Dealing with Systematic Error in Ocean Data Assimilation

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ABSTRACT

Assimilation of subsurface temperature into an ocean model is a common practice for the creation of ocean initial conditions for seasonal forecasts. It is shown that this procedure largely corrects for system bias, although the assimilation method assumes a bias-free first guess. It is also shown that univariate assimilation of temperature data has detrimental effects for the equatorial currents.

The relation between the presence of systematic error and the degradation of the velocity field is investigated by comparing the results of two schemes aiming at different objectives. The first scheme, designed to prevent the degradation of the equatorial currents, not only improves the velocity field, but also reduces by 20% the size of the temperature bias. The second scheme, designed to estimate and correct the bias of the system, has a beneficial impact on the equatorial currents. Results suggest that there are errors in the momentum equations even in the assimilation case, and that part of that error is due to the data assimilation procedure itself.

1 Introduction

The tropical oceans are thought to be the major source of predictability at seasonal time scales (Palmer and Anderson, 1994). Seasonal forecasts with dynamical coupled models require a good initialization of the thermal structure of the upper tropical oceans. A common practice is to assimilate observations of subsurface temperature, and sometimes surface elevation, into an ocean model driven by atmospheric fluxes. As a result, the data assimilation produces an upgrade of the 3D temperature field (Smith et al, 1991; Ji et al. 1995; Behringer el al., 1998, Segscheider et al, 2000, Ji et al, 2000, Alves et al 2002, Weaver el al 2003). Some schemes can also update the 3D salinity fields, using dynamical or statistical criteria (Troccoli et al, 2001; Vossepoel *et al.*, 1999). In most cases, the final result of the data assimilation process is an update to the density field. Alves *et al.* 2002, show that the initialization of the upper ocean by assimilation of temperature data is beneficial for the quality of the ENSO forecasts. Troccoli *et al.* 2001, Vialard *et al.* 2003, also show that in the Pacific, the quality of the density field is improved when using data assimilation. However beneficial, the data assimilation systems currently used for ocean initialization have problems. Among them, there are two deficiencies common to many assimilation systems: the presence of systematic error and the degradation of the equatorial velocities.

As for initilialization of atmospheric fields for numerical weather prediction, most of the schemes used for operational ocean data assimilation assume that the first guess given by the model background is unbiased. But unlike the atmosphere, this is frequently not the case in the ocean. 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.

The presence of systematic error in an analysis system may be due to model error, error in the forcing fields, or errors in the data assimilation method itself. It may come from the momentum equations or from the temperature equations. Bell *et al.* 2002 proposed a scheme for estimation and correction of the bias during the data assimilation. It assumes that the main source of bias in the system is in the momentum equations. This scheme has been implemented for testing purposes in the ocean data assimilation system (ODAS in what follows) used at ECMWF to initialized the seasonal forecast. In this paper we present and discuss some results.

The degradation of the equatorial currents in ODAS that update only the density field is a common problem (Burgers *et al.*2002, Bell *et al.* 2002, Vialard *et al.* 2003). Errors in the currents induced by the data assimilation prodecure can become an important source of systematic error. This possibility is investigated. It is shown that modifying the assimilation method to update the velocity fields when assimilating temperature data following the scheme proposed by Burgers *et al.* 2002, reduces the error in the velocity field as well as the bias in the temperature field.

The paper is structured as follows: in section 2, we describe the ODAS used in this study, and show the problems with bias and degradation of the velocity field. Section 3 discusses the implications of error in the momentum equations in an ODAS that only updates the density field. The impact of making velocity corrections following the scheme of Burgers *et al.* 2002 is presented in Section 4, while the bias correction proposed by Bell *et al.* 2002 is discussed in section 5. Section 6 offers a summary and some conclusions.

2 The ocean data assimilation system

The first guess of our data assimilation system is given 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). The model is global and has 29 vertical levels. Horizontal discretization is on an Arakawa E grid with a variable grid spacing: the zonal resolution is 1.4 degrees and the meridional resolution varies from 0.3 degrees in the equatorial region (within 10 degrees of the equator), smoothly increasing to 1.4 degrees polewards of 30 degrees.

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 over the top 400m with the exception of the top level where a strong relaxation to analyzed SSTs is applied (Reynolds and Smith 1995).

The model background errors are represented by Gaussian functions which are anisotropic and inhomogeneous. The formulation follows Smith et al. (1991), though some parameter values are different. Within 4 degrees of the equator the correlation length scale in the E/W direction is 1000 km while in the N/S direction it is 150 km. In the sub-tropics and high latitudes, polewards of 15 degrees, the correlation length scale is 300 km in all directions. Between the equatorial strip and the sub-tropics there is a smooth transition in correlation scales. 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 an the increase in uncertainty associated with the large gradients near the thermocline. The observations are given half the weight of the background, except in areas of strong stratification, where the observations are given more weight. A variation of this scheme is described in Alves *et al.* 2003.

The observations are from the GTSPP (Global Temperature Salinity Pilot 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

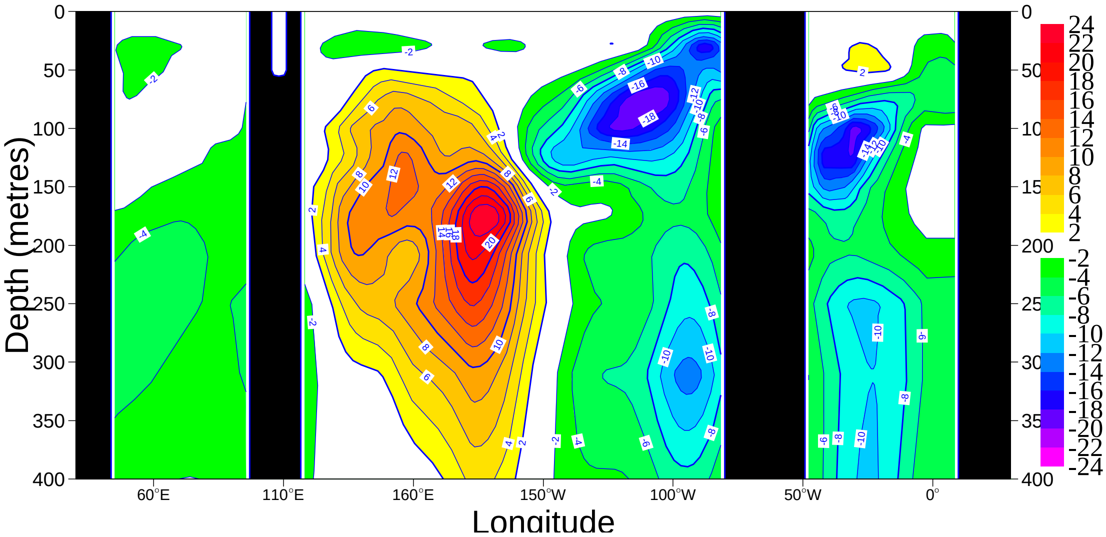


Figure 1: Equatorial long-depth section of mean assimilation temperature increment. Contours every 2°C/year. The mean corresponds to the time average during the period 1991-1998.

with a relaxation time-scale of 3 days. Salinity is changed beneath the surface layer in order to preserve the T-S relationship (Troccoli et al 2001). Monthly climatology of river runoff is included. There is a relaxation to Levitus climatological salinity. At the surface the relaxation time is 7 months, and in the subsurface it is 18 months. A weak relaxation to Levitus thermal analysis is also included.

The forcing fields used to drive the ocean model come from ERA15 for the period 1990 to 1993 and from Operations from 1994 onwards (ERA/OPS in what follows). As forcing fields we use daily fluxes of momentum, heat and fresh water. As with any estimate of ocean forcing, relatively large errors are likely to be present. These errors are likely to contaminate the model state during the integrations, and in particular they can introduce systematic bias to the ocean state. The integrations were carried out during the period 1990-1999. In what follows, we will refer to the stand-alone ocean integrations (i.e., ocean driven by forcing fluxes, without data assimilation) as control ($CNTL$) integrations. The integrations using the data assimilation will be referred to as *ASSIM* integrations.

2.1 Systematic error

Figure 1 shows the 1991-1998 average of a longitude-depth section of the assimilation increments along the Equator. 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, for instance, although it may be due to other mechanisms. In any case, figure 1 shows that the data assimilation is correcting the system bias.

Figure 2 shows a horizontal map of the zonal currents within the tropics for a) $CNTL$ and b) *ASSIM*. As a reference, the climatology from Reverdin *et al.* 1994 is shown in the paper by Weaver A., this issue. Away from the equator, the zonal current is improved, 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 Eastern Pacific, the degradation of the currents is visible not only at the surface, but also at depth. Figure 3 shows the zonal velocity along the equator over the first 300 m for both $CNTL$ and *ASSIM*. In the Eastern a)

b)

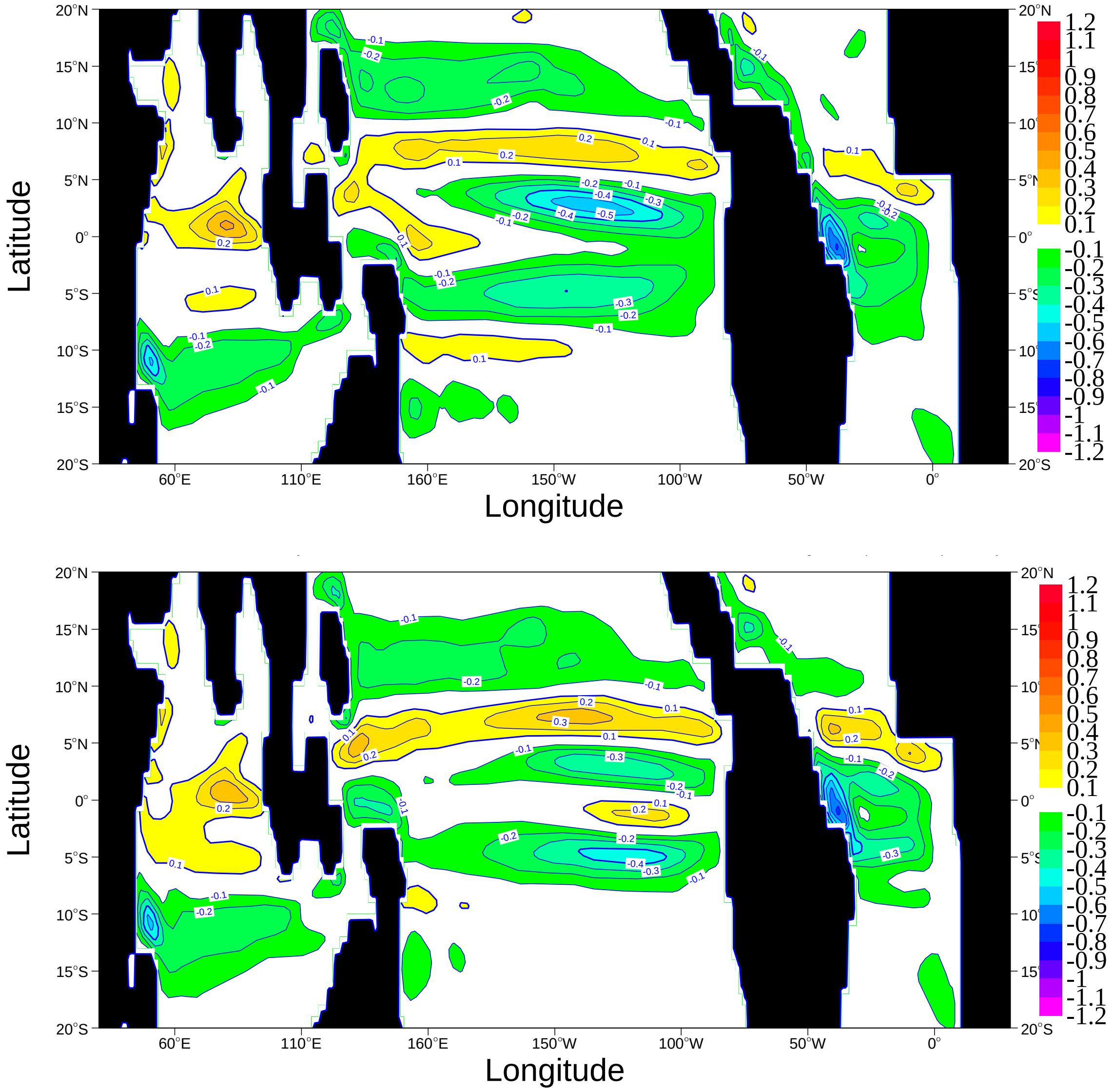


Figure 2: Mean zonal surface currents in the tropical oceans, from CNTL (a), from ASSIM (b) (1991-1998 average). The contour interval is 0.1 m/s

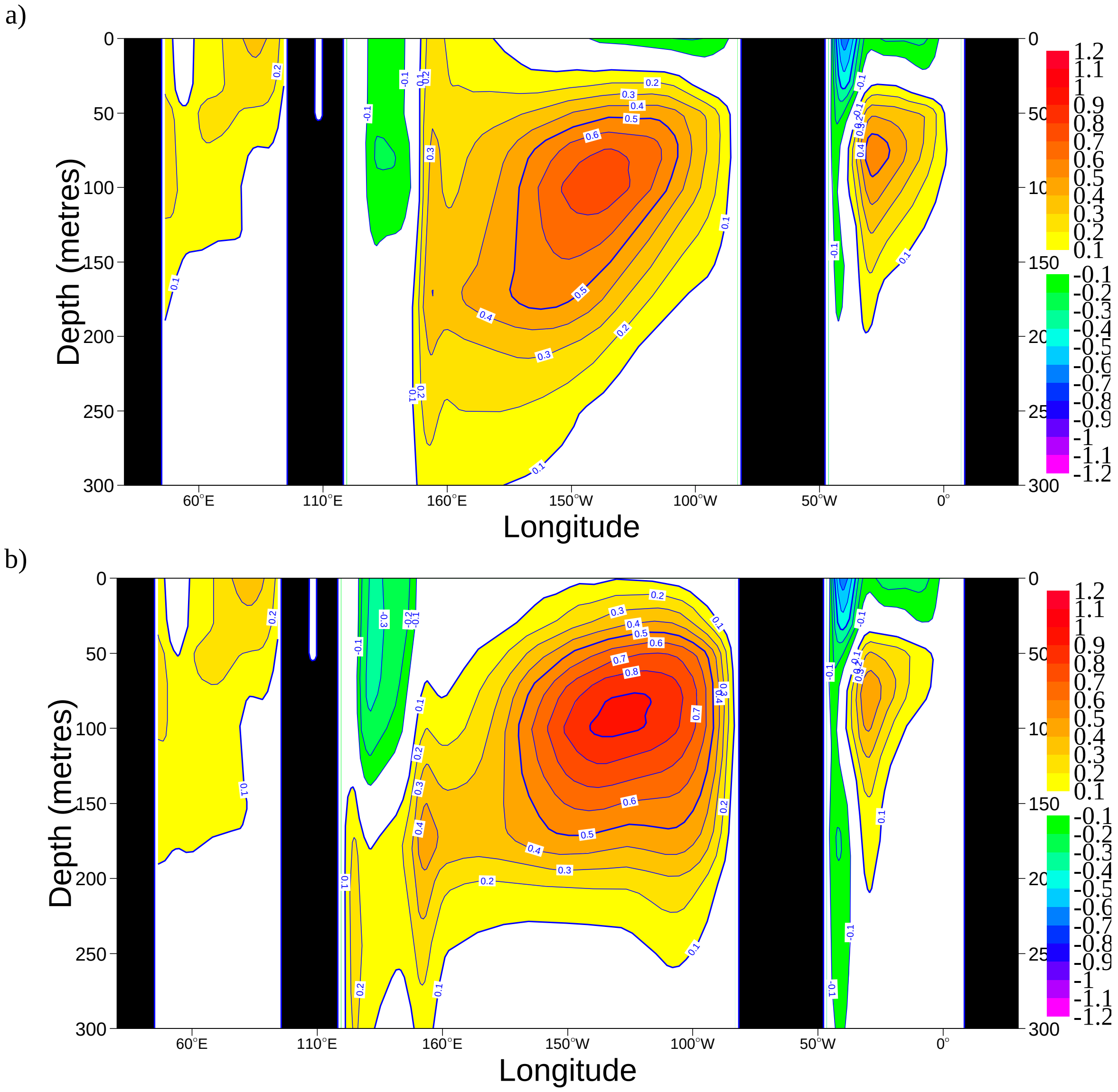


Figure 3: Equatorial depth-longitude section of the zonal velocity, from CNTL (a), from ASSIM (b) (1991-1998 time average). The contour interval is 0.1 m/s

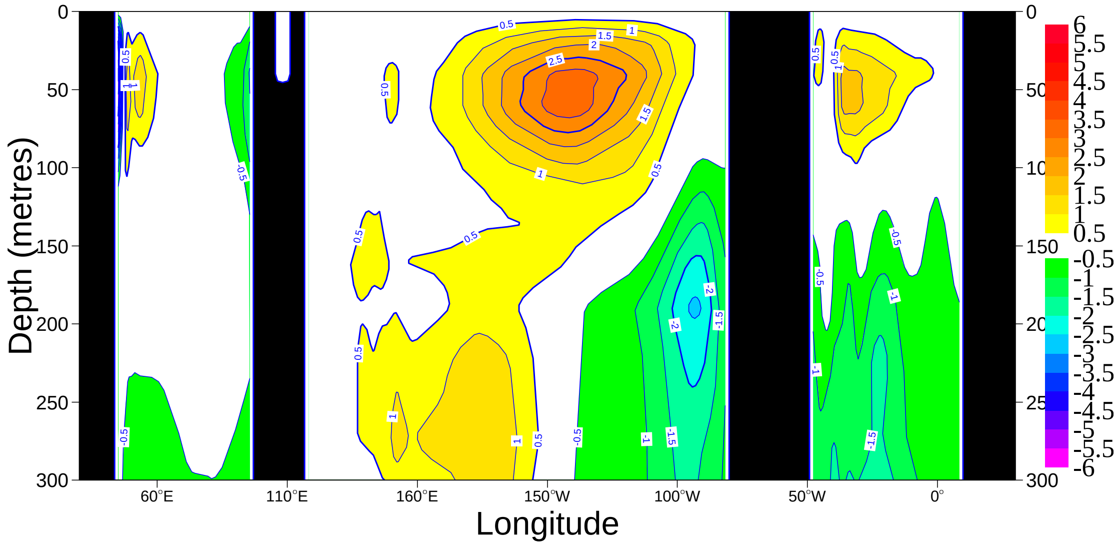


Figure 4: Equatorial longitude-depth section of the vertical velocity in the ASSIM run (1991-1998 average). Contour interval is 0.5m/day

Pacific, the structure of the undercurrent in *ASSIM* is too broad. Comparison with current data indicates that this is wrong. This error may be related to the unrealistic vertical circulation near the South American coast, characterized by very strong downwelling (see figure 4). The degradation of the surface velocity and the spurious vertical circulations appear also in other univariate systems (Vialard *et al.* 2003, Huddelston *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. Additionally, as noticed by Burgers *et al.* 2002, if the main source of error comes from the momentum equations, it may not be feasible to make adequate corrections if only the density field is updated.

3 Error in the momentum equation

In this section we will use the shallow water equations to illustrate the problems that arise from the assimilation of temperature data in the case when the main source of error resides in the momentum equations.

Let S_XY be a shallow water system (u_1, v_1, h_1), with Newtonian friction r, and external forcing (X,Y) in the momentum equations, as represented in equation 1.

$$\begin{aligned}
\frac{\partial u_1}{\partial t} - f v_1 + r u_1 + g' \frac{\partial h_1}{\partial x} &= X \\
\frac{\partial v_1}{\partial t} + f u_1 + r v_1 + g' \frac{\partial h_1}{\partial y} &= Y \\
\frac{\partial h_1}{\partial t} + H \left(\frac{\partial u_1}{\partial x} + \frac{\partial v_1}{\partial y} \right) &= 0
\end{aligned} \qquad (1)$$

Let S_Q be a shallow water system (u_2, v_2, h_2) with some heat source Q, as shown in equation 2

$$\begin{aligned}
\frac{\partial u_2}{\partial t} - f v_2 + r u_2 + g' \frac{\partial h_2}{\partial x} &= 0 \\
\frac{\partial v_2}{\partial t} + f u_2 + r v_2 + g' \frac{\partial h_2}{\partial y} &= 0 \\
\frac{\partial h_2}{\partial t} + H \left(\frac{\partial u_2}{\partial x} + \frac{\partial v_2}{\partial y} \right) &= Q
\end{aligned} \tag{2}$$

Let us introduce a constraint requesting that in equilibrium, the two systems should have the same values of the surface elevation (i.e., $h_1 = h_2$). For this to be achieved, the velocities have to be different, as can be seen in this example. Substracting 1 from 2 leads to the following equations:

$$\begin{aligned}
r u_e - f v_e &= -X \\
r v_e + f u_e &= -Y \\
H \left(\frac{\partial u_e}{\partial x} + \frac{\partial v_e}{\partial y} \right) &= Q
\end{aligned} \tag{3}$$

where $(u_e, v_e) = (u_2 - u_1, v_2 - v_1)$. Equation 3 indicates that the residual velocity field (u_e, v_e) follows the Ekman equation, its divergence being proportional to the heat source. Equations 2 provide an analogy for a data assimilation system in which only updates to the density fields (Q) are made. If the source of error lies in the momentum equations it will not be possible to obtain the correct values of the velocities by updating the density field. Equation 3 also implies that to infer the errors $(-X, -Y)$ of the momentum equations, density information Q is not enough, since it only offers information about errors in the divergence.

In the existing ODAS the presence of error in the momentum equation is very likely (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, that can introduce errors in the velocity field when disrupting the geostrophic balance between density and velocity. Burgers *et al.* 2002 proposed a scheme to prevent the disruption of the geostrophic balance by means of imposing constraints between the density and velocity increments. Alternatively, this scheme can also be interpreted as a heuristic way of inferring errors in the momentum equation, regardless their origin, and making corrections to the velocity field by some kind of approximation of equation 3. The scheme of Bell *et al.* 2002 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 Velocity adjustments

Imposing a geostrophic constraint between density and velocity increments is straightforward except near the equator where the geostrophic relationship breaks down. At the equator it is possible to apply some kind of requirement (using scaling, symmetry, or continuity arguments), and 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 should be different from zero, since it is at the equator that the currents are degraded most in the presence of data assimilation.

The criteria followed here for the equatorial solution assume a symmetric shape for the zonal velocity. It can be obtained from the y-derivative of the geostrophic relation in a β-plane. Using the example of the shallow water equations again, 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 4:

$$\begin{aligned}\Delta v_{eq} &= 0 \\ \Delta u_{eq} &= -\frac{g'}{\beta}\frac{\partial^2 \Delta h}{\partial y^2}\end{aligned} \tag{4}$$

where the updates to the meridional velocity are neglected. Outside the equator, the geostrophic balance is given by 5:

$$\begin{aligned}\Delta v_{neq} &= \frac{g'}{f}\frac{\partial \Delta h}{\partial x} \\ \Delta u_{neq} &= -\frac{g'}{f}\frac{\partial \Delta h}{\partial y}\end{aligned} \tag{5}$$

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°). Note that the blended solution also complies with geostrophy:

$$\begin{aligned}\Delta u &= \gamma\Big((1-e^{(y/y_0)^2})\Delta u_{neq} + e^{(y/y_0)^2}\Delta u_{eq}\Big) \\ \Delta v &= \gamma\Big((1-e^{(y/y_0)^2}\Big)\Delta v_{neq})\end{aligned} \tag{6}$$

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 5 shows the surface currents in the experiment $ASSIM_G$ where the gestrophic balance has been applied. Unlike the experiment *ASSIM*, the undercurrent does not surface. The mean value of the zonal current is more 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 4 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 1).

The geostrophic balance scheme to update the velocity field has been implemented in the operational version of the ODAS of the seasonal forecast system (S2) of ECMWF. 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).

5 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 approached is followed by the Bell *et al.* 2002 scheme for bias correction in a sequential data assimilation. Their scheme assumes that the systematic error in the system comes from errors in the formulation of the pressure gradient, i.e., the error has purely a divergent

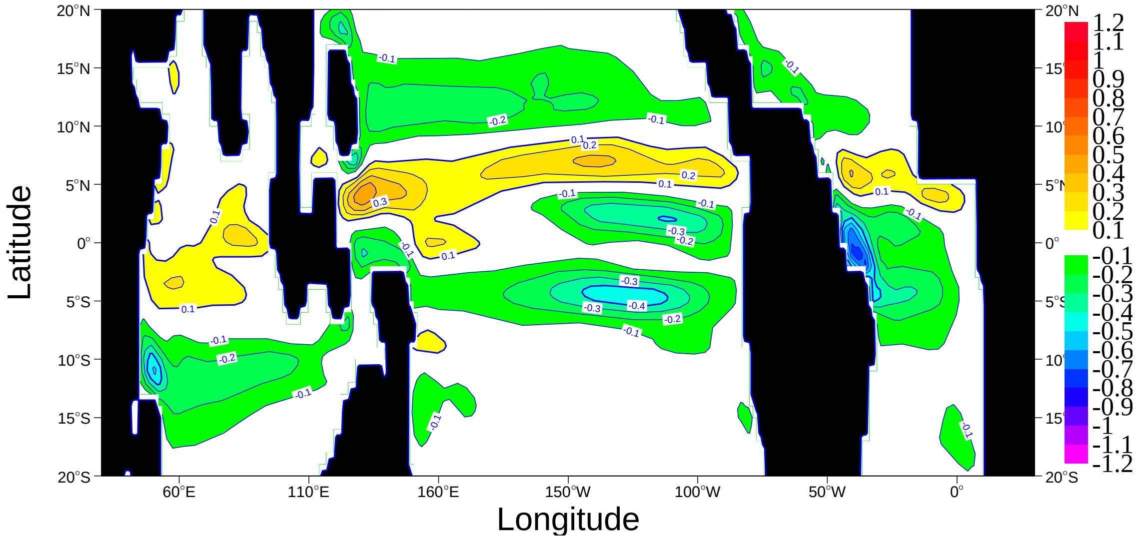


Figure 5: Mean zonal surface currents in the tropical oceans, from a data assimilation experiment where balanced updates to the velocity field are added (experiment ASSIM$_G$). For comparison see figure 2.

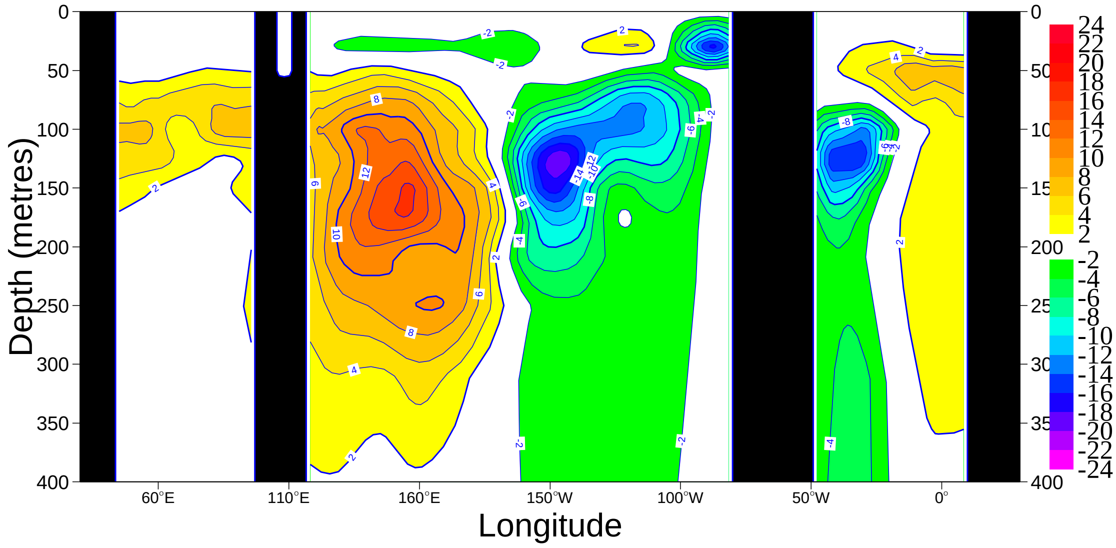


Figure 6: As figure 1, but from a data assimilation experiment where balanced updates to the velocity field are added (experiment ASSIM$_G$). Notice the reduction in the mean assimilation increment.

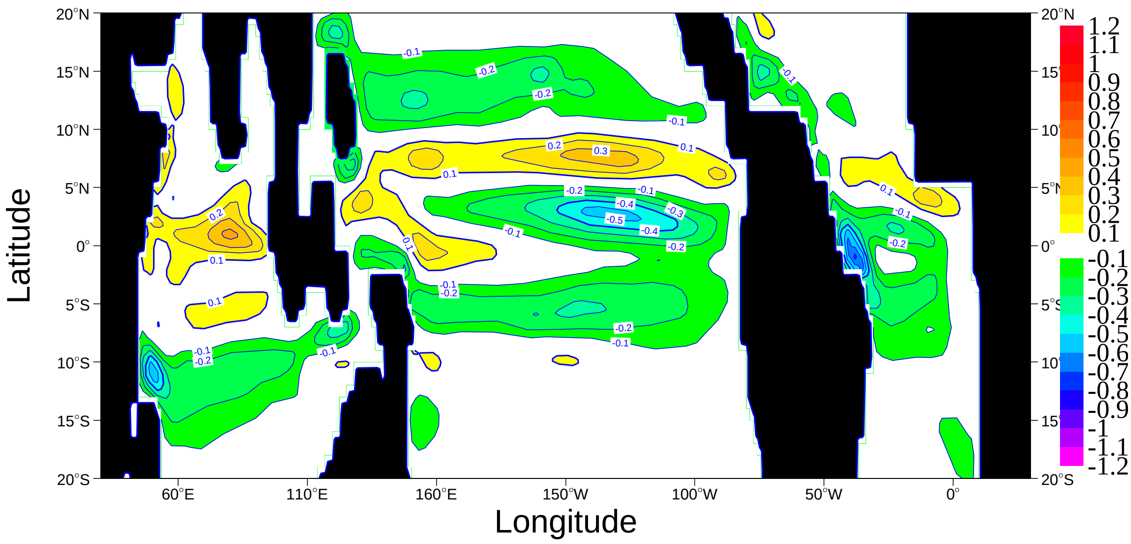


Figure 7: Mean zonal surface currents over the tropical oceans, from the data assimilation experiment where the bias is corrected (experiment ASSIM$_{B1}$). For comparison see figure 2.

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:

$$\begin{aligned}
\frac{\partial u}{\partial t} - fv + ru &= -g'\frac{\partial(h+h_b)}{\partial x} + X \\
\frac{\partial v}{\partial t} + fu + rv &= -g'\frac{\partial(h+h_b)}{\partial y} + Y \\
\frac{\partial h}{\partial t} + H\left(\frac{\partial u}{\partial x} + \frac{\partial v}{\partial y}\right) &= Q
\end{aligned} \tag{7}$$

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

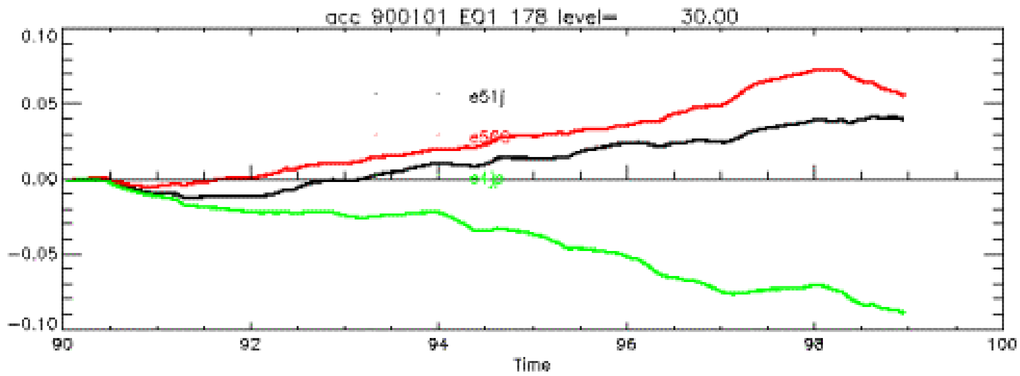
The bias term can be estimated using information from assimilation increments of density (or temperature and salinity). The time evolution for the bias term is proportional to the time integral of the density increments (Δh):

$$h_b(t) = h_b(t-1) - \alpha \Delta h(t) \tag{8}$$

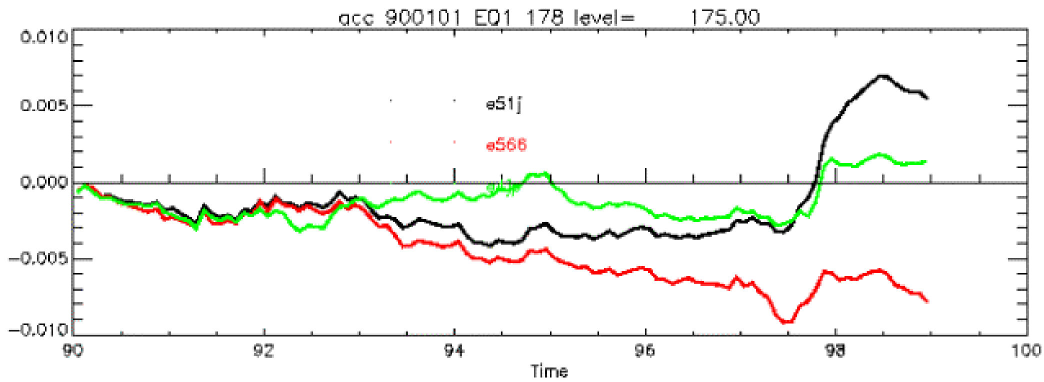
where α is a constant larger than zero but smaller than 1. If the estimation is correct, after a certain time, $\Delta h(t)$ would be zero, and correction term would reach a constant value.

The method has been applied to the data assimilation system described in section 2. The inclusion of the pressure gradient correction avoids degradation of the equatorial circulation. Figure 7 shows the zonal velocity in the bias correction experiment (*ASSIM*$_{B1}$), which is better than that from experiment *ASSIM* shown in figure 2b.

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 8 shows the time evolution of the accumulated assimilation increment for 3 different experiments at two locations. The experiments



a)



b)

Figure 8: Time series of the accumulated assimilation increment (see text).

correspond to the standard data assimilation *ASSIM* (green), and to two experiments where the bias has been corrected, 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 2 panels of figure 8 are for depths at 30m and 175m of a region in the eastern Equatorial Pacific (15W-90W, 5N-5S). The first feature to notice is the sensitivity of the scheme to the value chosen for α. Indeed, too large a value may cause an overcorrection. At 30m depth (8a) the evolution of the accumulated increment stabilizes for the experiments with the bias correction scheme, although there is a hint of overcorrection (the accumulated increments of $ASSIM_{B1}$ and $ASSIM_{B3}$ have different sign to those of experiment *ASSIM*). At deeper layers the evolution of the bias is far from constant; at 175m, the integrated increment shows large fluctuations in time, which are correlated with the interannual variability. The El Niño of 1997-1998 is clearly visible in figure 8b, for instance. 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:

$$h_b(t) \quad = \quad \beta h_b(t-1) - \alpha \Delta h(t) \qquad (9)$$

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 source of non stationary systematic errors.

6 Summary and conclusions

Assimilation schemes of the type used to initialize the ocean state for seasonal forecasts have problems with systematic error. On the one hand the assimilation increments do not average to zero, and on the other hand the velocity field of the analyzed state degrades. This is the case for the OI scheme presented here, that uses temperature information to update the model density field only. It is shown that imposing a balance relationship between density and velocity improves the velocity estimate at the same time as it reduces the bias in the mean. The method of imposing the balance could be generalized by introducing geographically-varying coefficients.

The Bell *et al.* method to estimate and correct the bias has also been implemented in the same assimilation system. In agreement with previous experiences, the bias correction method prevents the degradation of the equatorial currents. Although the method seems to work quite well in general, reducing the bias, it may be the source of other errors, since the assumption that the error is constant in time is not necessarily true. This may be particularly relevant in real time seasonal forecasting systems, with high interannual variability and probably flow-dependent errors, and where the quality of the forcing fields (usually from NWP systems) is likely to change. The idea of correcting the error in the momentum equations can still be used, however, and the estimation scheme could be easily generalized to cope with non stationary errors. Additionally, the scheme could be very useful for estimation (but not correction) of the errors.

7 Aknowledgements

Thanks are due to D. Anderson for helpful comments improving the manuscript.

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