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Exchanges

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Impact of temperature error models in a univariate ocean data assimilation system[1]

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Introduction

Ocean data assimilation systems combine observations with information from prediction models to produce an analysis or estimate of the ocean state. Statistical interpolation assimilation methods use observations to correct a model-based first guess and require specification of first-guess and observation error statistics. Often the first-guess error covariance (FGEC) is described by an analytical covariance function whose structure is not directly related to ocean dynamics. On the other hand, ensemble and reduced-space methods represent the FGEC by a low-rank approximation coming from the dynamical model. Here we examine the impact of adding a low-rank FGEC component to an operational univariate ocean data assimilation (ODA) system. Small-scale structures are eliminated from the mean temperature correction and positive impact is seen in the zonal currents.

Ocean data assimilation system

The ODA system uses the MOM-1 Pacific basin model with TAO, XBT and blended SST observations as described in (Behringer et al., 1998). At each assimilation time, the model first-guess is compared to observations and a temperature correction is calculated by minimizing a cost function (Derber and Rosati, 1989). The cost function rewards, with weight depending on the observation error covariance, temperature corrections that reduce mismatch between analysis and observations. Simultaneously, temperature corrections whose magnitude and spatial structure are incompatible with the FGEC are penalized. The spatial structure of the FGEC controls how first-guess errors are corrected in a neighbourhood of the observation, an important property when there are few observations.

Assimilation experiments

We compare a control analysis with one obtained using a FGEC model with low-rank component. The control analysis is produced using a FGEC model G^f with Gaussian horizontal correlations and temperature gradient dependent vertical correlations (Behringer et al., 1998). The reduced-space FGEC S^f has the form:

$$S^f = \alpha G^f_{\perp} + ZFZ^T = \alpha(I - ZZ^T)G^f(I - ZZ^T) + ZFZ^T \qquad (1)$$

where $0 \leq \alpha \leq 1$ is a tunable parameter, the columns of the matrix Z are the EOFs of a simulation and F is a symmetric positive definite matrix. This formulation, like that of Hamill and Snyder (2000) is simple to implement in an existing 3D-Var system; in this formulation however, we assume the reduced-space and analytical parts to be uncorrelated. For the special case $\alpha = 0$ whose results are presented here, calculation of the temperature correction is simplified. We consider the period March, 1993 - February, 1997 and use the reduced-space spanned by the first 80 EOFs.

Results

The mean temperature correction and the mean difference between observations and analysis are significantly different from zero, indicating systematic biases (Fig. 1). The reduced-space analysis is generally less constrained by observations than the control analysis. In both cases, the mean temperature correction is correlated with the mismatch between analysis and TAO data. In the control analysis, the mean temperature correction maxima and minima correspond to TAO locations, producing structures with length-scales on the order of the TAO mooring spacing. These structures do not appear in the analysed temperature field or its derivatives. In the reduced-space experiment, the mean temperature correction attempts to correct the same model and forcing deficiencies but does so with larger scale structures. In both experiments the impact on the analysed temperature fields (compared to simulation) is qualitatively similar. However, the impacts on the zonal currents are different (Fig. 2). The mean zonal surface current exceeds -50 cm/sec. in the Eastern Pacific for the control case while the measured value at (0°N,110°W) is -17.3 cm/sec. The equatorial undercurrent core in the control is weakened by about 12 cm/sec and shifted to the west compared to the reduced-space experiment. Similar impacts on zonal

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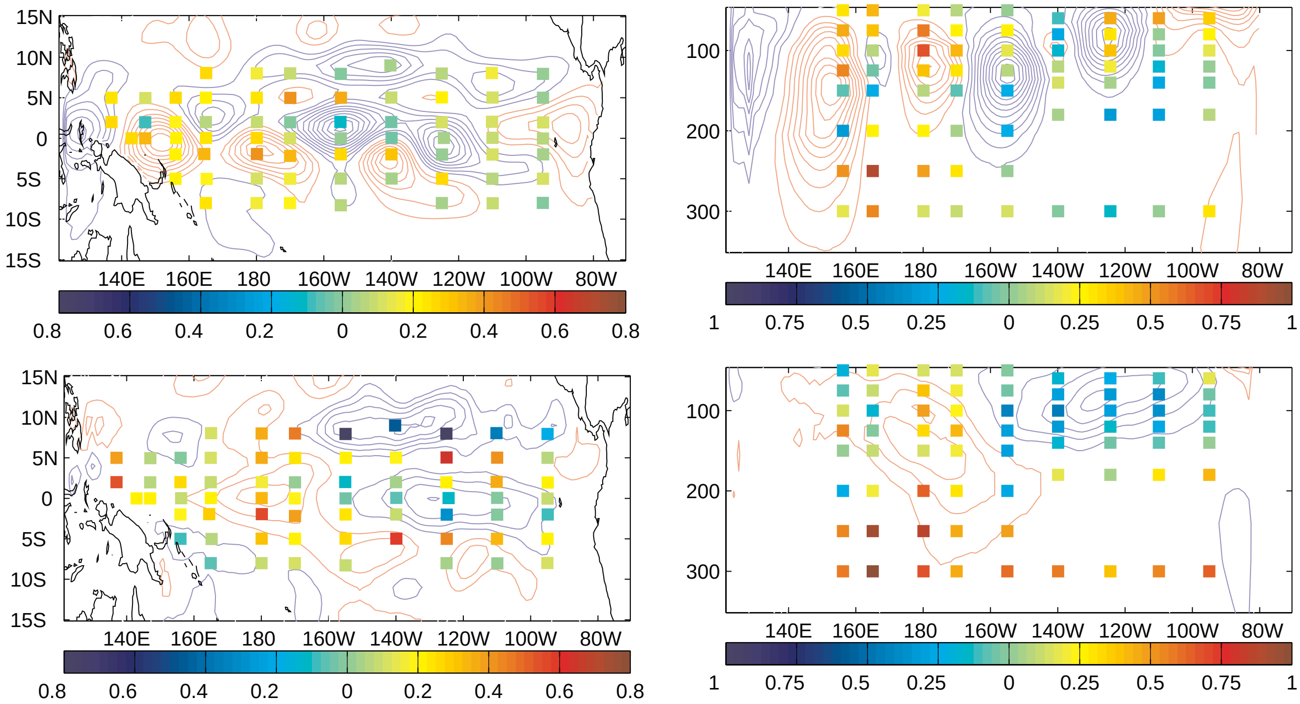

Fig. 1 (above): Mean temperature corrections (positive (negative) contours are red (blue)) and TAO observations minus analysis (colored squares) (a) vertically averaged (50 - 500m; contour interval of 0.004°C / hour) and (b) along the equator (contour interval of 0.008°C / hour)) for the control case. (c) and (d) as in (a) and (b) but for the reduced space analysis.

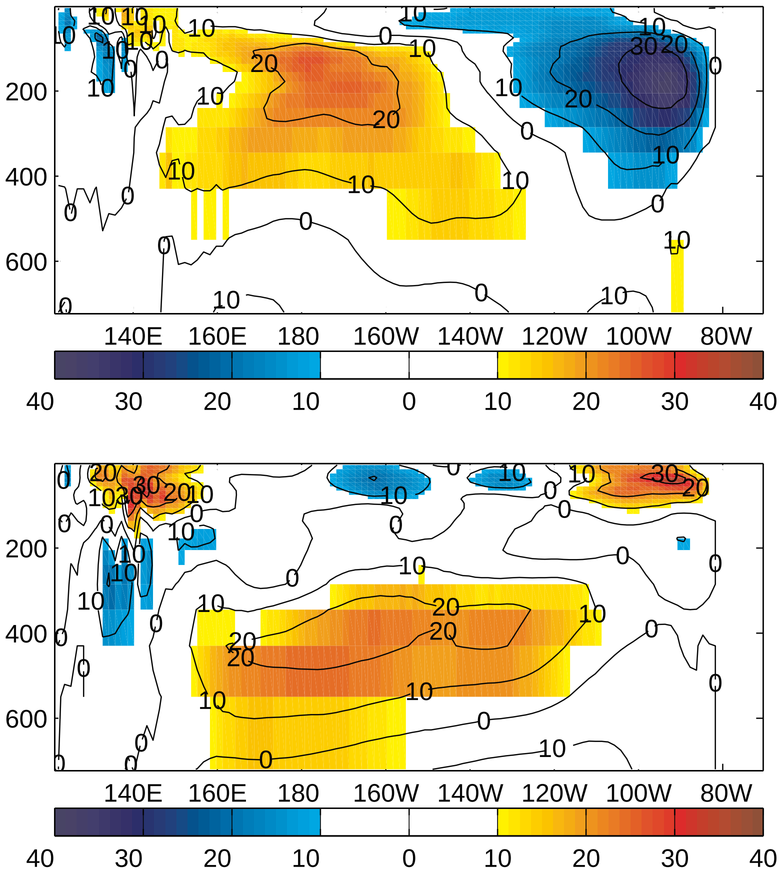

Fig. 2: Mean difference in cm/sec of simulation equatorial zonal currents and (a) control analysis and (b) reduced-space analysis.

velocity are seen when simulations are forced with time-independent mean temperature corrections.

Conclusions

Temperature error models in univariate ocean data assimilation systems impact zonal velocity. The temperature corrections produced using a reduced-space FGEC have less small-scale structure and were seen to have a positive impact on zonal currents.

In the reduced-space FGEC model used here (α= 0), errors are reduced only on the reduced-space which in the reduced-space Kalman filter causes divergence (Cohn and Todling, 1996). The choice here of simulation EOFs to span the reduced subspace is not necessarily appropriate even in the most idealized systems since the simulation EOFs do not include the effect of data assimilation or model error (Tippett et al., 2000). Therefore, likely there is benefit in considering a FGEC with both reduced and analytical parts (a>0). Future work will examine impact on forecast skill.

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