ENSO Amplitude Changes due to Climate Change Projections in Different Coupled Models

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ABSTRACT

Four climate system models are chosen here for an analysis of ENSO amplitude changes in 4 × CO2 climate change projections. Despite the large changes in the tropical Pacific mean state, the changes in ENSO amplitude are highly model dependant. To investigate why similar mean state changes lead to very different ENSO amplitude changes, the characteristics of sea surface temperature anomaly (SSTA) variability simulated in two coupled general circulation models (CGCMs) are analyzed: the Meteorological Research Institute (MRI) and Geophysical Fluid Dynamics Laboratory (GFDL) models. The skewed distribution of tropical Pacific SSTA simulated in the MRI model suggests the importance of nonlinearities in the ENSO physics, whereas the GFDL model lies in the linear regime. Consistent with these differences in ENSO regime, the GFDL model is insensitive to the mean state changes, whereas the MRI model is sensitive to the mean state changes associated with the 4 × CO2 scenario. Similarly, the low-frequency modulation of ENSO amplitude in the GFDL model is related to atmospheric stochastic forcing, but in the MRI model the amplitude modulation is insensitive to the noise forcing. These results suggest that the understanding of changes in ENSO statistics among various climate change projections is highly dependent on whether the model ENSO is in the linear or nonlinear regime.

1. Introduction

Recent studies have shown that there is considerable observational evidence that decadal variations of the El Niño–Southern Oscillation (ENSO) are part of the natural variability of the tropical Pacific (Trenberth and Shea 1987; Wang 1995; Gu and Philander 1995). Historical and paleoclimatic proxy records also suggest long-term variability in both the frequency and amplitude of ENSO on multidecadal to centennial time scales (Dunbar et al. 1994; Stahle et al. 1998; Mann et al. 2000; Cobb et al. 2003; D’Arrigo et al. 2005). In contrast to the natural low-frequency modulation of ENSO, the strong El Niños of 1982/83 and 1997/98 along with the more frequent occurrences of El Niño during the past few decades have raised the question of whether human-induced “greenhouse” warming impacts ENSO frequency and amplitude (Timmermann et al. 1999; Trenberth and Hoar 1997).

Results from several global climate modeling studies indicate that as global temperatures rise due to increased greenhouse gases, the mean state in the Pacific will shift toward a permanent El Niño–like state with greater relative surface warming in the equatorial eastern Pacific. While the mean state changes in the eastern Pacific are largely consistent among several different models, the changes in the ENSO statistics are quite different. For example, Knutson and Manabe (1995) and Knutson et al. (1997) found modest reductions in the ENSO amplitude in their climate change simulations. On the other hand, recent studies using higher-resolution coupled models project somewhat greater

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amplitude for future El Niño/La Niña events due to a strengthening of the equatorial Pacific thermocline (Timmermann et al. 1999; Collins 2000a). The origin of these differences is unknown and remains a difficult problem, given conflicting theories regarding the relationship between changes in the tropical Pacific mean state and ENSO modulation (see Flügel et al. 2004; Kirtman et al. 2005; Yeh and Kirtman 2005 for a detailed discussion).

To explain the different “climate change–ENSO amplitude” sensitivity in the CGCMs we examine whether the differences in the ENSO sensitivities can be explained by the so-called “null hypothesis” for ENSO (e.g., Flügel et al. 2004). The null hypothesis is that ENSO is accurately described by a linear autoregressive model with damped coupled feedbacks and linear Gaussian white noise forcing. Here, the noise is additive and does not depend on the state of the system. Under this null hypothesis, ENSO amplitude is sensitive to (i) the amplitude of the noise and (ii) how strongly the coupled feedbacks are damped. In this null hypothesis regime, where the linear operator does not change in time, there can be low-frequency modulation in the ENSO amplitude. This low-frequency modulation is directly due to the noise (Thompson and Battisti 2001; Flügel et al. 2004 or Kirtman et al. 2005). Flügel et al. (2004) argued that the observed ENSO resides in the stable linear regime invoking the null hypothesis for ENSO.

The intent of this paper is to examine whether the differences in the ENSO sensitivities in climate change projections can be interpreted within the context of this null hypothesis. We suggest that the climate change–ENSO amplitude sensitivity depends on whether a given model’s ENSO is fundamentally in the linear or nonlinear regime. To demonstrate this point we examine several coupled general circulation model (CGCM) simulations: four control simulations that use preindustrial greenhouse gas concentrations and four simulations using quadrupled CO₂ levels. Detailed descriptions of the CGCMs and experiments will be given in section 2. In the quadrupled (4 × CO₂) experiment, CO₂ increases at 1% yr⁻¹ to a level 4 times that of the present climate. After these 140 yr to quadrupling period, the CGCMs are integrated for an additional 150 yr to examine the long-term response of the climate system, although this may not be enough time for the climate system to reach equilibrium. In the control experiment, there is no anthropogenic or natural forcing for the entire simulation period. For the regime analysis we adopted the concept of the linearity or nonlinearity of ENSO using statistical methods. The reader is referred to Monahan and Dai (2004) regarding the details of this methodology.

2. Model and data

We use the selected CGCM simulations, namely, Model for Interdisciplinary Research on Climate 2, medium-resolution version (MIROC3_2_MEDRES), the Meteorological Research Institute CGCM (MRI_CGCM2_3_2a), the Geophysical Fluid Dynamics Laboratory Climate Model (GFDL_CM2_0), and Goddard Institute for Space Studies Model E-R (GISS_MODEL_E_R) (hereafter, MIROC, MRI, GFDL, and GISS; see Table 1 for references and additional model details). The CGCM simulations are made available by the Program for Climate Model Diagnosis and Intercomparison (PCMDI) Web site (http://www-pcmdi.llnl.gov/ipcc/about_ipcc.php). Table 1 summarizes the description of the preindustrial control run and 1% yr⁻¹ 4 × CO₂ run using the four CGCMs. For documentation and validation of these models see the PCMDI Web site at http://esg.llnl.gov/portal.)

The globally (60°N–60°S, 0°–360°) averaged sea surface temperature (SST) response to the increased CO₂ is shown in Fig. 1. Figure 1 shows a time series of global mean SST of the control experiment (thin) and the 4 × CO₂ experiment (thick) simulated in the MIROC (Fig. 1a), MRI (Fig. 1b), GFDL (Fig. 1c), and GISS (Fig. 1d) models. As noted above, the control experiment has

### Table 1. CGCM experiments used in this study.

<table>
<thead>
<tr>
<th>Model name (center)</th>
<th>Global oceanic resolution (latitude × longitude)</th>
<th>Simulation period</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>MIROC3_2_MEDRES (CCSR/NIES)⁹</td>
<td>192 × 256</td>
<td>Preindustrial control exp</td>
<td>500 yr</td>
</tr>
<tr>
<td>MRI_CGCM2_3_2a (MRI/Japan)</td>
<td>111 × 144</td>
<td>1% (yr CO₂ increase)⁻¹</td>
<td>350 yr</td>
</tr>
<tr>
<td>GFDL_CM2_0 (NOAA⁸ GFDL)</td>
<td>90 × 144</td>
<td>to quadrupling</td>
<td>500 yr</td>
</tr>
<tr>
<td>GISS_MODEL_E_R (NASA⁶ GISS)</td>
<td>46 × 72</td>
<td>290 yr</td>
<td>Hansen et al. (2000)</td>
</tr>
</tbody>
</table>

⁹ CCSR/NIES: Center for Climate Research Studies/National Institute for Environmental Studies.

⁸ NOAA: National Oceanic and Atmospheric Administration.

⁶ NASA: National Aeronautics and Space Administration.
constant CO\textsubscript{2} at preindustrial levels (thin), while in the 4 × CO\textsubscript{2} experiment (thick), CO\textsubscript{2} gradually increases to 4 times the present level over a period of 140 yr, then remains at that elevated level for the additional 150-yr simulation. Most of the global warming in the CGCMs occurs during the CO\textsubscript{2} buildup period, although global SSTs continue to increase slightly even after 140 yr. In the present study, the term “4 × CO\textsubscript{2} experiment” refers to data from the last 100 yr for the 4 × CO\textsubscript{2} experiment. The term “control experiment” refers to the entire period simulated by each CGCM in which there is no anthropogenic or natural forcing with constant CO\textsubscript{2}.

3. Impact of increased CO\textsubscript{2}

a. Mean sea surface temperature changes

Like many aspects of anthropogenic climate change, the future mean state of the tropical Pacific under enhanced greenhouse gases is uncertain. Figure 2 displays the SST changes simulated by four CGCMs (i.e., 4 × CO\textsubscript{2} minus the control). In the 4 × CO\textsubscript{2} experiment, the tropical Pacific SSTs increase by about 3.5°–5.5°C (MIROC), 3.0°–6.5°C (MRI), 1.5°–4°C (GFDL), and 1.5°–3.5°C (GISS), indicating that the climate sensitivity (the equilibrium mean temperature change for 4 × CO\textsubscript{2}) has significant uncertainty. Nevertheless, all the projections agree in the sense that the tropical Pacific warms considerably. All the models also agree that the warming is not uniform, particularly in the region of the equatorial Pacific (5°N–5°S) and the subtropical Pacific. The warming is projected to be large over much of the central and eastern tropical Pacific. The similarity in spatial pattern of three CGCMs (MIROC, MRI, and GFDL) is striking, and, in particular, a mean El Niño–like warming pattern is a prominent feature of all three of these simulations. The GISS model–projected warming is noticeably different from the other three simulations. The control simulation for all the models (except for the GISS model) simulate El Niño (La Niña) events with maximum peaks of ∼3.5°C (−3°C), and the spatial pattern of simulated El Niño and La Niña in the three CGCMs has large amplitude in the central and eastern tropical Pacific with an underestimation of the meridional extent of the anomalies (not shown).

Most global warming simulations from the Coupled Model Intercomparison Project (CMIP) archive exhibit mean El Niño–like warming (Collins and CMIP Modeling Groups 2005), although there are some exceptions. Recently, Boer et al. (2004) showed that the response in the tropical Pacific to increasing greenhouse gas concentrations is El Niño–like in its spatial structure using coupled models, feedback analysis in the tropical Pacific, and observation-based paleoclimate reconstructions.

b. Changes in SST anomaly variability

Figures 3a–d show the standard deviation of total SST anomaly (SSTA) simulated in the control experiment. The anomaly is defined as the deviation from the mean annual cycle calculated over the entire record for each model without removing any trends. For comparison, we show the same result based on the monthly mean observed SST data from the National Climate Data Center (Smith and Reynolds 2004) for the period of 1900–2002. The SSTA standard deviation for the MIROC, MRI, and GFDL models is 0.90°C (GISS), 0.71°C (observations). The MRI model is better at simulating the observed ENSO variability in
terms of amplitude. However, the spatial structure of SSTA variability simulated in the GFDL model, which shows a local maximum variance in the eastern tropical Pacific, is in better agreement with the observations. The GISS model severely underestimates the SST variability in the tropical Pacific with little or no evidence for ENSO events. The total standard deviation for the Niño-3.4 SST index simulated in GISS is 0.17°C in the control experiment. This low variability may result from the rather coarse horizontal resolution in the atmospheric general circulation model (AGCM).

Figures 4a–d show the SSTA standard deviation difference maps between the control experiment and the 4 × CO2 experiment. Note that the SSTA in the 4 × CO2 experiment is defined as the deviation from the mean annual cycle calculated over the last 100-yr pe-
period in each model. The magnitude of the SSTA standard deviation is markedly increased in the 4 × CO2 experiment for the MRI model (Fig. 4b). The remaining three models show little (GFDL) or no change (MIROC and GISS). In the MRI model the largest change of SSTA variability occurs in the eastern tropical Pacific. During the greenhouse warming experiment, the MRI model exhibits large changes in the ENSO amplitude, which are superimposed on an overall warming of the tropical Pacific mean state shown in Fig. 2b. However, in spite of large changes of mean state in the remaining three CGCMs (MIROC, GFDL, and GISS) there are no significant regions in which the SSTA standard deviation differences exceed 90% significance based on a chi-square test (Figs. 4a,c,d).

These results are consistent with previous studies that indicate that changes in ENSO amplitude associated with climate change projections are model dependent. It is still an open question as to whether the mean state changes force changes in the ENSO statistics (Kirtman and Schopf 1998; Fedorov and Philander 2000), whether the changes in the mean state are statistically independent of ENSO (Thompson and Battisti 2001; Flügel et al. 2004), or whether the changes are just a nonlinear residual (Schopf 2004). Although some of the models (e.g., MRI and GFDL) apparently produce reasonably realistic ENSO variability for the current climate and similar mean responses to increases in greenhouse gas concentrations, the impact on the overall ENSO statistics is markedly different. The issue then is how to understand the source of these different sensitivities, and, ultimately relate them to the observational record.

4. Analysis

In this section, we propose a hypothesis for the different climate change–ENSO amplitude sensitivities and provide supporting evidence. For simplicity, we focus on the results from the MRI and GFDL models since these two models produce reasonably realistic ENSO variability in the control experiment and relatively similar mean responses to increases in greenhouse gas concentrations, but very different changes in ENSO statistics. Our hypothesis is that the MRI model ENSO is in the nonlinear regime, so that changes in ENSO statistics are highly correlated with mean state changes (Kirtman and Schopf 1998). Conversely, the GFDL model ENSO is in the linear regime and the ENSO amplitude can be expected to be independent of the mean state (Flügel et al. 2004). In a linear damped stochastically forced system (i.e., first-order Markov process) where the stochastic forcing is Gaussian and white in time (i.e., includes all frequencies), there are low-frequency changes in the mean due to the low frequencies in the white noise forcing. However, since the linear dynamics of the system (i.e., the propagator) is independent of the noise, the low-frequency mean state changes are independent of low-frequency ENSO amplitude modulation. In a nonlinear system, the stability of the dynamical operator can change in response to low-frequency changes in the mean state. Therefore, in this nonlinear view low-frequency ENSO amplitude modulation and tropical mean state changes can be highly correlated.

This ENSO regime issue [see Kirtman et al. (2005) for a complete discussion] has received considerable
attention with respect to secular changes in ENSO statistics. Here we argue that this regime issue is also applicable to climate change projections. This is, perhaps, somewhat surprising since the changes in the mean state for secular variability are on the order of $0.2\degree - 0.4\degree$ C, whereas in the climate change projections the mean state changes are on the order of $3\degree - 7\degree$ C. Even if the ENSO regime is fundamentally linear, the changes in the mean state are so large that one would expect a fundamental change in the linear operator and, thus, the ENSO statistics. Apparently, for the GFDL model this is not the case.

Our conjecture is based on the argument that the amplitude of ENSO would be normally distributed if the coupled Pacific ocean–atmosphere were a linear system forced by Gaussian white noise (Burgers and Stephenson 1999; Flügel et al. 2004; the so-called null hypothesis for ENSO). To clarify our hypothesis and provide supporting evidence, we first show the probability density function (PDF) for the monthly Niño-3.4 SST index simulated in the MRI (solid) and GFDL (dashed) models for the control experiment (Fig. 5). The PDFs are plotted in terms of percent occurrence along the $y$ axis and as a function of their respective standard deviations along the $x$ axis. The Niño-3.4 SST index simulated in the GFDL model has a symmetric distribution that may be nearly Gaussian (although this has not been tested); however, that of the MRI model has a skewed distribution. Figure 5 shows that the MRI model cold SSTA is more probable than warm SSTA and that the probability of extreme warm events (greater than 2.5 standard deviations) is greater than extreme cold events (less than $-2.5$ standard deviation). We conjecture that the non-Gaussian nature of the MRI model indicates significant nonlinearity. Moreover, we cannot reject the null hypothesis for the GFDL model ENSO. The GFDL model ENSO maybe linear or nonlinear—the regime simply cannot be determined from this test.

Figure 6 shows the conditional PDF for the monthly Niño-3.4 index greater than $+1.8$ times the standard deviation and less than $-1.8$ times the standard deviation in the MRI and GFDL models. Note that one standard deviation of the Niño-3.4 index is $0.72\degree$ (MRI) and $0.90\degree$ C (GFDL). Consistent with the result in Fig. 5, the MRI model shows that the probability of a strong warm event is greater than strong cold events, indicating that a strong El Niño occurs more frequently than a strong La Niña. However, the GFDL model shows similar distribution of strong El Niño and La Niña occurrences.

From the observational record there is strong evidence that El Niño events are often stronger than La Niña events (Hannachi et al. 2003) and this asymmetry is an intrinsic nonlinear characteristic of the ENSO (An and Jin 2004). A linear system does not have this property. Based on the use of a simple model previous studies showed how nonlinearities can give rise to asymmetric behaviors of the ENSO (Jin et al. 2003). The simple PDF analysis shown here suggests that the nonlinear dynamics of the coupled system over the tropical Pacific is prominent in the MRI model. An and Jin (2004) provided a physical basis for the assessment of nonlinearity based on a heat budget analysis of the ocean mixed layer. They argued that the nonlinear dynamical heating enhanced the amplitude of El Niño events and reduced the amplitude of La Niña events and thus resulted in the El Niño–La Niña asymmetry.
The examination of the heat budget of the upper equatorial Pacific is beyond the scope of this particular study.

Some statistical methods have been proposed to identify nonlinearity and asymmetry of ENSO (Burgers and Stephenson 1999; Monahan 2001; Hannachi et al. 2003). They found that the tropical Pacific SST fields are significantly skewed. Skewness can be a measure of nonlinearity if the noise is purely additive (Burgers and Stephenson 1999). This is because skewness is a measure of the asymmetry of a PDF and is 0 for a normal distribution (White 1980). The skewness is one way to quantify deviations from normality. Skewness toward high values means that high extremes are more probable than low extremes. The moment coefficient of skewness is defined as the normalized third statistical moment,

$$\text{Skewness} = \frac{m_3}{(m_2)^{3/2}},$$

where $m_k$ is the $k$th moment,

$$m_k = \frac{\sum_{i=1}^{N} (x_i - \overline{x})^k}{N},$$

and where $x_i$ is the $i$th SSTA simulated in each model, $\overline{x}$ is the mean, and $N$ is the number of total periods in the control experiment. If the longer wing of a distribution occurs for values of $x_i$ higher than the mean, that distribution is said to have positive skewness. If the longer wing occurs for values of $x_i$ lower than the mean, the distribution is said to have negative skewness.

Figure 7 shows the skewness of the SSTAs simulated in the (a) MRI model and (b) GFDL model over the tropical Pacific in the control experiment. There is strong positive skewness exceeding 0.8 in the central tropical Pacific and weak negative skewness over the eastern subtropical Pacific in the MRI model. This indicates that the tropical warm SSTA simulated in the MRI model tends to be stronger than the cold SSTA, which is consistent with the result in Figs. 5 and 6. Moreover, this skewness pattern is similar to that computed from observations by Burgers and Stephenson (1999), although the maximum values in the model are displaced farther west than in observations. The skewness of the GFDL model is around 0.4 in the far eastern tropical Pacific and is about −0.4 in the central tropical Pacific; however, these values are not significant, suggesting that the SSTAs simulated by the GFDL model are normally distributed as shown in Fig. 5. According to White (1980), the threshold for significant skewness at the 95% confidence level is about ±0.4, indicating that the MRI model is significantly skewed, whereas the GFDL is near normal. Note that the ENSO amplitude simulated in the GFDL model is larger than that of the MRI model, however, the magnitude of skewness in the GFDL model is smaller than that of the MRI model. When we applied the PDF and skewness analysis to the MIROC model, no significant non-Gaussian properties were found (not shown). Similar to the GFDL model, there are no significant changes in the ENSO amplitude simulated in the MIROC model between the control and $4 \times CO_2$ experiment (Fig. 4a).

Based on 130 yr of observed estimates of SSTA, Monahan and Dai (2004) argued that the magnitude of the nonlinearity is a function of the strength of ENSO. Monahan and Dai (2004) also analyzed several CGCMs and found that the nonlinear structure in ENSO simulated in CGCMs is highly model dependent. They ar-
nged that the divergence between the nonlinearity of ENSO as simulated in different CGCMs is mainly from difficulties in representing the mean state and variance of the tropical Pacific. To test this idea in the MRI and GFDL model simulation, we assume that skewness is a measure of the magnitude of the nonlinearity and then examine how the skewness changes with increasing greenhouse gas concentrations. Figures 8a,b, which are the same as in Figs. 7a,b, show the skewness for the $4 \times CO_2$ experiment. The magnitude of the skewness in the MRI model increases to a maximum value of about 1.6 in the eastern tropical Pacific and there is strong negative skewness in the central tropical Pacific. However, the skewness in the GFDL model remains qualitatively unchanged, although there are some increases noted in the far eastern Pacific. These analyses seem to support the hypothesis that the MRI model may be in the nonlinear regime since both the amplitude and the skewness increase in the $4 \times CO_2$ experiment. Conversely, in the GFDL model neither the amplitude nor the skewness increases in the $4 \times CO_2$ experiment, indicating that we cannot reject the possibility that the ENSO system in this model is linear.

Another ENSO regime test is to examine how the low-frequency modulation of ENSO is related to the atmospheric (white) noise statistics. In the nonlinear regime, the amplitude modulation is largely independent of the noise, whereas in the linear regime the noise statistics are largely responsible for the amplitude modulation (Kirtman and Schopf 1998; Thompson and Battisti 2001; Flügel et al. 2004). This is because the noise is assumed to be white and therefore includes amplitude at all frequencies. We examine whether there is a relationship between the noise statistics and the ENSO amplitude modulation in the MRI and GFDL control simulations. This does not mean that we exclude the role of the ocean on the low-frequency modulation of ENSO amplitude. There have been several theories proposed to explain decadal modulation of ENSO, and its relationship with tropical decadal variability. Some of these theories are based on ocean dynamics, invoking changes in the subtropical–tropical cells strength (Kleeman et al. 1999; McPhaden and Zhang 2002; Nonaka et al. 2002) or oceanic teleconnections (Gu and Philander 1995; Liu et al. 2002).

To test the noise relationship, we assume that the ENSO signal can be isolated by applying running means. The noise is then defined as the residual between the total field and the running mean. This definition of the noise is definitively not white. The filter preferentially damp the low frequencies compared to high frequencies, although significant low-frequency variability remains, particularly in the noise amplitude [see von Storch and Zwiers (1999) for a discussion of the response function for running mean filters]. Unfortunately, this is not a particularly well-justified definition as noise can occur on all space and time scales. Nevertheless, it is an intuitive definition that is applicable in terms of separating the ENSO from “weather noise” in climate data (see Kirtman and Schopf 1998). The noise in the coupled system of interest here is at the air–sea interface. In this sense, noise is present in any of the air–sea flux terms (heat, momentum, and freshwater). Here we use wind stress as a proxy for noise in all the flux terms. It is our assertion that changes in wind stress noise will necessarily be consistent with changes in the noisiness of the heat and freshwater fluxes. To define the noise, a 9-month running mean is applied to the zonal wind stress anomaly simulated in the control experiment of the MRI and the GFDL models. The running mean is then subtracted.
from the data, leaving what will be referred to as atmospheric noise.

Figures 9a–c show the unfiltered zonal wind stress simulated in the MRI model, the zonal wind stress after the 9-month running mean has been applied, and the remaining atmospheric noise, respectively. The time series along the equator is plotted for the model period of 2051–60. The eastward propagation of filtered zonal wind stress (Fig. 9b) is apparent from the western to the central tropical Pacific. Both the filtered wind stress (Fig. 9b) and the noise field (Fig. 9c) have large variability in the western and central tropical Pacific between 130° and 210°E, however, the temporal scale of the noise field is considerably shorter than the filtered zonal wind stress. Figures 10a–c are the same as in Figs. 9a–c except for the GFDL model during the model period of 2100–2109. Similar to the MRI model, both the filtered wind stress and the noise field have large variability in the western and central tropical Pacific. However, the magnitude of filtered field is relatively weak with no indication of eastward propagation compared to that of the MRI model.

Figure 11a shows the time series of a 10-yr running mean of the Niño-3.4 amplitude\(^2\) (thick line) in the GFDL model and that of the 10-yr running mean of the atmospheric noise amplitude (thin line) averaged over the equatorial region (5°N–5°S, 130°–210°E). These time series define indices of low-frequency (decadal) modulation of ENSO and atmospheric noise amplitude, respectively. Figure 11a shows that the decadal modulation of ENSO and the noise amplitude in the GFDL model are nearly in phase. The simultaneous correlation between the two time series in Fig. 9 is 0.61. This in-phase relationship is not perfect but suggests that the noise is most likely the primary source of the decadal modulation of ENSO in the GFDL model. We applied the same analysis to the MRI model (Fig. 11b). In the case of the MRI model, however, the simultaneous correlation between the low-frequency modulation of ENSO and atmospheric noise amplitude is lower (0.29). Figures 12a,b are the same as in Figs. 11a,b except for the 4 × CO2 experiment. The in-phase relationship

\(^2\) Monthly Niño-3.4 (5°N–5°S, 170°–240°E) amplitude is defined as \(\sqrt{(\text{Niño-3.4})^2} \times (\text{Niño-3.4})\).
between the decadal modulation of ENSO and the noise amplitude in the GFDL is clearly shown in Fig. 12a. The low-frequency variability of the ENSO amplitude is nearly in phase with that of the noise amplitude in the GFDL model. In contrast, there are periods when the ENSO amplitude is in phase with the noise amplitude and periods when the ENSO amplitude is out of phase with the noise amplitude in the MRI model. The ENSO–noise amplitude relationship does not change much from the control run and the 4 × CO2 experiment, which is consistent with the null hypothesis for GFDL model and suggests that the MRI model is in the nonlinear regime.

Our result suggests that atmospheric noise plays a more prominent role in the low-frequency modulation of ENSO in the GFDL model compared to the MRI model in both the control run and the 4 × CO2 experiment. However, since the MRI correlation is statistically greater than zero, we cannot definitively conclude that the MRI model is insensitive to the noise.

5. Discussion

As a possible explanation for the large differences among the CGCMs in climate change–ENSO amplitude sensitivities, we have suggested examining the simulations in terms of the null hypothesis (linear) versus nonlinear ENSO. The skewness of SSTA and the relationship between noise amplitude and ENSO amplitude are used to test whether we can reject the so-called null hypothesis for ENSO (i.e., linearity). We can only claim that the results are consistent with the assumptions associated with a particular regime. However, there is strong evidence that the MRI model ENSO is in the nonlinear regime, but no such conclusion can be made regarding the GFDL model. A Gaussian PDF does not confirm linearity, whereas a non-Gaussian PDF does indicate significant nonlinearity. Conditional probabilities based on other ENSO variables may be Gaussian or non-Gaussian in the GFDL model. On the other hand, the fact that the MRI model is highly skewed clearly indicates that the model is in a nonlinear regime. The fact that the GFDL model is Gaussian suggests that the null hypothesis (i.e., a stochastically forced linear system) cannot be rejected. We can only note where the simulation is consistent or inconsistent with the null hypothesis for ENSO. Put simply, no conclusion regarding the linearity or nonlinearity of the GFDL model ENSO is possible with this test, whereas the MRI model ENSO is nonlinear.
Fig. 11. (a) The 10-y running Niño-3.4 amplitude (red) and the atmospheric noise amplitude (black) from the control experiment for the entire simulation period in the GFDL model. (b) Same as in (a), except for the MRI model. Note that the amplitude of the running mean Niño-3.4 (atmospheric noise) is indicated on the right (left) scale. Unit is °C and N m⁻¹ in the right and left scale, respectively.

Fig. 12. Same as in Fig. 11, except for the 4 × CO2 experiment in the (a) GFDL and (b) MRI models.
We do not exclude the possibility of entirely different interpretations. For example, it is possible to explain the differences between the GFDL and MRI models in terms of where they reside with respect to their Hopf bifurcation. In this case, nonlinearity in both models is of importance. In addition, we argued that the noise is purely additive. However, the assumption of Gaussian white noise in the tropical Pacific is not particularly well justified based on observations. Recently, Sura et al. (2005) have shown that non-Gaussian distribution can result from linear stochastically perturbed dynamics with multiplicative noise statistics. Moreover, there are some studies (Lengaigne et al. 2004) showing that the amplitude of the westerly wind burst–noise is modulated by the temperatures and vice versa, giving rise to a huge nonlinearity. Lengaigne et al. (2004) showed that the westerly wind events initiate an eastward displacement of the warm pool that promotes the occurrence of subsequent westerly wind events. Since westerly wind events are responsible for the development of ENSO, their coupled model exhibits self-sustained ENSO variability. In this case the second-order statistics of the “noise” are triggered and triggers SSTAs. A possible conceptual model for this case can be built by using multiplicative noise statistics. Multiplicative noise is often identified with state-dependent variations of stochastic feedbacks (Sura et al. 2005). Any system with multiplicative noise statistics can be transformed into a nonlinear stochastic system, which was recently illustrated in Eisenman et al. (2005) and Yu et al. (2003). This viewpoint on the noise statistics can lead to a different interpretation of the ENSO regime in the MRI and GFDL models. If the amplitude modulation of the noise, as in the GFDL model, is well correlated with the ENSO variance, this may be a strong signature of nonlinearity (ENSO changing noise and noise changing ENSO), rather than of linearity.

There are other possible explanations for the relatively minor changes in the GFDL ENSO amplitude. For example, it is well known that a change in the background state can change the amplitude of the coupled feedback associated with ENSO (Fedorov and Philander 2000); however, in this particular case it may be that the changes in the background state in the GFDL model are not large enough (or are compensated by other effects) so as to cause significant changes in ENSO amplitude. Indeed, when we diagnose the strength of the coupled feedback in the GFDL model, no appreciable changes are noted. The strength of the coupled feedbacks as well as changes in the vertical stratification are examined later in the manuscript.

In this study we focused on the ENSO regime issue (i.e., linear versus nonlinear) to explain changes in the ENSO amplitude; however, there are several other possible factors that can also contribute to changes in ENSO amplitude in the presence of a changing climate. ENSO amplitude can be affected by the subsurface temperature variability including mean thermocline depth and changes in vertical stratification (for detailed discussions see Timmermann et al. 1999; Timmermann 2001; Collins 2000b; Yang et al. 2005).

Here, we show the differences in subsurface temperatures between the control run and the $4 \times CO_2$ experiment for the MRI and GFDL simulations. Figure 13 displays the temperature changes (i.e., $4 \times CO_2$ minus the control) in the upper 270 m along the equator for the last 100 yr simulated in the control run and $4 \times CO_2$ experiment of the (a) GFDL and (b) MRI simulations, respectively. CI is 1°C and shading is above 3°C.
ment, the upper-ocean temperature increases by 1°–4°C (GFDL) and 1°–6°C (MRI) except for the western equatorial Pacific around 100 to 150 m deep in both the GFDL and MRI models. Because of the upper-ocean warming, the depth of the mean 20°C isotherm, a proxy of thermocline depth, is displaced downward in the 4 × CO2 experiment compared to the control run in both the GFDL and MRI models (not shown). The near-surface water warms more than the subsurface water in both the GFDL and MRI models, resulting in an increased vertical stratification. This is particularly clear in the MRI model, indicating that the vertical stratification increases in the MRI model more than in the GFDL model. The change in the vertical gradient of oceanic temperature from the control run to the 4 × CO2 experiment (not shown) is larger in the MRI model than the GFDL model. Nevertheless, the GFDL model shows relatively small changes in ENSO amplitude, possibly suggesting the importance of the so-called ENSO regime or null hypothesis issue.

We also computed atmospheric sensitivities in the MRI and GFDL models in order to diagnose the strength of the coupled feedbacks in the two models. The atmospheric sensitivity is defined as the covariance of the zonal wind stress anomalies averaged over 5°N–5°S, 130°–210°E and the Niño-3.4 SST index divided by the variance of the Niño-3.4 SST index (Timmermann et al. 1999). We found that the atmospheric sensitivity of the MRI model decreased from the control run [0.0088 Pa (°C)⁻¹] to the 4 × CO2 experiment [0.0058 Pa (°C)⁻¹]. Simply put, the atmosphere does not respond linearly to the increase in the SST variability in the MRI model. On the other hand, that of the GFDL model increases from the control run [0.0079 Pa (°C)⁻¹] to the 4 × CO2 experiment [0.0088 Pa (°C)⁻¹]. Although change in the strength of the coupled feedback is relatively small, the atmosphere responds linearly to small increase of SST variability (Fig. 4c) from the control run to the 4 × CO2 experiment in the GFDL model. It is noteworthy that the increases in atmospheric sensitivity of the GFDL model with increased SST do not mean that the atmosphere response has to be linear. It could be nonlinear as long as it is monotonic.

6. Concluding remarks

To understand how human-induced greenhouse warming affects ENSO amplitude we have examined four CGCM climate change projections along with their control simulations using preindustrial greenhouse gas concentrations. In the quadrupled (4 × CO2) experiment, CO2 increases at 1% yr⁻¹ to a level 4 times that of the present climate. After 140 yr of increasing CO2 levels, the CGCMs are integrated for an additional 150 yr without further increases in CO2. In contrast, there is no anthropogenic or natural forcing in the preindustrial control experiment.

In the 4 × CO2 experiment all the simulations project a mean tropical Pacific SST increase in the range of 1.5°–6.5°C. The spatial pattern for three of the CGCMs (MIROC, MRI, and GFDL) suggests an El Niño–like pattern to the warming. The GISS model is distinct in that the spatial pattern of the warming bears little similarity to El Niño. Changes in the amplitude of ENSO exhibit important differences among the four models. For example, the MRI model produces a significant increase in the amplitude of ENSO, whereas the GFDL, MIROC, and GISS models are largely insensitive in this regard.

We put forth the hypothesis that the ENSO amplitude differences were largely determined by the ENSO regime. In the so-called linear regime, the amplitude of ENSO is insensitive to changes in the mean state. In the nonlinear regime, the amplitude of ENSO is highly correlated to mean state changes. It should be noted that this hypothesis can be used to predict the “climate change–ENSO sensitivity” of CGCM simulations from the control run. To test this hypothesis, we analyzed the Niño-3.4 index statistics from the GFDL and MRI control and 4 × CO2 experiments. Based on the Niño-3.4 PDF analysis, we noted that the GFDL (and the MIROC) models are nearly Gaussian, suggesting that the linear regime applies. (The GISS model ENSO is too weak to apply the analysis.) Conversely, the MRI model has a distinctly skewed distribution, suggesting that it resides in the nonlinear regime. We also measured the ENSO nonlinearity in the MRI and GFDL models by calculating the skewness of the tropical Pacific SSTA. Consistent with the PDF analysis, there is a strong positive skewness in the tropical Pacific of the MRI model, however, that of the GFDL model is weakly skewed. Moreover, the magnitude of the skewness in the MRI model increases from the control to the 4 × CO2 experiment; on the other hand, there is no significant increase of the magnitude of the skewness in the GFDL model. This result further supports the suggestion that the GFDL model is in the linear regime and the MRI model is in the nonlinear regime.

This ENSO regime issue was also tested by examining the relationship between the low-frequency modulation of ENSO amplitude and atmospheric noise in the control simulations. Again, we found strong correlations between noise amplitude and ENSO amplitude modulation in the GFDL model as would be expected for a model in the linear regime, and weak correlations...
with the MRI model as expected for a model in the nonlinear regime. In this analysis, we are simply asserting that the Hasselmann hypothesis applied to ENSO can be viewed as a “null hypothesis” for low-frequency ENSO variability (see Flügel et al. 2004). In this sense, ENSO is viewed as a linear stochastically (white noise) forced system. The Hasselmann hypothesis is that white noise forcing of a linear system (i.e., a simple mixed-layer ocean) can produce a red noise response (Hasselmann 1976). When it is possible to reject this null hypothesis, as in the case of the MRI model, we see a very large sensitivity to the climate change scenario. Conversely, in the case of the GFDL model we are unable to reject the null hypothesis, and we see very little sensitivity to the change in the mean climate.

While Burgers and Stephenson (1999) suggested that in nature ENSO is non-Gaussian (i.e., nonlinear) based on the observations, this is the subject of some debate (Monahan 2001; Wang and McPhaden 2000). Resolving this issue has profound implications in terms of gaining confidence in CGCM climate change projections. Moreover, the skewness calculation described here provides a simple way to a priori predict whether a particular model will have any “climate change–ENSO amplitude” sensitivity.

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REFERENCE


