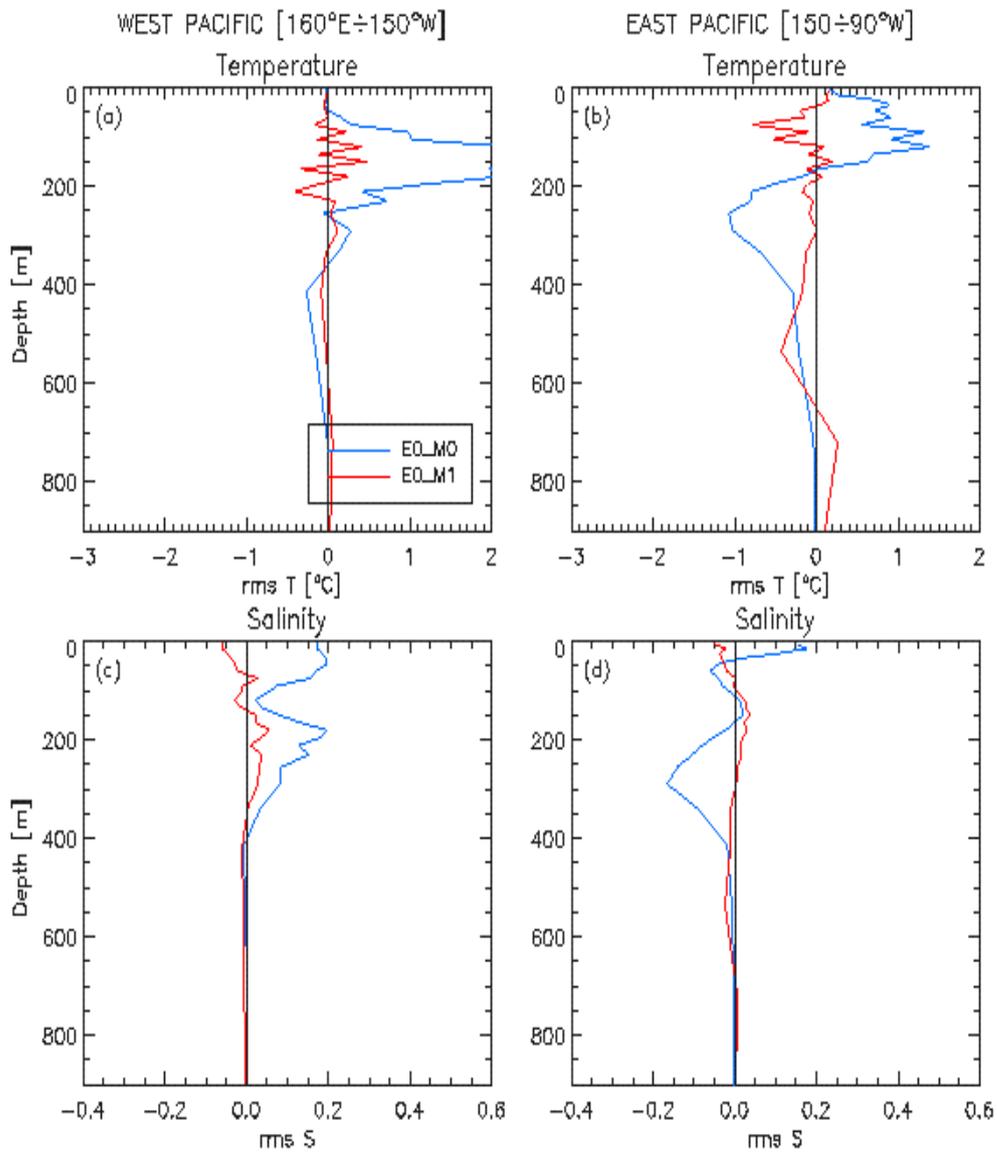


Figure 14: Independent observations minus analysis (1993-2002 average). The analysis are the CNTL (blue) and ASSIM (red) integrations from S2.

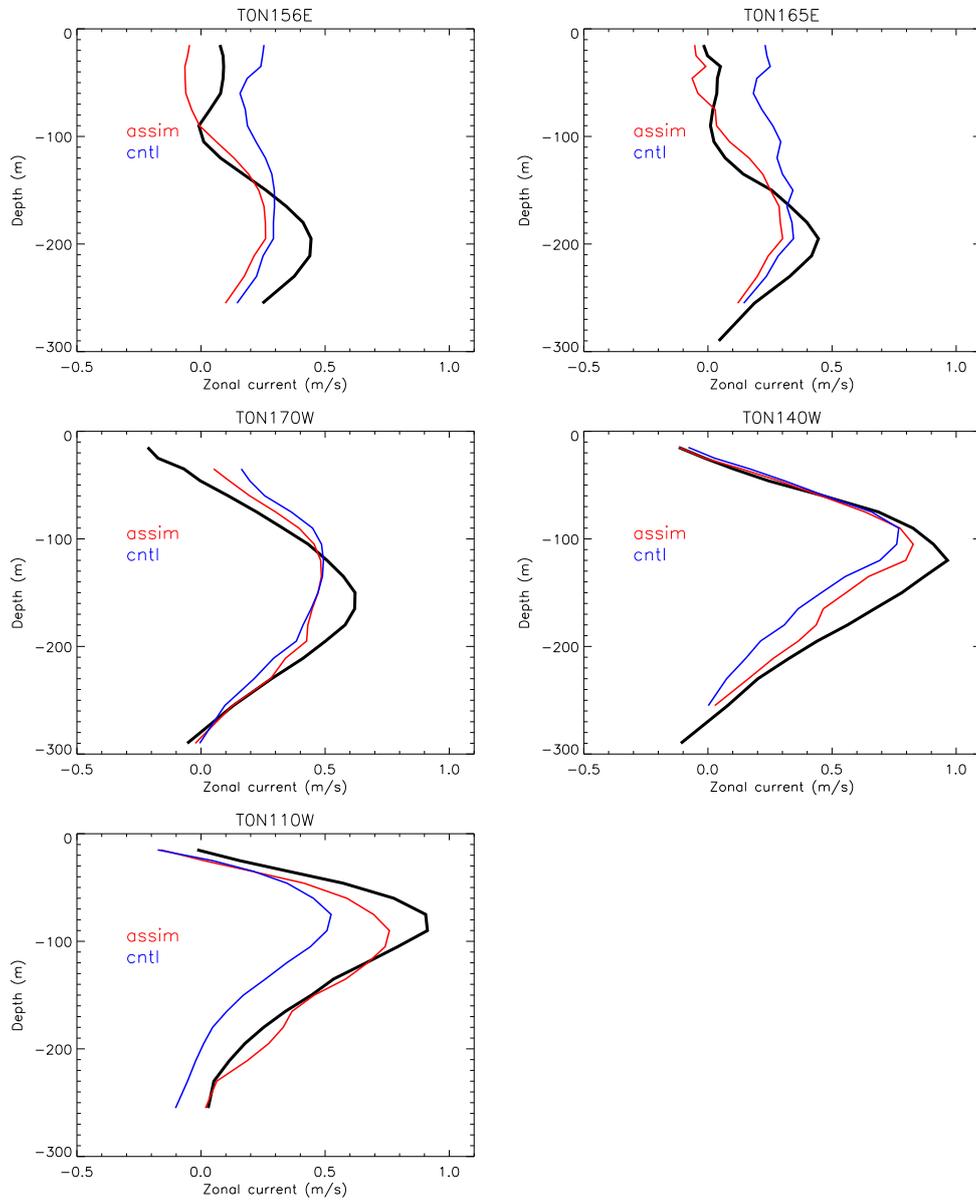


Figure 15: Comparisons with observed currents. Shown are the zonal velocities from ASSIM – S2 (red line), CNTL – S2 (blue line) and TAO currents.

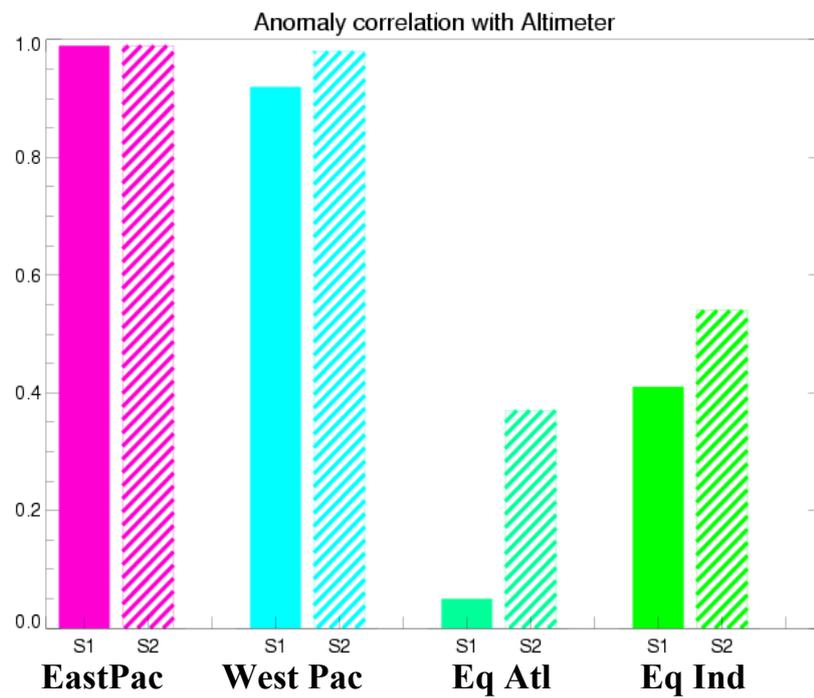


Figure 16: Correlation between the sea level from the altimeter data and the sea level from the ASSIM – S1 (solid bars) and ASSIM – S2 (dashed bars).

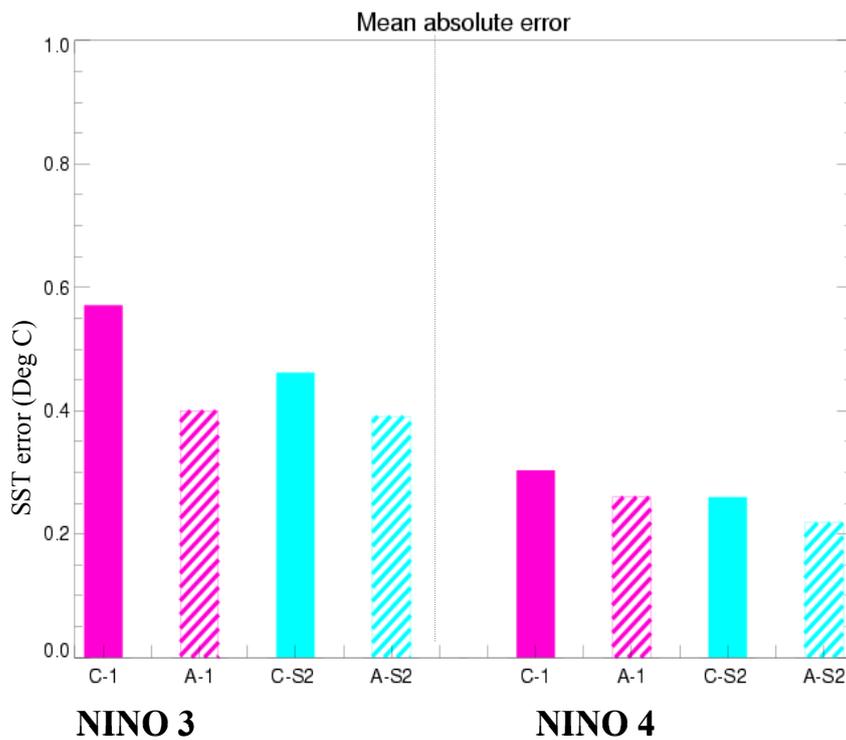


Figure 17: SST forecast errors in NIÑO3 and NIÑO4. Shown are results from S1A (pink bars) and S2 (blue bars), when the ocean initial conditions are taken from the ASSIM (dashed bars) and CNTL (solid bars) integrations. The bars represent the 0-6 month mean absolute error. The period for the statistics is the same used by Alves et al. 2003 (1991-1997).

and/or weakened vertical thermal gradient). Therefore, initialization of the subsurface will have a more direct effect on the forecast skill over this area. The processes that influence the interannual variability in NIÑO4 are more varied, some of them involving complex interaction with surface salinity and horizontal advection (Vialard *et al.* 2002,). For the data assimilation to have a noticeable impact on the representation of these processes it would be required to have a good representation of the mixed layer physics and adequate initialization of mixed layer salinity. This latter could be achieved by assimilating directly salinity data, or by deriving salinity information from the altimeter data (Vossepoel *et al.* 1999, Maes and Behringer, 2000).

Finally, the impact of data assimilation in NIÑO3 forecast error is smaller in S2 (16%) than in S1A (30%). It is difficult to interpret this result, since one should bear in mind the limits of a coupled model as a measurement tool. It indicates that in S2 the main causes of forecast error are others than those sampled by the existing methods of initializing the ocean (CNTL versus ASSIM). The remaining level of forecast error is a combination of predictability limit, model error, and errors in the ocean initial conditions not yet sampled.

6 Summary and conclusions

The simplest technique to provide ocean initial conditions is to run an ocean model forced with observed wind stress. It is shown that this technique is not satisfactory since errors in the forcing fields result in large uncertainty in the ocean subsurface. In the equatorial Pacific, assimilation of sub-surface ocean observations overcomes the problems due to wind error, correcting both the mean state and the interannual variability. In other areas however the data assimilation can contaminate the representation of the interannual variability,

especially in the presence of system bias where the data is sporadic in time, and/or by disruption of physical balances if there are not appropriate multivariate relationships.

An example of the latter has been illustrated using results of the ocean re-analysis from the previous seasonal forecasting system (S1). The univariate assimilation of temperature data degraded the interannual variability of the sea level in the equatorial Atlantic. The problem is reduced if the salinity field is updated during the assimilation process, by imposing a constraint between salinity and temperature variations based on the preservation the water mass properties. Some problems still remain, probably due to the presence of systematic error.

Results show that the equatorial currents can also be degraded during the univariate assimilation of temperature data. The spurious circulations induced by the assimilation procedure contribute to the systematic error. Imposing balance relationship between the density and the velocity field not only improves the estimation of the equatorial currents, but also reduces the size of the mean temperature increment.

Multivariate constraints for salinity and velocity have been implemented successfully in the data assimilation component of the current seasonal forecasting system S2. Comparison with independent data shows that in the equatorial Pacific the assimilation of subsurface temperature data improves the mean state of temperature, salinity and velocity.

Sub-surface data assimilation has also a positive impact on the SST seasonal forecasts. The initialization of the ocean by data assimilation reduces the error in NIÑO3 SST forecast by 30% in S1 and by 16% in S2. The impact in NIÑO 4, although positive, is smaller, in both S1 and S2.

The presence of systematic error poses a problem for obtaining reliable long term ocean reanalysis by assimilating data. The scheme proposed by Bell *et al.* 2003 to estimate and correct the bias by linking the temperature bias with errors in the pressure gradient offers promising results, since it prevents the degradation of the equatorial currents. Further developments are needed to allow for flow-dependent systematic error.

7 Appendix

S2 is broadly similar to S1, but there are a number of differences in the ocean, the ocean data assimilation, the atmospheric model and the method of ensemble generation. These are documented in Anderson *et al.* 2003, and summarized in table 1. The most relevant aspects of the ocean model and ocean data assimilation in S2 are outlined below.

In S2, the ocean model has 29 levels in the vertical compared to 20 in S1. Near the surface the level thickness is 10m compared with 20m in S1. In S2, the horizontal resolution is equivalent to 1 degree, with equatorial refinement in the meridional direction, where the resolution is 0.3 degrees (0.3Eq in table 1). For S1, the equivalent values are 2 and 0.5 degrees.

A substantial change has been made to the way salinity and velocities are handled in the assimilation process. In S1, no change is made to salinity nor to the velocity field following an OI correction to T, whereas in S2 these fields are also updated. Salinity is changed beneath the surface layer in order to preserve the T-S relationship (Troccoli *et al.* 2001). The update to the velocity field is calculated by imposing a geostrophic balance between the velocity increment and the density change resulting from the T and S increments (Burgers *et al.* 2002). As a way of dealing with systematic error, both subsurface temperature and salinity are weakly relaxed to the WOA98 climatology (18 months time-scale).

In S2, the data assimilation scheme remains OI as in S1, but the background error covariances have been changed. In particular the de-correlation scales have been reduced (see table 2). In both S1 and S2, the weight given to the data relative to the weight given to the background field varies with depth to account for an increase in uncertainty associated with the large gradients near the thermocline. The dependence with depth of both observations and background errors can be expressed as follows:

		System 1	System2
Atmosphere Model	cycle	IFS (15r8)	IFS (23r4)
	resolution	horizontal	T63
		vertical	31 levels
Ocean Model	cycle	HOPE h2e8	HOPE h2e13
	resolution	horizontal	2x2 (0.5Eq)
		vertical	20 levels
Ocean Data Assimilation	Scheme	OI	OI
	Data	Temperature	Temperature
	Salinity	none	$S(T)$
	velocity	none	geostrophy
	bias treatment	none	Levitus relaxation
	no of analysis	1	5
	SST	Relaxation	OI v1
Ensemble Generation		Lag average	burst mode (40)
			TP +WP+SP
Calibration	Period	1991-1996	1987-2001
	Atmos IC	ERA/OPS	ERA/OPS
	Ocean forcing	ERA/OPS (fc)	ERA/OPS (an)

Table 1: Summary of differences between system 1 and system 2.

$$Error(z) = f(a\sigma(z), bL \frac{\partial T}{\partial z}) \quad (7)$$

$$(8)$$

Where f represents a function dependent on two arguments. The first one ($a\sigma(z)$) is a prescribed dependence on z , constant in time and space, and the second term ($bL \frac{\partial T}{\partial z}$) is a flow-dependent term that represents the position of the thermocline, since it is proportional to the vertical temperature gradient. Parameters a and b have different values for the background and the observations, and are different for S1 and S2, as can be seen in table 2. In S1, the background and the observations are given the same weight (except in the thermocline). In S2, the observations are given half the weight of the background. The function f is the *max* function. This choice may need to be revised in the future, since it may introduce structures smaller than the de-correlation scales.

One other difference relates to how the model is forced to create ocean initial conditions. In S1 we used the daily 0-24 averaged forecast stresses from the atmospheric NWP system (fc in table 1). The forcing fields used to create ocean initial conditions as part of the ocean assimilation system come from ERA15 for the period prior to 1993 and from Operations from 1994 onwards (ERA/OPS). Model changes and changes to the analysis system were reflected in these stresses creating a low frequency variation that was unphysical and undesirable. By using analyzed winds rather than forecast stresses and calculating the daily mean stresses offline using a bulk formula, some of this variability could be reduced. The analysis is sampled 4 times per day to calculate the daily wind stress. We refer to this way of computing the stress an in table 1.

The ocean initial conditions are provided not from a single ocean analysis but from a 5-member ensemble of ocean analyses. The analyses differ in that a measure of uncertainty in the surface winds used to force the ocean is taken into account (WP in Table 1). In the absence of ocean data assimilation, the uncertainty in ocean state is relatively large, but in the presence of ocean data assimilation is much smaller (Vialard *et al.* 2003. The ensemble of forecasts is produced by using the 5 different ocean analyses and perturbing the surface of the ocean at the initial time, using SST perturbations (TP), and during the coupled integration by using stochastic physics (Buizza *et al.* 1999) (SP in table 1).

		System 1	System2
Observation error	a	1	0.5
	b	0.2	0.1
	L	25(m)	25 (m)
Background error	a	1	1
	b	0.4	0.2
	L(m)	25	25
Zonal scales (Km)	mid latitudes	400	300
	equator	1500	1000
Meridional scales (Km)	mid latitudes	400	300
	equator	200	150

Table 2: Summary of differences in the error covariances for temperature between the data assimilation components of system 1 and system 2.

The SSTs to which the ocean model is relaxed are different. The SST for S1 are the same as those used by the atmospheric analysis system, based on Reynolds OI version 1 (Reynolds and Smith 1995). For S2 we use the improved SST analyses from Reynolds OI version 2 (Reynolds *et al.* 2002).

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