Impacts, effectiveness and regional inequalities of the GeoMIP G1 to G4 solar radiation management scenarios

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A B S T R A C T
We evaluate the effectiveness and the regional inequalities of solar radiation management (SRM) in compensating for simultaneous changes in temperature and precipitation caused by increased greenhouse gas concentrations. We analyze the results from Earth System Models under four Geoengineering Model Intercomparison Project (GeoMIP) experiments with a modified form of the Residual Climate Response approach. Each experiment produces 50 model yrs of simulations: 13 models completed experiment G1 (offsetting 4 × CO2 via solar reduction); 12 models completed experiment G2 (offsetting CO2 that increased by 1% per year); 3 models completed experiment G3 (offsetting increasing radiative forcing under RCP4.5 with increasing stratospheric aerosol); and 7 models completed experiment G4 (injection of 5 Tg SO2 a⁻¹ into the stratosphere). The regional inequalities in temperature and precipitation compensation for experiments G1, G3 and G4 are significantly different from their corresponding noise backgrounds for most models, but for G2 they are not significantly different from noise. Differences in the regional inequalities and the actual effectiveness among the four SRM scenarios are not significant for many models. However, in more than half of the models, the effectiveness for temperature in the solar dimming geoengineering scenarios (G1 and G2) is significantly higher than that in the SO2 geoengineering scenarios (G3 and G4). The effectiveness of the four SRM experiments in compensating for temperature change is considerably higher than for precipitation. The methodology used highlights that a large across-model variation in the treatment of key geoengineering processes (such as stratospheric aerosols) and the quantification of damage caused by climate change creates significant uncertainties in any strategies to achieve optimal compensation effectiveness across different regions.

1. Introduction

Frustrated by the slow progress in carbon dioxide emission reduction, increasing numbers of scientists, politicians and members of the general public are devoting attention to geoengineering, a set of technologies designed to counteract anthropogenic climate change (e.g., Crutzen, 2006; Wigley, 2006; Shephard et al., 2009; Caldeira and Kepl, 2010). Solar radiation management (SRM) is a category of geoengineering that aims to block some solar radiation from reaching the Earth’s surface, e.g., by space mirrors in orbit (Mautner, 1989), stratospheric aerosol injection (e.g., Budyko, 1977; Crutzen, 2006) or marine cloud seeding (e.g., Latham, 1990).

Many previous studies of SRM used single models (e.g., Bala et al., 2008; Ricke et al., 2010; MacCracken et al., 2012; Fyfe et al., 2013).

As such, determining the modeled impacts and side effects of SRM on the Earth’s climate system at global and regional scales is confounded by questions of model dependence of the results. Rasch et al. (2008) compared the results from two models that simulated stratospheric sulfate aerosol injection, but the experiments performed with these models were not consistent, hence difficulties remained in interpreting aerosol effects. Jones et al. (2010) compared the responses of two models to the continuous injection of SO2 into the lower stratosphere at the rate of 5 Tg a⁻¹, an experiment very similar to GeoMIP experiment G4 described below. Although there were some similarities in temperature and precipitation response in these two models, their substantial differences prevented the authors from making robust conclusions about the modeled effects of stratospheric sulfate aerosol geoengineering.

To coordinate model simulations of SRM and determine the robust features of climate models to reduced shortwave radiative forcing or sustained layers of stratospheric aerosol, the Geoengineering Model Comparison Project (GeoMIP) was established (Kravitz et al., 2011; see also Fig. 1 for a graphical description of the four core experiments).
Several studies have investigated the climate responses to the GeoMIP G1 (e.g., Schmidt et al., 2012; Kravitz et al., 2013a,b; Tilmes et al., 2013) and G2 (Jones et al., 2013) experiments. These studies showed a regionally diverse impact on temperature and precipitation, with considerable agreement between models on broad features, such as a warming of the polar regions and cooling of the tropics relative to pre-industrial norms. Kravitz et al. (2014) explored the regional inequalities and effectiveness of global uniform SRM based on G1 multimodel results. GeoMIP studies of particular regions have thus far only focused on the Arctic responses under G1 (Moore et al., 2014), G3 and G4 experiments (Berdahl et al., 2014).

In this paper, we (1) examine the robustness of modeled global and regional temperature and precipitation responses in the four core GeoMIP experiments and (2) use the residual climate response (RCR) methodology (Moreno-Cruz et al., 2012; discussed in Section 2.3 below) to evaluate climate change compensation effectiveness and regional inequalities of temperature and precipitation in different SRM experiments. The RCR methodology allows for a simple quantitative comparison of different GeoMIP experiments, as it normalizes model results across all of the various experiments and summarizes, as a resultant vector, the net climate response of each climate variable irrespective of the numbers of models running each experiment. This allows us to assess the effectiveness of different types of geoengineering for compensating CO₂ increases. The structure of this paper is as follows: Section 2 describes the four GeoMIP experiments used in this study, as well as the data processing methods; Section 3 discusses global and regional temperature and precipitation changes, regional inequalities and the effectiveness of geoengineering in compensating for changes from CO₂ increases; finally, Section 4 provides a discussion of these results and their implications.

2. Data and analysis methods

2.1. GeoMIP experiment and model description

Among the four standard GeoMIP experiments, G1 and G2 are both designed to simulate reduced shortwave radiative forcing by decreasing solar irradiance, while G3 and G4 reduce net radiative forcing via the addition of sulfate aerosol precursors to the stratosphere. Experiment G1 balances an instantaneous quadrupling of CO₂ concentration from pre-industrial levels with a simultaneous solar irradiance reduction. The global mean top-of-atmosphere (TOA) radiation imbalance is specified to be within 0.1 W/m² relative to the pre-industrial control simulation for the 50-year experiment (Fig. 1). Experiment G2 is designed to balance a transient CO₂ increase (1% per year increase in concentration) from pre-industrial levels by gradually decreasing solar irradiance during the first 50 yrs of the experiment; after this period, SRM is switched off while CO₂ continues to increase at the rate of 1% per year for 20 yrs (Fig. 1). For comparison purposes, we also make use of three simulation results from CMIP5 (Taylor et al., 2012) that serve as the background greenhouse gas simulations for experiments G1 and G2: piControl, which refers to the pre-industrial control run; abrupt4xCO₂, which refers to the instantaneous quadrupling of CO₂ from pre-industrial levels; and 1pctCO₂, which refers to 1% per year CO₂ increase from pre-industrial levels.

Unlike G1 and G2, G3 and G4 are designed to reduce solar irradiance by stratospheric SO₂ injection (Fig. 1). Over the 50 yrs of G3, the injected SO₂ mass is gradually increased to counteract the gradually increased longwave radiative forcing specified under the RCP4.5 scenario, thus maintaining top-of-atmosphere net radiative flux at 2020 levels. In G4, the annual amount of SO₂ injected into
the stratosphere is a constant 5 Tg per year for the first 50 yrs of G4. G3 and G4 do not specify how the models handle aerosols, and the models differ widely in their representations of stratospheric chemistry, aerosol growth and dynamical transport schemes. Thus, it is expected that inter-model differences will be larger for G3 and G4 than G1 and G2 (Kravitz et al., 2011). The CMIP5 experiment rcp45, which is the future climate state forced by RCP4.5 (Taylor et al., 2012), is used for comparison purposes. The baseline climate for G1, G2 and the relevant greenhouse gas forcing experiment is an average of the pre-industrial control simulation picontrol over time. The RCR vector-based methodology requires a prior state against which comparisons can be made. In the G3 and G4 cases, this prior state cannot be simply the mean of picontrol because the RCP4.5 climate forcing continues from the historical forcing record, which has been non-stationary. Therefore, we chose the average climate under rcp45 over the period 2010–2029 as the baseline for G3, G4, and rcp45 (see Table 1).

During the first few years of all experiments, the short-term feedbacks and transient climate responses will evolve as the models adjust to the new imposed forcings. Therefore, all results reported here are averages over the years 11–50 of the simulations. We recognize that excluding only the first decade is insufficient to isolate the transient response from the steady state response, especially in the abrupt4xCO2 case, which imposes very large instantaneous changes in radiative forcing. This is a compromise between including enough years of simulation to obtain useful statistics regarding the climate response while excluding some of the more severe transient changes in the climate. Excluding the first decade is consistent with several previous GeoMIP studies (e.g., Schmidt et al., 2012; Kravitz et al., 2013a).

Table 1 lists the number of models available for each GeoMIP scenario and its associated background simulation. The names and general description of the models are given in SI Table 1. In this study, with its emphasis on regional variations, we focus on two important climate variables: near surface air temperature (SAT) and precipitation, with its emphasis on regional variations, we focus on two important scenario and its associated background simulation. The names and

## 2.2. Regionalization

We followed Giorgi and Francisco (2000) in defining 22 regions to investigate the patterns of temperature and precipitation change under SRM. These 22 regions cover most of the global land area, and regional boundaries were chosen to represent climatically and physiographically similar land areas. These regions are large enough to produce climate predictions that are more statistically robust than those obtained from grid cell level output (Giorgi and Francisco, 2000; Moreno-Cruz et al., 2012). We calculated the area weighted average of those obtained from grid cell level output (Giorgi and Francisco, 2000; Moreno-Cruz et al., 2012; MacMartin et al., 2013; Ricke et al., 2013; Kravitz et al., 2014).

### 2.3. Residual climate response method

To evaluate the potential regional inequalities resulting from SRM, as well as the effectiveness of SRM, Moreno-Cruz et al. (2012) introduced the RCR methodology with the objective of providing easily understood results suitable for policy- and decision-makers. In the RCR approach, anthropogenic climate change and the climate change compensated by SRM are represented by two vectors. Each component of these two vectors represents a given region's climate change under greenhouse gas increases or SRM. The angle between these two vectors then represents the difference between the SRM compensated climate and that under the CO2 equivalent (CO2e)-driven climate forcing alone.

The prerequisite of applying the RCR method is that regional responses are approximately linear over the forcing range of interest (Moreno-Cruz et al., 2012). Although the climate system is a non-linear system, and many climate responses are nonlinear, several studies (Ban-Weiss and Caldeira, 2010; Moreno-Cruz et al., 2012; MacMartin et al., 2013) have shown that modeled temperature and precipitation responses over the radiative forcing ranges of their studies are approximately linear with the amount of SRM.

The RCR approach is illustrated in Fig. 2. The origin O represents the reference state of a single climate variable Y (such as SAT or precipitation, but not a combination of SAT and precipitation as in Moreno-Cruz et al., 2012 and Kravitz et al., 2014; our approach avoids the problem of determining a relative importance among different variables). The regional changes in Y from the reference state due to elevated CO2e are represented as a 1 × n dimension vector \( \mathbf{Y}_{CO2e} \),

\[
\mathbf{Y}_{CO2e} = (Y_{CO2e1}, Y_{CO2e2}, \ldots, Y_{CO2en})
\]

where \( n \) is the number of regions in the globe. Each component of \( \mathbf{Y}_{CO2e} \) represents the CO2 increase induced \( Y \) change for a given region \( i = 1, 2, \ldots, n \). The residual change in \( Y \) under SRM is represented by the vector \( \mathbf{Y}_{RES} \),

\[
\mathbf{Y}_{RES} = (Y_{RES1}, Y_{RES2}, \ldots, Y_{RESn})
\]

In the vector \( \mathbf{Y}_{CO2e} \) and \( \mathbf{Y}_{RES} \), the change in \( Y \) in each region is normalized by the corresponding inter-annual variability of \( Y \) under the baseline climate, as was done by Ricke et al. (2010). The change compensated by SRM is represented by \( \mathbf{Y}_{SRM} \) and is \( \mathbf{Y}_{CO2e} - \mathbf{Y}_{RES} \). The angle \( \phi \) between \( \mathbf{Y}_{CO2e} \) and \( \mathbf{Y}_{SRM} \) represents the regional inequality in the effectiveness of compensating \( Y \) change by SRM and is calculated as follows:

\[
\phi = \cos^{-1}\left(\frac{-\mathbf{Y}_{CO2e} \cdot \mathbf{Y}_{SRM}}{||\mathbf{Y}_{CO2e}|| \cdot ||\mathbf{Y}_{SRM}||}\right)
\]

For a non-zero \( \mathbf{Y}_{SRM} \), if \( \phi \) is 0°, all regions are equally compensated by SRM; if \( \phi \) is 180°, SRM equally increases all regional changes from the

### Table 1

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Averaging period</th>
<th>Baseline climate</th>
<th>Number of models</th>
</tr>
</thead>
<tbody>
<tr>
<td>G1(^a)</td>
<td>abrupt4xCO2</td>
<td>Experiment year 11–50</td>
<td>Pre-industrial average</td>
</tr>
<tr>
<td>G2(^b)</td>
<td>1pctCO2</td>
<td>Experiment year 11–50</td>
<td>Pre-industrial average</td>
</tr>
<tr>
<td>G3</td>
<td>rcp45</td>
<td>Year 2030–2069</td>
<td>Average over 2010–2029 under rcp45</td>
</tr>
<tr>
<td>G4</td>
<td>rcp45</td>
<td>Year 2030–2069</td>
<td>Average over 2010–2029 under rcp45</td>
</tr>
</tbody>
</table>

\(^a\) CESM-CAM5.1-FV was not included in the noise calculation for G1 and G2 as its picontrol simulation only includes model 50 yrs. As a result, the noise calculation involved 12 models in G1 and 11 models in G2.

\(^b\) 4 models in total have completed G3, but we exclude GISS-E2-R from the G3 analysis (see text).
The quadratic function used here is a simple option, but we make no damage functional form applies equally to all regions or situations. Manne et al., 1995). Moreover, there is no indication that a single we are aware that other damage functional forms have been used in regions. The norm of \( \phi \) be reached by adjusting the radiative forcing due to SRM equally in all re- gions. The norm of \( \phi \) or norm of \( Y_{\text{CO}_2e} \) means a larger norm of \( Y_{\text{RES,OPT}} \).

Following Moreno-Cruz et al. (2012) and MacMartin et al. (2013), we prescribe that regional damages \( D \) are a quadratic function of the re- gional change normalized by the inter-annual variability of the baseline climate, so the damage caused by the change in \( Y \) could be approximately expressed as follows:

\[
D_{\text{CO}_2e} \propto \| Y_{\text{CO}_2e} \|^2 \tag{4}
\]

\[
D_{\text{RES}} \propto \| Y_{\text{RES}} \|^2 \tag{5}
\]

\[
D_{\text{RES,OPT}} \propto \| Y_{\text{RES,OPT}} \|^2 \tag{6}
\]

The percentage of damages compensated by SRM, as calculated from the regional change in the climate variable \( Y \), can be represented as:

\[
\left(1 - \frac{\| Y_{\text{RES,OPT}} \|^2}{\| Y_{\text{CO}_2e} \|^2}\right) \times 100\%. \tag{7}
\]

We define the quantity in Eq. (7) to be the actual effectiveness of particular SRM scenario. The optimal effectiveness of a particular SRM scenario for a given \( \phi \) is then:

\[
\left(1 - \frac{\| Y_{\text{RES,OPT}} \|^2}{\| Y_{\text{CO}_2e} \|^2}\right) \times 100\% = \left(1 - \sin^2 \phi \right) \times 100\%. \tag{8}
\]

An effectiveness of 100% means that the SRM perfectly compensated for all the change in climate variable \( Y \); if the effectiveness is negative, then the SRM increased the change in \( Y \), rather than compensating for it.

The adjustment percentage of the SRM-compensated change to obtain optimal compensation effectiveness in \( Y \) is calculated as:

\[
\left(1 - \frac{\| Y_{\text{CO}_2e} \|^2}{\| Y_{\text{SRM}} \|^2}\cos \phi \right) - 1 \times 100\%. \tag{9}
\]

Moreno-Cruz et al. (2012) applied RCR to one geoengineering scenario and for only a single model, whereas here we use RCR to quantify temperature and precipitation compensation effectiveness and regional inequalities in multiple models for four SRM scenarios. Each model’s compensation effectiveness and assessments of regional inequalities are taken as independent measurements for the purpose of producing multi-model ensemble means and standard deviations. To investigate the behaviors of \( \phi \), actual effectiveness, and optimal effectiveness due to natural variability, we divided the \( \text{picControl} \) runs of each model into several parts, each part containing 40 continuous yrs of simulation. We then define the first 40 yrs as the ‘reference’ case and the remainder as ‘perfect geoengineering’, in which the climate is exactly returned to preindustrial conditions. The differences between the ‘perfect geoengineering’ and ‘reference’ climates represent the noise caused by the model’s internal vari- ability. We define the ‘noise’ values of the angle \( \phi \), actual effectiveness, and optimal effectiveness from use of the RCR method on these ‘perfect geoengineering’ periods. Note that the differences between ‘perfect geoengineering’ and ‘reference’ in \( \text{picControl} \) may be not a good proxy of natural variability over 2010 to 2029 in RCP4.5, G3 and G4. We use it because there is no obvious way to find the ‘perfect geoengineering’ for the simulations from 2010 to 2029 in RCP4.5, and similarly for G3 and G4.

The regional inequalities in Kravitz et al. (2014) were demonstrated by regional differences in the path of temperature, precipitation and combined metric of temperature and precipitation changes under different strength of solar irradiation reduction. The Pareto improving, choosing the level of SRM that minimizes damages for all regions without making any region worse off (Moreno-Cruz et al., 2012), for temperature, precip- itation and combined metric of temperature and precipitation also ex- plored in Kravitz et al. (2014). We extend the work of Kravitz et al. (2014) by quantifying the regional inequalities and effectiveness repre- sented by these two variables using the RCR method for each of the four GeoMIP experiments. Furthermore, our method of assessing the level of natural variability allows us to test the significance of regional inequalities and effectiveness in each experiment for each model as well as the significance of differences among different experiments.
3. Results

3.1. Global and regional SAT changes

Figs. 3 and 4 show the multi-model ensemble mean of the SAT change at the grid and regional scales under different experiments. For GISS-E2-R, the global mean temperature and precipitation under G3 and rcp45 are very similar to each other (SI Fig. 1). There is no sign of change in global climate after sulfate aerosol has been injected, possibly due to the efficacy of SO2 forcing in GISS-E2-R being relatively small as compared to CO2 forcing. Therefore, the temperature and precipitation data from this model are not included in the G3 study.

The SAT under abrupt4xCO2 are obviously increased compared with piControl (Fig. 3a). The global average SAT increased 4.30 ± 0.75 °C (Table 2); these values are similar to those in previous studies (Schmidt et al., 2012; Good et al., 2013; Kravitz et al., 2013a).
regional scale SATs (Fig. 4a) show a statistically significant increase (95% significance level, see Section 2.2; the same significance level for regional change is used throughout this paper). G1 successfully addresses the substantial global mean warming under abrupt4xCO2, restoring the global average SAT to its pre-industrial level (Table 2), but with relative warming over polar regions and cooling over the tropics (Fig. 3b). Previous studies (e.g., Govindasamy and Caldeira, 2000; Schmidt et al., 2012; Kravitz et al., 2013a) attribute the main reason for this SAT change pattern to the balancing of longwave greenhouse gas forcing by seasonally and latitudinally varying shortwave forcing. The regional scale land ensemble mean SAT change ranges from −0.28 °C to 0.96 °C (Fig. 4a).

SAT change under 1pctCO2 is much smaller but similar in spatial pattern to abrupt4xCO2 (Fig. 3c). G2 SAT change also has similar patterns to change under G1 but with smaller magnitude and lower model agreement (Fig. 3d). This is likely due to the similar global radiative forcing spatial patterns between G1 and G2. Regional scale land ensemble mean SAT change is between 0.00 °C and 0.27 °C (Fig. 4b). The SATs are significantly increased over much of the northern mid- and high-latitude land areas, but no regional scale SAT ensemble mean is larger than the corresponding across-model variation (defined as the multi-model ensemble standard deviation here and throughout this paper).

Over the period from 2030 to 2069, the global average SAT under rcp45 increased by 0.81 ± 0.21 °C compared with the baseline (average over 2010–2029 under rcp45; Table 2). Additionally, all regional land SATs are significantly increased by 0.65 °C to 1.56 °C.

Under G3, the global mean SAT considerably increases by 0.23 ± 0.28 °C (Table 2) relative to the baseline. In contrast with G1 and G2, under which the SAT decreased generally over low latitude oceans, the SAT decrease areas under G3 are far fewer and more dispersed, mainly over mid and high latitudes such as central Asia, north Atlantic Ocean, northwest Australia, north Pacific Ocean and around Antarctica. At regional scales, the ensemble mean land SAT changes range from 0.08 °C to 0.72 °C. However, none of the regional changes are significant because of the small number of models in the G3 ensemble and the large across-model variation.

For the geoengineering scenario G4, the 40 year annual global mean SAT increased by 0.28 ± 0.31 °C (Table 2). This is a slightly higher rise than under G3. The regional scale SAT increases range between 0.11 °C and 0.66 °C. The SATs in the 9 regions are significantly increased under G4. All the regional land SAT ensemble means under G4 increased relative to the baseline, and most regions have larger increases than under G3. This illustrates that the greenhouse gas induced radiative forcing in rcp45 dominates that from 5 Tg a⁻¹ SO₂ stratospheric injection over the 2030 to 2069 period.

### 3.2. Global and regional precipitation change

Figs. 5 and 6 show precipitation changes at the grid scale and regional scale, respectively. The global average precipitation increases by 0.15 ± 0.06 mm day⁻¹ under abrupt4xCO2 (Table 2 and Fig. 5a). Precipitation is strongly and robustly (at least ten of thirteen models agree on the sign of the change) increased over high latitude regions and the equatorial ocean. Precipitation robustly decreases under the sinking part of the Hadley Cell. These change patterns were also found by Schmidt et al. (2012) and Kravitz et al. (2013a).

Globally averaged precipitation under G1 is decreased by −0.13 ± 0.04 mm day⁻¹ (Table 2). The largest precipitation decrease occurs over equatorial parts of the Pacific Ocean. The multi-model mean precipitation in 19 regions is decreased under G1; changes in 16 of those regions are statistically significant (Fig. 6a). The patterns and global average of precipitation changes under G1 are consistent with those discussed by Schmidt et al. (2012) and Kravitz et al. (2013a). A reduction in solar radiation imposed upon abrupt4xCO2 causes an initial suppression in precipitation. This suppression is sustained throughout experiment G1 because of the lack of a slow response, primarily because the strongest feedbacks are related to global mean temperature changes, which are small (Kravitz et al., 2013b). From an energetic perspective, the suppression in precipitation under G1 is primarily a result of the decrease of evaporative flux from the surface to the atmosphere (Kravitz et al., 2013b). Evaporative flux decreases are in part caused by an increase in atmospheric stability due to reduced insolation having a greater cooling effect on the surface than the mid-troposphere (Bala et al., 2008; Kravitz et al., 2013a). Evaporation decreases are also due to the CO₂ physiological effect, whereby plants close their stomata under high CO₂ conditions, reducing evapotranspiration over land (Fyfe et al., 2013; Kravitz et al., 2013b; Timilsina et al., 2013).

Precipitation changes under G2, G3, and G4 have weaker magnitudes than under abrupt4xCO2 while exhibiting similar spatial patterns. Under G2, the precipitation pattern is also similar to that under G1, which may due to the similarity of the patterns of radiative forcing, but with a smaller magnitude of change and lower model agreement. Only 5 of the 22 regions show statistically significant changes in precipitation under G2.

Globally averaged precipitation under rcp45 between 2030 and 2069 is moderately increased by 0.04 ± 0.02 mm day⁻¹ compared with the baseline. The patterns of precipitation change under rcp45 are similar to those under abrupt4xCO2 and 1pctCO2. Regional-scale land precipitation changes range from −0.07 to 0.14 mm day⁻¹. The ensemble mean precipitation is increased in 18 regions, and in 9 of those regions, the precipitation changes are statistically significant. The Amazon Basin has the largest across-model precipitation change variation.

The ensemble mean of the global average precipitation change under G3 is negligible relative to the baseline, and the across-model variation (0.02 mm day⁻¹) is much larger than the ensemble mean. No regional change in any land region is significant.

Under G4, the ensemble mean of the global average precipitation change is also negligibly small with large across-model variation. The ranges of change of regional scale precipitation under G4 overlap closely with those under rcp45. Precipitation is significantly increased over East Asia and significantly decreased over the Amazon Basin under G4.

### 3.3. Effectiveness and related regional inequalities of different SRM scenarios

Fig. 7 shows the regional inequality, and Fig. 8 the actual effectiveness (line and point) and corresponding noise (box) of individual models for scenarios G1 to G4 for temperature and precipitation. G1 has low noise in regional inequality of temperature (0.6°–1.1°; Fig. 7), while the noise is larger for G3 and G4 (3.4°–8.6°) and larger again for G2 (3.5°–11.7°). Note that similar regional inequalities between different models do not necessarily mean that the regional changes of these models are similar, as regional inequality depends on the temperature or precipitation changes in 22 regions under both the SRM scenario and the corresponding elevated CO₂ scenario. Regional inequality noise in precipitation (G1: 4.0°–8.0°; G2: 21.8°–37.8°; G3 and G4: 13.2°–42.6°) is larger than for temperature. The regional inequality of temperature for all models under G1, G3, and G4 is statistically significant (defined as being larger than their corresponding noise levels; we
Fig. 5. The same as that for Fig. 3 but for precipitation anomalies.
use this definition in the remainder of this paper). For G2, 5 of 11 models have a regional inequality of temperature that is significantly different from noise. The regional inequalities of precipitation for all G1 and G3 models, as well as 6 of 7 G4 models, are significantly different from their corresponding noise levels. For G2, the regional inequality of precipitation is significantly different from noise in 6 of 11 models. G4 has the largest regional inequality across-model variations (multimodel ensemble standard deviation) for both temperature and precipitation.

Although temperature and precipitation inequalities of G1 are smaller than G2 for most of models, none of them are significant as none of the regional inequality differences between G1 and G2 are larger than corresponding noise in G2 (Fig. 7). The temperature and precipitation
region inequality differences between G3 and G4 are not significant for 2 of 2 models that simulated both G3 and G4. Most models under the solar dimming geoengineering scenarios (G1 and G2) have temperature and precipitation regional inequalities smaller than under the CO2 geoengineering scenarios (G3 and G4), but no more than half of the models are significantly smaller.

Fig. 8 shows that for actual effectiveness of temperature, G1 also has the smallest noise among the four experiments (0.01%–0.08%) and is the closest to 100% effective (98.7%–99.8%). The noise in actual effectiveness of temperature is 0.5%–5.6% for G2 and 0.5%–3.0% for G3 and G4. Under G2, 8 of 12 models are significantly different from the noise, and all models in G3 and G4 are significantly different from the noise. For actual effectiveness of precipitation, the noise in G1 models is small (0.6%–2.1%). G2, G3 and G4 have a larger noise (G2: 19.7%–57.6%; G3 and G4: 6.3%–58.5%). Actual effectiveness of precipitation for G1 to G4 is significantly different from their corresponding noise for most models (G1: 12/12; G2: 6/11; G3: 3/3; G4: 6/7).

For 8 of 11 models that simulated both G1 and G2, temperature actual effectiveness of G1 is significantly higher than G2 (Fig. 8). However, only 3 of 11 models’ precipitation actual effectiveness of G1 are significantly higher than G2. Temperature actual effectiveness of G3 is significantly higher than that of G4 for 2 of 2 models while none of models’ precipitation actual effectiveness of G3 is significantly higher than that of G4. More than half of the models under the solar dimming geoengineering scenarios (G1 and G2) have temperature actual effectivenesses that are significantly higher than under the SO2 geoengineering scenarios (G3 and G4).

For precipitation actual effectiveness, G1 is significantly higher than for G4 and G2 and significantly higher than G3 for more than half the models. G1 has a large across model variation for precipitation regional inequality and actual effectiveness, but the differences between GISS-E2-R and the other models dominating (see Figs. 7 and 8).

The high compensation effectiveness, small regional inequality for SAT, and the lower compensation effectiveness with larger regional inequality for precipitation under G1 are all consistent with the results of Moreno-Cruz et al. (2012), although Moreno-Cruz et al. (2012) only used one model. Previous studies also showed the difficulty of simultaneous perfect compensation of temperature and precipitation change by uniform SRM (e.g., Bala et al., 2008; Ricke et al., 2010; Moreno-Cruz et al., 2012; Kravitz et al., 2013a; Tilmes et al., 2013).

Optimal compensation effectiveness is higher than actual compensation effectiveness in all the four GeoMIP experiments (SI Fig. 2, Table 3). G4 has the largest SAT and precipitation ensemble mean compensation effectiveness increase, changing from 80% to 95% and from 46% to 59%, respectively (Table 3). These effectiveness differences show that none of the four geoengineering experiments is at their highest potential to compensate for temperature and precipitation changes under the corresponding greenhouse gas forcing experiments. The adjustment percentage of SRM-compensated change needed to achieve optimal compensation effectiveness (SI Fig. 3, Table 3) under G1 and G2 indicates that these two experiments should have weaker solar reduction to reach optimum precipitation compensation effectiveness. This is because the hydrological cycle is more sensitive to short wave
surface warming than it is to greenhouse gas induced surface warming (e.g., Bala et al., 2008; Kleidon and Renner, 2013). Thus, although the cooling induced by solar irradiance reduction under $G_1$ and $G_2$ successfully counteracted the warming induced by CO$_2$ elevation, the resulting weakening of the hydrological cycle due to geoengineering is greater than the strengthening due to elevated CO$_2$. The adjustment percentage of SRM-compensated change under other experiments is not significant for precipitation in $G_3$ and $G_4$ and not significant for SAT in any experiment. The across-model variation of adjustment percentages to achieve optimal compensation effectiveness for SAT and precipitation is larger than the across-model variations in the other three metrics (regional inequality, actual compensation effectiveness and optimal compensation effectiveness) used in this study. This is because across-model variations in the other three metrics contribute to the across-model variation of the adjustment percentage. The adjustment percentage across-model variation for SAT and precipitation under $G_3$ and $G_4$ is larger than those under $G_1$ and $G_2$.

4. Discussion and conclusions

In this study four GeoMIP experiments were analyzed using the results from up to 13 earth system models. We first investigated the robustness of global and regional SAT and precipitation change. We then explored the regional inequality, climate compensation effectiveness and adjustment percentage of SRM-compensated change needed to achieve optimal climate compensation effectiveness based on multimodel results.

### Table 3
Multi-model ensemble mean and standard deviation of regional inequality $\psi$ (°; Eq. (3)), actual and optimal compensation effectiveness (%) (Eqs. (7) and (8)) and adjustment percentage (%) (Eq. (9)) of SRM compensated change under experiment $G_1$, $G_2$, $G_3$ and $G_4$ for near surface air temperature (T) and precipitation (P). All models available for each experiment in SI Table 1 are used. All the values in this table are the result of rounding original floating point value to nearest integer.

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Regional inequality $\psi$ (°)</th>
<th>Actual effectiveness (%)</th>
<th>Optimal effectiveness (%)</th>
<th>Adjustment percentage (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>T</td>
<td>P</td>
<td>T</td>
<td>P</td>
</tr>
<tr>
<td>G1</td>
<td>3 ± 1</td>
<td>20 ± 11</td>
<td>99 ± 0</td>
<td>77 ± 32</td>
</tr>
<tr>
<td>G2</td>
<td>6 ± 2</td>
<td>29 ± 6</td>
<td>93 ± 7</td>
<td>66 ± 10</td>
</tr>
<tr>
<td>G3</td>
<td>8 ± 1</td>
<td>39 ± 6</td>
<td>86 ± 6</td>
<td>48 ± 18</td>
</tr>
<tr>
<td>G4</td>
<td>11 ± 6</td>
<td>39 ± 14</td>
<td>80 ± 20</td>
<td>46 ± 31</td>
</tr>
</tbody>
</table>
As previous studies have shown (e.g., Jones et al., 2013; Kravitz et al., 2013a), under the idealized SRM experiments of G1 and G2, the global average SATs are successfully restored close to pre-industrial levels, although with a relative tropical decrease and polar increase pattern. Here we quantify that the corresponding effectiveness, as measured by the RCR method, is quite high. However, these two experiments resulted in reduced global precipitation, thus their corresponding precipitation effectiveness is much smaller than those for SAT.

Among the four SRM scenarios, the regional inequalities of temperature and precipitation compensation for G1, G3 and G4 are significantly different from their corresponding noise levels for most of models. However, the regional inequalities of temperature and precipitation compensation for G2 are not significantly different from the noise for most, and half of models respectively. This may be caused by the low signal to noise ratio in G2. The regional inequality and actual effectiveness differences among the four SRM scenarios for many models are not significant compared with the noise, especially for regional inequality. However, in more than half the models, temperature actual effectiveness under the solar dimming geoengineering scenarios (G1 and G2) is significantly higher than that under the SO2 geoengineering scenarios (G3 and G4).

The difference between actual and optimal effectiveness supports earlier analysis (MacMartin et al., 2013) that balancing the TOA radiation budget does not produce equal regional responses. The optimum effectiveness can be reached by reducing or increasing the SRM, but the result depends on the choice of regions, the weighting given to each region, and the metric used to aggregate all regions; this was also deduced from the single-model experiments (Moreno-Cruz et al., 2012). Our multi-model analysis brings extra information on the sensitivity of these results to model physics. Cleary results differ depending on the model used, especially in the case of highly complex simulations such as SO2 injections. This results in much across-model noise, but a reasonably robust conclusion that aerosol injection is less effective that solar dimming, and more likely to result in regional inequalities of climate response. Here we have assumed only globally uniform forcing from SRM. If non-uniform optimization is available, via spatial and temporal varying SRM, the regional inequality will certainly be different. Residual temperature and precipitation changes in the worst-off region (however that is defined), or the required solar reduction for the same residual climate change, may be reduced (MacMartin et al., 2013). The metrics we use here show, as expected, that precipitation is inherently more variable across different regions than temperature. The large across-model variation in the adjustment percentage of compensated SAT and precipitation change by SRM to achieve optimal compensation effectiveness sheds light on the uncertainty accumulation effect in optimizing compensation effectiveness of SRM.

While caution is needed to interpret the results based purely on the RCR methodology in this study, the findings are in broad agreement with other studies using different methods or considerably fewer models. The RCR methodology is a useful tool that aids in the visualization and comparison of multiple model climate fields across many regions in a simple set of metrics. The regions here are assumed equally weighted, but it is easy to adjust the weighting based on economic or population loadings as desired (e.g. Moreno-Cruz et al., 2012). Perhaps more fundamentally, we used (as have others) a simple quadratic damage function for climate change. In practice, such decisions are beyond the remit of the natural sciences and ultimately are decided by societal values. However, the inputs to the analysis come from earth system models and, therefore, are limited by the quality of the climate system representation in those models. Although the four SRM experiments in GeoMIP represent far from real-world implementations of the SRM, the robust features and contrasting areas of doubt are becoming clearer. To move towards potentially more useful regional or seasonal geoengineering modeling requires advances, the identification of key region-specific damage functions, and better treatment of geoengineering methods in the earth system models.

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