A New Method of Comparing Forcing Agents in Climate Models*

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(Manuscript received 30 September 2014, in final form 3 August 2015)

ABSTRACT

The authors describe a new method of comparing different climate forcing agents (e.g., CO₂ concentration, CH₄ concentration, and total solar irradiance) in climate models that circumvents many of the difficulties associated with explicit calculations of efficacy. This is achieved by introducing an explicit feedback loop external to a climate model that adjusts one forcing agent to balance another while keeping global-mean surface temperature constant. The convergence time of this feedback loop can be adjusted, allowing for comparisons of forcing agents to be achieved with relatively short simulations. Comparisons between forcing agents are highly linear in concordance with predicted scaling relationships; for example, the global-mean climate response to a doubling of the CO₂ concentration is equivalent to that of a 2.1% change in total solar irradiance. This result is independent of the magnitude of the forcing agent (within the range of radiative forcings considered here) and is consistent across two different climate models.

1. Introduction

One of the cornerstone problems in climate science is understanding the climate system's response to changes in climate forcing agents, such as the concentration of

CO₂ and other greenhouse gases, total solar irradiance, and different types of aerosols. For example, formulating any climate target or emissions path requires knowledge of how to compare the effects of different greenhouse gases with different radiative properties and atmospheric lifetimes (Fuglestad et al. 2003). Broadly speaking, this problem has typically been separated into radiative forcing (how much additional energy is introduced into the climate system due to a change in CO₂) and climate response (how the climate system then changes in response to this additional energy).

For the same radiative forcing, different forcing agents can result in a different global-mean climate response. To adjust for this, a standard approach in comparing forcing agents is to define a relative efficacy

Denotes Open Access content.

* Supplemental information related to this paper is available at the Journals Online website: <http://dx.doi.org/10.1175/JCLI-D-14-00663.s1>.

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DOI: 10.1175/JCLI-D-14-00663.1

between them (Hansen et al. 2005, also see section 2). This requires an explicit calculation of both radiative forcing and temperature response for both forcing agents, undertaken with separate simulations for each agent. As we will show in the following section, one of the dominant challenges of this approach is that because radiative forcing and climate response coevolve with time (Andrews et al. 2012), errors in calculating efficacy can arise. Here we describe an alternative method for comparing climate forcing agents in climate models that largely circumvents some of these difficulties, especially those related to ambiguities due to temperature-related feedbacks. Climate feedbacks are state dependent (i.e., depend upon surface air temperature) (e.g., Jarvis 2011; Armour et al. 2013; Cao et al. 2012). In our comparisons of forcing agents, the amount of one agent is chosen to balance the global-mean temperature effect of another; by doing so, the effect of climate feedbacks is greatly reduced.

The tool we use to accomplish this intercomparison is one that we have developed for climate modeling, wherein a feedback loop is explicitly introduced into a climate model simulation without the need for recoding (section 3); as such, this tool can be used on models of arbitrary complexity and can be readily ported between models. We illustrate application of this method for three forcing agents in two climate models: total solar irradiance (S_0), carbon dioxide concentration (CO_2), and methane (CH_4).

In illustrating this method we consider the following questions:

- 1) Can this new method be used to compare climate forcing agents in climate models in a robust way? For example, can one obtain an answer like “ $2 \times \text{CO}_2$ is equivalent to an X% change in total solar irradiance”?
- 2) Is the modeled behavior linear within the expected relationships between the forcing agents? That is, if $2 \times \text{CO}_2$ is equivalent to X% solar, is $4 \times \text{CO}_2$ equivalent to 2X% solar?
- 3) How similar are the relationships between the different forcing agents in different climate models?

This alternative method of comparing forcing agents has advantages and disadvantages relative to the current approach of computing radiative forcing and efficacy; as such, we view our method as complementary to more traditional approaches. While this alternative does not directly permit calculations of radiative forcing by the definitions of Hansen et al. (1997, 2005), it gives a direct estimate of the required change in different forcing agents to exert equivalent global-mean temperature changes.

2. Efficacy of climate forcing agents

Radiative forcing is a measure of the rate of additional energy added to the climate system as a result of a change in a forcing agent (Forster et al. 1997). Under the assumptions that climate feedback strengths are nearly constant over a wide range of time scales and that similar magnitudes of global-mean forcing yield similar global-mean climate responses, calculations of radiative forcing can lead to a useful first-order estimate of steady-state temperature change (e.g., Forster et al. 1997; Hansen et al. 1997; Fuglestad et al. 2003). More simply, the relationship between global-mean steady-state temperature change ΔT and radiative forcing ΔR can be approximated as $\Delta T = \lambda \Delta R$, where λ is a “feedback parameter” (with units $\text{K m}^2 \text{W}^{-1}$). The feedback parameter λ describes an aggregation of many different local feedbacks, each of which depends upon the specific spatial pattern of temperature change induced by a radiative forcing (Armour et al. 2013).

Different climate forcing agents with the same global-mean radiative forcing can have different global-mean temperature responses; Hansen et al. (2005) introduced the concept of *efficacy* to account for these differences among different forcing agents. The formal definition of efficacy is

$$E_x = \frac{\Delta T_x / \Delta R_x}{\Delta T_{\text{CO}_2} / \Delta R_{\text{CO}_2}} = \frac{\lambda_x}{\lambda_{\text{CO}_2}}, \quad (1)$$

where E_x is efficacy (unitless), T is global, annual mean temperature (K), R is global, annual mean radiative forcing (W m^{-2}), x refers to any given forcing agent, CO_2 refers to a fixed concentration of CO_2 that is used as a reference point, and λ_x and λ_{CO_2} are the (global) feedback parameters associated with forcing x and CO_2 , respectively. The primary purpose of efficacy is to account for the fact that λ_x is different for different forcing agents, and in doing so, the relationship $\Delta T = \lambda_x \Delta R_x = \lambda_{\text{CO}_2} E_x \Delta R_x$ will then hold for each agent. We note that all of the parametric and structural uncertainties inherent to climate models do not preclude the calculation of efficacy, although the efficacy of any particular forcing may differ across models; indeed, a strength of our alternative method of comparing climate forcing agents is that it does not require intimate knowledge of the individual processes that are incorporated into emergent climate responses.

Comparing forcing agents using the metric of efficacy requires careful determination of radiative forcing and climate response (RFCR) for the forcing agents. Figure 1 shows a plot of global-mean temperature change against global-mean top-of-atmosphere net

FIG. 1. Scatterplot for atmosphere–ocean general circulation model simulations of an abrupt quadrupling of the CO_2 concentration, starting from a stable preindustrial control run. In each panel, red circles show the global-mean, monthly averaged temperature change (x axis) against the global-mean, top-of-atmosphere net radiative flux change (y axis) for the first year of simulation. Green dots show annual averages for years 2–30. Blue dots show annual averages for years 31–150. Squares show the x and y intercepts obtained from ordinary least squares regression (thin colored lines) through the respectively colored points. The bottom two panels show results for GISS-E2-R and CESM, the models used in the present study.

radiative flux change for an abrupt increase in the CO_2 concentration in four fully coupled atmosphere–ocean general circulation models (AOGCMs). If one assumes a linear relationship between ΔR and ΔT , then radiative forcing should be given by the y intercept of a regression line through the points plotted in Fig. 1, and the steady-state temperature response should be the x intercept of that regression line. This is the theoretical basis for the so-called *Gregory method* for estimating RFCR (Gregory et al. 2004). However, the slope of the relationship between ΔT and ΔR may change with time if the global feedback strength is state dependent (as is seen in Fig. 1). Different parts of the climate system respond at different rates and with local patterns that depend upon the particular forcing agent. This leads to an evolving pattern of warming and hence evolving relative contributions of different local feedbacks to the

overall aggregate feedback relationship between radiative forcing and global-mean temperature (Armour et al. 2013).

Because no single value of λ will work for all forcing agents, Hansen et al. (1997, 2005) began to assess multiple potential definitions of radiative forcing, which vary based on which adjustment processes are included in calculations of forcing, with the goal of determining a definition of radiative forcing that most accurately predicts the temperature response. Each definition has its own particular merits and shortcomings (Hansen et al. 2005), but it has been shown that the best estimates of steady-state temperature change in response to radiative forcing are obtained from calculations of radiative forcing that include climate system adjustments that respond rapidly to changes in radiative forcing in the absence of temperature changes (Hansen et al. 1997,

2005). Here we call these *rapid adjustments*. We note that our definition of rapid adjustments is more specific than the definition of [Stocker et al. \(2013\)](#): “The response to an agent perturbing the climate system that is driven directly by the agent, independently of any change in the global mean surface temperature.” Their definition permits local temperature responses that occur in the absence of global-mean temperature change, as in the simulations described in subsequent sections. In the present work, we find it necessary to distinguish truly radiative adjustments, which we call rapid adjustments, from local feedbacks that are operating in response to local temperature changes.

Many of the rapid adjustments, including cloud and water vapor adjustments, happen on time scales of days to weeks ([Andrews et al. 2012](#); [Cao et al. 2012](#)). This effectively means that to obtain the most accurate value of ΔR for the assumed relationship between ΔR and ΔT , the first few points in [Fig. 1](#) should be discarded, as they represent a time period over which the climate system has not fully responded to these rapid adjustment processes.

[Gregory et al. \(2004\)](#) proposed that regression should be performed on plots of annually averaged temperature change versus annually averaged net top-of-atmosphere radiative flux changes. By taking annual averages, the impact of rapid adjustments on the slope of this relationship are reduced and are (for the most part) then included in the estimate of radiative forcing. One also does not need to account for dependence on shorter-term variability, such as the diurnal and seasonal cycles. The regression plot ([Fig. 1](#)) also clearly illustrates that the net global feedback depends upon the forcing agent and on the climate state; this introduces uncertainty into the regression-based forcing estimates (e.g., [Gregory and Webb 2008](#); [Andrews et al. 2012](#)).

Nonlinearities play a role in causing or exacerbating some of these uncertainties; these nonlinearities can be in either the radiative forcing or the climate response ([Caballero and Huber 2013](#)). For example, as we discuss in [section 4](#) below, the relationship between CO_2 concentration and radiative forcing is generally logarithmic, but there is a departure from this logarithmic behavior for high CO_2 concentrations. Climate feedbacks are state dependent; as an example, the strength of the ice-albedo feedback in the present-day climate would not be the same in a high CO_2 climate in which all sea ice has melted. Feedbacks are responsible for substantial uncertainties in determining climate response; in particular, shortwave cloud feedbacks are the largest source of uncertainties in determining steady-state temperature change ([Andrews et al. 2012](#); [Sherwood et al. 2014](#)). Because feedbacks are state dependent, the period over which climate response is measured will influence the

results. [Hansen et al. \(2005\)](#) chose to calculate values of efficacy using an average of the temperature response over years 80–120 of the simulation. Using a different period would result in a different temperature change and hence a different calculated value of efficacy. Indeed, the principle uncertainty in calculating efficacy is due to the temperature response ([Hansen et al. 2005](#)). However, even for the same forcing agent, [Hansen et al. \(2005\)](#) found that different magnitudes of forcing resulted in different values of efficacy. For example, comparing different levels of CO_2 concentration, [Hansen et al. \(2005\)](#) found that the efficacy relative to 1.5 times the pre-industrial concentration varied by 22% for concentrations of CO_2 between $1/8$ and 8 times the preindustrial value.

Another method of calculating radiative forcing is called radiative flux perturbation ([Rotsteyn and Penner 2001](#); [Hansen et al. 2005](#); [Haywood et al. 2009](#)). This method involves calculating the net top-of-atmosphere radiative flux change when a change in radiative forcing is applied to a model simulation with fixed sea surface temperatures and sea ice. This simulation prevents changes in sea surface temperature, thus preventing many of the long-term temperature-dependent feedbacks from operating. However, because land temperatures are permitted to change (land adjustments are considered part of the rapid adjustments), global-mean temperature does change in these simulations, and the magnitude of the change depends upon the magnitude of the applied forcing. Therefore, radiative flux perturbation simulations also introduce uncertainties into comparisons of forcing agents.

3. Explicit feedback in climate models

Comparisons of climate forcing agents are complicated by the issues described in the previous section. Here we describe an alternative method of comparing forcing agents that does not require use of any of the techniques described in the previous section to obtain estimates of radiative forcing or temperature response.

a. A new method of comparing climate forcing agents

Instead of the efficacy approach outlined in [section 2](#), in which both radiative forcing and temperature change are calculated for each forcing agent, we propose to directly compare forcing agents, implicitly computing the ratio as

$$\frac{T_x}{T_{\text{CO}_2}} = \frac{\lambda_x \Delta R_x}{\lambda_{\text{CO}_2} \Delta R_{\text{CO}_2}}. \quad (2)$$

Such an approach has been used in geoengineering simulations in which an increase in the CO_2 concentration is

counterbalanced by a decrease in another forcing agent (total solar irradiance or stratospheric sulfate aerosols) such that global-mean temperature does not change, even in a fully coupled atmosphere–ocean general circulation model. We follow exactly the same approach: one forcing agent is abruptly changed by a fixed amount, and another forcing agent is adjusted such that global-mean temperature is unchanged. Like calculations of efficacy, the climate models are treated as black boxes; no explicit knowledge of the inherent processes or uncertainties are necessary to compute the emergent climate responses to combinations of radiative forcing agents.

Different forcing agents exert radiative forcing with different spatial patterns, leading to different distributions of local feedbacks. Under this new method, local feedbacks can still induce a climate response, but the mean climate response is prescribed to have zero temperature change. One of the challenges Hansen et al. (2005) encountered in computing efficacy is that the mean climate state changed in response to the applied forcing, and because some climate feedbacks are nonlinear (state dependent), efficacy was effectively being computed for this new climate state. In contrast, our alternate approach more closely approximates a comparison of forcing agents evaluated at a well-defined, chosen baseline (we choose preindustrial). Nonzero local feedbacks can still introduce nonlinearities, but the state dependence is greatly reduced by keeping the global-mean temperature fixed. Note that the state-independent climate response could be isolated with our proposed alternative method if the geographical distributions of the imposed forcings were modified to offset all local temperature changes as well.

Similar ideas have been explored in the past. For example, Wigley (1998) introduced the forcing equivalence index, whereby emissions of other greenhouse gases are equated to emissions of CO₂ in terms of their respective radiative forcings. Through inverse calculations, a particular basket of emissions of various forcing agents could be determined for a given target value of radiative forcing. Govindasamy et al. (2001) further explored the applicability of approximating RFCR of other forcing agents through simulations of equivalent CO₂.

There are several important advantages of our approach. Instead of computing radiative forcing and climate response to determine efficacy, allowing uncertainties in both radiative forcing and climate response to propagate through this calculation, our method does not depend upon such explicit calculations. Our method also avoids some of the nonlinearities that arise due to state dependence of climate feedbacks, as described above. The results of this sort of comparison can identify the

different local responses of each forcing agent, which may provide insight into which feedbacks are directly excited by a particular forcing agent. As our method does not require explicit determination of radiative forcing, that would still need to be separately calculated if desired.

b. Explicit feedback

Determining how much of one forcing agent is required to offset another could be determined by trial and error. Many past simulations of geoengineering, in which solar irradiance was reduced to offset increases in CO₂ concentration, used this approach (Kravitz et al. 2013a), but required several attempts.

A more elegant method of achieving temperature balance uses *explicit feedback*. In geoengineering simulations, the departures from the climate objective (in this case, the same global-mean temperature as in the pre-industrial era) are assessed each year, and total solar irradiance (S_0) is increased or reduced accordingly to compensate for these departures (Jarvis and Leedal 2012; MacMartin et al. 2014). This method effectively introduces an explicit feedback loop around the climate model. Kravitz et al. (2014) showed that using this feedback loop to adjust S_0 results in higher accuracy in achieving the climate objective than predicting the required amount of solar reduction ahead of time and is robust to uncertainties in RFCR of both CO₂ and S_0 . It can be used for both abrupt changes in forcing agents as well as transient changes with no alteration of implementation (MacMartin et al. 2014; Kravitz et al. 2014). Although this methodology was originally developed for geoengineering simulations, no conceptual changes are required to adapt the method to other climate forcing agents; this feedback loop can be used to offset any climate forcing agent with another.

The concept of explicit feedback is identical to the mechanisms by which internal climate feedbacks operate, although the manifestations of these two categories of feedback are different. Internal climate feedbacks combine to produce emergent climate behavior, whereas the explicit feedback loop is used to impose a particular climate behavior.

We used proportional-integral control for implementation of this feedback loop:

$$\Delta F_{i+1} = k_p \Delta T_i + k_I \sum_{j=1}^i \Delta T_j, \quad (3)$$

where ΔF is the forcing agent being adjusted by the feedback loop (fraction of total solar irradiance or concentration of CO₂ or CH₄), i is the year of the model that was just completed, ΔT is the global-mean

temperature departure from its preindustrial value, and k_P and k_I are (dimensional) constants called *control gains*. As an example, when the feedback loop is used to adjust total solar irradiance, k_P and k_I have units of $\Delta S_0 \text{ K}^{-1}$. The control gains for any particular comparison can be chosen based on the presumed structural form of the radiative forcing relationship between the two forcing agents (section 4) so as to maintain a roughly constant convergence rate in comparing different forcing agents. The difference in efficacies between the two forcing agents will only result in some relatively small change in the convergence time of the feedback loop. Kravitz et al. (2014) showed that the resulting coupled system is robust to some amount of change in the values of these gains. Higher control gains will result in faster convergence at the expense of a larger response to natural variability; here we choose gains that give a convergence time constant of approximately three years. We note that if the chosen gains are too large, instability can result (MacMartin et al. 2014). MacMartin et al. (2014) discusses the procedure for determining a good estimate of the control gains for a desired loop convergence rate.

As was discussed by MacMartin et al. (2014) and Kravitz et al. (2014), proportional-integral control is sufficient for our purposes, although more advanced techniques could certainly be used to reach different climate objectives or satisfy certain criteria (e.g., Jarvis and Leedal 2012; Jarvis et al. 2009). Matching the emissions-based objectives of Wigley (1998), rather than the concentration-based objectives in our study, would require a different control algorithm than the one used here.

In the explicit feedback loop, adjustments every year are sufficient for the purpose of comparing climate forcing agents. Multiyear adjustment time scales (resulting in longer time delay between temperature changes and the consequent adjustments to forcing) can cause amplification of natural variability in certain frequency bands and can result in oscillatory behavior of the feedback loop (MacMartin et al. 2014). However, using an adjustment interval that is too short will not allow the climate system to fully respond to processes associated with rapid adjustments (as described in section 2). Different models have different time scales of these rapid climate adjustment processes, meaning that on a time scale of weeks to months, some models may have fully responded to the rapid adjustments, whereas some may not have done so. Moreover, the forcing in a single season cannot be considered independent of forcings in different seasons (Forster et al. 1997); accounting for higher frequencies (like the seasonal and diurnal cycles) can introduce complications into the

operation of the feedback loop. Using a time scale of one year serves as a useful compromise, allowing the climate system to respond to the rapid adjustments, avoiding the complexities of incorporating seasonal adjustments, and avoiding problems due to time delay.

Incorporating the explicit feedback loop is best accomplished externally to the climate model (Fig. 2). Explicit feedback external to the climate model, as opposed to inserting the feedback loop into the model code, has several distinct advantages:

- 1) Because the feedback loop is external to the climate model, there is no need to recode the model. As such, this method can be used with models of arbitrary complexity and can be ported to different models quite easily.
- 2) The dynamical behavior determined by the explicit feedback is kept separate from the dynamics of the model. As such, the dynamics of each separate component can be evaluated, as can the emergent dynamics of the coupled climate–explicit feedback system. For this particular study, the dynamics of a proportional-integral controller may not be all that interesting, but more complicated feedback rules or complex models could be used in place of this simple algorithm; in such cases, understanding the dynamics of each part separately could be useful.
- 3) This method is adaptable to diverse climate goals. For example, this method could be used to compare relative effects of different forcing agents on Arctic sea ice by devising a feedback loop that analyzed sea ice extent every year instead of global-mean temperature. Also, with some care, one could devise a feedback loop to compare the regional effects of forcing agents instead of global effects, as MacMartin et al. (2013) explored.

c. Experiment design

Using the feedback loop described in section 3b, we perform a series of simulations in which one climate forcing agent is offset by another at near-constant global-mean temperature. We illustrate this application here in two different climate models for three forcing agents: S_0 , CO_2 , and CH_4 . We expect this methodology will be useful for a number of different forcing agents (see section 5).

Each simulation involves a pair of climate forcing agents. One forcing agent is increased or decreased instantaneously and subsequently held at a fixed value. The other forcing agent is then modified by the explicit feedback loop such that global-mean temperature is as close to its baseline value as possible. (Although we used a preindustrial control simulation, any steady-state

FIG. 2. Schematic describing how to implement explicit feedback in a climate model. The model and feedback loop are separated to allow diagnoses of the dynamical behavior of each component, as well as the emergent behavior of the coupled system.

climate would be sufficient.) For example, CO_2 might be instantaneously quadrupled, and S_0 could be reduced to compensate for this increase in radiative forcing. There are six pairs of the forcing agents S_0 , CO_2 , and CH_4 :

- 1) Fix CO_2 and modify S_0 .
- 2) Fix CH_4 and modify S_0 .
- 3) Fix CO_2 and modify CH_4 .
- 4) Fix CH_4 and modify CO_2 .
- 5) Fix S_0 and modify CO_2 .
- 6) Fix S_0 and modify CH_4 .

Combination 1 is similar to the proposed method of conducting geoengineering simulations by [Jarvis and Leedal \(2012\)](#), and this same setup was used by [MacMartin et al. \(2014\)](#) and [Kravitz et al. \(2014\)](#).

All six sets of simulations were performed using GISS ModelE2 ([Schmidt et al. 2014](#)), a fully coupled AOGCM that participated in phase 5 of the Coupled Model Inter-comparison Project (CMIP5; [Taylor et al. 2012](#)). Combinations 1 and 2 were also performed using CESM1.0.2 ([Hurrell et al. 2013](#)), another fully coupled AOGCM that participated in CMIP5.

4. Results

The amount of one forcing agent that offsets another depends both on differences in the local climate

responses and differences in radiative forcing. Thus, it might be expected that, to first order, the results would follow the same scalings as those of instantaneous radiative forcing (radiative transfer) calculations, including model-dependent differences due to rapid adjustments and local feedbacks, as well as differences in radiation code. [Myhre et al. \(1998\)](#) found the best fits for the instantaneous radiative forcing (ΔF) of several well-mixed greenhouse gases, repeated here:

$$\Delta F(\text{CO}_2) = 3.708 \log_2(\text{XCO}_2), \quad (4)$$

$$\Delta F(\text{CH}_4) = 0.963(\sqrt{\text{XCH}_4}), \quad (5)$$

where XCO_2 and XCH_4 are multipliers of the pre-industrial concentrations of CO_2 and CH_4 , respectively. The coefficient in Eq. (5) was calculated using the implicit assumption of a preindustrial baseline CH_4 concentration of 715 ppb. Although [Myhre et al. \(1998\)](#) did not evaluate total solar irradiance [we denote a multiplier of total solar irradiance by $(1 + X)S_0$], ΔF from solar irradiance changes is approximately linear with the perturbation XS_0 ([Andrews et al. 2009](#)).

a. Regressed functional relationships

Figure 3 shows the results of fixing the CO_2 concentration in GISS ModelE2 and varying S_0 ; the CO_2

FIG. 3. Changing total solar irradiance (S_0) with fixed CO_2 concentrations (colored lines, each indicating a multiplier of the preindustrial CO_2 concentration) such that global-mean temperature departure from the preindustrial value (ΔT) is near 0. ($|\Delta T| \leq 0.004$ K for all simulations, with standard deviation over years 11–70 of no more than 0.088 K.) All simulations in this figure were performed with GISS ModelE2. $(1 + X)S_0$ denotes a multiplier of the preindustrial value of total solar irradiance. Here S_0 was modified for years 1–70. For years 71–90, the average value of XS_0 over years 11–70 was prescribed for each model run, and the feedback loop was disengaged.

concentration is set at values ranging between 0.25 times the preindustrial CO_2 level and 16 times that level. Using the feedback loop described in section 3 allows for rapid convergence to the prescribed target such that the model's response to varying concentrations of CO_2 can be characterized within 10 years (or approximately 3 times the convergence time scale of the feedback loop).

Once the model has converged, one can average over the remaining simulation years to obtain a relationship between CO_2 concentration change and solar irradiance change (Fig. 4). We assessed stability by first employing the feedback in this configuration for 70 years. For years 71–90, we then disengaged the feedback loop and ran each of the simulations with their respective fixed CO_2 concentrations, with fixed values of XS_0 that were the converged values obtained from the feedback loop. Figure 3 shows that the feedback loop does indeed recover a value of XS_0 for which the model does not drift (as can be differentiated from natural variability). Because the feedback loop converged within 10 years, such long simulations were not strictly necessary and were simply to illustrate that, once converged, the resulting amount of the offsetting forcing agent does not drift.

The regressed relationship between $\log_2(X\text{CO}_2)$ and XS_0 changes is almost perfectly linear ($R^2 \sim 1.00$):

a $2.08 \pm 0.04\%$ change in S_0 is equivalent to a doubling of the CO_2 concentration, where the error range indicates one standard deviation [Table 1, Eq. (T1)]. Performing the same calculations in CESM1.0.2 yields a regressed slope of $2.16 \pm 0.11\%$ S_0 for a doubling of the CO_2 concentration [Table 1, Eq. (T2)], with an R_2 value of ~ 1.0 . The regressed slope for CESM1.0.2 is approximately 3.8% different from the slope value for GISS ModelE2, although this difference is not statistically significant. These results are consistent with the findings of Kravitz et al. (2013a,b), that offsetting CO_2 changes with S_0 changes largely suppresses the effects of temperature-induced feedbacks, which are the predominant sources of nonlinearities in climate response.

The regressed relationships corresponding to offsetting methane changes via changing S_0 are given in Table 1, Eqs. (T3)–(T4). Figure 5 shows that GISS ModelE2 and CESM1.0.2 have similar relationships between $\sqrt{X\text{CH}_4}$ and XS_0 , again with a high degree of linearity with forcing; the differences in regression slopes are also not statistically significant. The predicted scaling relationships from Myhre et al. (1998) accurately describe the calculated relationships between the forcing agents investigated here, although the parameters within the relationships

FIG. 4. Results from changing solar irradiance (S_0) to offset changes in CO_2 concentration. XS_0 denotes a multiplier of the preindustrial value of total solar irradiance, and $X\text{CO}_2$ denotes a multiplier of the preindustrial CO_2 concentration. Blue points are calculated from the value of XS_0 obtained in GISS ModelE2, averaged over years 10–70 of the simulations, when the modified value of S_0 has approximately stabilized. The blue line indicates ordinary least squares regression through the black points. The blue shading indicates a 95% confidence interval (two-tailed unpaired Student's t test) of the regression fit. The red dots, line, and shading are the analogous quantities for CESM1.0.2, averaged over years 10–50 of the simulations. The green lines indicate the default values of $XS_0 = X\text{CO}_2 = 1$.

differ from those of Myhre et al. (1998) (see section 4b below). Transitivity of the regressed relationships is discussed in the supplemental online material.

For climate models that are properly spun up (i.e., a preindustrial control simulation that shows no temperature trend), the feedback loop will converge to these default values (e.g., changing S_0 while $X\text{CO}_2 = 1$ should result in a recovery of $XS_0 = 0$), but subject to natural variability. Assuming linearity, this means that a single simulation is sufficient to define a relative forcing relationship between two forcing agents. However, in some cases, the regression lines do not pass through the default model values (indicated by the green lines in Figs. 4–7). The spectrum of natural variability is indistinguishable from white noise radiative forcing (MacMynowski et al. 2011), so uncertainties in radiative forcing due to natural variability should be independent of the forcing agent. However, exerting a particular radiative forcing requires a smaller relative change in the CO_2 concentration than the relative change in the CH_4 concentration to exert the same radiative forcing. Since the feedback loop operates on concentration, not radiative forcing, uncertainties in recovering the default model values might be expected to be exacerbated for forcing agents requiring larger relative changes. For example, the default model values are recovered quite

TABLE 1. Regressed functional relationships obtained for all simulations, as described in section 4a. All values are rounded to four decimal places.

Equation	No.
$XS_0(\text{GISS}) = -0.0208 \log_2(X\text{CO}_2) - 0.0010$	(T1)
$XS_0(\text{CESM}) = -0.0216 \log_2(X\text{CO}_2) - 0.0060$	(T2)
$XS_0(\text{GISS}) = -0.0073 \sqrt{X\text{CH}_4} + 0.0051$	(T3)
$XS_0(\text{CESM}) = -0.0054 \sqrt{X\text{CH}_4} + 0.0016$	(T4)
$\sqrt{X\text{CH}_4}(\text{GISS}) = -2.9866 \log_2(X\text{CO}_2) + 0.6210$	(T5)
$\log_2(X\text{CO}_2)(\text{GISS}) = -0.3284 \sqrt{X\text{CH}_4} + 0.2037$	(T6)
$\log_2(X\text{CO}_2)(\text{GISS}) = -37.1243 XS_0 + 0.0197$	(T7)
$\sqrt{X\text{CH}_4}(\text{GISS}) = -120.2520 XS_0 + 0.7713$	(T8)

well in GISS ModelE2 for changing solar irradiance and are recovered comparatively poorly for changing CO_2 or CH_4 . As is discussed in the following section, this result parallels our findings regarding the amount of error introduced into the regressed relationships for a given combination of forcing agents.

Hansen et al. (2005) found a positive slope between radiative forcing and values of efficacy. This means that for climates that are “near” the current climate, the climate response is more sensitive to a positive radiative forcing than a negative one of the same magnitude. Our method has no such asymmetries in forcing. Putting this result in the context of the work of Caballero and Huber (2013), this asymmetric feature is thus presumably due to the temperature-related feedbacks and is not an intrinsic characteristic of the applied forcing.

Some of the relationships given in Table 1 are only valid within a certain range of radiative forcing. Figure 6 illustrates saturation (concentrations of methane cannot be reduced below zero), which is one potential reason this range could be limited. For values of $X\text{CH}_4 \leq 0.1$, there is very little methane in the atmosphere, and the scaling relationship depicted in Fig. 6 fails. This figure effectively shows that removal of all of the methane from the atmosphere could be radiatively balanced by an increase in the concentration of CO_2 by less than 5% above the preindustrial concentration. This result does not contradict the known result that methane has a global warming potential 33 times greater than that of CO_2 on a 100-yr time scale (Shindell et al. 2009) or that many non- CO_2 greenhouse gases are more effective than CO_2 at producing global warming (Hansen et al. 2005). It simply reflects the fact that the CO_2 concentration is much higher than the CH_4 concentration, so a large relative change in CH_4 can be offset by a small relative change in CO_2 .

Figure 7 also illustrates that these regressed relationships are only valid within a certain range of applied forcing. The bottom panel of Fig. 7 has already approached a limit of applied forcing, in that values of XS_0 even slightly greater than zero cannot be offset by

FIG. 5. As in Fig. 3, but for CH_4 instead of CO_2 . Values for GISS ModelE2 (blue) were averaged over years 10–30 of the simulations, and values for CESM1.0.2 (red) were averaged over years 10–50 of the simulations. The green lines indicate the default values of $\text{XS}_0 = \text{XCH}_4 = 1$.

any reductions in methane concentration. Conversely, large reductions in XS_0 can be offset by large increases in CO_2 or CH_4 , although there is no reason to expect that such high values of CO_2 or CH_4 in Fig. 7 are realistic or realistically represented in the climate model configurations used in this study. The results displayed in Fig. 7 also suggest that the relationship between $\log_2(\text{XCO}_2)$ and XS_0 may be nonlinear for sufficiently low or high values of XS_0 , resulting in nonlinear transitions to different climate regimes (Hansen et al. 2005); the top panel of Fig. 7 suggests that the relationship between $\log_2(\text{XCO}_2)$ and XS_0 becomes nonlinear for XS_0 ranging between -0.2 and -0.1 . Thus, we can identify at least two potential sources of nonlinearities in our simulations: 1) although global-mean temperature remains unchanged in our simulations, local temperatures do not, so the state dependence of the feedbacks are minimized, not eliminated; and 2) in a certain range of forcings, the adjusted radiative forcing may be inherently nonlinear, as was illustrated in Fig. 6 for CH_4 (e.g., Caballero and Huber 2013).

In particular, the high values of CO_2 and CH_4 in Fig. 7 prompt questions about whether such concentrations are meaningful beyond a purely radiative calculation. For example, biogeochemical carbon uptake over land and ocean is one of the dominant uncertainties in the carbon cycle (Gregory et al. 2009). This feedback depends upon the CO_2 concentration (i.e., it is not a temperature-related feedback). Also, emitted methane decays into CO_2 on a decadal time scale and has other implications for atmospheric chemistry (Seinfeld and Pandis 2006). Accounting for these feedbacks

FIG. 6. (top) Results from changing CH_4 concentration to offset changes in CO_2 concentration and (bottom) vice versa in GISS ModelE2. The black points are calculated as in Fig. 3 from averages over years 10–40 of the simulations. The blue lines and shading are calculated from ordinary least squares regression over the black points, as in Fig. 3. In the top panel, all black points are used in calculating the regression. In the bottom panel, only points corresponding to $\text{XCH}_4 \geq 0.5$ are used, as the other simulations are indistinguishable from each other due to very low CH_4 concentrations and consequently low signal-to-noise ratios. The green lines indicate the default values of $\text{XCO}_2 = \text{XCH}_4 = 1$.

in our experimental setup would require a different controller algorithm that modifies emissions rather than concentration, which is outside the scope of the present study.

b. Instantaneous forcing and rapid adjustments

Combining Eqs. (4) and (5) and solving for ΔF yields formulations that compare CO_2 and CH_4 [similar to Eqs. (T5) and (T6)]:

$$\sqrt{\text{XCH}_4} = -3.8525 \log_2(\text{XCO}_2) + 1 \quad (6)$$

$$\log_2(\text{XCO}_2) = -0.2596 \sqrt{\text{XCH}_4} + 0.2596. \quad (7)$$

Because Eqs. (6) and (7) are estimates using instantaneous forcing, the coefficients would not be expected to match those of Eqs. (T5) and (T6), which include the rapid adjustments. Figure 8 shows a comparison of the scaling relationships derived for both instantaneous radiative forcing and calculations using the feedback method. The slopes of the two formulations

FIG. 7. Results from changing (top) CO_2 concentration or (bottom) CH_4 concentration to offset changes in total solar irradiance (S_0) in GISS ModelE2. The black points are calculated as in Fig. 3 from averages over years 25–40 and 20–40, respectively. The blue lines are calculated from ordinary least squares regression over the black points, as in Fig. 3. (For the top panel, the cyan line is regression through all points, the blue solid line is regression excluding the point corresponding to $XS_0 = 0.8$, and the blue dashed line is extrapolation of the blue solid line.) No confidence intervals are shown, as the standard deviations of the parameters in the regression fits are too large to be plotted meaningfully. The green lines indicate the default values of $XS_0 = X\text{CO}_2 = X\text{CH}_4 = 1$.

corresponding to Eqs. (6) and (7) differ by 22.5% and 26.5%, respectively.

5. Discussion and conclusions

In the introduction, we posed three questions that we will now revisit:

- 1) Can this new method be used to compare climate forcing agents within climate models in a robust way? Yes (subject to having sufficiently high signal-to-noise ratios).
- 2) Is the modeled behavior linear given the appropriate scaling relationships? Yes, they are consistent with the scaling relationships provided by Myhre et al. (1998). The smallest R_2 value from our regression fits is 0.97. There is some evidence for nonlinearities, particularly for large magnitudes of forcing (e.g., $XS_0 = -0.2$), but most of the nonlinearities that would be induced by temperature-related feedbacks have been suppressed.
- 3) How similar are the relationships between the different forcing agents in different climate models? For the forcing agents considered in both models, GISS ModelE2 and CESM1.0.2 produce relationships that are not statistically different from each other.

FIG. 8. (top) Comparisons of the required amount of CH_4 concentration change to offset changes in CO_2 concentration and (bottom) vice versa, as in Fig. 6. The blue lines and shading show results from regression on simulations conducted in GISS ModelE2, as in Fig. 6. The red lines show results from solving the expressions for radiative forcing from CO_2 and CH_4 in Eqs. (4) and (5) (section 2).

By introducing an explicit feedback loop into a climate model, we have shown a way of robustly comparing different climate forcing agents within climate models as a possible alternative to direct computations of efficacy (Hansen et al. 2005). Because feedbacks associated with global-mean temperature are suppressed, the relationships between the forcing agents are quite linear relative to the scaling relationships expected from radiative transfer calculations. Relatively short simulations are sufficient because the time constant for convergence is a design choice associated with the (external) feedback gains rather than a property of the climate system.

A closely related alternative to our proposed approach could be that, in addition to using feedback to adjust one forcing agent to balance another, one could simultaneously prescribe climatological sea surface temperatures and sea ice, as in calculations of effective radiative forcing. By suppressing longer time-scale dynamics, this method could enable shorter convergence times and allow for even shorter simulations to be used. Using an approach more similar to methods used to calculate radiative forcing could also have advantages in interpretation of the results. Depending upon the objectives of the comparison, one should be careful to choose the appropriate methodology. Comparisons of the results from these two methods could be useful in elucidating broader issues in efficacy and RFCR.

Table 1 shows that GISS ModelE2 and CESM1.0.2 obtain similar relationships for the experiments that were conducted by both models. Some of the differences

between the models could be due to the use of different radiation codes. Additional differences are likely due to different parameterizations of the processes involved in the rapid adjustments, with shortwave cloud effects being the most uncertain (e.g., [Andrews et al. 2012](#)). Despite these different parameterizations and radiation codes, differences in regressed slopes between the two models are 4% and 26% for the experiments in which S_0 is modified to offset CO_2 and CH_4 changes, respectively; these differences are not statistically significant. GISS ModelE2 and CESM1.0.2 are known to have quite different sensitivities to both CO_2 and solar forcing (e.g., [Kravitz et al. 2013a](#)), so the small differences in regressed slopes between the two models suggests that climate feedbacks are a large source of uncertainty in climate model response to radiative forcing. We note that this conclusion was obtained without requiring knowledge of the structural and parametric uncertainties in the models considered in this study; exploring these sources of uncertainty, as well as potential contributions from uncertainties in rapid adjustments or different radiation codes, would be useful but is beyond the scope of the present work.

Although all of the simulations resulted in no global-mean temperature change, offsetting a change in CO_2 by a change in S_0 will not return local temperatures to their preindustrial values. [Figure 9](#) shows that in cases where CO_2 is increased, and S_0 is reduced, the tropics are overcooled, and the poles are undercooled. In cases where CO_2 is decreased, the opposite temperature pattern is seen. This is primarily due to the latitudinal dependence of the magnitude of solar radiation incident at the surface, whereas the radiative effects of CO_2 are more spatially uniform ([Govindasamy and Caldeira 2000](#)). These temperature patterns are robust across all models that have simulated geoengineering by offsetting CO_2 increases with solar constant reductions ([Kravitz et al. 2013a](#)). In principle, one could design a feedback loop that accounts for regional temperature changes, although such implementations are necessarily more complicated than global implementation ([MacMartin et al. 2013](#)).

[Figure 10](#) shows that offsetting CO_2 changes by modifying the methane concentration results in local temperature changes over some land regions and at high latitudes. The changes over land regions can be understood as manifestations of the CO_2 -physiological effect, which is included in GISS ModelE2. Increases in CO_2 cause plants to close their stomata, reducing evapotranspiration and hence latent heat flux from the surface to the atmosphere, causing surface warming (e.g., [Field et al. 1995](#); [Sellers et al. 1996](#); [Dong et al. 2009](#)). Evidence for this feedback would be expected in

[Fig. 10](#), as the physiological effect is not dependent on the methane concentration. The high-latitude temperature changes are likely due in part to lapse rate feedbacks that are artifacts of the prescribed vertical distribution of methane. The lapse rate feedback is one of the predominant mechanisms governing Arctic amplification ([Pithan and Mauritsen 2014](#)). In GISS ModelE2, methane is predominantly at lower altitudes, with comparatively little aloft. As such, an increase in methane to compensate for reduced CO_2 would result in less net absorption aloft and more near the surface, thus causing surface warming. The opposite pattern would be expected (and indeed is seen in [Fig. 10](#)) for reductions in the methane concentration to compensate for CO_2 increases. Other likely contributing factors are differences in the absorption spectra between CO_2 and CH_4 , which manifest at the poles due to the latitudinal distribution of insolation and hence total absorption of solar irradiance by greenhouse gases.

Our results here are qualitatively different from those of [Govindasamy et al. \(2001\)](#), who found that positive feedbacks operating at low latitudes (e.g., the water vapor feedback) are stronger than high-latitude positive feedbacks. Our results are consistent with those of [Hansen et al. \(1997\)](#) who found that high-latitude forcing yields a larger response than low-latitude forcing. GISS ModelE2 is a newer version of the model used by [Hansen et al. \(1997\)](#), so the fact that we obtained qualitatively similar results is perhaps not unexpected. [Hansen et al. \(1997\)](#) note that climate model response is highly sensitive to the structure and parameterizations each model includes, so we are not at present able to ascertain why our results are qualitatively different from those of [Govindasamy et al. \(2001\)](#); they noted a similar difficulty in comparisons to the results of [Hansen et al. \(1997\)](#).

Local feedbacks that operate on the temperature patterns in [Figs. 9 and 10](#) can result in a nonzero global temperature response, which would be compensated by our explicit feedback loop. If such an effect were present, the amount of a forcing agent required to offset another could change over the course of the simulations presented here, particularly for strong magnitudes of forcing. The results presented here (e.g., [Fig. 3](#)) show no such time dependence, even in the presence of somewhat large local temperature changes; after the simulation has stabilized, the recovered value of the forcing agent remains constant. This suggests that for the cases considered here, the effects of these local feedbacks on global-mean temperature are small as compared to natural variability.

We evaluated results for three forcing agents. It would clearly be valuable to apply this method to the full suite of forcing agents explored by [Hansen et al. \(2005\)](#). In

FIG. 9. 50-yr average of temperature differences from a preindustrial control simulation for six simulations in which the CO_2 concentration was held fixed, and S_0 was modified. Values above each panel indicate the polar (average over 80°–90°N and 0°–10°S) minus tropical (average over 10°S–10°N) temperature.

particular, we would be interested to compare our method with the results from Hansen et al. (2005) for forcings that have efficacies far from unity or forcings with heterogeneous spatial distributions. As an example, aerosols are not uniformly distributed horizontally, and they can occur as thin layers in the vertical direction, with the resulting RFCR dependent upon the spatial distribution of the aerosols. Moreover, different models

represent these spatial distributions differently. Without controlling for these inhomogeneities, comparisons of aerosols with well-mixed greenhouse gases would not necessarily yield robust conclusions, although it would be interesting to assess robustness across the default model configurations. An area of research we plan to pursue would involve an exploration of how the results of these explicit feedback intercomparisons would

FIG. 10. 10-yr average of temperature differences from a preindustrial control simulation for six simulations in which the CO₂ concentration was held fixed, and the CH₄ concentration was modified. Values above each panel indicate the polar (average over 80°–90°N and 0°–10°S) minus tropical (average over 10°S–10°N) temperature.

change for different spatial distributions of aerosols. Parallel investigations could involve model intercomparisons using specified distributions of forcing agents (e.g., aerosols, ozone, and land use changes) to determine the role of intermodel spread in determining the relationships between the different forcing agents.

This method of using external feedbacks could be adapted to provide a different method of understanding

intermodel differences in predicting future climate change. In the current scenario design for future climate change (e.g., the Representative Concentration Pathways; Meinshausen et al. 2011), each climate model is given a table of prescribed concentrations of forcing agents, corresponding to a certain precalculated radiative forcing. The climate models are then run to produce predictions of future climate change. Instead, one could

prescribe a future trajectory of climate change (e.g., global-mean temperature change) and use explicit feedback to adjust the concentrations of various forcing agents. For example, if it were decided that global-mean temperature change for the preindustrial era should not exceed 2°C, then for a given scenario of CO₂ emissions, one could determine the “allowable” amount of emissions of other forcing agents under that scenario.

Acknowledgments. We thank the climate physics group in the Atmospheric Sciences and Global Change Division at Pacific Northwest National Laboratory for helpful discussions and comments. In particular, we thank Karthik Balaguru, Susannah M. Burrows, Jennifer Comstock, Yang Gao, Steve Ghan, Po-Lun Ma, Yun Qian, Beat Schmid, Balwinder Singh, Steve Smith, and Jin-Ho Yoon. We also thank three anonymous reviewers for their helpful comments. Ben Kravitz is supported by the Fund for Innovative Climate and Energy Research (FICER). The Pacific Northwest National Laboratory is operated for the U.S. Department of Energy by Battelle Memorial Institute under Contract DE-AC05-76RL01830. Resources supporting this work were provided by the NASA High-End Computing (HEC) Program through the NASA Center for Climate Simulation (NCCS) at Goddard Space Flight Center. Andrew Jarvis was supported by Engineering and Physical Sciences Research Council (EPSRC) Grant EP/I014721/1.

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