Climate Variability and Weather Noise

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UNIVERSITY OF MIAMI

CLIMATE VARIABILITY AND WEATHER NOISE

By

Hosmay Lopez

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CLIMATE VARIABILITY AND WEATHER NOISE

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There is an active research debate regarding how weather and climate interact – this is particularly noted in terms of understanding ENSO predictability and the influence of “weather noise”. This weather noise view argues that the irregularity of ENSO and ultimately the loss of predictability are largely driven by stochastic forcing. If the stochastic forcing or noise is of primary importance then it is possible that the details (e.g., space-time structure and state dependence) of the noise are also important – that is weather and climate interactions. The overarching goal of this dissertation research is to develop a framework to study the role, if any, that noise plays in sustaining/modifying/modulating ENSO and tropical Pacific climate variability and predictability. The methodology used here follows two different approaches: (a) assessing the impact of the noise in a non-phenomenological manner recognizing that it can occur on all temporal and spatial scales and (b) assuming the noise is associated with a specific phenomena with clear constraints on its location and spatial-temporal structure.

A noise reduction technique, namely the interactive ensemble (IE) approach is adopted to reduce non-phenomenological noise at the air-sea interface due to internal atmospheric dynamics in a state-of-the-art coupled general circulation model (CGCM), namely the Community Climate System Model (CCSM3). To study the impact of weather noise and resolution in the context of a CGCM, two IE experiments are
performed at different resolutions. Atmospheric resolution is an important issue since the noise statistics will depend on the spatial scales resolved. A simple formulation to extract atmospheric internal variability is presented. The results are compared to their respective control cases where internal atmospheric variability is left unchanged.

The non-phenomenological noise reduction has a major impact on the coupled simulation and the magnitude of this effect strongly depends on the horizontal resolution of the atmospheric component model. Specifically, applying the noise reduction technique reduces the overall climate variability more effectively at higher resolution. This suggests that “weather noise” is more important in sustaining climate variability as resolution increases. ENSO statistics, dynamics, and phase asymmetry are all modified by the noise reduction, in particular ENSO becomes more regular with less phase asymmetry when noise is reduced. All these effects are more marked for the higher resolution case. In contrast, ENSO frequency is unchanged by the reduction in the weather noise, but its phase-locking to the annual cycle is strongly dependent on noise and resolution. At low resolution the noise structure is similar to the signal, whereas the spatial structure of the noise deviates from the spatial structure of the signal as resolution increases. It is also suggested that event-to-event differences are largely driven by atmospheric noise as opposed to chaotic dynamics within the context of the large-scale coupled system, suggesting that there is a well-defined “canonical” event.

The next step is to study the importance of phenomenological noise forcing of the climate system. Here, westerly wind bursts or events (WWBs or WWEs) are taken as example of phenomenological noise forcing of the tropical Pacific Ocean. The impact of parameterized WWBs on ENSO variability in CCSM3 and CCSM4 is analyzed. To study
the impact of WWBs three experiments are performed. In the first experiment, the model is integrated for several hundred years with no prescribed WWBs events (i.e., the control). In the second case, state-independent WWBs events are introduced. In other words, the occurrence, location, duration, and scale of the WWBs are determined (within bounds) randomly. For the third case, the WWBs are introduced but as multiplicative noise or state-dependent forcing, modulated by SST anomalies.

State-dependent case produced larger ENSO. There is very little difference between the control and the state-independent WWB simulations suggesting that the deterministic component of the burst is responsible for reshaping the ENSO events. There is a shift towards a more self sustained mechanism as the experiments progress from the control to the state dependent WWBs. Overall, the parameterized WWBs have the capability to modify the ENSO regime in the CGCM, demonstrating the importance of sub-seasonal variability on interannual time scales.

This study also investigates the effect of parameterized WWBs on the diversity of ENSO warm events, namely eastern Pacific (EP) and central Pacific (CP) ENSO in CCSM3 and CCSM4. It is found that parameterized WWBs tend to enhance EP variability more relatively to CP variability. This enhancement in the case of state-dependent WWBs forcing is due to an increase in the so-called thermocline feedback as opposed to the so-called zonal advective feedback.

Lastly, we test whether phenomenological stochastic forcing of the form of WWBs impacts ENSO predictability. An ensemble ENSO prediction experiment is presented in which CCSM3 control and CCSM3 with state-dependent WWBs parameterization are used as both truth and as predictor systems. The inclusion of WWBs
does not improve nor degrades ENSO predictability if the truth lacks WWBs activity. ENSO predictability increases substantially if a forecast system that produces WWBs activity is used to predict a truth that includes these wind events. It is also found that the so-called forecast spring prediction barrier (SPB) is partially caused by the lack of WWBs representation in the forecast system.

The argument for the SPB is that the coupled system is more susceptible to noise forcing in spring. The signal-to-noise ratio (SNR) is larger with WWBs, so it must be that the increase in the signal due to state-dependent WWBs is more important that the added noise. These results were further validated with the more recent version of this model, namely CCSM4. It turned out that CCSM4, at least with the coarse resolution used here, has a much-reduced seasonality in the SNR and therefore reduced seasonality in the forecast skill of SSTA. To further test these results, CCSM3 with and without WWBs parameterization were used to make real predictions of observed tropical Pacific SSTA. It was demonstrated that predictability skill are enhanced when WWBs were included and these improvements were mostly over the low SNR season. These results were further validated by a case study of a warm event with considerable WWBs activity, mimicking the strong 1997-98 event. It was found that the presence of WWBs in the prediction system enhances the forecast ensemble spread, leading to a more reliable probabilistic forecast. But most importantly, the number of ensemble members depicting the correct “truth” increases considerably. This is best observed for those forecasts progressing through the SPB.
Dedication

This dissertation is dedicated to my parents, Homero Lopez and Magaly Perez, whose support and guidance that made me a better human being. Also, I want to dedicate this work to my wife, Fabiola Castrillo for providing me with so many great moments. A special dedication also goes to my son, Hosmay Lopez, Jr., for motivating me to continue working and fulfilling my life with happiness.
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Finally, I am eternally thankful to the United States of America for allowing me, a foreign born citizen to fulfill my dream of obtaining an education, a dream that would not have been possible in my home country.
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Chapter 1

Introduction

There are currently two main hypotheses that describe the loss of predictability of the tropical Pacific coupled system. One school of thought asserts that El Niño Southern Oscillation (ENSO) is intrinsically chaotic because of the nonlinear dynamics of the coupled system (Zebiak and Cane 1987; Münstich et al. 1991; Jin et al. 1994; Tziperman et al. 1994; Chang et al. 1994; Zebiak 1989; Tziperman et al. 1995; Wang et al. 1999), and while stochastic forcing can affect predictability, it is of secondary importance compared to the uncertainty in the initial conditions. Here, the slow component of the coupled system has two major natural modes of variability: the annual cycle, which is a response to external forcing, and internal modes (e.g. ENSO), which is due to air-sea coupling. ENSO interaction with the annual cycle could possibly produce irregularities and the loss of predictability. The second school of thought argues that the irregularity of ENSO and ultimately the loss of predictability are largely driven by stochastic forcing (e.g., Kirtman and Schopf 1998; Eckert and Latif 1997; Blanke et al. 1997; Penland and Matrosova 1994; Penland and Sardeshmukh 1995; Flügel and Chang 1996; Moore and Kleeman 1996; Kleeman and Moore 1997; Xue et al. 1997; Chen et al. 1997; Moore and Kleeman 1999a,b; Thompson and Battisti 2001; Kleeman et al. 2003; Flügel et al. 2004; Zavala-Garay et al. 2003, 2004, 2005, 2008). If the stochastic forcing or noise is of primary importance then it is possible that the details (e.g., space-time structure and state dependence) of the noise are also important. McPhaden (2004) found that in order to predict ENSO development, it is not sufficient to know its preferable condition, (e.g., heat
content buildup along the equator) highlighting the importance of stochastic forcing on the coupled system.

Implicitly the stochastic view makes use of scale-separation to divide the tropical dynamic system into fast and slow time scales, although noise does occur on all space and time scales. Here, the fast time scale is originated from the life cycle of tropical atmospheric convection, while the slow time scale derives from the relaxation time of the ocean basin modified by air-sea coupling. If variability from the fast component projects onto the pattern of susceptibility, it could perturb the couple system. These patterns may vary among different coupled models and the system may rapidly develop a very characteristic response, which in some coupled models strongly resembles a westerly wind burst (WWBs; Moore and Kleeman 1999).

For example, Moore and Kleeman (1999a, b) calculated the stochastic optimal of an intermediate coupled model and argued that their spatial structure is consistent with the spatial structure associated with observed (WWBs). That is, the space-time statistics of the noise may be important in producing optimal growth (i.e., produce larger response in the coupled system). Kirtman and Shukla (2001) argued that wind stress noise associated with the Indian summer monsoon has a specific structure in the tropical Pacific that can trigger ENSO. Zavala-Garay et al. (2003) found that perturbation growth due to stochastic forcing is more favorable over the western/central Pacific where SST is moderately warm and more sensitive to noise forcing. WWBs are example of atmospheric stochastic forcing of ENSO, as they appear to be associated with internal variability of the atmosphere (e.g. Zhang and Gottschalck, 2002; Hendon et al., 2007) yet also seems to influence ENSO events. Luther et al. (1983) concluded that the weakening
of trade winds over the central Pacific before El Niño, from 1950 to 1978, was related to a series of strong WWBs. Westerly wind anomalies excite downwelling Kelvin waves that propagates eastward about the equator (Harrison and Schopf 1984; McPhaden et al. 1988; McPhaden et al. 1992; McPhaden 1999; Lengaigne et al. 2002). The effects of WWBs on sea surface temperature (SST) in the Pacific were studied by Vecchi and Harrison (2000). In that study, they found that WWBs represent a fundamental process for waveguide warming during the onset of El Niño and for eastern and central Pacific warm SSTA maintenance during El Niño.

These WWBs seem to result from various mechanisms. First, from the Madden-Julian oscillation (MJO; Chen et al. 1996), even though a statistical relationship between the MJO and WWBs has not been well established. Zhang and Gottschalck (2002) indicated a tendency for larger SST anomalies of ENSO warm events in the eastern Pacific, to be preceded by stronger oceanic Kelvin wave anomalies induced by the MJO in the western Pacific. Second, cold surges from mid-latitude over the western Pacific (Love 1985; Chu 1988; Kiladis et al. 1994). Yu and Rienecker (1998) indicated in their case study of the 1997–98 El Niño that WWBs were associated with cyclones induced by a northerly surge in phase with the convective passage of the MJO. Yu et al. (2003) showed that changes in northerly surge pathways, influenced by ENSO phases, were related to WWBs occurrences through cyclone formations over the western Pacific. However, it remains statistically unclear whether the surges are essential for WWBs occurrences and the possibility that the MJO prepares the favorable environment for intrusion of cold surges. Third, WWBs can result from tropical cyclones (Keen 1982), or a combination of the three (Yu and Rienecker 1998). WWBs associated with twin
cyclones over the western Pacific, accelerated the development of the 1986-87 El-Niño event (Nitta and Motoki, 1987; Nitta, 1989). Murakami and Sumathipala (1989) emphasized that collective occurrences of WWBs lasting 7–20 days over the western Pacific were related to ENSO.

WWBs anomalies have typical amplitude of about 7 ms$^{-1}$ and they may last for up to 20 days (Harrison and Vecchi 1997). There is a large range of definitions for WWBs in the literature. Verbickas (1998) found that these bursts occur on average 3 times per year, with a higher incidence during the warm phase of El Niño Southern Oscillation ENSO (or El Niño). WWBs events are commonly viewed as completely stochastic processes, independent of any oceanic forcing. This is due to its short time scale, which may suggest they are external to equatorial Pacific interannual variability, although as recent literature suggests and as we argue here this is the subject of some debate.

The understanding of the importance of the stochastic forcing is complicated by this possibility that the noise may be state dependent. A case in point is the results of Kirtman et al. (2005) who found that the spatial structure of the dominant wind stress noise was remarkably similar to the spatial structure of the coupled signal and that the noise was state-dependent. Jin et al. (2007) formulated a simple coupled model to examine how state-independent noise versus state-dependent noise affected ENSO variability. In that study, they found that, unlike state-independent noise, state-dependent noise alters the ensemble mean evolution of ENSO, and amplifies the ensemble spread during ensemble forecast.

Recent work has suggested that WWBs also contain a deterministic component, modulated by the SST. Based on observations, Yu et al. (2003) suggested that when the
tropical Pacific warm pool is extended WWBs are more likely to occur. Tziperman and Yu (2007) analyzed scatterometer observations and showed that the characteristics of WWBs depend on the large-scale SST field and are therefore not purely stochastic. The 1997-98 El Niño, which was poorly predicted by most models, had a high occurrence of these wind bursts. During this ENSO event, WWBs were observed to migrate eastward with the 29°C SST isotherm (McPhaden 1999). The western Pacific WWBs precede El Niño, when the Pacific warm pool extends further east, and are not considered as purely stochastic (e.g., Zhang and Gottschalk 2002; McPhaden et al. 2006; Seiki and Takayabu 2007; Kug et al. 2008). WWBs induced by westerly background states associated with ENSO were shown using observational data (Seiki and Takayabu 2007), GCM data (Kug et al. 2009; Sooraj et al. 2009), and CMIP3 multimodel data (Seiki et al. 2011). Seiki and Takayabu, (2007) found that WWB frequencies for a western Pacific region were lag correlated with SST anomaly over the Niño-3 region. The same study hence found that WWBs tended to occur in sequence, from the western to eastern Pacific, leading the El Niño peak by 1-9 months.

Using a hybrid coupled model, Eisenman et al. (2005) showed that when the WWBs are dependent on SST, they have the same effect as strengthening ocean-atmosphere coupling. They also showed that when WWBs are fully deterministic, the ENSO events have twice the amplitude of that when the bursts are completely stochastic. This is due to the enhancement of the slow component (i.e. interannual component) of the WWBs (Roulston and Neelin 2000). This potentially affects the ENSO predictability and prediction, because a stronger coupling can lead to a more self-sustained ENSO.
Objectives

The understanding of the importance of the stochastic forcing of the climate system is complicated by the possibility that the noise may be state dependent. This work intends to disentangle the interactions between weather and climate from two different perspectives. First, noise is treated as “non-phenomenological” stochastic forcing of the climate system with no predetermined spatial and temporal scale. Second, noise is analyzed in terms of “phenomenological” stochastic forcing of the form of westerly wind burst (WWBs). Here, the noise has a well-defined structure based on observational records. Sets of experiments are performed by employing a state-of-the-art Coupled General Circulation Models (CGCMs). The overall goal of this study is to quantify the importance of stochastic noise forcing in sustaining, modulating, and modifying climate variability and more specifically El Niño Southern Oscillation (ENSO) variability and predictability.

Chapter 2 seeks to understand how internal atmospheric dynamics noise affects the coupled climate system at different resolutions. This is an important question here, given that the ocean response depends on the space-time structure of the noise forcing, and as noted above, the statistics of the noise is likely to be dependent on model resolution. In order to tackle this question, we make use of the Interactive Ensemble (IE) strategy proposed by Kirtman and Shukla (2002) and applied to CCSM3 (Kirtman et al., 2009; Kirtman et al., 2011), so that any signal dependence in the noise statistics is retained. The IE technique was specifically developed with the purpose of studying the relative importance of stochastic (weather noise) forcing and deterministic coupling in generating climate variability in CGCMs. This noise reduction technique is different from the a posteriori ensemble averaging of multiple coupled model realizations in that the
ensemble averaging is done to the atmospheric fluxes as the CGCM evolves, therefore it is viewed as fully interactive. Using the IE technique Kirtman and Shukla (2002) suggested that noise reduction only slightly decreased the amplitude of ENSO in the COLA anomaly coupled model (Kirtman et al. 2002), shortened its periodicity, and increased its regularity. In a separated IE study, Yeh and Kirtman (2004a,b) diagnosed SST variability in the North Pacific and argued that the local effect of noise forcing dominated the variability and blurred the tropical-midlatitude SST teleconnections. Wu and Kirtman (2004a, b) made use of the IE technique to isolate the importance of coupled air-sea feedbacks over warm tropical oceans for monsoon-global ocean teleconnections.

Here, we aim at understanding how ENSO is affected by internal atmospheric dynamics and how atmospheric model resolution might influence these interactions. We seek to diagnose the role of atmospheric noise in the diversity of ENSO, including event-to-event and phase (warm-to-cold) asymmetry. And lastly, examine the role the signal plays (if any) in modifying noise amplitude and spatial structure at different resolution.

Chapter 3 advances a procedure for examining how both state dependent and state independent stochastic forcing affects ENSO variability in a sophisticated coupled model. While our focus is on state dependence, the approach can also be used to examine some elements of the sensitivity to the spatial structure. There are two aspects to our approach that we highlight here. First, we examine the impact of the stochastic forcing within the context of a state-of-the art coupled general circulation model. Second, in terms of introducing the stochastic forcing, we take a phenomenological approach in that we focus on WWBs and parameterize their effect (both state independent and state dependent) in the coupled model. This is the first time that a state dependent and state independent
WWB parameterization has been incorporated into a state-of-the-art coupled general circulation model.

The purpose of Chapter 4 is to study the effect of WWBs on both eastern Pacific (EP) and central Pacific (CP) ENSO events and to establish any similarities/differences that may arise. EP events have maximum SST anomalies near the South American coast. In contrast, CP events have SST anomalies over the central Pacific. For this, we take a numerical modeling approach. A set of experiments is performed for each model where state-independent and state dependent WWBs are parameterized. Results are compared to control simulations from both models. Chapter 3 describes the implementation of the WWBs parameterization and its effects in both CCSM3 and CCSM4. Here we expand on Chapter 3 to separately examine the effects on CP and EP events.

There are two possible scenarios that may lead to ENSO modulation by these WWBs that are motivation for the work described here. First, WWBs can impact zonal currents through air-sea momentum fluxes. This is dominated by a localized response, but these wind anomalies occurs on a fairly large scale and over regions of strong zonal temperature gradients. This potentially modifies the zonal advective feedback potentially favoring CP events. Second, westerly momentum forces downwelling Kelvin waves that can enhance/sustain an existing warm event through waveguide warming. This is more associated with thermocline dynamics and EP events. Both of these possible scenarios will be tested with and without the WWBs inclusion.

Results in Chapter 3 suggest that WWBs significantly alter ENSO predictability. Chapter 5 attempts to quantify ENSO predictability using CCSM3 with the state-dependent WWB parameterization, and compares it to the control case without WWB.
For this, four sets of retrospective forecast experiments are made. These forecasts will be validated using previous CCSM3 runs with and without the state-dependent WWB. Forecasts will be initialized for four different seasons, namely March, June, September, and December initial conditions. Some of the more relevant results will be validated using a more sophisticated model, namely CCSM4.

We also examine the “so-called” boreal spring prediction barrier of ENSO forecasts (SPB) and how this is modified by WWBs. The seasonality of predictability skill of tropical Pacific SSTA is well documented. There are currently two hypotheses for the breakdown of ENSO forecast skill during the SPB. The first hypothesis relates the seasonality of SSTA variance (i.e., signal) to that of stochastic (noise) forcing. Webster and Yang, 1992; Xue et al., 1994 argued that SSTA variance is weaker during boreal spring, therefore is more sensitive to contamination by noise forcing. The second hypothesis suggests that the air-sea coupling strength is weakest during the boreal spring (Zebiak and Cane, 1987). Using an ensemble prediction system, Zheng and Zhu (2010) found that low signal-to-noise ratio (SNR) during the boreal spring limits the predictability through that season. Duan and Wei (2013) showed that error growth due to spring prediction barrier (SPB) depend remarkably on the ENSO phase with El Niño phase yielding a more prominent spring prediction barrier than for La Niña phase. This study will examine how WWBs affect the seasonality in ENSO forecast skill.
Chapter 2

Internal atmospheric dynamics and resolution: Non-phenomenological noise reduction

In the context of this chapter, we refer to noise as the stochastic component of atmospheric fluxes at the air-sea interface. In most previous work, stochastic forcing was externally prescribed and derived as some approximation to weather noise statistics that is state independent. The difference here is that weather noise is internally produced by the atmospheric model and is state dependent. The goals/purposes of this chapter are to:

1) Understand how ENSO is affected by noise due to internal atmospheric dynamics (i.e. atmospheric noise) and how atmospheric model resolution might influence these interactions;

2) Diagnose the role of atmospheric noise in the diversity of ENSO, including event-to-event and phase (warm-to-cold) asymmetry;

3) Examine the role the signal plays (if any) in modifying noise amplitude and spatial structure at different resolution.

The first goal is a general issue that will be discussed throughout this chapter. The second goal is mainly aiming at assessing the importance of noise forcing in sustaining/modifying/diversifying what is often called “signal”. The third goal is attempt to understand the role of the signal in modulating the noise, namely signal dependent noise. A state-of-the-art Coupled General Circulation Model (CGCM) will be used to address the three goals noted above.
The CGCM used in this work is the Community Climate System Model version 3 (CCSM3) from the National Center for Atmosphere Research (NCAR). This model is an earth system model comprised of four geophysical components consisting of atmosphere, land, ocean, and sea ice components all linked by a flux coupler. The coupler exchanges information among the components interactively while the model is running. The atmosphere is modeled by the Community Atmosphere Model version 3 (CAM3). The land surface is modeled by the Community Land Surface Model version 3.0 (CLM3). The oceans are represented using the Parallel Ocean Program version 1.4.3 (POP) and the sea ice is modeled by the Community Sea Ice version 5 (CSIM5).

In this work, CAM3 and CLM3 have horizontal resolution of T42 (128 longitude and 64 latitude points, or ~ 280 km) for the low-resolution case and T85 (256 longitude and 128 latitude points, or ~ 140 km) for the medium resolution case. There are 26 atmospheric vertical levels for all experiments. For the POP and CSIM5, the horizontal resolution is approximately 1° in the longitude and variable in the latitude direction with finer resolution, about 1/3°, near the equator. The POP has 40 vertical levels with level thickness monotonically increasing from approximately 10 to 250 meters with depth.

CCSM3 uses a daily coupling interval for the ocean component and an hourly coupling frequency for the other components of the climate system. Air-sea coupling is conservative and transfers momentum, heat, fresh water, sensible, latent, and radiative heat fluxes between the ocean and atmosphere. At every hour, the atmosphere component communicates to the coupler time-averaged wind speed, humidity, potential temperature, precipitation, air density, geopotential height of the lowest grid level, fluxes of net surface solar and long-wave radiation. The ocean component sends the coupler the upper-
level time-averaged temperature and velocity at the end of the coupling period. With these inputs from the ocean and atmosphere, the coupler calculates momentum, heat, and fresh water fluxes hourly, and then passes them to the ocean model as daily means.

A detailed description of CCSM3 simulation of ENSO is found in Collins et al. (2006) and for ENSO prediction in Kirtman and Min (2009). Here, some of the most relevant issues with this model are highlighted. Interannual SSTA associated with ENSO extend too far to the west in CCSM3 as compared to observations. This is consistent with the well-documented westward displacement of the mean eastern Pacific cold tongue position. The SSTA also shows a strong meridional confinement about the equator compared to observations. This confinement can be the result of significantly narrow zonal wind stress forcing in CCSM3. Deser et al. (2006) found that the meridional confinement of zonal wind stress is related to the high frequency of interannual variability in CCSM3, and the mechanism for this is described in Kirtman (1997). Despite the well-known errors in ENSO statistics, CCSM3 has also been shown to have reasonable ENSO prediction skill. For instance, Kirtman and Min (2009) compared CCSM3 ENSO predictions to the operational NOAA Climate Forecasting System (CFS), and found that both the deterministic and probabilistic forecast quality in the Niño3.4 region was comparable.

2.1 The Interactive Ensemble technique

The IE strategy has been used to diagnose the ENSO-Monsoon relationship (Wu and Kirtman, 2003) and mechanisms for low-frequency SST variability (Yeh and Kirtman, 2004; Wu et al. 2004; Schneider and Fan 2007) among others. It uses multiple
realizations of the atmospheric model (CAM) coupled to a single realization of the ocean model (POP), a single realization of the sea-ice model and a single realization of the land-surface model. The coupling of the multiple realizations of CAM to the single realizations of the other component models is accomplished through the CCSM coupler. The purpose of this coupling strategy is to significantly reduce the stochastic forcing of the ocean due to internal atmospheric dynamics. Ensemble averaging of fluxes of heat, momentum and fresh water produced by the individual CAM ensemble members before they are passed to POP effectively filters the noise in the fluxes due to internal atmospheric dynamics. The sea-ice and land surface models are also coupled to the ensemble mean fluxes. Additional details can be found in Kirtman et al. (2009).

The interactive ensemble strategy works as follows (Fig. 2.1). Each realization of CAM is statistically identical; the only difference among the CAM ensemble members is the initial condition. Because the atmosphere is sensitively dependent on initial conditions, the CAM realizations evolve differently. As the interactive ensemble evolves, each CAM realization experiences the same SST predicted by the ocean component. POP, on the other hand, experiences surface fluxes of heat, momentum and freshwater that are the ensemble average of the CAM realizations. The CAM realizations are noise independent (i.e., the noise among the ensemble members is uncorrelated), but since they are all coupled to the same SST, they have the same SST forced signal. The interactive ensemble coupling does not modify the internal dynamics of the individual CAM realizations, up to any changes in the mean state and the character of the SST variability. This is because the ensemble averaging is only applied to the fluxes of heat, momentum
and freshwater as they are passed to the ocean component. In our experiments, both low and medium-resolution IE are implemented using six atmospheric GCMs realizations.

**Figure 2.1** Schematic representation of the Interactive Ensemble technique (Kirtman and Shukla, 2002).

### 2.2 Impact of IE on the mean state

Here, we will discuss the impact of applying the IE to low and medium resolution atmospheric component models, with the ocean having the same $1^\circ$ resolution. We compare 200-year simulations of the control and its respective IE (see table 2.1 for experiment description). The author remind the reader that any differences between control and the IE experiment in CCSM3 is assume to be caused by internal atmospheric dynamics – we cannot completely eliminate the possibility of non-linearity in, for example, the signal or the mean state.
Table 2.1 Experiments description, the ocean resolution is the same for all experiments.

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Description</th>
<th>Atmosphere resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>T42-CTL</td>
<td>Low resolution control</td>
<td>T42 (~2.8°)</td>
</tr>
<tr>
<td>T42-IE</td>
<td>Low resolution interactive ensemble</td>
<td>T42 (~2.8°)</td>
</tr>
<tr>
<td>T85-CTL</td>
<td>Mid resolution control</td>
<td>T85 (~1.4°)</td>
</tr>
<tr>
<td>T85-IE</td>
<td>Mid resolution interactive ensemble</td>
<td>T85 (~1.4°)</td>
</tr>
</tbody>
</table>

The primarily focus here is on climate variability, but as noted above it is also possible that the mean climate could be affected, and could contribute to the differences in the simulations. This is because the coupled model is “tuned” using only one atmospheric GCM, and reducing noise can have a rectifying effect on the mean (see also Kirtman et al. 2009; Kirtman et al. 2011). Figure 2.2, for example, shows the mean SST along the equatorial Pacific, for both low and medium-resolution control and IE simulations along with observational estimates. The general SST gradient is captured in all simulations, and is fairly consistent among the simulations. Notable differences are in the far western Pacific and far eastern Pacific. For example, the warm pool bias appears (or more precisely the warm SST plateau in the west Pacific) to be reduced in both simulations with IE. Note that the medium-resolution (T85-control) experiment does the worst job in depicting the observed SST plateau west of 160E. The T42-control simulation has a large warm bias in the far west of the basin, but there is some hint of an SST plateau around 140E. It should be noted the author is not arguing that the IE is the way to improve the simulation in the west Pacific, but rather it provides a potential mechanistic understanding of the source of the warm pool bias.
The application of IE also slightly reduces the SST bias just off the coast of South America. This is also true irrespective of the resolutions examined here, again potentially suggesting sources for these errors. A region where IE degrades the mean climate is in the cold tongue, especially between 120W and 90W. Note that T85-IE is arguably the worst simulation in this region with cold bias of about 2°C. Overall there are regions where the IE reduces errors and regions where the IE enhances errors. This is especially noted for the medium-resolution configuration. It appears that the IE tends to improve the simulation in regions where the atmosphere strongly forces the ocean (e.g. warm pool region), whereas it degrades simulation in other regions (e.g. cold tongue). This degradation or improvement may be model dependent, but is not resolution dependent in this model.

Taking a more global perspective, Fig. 2.3 shows the mean SST difference (IE minus control) for both low (top) and medium (bottom) resolution. Most of the
differences are over the mid-latitudes. The relatively warm bias in both IE simulations are
a result of reduced turbulent mixing in the upper ocean due to the noise reduction. This is
mostly seen in the North Pacific region. In the North Atlantic much of the differences are
not an ocean mixed-layer response, but are associated with changes in the meridional
overturning circulation (see Kirtman et al. 2011). The strong cold bias in the southern
ocean at low resolution is not apparent in the medium resolution case. This is a region of
very strong ocean eddy activity and applying the IE at different resolutions may be
affecting how the atmosphere interacts with the rectified effect of these eddies.

Figure 2.3 Mean SST difference (IE minus control experiment), for low (top) and high
resolution (bottom). Contour interval is 0.2°C with values less than 0.6 suppressed. Also
contouring values that are greater than the 99% confidence level based on a Student-T
test.


2.3 Tropical Pacific variability and IE

Before looking at how ENSO is modified by IE, we analyze in general, variability in the tropical Pacific. An analysis of variance is performed for SSTA, zonal wind stress ($\tau_x$), and precipitation. Variance is calculated using anomalies obtained by removing the climatological annual cycle from each field. The variances for precipitation and $\tau_x$ are calculated from the ensemble mean of those fields, which is used to force the ocean component. Figure 2.4 shows the standard deviation ratio (i.e., $\sigma_{IE}/\sigma_{CTL}$) for IE divided by control for both T42 and T85 simulations. Shaded contours indicate 99% statistical significant based on F-test with smaller values indicating regions of large variance reduction – the results are statistically significant almost everywhere.

**Figure 2.4** SST (top), zonal wind stress (middle), and precipitation (bottom) standard deviation ratio along the tropical Pacific sector. The ratio is defined as IE divided by the control experiment for T42 (left) and T85 (right) resolution cases. Shaded contours indicate 99% statistical significance using an F-test.
Overall, the SST standard deviation ratio (IE/control) ranges from 0.5 at T85 and to about 0.65 for T42 in the equatorial Pacific. This ratio is a useful diagnostic for quantifying the coupled feedback strength. That is, Kirtman et al. (2005) demonstrated that when the standard deviation ratio is greater than 1.0, unstable coupled feedback and non-linear dynamics are likely important in forcing SST variability. When the ratio falls between 0.4 and 1.0, unstable coupled feedbacks, non-linearity, or ocean dynamics may play a significant role. When this ratio is less than 0.4, SST variability is mostly due to atmospheric noise forcing alone. This critical standard deviation ratio of 0.4 (i.e., 1/6 variance ratio) is based on six atmospheric ensemble members. Non-linearity and coupled feedbacks are likely to be important in determining the dynamical regime of CCSM3 as described in Kirtman et al. (2009).

The differences in variance reduction between the medium (0.5) and low (0.65) resolution simulations are also statistical significant at 99% confidence level based on an F-test. This, along with Fig. 2.4 suggests that the variability in the T85 control case is more noise dependent than the T42 control, i.e., the variance reduction at T85 is larger than T42. Most of the reduction in variance occurs away from the equator for both resolutions. This is generally seen by considerable lower standard deviation ratios away from the equator.

In the deep tropical Pacific at T42, the spatial structure of the standard deviation ratio ($\sigma_{IE}/\sigma_{CTL}$) for SSTA and zonal wind stress resembles the spatial structure of the control standard deviation (i.e., $\sigma_{CTL}$). This is in contrast to T85 where the variance reduction has a distinctly different spatial structure than the control standard deviation. The T42 results presented here are consistent with the Kirtman et al. (2005) results for the
COLA T42 model in that the dominant noise patterns is largely projected on the “signal” patterns. As resolution increases the dominant noise structures start to deviate from the signal patterns significantly. This will be discussed in more detail later in the chapter.

![Figure 2.5](image)

**Figure 2.5** Standard deviation fraction (IE/control) difference (T42 minus T85 resolution) for sea surface temperature anomaly (SSTA, top), zonal wind stress anomaly (middle), and precipitation (bottom). Anomalies are defined as deviation from the annual cycle. Positive contours associated with T85IE having a larger variance reduction than T42IE.

Similar to the SST, the variance reduction for the wind stress and precipitation is more marked for T85 case (i.e., lower values of variance fraction). Most of the region shows values less than 0.5 for wind stress. The precipitation structure is more complicated, it has values close to 1 over the southeast tropical Pacific “ocean desert” region for both resolutions. This is mostly due to very small precipitation variances in
both simulations. An interesting pattern emerges at T85 with ratios less than 0.3 over the cold tongue. This is a region of very cold SST bias (Fig. 2.2) for T85IE case, which may be playing a role in suppressing noise-induced variability or in reducing the noise.

The difference (i.e. $\sigma_{T42IE}/\sigma_{T42CTL}$ minus $\sigma_{T85IE}/\sigma_{T85CTL}$) in the ratio of the standard deviation is plotted in Fig 2.5. Note that regions with positive values indicate that IE coupling at T85 has a larger variance reduction effect than IE coupling at T42. Alternatively, negative values indicate that IE has a bigger impact at T42 compared to T85. In most places throughout the tropical Pacific the IE coupling has more impact at T85 for all fields shown. There is a 10% to 15% more reduction in SST, and zonal wind stress standard deviation at T85 versus T42 resolution. The precipitation variance shows up to a 35% larger reduction in the standard deviation with T85. This result suggests that weather noise has a larger role in the simulated climate of the T85 model than in the T42 model. These results are also true for surface heat flux (not shown). These differences in ratios remain even when sub-sampling by just using 50 years of data instead of the 200 years.

### 2.3.1 ENSO characteristics - Variance

In this Section we diagnose how the IE implementation affects ENSO at different resolutions. Table 2.2 provides a quantitative comparison of Niño3.4 SSTA by showing the second, third, and four statistical moments with their respective confidence interval at a 99% level. The observed standard deviation is 0.83°C. The two control experiments suggest higher than observed variability of ENSO, with the medium resolution being closer to observed (e.g., $\sigma_{T42CTL} = 0.91°C$ and $\sigma_{T85CTL} = 0.88°C$); this is consistent with
Deser et al., 2005. Implementing the IE noise reduction technique consistently reduces ENSO variability (e.g., $\sigma_{\text{T42IE}} = 0.580^\circ\text{C}$ and $\sigma_{\text{T85IE}} = 0.510^\circ\text{C}$), and this is consistent with Figs. 2.4 and 2.5 discussed above. The differences in standard deviation discussed before are statistically significant at 99% confidence level for all cases. The higher resolution case is the most affected by IE. The positive skewness of the observed ENSO is described by the third moment. Note that the low-resolution control is negatively skewed (significant to a 99% level). A near-zero skewness is obtained by the noise reduction at T42. Differences in the third moment for the T85 cases are also statistical significant. Comparison for the fourth moment for all cases is not obvious due to a lack of statistical significance. Irrespective of resolution, internal atmospheric dynamics is a key component in determining the overall shape of the PDF. The Niño3.4 power spectra (not shown) is not modified by the noise reduction other than at very low (decadal) frequencies where there is some power decrease when atmospheric noise is reduced.

### Table 2.2
Second, third, and four statistical moments associated with Niño3.4 SSTA described by the probability density function (PDF) on fig. 12. The statistical significant interval is also shown to a 99% confidence level.

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Observed</th>
<th>T42ctl</th>
<th>T42IE</th>
<th>T85ctl</th>
<th>T85IE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stand. Dev.</td>
<td>0.83±0.05</td>
<td>0.91±0.03</td>
<td>0.58±0.02</td>
<td>0.88±0.03</td>
<td>0.51±0.02</td>
</tr>
<tr>
<td>Skewness</td>
<td>0.278±0.21</td>
<td>-0.22±0.09</td>
<td>-0.088±0.11</td>
<td>0.097±0.098</td>
<td>-0.117±0.11</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>0.055±0.34</td>
<td>-0.296±0.17</td>
<td>0.078±0.18</td>
<td>-0.180±0.19</td>
<td>0.0524±0.18</td>
</tr>
</tbody>
</table>
Figure 2.6 shows the variance by calendar month associated with Niño3.4 SST anomaly. The solid-black line depicts observed estimates, whereas the various simulations are noted in the legend. All the experiments agree, in a general sense, there is a reduction in variance during the boreal spring, and the two IE experiments show an overall reduction in variance compared to the control that is consistent with Figs. 2.4 and 2.5. Atmospheric resolution affects the seasonal variations in variance. This is particularly pronounced during late boreal spring and boreal summer where the two control variances are relatively similar, but the T85IE variance is considerably smaller than the T42IE variance. Most of the enhanced reduction of variance associated with T85IE seen in Fig. 2.5 appears to be associated with this limited period of the annual cycle. This is a season often characterized by low signal-to-noise ratio; this may suggests that SST variability during this period is mostly noise induced. We will also comeback to this issue later in this chapter.

![Figure 2.6](image)

**Figure 2.6** Seasonality of SST anomaly variance over the Niño3.4 region for observed and model experiments. Anomaly is defined as the deviation from the seasonal mean.
2.3.2 ENSO Composite Evolution

Here we explore the effects of atmospheric noise and resolution in terms of the evolution of composite of warm and cold events. The composite analysis is based on the warm and cold events that have a December-January-February (DJF) Niño3.4 SSTA greater than one standard deviation. Based on this threshold and that we have about 200 years of monthly data from all cases, the composite includes more than 40 events both warm and cold from each experiments.

Figure 2.7 Hovmoller diagram of composite analysis for warm (El Niño) events greater than one standard deviation. The horizontal axis corresponds to longitude across the equatorial Pacific Ocean. The vertical axis correspond to lead time in months, where year(0) is prior and year(1) is post the peak event. Composite based on Niño3.4 sea surface temperature anomaly (SSTA, °C).
Figure 2.7 shows the lag/lead composite warm events for T42ctl (top-left), T42IE (top-right), T85ctl (bottom-left), and T85IE (bottom-right). The panels represent SST evolution from March of year 0 (leading to the extreme event) to May of year +1 (after the event). For all panels in Fig. 2.7, the quantities are meridionaly averaged from 2°S-2°N. Notably the T42ctl simulation has stronger warm anomalies in the western Pacific that first appear in mid-summer and persist through the fall. In the T42ctl simulation, the warm SSTAs begin to emerge by late May(0) and migrate westward until reaching a maximum extent in January(+1). The maximum T42ctl SSTAs (~1.8°C) is located in the Niño3.4 region with a hint of eastward propagation. This maximum occurs during DJF and is also associated with significant activity in precipitation and zonal wind stress (not shown). Just like for the T42ctl case, Fig. 2.7 (bottom-left) shows the composite for T85ctl. The warm SSTAs begin to emerge around April(0) which is about 2 months earlier than those at T42 resolution, then they propagate westward reaching maximum amplitude and western extent during boreal winter. Interesting, the El Niño amplitude is ~0.2°C warmer at T85 than at T42 case whereas for the cold (La Niña) cases (not shown) T42 has slightly larger amplitude. The results on ENSO phase asymmetry will also be discussed later.

Another notable difference is the stronger warm events near the South American coast at higher resolution from June to December. This is a region of significant warm SST bias. The precipitation and zonal wind stress activity are very similar to those from T42ctl but slightly weaker (not shown). Most of the precipitation activity occurs during the warmest SSTAs with a clear eastward propagation but does not reach as far east as
those from T42ctl, presumably due to cold mean state bias over the cold tongue as discussed earlier (see discussion on Fig. 2.2).

The noise-reduced warm events composite are shown for T42IE (Fig. 2.7 top-right) and T85IE (Fig. 2.7 bottom-right). Applying the IE noise reduction technique at higher resolution (Fig. 2.7 bottom) leads to a significant reduction in amplitude, which is consistent with the standard deviation ratios shown in Fig. 2.4. In fact, as the variance analysis indicates, the reduced atmospheric noise at the air-sea interface has a greater effect on the composite at higher atmospheric model resolution. There are additional points to note in the bottom-right panel of Fig. 2.7. First, there is a lack of a well-defined maximum in the composites, suggesting that the phase locking to the annual cycle is weakened in the T85IE simulation. Second, as in T85ctl, SSTA first emerges during April(0), which is earlier than at T42. This suggests that any difference in when the initial SSTA emerges is independent of atmospheric internal variability and probably more related to other processes that are sensitive to atmospheric model resolution. Careful inspection of Fig. 2.7 also indicates a relatively large reduction in the T85IE ENSO composite during late boreal spring and summer, which is consistent with the reduction of variance reduction seen in Fig. 2.6.

The robustness of the composite warm events is assessed in Fig. 2.8 (left column) and cold events (right column). The motivation is that we seek to document how much of the differences among events can be attributed to noise at the air-sea interface and how much is due to fundamental non-linearity within the context of the coupled system. The spread among events in the above composite is also shown in Fig. 2.8 along with estimates of the deviations about the composite mean. The events represent the Niño3.4
SSTA evolution from early boreal spring to the following spring. Each event is depicted in grey-thin line, the ensemble mean is indicated by black-thick line, and the spread for a given month is denoted by red-bars. Overall, there is considerable spread for warm events in T42ctl with only a few events peaking earlier or later than the ensemble mean peak in DJF. For T42IE, there is a noted reduction in the spread as well as the amplitude of events. Also noted is the flattening of the ensemble mean curved without a well defined peak season. Most of the spread for T42ctl is observed from late boreal spring through fall leading to the DJF composite ENSO peak. This is in contrast with T42IE where there is an indication of preferentially larger relative spread during boreal summer, which is associated with flattening of composite SSTA from August to the following January.

The T85ctl has similar features as those discussed for T42ctl. The spread for both control cases are of similar magnitude. For T85IE, the ensemble mean of events are even flatter than those from T42IE. Also, there is a more marked reduction in the spread; basically most warm events for this case evolve similarly without a well-defined peak. The overall impression from Fig. 2.8 is that noise at the air-sea interface has a larger role in the differences among warm events in the T85 model compared to the T42 model.

If atmospheric noise is state-dependent, then it might be expected that the noise reduction associated with IE will be different for cold events. For this, we repeat the composite analysis but for La Niña cases (Fig. 2.8 right column). Similar to the warm events, the T42ctl case shows significant spread among events compared to the T42IE case. In contrast to warm events, the spread for T42ctl is consistently large throughout the evolution of the cold event. The T85ctl cold composite has the largest spread among the experiments and all warm and cold composites. For this case, there is significantly large
spread early in the evolution of the event (e.g., May-to-July). Similar to the warm events, the ensemble mean of cold events evolution is flatter for the IE cases compared to the corresponding control. The T85IE model produces the least spread with most cold events evolving similarly. As previously mentioned, the noise reduction has a larger impact in the T85 model. In addition, it appears to have an asymmetric effect also, with the La Niña phase being more affected than the El Niño phase.

**Figure 2.8** Composite analysis for warm (El Niño) events evolution expanding from boreal spring of the year (0) leading to the event to the following spring. T42CTL (top-left), T42IE (top-right), T85ctl (bottom-left), and T85IE (bottom-right). Showing all individual events (grey-thin line), the ensemble mean of events (black-thick line), and the spread of events (red bars).
As further evidence of the asymmetric effect of the noise reduction we computed the change in spread for warm and cold events. For this, a mean spread value is found by averaging the spread for all months of the composite in Fig. 2.8 for each case and ENSO phase. For warm events, the spread of IE experiment is 46% of the control experiment at T42 (i.e., ratio of IE/CTL). In contrast the change in spread is 40% at T85. Similarly, the spread for cold events of T42IE case is only 27% of the control and T85IE is 23% of control.

2.3.3 ENSO Phase Asymmetry

Thus far, we have provided an overall picture how the IE coupling affects the variability in the tropical Pacific and the evolution of ENSO as a function of atmospheric model resolution. We also identified three issues that require more in depth analysis, namely: (1) the structural similarities or differences between the signal and the noise (see Fig. 2.4 and associated discussion); (2) the sensitivity of the annual cycle of variance to IE coupling and resolution (see Fig. 2.6 particularly in late boreal spring and summer); and (3) the differences in the effects of the IE coupling on ENSO phase asymmetry. We address these issues in reverse order and begin this sub-section with a more in depth analysis of the phase asymmetry (i.e., issue 3; particularly Fig. 2.11). The annual cycle sensitivity is addressed in more detail in the discussion of Fig. 2.13 (i.e., issue 2) and spatial structure issues are diagnosed in the discussion of Fig. 2.15 at the end of this chapter.
Figure 2.9 ENSO linear (symmetric) responses for sea surface temperature anomaly SSTA (shaded, °C) and surface wind stress (vector, Nm$^{-2}$). The linear ENSO response is defined by subtracting the warm events composite from the cold events composite and dividing by 2 due to opposite polarity. The composite for both ENSO phases includes over 30 events, defined by magnitudes greater than one Niño3.4 SSTA standard deviation. Panel a) corresponds to T42ctl, b) to T42IE, c) to T85ctl, and d) to T85IE respectively.
Figure 2.10 Same as 2.9, but for the ENSO non-linear (asymmetric) response. The asymmetric or phase-asymmetry is defined by adding the warm to the cold event composite. Panel a) corresponds to T42ctl, b) to T42IE, c) to T85ctl, and d) to T85IE respectively.
Figures 2.7 and 2.8 focused on the composite evolution of events; here, we examine how the IE and resolution affects ENSO phase asymmetry in more detail. To study the impact of noise forcing on ENSO phase asymmetry, the composite analysis discussed above is used to examine the differences between warm and cold events. Warm and cold events greater than one standard deviation are averaged. Then, the symmetric (asymmetric) ENSO response is defined by subtracting (adding) the warm composite to the cold composite. Due to the opposite polarity of warm and cold phase, the symmetric part is then, divided by 2. For each experiments, there are over 40 warm and cold events contributing to the composites. Figure 2.9 and 2.10 show the symmetric and asymmetric ENSO response respectively for T42ctl (a), T42IE (b), T85ctl (c), and T85IE (d) respectively. SSTAs [°C] are depicted by shaded contours and wind stress [Nm⁻²] by vector contours.

2.3.3.1 Low (T42) resolution

For T42ctl (Fig. 2.9a), the symmetric component of ENSO has SSTA that is narrowly confined to the equator, with higher amplitudes in the central basin. Significant equatorial wind stress convergence is associated with positive precipitation (not shown) anomaly over most of the positive SSTA region. Also, moderate divergence and negative precipitation (not shown) anomalies are observed off the equator. Overall, almost all the symmetric ENSO signal is confined to a narrow band from 10°S to 10°N.

Fig. 2.10a shows the asymmetric ENSO component, or equivalently the phase asymmetry between warm and cold events for T42ctl. Note the difference in contour interval with respect to Fig. 2.10 indicating that the asymmetric component is on the
order of 25% of the symmetric component. The positive center of action off the coast of South America in SST (Fig. 2.10a) suggests that the warm phase has larger amplitude there. This is consistent with observational estimates (Chiang and Vimont, 2004). Overall, the cold phase dominates throughout most of the domain, especially over the western portion of the basin. Unlike the symmetric component, there is some off-equatorial activity, in the wind stress and SST. For precipitation, most of the phase difference is confined to the equator and is very similar to the symmetric component (not shown).

Similarly, Fig. 2.9b and 2.10b depicts the symmetric and asymmetric ENSO response in T42IE. There is a clear reduction in amplitude (about 20%) for the symmetric response in IE. The overall spatial coherence is unchanged for SST, precipitation (not shown), and wind stress. Perhaps, the biggest difference is in the reduced western extent of the SST and precipitation signal. For the IE experiment, the eastward shift could be associated with the slight cooling of SSTs over the western Pacific shown earlier. This cooling is associated with a reduction of the zonal SST gradient (bias) over the warm pool region, and whether it is directly the cause of this eastward shift in the anomalies remains an open question. For the asymmetric response (Fig. 2.10b), the warm SST center of action off the coast of Peru weakens significantly, suggesting that whatever is responsible for it is related to the weather noise forcing. As with T42ctl, most of the asymmetry is negative, especially in the western Pacific and just off the equator. Most of the phase asymmetry beyond 10° north and south weakens but what variability remains lies within the 10°S-10°N latitudinal bands. This argues that most of the noise reduction is away from the equator, or at least, noise has a greater relative effect there.
2.3.3.2 Medium (T85) resolution

The same analysis is repeated using the T85 simulations. Again, more than 40 warm and cold events contribute to the composite for both control and IE experiments. Before comparing the effect of the IE technique, we first describe difference in the control runs (Figs. 2.9a, 2.9c, 2.10a and 2.10c). For the symmetric response (Fig. 2.9a and 2.9c), the amplitude of the symmetric signal is reduced in the east in T85, and a slight reduction in the west. The more marked differences are in the asymmetric response (Fig. 2.10a vs. 2.10c). Here, it is clearly shown that at higher resolution, the ENSO phase asymmetry increases significantly, and the structure sharpens dramatically. This sharper structure is most apparent in the western Pacific where the T85 model has a well-defined sideways cold “v” pattern that is blurred and even difficult to detect in the T42 model. The warm signal in the center of the “v” is also more clearly defined in the T85 model. The strong warm asymmetric signal seen in T42ctl (Fig. 2.10a) is completely removed and even weakly negative in T85ctl.

Figures 2.9d and 2.10d depict the symmetric and asymmetric ENSO response for T85IE experiment. For the symmetric response, the amplitude of anomalies is significantly smaller compared to T85ctl. In fact, variance drops by about 50%, this is a considerably larger drop than at T42 resolution. Again, this is consistent with all previous analyses. Most of the symmetric response is located over the central basin and in a narrow equatorial latitudinal band. When looking at the phase asymmetry, the overall reduction in amplitude is consistent in the two resolution IE experiments. The most marked reduction at T85 is the cold sideways “v” pattern in the western Pacific. This is a region were the T85ctl simulation has considerable rainfall variability that is apparently
associated with asymmetric SSTA variability that is not captured at T42, and that is significantly reduced when the IE coupling is applied. We should also note that this is a region where CCSM3 has particular difficulty in capturing the mean structure of the SST (see Fig. 2.2) and rainfall, and is the region where the IE apparently improves the overall structure of the western Pacific warm pool plateau (see Fig 2.2).

The ENSO phase asymmetry while different at different resolutions is clearly dependent on the noise. However, it is not clear whether the changes in the symmetric and asymmetric component are simply associated with the overall variance reduction or whether there are some asymmetric effects due to the noise reduction. Simply put, is the observed reduction in asymmetry due to noise or is it a result of significant amplitude reduction in the symmetric component?

To address the above question, Figure 2.11 describes the ratio of IE versus control experiments and for symmetric (red) and asymmetric (blue) components calculated as a variance using the SSTA composite squared across the equatorial Pacific. The components are meridionally averaged from 10S to 10N. There are two diagnostic elements evaluated in Fig. 2.11:

(i) Impact of noise reduction separately for the symmetric and asymmetric components evaluated across atmospheric model resolution. The horizontal dashed-green line corresponds to variance reductions that are significant at a 95% confidence level based on F-test. Essentially, if the blue and/or red lines are below the green dashed line, then the IE coupling significantly reduces the variance of the symmetric component in the case of the red line and/or the asymmetric component in the case of the blue line. If the red or blue are above
the green, then the variance reductions fail to be significant according to this F-test. The larger variance reduction at T85 is readily apparent, and perhaps more interesting is that the variance reduction is larger for the asymmetric component. This can be seen by the fact that the blue line in the top panel generally lies above the red, and generally lies below the red in the bottom panel. Indeed, there are large regions where the T42 asymmetric component is not significantly reduce in the IE simulation, whereas in the T85 case the red and blue lines are well separated from the 95% confidence line.

(ii) *Impact of noise reduction on symmetric and asymmetric components within a specific resolution.* Regions depicted by grey shading indicate where the IE effect on phase asymmetry (e.g. warm plus cold) is different than the IE effect on phase symmetry to a 95% confidence level based on a Student T-test for a particular resolution. In other words, if the IE effect was the same for the symmetric and asymmetric components of say the T42 model, then the red and blue curves in the top panel would be statistically indistinguishable. The same argument applies for the T85 case. For T42 resolution, the effect of noise reduction on the asymmetric component is smaller than that on the symmetric component that is statistically significant for fairly large regions of the central Pacific. In the west Pacific, at T42 the IE effect is larger for the asymmetric component. In the east Pacific the reduction is similar for both the symmetric and asymmetric components. At T85, throughout much of the west and central Pacific the IE effect is significantly larger to the asymmetric component.
There are some final points to note with Fig. 2.11. For example, there are regions (i.e., around 160E longitude) where the ratio is greater than one in the T42 model, and this is also evident in Fig. 2.10b. The positive center of action off the coast of South America in the T42 model (Fig. 2.10a) is reduced by a similar amount both the symmetric and asymmetric component, therefore we conclude that this reduction is due to the overall reduction in variance and is not specific to ENSO asymmetry. At T85 (Fig. 2.11 bottom), the asymmetry is strongly degraded (i.e., ~0.2 or 20%) and is significantly different than the symmetric effect for most of the central and eastern Pacific. Recall from Fig. 2.10c and 2.10d that these are the regions of largest differences in phase showing the cold sideways “v” pattern.

**Figure 2.11** Ratio of IE versus control experiments (T42 top) and (T85 bottom) for symmetric (red) and asymmetric (blue) lines across the equatorial Pacific. The horizontal dashed-green line corresponds to variance ratios significance to a 95% confidence level
based on F-test. Regions depicted by grey shade indicate where the phase asymmetry (e.g. warm plus cold) are different than the phase symmetry to a 95% confidence level based on a Student T-test.

The marked reductions in amplitude over both symmetric and asymmetric ENSO characteristics further highlight the importance of weather noise in ENSO dynamics. More interestingly, the importance of the noise appears to increase with resolution. This resolution dependence is clearly shown in the asymmetric component plots, where T85ctl is the most asymmetric simulation and T85IE is the least asymmetric of all the experiments. Also, the marked reduction in asymmetry at T85 appears to be different than just a reduction in the amplitude of the symmetric component. That is, much of the asymmetry at T85 is noise driven.

### 2.3.4 ENSO phase asymmetry induced by noise

The source of the asymmetry is an ongoing debate in the ENSO community. Timmermann et al. (2003) proposed a non-linear bursting scenario for extreme warm events. Differences in amplitude between El Niño and La Niña phase could be attributed to non-linear dynamical thermal advection (Jin et al. 2003). Kang and Kug (2002) suggested that atmospheric non-linear response to warm and cold SSTA could lead to ENSO phase asymmetry. These results suggest that at least some of that asymmetry is due to atmospheric internal dynamics noise at the air-sea interface. There are at least two possible mechanistic explanations for how the noise supports asymmetry: (i) that the noise is different for warm vs. cold events (i.e., non-linearity in the noise forcing itself), or (ii) that warm and cold events respond differently to the same noise (i.e., non-linearity in the response to the noise forcing).
We consider here (i) above, that is the possibility that the noise is different for warm and cold events. In order to examine the potential for non-linearity in the response to the noise forcing (i.e., ii above), additional experiments may be required which are beyond the scope of this study.

To address the first possibility – namely that the noise statistics are different for warm and cold events we examine the wind stress noise separately for warm and cold events. One of the advantages of the IE technique is that there are six atmospheric realizations that are responding to the same ocean forcing. Therefore, it is possible to quantify atmospheric internal variability by simply analyzing the ensemble spread among the atmospheric simulations. Here, we define the ensemble spread based on all possible differences among the ensemble members, this yields N=15 different combinations.

\[
\text{Ensemble spread} = \left[ \frac{1}{N} \sum_{i=1}^{N} (x_i - x_{i+1})^2 \right]^{1/2}
\]  
(2.1)

Equation (2.1) is suitable for our IE cases where multiple atmospheric simulations are readily available. Given that our control simulations only contain one atmosphere coupled to one ocean, (2.1) cannot be used for extracting the atmospheric noise. For the control simulation, we attempt to extract the noise using the following procedure. First, a given variable \(x^k(t)\) can be decomposed by a linear signal \(L_n(t)\), a non-linear signal \(NL(t)\), and noise as described in (2.2). Here, \(k\) represents the ensemble member, which for control case is just \(x(t)\) since there is only one ensemble member. For our case, variable \(x(t)\) is either precipitation or zonal wind stress. The linear signal is just modeled by a simple linear regression between Niño3.4 SSTA and variable \(x(t)\). A remainder \(R(t)\) can
be obtained by subtracting the linear signal from the total field \( x(t) \), so that \( R(t) \) includes the non-linear signal plus the noise component. Here, we refer to \( NL(t) \) as the component of the signal that is not extracted by the linear regression. In order to separate the noise in the remainder, we make use of composite averaging as in (2.3). The \( \overline{R(t)} \) term inside the square bracket in (2.3) denotes the composite averaging for \( N \) warm or cold events. If \( N \) is large enough, \( \overline{R(t)} \) should mostly contain the non-linear signal associated with those \( N \) events. Finally, a spread or noise can be obtained by the root-mean-square difference between the residual \( R(t) \) and \( \overline{R(t)} \).

\[
\begin{align*}
x^k(t) &= Ln(t) + NL(t) + Noise^k(t) \\
\text{Noise}(t) &= \left[ \frac{1}{N} \sum_{i=1}^{N} (R_i(t) - \overline{R(t)})^2 \right]^{1/2}
\end{align*}
\] (2.2) (2.3)

Given both the control and the IE simulations we can test whether (2.1) and (2.3) provide similar noise estimates. Figure 2.12 depicts equatorial Pacific Hovmoller diagrams of zonal wind stress noise evolution during warm (El Niño) events. Panels (a) and (d) correspond to T42IE and T85IE noise calculated using equation (1), where (b) and (e) correspond to T42IE and T85IE noise using equation (2.3). Panels (c) and (f) are similar to (b) and (e) respectively but equation (2.3) is applied to the ensemble mean of \( x^k(t) \) (\( N=6 \) for IE cases) wind stress given that that is what forces the ocean model. The composite are based on Niño3.4 SSTA. The first point to make here is that both definitions of noise (i.e., equations 2.1 and 2.3) produce similar noise estimates. This can be seen by the fact that Fig. 2.12a is very similar to Fig. 2.12b and Fig. 2.12d is very similar to Fig 2.12e. This also holds for precipitation (not shown). Results from (2.3) have slightly less localized amplitude than those from (2.1) but the general structure in
evolution corresponds well. Based on Fig. 2.12 we assert (2.3) is a reasonable estimate of the noise evolution and can be used to compare noise in the control with IE where only one atmosphere simulation is readily available.

**Figure 2.12** Hovmoller diagram depicting zonal wind stress \([10^3 \text{Nm}^2]\) noise evolution during warm (El Niño) events. Panels (a) and (d) correspond to T42IE and T85IE noise calculated using equation (2.1), where (b) and (e) correspond to T42IE and T85IE noise using equation (2.3). Panels (c) and (f) are similar to (b) and (e) respectively but equation (2.3) is applied to the ensemble mean (\(N=6\) for IE cases) wind stress given that that is what forces the ocean model. The horizontal axis corresponds to longitude across the equatorial Pacific Ocean. The vertical axis corresponds to lead-time in months. Composite is based on Niño3.4 sea surface temperature anomaly (SSTA).
The second point to make with Fig. 2.12 is that the noise is considerably smaller when equation (2.3) is applied to the ensemble mean of $x^k(t)$. This is expected and is highlighting how the IE technique works. The noise in panels (b) and (e) can be thought as atmospheric internal dynamics (AID) for a particular atmosphere ensemble member indicating that individual IE ensemble members can be used to estimate noise in the control, whereas panels (c) and (f) are the actual wind stress noise forcing to the ocean when the IE technique is applied.

Figure 2.13 shows the evolution of the noise for zonal wind stress for warm and cold events for all four simulations. For the control simulations it appears that noise evolution between warm and cold events is fundamentally different. For example, for the T42ctl case, the cold phase appears to have larger noise amplitude during the growth phase (e.g., from May to November) than that of the growth phase of warm events. In contrast, there is larger noise amplitude for warm events during the maximum SSTA. Similarly, the T85ctl case has the largest noise for the La Niña phase with a late spring maximum well over $12 \times 10^{-3}$ Nm$^{-2}$. Recall that this is the season of very significant cold SSTA spread (see Fig. 2.8 T85ctl panel). Also, Fig. 2.6 shows more late boreal spring variance in T85ctl compared to T42ctl, where T85IE variance is consistently smaller than T42IE throughout the year. This suggests that the enhanced SSTA variance in T85ctl (Fig. 2.6) during late spring is highly noise induced.

The noise asymmetry is largely reduced for the IE cases. The T42IE model has some apparent phase dependence and any phase dependence in the T85IE simulation is difficult to detect at best. The bottom line is that the phase asymmetry in both the SSTA evolution and the noise statistics is clobbered by the IE coupling.
Figure 2.13 Hovmoller diagram depicting zonal wind stress [$10^{-3}$ Nm$^{-2}$] noise evolution during warm (El Niño) events (left column) and during cold (La Niña) events (right column) for each experiment (rows). The horizontal axis corresponds to longitude across the equatorial Pacific Ocean. The vertical axis correspond to lead time in months, where year(0) is prior and year(1) is post the peak event. Composite is based on Niño3.4 sea surface temperature anomaly (SSTA) with horizontal black-dashed line representing zero-lag. The noise is defined by equation (2.3) applied to the ensemble mean ($N=1$ for control and $N=6$ for IE cases) wind stress given that that is what forces the ocean model.
Given that the noise amplitude may depend on the signal amplitude, we cannot definitively determine from Fig. 2.13 whether the noise is larger in T85 or T42. We can address this to some extent by considering the signal-to-noise ratio where the noise is defined by (2.3) for all cases. Figure 2.14 shows the zonal wind stress signal-to-noise ratio evolution (shaded) during warm ENSO events (left-column), similarly for cold events (middle-column). Black contours show where the signal-to-noise ratio equals unity for reference. Differences in warm minus cold signal-to-noise ratio are shown (right-column), with black contours depicting differences with magnitude equals unity. The composite is based on Niño3.4 sea surface temperature anomaly (SSTA), similar to those previously shown. The signal is defined as the absolute value of the ensemble mean anomaly. For all cases, the highest signal-to-noise ratios are observed over the central Pacific, and this is mostly over the maximum SSTA variance region. Consistent with Fig. 2.13, warm events are less noisy than cold events for the control simulations. Interesting, the higher resolution case depicts significantly smaller signal-to-noise ratios compared to the low-resolution case, suggesting that T85 has more noise than T42 relative to the signal amplitude. This is especially true for cold events. Moreover, the warm-cold asymmetry in the signal-to-noise ratio is larger in amplitude and has a more coherent structure for both control cases with respect to the IE cases. This simply means there is less phase asymmetry in the IE simulations.
Figure 2.14 Zonal wind stress signal-to-noise ratio evolution (shaded) during warm ENSO events (left-column), similarly for cold events (middle-column). Black contours show where the signal-to-noise ratio equals unity. Differences in warm minus cold signal-to-noise ratio are shown (right-column) with black contours depicting differences equals 0.5. Composite is based on Niño3.4 sea surface temperature anomaly (SSTA).

Thus far, we have demonstrated that atmospheric noise is fundamental in sustaining ENSO variability and asymmetry, particularly as the resolution increases. What has not been clarified is that if the relative structure of the noise with respect to the signal is responsible for the marked resolution dependence in these results. That is, as
resolution increases the dominant noise structure start to deviate from the dominant signal patterns. Recall that Kirtman et al. (2005) with a T42 model argued that the noise and signal spatial structures were similar, and that we hypothesized here that this was the case with the T42 case, but not T85. To test this hypothesis, we compare the noise structure presented in Fig. 2.13 with the signal structure. The author remind the reader that the noise is calculated using (2.3) and the signal is defined as the ensemble mean for all events, or just the first two terms on the right-hand-side of (2.2).

Figure 2.15 describes the zonal wind stress [10^{-3} \text{ Nm}^{-2}] structure across the equator for the (a) T42 and (b) T85 models. Thick-dashed lines depict the signal and thick-solid lines depict the noise for the control (black) and IE (grey). Atmosphere internal dynamics (AID) is determined by applying (2.3) to each individual IE ensemble member and is indicated by thin-dotted lines. All fields are meridionaly averaged from 20^N to 20^S. Note that for the two control cases (i.e., T42ctl and T85ctl) the AID and noise is the same as there is only one atmosphere for these cases. Alternatively, the noise felt by the ocean component in the IE simulations (thick solid grey line) is calculated by applying (2.3) to the ensemble mean wind stress. The curves denoted as noise are the standard deviation, and hence are positive definite (see y-axis on the right). The signal fields include the sign dependence (see y-axis on the left).

Figure 2.15 is also annotated with signal-independent noise reduction (\delta SI) highlighted by a blue arrow, and signal-dependent noise reduction (\delta SD) shown by a red arrow. The signal-independent noise reduction can be estimated as the difference between the thin grey dashed curves and the thick solid grey curve. This is because the noise standard deviation in the individual ensemble members (thin grey dashed curves)
and the noise standard deviation in the ensemble mean (think solid grey curve) are calculated from the same IE simulation where all atmospheric ensemble members feel the same SST (i.e., same signal). The atmospheric ensemble members have the same signal; therefore, the differences noted in the Fig. 2.15 are the signal independent noise reduction. Alternatively, the signal dependent noise differences (δSD) can be estimated by comparing the control noise standard deviation with the noise standard deviation of each individual ensemble member in the IE simulation. Here we are assuming that the individual IE ensemble member would have the same noise standard deviation as the control if the IE SST was the same as the control SST. Of course, the control SST and IE SST have very different signals, and therefore the differences in the noise standard deviations are assumed to be signal dependent noise – at least in the sense of the overall amplitude.

A few important points to note with Fig. 2.15:

- The amplitude reduction in the zonal wind stress signal is significantly larger at T85 (compare grey dashed with black dashed), consistent with reduction in SSTA signal.

- The zonal structure of the wind stress signal is more similar to the noise structure at lower (T42) resolution. This can be seen by noting that the noise in the T42 simulation is more peaked in the central Pacific where the signal also peaks. At T85 the noise amplitude has a minimum where the signal has a peak in the central Pacific. This is also consistent with Fig. 2.4 in that the spatial structure of variance ratio (σIE/σCTL) resembles the spatial structure of the control (σCTL) at T42 but is different at T85.
There is little changes in the amplitude of the noise due to changes in the signal (δSD) east of 150W suggesting that most of the noise over the cold-tongue region is state independent. The largest δSD are west of 150W suggesting that most of the state dependent noise occurs over the warm-pool region. This is irrespective of model resolution except that at T85 the δSD extends further east.

**Figure 2.15** Zonal wind stress \([10^{-3} \text{Nm}^{-2}]\) structure across the equator for; (a) T42 and (b) T85 resolution model. Thick-dashed lines depict the signal and thick-solid lines depict the noise for control (black) and IE (grey) experiment. Atmosphere internal dynamics (AID) for each IE ensemble member is shown by thin-dotted lines. Signal-independent noise reduction (δSI) is highlighted by blue arrow, whereas signal-dependent noise reduction (δSD) is shown by red arrow. All fields are meridionaly averaged from 2°N to 2°S.
The main focus of this chapter was to study the impact of non-phenomenological atmospheric “weather” noise in the climate system, specifically on tropical Pacific interannual variability and ENSO. A state-of-the-art CGCM model, namely CCSM3, was adopted for this purpose. Our hypothesis was that the effect of the noise would be strongly dependent on atmospheric model resolution. In order to test this hypothesis, four different experiments were compared. In particular, two control experiments were presented at different resolutions, a low resolution $\sim 2.8^0$ and a medium resolution $\sim 1.4^0$ grid spacing for the atmospheric component with the same ocean model resolution for all cases. Two additional experiments were performed at these resolutions where the impact of internal atmospheric dynamics was suppressed by a noise reduction technique. The noise reduction technique adopted was the interactive ensemble approach from Kirtman and Shukla (2002) where ensemble averages of multiple AGCM realizations are coupled to a single OGCM as the model evolves.

It was found that ENSO statistics (amplitude, phase locking with the annual cycle, phase asymmetry) are strongly related to the noise forcing and to the atmospheric model resolution. This supports the argument (at least in this model) that the “canonical” warm and cold events are linear and that the simulated asymmetry is either associated with differences in the space-time structure of the noise (i.e., non-linearity in the noise) or in the response to the noise (i.e., non-linearity in the response). While we did not examine the non-linearity in the response to the noise, we did demonstrate that noise itself is asymmetric, with larger spread in the zonal wind stress during La Niña events. Certainly, these results should be tested with even higher resolution atmospheric models and different coupled systems. Of course issues related to ocean resolution should also be
investigated. Nevertheless, the results suggest that many properties of ENSO statistics (amplitude, phase locking with the annual cycle, phase asymmetry) are resolution dependent through the noise forcing. This raises important question regarding how well do we need to resolve weather statistics in order to capture the correct mechanisms for climate variability. The noise reduction technique presented in this chapter filters atmospheric noise independent of its temporal, spatial scale, and geographical constraints, e.g., “non-phenomenological” noise. This does not allow the study of more specific “phenomenological” types of noise, such as westerly wind bursts (WWBs). The next chapter will attempt to study the effect of this noise type on ENSO.
Chapter 3

Interactive Westerly Wind Bursts

In this chapter, we study the effect of phenomenological noise forcing of the form of westerly wind burst (WWBs) in modulating ENSO variability in a CGCM, namely CCSM3. The model used here is the same as that used in the previous chapter to study weather noise in a more general way. This model does not produce the observed structure of these wind events therefore we parameterize it. WWBs are strongly linked to the onset and development of El Niño events, and we attempt to include this state dependence in our parameterization. In the previous chapter, noise was removed from the CGCM by means of filtering without imposing a constraint on the specific scale and location of the noise, whereas in this chapter, noise that has a well-defined scale and location structure is added to a CGCM.

Before describing how the observed WWBs characteristics, we note that the probability density function (PDF) of the decoupled atmospheric variability in the western Pacific is nearly Gaussian (with some asymmetry clearly linked to ENSO). So easterly anomalies have about the same probability to occur. The focus of this chapter is on their westerly portion only as the title suggest. The intent of this chapter is to diagnose how the “observed” characteristics of WWBs affect ENSO statistics and dynamics. Essentially, we examine how atmospheric noise that has specific temporal and spatial scales and is geographically constrained impacts the simulated variability. This is in contrast to “non phenomenological” atmospheric noise that can be isolated with say, the IE approach presented in Chapter 2. Other reason for limiting the noise to be just eastward is due to its relative importance in forcing equatorial SST variability. Also,
this noise forcing is preferentially westerly for ENSO warm events. As demonstrated by studies cited in Chapter 1, WWBs are linked to tropical Pacific SST and appear to be state-dependent. Perhaps, the greatest motivation for this study is to investigate such state-dependence of WWBs on ocean state variables.

### 3.1 Westerly Wind Bursts

Before describing the characteristics of the WWBs being added as noise in the model, it is important to note the general structure of the noise produced by the atmospheric component itself. By making use of the Interactive Ensemble technique (Kirtman et al., 2009), the atmospheric internal variability (noise) was separated from the signal for the zonal wind (see Chapter 2). Most of the noise activity occurs outside the observed WWBs domain, and is largest in amplitude further east (Fig. 2.15). In fact, the noise is the strongest over the same region as the ensemble mean and it has greater amplitude during the cold phase of ENSO. But overall, its magnitude \((U < +5\text{m/s})\) is under the lower bound of what would be considered the typical amplitude of a WWBs \((U > +5\text{m/s})\). This is one of the motivations for this work, the absence of observed features (WWBs) in this model and its importance for ENSO. These winds do not match the observed temporal and spatial characteristics of WWBs. Given this, we have assumed that there is little or none WWBs activity in CCSM3, at least for the T42 resolution used in these experiments.

Before describing the experiment setup, the author would like to comment on the model used. Even though CCSM3 is known to have significant bias, it is considered a state-of-the-art climate system, and is still used in many studies (i.e., CMIP3 comparisons
of ENSO – see DiNezio et al. 2012). The atmospheric component produces its own noise, which presumably occurs on all space and time scales. The Eisenman et al (2005) results discussed in chapter 1 may be easier to interpret, but this is due to the simplicity of the model. It is unclear whether the Eisenman et al (2005) can be generalized or understood within the context of a complex coupled model that attempts to simulate all the relevant physical and dynamical interactions associated with climate variability in the tropics. We do not argue that our results are an “improvement” beyond Eisenman et al (2005), but we do assert that attempting this problem in a sophisticated coupled CGCM is a natural follow on from this earlier work and does provide new insights.

The WWBs parameterization is derived based on 50 years of atmospheric reanalysis data and observed estimates of tropical Pacific SST. The details of the parameterization are given in Gebbie and Tziperman (2009) and are followed without modification in the Appendix. To study the impact of WWBs three experiments are performed. In the first experiment, the model (CCSM3) is integrated for several hundred years with no prescribed WWB events (i.e., control). In the second case, fully stochastic WWB events are introduced. In other words, the occurrence, location, duration, and scale of the WWBs are determined (within bounds) randomly. These wind events are always positive (eastward) without a westward counterpart and are totally independent of the state variables (e.g. SST), and can be thought of as additive noise.

For the purely stochastic case, the wind events associated with the WWBs are only dependent on the seasonal cycle. This is because the bursts are introduced in the model as noise with stationary statistics (e.g., Eckert and Latif 1997). Given that the noise is stationary in time or only dependent on the seasonal cycle; its occurrence will not
depend on interannual variability such as ENSO. The burst amplitude, position, fetch, and duration are random within some specified bounds.

For the third case, the WWBs is introduced as multiplicative noise or state-dependent forcing, modulated by the SST. In this case, all aspects of the parameterized WWBs including the amplitude, scale, location, duration and probability of occurrence are dependent on the SSTA (see next sub-section for additional discussion of this dependence). An example of the parameterized WWBs is shown in Fig. 3.1. Here we show the parameterized zonal wind anomaly using observed estimates of the SSTA (Fig. 3.1; right panel), so in this case we are applying the state dependent formulation. Figure 3.1 includes three panels on the left each of which corresponds to a different realization of the parameterization, but with the same prescribed SSTA (right most panel). Differences among the three left panels indicate the stochastic component parameterization, but the preference for enhanced WWB activity during warm periods (i.e., the deterministic component) remain detectable in all three realizations. Fig. 3.1 demonstrates several properties of the parameterization. For example, the duration, the amplitude, the location of the central longitude and the frequency of occurrence are all modeled by the parameterization. The central latitude is also predicted, but this cannot be detected in Fig. 3.1. The stochastic component is easily detectable by the fact that there are notable differences among the three panels. The deterministic component is detectable via the fact that the amplitude and frequency of occurrence is notably larger during neutral and warm periods (i.e., Jan1982-Dec1984) compared to cold periods (i.e., Jan1985-Nov1986). The details of the state-dependent WWB parameterization are discussed in the following section and further described in the appendix section.
Figure 3.1 Hovmoller diagram showing three state-dependent WWBs realizations (3 left panels) [m/s] using the same observed SSTA (right panel) [°C], showing cross-section along the equatorial Pacific Ocean. Time increases up the page and covers from January 1982 to December 1986. Stochastic component depicted by the difference among the three realizations. The deterministic component is highlighted by the increased WWBs activity during warm events.

3.2 State-dependent WWBs parameterization

This sub-section provides some details of the WWBs parameterization. Some of the technical issues involved in including the parameterization in CCSM3 are also highlighted. Refer to the Appendix for detailed description. For the purposes of this study, WWBs are defined as zonal wind anomalies greater than 5 m/s that persist from 2 to 40 days, and with a zonal fetch of up to 500 km.

The bursts are a function of temporal and spatial parameters; amplitude $A$, time of peak wind $T_0$, the event duration (persistence) $T$, the central longitude and latitude $X_0$ and $Y_0$, the zonal and meridional fetch $L_x$ and $L_y$, and the probability of occurrence of a burst event $P$. This parameter is actually used as a trigger for both state independent and
dependent WWBs. The only difference is that in the former, the probability is determine based on observed monthly climatology whereas in the later, it is strongly modulated by the low frequency variability of SST. The frequency of occurrence of the burst depends on SSTA in the state-dependent case, but the duration of the events remain constrained to be less than 40 days.

Figure 3.2 shows the observed climatology for each of the 7 parameters used to construct WWBs as a function of the calendar month. Note that the amplitude of WWBs is well over 5m/s, which is the mean amplitude of the observed Trade winds in the tropical Pacific. There is strong seasonality in the amplitude of WWBs, with stronger bursts during boreal winter. WWBs are observed to migrate eastward with the warm pool edge, this is easily observed by $X_0$ (central longitude) parameter. This parameter shows about ~700km (or 7° longitude) in seasonal variation, with boreal winter bursts being further east. The seasonality of $X_0$ is very similar to the structure of the warm pool edge during warm ENSO events. The zonal fetch, or $L_x$ parameter is mostly over 2000km (~20° longitude), depicting the large-scale nature of WWBs. Variation in the meridional parameters (i.e., $L_y$ and $Y_0$) are subtle compare to the zonal parameters, but still showing some seasonality. The duration (i.e., persistence) of a WWBs ranges from about 8 days in boreal spring to about 13 days during boreal winter. Similar to the amplitude and $X_0$, this parameter mimics the seasonal dependence of SSTA variance in the central Pacific. Therefore, hinting at a state-dependence of WWBs to the underlying ocean state. The probability of occurrence parameter describes an interesting bimodal structure in the seasonality with a maximum during boreal winter and a secondary maximum during boreal spring. A WWBs event during boreal winter could reinforce/damp an existing
warm/cold SSTA further east via downwelling Kelvin wave. On the other hand, a boreal spring WWBs may trigger a warm event through the same mechanism.

![Figure 3.2 Observed climatology for each of the 7 parameters used to construct a WWBs.](image)

One difficulty in applying the WWBs parameterization in the state-dependent case is that parameterization requires SSTA (see Appendix), whereas the model predicts total SST. This implies that as the CGCM is running model SST climatology needs to be identified. This is accomplished via an anomaly coupling strategy (e.g., Kirtman et al. 2001). The anomaly coupling is only applied to the WWBs parameterization – the model remains fully coupled in all other aspects. The second issue with this parameterization is that the SVD analysis is trained on observed SSTA and the modeled SSTA may well differ from observation. To demonstrate that the state-dependent parameterization here is
suitable for this model, some WWBs characteristics are plotted in Fig. 3.3 obtained using observed and modeled (CCSM3) SST anomalies. This figure is showing a time evolution of WWBs for 10 years period along the equatorial pacific. The x-axis on all plots corresponds to time [in years]. The CGCM produce too frequent warm and cold events, affecting the periodicity of the wind burst due to its SSTA dependence. But, overall, all WWBs parameters agrees with observation, especially those related to structure like central latitude, longitude (not shown), zonal, and meridional fetch. The amplitudes are also similar, with the exception of the very strong ENSO event of 1997/98. Based on these, it can be said that the parameterization is suitable for this model.

Figure 3.3 State-dependent WWBs realization when using observed (top 2 panels) and CCSM3 (bottom 2 panels) SSTA. Time increment from left to right (~10 years) and longitude from bottom to top across the Pacific.
3.2.1 Time and space scale of parameterized WWBs

The temporal and spatial scales of the bursts (both state-independent and state-dependent) are consistent with observation, zonal fetch greater than 500km and persistence from 2 to 40 days, consistent with some of the classic definitions: Harrison and Vecchi (1997), Hartten (1996), Murakami and Sumathipala (1989) to list a few. According to such scales, a burst can range from synoptic to intra-seasonal scales. The synoptic component of WWBs could be related to cold surge from mid-latitude (Yu and Rienecker, 1998) and/or tropical cyclone occurrence (Keen et al., 1982).

A WWBs is decomposed according to (3.1) by its synoptic (syn) plus intra-seasonal (IS) component.

\[ U_{wwb} = U_{syn} + U_{IS} \]  

(3.1)

In order to separate the two components in (3.1), a bandpass filter is applied to \( U_{WWB} \) with power at a period window of 30 to 90 days for \( U_{IS} \) (intra-seasonal) and 2 to 10 days for \( U_{SYN} \) (synoptic) component.

One may ask which of the two components in (3.1) is responsible in introducing more variability? To answer the question, the standard deviation of WWBs is plotted in Fig. 3.4. The horizontal domain comprise of the equatorial western Pacific (over the main forcing region). This figure shows both cases and each WWBs component defined in (3.1). The data used here includes over 35000 daily records for all longitudes and cases. The peak variability is located about 160E for all components. The intra-seasonal component is responsible for most of the total WWBs variability for both parameterization types. The synoptic component contribution is very small.
Figure 3.4 Westerly Wind Burst (WWBs) standard deviation across the forcing region over the western Pacific for state-independent (a) and state-dependent (b) bursts.

The Kelvin wave (K) forcing associated with the WWBs events is defined as the response to zonal wind from WWBs integrated along the characteristic lines of Kelvin waves (Kessler et al. 1995), equation (3.2). The constant $c=2.4\text{m/s}$ is the observed phase speed, $x=0$ is taken as the western boundary following Zhang and Gottschalk, 2002.

$$K_{WWB}(x_0, t_0) = \int_0^{x_0} u_{WWB} \left( x, t_0 - \frac{x_0 - x}{c} \right) dx \quad (3.2)$$

Equation 3.2 is solved for each of the 2 sub-groups of WWBs. Figure 3.5 shows cross equatorial Pacific inter-annual SSTA ($^0\text{C}$) and the respective kelvin wave forcing ($10^1\text{m}^2/\text{s}$, shaded) for the total, intra-seasonal, and synoptic component respectively for the state-independent case. The respective WWBs are also shown as the $5\text{m/s}^{-1}$ contours. Same as Fig. 3.5, Fig. 3.6 displays the state-dependent case. There is a clear eastward propagation for the kelvin wave forcing emanating from the forcing region. From simple
eye inspection, the IS component appears to have larger amplitude than the synoptic component. Note the strong correlation of the K-forcing with SSTA for the state-dependent case (Fig. 3.6), also the bursts are slightly stronger here due to positive coupled feedback. Interestingly, the synoptic term appears to increase in the state-dependence case. This also leads to the question of coupled feedback working in favor of more local atmospheric convection during warm SST, further amplifying the fast (synoptic) component of WWBs.

![Figure 3.5](image)

**Figure 3.5** Time-longitude interannual SSTA (°C) across the Pacific a). The kelvin wave forcing $10^{-3}$ (m$^2$/s) from daily WWBs data (shaded) and WWBs (only the 5m/s contour shown) for a) total, b) intra-seasonal, and c) synoptic component. State-independent case.
It remains to discuss whether the synoptic or intra-seasonal WWBs components have equivalent effect on ENSO. For this, the daily K-index time series is interpolated to monthly means then compared to inter-annual SST anomalies associated with that of ENSO variability. Figure 3.7 describes a scatterplot of SSTA versus the K-forcing for synoptic (blue) and IS (red). A best-fit line is also included with their respective color. Most of the forcing is done by the IS-type for both parameterizations. In the state-independent case, there is virtually no correlation of any component with SST anomalies. This is expected given the fully-stochastic parameterization here.

Now lets look at the state-dependent case. There are some interesting things in the scatterplot. Again, the IS component forcing has the most power, but this time, the strong forcing is also concentrated over the warm SST sector. This implies that during warm ENSO events, the IS component forcing contributes the most. Even more interesting than

Figure 3.6 Same as Fig. 3.5 but for the state-dependent case.
that is what occurs with the synoptic-type forcing. Note that for the cold SST sector, there is barely any synoptic K-forcing as compared to the IS component. Now, for the warm SST sector, the synoptic-type forcing increases dramatically.

**Figure 3.7** Scatterplot of inter-annual SST anomalies over NINO3.4 region versus Kelvin wave forcing for synoptic (blue) and intra seasonal (red) WWBs forcing.

### 3.3 Observed versus parameterized WWBs

This section further describes the observed characteristics of WWB and compare it to that obtained from the parameterization. First, a brief description of how the bursts are extracted from observations is provided. The wind data is the 1000mb zonal wind from the NCEP/NCAR Reanalysis Project, extending from 01 January 1948 to 31 December
2011. The data has a 2.5° by 2.5° horizontal resolution and a daily time interval, same as the coupling interval of the ocean component of CCSM3 model. The data includes the tropical Pacific basin from 20°S to 20°N in latitude and from 120E to 80W.

There are many definitions of WWBs in the literature; therefore, extracting these events from the zonal wind data is not trivial. Some WWBs definitions are listed in the following studies. For example, Harrison and Vecchi (1997) used anomalous surface winds relative to the monthly climatology to identify WWBs. Hartten (1996) used a WWB criterion in which 1000-hPa zonal winds exceeded 5 ms\(^{-1}\) with a zonal extent over 10° and lasting for at least 2 days. On the other hand, Murakami and Sumathipala (1989) used bandpass-filtered 850-hPa zonal winds and identified WWBs with abrupt accelerations of westerly winds. Here, we will define WWBs in a way that is consistent with our state-independent and state-dependent parameterizations described earlier. The seasonal cycle is removed to produce a wind anomaly. Then, a wind event is defined when:

1. Wind anomalies averaged from 2.5°N to 2.5°S lasts from 2 to 40 days.
2. The above condition has a minimum zonal fetch of 500km.
3. Conditions 1 and 2 have anomalies exceeding +5ms\(^{-1}\)

The meridional constrain imposed in condition 1 is chosen based on the known effect of WWBs on Kelvin wave excitation and amplification and in agreement with our WWBs parameterization (see Fig. 3.3). The 2 to 40 days frequency band is meant to include both, synoptic and intra-seasonal variability characteristics observed in WWBs. Condition 2 follows from 1 and the typical zonal scale in the tropics. Condition 3 is chosen so that a burst is defined when a total reversal of the Trade Winds occurs in the
western Pacific, based on climatology. As any other definition of WWBs in literature, ours is empirical. Figure 3.8 depicts a hovmoller diagram of observed SSTA (0°C, shaded) and observed WWBs (5 m s^{-1}, black contour) along the equatorial Pacific. Also, showing the 28°C isotherm (grey line) as proxy to warm pool edge. Time increases up the page from January 1971 to December 2000. Figure 3.8 shows the observed WWBs according to our definition during the 1970s to 1990s. All bursts are greater than 5 ms^{-1} as defined, with amplitude close to that of the state-independent case. Most of the bursts are clustered as a large-scale feature in the zonal direction with highly variable temporal structure. The majority of the observed WWBs occurred during the El Niño phase of 1982/83, 1992/93 and 1997/98, with weaker bursts during the semi-permanent warm period from 1993 to 1995, consistent with the idea of the state-dependent formulation for the parameterization.

**Figure 3.8** Hovmoller diagram of observed SSTA (0°C, shaded) and observed WWBs (5 m s^{-1}, black contour) along the equatorial Pacific. Also, showing the 28°C isotherm (grey line) as proxy to warm pool edge. Time increases up the page from January 1971 to December 2000.
Our state-independent WWBs parameterization comprises of a stochastic component plus a seasonal cycle, whereas our state-dependent WWBs includes a deterministic component with interannual time-scale (tropical Pacific SSTA) along with a stochastic component plus the seasonal cycle. The observed WWBs has a strong interannual component. This feature is highlighted in Fig. 3.9 that shows a power spectrum of parameterized and observed WWB index defined by the area average from 140E to 160W and from 2.5S to 2.5N. Note that for all 3 cases, there is power at about ~0.1 frequency band, corresponding to the seasonality of WWB. The state-independent bursts are largely white noise, but with a small hint of more power at high frequencies. Most of the power in the state-dependent and observation resides in the interannual band, especially that related to ENSO-like variability. For the observed case, this suggests a strong dependence on tropical Pacific variability.

![Figure 3.9](image-url)  
*Figure 3.9* Power spectrum of Westerly Wind Burst index (area averaged from 140E to 180 longitude and 5S to 5N). Observed (red), parameterized state-independent (blue), and parameterized state-dependent (green). All parameterized burst are those coming out of CCSM3. Power in [dyne/cm²]².
3.4 ENSO variability and WWBs: CCSM3

We first discuss how the mean state and seasonal cycle are modified by the inclusion of state dependent and state independent noise. The long-term mean of ocean surface variables are largely unaffected by the different WWBs parameterizations in these experiments. For example, Fig. 3.10 displays the Niño 3.4 annual cycle for our three experiments. It is very common for current CGCM to underestimate the seasonal cycle, or to have a dominant semi-annual component (Mechoso et al. 1995; Latif et al. 2001). First, it is important to remind the reader that CCSM3 has a well-known semi-annual seasonal cycle along the equator depicted in Fig. 3.10. (CCSM4 has an improved annual cycle, but this does not appear to impact how the parameterization affects the model). Using CCSM3, Pan et.al, (2010) formulated an empirical heat flux adjustment that was able to simulate a more realistic mean state and seasonal cycle.

![NINO 3.4 Seasonal Cycle](image)

**Figure 3.10** CCSM3 Niño 3.4 SST seasonal cycle [°C], control (black), state-independent (red), and state-dependent (green) experiments.
For all the experiments, the general time dependence of the annual cycle is unaltered. The state-dependent case has an overall warmer ocean surface, especially for the latter part of the year. The warming does not appear to be important, since the maximum amplitude is only two tenths of a degree for the months of August and September. We believe that this difference has a relatively small influence on our results, and suggests that applying anomaly coupling for the WWB parameterization is a reasonable approach.

The time evolution of equatorial Pacific SST anomaly and the WWBs is shown in Fig. 3.11, for the control case. Note that the WWBs shown have been converted into a wind stress as applied in the model (i.e., assuming a constant drag coefficient) and are in [dynes cm$^{-2}$]. Figure 3.11 shows the Niño 3.4 index (top), sea surface temperature anomaly (SSTA) along the equator for the Pacific Ocean (bottom). These time series are taken randomly from 20 model years, but the time is consistent for all panels. Similarly, Figs. 3.12 and 3.13 describe these fields for the state independent and state dependent forcing cases respectively.

![Figure 3.11](image)

**Figure 3.11** CCSM3 control experiment time evolution of 20 model years of Niño 3.4 index °C (top) and SST anomaly along the equator in °C (bottom). X-axis represents time expanding 20 model years.
Figure 3.12 Same as fig. 3.11, but for the state-independent case. Also included, WWB [dyne/cm$^2$] (bottom panel). The WWBs do not exceed 0.2 dyne/cm$^2$.

Figure 3.13 Same as figure 3.12, but for the state-dependent case. Here, the WWBs exceed 0.3 dyne/cm$^2$. 
There are no wind bursts in the control case (Fig. 3.11). In the state-independent case, the bursts are irregular in time (i.e., the probability of occurrence is about 4 bursts per year) but with little or no interannual variations (Fig. 3.12 bottom). Comparing this with the state-dependent case (Fig. 3.13 bottom), it is evident that the spatial and temporal characteristic of the WWBs are modified by the coupling with the SST. In the state-dependent experiment, the WWBs are strongly coupled to the warm events. Despite the strong interannual variability it is important to keep in mind that seasonality still plays a role here, but it is relatively minor. See the previous section for more on the seasonal dependence of WWBs.

There are notable differences in the strength of the WWBs for the state-independent and state-dependent forcing simulations. For example, it is evident that in the state dependent case the WWBs have larger amplitude than in the state-independent parameterization. This is due to positive atmospheric feedback in that the WWBs increase the amplitude of the warm SSTA, which in turn increase the WWBs. The positive feedback works as follows. Since our WWBs are centered at the equator, they will force downwelling Kelvin waves that will propagate eastward producing a warm SSTA in the eastern Pacific. This SSTA will reinforce atmosphere convection, strengthening the westerlies, which will have a positive feedback on the SSTA. Apparently there is no difference in the location of the warm pool edge among the three cases; therefore, the ocean advection feedback is not playing a major role in the strengthening of the bursts in the model. From Fig. 3.13, it is also evident that there is a high correlation between the WWBs and the SSTA in the central and eastern Pacific; this will be further analyzed in this section.
Comparing the SSTA for the three cases (Figs. 3.11 bottom and, 3.12, and 3.13 middle) there appears to be evidence of a reduction of the bias towards more cold events in the state-dependent case with respect to the control case. This issue will also be discussed later in this section. The amplitude of ENSO events also appears to increase in the state-dependent case, but no doubling in intensity as seen Eisenman et al (2005). This may be because our WWBs are state-dependent and they were completely deterministic in Eisenman et al. (2005). The experimental design and the models used are quite also different.

To quantify the reduction of the cold bias, we count how many ENSO events, in both extremes, were observed during 201 model years. These events were also separated into different strengths. Table 3.1a shows the December, January, and February (DJF) Niño 3.4 (area average from 170E to 120E and 5S to 5N) extreme cold events count for 201 model years. The first column is the amplitude of the cold events in degrees Celsius. Table 3.1b is in the same format but for warm events. The state independent noise forcing case produces about 25 percent less ENSO overall when compare to the control run (excluding the very extremes), this reduction is yet not well understood, but does indicate a more peaked distribution with weaker tails. The state dependent WWBs forcing experiment produces more ENSO events in both phases. This is true for all magnitude events, which can be seen by comparing the values horizontally in Table 3.1. For the very extreme warm (cold) events, the ratio of the number of events in the control to the number of events in the state dependent WWBs forcing experiment is 1/4 (1/3).
Table 3.1 CCSM3 December-January-February (DJF) averaged Nino3.4 SSTA, number of cold (a) and warm (b) events out of 201 model years. Magnitude (threshold) given in column 1 [°C].

<table>
<thead>
<tr>
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<th>°C</th>
<th>Control</th>
<th>State-Ind</th>
<th>State-Dep.</th>
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<tbody>
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<td>&lt; -1.00</td>
<td>40</td>
<td>30</td>
<td>61</td>
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<td>&lt; -1.50</td>
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<td>15</td>
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<td>&lt; -1.75</td>
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<td>8</td>
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<td>&lt; -2.00</td>
<td>7</td>
<td>7</td>
<td>21</td>
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<td>b)</td>
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<td>&gt; 1.00</td>
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The state dependent WWBs experiment appears to reduce the bias towards more cold than warm events as in the control. This can be detected by comparing cold versus warm events of similar amplitudes in Tab. 3.1. The ratio of cold to warm events (greater than one degree Celsius) is about one for the control and state-independent cases, while is about 0.83 for the state-dependent. Only in the very extreme cases, the La Niña phase dominates, with a ratio of 5.25 of cold to warm extremes. This ratio is 7 for the control and the state-independent cases. As a result, we argue that there is a shift from an ENSO that is episodic or event driven to more of an oscillation as the experiments progress from the control to the state dependent WWBs case. That is, in the state-dependent case, the number of ENSO neutral winters (i.e., December-February Nino3.4 SSTA less than 1°C ) is similar to the number of ENSO active winters (i.e., either warm or cold), suggesting that the system has become more oscillatory.
A histogram of the Niño 3.4 SSTA is shown in Fig. 3.14. Also, the second, third, and fourth statistical moments are shown with their respective 99% confidence interval obtained by a statistical bootstrapping procedure. No significant differences are observed between the control and the state independent forcing cases, only that the later displays a more peaked distribution. This is consistent with table 3.1, which indicated fewer extreme events in the state-independent case compared to the control (or the state-dependent simulation). The control and the state-independent cases have similar skewness, but the second (fourth) statistical moment is smaller (more positive) for the later.

**Figure 3.14** CCSM3 histograms of Niño 3.4 SSTA for 201 model years. Control (top), state-independent (middle), and state-dependent (bottom). Normal distribution fitted (red). The y-axis represents the occurrence (in months). Also showing standard deviation, skewness, and kurtosis coefficient plus their statistical significance at a 99% confidence level.
There are, however, notable differences between the state dependent stochastic forcing and the control (or state independent stochastic forcing) simulations. For example, the standard deviation is larger and kurtosis is more negative suggesting an increase in ENSO event count. Also a closer to zero skewness coefficient than in the control or state independent case, depicting a reduction in the cold bias (or the ratio of cold over warm events). Note that the third moment remains negative, due to the very strong cold events, which for this state-dependent case, sometimes exceed -3°C. The still negative skewness is a product of the overwhelmingly dominating cold event at magnitudes greater than 1.75°C. That is, there are more cold than warm events at this amplitude, producing a longer left tail in the histogram. Consistent results are obtained by analyzing wind stress anomaly on the central Pacific (not shown).

Thus far, it was shown that state-dependent noise in the form of WWBs modifies some of the broad ENSO statistics. Here we examine how the parameterized WWBs affect ENSO dynamics and its spatial characteristics. For example, Figure 3.15 depicts tropical Pacific SST standard deviation for observed, control, state-independent, and state-dependent case. Some of the well-known CCSM3 biases described in the previous sections can also be detected here. Comparing the control case with observation there is a clear confinement of SST variability about the equator in the model. This is especially true in the eastern portion of the basin. Another discrepancy with observation is the location of maximum variability. The model has variability that is too strong in the far western Pacific this is associated with too shallow thermocline and the lack of thermocline plateau in the warm pool region. There is a small reduction in the standard deviation for the state-independent case as compared to control. Surprisingly, most of the
differences are over the eastern part of the basin, while this decrease in variability is small, it is statistically significant as described in Fig. 3.14. This may be hinting that state-independent noise actually damps ENSO in this model (stochastic forcing in already chaotic systems can be shown to damp variability; see Siqueira and Kirtman 2012). On the other hand, state-dependent noise increases the interannual variability. The enhancement occurs throughout the basin, with a strong impact over the Nino3.4 region. Overall, there are no significant changes in the horizontal structure but only in the amplitude of variability.

Figure 3.15 Tropical Pacific SSTA standard deviation [°C] for: observed and CCSM3 control, state-independent, and state-dependent case.
To diagnose the impact on ENSO dynamics we also examine correlations between state variables and the WWBs. The correlation of sea surface temperature (SST, shaded) and a WWBs index (the area average of WWBs from 5S to 5N and from 140E to the date line) is shown in Fig. 3.16 (shaded). Similar, but for sea surface height (SSH) and WWB index is depicted by contours. The control run is not shown since it does not have WWBs. We see that there is no correlation between SST and the WWBs for the state-independent case (Fig. 3.16 top). This result is somewhat of a surprise. One possibility could have been that the additive WWBs served to increase the amplitude of an ongoing warm event. If this were robust, we would expect to see some WWBs activity for the strongest warm events. Our analysis indicates that there is no relationship at all between state-independent bursts and tropical Pacific interannual variability.

Figure 3.16 Correlation of SSTA (shaded), SSHA (contour) with a WWB index (WWB average over 140-180 longitude and 5S-5N latitude), state-independent (top) and state-dependent (bottom). Results are for CCSM3.
High correlation is observed in the state-dependent case (Fig 3.16 bottom), from about the central longitude of the bursts eastward. Some negative correlation is detected in the western Pacific off equatorial region. Similar patterns are observed for the sea surface height (contour) and zonal wind stress (not shown). Any weak correlation that is detected between any of these state variables and the WWBs in the state-independent case is the result of local air-sea interaction, especially in the SSH. For the multiplicative forcing case, the WWBs are positively (negatively) correlated with SSH anomaly in the eastern (western) Pacific, linked through SST anomaly by state dependence in the WWB parameterization. We also detect some off-equatorial signal in the SSH (contour), which suggest the potential importance off-equatorial wave activity.

In terms of the SSH variance (Fig. 3.17), some basic differences among the experiments are observed, but the overall spatial distribution of regions with high variance (regions inside a box) are similar. Along the equator in the central Pacific (approximately the Niño 3.4 region), the variance is due to equatorial Kelvin waves, whereas those off the equator are due to Rossby waves (i.e. regions 2 and 3). Given the importance of equatorial wave dynamics in modulating ENSO, we examine the correlation of some state-variables with Niño3.4 region. Figure 3.18 shows the lag-lead correlation of SSH anomaly (shaded) along the equator with SSTA index in Niño3.4 region of Fig. 3.17. Similarly, the SSTA (contour) is also shown. It is noted that the Niño3.4 region is strongly correlated with SSHA along the equator, especially east of the date line. This is clearly shown in Fig.3.18 at zero-lag. The correlation analysis suggest that state-dependent parameterization enhances lag-lead coherence in correlation, again supporting the assertion that state-dependent noise drives the system away from an
episodic ENSO to a more oscillatory ENSO. This increased lag-lead coherences is also seen when examining the correlation along $7^\circ$ North (not shown) with the only difference in phase speed (slower than at the equator) and direction of propagation (westward). Correlation is strongly reduced by the state-independent WWBs implementation as compared to control, especially at lags. This is a surprising result given that ENSO statistics itself did not change much when the bursts are state-independent.

**Figure 3.17** Sea Surface Height (SSH) variance [cm$^2$] across the tropical Pacific, control (top), state-independent (middle), and state-dependent case (bottom). Results are for CCSM3.
Figure 3.18 Lag-lead correlation of Sea Surface Height Anomaly (SSHA) along the equator (shaded) and Sea Surface Temperature Anomaly (SSTA, contour) with Niño3.4 SSTA index. Positive lag means that Niño3.4 lags by as many months. Horizontal axis depicts longitude and vertical axis describes lags (months).

As further evidence for the increase temporal coherence in state-dependent case, we perform a composite analysis of ocean surface variables and the parameterized WWBs. Figures 3.19 show a multi-year lag-lead composite of SST, SSH, and WWBs averaged from 5S to 5N along the equatorial Pacific Ocean for the control (left), state-independent (center), and state-dependent (right) cases, respectively. The composite includes the top 5 warm events based on Niño 3.4 SSTA centered at time zero lag. These 5 top events are chosen based on the Niño 3.4 index for December-January-February (DJF) average. To the far right of Fig. 3.19 is a time series composite of the WWBs index (140E to 180 longitude and 5S to 5N latitude) for state-independent (black line) and state-independent (red line) case. The relatively weak composite WWBs amplitude in the state
independent case suggests that strong WWBs are not indicative of strong ENSO events (see also Fig. 3.20). Conversely, strong WWBs are coupled to strong warm events in the state dependent case. The composites suggest that the state-independent case is even less oscillatory (or more damped) than the control simulation. The state independent noise reduces the lag-lead temporal coherence of the ENSO events. For instance, lag and lead SSH anomalies are notably weaker than in the control simulation. The SSTA are confined to relatively small lags and leads where the composite apparently has little or no SSTA precursors.

In the state-dependent case (Fig. 3.19) the lag-lead composite suggests a considerably stronger oscillatory behavior. This is also supported by the lag-lead correlation shown in Fig. 3.18. The biennial ENSO period is also captured by this composite. Moreover, Fig. 3.19 shows the eastward propagation of SSHA clearly depicted throughout the composite at all lags. The WWBs cycle shows a strong interannual dependence due to its coupling with the SST, but the annual cycle dependency of the WWBs is difficult to detect give the larger interannual signal. In the case of the state dependent composite there is a clear oscillatory pattern as a precursor to the strongest warm events. However, once the strong warm event has occurred there is little post event signal. This behavior is not only seen in SST and SSH but also in the WWBs amplitude. There appears to be a low frequency build-up or development for the strongest warm events in the state dependent case that is not detected in either the control or the state independent case.
Figure 3.19 Composite of top 5 (strongest) ENSO warm events for control, state independent, and state dependent case. Showing Sea Surface Temperature Anomaly (SSTA) in $[^{[C]}]$ (shaded) and Sea Surface Height Anomaly (SSHA) in [cm] (contour) across the equator averaged from 5S to 5N. Also showing WWBs composite (right) in [dyne/cm$^2$] for state independent (black) and dependent (red). Composites are based on December-January-February (DJF) Niño3.4 index; defined by area-averaged SSTA from 170W to 120W longitude and 5S to 5N latitude.

The above lag-lead correlations and composites are based on the state of ENSO. Alternatively, here we examine composites based on the parameterized wind bursts. Figure 3.20 shows the composite for the state-independent (left) and dependent (center) case and the bursts (right). Note that the SSTA and SSHA are very weak even at 0-lag for the state independent case. Again, indicating the state independent bursts are not particularly correlated with the strength of the warm events. The SSHA only shows a small local response to the westerlies a few months after they occur. This is due to local Ekman pumping produced by the positive zonal wind stress along the equator. It is also clear that the burst centered at 0-lag is the strongest (black line), but its persistence in
time is short compared to the state-dependent case. As expected for the state-dependent case, there are no precursors associated with the WWBs composite. The parameterization is localized in time. However, the state dependent WWBs do seem to have considerable lead-time coherence. From lag-0 up to leads of 36 months the increased oscillatory nature of the simulation is detected in both the SSHA and the SSTA. This further supports the hypothesis made earlier that WWB (state-dependent) can shift the system to a more oscillatory regime.

![Figure 3.20](image)

**Figure 3.20** Composite of top 5 (strongest) WWBs events for state independent (left) and state dependent case (center). Sowing SSTA in [°C] (shaded) and SSHA in [cm] (contour) across the equator averaged from 5S to 5N. Also showing WWBs composite (right) in [dyne/cm²] for state independent (black) and dependent (red). Composites are based on WWBs index; define by area- averaged bursts from 140E to 180 longitude and 5S to 5N latitude.
The decrease (increase) in SSH west (east) of the burst is evident in Fig. 3.20 (middle). The strongest height anomaly occurs two years after the strongest bursts. This is true not only east of the Dateline, but also on the western portion of the basin, where very strong positive anomalies are present. Similar to our lag-lead correlation analysis, these SSHA in the western basin propagate eastward, reaching the central (eastern) part of the basin in about six (nine) months. This may be important in ENSO forecasting using this model given that SSHA can be a precursor to warming in the eastern part of the basin. Figure 3.20 is a clear example of how the state dependent noise can drive ENSO from an episodic event regime to a self-sustained oscillatory regime.

The strongest SSTA variability is located over the central Pacific basin (180-140W) for all cases. This is the result of errors in the model, and although we have not completely diagnosed these errors, at least some of this problem is due to mean state biases. For the state-dependent case, SSTA variability increases throughout the basin, especially over the central Pacific. In contrast with control and state-independent cases, SSTA variability is enhanced over the eastern basin (east of 120W) when the WWBs depends on SST. A possible reason for this is that the effect of downwelling Kelvin waves, forced by WWBs, on SSTA counteracts some of the local cold bias. A composite analysis of potential temperature across the Pacific and at depths (not shown) is performed. For the state-independent case, it was noted that both warm and cold ENSO events have about the same magnitude as the control. There are weak signal over the central Pacific where state-independent warm events are slightly warmer (~0.4°C). The thermocline depth is remarkably similar for both cases during warm and cold events. On the other hand, for the state-dependent case, both warm and cold events have greater
amplitude. During warm events, there is significant reduction of the zonal thermocline gradient. Such reduction is associated with downwelling Kelvin wave forcing by WWBs and it has a greater impact over the far east where there is a deepening of about 50 meters as compared to control. We argue that equatorial wave dynamics is playing a significant role in the enhanced variability due to state-dependent WWBs, but a significant part of its effect over the far eastern portion of the basin is counteracted by the mean state bias in that region. This issue of eastern versus western Pacific impact of WWBs will be discussed in detail in Chapter 4.

3.5 Model sensitivity: CCSM3 and CCSM4

Arguably, CCSM3 has a flawed ENSO and annual cycle and it is possible that these errors affect the interaction between the model ENSO and the parameterized WWBs. Here we examine some elements of model dependence by introducing the WWBs parameterization into CCSM4, which is known to have a significantly improved ENSO and annual cycle. In this section, only the most critical results described earlier are recreated. One reason is that the CCSM4 runs are relatively shorter, about 100 years, and because we used a coarser resolution model. The lower resolution for CCSM4 was chosen based on computational time constraints. The aim of this section is not to make model-to-model comparison, but to examine whether the differences observed among experiments are model dependent.

There are significant improvements physically and numerically from CCSM3 to CCSM4, only some of those related to this study are noted here. The atmosphere component employs an improved deep convection scheme by inclusion of sub-grid
convective momentum transport and a more realistic dilution approximation for the
calculation of convective available potential energy (Neale et al., 2008). The atmospheric
component of CCSM4 has the same 26 vertical levels, but with reduced horizontal
resolution (i.e., 5° longitude by 4° latitude resolution). The dynamical core uses the finite
volume formulation as opposed to the spectral dynamic core in CCSM3.

The ocean model component of CCSM4 uses Parallel Ocean Program version 2
(POP2) numeric (Danabasoglu et al., 2011). This updated version of POP includes a
simplified version of the near boundary eddy flux parameterization of Ferrari et al.
(2008), vertically-varying isopycnal diffusivity coefficients (Danabasoglu and Marshall,
2007), an abyssal tidally driven mixing parameterization, modified anisotropic horizontal
viscosity coefficients with much lower magnitudes than in CCSM3 (Jochum et al., 2008),
and a modified K-Profile Parameterization with horizontally varying background vertical
diffusivity and viscosity coefficients (Jochum, 2009). The number of vertical levels has
been increased from 40 levels in CCSM3 to 60 levels in CCSM4. The horizontal grid
used here is a displaced pole version, with about 3° in the longitude and variable in the
latitude direction with finer resolution, about 1°, near the equator.

First, we examine the interannual variability in the tropical Pacific. Figure 3.21
shows SST standard deviation for observed, control, state-independent, and state-
dependent case, similar to Fig. 3.15 but for CCSM4. The SST variability in the eastern
basin is closer to observations in this model than in its previous version, but the excessive
variability in the western Pacific remains. Some modest increases in the meridional scale
of the SSTA can be detected. In contrast with CCSM3, some enhancement in variability
is observed for the state-independent case, especially in the cold tongue region. There is
also a widening in the north-south direction of the variability for both parameterizations, which was unobserved in the case of CCSM3. For the state-dependent case, there is significant amplification of SST variability throughout the basin, consistent with CCSM3. Overall the biggest contrast between the models is in the state-independent case.

Figure 3.21 Same as fig. 3.15 but for CCSM4.

In order to compared the WWBs parameterization between CCSM3 and CCSM4, correlation of SST (shaded) and SSH (contour) with a WWBs index are shown in Fig. 3.22. The index, as before, is the area averaged bursts from 140E to 180 longitude and from 5S to 5N latitude, this is the same as Fig. 3.16 from CCSM3. Again, the control case
is not shown (e.g. no WWBs). Consistent with CCSM3, there is little or no correlation between the state-independent bursts and state variables as expected. On the other hand, a clear large-scale pattern emerges in the correlation pattern for the state-dependent case. Note that both SST and SSH depicts the structure observed during warm ENSO events. There are notable differences between this figure and that associated with CCSM3. In particular, the meridional structure in SST is considerably broader in CCSM4, which is consistent with the longer ENSO period. Such difference is analogous to the contrast of inter-annual variability between the to models, where in CCSM3, SST anomalies are confined close to the equator. Another difference of note is in the amplitude of the correlation. It is unclear whether such changes are attributed to different ENSO dynamics between the models, or differences in resolution.

Figure 3.22 Same as fig. 3.16 but for CCSM4.
Now, let’s concentrate on how ENSO dynamics is modified by both WWBs parameterizations in CCSM4. For this, the lag–lead correlation is repeated but for CCSM4 (i.e., compare Fig. 3.18 and 3.23). Note that Fig. 3.23 is the same as Fig. 3.18 except that longer lags and leads are included consistent with a longer ENSO period. Similar to CCSM3, adding state-independent WWBs has little detectable impact. In the state-dependent case, an enhanced oscillatory pattern is observed, as was found with CCSM3. These results suggest that some of the broad qualitative effects of the WWBs parameterization are model (version) independent at least in the context of CCSM.

![Image](https://example.com/figure323.png)

**Figure 3.23** Same as fig. 3.18 but for CCSM4.

To further illustrate the impact of the parameterization in both models, a power spectrum of Nino3.4 SST anomalies is shown in Fig. 3.24. The SST index is obtained from the first principal component (PC) of an EOF analysis of tropical Pacific SST. EOF1 describes variability associated with that of ENSO. The power spectrum
calculation was also performed on just SST anomalies for the Nino3.4 region and the results were very similar to that obtained from PC1. Figure 3.24 includes all three cases from CCSM3 (solid) and CCSM4 (dashed), with the 99% F-test confidence level (black curve). This clearly shows the quasi-biennial ENSO period in CCSM3 and the longer period in CCSM4.

![NINO 3.4 Power Spectrum](image)

**Figure 3.24** Power spectrum of Nino3.4 SST anomaly reconstructed from the 1st EOF of tropical Pacific SST. Showing CCSM3 (solid) and CCSM4 (dashed). Control experiments in red, state-independent in blue, and state-dependent in green, 99% F-test confidence level (black).

Comparison on Fig. 3.24 is only made for those frequency bands that pass the F-test. These include the periods of 18-26 months (CCSM3) and 42-78 months (CCSM4). In both models, there is little difference between the control (red) and state-independent (blue) case. Only a slight shift toward higher frequencies is detected in the state-independent. For the state-dependent case (green), a clear increase in power is observed
for both models. There is also a slight widening of the power band at ENSO frequencies. This becomes more obvious when looking at the area under the curve bounded by the confidence F-test line. An increase power in those frequency bands is also an indication of enhanced oscillatory behavior, as was shown with lag-correlation and composite analysis in previous sections. Both models show similar sensitivity to the inclusion of both the state independent and state dependent WWB parameterization. For CCSM4, the difference between state-dependent and control appears to be less than in CCSM3. This is because for the former model, the curves are located at lower frequencies. In reality, the area under the curve for both model are increased consistently by the inclusion of state-dependent noise.

3.6 WWBs parameter sensitivity

This section discusses the sensitivity of ENSO to modifications of WWBs parameters. For this, experiments are performed by varying some of the WWBs parameters discussed at the beginning of this chapter and in the Appendix. Due to the computational cost and time constraints, only a few modifications will be made. Both state independent and state dependent formulation will be used. The motivation for further studying of the state independent case is that as shown previously, it appears to damp ENSO. This will be further examined here. A motivation for studying parameter sensitivity in the state dependent case is that it appears to completely shift the ENSO dynamics, at least in the contest of CCSM3 and CCSM4 models. Also, correlation of SST and wind stress associated with WWBs does not account for the fully observed link between the two fields. For example, Tziperman and Yu (2007) found that instead of correlating the full
WWBs related wind field with SST, one should correlate the WWBs characteristics (e.g. amplitude, duration, probability of occurrence, and horizontal structure) then more of WWBs variability can be linked to SST. This was the motivation for the development of a state-dependent parameterization of WWBs and our motivation here. The parameter sensitivity study is only performed for CCSM3.

3.6.1 State independent WWBs

Modifications to the state-independent experiments are described in table 3.2. Only one modification per parameter is done. For all cases, we have about 60 years of CGCM simulations. The original state-independent WWBs experiment will be referred as B2 here forward.

Table 3.2 Description of state independent experiment modifications

<table>
<thead>
<tr>
<th>Experiment Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>B2_A</td>
<td>Double the amplitude</td>
</tr>
<tr>
<td>B2_E</td>
<td>The central longitude is 20° further east</td>
</tr>
<tr>
<td>B2_N</td>
<td>The central latitude is 5° further north</td>
</tr>
<tr>
<td>B2_P</td>
<td>Probability of occurrence is double</td>
</tr>
<tr>
<td>B2_T</td>
<td>The duration time is double</td>
</tr>
</tbody>
</table>

Figure 3.25 depicts the annual mean SST along the equatorial Pacific for experiments B2_A, B2_E, B2_P, and B2_T. The cold bias on the central and eastern Pacific appears in all cases, such bias is well documented in previous work. Overall there is little difference shown in the mean climate by modifying parameters for this state independent formulation. This minor change is observed when the difference between experiment and the original formulation of WWBs is plotted. Differences that are
statistical significant to 99% confidence levels from a student-T test are shaded grey. For most cases a localized warming (~0.1°C) is observed in the general location of the bursts. Such warming is significantly stronger for the case of increased amplitude (B2_A) with ~0.40C warmer. Note that the biggest difference is not over the cold tongue region. The generalized warming could be a local Ekman type response to westerlies symmetric about the equator. Beyond localized effects; the mean state appears to be insensitive to state independent WWBs parameterization. This may not be the case for ENSO, which could be highly modulated by stochastic forcing whether state independent or not.

To examine sensitivity of ENSO to the details of the state independent WWB Fig. 3.26 shows the lag auto-correlation of Niño3.4 SST anomaly index for all experiments. Such analysis helps study the oscillatory behavior of a mode and its periodicity. The black dashed curve represent the default formulation describe in section 3.4. Note how the lag coherence falls quickly and reaches zero by month 6, this is consistent for all cases. Beyond 6 months differences emerge. The biggest differences are for the cases B2_T, B2_A, and B2_N (see table 3.2). When the persistence is increased, there is a slight increase in oscillation period of about 1-2 months. These differences are minor and at long lags (beyond 24 months). The big change occurs when the amplitude is doubled or the central latitude of the burst is placed in the Northern hemisphere. For both cases, ENSO appears to be strongly damped with little lag coherence. This is consistent with results in the previous section. To further examine this point, Fig. 3.27 shows the power spectrum of Niño 3.4 SST anomalies reconstructed from the first empirical orthogonal function (EOF) and principal component (PC). For this analysis, the seasonal cycle was removed, therefore the EOF has the structure of ENSO and PC has a quasi-biennial
period, corresponding to ENSO in this model. Just like for the autocorrelation, the flattening of the power curve describe damping of the ENSO mode. It is observed that most of the impact is due to increase amplitude of the stochastic noise in the western Pacific. Also placing such burst events further north further damps variability associated with ENSO. A narrowing in the spectrum and a shift toward lower frequencies is observed when the duration of the burst is increased (B2_T). This difference is minor and not yet understood. Parameters such as eastern extent and probability of occurrence seem to have little affect on ENSO. State independent WWB appear to have only a minor impact on the simulated ENSO. There are parameters, such as amplitude and persistence that appears to be important.

Figure 3.25 Annual mean SST for the state-independent WWBs case (top-left) and difference (experiment minus state independent). Contour interval for the differences are 0.1°C. Differences that are statistical significant to 99% confidence levels from a student-T test are shaded grey.
Figure 3.26 Auto-correlation of Niño3.4 SSTA. Dashed curve corresponds to unmodified state independent experiment.

Figure 3.27 Power spectrum reconstructed from the first EOF of tropical Pacific SSTA for each experiment.
3.6.2 State dependent WWBs

The experiments to study the state dependent parameterization are described in table 3.3. All modifications presented in this section are the same as those described in the previous sub-section. The only difference is in the parameterization itself (state dependent here). In this section, the default state-dependent case will be referred as B3.

Table 3.3 Description of state dependent experiment modifications

<table>
<thead>
<tr>
<th>Experiment Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>B3_A</td>
<td>Double the amplitude</td>
</tr>
<tr>
<td>B3_E</td>
<td>The central longitude is 20° further east</td>
</tr>
<tr>
<td>B3_N</td>
<td>The central latitude is 5° further north</td>
</tr>
<tr>
<td>B3_P</td>
<td>Probability of occurrence is double</td>
</tr>
<tr>
<td>B3_T</td>
<td>The duration time is double</td>
</tr>
</tbody>
</table>

The annual mean SST along the tropical Pacific is shown in Fig. 3.28 (left), here the contour colors correspond to those in Fig. 3.25. Modest differences in the mean are observed for all cases except when the amplitude is doubled. The double amplitude experiment will be discussed later. Note that as in Fig. 3.25, the response is mainly local to where the modifications to the burst are located. For the B3_E case, there is a slight warming (~0.10C) east of the date line and extending well into the central basin. The case B3_P, the warming is co-located over the main WWB region with amplitude of about 0.20C. This warming is very similar with B3_T case. Increasing persistence appears less effective than increasing probability of a burst to occur in modifying the mean state. The big impact resides in the case where the amplitude of the state-dependent burst is doubled. Note that the differences between B3_A and the default state dependent case
resemble that of ENSO itself. It has amplitude of more than 0.5°C throughout the basin with the largest differences in the central Pacific.

We suggest two possible explanations for the structural difference seen in Fig. 3.28. One is that the very strong westerlies could have restructured the thermocline in the basin, that is, reduced the zonal gradient. This should give strong warming for most of the central and eastern basin, and cooling in the west. The other possible explanation is that vertical stratification in temperature may have been increased east of the date line, making it very difficult for upwelling to cool the surface.

**Figure 3.28** Same as 3.25, but for state-dependent experiment

Similar to the analysis from the previous sub-section, the interannual variability and ENSO is studied here using lag correlation and the power spectrum. Figure 3.29 is
analogous to Fig. 3.26, and depicts the Niño3.4 lag auto correlation for all state dependent cases. The default parameterization discussed in section 3.4 is shown in dashed. Unlike the state independent cases, here most parameters have some impact on ENSO variability. Note that the de-correlation time scale is slightly different for most cases, the first zero cross are different among the experiments. Increasing the amplitude of WWBs does have a relatively impact. Note that the period of oscillation increase from ~24 to ~36 months. This increase in the period can be seen in B3_E (further east burst) also but less pronounced. Also, both of these cases show weaker oscillatory behavior. Another increment in the period of oscillation is depicted for B3_N, this could be associated with equatorial wave dynamics in that higher meridional modes are excited by these burst. Interestingly, this behavior was not observed for the sate independent counterpart (i.e., B2_N of Fig. 326). Increasing the probability and persistence has little impact, only that the later appears to have reduced the lag coherence (weaker correlation at lags). The power spectrum (Fig. 3.30) further underscores the results noted above. Here, as in the previous subsection, the power spectrum is for Niño 3.4 reconstructed from an EOF analysis. Note how there is a strong shift towards lower frequencies when the intensity of the burst is increased (dark blue curve), also a slight shift is observed for B3_E (green). It is worth noting that the increased variance in the state dependent versus the state independent case can be seem by comparing Fig. 3.30 with Fig. 3.27. This is consistent with results from section 3.4.
Figure 3.29 Same as 3.26, but for state-dependent experiment.

Figure 3.30 Same as 3.27, but for state-dependent experiment.
To further visualize the impact of state dependent parameterization on the tropical Pacific, composites of top five warm events are shown in Fig. 3.31. Here, the composites are based on the strongest five events based on Niño3.4 SST anomalies averaged over December-January-February (DJF). The composites comprise a 73-month period centered at zero-lag. The x-axis is longitude across the basin, the vertical axis is time running from bottom to top. The contour interval and colors are the same throughout, with magnitudes less than 0.5°C suppressed. Before noting any differences, we concentrate on the similarities among the experiments. The SST anomalies extent too far into the western basin, this was previously discussed. There is also a well define eastward propagation of the anomalies from the central to the eastern part of the basin. By visual inspection, marked differences are observed. For example, the six cases can be divided into two groups. The strongly regular ENSO group, comprising of B3 (default state dependent), B3_N, and B3_P. The second group is the irregular ENSO group; this includes B3_A, B3_E, and B3_T. This division can further be observed in Fig. 3.29 and is only based on the oscillatory characteristics of modeled events. The first group shows a strong oscillatory tendency with a short period. This group also has significant lag coherence at longer lags, an example is the strong cold event at -36 months for these three cases. The second group is more interesting, especially B3_A, here, there is a significant change in the dynamics of ENSO. The increased period is clearly observed; also the duration of the warm event is fairly large. This is totally different from the other cases. Interestingly, increasing the persistence or moving the bursts further east has a relatively large impact. For these cases, the duration of the warm events are similar (with
B3_A as exception) but the tendency of fast switching from warm to cold disappears. Also the lag coherence agrees more with observations.

Figure 3.31 Composite of top 5 warm event SSTA anomaly ($^\circ$C) for each of the parameter sensitivity experiment. The y-axis represent time lag (months) increasing up the page. Composite is centered at 0-lag.

Based on the results obtained in this section we hypothesize that the stochasticity of the WWBs are of little importance in modulating ENSO and tropical Pacific variability. The slow component (i.e., SST related, Fig. 3.9) or deterministic component is affected. The clear example is comparing B3_P and B3_T. The former case is meant to increase the stochastic component according to the WWBs parameterization scheme, whereas the later increases the deterministic characteristics more. What does increasing
the deterministic component mean? Recall that the state-dependent WWB model assigns probability of a burst to occur depending on the SST state. If the possibility of a burst to occur is doubled (e.g. B3_P), then more WWB will be triggered independently of SST, increasing its stochasticity. On the other hand, if the persistence is doubled (e.g. B3_T), this will only take effect if a burst is already triggered. Most of the bursts in the state-dependent case occur during warm SST events; therefore enhancing the persistence of WWB is analogous to enhancing its deterministic component.

3.6.3 Deterministic WWBs

From the results presented in the previous sections, it is hypothesize that the deterministic component of WWBs is responsible for most of the SSTA and ENSO modulation, with the stochastic component having a minor role. This is in part due to the presence of a two-way SST-WWBs feedback where WWBs affects SST via wave-guide warming by means of downwelling Kelvin wave. In turn, the timing and characteristics of WWBs are largely modulated by the large-scale SST (Yu et al. 2003; Batstone and Hendon 2005; Tziperman and Yu 2007). By definition, this two-way feedback mechanism only works if the bursts are state-dependent.

To test the hypothesis that the deterministic component of WWBs is more important in modulating ENSO, the WWBs parameterization (see Appendix) is modified to only produce fully deterministic WWBs. The modification is only done in the triggering mechanism. Thus far, the state-independent bursts are triggered randomly within observational constraints. For the state-dependent case, a burst is triggered based on the SST field but the timing of individual bursts contains a stochastic component. For
the deterministic case, a burst is triggered based only on the SST state. The probability $P$ of occurrence is set to 1 for El Niño (warm SST) and is set to 0 for La Niña (cold SST). All other parameters (e.g., amplitude, duration, spatial structure) are determined similar to the state-dependent case (see Appendix).

**Figure 3.32** Probability density function (PDF) for Niño3.4 SSTA.

Figure 3.32 Show the probability density function (PDF) for Niño3.4 SSTA for CCSM3 control (black), state-independent (red), state-dependent (blue), and deterministic WWBs (green). The distribution is very similar between the state-independent and control as discussed in Fig. 3.14. Meanwhile, the PDF of the deterministic WWBs experiment is remarkably similar to that of the state-dependent case. The distribution is broader in both extremes, suggesting enhanced variance. The similarity between control and state-independent and the similarity between state-independent and deterministic WWBs serve as further evidence that the deterministic (slow) component of WWBs is more important in modulating ENSO. This is consistent
with Roulston and Neelin (200) and Eisenman et al. (2005). Refer to the discussion of Fig. 3.14 for further details.

In this chapter, we presented a procedure for examining how both state dependent and state independent phenomenological noise forcing affects ENSO variability in a sophisticated coupled model. There are two aspects to our approach that are highlighted here. In the previous chapter, the impact of stochastic forcing within the context of a state-of-the-art CGCM was examined. In this chapter, we introduce the stochastic forcing as a phenomenological approach. That is, we focus on WWBs and parameterize their effects (both state independent and state dependent) in the coupled model. This is the first time that a state dependent and state independent WWBs parameterization has been incorporated into a state-of-the-art CGCM.

It is clear from the results presented in this chapter that the state-dependence in the noise has a profound impact on overall ENSO variability, whereas state-independent WWBs had only a minimal impact on interannual variability. To provide some assessment of model dependence in these overall results, the parameterization was also applied to CCSM4, albeit at lower spatial resolution. The results were shown to be consistent between models. Results presented in this chapter suggest that WWBs have an effect on predictability and this will be addressed in Chapter 5. Also, we might expect WWBs to impact EP versus CP ENSO events because the underlying mechanisms (e.g., thermocline and zonal advective feedbacks) associated with ENSO diversity could be altered by these wind events. The next step to follow is to study the impact, if any, of WWBs on ENSO diversity. That is, what role does WWBs in modulating the so-called eastern versus central Pacific events.
Chapter 4

Eastern (EP) versus Central (CP) Pacific events and WWBs

In this chapter, we follow the work presented in Chapter 3 and extend it to separately analyze the effect of WWBs on Central Pacific (CP) versus Eastern Pacific (EP) ENSO events. Relative to the huge body of literature on the topic of ENSO diversity, this is somewhat unique as it is a focused, process-based investigation. Recently, there has been substantial scientific discussion regarding the role of WWBs in modifying ENSO (Eisenman et al. 2005; Gebbie et al. 2007). In Chapter 3 it was found that interannual SST variability is enhanced by state-dependent WWBs, whereas state-independent WWBs has little effect on ENSO. In this chapter, ENSO diversity is analyzed within the contest of CCSM3 and CCSM4 models described in Chapter 2 and 3. The WWBs parameterization follows the work described in Chapter 3, see Appendix for detailed description of the parameterization.

There are recent studies arguing that ENSO may be classified into two difference types of events (Larkin and Harrison 2005a; Yu and Kao 2007; Ashok et al. 2007; Kao and Yu 2009; Kug et al. 2009), although this is the subject of some debate (Giese and Ray 2011). These two classifications are known as: (i) Eastern Pacific (EP) ENSO, which has maximum Sea Surface Temperature (SST) anomalies near the South American coast (Rasmusson and Carpenter 1982); and (ii) Central Pacific (CP) ENSO (Kao and Yu 2009), with maximum SST anomalies over the central Pacific where the zonal advective feedback mechanism is playing a larger role (Collins et al. 2010). The evolution of EP ENSO is linked to thermocline variations and feedbacks, whereas CP events are more directly related to air-sea interaction over the central Pacific. The mechanisms for EP
events rely heavily on thermocline feedbacks and appear to be well captured by the so-called delayed oscillator (Schopf and Suarez 1988; Suarez and Shopf 1988; Battisti and Hirst 1989) or the recharge oscillator (Jin 1997). The mechanisms for CP events are less clear, but studies are emerging. For example, Yu et al. (2010) argued that extratropical sea-level pressure (SLP) variations forces CP ENSO through enhanced zonal advective feedback. That is, CP ENSO is an extratropically excited mode of tropical Pacific variability (Yu and Kim 2011a; Furtado et. al., 2012).

There are two possible scenarios that may lead to ENSO diversity modulation by WWBs. First, westerly winds can impact zonal currents through air-sea momentum fluxes. This is dominated by a localized response, but these wind anomalies occurs on a fairly large scale and over regions of strong zonal temperature gradients. This potentially modifies the zonal advective feedback potentially favoring CP events. Second, westerly momentum forces downwelling Kelvin waves that can enhance/sustain an existing warm event through waveguide warming. This is more associated with thermocline dynamics and EP events as these Kelvin waves can give rise to warming over the eastern Pacific (Gebbie et al. 2007). The very strong 1997-98 El Niño event was dominated by EP characteristics and was associated with significant Kelvin waves activity. These waves were forced by WWBs produced by northerly surge from mid-latitude in phase with the convective passage of the Madden Julian oscillation or MJO (Yu and Rienecker 1998).

### 4.1 ENSO diversity

ENSO events are often described by a regional SST anomaly index. Here we use Niño3 (N3, area average SSTA from 110W to 190W and 5S to 5N) to describe eastern
Pacific variability. A typical index used to describe central Pacific variability is Niño4 (N4, 160E to 190W and 5S to 5N). However, some care needs to be taken here because EP and CP ENSO respond to different mechanisms and can co-exist (Kao and Yu 2009). Given this, contrasting SST anomalies in a specific region cannot be used to separate these two events completely as they may both contribute to SST variation in the same region. For example, the “EMI” index (Ashok et al. 2007) attempts to resolve this issue. The EMI index is based on observed SSTA patterns defined by empirical orthogonal function analysis (EOF).

For the purpose of this study, the problem with the EMI index is that it is based on observational estimates of the EOFs, which may significantly differ from the model based EOFs. In order to address this problem, we use a CP index based on partial regression-EOF analysis. Specifically, SSTA are partially regressed onto EMI and Niño3 index. The SSTA that is correlated to Niño3 but not to the EMI index are removed before performing the EOF analysis. Then, the first principal component (PC1) is used as CP index. Similarly, we can extract SST anomalies correlated to EMI index but not to Niño3 index from the full SST anomalies, perform EOF, and use PC1 as a new Niño3 or EP index. We will refer to these as CP-PC1 and EP-PC1 index respectively. This approach prevents the issue about structural changes in the EOFs. Partial regression is an alternative technique to ordinary least-square regression. It is of most use when predictor (i.e., independent) variables (e.g., Niño3 and EMI herein) are highly correlated, as could be the case for the models used here. This technique is used to separate the effect of each independent variable on the dependent variable with the influence of the remaining independent variables held constant. This is in contrast with Kao and Yu (2009) and Kim
et al. (2012) in that they used ordinary regression. The calculation is applied in exactly the same way for all the simulations.

The regression-EOF analysis of the SSTA in the tropical Pacific is shown in Fig. 4.1. Normalized EP principal component 1 (PC1, red) and CP (PC1, blue) for observed (a), CCSM3 (b) and CCSM4 (e) are shown. Spatial patterns [°C] associated with EP-PC1 are depicted by shading for CCSM3 (Fig. 4.1c) and CCSM4 (Fig. 4.1f). Similarly, patterns associated with CP-PC1 are shown by shading for CCSM3 (Fig. 4.1d) and CCSM4 (Fig. 4.1g). Observed patterns associated with EP-PC1 and CP-PC1 are also depicted by black contours for comparison. The observed EP (CP) pattern explains 57% (26%) of the total SST variance, whereas for CCSM3 it is 44% (12%), and CCSM4 it is 66% (40%) respectively. The observed EP and CP EOF patterns are very similar to EOF1 and EOF2 obtained by Ashok et al. (2007) and Takahashi et al. (2011). The reason why our CP pattern contains larger variance than EOF2 from these studies is due to the removal of EP variability before the EOF analysis is applied.

CCSM3 and CCSM4 agree fairly well with observations for the EP pattern (Fig. 4.1b and 4.1f) in terms of location and amplitude. CCSM3 produces a narrower than observed SSTA structure, and CCSM4 has slightly stronger amplitude further into the central Pacific and larger negative loadings in the western equatorial Pacific. Both observed and modeled EP pattern corresponds to the traditional ENSO events with higher amplitudes just off the Peruvian coast. CCSM3 produces a weaker than observed CP pattern (Fig. 4.1d), especially south of the equator, and CCSM4 reproduces a CP patterns (Fig. 4.1g) that is shifted to the west by 10° of longitude compared to the observed. This westward shift is also present in the Climate Forecasting System (CFS) model shown by
Kim et al. (2012). The negative loading off South America for the CP patterns is considerably smaller -0.2°C for both models compared to -0.4°C for observational estimates. The rotated v-shaped positive loading is well represented by CCSM4, but with significantly larger magnitude over the far western basin than observed.

**Figure 4.1** EP and CP empirical orthogonal function (EOF) decomposition for SST anomaly along the Pacific Ocean. Normalized EP principal component 1 (PC1, red) and CP (PC1, blue) for observed (a), CCSM3 (b) and CCSM4 (e). Spatial patterns [°C] associated with the PCs are shown by shaded contour for EP-PC1 for CCSM3 (c) and CCSM4 (f). Similarly, for patterns associated with CP-PC1 for CCSM3 (d) and CCSM4 (g). Observed patterns are depicted by black contours.

CCSM4 (Fig. 4.1e) and observations (Fig. 4.1a) have periods of strong (>2σ) EP-PC1 that are characterized by weak or negative CP-PC1. The cold periods from EP-PC1 are also characterized by cold CP-PC1 in CCSM4 and observation. Periods of strong
warm EP and cold CP can be viewed as one ENSO regime, and periods of modest warm and cold EP along with in phase CP can be viewed as another regime. Takahashi et al. (2011) point to these two different regimes, distinguishing cold and moderate warm events from the strong EP warm events, this is discussed in more detail later. These regimes are not easily identified for CCSM3 (Fig. 4.1b).

**Figure 4.2** Coefficient of determination $R^2$ between EP-PC1 and CP-PC1 as a function of lead-time.

Before analyzing the impact of WWBs on the different ENSO regimes, it is necessary to test whether the EP and CP events are well separated by the partial regression-EOF analysis presented here. For this, the coefficient of determination $R^2$ between the two indices, namely EP-PC1 and CP-PC1 are calculated. This is shown in Fig. 4.2 as a function of lead-time for observed estimates and both models. $R^2$ is a measure of the variance explained by the projection between the two indices. It is evident that $R^2$ remains well below 10% for observation and CCSM3 for most lead-times.
CCSM4 presents slight larger values (e.g., ~20%) when EP-PC1 leads by 1-4 months. These low $R^2$ values at all lead-times for our models and observation estimates demonstrated that our EP and CP indices are not significantly correlated at any lead-time.

### 4.2 Effects of WWBs on EP and CP ENSO events

Here, the effect of WWBs on the modes described in Fig. 4.1 are discussed. For this, table 4.1 shows the SSTA standard deviation [$^\circ$C] for all model experiments (rows) and various indices (columns). The plus/minus values represents the 99% confidence level based on a bootstrapping technique. First we describe results that apply for both models and all experiments. For example, CCSM4 has stronger variability than CCSM3. Niño4 has slightly weaker variability than Niño3 for both models and all experiments. The EMI index has significantly weaker variance than those from Niño4. The similarities between Niño3 and EP-PC1 suggest that both indices can be used to described EP ENSO variability, recall that the later index has EMI variability removed. In contrast, CP-PC1 index has a significant reduction in variance compared to EMI. This could be due to the influence of EP ENSO on the later, and this influence is removed by the partial regression-EOF analysis. Therefore, it can be said that neither Niño4 nor EMI index are “clean” indicators of CP ENSO variability in these models due to some influence from EP ENSO events on these regions. With this in mind, the discussion of CP ENSO variability will be based on the defined CP-PC1 index hereafter.
Table 4.1 Standard deviation for various defined SST anomaly indices and ENSO positive feedbacks mechanism (columns) for each of the model (rows), control (ctl), state-independent (SI), and state-dependent (SD) experiments. The standard deviations are given with plus/minus their 99% confidence level based on a bootstrapping technique.

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Niño3</th>
<th>Niño4</th>
<th>EMI</th>
<th>EP-PC1</th>
<th>CP-PC1</th>
<th>Thermocline Feedback</th>
<th>Adective Feedback</th>
</tr>
</thead>
<tbody>
<tr>
<td>CCSM3-ctl</td>
<td>0.87 ± 0.02</td>
<td>0.75 ± 0.02</td>
<td>0.48 ± 0.01</td>
<td>0.86± 0.02</td>
<td>0.23± 0.01</td>
<td>72.6±3.2</td>
<td>19.7±0.6</td>
</tr>
<tr>
<td>CCSM3-SI</td>
<td>0.84 ± 0.02</td>
<td>0.76 ± 0.02</td>
<td>0.50 ± 0.01</td>
<td>0.83± 0.02</td>
<td>0.25± 0.01</td>
<td>70.2±3.5</td>
<td>20.6±0.6</td>
</tr>
<tr>
<td>CCSM3-SD</td>
<td>1.13 ± 0.03</td>
<td>0.97 ± 0.02</td>
<td>0.61 ± 0.01</td>
<td>1.13± 0.02</td>
<td>0.27± 0.01</td>
<td>87.6±3.8</td>
<td>24.7±0.7</td>
</tr>
<tr>
<td>CCSM4-ctl</td>
<td>1.20 ± 0.06</td>
<td>1.12 ± 0.04</td>
<td>0.83 ± 0.03</td>
<td>1.19± 0.06</td>
<td>0.51± 0.01</td>
<td>71.0±5.5</td>
<td>24.5±1.7</td>
</tr>
<tr>
<td>CCSM4-SI</td>
<td>1.42 ± 0.07</td>
<td>1.23 ± 0.04</td>
<td>0.85 ± 0.03</td>
<td>1.41± 0.07</td>
<td>0.51± 0.01</td>
<td>86.9±7.1</td>
<td>31.1±3.0</td>
</tr>
<tr>
<td>CCSM4-SD</td>
<td>1.68 ± 0.07</td>
<td>1.44 ± 0.04</td>
<td>1.01 ± 0.03</td>
<td>1.67± 0.07</td>
<td>0.62± 0.01</td>
<td>103.1±8.1</td>
<td>33.4±2.7</td>
</tr>
</tbody>
</table>

Now we make comparisons among the models and experiments. As demonstrated in Chapter 3, CCSM3 is insensitive to SI WWBs; this is true for both EP and CP ENSO variability. The small differences between SI and control in this model are not significant. In contrast, the SI WWBs do enhance CCSM4 SSTA variance (see Chapter 3). Interestingly, this increase occurs mostly for EP events and not for CP events. Both models experience significant variance increases when the WWBs are introduced as SD noise. As with CCSM4 SI, most of the differences with respect to control are for EP events. Essentially, the WWBs activity, which is mostly located over the warm pool edge, more readily produces waveguide-type of variability as oppose to more localized “advective-type” effects.

The last two columns in table 4.1 indicate the standard deviation of the thermocline and zonal advective feedbacks. These terms are defined by (4.1) and (4.2) below, which corresponds to vertical advection of temperature anomalies T' by the mean upwelling \( \bar{\psi} \) and horizontal advection of mean temperature \( \bar{T} \) by
anomalous zonal currents $u'$. These feedbacks mechanisms are integrated over the upper 100m depth and averaged over most of the tropical Pacific basin that includes Niño4 and Niño3 regions. Here, $\rho$ is the seawater density and $c_p$ represents the specific heat of seawater at constant pressure.

$$Thermocline\ feedback = \rho c_p \int \bar{w} \frac{\partial T'}{\partial z} dz$$

$$Advective\ feedback = \rho c_p \int u' \frac{\partial \tau}{\partial x} dz$$

The systematic increase in variance from control to SD for both models corresponds well with increase in variance for the positive feedbacks mechanisms. CCSM3 and CCSM4 have more vigorous thermocline feedbacks compared to the advective feedback and this difference is enhanced by SD WWBs. Changes in the thermocline feedback are not significant when comparing the control to SI WWBs experiments for CCSM3. In contrast, both feedback mechanisms are enhanced in the SI WWB CCSM4 (99% confidence level). The SD WWBs enhances thermocline and zonal advective feedbacks variance for both models.

Figure 4.3 shows a scatter diagram of EP-PC1 versus CP-PC1 for CCSM3 (left column) and CCSM4 (right column). The control results are in the top row (Fig. 4.3a and 4.3d), the SI WWB experiments are in the middle row (Fig. 4.3b and 4.3e), and SD WWB results are in the bottom row (Fig. 4.3c and 4.3f). This scatter diagram approach to quantify CP vs. EP ENSO was first introduced by Takahashi et al. (2011). All panels include a period of 115 years for all months (grey dots) and only for December-January-February (DJF, blue dots). The black axes correspond to typical tropical Pacific SST indices. These include: Trans-Niño Index (TNI, Trenberth and
The relationship between these various indices is derived from multiple linear regressions of SST anomalies in the respective regions with EP-PC1 and CP-PC1. The correlation between any two axes shown is readily obtained by the cosine of the angle between the given axes. It is clear that the defined EP-PC1 index is significantly correlated to Niño3 for all cases (the angle between these axes is near zero). The CP-PC1 index is strongly correlated with EMI (between 0.82 and 0.9 depending on experiment).

We first focus on the results of the control experiments (Fig. 4.3a and 4.3d). CCSM3 has less organized structure in the scatter than CCSM4. This relatively large spread also survives when we look at just the boreal winter season (DJF). The enhanced structure in CCSM4 is mostly oriented along the blue diagonal, which correspond to the linear least-squares fit between CP-PC1 and EP-PC1, although there is some curving in the northeast quadrant. The CCSM4 cold and weak warm events (according to Niño3) follow the slope of Niño4 (N4) axis. Meanwhile, for the very strong EP events, the scatter slopes along an axis that is parallel to N3; hence the curving in the northeast quadrant. This suggests that cold and weak warm events dominate over the central Pacific whereas strong warm events are confined to the eastern Pacific. This kind of regime structure is difficult to detect in the CCSM3 control simulation.
Figure 4.3 Scatter diagram of EP-PC1 versus CP-PC1 for CCSM3 (left column) and CCSM4 (right column), control (a and d), state-independent (b and e), and state-dependent (c and f). All panels include a period of 115 years for all months (grey dots) and only for December-January-February (DJF, blue dots). The black axes correspond to typical tropical Pacific SST indices. These are derived from multiple linear regressions of SST anomalies in these regions with both PCs.
Figure 4.4 Scatter diagram of EP-PC1 versus CP-PC1 for observed SSTA from January 1950 to December 2001. Grey dots include all months and black dots only show December-January-February (DJF). The grey axes correspond to typical tropical Pacific SST indices. These are derived from multiple linear regressions of SST anomalies in these regions with both PCs. The very strong EP (i.e., 1972-73, 1982-83, and 1997-98) warm events are highlighted (red, green, and blue) respectively.

In terms of the SI WWBs experiments (Fig. 4.3b and 4.3e), the EP-PC1 CP-PC1 phase space appears to be largely unaffected by the parameterization, this is particularly true for CCSM3. In CCSM4 there is some indication of an increase in the curvature giving a hint of a horseshoe pattern in the phase diagram. This horseshoe pattern becomes particularly marked for SD WWBs in CCSM4 and to a lesser degree in CCSM3. Perhaps the most marked change is the enhancement of the horseshoe structure that corresponds to very strong EP-PC1 and weak or negative CP-PC1 events that were not present in the CCSM4 control (Fig 4.3d), CCSM3 control (Fig. 4.3a) or CCSM3 SI WWBs (Fig. 4.3b). For the SD WWBs experiments, the horseshoe pattern is detected in CCSM3 (Fig. 4.3c) particularly for boreal winter (DJF) season
and is considerably more pronounced in CCSM4 (Fig. 4.3f). This horseshoe pattern is also present in observed SSTA (Fig. 4.4). Note that the very strong EP events of 1972-73, 1982-83, and 1997-98 are located on the southeast quadrant of the scatterplot. These events were accompanied significant WWBs activity (Fig. 3.8).

Here we focus on the extreme EP events depicted in Fig. 4.3. For this, Fig. 4.5 look at composites from extreme (>1.5σ) EP-PC1 warm events for SI and SD WWBs experiments. Temperature anomalies as a function of depth are shown by thin black contours. The shading corresponds to the differences in the composites – that is SI minus control (top row) and SD minus control (bottom row). The 20°C isotherm is depicted by black (grey) thick line for control (WWBs) experiment. WWBs induced stress composites [10Nm^2] are depicted above each panel by grey shading. It is important to note that WWBs for SI cases appears much weaker than those from the SD cases. This is mainly due to composite averaging, which tends to damp SI signals since they are not state dependent.

Consistent with Fig. 4.3, CCSM4 has significantly stronger extreme EP-PC1 events as compared to CCSM3 – the cold regions get colder and the warm regions get warmer. There is no detected impact of SI WWBs on CCSM3 at any depth (Fig. 4.5 top-left) and the thermocline position is nearly identical to that of control. In contrast, CCSM4 is sensitive to the SI WWB parameterization (Fig. 4.5 top-right). The east-west dipole observed in the control is further enhanced by the inclusion of SI WWBs with most of the effect at thermocline depth. The composite thermocline is nearly flat and significantly shallower (deeper) in the CP (EP) as compared to control. For the SD WWBs, both models enhance the east-west temperature dipole observed in the control
case. Again, CCSM4 is more responsive to WWBs, which for this case shows a reversal in the tilt of the thermocline.

Figure 4.5 Composites from extreme (>1.5σ) EP-PC1 warm events for state-independent (SI) and state-dependent (SD) WWBs experiments. Temperature anomaly are shown by thin black contours (1°C interval). The blue-red shading corresponds to experiment minus control temperature anomaly. The 20°C isotherm is depicted by black (grey) thick line for control (WWBs) experiment. WWBs induced stress composites [10Nm⁻²] are depicted above each panel by grey shading.

A similar analysis is followed in order to describe the effect of WWBs on CP warm events. Similar to Fig. 4.5 for EP events, Fig. 4.6 depicts composite analysis for CP events. For CCSM3, both experiments and the control show relatively weak sub-surface thermal anomalies during CP-type events. Temperature anomalies of only ~0.5°C occurs over the western Pacific. Unlike for EP-type events, the CP events are little affected by the inclusion of SI or SD WWBs. The CCSM4 simulations are closer to the observed
estimates of the thermal structure during CP events with near surface warm temperature anomalies over cold anomalies at thermocline depth (Ashok et al. 2007). There is little difference for the SI WWBs model, only slight cooling at thermocline depth with respect to control. For the SD WWBs, some warming occurs at thermocline depth and eastward of the maximum amplitude of CP events. Unlike for the EP events, CP events are not significantly enhanced by either type of WWBs forcing.

Figure 4.6 Same as Fig. 4.5 but for CP warm events. Contour intervals are 0.5°C

4.3 ENSO regimes

CCSM4 appears to reproduce the non-linear (i.e., horseshoe) structure in the EP-CP phase space that is apparent in observations (see Takahashi et al. 2011 for the observed picture). This is especially true when WWBs are added to the model. Motivated by this, we follow a similar analysis as in Takahashi et al. (2011) where different ENSO regimes
were identified. From Fig. 4.3, three sub-groups (regimes) are analyzed. Regime (i) includes very strong EP events (> 2σ EP-PC1), which we refer to as EP events. Regime (ii) includes moderate EP-PC1 warm events and moderate CP-PC1 warm events. We refer to this as basin-wide (BW) events. The third regime (iii) referred to as CP includes those events with large values of CP-PC1 and relatively small values of EP-PC1. In order to have a larger sample size, we study these events for all three CCSM4 simulations together. This yields 35 events of EP-type, 26 of BW-type, and 20 events of CP-type.

Figure 4.7 shows EP (left column), BW (center column), and CP (right column) 48 months composite evolution of phase-space (top row), starting at the plus sign and reaching zero-lag at the black circle. The grey axes correspond to typical tropical Pacific SST indices. The middle row shows the SSTA evolution across the equatorial Pacific with time increasing up the page and zero-lag denoted by horizontal dashed line. Bottom row show the thermal structure (shaded) and thermocline depth (black line) across the Pacific at zero lag.

The EP regime is characterized by large warm (cold) temperature anomalies over the east (western) Pacific at thermocline depth; this includes a very flat zonal thermocline structure. During these events, temperature anomalies propagate from west-to-east before peaking in the EP (Fig. 4.7 middle row). The BW regime depicts basin-wide warming while retaining a stronger thermocline tilt compared to the peak phase of the EP regime. The anomalies are much weaker than those from EP regime, but still with significant anomalies at thermocline depth. The BW events tend to develop along the Niño4 axis until reaching zero-lag. Damping first occurs along the CP axis after the events peak, this is followed by the decay of the anomalies to near neutral throughout the basin. For the CP
regime (Fig. 4.7 right column), the warm temperature anomalies are confined to the western Pacific with thermocline structure similar to the BW regime except in the far eastern Pacific. Here, the phase diagram suggests that temperature anomalies propagate from east-to-west reaching the central Pacific with near-zero eastern Pacific anomaly. Beyond this, the anomalies decay following the CP axis. This westward propagation is also evident in the SSTA evolution (Fig. 4.7 middle row).

Based on the results obtained in this chapter and Chapter 3 it can be concluded that the fast-varying (stochastic) component of the WWBs has little importance in modulating ENSO diversity due to its inability in projecting its power on to interannual frequencies. The slow component (SST related) or deterministic component is playing a bigger role. This result could have repercussions in ENSO predictability and prediction. That is, a forecast system may only need to capture the basic statistics of the noise forcing instead of aiming at predicting the event-by-event specific details. Indeed, even in a more general sense the issue of ENSO predictability in the presence of the WWBs parameterization requires further study. For instance, intuitively one would argue that adding noise to a system should decrease predictability due to increased irregularity of ENSO. However, the increase oscillatory character and power in the state-dependent case seems to suggest enhanced predictability. The results presented in this chapter suggest that WWBs, more so state-dependent WWBs case, play an important role in enhance EP ENSO events. This could have some repercussion on the predictability of strong EP events like the 1997/98 El Niño (see Fig. 3.8). This issue of ENSO predictability under the presence of state-dependent WWBs forcing will be analyzed in detail in Chapter 5.
Figure 4.7 EP (left), BW (center), and CP (right) 48 months composite evolution of phase-space (top row), starting at the plus sign and reaching zero-lag at the black circle. The grey axes correspond to typical tropical Pacific SST indices. Middle row show the SSTA evolution across the equatorial Pacific with time increasing up the page and zero lag denoted by horizontal dashed line. Bottom row show the thermal structure (shaded) and thermocline depth (black line) across the Pacific at zero lag.
Chapter 5

ENSO predictability: State dependent WWBs

The debate of whether ENSO resides in a chaotic versus a stochastically forced system is of great importance in understanding its predictability. This is because the theoretical predictability upper-limit depends on the source of irregularity. The two mentioned views have strong implication in ENSO predictability. ENSO predictability has been typically studied using idealized twin experiments to investigate error growth due to initial conditions uncertainties, e.g., as in Goswami and Shukla (1991); Kleeman and Moore (1997); Thompson and Battisti (2000). In general, the chaotic system exhibits much longer predictability time scales than the stochastically forced system (from a few years to a few months respectively). Most of our knowledge is based on very short and unreliable observed data and relatively simple models that include stochastic processes in and ad hoc manner and oversimplified coupling and nonlinear dynamics.

As mentioned in Chapter 3, WWBs are often linked to the onset and development of El Niño events (Kerr 1999; Fasullo and Webster 2000; MacPhaden 2004), and there is evidence that ENSO is modulated by WWBs (Eisenman et al. 2005; Gebbie et al. 2007). This was further shown in term of ENSO dynamics (Chapter 3) and ENSO diversity (Chapter 4). Here, we test the hypothesis whether the presence of WWBs in either the prediction system and/or the truth impacts predictability. For this, idealized prediction experiments were designed where deterministic and probabilistic skill assessments are used to quantify the effect of these WWBs on the predictability of ENSO.

Predictability experiments involving state-dependent WWBs have been done using a hybrid-coupled model (Gebbie and Tziperman, 2009). In this case it was found
that the overall statistical measures of predictability was neither degraded nor improved by the inclusion of WWBs. The implementation of WWBs did improve the prediction of the onset and development of the exceptionally large 1997 El Niño event, suggesting a potential for ENSO prediction improvement. This is possible because there is some predictability in the statistics of WWBs. These events could affect ENSO predictability in that stochastic forcing in the form of state-dependent WWBs transitioned ENSO from a chaotic to a more self-oscillatory (less-chaotic) regime. On the other hand, WWBs may not affect predictability because individual WWBs events may be triggered by the state dependent formulation used here a few weeks earlier or later for a given SST structure. This may not affect the ENSO predictability given that only the slow component (SST related) appears to be important, (Fig. 4 of Gebbie and Tziperman, 2007). If the precise timing of individual WWBs is not as important as the slow component (Roulston and Neelin 2000; Eisenman et al. 2005; Zabala-Garay et al. 2005) then one could argue that the stochastic component of WWBs does not affect ENSO predictability. This chapter will test both of these possibilities. That is, a set of experiments will be developed in order to examine ENSO predictability with and without the presence of state-dependent WWBs.

This chapter also aims at the study of the “so-called” boreal spring prediction barrier of ENSO forecasts (SPB) and how WWBs impact this prediction barrier. The seasonality of prediction skill for tropical Pacific SSTA is well documented (Balmaseda et al., 1995; Xue et al., 2000; McPhaden, 2003; Oldenborgh et al., 2005; Zheng and Zhu, 2010). There are currently two hypotheses for the breakdown of ENSO forecast skill during the SPB. The first hypothesis relates the seasonality of SSTA variance (i.e.,
signal) to that of stochastic (noise) forcing. For example, Webster and Yang, 1992; Xue et al., 1994 argued that SSTA variance is weaker during boreal spring, therefore is more sensitive to contamination by noise forcing. The second hypothesis suggests that the air-sea coupling strength is weakest during the boreal spring (Zebiak and Cane, 1987). Using an ensemble prediction system, Zheng and Zhu (2010) found that low signal-to-noise ratio (SNR) during the boreal spring limits the predictability through that season. Duan and Wei (2013) showed that error growth due to spring prediction barrier (SPB) depends remarkably on ENSO phase with the El Niño phase yielding a more prominent spring prediction barrier than for the La Niña phase. This chapter will examine if the prescience of WWBs or lack of thereof is a possible source of seasonality in ENSO forecast skill.

5.1 Experiment description

Here we advance a procedure to quantify the ENSO predictability using CCSM3 with the state-dependent WWBs parameterization (WB experiment here forward) and compare it to the control case without WWBs (CTL here forward). For this, four sets of idealized forecast experiments are made. These forecasts will be validated using previous CCSM3 runs with and without the state-dependent WWBs (see Chapter 3 and Appendix for description of the parameterization). That is, CCSM3 will be used to forecast itself with 4 idealized experiments: (i) CTL forecasting CTL, (ii) CTL forecasting WB, (iii) WB forecasting CTL, and (iv) WB forecasting WB. This is more clearly explained in Table 5.1 where the experiment name follows the notation of PREDICTORtoPREDICTAND to describe which model is predicting which control (or “truth”) simulation. The idealized forecasts cover a 30-year period. Each forecast is initialized on 1 March, 1 June, 1
September, and 1 December yielding a total of 120 idealized forecasts each of which have 5-ensemble members. The CGCM resolution and WWBs parameterization employed in this chapter is identical to those from Chapters 3 and 4.

Table 5.1 Four possible experimental setup for retrospective forecast.

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Description</th>
<th>Truth (verification)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CTLtoCTL</td>
<td>Model without WWB parameterization forecast →</td>
<td>Model without WWB</td>
</tr>
<tr>
<td>CTLtoWB</td>
<td>Model without WWB parameterization forecast →</td>
<td>Model with WWB</td>
</tr>
<tr>
<td>WBtoCTL</td>
<td>Model with WWB parameterization forecast →</td>
<td>Model without WWB</td>
</tr>
<tr>
<td>WBtoWB</td>
<td>Model with WWB parameterization forecast →</td>
<td>Model with WWB</td>
</tr>
</tbody>
</table>

The cases, CTLtoCTL and WBtoCTL are, in some sense, unrealistic in that WWBs do occur in nature, whereas, the “truth,” for these two cases does not have WWBs activity. The case, CTLtoWB mimics what often occurs with real ENSO prediction in that CGCMs that lacks WWBs but the truth includes WWBs. Lastly, WBtoWB represents a forecast system that is able to capture the statistics of the “observed” WWBs. Our intent is to document how this impacts predictability. Some of the results obtained with CCSM3 will be further tested using the more recent version of this model (CCSM4).

5.1.1 Initialization technique

In terms of introducing initial perturbations, there are two widely used techniques. One is the stochastic optimal, calculated from the true linear dynamic operator (Kleeiman and Moore, 1997; Moore and Kleeiman, 1996, 1997, 1999b,a; Chen et al., 1997); or from an empirical propagator derived from observational data or model output (Blumenthal, 1991; Xue et al., 1997; Penland and Matrasova, 1995; Fan et al., 2000; Kleeman et al., 2003; Kallimmel and Kirtman, 2007). The other technique is the bred vector, calculated
from simple model (Cai et al., 2003) and sophisticated coupled GCM (Yang et al., 2006; Vikhliaev and Kirtman, 2007). Currently, neither of these techniques is used in operational ENSO forecasting for ensemble generation. This is primarily due to computational expense.

Here we use a simple procedure that was implemented in Kirtman (2003) and Kirtman and Min (2009) and is used for real-time prediction as part of the NMME project (Kirtman et al. 2013). For each retrospective forecast, the fully coupled model will be integrated forward for \( N \) days, and then these results will be used as the initial condition. That is, the calendar will be reset back \( N \) days to the initial time, for our case this is the first of the month. This method will introduce initial error (day \( N \) minus day 1) that is dynamically consistent throughout all model components. \( N \) is chosen here to be between 3 and 12 days so that is short enough for seasonal effects to be unimportant and just long enough for synoptic scale processes (weather) to be responsible for most of the initial condition error. By construction, most of the uncertainties are introduced by the atmospheric component, with small contribution from the other components. The advantage of this approach versus just introducing a random atmospheric perturbation is that in the later, uncertainties in any individual forecast could be underestimated. However, we are likely underestimating the uncertainty due to ocean initial condition uncertainty.

The inclusion of state-dependent noise appears to have a large impact on an already chaotic system as discussed in Chapter 3. It is suggested that stochastic forcing in the form of state-dependent WWBs transitioned ENSO from a chaotic to a more self-oscillatory (less-chaotic) regime. If that is the case, then using WB to predict WB (a less
chaotic predicting a less chaotic) should yield a longer predictability limit compared to CTL predicting WB experiments. We also hypothesize that, CTL predicting WB should do the poorest job out of the four configurations. This hypothesis is based on the fact that adding noise to a stable (non-chaotic system) tends to induce chaos, whereas if the system is already chaotic, which is our case, adding noise could increase stability and predictability (Siqueira and Kirtman, 2012).

5.1.2 Deterministic skill assessment

To quantify the predictability of the retrospective forecasts, deterministic and probabilistic verification techniques will be employed. Deterministic verification techniques will be applied to all possible initial conditions and to each individual hindcast as well. Some of the deterministic techniques include anomaly correlation of forecast versus observation, root mean square (RMSE) error, and ensemble spread analysis.

The purpose of this chapter is to quantify ENSO predictability using CCSM3 as the predictor as well as the predictand (“truth”). But, it is important to remove systematic errors in SSTA before any analysis on skill score is performed. For this, we follow a simple formulation (5.1) in order to remove this error, similar to Kirtman and Min (2009). Here, (see 5.1) each ensemble member (M=5) and each 1-year forecast (N=30 total forecast) are averaged. The systematic error is then obtained by removing the observed climatology, so we have systematic error defined for each initial condition restart and each forecast lead-time (τ).

\[
SST_{sys}(\tau) = \frac{1}{M \times N} \sum_{k=1}^{M} \sum_{yr=1}^{N} SST_{yr}^{k}(\tau) - SST_{obs}(\tau)
\]  

(5.1)
It is then possible to obtain SSTA for each forecasts ensemble member $k$ as described in (5.2) for a given forecast lead time $\tau$.

$$SSTA_{yr}^k(\tau) = SST_{yr}^k(\tau) - SST_{obs}(\tau) - SST_{sys}(\tau)$$  (5.2)

Now that interannual anomalies are obtained, the forecasts skill can be quantify by means of root-mean-square-error RMSE (5.3), saturation RMSE (5.4), anomaly correlation (5.5), and forecast ensemble spread (5.6).

$$RMSE(\tau) = \left[ \frac{1}{M \times N} \sum_{k=1}^{M} \sum_{yr=1}^{N} \left( SSTA_{yr}^k(\tau) - SSTA_{obs}^{yr}(\tau) \right)^2 \right]^{1/2}$$  (5.3)

$$RMSE_{sat}(\tau) = \frac{RMSE(\tau)}{\left[ \sigma_k^2 + \sigma_{obs}^2 \right]^{1/2}}$$  (5.4)

$$Correl(\tau) = \frac{1}{N} \sum_{yr=1}^{N} \left( SSTA_{yr}^k(\tau) \times SSTA_{obs}^{yr}(\tau) \right) \frac{1}{\sigma_k \sigma_{obs}}$$  (5.5)

$$Spread(\tau) = \left[ \frac{1}{P \times N} \sum_{k=1}^{M} \sum_{j=k}^{N} \left( SSTA_{yr}^k(\tau) - SSTA_{yr}^{j}(\tau) \right)^2 \right]^{1/2}$$  (5.6)

Here, the RMS error is a measure of the difference between the forecast and observation whereas the ensemble spread measures the difference among ensemble members. Saturation RMSE is a useful quantity in that it measures the RMSE normalized by the sum of the variances of the forecast model and the truth. This allows for easier description in terms of how important error growth is relative to the system’s own natural variability. A forecast system is said to be saturated with error if $RMSE_{sat} > 1$. This occurs when the anomaly correlation is less than or equal to zero. This relationship is best seen in (5.7).

$$RMSE^2 = \sigma_k^2 + \sigma_{obs}^2 - 2\sigma_k \sigma_{obs} Correl(k,obs)$$  (5.7)
Expression (5.7) is similar to a simple cosine law (5.8). Given this, it is possible to express RMSE and anomaly correlation in a single diagram (Taylor, 2001). A Taylor diagram describes how closely a set of forecasts or model simulations reproduces a given observation. This Taylor diagram makes use of (5.7) to represent three different statistics simultaneously, namely RMSE, anomaly correlation, and the standard deviation of a model simulation with respect to a truth.

### 5.1.3 Probabilistic skill assessment

To study probabilistic skill, a method known as relative operating characteristics (ROC) (Mason and Graham, 1999) is adopted. The ROC is a probabilistic method of forecast skill assessment based on a 2x2 contingency table and simple ratios. Table 5.2 represent a contingency table for a system with \( n \) total observations for which there are \( e \) total number of events and \( e' \) total number of nonevents. The total number of warnings are given by \( w \) and no warnings by \( w' \). With these, there are four possible outcomes: a hit \( h \), if a warning is issued for an occurring event; a miss \( m \), if no warning is issued for an occurring event; a false alarm \( f \), if a warning is provided and no event occurs; and a correct rejection \( c \), if the forecast system issues no warning and no event occurs. The probabilistic skill of a forecast system is based on comparison of hit rates and false alarm rates (Swets, 1973). These ratios are found by:

\[
\text{hit rate} = \frac{h}{h + m} = \frac{h}{e} = p(W|E) \tag{5.9}
\]

\[
\text{false alarm rate} = \frac{f}{f + c} = \frac{f}{e'} = p(W|E') \tag{5.10}
\]
Table 5.2 Two-by-two contingency table for forecast verification (Mason and Graham, 1999).

<table>
<thead>
<tr>
<th></th>
<th>Observations</th>
<th>Forecasts</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Warnings, W</td>
<td>No Warnings, W'</td>
</tr>
<tr>
<td>Event, E</td>
<td>h</td>
<td>m</td>
</tr>
<tr>
<td>Nonevent, E'</td>
<td>f</td>
<td>c</td>
</tr>
<tr>
<td>Total</td>
<td>w</td>
<td>w'</td>
</tr>
</tbody>
</table>

For the ROC method, two different events are considered, the upper and lower tercile of let say NINO3.4. The upper (lower) tercile correspond to warm (cold) events. The ROC calculation is sensitive to sample size; therefore each grid point in the NINO3.4 region is normalized by its local standard deviation before averaging all points into a regional index. A contingency table describing the forecast skill versus observation is then used to construct the ROC curve for which hit rates are compared to false alarm rates. The hit rate indicates the proportion of events for which a warning was issued correctly, providing an estimate of the probability that an event will be forewarned. The false alarm rate is the proportion of nonevents for which a warning was issued incorrectly. More description on ROC curve will be provided later in this Chapter.

5.2 CCSM3 as the truth

Here, CCSM3 is used as “truth” in that we have control of the WWBs occurrence. That is it is the goal to quantify predictability with and without the presence of these wind events in both the “truth” and in the predictor models. Given that previous CCSM3 simulations are used as observations for which the forecast are verified against, it is necessary to identify some of the strengths and weakness of this model that are specifically pertinent
to the results presented here. For this, Fig. 5.1 depicts the observed (top) annual mean sea surface temperature (SST) for the period from January 1950 to December 2001. The middle and bottom panels of Fig. 5.1 show the difference of CTL minus observed and WB minus observed annual mean SST respectively. Only differences that are statistical significant to 99% confidence are shown. Both CTL and WB show similar systematic errors, which is expected since they both are runs from the same model – the WWBs do not seem to affect the climatology of the model very much. CCSM3 tends to produce warm bias over regions of marine stratocumulus clouds. This is caused by a lack of cloudiness, therefore producing enhance shortwave radiation at the surface. A significant cold bias is located over the North Pacific and for most of the Atlantic Ocean. The inclusion of WWBs has little effect on the mean state. From Fig. 5.1 (middle) and (bottom), we can argue that both CTL and WB present similar systematic errors with respect to observed SST, therefore comparison between their interannual predictability will not be jeopardize by significant differences in their basic state.

Along with some of the mean state bias, CCSM3 also have some difficulties reproducing the observed seasonal evolution of SST along the equator. It is very common for current CGCMs to underestimate the seasonal cycle, or to have a dominant semi-annual component (Mechoso et al., 1995; Latif et al., 2001). CCSM3 has a well-known semiannual seasonal cycle along the equator and the inclusion of state-dependent WWBs neither modified nor improved this bias (see Fig. 3.10 on Chapter 3). Specifically, we showed that in the presence of state-dependent WWBs, the model produced a slightly warmer SST that was consistent throughout the year and the warming was just a mere two tenths of a degree (Niño3.4 region) as compared to a control case.
Figure 5.1 Observed annual mean SST (top), CTL minus observed (middle), and WB minus observed (bottom). Only contouring difference that are significant to a 99% confidence level based on a student-T test.

5.2.1 CTL as the truth

In this section, the predictability of CTL will be assessed using a previous 30-year simulation of the control CCSM3 as the truth. A series of 12 month forecasts spanning
this 30-yr period each having 5 ensemble members is produced. Here, CTLtoCTL forecast skill is compared to that of WBtoCTL. That is, the “truth” for which the forecasts are verified against, does not include WWBs.

5.2.1.1 Annual mean

Here, we highlight the differences between the truth (i.e., CTL) annual mean from those produced by the hindcasts (i.e., CTLtoCTL and WBtoCTL). Fig. 5.2a shows the annual mean SST along the tropical Pacific for CTL. Fig. 5.2b and 5.2c shows the differences in the annual mean, CTLtoCTL minus CTL and WBtoCTL minus CTL respectively, that is forecast minus truth as described by (5.1). Here, the mean for the forecasts are calculated using the ensemble mean of all members and using all lead times from all possible ICs. Differences in means are depicted by black contours and corresponding 99% significance level from a two-tail Student-t test are shown by grey shading. Control model predicting itself (CTLtoCTL) does a good job in reproducing the mean state of the truth (CTL). The WBtoCTL model (Fig. 5.2c) depicts significantly warmer SST of up to 0.4°C than CTL. This warming occurs throughout the central and eastern Pacific with the larger magnitude over Niño4 and Niño3.4 region. These warming are significantly larger than the differences between the long CTL and WB simulations presented in Chapter 3. The warmer SST is a result of positive zonal wind stress induced by the WWBs that is absent in the truth. The warmer SST due to WWBs may be attribute to different processes. First, zonal advective mechanism, where warm-pool water is advected eastward by the WWBs induced anomalous current. Also, induced downwelling Kelvin waves by westerly momentum input. These mechanisms were thoroughly discussed in chapter 4. This last
mechanism is more associated with thermocline processes that are able to remotely affect the eastern Pacific SST. The mean state bias is greatly reduced when only the short (1-3 month) lead times are used for mean calculation (not shown). All the bias that remains is localized and confined to the WWBs region.

**Figure 5.2** Annual mean SST along the tropical Pacific for CTL a). Panels b) and c) show differences in the annual mean, CTLtoCTL minus CTL and WBtoCTL minus CTL respectively for all lead-times. Differences in means are depicted by black contours and corresponding 99% significance level from a two-tail Student-t test are shown by color shading.
5.2.1.2 Mean annual cycle

Current CGCMs still have problems in simulating the observed seasonal cycle of SST and CCSM3 is not an exception. Fig. 5.3 shows the mean annual cycle of SST for the Niño3.4 region for each of the four ICs. Grey bars show CTL model “truth”, where CTLtoCTL (WBtoCTL) is depicted by red (blue) line. Filled circles denote where the forecast mean for that given month is statistically different than the “truth” at a 99% confidence level using a two-tail student t-test. CTL shows a weak semi-annual cycle for Niño3.4 region, which is not observed. This is a typical systematic error of most CGCMs (Mechoso et al., 1995; Latif et al., 2001). The July-October minimum in SST is well observed in nature. The secondary minimum early in the calendar year is a bias of this model.

The simulated SST seasonal cycle is well represented by both predictor models independent of the month of initialization. Note that for March ICs (Fig. 5.3 top-left), differences between forecast and truth are not significant, even for WBtoCTL model. For the remaining ICs, the systematic bias becomes larger as lead-time increases; this is true regardless of predictor model. Most of the SST bias presents as warming, occurring throughout the central and eastern Pacific with the larger magnitude over Niño4 and Niño3.4 region. The warmer SST is a result of positive zonal wind stress induced by the WWBs, absent in the truth. The warmer SST due to WWBs may be attribute to different processes. These processes were discussed in the previous sub-section. These systematic errors are removed before analyzing the predictability skill of interannual SSTA.
Figure 5.3 Mean annual cycle of SST for the Niño3.4 region for each of the four ICs. CTL model “truth” is shown by grey bars, where CTLtoCTL (WBtoCTL) is depicted by red (blue) line. Filled circles denote where the forecast mean for that given month is statistically different than “truth” to a 99% confidence level using a two-tail student t-test.

5.2.1.3 Interannual variability

To define interannual variability, the seasonal cycle is removed from both the truth and the predictions. It is important to account for systematic errors as pointed by the last subsections and equation (5.1).

Figure 5.4 depicts hindcast evolution for the 4 different initial conditions, only showing 14 of the total 30-years of forecasts. The systematic error has been removed following (1) above. Niño3.4 SSTA (°C) are shown on the top portion of each panel and labeled on the left vertical axis. A horizontal dashed line marks the 0°C anomaly. Thick lines give the ensemble mean forecasts where each ensemble member is given by thin lines. The ensemble mean WWBs index is depicted in the bottom of each panel and
Figure 5.4 Hindcast evolution for the 4 different initial conditions, only showing 14 of the total 30-year worth of forecasts. Niño3.4 SSTA ($^\circ$C) are shown on the top portion of each panel and labeled on the left vertical axis. A horizontal dashed line marks the $0^\circ$C anomaly. The ensemble mean forecasts are given by thick lines where each ensemble member is given by thin lines. The ensemble mean WWB index is depicted in the bottom of each panel and labeled on the right vertical axis (dynes/cm$^2$). For the truth (CTL) does not have WWBs activity. WWBs for forecasts are depicted as blue bars. The color scheme is consistent throughout the plot.
labeled on the right vertical axis (dynes/cm²). So, for our purposes here the blue bars represent the “forecasted” WWBs, when the “observed” or “truth” does not include this process. The color scheme is consistent throughout the plot. It is worth noting that this 14-year period contains a diverse ENSO time series with strong warm and cold events and quiescent periods (e.g., model years 1564-1566).

Overall, it appears that the very strong events are generally better forecasted than the quiescent periods. The later are characterized by significant spread in the forecasts. There are also hints at seasonality in the forecasts in that June and September ICs forecast appear to outperform March and December initialized forecasts in terms of depicting amplitude with considerably less spread. Interesting, many forecasts initialized in boreal winter/spring struggle to produce the correct ENSO phase, this is associated with the spring-prediction-barrier (SPB). Also note that the state dependence of WWBs, with most of the amplitude corresponding to warm SST anomalies.

a. Deterministic forecasts skill

In Fig. 5.4, we identified some of the general strengths/weakness of the forecast models. Here we provide quantified metrics of how well CTLtoCTL and WBtoCTL perform. Figure 5.5 presents Taylor diagrams depicting statistical comparisons of interannual forecast skill of Niño3.4 SSTA for the different initial conditions given at the top-right of each panel. The statistics are calculated for all lead times. Solid black circle represents truth that has a standard deviation of about 1°C measured by the semi-circular dashed line. Open circles represent forecast ensemble members, whereas closed circles shows the ensemble mean for CTLtoCTL (red) and WBtoCTL (blue). Standard deviation (°C) is indicated in the radial distance from the origin and is labeled in the x and y-axis.
Anomaly correlation is measured by the radially pointing dashed lines and labeled by the semi-circular axis. The concentric green circles measure the root mean square error ($^\circ$C) with respect to truth. All statistics shown considers the 30 years hindcast period.

Before comparing each forecasts model, we assess the dependence of forecasts skill on ICs. It is evident that those forecasts initialized in June and September are closer to the truth, this is consistent with last figure. For these initial conditions months, the forecasts are closer to the “truth” or CTL mainly due to an improvement in the skill of depicting the correct phase; this is given by the enhanced correlation. Surprisingly, there is not significant difference in the standard deviation, given by the semi-circular dashed line. This skill metric for the individual ensemble members indicates that the forecasts with MAR ICs having the larger spread in the skill compared to the other initial conditions.

We now compare the two experiments (i.e., red vs. blue in Fig. 5.5). Surprisingly, it appears that WBtoCTL reproduces the “truth” variance better than CTLtoCTL, independent of ICs. In contrast, the CTLtoCTL outperforms the WBtoCTL in depicting the correct phase (i.e., larger correlation coefficients). In terms of RMSE, CTLtoCTL appears to be slightly closer to the truth.

Deterministic verification for Niño3.4 SSTA forecasts for each initial condition as a function of lead-time (months) is shown in Fig. 5.6. The figure shows root mean square error RMSE (A), saturation RMSE (B), forecasts ensemble spread (C), and anomaly correlation (D). Panel (E) shows standard deviation of WWBs index (area average from 140E to 180 longitude and 5S to 5N latitude), this is taken as the ensemble mean of WBtoCTL (blue). Units are [$^\circ$C] for panels (A) and (C) and [dynes/cm$^2$] for panel (E),
panels (B) and (D) are unitless. Red lines correspond to CTLtoCTL where blue corresponds to WBtoCTL. MAR ICs show a rapid RMSE growth (A) early in the forecasts period for both models. Interestingly, the error growth plateau at about $0.6^\circ$C after lead-time 6. For JUN, SEP, and DEC ICs, the error growth is rapid through all 12 months lead-time. The CTLtoCTL forecasts have slightly smaller RMSE than WBtoCTL. Note that the RMSE does not saturate (panel B) for any model or ICs, suggesting that the model has an estimated limit of predictability that goes beyond 12 months. This is certainly not the case for real forecast experiments (Kirtman and Min 2009).

![Taylor diagram](image)

**Figure 5.5** Taylor diagram depicting statistical comparison of interannual forecast skills for the different initial conditions for all lead times. Solid black dot represent truth. Open circles represent forecast ensemble members whereas closed circles shows the ensemble mean for CTLtoCTL (red) and WBtoCTL (blue). Standard deviation ($^\circ$C) is measure as...
the radial distance from the origin and is labeled in the x and y-axis. Correlation is measured by the radially pointing dashed lines labeled by the semi-circular axis. The concentric green circles measure the root mean square error (°C) with respect to truth.

Surprising, MAR ICs have smaller saturation RMSE values for both prediction systems. This is because forecasts initialized in March evolve through the high SST variance season (i.e., June to February). This high variance season is associated with high signal-to-noise ratio (see, Chapter 2) and how this relates to forecast skill will be discussed later. This is more easily observed by analyzing panel B for MAR ICs for which the saturation RMSE value remains very low (i.e., ~0.4, or 40% saturation) for the first 9 months lead. Then, there is a rapid increase in saturation RMSE thereafter. This rapid saturation RMSE growth is also observed in the anomaly correlation (panel D).

Overall, the forecasts ensemble spread (C) increases with lag for both models. Not surprisingly, WBtoCTL has more spread due to WWBs noise (panel E). Interestingly, the WWBs inclusion and consequently the enhanced spread in WBtoCTL do not affect the deterministic predictability of this model with respect to CTLtoCTL. We consider the impact on probabilistic measure of predictability later. Overall, there are some subtle differences between the two forecast systems, but they both generally have similar forecasts skill.
Figure 5.6 Deterministic forecasts verification for each initial condition as a function of lead-time (months) for Niño3.4 SSTA. Showing root mean square error RMSE (A), saturation RMSE (B), forecasts ensemble spread (C), and anomaly correlation (D). Panel (E) shows standard deviation of WWBs index (area average from 140E to 180 longitude and 5S to 5N latitude), this is taken as the ensemble mean of WBtoCTL. Units are [°C] for panels (A) and (C) and [dynes/cm²] for panel (E), panels (B) and (D) are unitless.
Figure 5.7 RMSE (solid) and saturation RMSE (dashed) for CTLtoCTL (red) and WBtoCTL (blue) for Niño3.4 SSTA. RMSE has units of °C, saturation RMSE are unitless.
Figure 5.8 Anomaly correlations for CTLtoCTL (red) and WBtoCTL (blue for each ICs case as a function of forecast lead-time.
The deterministic forecasts skill of the model is also analyzed for warm and cold events separately. This is especially important for this study because the WWBs parameterization is skewed toward warm events, therefore one may expect that there should be some asymmetric effect on the predictability as well. Figure 5.7 shows the RMSE (solid) and saturation RMSE (dashed) for CTLtoCTL (red) and WBtoCTL (blue) for Niño3.4 SSTA. The RMSE are measure in °C, whereas the saturation RMSE are unitless with values greater than unity suggesting error saturation. Anomaly correlation can be discussed simultaneously with RMSE as the two quantities are related by (7). For this, Fig. 5.8 shows the anomaly correlation for CTLtoCTL (red) and WBtoCTL (blue) each ICs case. A few general points are noted from Figs. 5.7 and 5.8. First, CTLtoCTL and WBtoCTL have comparable deterministic skill, indicating that the inclusion of WWBs as noise forcing did not improve nor degrade the forecast skill of CCSM3 model. Here, we analyze the forecast skill for warm and cold for each ICs separately:

- **MAR ICs**: There is little distinction in the predictability as measured with these metrics for warm and cold events
- **JUN ICs**: Forecast skill in term of both RMSE and anomaly correlation remains very high for the first 9-month lead-time. There is a rapid drop in predictability beyond 9-months, which corresponds to forecasts past February of the following year. RMSE saturates at around 11 and 12-month leads for CTLtoWB, and WBtoWB model respectively for cold events (Fig. 5.7). This is also observed in the anomaly correlation plot with the cold phase having a considerable larger drop in skill than the warm phase
- **SEP ICs**: RMSE and correlation suggest high forecast skill for all models up
to 6-month lead. There is a well-defined springtime forecast barrier, which is more pronounced for cold than warm events. After this season, the skill of the forecasts tends to recover for both numerical models.

- **DEC ICs:** The forecasts are characterized by very rapid error growth at short lead-times. This is more notable for the cold phase from lead-times 3 to 5 month with a well-defined spring prediction barrier. The skills of the two models are nearly indistinguishable for either phase.

There is an evident SPB and more so during cold events. This is apparently linked to low signal-to-noise ratio in the wind stress over the central equatorial Pacific, which is discussed more later. As noted in Chapter 2, there is considerably more wind stress noise from March to June during the cold phase as compared to the warm phase for this model.

b. Probabilistic forecasts skill

The probabilistic skill is assessed in terms of the Relative Operation Characteristics (ROC) score described in section 5.1.3. For this, a ROC curve is calculated for each Niño3.4 grid point (i.e., approximately 600 data points) for each model and ENSO phase. Figure 5.9 describes the ROC curve for each ICs at lead time 6 months. CTLtoCTL (WBtoCTL) warm events are shown by solid red (blue) lines and cold events are shown by dashed red (blue) lines.

The numerical values given in the legend corresponds to the area under the curve. The higher the score, the more skilful the forecast. An ideal forecast skill system would have relatively large hit rates and small false alarm rate so that all the points on the ROC curve would be clustered in the upper-left corner of the diagram. An unskilful forecast
system would have all points close to the diagonal in the ROC diagram. That is, hit and false alarm rates are comparable. The interior points on a ROC curve indicate the total number of ensemble members forecasting the event. Starting from the bottom-left corner, the first point describes the hit versus false alarm rate for 5 out 5 ensemble members. Moving toward the upper-right corner, the second point indicates the skill if 4 out the total 5 members forecast the event and so forth. The last interior point toward the upper-right corner depicts the skill if only 1 out of 5 members forecast the event. Note that, the hit rate and false alarm rate increases as the number of ensemble members forecasting the event decreases.

**Figure 5.9** ROC curve for each ICs at lead time 6 months. CTLtoCTL (WBtoCTL) warm events are shown by solid red (blue) lines and cold events are shown by dashed red (blue) lines. The numerical values given in the legend corresponds to the area under the curve.
It is noted that forecasts initialized in June are the most skillful at 6 months lead, whereas those initialized in December are the least skillful. There are small differences in the probabilistic skill of warm versus cold events for JUN and SEP ICs. Late boreal winter/spring initial conditions show a tendency for cold event forecasts being less skillful than warm events forecasts, especially for CTLtoCTL model. This is consistent with Chapter 2 in that cold events have lower signal-to-noise ratios in the zonal wind stress for this model. Differences in forecasts skills among the models are also small. CTLtoCTL appears to be slightly more skillful for MAR and DEC ICs but these differences are very subtle. These results are consistent with deterministic forecasts verification from previous subsections.

Figure 5.9 only describes the probabilistic skills at 6 months forecast lead-time. To quantify the skill for all lead times, the ROC score index, or area under the ROC curve is shown in fig. 5.10 for all lead times. The curve is very similar to the anomaly correlation with values equal to zero suggesting a no skill forecast. Here, MAR ICs have a rapid decrease at short lead times, then the ROC score remains steady. There is a significance reduction in the ROC score during the boreal spring for all ICs and models independent of the ENSO phase. Differences in skill score between models are small at most lead times. Similarly, there are modest differences in the skill score between warm and cold events. Most of the differences occur once the forecasts evolve past the boreal spring, especially for the WB3toCTL model. It appears that state dependent WWBs increases the skill score of warm events with respect to cold events during March-April-May (MAM) period but only for MAR and DEC ICs.
5.2.2 WB3 as the truth

The predictability of WB will be assessed using a previous 30 years run of CCSM3 with parameterized state-dependent WWBs as the truth. A series of 12 month forecast spanning these 30yr periods each having 5 ensemble members is produced. Here, CTLtoWB forecast skills are compared to that of WBtoWB. The analysis presented in this section follows that from section 5.2.1 where CTL was used as the predictand.

5.2.2.1 Annual mean

Similar to Fig. 5.2, Fig. 5.11 shows the mean state difference between the hindcasts and truth (WB). Fig. 5.11a) shows the annual mean SST along the tropical Pacific for WB. Fig. 5.11b) and c) shows the differences in the annual mean, CTLtoWB minus WB3 and WB3toWB3 minus WB3 respectively, that is forecast minus truth using all lead times in
Figure 5.11 SST annual mean of WB (°C) along the tropical Pacific Ocean a). CTLtoWB minus WB and WBtoWB minus WB are shown in panels b) and c) respectively. For (B) and (C), the annual mean of the forecasts is calculated using the ensemble mean from all forecast leads times from all possible restart. The difference in means (b and c) is depicted in black contour (0.1°C interval). Differences that are significant the 99% confidence level using a two-tail student t-test are color shaded.

the calculation of the mean. Note that CTLtoWB in Fig. 5.11b) presents a significant cold bias with respect to the truth. Again, this is considerably larger than would be expected by simply comparing the control simulation with the WB simulation (see Chapter 3). This bias is ~0.5°C eastward of the main WWBs region (e.g., 140E to 180 and -5S to 5N). The reason why WB is warmer there is due to both local downwelling produced by westerlies and the eastward propagating downwelling Kelvin wave signal. These are not
present in CTLtoWB. Significantly less bias ~-0.1°C (not significant at 99% confidence) is observed for WBtoWB (Fig. 5.11c) which has the WWBs events. The mean state bias is greatly reduced when only the short (1-3 month) lead times are used for mean calculation (not shown). All the bias that remains is localized and confined to the WWBs region.

5.2.2.2 Mean annual cycle

Similar to the analysis presented in section 5.2.1.2, the mean annual cycle for WB model is described in Fig. 5.12. Mean annual cycle of SST for the Niño3.4 region for each of the four ICs. WB model “truth” is shown by grey bars, where CTLtoWB (WBtoWB) is depicted by red (blue) line. Filled circles denote where the forecast mean for that given month is statistically different than “truth” to a 99% confidence level using a two-tail student t-test. There is a robust semi-annual cycle over Niño3.4 region, which is not observed in nature but was also noted in CTL model. WBtoWB present some bias with respect to the truth, but this is much smaller than those from CTLtoWB and are statistical insignificant. Note that the systematic error of CTLtoWB model increases with lead-time, but the boreal spring season appears to be the most problematic for this model, with the exception of those forecasts initialized in March (Fig. 8 top-left). Even thought CTLtoWB reproduces the general evolution of the “truth” SST, the amplitude of the seasonal cycle is on the order of 0.5°C cooler. As discussed in section 5.2.1.2, this is generally due to the warming effect of WWBs activity, but why this is so much larger than the differences in the two long simulations remains unclear. Here, the systematic bias in the seasonal cycle is removed just like in the previous chapter before interannual
predictability is analyzed.

Figure 5.12 Mean annual cycle of SST for the Niño3.4 region for each of the four ICs. WB model “truth” is shown by grey bars, where CTLtoWB (WBtoWB) is depicted by red (blue) line. Filled circles denote where the forecast mean for that given month is statistically different than “truth” to a 99% confidence level using a two-tail student t-test.

5.2.2.3 Interannual variability

In this subsection we are examining how well the interannual variability is forecasted by the models. Figure 5.13 depicts hindcast evolution for the four different initial conditions, only showing 14 of the total 30-years worth of forecasts. Niño3.4 SSTA (°C) are shown on the top portion of each panel and labeled on the left vertical axis. A horizontal dashed line marks the 0°C anomaly. The ensemble mean forecast are given by thick lines where each ensemble member is given by thin lines. A WWBs index is depicted in the bottom of each panel and labeled on the right vertical axis (dynes/cm²). For the truth, this is shown as black thick line whereas for the ensemble mean WWBs for forecasts are
depicted as blue bars. Before describing Fig. 5.13 we remind the reader that there are no WWBs events in CTLtoWB. For all ICs, the 14-year span corresponds to the same period (e.g., January 1563 to December 1576 of model year).

CCSM3 has rich and diverse interannual variability with the WWB parameterization included (see Chapter 3). This can be seen by the 14 years period that includes persistent warm anomalies (e.g., years 1563-1566) that are considerably longer than the ENSO period itself in the control version of CCSM3. This period shows significant WWBs activity throughout (thick-black line). A vigorous oscillatory period with fast change from warm-to-cold events (e.g., years 1566-1572), this shows intense but relatively periodic WWBs activity (thick-black line). There is also a relatively quiescent period (e.g., year 1572-1576), where WWBs are still present but with less amplitude than during the previous two. It is evident that ENSO growing phases are well forecast by the ensemble means from both CTLtoWB (red) and WBtoWB (blue). The two models appear to perform better during the strong oscillatory period mentioned earlier, this is especially true for JUN and SEP ICs. This is often during the growing phase of a significant event. During these strong oscillation periods, the MAR ICs are not picking up the maximum amplitude of the events, and there is considerably large ensemble spread for both models. This lack of skill for the MAR ICs is compared to those forecasts initialized with JUN and SEP. ICs.

For DEC ICs, the models struggle in terms of capturing the amplitude. This is due in some part to the forecast spring barrier occurring earlier in the forecast. Both models struggle considerably during the persistent warm period (e.g., years 1563-1566). They show significant ensemble spread and a tendency to end this warm anomaly too early,
Figure 5.13 Hindcast evolution for the 4 different initial conditions, only showing 14 of the total 30 year worth of forecasts. Niño3.4 SSTA (°C) are shown on the top portion of each panel and labeled on the left vertical axis. A horizontal dashed line marks the 0°C anomaly. The ensemble mean forecasts are given by thick lines where each ensemble member is given by thin lines. A WWB index is depicted in the bottom of each panel and labeled on the right vertical axis (dynes/cm^2). For the truth, this is shown as black thick line whereas for the ensemble mean WWBs for forecasts are depicted as blue bars. The color scheme is consistent throughout the plot.
this is especially true late and/or early in the year. Overall, forecasts initialized in June and September tends to reproduce this warm period with greater accuracy than with the March and December ICs. Surprisingly, forecasts initialized in December appear to capture the quiescent period (e.g., year 1572-1576). For MAR, JUN, and SEP ICs, there is a tendency for the models to produce larger anomalies than the truth along with significant spread in the forecast. There is significant agreement, at least in the ensemble mean WWBs, as to when high WWBs activity is produced. That is, the ensemble mean WWBs realization is picking up the deterministic component of these events.

a. Deterministic forecasts skill

This sub-section compares the deterministic skill of CTLtoWB to WBtoWB. Similar to Fig. 5.13 from the last subsection, Fig. 5.14 presents Taylor diagrams depicting statistical comparison of interannual forecast skills of Niño3.4 SSTA for the different initial conditions given at the top-right of each panel. All statistics shown are based on entire the 30 year hindcast period. For both models, the forecasts are better for JUN and SEP ICs with DEC ICs being the worse. For the later, the anomaly correlation and standard deviation are the worse. Interestingly, forecasts initialized in September appear to have the least spread in these skill metrics (measured by the distance among members). The spread in the skill metrics is largest for MAR ICs. Overall, the ensemble mean forecast for CTLtoWB and WBtoWB underestimate the variability of the truth, this is expected due to ensemble averaging. WBtoWB consistently outperforms CTLtoWB model. Individual ensemble members do reproduce Niño3.4 variability better than the ensemble mean and again this tends to be better with WBtoWB as predictor. In contrast, the forecast ensemble mean tends to outperform individual members in describing the phase
of Niño3.4 anomalies described by the correlation index. Overall, the forecasts ensemble mean is a better measure of the truth and WBtoWB consistently outperform CTLtoWB as predictors of interannual variability in WB model. This appears more clearly for forecasts initialized in March and December.

Figure 5.14 Taylor diagram depicting statistical comparison of interannual forecast skills for the different initial conditions. Solid black dot represent truth. Open circles represent forecast ensemble members whereas closed circles shows the ensemble mean for CTLtoWB (red) and WBtoWB (blue). Standard deviation (°C) is measure as the radial distance from the origin and is labeled in the x and y-axis. Zero-lag correlation is measured by the radially pointing dashed lines labeled by the semi-circular axis. The concentric green circles measure the root mean square error (°C) with respect to truth.

Figure 5.15 shows time-longitude cross-sections along the equatorial Pacific of root mean square error RMSE (A), saturation RMSE (B), forecast ensemble spread (C),
and forecast correlation (D). These correspond to MAR and JUN ICs. The y-axis labels correspond to forecasts lead times in months. Note that for MAR ICs, CTLtoWB has slightly faster RMS error (panel A) growth as that of WBtoWB, this is especially true over the central Pacific. Also, the RMSE amplitude is larger for CTLtoWB, which goes along with larger error saturation (panel B). This is best observed in Fig. 5.17a where the ratio of saturation RMSE of CTLtoWB over WBtoWB is about 1.5, or 50% larger error for CTLtoWB early in the forecast period. There is significantly more spread in WBtoWB (panel C), but the spread in this model has a similar structure to its RMSE (panel A). This is no true for CTLtoWB, where the spread is geographically different and consistently smaller than its RMSE. This suggests that WBtoWB is “well calibrated” in the sense that the spread and RMSE are similar in structure and amplitude. As measured by the anomaly correlation (panel D), WBtoWB have similar skill than CTLtoWB, with the former having slightly higher correlation over the western and central Pacific. This is best described by the differences (i.e., CTLtoWB minus WBtoWB) in anomaly correlation squared shown in Fig. 5.17b.

For JUN ICs in Fig. 5.15, the differences in RMSE, saturation RMSE, and anomaly correlation between the two models are subtle, whereas WBtoWB still show significant more spread than CTLtoWB. There is a hint of significant forecast errors late in the forecast period (e.g., lead of 10-12 months), this is observed by significant low correlation and near error saturation values (panels D and B respectively). These lead times correspond to the months from March to May of the following year; therefore, it is likely to be related to the spring barrier. As compared to MAR ICs, forecasts initialized in June have higher deterministic skill at lead times less than 10 months.
Figure 5.15 Time-longitude plot across the equatorial Pacific of root mean square error RMSE (A), saturation RMSE (B), forecast ensemble spread (C), and forecast anomaly correlation (D). These correspond to March and June initial conditions. Panels (A) and (C) has units of °C, whereas (B) and (D) are unitless. The y-axis labels correspond to forecasts lead times in months.

Figure 5.16 Same as Fig. 5.15, but for September and December initial conditions.
Figure 5.17 Time-longitude plot across the equatorial Pacific of a) ratio of saturation RMSE (CTLtoWB) divided by saturation RMSE (WBtoWB). Column b) show differences in anomaly correlation squared (CTLtoWB minus WBtoWB, black contour), differences in correlation that are 95% significant are shaded.

To analyze the remaining two ICs, Fig. 5.16 show similar statistics as those from Fig. 5.15 but for SEP and DEC ICs. Forecasts initialized in September have high skill throughout the first 6 months lead-time. Beyond February, there is a sharp increase (decrease) in RMSE (correlation) for both models. As with June initialization, the two
models have comparable skill in term of anomaly correlation. WBtoWB performs better over the central basin in terms of the RMSE, but both models reach near-saturation error values of 0.9 at lead times greater than 6 months. The saturation RMSE ratio of CTLtoWB over WBtoWB is about 1.5 for lead-times from 2 to 7 months (Fig. 5.17a). Differences in anomaly correlation present slight improve spring season for WBtoWB with respect to CTLtoWB (Fig. 5.17b). As with the MAR and JUN ICs, WBtoWB has higher ensemble spread, but this is actually closer to the RMSE value than for the CTLtoWB model. Considering the DEC ICs, the predictability barrier appears very early in the forecast period (lead of 3 months). Here, CTLtoWB does the poorest job as measured by the RMSE, saturation RMSE, and correlation. The RMSE has a strong tendency to increase along with some error saturation over the western Pacific in the CTLtoWB case. The anomaly correlation (panel D) for CTLtoWB shows a large region of near zero values that persist until about lead-time 9-month over the central Pacific. This unskillful region is almost absent in WBtoWB, where correlation drop is not as dramatic. This is best seen in Fig. 5.17a and b in term of saturation RMSE ratio and difference in anomaly correlation squared. Overall, WBtoWB shows considerable improvement based on those measures for the entire Pacific basin, from February to June. Despite the fairly large ensemble spread in WBtoWB, this model appears to improve significantly the issues with the forecasts spring barrier for hindcasts initialized in December. Interestingly, forecasts initialized in June and September still presents such barrier in both models, this is not as clear for those forecasts started in March since the ICs coincide with the spring barrier itself.
Figure 5.18 Deterministic forecasts verification for each initial condition as a function of lead-time (months) for Niño3.4 SSTA. Showing root mean square error RMSE (A), saturation RMSE (B), forecasts ensemble spread (C), and anomaly correlation (D). Panel (E) shows standard deviation of WWBs index (area average from 140E to 180 longitude and 5S to 5N latitude), this is taken as the ensemble mean of WB3toWB3 (blue) and the truth (black). Units are $[^\circ C]$ for panels (A) and (C) and [dynes/cm$^2$] for panel (E), panels (B) and (D) are unitless.
To assess the seasonality in forecast skill further, Fig. 5.18 shows in the same format as Fig. 5.6, deterministic verification for Niño3.4 SSTA forecasts for each initial condition as a function of lead-time. For all skill metrics WBtoWB performs better, especially for December and March initial conditions. For MAR ICs, the low WWBs variance season occurs early in the forecast (panel E). For December initialization, the WWBs variance is at its maximum early in the forecast period, and then it reaches a minimum at about 5-months lead-time. There is some indication that WWBs forcing might be present in the ICs so that it has an impact on forecast skill. Given this, it appears that there is a preferred season where the prediction system is more susceptible to WWBs forcing. Interestingly, the forecasts skill of the two models (with and without WWBs) does not improve nor worsen for forecasts initialized in June or September. This might suggest that the presence/absence of WWBs semi-stochastic forcing does little to modify Niño3.4 SSTA predictability for those ICs months. Another interesting aspect in Fig. 5.18 is that it appears that error growth is the fastest for forecasts initialized earlier in the calendar year. This is detected by the relatively large RMSE, saturation RMSE and spread at lead 1 month for MAR and JUN ICs as compare to those from SEP and DEC ICs.

The fact that the forecast SPB is more pronounce for warm events in this model and that prediction system that includes WWBs tends to reduce it suggests that WWBs may be an important component of the SPB. As before we assess the deterministic forecasts skill of the model separately for warm and cold events. Figure 5.19 describes the RMSE (solid lines) and saturation RMSE (dashed lines) for CTLtoWB (red) and WBtoWB (blue) forecast. The left (right) column represents El Niño (La Niña) events.
RMSE units are $^{0}\text{C}$, whereas saturation RMSE are unitless. We discuss the RMSE and the anomaly correlation (Fig. 5.20) together. The following is noted from Figs. 5.19 and 5.20:

- **MAR ICs:** Both models show high RMSE (Fig. 5.19) at short lead-times but the saturation error growth plateau at little above 40% saturation. While differences in skill between CTLtoWB and WBtoWB are minor for cold events, the WBtoWB forecasts have about 10% better skill at predicting warm events based on saturation RMSE and anomaly correlation.

- **JUN ICs:** Saturation RMSE (Fig. 5.19) remains low until 9-months lead for both warm and cold phases. Beyond this point, the forecast experiences rapid error growth and a significant drop in anomaly correlation (Fig. 5.20) leading to error saturation for CTLtoWB at 12-month leads for warm events. WBtoWB is the more skillful model in terms of saturation RMSE (Fig. 5.19) and anomaly correlation (Fig. 5.20) with about 10% less error than CTLtoWB model.

- **SEP ICs:** Here, the forecast skill measured by RMSE and anomaly correlation remains high up until lead-time 6-month (February verification month). For cold events, both models have similar skill up to 8-month leads with CTLtoWB performing slightly better beyond that lead.

- **DEC ICs:** There is a rapid loss in forecast skill at relatively short lead-times (i.e., less than 6-month). This is especially true for warm events and more notable for CTLtoWB where error saturates at around 6 months into the forecast. For warm events, WBtoWB forecast outperform CTLtoWB during
this period themed spring forecast barrier. Interesting, WBtoWB skill remains relatively large throughout the 12-month period with much less apparent spring forecast barrier for warm events.

**Figure 5.19** RMSE (solid) and saturation RMSE (dashed) for CTLtoCTL (red) and WBtoCTL (blue) for Niño3.4 SSTA. RMSE has units of 0°C, saturation RMSE are unitless.
Figure 5.20 Anomaly correlation for CTLtoWB (red) and WBtoWB (blue) as a function of forecast lead-time.

Some other general points are noted from Figs. 5.19 and 5.20. The cold phase tends to be more predictable than the warm phase, especially for forecasts evolving during the boreal spring. This is contrasting with results from section 3, where the opposite was observed. There is significant forecast skill improvement in WBtoWB for
warm events particularly during the boreal spring. Even though, forecast skill drops significantly during the SPB, they appear to recover for both models.

b. Probabilistic forecasts skill

The probabilistic skill of the forecasts models is assessed in terms of the ROC score described in section 5.1.3. Figure 5.21 shows the ROC curve for each ICs at lead time 6 months. Forecasts initialized in June have the highest ROC score with most points clustered by the upper-left corner. On the other hand, December initialization shows the least probabilistic skill, especially for CTLtoWB with ROC curve much closer to the diagonal. Here, WBtoWB shows significantly more skill with higher hit rates and lower false alarm rates than CTLtoWB for both ENSO phases. Note that the forecast skill of warm events is larger than that of cold events (~10%) if a significant number of (e.g., 3 or more out of 5) ensemble members forecast the events. The opposite (~10% higher probabilistic skill for cold events) occurs if only a few (e.g., 2 or less out of 5) ensemble members forecast the event. A ROC curve is calculated for each grid-point of Niño3.4 region (i.e., about 612 curves); therefore, it is possible that these 10% differences in skill score are robust.

A possible explanation for the phase asymmetry in forecast skill with increased ensemble size is that the statistics of WWBs are better represented as the number of ensemble members issuing a correct warning increase. That is, the higher the number of ensemble members forecast the event, the higher the probability of depicting the statistics of WWBs by the prediction system. Please recall that the state-dependent WWBs parameterization comprises of a deterministic (i.e., SST anomaly dependent) and a stochastic (i.e., random) component. Therefore, ensemble averaging will increase the
relative importance of the deterministic component to that of the stochastic component as the ensemble size increases. This could explain why the hit rates are larger for warm events, which by design typically have more WWBs activity than cold events. As the number of ensemble members issuing a warning decreases, the stochastic component of WWBs parameterization may become more important relative to the deterministic component, introducing errors due to the random component of WWBs as the forecast evolves. For MAR ICs, WBtoWB has slightly better probabilistic skills than CTLtoWB, more so for cold events. This is somewhat of a surprise since there is only weak WWBs activity during cold events. Differences for SEP ICs are subtle.

Figure 5.21 ROC curve for each ICs at lead time 6 months. CTLtoWB (WBtoWB) warm events are shown by solid red (blue) lines and cold events are shown by dashed red (blue) lines. The numerical values given in the legend corresponds to the area under the curve.
Figure 5.22 Area under the ROC curve, or just the ROC score index for each of the ICs as a function of forecast lead-time for warm (solid) and cold (dashed) events.

Figure 5.22 depicts the area under the ROC curve, or just the ROC score index for each of the ICs as a function of forecast lead-time for warm (solid) and cold (dashed) events. Overall, the ROC score remains above 0.6 for during the forecast period, suggesting good probabilistic skill throughout. For MAR ICs, WBtoWB is more skillful and well separated from CTLtoWB for both phases. This can be detected by comparing the solid blue with the solid red and the dashed blue with the dashed red line. Also, for MAR ICs, the 1-month lead score is already less than 0.9 for all cases, this is consistent with considerable large deterministic forecast error at short leads. For JUN ICs, the skill of cold events is considerably larger than for warm events, especially at lead-times
shorter than 8-months corresponding to boreal winter. Both models have similar skill score for forecasts initialized in September independent on the ENSO phase. For DEC ICs, WBtoWB has better skill than CTLtoWB for both warm and cold phases. This is consistent with deterministic verification and it is somewhat a surprise in that the WWBs are highly skewed toward warm events.

5.3 Model dependence

More recent versions of CCSM have a more realistic ENSO. Here we examine how a more recent version of CCSM (i.e., CCSM4) impacts our results. We focus on the forecast initialized in December, as these are the most affected by the WWB parameterization. The CCSM4 experiments are at lower resolution (i.e., 4x5° atmospheric resolution), this was chosen based on computational constraints. The aim of this section is not to make model-to-model comparison, but to examine whether the differences observed among experiments are model dependent.

Results from real prediction experiments using observed ocean state, as initial conditions for verification are also included. This is motivated by the fact that WWBs do occur in nature and we want to test the results from our idealized prediction experiment. Also, we intend to test if the WWBs parameterization could lead to improvement of real ENSO predictions. For this, CCSM3 control (i.e., CTLtoOBS) and CCSM3+WB (i.e., WBtoOBS) models are used to predict observed SSTA. The prediction experiment comprises of 6 ensemble members and the forecasts are initialized in 01 January from 1982 to 1998. Each forecasts covers 12-month period. CCSM3 is run with the same resolution as those experiments presented in the previous sections.
The saturation RMSE error is chosen to quantify deterministic forecasts skill given that it describes a normalized RMSE, which simplifies comparisons among the prediction systems. Saturation RMSE as function of lead-time is depicted in Fig. 5.23 for observed (a), CCSM4 control (b), CCSM4+WB (c), CCSM3 control (d), and CCSM3+WB (e) as predictands. Forecasts of observed SSTA were initialized in January, whereas for CCSM3 and 4 forecasts were initialized in December. Persistence forecasts are shown in grey, control model as predictor (red), and WB model as predictor (blue). Horizontal dashed line corresponds to error saturation. Overall WBtoOBS (a) is more skillful than CTLtoOBS (a), this is consistent with panels (c) and (e) and the previous sections suggesting that the WWBs parameterization improves Niño3.4 SSTA prediction by about 20% in term of saturation RMSE. Forecasts ensemble spread are also increased by inclusion of state-dependent WWBs (not shown); this is particularly important in terms of forecasting probabilities. WBtoCTL CCSM4 (Fig. 5.23b) is the only case where WWBs inclusion degrades forecast skill. Interestingly, CCSM4+WB (Fig. 5.23c) appears to have higher predictability with lower saturation RMSE values than any other case. Overall, there is some model sensitivity, but it is clear the inclusion of the WWB parameterization improves the predictability metrics used here independent of model formulation.
Figure 5.23 Saturation RMSE as function of lead-time observed (a), CCSM4 control (b), CCSM4+WB (c), CCSM3 control (d), and CCSM3+WB (e) as predictands. Forecasts of observed SSTA were initialized in January, whereas for CCSM3 and 4 forecasts were initialized in December. Persistence forecasts are shown in grey, control model as predictor (red), and WB model as predictor (blue). Horizontal dashed line corresponds to error saturation.

One issue we should look into is if our models are well calibrated. In this context, a well-calibrated system is one that the “truth” lies inside the plume of the forecasts. It is assumed (although it remains to be verified) that CTLtoCTL and WBtoWB are always
inside the plume because there is no model error, whereas CTLtoWB and WBtoCTL have implied model errors and the truth might lie outside the plume. For this, Fig. 5.24 shows forecast of Niño3.4 SSTA (°C) at lead-time 6 months for the entire forecast period. Top panel shows CCSM3 control as “truth” (black) with CTLtoCTL (red triangles) and WBtoCTL (blue triangles). Bottom panel shows CCSM3+WB as “truth” (black) with CTLtoWB (red triangles) and WBtoWB (blue triangles). All forecasts were initialized in December and verified in May, which corresponds to a lead-time of 6-months. Only the DEC ICs are analyzed here as WWBs have the largest impact in ENSO predictability for this case. It appears that both CTLtoCTL and WBtoCTL predictor systems are well calibrated for CCSM3 model as “truth” (Fig. 5.24 top). There is only one forecast period where all ensemble members of both models fail to capture the event (i.e., for year 1570). Only one other event appears to be poorly calibrated (1547), but only for WBtoCTL. Both of these poorly calibrated cases are cold events. The fairly good calibration is somewhat surprising in that it is reasonable to speculate that the WBtoCTL forecasts would be poorly calibrated since the predictions and truth are drawn from different systems.

The calibration for CCSM3+WB as “truth” (Fig. 5.24 bottom) is in contrast with the above in that there are several periods where the forecast plume of CTLtoWB model fails to encompass the “truth”. For example, the forecast for model years 1553, 1554, 1556, 1557, 1560, 1561, 1567, 1572, 1575, 1576, 1577, 1578, and 1580 all fail to surround the “truth.” Therefore, it can be said that CTLtoWB is not a well-calibrated forecast system. There are just a few examples where WBtoWB forecast plume fail to include the “truth”, such as model years 1572, 1575, 1576, and 1578. As a caveat here,
we should note that larger ensemble sizes should improve the calibration for CTLtoCTL and WBtoWB, but this is not obviously the case for CTLtoWB and WBtoCTL. Indeed, the results for CTLtoWB suggest that additional ensemble members are unlikely to improve the calibration.

**Figure 5.24** Forecast verification of Niño3.4 SSTA (°C) at lead-time 6 months for the entire forecast period. Top panel shows CCSM3 control as “truth” (black) with CTLtoCTL (red triangles) and WBtoCTL (blue triangles). Bottom panel shows CCSM3+WB as “truth” (black) with CTLtoWB (red triangles) and WBtoWB (blue triangles). All forecasts were initialized in December and verified in May, which corresponds to lead-time 6-months.
Figure 5.25 Same as Fig. 5.24 but for CCSM4

Model calibration is also tested for those forecasts from CCSM4. Figure 5.25 looks at forecast verification of Niño3.4 SSTA (°C) at lead-time 6 months for the entire forecast period, similar to Fig. 5.24 but for CCSM4. For CCSM4 control as “truth” (Fig. 5.25 top), there are a few examples where the forecast plume of CTLtoCTL (e.g., 1617, 1624, 1625, 1630, 1634, and 1638 model year) fails to include the “truth”, similarly for WBtoCTL (e.g., 1616, 1619, 1624, 1630, 1631, and 1634 model year). This is in contrast with CCSM4+WB as “truth” (Fig. 5.25 bottom), where both forecasts systems (i.e., CTLtoWB and WBtoWB) are well calibrated, with a few exceptions. Also note that for
this case, the Niño3.4 SSTA are considerably larger than those from control CCSM4 (Fig. 5.25 top) and those from CCSM3 models (Fig. 5.24). These results are also consistent with the considerably enhanced predictability for CCSM4+WB (e.g., Fig. 5.23) with respect to the other cases.

5.4 Boreal spring prediction barrier

The seasonality of predictability of tropical Pacific SSTA is often related to (i) the seasonality of SSTA variance (i.e., signal) to that of stochastic (noise) forcing, or (ii) to the seasonality of the air-sea coupling strength. The low signal-to-noise ratio (SNR) during the boreal spring limits the predictability through that season. It has been shown that error growth due to spring prediction barrier (SPB) depends remarkably on the ENSO phase with El Niño phase yielding a more prominent spring prediction barrier than for La Niña phase.

Here we examine on the source of seasonality of forecast skill for our real forecasts with CCSM3 and our idealized forecast with CCSM3 and CCSM4. For this, we concentrate on the evolution of the SNR in the presence of state-dependent WWBs during the forecast period and its role on the lost of predictability during boreal spring. We use the definition of the signal and noise from Chapter 2, where the signal is defined as the square of the ensemble mean and noise as the mean square of the deviation from the ensemble mean (see equation 2.3). The ensemble mean is defined by compositing extreme events (e.g., warm or cold events) from the truth, not the forecasts.

Figure 5.26 shows composite of SNR of zonal wind stress (left-column) across the equatorial Pacific and Niño3.4 forecast anomaly correlation (right-column) for the truth given by real forecast with CCSM3 (a), idealized CCSM4 control (b), idealized
CCSM4+WB (c), idealized CCSM3 control (d), and idealized CCSM3+WB (e). Composites are defined by December-January-February (DJF) Niño3.4 SSTA with forecast lead-time increasing up the page. Most of the relative high SNR in zonal wind stress occurs over the Niño4 region (i.e., 160E to 150W), this is west of the maximum SSTA located over Niño3.4 (i.e., 170W to 120W). It comes as no surprise that the temporal evolution of high SNR is similar to SSTA evolution for ENSO events (not shown), with SNR peaking from June to January of the following year. This period is associated with the growth phase of ENSO events. From Chapter 2, it was found that the zonal wind stress noise over the western and central Pacific has a large state-dependent component. In contrast, most of the noise over the eastern Pacific was state independent, which is associated with very low SNR (e.g., Fig. 5.26). The springtime (e.g., February-to-May) SNR minima are more pronounced for observation and the CCSM3+WB model (i.e., Fig. 5.26a and 5.26d). Significant WWBs (not shown) activity occurs during winter and early spring in CCSM3+WB and CCSM4+WB, consistent with the observed climatology of these wind burst (Fig. 3.2), which, at least partially explains the low signal to noise ratio.

The time evolution of SNR corresponds to the forecast anomaly correlation (Fig. 5.26 right-column) for each case. There is a considerable drop in anomaly correlation for those forecasts extending to the spring and this drop in deterministic skill is more pronounced for the CCSM3+WB “truth” (Fig. 5.26e) and observed (Fig. 5.26a). That is, WWBs activity in the “truth” enhances the spring barrier for these two cases. This is not the case for CCSM4 model as “truth” (Fig. 5.26c). The parameterized WWBs in CCSM4 render the SNR in the model unrealistically high with little seasonality. This causes
CCSM4+WB to be considerably more predictable than the remaining “truths”. Forecast skill (both deterministic and probabilistic) is enhanced if the prediction system (i.e., WBtoWB and WBtoOBS) includes WWBs, this is best noted for forecasts that evolve through the SPB.

Figure 5.26 Composite of signal-to-noise ratio of zonal wind stress (left-column) across the equatorial Pacific and Niño3.4 forecast anomaly correlation (right-column) for the
truth given by observed (a), CCSM4 control (b), CCSM4+WB (c), CCSM3 control (d), and CCSM3+WB (e). Composites are defined by December-January-February (DJF) Niño3.4 SSTA. Forecast lead-time increases up the page.

CCSM4 control (Fig. 5.26b) shows some seasonality in the SNR with high (low) values late (early) in the calendar year. Similar to CCSM3, most of the high SNR occurs over the Niño4 region. The largest drop in anomaly correlation (Fig. 5.26b) occurs during periods of significant reduction in SNR. For CCSM4+WB, there is little seasonality in SNR (Fig. 5.26c) with ratios greater than 1 throughout the western Pacific. This is consistent with the considerably smaller drop in forecasts skill even for persistence at any lead-time. It appears that the addition of WWBs on CCSM4 renders the system more predictable because there is a considerable increase in the signal as oppose to the noise added by the stochasticity of these WWBs. In comparison to observations, this appears to be unrealistic and underscores the point that predictability estimates are model dependent and strongly related to the fidelity of the model.

It comes as a surprise that inclusion of WWBs does not hurt/help the skill of forecasts if the “truth” lacks these wind events. This is clearly shown in Fig. 5.26d by the similar evolution of anomaly correlation. The forecast skill recovers after the boreal spring low, which is consistent with increased SNR thereafter. The overall message from Fig. 5.26 is that forecasts skill score of Niño3.4 SSTA are greatly affected by SNR in zonal wind stress. But, there is room for improvement if the predictor system can capture the overall statistics of WWBs activity as seen in Fig. 5.26a and Fig. 5.65e. This is also true for CCSM4 (Fig. 5.26c), but this case is unrealistic (e.g., compare panels a and c) due to little seasonality in the SNR in this case.
5.5 Forecast skill of extreme event

Thus far, the predictability of the various models presented here has been assessed based on statistical techniques, including deterministic and probabilistic methods. Whereas, we examined how the WWBs affect extreme events in chapter 4. Here we assess how the WWBs affect the predictability of extreme events. Indeed, can we assess whether extreme events are more predictable with WBtoWB compared to all the other combinations. For this, we look at specific warm events and its corresponding forecast evolution with and without WWBs parameterization. Here, we select a warm event that has significant WWBs activity similar to what was observed in the 1997/98 El Niño event. The motivation for this is that the real system (nature) has WWBs most forecast systems do not. This is similar to what it is done in this section where CTLtoWB is compared to WBtoWB.

Figure 5.27 describes time-longitude plot of a particular warm event SSTA (shaded) and WWBs (thick-black contours) evolution for MAR ICs. The truth or WB is shown in a), CTLtoWB forecast ensemble mean in b) and WBtoWB in h). The 5 ensemble members for CTLtoWB are depicted from c) to g) and those from WBtoWB are depicted from i) to m). The warming for this event begins during early boreal spring and is associated with WWBs activity Fig. 5.27a. The strongest SSTA are mostly located over the central Pacific, emerging in late boreal summer and lasting into the following year. This event is very typical for CCSM3 with smaller anomalies over the eastern Pacific. In terms of the ensemble mean, CTLtoWB and WBtoWB do a poor job at capturing this event. The anomalies are considerably weaker than the truth, although there is slight improvement for the ensemble mean WBtoWB case. As expected (i.e.,
comparing an ensemble mean to a single realization), the ensemble mean WWBs are considerably less intense than for the truth. On the other hand, we note that at least one (Fig. 27k) and arguably (Fig. 27m) of the ensemble members for the WBtoWB case include the “truth” as a possible realization. This is possibility is only marginally included in the CTLtoWB forecasts (Fig. 27f).

![Diagram](image)

**Figure 5.27** Time-longitude plot of warm event SST anomaly (shaded, °C) and WWBs (thick-black contours for 1, 2, and 3x10^{-2}Nm^{-2} levels) evolution for March ICs. The truth or WB is shown in a), CTLtoWB forecast ensemble mean in b) and WBtoWB ensemble mean in h). The 5 ensemble members for CTLtoWB are depicted from c) to g). The 5 ensemble members for WBtoWB are depicted from panels i) to m).

Similar to Fig. 5.27, Fig. 5.28 describes the evolution of the same warm event but for JUN ICs. This event appears to persist through the boreal winter into the following spring (Fig. 5.28a). Significant WWBs activity is associated with strong SSTA that propagate eastward during December-January-February (DJF). The ensemble mean
forecasts (Fig. 5.28b and h) are considerably better than those from MAR ICs, especially at shorter leads up to DJF. Then, the forecasts terminate the event too early, more so for CTLtoWB where cold anomalies emerge beyond March. WBtoWB does have some of the observed WWBs activity but this did not translate into a much-improved forecast. For the WBtoWB forecasts, a few ensemble members extend the warm event into the subsequent boreal spring as the truth. In contrast, all CTLtoWB members terminate the event too early and follow with a cold event.

**Figure 5.28** Same as Fig. 5.27, but for June ICs.

In the same format, Fig. 5.29 shows the forecast evolution for SEP ICs. As before, the ensemble mean forecasts tend to terminate the event during the boreal spring season, whereas the SSTA of the truth are considerably positive up to the boreal summer. The WBtoWB forecast appear to be closer to the truth SSTA than CTLtoWB, but the WWBs
cease during boreal spring as the forecast transition too early into cold events. There are few exceptions, e.g., j) and m) of WBtoWB where the warm SSTA survives through the spring season, but is considerably smaller than the “truth.” These two members are characterized by some WWBs activity during that spring season.

![Figure 5.29](image)

**Figure 5.29** Same as Fig. 5.28, but for September ICs.

The forecast evolution for DEC ICs is shown in Fig. 5.30. The warm event terminates in boreal summer (Fig. 5.30a), approximately lasting for 18 months. The ensemble mean forecast for CTLtoWB (Fig. 5.30b) shows a rapid termination of the warm event followed by a moderate cold event. This is a forecasts bust in term of ENSO phase. Similarly, most ensemble members of this experiment predict a sudden phase change. The forecasts are in better agreement for the WBtoWB experiment. Here, the ensemble mean forecast (Fig. 30h) extends the warm SSTA up to the boreal summer even
though the amplitude is considerably smaller than the truth. Significant WWBs activity causes the warm event to extend further into the forecast period. It is remarkable how strong the tendency is for the model to make the transition to cold SST anomalies, more so for CTLtoWB prediction system.

**Figure 5.30** Same as Fig. 5.27, but for December ICs.
Chapter 6

Summary and discussion

For the past several years, there has been strong debate as to whether the coupled tropical Pacific climate system, and more so ENSO are modulated by atmospheric “weather” noise forcing. Weather noise is hypothesized to be responsible for the irregularity of ENSO and the loss of predictability, and in the case of WWBs, to be responsible for extreme events. This issue has inspired the author to develop a frame of work in order to study the role, if any, that weather noise plays in sustaining/modifying/modulating ENSO and tropical Pacific climate variability and predictability. The methodology used here follows two different approaches. These are: (a) noise is non-phenomenological and can occur on all temporal and spatial scales and (b) noise is phenomenological with specific constrain on its location and spatial-temporal structure. For the first approach, noise was filtered out of the coupled system and its effect studied at different spatial resolution, refer to Chapter 2. For the second approach, WWBs were added to the coupled system as phenomenological stochastic forcing, both state-independent and state-dependent. Its effect on ENSO variability was studied in Chapter 3, ENSO diversity in Chapter 4, and ENSO predictability in Chapter 5. Next, we summarize the overarching results of this investigation and its possible repercussions on future studies.

The first step was to analyze non-phenomenological stochastic forcing at different atmospheric model resolution. This is an important question in that the ocean response depends on the space-time structure of the noise forcing, and the statistics of the noise is likely to be dependent on model resolution. In Chapter 2, a state-of-the-art climate system model, namely CCSM3, was adopted in order to study the effect of weather noise and its
resolution on tropical Pacific variability. The analysis used the interactive ensemble coupling technique to reduce the noise and focused on understanding the impact of the noise without any phenomenological interpretation. In other words, the noise reduction was treated in a purely statistical manner within the context of the coupled model.

Over the tropical Pacific Ocean, the noise reduction has significant impacts almost everywhere in both the mean and the variability. These changes include increased cold bias over the eastern Pacific, closer to observed SST simulation over the warm pool including, the appearance of a SST plateau west of 160E longitude, an observed feature that is not simulated on the control simulations. One of the systematic errors of this model is the warmer than observed SST off the South American coast, this is also reduced by the noise reduction. These results are more marked with the higher resolution case. The improvements noted above should not be interpreted as an argument for using the IE technique for direct model improvement. This is merely a diagnostic that suggests that the AGCM noise may be too strong in these particular regions.

We analyzed the variability of SST, zonal wind stress, and precipitation anomalies. Variance ratios between IE and control cases suggest that noise is more important in forcing tropical Pacific variability as resolution increases. From both resolutions, noise appears to play no role in the ENSO period, at least for this particular model. Noise does impact the PDF of ENSO. For example, in the absence of noise, the PDF becomes more peaked toward the mean. ENSO phase locking to the annual cycle is also modified by noise reduction.

This study along with many studies listed earlier hints at the importance of atmospheric internal variability in producing ENSO irregularities. The irregularity among
ENSO events was studied using two different approaches here. First, we separately quantified differences among warm events and differences among cold events. It was observed that both control simulations depicted similar and significant spread for the El Niño as the events evolved during the calendar year. Reducing the noise reduces the spread of events, especially for the higher resolution case where most events evolved similarly. For the La Niña phase, the higher resolution control model shows the most irregularity among experiments. This irregularity is stronger during late boreal spring, which corresponded to significantly stronger zonal wind stress noise forcing. This suggests that most of the event-to-event differences are driven by atmospheric noise as opposed to chaotic dynamics within the context of the large-scale coupled system. Moreover, this also suggests that there is a well-defined “canonical” event in this coupled model.

We also studied ENSO phase asymmetry. The higher resolution control has the most asymmetry, and the higher resolution noise-reduced IE case has the least asymmetry. That is, applying the noise reduction technique had the largest impact in reducing the asymmetry of ENSO at T85 resolution. It was found that the ENSO phase asymmetry is strongly related to the noise forcing. This supports the argument (at least in this model) that the “canonical” warm and cold events are linear and that the observed asymmetry is either associated with differences in the space-time structure of the noise (i.e., non-linearity in the noise) or in the response to the noise (i.e., non-linearity in the response). While the non-linearity in the response to the noise was not examined, it was demonstrate that noise itself is asymmetric, with larger spread in the zonal wind stress during La Niña events. This has repercussions for predictability problems, suggesting that
the cold phase of ENSO may be more difficult to predict given the relatively large amplitude of the noise and the low signal-to-noise ratio. In contrast, El Niño events are noisier when it comes to precipitation. This is no surprise as that the tropical Pacific is more convectively active then. This may suggests that predicting the extra-tropical imprint of ENSO is more difficult for El Niño than for La Niña phase.

Analysis on the zonal wind stress across the tropical Pacific suggested that the spatial structure of the noise start to deviate from the signal as resolution increases. It was found that the signal independent noise was reduced by a factor of 1/6 when the IE technique is applied to 6 atmospheric ensemble members. This effect is independent on model resolution and independent of longitude. In contrast, most of the reduction in amplitude of noise due to reduction in the signal occurred over the warm pool region. This hints at that state-dependent noise on zonal wind stress occurs mostly over the western Pacific, probably associated with enhanced atmospheric convection due to warmer SST. As described in this study, internal atmospheric dynamics is of paramount importance in maintaining tropical climate variability. Moreover, the relative importance of noise varies with atmospheric model resolution. This could have large implications as the community begins to comprehensively address the issue of required model resolution.

In contrast to the interactive ensemble approach, we also chose to investigate the impact of noise from a phenomenological perspective. In this case we added the noise as opposed to removing or reducing in the interactive ensemble case. Chapter 3 focused on WWBs, which were introduced in CCSM3 as state dependent and state independent stochastic forcing. This is the first time that a state dependent and state independent WWBs parameterization has been incorporated into a state-of-the-art CGCM. It was
shown that state independent WWBs had only a minimal impact on the mean state or the interannual variability, while state dependent noise modified both, although the impact on the mean was relatively small. We also tested the parameterization in CCSM4 to assess model dependence.

Perhaps, the most striking result presented here was the fact that the state-independent WWBs had a minimal effect on the overall variability in CCSM3 and CCSM4. This is consistent with Zebiak (1989), using a simplified or intermediate coupled model of the tropical Pacific. Arguably, the biggest impact of the state independent WWBs parameterization was in the number of ENSO events (both warm and cold phases), which appear to be reduced by the inclusion of state-independent stochastic forcing. One possibility for this damping is the interference of this type of noise forcing with existing ENSO events. This is also consistent with dynamical systems theory that adding state-independent stochastic forcing to a chaotic system reduces the variability (Siqueira and Kirtman 2012). Increasing the strength of the state-independent WWBs, leading to further damping, validated this.

CCSM4 is slightly more sensitive to state-independent noise forcing than CCSM3. Whether this difference is due to changes in the physics of ENSO in the model or is related to the reduced resolution remains an open question. The increase in tropical Pacific standard deviation does no translate into increased lag-lead correlation. Correlation at all lags remains consistent with the control case. It is interesting that state-independent noise has little effect on both models. Most of the differences were associated with a slight damping of ENSO in the case of CCSM3 and enhanced variability in CCSM4. This difference is depicted in the standard deviation and lag
correlation analysis. This is consistent for both models, and is consistent with non-linear
dynamical system theory (see Siqueira and Kirtman, 2012) that suggested that variability
of an unstable non-linear chaotic system is reduced in the presence of noise. This
suggests that CCSM3 behaves more like an unstable non-linear chaotic system than
CCSM4.

For the state-dependent case independent of model version (i.e., CCSM3 or
CCSM4), the simulation had more ENSO events relative to control and state-independent
case, and the bias towards more cold events than warm events was reduced. Here, the
number of years with warm or cold events matched those without ENSO, suggesting that
the ocean-atmosphere system in the tropical Pacific shifted from an episodic event regime
to more of an oscillatory regime. We also detected an increase in ENSO amplitude.

Chapter 4 further evaluates the results from Chapter 3 in order to study the effect
of state-independent and state-dependent WWBs on EP versus CP-type ENSO events. It
was found that commonly used Niño3 regional index is a good indicator to quantify EP
ENSO variability. In contrast, commonly used CP indices like Niño4 and EMI appear to
include some EP variability in the models examined here, therefore these indices may not
be able to cleanly separate CP from EP variability. Given this, we used an index, which is
able to linearly remove EP effects over the CP-type events via partial regression and EOF
analysis.

For the control cases (i.e., no WWBs), CCSM3 lacks the observed non-linear
structure in the EP-CP PCs phase space as described in Takahashi et al. (2011), whereas
CCSM4 does capture some aspects of the observed pattern. EP variability dominates CP
for both models. CCSM3 is insensitive when the WWBs are added as state-independent
forcing for both EP and CP events. This is in contrast with CCSM4, where there are some hints of enhanced EP variability. Both models agree in term of state-dependent WWBs. With state-dependent WWBs, the response is largely in the EP events. This suggests that the effect of the WWB parameterization is most readily apparent in thermocline feedbacks as opposed to zonal advective feedbacks, and hence the larger response for EP events. This model result is also consistent with the fact that the very strong 1972-73, 1982-83, and 1997-98 EP El Niño events were accompanied by the strongest WWBs activity on record.

The state-independent WWBs parameterization produces bursts that are equally likely to occur during any ENSO phase. The fact that CCSM3 is insensitive to this type of forcing could be related to the lack of non-linearity in the EP-CP phase space. It could be that CCSM3 only responds to state-dependent WWBs because the parameterization is skewed toward warm events. On the other hand, CCSM4 control already has these non-linear characteristics; therefore it may be more sensitive to both state-independent and dependent noise forcing. These results need further testing with modeling experiments and longer observational records as they become more readily available.

The last step was to study ENSO predictability in the presence of state-dependent phenomenological noise forcing of the form of WWBs. For this, idealized prediction experiments were designed where deterministic and probabilistic skill assessments were used to quantify the effect of state-dependent WWBs on the predictability of ENSO. The model employed here, namely CCSM3 was used as the truth and as prediction system. A set of twin experiments was performed where the forecast skill of the control model is compared to that of CCSM3+WWBs (i.e., CCSM3 with state-dependent WWBs
parameterization), yielding a 2x2 table with four possible cases. Here, the hypothesis whether the presence of WWBs in either the prediction system and/or the truth impacts predictability was tested.

Overall, there is strong seasonality in the predictability of ENSO, consistent with previous studies. This seasonality was presented in terms of not only in deterministic (e.g., anomaly correlation, RMSE, ensemble spread) but also on probabilistic (e.g., ROC score) forecast verification. The skill of the models is strongly dependent on the season of initialization. Forecasts initialized during boreal summer and fall has the highest skill in terms of deterministic and probabilistic measures. This is true independent of the truth (i.e., CCSM3 or CCSM3+WB), where the inclusion of WWBs did not improve nor degrade the forecast skill for these ICs. Forecasts initialized in December and March had a considerable drop in skill at short lead times, more so when the prediction system lacked WWBs.

The predictability analysis was also performed for warm and cold events separately. This is necessary as the WWBs parameterization is state-dependent and therefore skewed towards warm events. When predicting CCSM3 control, the inclusion of WWBs as noise forcing did not improve nor degrade the forecast skill. The cold phase was observed to be less predictable deterministically, but the warm and cold phase has similar probabilistic skill. These results contrast with those from predicting CCSM3+WB. In this case, the cold phase tends to be more predictable than the warm phase, especially for forecasts evolving during the boreal spring. A possible explanation for this discrepancy is that for CCSM3 control, cold events were shown to be noisier than
warm events in the wind stress (see Chapter 2). Whereas, for CCSM3+WB, the added noise by WWBs leads to reduced warm event predictability with respect to cold events.

Most of the forecast skill improvement when WWBs are included in the prediction system for warm events occurs during the boreal spring. Even though, forecast skill drops significantly during this time of the year. It was observed that the SPB is more pronounced for warm events for CCSM3+WB model. The inclusion of WWBs led to enhanced predictability during that season, suggesting that these wind events are an important component in producing the SPB.

How do we understand the effect of WWBs on the SPB? First, there is a significant drop in predictability during boreal spring. This was detected for prediction systems that do not include WWBs. Second, a SNR analysis shows that low (high) predictable seasons are associated with low (high) SNR in the zonal wind stress and that the inclusion of WWBs in the predictor system tends to reduce the loss of skill during the boreal spring (i.e., low SNR) season. Essentially, the argument for the SPB is that the coupled system is more susceptible to errors or noise in the forcing in spring, and if WWBs are completely absent in the prediction system, then the errors are relatively large. Finally, if the prediction system includes WWBs there is some possibility of capturing the statistics of the WWBs and hence reduce some of the errors during spring. WWBs in nature are difficult to predict, and indeed are absent in most prediction systems. So, part of the spring barrier is due to an inability to predict these WWBs.

These results were further validated with the more recent version of this model, namely CCSM4. It turned out that CCSM4, at least with the coarse resolution used here, has a much-reduced seasonality in the SNR and therefore reduced seasonality in the
forecast skill of SSTA. To further test these results, CCSM3 with and without WWBs parameterization were used to make real predictions of observed tropical Pacific SSTA. WWBs are well known to exist; therefore their impact on observed SSTA are imbedded in the initial conditions. Given this, CCSM3 predicting observed SSTA mimics the experiments of CCSM3 predicting CCSM3+WB. It was demonstrated that predictability is enhanced when WWBs were included and these improvements were mostly over the low SNR season. These results were further validated by a case study of a warm event with considerable WWBs activity, mimicking the strong 1997-98 event. It was found that the presence of WWBs in the prediction system enhances the forecast ensemble spread, leading to a more reliable probabilistic forecast. But most importantly, the number of ensemble members depicting the correct “truth” increases considerably. This is best observed for those forecasts progressing through the SPB.

Based on the results presented here, state-dependent WWBs are an important component in modulating ENSO dynamics and thus predictability. The inclusion of these wind events increased the ensemble forecast spread due to its stochastic component. Despite this increase in spread, the forecast skill was improved using both deterministic and probabilistic measures. This validates our hypothesis that the presence of WWBs in either the prediction system and/or the truth impacts ENSO predictability.

The issue of ENSO predictability in the presence of the WWBs parameterization also requires further study. For instance, intuitively one would argue that adding noise to the system should decrease predictability due to increased irregularity of ENSO. However, the increase oscillatory character and power in the state-dependent case enhanced predictability as was shown in Chapter 5. This argues that weather noise is of
paramount importance in sustaining and modifying ENSO variability. Given this, future work will expand on this study. For example state-dependent WWBs parameterization will be included in a prediction system (e.g., CCSM3 or 4) in order to perform predictability experiments of observed SSTA with more diverse initial conditions. Also, the effects of state-independent WWBs on ENSO predictability will be tested and compared to those of state-dependent WWBs presented here. Another important future step is to repeat these predictability experiments with WWBs but using a noise reduced CGCM, like those presented in Chapter 2. This is necessary in that other types of weather noise (e.g., non-phenomenological from Chapter 2) impact tropical Pacific variability and that the effect of WWBs may be blurred by the presence of this non-phenomenological noise. The predictability experiments should be extended to further analyze eastern versus central Pacific ENSO events. The notion of the interactive ensemble as a noise reduction technique can be implemented in further studies of ENSO diversity.

Finally, the results presented in this study suggest that there is potential for ENSO prediction improvement, even if the coupled climate system behaves as a linear stochastically forced system. This is possible if the observed statistics of state-dependent WWBs are captured by the forecast system. These findings have positive implications for future studies, as the climate dynamics community becomes more aware of the role of weather noise in modulating climate variability and predictability.
Appendix

The Westerly Wind Burst Parameterization

A WWBs is defined as a zonal wind anomaly after removing the seasonal cycle that exceeds 5ms⁻¹ amplitude, a zonal fetch greater than 500km, and a lasting from 2 to 40 days. Given this, the zonal wind can be decompose as in (1A) where $\bar{u}$ is the zonal wind climatology, $u'$ represents the zonal wind anomaly not associated with WWBs, and $u_{wb}$ is the zonal wind anomaly associated with WWBs.

$$u_x = \bar{u} + u' + u_{wb}$$  \hspace{1cm} (1A)

It is assumed that WWBs can be modeled by a Gaussian in space and time, (Luther et al. 1983; Fasullo and Webster 2000; Yu et al. 2003; Eisenman et al. 2005). The zonal wind anomalies associated with WWBs are given as

$$u_{wb}(x, y, t) = A \exp \left( -\frac{(t - T_0)^2}{T^2} - \frac{(x - X_0)^2}{L_x^2} - \frac{(y - Y_0)^2}{L_y^2} \right)$$  \hspace{1cm} (2A)

The bursts are a function of temporal and spatial parameters; where A is amplitude, $T_0$ is the time of peak wind, T is the event duration (persistence), $X_0$ and $Y_0$ are the central longitude and latitude, and $L_x$ and $L_y$ are the zonal and meridional fetch. Note that the probability of occurrence of a burst event does not appear in (2A). This parameter is actually used as a trigger for both state independent and dependent WWBs. The only difference is that in the former, the probability is determine based on observed monthly climatology whereas in the later, it is strongly modulated by the low frequency variability of SST. The frequency of occurrence of the burst depends on SSTA in the state-dependent case, but the duration of the events remain constrained to be less than 40 days.
The WWBs state is represented by the following vector (3A),

\[
\mathbf{w} = \begin{bmatrix} A; x_0; y_0; L_x; L_y; T; P \end{bmatrix} \quad (3A)
\]

constructed by the parameters in (2A). In the case of state-dependent parameterization, the WWBs state shown by (3A) can be predicted from SST by

\[
w(t) = S_q(t)\mathbf{W}_{wwb} + \overline{\mathbf{w}}(t) \quad (4A)
\]

where \( S_q \) contains the first \( q \) SST modes at time \( t \). Here, \( q \) is chosen to be 7 based on a statistical robustness test (Gebbie and Tziperman 2008).

The SVD modes of the SST decomposition with the wind stress are projected into the modeled SSTA to obtain projection coefficients, or \( S_q(t) \). These coefficients are then projected into the regression coefficients of each WWB, or \( \mathbf{W}_{wwb} \). The WWB climatology \( \overline{\mathbf{w}}(t) \) is added to this result to account for the observed seasonality dependence. Using the parameters noted above a burst is then constructed following equation 2A. The addition of the WWB climatology is also done in the state-independent parameterization in order to be consistent with observations and with the state-dependent case. Once a wind burst is predicted to occur based on the parameterization (both state independent or dependent), the zonal wind anomaly is interpolated to the ocean model grid and converted to wind stress assuming a constant drag coefficient. The parameterization is applied as the coupled model evolves (e.g. interactively) and it produces a burst structure depending on seasonality (state independent case) and interannual SST structure (state dependent case). In other words, it is a fully interactive parameterization.

It remains to describe how a WWBs is triggered and how it evolves in time. The triggering mechanism makes use of a simple random number \( n \), sampled at every model
time step from a distribution between 0 and 1. A burst is triggered if $P > n$. The mean value of $P$ is set so that it constraint the number of WWBs produced in a year based on observation. For the state-dependent formulation, the probability of occurrence is determined by the underlying SST, but the timing of individual WWBs still contains a stochastic element. The distribution in time of WWBs is determined between the triggering time and the time of peak wind $T_0$. Here, the triggering time is set to occur at $2.5T$ before the peak time, where $T$ is the duration of WWBs. This guaranties a delay between the peak wind and the SST not longer than a month. A peak time that is simultaneous with the triggering time produces only the second half of the WWBs life cycle. Whereas, a peak time that is much later than the triggering time implies a long delay between the WWBs and SST feedback.
Bibliography


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