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An Improved Procedure for El Niño Forecasting: Implications for Predictability

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A coupled ocean-atmosphere data assimilation procedure yields improved forecasts of El Niño for the 1980s compared with previous forecasting procedures. As in earlier forecasts with the same model, no oceanic data were used, and only wind information was assimilated. The improvement is attributed to the explicit consideration of air-sea interaction in the initialization. These results suggest that El Niño is more predictable than previously estimated, but that predictability may vary on decadal or longer time scales. This procedure also eliminates the well-known spring barrier to El Niño prediction, which implies that it may not be intrinsic to the real climate system.

Indices of El Niño, such as equatorial Pacific sea-surface temperature (SST) anomalies, can presently be predicted by statistical models several months in advance and by physical coupled ocean-atmosphere models at lead times exceeding 1 year (1–3). It is not yet known how much more room there is for improvement in modeling, observation, and forecasting techniques. There is surely a limit to predictability intrinsic to the natural system, a consequence of its chaotic and random nature (4). For weather prediction, estimates of this intrinsic limit can be made from models, but we do not have comparable confidence that any of the existing models capture the relevant features of nature's ENSO (El Niño–Southern Oscillation) cycle.

One sure bound on intrinsic predictability is the skill of actual predictions. All prior forecast procedures showed a marked drop of skill in forecasts that tried to predict across the boreal spring (2, 5–8). The so-called “spring barrier” (“autumn barrier” in the Southern Hemisphere) has been taken as an intrinsic feature of the climate system because, in addition to being common to all forecast models, it appears in auto-correlations of observational indices of ENSO (9). The results reported here, however, show only a barely perceptible drop in the skill of springtime forecasts. Previous rather pessimistic theoretical estimates of intrinsic predictability (5) must be revised upward to be consistent with the increase in actual skill demonstrated here.

The earliest of the physically based ENSO forecast models is the intermediate coupled model developed by Cane and Zebiak (CZ model) (1, 6). The predictive ability of this model has been demonstrated extensively (1, 2, 10) but has not been

significantly improved since the model was first introduced almost a decade ago. Although this model's predictive skill is most likely limited by its incomplete physics, the overall skill of more complicated coupled general circulation models is not significantly greater at present (2, 7).

One possible limitation on many of the forecast systems is the initialization procedure (1, 2). Errors in initial conditions are a result of inaccuracies in the observations and deficiencies in the models using the observations. These errors may be 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 (2, 5, 11–13). 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 stand-alone mode by assimilating observations of SST, thermocline depth, or sea level into an ocean model before coupling with an atmosphere model (13–16). The problem with this approach is that no interactions are allowed between the oceanic and atmospheric components during initialization, so the coupled system is not well balanced initially and may experience a shock when the forecast starts. Recently, a coupled approach has also been introduced in which SST and wind data were assimilated into a coupled system for forecast initialization (15), but the observations were given such strong weights that the procedure was equivalent to initializing the ocean in a decoupled mode.

We improved the predictive skill of the

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CZ model by making the initial conditions more self-consistent, without incorporating additional data. Previously, the CZ model had been initialized by first forcing the oceanic component with observed wind stress and then using the model-simulated SST to force the atmospheric component. In our methodology here, the model was initialized in a coupled manner, with the use of a simple data assimilation procedure in which the coupled model wind stress anomalies were nudged toward observations. We obtained initial conditions for each forecast by running the nudged coupled model for the period from January 1964 up to the forecast starting time. Specifically, at each time step the anomalous wind stress τ_m generated in the coupled model was modified to $\alpha\tau_o + (1 - \alpha)\tau_m$, where τ_o is the observed anomalous wind stress and α a function of latitude.

In all of our experiments, α had its minimum value, a , at the most equatorial grid points (1°N and 1°S), increased in increments of 0.1 per grid point (each 2° of latitude) up to the latitude where it attained the value b , and was held at b thereafter. The optimal values for a and b were found to be 0.25 and 0.55, respectively. The reason for choosing this particular form for α and the model sensitivity to the nudging parameters a and b is discussed below. When $\alpha = 1$ everywhere, the original CZ initialization scheme was recovered. Our procedure here trusts the coupled model to hindcast the essential interannual variability of the ocean-atmosphere system if merely nudged toward reality with the use of the observed wind stress. The model winds are given more weight in the equatorial region and less weight in the higher latitudes.

In the standard hindcasts (we refer to the results from the original and the revised procedures as "standard" and "new," respectively), the Florida State University wind field (17) was used to initialize the ocean model. For both the standard and new cases, the wind stress showed large interannual oscillations, but the latter is much less noisy (Fig. 1A). The impact of this difference is evident in equatorial thermocline depth anomalies (Fig. 1B), a measure of the anomalous upper ocean heat content. The energetic high-frequency fluctuations evident in the original procedure were largely eliminated in the new one. Although the oceanic component alone generated high-frequency fluctuations when forced by the observed wind stress anomalies, the coupled model preferentially selected the low-frequency, interannual variability. The new initialization also resulted

Fig. 1. (A) Zonal wind stress anomalies along the equator, as a function of time and longitude, for the standard and new cases. The left panel shows observed wind stress anomalies derived from the Florida State University analyses, as used to initialize the standard CZ model. The right panel shows the nudged wind stress anomalies obtained with the new initialization procedure described here. (B) Corresponding model thermocline depths in the two cases.

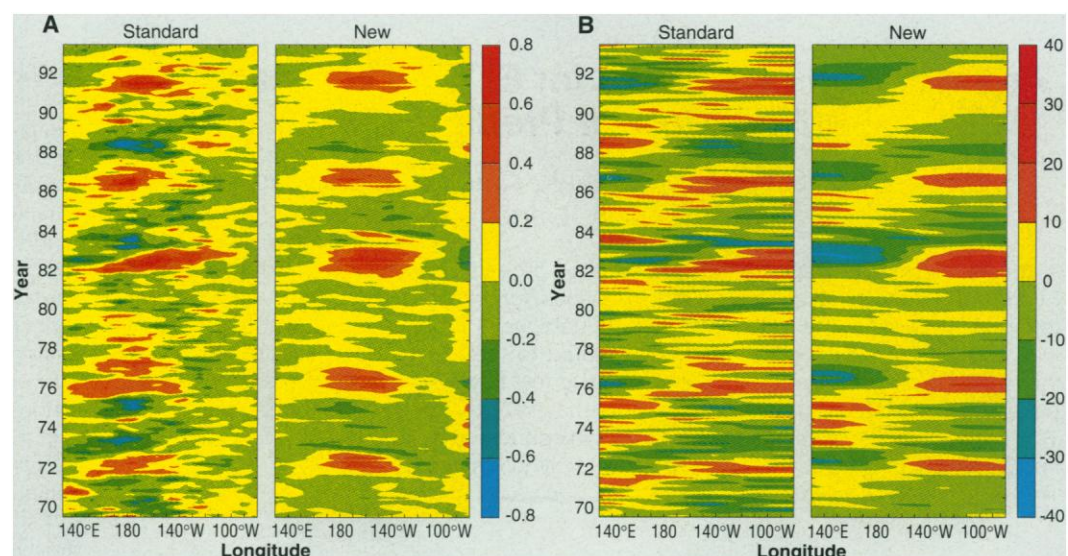
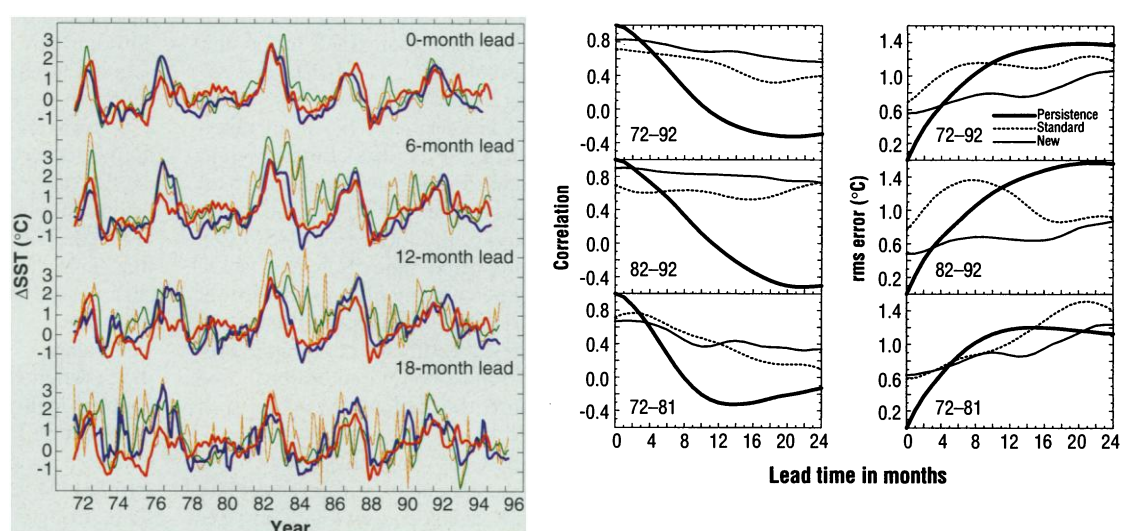


Fig. 2 (left). Time series of observed and forecast NINO3 SST anomalies. Forecasts with lead times of 0, 6, 12, and 18 months are shown in different panels for the standard and new cases. The observed anomalies (red) are repeated from panel to panel. In each panel, there are two curves for the standard case, one for individual forecasts (orange) and the other for the averages of six consecutive forecasts (green). Only individual forecasts are shown for the new case (blue). **Fig. 3 (right).** Correlations and rms errors between predicted and observed NINO3 SST anomalies for three different time periods. In each panel, results from the standard, new, and persistence forecasts are shown for comparison. Persistence forecasts were obtained by assuming initial SST anomalies remained constant.



in a shallower thermocline in the western equatorial Pacific during most ENSO events, with implications for the termination of these warm episodes (6, 18).

The forecasts made with the two different sets of initial conditions are compared in Fig. 2 in terms of the SST anomaly averaged over the Pacific Ocean NINO3 region (5°S to 5°N ; 90°W to 150°W), a commonly used index of ENSO episodes. The standard model was able to predict the onsets of the large warming events more than 1 year in advance, but there were several false alarms in the intermediate periods and noticeable scatter in the forecasts, especially at longer lead times. The performance with the new initial conditions was improved, as the number and magnitude of erroneous forecasts were considerably reduced in the periods between large warming events. In particular, the troublesome prolongation of the 1982–1983 El Niño in the standard forecasts was completely eliminated with the new initialization. Much of the scatter among the long-lead forecasts was also eliminated. Averaging several consecutive forecasts helped to reduce the uncertainty in the standard case but was not needed in the case with the new scheme, which indicates that the new forecasts were more stable and consistent.

We calculated correlations and rms (root mean square) errors between predicted and observed NINO3 SST anomalies for the period from 1972 to 1992 and for two subperiods representing the relatively quiet 1970s and the ENSO-active 1980s (Fig. 3). In the standard case, the correlation for the whole period was greater than 0.6 up to a lead time of 10 months, but the rms error was not much better than that for the persistence forecast. This predictive skill is representative of the state-of-the-art of ENSO prediction (2, 7). In the case with the new initialization procedure, the predictive skill was significantly improved in terms of both correlation and rms error scores. For the period from 1972 to 1992, the correlation increased to more than 0.6 for lead times up to 20 months. As compared to the standard case, the correlation was 0.1 to 0.2 higher and the rms error was 0.2° to 0.4°C lower at all lead times. The predictive skills in the two subperiods were quite different from each other.

For the period from 1972 to 1981, the skill was generally poor for lead times longer than a few months, and the new scheme did not help much. For the period from 1982 to 1992, however, the skill was generally better and the improvement by the new scheme was most pronounced. The poorer skill for the 1970s may be a result of poorer data quality and a lower signal-to-noise ratio during that period (7).

In the standard case, skill was strongly dependent on season (Fig. 4). The spring barrier was difficult to pass, especially when it was confronted more than 9 months into the forecast. In the new case, there was a gradual and uniform falloff of skill with lead time and only a slight seasonal variation. Spring was 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 (13). 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 at a minimum, even if there is no seasonality in the magnitude of forecast errors. Our results thus suggest for the first time that a spring predictability barrier is not intrinsic to the real climate system.

One way to measure predictability is to calculate the spread among individual forecasts (19) (Fig. 5). As expected, the standard and new cases are different in predictability. In the standard case, the initial rms error (the start point of each curve) increased rapidly with the number of months of initial separation n , which indicates rapid error growth with lead time. When n is small, 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 (5). In the new case, the curves for different values of n are flatter and more tightly packed and are displaced considerably toward smaller values. The initial separation increases with n slowly, and for each n the separation grows at a similar rate. A considerable portion of the short time scale, rapid error growth has been eliminated.

Considering that this initialization scheme is so simple and does not require any

more observational data than the wind stress used in the original scheme, the fact that such an improvement of predictive skill can be achieved over a rather large ensemble of forecasts may seem surprising. 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, on a large scale and with a low frequency. The high-frequency components of the initial conditions, some of which have spatial patterns similar to the model's ENSO mode, degrade the forecast performance (20). By filtering these signals, 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.

In addition, if there are systematic differences in the spatial structure of observed and model variables, the nudging methodology will lessen the mismatch and may improve the forecast performance. Any mismatches associated with data errors will also be reduced by the procedure. In all of these ways, the nudging procedure acts to reduce initialization shock—the transition from hindcast to forecast mode. Though other coupled models differ significantly from this one (for example, in containing internal high-frequency variance), they all exhibit modes of variability that differ in some way from nature. In such situations, a nudging or more elaborate assimilation procedure that invokes the coupled model offers 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 variability.

Fig. 4. Correlation between predicted and observed NINO3 SST anomalies for the period from 1972 to 1992, 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. Numbers shown at the right are correlation values.

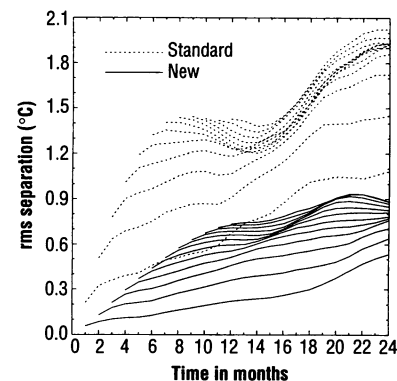
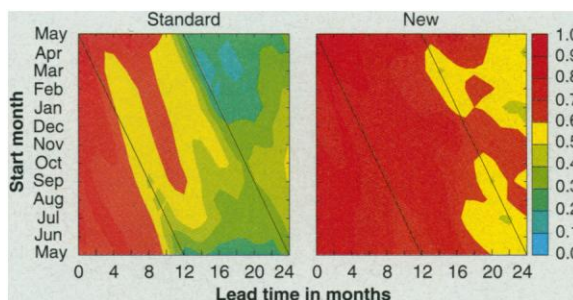


Fig. 5. Growth of rms separations, as a function of time, determined from all pairs of forecasts beginning 1 month apart, up to 12 months apart, for the standard and new cases. Shown for each case are 12 curves for different initial separations that are indicated by the start point of each curve. The 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.

Generally, the nudging parameter α 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 α latitude-dependent with smaller values toward the equator because the wind anomalies produced by this model are more reliable near the equator than elsewhere (6). To minimize data noise and data-model incompatibility, we put more weight on the model winds as long as they are not too unrealistic. Thus, the choice of this particular form for α 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 α . Such a procedure clearly presents the problems of artificial forecast skill. We addressed 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, we used the period from 1972 to 1985 to derive empirically the optimal choice of α and the period from 1986 to 1992 as an indication of the skill that could have been obtained in true forecast mode. It is clear that there is a wide range of nudging parameters that score higher than the standard scheme ($a = b = 1$), but the optimal choice for the period from 1972 to 1985 is the values $a = 0.25$ and $b = 0.55$ (Table 1). If we had made these tests in 1986, these are

the values that we would have chosen. Thus, the subsequent forecasts made for the period from 1986 to 1992 can be considered free of artificial skill. The results for this period are superior by an even wider margin (Table 1).

The experimental ENSO forecasts made by the CZ model are improved without additional observational data for model initialization. The key is a simple procedure to generate self-consistent initial conditions using the coupled model and observed wind stress anomalies. In essence, the coupled model 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. 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 invoking the Asian monsoon or other processes outside the tropical Pacific Ocean.

Our forecasts here are not without shortcomings. For instance, they do a poor job of distinguishing the amplitude of different ENSO extremes (Fig. 2). Though the gradual warming from 1988 to 1992 is well

predicted, the short warm episodes in 1993 and late 1994 are missed. The skill of the forecasts increased in the 1980s, especially for the transitions from warm to cold events, but was unchanged for the 1970s. Perhaps the assimilation of additional data (SST, 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.

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

Nudging parameter		Lead time in months						
a	b	0	3	6	9	12	15	18
1972-1985								
1.00	1.00	0.77	0.71	0.63	0.57	0.51	0.35	0.24
0.25	0.45	0.80	0.77	0.72	0.62	0.58	0.46	0.34
0.25	0.55	0.83	0.82	0.75	0.65	0.64	0.56	0.52
0.25	0.65	0.80	0.77	0.72	0.63	0.60	0.46	0.36
0.25	0.75	0.87	0.84	0.74	0.59	0.50	0.31	0.29
0.25	0.95	0.87	0.84	0.75	0.60	0.50	0.33	0.30
0.20	0.60	0.79	0.77	0.72	0.63	0.58	0.45	0.29
0.30	0.50	0.80	0.78	0.72	0.63	0.58	0.45	0.32
0.30	0.60	0.83	0.81	0.74	0.64	0.61	0.47	0.35
0.30	0.80	0.83	0.80	0.68	0.53	0.47	0.29	0.25
0.32	0.32	0.78	0.72	0.64	0.51	0.34	0.08	-0.06
0.50	0.50	0.83	0.80	0.71	0.54	0.38	0.07	-0.10
0.60	0.60	0.81	0.80	0.72	0.62	0.53	0.27	-0.15
1986-1992								
1.00	1.00	0.67	0.69	0.76	0.74	0.62	0.52	0.50
0.25	0.55	0.83	0.85	0.82	0.79	0.80	0.79	0.80
0.25	0.75	0.79	0.81	0.74	0.66	0.63	0.47	0.35
0.25	0.95	0.76	0.75	0.71	0.66	0.65	0.62	0.45
0.30	0.60	0.80	0.83	0.74	0.63	0.60	0.50	0.33
0.32	0.32	0.81	0.85	0.80	0.75	0.73	0.71	0.59