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Bias correction of an ocean-atmosphere coupled model

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Abstract. A serious problem in the initialization of a climate forecast model is the model-data incompatibility caused by systematic model biases. Here we use the Lamont model to demonstrate that these biases can be effectively reduced with a simple statistical correction, and the bias-corrected model can have a more realistic internal variability as well as an improved forecast performance. The results reported here should be of practical use to other ocean-atmosphere coupled models for climate prediction.

1. Introduction

In recent years, much research effort in climate prediction has been devoted to model initialization and data assimilation issues. An outstanding problem in this research area is the model-data incompatibility caused by large systematic model biases. For various reasons, even the most comprehensive general circulation models (GCMs) are not immune to this problem, let alone the models with highly simplified physics such as the Lamont model [*Cane et al.*, 1986; *Zebiak and Cane*, 1987]. Without an effective method to reduce the model-data mismatch, assimilating real data into the initial state of a forecast model could result in an initialization shock, which would prevent the model from achieving its optimal predictive skill.

One way to deal with this problem is to assign less weight to observational data to make initial conditions more consistent with the intrinsic model structure. For example, by using a coupled data assimilation procedure that relies more on model winds than on observed ones, we were able to reduce the initialization shock of the Lamont model and greatly improve the model's forecast skill for the 1980s [*Chen et al.*, 1995]. This approach implicitly assumes that the model does not need much data to keep itself on track, evidently the case for the 1980s and early 1990s, when the observed ENSO bore a strong resemblance to the model's internal variability. However, the assumption does not hold for recent years, when the model simply could not work well without a strong helping hand from data [*Chen et al.*, 1998, 1999]. In any case, a forecast scheme that neglects the majority of available observations for initialization cannot be optimal.

Moreover, as long as model biases are intact, a forecast system will not be able to predict the spatial structure of ENSO even when it gets the temporal evolution right. As shown in Figure 1, the same types of systematic biases are found in all three previous versions of the Lamont model, whether the model was initialized with only observed wind stress (LDEO1) [*Cane et al.*, 1986], both observed and model wind stress with more weight on the latter (LDEO2) [*Chen et al.*, 1995], or a combination of wind stress and sea level from both observation and model (LDEO3) [*Chen et al.*, 1998]. The model biases in wind stress include the large off-equatorial easterlies in the eastern tropical Pacific and the absence of equatorial easterlies in the far western Pacific. The model-predicted warm event tends to shift northward around 130°W and southward near the eastern boundary.

In order to make full use of data without much initialization shock, and to predict both temporal and spatial structure of ENSO, we have to correct the systematic model biases. Not much attention has been paid to this problem in the past. An exception is the enlightening work of Barnett et al. (1993), which is particularly relevant to our present study. In the development of their hybrid forecast model, they found it necessary to correct the sea surface temperature (SST) biases of their ocean GCM before passing the SST fields to the statistical atmosphere model. They built their error corrector based on model output statistics (MOS) and used both model SST and sea level as predictors. In the present study, we applied a similar method in a more sys-

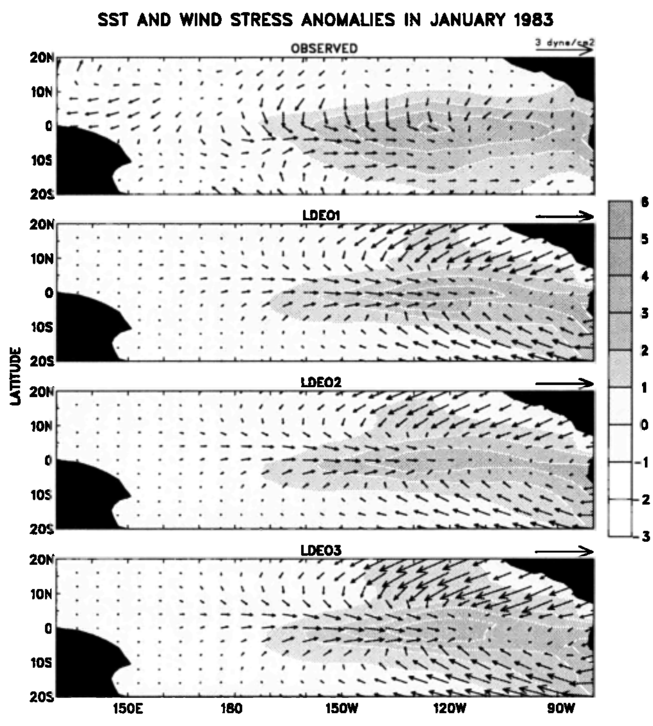

Figure 1. Observed and forecast SST and wind stress anomalies in January 1983. Forecasts were made at 3-month lead by the Lamont model with three different initializations.

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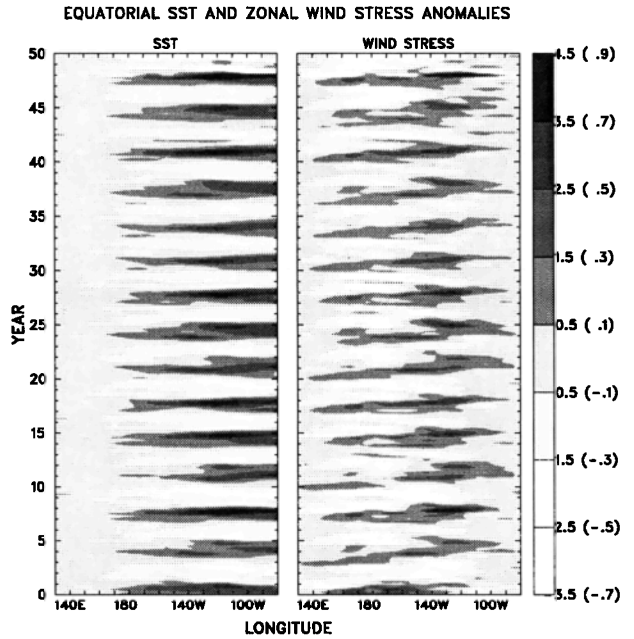

Figure 2. Time-longitude plots of the equatorial SST and zonal wind stress anomalies from the bias-corrected Lamont model (LDEO4).

tematic way to correct the biases of wind stress, SST and sea level fields of the Lamont model, with the intention of improving the model's realism as well as its forecast performance.

2. Methodology

The bias correction method used here is based on the regression of model errors and model states in a reduced space of empirical orthogonal functions (EOFs). The EOFs and regression coefficient matrices were obtained using 16 years (1970-85) of observational data and model output. The observational data include the CAC SST analyses [*Reynolds and Smith*, 1994], the FSU wind stress analyses [*Goldenberg and O'Brien*, 1981], and the sea level product based on tide-gauge observations [*Cane et al.*, 1996]. The model output is from forced model runs, that is, the SST and sea level from the ocean model forced with the FSU winds, and the wind stress from the atmosphere model forced with the CAC SST fields. Defining E as the error of a model variable and S as the model state consisting of anomalous SST, wind stress and sea level, we have

$$E(t,x) = \sum_n \alpha_n(t) e_n(x), \tag{1}$$

$$S(t,x) = \sum_n \beta_n(t) s_n(x), \tag{2}$$

where t is time and x is the spatial domain of the tropical Pacific (20°S to 20°N, and 130°E to 85°W); α and e are the temporal and spatial coefficients of the model error EOFs, and β and s are the corresponding coefficients for the multivariate EOFs (MEOFs) of the model state. The three variables that define the model state are weighted equally in calculating the MEOFs. The regression coefficients r relating the error of a model variable and the model state is defined as

$$r_{nm} = \sum_t \alpha_n \beta_m / \sum_t \beta_m^2. \tag{3}$$

The procedure of bias correction at a particular time t is as follows. First, the current model state and the state MEOFs are used to obtain β:

$$\beta_n(t) = \sum_x S(t,x) s_n(x), \tag{4}$$

then α for a particular model variable is calculated according to

$$\alpha_m(t) = \sum_n r_{nm} \beta_n(t), \tag{5}$$

and finally the biases are estimated using (1) and are subtracted from the model fields. The same procedure is applied to correct model wind stress, SST, and sea level at each time step. This amounts to adding an interactive statistical component to the coupled model, and therefore is not just a MOS correction on model output. There are two important practical questions that need to be addressed here. One is how many EOF and MEOF modes should be retained. By trial and error, we chose 6 EOF modes for SST, 8 EOF modes for wind stress and sea level, and 8 MEOF modes for ocean state. The model behavior is not particularly sensitive to the number of modes as long as 5-8 modes are included. The other question is whether to make the EOFs and MEOFs time invariant (one model for all times), or to construct a separate set for each calendar month [*Barnett et al.*, 1993]. We chose the latter because it leads to more realistic model behavior. Hereafter we refer to this bias-corrected model as LDEO4 to distinguish it from three previous versions of the Lamont model.

3. Results

The internal variability of LDEO4 was investigated in a 100-year model run. The only external forcing was a patch of westerly wind stress in the western equatorial Pacific during the first 6 months of the experiment. Figure 2 shows the model SST and zonal wind stress anomalies along the equator for the first 50 years. The model's internal variability is dominated by a 3-4 year oscillation that has comparable amplitude and zonal extent to observed ENSO, but tends to be more regular. There appears to be an eastward propagation, especially in wind stress anomaly, that

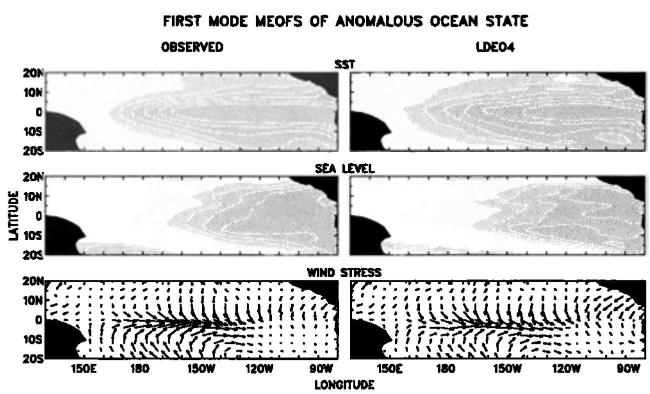

Figure 3. First mode multivariate EOFs calculated from 24 years (1975-98) of observation (24% variance) and from 50 years of LDEO4 model run (36% variance).

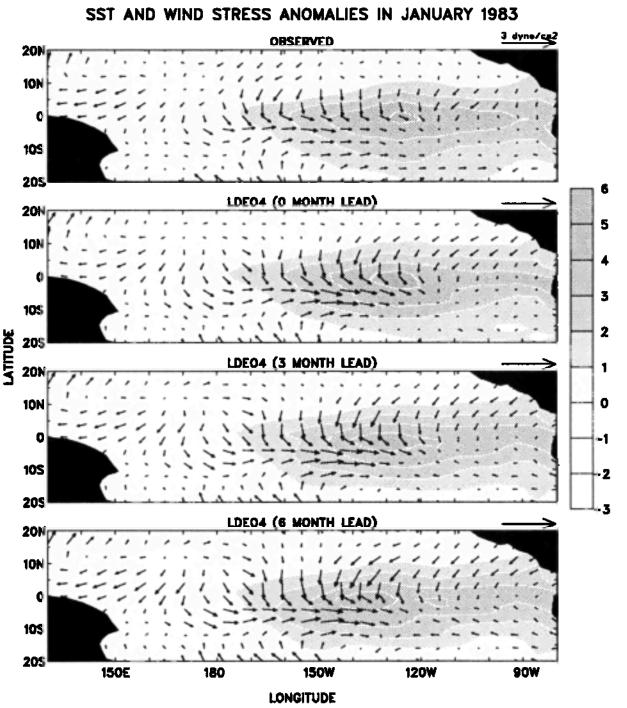

Figure 4. Observed and forecast SST and wind stress anomalies in January 1983. Forecasts were made by LDEO4 at lead times of 0, 3, and 6 months.

again agrees well with observed ENSO. This is a distinctive improvement over the original Lamont model, whose interannual variability is essentially a standing mode [*Zebiak and Cane*, 1987]. The spatial structure of the dominant coupled mode in LDEO4 is depicted in Figure 3, where the first mode MEOFs of the model SST, sea level and wind stress are compared with those constructed from 24 years (1975-98) of observational data. The general agreement between the two is quite striking, although there remain some small differences.

Now let us examine the forecast performance of LDEO4. Here the model was initialized with observed winds as in LDEO1 and with observed sea level as in LDEO3. Figure 4 shows the LDEO4 forecasts at different lead times verified in January 1983. It is obvious that LDEO4 does a much more credible job in predicting the spatial structure of the 1982-83 warm event, as compared to the previous versions of the model (Figure 1). The large off-equatorial easterlies in the east were largely reduced, the equatorial easterly in the far west was well reproduced, and the SST pattern was more in line with the observed El Niño. One may argue that the drastic improvement here is artificial because this event is included in the training period of our bias correction model. Then perhaps it is more convincing to compare the results for December 1997 (Figure 5). LDEO1 and LDEO 2 (not shown) underpredicted this warm event while LDEO3 overpredicted it. The same patterns of biases found in the forecasts of the 1982-83 event by LDEO1-3 (Figure 1) are also evident here. LDEO4, being almost bias free, again produced the best forecast for the 1997-98 El Niño.

We have evaluated the LDEO4 forecasts of NINO3 (SST anomaly averaged from 5°S to 5°N, and 90°W to 150°W) at different lead times for the period from 1972 to 1998. The model predictions were generally good, certainly measuring up to the state of the art. There still remain some problems that are common to many models, such as the inability to predict the onset of the 1997-98 El Niño at long lead times. Figure 6 compares the forecast skill of LDEO4 to that of LDEO1-3 for two different periods: one from 1972 to 1985 and the other from 1986 to 1998. The model should be free of artificial skill for the latter period, since the observational data from that period were not used for training. For the 1972-85 period, LDEO1 had the lowest correlation score and the largest root mean square (rms) error; LDEO2 and LDEO3 were comparable with each other in skill and were much better than LDEO1; LDEO4 was clearly the winner in terms of both correlation and rms scores. For the 1986-98 period, LDEO4 was still the best in both scores; LDEO3 was a close runner-up due to its rather successful prediction of the 1997-98 El Niño (Chen et al., 1998); LDEO1 and LDEO2 did not score high in this period because they missed almost everything after the 1991-92 event.

4. Discussion

The formalisms typically used in ocean and atmosphere data assimilation technuques take a "textbook" approach and assume model biases do not exist. In practice, the "unbiased" a priori error estimates are often inflated in order to achieve consistency in a posteriori verification. Consequently, almost all successful uses of data assimilation in ENSO forecasting weight models unrealistically high compared to observations. This is particularly true for adjoint methods, which treat the model as if it had zero error. Another way of describing the same problem is to say that there is an initialization shock when data are inserted into initial model states without taking account of model biases.

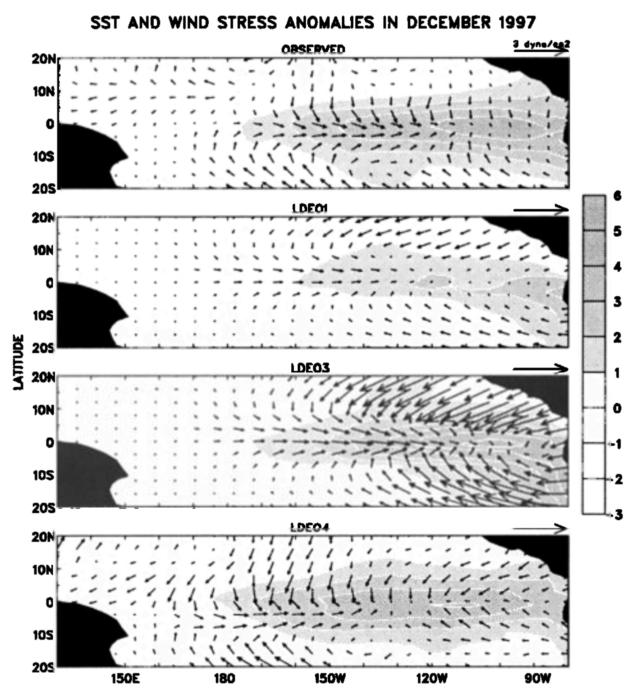

Figure 5. Observed and forecast SST and wind stress anomalies in December 1997. Forecasts were made at 6 month lead by LDEO1, LDEO3, and LDEO4.

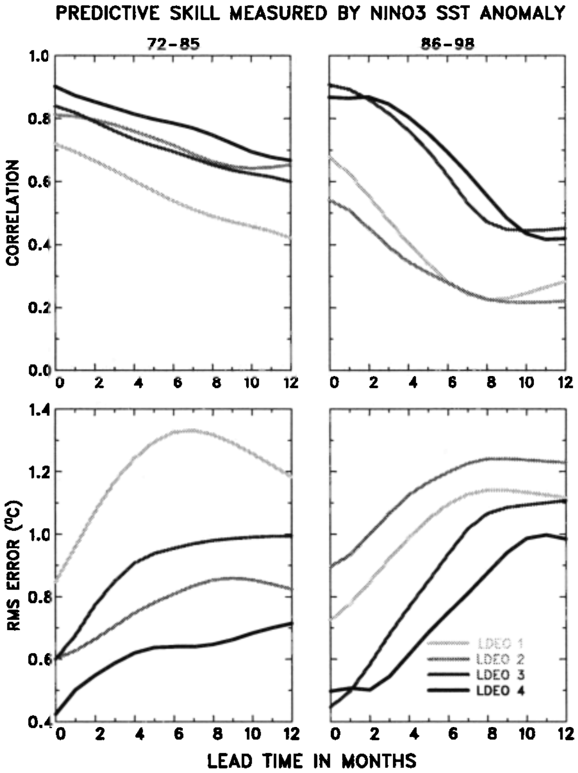

Figure 6. Correlations and rms errors between model forecast and observed NINO3 index for 1972-82 and 1986-98 periods. Different grey-scales are assigned to the different curves representing four versions of the Lamont model.

The adjoint methods take the ultimate path to remove it, sacrificing the data if need to. In other schemes, the data-model difference projects onto rapidly growing error modes, resulting in a poor forecast.

We have demonstrated in this study that the systematic biases of the Lamont model can be effectively reduced with a simple statistical correction based on the regression between the leading EOFs of the model errors and the leading MEOFs of the model states. The bias-corrected model not only performs better in ENSO forecasting, but also exhibits a more realistic internal variability. It is important to note that the bias correction is an integral part of the coupled model so that, for instance, the bias-corrected SST field will be used for the next computation of the wind field, and so on. This is why a bias-corrected model can have a different, and hopefully more realistic, internal variability. The bias correction procedure reported here should be generally applicable to other coupled ocean-atmosphere models, albeit the specifications of the optimal statistical corrector may differ.

Having a bias-corrected model makes it more straightforward to assimilate data for model initialization, which is the motivation of this study in the first place. The predictive skill of the original Lamont model (LDEO1) was severely limited by the initialization shock caused by large model biases. Previously, the only way to make a smooth start from initial state with this model is to put less weight on observational data during initialization (LDEO2 and LDEO3). With the systematic biases corrected, the model (LDEO4) experiences no shock even when initialized with full observed wind stress anomaly field as in LDEO1, because the model wind stress anomaly is now very similar to the observed. However, we are still not able to initialize the model with full observed SST and sea level data without a shock, which suggests that our correction on SST and sea level is probably not as effective as that on wind stress. More analysis on this issue is needed.

The model performance is still far from perfect. The most obvious shortcoming is its relatively poor forecast skill in recent years. This is a common problem for all ENSO forecast models and there must be a physical reason for it. We cannot expect to solve this problem by merely reducing systematic model biases. We consider the bias correction procedure described here as a practical tool for forecast models rather than the ultimate solution for model deficiencies. Nevertheless, careful analyses of the EOF modes of model biases may help us to identify model problems and improve model physics, and eventually alleviate the need for bias correction. On the other hand, because of specific model design, it may not be possible for some models, including the Lamont model, to physically eliminate model biases without fundamentally rebuilding the model. In such cases, statistical bias correction is certainly a useful way to bridge the gap between the model and reality.

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References

Barnett, T. P., M. Latif, N. Graham, M. Flugel, S. Pazan, and W. White, ENSO and ENSO-related predictability. Part I: Prediction of equatorial Pacific sea surface temperature with a hybrid coupled ocean-atmosphere model, *Journal of Climate*, *6*, 1545-1566, 1993.

Cane, M. A., S. E. Zebiak, and S. C. Dolan, Experimental forecasts of El Niño, *Nature*, *321*, 827-832, 1986.

Cane, M. A., A. Kaplan, R. N. Miller, B. Tang, E. C. Hackert, and A. J. Busalacchi, Mapping tropical Pacific sea level: Data assimilation via a reduced state space Kalman filter, *J. Geophys. Res.*, *101*, 22599-22617, 1996.

Chen, D., S. E. Zebiak, A. J. Busalacchi and M. A. Cane, An improved procedure for El Niño forecasting: implications for predictability, *Science*, *269*, 1699-1702, 1995.

Chen, D., M. A. Cane, S. E. Zebiak, and A. Kaplan, The impact of sea level data assimilation on the Lamont model prediction of the 1997/98 El Niño, *Geophys. Res. Lett*, 25, 2837-2840, 1998.

Chen, D., M. A. Cane, and S. E. Zebiak, The impact of NSCAT winds on predicting the 1997/98 El Niño: A case study with the Lamont model, *J. Geophys. Res.*, 104, 11321-11327, 1999.

Goldenberg, S. B., and J. J. O'Brien, Time and space variability of tropical Pacific wind stress. *Mon. Wea. Rev.*, 109, 1190-1207, 1981.

Reynolds, R. W. and T. M. Smith, Improved global sea surface temperature analyses. *J. Climate*, 7, 929-948, 1994.

Zebiak, S. E. and M. A. Cane, A model El Niño-Southern Oscillation, *Mon. Wea. Rev.*, *115*, 2262-2278, 1987.

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