Fast and slow climate responses to CO₂ and solar forcing: A linear multivariate regression model characterizing transient climate change

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Abstract

Climate change in response to a change in external forcing can be understood in terms of fast response to the imposed forcing and slow feedback associated with surface temperature change. Previous studies have investigated the characteristics of fast response and slow feedback for different forcing agents. Here we examine to what extent that fast response and slow feedback derived from time-mean results of climate model simulations can be used to infer total climate change. To achieve this goal, we develop a multivariate regression model of climate change, in which the change in a climate variable is represented by a linear combination of its sensitivity to CO₂ forcing, solar forcing, and change in global mean surface temperature. We derive the parameters of the regression model using time-mean results from a set of HadCM3L climate model step-forcing simulations, and then use the regression model to emulate HadCM3L-simulated transient climate change. Our results show that the regression model emulates well HadCM3L-simulated temporal evolution and spatial distribution of climate change, including surface temperature, precipitation, runoff, soil moisture, cloudiness, and radiative fluxes under transient CO₂ and/or solar forcing scenarios. Our findings suggest that temporal and spatial patterns of total change for the climate variables considered here can be represented well by the sum of fast response and slow feedback. Furthermore, by using a simple 1-D heat-diffusion climate model, we show that the temporal and spatial characteristics of climate change under transient forcing scenarios can be emulated well using information from step-forcing simulations alone.

1. Introduction

A key issue in understanding and predicting climate change is the response of climate system to external forcing. Traditionally, climate change in response to an external forcing is examined in terms of its equilibrium response and/or temporal evolution over different time scales. Over the past decade, the framework of fast response and slow feedback has emerged as a useful paradigm for understanding climate system response to a change in external forcing such as atmospheric carbon dioxide concentration or solar irradiance [e.g., Gregory and Webb, 2008; Andrews et al., 2009; Bala et al., 2009]. Fast response usually refers to rapid climate adjustment to an imposed external forcing that occurs before substantial change in surface temperature, and slow feedback refers to climate response that is associated with a change in surface temperature. In practice, fast response and slow feedback are usually obtained by the regression method proposed by Gregory et al. [2004]. This method involves linear regression of model-simulated time series (usually annual mean) of the change in a climate variable (e.g., top-of-atmosphere radiative fluxes and precipitation) against the time series (usually annual mean) of the change in global mean surface temperature. The resulting intercept of the regression represents the magnitude of fast response (i.e., climate change in the absence of global and annual mean surface temperature change); the slope of the regression represents the magnitude of slow feedback (i.e., climate change associated with per degree change of global mean surface temperature).

Fast response and slow feedback are usually differentiated conceptually by distinguishing climate changes that occur independently of from those that depend on changes in surface temperature. Several different definitions of fast response have been offered. For example, fast response defined here under the constraint of zero global mean surface temperature change includes feedback from atmospheric processes and local surface temperature change. Alternatively, fast response could be defined by fixing sea surface temperature (SST) around the globe [e.g., Hansen et al., 2005; Bala et al., 2009], which includes feedback from change in...
land surface temperature and atmospheric processes. By fixing both SST and land surface temperature [e.g., Shine et al., 2003], fast response could be defined in terms that involve only change in atmospheric processes. Held et al. [2010], by examining temperature response to an abrupt return to preindustrial forcing, defined a fast component that responds quickly to changes in forcing with a time scale of a few years and a slow component that responds very sluggishly to reduction in radiative forcing.

Depending on the purpose of study, fast response and slow feedback could involve adjustment of different components of climate system at different time scales. Factors that might be considered part of the slow feedback for a study focused on changes occurring in the first years after a forcing change might be considered as part of the forcing for a study focused on changes that occur over centuries. In such a long-term analysis, processes occurring on time scales less than a few decades, including the adjustment of atmosphere, land surface, and ocean mixed layer, can be considered as fast response, and deep-ocean processes occurring on longer time scales can be considered as feedback. Therefore, there is no single clear distinction between response and feedback. Nevertheless, the conceptual framework of fast response and slow feedback helps to improve our understanding of climate change to external forcing by distinguishing adjustments separated by a specific time scale and/or process.

The response-feedback framework has been applied to the study of a variety issues related to climate change. One widely used application is to diagnose effective radiative forcing and climate feedback in climate model simulations. For example, Gregory et al. [2004] used the regression method to diagnose effective radiative forcing and climate feedback parameters in Hadley Center Climate Model simulations. Andrews et al. [2012, 2015] used the regression method to diagnose effective radiative forcing and climate feedback in atmosphere-ocean general circulation models (AOGCMs) that participated in phase 5 of the Coupled Model Intercomparison Project (CMIP5). Huneeus et al. [2014] used the regression method to diagnose forcing and feedback in AOGCMs participating in Geoengineering Model Intercomparison Project (GeoMIP) that involves model simulations with increased atmospheric CO2 concentrations and reduced solar irradiance. Doutriaux-Boucher et al. [2009] and Andrews et al. [2011] used the regression method to diagnose fast climate adjustment in response to CO2-physiological forcing (i.e., climate forcing associated with the direct effect of atmospheric CO2 on plant stomata).

The decomposition of climate change into a component of fast response and slow feedback also contributes to our understanding of the behavior of the climate system. For example, Gregory and Webb [2008] found that rapid tropospheric cloud adjustment plays an important role in determining equilibrium climate sensitivity and could affect time-dependent climate projections. Furthermore, a number of modeling studies found that precipitation responds differently to CO2 and solar forcing mainly as a result of different fast precipitation response to these two forcing agents [e.g., Andrews et al., 2009; Bala et al., 2009; Cao et al., 2011]. Thorpe and Andrews [2014] found that CMIP5 model simulations show little or no increase in global precipitation over the historical period because the increase in precipitation from surface warming (slow feedback) is largely offset by the direct effect from CO2 and black carbon forcing (fast response).

In this work, we develop a multivariate regression model of climate change that represents the annual mean change in a climate variable as a linear combination of its sensitivity to CO2 and/or solar forcing (fast response) and sensitivity to change in annual and global mean surface temperature (slow feedback). We use the forcing-feedback framework to examine the representation of total climate change in terms of fast response to CO2 and solar forcings, and slow feedback associated with global mean temperature change. In specific, we investigate to what extent time-dependent climate change and its spatial pattern can be represented as a linear combination of fast response and slow feedback.

We emphasize a few novel aspects of this study. First, our regressions analysis is based upon regressions involving time-mean results from several simulations, rather than regressions involving time series data from a single simulation (or ensemble of simulations) that is typically used in previous studies. This multivariate regression approach allows simultaneous estimation of the fast response to each of several different climate forcings (e.g., a change in CO2 forcing or solar forcing). Second, our study presents an advance over the normal pattern scaling approach [e.g., Santer et al., 1990; Mitchell, 2003] in that this work explicitly takes into account the fast response component associated with different forcing agents, in addition to the component that scales with global mean temperature change that is considered in the pattern scaling approach. Furthermore, we focus on the analysis of the extent to which transient climate change and its spatial pattern can be represented by the sum of fast response and slow feedback. Few previous studies have focused on this issue.
The structure of this study is organized as following. Section 2 presents the method used in this study, including the design of HadCM3L simulation experiments and construction of the regression model. In section 3, we compare climate change estimated from regression model with those from HadCM3L transient simulations for a variety of climate variables at global, zonal, and model-grid scales. Discussion and conclusions are provided in section 4.

2. Methods

2.1. Climate Model and Simulation Experiments

Here we use UK Met Office Hadley Center AOGCM, HadCM3L [Cox et al., 2000]. HadCM3L has a horizontal resolution of 3.75°longitude and 2.5°latitude for both the atmosphere and ocean with 19 nearly horizontal levels in the atmosphere and 20 horizontal levels in the ocean. A quasi-equilibrium state of preindustrial climate was obtained from a 3000 year model spin-up simulation under a constant atmospheric CO2 concentration of 280 ppm and a default solar irradiance of 1365 W m⁻². Starting from this quasi-equilibrium climate state, step-forcing and ramp-forcing simulations were performed as described below and illustrated in Figure 1.

Step-forcing simulations for regression model training: Starting from the end-state of 3000 year spin-up simulation, HadCM3L was first integrated with 1 × CO₂, 2 × CO₂, and 4 × CO₂ for an additional 1000 years. Then, starting from the end state of each of these three 1000 year runs, we performed nine 50 year simulations that involve step changes to one of the three different atmospheric CO₂ concentration levels (1 × CO₂, 2 × CO₂, and 4 × CO₂), and to one of three different solar irradiance levels (0%, +2%, or −2% change from default solar constant). Since we have three initial conditions (1 × CO₂, 2 × CO₂, and 4 × CO₂), three CO₂ levels (1 × CO₂, 2 × CO₂, and 4 × CO₂), and three solar irradiance levels (0%, +2%, or −2% change from default solar constant), this yields 27 simulations in total (Table S1 in the supporting information), which were used in the construction of the regression model as described in section 2.2. We used these 27 step-forcing simulations with different initial conditions and forcings to train a multivariate regression model, and then we applied the regression model to emulate HadCM3L transient simulations under a wide range of CO₂ and/or solar forcing scenarios.

Ramp-forcing simulations for regression model testing: Starting from the end-state of 3000 year model spin-up, a set of three simulations with gradual changes in atmospheric CO₂ and/or solar irradiance was performed with each simulation lasting for 330 years.

CO₂_updn: Atmospheric CO₂ increases at a rate of 1% per year for 140 years to reach 4 × CO₂ followed by a 50 year stabilization at 4 × CO₂, and then decreases at a rate of 1% per year for 140 years to 1 × CO₂. In the model simulations with CO₂ forcing, including both step-forcing and ramp-forcing runs, changing atmospheric CO₂ affects global climate through its radiative effect as well as the direct effect on plant stomata, i.e., CO₂-physiological forcing [Sellers et al., 1996; Doutriaux-Boucher et al., 2009; Cao et al., 2010].

Solar_updn: Solar irradiance increases linearly to an increase of 4% by year 140. Then, solar irradiance is kept constant for 50 years and then decreases linearly for 140 years to its control value.

CO₂_updn + Solar_dnup: Atmospheric CO₂ follows the pathway of CO₂_updn but the change of solar irradiance is of opposite direction to Solar_updn. This experiment mimics the effect of sunshade Solar Radiation Management (SRM) climate geoengineering scheme [Caldeira et al., 2013; Kravitz et al., 2013], in which reduced solar irradiance is used to offset the warming effect from increasing atmospheric CO₂.

These three above ramp-forcing simulations are used to test the performance of the regression model in emulating transient climate projections.

2.2. Construction and Application of Linear Regression Model

Using the results from the 27 step-forcing simulations, we could in principle perform the linear regression in the form of:

ΔV = kC,V ΔC + kS,V ΔS + kT,V ΔT

In our analysis, equation (1) can represent the change in any climate variable (ΔV) as a linear function of its sensitivity to a doubling of atmospheric CO₂ (ΔC), a 1% increase in solar irradiance (ΔS), and 1 K increase in annual and global mean surface temperature (ΔT). Because the radiative forcing of CO₂ scales approximately with the
logarithm of atmospheric CO₂, we define \( \Delta C = \log_2 (p\text{CO}_2/p\text{CO}_2\text{ref}) \), where \( p\text{CO}_2\text{ref} = 1 \times \text{CO}_2 = 280 \text{ ppm} \). The regression coefficients of \( k\text{C}_V, k\text{S}_V, \) and \( k\text{T}_V \) represent the sensitivity of the change in a climate variable to a doubling of CO₂, a 1% increase in solar irradiance, and 1 K increase in global and annual mean surface temperature, respectively.

For each of the 27 step-forcing runs, we calculated 50 year mean values of \( \Delta T \) and \( \Delta V \). Then, we used these time-mean values of \( \Delta T \) and \( \Delta V \) across 27 simulations, together with the prescribed values of \( \Delta C \) and \( \Delta S \) in each of the 27 runs, to perform linear regression of equation (1). Thus, for each variable \( V \) considered, our linear regression involves solution for three coefficients \( (k\text{C}_V, k\text{S}_V, \) and \( k\text{T}_V) \) based on 27 sets of four known numbers \( (\Delta V, \Delta C, \Delta S, \) and \( \Delta T) \). The regression was applied repeatedly on global, zonal, and grid mean values of \( \Delta V \). Global and annual mean changes of surface temperature were used in all regressions.

After the regression coefficients of \( k\text{C}_V, k\text{S}_V, \) and \( k\text{T}_V \) were obtained, the regression model was applied to emulate HadCM3L-simulated transient climate change under ramp-forcing scenarios in the following form:

\[
\Delta V(t) = k\text{C}_V \Delta C(t) + k\text{S}_V \Delta S(t) + k\text{T}_V \Delta T(t) \tag{2}
\]

where \( \Delta V(t) \) represents the time variation of the variable of interest and \( \Delta C(t) \) represents the time variation of atmospheric CO₂ content according to the following equation:
\[ \Delta C(t) = \log_2 \left( \frac{pCO_2(t)}{pCO_2(\text{ref})} \right) \]

and \( \Delta S(t) \) represents the change in solar irradiance according to the equation:

\[ \Delta S(t) = 100\% \times \left( \frac{\text{Solar}(t) - \text{Solar}(\text{ref})}{\text{Solar}(\text{ref})} \right) \]

where \( pCO_2(t) \) and \( \text{Solar}(t) \) are prescribed atmospheric CO\(_2\) concentrations and solar irradiance in the ramp-forcing simulations; \( CO_2 \) (ref) and \( \text{Solar} \) (ref) are the reference CO\(_2\) concentration (280 ppm) and solar irradiance (1365 W m\(^{-2}\)). \( \Delta T(t) \) is time series of global and annual mean surface temperature change under ramp-forcing scenarios, which can be taken either from HadCM3L ramp-forcing simulations or from prediction by a 1-D climate model as described below.

### 2.3. Conjoining the Linear Regression Model With a One-Dimensional (1-D) Heat Diffusion Climate Model

The regression model as described above can be used to estimate a wide range of climate parameters once the time series of external forcing and the change in annual and global mean surface temperature are known. Temperature change, \( \Delta T(t) \), can be directly taken from HadCM3L CO\(_2\)/solar ramp-forcing simulations. Alternatively, \( \Delta T(t) \) can be estimated from a 1-D heat-diffusion climate model that is trained by step-forcing simulations.

Following the method of MacMynowski et al. [2011] and Caldeira and Myhrvold [2012], we consider a 1-D climate model with heat-diffusion into a semi-infinite medium, which has a known form of response function that links temperature change to imposed forcing. The response function of the 1-D model has three parameters, effective radiative forcing (\( F \)), climate feedback parameter (\( \lambda \)), and characteristic time scale (\( \tau \)), which can all be calibrated from step-forcing simulations. We use the calibrated response function to estimate global and annual mean surface temperature change under CO\(_2\)/solar ramp-forcing scenarios, which can be used as \( \Delta T(t) \) in the regression model of equation (2). In this way, climate change under transient forcing scenarios can be emulated using information from step-forcing simulations alone. The detailed description of the 1-D model is provided in the Appendix section.
3. Results

3.1. Regression Model Predicted Global Mean Climate Change Using HadCM3L-Simulated Global Mean Temperatures

We first apply the regression model to predict global mean climate change. Here regression coefficients, as listed in Table S2 for variables of precipitation, runoff, soil moisture, cloudiness, and top-of-atmosphere (TOA) radiative fluxes, are obtained by applying the regression model of equation (1) on global mean $\Delta V$. These coefficients represent the sensitivity of the change in a climate variable to external forcing (fast response) and the change in global mean surface temperature (slow feedback). For example, the multivariate regression yields that in the absence of change in global mean temperature, response of global precipitation to atmospheric CO2 increase is negative, but to solar irradiance increase is not significantly different from zero (Table S2). This result is in broad agreement with previous studies that regress precipitation change against temperature change in a single simulation with either CO2 or solar forcing [Andrews et al., 2009; Bala et al., 2009].

We note that the multivariate regression model used here implicitly assumes that the sensitivity to global temperature change is the same for CO2 and solar forcing. We perform additional regressions that are applied on step-forcing simulations with change in CO2 forcing only or solar forcing only; the corresponding regression coefficients are shown in Tables S3 and S4. Regression coefficients obtained this way typically have uncertainty ranges that overlap those obtained from the multivariate regression model using all simulations simultaneously (Tables S3 and S4). Thus, while our analysis cannot rule out real differences in the slow feedback in response to different forcing agents, our results do not provide strong support for such differences.

We further note that the multivariate regression model used here considers sensitivity of climate change to external forcing and global temperature to be constant over time. We recognize that effective radiative fluxes change with time.
Forcing and climate feedback parameter have been shown to evolve with time [Gregory et al., 2004; Andrews et al., 2015]. Therefore, the sensitivity of climate change to external forcing and global temperature would depend somewhat on the magnitude of forcing and background climate state. Thus, our regression coefficients should be interpreted as indicating a mean response on the 50 year time scale, recognizing that there could be different results obtained for very short or very long time scales.

Now we use the regression model to predict HadCM3L-simulated climate change in the CO2 and/or solar ramp-forcing simulations. Time evolution of climate fields predicted from regression model of equation (2) and HadCM3L-simulations is compared in Figures 2–5. In general, the regression model captures the overall behavior of HadCM3L-simulated time evolution for a set of climate variables including precipitation, runoff, soil moisture, cloudiness, and TOA shortwave and longwave radiative fluxes. The regression model shows skill in capturing the time evolution of climate change in scenarios with individual or combined CO2/solar forcing. For example, in the simulation where solar forcing approximately offsets CO2 forcing (CO2_updn + Solar_dnup), global mean temperature change is near zero, but there remains substantial changes in the hydrological cycle (Figures 2 and 3) and cloudiness (Figure 5). This characteristics of climate change is well captured by the regression model. Previous modeling studies have shown that when the warming effect from increased CO2 is offset by reduced solar irradiance, there would be a noticeable decrease in global precipitation [Bala et al., 2008; Boucher et al., 2013].

Some mismatches are observed between the results from regression model and from HadCM3L simulations. For example, during the ramp-down phase of CO2_updn the regression model apparently underestimates HadCM3L-simulated precipitation change (Figure 2) with the mismatch mainly observed over land (Figure 3). We speculate that part of the mismatch could be associated with the nonlinearity of CO2-physiological forcing, but additional simulations that separate CO2-radiative and physiological effects are needed to further explore this issue. It is possible that temporal variations in sensitivities to CO2 and solar forcing or to global mean temperature response could also contribute to these mismatches.

Apparently, the regression model does a better job in capturing the trend of climate evolution than the year-to-year variability. In particular, the predicted variability of land precipitation, runoff, soil moisture, (Figures 2 and 3), and cloudiness (Figure 5) by the regression model is much smaller than that predicted by HadCM3L simulations, indicating that the variability of these fields is not able to be explained by the variability of model-simulated global mean surface temperature alone.
3.2. Regression-Model Predicted Zonal Mean Climate Change Using HADCM3L-Simulated Global Mean Temperatures

We now apply the regression model to predict zonal mean climate change. Here regression coefficients at each latitude, as shown in Figures S1 and S2 in the supporting information, are obtained by applying the regression model of equation (1) on zonal mean \( \Delta \nu \) (with global mean surface temperature change \( \Delta T \) as independent variable). As shown in Figures 6 and S3, the regression model shows skill in emulating...
HadCM3L-simulated pattern of zonal mean climate change, including surface air temperature, precipitation, runoff, soil moisture, and cloudiness. For example, as shown in Figure 6, in response to increased CO$_2$ and solar forcing (stabilizing period of CO$_2_{\text{updn}}$ and Solar$_{\text{updn}}$), HadCM3L simulated an increase in precipitation in the tropics and mid-to-high latitude and a decrease in precipitation in the subtropics. This pattern of precipitation change is well captured by the regression model (Figure 6). In the case where CO$_2$ forcing is offset by solar forcing (CO$_2_{\text{updn}}$ + Solar$_{\text{dnup}}$), HadCM3L simulated an overall decrease in precipitation in the tropical region, which is also well captured by the regression model (Figure 6).

Figure 7. Geographical distribution of regression coefficients $k_{T_V}$, $k_{C_V}$, and $k_{S_V}$ for variable $V$ of surface temperature ($T$), precipitation ($P$), runoff ($R$), and soil moisture ($M$). Only values that are significant at 5% level are shown. Numerical values shown in each panel are global mean values.
3.3. Regression Model Predicted Climate Change at Grid Scale Using HADCM3L-Simulated Global Mean Temperatures

We then apply the regression model to predict spatial distribution of climate change. Here regression coefficients at each model grid for surface temperature, precipitation, runoff, soil moisture (Figure 7) and cloudiness (Figure S4) are obtained by applying the regression model of equation (1) on $\Delta V$ at each model grid point (with global mean surface temperature change $\Delta T$ as independent variable). As shown in Figures 7 and S4, there appears to be an anticorrelation between the regression coefficients for response to temperature change and regression coefficients for response to CO$_2$/Solar forcing change. That is, in regions where coefficients for temperature is positive (negative), coefficients for CO$_2$/Solar forcing is negative (positive).

On a global scale for some variables such as precipitation and clouds, this result makes intuitive sense. For example, both increased atmospheric CO$_2$ content and increased solar forcing tend to cause the atmosphere to gain energy and stabilize it; in contrast, increased near surface temperatures tend to destabilize the atmosphere. It is possible that the spatial response to factors that tend to cause the atmosphere to stabilize would typically be opposite in sign of the spatial response to factors that would tend to destabilize the atmosphere. Nevertheless, the spatial pattern of anticorrelation observed here could be also partly due to the compensating biases associated with the multivariate regression method.

It is also interesting to note that the spatial pattern of fast temperature response ($k_{CT}, k_{ST}$) appears to correlate with the fast precipitation response ($k_{CP}, k_{SP}$) (Figure 7), particularly for the tropical ocean where the regions with positive/negative fast temperature change corresponds to the regions with positive/negative fast precipitation change. This correlation suggests that in addition to direct effect of CO$_2$/solar forcing, fast precipitation response is partly associated with fast temperature response.

With these coefficients (Figures 7 and S4), the regression model is applied to predict the geographical distribution of climate change based on atmospheric CO$_2$, solar irradiance, and change in global mean surface temperature. We compare the spatial distribution of surface temperature (Figure 8), precipitation (Figure 9), runoff...
Figure 9. Spatial distribution of annual mean precipitation change from HadCM3L ramp-forcing simulations and regression model result as well as their differences (regression model results minus HadCM3L simulations). See caption of Figure 8 for more detail.

Figure 10. Spatial distribution of annual mean runoff change from HadCM3L ramp-forcing simulations and regression model result as well as their differences (regression model results minus HadCM3L simulations). See caption of Figure 8 for more detail.
(Figure 10), soil moisture (Figure 11), and total cloudiness (Figure S5) between HadCM3L simulations and regression model results. All results shown are mean values averaged between years 150 and 180 when atmospheric CO$_2$ and/or solar irradiance are stabilized at their peak levels. The contribution to total climate change from the component of fast response associated with CO$_2$ forcing ($k_{C,V} \times \Delta C$) and/or solar forcing ($k_{S,V} \times \Delta S$), and the component of slow feedback associated with temperature change ($k_{T,V} \times \Delta T$) are shown in Figures S6 to S10. As shown in Figures 8–11 and S5, the regression model shows skill in emulating HadCM3L-simulated spatial distribution of climate change. For example, as shown in Figure 9, in the case of CO$_2$ updn and Solar updn, HadCM3L simulates a large-scale increase in precipitation over the equatorial Pacific and an overall decrease in precipitation over tropical land. This pattern of precipitation change, which is well captured by the regression model, is in broad agreement with the multimodel mean projections of tropical precipitation change by the end of this century [Bony et al., 2013]. In the simulation of CO$_2$ updn + Solar_dnup, precipitation decreases in large parts of the world, which is also well captured by the regression model.

In Figure 12, a Taylor diagram [Taylor, 2001] is used to summarize the statistics of the change in surface air temperature, precipitation, runoff, soil moisture, and total cloudiness as shown in Figures 8–11 and S5. For the fields presented here, the correlation coefficients between regression model and HadCM3L-simulation results range between 0.87 and 0.97 for the experiment of CO$_2$ updn, 0.74–0.94 for the experiment of Solar updn, and between 0.62 and 0.89 for the experiment of CO$_2$ updn + Solar_dnup (Figure 12 and Table S5). For surface air temperature, precipitation, runoff, soil moisture, and total cloudiness, absolute RMS errors in the regression model prediction, relative to HadCM3L ramp-forcing simulations, range from 0.3 to 0.6 K, 0.3 to 0.6 mm d$^{-1}$, 0.09 to 0.17 mm d$^{-1}$, 18 to 26 kg m$^{-2}$, and 0.02 to 0.03, respectively (Table S5).

### 3.4. Regression Model Predicted Climate Change Using Temperatures From a Calibrated 1-D Heat-Diffusion Climate Model

In the results presented above, time series of global mean surface temperature $\Delta T$ used in the regression model of equation (2) for predicting transient climate change is taken from HadCM3L CO$_2$/solar ramp-forcing simulations. Alternatively, we can estimate $\Delta T$ under these ramp-forcing scenarios using a 1-D heat-diffusion model.
climate model that is calibrated based on the results from step-forcing simulations (refer to section 2.3 and the Appendix section). As shown in Figure 2, the 1-D climate model emulates well HadCM3L-simulated global mean temperature change under CO2/solar ramp-forcing scenarios. Therefore, we can use 1-D model predicted temperature change, instead of HadCM3L-simulated temperature change, as an independent variable in the regression model of equation (2).

This method of estimating global mean climate change shows similar skill in emulating HadCM3L simulation results as does the method of using temperatures from the HadCM3L simulations in the regression equations, but with the loss of year-to-year climate variability (compare red and blue lines in Figures 2–5). The spatial distributions of surface air temperature, precipitation, runoff, soil moisture, and total cloudiness projected using temperature from the 1-D climate model are nearly as good as those projected using temperature taken directly from HadCM3L simulations (compare Figure 12 with Figure S11 and Table S5 with Table S6). This exercise demonstrates the potential to use only information from step-forcing simulations to predict transient climate change and its spatial distribution for a wide range of forcing scenarios.

4. Discussion and Conclusions

Using time-mean results from a set of HadCM3L step-forcing simulations, we constructed a multivariate regression model in which the change in a climate field, including surface temperature, precipitation, runoff, soil moisture, and cloudiness, is represented by the linear sum of its sensitivity to CO2 forcing, solar forcing, and change in global mean surface temperature. A large number of step-forcing simulations were used to reduce parameter uncertainty and so that the regression model would be applicable over a broad range of ramp-forcing scenarios.
We have shown that the multivariate regression model, which is trained by HadCM3L step-forcing simulations, demonstrates skill at emulating HadCM3L-simulated transient climate change under ramp-forcing scenarios. The regression model not only reproduces well HadCM3L-simulated global mean climate change, but also captures HadCM3L-simulated spatial distribution of climate change. Our results suggest that transient climate change can be approximated by a linear combination of response to external forcing and response to the change in global mean surface temperature. Here we have tested the behavior of the multivariate linear regression model under CO2 and solar forcing. The testing of the linear assumption for climate response to other forcing agents, such as aerosol and land use that are more spatially inhomogeneous, merits further study. As an analog of testing linear assumption of climate response to localized forcing, previous studies assumed that regional atmospheric response can be approximated as the sum of the response to each localized sea surface temperature forcing [Barsugli and Sardeshmukh, 2002; Li et al., 2012]. Further, here we tested the linear assumption for a limited set of climate variables including temperature, precipitation, runoff, soil moisture, cloudiness, and TOA radiative fluxes. The testing of the regression model for other variables, such as ocean circulation and vegetation change, merits further study. Also, a multimodeling study is needed to investigate the robust performance of the regression model and associated nonlinearity.

Gregory et al. [2004] noted that in some climate model simulations, effective radiative forcing and the climate feedback parameter apparently evolve with time. This phenomenon was analyzed in greater detail by other studies [e.g., Winton et al., 2010; Armour et al., 2013; Andrews et al., 2015], which found that time evolution of regional surface temperature patterns could influence the time evolution of both effective radiative forcing and the climate feedback parameter. Nevertheless, as the close correspondence between our purely linear analysis and the full three-dimensional simulation results indicates, substantial insight into climate system processes can be gained by a time-invariant linear analysis. However, we do note that this correspondence is far from perfect; some of the departure between linear projections and the full three-dimensional simulation results are likely associated with time-dependent factors as discussed by Armour et al. [2013] and Andrews et al. [2015]. Additionally, some of the departure is likely due to there being some degree of nonlinearity in the climate system response to increasing climate forcing at a given point in time. In the case of gradual changes in external forcings such as a 1% per year increase in CO2, each incremental change in external forcing will induce a fast response that occurs before temperature-related feedback. These incremental changes related to the fast response accumulate and make an important and significant contribution to the total climate response. Consideration of the temporal evolution in the first month after a change in forcing may be extremely valuable in helping to understand the physics of the rapid climate system response to a forcing change [Cao et al., 2012], but it may not be critical to estimating the magnitude of the fast response as it applies to long-term climate change.

Our study also suggests new approach for emulating GCM-simulated transient climate change using results from only step-forcing simulations. By using the regression model, together with a 1-D heat-diffusion climate model that is calibrated from step-forcing simulations, we demonstrate that both the temporal evolution and spatial pattern of climate change under transient forcing scenarios can be well reproduced. One common approach used in the emulation of GCM results is pattern scaling [Santer et al., 1990; Mitchell, 2003], which assumes that regional climate change scales linearly with the change in global mean temperature. A simple climate modeling framework based on the linear impulse-response theory was also proposed to reproduce global mean transient climate change from CO2 step forcing experiments [Good et al., 2011, 2012]. In addition, Geoffroy and Saint-Martin [2014] showed that regional pattern of transient surface warming can be represented by a time-space decomposition of step-forcing simulations. Here we demonstrate the feasibility of using step-forcing experiments to predict GCM-simulated climate change, including temperature, precipitation, runoff, soil moisture, and cloudiness at global, zonal, and model-grid scales under a range of transient CO2/solar forcing scenarios. The setup of step-forcing experiments in this study may not be ideal, but the potential of using step-forcing simulations to predict transient climate change is of great interest.

Our results suggest that transient climate response, in terms of both temporal evolutions and spatial patterns, can be approximated with the linear sum of response to the change in external forcing and response to the change in global mean surface temperature. Our results also indicate that climate response to different forcings, as it applies to long-term climate change, could in principle be estimated using time-mean results from a set of climate simulations with step-function forcings. These approaches may prove valuable in integrated assessment models or other contexts, in which a rapidly executing approximation to the climate system is desirable.
Appendix A

A1. One-Dimensional (1-D) Heat-Diffusion Climate Model to Estimate Temperature Change Under CO₂/Solar Ramp-Forcing Scenarios

We can emulate HadCM3L-simulated global and annual mean temperature change in CO₂/solar ramp-forcing simulations using results from 27 step-forcing simulations as detailed in the following.

A1.1. Construction of a 1-D Heat-Diffusion Model

Following MacMynowski et al. [2011] and Caldeira and Myhrvold [2012], we consider a 1-D model representing heat diffusion into a semi-infinite slab.

\[ \frac{\partial T}{\partial t} = \alpha \frac{\partial^2 T}{\partial z^2} \]  
(A1)

with boundary condition

\[ k \frac{\partial T}{\partial z} \bigg|_{z=0} = F - \lambda T(t,0) \]  
(A2)

where \( \alpha, \lambda, \) and \( F \) are vertical diffusivity, climate feedback parameter, and effective radiative forcing, respectively.

K = \( C_P \rho a \) (\( C_P \) is heat capacity, and \( \rho \) is the density of seawater). \( T \) is temperature.

According to MacMynowski et al. [2011] and Caldeira and Myhrvold [2012], temperature change in response to a step forcing in the 1-D model can be expressed as

\[ T(t) = F \ast h(t) \]  
(A3)

where \( h(t) \) is the response function to forcing \( F \).

\[ h(t) = \frac{1}{\tau} \left( 1 - e^{t/\tau} \text{erfc} \left( \sqrt{t/\tau} \right) \right) \]  
(A4)

where \( \tau = k^2 / (\lambda a) \) is the characteristic time scale.

A1.2. Calibrate Parameters of the 1-D Model Using Step-Forcing Simulation Results

There are three parameters in equations (A3) and (A4), \( F, \lambda, \) and \( \tau \), which can be estimated using results from step-forcing simulations. First, we estimate effective radiative forcing \( F \) and climate feedback parameter \( \lambda \) by performing regression in the similar form of equation (1). That is:

\[ \Delta V = F_C \Delta C + F_S \Delta S + \lambda \Delta T \]  
(A5)

Here \( \Delta V \) is the change in global and annual mean top-of-atmosphere (TOA) downward net flux. \( F_C \) and \( F_S \) represent effective radiative forcing per doubling of atmospheric CO₂ and per 1% increase in solar irradiance.

Thus, \( F \) in equation (A3) can be represented as the sum of \( F_C \) and \( F_S \). Using time-mean results of the 27 step-forcing simulations, regression of equation (A5) yields a value of 3.3 W m⁻², 1.6 W m⁻², and −1.1 W m⁻² K⁻¹ for \( F_C, F_S, \) and \( \lambda \), respectively (Table S2).

With these known values of \( F_C, F_S, \) and \( \lambda \), we can represent time series of temperature change in the form of equation (A3) for each of the 27 step-forcing simulations with only one unknown parameter of \( \tau \). We then determine \( \tau \) by minimizing the sum of square difference between the 27 50-year time series of temperature change simulated from step-forcing runs and estimated from equation (A3). This yields a value of 10.2 years for \( \tau \).

A1.3. Use 1-D Model to Predict Temperature Change Under CO₂/Solar Ramp-Forcing Scenarios

Global mean surface temperature change under the CO₂/solar ramp-forcing scenarios can be estimated as:

\[ T(t) = \int_0^t h(t - \tau) F(\tau) d\tau \]  
(A6)

where the response function \( h \) takes the form of equation (A4). Time history of forcing \( F(\tau) \) takes the form of
where $\text{CO}_2(t)$ and Solar($t$) are prescribed time history of atmospheric $\text{CO}_2$ concentrations and solar constant; $\text{CO}_2(\text{ref})$ and Solar (ref) are default $\text{CO}_2$ concentration (280 ppm) and solar constant (1365 W m$^{-2}$). Parameter values of $\lambda$, $\tau$, $F_P$, and $F_S$ used in equation (A6) and (A7) are those determined in section A1.2. As shown in Figure 2, temperature change estimated from equation (A6) compares well with that simulated from HadCM3L $\text{CO}_2$/Solar ramp-forcing simulations.

References


Cao, L., G. Bala, and K. Caldeira (2012), Climate response to changes in atmospheric carbon dioxide and solar irradiance on the time scale of days to weeks, Environ. Res. Lett., 7, 034015.


