Does the Lack of Coupling in SST-Forced Atmosphere-Only Models Limit Their Usefulness for Climate Change Studies?

JIE HE AND BRIAN J. SODEN

Rosenstiel School of Marine and Atmospheric Science, University of Miami, Miami, Florida

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ABSTRACT

Atmospheric general circulation models (AGCMs) are often considered inadequate for studying natural climate variability because of their lack of coupling with an underlying ocean. This lack of two-way air–sea coupling results in an inconsistency in surface energetics. This study aims to determine whether the lack of two-way air–sea coupling also undermines an AGCM's ability to simulate anthropogenic climate change. A comparison between coupled and atmospheric GCM simulations shows that anthropogenic climate change can be well reproduced by an AGCM and that errors due to the lack of two-way coupling are primarily limited to internal variability. Simulations using a stochastic linear model are shown to further support this conclusion. These results suggest a greater utility for AGCMs as computationally efficient tools for understanding and downscaling coupled model simulations of anthropogenic climate change.

1. Introduction

Simulations of atmospheric general circulation models (AGCMs) have been widely used in studies of natural and anthropogenic climate change. For example, high-resolution time-slice AGCM simulations have been used in an effort to improve representation of regional precipitation change (e.g., Coppola and Giorgi 2005; May 2008; Kopparla et al. 2013). Likewise, AGCMs forced with prescribed sea surface temperature (SST) and radiative forcing changes (e.g., Deser and Phillips 2009; Ma et al. 2012; Bony et al. 2013) have been used to understand anthropogenic changes in the atmospheric circulation and analyze discrepancies between observed and simulated climate trends (e.g., Shin and Sardeshmukh 2011). However, AGCMs are often criticized for the absence of coupling with an underlying ocean. This coupling is necessary in order for the SST to respond to the atmospheric forcing. Studies have shown that the lack of two-way coupling causes an inconsistency in surface energy fluxes and limits an AGCM's ability to accurately simulate natural climate variability (e.g., Barsugli and Battisti 1998; Wu et al. 2006; Wang et al. 2005). However, no studies have demonstrated the importance of two-way coupling on model projections of anthropogenic climate change.

Model simulations of natural climate variability have shown that the lack of two-way coupling is most problematic in regions where atmospheric forcing strongly regulates the ocean mixed layer. These regions include the midlatitudes (e.g., Cayan 1992; Deser and Timlin 1997; Barsugli and Battisti 1998) and certain parts of the tropics, for example, the Indian Ocean (e.g., Wu and Kirtman 2004; Krishna Kumar et al. 2005; Wang et al. 2005). In the midlatitudes, the lack of two-way coupling results in a substantial reduction in atmospheric variability and large spurious surface energy fluxes (Barsugli and Battisti 1998; Bretherton and Battisti 2000; Chen et al. 2013). In the Indian Ocean, the lack of two-way coupling causes misrepresentation of the relationship between the summer monsoon and El Niño–Southern Oscillation (Wu and Kirtman 2004; Krishna Kumar et al. 2005; Wang et al. 2005).

While the importance of coupling with an underlying ocean has been clearly demonstrated for natural climate variability, its importance for anthropogenic climate

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Corresponding author address: Jie He, Rosenstiel School of Marine and Atmospheric Science, University of Miami, 4600 Rickenbacker Causeway, Miami, FL 33149.
E-mail: jhe@rsmas.miami.edu

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change remains unclear. Obviously, a full interaction between ocean and atmosphere is necessary for predicting the pattern and amplitude of SST change in response to external forcing (e.g., Xie et al. 2010; Zheng et al. 2010). Here we seek to assess the accuracy of AGCM simulations that are forced with anthropogenically driven changes in SST, yet are not constrained by two-way coupling to have energetically consistent air–sea fluxes. This question is not simply an academic one, but has important practical implications as AGCM simulations with prescribed SST changes offer a potentially valuable tool for downscaling coupled simulations (e.g., Coppola and Giorgi 2005; May 2008; Kopparla et al. 2013), yet the fidelity of such simulations is not clear.

Previous studies have examined this topic, but none have provided a conclusive answer due to limitations in the experimental design. For example, Cash et al. (2005) found that the 500-hPa height response to $2 \times CO_2$ from the AGCM simulations had a similar pattern but much smaller magnitude than that from the coupled simulations. However, the SST used to force the AGCMs differed substantially from the SST in the coupled simulations in certain regions. Therefore, differences in the 500-hPa height response could be due to differences in SST forcing instead of the lack of two-way coupling. He et al. (2014) found large discrepancies in the circulation responses between the coupled and AGCM simulations. However, the AGCM simulations did not include the same radiative forcing used in the coupled model simulations. Therefore, they were unable to determine whether the discrepancies were a result of two-way coupling or differences in external forcing.

In this study, we compare AGCM and coupled model simulations with consistent boundary conditions and radiative forcing to examine the importance of two-way coupling on anthropogenic climate change. We find that coupled model simulations of anthropogenic climate change can be well reproduced by AGCMs and that errors due to coupling with an underlying ocean are primarily limited to internal variability.

2. Model and methods

a. Model simulations

The primary model archive for this study is a set of simulations conducted with the Community Earth System Model (CESM) (Hurrell et al. 2013). The fully coupled configuration of CESM consists of atmosphere [Community Atmosphere Model, version 4 (CAM4)], ocean [Parallel Ocean Program, version 2 (POP2)], land [Community Land Model, version 4 (CLM4)], and sea ice [Community Ice Code, version 4 (CICE4)] models. The atmosphere and land models are run on a finite-volume grid of approximately 1.9° latitude by 2.5° longitude resolution, whereas the ocean and sea ice models are run on a displaced pole grid of approximately 1° resolution.

As stated above, the main objective of this paper is to study the impact of two-way coupling on climate change that is a result of external forcing instead of internal variability. To isolate the externally forced climate change, we compare coupled and AGCM simulations with different concentrations of CO_2. Four sets of simulations are performed with CESM, labeled according to their coupling and forcing characteristics. The CPL_PI simulation is run with fully coupled CESM with CO_2 fixed at the preindustrial level of 284.7 ppm. The CPL_1pct simulation is also run with fully coupled CESM with CO_2 initiated at 284.7 ppm and increasing at $1\% \text{ yr}^{-1}$ (1pctCO2). The AMIP_PI and AMIP_1pct simulations are the so-called perfect Atmospheric Model Intercomparison Project (AMIP) reproduction of the CPL_PI and CPL_1pct simulations, respectively. In the AMIP_PI and AMIP_1pct simulations, only the atmosphere and land models are active and are forced with the same atmospheric composition as the coupled simulations and the daily mean SST and sea ice concentration from the coupled simulations. It is important to note that obtaining the magnitude and pattern of SST change from the coupled simulations is essential for ensuring correct SST forcing for the AGCM simulations. Our experiments aim to determine whether AGCMs are able to accurately reproduce the anthropogenic climate change that result from such SST change, despite the energetically inconsistent surface fluxes due to the lack of coupling with an underlying ocean. Assuming the diurnal cycle of the boundary conditions is not important for long-term climate response, the difference between the "perfect AMIP" and the coupled simulations is entirely due to the lack of coupling with an underlying ocean. We also conduct the perfect AMIP simulations with monthly mean SST and sea ice concentration; the change in the temporal resolution of the boundary conditions from daily to monthly means does not change the conclusions of this paper (see the supplementary material).

b. Methods

We use a 10-yr epoch difference to characterize the change in the climatic mean state. Climate change under no external forcing (or entirely due to internal variability, herein referred to as $1 \times CO_2$) is calculated as the epoch difference between years 11–20 and 1–10 in the preindustrial simulations. This approach is validated using different epochs [e.g., (years 41–50) − (years 11–20)], which does not change our conclusions. Climate change at

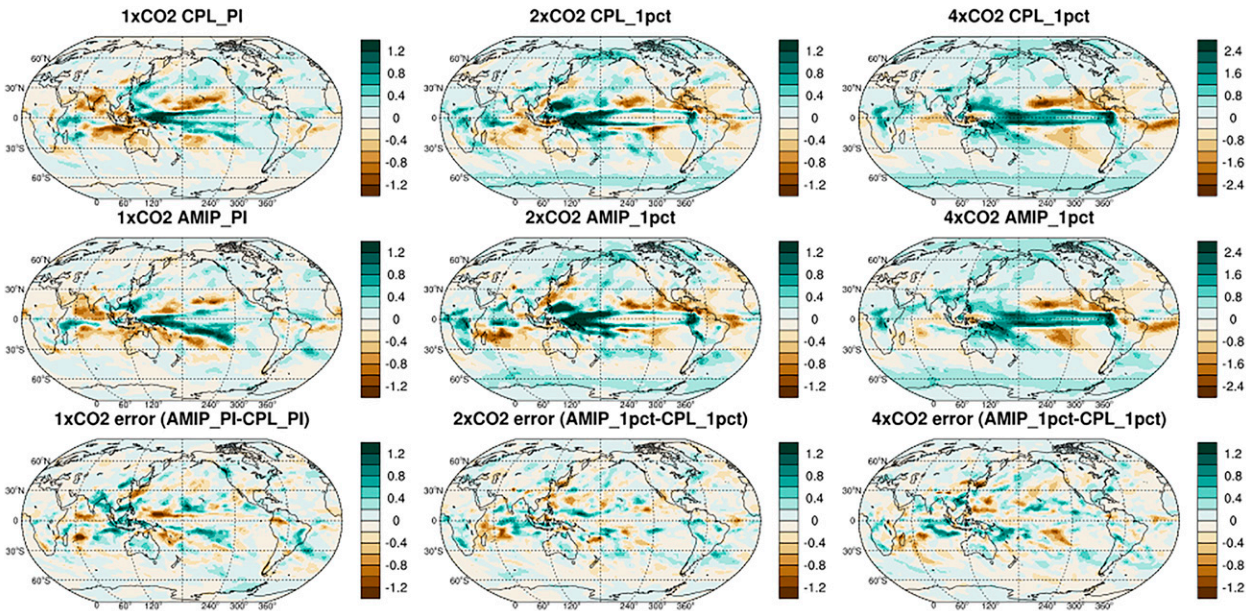

FIG. 1. Precipitation change (mm day^{-1}) at (left) $1 \times CO_2$, (center) $2 \times CO_2$, and (right) $4 \times CO_2$ from (top) coupled, (middle) perfect AMIP simulations, and (bottom) error defined as the difference between the perfect AMIP and coupled simulations.

the time of $2 \times CO_2$ ($4 \times CO_2$) is calculated as the epoch difference between years 71–80 (141–150) and 1–10 in the 1pctCO2 simulations. The use of epoch differences to calculate climate change is validated using linear climate trends, which does not change our conclusions (not shown). The analysis presented here focuses primarily on precipitation change, which is a highly variable quantity of significant socioeconomic importance. However, our main conclusion does not depend on the choice of variable.

While AGCM simulations have been widely used to study the changes in the mean state, they are also valuable in analyzing anthropogenic changes in climate extremes (e.g., Kharin et al. 2005; Allan and Soden 2008). It is therefore important to also evaluate the impact of two-way coupling on simulations of anthropogenic changes in climate extremes. To examine this, we compute the 10-yr mean of the 99th percentile daily mean value at each grid point as an index of climate extremes. This calculation of climate extremes has been commonly used in previous studies (e.g., Emori and Brown 2005) and is validated using the 100th percentile and the 95th percentile, which does not alter our conclusions.

3. Results

a. *CESM simulations*

We first examine the impact of two-way coupling on anthropogenic changes in the climatic mean state. Consider changes in the 10-yr mean precipitation at the time of $2 \times CO_2$ from the 1pctCO2 simulations (Fig. 1, center). Both the CPL_1pct and AMIP_1pct simulations show increased precipitation over central Africa, the west Indian Ocean, and the western tropical Pacific Ocean and decreased precipitation over the east Indian Ocean, the eastern subtropical Pacific Ocean, and the western Atlantic Ocean. Overall, the precipitation change at $2 \times CO_2$ is well reproduced by the AMIP_1pct simulation. However, errors due to the lack of two-way coupling exist over certain regions, including the southern Indian Ocean, the Australian continent, the North Pacific, and the southwestern Pacific. In these regions, the magnitude of errors is approximately the same as that of precipitation change itself. The spatial correlation between the coupled and uncoupled precipitation change at $2 \times CO_2$ is 0.79 (Table 1).

Although $2 \times CO_2$ has been traditionally considered as a large enough forcing to isolate the externally forced signal from internal variability, this is not always the case. Deser et al. (2012a,b) showed that the climate change at the time of $1.5 \times CO_2$ under the SRES A1B scenario is dominated by internal variability. Likewise,

TABLE 1. Spatial correlation of changes in precipitation, latent heat, vertical velocity at 500 hPa (Omega500), and SLP in the coupled and perfect AMIP simulations at $1 \times CO_2$, $2 \times CO_2$, and $4 \times CO_2$.

	Precipitation	Latent heat	Omega500	SLP
$1 \times CO_2$	0.60	0.37	0.45	0.22
$2 \times CO_2$	0.79	0.79	0.64	0.83
$4 \times CO_2$	0.93	0.95	0.85	0.87

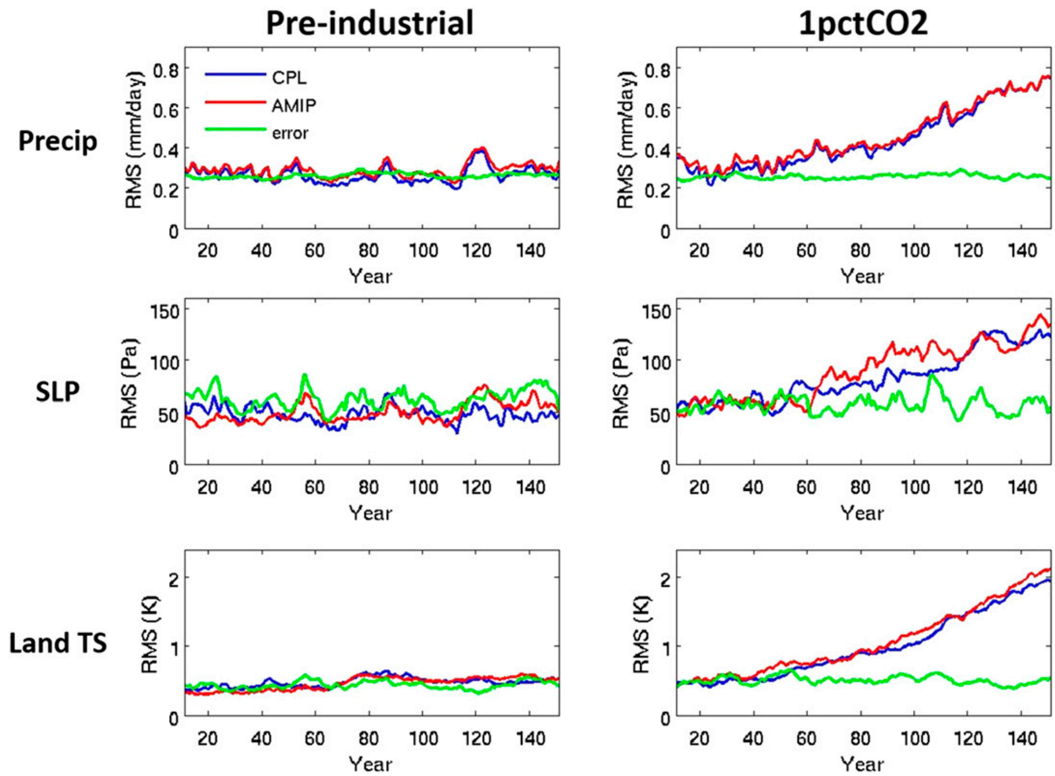

FIG. 2. Moving RMS of changes in the 10-yr mean (top) global precipitation, (middle) global SLP, and (bottom) relative land surface temperature calculated as the difference between the moving epoch, which moves from years 11–20 to years 151–160 at a time step of 1 yr, and the reference epoch, which is fixed as years 1–10, from the (left) preindustrial simulations and (right) 1pctCO2 simulations. The RMS is integrated over the globe. The relative land surface temperature change is calculated by removing the global mean land surface temperature change from the total change. Numbers on the *x* axis represent the first year of the moving epoch. Blue and red represent the moving RMS from the coupled and perfect AMIP simulations, respectively. Green represents the moving RMS of errors, which is the difference between the climate change in the perfect AMIP simulations and that in the coupled simulations.

changes in the 10-yr mean precipitation at $2 \times CO_2$ from the CPL_1pct simulation (Fig. 1, top center) have approximately the same magnitude and spatial coverage as that at $1 \times CO_2$ (Fig. 1, top left), which is entirely due to internal variability. Therefore, a large part of the precipitation change at $2 \times CO_2$ is a result of internal variability and a higher level of CO_2 increase is needed to elevate the externally forced signal above the internal variability. At the time of $4 \times CO_2$, the magnitude of precipitation change is approximately double that of internal precipitation variability (note the difference between the scales for the top-right and top-left panels in Fig. 1). Therefore, we can neglect internal variability and consider the precipitation change at $4 \times CO_2$ as mostly a response to CO_2 increase.

At the time of $4 \times CO_2$, changes in the 10-yr mean precipitation are almost identical in the CPL_1pct and AMIP_1pct simulations. The spatial correlation between the coupled and uncoupled precipitation change rises to 0.93. The improvement of AGCM's performance with the increase of external forcing can also be seen in other variables (Table 1). This means that coupling with an underlying ocean becomes less crucial as the externally forced change increases relative to the internal variability. Furthermore, as the external forcing increases, the magnitude and the spatial coverage of errors due to the lack of two-way coupling remain approximately the same (cf. Fig. 1, bottom). This indicates that the lack of coupling with an underlying ocean primarily affects the simulation of internal variability instead of the externally forced climate change.

To further show that errors due to the lack of two-way coupling in the perfect AMIP simulations are primarily related to internal variability, we calculate the moving RMS of epoch precipitation difference and errors using years 1–10 as the reference epoch (Fig. 2, top). For the preindustrial simulations, the RMS of changes in the 10-yr mean precipitation, which are entirely due to internal variability, stays approximately the same throughout the duration of the simulations. The errors in the epoch

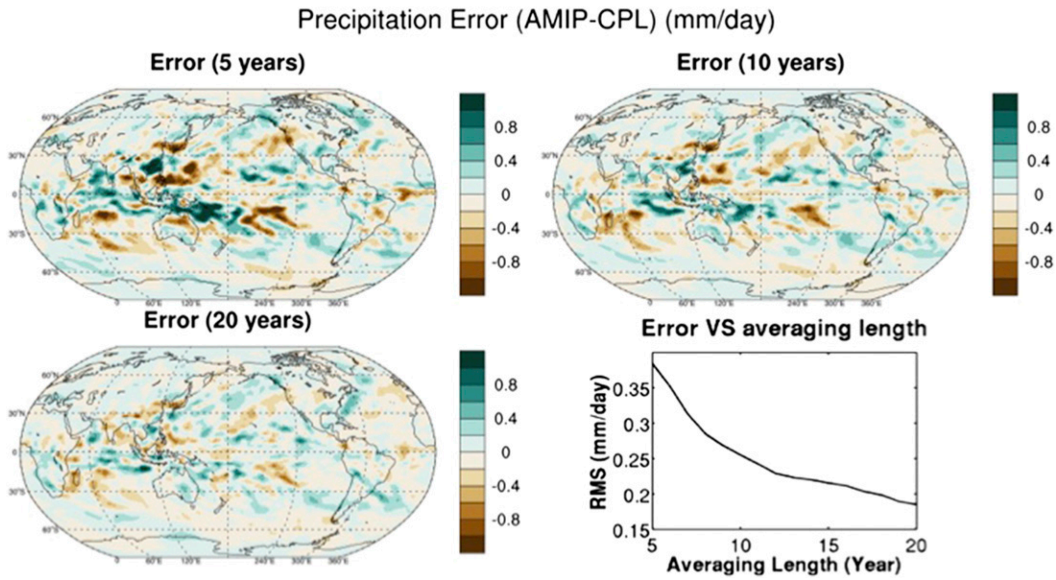

FIG. 3. Precipitation errors at $4 \times CO_2$ as a function of the averaging length of epochs used to calculate precipitation change. Maps of errors for averaging length of (top left) 5 yr [(years 141–145) − (years 1–5)], (top right) 10 yr [(years 141–150) − (years 1–10)], and (bottom left) 20 yr [(years 141–160) − (years 1–20)]. The three maps use the same color scale. (bottom right) The RMS error as a function of averaging length.

difference have approximately the same RMS as the epoch difference itself. For the 1pctCO2 simulations, the RMS of each epoch difference increases as the CO_2 concentration rises, but the RMS errors stay the same as that from the preindustrial simulations despite the increasing CO_2. This indicates that errors are insensitive to the presence or magnitude of the external forcing.

The moving RMS for changes in the 10-yr mean sea level pressure (SLP; Fig. 2, middle) and relative land surface temperature (Fig. 2, bottom) shows similar characteristics. Because SLP is more susceptible to internal variability compared to precipitation and surface temperature (Deser et al. 2012b), the separation of SLP change from the errors happens more slowly in the 1pctCO2 simulation. Therefore, a high level of CO_2 forcing is needed in the AGCM simulations to overcome the errors.

To confirm that the errors are indeed related to internal variability, we show precipitation errors at $4 \times CO_2$ as a function of the averaging length of epochs that are used to calculate precipitation change (Fig. 3). As the averaging length increases, internal variability is reduced while the external forcing stays the same. As a result, errors due to lack of two-way coupling are reduced. The magnitude of precipitation errors for the averaging length of 20 yr is about half of that for averaging length of 5 yr (Fig. 3, bottom right). All the above evidence demonstrates that errors due to the lack of two-way coupling are related to internal variability, rather than externally forced climate change.

In addition to changes in the climatic mean state, we also examined the impact of two-way coupling on anthropogenic changes in climate extremes. Here, we present our results with changes in precipitation extremes, land warm extremes, and land cold extremes, which are the most commonly studied variables of extreme climate changes. Figure 4 shows the moving RMS of changes in the global precipitation extremes, the land warm extremes, and the land cold extremes. Compared to the mean precipitation (Fig. 2, top), precipitation extremes (Fig. 4, top) have larger amplitude in both the internal variability and the externally forced change (e.g., Emori and Brown 2005; Allan and Soden 2008). And as expected, precipitation extremes also have a larger amplitude in the errors due to the lack of two-way coupling, and a separation of signal and the errors requires a higher level of CO_2 forcing. Nevertheless, the RMS errors are still the same in the preindustrial and the 1pctCO2 simulations and stays flat during the increase of CO_2. This indicates that errors in the simulation of precipitation extremes are only related to the internal variability rather than the externally forced change.

Similar to the precipitation extremes, the moving RMS for the land warm extremes (Fig. 4, middle) and land cold extremes (Fig. 4, bottom) also shows insensitivity of errors to the external forcing. The evidence indicates that AGCMs are able to reproduce the anthropogenic changes in climate extremes.

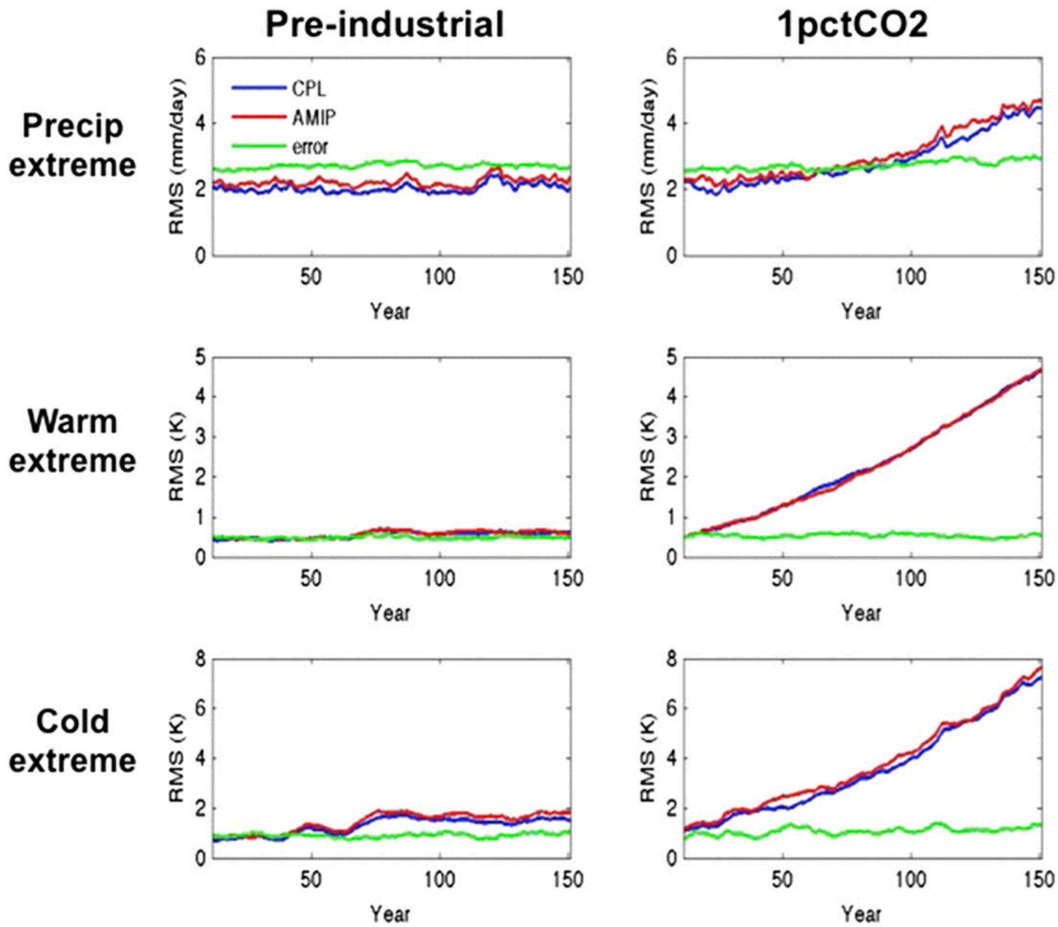

FIG. 4. As in Fig. 2, but for changes in (top) global precipitation extremes, (middle) land warm extremes, and (bottom) land cold extremes.

b. Stochastic linear model

The insignificance of coupling with an underlying ocean in the simulation of long-term climate change can be explained using a one-dimensional, stochastic, linear, coupled model. This model is a modified version of that in Barsugli and Battisti [1998, their Eqs. (1) and (2)], which was used to study the effect of ocean coupling on natural climate variability. We kept the air–sea interaction terms and atmospheric stochastic forcing term from the original model and combined the original radiative damping term with an external forcing term to form a model suitable for studying both internally generated and externally forced climate change:

$$\frac{d\mathrm{Ta}}{dt} = \lambda_A(\mathrm{SST} - \mathrm{Ta}) + F_A + N_A \quad \text{and} \tag{1}$$

$$\frac{d\mathrm{SST}}{dt} = \lambda_O(\mathrm{Ta} - \mathrm{SST}) + F_O. \tag{2}$$

Equations (1) and (2) are the simplified atmospheric model and ocean model, respectively. Subscript A refers to atmosphere, whereas subscript O refers to ocean. The variables Ta and SST are the atmospheric temperature anomaly and the sea surface temperature anomaly, respectively, and λ is the linearized coefficient of combined sensible and latent heat flux. The value for λ_A is $23.9 \times 10^{-7}\,\mathrm{s}^{-1}$ and for λ_O it is $12.7 \times 10^{-8}\,\mathrm{s}^{-1}$. These coupling coefficients depend on the surface wind speed and stability and are here set to represent the midlatitudes, following Barsugli and Battisti (1998). The radiative forcing terms, F_A and F_O are set to -2.16 and $2.80\,\mathrm{W\,m^{-2}}$, based on the radiative energy balance of the atmospheric column and at the ocean surface in the CPL_1pct simulation. The term N_A denotes the atmospheric Gaussian white noise forcing with a standard deviation of 1.0 K, following Barsugli and Battisti (1998). The time step for integration is set to 6 days. Although this idealized model may have various applications, its purpose here is to provide a simple framework for understanding the basic effects of two-way coupling on long-term climate change. While there is

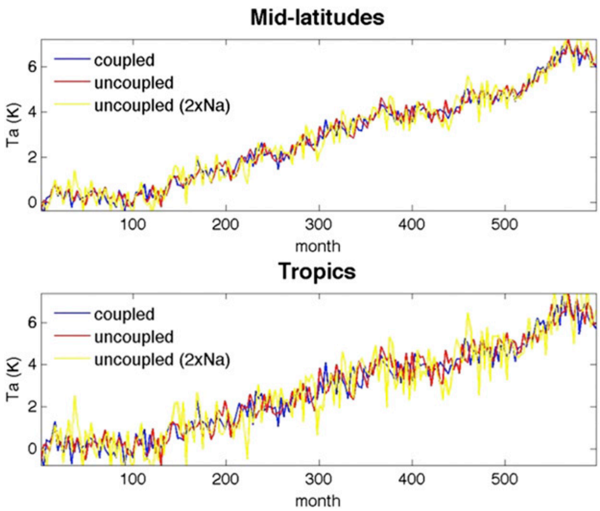

FIG. 5. Time series of 3-month mean atmospheric temperature anomaly from the one-dimensional stochastic model for the (blue) coupled integration, (red) uncoupled integration, and (yellow) uncoupled integration with double stochastic forcing. SST is the same in all three integrations for (top) midlatitude and (bottom) tropical models.

some sensitivity to the parameters, the qualitative analysis presented is valid for a wide range of parameters. For example, to also apply this idealized model to the tropics, we reduce the coupling coefficients by one-half to account for the decrease of surface wind speed from midlatitudes to the tropics (Wu et al. 2006). We will show results from both the midlatitude and tropical versions of this model.

The coupled stochastic model was integrated for 600 months. The SST output was then used to force the uncoupled atmospheric model. The only difference between the coupled and uncoupled integrations is that the stochastic forcing is consistent with the SST forcing in the coupled integration but inconsistent with the SST forcing in the uncoupled integration. This results in different paths of the atmospheric temperature change (Fig. 5). Furthermore, this inconsistency between the ocean mixed layer and the atmosphere leads to spurious surface energy fluxes (Wu et al. 2006; Chen et al. 2013) and reduces the variance of the atmospheric temperature (Barsugli and Battisti 1998; Bretherton and Battisti 2000). Therefore, the internal variability of atmospheric temperature cannot be perfectly reproduced in the uncoupled simulation. However, the long-term change of atmospheric temperature is the same in the coupled and uncoupled integrations (Fig. 5; with a trend of 0.24 K yr^{-1}). The insensitivity of long-term climate change to the existence of two-way coupling can be easily understood from this simple stochastic model. Because the long-term mean of the stochastic forcing term is zero, the long-term effect of stochastic forcing on the atmospheric temperature is also zero. Therefore, the long-term change in the atmospheric temperature is entirely determined by the atmospheric radiative forcing term and the SST forcing term, which are the same in the coupled and uncoupled integrations. The insignificance of the stochastic forcing term for long-term climate simulation is further shown in Fig. 5 (yellow line) by doubling the amplitude of the stochastic forcing term in the uncoupled atmospheric model. Although the increase of stochastic forcing affects the variability of atmospheric temperature, the long-term trend of atmospheric temperature is unaffected.

4. Summary and discussion

This paper examined the role of two-way coupling in model simulations of anthropogenic changes in both the climatic mean state and climate extremes. Results from the coupled and uncoupled simulations of the CESM showed that errors due to the absence of coupling with an underlying ocean did not change in magnitude or spatial coverage despite the increase of CO_2. The insensitivity of errors to the intensity of external forcing indicates that errors due to lack of two-way coupling are primarily related to the internal variability instead of externally forced change. A comparison between the coupled and AGCM simulations under preindustrial conditions showed that the magnitude of errors due to lack of two-way coupling is comparable to the magnitude of decadal variability. However, errors become smaller as the signature of external forcing rises above internal variability and the AGCM successfully reproduced the precipitation change from the coupled simulation at the time of $4 \times CO_2$. These results justify the use of AGCMs for simulating anthropogenic changes in both the climatic mean state and climate extremes, but one should ensure that the magnitude of anthropogenic climate change is large enough to overcome the errors related to internal variability.

The insignificance of coupling with an underlying ocean in simulations of long-term climate change was explained using a stochastically forced linear model. Decoupling causes an inconsistency between the atmospheric stochastic forcing and the prescribed SST, which affects the simulation of internal climate variability. However, it does not affect the simulation of long-term climate change because the long-term mean contribution of stochastic forcing is zero. The analysis based on the linear model is consistent with the results from the comprehensive model and suggests that the results shown here from the CESM are applicable to all CGCMs.

It is important to note that the insignificance of coupling with an underlying ocean does not imply insignificance of air–sea interaction. In a ‘‘perfect AMIP’’ simulation, the effect of air–sea interaction is partially incorporated in the pattern and magnitude of the prescribed SST changes, albeit in a ‘‘one way’’ setup. Our results show that AGCMs can accurately reproduce the anthropogenic climate change that is a result of such an SST change, despite the lack of constraints for energetically consistent surface fluxes. This is in contrast to the behavior of AGCMs in seasonal forecast, in which a lack of two-way coupling could lead to errors even if a perfect SST anomaly is prescribed (e.g., Kumar et al. 2008).

Our results have important practical applications in that AGCMs can be integrated at much higher resolutions than coupled models, allowing for potentially more realistic simulations of regional anthropogenic climate change (e.g., Coppola and Giorgi 2005; May 2008; Kopparla et al. 2013). For these regional time-slice experiments, coupled simulations may still be required to obtain the pattern of anthropogenic SST change, especially in regions where the pattern of SST change has a large climate impact. For example, over tropical oceans, the pattern of SST change is essential in driving changes in precipitation and atmospheric circulation (e.g., Xie et al. 2010; Zheng et al. 2010; Ma et al. 2012). On the other hand, the pattern of anthropogenic SST change has little impact on climate change over the extratropics and land (He et al. 2014), which suggests the possibility of simulating extratropical and land climate change using stand-alone AGCMs that do not include the pattern of SST change.

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