Predictabiliy of ENSO

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There is currently a debate regarding the processes that ultimately limit the predictability of the El Niño-Southern Oscillation (ENSO – customarily depicted by the equatorial Pacific SSTA). According to this debate, ENSO may fall into one of three regimes. In the first regime, ENSO is intrinsically chaotic due to the non-linear dynamics of the coupled system. The loss of predictability in this case is primarily due to the uncertainty in the initial conditions. In the second regime, ENSO is self-sustained (due to weak non-linearity) and is periodic, i.e., perfectly predictable. The irregularity of ENSO is due to external weather noise and the loss of predictability is primarily due to this external stochastic forcing. In the third regime, ENSO is damped and stochastically forced by external weather noise. The non-normality of the coupled system allows for limited time super-exponential perturbation growth, and the predictability is limited by the stochastic forcing exciting these optimally growing modes or how efficiently initial condition errors project onto the optimally growing modes. Put simply, the current debate is that ENSO predictability is either limited by initial condition uncertainty or uncertainty as the forecast evolves (i.e., weather noise).

The limit of ENSO predictability is highly dependent on which regime is “in play”. For example, in the damped regime, the limit of predictability is on the order of 9-15 months, whereas in the chaotic regime the limit is considerably longer (15-24 months). In the self-sustained and stochastically forced regime ENSO appears to vacillates between highly predictable regimes (oscillatory and self-sustained) and periods of low predictability when the variability is driven by the noise. In this case, whether ENSO resides in the predictable or the unpredictable regime is determined by low frequency variability in the background state. Conversely, in the damped regime the background state changes are merely a sampling issue and changes in predictability are associated with how the stochastic forcing projects onto the optimally growing modes. In this case, variations in predictability are a random walk process.

Here we show an example using a relatively simple model of ENSO how the system can vacillate from highly predictable epochs to periods of relatively low predictability. Figure 1 shows the evolution of Nino3.4 SST from a coupled model of ENSO for two different epochs (red curve). These periods were chosen from a long simulation of the model. The dashed green curves show predictability calculations where we have assumed no initial condition error, but there is uncertainty as the forecast evolves. The "forecast (green curves)" and "observations (red curves)" have different weather noise. How closely the green curves track the red curves indicates the limit of predictability. Although not shown here, this can be quantified by calculating the correlation and the root mean square error. By visual inspection of Fig. 1, it is clear that there is much less predictability in the upper panel relative to the lower panel. The point to emphasize with Fig. 1 is that predictability is limited by uncertainty as the forecast evolves (i.e., weather noise) without initial condition error. Even with perfect initial conditions there will be periods (upper panel) where predictability is relatively low (as in the early 1990s) and periods where predictability is relatively high (as in the 1980s). Part of the debate is whether the predictable and unpredictable periods are, in fact, themselves predictable.

It is important to note that all of our estimates of ENSO predictability are model-based estimates and that model error significantly impacts these estimates. For example, if the model of ENSO is a simple sine wave, then estimates of predictability would indicate that ENSO is perfectly predictable. We know this is not the case. On the other hand, if the model of ENSO is persistence, then we expect that the estimates of the limit of predictability would be much too short. In other words, we cannot ignore the impact of model error on the estimates of the limit of predictability, and this is why model fidelity and actual prediction skill assessments need to be married to predictability studies. The simple model results noted above are very useful for understanding and formulating hypotheses, but these ideas must be tested in models that have realistic ENSO variability and produce credible ENSO predictions.

**Predictability Using Coupled Models**

From the perspective of making ENSO predictions with state-of-the-art coupled general circulation models (CGCMs), it is not obvious identifying the correct regime. Presumably, the CGCMs include the possibility of all three regimes. However, in terms of improving predictions and realizing predictability, we need to identify and better characterize the mechanisms that limit predictability in CGCMs. Here we show results from the new NOAA coupled forecast system (CFS).

The NOAA CFS coupled model is among the best in world in terms of ENSO prediction. In this example we diagnose how both initial condition uncertainty and uncertainty as the forecast evolves impacts the estimate of the limit of predictability.

Figures 2a and 2b show the Nino3.4 SST root mean square (rms) error for a set of predictability calculations with CFS. The rms spread of the ensemble is also shown in Fig. 2. Both the spread and the error are reasonable metrics for estimating the limit of predictability and closely track one another here. The predictability calculation is based on the ensemble CFS forecasts where we have used one of the ensemble members to represent the "truth." In order to reduce the impact of weather noise as the forecast evolves we have applied the interactive ensemble coupling [??? – what is this] strategy to the CFS and have performed a sequence of prediction experiments [are the details of these experiments important???] that mimic the CFS control forecast. Relatively large values of the rms error indicate that predictability is lost. The yellow rms error curve in Fig. 2a corresponds to assuming that there is both uncertainty in the initial condition and uncertainty as the forecast evolves. The blue rms error curve in both Fig2a and 2b corresponds to the case of no initial conditions uncertainty and much reduced uncertainty as the forecast evolves. The blue curves in both panels are identical. Finally, the yellow curve in Fig. 2b corresponds to the rms error assuming no initial condition uncertainty, but with uncertainty as the forecast evolves. By comparing both sets of yellow curves with the blue we conclude the following:

(i) Initial condition uncertainty leads to a very rapid initial loss of predictability (Fig 2a yellow compared to Fig 2b yellow).

(ii) Uncertainty as the forecast evolves clearly limits predictability (Fig. 2b yellow vs. blue), but initial condition uncertainty is the dominating factor.

(iii) The predictability curves lie considerable below the errors in actual forecasts (not shown). This indicates that the model estimate of the limit of predictability is much longer than is currently realized in actual forecast mode.

As noted earlier, despite the fact that the CFS is one of the best ENSO forecast models, the argument that initial condition uncertainty dominates is a model dependent result, and is highly influenced by model error. In fact, current thinking suggests the "ENSO mode" of the coupled model is significantly different from the "ENSO mode" of nature; therefore, the rapid rms error growth at the initial time may be influenced by the dissimilarity between the model and observed "ENSO mode". Nevertheless, these results do suggest that reducing initial condition uncertainty, particularly in the ocean, will improve prediction, and that correctly initializing the "ENSO mode" of the coupled model will also have a significant impact on forecast skill. In addition, correctly representing the *statistics* of weather noise in climate forecast models is likely to improve ENSO prediction skill. All of these results indicate significant potential to improve ENSO forecasts, however, the importance of model fidelity in this regards cannot be overstated.

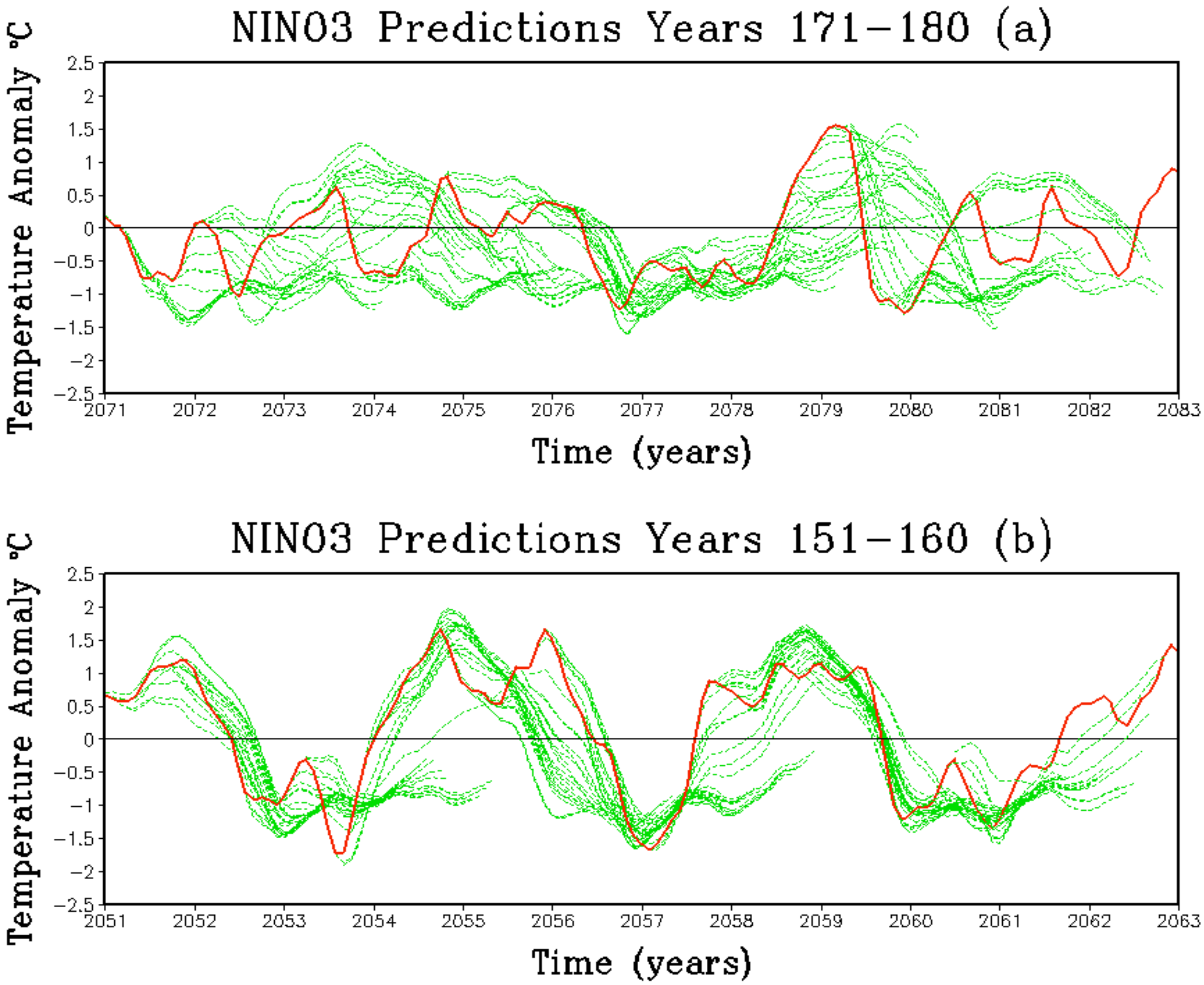
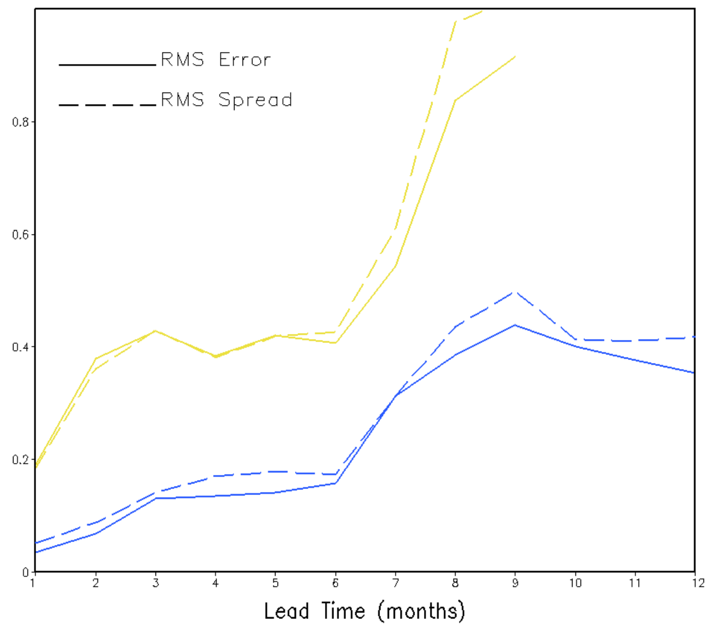



Figure 1: Evolution of the Nino3.4 SSTA from the simulation (red curve) and from the predictability experiments (green dotted lines) for a non-specific time period. The predictability experiments and the simulation have different weather noise realizations. The initial conditions for the predictability calculations are identical to the simulation.


RMS Error
RMS Spread
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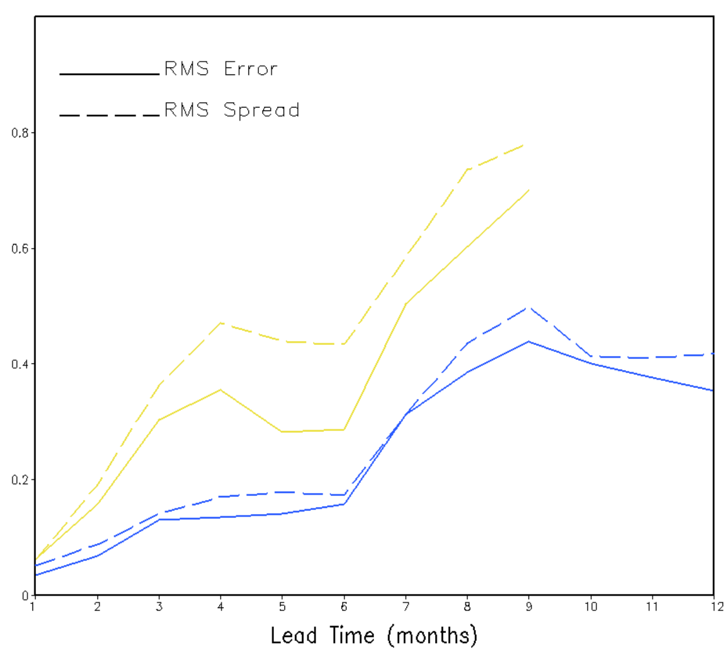
Lead Time (months)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Lead Time (months)

Figure 2: NOAA Coupled Forecast System (CFS) predictability calculations. The solid curves show the root mean square error (deg-C) and the dashed curves show the ensemble forecast root mean square spread. The predictability calculation is based on using one ensemble member at the “truth” for verification. The blue curves in both the top and bottom panels are the same and indicated the predictability assuming no initial condition error and much reduced weather noise as the forecast evolves. In yellow curves in top panel show the predictability assuming both initial condition uncertainty and uncertainty as the forecast evolves. The yellow curves in the bottom panel show the predictability assuming no initial condition uncertainty, but continued weather noise as the forecast evolves.