Predictability and Error Growth in a Coupled Ocean-Atmosphere Model

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Abstract

Error growth rates in a dynamical coupled ocean-atmosphere prediction system are calculated by examining forecasts made from a large number of initial conditions based on consecutive months. The error is defined as the difference between consecutive forecasts valid at the same time. The error growth calculations have been made using the forecasts from the original Zebiak-Cane model in which initial conditions for coupled predictions were obtained by forcing the ocean model with observed wind stress. The error growth calculations are repeated for revised forecasts using the same model, but with initial conditions obtained by combining the wind stress from observations and the coupled model simulation. The revised initialization scheme gives greater hindcast skill. It is found that the growth rate of the initial errors for forecasts from the revised initialization procedure is higher than that for the original procedure. The greater hindcast skill of the revised initialization scheme is entirely due to reduction of the initial error. These results are encouraging for more complex prediction systems, where it is anticipated that reductions in initial errors via data assimilation techniques will lead to improvements in forecast skill.

1. Introduction

In a recent paper, Chen et al., (1995; hereafter referred to as CZBC) introduced an initialization procedure into the Zebiak and Cane (1987; hereafter referred to as ZC) coupled ocean-atmosphere prediction system that dramatically improved the hindcast skill of eastern tropical Pacific sea surface temperature anomalies (SSTA). In the original ZC prediction system, the ocean initial conditions for the coupled model prediction were obtained by forcing the ocean model with Florida State University (FSU; Goldenberg and O'Brien, 1981) observed wind stress. In the CZBC model, the initial conditions for the coupled predition system are obtained by integrating the coupled model; however, the wind stress felt by the ocean model is nudged towards the FSU observations. The best hindcast skill was obtained with relatively weak nudging in the deep tropics and strong nudging in the subtropics.

In the ZC model, there is substantial dependence of hindcast skill on the initial time of the hindcast. Hindcasts initialized in January have smaller skill compared to those initialized in April especially at longer lead times. It has been suggested that this seasonal dependence of hindcast skill is the result of relatively large error growth during the boreal spring season. In the results of CZBC, much of the seasonal dependence of the hindcast skill appears to be eliminated. By enhancing the lead time for skillful hindcasts, CZBC suggested that the initialization procedure improved the predictability of the model and eliminated the so-called spring prediction barrier. In this paper we examine the error growth characteristics for both the ZC and the CZBC model, and investigate the reasons for improved predictions in the CZBC model.

In the framework of a dynamical model with a given initial condition, the lead time of useful forecasts depends on:

a) The accuracy and internal consistency of the initial conditions

b) The accuracy of the model formulation

c) The rate of growth of errors in the initial conditions and errors in the model formulation.

Since the ZC and the CZBC prediction systems have identical models, the differences in the hindcast skill must be either due to differences in the accuracy and internal consistency of the initial conditions or differences in the growth rate of initial errors. For a dynamical prediction system, error growth rate is a useful and convenient measure of predictability. If the error growth rate is reduced either by the initialization procedure or by improving the model, then it can be said that the predictability of the prediction system has improved. Of course, even if improved hindcast skill is due solely to a reduction of the initial errors, the lead time of useful forecasts will increase. In order to address the question of whether the improved hindcast skill of the CZBC model was due to reduction in the error growth rate or due to reduction in the initial error, we have calculated the error growth in a large sample of hindcasts from both the ZC and CZBC forecast systems. The methodology for calculating the error growth rates and the results of these calculations are described in Sections 2 and 3.

The procedure we have followed to investigate the predictability of the coupled system was pioneered by Lorenz (1982) to study the growth rate of one day forecast errors in a weather prediction model. Lorenz (1982), and more recently Simmons et al. (1995), calculated the error growth in a large sample of forecasts from consecutive atmospheric initial conditions from the European Centre for Medium-Range Weather Forecasts (ECMWF). By calculating the rate of growth of an initial error (where error is defined as the difference between consecutive forecasts valid at the same time), they estimated the potential improvements in future predictions by reducing the one day forecast error. They also showed that even if no model improvements were possible, forecasts beyond one day could be improved simply by reducing the one day forecast error. Here we show that CZBC have indeed improved long range forecasts of tropical Pacific SSTA by reducing the one month forecast error.

2. Error Growth Calculations

Following Goswami and Shukla (1991), we have calculated the growth rate of errors in predicting SSTA over the NINO3 region (150°W-90°W, 5°S-5°N). The initial error is defined to be equal to the one month prediction error for all hindcasts during the 25 year period (1970-1994). Suppose ψ_{ij} is the predicted NINO3 SSTA corresponding to the jth month of the ith prediction. The mean error as a function of lead time (k=1,..,18 months) where the initial error is equal to the one month prediction error is

$$E(k) = \sum_{i=0}^{N-1} [\frac{(\psi_{i,k} - \psi_{i+1,k-1})^2}{N}]^{1/2}. \qquad (1)$$

In the calculations presented here N=288 for both the ZC and CZBC hindcasts and i=0 corresponds to the forecasts initialized in January 1970.

To get a quantitative estimate of the growth rate of initial errors and the saturation value we have assumed that the error growth is governed by

$$\frac{dE}{dt} = \alpha E \ (1 \ - \ E/E_\infty) \qquad (2)$$

where α is the error growth rate and E_∞ is the error saturation value (Lorenz, 1982; Dalcher and Kalnay, 1987). In estimating α and E_∞ we have used centered time differencing and applied a least squares fit.

3. Results

Figure 1 has two panels. The top panel is for the original ZC model, and the bottom panel is for the CZBC model. The dotted curves show the forecast root mean square (rms) error with respect to actual observations of NINO3 SSTA. The dash-dot curves show the forecast rms error with respect to NINO3 SSTA produced by forcing the ocean model with observed FSU wind stress in the case of the ZC model and the coupled initialization in the case of the CZBC model. The solid lines show the rms error calculated from equation (1) which is a measure of the differences between consecutive forecasts valid at the same time. The dashed lines are obtained by fitting equation (2) to the solid line. The most dramatic difference between the ZC and the CZBC prediction systems is the reduction of one month forecast error with respect to the model SST obtained by forcing the ocean model with observed wind stress. The forecast rms error with respect to observations even at the zero lead time is higher for the ZC model (0.83 °C) compared to the CZBC model (0.67°C). These curves clearly suggest that the initial conditions in the CZBC model are in greater dynamical equilibrium with the coupled model than in the ZC model.

The growth rates, saturation values and doubling times for both the ZC and the CZBC hindcasts are shown in Table 1. For the results shown in Fig. 1 and Table 1, the same number of hindcasts (N=288) and initial dates are used. In calculating the constants in the error equation (2) lead times of 2 to 18 months are used. In both cases the curve for the error equation follows the model error quite well and it is clear that the rms error for the ZC prediction system is considerably larger than the rms error for the CZBC system. In contrast to the rms error however, Table 1 shows that the error growth rate is smaller for the ZC system. The error doubling time in the ZC system is

7.2 months, whereas the errors double in 5.1 months in the CZBC system. It should also be noted that the saturation value for the CZBC system is considerably smaller than that for the ZC system.

Given that the initialization procedure gives a more balanced initial condition, one would have hoped that the error growth rate would be reduced, however, as Table 1 shows this is not the case. The initialization procedure reduces the initial error so much, that even though the error growth rate is somewhat larger the hindcast skill is signifigantly better. This indicates that the entire enhancement of the hindcast skill is due to the reduction of the initial error.

In order to address the seasonality of the hindcast skill we have also calculated the error growth rate for the CZBC system as a function of season. In this case we have used lead times of 2 to 10 months in fitting the error equation. Beyond 10 months the seasonally sampled errors do not fit the error growth equation (2). The error doubling times are smallest for hindcasts initialized in March-May and December-February (1.7 months) and largest for hindcasts initialized in June-August (3.7 months).We were unable to obtain meaningful solution to equation (2) for predictions initialized in September-November. While this result indicates that some kind of spring prediction barrier remains in the model, the sample size needs to be significantly increased before the seasonality in the error growth statistics can be adequately diagnosed.

We have also made some preliminary calculations of the error growth for the Center for Ocean-Land-Atmosphere Studies (COLA) prediction system described in Kirtman et al., (1996). Both the atmospheric and the oceanic components of the COLA prediction system are state-of-the-art general circulation models and the procedure for initializing the predictions is described in Kirtman and Schneider (1996). Based on a relatively small sample of 60 cases, we have estimated the error growth rates using the first 10 months of the hindcasts. The initial errors and the growth rates for the

COLA prediction system are comparable to those of the ZC system. Given the impressive improvements in hindcast skill obtained by CZBC, we are encouraged that by reducing the initial error in the more complex prediction system, the forecast skill could also be improved.

It is of some interest to note that, from error growth considerations, the manner in which the CZBC model has improved the skill of forecasts is quite similar to the improvement of short range forecast skill of the ECMWF model: by reducing the initial error while increasing the error growth rate. What is most interesting and encouraging about the CZBC model is that there is still a large difference between the growth rate of forecast errors and growth rate of error between consecutive forecasts, and therefore, there is considerable scope to improve the forecasts by improving the model.

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References

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

Dalcher, A., and E. Kalnay, 1987: Error growth and predictability in operational ECMWF forecasts. *Tellus*, **39A**, 474-491.

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

Goswami, B. N., and J. Shukla, 1991: Predictability of a coupled ocean-atmosphere model. *J. Climate*, **4**, 3-22.

Kirtman, B. P., J. Shukla, B. Huang, Z. Zhu, E. K. Schneider, 1996: Multiseasonal predictions with a coupled tropical ocean global atmosphere system. *Mon. Wea. Rev.*, (in press).

Kirtman, B. P., and E. K. Schneider, 1996: Model based estimates of equatorial Pacific wind stress. *J. Climate* (in press).

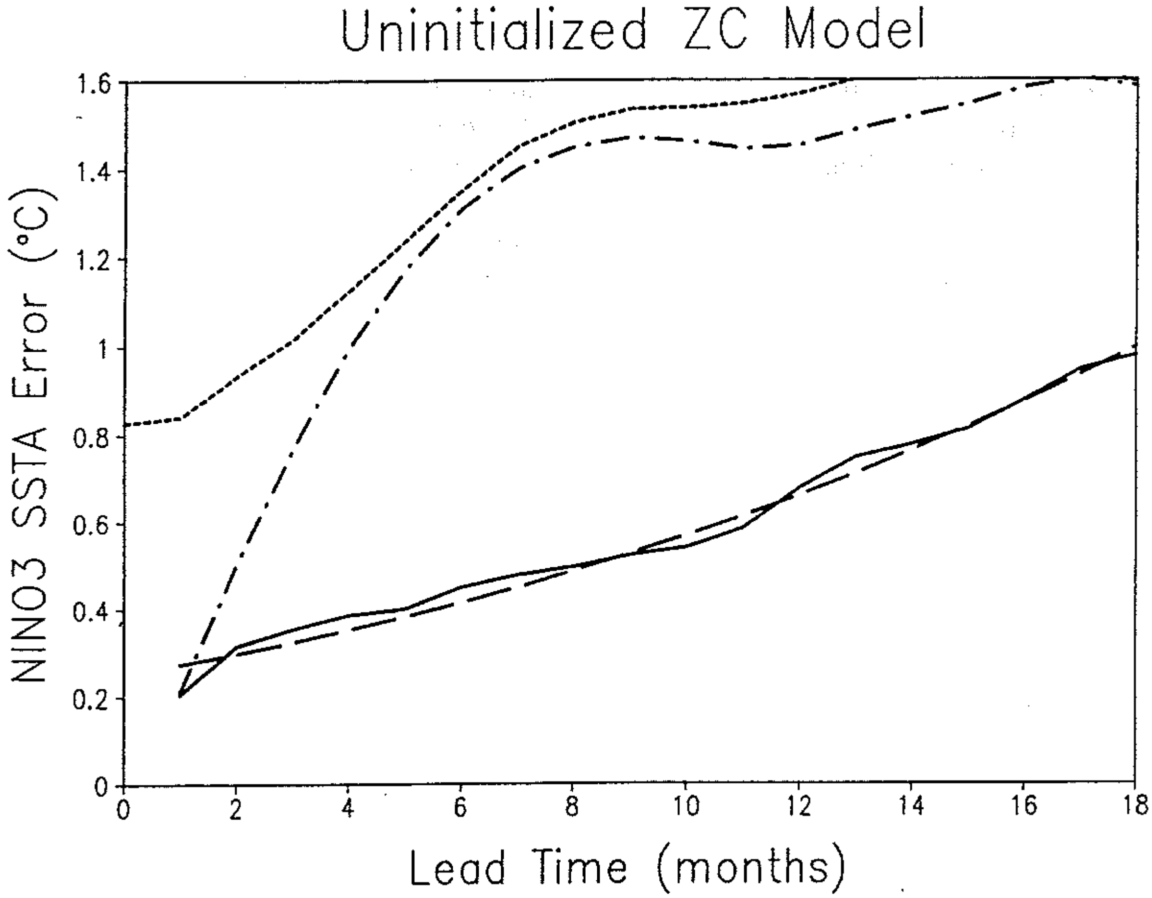
Lorenz, E. N., 1982: Atmospheric predictability experiments with a large numerical model. *Tellus*, **34**, 505-513.

Simmons, A.J., R. Mureau, T. Petroliagis, 1995: Error growth and estimates of predictability from the ECMWF forecasting system. *Quart. J. Roy. Meteor. Soc.*, **121**, 1739-1771.

Captions

Figure 1: Forecast rms error as a function of lead time for NINO3 SSTA with respect to observations (dotted line); with respect to model SSTA forced by observed wind stress (dash-dot line); as calculated from equation (1) (solid line) and equation (2) (dashed line) see text.

Table 1: Growth rate, doubling time and saturation of errors calculated using the fitted model (2) for both the ZC and CZBC prediction systems.


Uninitialized ZC Model
NINO3 SSTA Error (°C)
Lead Time (months)
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
2
4
6
8
10
12
14
16
18

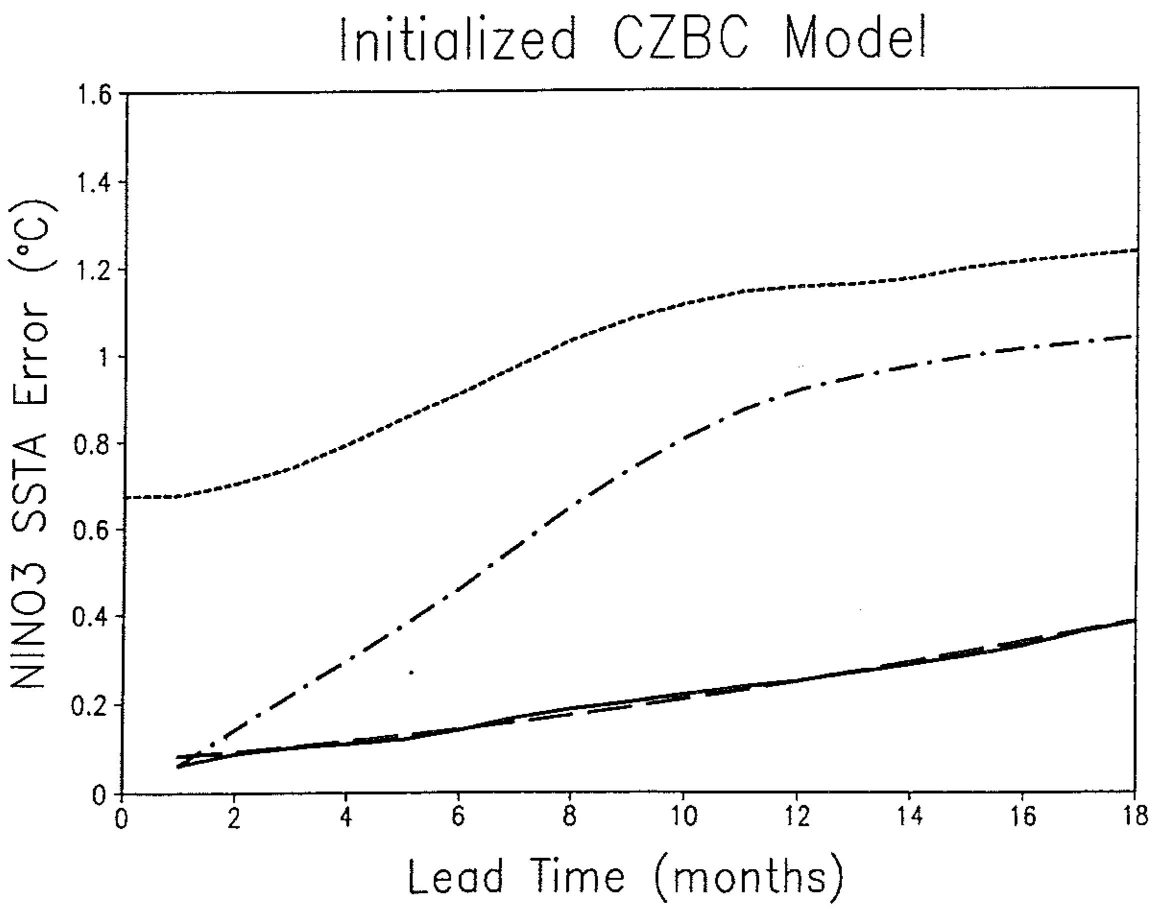

Initialized CZBC Model
NINO3 SSTA Error (°C)
Lead Time (months)
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
2
4
6
8
10
12
14
16
18

Figure 1

Table 1 - Error Growth Statistics

Prediction System	ZC	CZBC
Growth Rate	0.096 $months^{-1}$	0.14 $months^{-1}$
Doubling Time	7.2 months	5.1 months
Saturation Value	3.15 °C	0.67 °C