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

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Abstract

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 years of simulations: 13 models completed experiment *G1* (offsetting $4 \times \text{CO}_2$ via solar reduction); 12 models completed experiment *G2* (offsetting CO_2 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 $5 \text{ Tg SO}_2 \text{ a}^{-1}$ 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 SO_2 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 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.

Keywords

Solar Radiation Management; regional inequality; regional climate compensation effectiveness; GeoMIP

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., Shepherd et al., 2009; Caldeira and Keith, 2010; Crutzen, 2006; Wigley, 2006). 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; Fyfe et al., 2013; MacCracken et al., 2012; Ricke et al., 2010). 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 Figure 1 for a graphical description of the four core experiments). Several studies have investigated the climate responses to the GeoMIP *G1* (e.g., Kravitz et al., 2013a, 2013b; Schmidt et al., 2012; 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* multi-model 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).

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

115 **2. Data and Analysis Methods**

116 *2.1 GeoMIP experiment and model description*

117 Among the four standard GeoMIP experiments, *G1* and *G2* are both designed to
118 simulate reduced shortwave radiative forcing by decreasing solar irradiance, while *G3*
119 and *G4* reduce net radiative forcing via the addition of sulfate aerosol precursors to

120 the stratosphere. Experiment *G1* balances an instantaneous increase in CO₂ four times
121 that of pre-industrial levels with a simultaneous solar irradiance reduction. The global
122 mean top-of-atmosphere (TOA) radiation imbalance is specified to be within 0.1
123 W/m² relative to the pre-industrial control simulation for the 50-year experiment
124 (Figure 1). Experiment *G2* is designed to balance a transient CO₂ increase (1% per
125 year increase in concentration) from pre-industrial levels by gradually decreasing
126 solar irradiance during the first 50 years of the experiment; after this period, SRM is
127 switched off while CO₂ continues to increase at the rate of 1% per year for 20 years
128 (Figure 1). For comparison purposes, we also make use of three simulation results
129 from CMIP5 (Taylor et al., 2012) that serve as the background greenhouse gas
130 simulations for experiments *G1* and *G2*: *piControl*, which refers to the pre-industrial
131 control run; *abrupt4xCO2*, which refers to the instantaneous quadrupling of CO₂ from
132 pre-industrial levels; and *1pctCO2*, which refers to 1% per year CO₂ increase from
133 pre-industrial levels.

134 Unlike *G1* and *G2*, *G3* and *G4* are designed to reduce solar irradiance by
135 stratospheric SO₂ injection (Figure 1). Over the 50 years of *G3*, the injected SO₂ mass
136 is gradually increased to counteract the gradually increased longwave radiative
137 forcing specified under the RCP4.5 scenario, thus maintaining top-of-atmosphere net
138 radiative flux at 2020 levels. In *G4*, the annual amount of SO₂ injected into the
139 stratosphere is a constant 5 Tg per year for the first 50 years of *G4*. *G3* and *G4* do not
140 specify how the models handle aerosols, and the models differ widely in their
141 representations of stratospheric chemistry, aerosol growth and dynamical transport

142 schemes. Thus, it is expected that inter-model differences will be larger for *G3* and
143 *G4* than *G1* and *G2* (Kravitz et al., 2011). The CMIP5 experiment *rcp45*, which is the
144 future climate state forced by RCP4.5 (Taylor et al., 2012), is used for comparison
145 purposes. The baseline climate for *G1*, *G2* and the relevant greenhouse gas forcing
146 experiment is an average of the pre-industrial control simulation *piControl* over time.
147 The RCR vector-based methodology requires a prior state against which comparisons
148 can be made. In the *G3* and *G4* cases, this prior state cannot be simply the mean of
149 *piControl* because the RCP4.5 climate forcing continues from the historical forcing
150 record, which has been non-stationary. Therefore, we chose the average climate under
151 *rcp45* over the period 2010–2029 as the baseline for *G3*, *G4*, and *rcp45* (see Table 1).

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

162 Table 1 lists the number of models available for each GeoMIP scenario and its
163 associated background simulation. The names and general description of the models

164 are given in SI Table 1. In this study, with its emphasis on regional variations, we
165 focus on two important climate variables: near surface air temperature (SAT) and
166 precipitation, as in several previous studies (Kravitz et al., 2014; MacMartin et al.,
167 2013; Moreno-Cruz et al., 2012; Ricke et al., 2010; Ricke et al., 2013).

168 *2.2 Regionalization*

169 We followed Giorgi and Francisco (2000) in defining 22 regions to investigate
170 the patterns of temperature and precipitation change under SRM. These 22 regions
171 cover most of the global land area, and regional boundaries were chosen to represent
172 climatically and physiographically similar land areas. These regions are large enough
173 to produce climate predictions that are more statistically robust than those obtained
174 from grid cell level output (Giorgi and Francisco, 2000; Moreno-Cruz et al., 2012).
175 We calculated the area weighted temperature or precipitation change for each region
176 in each model. The 95% significance level of temperature or precipitation change for
177 each region was also calculated with a two-tailed *Student's t*-test assuming each
178 model's data was independent.

179 *2.3 Residual climate response method*

180 To evaluate the potential regional inequalities resulting from SRM, as well as the
181 effectiveness of SRM, Moreno-Cruz et al. (2012) introduced the RCR methodology
182 with the objective of providing easily understood results suitable for policy- and
183 decision-makers. In the RCR approach, anthropogenic climate change and the climate
184 change compensated by SRM are represented by two vectors. Each component of

185 these two vectors represents a given region's climate change under greenhouse gas
186 increases or SRM. The angle between these two vectors then represents the difference
187 between the SRM compensated climate and that under the CO₂ equivalent
188 (CO₂e)-driven climate forcing alone.

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

196 The RCR approach is illustrated in Figure 2. The origin **O** represents the
197 reference state of a single climate variable *Y* (such as SAT or precipitation, but not a
198 combination of SAT and precipitation as in Moreno-Cruz et al., 2012 and Kravitz et
199 al., 2014; our approach avoids the problem of determining a relative importance
200 among different variables). The regional changes in *Y* from the reference state due to
201 elevated CO₂e are represented as a $1 \times n$ dimension vector $\mathbf{Y}_{\text{CO}_2\text{e}}$,

$$\mathbf{Y}_{\text{CO}_2\text{e}} = (y_{\text{CO}_2\text{e}_1}, y_{\text{CO}_2\text{e}_2}, \dots, y_{\text{CO}_2\text{e}_i}, \dots, y_{\text{CO}_2\text{e}_n}) \quad (1)$$

202
203 where n is the number of regions in the globe. Each component of $\mathbf{Y}_{\text{CO}_2\text{e}}$ represents
204 the CO₂e increasing induced *Y* change for a given region $i=1,2,\dots,n$. The residual
205 change in *Y* under SRM is represented by the vector $\mathbf{Y}_{\text{RES}}$,

$$\mathbf{Y}_{\text{RES}} = (Y_{\text{RES}_1}, Y_{\text{RES}_2}, \dots, Y_{\text{RES}_i}, \dots, Y_{\text{RES}_n}) \quad (2)$$

206

207 In the vector $\mathbf{Y}_{\text{CO}_2\text{e}}$ and $\mathbf{Y}_{\text{RES}}$, the change in Y in each region is normalized by the
 208 corresponding inter-annual variability of Y under the baseline climate, as was done by
 209 Ricke et al. (2010). The change compensated by SRM is represented by $\mathbf{Y}_{\text{SRM}}$ and is
 210 $\mathbf{Y}_{\text{CO}_2\text{e}} - \mathbf{Y}_{\text{RES}}$. The angle φ between $-\mathbf{Y}_{\text{CO}_2\text{e}}$ and $\mathbf{Y}_{\text{SRM}}$ represents the regional inequality
 211 in the effectiveness of compensating Y change by SRM and is calculated as follows:

$$\varphi = \cos^{-1} \left(\frac{-\mathbf{Y}_{\text{CO}_2\text{e}} \cdot \mathbf{Y}_{\text{SRM}}}{\|\mathbf{Y}_{\text{CO}_2\text{e}}\| \|\mathbf{Y}_{\text{SRM}}\|} \right) \quad (3)$$

212

213 For a non-zero $\mathbf{Y}_{\text{SRM}}$, if φ is 0° , all regions are equally compensated by SRM; if
 214 φ is 180° , SRM equally increases all regional changes from the elevated CO_2e instead
 215 of compensating for them. $\mathbf{Y}_{\text{RES_OPT}}$ is the minimum-norm residual change for a given
 216 angle between $\mathbf{Y}_{\text{CO}_2\text{e}}$ and $\mathbf{Y}_{\text{SRM}}$. Geometrically, $\mathbf{Y}_{\text{RES_OPT}}$ is perpendicular to $\mathbf{Y}_{\text{SRM}}$ and
 217 represents the minimum distance from the baseline to $\mathbf{Y}_{\text{SRM}}$. $\mathbf{Y}_{\text{RES_OPT}}$ is assumed to
 218 be reached by adjusting the radiative forcing due to SRM equally in all regions. The
 219 norm of $\mathbf{Y}_{\text{RES_OPT}}$ depends on φ and the norm of $\mathbf{Y}_{\text{CO}_2\text{e}}$. A larger φ or norm of $\mathbf{Y}_{\text{CO}_2\text{e}}$
 220 means a larger norm of $\mathbf{Y}_{\text{RES_OPT}}$.

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

$$D_{\text{CO}_2\text{e}} \propto \|\mathbf{Y}_{\text{CO}_2\text{e}}\|^2 \quad (4)$$

$$D_{\text{RES}} \propto \|\mathbf{Y}_{\text{RES}}\|^2 \quad (5)$$

$$D_{\text{RES_OPT}} \propto \|\mathbf{Y}_{\text{RES_OPT}}\|^2 \quad (6)$$

225

226 The damages caused by climate change are difficult to quantify and we are aware
 227 that other damage functional forms have been used in previous studies (e.g., Cline,
 228 1992; Manne et al., 1995; Peck and Teisberg, 1992; Peck and Teisberg, 1994).
 229 Moreover, there is no indication that a single damage functional form applies equally
 230 to all regions or situations. The quadratic function used here is a simple option, but
 231 we make no claim that it is more or less valid than other choices.

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

$$234 \quad \left(1 - \frac{\|\mathbf{Y}_{\text{RES}}\|^2}{\|\mathbf{Y}_{\text{CO 2e}}\|^2}\right) \times 100\% \quad (7)$$

235 We define the quantity in Equation 7 to be the actual effectiveness of particular SRM
 236 scenario. The optimal effectiveness of a particular SRM scenario for a given φ is then:

$$237 \quad \left(1 - \frac{\|\mathbf{Y}_{\text{RES_OPT}}\|^2}{\|\mathbf{Y}_{\text{CO 2e}}\|^2}\right) \times 100\% = (1 - \sin^2 \varphi) \times 100\% \quad (8)$$

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

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

$$243 \quad \left(\frac{\|\mathbf{Y}_{\text{CO 2e}}\| \cdot \cos(\varphi)}{\|\mathbf{Y}_{\text{SRM}}\|} - 1\right) \times 100\% \quad (9)$$

244 Moreno-Cruz et al. (2012) applied RCR to one geoengineering scenario and for only a
 245 single model, whereas here we use RCR to quantify temperature and precipitation
 246 compensation effectiveness and regional inequalities in multiple models for four SRM

247 scenarios. Each model's compensation effectiveness and assessments of regional
248 inequalities are taken as independent measurements for the purpose of producing
249 multi-model ensemble means and standard deviations. To investigate the behaviors of
250 ϕ , actual effectiveness, and optimal effectiveness due to natural variability, we
251 divided the *piControl* runs of each model into several parts, each part containing 40
252 continuous years of simulation. We then can define the first 40 years as the
253 'reference' case and the remainder as 'perfect geoengineering', in which the climate is
254 exactly returned to preindustrial conditions. The differences between the 'perfect
255 geoengineering' and 'reference' climates represent the noise caused by the model's
256 internal variability. We define the 'noise' values of the angle ϕ , actual effectiveness,
257 optimal effectiveness from use of the RCR method on these 'perfect geoengineering'
258 periods. Note the differences between 'perfect geoengineering' and 'reference' in
259 *piControl* may be not a good proxy of natural variability over 2010 to 2029 in
260 RCP4.5, *G3* and *G4*. We use it because there is no obvious way to find the 'perfect
261 geoengineering' for the simulations from 2010 to 2029 in RCP4.5, and similarly for
262 *G3* and *G4*.

263 The regional inequalities in Kravitz et al. (2014) were demonstrated by regional
264 differences in the path of temperature, precipitation and combined metric of
265 temperature and precipitation changes under different strength of solar irradiation
266 reduction. The Pareto improving, choosing the level of SRM that minimizes damages
267 for all regions without making any region worse off (Moreno-Cruze et al., 2012), for
268 temperature, precipitation and combined metric of temperature and precipitation also

269 explored in Kravitz et al.(2014). We extend the work of Kravitz et al. (2014) by
270 quantifying the regional inequalities and effectiveness represented by these two
271 variables using the RCR method for each of the four GeoMIP experiments.
272 Furthermore, our method of assessing the level of natural variability allows us to test
273 the significance of regional inequalities and effectiveness in each experiment for each
274 model as well as the significance of differences among different experiments.

275 **3. Results**

276 *3.1 Global and regional SAT changes*

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

284 The SAT under *abrupt4xCO2* are obviously increased compared with *piControl*
285 (Figure 3a). The global average SAT increased $4.30 \pm 0.75^{\circ}\text{C}$ (Table 2); these values
286 are similar to those in previous studies (Schmidt et al., 2012; Good et al., 2013;
287 Kravitz et al., 2013a). All the regional scale SATs (Figure 4a) show a statistically
288 significant increase (95% significance level, see section 2.2; the same significance
289 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 (Figure 3b). Previous studies (e.g., Govindasamy and Caldeira, 2000; Kravitz et al., 2013a; Schmidt et al., 2012) 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 (Figure 4a).

SAT change under *1pctCO2* is much smaller but similar in spatial pattern to *abrupt4xCO2* (Figure 3c). *G2* SAT change also have similar patterns to change under *G1* but with smaller magnitude and lower model agreement (Figure 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 (Figure 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 $0.81 \pm 0.21^\circ\text{C}$ 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 moderately increases by $0.23 \pm 0.28^\circ\text{C}$ (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 $0.28 \pm 0.31^\circ\text{C}$ (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 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

Figures 5 and 6 show precipitation changes at the grid scale and regional scale, respectively. The global average precipitation increases by $0.15 \pm 0.06 \text{ mm day}^{-1}$ under *abrupt4xCO2* (Table 2 and Figure 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).

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

352 Precipitation changes under *1pctCO2* have weaker magnitudes than under
353 *abrupt4xCO2* while exhibiting similar spatial patterns. Under *G2*, the precipitation
354 pattern is also similar to that under *G1*, which may due to the similarity of the patterns
355 of radiative forcing, but with a smaller magnitude of change and lower model

356 agreement. Only 5 of the 22 regions show statistically significant changes in
357 precipitation under *G2*.

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

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

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

374 3.3 Effectiveness and related regional inequalities of different SRM scenarios

375 Figure 7 shows the regional inequality, and Figure 8 the actual effectiveness (line
376 and point) and corresponding noise (box) of individual models for scenarios *G1* to *G4*
377 for temperature and precipitation. *G1* has low noise in regional inequality of

378 temperature ($0.6^{\circ}\sim 1.1^{\circ}$; Figure 7), while the noise is larger for *G3* and *G4* ($3.4^{\circ}\sim 8.6^{\circ}$)
379 and larger again for *G2* ($3.5^{\circ}\sim 11.7^{\circ}$). Note that similar regional inequalities between
380 different models does not necessarily mean that the regional changes of these models
381 are similar, as regional inequality depends on the temperature or precipitation changes
382 in 22 regions under both the SRM scenario and the corresponding elevated CO_2
383 scenario. Regional inequality noise in precipitation (*G1*: $4.0^{\circ}\sim 8.0^{\circ}$. *G2*: $21.8^{\circ}\sim 37.6^{\circ}$,
384 *G3* and *G4*: $13.2^{\circ}\sim 42.6^{\circ}$) is larger than for temperature. The regional inequality of
385 temperature for all models under *G1*, *G3*, and *G4* are statistically significant (defined
386 as being larger than their corresponding noise levels; we use this definition in the
387 remainder of this paper). For *G2*, 5 of 11 models have a regional inequality of
388 temperature that is significantly different from noise. The regional inequalities of
389 precipitation for all *G1* and *G3* models, as well as 6 of 7 *G4* models, are significantly
390 different from their corresponding noise levels. For *G2*, the regional inequality of
391 precipitation is significantly different from noise in 6 of 11 models. *G4* has the largest
392 regional inequality across-model variations (multimodel ensemble standard deviation)
393 for both temperature and precipitation.

394 Although temperature and precipitation inequalities of *G1* are smaller than *G2*
395 for most of models, none of them are significant as none of the regional inequality
396 differences between *G1* and *G2* are larger than corresponding noise in *G2* (Figure 7).
397 The temperature and precipitation regional inequality differences between *G3* and *G4*
398 are not significant for 2 of 2 models that simulated both *G3* and *G4*. Most models
399 under the solar dimming geoengineering scenarios (*G1* and *G2*) have temperature and

precipitation regional inequalities smaller than under the SO₂ geoengineering scenarios (*G3* and *G4*), but no more than half of the models are significantly smaller.

Figure 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 larger noise (*G2*: 19.7%~57.6%; *G3* and *G4*: 6.3~ 58.5%). Actual effectiveness of precipitation for *G1* to *G4* are 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* (Figure 8). However, only 3 of 11 models' precipitation actual effectiveness of *G1* are significantly higher than *G2*. Temperature actual effectiveness of *G3* are significantly higher than *G4* for 2 of 2 models while none of models' precipitation actual effectiveness of *G3* are significantly higher than *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.

422 *G1* has a large across model variation for precipitation regional inequality and
423 actual effectiveness, with the differences between GISS-E2-R and the other models
424 dominating (see Figure 7 and 8).

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

432 Optimal compensation effectiveness is higher than actual compensation
433 effectiveness in all the four GeoMIP experiments (SI Figure 2, Table 3). *G4* has the
434 largest SAT and precipitation ensemble mean compensation effectiveness increase,
435 changing from 80% to 95% and from 46% to 59%, respectively (Table 3). These
436 effectiveness differences show that none of the four geoengineering experiments are
437 at their highest potential to compensate for temperature and precipitation changes
438 under the corresponding greenhouse gas forcing experiments.

439 The adjustment percentage of SRM-compensated change needed to achieve
440 optimal compensation effectiveness (SI Figure 3, Table 3) under *G1* and *G2* indicates
441 that these two experiments should have weaker solar reduction to reach optimum
442 precipitation compensation effectiveness. This is because the hydrological cycle is
443 more sensitive to short wave surface warming than it is to greenhouse gas induced

444 surface warming (e.g., Bala et al., 2008; Kleidon and Renner, 2013). Thus, although
445 the cooling induced by solar irradiance reduction under *G1* and *G2* successfully
446 counteracted the warming induced by CO₂ elevation, the resulting weakening of the
447 hydrological cycle due to geoengineering is greater than the strengthening due to
448 elevated CO₂. The adjustment percentage of SRM-compensated change under other
449 experiments is not significant for precipitation in *G3* and *G4* and not significant for
450 SAT in any experiment. The across-model variation of adjustment percentages to
451 achieve optimal compensation effectiveness for SAT and precipitation are larger than
452 across-model variations in the other three metrics (regional inequality, actual
453 compensation effectiveness and optimal compensation effectiveness) used in this
454 study. This is because across-model variations in the other three metrics contribute to
455 the across-model variation of the adjustment percentage. The adjustment percentage
456 across-model variation for SAT and precipitation under *G3* and *G4* is larger than
457 those under *G1* and *G2*.

458 **4. Discussion and Conclusions**

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

465 As previous studies have shown (e.g., Kravitz et al., 2013a; Jones et al., 2013),
466 under the idealized SRM experiments of *G1* and *G2*, the global average SATs are
467 successfully restored close to pre-industrial levels, although with a relative tropical
468 decrease and polar increase pattern. Here we quantify that the corresponding
469 effectiveness, as measured by the RCR method, is quite high. However, these two
470 experiments resulted in reduced global precipitation, thus their corresponding
471 precipitation effectiveness is much smaller than those for SAT.

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

483 The difference between actual and optimal effectiveness supports earlier analysis
484 (MacMartin et al., 2013) that balancing the TOA radiation budget does not produce
485 equal regional responses. The optimum effectiveness can be reached by reducing or
486 increasing the SRM, but the result depends on the choice of regions, the weighting

487 given to each region, and the metric used to aggregate all regions - this was also
488 deduced from the single-model experiments (Moreno-Cruz et al., 2012). Our
489 multi-model analysis brings extra information on the sensitivity of these results to
490 model physics. Clearly results differ depending on the model used, especially in the
491 case of highly complex simulations such as SO₂ injections. This results in much
492 across-model noise, but a reasonably robust conclusion that aerosol injection is less
493 effective than solar dimming, and more likely to result in regional inequalities of
494 climate response. Here we have assumed only globally uniform forcing from SRM. If
495 non-uniform optimization is available, via spatial and temporal varying SRM, the
496 regional inequality will certainly be different. Residual temperature and precipitation
497 changes in the worst-off region (however that is defined), or the required solar
498 reduction for the same residual climate change, may be reduced (MacMartin et al.,
499 2013). The metrics we use here show, as expected, that precipitation is inherently
500 more variable across different regions than temperature. The large across-model
501 variation in the adjustment percentage of compensated SAT and precipitation change
502 by SRM to achieve optimal compensation effectiveness sheds light on the uncertainty
503 accumulation effect in optimizing compensation effectiveness of SRM.

504 While caution is needed to interpret the results based purely on the RCR
505 methodology in this study, the findings are in broad agreement with other studies
506 using different methods or considerably fewer models. The RCR methodology is a
507 useful tool that aids in the visualization and comparison of multiple model climate
508 fields across many regions in a simple set of metrics. The regions here are assumed

509 equally weighted, but it is easy to adjust the weighting based on economic or
510 population loadings as desired (e.g. Moreno-Cruz et al., 2012). Perhaps more
511 fundamentally, we used (as have others) a simple quadratic damage function for
512 climate change. In practice, such decisions are beyond the remit of the natural
513 sciences and ultimately are decided by societal values. However, the inputs to the
514 analysis come from earth system models and, therefore, are limited by the quality of
515 the climate system representation in those models. Although the four SRM
516 experiments in GeoMIP represent far from real-world implementations of the SRM,
517 the robust features and contrasting areas of doubt are becoming clearer. To move
518 towards potentially more useful regional or seasonal geoengineering modeling
519 requires advances, the identification of key region-specific damage functions, and
520 better treatment of geoengineering methods in the earth system models.

521

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523

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Figures

Figure 1 GeoMIP *G1* to *G4* schemes (reprinted from Kravitz et al., 2011). *G1* is started from a control run. The instantaneous quadrupling of CO₂ concentration from pre-industrial levels is balanced by a reduction in the solar constant until year 50. *G2* also started from a control run. The positive radiative forcing of an increase in CO₂ concentration of 1% per year is balanced by a decrease in the solar constant until year 50. *G3* approximately balances the positive radiative forcing from the RCP4.5 scenario by an injection of SO₂ or sulfate aerosols into the tropical lower stratosphere from year 2020 to year 2069. *G4* experiment is based on the RCP4.5 scenario, where immediate negative radiative forcing is produced by an injection of SO₂ into the tropical lower stratosphere at a rate of 5 Tg yr⁻¹ from year 2020 to year 2069.

Figure 2 RCR model illustration. **O** represents the baseline of climate variable *Y*. **Y**_{CO_{2e}} represents the regional changes of climate variable *Y* from the baseline **O** with elevated CO_{2e}. **Y**_{RES} represents the residual change in variable *Y* under SRM. Angle φ represents the regional inequality in the effectiveness of compensating *Y* change by SRM. **Y**_{RES_OPT} represents the optimal residual change for the give angle φ .

Figure 3 Ensemble mean of SAT anomalies for *G1* - *piControl*, *abrupt4xCO2* - *piControl*, *G2* - *piControl*, *1pctCO2* - *piControl*, *G3* - *rcp45_2010_2029*, *G4* - *rcp45_2010_2029*, *rcp45_2030_2069* - *rcp45_2010_2029*. For *G1* - *piControl*, *abrupt4xCO2* - *piControl*, stippling indicate where fewer than 10/13 models agreed on the sign of change; fewer than 9/12 models agreed for *G2* - *piControl* and *1pctCO2* - *piControl*; fewer than 6/8 models agreed for *rcp45_2030_2069* - *rcp45_2010_2029*; fewer than 2/3 models agreed for *G3* - *rcp45_2010_2029*; fewer than 5/7 models agreed for *G4* - *rcp45_2010_2029*.

Figure 4 Ensemble mean and standard deviation of area-weighted near surface air temperature for 22 regional anomalies in *G1* - *piControl*, *abrupt4xCO2* - *piControl*, *G2* - *piControl*, *1pctCO2* - *piControl*, *G3* - *rcp45_2010_2029*, *rcp45_2030_2069* - *rcp45_2010_2029*, *G4* - *rcp45_2010_2029*. Diamonds indicate the regional anomalies passed a *Student's t* test at the significance level of 0.05.

Figure 5 As for Figure 3 but for precipitation anomalies.

Figure 6 As for Figure 4 but for precipitation regional anomalies.

Figure 7 Individual model, multi-model ensemble mean and standard deviation of regional inequality φ (°; equation 3) of experiment *G1*, *G2*, *G3* and *G4* for near surface air temperature and precipitation. Calculated noise levels for *G3* and *G4* are

734 the same for same model as both experiments used *rcp45* as the elevated CO₂e
735 scenario. CESM-CAM5.1-FV was not included in the noise calculation for *G1* and
736 *G2* as its *piControl* simulation only includes model 50 years.

737

738 **Figure 8** As for Figure 7 but for actual compensation effectiveness (%; equation 7).

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Tables

Table 1 Experiments used in this study.

experiment		Averaging period	Baseline climate	Number of Models
SRM	No SRM			
<i>G1</i> ^{&}	<i>abrupt4xCO2</i>	experiment year 11-50	pre-industrial average	13
<i>G2</i> ^{&}	<i>1pctCO2</i>	experiment year 11-50	pre-industrial average	12
<i>G3</i> ⁺	<i>rcp45</i>	year 2030-2069	average over 2010-2029 under <i>rcp45</i>	3
<i>G4</i>	<i>rcp45</i>	year 2030-2069	average over 2010-2029 under <i>rcp45</i>	7

[&] CESM-CAM5.1-FV was not included in the noise calculation for *G1* and *G2* as its *piControl* simulation only includes model 50 years. As a result, the noise calculation involved 12 models in *G1* and 11 models in *G2*.

⁺ 4 models in total have completed *G3*, but we exclude GISS-E2-R from the *G3* analysis - see text.

Table 2 Ensemble mean and standard deviation of global average of SAT and precipitation change for *G1* - *piControl*, *abrupt4xCO2* - *piControl*, *G2* - *piControl*, *1pctCO2* - *piControl*, *G3* - *rcp45_2010_2029*, *G4* - *rcp45_2010_2029*, *rcp45_2030_69* - *rcp45_2010_2029*.

experiment	ΔT (°C)	ΔP (mm day ⁻¹)
<i>G1</i> - <i>piControl</i>	0.05±0.25	-0.128±0.043
<i>abrupt4xCO2</i> - <i>piControl</i>	4.30±0.75	0.152±0.055
<i>G2</i> - <i>piControl</i>	0.07±0.20	-0.020±0.010
<i>1pctCO2</i> - <i>piControl</i>	0.71±0.15	0.023±0.006
<i>G3</i> - <i>rcp45_2010_2029</i>	0.23±0.28	0.000±0.019
<i>G4</i> - <i>rcp45_2010_2029</i>	0.28±0.31	0.001±0.025
<i>rcp45_2030_2069</i> - <i>rcp45_2010_2029</i>	0.81±0.21	0.043±0.018

Table 3 Multi-model ensemble mean and standard deviation of regional inequality φ ($^{\circ}$; equation 3), actual and optimal compensation effectiveness (%) equation 7 and 8) and adjustment percentage (%) of SRM compensated change under experiment *G1*, *G2*, *G3* and *G4* 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.

experiment	regional inequality φ ($^{\circ}$)		actual effectiveness (%)		optimal effectiveness (%)		adjustment percentage (%)	
	T	P	T	P	T	P	T	P
G1	3 $\pm$ 1	20 $\pm$ 11	99 $\pm$ 0	77 $\pm$ 32	100 $\pm$ 0	86 $\pm$ 14	1 $\pm$ 5	-18 $\pm$ 15
G2	6 $\pm$ 2	29 $\pm$ 6	93 $\pm$ 7	66 $\pm$ 10	99 $\pm$ 1	76 $\pm$ 8	14 $\pm$ 35	-20 $\pm$ 16
G3	8 $\pm$ 1	39 $\pm$ 6	86 $\pm$ 6	48 $\pm$ 18	98 $\pm$ 0	60 $\pm$ 10	31 $\pm$ 51	-13 $\pm$ 40
G4	11 $\pm$ 6	39 $\pm$ 14	80 $\pm$ 20	46 $\pm$ 31	95 $\pm$ 4	59 $\pm$ 23	71 $\pm$ 91	20 $\pm$ 62

Figure 1 (color reproduction on web and in print)

Figure 2 (color reproduction on web and in print)

Figure 3 (color reproduction on web and in print)

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Figure 5 (color reproduction on web and in print)

Figure 6 (color reproduction on web and in print)

Figure 7 (color reproduction on web and in print)

Figure 8 (color reproduction on web and in print)

temperature actual effectiveness

precipitation actual effectiveness