

1 **Influence of ENSO on stratospheric sulfur dioxide injection in the CESM2 ARISE-**  
2 **SAI-1.5 simulations**

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9 **Key Points:**

- 10 • The SAI controller applied in the CESM2 ARISE-SAI-1.5 simulation is significantly  
11 impacted by ENSO.
- 12 • The lagged response of the current SAI controller could lead to an increase in the  
13 variance of global mean surface temperature.  
14

## 15 **Abstract**

16 Climate and Earth system models are important tools to assess the benefits and risks of  
17 stratospheric aerosol injection (SAI) relative to those associated with anthropogenic climate  
18 change. A “controller” algorithm has been used to specify injection amounts of sulfur dioxide in  
19 SAI experiments performed with the Community Earth System Model (CESM). The experiments  
20 are designed to maintain specific temperature targets, such as limiting global mean temperature  
21 to 1.5°C above the pre-industrial level. However, the influence of natural climate variability on  
22 the injection amount has not been extensively documented. Our study reveals that more than  
23 70% of the year-to-year variation in the total injection amount (excluding the long-term trend) in  
24 CESM SAI experiments is attributed to the El Niño-Southern Oscillation (ENSO). A simplified  
25 statistical model further suggests that the intrinsic, lagged response of the controller to the  
26 climate can increase the variance of global mean temperature in the model simulations.

## 27 **Plain Language Summary**

28 As global temperatures rise due to increasing greenhouse gas (GHG) emissions, more attention  
29 has been given to exploring the feasibility of stratospheric aerosol injection (SAI) as a means of  
30 counteracting global warming. Several SAI simulations based on numerical climate models  
31 utilize a "controller" algorithm to maintain global temperatures by adjusting aerosol injection  
32 amounts on an annual basis. However, our findings reveal a strong influence of El Niño-  
33 Southern Oscillation (ENSO) on the "controller" regarding the injection amounts. This  
34 unexpected influence goes beyond the original design intent of the controller. Statistical analyses  
35 further indicate that the current controller, while successfully preventing global warming, can  
36 lead to an increased variance in global mean temperature.

## 37 **1 Introduction**

38 To mitigate global warming and projected future increases in weather and climate  
39 extremes, greenhouse gas emissions must be dramatically reduced (Meinshausen et al., 2009;  
40 IPCC, 2021). However, current and planned emission reductions will likely not be sufficient to  
41 limit global warming to well under the 2°C goal of the Paris Agreement. This motivates studies  
42 exploring climate intervention (or ‘geoengineering’) as a possible approach to stabilize or reduce  
43 global temperatures and possibly buy more time for emission reductions and the implementation  
44 of climate adaptation measures. Stratospheric aerosol injection (SAI) may be one of the most  
45 effective climate intervention approaches (e.g., Caldeira et al., 2013; NRC, 2015; Xu et al., 2020;  
46 NASEM, 2021). By forming reflective aerosols in the stratosphere through injections of sulfate  
47 particles (e.g., sulfur dioxide), SAI aims to reflect a small percentage of incoming solar radiation,  
48 thus potentially offsetting greenhouse gas warming and minimizing some of the risks associated  
49 with anthropogenic climate change.

50 Climate model simulations have been used to investigate both the benefits and potential  
51 risks of SAI in the context of climate change (e.g., Kravitz et al., 2015; Mills et al., 2017; Richter  
52 et al., 2022). MacMartin et al. (2014) introduced an SAI ‘controller’ algorithm to determine the  
53 injection amounts and locations of sulfur dioxide needed each year to reach and maintain  
54 prescribed temperature targets, such as the global mean surface temperature (GMST), the  
55 hemispheric temperature gradient, and the pole-to-Equator temperature gradient (referred to as  
56 T0, T1, and T2, respectively in Kravitz et al. 2017). To achieve this, at the end of each simulated  
57 year, the controller calculates and compares the annual-mean values of GMST, T1, and T2 with

58 the respective values from the target climate period. A matrix calculation (based on the climate  
59 sensitivity to SAI) is then applied to calculate the amount of sulfate particles needed at different  
60 latitudes for the next year to offset the differences in GMST, T1, and T2 between the current  
61 year and the target climate.

62 The National Center for Atmospheric Research (NCAR) recently released a new  
63 ensemble of SAI experiments using the Community Earth System Model, version 2 (CESM2;  
64 Danabasoglu et al. 2020), which also employed this controller algorithm (Richter et al. 2022).  
65 The Assessing Responses and Impacts of Solar climate intervention on the Earth system with  
66 Stratospheric Aerosol Injection (ARISE-SAI) results demonstrate the effectiveness of the  
67 controller algorithm in maintaining the GMST at 1.5°C above its pre-industrial value (Fig. S1a).  
68 The ensemble-averaged sulfate injection amount in ARISE-SAI-1.5 shows a nearly-linear  
69 increase with time, which resembles the increase in greenhouse gas (GHG) concentrations under  
70 the moderate Shared Socioeconomic Pathway scenario of SSP2-4.5 scenario (O'Neill et al.,  
71 2016) used in the simulations. However, the total injection amounts differ significantly across  
72 individual ensemble members (Fig. S1b). This suggests that the controller may be responding not  
73 only to the forced warming but also to inter-annual temperature fluctuations driven by model-  
74 generated internal variability (thin blue lines in Fig. S1a). The El Niño-Southern Oscillation  
75 (ENSO) is one of the most dominant modes of internal variability that influences both global as  
76 well as regional climate (Ropelewski & Halpert, 1987; Wang et al., 2017). Thus, it is possible  
77 that inter-annual variations in injection amounts are related to the controller's response to ENSO,  
78 over and above the injection amounts needed to offset the externally-forced global warming.  
79 Such responses might introduce unexpected fluctuations in both the SO<sub>2</sub> injection amount and  
80 GMST.

81 Another issue related to the controller is the 'lagged response' intrinsic to the controller  
82 algorithm. The injection amount determined by the controller for the following year is based on  
83 the current year's climate. If ENSO influences the controller, the injection amount for the  
84 following year will be calculated based on both the forced warming and the ENSO-driven  
85 temperature changes from the current year. However, as the phase of ENSO can change quickly,  
86 even by the following year (Stein et al., 2010). this may lead to a mismatch between the injection  
87 amount and the ENSO-driven temperature variation. Consequently, the injection amounts may  
88 not adequately maintain the temperature targets, or they may even exacerbate temperature  
89 fluctuations in the following year. This mismatch may thus introduce potential side effects to  
90 global and regional climate, particularly during years with quick transitions of ENSO.

91 Inspired by the two potential issues described above, we focus on two questions in this  
92 study: (1) How much does ENSO impact the injection amounts determined by the controller; and  
93 (2) to what extent does the lagged response of the controller affect the simulated climate?

## 94 **2 Data and Methods**

### 95 **2.1 Model simulations**

96 Our analyses are based on ensemble simulations using the Community Earth System  
97 Model, version 2, with the Whole Atmosphere Community Climate Model, version 6  
98 (CESM2(WACCM6); Danabasoglu et al., 2020). For studies of climate intervention using SAI,  
99 representation of the entire stratosphere, including dynamics and chemistry, is needed to capture  
100 the transport of stratospheric aerosols and their interactions with stratospheric constituents such

101 as water ozone and water vapor. Similarly, representing key processes and interactions between  
102 multiple Earth system components is important, including coupling between the atmosphere,  
103 land, ocean, and sea ice, as well as prognostic aerosols and interactive chemistry.

104 The ARISE-SAI experiments utilize a moderate emission scenario (SSP2-4.5) and  
105 simulate SAI deployment in 2035 with a goal of keeping GMST near 1.5°C above the pre-  
106 industrial level (Richter et al. 2022). A 10-member ensemble of ARISE-SAI is compared to an  
107 identical 10-member ensemble experiment without SAI (SSP2-4.5 hereafter). More technical  
108 details can be found in Richter et al. 2022. We analyze monthly outputs of near-surface air  
109 temperature (SAT) and sea surface temperature (SST).

110 The controller in ARISE-SAI injects sulfur dioxide (SO<sub>2</sub>) into four one-grid boxes (15°S,  
111 15°N, 40°S, and 30°N at 180° longitude) at an altitude of 21.6 km. In this study, we focus solely  
112 on the total SO<sub>2</sub> injection amount, which is calculated by adding the amounts at all four injection  
113 locations obtained from the controller log document. To investigate the year-to-year changes in  
114 injection amount, we calculate the difference in the total SO<sub>2</sub> injection amount between the  
115 following year and the current year ( $\Delta\text{SO}_2$  hereafter).

## 116 **2.2 ENSO in the model simulations**

117 As described earlier, year-to-year variations of the total SO<sub>2</sub> injection amount may be  
118 related to model-generated internal variability, particularly that driven by ENSO. ENSO is a  
119 dominant inter-annual mode of climate variability that strongly impacts global temperature (Cai  
120 et al., 2015). Our focus, therefore, is on the potential impact of ENSO on the total injection  
121 amount in ARISE-SAI.

122 We compute and examine the commonly-used Oceanic Niño Index (ONI; NOAA 2019)  
123 to represent ENSO in CESM2 simulations. Specifically, a standardized ONI is calculated as the  
124 3-month running mean of SST anomalies over the east-central tropical Pacific (5°N–5°S, 170°W–  
125 120°W). The SST anomalies are relative to a 35-year base period from 2035 to 2069. Ensemble-  
126 mean values of SST are subtracted from each simulation realization prior to the calculation in  
127 order to remove the SST changes driven by external forcings. In order to be comparable with the  
128 total sulfate injection amount, which varies annually, the annual mean of ONI is analyzed.

## 129 **2.3 Simplified statistical model**

130 The controller algorithm determines the SO<sub>2</sub> injection amount for the coming year based  
131 on the annual mean temperatures of the past year. However, the GMST and the meridional  
132 gradients in temperature for the coming year could differ significantly from the previous year  
133 due to ENSO activity. To investigate how the lagged response of the controller influences the  
134 variance of GMST in the simulations, we designed a simplified statistical model (SSM hereafter)  
135 based on the GMST from the ARISE-SAI and the SSP2-4.5 simulations.

136 The SSM simplifies the climate system and considers GMST changes only. The GMST  
137 in the SSM is set as follows:  $T = T_{GHG} + T_{ENSO}$ , where  $T_{GHG}$  and  $T_{ENSO}$  represent the GHG  
138 warming and the ENSO-driven GMST changes, respectively. To keep in line with the ARISE-

139 SAI and SSP2-4.5 experiments, the linear fit of the ensemble-mean GMST from the SSP2-4.5  
 140 experiment is applied to represent  $T_{GHG}$  (shown as dashed blue line in Fig. S2a).

141 In climate models and observations, ENSO-driven GMST changes occur over different  
 142 frequencies, and these may affect the climate impacts introduced by the controller’s lagged  
 143 response. Therefore, to analyze the impacts of the lagged response on GMST variance given a  
 144 certain ENSO frequency,  $T_{ENSO}$  in the SSM is simplified to be an idealized monthly time series  
 145 with a specified variation frequency:  $T_{ENSO} = A * \sin(\omega t + \varphi)$ , where  $A$  (the magnitude of  
 146 ENSO-driven GMST) is obtained based on the linear regression between ONI and detrended  
 147 GMST in the SSP2-4.5 simulation. The variation frequency and the initial condition of  $T_{ENSO}$  are  
 148 specified by changing the value of  $\omega$  and  $\varphi$ , respectively. A sample  $T_{ENSO}$  with a 3-year  
 149 frequency is shown in Fig. S2a.

150 In response to SAI, the SSM has linear sensitivity to the sulfate injection amount, which  
 151 is calculated based on the linear regression between the total sulfate injection amount in ARISE-  
 152 SAI and the difference in GMST between SSP2-4.5 and ARISE-SAI (referred to as the “avoided  
 153 global warming”; Fig. S2b). We use the same controller algorithm in the SSM as is used in  
 154 ARISE-SAI. Since the SSM only considers GMST and has no spatial information, T1 and T2 are  
 155 fixed to the target values so that the controller does not respond to these two criteria. It is worth  
 156 noting that ENSO activity could also influence the sulfate injection locations by changing T1 and  
 157 T2. However, since our focus here is only on the total sulfate injection amount (which is  
 158 dominated by the GMST changes), it is reasonable to ignore these two indices in the SSM for  
 159 now.

## 160 **3 Results**

### 161 **3.1 Effects of ENSO on the SO<sub>2</sub> injection amount**

162 In addition to significant long-term warming induced by increases in GHG  
 163 concentrations, ENSO variations can also strongly influence GMST on interannual timescales.  
 164 This holds true in the ARISE-SAI simulations. Shown in Fig. 1 is the annual mean time series of  
 165 ONI, GMST anomalies above the pre-industrial level, as well as  $\Delta\text{SO}_2$  from all ten ensemble  
 166 members of ARISE-SAI. The average correlation between ONI and GMST is around 0.71,  
 167 which reveals that approximately 50% of the year-to-year variability of GMST in ARISE-SAI  
 168 can be attributed to variations of ENSO.

169 In addition,  $\Delta\text{SO}_2$  also shows significant year-to-year variation above the steadily  
 170 increasing injection amount that is required to counter increasing GHG forcing with time (orange  
 171 lines in Fig. 1). After the ramp-up period (first five years), when the controller initializes the  
 172 deployment with a mild increase in injection amounts to required values, the variability of  $\Delta\text{SO}_2$   
 173 is similar to that of GMST and ONI, and this is especially during strong ENSO events. Overall,  
 174 the correlation between ONI and  $\Delta\text{SO}_2$  is around 0.53. Since the controller determines the  
 175 injection amounts based on the annual mean GMST from the preceding year, it is clear that  
 176 ENSO strongly influences the controller’s decision. In particular, compared to the total injection  
 177 amount (Fig. S1b), the year-to-year variation of  $\Delta\text{SO}_2$  accounts for about 5% to 10% of the total  
 178 injection amount in any given year, indicating that the controller’s response to ENSO should be

179 large enough to detect even during the later period of ARISE-SAI (when the required injection  
180 amount is far greater in order to counter the larger GHG forcing).

181 Although year-to-year variations of  $\Delta\text{SO}_2$  are highly correlated with ENSO, some large  
182 values of  $\Delta\text{SO}_2$  are unrelated to ENSO-driven GMST changes (e.g., the first few years in  
183 member 10; Fig. 1). Since only about 50% of the GMST variance is linearly associated with  
184 ENSO, it is possible that other sources of internal variability may be affecting the variation of  
185  $\Delta\text{SO}_2$ , a topic that is outside of the scope of this paper but is likely worthy of further exploration.

186 To further investigate inter-annual fluctuations of  $\Delta\text{SO}_2$ , Fig. 2a shows the composite  
187 map of surface air temperature (SAT) for times when the standardized  $\Delta\text{SO}_2$  time series is above  
188 0.5 minus when it is below -0.5. The resulting composite pattern looks remarkably El Niño-like  
189 (Cane & Zebiak, 1985). In particular, consistent with the high correlation between ENSO and  
190  $\Delta\text{SO}_2$  shown in Fig. 1, a strong El Niño (La Niña) event corresponds to a positive (negative)  
191  $\Delta\text{SO}_2$ , indicating the controller is changing its injection rates to offset the warm or cool anomaly  
192 in GMST.

193 To quantify how much the composite map of  $\Delta\text{SO}_2$  can be explained by ENSO, a linear  
194 regression between  $\Delta\text{SO}_2$  and ONI was constructed as:  $\Delta\text{SO}_2 = \beta * \text{ONI} + r$ , where  $\beta * \text{ONI}$  is  
195 the ENSO-driven  $\Delta\text{SO}_2$ , and the residual ( $r$ ) represents the non-ENSO driven changes in  $\Delta\text{SO}_2$ .  
196 About 72% (with a global pattern correlation between Fig. 2a and 2c of 0.85) of the SAT spatial  
197 pattern driven by  $\Delta\text{SO}_2$  can be explained by the ENSO activity, which again emphasizes that  
198 interannual variability of the total sulfate injection in ARISE-SAI are dominated by ENSO, an  
199 aspect that yet to be documented.

200 After removing the linear effects of ENSO, the residual pattern of SAT (Fig. 2d) shows  
201 warm anomalies over the middle-to-high latitudes of the Northern Hemisphere as well as over  
202 tropical regions outside of the western tropical Pacific, reminiscent of a weak El Niño pattern.  
203 This suggests that other modes of internal variability (e.g., the North Atlantic Oscillation or the  
204 Pacific Decadal Oscillation) might also be important in affecting year-to-year variations of  
205  $\Delta\text{SO}_2$ .

### 206 **3.2 Lagged response of the controller and increased GMST variance**

207 At the end of each simulated year, the ARISE-SAI controller calculates the injection  
208 amounts needed for the next year based on the preceding year's annual mean temperature indices  
209 (GMST, T1, and T2). However, since ENSO can change phases quickly within a single year, the  
210 temperature indices, especially GMST (T0), might also change quickly in response to this ENSO  
211 variability. In this situation, the previously determined injection amount may not adequately  
212 satisfy the injection needs of the coming year, or, it may even exacerbate temperature  
213 fluctuations.

214 The schematic diagram in Fig. 3a shows an idealized case of ENSO quickly transitioning  
215 from a warm event in year one to a cold event in year two. By the end of the first year, the  
216 controller would detect an ENSO-driven global warming anomaly and increase the injection  
217 amount in the second year to offset not only the incremental GHG warming but also the warming  
218 driven by El Niño. However, if a cold event (La Niña) occurs naturally in year two, the

219 controller's decision would lead to an even greater global cooling than would have otherwise  
220 occurred without the controller. Similarly, in the case of ENSO quickly transitioning from a cold  
221 event (La Niña) to a warm event (El Niño), the controller would decrease the injection amount  
222 by too much and not adequately offset the GHG warming. It follows from this basic example that  
223 the year-to-year variability of GMST might ultimately be larger than expected due to the  
224 controller responding to ENSO variability. Fast ENSO transitions are apparent in both the  
225 ARISE-SAI simulations (e.g., 2056–2057 in Member 004, and 2051–2052 in Member 005; Fig.  
226 1) and in observations (e.g., 2010–2011; not shown).

227 To further examine how the controller's response to ENSO affects the variance of  
228 GMST, we developed a simplified statistical model based on the ARISE-SAI and SSP2-4.5  
229 simulations, in which the idealized "ENSO" signal has only one specific variation frequency (see  
230 Section 2.3). When the variation frequency of ENSO is twice the controller's detection  
231 frequency (i.e., two years, shown in Fig. 3b), the controller's decision follows the mechanism  
232 described in Fig. 3a and leads to a 34% increase in the variance of GMST. However, this is an  
233 extreme case, since ENSO typically varies from two to seven years.

234 We thus further explore the controller's decisions for different ENSO frequencies (Fig.  
235 S3). The results show that the controller algorithm always introduces increased variance in  
236 GMST, but the magnitudes of this additional variance depend strongly on the hypothetical ENSO  
237 frequency. Specifically, when ENSO varies at relatively high frequencies (e.g., panels a and c in  
238 Fig. S3), the GMST variance increases by more than 20%. At lower frequencies (such as seven  
239 years in Fig. S3d), the controller can adequately account for most ENSO-induced GMST  
240 changes, and it only introduces a small increase in the variance of GMST. In other words, the  
241 lagged response of the controller is strongly impacted by the frequency of ENSO variability.

242 Considering the potential issue introduced by the lagged response of the controller, we  
243 further test how the variance of GMST would change if the controller made injection decisions  
244 on timescales other than annual. For instance, if the controller changed injection amounts every  
245 two years (Fig. 4b), the variance of GMST would significantly increase, and GMST would still  
246 slowly increase despite the continuous sulfate injection. More extreme cases occur when the  
247 controller injects even less often, such as every five years (Fig. 4c). In this case, the controller  
248 fails to offset the GHG warming because the injection amount is always behind the increasing  
249 GHG concentrations.

250 A more intuitive way to prevent introducing spurious variance due to the controller's  
251 lagged response would be to detect temperature indices more frequently than once-per-year.  
252 Results from the SSM for a controller that changes injection amounts monthly are shown in Fig.  
253 4d. In this case, the variance of GMST is decreased by about 30%, which means the controller  
254 mutes part of the ENSO-driven GMST variation. However, muting ENSO-driven GMST  
255 variability to such an extent might also introduce unexpected climate impacts both globally and  
256 locally.

257 Comparing the GMST variance between the SSP2-4.5 and ARISE-SAI ensemble  
258 simulations (Fig. 5a), it is clear that the averaged GMST variance in ARISE-SAI is greater than  
259 that in SSP2-4.5 in both early and late periods (2040–2054 and 2055–2069), consistent with the  
260 results from the SSM. Despite largely maintaining the mean values of temperature indices,

261 ARISE-SAI introduces significantly greater GMST variance compared to the climate of the  
262 target period (2020–2034 in SSP2-4.5). The SSP2-4.5 simulations show a decrease in the GMST  
263 variance because of GHG warming; however, variances across individual simulations exhibit a  
264 large spread. Thus, due to the limited ensemble sizes (10 members in both the SSP2-4.5 and  
265 ARISE-SAI cases), the variance comparison here contains large uncertainties. The results in Fig  
266 5, therefore, are intriguing but are inconclusive on their own. Additional ensemble members  
267 would be required to more confidently state that the lagged response of the controller is driving  
268 the differences in GMST variance evident between the SSP2-4.5 and ARISE-SAI simulations.

#### 269 **4 Conclusions and Discussion**

270 The controller algorithm in the ARISE-SAI simulations greatly accomplishes its primary  
271 goal; that is, to offset GHG warming by maintaining GMST and meridional temperature  
272 gradients at the target values. However, we have shown that the controller is also strongly  
273 impacted by ENSO activity, and its lagged response to the temperature targets can introduce a  
274 mismatch between injection amounts and ENSO-driven temperature variation, and thus, lead to  
275 increases in GMST variance. This is especially true for the case when ENSO varies on similar  
276 timescales to the controller’s detection frequency (set at one year in the ARISE-SAI  
277 simulations). Given these two factors, it may therefore be worthwhile to focus efforts on  
278 distinguishing and removing GMST variations driven by ENSO from the algorithm, a topic of  
279 ongoing work.

280 In addition, the residual map of the composite analysis in Fig. 2d suggests that other  
281 modes of internal climate variability may also disturb the controller, although with smaller  
282 magnitudes than that due to ENSO. Additional analyses involving the hemispheric temperature  
283 gradient and the equator-to-pole gradient (T1 and T2) could be beneficial to further understand  
284 the controller’s behavior in response to such modes.

285 Lastly, we have focused on the global mean temperature in this study. Additional analysis  
286 is warranted to determine whether the controller’s response to ENSO introduces detectable  
287 regional climate impacts.

288

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295 **Open Research**

296 The CESM2-WACCM6-SSP2-4.5 (<https://doi.org/10.26024/0cs0-ev98>) and CESM2-  
297 WACCM6-ARISE-SAI-1.5 (<https://doi.org/10.5065/9kcn-9y79>) simulations applied in this study  
298 are produced and maintained by the National Center for Atmospheric Research (NCAR), both of  
299 which are publicly available from: <https://www.cesm.ucar.edu/community-projects/arise-sai>. All  
300 Python codes related to this study are available at [https://github.com/C-R-](https://github.com/C-R-Diao/ARISE_Controller_ENSO)  
301 Diao/ARISE\_Controller\_ENSO. At the time of publication, the codes will be converted to a  
302 permanent repository on Zenodo.

303

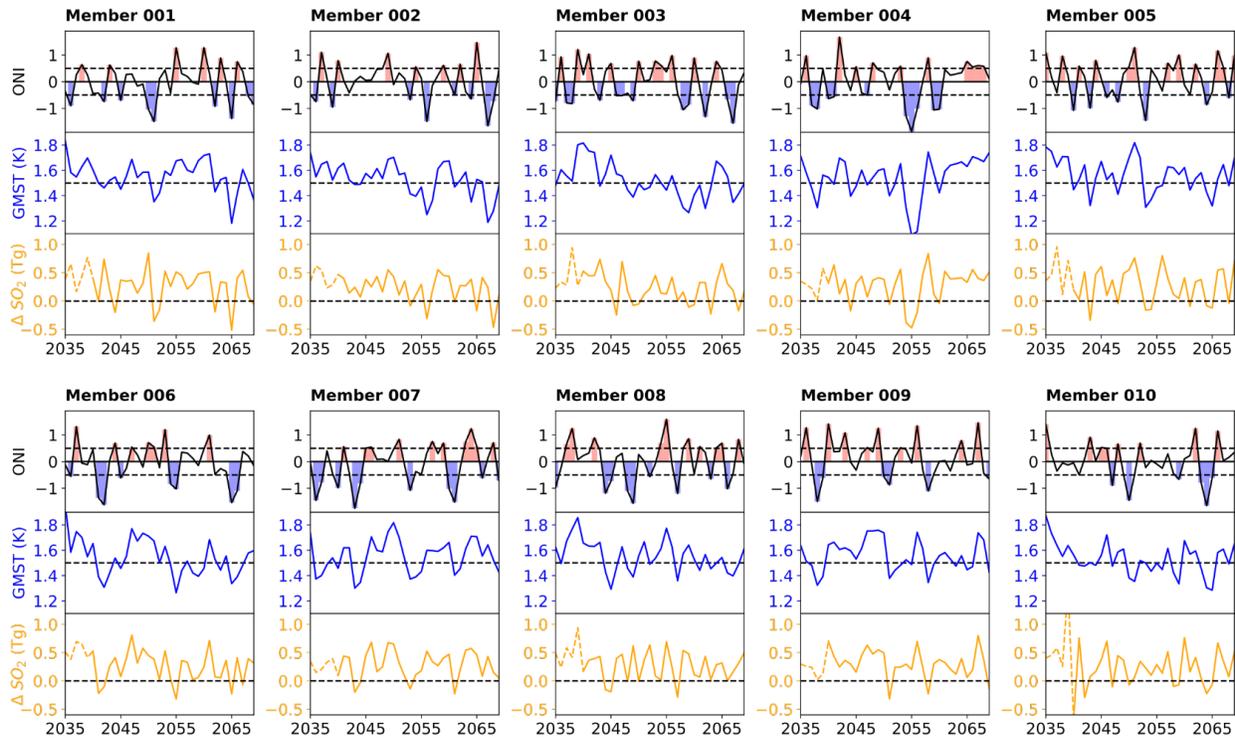
304 **References**

- 305 Ben Kravitz, Douglas G. MacMartin, Michael J. Mills, Jadwiga H. Richter, Simone Tilmes,  
306 Jean-Francois Lamarque, Joseph J. Tribbia, Francis Vitt. (2017). First Simulations of  
307 Designing Stratospheric Sulfate Aerosol Geoengineering to Meet Multiple Simultaneous  
308 Climate Objectives. *Journal of Geophysical Research: Atmospheres*, 122(23), 2169–  
309 2897X.
- 310 Cai, W., Santoso, A., Wang, G., Yeh, S.-W., An, S.-I., Cobb, K. M., Collins, M., Guilyardi, E.,  
311 Jin, F.-F., Kug, J.-S., Lengaigne, M., McPhaden, M. J., Takahashi, K., Timmermann, A.,  
312 Vecchi, G., Watanabe, M., & Wu, L. (2015). ENSO and greenhouse warming. *Nature*  
313 *Climate Change*, 5(9), 849–859.
- 314 Cane, M. A., & Zebiak, S. E. (1985). A Theory for El Niño and the Southern Oscillation.  
315 *Science*, 228(4703), 1085–1087.
- 316 Kravitz, B., Robock, A., Tilmes, S., Boucher, O., English, J. M., Irvine, P. J., Jones, A.,  
317 Lawrence, M. G., MacCracken, M., Muri, H., Moore, J. C., Niemeier, U., Phipps, S. J.,

- 318 Sillmann, J., Storelvmo, T., Wang, H., & Watanabe, S. (2015). The Geoengineering  
319 Model Intercomparison Project Phase 6 (GeoMIP6): simulation design and preliminary  
320 results. *Geoscientific Model Development*, 8(10), 3379–3392.
- 321 MacMartin, D. G., Kravitz, B., Keith, D. W., & Jarvis, A. (2014). Dynamics of the coupled  
322 human–climate system resulting from closed-loop control of solar geoengineering.  
323 *Climate Dynamics*, 43(1), 243–258.
- 324 Meinshausen, M., Meinshausen, N., Hare, W., Raper, S. C. B., Frieler, K., Knutti, R., Frame, D.  
325 J., & Allen, M. R. (2009). Greenhouse-gas emission targets for limiting global warming  
326 to 2 degrees C. *Nature*, 458(7242), 1158–1162.
- 327 Mills, M. J., Richter, J. H., Tilmes, S., Kravitz, B., MacMartin, D. G., Glanville, A. A., Tribbia,  
328 J. J., Lamarque, J.-F., Vitt, F., Schmidt, A., Gettelman, A., Hannay, C., Bacmeister, J. T.,  
329 & Kinnison, D. E. (2017). Radiative and chemical response to interactive stratospheric  
330 sulfate aerosols in fully coupled CESM1(WACCM). *Journal of Geophysical Research*,  
331 122(23), 13,061–13,078.
- 332 National Academies of Sciences, Engineering, and Medicine. (2021). *Reflecting Sunlight:  
333 Recommendations for Solar Geoengineering Research and Research Governance*.  
334 National Academies Press.
- 335 National Oceanic and Atmospheric Administration. (2019). *Cold & Warm Episodes by Season*.  
336 [https://origin.cpc.ncep.noaa.gov/products/analysis\\_monitoring/ensostuff/ONI\\_v5.php](https://origin.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ONI_v5.php)
- 337 National Research Council. (2015). *Climate Intervention: Reflecting Sunlight to Cool Earth*.  
338 National Academies Press.
- 339 O’Neill, B. C., Tebaldi, C., van Vuuren, D. P., Eyring, V., Friedlingstein, P., Hurtt, G., Knutti,  
340 R., Kriegler, E., Lamarque, J.-F., Lowe, J., Meehl, G. A., Moss, R., Riahi, K., &

- 341 Sanderson, B. M. (2016). The Scenario Model Intercomparison Project (ScenarioMIP)  
342 for CMIP6. *Geoscientific Model Development*, 9(9), 3461–3482.
- 343 Richter, J. H., Visionsi, D., MacMartin, D. G., Bailey, D. A., Rosenbloom, N., Dobbins, B., Lee,  
344 W. R., Tye, M., & Lamarque, J.-F. (2022). Assessing Responses and Impacts of Solar  
345 climate intervention on the Earth system with stratospheric aerosol injection (ARISE-  
346 SAI): protocol and initial results from the first simulations. *Geoscientific Model  
347 Development*, 15(22), 8221–8243.
- 348 Ropelewski, C. F., & Halpert, M. S. (1987). Global and Regional Scale Precipitation Patterns  
349 Associated with the El Niño/Southern Oscillation. *Monthly Weather Review*, 115(8),  
350 1606–1626.
- 351 Stein, K., Schneider, N., Timmermann, A., & Jin, F.-F. (2010). Seasonal Synchronization of  
352 ENSO Events in a Linear Stochastic Model. *Journal of Climate*, 23(21), 5629–5643.
- 353 Tilmes, S., Richter, J. H., Kravitz, B., MacMartin, D. G., Mills, M. J., Simpson, I. R., Glanville,  
354 A. S., Fasullo, J. T., Phillips, A. S., Lamarque, J.-F., Tribbia, J., Edwards, J., Mickelson,  
355 S., & Ghosh, S. (2018). CESM1(WACCM) Stratospheric Aerosol Geoengineering Large  
356 Ensemble Project. *Bulletin of the American Meteorological Society*, 99(11), 2361–2371.
- 357 Wang, C., Deser, C., Yu, J.-Y., DiNezio, P., & Clement, A. (2017). El Niño and Southern  
358 Oscillation (ENSO): A Review. In P. W. Glynn, D. P. Manzello, & I. C. Enochs (Eds.),  
359 *Coral Reefs of the Eastern Tropical Pacific: Persistence and Loss in a Dynamic  
360 Environment* (pp. 85–106). Springer Netherlands.
- 361 Xu, Y., Lin, L., Tilmes, S., Dagon, K., Xia, L., Diao, C., Cheng, W., Wang, Z., Simpson, I., &  
362 Burnell, L. (2020). Climate engineering to mitigate the projected 21st-century terrestrial

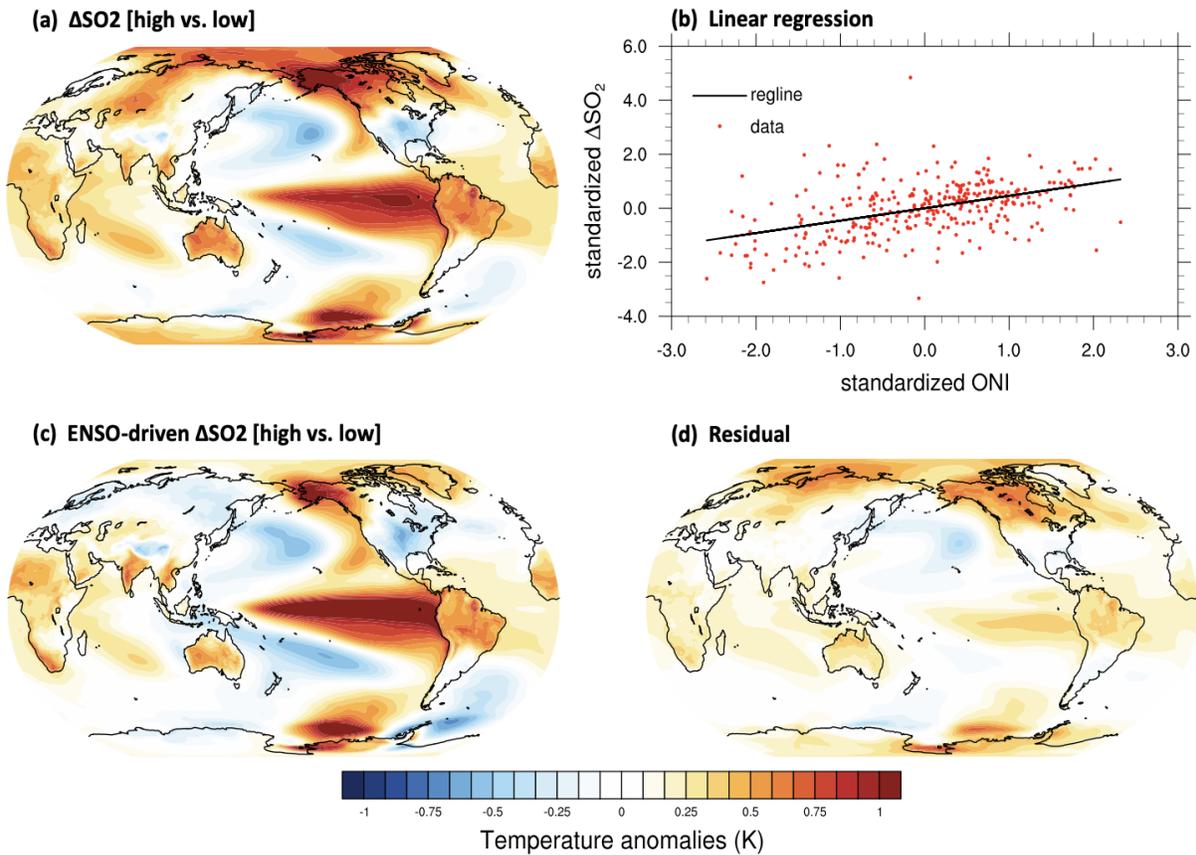
363           drying of the Americas: a direct comparison of carbon capture and sulfur injection. *Earth*  
364           *System Dynamics*, 11(3), 673–695.



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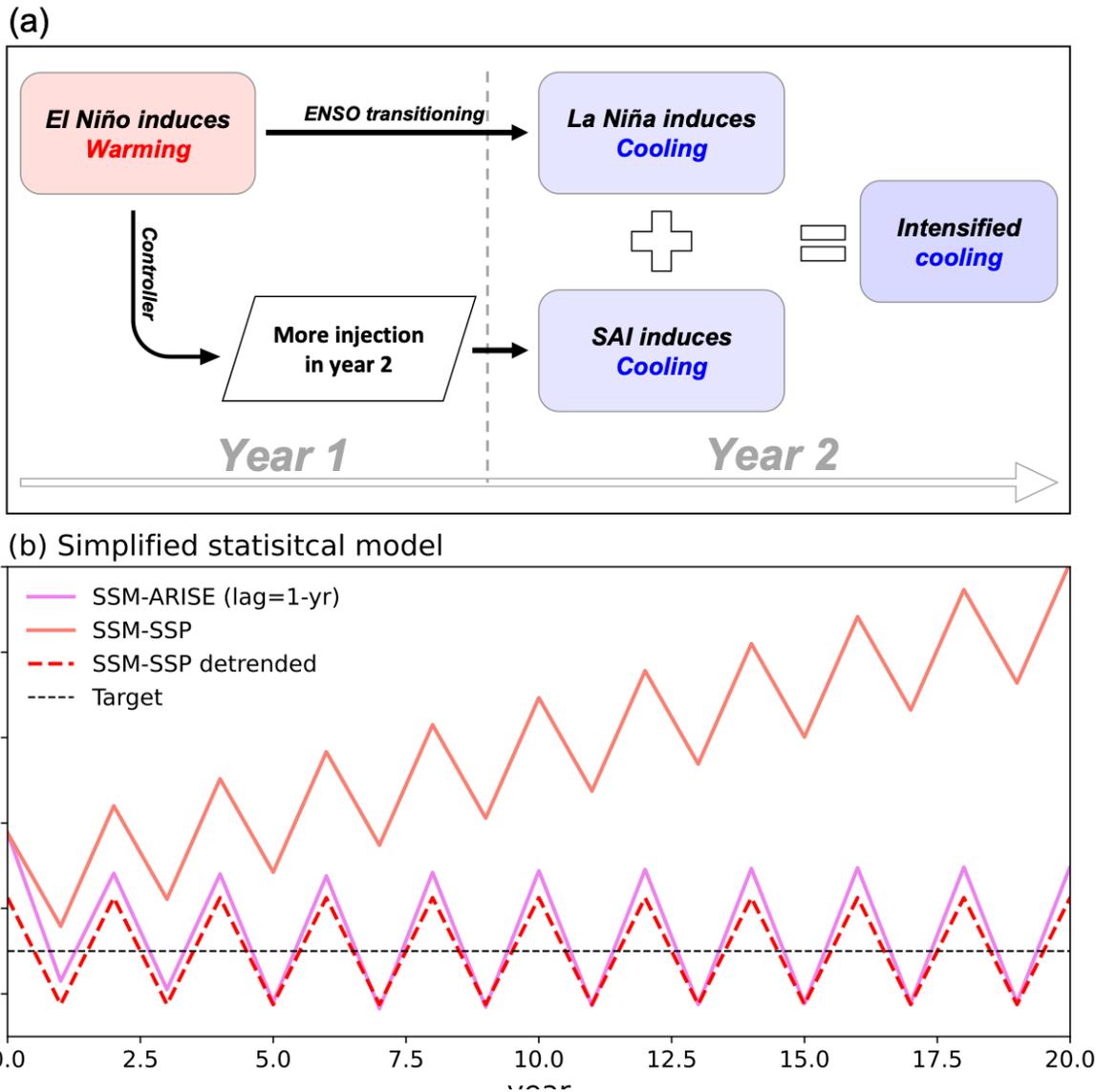
366 **Figure 1.** The annual-mean time series of (upper) Oceanic Niño Index (ONI), (middle) GMST  
 367 anomalies above the pre-industrial level, and (lower)  $\Delta\text{SO}_2$  for each realization in ARISE-SAI  
 368 simulation. The annual ONI anomalies are calculated based on the average of monthly ONI;  
 369 years with ONI anomalies greater than 0.5 °C (less than -0.5°C) are marked with red (blue) bars.  
 370 The first five years (1935–1939, shown as dashed lines in  $\Delta\text{SO}_2$  panels) are the ramp-up periods  
 371 according to the controller algorithm.  
 372

## Composite map: surface temperature



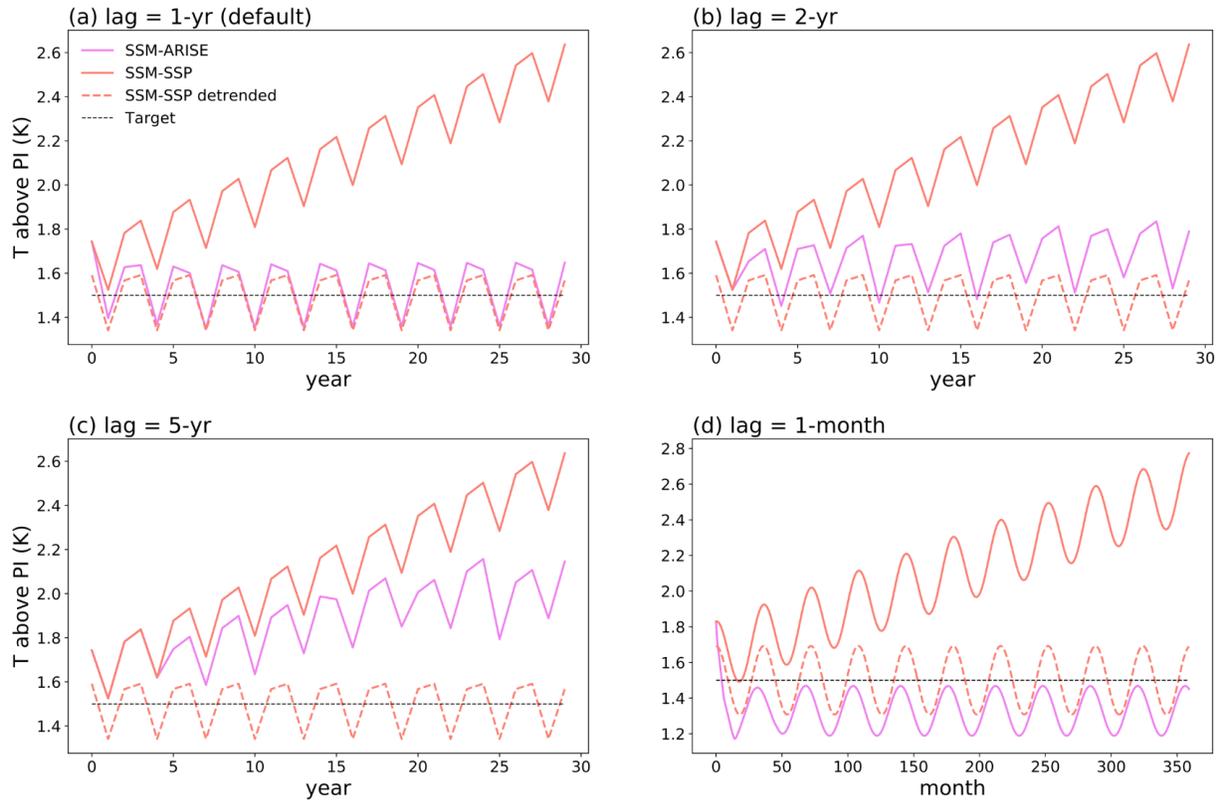
373  
 374 **Figure 2.** (a) The composite map of surface air temperature (SAT) anomalies in ARISE-SAI  
 375 when  $\Delta\text{SO}_2$  (standardized) is greater than 0.5 compared to when  $\Delta\text{SO}_2$  is less than -0.5.  
 376 Composite samples are picked from all ensemble members. (b) Linear regression between  
 377 standardized ONI and  $\Delta\text{SO}_2$  based on all ten realizations from ARISE-SAI. (c) Same as panel (a)  
 378 but for ENSO-driven  $\Delta\text{SO}_2$  calculated from the linear regression in panel (b). (d) The residual  
 379 map of (a) - (c)

380



381  
 382 **Figure 3.** (a) Schematic of intensified cooling during an ENSO quick transitioning case. (b) The  
 383 results of climate intervention in the simplified statistical model (SSM; see Section 2.3) with  
 384 idealized “ENSO” at a fixed frequency of 2 years. The red line represents the GMST without  
 385 climate intervention (SSM-SSP), whereas the blue line represents the GMST with climate  
 386 intervention (SSM-ARISE). The orange line indicates the detrended GMST without climate  
 387 intervention (SSM-SSP detrended), which is driven by the idealized ENSO in the SSM. See the  
 388 Method section for a detailed description of the SSM.

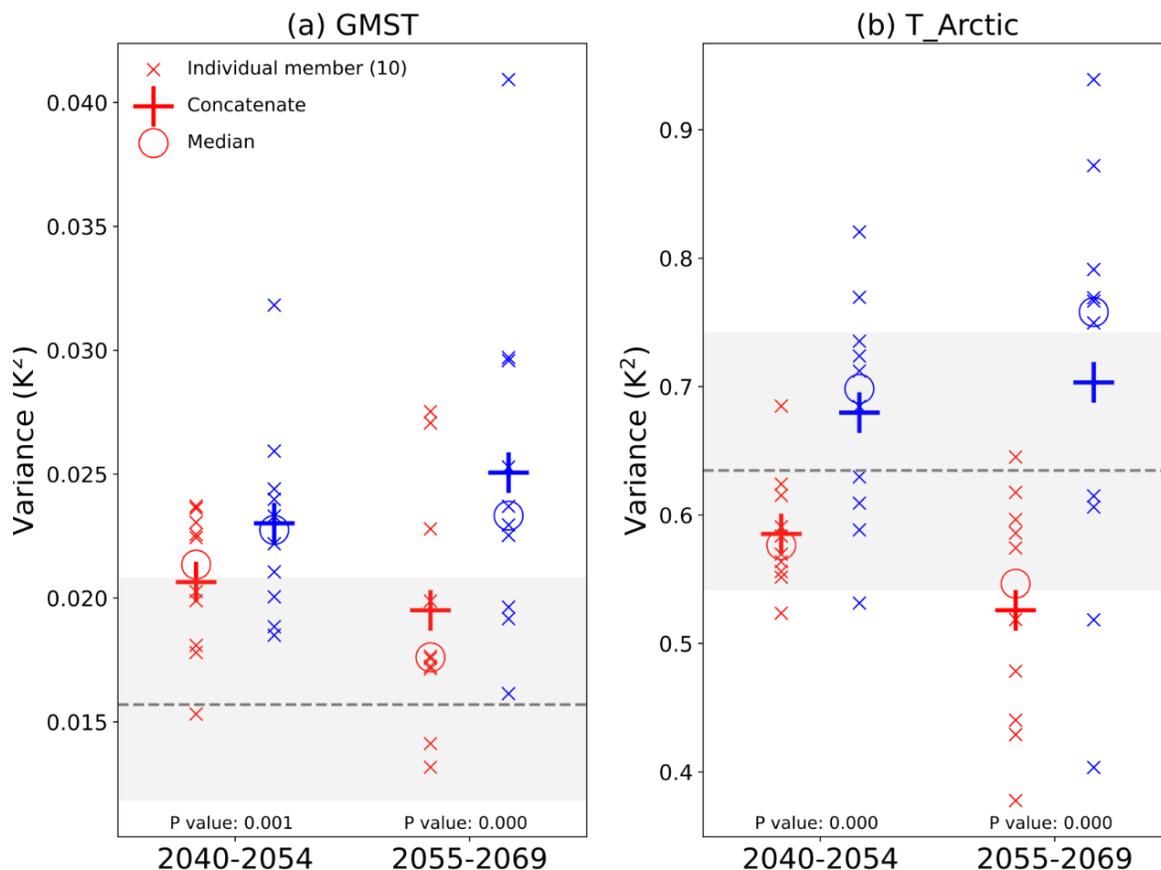
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390

391 **Figure 4.** Similar to Fig 4b, but shows the climate intervention results based on the SSM with  
 392 different controller detection frequencies ranging from 1 month to 5 years. The frequency of the  
 393 idealized ENSO is fixed at three years in all four cases.

394



395

396 **Figure 5.** The variance of (a) annual global mean surface temperature (GMST) and (b) the  
 397 annual Arctic surface temperature ( $T_{\text{Arctic}}$ ) in SSP2-4.5 (red) and ARISE-SAI (blue)  
 398 simulations for the period of (left) 2040–2054 and (right) 2055–2069. Cross marks represent the  
 399 results of each individual ensemble member (10 in each simulation), whereas the circle marks  
 400 represent the median. The plus marks indicate the variance of concatenated long-term GMST and  
 401  $T_{\text{Arctic}}$ . The grey shading and dashed line represent the variance spread of GMST for the target  
 402 period of 2020-2035 from SSP2-4.5 and the variance of concatenated GMST, correspondingly.