The Interactive Ensemble Strategy for Quantifying ENSO Predictability

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1. Introduction

A fundamental problem in understanding the mechanisms that cause low frequency variability of SST in mid-latitudes has been separating the relative roles of "one-way" versus "two-way" interactions. In the common explication of "one-way" interactions, stochastic forcing due to internal atmospheric dynamics drives low frequency variability of the ocean. The atmosphere does not respond to the resulting ocean variability. Conversely, in two-way interactions, coupled feedbacks between the ocean and atmosphere are important elements driving the variability. The feedbacks may be unstable leading to self-sustained oscillations, or they can be damped requiring stochastic forcing, but still producing a preferred time scale. In the mid-latitudes the feedbacks (if they exist) are most likely damped. Similar arguments apply to El Nino and the Southern Oscillation (ENSO), although coupled feedbacks are assumed to be important and the debate is more nuanced.

For example, according to this debate, ENSO may fall into one of three regimes. 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 (e.g., Thompson and Battisti, 2001), whereas in the chaotic regime the limit is considerably longer (15–24 months; e.g., Goswami and Shukla, 1991). In the self-sustained and stochastically forced regime ENSO appears to vacillate 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 (Kirtman and Schopf, 1998). 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 (Flugel et al., 2004).

From the perspective of making ENSO predictions with state-of-the-art coupled general circulation models (CGCMs), it is not obvious whether is matters which regime is correct. 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. Hence, there is a vigorous debate regarding the relative importance of external (uncertainty in initial conditions and boundary conditions) and internal (atmosphere-ocean feedbacks and noise due to internal atmospheric dynamics) factors in limiting the model prediction skill and forecast error.

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. This is precisely the strategy that is used here.

This report briefly describes the results from three studies examining the role of weather noise in climate variability. The unifying theme of these studies is the use of the interactive ensemble coupling strategy (Kirtman and Shukla 2002; see below), which is specifically designed to isolate the role of noise in climate variability.

2. The interactive ensemble: testing the "null hypothesis"

From the discussion above, it is clear that noise or stochastic variability in the components of the climate system can have a profound impact on the interactions among the various components, coupled climate variability in general and predictability. In order to understand how noise impacts climate variability, COLA has developed a novel CGCM technique for isolating how noise impacts climate variability and predictabiltiy. This technique is referred to as an interactive ensemble (Kirtman and Shukla 2002). The interactive ensemble strategy uses multiple realizations of the atmospheric model coupled to a single realization of the ocean model. The purpose of the interactive ensemble strategy is to significantly reduce the stochastic forcing of the ocean due to internal atmospheric dynamics. In some sense, the interactive ensemble is a sophisticated CGCM in which numerical experiments can be implemented that had previously only been possible in simple theoretically motivated models. The interactive ensemble strategy works as follows. The AGCM is identical for each ensemble member and the AGCM realizations only differ in their initial conditions. Because the atmosphere is sensitively dependent on initial conditions, the AGCM realizations evolve differently. As the interactive ensemble evolves, each AGCM realization experiences the same SST predicted by the OGCM. The OGCM, on the other hand, experiences surface fluxes of heat, momentum and freshwater that are the ensemble average of the AGCM realizations. The AGCM realizations are noise independent (i.e., the noise among the ensemble members in uncorrelated), but since they are all coupled to the same SST, they have the same signal. The models are fully interactive in that the component models exchange fluxes and SST once a day. The interactive ensemble has been implemented in a "proof of concept" study (Kirtman and Shukla, 2002) using the COLA anomaly coupled model (Kirtman et al. 2001), and more recently, has been used to diagnose how "weather noise" impacts ENSO predictability in the NOAA Coupled Forecast System (Stan and Kirtman, 2007) and the role of ocean noise (Kirtman et al. 2007).

The interactive ensemble coupling strategy has been used in a number of studies to examine role of internal atmospheric dynamics in forcing and modulating low frequency climate variability. For example, Yeh and Kirtman (2004) examined the relationship between decadal variability in the tropical mean state and ENSO variance using three CGCM multi-century simulations – a control simulation and two interactive ensemble simulations with six and twelve ensemble members, respectively. They found two important "modes" of tropical decadal variability. The first mode explains approximately 40% of the tropical low frequency variability, has basin scale, is unrelated to low frequency variations of ENSO amplitude, and appears to be forced by atmospheric noise. This first mode is consistent with the theory that ENSO is linear, damped and stochastically forced, suggesting that changes in tropical mean state (associated with this first mode) and ENSO variance are due to sampling issues. On the other hand, the second mode (~15% of the variance) is unambiguously correlated to low frequency changes in ENSO variance demonstrating that there is a component of the ENSO variability that cannot be explained by the null hypothesis given by the linear theory. The null hypothesis for tropical ENSO variability was further explored in Kirtman et al. (2005) by examining the relationship between the ensemble mean and the ensemble spread in the interactive ensemble CGCM and that expected from applying the interactive ensemble approach to the damped linear stochastically forced theory. In this case, the approach is to use the individual atmospheric ensemble members as a tool to explore predictability. For example, Kirtman et al. (2005) compared the relationship between zonal wind stress ensemble spread and ensemble mean. The ensemble mean and spread were calculated separately for each month so that they can be related to the phase of ENSO. In the interactive ensemble CGCM, there is a clear link between the ensemble mean and the ensemble spread. During cold ENSO events (i.e., large easterly anomalies) the ensemble spread is relatively small and during warm events the spread is large. No such relationship occurs according to the linear theory.

Kirtman et al. (2005) presented a simple linear one-dimensional coupled model that has damped feedbacks and prescribed white noise in both *the ocean and the atmosphere.* They compared the SST variance produced with and without applying the interactive ensemble coupling strategy. Three ranges of values for the ratio of the variances were considered. (i) If the ratio is on the order of 1/6, they concluded that the null hypothesis is likely to be correct (i.e., a stochastically forced system with stable coupled feedbacks) and *the ocean noise is relatively small*. (ii) If the variance ratio is between 0.5 and 1.0 then either the null hypothesis is correct and the ocean noise is playing a significant role or the null hypothesis is incorrect and there are unstable coupled feedbacks or important non-linearities. In other words, we can make no definitive conclusion, so we need addition experiments to isolate the role of the ocean noise. (iii) If, on the other hand, the ratio exceeds 1.0, then they concluded that there are unstable coupled feedbacks and/or important non-linearities (e.g., multiplicative noise).

The Indo-Pacific SSTA variance from the control CGCM run is shown in Fig. 1(top) and the variance ratio of the CGCM interactive ensemble to the control is shown in Fig. 1(bottom). Using the theoretical model as a guide, we conclude that there are substantial regions in the western and central tropical Pacific and the eastern south tropical Indian Ocean where there are unstable coupled feedbacks and non-linearity. In the un-shaded regions, there may be some contribution due to the internal ocean dynamics, but the coupled feedbacks are likely to be unimportant. Figure 1b also shows that there are surprisingly large regions, particularly in the eastern Pacific, where we cannot eliminate noise due to *internal ocean dynamics* as a

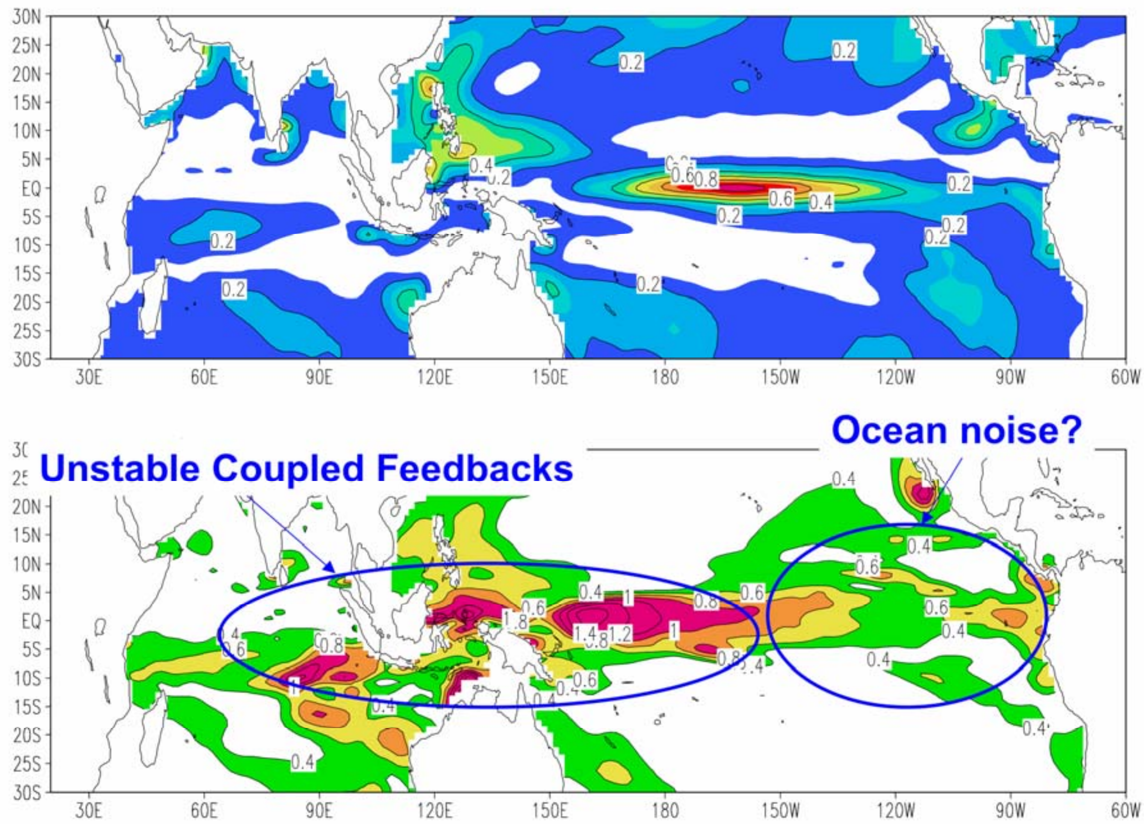

Figure 1: The top panel shows the SSTA standard deviation based on 100-years of data for the control CGCM. The contour interval is 0.2 $^oC^2$. The bottom panel shows the SSTA variance ratio for the interactive ensemble CGCM divided by the control CGCM. The contour interval is 0.2.

contributor to the SST variability. Despite the fact that the ocean model is not eddy resolving, it does produce noise due to internal ocean dynamics (i.e., transients), although the statistics are likely to have significant errors. One possible explanation for the results in the eastern Pacific is that tropical ocean instability waves, albeit poorly represented, are making a significant contribution to the SSTA variability.

3. Noise and ENSO predictability

Stan and Kirtman (2007) have performed a set of identical twin ENSO experiments that are specifically designed to examine how uncertainty in the oceanic initial condition versus uncertainty (or internal atmospheric noise) as the forecast evolves limits ENSO predictability. These experiments were performed with the NOAA CFS model using the operational coupling strategy and the interactive ensemble coupling strategy. For example, Fig. 2 shows the Nino3.4 retrospective forecast root mean squared error and ensemble spread from the control CFS and the interactive ensemble CFS (CFSIE). The solid blue and red curves indicate the root mean squared errors based on twenty-four forecast cases (i.e., Jan. 1981, …, Jan. 2004) initialised on January 1st. Each forecast case is a five-member ensemble. The dashed curves correspond to the spread among the ensemble members calculated as a root mean difference among the members. For comparison, the observed standard deviation times $\sqrt{2}$ is shown in black. This would correspond for forecast error saturation assuming the model has the correct variance. In a broad sense, the blue curves correspond to ENSO forecasts made with a version of the coupled model with reduced noise due to internal atmospheric dynamics and the red curves correspond to the control model.

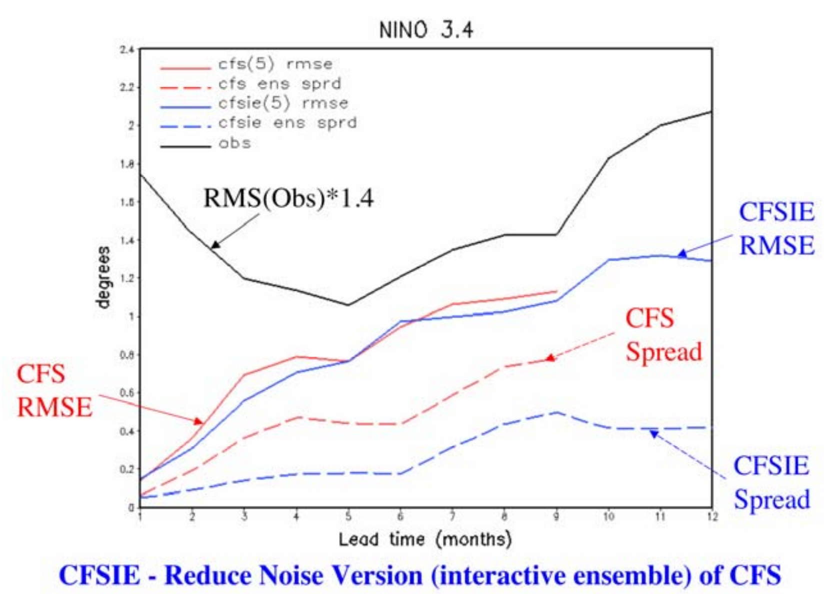

Figure 2: Deterministic verification: rms error (solid line) and ensemble spread (dashed line) for predicted SST. The black thin lines give the standard deviation of the observations times root 2 (i. e., saturation). The red lines correspond to CFS forecasts and the blue lines correspond to CFSIE forecasts.

There are a number of points to highlight with this Fig. 2. For instance, the noise reduction due to the interactive ensemble has a modest, at best, impact on the forecast errors, but significantly reduces the forecast spread. The forecast error is well below saturation for all 9 months in the case of CFS and all 12 months in the case of CFSIE. Correlation coefficients suggest that the forecasts lose skill (correlation below 0.6) for these January cases at around 6 months (not shown). With both the CFS and CFSIE forecasts the spread in considerably smaller than the forecast error. If the forecast system is perfect, then the spread and error should grow at exactly the same rate (i.e., the dashed and solid curves should lie on top of each other). There are two interesting possible interpretations of the relative small spreads: (i) the forecast systems are over confident (i.e., spread is too small and error is about right), which we can examine by comparing CFS and CFSIE using probabilistic verification techniques or that (ii) errors in the model or initial conditions are seriously limiting the prediction skill below what would be expected from the spread (i.e., error is too large and spread is about right). The correct answer most likely lies in between these two possibilities; however, the additional analysis not shown here indicates that we can at least argue that errors in the amplitude of weather noise are relatively unimportant when compared to error in the initial conditions.

4. Atmospheric noise and Western Pacific variability

A well known systematic error in most CGCMs is that the simulated ENSO events extend too far into the western Pacific. Often, but not always, the models have ENSO periodicities that are also too fast compared to observations. The conventional wisdom is that the westward extension of the ENSO events and the fast periodicity is due to the cold tongue mean state errors. Simply, errors in the mean state are the cause for the errors in the anomalies. We suggest that the errors in the mean state are, at least in part, due to errors in the simulated ENSO; and that the errors in the simulated ENSO are due to errors in the statistics of the tropical atmospheric weather. In other words, if there are large errors in the simulation of the weather statistics, then the climate simulation is seriously degraded.

The theoretical coupled model presented in Wu et al. (2006) suggests the source of the western Pacific and the potential solution. Wu et al. (2006) show that when the correlation between the latent heat flux (our convention here is that latent heat flux is positive upward) and SST anomalies is strongly negative, the SST variability can be viewed as strongly forced by atmospheric variability (noise). Conversely, when the ocean forcing dominates the correlation is positive. Figure 3 (in part taken from Wu et al. 2006) shows this correlation from satellite based observational estimates (top left) and the COLA anomaly coupled model (bottom left; Kirtman et al. 2002). Clearly, near the equator in the western Pacific the coupled model fails to capture the observed relationship. This is also true in significant regions of the tropical Indian and Atlantic Oceans. The theoretical model suggests two possible interpretations of this result: (a) the ocean is too strongly forcing the atmosphere or (b) the atmosphere is not forcing the ocean enough. Wu et al. (2006) describes the theoretical basis for these possible interpretations.

The theoretical model also suggests a possible solution to this air-sea feedback problem, namely we need to change the relative strength of the atmosphere forcing of the ocean or the ocean forcing of the atmosphere. Our approach for increasing the atmospheric noise forcing of the ocean is to "whiten" the air-sea fluxes of heat, momentum and freshwater by perturbing the interactive ensemble coupling strategy.

The original interactive ensemble uses the ensemble mean fluxes. In this case, we introduce the "Random Interactive Ensemble" where for each coupling interval instead of using the ensemble mean (i.e., standard interactive ensemble) we randomly chose one ensemble member to interactive with the ocean. As with the standard interactive ensemble, each atmospheric ensemble member feels the same SST and the coupling is applied daily. In this application, there are six atmospheric ensemble members so that on average each atmosphere interacts with the ocean every six days. The resulting correlation is also shown in Fig. 3 (top right). As predicted by the theoretical model, the correlation has changed sign in the western Pacific. We emphasize that this is more than simply reducing the amplitude of the correlation – it has actually changed sign. The entire ENSO system in this simulation has shifted further to the east with a consistent increase in the periodicity. This suggests the air-sea physics in the western Pacific can have a profound impact on the ENSO simulation. This impact is more that merely making the ENSO more irregular; it is shifting the system eastward modifying the oceanic time-scales (via wave dynamics) and even modifying the global teleconnections by shifting the region of maximum rainfall anomalies to the east. The changes in the periodicity and the eastward shift of the variability can easily be detected in Fig. 4, which shows the lag-lead regression of Nino3.4 SSTA onto equatorial Pacific SSTA. In essence, adding noise in the western Pacific heat flux has modified the coupled signal without explicit changes to either the atmospheric or oceanic component model.

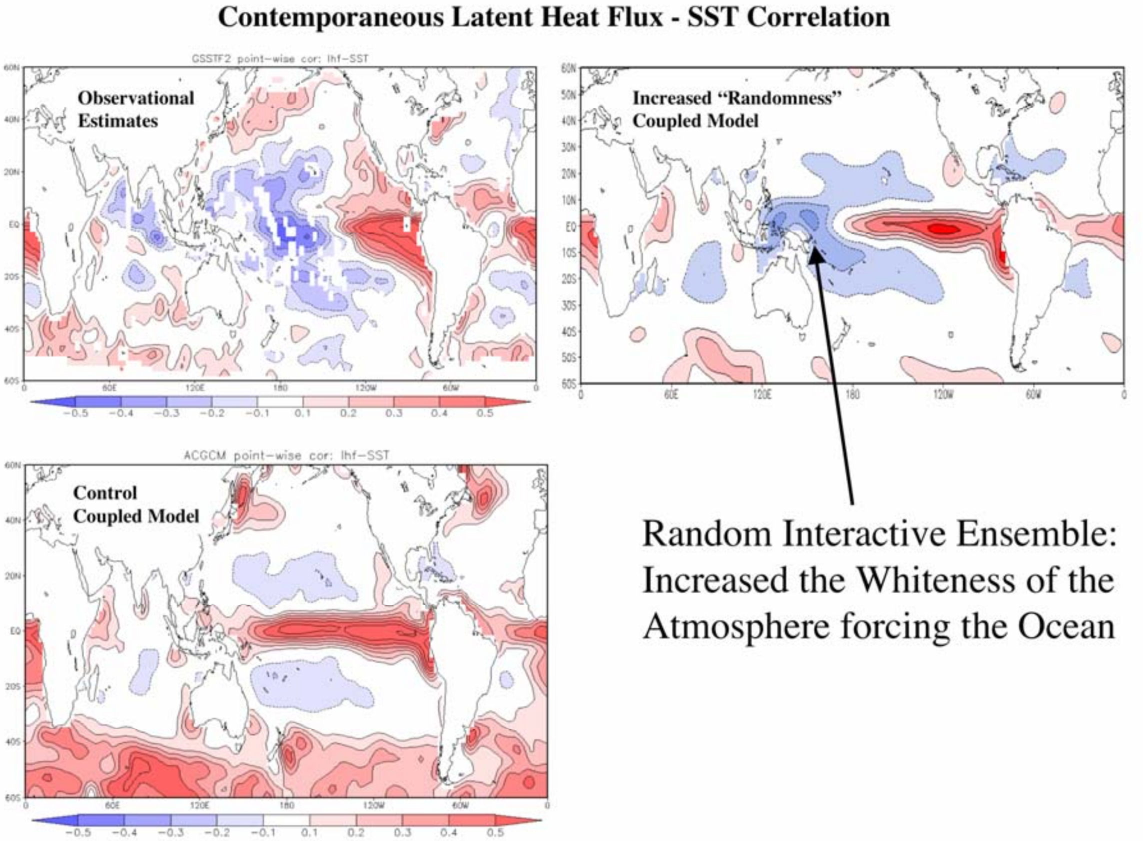

Figure 3: Point correlation between latent heat flux and SST from (top left) observational estimates, (bottom left) control coupled model and (top right) random interactive ensemble.

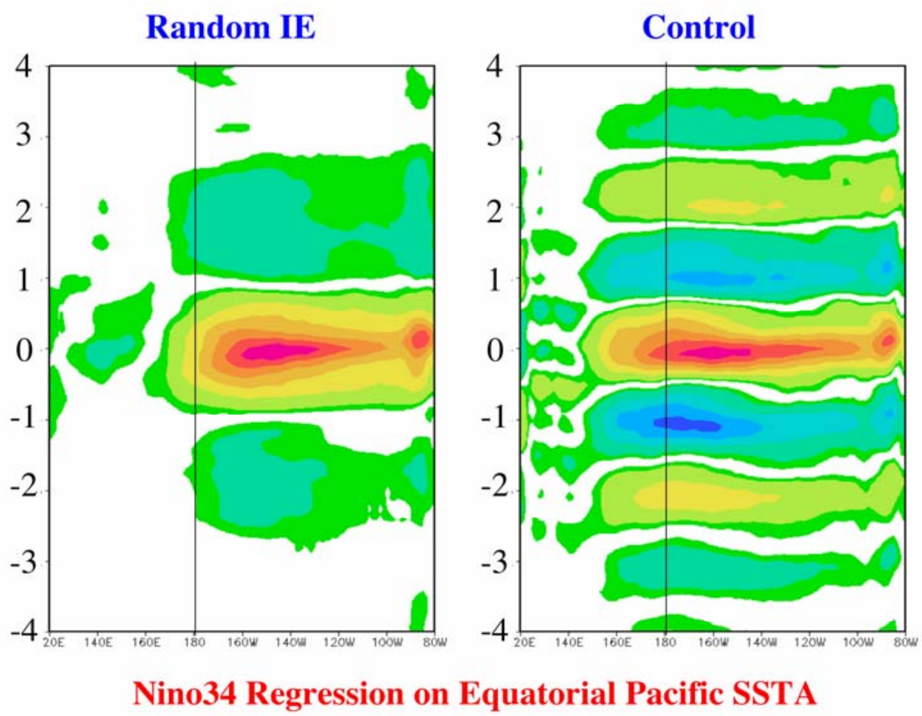

Figure 4: Nino3.4 lag-lead regression with SST along the equatorial Pacific from (left panel) the random interactive ensemble and the control coupled model (right panel).

5. Concluding remarks

Here we have described how the interactive ensemble coupling strategy can be used to understand the role of "weather noise" in climate variability. Specifically, we have shown that with the COLA coupled model there are significant regions of the western Pacific and Indian Ocean where the "null hypothesis" cannot explain the simulated climate variability. We have also applied the interactive ensemble coupling strategy to the ENSO predictability problem and found that initial condition error (due to model limitations) is the dominant limiting factor in prediction skill. Finally, we showed how errors in the noise statistics in the western Pacific can have a profound impact on the structure and periodicity of the simulated ENSO.

6. References

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