Initialization and Predictability of a Coupled ENSO Forecast Model*

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ABSTRACT

The skill of a coupled ocean–atmosphere model in predicting ENSO has recently been improved using a new initialization procedure in which initial conditions are obtained from the coupled model, nudged toward observations of wind stress. The previous procedure involved direct insertion of wind stress observations, ignoring model feedback from ocean to atmosphere. The success of the new scheme is attributed to its explicit consideration of ocean–atmosphere coupling and the associated reduction of “initialization shock” and random noise. The so-called spring predictability barrier is eliminated, suggesting that such a barrier is not intrinsic to the real climate system. Initial attempts to generalize the nudging procedure to include SST were not successful; possible explanations are offered. In all experiments forecast skill is found to be much higher for the 1980s than for the 1970s and 1990s, suggesting decadal variations in predictability.

Table 1. Forecast–observation correlation for the periods from 1972 to 1985 and from 1986 to 1992.

<table>
<thead>
<tr>
<th>Nudging parameter ab</th>
<th>Lead time in months</th>
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</thead>
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<tr>
<td>0.25 0.55 0.80 0.82 0.75 0.65 0.64 0.56 0.52</td>
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<tr>
<td>0.25 0.65 0.80 0.77 0.72 0.63 0.60 0.46 0.36</td>
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<td>0.25 0.65 0.80 0.77 0.72 0.63 0.60 0.46 0.36</td>
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<td>0.30 0.80 0.83 0.80 0.68 0.53 0.47 0.29 0.25</td>
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<td>0.50 0.50 0.83 0.80 0.71 0.54 0.38 0.07 −0.10</td>
<td>0.32 0.32 0.78 0.72 0.64 0.51 0.34 0.08 −0.06</td>
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<td>0.60 0.60 0.81 0.80 0.72 0.62 0.53 0.27 −0.15</td>
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One possible limitation on many of the forecast systems is the initialization procedure (Cane et al. 1986; Latif et al. 1993). Errors in initial conditions are due to inaccuracies in the observations and deficiencies in the models using the observations. These errors may be

1. Introduction

A hierarchy of coupled ocean–atmosphere models has been developed during the last decade for predicting El Niño–Southern Oscillation (ENSO), the largest interannual fluctuation in the world’s climate system. Among them, the earliest physically based model is the intermediate coupled model designed by Cane and Zebiak (hereafter CZ model) (Cane et al. 1986; Zebiak and Cane 1987). The predictive ability of this model has been demonstrated extensively but has not been significantly improved since the model was first introduced almost a decade ago. Although it has been suggested that incomplete model physics puts a limit on this model’s predictability (Goswami and Shukla 1991), the overall skill of more complicated coupled general circulation models presently does not significantly exceed that of the CZ model (Barnston et al. 1994). Since the predictive skill of even the best available models is far from perfect, there appears to be considerable room for improvement in modeling, observation, and forecasting technique. However, it is not yet known how much room there is.

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reduced by empirically truncating an empirical orthogonal function representation of the data; retaining large-scale low-frequency signals; and discarding small-scale, high frequency variability or noise (Blumenthal 1991; Barnett et al. 1993; Xue et al. 1994). This is a common procedure in hybrid coupled models where an ocean circulation model is coupled to a statistical model of the atmosphere. Alternatively, one may assimilate data into a coupled forecast model. The most common approach is to improve the ocean initial conditions in a standalone mode by assimilating observations of SST, thermocline depth, or sea level into an ocean model prior to coupling with an atmosphere model (Xue et al. 1994; Ji et al. 1995; Fischer et al. 1995). Recently a coupled approach has also been introduced in which SST and wind data were assimilated into a coupled system for forecast initialization (Rosati et al. 1997), but the observations were given such strong weights that the procedure was equivalent to initializing the ocean in a decoupled mode.

Previously the CZ model has also been initialized without explicit consideration of air–sea interaction. The oceanic component is first forced by observed wind stress anomalies, and then the model-simulated SST anomalies are used to force the atmospheric component. There are at least two potential problems with this approach. First, since no interactions are allowed between the oceanic and atmospheric components during initialization, the coupled system is not well balanced initially and may experience a shock when the forecast starts. Second, since no oceanic data are used in the initialization process, the initial oceanic state, which contains the thermal inertia (the “memory”) of the system, may be seriously flawed due to errors in the observed wind history and the model formulation. Recently we have reported a new initialization procedure.

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**Fig. 1.** (a) Zonal wind stress anomalies along the equator, as a function of time and longitude, for the standard and new cases. (Left) Observed wind stress anomalies derived from the Florida State University analyses, as used to initialize the standard CZ model. (Right) The nudged wind stress anomalies obtained using the new initialization procedure. (b) and (c) Corresponding model SST and thermocline depth anomalies in the two cases.
that significantly improved the predictive skill of the CZ model by making the initial conditions more self-consistent (Chen et al. 1995). Here we provide a more thorough analysis of the impact of this procedure and further explore the predictability of the CZ model.

The rest of the paper is organized as follows. The simple data assimilation method and its justification are described in the next section. Section 3 presents model results with emphasis on the impact of initialization; the seasonality, decadal variability, and spatial dependence of the forecast skill; and the predictability of the CZ model. Finally some important implications are summarized and discussed in section 4.

2. Initialization procedure

Our new methodology is to initialize the model in a coupled manner, using a simple data assimilation procedure in which the coupled model wind stress anomalies are nudged toward observations. Initial conditions for each forecast are obtained by running the nudged coupled model for the period from January 1964 up to the forecast starting time. Specifically, at each time step the coupled-model-generated anomalous wind stress vector \( \tau_m \) is modified to \( \alpha \tau + (1 - \alpha) \tau_o \), where \( \tau_o \) is the observed anomalous wind stress vector and \( \alpha \) is a function of latitude. In all of our experiments \( \alpha \) has its minimum value, \( \alpha \), at the most equatorial grid points (1°N and 1°S); increases in increments of 0.1 per grid point (each 2° of latitude) up to the latitude where it attains the value \( b \); and is held at \( b \) thereafter. The optimal values for \( \alpha \) and \( b \) are found to be 0.25 and 0.55, respectively. When \( \alpha = 1 \) everywhere, the initialization scheme used in the original CZ model is recovered. The new procedure assumes the coupled model can hindcast the essential interannual variability of the ocean-atmosphere system if merely nudged toward reality with observed wind stress. The model winds are given more weight in the equatorial region and less weight in the higher latitudes.

Generally speaking, the nudging parameter \( \alpha \) should be a function of time and space, dependent on the error characteristics of both observed and model-produced wind stress anomalies. As a first step, we have made \( \alpha \)
latitude dependent with smaller values toward the equator. This is because the wind anomalies produced by this model are more reliable near the equator than elsewhere (Zebiak 1986, 1990). To minimize data noise and data model incompatibility, the rule of thumb is to put more weight on the model winds as long as they are not too unrealistic. Thus the choice of this particular form for $\alpha$ is a trade-off between the impact of noisy data and drifting away from reality. Numerous retrospective forecast experiments were performed to find the optimal values for parameters $a$ and $b$, which determine the size and latitude dependence of $\alpha$. Such a procedure clearly presents the danger of artificial forecast skill. We address this by considering two independent periods for forecast evaluation, one from 1972 to 1985 and the other from 1986 to 1992. The year 1986 represents the beginning of the period that actual real-time forecasts have been made with the CZ standard model. Here the 1972–85 period is used to empirically derive the optimal choice of $\alpha$, and the 1986–92 period is used as an indication of the skill that could have been obtained in true forecast mode.

Forecast–observation correlations and rms errors for these two periods are shown in Tables 1 and 2 in terms of the Nino-3 index, the sea surface temperature (SST) anomalies averaged over the region $5^\circ S$–$5^\circ N$ and $90^\circ$–$150^\circ W$. The correlation skill and rms error are presented as a function of lead time for selected combinations of $a$ and $b$. It is clear that there is a wide range of nudging parameters that scores higher than the standard scheme ($a = 1$, $b = 1$), but the optimal choices for the 1972–85 period are the values $a = 0.25$, $b = 0.55$. They have the best correlation skill for lead times of 6 months or longer, and their skill at shorter lead times is comparable to the highest correlations at those times. This pair of nudging parameters also gives the smallest rms errors at long lead times. If we had made these tests in 1986, these are the values that would have been chosen. Thus the subsequent forecasts made for the 1986–92 period can be considered free of artificial skill. It is interesting to note that the correlations for the 1986–92 period are superior by an even wider margin, and the rms errors are still relatively small. Thus our parameter choice is quite robust.

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<th>Nudging parameter</th>
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3. Results

a. Initial conditions

Figure 1a shows the zonal wind stress anomalies at the equator from the standard and new hindcasts (henceforth, we will refer to the results from the original and revised procedures as “standard” and “new,” respectively). In the standard hindcasts, the Florida State University wind field (Goldenberg and O’Brien 1981) was used to initialize the ocean. For both the standard and new cases the wind stress shows large interannual oscillations, but the latter is much less noisy. Figures 1b and 1c demonstrate the impact of this difference on SST and equatorial thermocline depth anomalies. The latter may be interpreted as a measure of the anomalous upper-ocean heat content. Again, there is a striking difference between the standard and new cases: the energetic high-frequency fluctuations evident in the original procedure are largely eliminated in the new one. While the oceanic component alone generates high-frequency fluctuations when forced by the observed wind stress anomalies, the coupled model influence preferentially selects the low-frequency, interannual variability. The new initialization also results in a shallower thermocline in the western equatorial Pacific during most ENSO events, with implications for the termination of these warm episodes, which we remark on below.

b. SST forecasts

The forecasts made with the two different sets of initial conditions are compared in Fig. 2 in terms of...
Nino-3 SST anomalies. The standard forecasts capture the onsets of the large warming events more than one year in advance, but there are several “false alarms” in the intermediate periods and noticeable scatter, especially at longer lead times. The performance with the new initial conditions is improved, as the number and magnitude of erroneous forecasts have been reduced considerably in the periods between large warming events. In particular, the troublesome prolongation of the 1982–83 El Niño in the standard forecasts is completely eliminated with the new initialization. A large fraction of the scatter among long-lead forecasts has also been eliminated. All of these improvements are further demonstrated by the forecast trajectories shown in Fig. 3. It is important to note that averaging several consecutive forecasts helps to reduce the uncertainty in the standard case (Fig. 2) but is not needed in the case with the new scheme, again indicating that the forecasts are more stable and consistent.

The period from early 1983 to mid-1984 is analyzed in greater detail in Fig. 4. The observed SST anomaly distribution in January 1983 was typical of a mature El Niño event, with maximum warming found in the Nino-3 region (Fig. 4a). Six months later this maximum disappeared and the largest positive anomaly shifted to near the South American coast. By January 1984 SST anomalies had decreased to less than 1°C for most of the basin, followed by further cooling during the next 6 months. Model forecasts of this sequence are presented in Figs. 4b and 4c for the standard and new cases. Although the initial SST fields in January 1983 for the two cases are quite similar to each other, and roughly resemble the observed El Niño, the two forecast sequences are very different. In the standard case, the warming event is actually strengthened during the first 12 months, and even after a strong subsequent cooling the SST is still too warm in July 1984. In the new case, however, the observed cooling sequence is well predicted despite some errors in spatial patterns. Referring to Fig. 1c, it can be seen that in January 1983 the western equatorial thermocline depth is much more elevated in the new case than in the standard case. This highlights
the importance of subsurface thermal structure in controlling forecast trajectories, consistent with previous findings (e.g., Latif et al. 1993).

c. Predictive skill and decadal variability

Correlations and rms errors between predicted and observed Nino-3 SST anomalies were calculated for the period from 1972 to 1995 and for three subperiods of 8 years each (Fig. 5). In the standard case, the correlation for the whole period is higher than 0.5 up to a lead time of 9 months, but the (uncorrected) rms error is not much better than the persistence forecast. This predictive skill is representative of the state-of-the-art of ENSO prediction (Latif et al. 1993; Barnston et al. 1994). In the case with the new initialization procedure, the predictive skill is significantly improved in terms of both correlation and rms error scores. For the 1972–92 period the correlation is now higher than 0.5 up to a lead time of more than 24 months. As compared to the standard case, the correlation is 0.1–0.3 higher and the rms error is 0.2°–0.4°C lower at all lead times. The predictive skills in the three subperiods are quite different from one another. For the 1972–79 period, the skill is generally low and the new scheme helps only at long lead times. For the 1980–87 period, the skill of the new scheme is very high and the improvement is most pronounced. For the 1988–95 period, the skill of the new scheme is comparable to the old one at lead times shorter than 6 months but much improved at longer lead times. The lower skill for the 1970s may be a result of poorer data quality and lower signal-to-noise ratio during that period (Barnston et al. 1994), but it may also be a result of real decadal climate changes that are not captured by the model. Although the model misses the two short warming events in 1993 and 1994, the new scheme has a moderate skill for the 1988–95 period because it captures the warming trend from late 1980s to early 1990s (Figs. 2 and 3).

d. Seasonality

A common problem in ENSO prediction is the so-called spring barrier: a marked dropoff of the predictive skill surrounding the northern spring season (Webster and Yang 1992; Latif et al. 1993; Goswami and Shukla 1991; Barnston et al. 1994). Figure 6 illustrates the seasonal dependence of the skill. The straight lines in the
The figure indicates the time when the forecast verification month is May. In the standard case, the skill is strongly dependent on season. The spring barrier is difficult to pass, especially when it is confronted more than 9 months into the forecast. In the new case, there is a gradual and uniform falloff of skill with lead time, and only a slight seasonal variation. Spring is no longer a serious barrier. The slight seasonality that does show up is consistent with the annual cycle of the signal-to-noise ratio in observational data, which has a minimum in spring (Xue et al. 1994). That is, if the system consists of a predictable signal plus noise, then a decrease in correlation skill can be expected at the time when the signal variance is minimum, even if there is no seasonality in the magnitude of forecast errors. As discussed by Chen et al. (1995), the new results suggest for the first time that a spring predictability barrier is not intrinsic to the real climate system.

e. Predictability

One way to measure predictability is to calculate the spread among individual forecasts (Lorenz 1982). Figure 7 shows the rms differences, as a function of time, determined from all pairs of forecasts beginning n months apart, where n ranges from 1 to 12. As expected, the standard and new cases are very different in predictability. In the standard case, the initial rms error for all forecast pairs (the start point of each curve) increases rapidly with n, indicating rapid error growth with lead time. When n is small (small initial separation), the separation grows fast and monotonically; when n is large, the separation first tends to decrease and then increase rapidly. This is consistent with previous findings (Goswami and Shukla 1991). In the new case, the curves for different n’s are flatter and more tightly packed, and are displaced considerably toward lower values. The initial separation increases with n slowly, and for each n the separation grows at a similar rate. These results confirm what was suggested above: the predictability is much higher in the new case than in the standard case. A considerable portion of the short timescale, rapid error growth has been eliminated.

f. Spatial dependence

So far the model’s predictive skill has been measured only by the Nino-3 index. The spatial distribution of
Fig. 5. Correlations and rms errors between predicted and observed Nino-3 SST anomalies for four different time periods. In each panel results from the standard, new, and persistence forecasts are shown for comparison. Persistence forecasts are obtained by assuming initial SST anomalies remain constant.

Fig. 6. Correlation between predicted and observed Nino-3 SST anomalies for the period from 1972 to 1995, as a function of start month and lead time, for the standard and new cases. The straight solid lines denote the verification month of May.
FIG. 7. Growth of rms separations, as a function of time, determined from all pairs of forecasts beginning 1, 2, . . . , 12 months apart for the standard and new cases. Shown for each case are 12 curves for different initial separations, which are indicated by the start point of each curve. The lowest curve in each case is the rms difference between all pairs of forecasts with initial conditions separated by 1 month in time, and so on.

SST correlation for the 1972–95 period in the tropical Pacific is shown in Figs. 8a and 8b for the standard and new cases, respectively. The correlation score has similar spatial structure in the two cases; it is relatively high in the eastern and central equatorial Pacific but decreases toward the west and higher latitudes. However, at longer lead times, the highest correlation moves to the south of the equator in the standard case, whereas it remains at the equator in the new case. As compared to the standard case, the correlation in the new case is generally much higher and decreases slower with lead time, a result consistent with what we have found for Nino-3. One exception is in an equatorial band near the date line, where the standard hindcasts (at 0-month lead) have higher correlation with observations. Further skill improvement may be achieved by making the wind nudging parameter longitude dependent. A more thorough analysis of the spatial error distribution of both observed and model-produced wind fields should guide such refinements of the assimilation scheme.

g. EOF analyses

To further explore the reasons for the improvement of the new over the standard forecasts, we have applied empirical orthogonal function (EOF) analyses on the initial wind stress difference between the two cases. Twelve selected EOFs and corresponding expansion coefficients (time series) are shown in Figs. 9a and 9b, respectively. The first three EOFs account for nearly 90% of the total variance, and their time series are characterized by large interannual fluctuations associated with ENSO. These EOFs represent the large-scale, low-frequency, systematic differences between the observed and model-produced wind stress anomalies. Higher EOF modes are dominated more by high-frequency variations but still have organized large-scale features up to mode 20. The EOFs higher than 20 are basically small-scale, high-frequency, random noises. Thus the difference between the new and standard initial wind stress anomalies consist of three components: systematic difference in ENSO-related spatial patterns, high-frequency large-scale fluctuations, and random noise.

The relative contributions of these different EOF modes to the improvement of forecast skill can be estimated by adding them one by one to the standard wind stress anomalies for forecast initialization. Correlations and rms errors between predicted and observed Nino-3 SST anomalies are shown in Fig. 10 for the standard case, the cases with different EOFs added, and the new case. The first three EOFs explain about half of the improvement in correlation skill for lead times shorter than 8 months, but their contribution decreases rapidly toward higher lead times. The rms error is not much reduced with the addition of these EOFs. When the first 20 EOFs are included, the skill improvement by the new scheme is explained up to 80% at short lead times and about 40% at long lead times, and a large portion of the rms error reduction is accounted for. At least 100 EOFs are needed to approximately reproduce the skill of the new scheme. Therefore, all three components of the initial wind stress anomaly difference are important, despite their disparity in the percentage of the total variance explained. The reduction of the large systematic error and high-frequency fluctuation is responsible for most of the skill improvement at short lead times, and the elimination of the small random noise in the initial wind stress is essential for the skill improvement at long lead times.

h. SST assimilation

In principle, the coupled data assimilation method described in section 2 can be applied to data other than wind stress. SST is an obvious choice because of its availability and coverage. For predicting ENSO indices based on SST, one would assume that assimilating SST data during initialization can at least improve forecasts at short lead times. We have tried two cases in which SST observations are assimilated with the same nudging formula used for wind stress. In one case (standard + SST), observed wind stress anomalies are used to force the model while the SST anomalies are nudged toward observations. In the other case (new + SST), both wind stress and SST anomalies are nudged toward observations. The predictive skill in terms of Nino-3 SST anomaly is presented in Fig. 11 for the two cases. Except...
for hindcasts (zero lead time), the skill here is much lower than that shown in Fig. 5. SST nudging largely degrades model performance with or without wind nudging.

In the standard + SST experiments, the SST is nudged toward observations, but at the same time away from what results from model physics. Since there is no feedback onto the wind (and thus no assimilation into the coupled model), the result is a set of initial conditions that are uniformly less consistent with the model than in the standard case. It is perhaps not surprising that the performance is degraded. The new + SST experiments, on the other hand, do provide for some feedback of observed SST onto model winds. The poor performance in this case could result from a poor choice of nudging parameters or systematic errors in model winds introduced by assimilating SST. The latter is known to be a potential problem, from the results of Zebiak (1986, 1990). Even without this limitation, there is good reason to expect that the appropriate nudging parameters for the wind and SST combined assimilation would differ from those for the wind-only assimilation. Clearly, a more sophisticated assimilation procedure that explicitly accounts for the error characteristics of both wind and SST is needed. This is being pursued presently.

Note that neither of our simple SST assimilation experiments is parallel to the wind-only assimilation. The parallel experiment would be to assimilate only SST information, and not wind. We have not even attempted this because of the serious errors in off-equatorial winds produced by the simple atmospheric model (Zebiak 1990). Without observations to constrain the off-equatorial winds, the hindcast thermocline field would be seriously degraded, and with it, the forecast skill. The situation would be different if subsurface thermal data were assimilated; this also is being pursued.
4. Discussion and summary

Considering that the new initialization scheme is so simple and does not require any more observational data than the wind stress used in the original scheme, it may seem quite surprising that such a dramatic improvement of predictive skill can be achieved over a rather large ensemble of forecasts. In fact, improvement of this magnitude has not been achieved with any other forecast system to date. From Fig. 1, it is clear that including the coupled model in initialization has the effect of filtering out high-frequency signals present in the standard initial conditions. This occurs because the dominant mode of variability in the coupled model is ENSO-like, that is, large scale and low frequency. The high-frequency components of the initial conditions, which act as noise to the coupled model, degrade the forecast performance. By filtering these components, the new initialization procedure effectively reduces the mismatch between initial conditions and the model’s intrinsic variability, while retaining the essential large-scale, low-frequency information.

The nudging procedure affects more than just “noise” in the system—it also affects the signal. For instance, if there are systematic differences in the spatial structure of observed and (unassimilated) model variables, the nudging procedure will lessen this mismatch and may improve forecast performance (relative to straight insertion or no assimilation). Whether this will be true in practice depends on the nature and magnitude of the model errors. In our experiments, wind nudging reduced the systematic difference between observed and model winds, leading to improved forecast skill. However, combined SST–wind nudging did not improve performance over just wind nudging, although the result might change with a more careful tuning of assimilation parameters. In general one can expect a trade-off between...
the degree of realism of initial conditions and the degree of conformity to model physics that can be balanced optimally only with a comprehensive assimilation scheme. One of the most important aspects of this balancing is the reduction of “initialization shock” — the transition from hindcast to forecast mode. For all coupled forecast models one expects smaller initialization shock to lead to improved forecasts.

Though other coupled models differ significantly from this one (e.g., in containing internal high-frequency variance), they all exhibit modes of variability that differ in some way from nature. In all such situations, a nudging or more elaborate assimilation procedure that invokes the coupled model offers the potential for improvement. Of course, a prerequisite for the potential to be realized in predicting ENSO is that the coupled model exhibits realistic ENSO-like natural variability.

The new forecasts are certainly improved but are not without shortcomings. They do a poor job of distinguishing the amplitude of different ENSO extremes (Fig. 2). For example, the 1976–77 event is largely over-predicted. Though the gradual warming from 1988 to 1992 and the present cold phase are well captured, the short warm episodes in 1993 and late 1994 are missed. The shorter-lead standard forecasts do better with these (as do a number of other forecast procedures). The skill of the forecasts increased dramatically in the 1980s, especially for the transitions from warm to cold events, but was not much improved for the 1970s. Perhaps the assimilation of additional data (sea level, subsurface thermal structure) will be a remedy. However, decadal variations in prediction skill appear to be common among all forecast schemes. Further research will tell us whether these decadal variations in forecast skill result from processes poorly treated by present models, or whether they reflect changes in the predictability of the real climate system.

In summary, the experimental ENSO forecasts made by the CZ model for a period of more than two decades are significantly improved without using additional observational data for model initialization. The key to the success is a simple procedure to generate self-consistent initial conditions using the coupled model and observed wind stress anomalies. In essence, the coupled model
Fig. 9b. Normalized expansion coefficients for corresponding EOF modes.

Fig. 10. Correlations and rms errors between predicted and observed Nino-3 SST anomalies for the standard case, the cases with different EOFs added, and the new case.
itself is used to dynamically filter the initial conditions for the forecast. There are a number of implications. First, the performance of a coupled ENSO forecast model depends crucially on initialization; a good initial state for this model is one that contains principally the low-frequency signal relevant to ENSO. The character of the initial conditions is at least as important as model deficiencies in limiting the predictive skill of the original CZ forecast system. Second, the predictability of ENSO in a coupled model is likely to be affected by high-frequency fluctuations forced by the initialization procedure. Careful attention to this issue will likely be important for coupled models at all levels of complexity.

Third, the seemingly inevitable “spring barrier” in ENSO prediction is largely eliminated by improving initial conditions. This suggests that the spring barrier is not intrinsic to the tropical Pacific climate system and may be overcome without modeling the Asian monsoon or other processes outside of the tropical Pacific Ocean. Fourth, although the simple nudging scheme used in this study may not be directly applicable to other models, the approach of using both coupled model and observational data for initialization should be generally useful, as all schemes are limited by model/data mismatches in some form. A trade-off scheme will always be necessary since neither data nor models will ever be perfect.

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