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Explicit feedback and the management of uncertainty in meeting climate objectives with solar geoengineering

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Abstract
Solar geoengineering has been proposed as a method of meeting climate objectives, such as reduced globally averaged surface temperatures. However, because of incomplete understanding of the effects of geoengineering on the climate system, its implementation would be in the presence of substantial uncertainties. In our study, we use two fully coupled atmosphere–ocean general circulation models: one in which the geoengineering strategy is designed, and one in which geoengineering is implemented (a real-world proxy). We show that regularly adjusting the amount of solar geoengineering in response to departures of the observed global mean climate state from the predetermined objective (sequential decision making; an explicit feedback approach) can manage uncertainties and result in achievement of the climate objective in both the design model and the real-world proxy. This approach results in substantially less error in meeting global climate objectives than using a predetermined time series of how much geoengineering to use, especially if the estimated sensitivity to geoengineering is inaccurate.

Keywords: feedback, geoengineering, climate modeling

1. Introduction

Solar geoengineering has been proposed as a means of avoiding some consequences of elevated greenhouse gas levels (e.g., Crutzen 2006 and Shepherd *et al* 2009). An example use of solar geoengineering is to meet a chosen societal climate objective (e.g., reduced global, annual mean surface temperature) while mitigation efforts are accelerated. However, in addition to technical and political uncertainties regarding the deployment of solar geoengineering (Lenton and Vaughan 2009, Blackstock and Long 2010), there remains considerable uncertainty over the climate response produced by greenhouse gases and solar geoengineering (IPCC 2007). Although future research may narrow these uncertainties, a significant proportion will remain irreducible (Lempert 2002). As such, any solar geoengineering strategy must be able to achieve its specified objectives in the presence of these uncertainties. In this letter, we show that explicit feedback on the climate state is an effective strategy even with large uncertainties.

Climate models have become an invaluable tool in investigating the effects of solar geoengineering, as they provide the ability to assess geoengineering strategies while avoiding many of the numerous risks of testing or deployment in the real world. To accurately determine the effects of geoengineering, these models must represent the dynamical behavior of the climate system; most frequently, these are coupled atmosphere–ocean general circulation models (AOGCMs). Note that in this letter, the word *dynamics* follows the standard systems engineering definition, which is in reference to time-varying system behavior. This is in contrast to the term *statics*, which denotes equilibrium or steady-state behavior. We do not use the term dynamics to describe change in circulation or other such concepts that describe geophysical fluid flow, although we do recognize the unfortunate circumstance that both climate science and engineering have conflicting definitions for this term.

Because climate models imperfectly represent real-world dynamics, using them to design a geoengineering strategy can introduce error in meeting the climate objective in real-world deployment; our purpose here is to assess that error and methods to reduce it. We use two different AOGCMs to illustrate design and deployment of a geoengineering strategy. One model is called the *design model* because we use it to design the geoengineering strategy. The second is referred to as the *real-world proxy*; the designed geoengineering strategy is implemented in this model. Our only requirements for the choice of these models is that the real-world proxy adequately represents the dynamical behavior of the real-world climate (that is, it serves as a useful proxy of real-world climate behavior) and that the control design model adequately represents the dynamical behavior of the real-world proxy (that is, it is a good, but imperfect, model of the real-world proxy).

In this letter, we explore two methods of designing a geoengineering strategy, focusing on the ability of each method to achieve the specified climate objective given incomplete knowledge of the climate system. One method is to calculate the amount of geoengineering (e.g., solar irradiance reduction or stratospheric sulfate aerosol injection amount) to achieve the climate objective, test it in the design model, and repeatedly tweak the amount of geoengineering in a series of iterative simulations until the objective is met in the design model. The final time series of the amount of geoengineering is then prescribed in the real-world proxy. Given the complexities of the design model, this procedure cannot be achieved through model inversion and instead is achieved iteratively. This iterative method has been performed in previous studies of solar geoengineering (Kravitz *et al* 2011, 2013). We refer to this method as the *predictive method*, as the time series of how much geoengineering to use is predicted and prescribed prior to deployment in the real world. An alternative method is to use the design model to estimate the sensitivity of the real-world proxy to solar geoengineering and to design an online explicit feedback strategy. This strategy is one in which geoengineering is deployed in the real-world proxy, the departure from the climate objective is regularly observed, and the amount of geoengineering is adjusted based on those observed departures and the estimated sensitivity (Jarvis and Leedal 2012, MacMartin *et al* 2013b). Put more simply, societal decisions can act as a thermostat on the climate, increasing the amount of geoengineering if the climate is too warm, and decreasing the amount if the climate is too cold. We refer to this as the *feedback method*. This latter method is an example of a broader set of implementation strategies called Sequential Decision Making frameworks (Hampitt *et al* 1992, Jarvis *et al* 2008, Parson and Karwat 2011, Jarvis and Leedal 2012), in which past observations are used to update future decisions.

MacMartin *et al* (2013b) illustrated and explored some of the important intricacies involved in the feedback method as applied to solar geoengineering, focusing on how to design the explicit feedback strategy and the resulting dynamic effects, such as those due to natural variability. Here we expand upon that study by focusing on the issue of model uncertainty. MacMartin *et al* (2013b) illustrated the utility of explicit feedback in the same model that they used to design the feedback algorithm. However, using the exact same model that was used to design the feedback strategy does not address how the use of explicit feedback results in insensitivity to the mismatch in dynamics between the design model and the system in which geoengineering would be deployed. The concern of porting the feedback strategy from the design model to the real world is quite important, given that different climate models have different climate sensitivities and response time constants (Caldeira and Myhrvold 2013). Moreover, MacMartin *et al* (2013b) had the luxury of performing as many simulations as desired while tuning the feedback strategy. However, this does not accurately represent the fact that society cannot simply 'start over' if the correct amount of geoengineering is not implemented the first time.

2. Experiment design

In this study, we use the AOGCM HadCM3L (Jones 2003) as our design model, as in MacMartin *et al* (2013b). As our real-world proxy, we use the AOGCM GISS ModelE2 (Schmidt *et al* 2006). These models were developed independently and have different dynamical responses to both CO_2 and solar irradiance reduction (Kravitz *et al* 2013). GISS ModelE2 has an equilibrium climate sensitivity of 2.6 K for a doubling of CO_2 from the preindustrial concentration (Drew Shindell, personal communication), 50% of which is realized within the first decade of simulation. However, HadCM3L has an equilibrium climate sensitivity of 3.2 K, 60% of which is realized within the first decade of simulation. These values of equilibrium climate sensitivity differ by 0.6 standard deviations of a 15-model ensemble mean of models participating in the Coupled Model Intercomparison Project Phase 5 (Andrews *et al* 2012, Taylor *et al* 2012). Figure 1 shows that the global mean climate response of the two models to CO_2 spans a large range of the responses of the CMIP5 models. As such, we conclude the global temperature responses of these two models are sufficiently different to illustrate the power of explicit feedback in meeting climate objectives.

A solar irradiance reduction of 2.2% roughly offsets a doubling of CO_2 in either model. To capture the uncertainty in

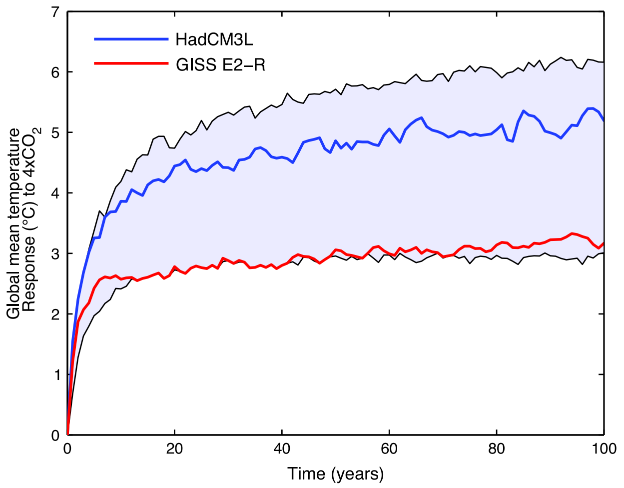

Figure 1. Global mean temperature response to an abrupt quadrupling of CO_2 concentration from preindustrial levels in HadCM3L (blue) and GISS ModelE2 (red). Shaded area denotes the range of responses for 25 models participating in the Coupled Model Intercomparison Project Phase 5 (Taylor *et al* 2012).

either solar efficacy or the radiative forcing from some particular geoengineering strategy (e.g., a stratospheric loading of sulfate aerosols), we also explicitly modify the effectiveness of solar geoengineering relative to CO_2, described below. Indeed, this uncertainty is more important than the uncertainty in climate sensitivity, as the latter would scale the temperature response to radiative forcing but not the amount of solar reduction required to achieve a particular objective.

Our chosen climate objective is to maintain global, annual mean surface air temperature in ModelE2 at 2020 levels over the years 2020–2100 against a background CO_2 concentration following the RCP4.5 scenario (Meinshausen *et al* 2011) by modulating solar irradiance. To modulate the solar constant automatically, we use Proportional–Integral (PI) control:

$$\Delta S_{0_{i+1}} = k_{\mathrm{P}}(T_i - T_{\mathrm{goal}}) + k_{\mathrm{I}} \sum_{j=2020}^{i} \left(T_j - T_{\mathrm{goal}}\right) \qquad (1)$$

where $\Delta S_{0_{i+1}}$ is the change in top of atmosphere insolation (W m^{-2}) to be prescribed in the real-world proxy in year $i+1$, T_i is the globally averaged surface air temperature of the real-world proxy in year i, T_{goal} is the climate objective, and k_{P} and k_{I} are time-invariant coefficients called *control gains* with units W m^{-2} K^{-1}. PI control was chosen for this implementation because the proportional term can be used to tune the sensitivity of the feedback response, and the integral term ensures zero steady-state error by correcting sustained errors in meeting the climate objective, effectively providing perfect memory of failure in reaching the objective in past years. More complex control algorithms could also be useful, but the chosen algorithm is sufficient to demonstrate the robustness to uncertainty that results from using explicit feedback. (For more details as to why PI control is sufficient for this problem, as well as a thorough discussion of the effects of PI control on the frequency response of the climate system, please see MacMartin *et al* 2013b.) This simple control algorithm may be insufficient for achieving goals on a regional scale, particularly if climate behavior in those regions is non-monotonic with CO_2 changes.

To compute the control gains, we implemented PI control in the design model; figure 2 shows a five member ensemble of HadCM3L simulations using PI control with control gains $k_{\mathrm{P}} = 4$ W m^{-2} K^{-1} and $k_{\mathrm{I}} = 2\pi$ W m^{-2} K^{-1}. This choice of k_{I} yields a convergence time constant of roughly two years in response to error (figure 8 of MacMartin *et al* 2013b). The value of k_{P} was chosen to minimize amplification of natural climate variability in certain frequency bands, which is an inevitable consequence of using explicit feedback (see MacMartin *et al* 2013b for further details). Each of these five simulations includes response to both greenhouse gas changes and internal climate variability. To reduce the effects of response to natural variability, these five simulations were averaged to produce a best estimate of the required solar reduction to achieve our chosen climate objective. If this strategy were ever implemented in the real world, many more ensemble members could be averaged to further reduce the effect of natural variability on the required solar reduction, although five members is sufficient to make the point that the feedback method results in higher fidelity to the objective than the predictive method. A lower order model (e.g., a box diffusion model as used by MacMynowski *et al* 2011) can accurately represent the response of global mean temperature to radiative forcing, but such a model is insufficient for determining the appropriate solar reduction for meeting multiple objectives, including regional objectives. As such, although we only attempt to control global mean temperature in this letter, we have used an AOGCM as the design model to illustrate a wide range of issues that would arise in more complicated implementations of explicit feedback.

For the predictive method, the solar reduction shown in figure 2(a) is prescribed in GISS ModelE2. For the feedback method, PI control is used directly in GISS ModelE2 to update the amount of solar reduction in a given year based on temperature departures from the objective in previous years. In the feedback method, HadCM3L is used only to determine the control gains.

The real-world climate sensitivity is unknown, and more critically for determining the appropriate amount of geoengineering, the relative sensitivity between the response to greenhouse gas forcing and solar reductions is unknown. While the design model is intended to approximate the real world (or in our case, the model used as a proxy for the real world), our experimental design should explicitly take into account the high potential for our design model to misestimate the sensitivity to solar geoengineering. We thus performed three pairs of simulations to show that the prescribed approach requires much higher model accuracy than is required when using explicit feedback. Each pair, identified by a particular value of λ (referring to the strength of the model response to solar reduction), consists of a simulation using the predictive method and a simulation using the feedback method.

For the first pair of simulations (referred to as 1λ), error is only due to whatever differences already exist between HadCM3L and ModelE2; being able to achieve a desired

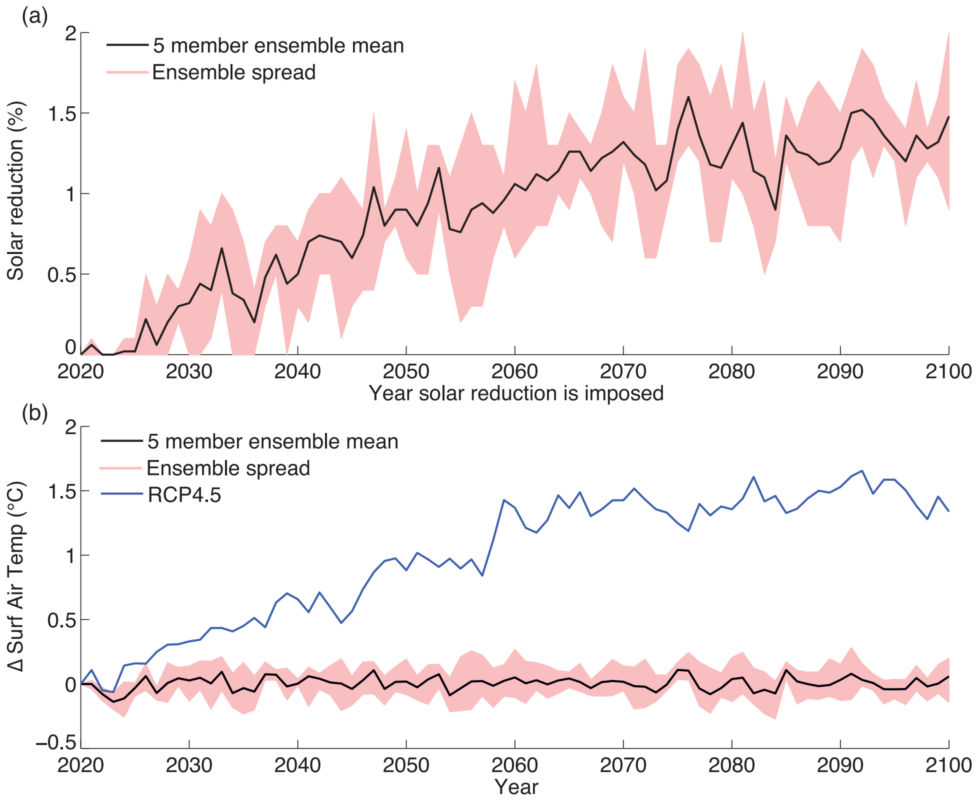

Figure 2. Time series of solar reduction and globally averaged surface air temperature response in HadCM3L under an RCP4.5 scenario in which explicit feedback on temperature was used to reduce insolation beginning in year 2020 (section 2). The climate was maintained at globally averaged temperatures at 2020 levels to within natural variability. Plotted temperature values are differences in temperature from this objective. Red shading shows the range of forcing and response of five ensemble members, and black line shows the ensemble mean. For reference, blue line in lower panel shows temperature time series for RCP4.5.

objective despite these differences is already a significant achievement. We also consider what the effect would be if there was significantly larger error by simulating ModelE2 as if the sensitivity to solar reductions were either increased or decreased. We implement this not by changing anything intrinsic to ModelE2, but instead by deliberately scaling the solar reductions that are applied to the model. This is completely equivalent in its effect to changing how strongly the model responds to a given solar forcing. In one pair of simulations (referred to as $3/2\lambda$), we increase the effective sensitivity to solar reductions by 50% by scaling either the solar reduction time series (for the predictive method; figure 2) or the control gains (for the feedback method) by 3/2. By equation (1), implementing this scaling in the feedback method gives a 50% larger solar reduction in response to a deviation between observed and desired temperature. This is equivalent in response to using the same gains as in the 1λ case but having a model with 50% higher sensitivity to a given solar reduction. The remaining pair of simulations ($2/3\lambda$) reduces the effective sensitivity to solar reductions in a similar fashion. Andrews *et al* (2012) found that the standard deviation of equilibrium climate sensitivity among 15 CMIP5 models is approximately 25% of the ensemble mean value, so our chosen 50% uncertainty range is a reasonable representation of model response to radiative forcing. These two cases represent a substantial amount of uncertainty to be managed by explicit feedback. Table 1 lists the control gains used in the feedback method.

Table 1. Control gains (section 2, equation (1)) used in the feedback method simulations in ModelE2. All values have units W m^{-2} K^{-1}.

Simulation	k_P	k_I
1λ	4	2π
$3/2\lambda$	6	3π
$2/3\lambda$	8/3	$4\pi/3$

One important distinction in our simulations is that for both the prescribed and the feedback methods, each case (i.e., each estimated sensitivity to geoengineering) was simulated in ModelE2 exactly once. By taking this approach, we approximate the situation that would be faced in real-world deployment: to avoid the consequences of too much or too little geoengineering, the correct amount of geoengineering must be implemented the first time, despite the presence of irreducible uncertainties.

3. Comparison of predictive and feedback methods

Figure 3(a) shows the simulated effectiveness of both the predictive and feedback approaches in achieving a desired climate objective for the 1λ case. This case has the inherent

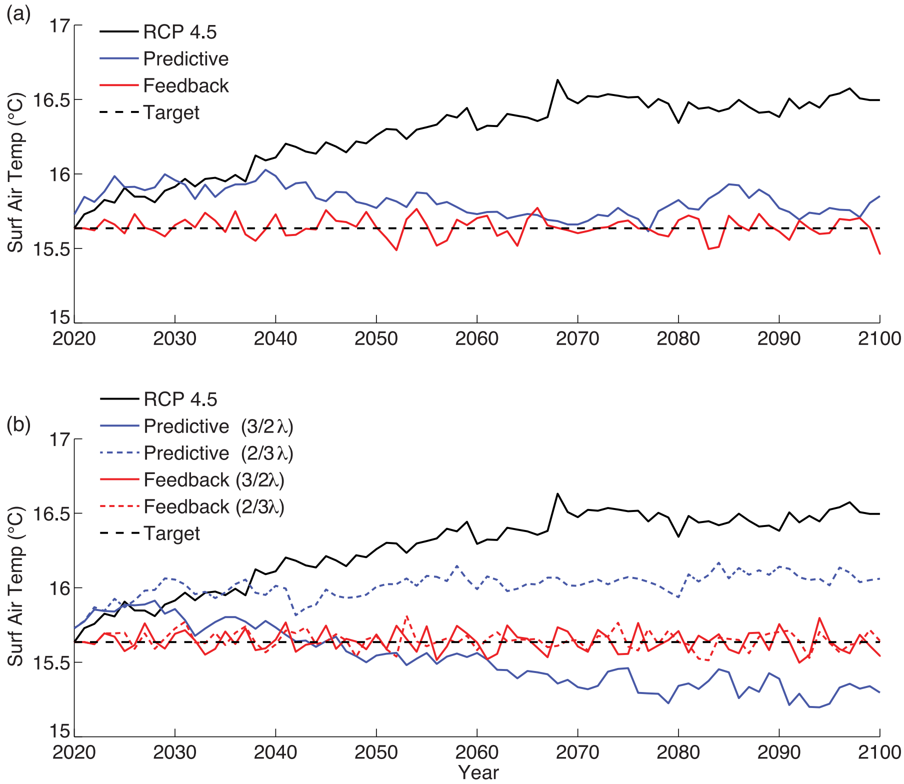

Figure 3. Time series of surface air temperature response in GISS ModelE2 for solar reduction beginning in 2020. Black solid line shows RCP4.5, and black dashed line shows the temperature target (2020 levels). The top panel compares the predictive simulation using the best estimate of the required solar reduction as obtained from HadCM3L (blue) and the feedback simulation (red). The bottom panel shows similar predictive and feedback simulations where the predicted sensitivity of GISS ModelE2 is multiplied by 3/2 (denoted $3/2\lambda$) or 2/3 (denoted $2/3\lambda$) (section 2). The feedback method outperforms the predictive method in every case.

assumption that the design model accurately represents the sensitivity of the real-world proxy to geoengineering. As a convenient metric of fidelity to the climate objective, for any simulation, we can calculate the RMS misfit over the years 2020–2100:

$$\mathrm{RMS}(T) = \sqrt{\frac{1}{81}\sum_{i=2020}^{2100}\left(T_i - T_{\mathrm{goal}}\right)^2} \qquad (2)$$

where T_i is the globally averaged surface air temperature in year i and T_{goal} is the climate objective, which is globally averaged temperature in the year 2020. The RMS misfit of the predictive method in achieving the chosen target climate is 0.203 °C for the 1λ case, or 30% of the RMS misfit for RCP4.5 with no solar reduction. The feedback method has an RMS misfit of 0.066 °C, or 10% of the RMS misfit for RCP4.5. 210 years of a stable preindustrial control simulation with ModelE2 (not shown) yields an RMS difference from the preindustrial mean of 0.079 °C. These results indicate that the RMS misfit of the predictive method is in part due to inaccurate representations of the dynamics of ModelE2 by HadCM3L. Implementation of PI control will attenuate natural variability across a broad band of low frequencies and amplify variability in a narrow band of relatively higher frequencies (called the 'waterbed effect', as discussed in detail by MacMartin *et al* 2013b). This can in part explain the lower RMS misfit in the feedback simulation than is found in the control simulation.

Table 2. RMS misfits in achieving the climate objective (equation (2)) for each of the simulations (section 2). All values have units °C and are rounded to three decimal places.

Simulation	Prescribed	Feedback
RCP4.5	0.678	N/A
Preindustrial control	0.079	N/A
1λ	0.203	0.066
$3/2\lambda$	0.231	0.073
$2/3\lambda$	0.386	0.059

Figure 3(b) compares the 1λ, $3/2\lambda$, and $2/3\lambda$ cases, illustrating the results from potential misestimation of the sensitivity of the real-world proxy to geoengineering. Mismatches between the dynamics of HadCM3L and ModelE2 are exacerbated as compared to the results in figure 2(a), causing large inaccuracies in the predictive method in reaching the chosen climate objective. The RMS misfit increases to 34% of the ModelE2 RMS misfit for RCP4.5 if the model's sensitivity to solar reduction is 3/2 of the predicted magnitude. The RMS misfit increases to 57% of the ModelE2 RMS misfit for RCP4.5 if the sensitivity is 2/3 as large as was predicted. The feedback method is quite insensitive to uncertainty within the range explored here; RMS misfits for all feedback simulations are no more than 11% of the ModelE2 RMS misfits for RCP4.5 (also see table 2).

4. Conclusions

In this work, we have extended the work of MacMartin *et al* (2013b) to address several very important concerns in the design and implementation of geoengineering strategies, should society choose to pursue geoengineering. We summarize our main findings:

- We have shown that explicit feedback can be used to help manage the inevitable uncertainties present in implementation of geoengineering, despite the complex responses of state-of-the-art climate models. The simple algorithm of PI control is sufficient for this particular application, although more complex control algorithms could be used to achieve different objectives.
- Due to the absence of perfect knowledge of the climate system, as well as the requirement that geoengineering achieve its specified climate objective on the first attempt, sequential decision making (i.e., explicit feedback) is more adept at achieving the climate objective than a predictive method.
- If using explicit feedback, it is not necessary for the design model to perfectly represent the dynamical behavior of the real world, such as the sensitivity of the real world to geoengineering. Similarly, one can interpret this as insensitivity to the choice of the control gains.

In such a simplistic setup as ours, the predictive method may produce results that are 'close enough' to the desired objective, where the tolerance limit is decided in advance. Indeed, previous studies have shown the predictive method to be quite effective when offsetting an increase in CO_2 with solar reductions (Kravitz *et al* 2013). However, should society ever choose to deploy geoengineering, its implementation is unlikely to be so simple. For example, uniform global-scale geoengineering, such as is represented in our simulations, results in regional climates that are not fully restored to their preindustrial values (e.g., Govindasamy and Caldeira 2000 and Kravitz *et al* 2013). More realistic simulations could include more complicated geoengineering strategies, such as non-uniform solar reduction (MacMartin *et al* 2013a) or marine cloud brightening (e.g., Latham *et al* 2008, 2012). Moreover, more realistic future climate representations would likely include changes in other forcing agents, such as aerosol emissions, which have both radiation and cloud interactions. With these complicated scenarios, use of the prescribed method becomes more difficult, as uncertainties in climate system response to geoengineering increase. However, these complications would enhance rather than diminish the value of sequential decision making approaches. Future research could also investigate the ability of multi-objective feedback implementation in achieving regional objectives, i.e., implementation of control algorithms that monitor multiple fields and adjust multiple climate parameters, although such techniques have their own difficulties, particularly if regional climate responses are non-monotonic.

In real-world deployment, once it became clear that the temperature error in the predictive method was as large as in figure 2(b), the level of solar geoengineering would likely be adjusted to reduce the error, which is essentially an implementation of explicit feedback with a significant time delay in decision making. Time delay increases amplification of natural variability, and with sufficiently high gains, time delay in feedback implementation can cause system instabilities, e.g., oscillating or divergent temperature time series instead of one that converges to the climate objective (MacMartin *et al* 2013b). One challenge of using explicit feedback to manage uncertainty in solar geoengineering implementation is that technical requirements to frequently update the level of solar reduction may be incompatible with relatively slower decision making processes.

Both models in this study are quite adept at reproducing the climate of the 20th century (Jones 2003, Schmidt *et al* 2006), particularly the global mean temperature record. Although the equilibrium climate sensitivities of the two models can be calculated, we are unable to compare the difference in sensitivities between the two models with the differences between each model and the real-world climate sensitivity because the real-world climate sensitivity is unknown. The latest estimates of the likeliest values of equilibrium climate sensitivity are 1.5–4.5 °C (Stocker *et al* 2013); the upper limit of this range is approximately 45% higher than the climate sensitivity of HadCM3L. Although this range is larger than the difference in climate sensitivities between the two models in this study, it is quite similar to the range of uncertainties in climate model response represented here, as captured by the parameter λ.

We have illustrated a technical approach to managing uncertainties in solar geoengineering. The results we present are a useful contribution to the discussion of geoengineering, but we cannot address the wide range of concerns to be addressed in evaluating the benefits and risks of geoengineering (Robock 2008, Robock *et al* 2009). These could include effects on other parts of the climate (e.g., ozone depletion from stratospheric aerosol injection), impacts of climate changes (e.g., effects on agriculture), or non-climatic concerns (e.g., geopolitical strife over decisions about how and how much to geoengineer). Our use of explicit feedback only demonstrates management of certain kinds of uncertainties, not others. Moreover, management of uncertainties is not the only consideration in geoengineering studies, and any future decision to deploy geoengineering or determine its goals would require the presence of appropriate governance structures.

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