This is a non-peer reviewed preprint submitted to EarthArXiv

Potential for Perceived Failure of Stratospheric Aerosol Injection Deployment

Patrick W. Keys[1*], Elizabeth A. Barnes[2], Noah S. Diffenbaugh[3], James W. Hurrell[2] and Curtis M. Bell[4]

[1] School of Global Environmental Sustainability, Colorado State University
[2] Department of Atmospheric Science, Colorado State University
[3] Department of Earth System Science and Woods Institute for the Environment, Stanford University
[4] International Programs Department, United States Naval War College

***Corresponding Author:** Patrick W. Keys

Email: patrick.keys@colostate.edu

Author Contributions: PWK and EAB conceived the study; EAB developed the code; PWK, EAB and NSD designed and conducted the analysis; EAB, PWK and NSD created the figures; all authors contributed to writing the paper.

Funding: PWK, EAB, and JWH were funded by the Defense Advanced Research Projects Agency #HR00112290071. NSD was supported by Stanford University.

Acknowledgements: The views expressed here do not necessarily reflect the positions of the U.S. Naval War College and the United States government.

Keywords: climate change; internal climate variability; solar geoengineering; perception; mitigation

Abstract

As anthropogenic activities continue to warm the Earth, the fundamental solution of reducing greenhouse gas emissions remains elusive. Given this mitigation gap, global warming may lead to intolerable climate changes as local adaptive capacity is exceeded. Thus, there is emerging interest in solar radiation management, which is the process of deliberately increasing Earth's albedo to cool the planet. Stratospheric aerosol injection (SAI) — the theoretical deployment of particles in the stratosphere to enhance reflection of incoming solar radiation — is one possible strategy to slow, pause or reverse global warming. If SAI is ever pursued it will likely be for a specific aim, such as allowing more time to implement mitigation strategies, lessening the impacts of extremes, or significantly reducing the odds of reaching a biogeophysical tipping point. Using an ensemble of climate model simulations that employ SAI, we quantify the probability that internal climate variability masks the effectiveness of SAI deployment regionally. We find that, when global temperature is stabilized, substantial land areas continue to experience warming temperatures. For example, up to 55% of the global population experiences rising temperatures over the decade following SAI deployment, and large areas exhibit high probability of extremely hot years. These conditions could cause SAI to be perceived as a failure. Countries with the largest economies experience some of the largest probabilities of this perceived failure. The potential for perceived failure of even the most successful SAI strategy could therefore have major implications for policy decisions in the years immediately following deployment.

Introduction

Anthropogenic climate change, primarily driven by increasing concentrations of atmospheric greenhouse gasses, has caused Earth's global mean temperature to reach its warmest level in at least the last 2,000 years (IPCC, 2021). This global warming may exceed 1.5°C above pre-industrial temperatures later this decade, at least for a short-period of time, and most years are likely to exceed the 1.5°C threshold by 2040 across a range of emissions scenarios (IPCC 2021). By the middle of this century (2041-2060), warming in excess of 2.0°C would be reached under intermediate, high and very high emission scenarios (IPCC, 2021), and current policies have the world on track to warm by roughly 3.0°C by the end of the century (UNEP, 2021). Moreover, emissions scenarios that target global temperature stabilization at either 1.5 or 2.0°C require net-zero carbon emissions trajectories, which in practice will necessitate new and enormously-scaled-up carbon dioxide removal technology (NASEM, 2019).

In parallel with global policy shortfalls, current levels of warming are driving substantial impacts on human and natural systems (IPCC 2022). For example, climate change is already leading to intensification of extreme events such as extreme heat, heavy rainfall, intense droughts, extreme wildfire weather and marine heatwaves (IPCC, 2022b). These and other climate changes are leading to a broad suite of impacts, such as migration of ecological niches (Sheldon, 2019), increases in global tree mortality (Hartmann et al., 2022), increases in financial losses from extremes (e.g., Davenport et al., 2021), and amplification of existing economic inequality (Diffenbaugh & Burke, 2019) and social injustices (Dietz et al., 2020). Furthermore, there is the possibility that biogeophysical tipping points may lead to new states in key Earth systems, such as irreversible Antarctic ice loss, tropical rainforest dieback, and slowing ocean circulations (Lenton et al., 2019). These tipping points are highly uncertain — in terms of whether, when, and how they may occur (IPCC, 2021). Despite this uncertainty, there is paleoclimate evidence that tipping points have been crossed in the past, and emerging evidence that they could be crossed as a result of anthropogenic changes (Boers & Rypdal, 2021; Lohmann & Ditlevsen, 2021; Rosier et al., 2021).

In an effort to grant humanity additional time to sufficiently reduce greenhouse gas emissions, lessen the existing negative impacts of climate change, and avoid transgression of irreversible tipping points, there is renewed interest in developing an international research agenda on solar radiation management (SRM) — a speculative form of climate change response that has the potential to offset human-induced warming by reflecting solar energy back to space before it enters and warms the planetary environment (NASEM, 2021).

There are numerous challenges for advancing SRM science and research. First, there are substantial ethical questions concerned with committing future generations to an uncertain technology and the potential burden of continuing climate intervention in perpetuity (Keith, 2021) or deciding when and how to ramp down SRM deployment (Jones et al., 2013; Long & Shepherd, 2014; MacMartin et al., 2018; McCusker et al., 2014). Second, there are important concerns related to how climate intervention may drive changes in essential Earth system processes (Irvine et al., 2016; Tjiputra et al., 2016). Third, there are concerns that the negative consequences arising from SRM would disproportionately burden populations that are systematically already burdened by climate change impacts, global dispossession of resources, and wealth inequality (Buck, 2012; Flegal & Gupta, 2018). Research investigating public opinion has found considerable heterogeneity in attitudes toward either research or use of climate intervention (Mahajan et al., 2019).

In addition to these social challenges, there exist basic scientific questions about how to distinguish the climate effects of SRM from anomalies driven by internal variability of the Earth system (Fröb et al., 2020; MacMartin et al., 2019). Internal climate variability can lead to substantial short-term variation in socially-relevant climate phenomena, such as the frequency of extreme heat and cold spells (Diffenbaugh et al., 2017), the severity of drought (Diffenbaugh et al., 2015), the path of the midlatitude storm tracks (Woollings et al., 2018), changes in regional temperature and precipitation (Deser, 2020), the state of Arctic sea ice (Labe et al., 2018), or the strength of tropical modes of variability such as the El Nino Southern Oscillation (Cai et al., 2021) or the Madden-Julian Oscillation (Martin et al., 2021). Research on the interaction between human-induced climate impacts, or "signals", and internal climate variability, or "noise", is a critical area of climate change science, not least for supporting policymakers and the public in navigating the expectations of climate change action against a backdrop of a constantly, internally-varying climate system (Mankin et al., 2020).

Stratospheric aerosol injection (SAI) is the theoretical SRM strategy of releasing particles into the stratosphere to slow, pause, or reverse global warming (Keith, 2020). While climate simulations provide evidence that the long-term result of SAI could lead to stabilized global temperatures (MacMartin et al., 2018), the impacts of SAI may be regionally heterogeneous with temperature and precipitation varying considerably (Ban-Weiss & Caldeira, 2010; Kravitz et al., 2014; Ricke et al., 2010). Moreover, internal climatic variability may mask the short-term perceived effectiveness of SAI. That is, it is possible that while SAI could stabilize mean global temperatures, the perceived effectiveness on *regional* scales may be overwhelmed by local climatic variability over the short term. Psychologically, a climate change-related event connects to people's perceptions most clearly when it is directly and locally relevant (Borick

& Rabe, 2017; Brügger et al., 2021). Moreover, people who are residents of a specific location may tacitly incorporate 10-year trends in their perception of changes in climate (Shao et al., 2016). Hence, local changes in climate – such as continued warming or the occurrence of extreme events – may cause climate interventions such as SAI to be perceived as a failure. Given the potential for SAI to abruptly cease, and the likelihood of rapid climate change following such cessation (Baur et al., 2022; e.g., McCusker et al., 2014; Parker & Irvine, 2018), the perception of failure carries particular risks.

If SRM is ever pursued, it will likely be for a specific social or geophysical aim (Buck, 2012). This may include halting an anticipated geophysical tipping point, such as accelerated Antarctic ice loss (Garbe et al., 2020)permafrost melting or forest die-off, or lessening the impacts of extremes, such as deadly heat waves in large population centers (Mora et al., 2017). Yet, if climate variability were to mask the short-term perceived effectiveness of climate intervention it could undermine coordinated, international policy action to address climate change broadly (Ricke & Caldeira, 2014). Understanding the masking effects of climate variability on regional scales will thus be critical for interpreting the potential perceived success of any SRM strategy in the immediate years following deployment.

To systematically distinguish the different possible outcomes associated with the masking effect of internal climate variability, we introduce a set of archetypal regional responses that could unfold under SAI. These archetypes are motivated by the fact that, in the period prior to SAI deployment, a given region could be warming or not due to internal climate variability, even in the context of global-scale warming (Deser et al., 2012). Similarly, following deployment, that region could either experience warming or not, even if the global temperature is stabilized. Thus, we define four archetypes of perceived success of climate intervention, based on four categories of pre- and post-deployment experience: 1) Rebound Warming (i.e. no warming followed by warming); 2) Continued Warming (i.e. warming followed by more warming); 3) Stabilization (i.e. no warming either before or after deployment); and, 4) Recovery (i.e. warming followed by no warming). The phenomena “Rebound Warming” and “Continued Warming” could both be locally perceived as a failure of SAI to deliver on its intended purpose; hence, throughout the rest of this work, the phrase ‘perceived failure’ refers to the combination of these two archetypes.

Past research into global SRM strategies has employed climate models to simulate how the Earth system may respond to different intervention approaches (Kravitz et al., 2011). Here, we leverage just one of them: the Assessing Responses and Impacts of SRM on the Earth system with Stratospheric Aerosol Injection (ARISE-SAI) ensemble carried out with the Community Earth System Model, version 2

(Danabasoglu et al., 2020). ARISE-SAI simulates a plausible deployment of SAI, designed to hold global mean temperature at 1.5°C based on the SSP2-4.5 emissions scenario (Fig. 1A) (Richter et al., 2022). Extending out to the year 2069, ARISE-SAI includes 10 ensemble members, each initiated from slightly different initial conditions to allow for a quantification of the irreducible uncertainty arising from internal climate variability (e.g., Kay et al., 2015). The 1.5°C threshold is relevant for global policy discourse in part because this is a global mean temperature increase beyond pre-industrial conditions that is considered both an important Earth system threshold, as well as a key focus of global climate policy negotiations enshrined in the UN Paris Agreement (Xu & Ramanathan, 2017). The fact that ARISE-SAI simulates SAI deployment that stabilizes global temperature at 1.5°C while also representing the effect of internal variability via a substantial number of ensemble members makes ARISE-SAI a unique testbed for probing the probability of perceived failure of climate intervention.

Results

Increases in greenhouse gas concentrations and other anthropogenic forcings under the SSP2-4.5 scenario drive increases in temperatures globally (Fig. 1A), as seen in the forced (ensemble-mean) response during the 2015-2034 pre-deployment period of ARISE-SAI (Fig. 1B). Visualizing the ensemble mean reduces many of the effects of internal climate variability, even though an ensemble of more than 10 members is likely needed to fully remove such effects regionally (e.g., Deser et al., 2012; Milinski et al., 2020). Over the longer post-deployment period of 2035-2069, the ensemble mean exhibits a clear picture of temperatures generally holding steady throughout the rest of the simulation (Fig. 1A), indicative of SAI acting to stabilize temperatures even regionally (Fig. 1C). In reality, however, any area's actual climate trajectory will be a combination of both the forced response and internal climate variability, which would be analogous to a single ensemble member (Fig. 1D,E) rather than the ensemble mean.

Focusing on the decade prior to SAI deployment (pre-deployment decade; 2025-2034), any ensemble member (e.g. member #9) will exhibit a large range of temperature trends regionally under SSP2-4.5 (Fig. 1D), even though the forced response is overwhelmingly warming. This is because internal climate variability can drive short-term trends in temperature that can partially mask (or augment) the longer-term, forced warming trend. What is perhaps less appreciated is that internal climate variability can similarly mask the effects of SAI on a regional scale. In the decade following continuous SAI deployment (post-deployment decade; 2035-2044), ensemble member #9 exhibits warming temperatures over 49% of the land surface (Fig. 1E), where warming is defined as decadal temperature trends larger than 0.1 °C/decade. This threshold value is chosen to reflect the approximate warming over the observational record (NOAA National Centers for Environmental Information, published online January 2021); temperature trends less than this are referred to here as `not warming' since they capture both cooling as well as small positive trends. Thus, the effects of internal climate variability can cause the magnitude of regional warming trends in the post-deployment decade to far exceed the forced trend from SAI.

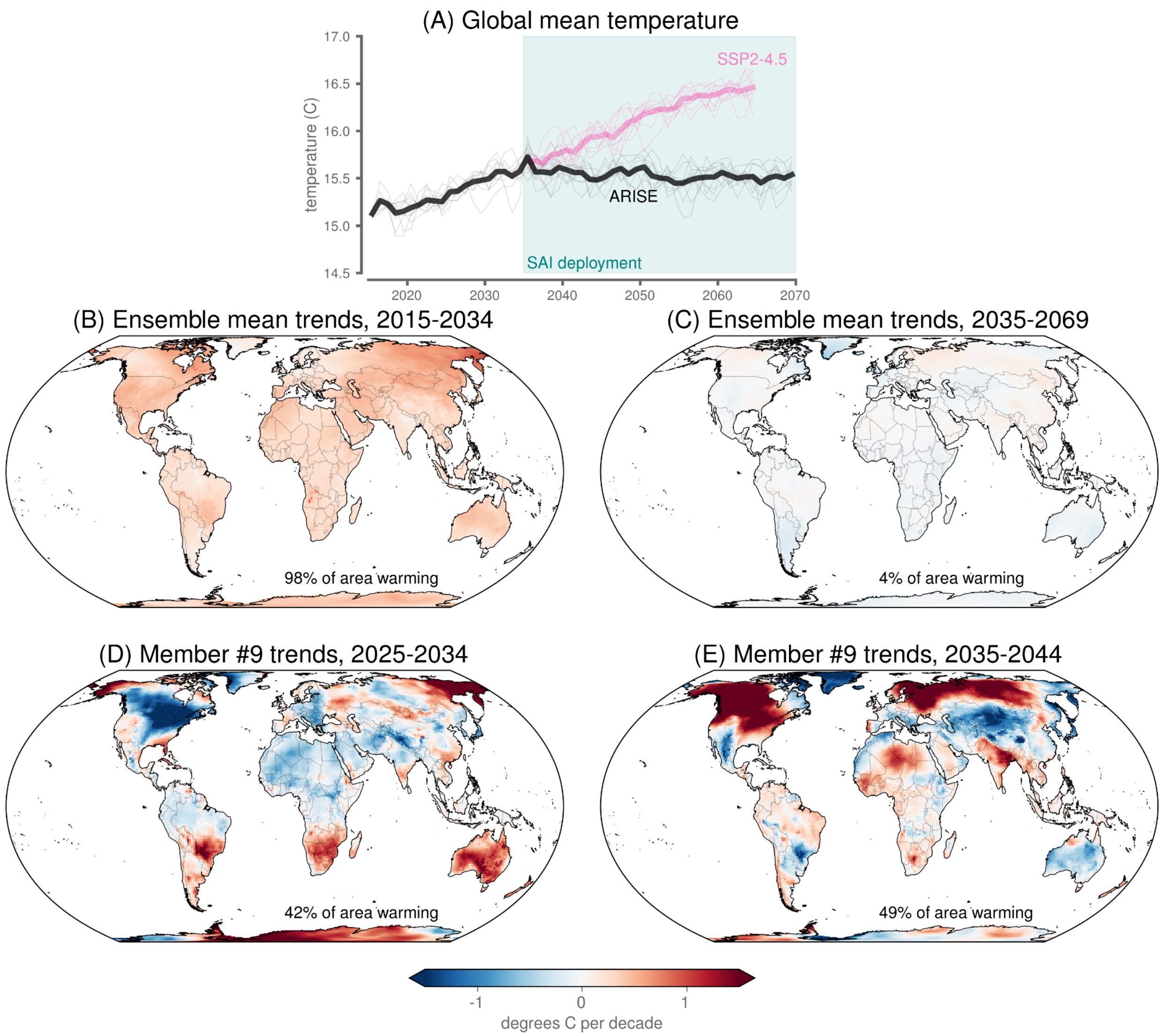

Figure 1. Surface temperature trends. (A) Global mean surface temperature. Gray lines denote individual ensemble members and the black line denotes the ensemble mean. **(B,C)** Ensemble-mean trends over **(B)** 2015-2034 under SSP2-4.5 and **(C)** 2035-2069 with ARISE-SAI deployment. **(D,E)** Trends over the **(D)** pre-deployment decade and **(E)** post-deployment decade for ensemble member #9. **(B-D)** The percentage in the bottom of the maps denotes the percentage of land area that exhibits warming trends as defined in the text.

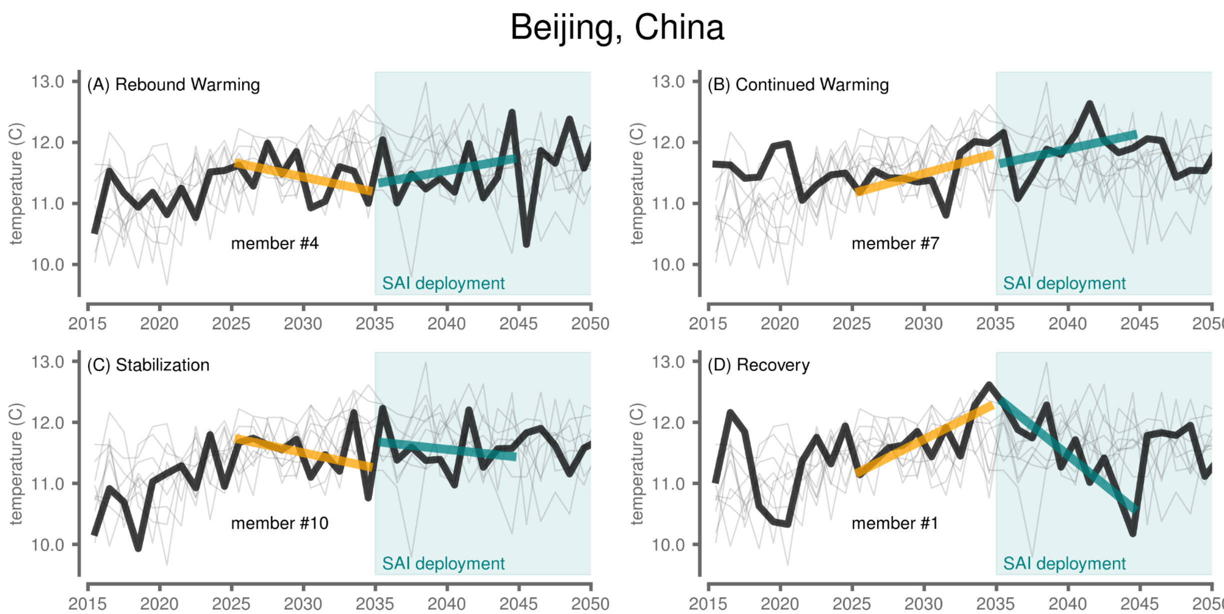

Figure 2. Pre-deployment and post-deployment surface temperature trends for Beijing, China. Each panel highlights a different ensemble member denoted in each panel by the thick black line, with the other nine members shown as thin gray lines. SAI deployment is initiated in the year 2035 (teal shading). Ten-year linear best-fit lines are shown for 2025-2034 (orange) and 2035-2044 (teal).

Beijing, China, provides an example of how a single region can experience each of the four archetypal responses under different individual realizations of the ARISE-SAI experiment (Fig 2). Ensemble member #1 exhibits the Recovery archetype (Fig 2D), where SAI would potentially be labeled a success in that the perception of temperature change would swing from an increase in local temperature prior to deployment to a stabilization or decrease in temperature after deployment. However, in member #4, Beijing experiences Rebound Warming (Fig 2A), with cooling over the pre-deployment period followed by warming over the post-deployment period. Likewise, in member #7, Beijing experiences Continued Warming (Fig 2B), with substantial warming during both the pre- and post-deployment decades.

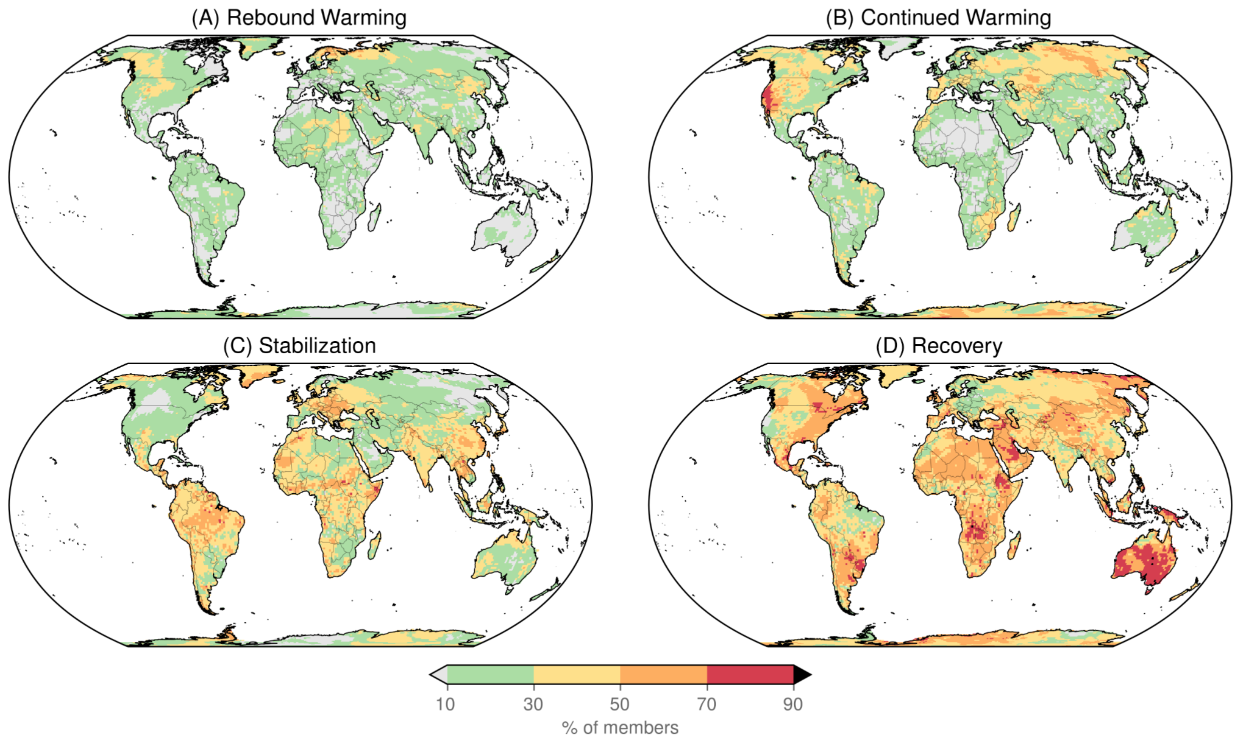

Figure 3. Archetypal regional responses to ARISE-SAI. The percent of ensemble members that exhibit specific archetypal responses over the ten years pre- and post-deployment: **(A)** Rebound Warming (not warming followed by warming), **(B)** Continued Warming (warming followed by warming), **(C)** Stabilization (not warming followed by not warming) and **(D)** Recovery (warming followed by not warming).

All four archetypal regional responses can be found across the globe, with varying probabilities across the ARISE-SAI ensemble (Fig 3). While some regions, notably Australia and parts of Africa, exhibit high probability of the Recovery archetype (Fig 3D), substantial parts of the land surface experience high probability of either Rebound Warming or Continued Warming. Repeated occurrence of perceived failure in the same location across multiple ensemble members can be largely understood as internal climate variability persistently masking the effect of SAI deployment (although more than ten ensemble members would be required to completely rule out the possibility of a weak, short-term response to SAI itself; Fig. 1C).

Aggregating the occurrence of Rebound Warming and Continued Warming across all ensemble members yields the probability (computed as the percent of the 10 ensemble members) of internal variability leading to perceived failure of SAI (Fig 4A and 4B). While some regions of the planet experience near-zero probability of perceived failure under ARISE-SAI deployment, there are other regions that experience greater than 50% probability of perceived failure. East Antarctica — a region of global importance and priority with respect to the potential for substantial changes in sea level (Rignot et al., 2019) — appears particularly prone to climate variability masking the effectiveness of climate intervention. Likewise, much of northern Eurasia and the western half of North America experience a very high probability of perceived failure in the decade following deployment. For the case of North America, Pacific Decadal Variability – which CESM is known to simulate with high fidelity (Capotondi et al., 2020) – could be a key factor confounding the effects of climate intervention (Fig. S3).

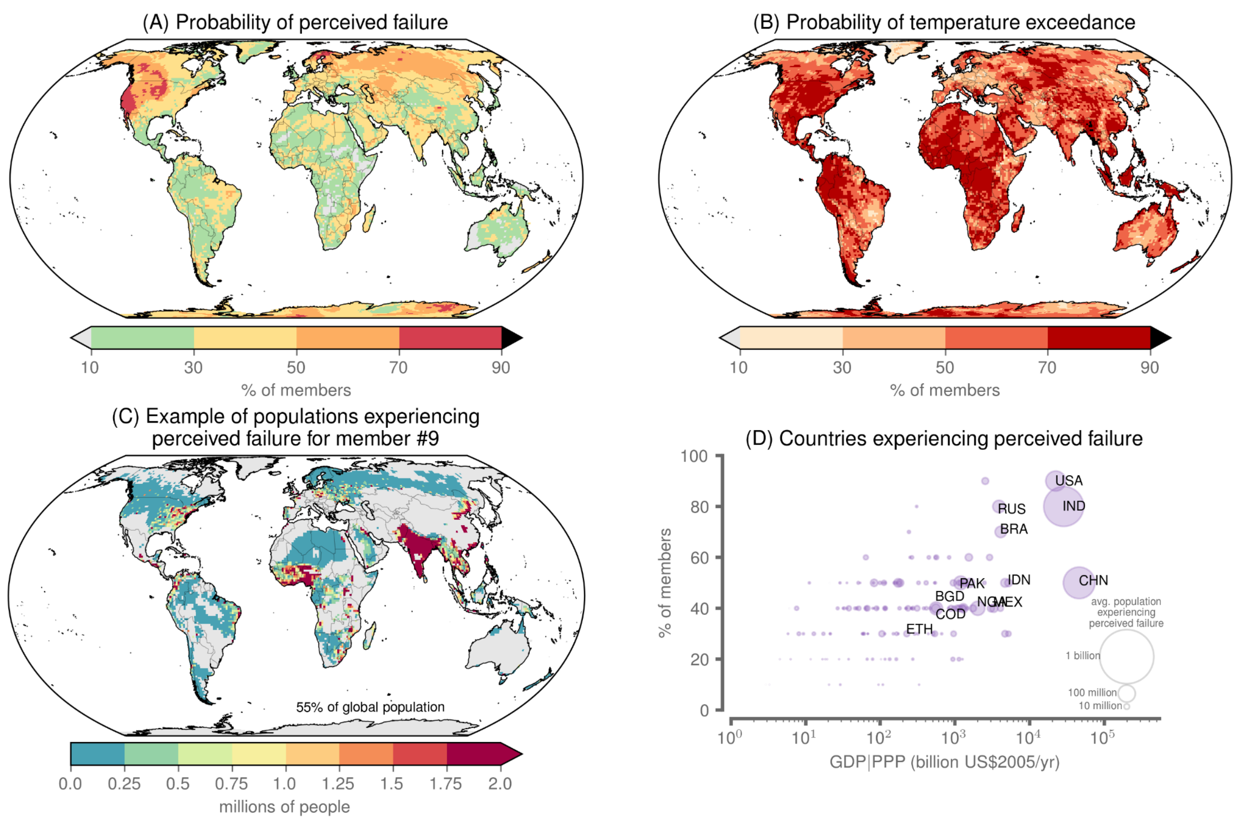

Figure 4. Perceived failure over the ten years following SAI deployment under ARISE. (A) Probability of perceived failure over the post-deployment period, where the probability is computed as the fraction of ensemble members exhibiting warming trends. **(B)** Probability of a location exceeding its 2015-2034 (pre-deployment) maximum annual-mean temperature in the decade following SAI deployment (2035-2046). **(C)** Projected number of people at each location experiencing perceived failure of SAI over the post-deployment period in ensemble member #9 using projected populations for 2040. Gray denotes regions not experiencing perceived failure in that particular ensemble member. **(D)** Percent of members with 10% or more of a country's projected 2040 population (see Fig S5 for alternative population thresholds) experiencing perceived failure following SAI deployment versus the country's

projected 2040 GDP in units of purchasing power parity (PPP). Circle area corresponds to the projected 2040 population experiencing perceived failure averaged across ensemble members.

Our perceived failure metric relies on quantifying decadal temperature trends. However, given the myriad impacts of extreme heat on natural and human systems (Diffenbaugh et al., 2017; Ebi et al., 2021), an alternative metric for the perceived effectiveness of SAI could instead be a measure of the experience of temperature extremes following deployment. We find that, although the forced response in ARISE-SAI results in a stabilization of global temperatures (Fig. 1A,C), it is still very likely that record hot temperatures will occur following deployment (Fig. 4B). Broad areas of Africa, Eurasia, North America, South America and Antarctica exhibit at least 70% of ensemble members exhibiting their warmest annual-mean temperatures in the decade following SAI deployment, relative to temperatures prior to deployment (2015-3024). Moreover, the regions experiencing persistently high perceived failure of SAI (Fig 4A) do not directly correspond to the regions experiencing extremely high mean annual temperatures (Fig 4B). This finding underlines that multiple climate metrics are necessary when considering the perceived effectiveness of SAI.

Given the importance of local experiences for informing perceptions of climate change (Brügger et al., 2021), we next explore the populations exposed to perceived failure of SAI. Using gridded population data projected for 2040 in SSP-2 (Gao, 2017, 2020), we find that between 10% and 55% of the global population experience perceived failure across the ten-member ARISE-SAI ensemble (Fig S4). The most severe example is shown in Fig 4C for ensemble member #9, where substantial populations in India, Southeast Asia, the Eastern United States, and West Africa experience perceived failure over the decade following SAI deployment.

Perceptions of climate change-related phenomena can be related to both individual local experiences, as well as collective socio-cultural experiences (Brügger et al., 2021; Renn, 2011; Sambrook et al., 2021). Thus, to further explore the socio-economic reality of perceived failure of SAI at the national level, we compare the probability of country-level perceived failure against country-level gross domestic product in 2040 (in units of purchasing power parity, PPP) (Crespo Cuaresma, 2017). All of the largest economies in the world experience substantial probability of perceived failure in the post-deployment decade (Fig 4D). The implication is that the countries with the most geopolitical and global economic power — and perhaps those with the most financial capacity to deploy continuous SAI to manage global temperatures (Smith & Wagner, 2018) — experience at least a 50% probability of large populations perceiving failure of SAI. These countries not only have large populations potentially perceiving failure of SAI, but also cover substantial land areas, potentially increasing the odds of climatic variability masking the benefits of SAI. Yet, the fact remains that the countries that are apparently most prone to high probability of perceived failure are those with the largest populations and the largest economies.

Discussion

The 'fast' dimension of climate intervention is a notable advantage of SAI relative to other climate intervention approaches (Mahajan et al., 2019; NASEM, 2021). However, we find that in substantial regions of the world, SAI as simulated by the ARISE simulations may not be locally perceived as effective, even after ten years of continuous deployment. Given the political and economic costs associated with climate intervention, and increasing stakes associated with a warming planet, this gap in time between deployment and local perceived effectiveness could serve to undermine the 'fast' dimension of SAI intervention. Moreover, SAI is a technology that could potentially be deployed quickly by a small group of actors (or a single actor), owing to its relatively low cost and ease of deployment from a single location on the planet (e.g., within the borders of a single country) (Keith, 2020; Smith & Wagner, 2018).

In light of our findings, several priorities emerge for a forward-thinking SAI research agenda. First, the prevalence of perceived failure suggests countries should expect public doubt in the short-term effectiveness of SAI. The expectation of precise manipulation would be markedly inaccurate (National Research Council et al., 2015). However, this issue will also emerge in the midst of more general efforts to reduce emissions (IPCC, 2022a), as internal climate variability will likely produce continued warming in some regions in the years following aggressive policies aimed at reducing greenhouse gas emissions—potentially leading to similar 'perceptions of failure' in the climate policy itself. Thus, whether or not SAI is pursued, countries must recognize that internal climate variability will need to be anticipated and well-articulated if continued public support is desired. Furthermore, this articulation must occur amidst a communication environment that is already fraught with climate-related mis-information (Lewandowsky & Whitmarsh, 2018).

Given that specific regions of the planet are predisposed to large internal climate variability, such as the El Niño Southern Oscillation or the Pacific Decadal Oscillation (Newman et al., 2016), it is likely that these regions will also experience persistent masking of SAI effectiveness. Such understanding of regionally persistent masking of SAI effectiveness will complement and contribute to the growing literature on detection and attribution of deployment of climate intervention (Fröb et al., 2020; MacMartin et al., 2019). Further, because the possibility of perceived failure extends beyond SAI, knowledge of specific regionally persistent internal variability will benefit other climate mitigation policies, especially those contingent on public support (Fankhauser et al., 2021).

Conclusions

We highlight the need for continued research and understanding of how climate variability may mask climate intervention in the years immediately following deployment. If climate intervention is ever pursued, it will likely be pursued for a specific social or geophysical aim, but climate variability may mask the short-term perceived effectiveness of that intervention, including in target geographical areas, ecosystems or economic sectors for which the intervention was deployed in the first place. Our results thus suggest that the scientific community must better frame what the success of SAI – and climate intervention more broadly – looks like in the context of internal climate variability. Specifically, it will be important to understand how key global drivers of variability, such as coupled ocean-atmosphere modes operating on decadal timescales, may mask the intended results of climate intervention strategies, and to what extent this masking will be predictable or detectable. Our analysis provides a foundation for that understanding, and motivation for improving the ability of global policy and scientific organizations to better frame the stakes associated with the deployment of climate intervention in the future.

Methods

ARISE Data

Gridded, monthly near surface air temperature fields (variable name TREFHT) were obtained from the ensemble of simulations performed for the Assessing Responses and Impacts of SRM on the Earth system with Stratospheric Aerosol Injection (ARISE-SAI) (Richter et al., 2022). The ARISE ensemble was simulated with the Community Earth System Model, version 2 (Danabasoglu et al., 2020) using WACCM6 (Whole Atmosphere Community Climate Model Version 6, WACCM6) (Meehl et al., 2020). We average together the gridded, monthly fields to produce annual-mean fields, with each field having a grid resolution of 0.94240838 degrees latitude by 1.25 degrees longitude.

The ARISE data set includes two sets of simulations composed of ten ensemble members each. The first set follows the SSP2-4.5 emissions scenario while the second is identical to the first but with the inclusion of stratospheric aerosol injection (SAI) beginning in the year 2035. The location and amount of aerosols released into the stratosphere each year is determined by a controller algorithm that works to keep global mean temperature, the north-south temperature gradient, and the equator-to-pole temperature gradient at values based on the 2020-2039 mean of the SSP2-4.5 simulations with CESM2 (WACCM6) (Meehl et al., 2020). Further details about the ARISE SAI configuration and aerosol injection strategy are provided in (Richter et al., 2022).

Probability of perceived failure

Decadal trends of annual mean temperature at each gridpoint are computed using linear, least-squares regression over two ten-year periods: (1) the pre-deployment decade (2025-2034) and (2) the post-deployment decade (2035-2044). Since SAI under ARISE is designed to stabilize global-mean temperature (not to reverse the warming trend and induce cooling), we define "warming" as any decadal trend that exceeds 0.1°C per decade. A warming threshold of 0.1°C per decade is chosen to reflect the approximate warming we have thus far experienced over the observational record (NOAA National Centers for Environmental Information, published online January 2021). All trend magnitudes less than this are considered "not warming". We thus classify each of the ensemble members, for each location, as falling into one of the four archetypes of perceived success of climate intervention, based on the pre- and/or post-deployment trends: 1) Rebound Warming (i.e. no warming followed by warming); 2) Continued Warming (i.e. warming followed by more warming); 3) Stabilization (i.e. no warming either before or after deployment); and, 4) Recovery (i.e. warming followed by no warming). The combination of Rebound warming and Continued warming represent the experience of potential "perceived failure", as both exhibit warming trends over the post-deployment decade that exceed 0.1°C per decade. The probability of perceived failure is then computed as the percent of ensemble members (out of 10) that experience perceived failure at each location.

Populations and country-level statistics for those experiencing perceived failure

Projected, gridded population data for the year 2040 were downloaded from SEDAC for Shared Socioeconomic Pathway 2 (SSP2) (https://sedac.ciesin.columbia.edu/data/collection/popdynamics/maps/services). The SEDAC data was downloaded in netcdf format at a resolution of one eighth of a degree and was then re-gridded to the ARISE/CESM2 grid using the sum function. The global population is perfectly conserved in this regridding process. The population experiencing perceived failure is then computed as the sum of the populations at each gridpoint where the post-deployment decade exhibits warming trends greater than 0.1 °C. Projected gross domestic product (GDP; in units of purchasing power parity) data for the year 2040 under SSP2 were downloaded as shapefiles from IIASA at the country level (https://tntcat.iiasa.ac.at/SspDb/dsd?Action=htmlpage&page=10). Temperature trends, projected population, and projected GDP were then calculated within each country boundary using the python packages *regionmask* and *geopandas.*

Fig. 4D includes the percent of members with 10% or more of a country's projected 2040 population experiencing perceived failure following SAI deployment. Fig S5 displays results for the same analysis using alternative population thresholds (i.e. 5%, 10%, 25% and 50%).

Probability of exceeding pre-deployment maximum temperature

For each gridpoint, we computed the maximum annual-mean temperature across all available years prior to SAI deployment (2015-2034). This was done for each ensemble member separately to simulate perceptions within each individual realization of the climate system. The probability of exceeding the pre-deployment maximum temperature was then defined as the number of ensemble members (out of 10) that exceeded their pre-deployment maximum in the decade following deployment (2035-2044).

References

Ban-Weiss, G. A., & Caldeira, K. (2010). Geoengineering as an optimization problem. *Environmental Research Letters: ERL [Web Site]*, *5*(3), 034009.

Baur, S., Nauels, A., & Schleussner, C.-F. (2022). Deploying Solar Radiation Modification to limit warming under a current climate policy scenario results in a multi-century commitment. In *Earth System Dynamics Discussions*. https://doi.org/10.5194/esd-2022-17

Boers, N., & Rypdal, M. (2021). Critical slowing down suggests that the western Greenland Ice Sheet is close to a tipping point. *Proceedings of the National Academy of Sciences of the United States of America*, *118*(21). https://doi.org/10.1073/pnas.2024192118

Borick, C. P., & Rabe, B. G. (2017). Personal experience, extreme weather events, and perceptions of climate change. In *Oxford research encyclopedia of climate science*.

Brügger, A., Demski, C., & Capstick, S. (2021). How Personal Experience Affects Perception of and Decisions Related to Climate Change: A Psychological View. *Weather, Climate, and Society*, *13*(3), 397–408.

Buck, H. J. (2012). Geoengineering: re-making climate for profit or humanitarian intervention? *Development and Change*, *43*(1), 253–270.

Cai, W., Santoso, A., Collins, M., Dewitte, B., Karamperidou, C., Kug, J.-S., Lengaigne, M., McPhaden, M. J., Stuecker, M. F., Taschetto, A. S., Timmermann, A., Wu, L., Yeh, S.-W., Wang, G., Ng, B., Jia, F., Yang, Y., Ying, J., Zheng, X.-T., … Zhong, W. (2021). Changing El Niño–Southern Oscillation in a warming climate. *Nature Reviews Earth & Environment*, *2*(9), 628–644.

Capotondi, A., Deser, C., Phillips, A. S., Okumura, Y., & Larson, S. M. (2020). ENSO and pacific decadal variability in the community earth system model version 2. *Journal of Advances in Modeling Earth Systems*, *12*(12). https://doi.org/10.1029/2019ms002022

Crespo Cuaresma, J. (2017). Income projections for climate change research: A framework based on human capital dynamics. *Global Environmental Change: Human and Policy Dimensions*, *42*, 226–236.

Danabasoglu, G., Lamarque, J.-F., Bacmeister, J., Bailey, D. A., DuVivier, A. K., Edwards, J., Emmons, L. K., Fasullo, J., Garcia, R., Gettelman, A., Hannay, C., Holland, M. M., Large, W. G., Lauritzen, P. H., Lawrence, D. M., Lenaerts, J. T. M., Lindsay, K., Lipscomb, W. H., Mills, M. J., … Strand, W. G. (2020). The community earth system model version 2 (CESM2). *Journal of Advances in Modeling Earth Systems*, *12*(2). https://doi.org/10.1029/2019ms001916

Davenport, F. V., Burke, M., & Diffenbaugh, N. S. (2021). Contribution of historical precipitation change to US flood damages. *Proceedings of the National Academy of Sciences of the United States of*

America, *118*(4). https://doi.org/10.1073/pnas.2017524118

Deser, C. (2020). "certain uncertainty: The role of internal climate variability in projections of regional climate change and risk management." *Earth's Future*, *8*(12). https://doi.org/10.1029/2020ef001854

Deser, C., Phillips, A., Bourdette, V., & Teng, H. (2012). Uncertainty in climate change projections: the role of internal variability. *Climate Dynamics*, *38*(3-4), 527–546.

Dietz, T., Shwom, R. L., & Whitley, C. T. (2020). Climate Change and Society. *Annual Review of Sociology*. https://doi.org/10.1146/annurev-soc-121919-054614

Diffenbaugh, N. S., & Burke, M. (2019). Global warming has increased global economic inequality. *Proceedings of the National Academy of Sciences of the United States of America*, *116*(20), 9808–9813.

Diffenbaugh, N. S., Singh, D., Mankin, J. S., Horton, D. E., Swain, D. L., Touma, D., Charland, A., Liu, Y., Haugen, M., Tsiang, M., & Rajaratnam, B. (2017). Quantifying the influence of global warming on unprecedented extreme climate events. *Proceedings of the National Academy of Sciences of the United States of America*, *114*(19), 4881–4886.

Diffenbaugh, N. S., Swain, D. L., & Touma, D. (2015). Anthropogenic warming has increased drought risk in California. *Proceedings of the National Academy of Sciences of the United States of America*, *112*(13), 3931–3936.

Ebi, K. L., Vanos, J., Baldwin, J. W., Bell, J. E., Hondula, D. M., Errett, N. A., Hayes, K., Reid, C. E., Saha, S., Spector, J., & Berry, P. (2021). Extreme Weather and Climate Change: Population Health and Health System Implications. *Annual Review of Public Health*, *42*, 293–315.

Fankhauser, S., Smith, S. M., Allen, M., Axelsson, K., Hale, T., Hepburn, C., Kendall, J. M., Khosla, R., Lezaun, J., Mitchell-Larson, E., Obersteiner, M., Rajamani, L., Rickaby, R., Seddon, N., & Wetzer, T. (2021). The meaning of net zero and how to get it right. *Nature Climate Change*, *12*(1), 15–21.

Flegal, J. A., & Gupta, A. (2018). Evoking equity as a rationale for solar geoengineering research? Scrutinizing emerging expert visions of equity. *International Environmental Agreements: Politics, Law and Economics*, *18*(1), 45–61.

Fröb, F., Sonntag, S., Pongratz, J., Schmidt, H., & Ilyina, T. (2020). Detectability of artificial ocean alkalinization and stratospheric aerosol injection in MPI-ESM. *Earth's Future*, *8*(10). https://doi.org/10.1029/2020ef001634

Gao, J. (2017). *Downscaling Global Spatial Population Projections from 1/8-degree to 1-km Grid Cells* (NCAR Technical Note NCAR/TN-537+STR .). National Center for Atmospheric Research. https://doi.org/10.5065/D60Z721H

Gao, J. (2020). *Global 1-km Downscaled Population Base Year and Projection Grids Based on the Shared Socioeconomic Pathways, Revision 01* [Data set]. NASA Socioeconomic Data and

Applications Center (SEDAC). https://doi.org/10.7927/q7z9-9r69

Garbe, J., Albrecht, T., Levermann, A., Donges, J. F., & Winkelmann, R. (2020). The hysteresis of the Antarctic Ice Sheet. *Nature*, *585*(7826), 538–544.

Hartmann, H., Bastos, A., Das, A. J., Esquivel-Muelbert, A., Hammond, W. M., Martínez-Vilalta, J., McDowell, N. G., Powers, J. S., Pugh, T. A. M., Ruthrof, K. X., & Allen, C. D. (2022). Climate Change Risks to Global Forest Health: Emergence of Unexpected Events of Elevated Tree Mortality Worldwide. *Annual Review of Plant Biology*, *73*, 673–702.

IPCC. (2021). *Summary for Policymakers: Vol. Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergoernnmental Panel on Climate Change* (Masson-Delmotte, V., P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M.I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T.K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, and B. Zhou (ed.)). Intergovernmental Panel on Climate Change. https://doi.org/10.1017/9781009157896.

IPCC. (2022a). *Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press. https://doi.org/10.1017/9781009157926

IPCC. (2022b). *Summary for Policymakers: Vol. Climate Change 2022: Impacts, Adaptation, and Vulnerability. Contribution of Working Group II to the Sixth Assessment Report of the Intergoernnmental Panel on Climate Change*. Cambridge University Press.

Irvine, P. J., Kravitz, B., Lawrence, M. G., & Muri, H. (2016). An overview of the Earth system science of solar geoengineering. *Wiley Interdisciplinary Reviews. Climate Change*, *7*(6), 815–833.

Jones, A., Haywood, J. M., Alterskjaer, K., Boucher, O., Cole, J. N. S., Curry, C. L., Irvine, P. J., Ji, D., Kravitz, B., Egill Kristjánsson, J., Moore, J. C., Niemeier, U., Robock, A., Schmidt, H., Singh, B., Tilmes, S., Watanabe, S., & Yoon, J.-H. (2013). The impact of abrupt suspension of solar radiation management (termination effect) in experiment G2 of the Geoengineering Model Intercomparison Project (GeoMIP). *Journal of Geophysical Research*, *118*(17), 9743–9752.

Kay, J. E., Deser, C., Phillips, A., & Mai, A. (2015). The Community Earth System Model (CESM) large ensemble project: A community resource for studying climate change in the presence of internal climate …. *Bulletin of the*. https://journals.ametsoc.org/view/journals/bams/96/8/bams-d-13-00255.1.xml

Keith, D. W. (2020). Geoengineering the Climate: History and Prospect 1. In *The Ethics of Nanotechnology, Geoengineering and Clean Energy* (pp. 207–246). Routledge.

Keith, D. W. (2021). Toward constructive disagreement about geoengineering. *Science*, *374*(6569), 812–815.

Kravitz, B., MacMartin, D. G., Robock, A., Rasch, P. J., Ricke, K. L., Cole, J. N. S., Curry, C. L., Irvine, P. J., Ji, D., Keith, D. W., Kristjánsson, J. E., Moore, J. C., Muri, H., Singh, B., Tilmes, S., Watanabe, S., Yang, S., & Yoon, J.-H. (2014). A multi-model assessment of regional climate disparities caused by solar geoengineering. *Environmental Research Letters: ERL [Web Site]*, *9*(7), 074013.

Kravitz, B., Robock, A., Boucher, O., Schmidt, H., Taylor, K. E., Stenchikov, G., & Schulz, M. (2011). The geoengineering model intercomparison project (GeoMIP). *Atmospheric Science Letters*, *12*(2), 162–167.

Labe, Z., Magnusdottir, G., & Stern, H. (2018). Variability of Arctic Sea Ice Thickness Using PIOMAS and the CESM Large Ensemble. *Journal of Climate*, *31*(8), 3233–3247.

Lenton, T. M., Rockström, J., Gaffney, O., Rahmstorf, S., Richardson, K., Steffen, W., & Schellnhuber, H. J. (2019). Climate tipping points - too risky to bet against. *Nature*, *575*(7784), 592–595.

Lewandowsky, S., & Whitmarsh, L. (2018). Climate communication for biologists: When a picture can tell a thousand words. *PLoS Biology*, *16*(10), e2006004.

Lohmann, J., & Ditlevsen, P. D. (2021). Risk of tipping the overturning circulation due to increasing rates of ice melt. *Proceedings of the National Academy of Sciences of the United States of America*, *118*(9). https://doi.org/10.1073/pnas.2017989118

Long, J. C. S., & Shepherd, J. G. (2014). The Strategic Value of Geoengineering Research. In B. Freedman (Ed.), *Global Environmental Change* (pp. 757–770). Springer Netherlands.

MacMartin, D. G., Irvine, P. J., Kravitz, B., & Horton, J. B. (2019). Technical characteristics of a solar geoengineering deployment and implications for governance. *Climate Policy*, *19*(10), 1325–1339.

MacMartin, D. G., Ricke, K. L., & Keith, D. W. (2018). Solar geoengineering as part of an overall strategy for meeting the 1.5°C Paris target. *Philosophical Transactions. Series A, Mathematical, Physical, and Engineering Sciences*, *376*(2119). https://doi.org/10.1098/rsta.2016.0454

Mahajan, A., Tingley, D., & Wagner, G. (2019). Fast, cheap, and imperfect? US public opinion about solar geoengineering. *Environmental Politics*, *28*(3), 523–543.

Mankin, J. S., Lehner, F., Coats, S., & McKinnon, K. A. (2020). The value of initial condition large ensembles to robust adaptation decision-making. *Earth's Future*, *8*(10). https://doi.org/10.1029/2020ef001610

Martin, Z., Son, S.-W., Butler, A., Hendon, H., Kim, H., Sobel, A., Yoden, S., & Zhang, C. (2021). The influence of the quasi-biennial oscillation on the Madden–Julian oscillation. *Nature Reviews Earth & Environment*, *2*(7), 477–489.

McCusker, K. E., Armour, K. C., Bitz, C. M., & Battisti, D. S. (2014). Rapid and extensive warming following cessation of solar radiation management. *Environmental Research Letters: ERL [Web*

Site], *9*(2), 024005.

Meehl, G. A., Arblaster, J. M., Bates, S., Richter, J. H., Tebaldi, C., Gettelman, A., Medeiros, B., Bacmeister, J., DeRepentigny, P., Rosenbloom, N., Shields, C., Hu, A., Teng, H., Mills, M. J., & Strand, G. (2020). Characteristics of future warmer base states in CESM2. *Earth and Space Science (Hoboken, N.J.)*, *7*(9). https://doi.org/10.1029/2020ea001296

Milinski, S., Maher, N., & Olonscheck, D. (2020). How large does a large ensemble need to be? *Earth System Dynamics*, *11*(4), 885–901.

Mora, C., Dousset, B., Caldwell, I. R., Powell, F. E., Geronimo, R. C., Bielecki, C. R., Counsell, C. W. W., Dietrich, B. S., Johnston, E. T., Louis, L. V., Lucas, M. P., McKenzie, M. M., Shea, A. G., Tseng, H., Giambelluca, T. W., Leon, L. R., Hawkins, E., & Trauernicht, C. (2017). Global risk of deadly heat. *Nature Climate Change*, *7*(7), 501–506.

NASEM. (2019). *Negative Emissions Technologies and Reliable Sequestration: A Research Agenda*. National Academies Press.

NASEM. (2021). *Reflecting Sunlight: Recommendations for Solar Geoengineering Research and Research Governance*. National Academies Press.

National Research Council, National Research Council (U.S.). Division on Earth and Life Studies, National Research Council (U.S.). Ocean Studies Board, National Research Council (U.S.). Board on Atmospheric Sciences and Climate, & Committee on Geoengineering Climate: Technical Evaluation and Discussion of Impacts. (2015). *Climate Intervention: Reflecting Sunlight to Cool Earth*. National Academies Press.

Newman, M., Alexander, M. A., & Ault, T. R. (2016). The Pacific Decadal Oscillation, Revisited. *Journal of Climate*, *29*(12), 4399–4427.

NOAA National Centers for Environmental Information. (published online January 2021). *State of the Climate: Monthly Global Climate Report for Annual 2020*. National Oceanographic and Atmospheric Administration. https://www.ncei.noaa.gov/access/monitoring/monthly-report/global/202013

Parker, A., & Irvine, P. J. (2018). The risk of termination shock from solar geoengineering. *Earth's Future*, *6*(3), 456–467.

Renn, O. (2011). The social amplification/attenuation of risk framework: application to climate change. *Wiley Interdisciplinary Reviews. Climate Change*, *2*(2), 154–169.

Richter, J., Visioni, D., MacMartin, D., Bailey, D., Rosenbloom, N., Lee, W., Tye, M., & Lamarque, J.-F. (2022). Assessing Responses and Impacts of Solar climate intervention on the Earth system with stratospheric aerosol injection (ARISE-SAI). In *EGUsphere* (pp. 1–35). https://doi.org/10.5194/egusphere-2022-125

Ricke, K. L., & Caldeira, K. (2014). Natural climate variability and future climate policy. *Nature Climate*

Change, *4*(5), 333–338.

Ricke, K. L., Morgan, M. G., & Allen, M. R. (2010). Regional climate response to solar-radiation management. *Nature Geoscience*, *3*(8), 537–541.

Rignot, E., Mouginot, J., & Scheuchl, B. (2019). Four decades of Antarctic Ice Sheet mass balance from 1979–2017. *Proceedings of the*. https://www.pnas.org/content/116/4/1095.short

Rosier, S. H. R., Reese, R., Donges, J. F., De Rydt, J., Gudmundsson, G. H., & Winkelmann, R. (2021). The tipping points and early warning indicators for Pine Island Glacier, West Antarctica. *The Cryosphere*, *15*(3), 1501–1516.

Sambrook, K., Konstantinidis, E., Russell, S., & Okan, Y. (2021). The Role of Personal Experience and Prior Beliefs in Shaping Climate Change Perceptions: A Narrative Review. *Frontiers in Psychology*, *12*, 669911.

Shao, W., Garand, J. C., Keim, B. D., & Hamilton, L. C. (2016). Science, scientists, and local weather: Understanding mass perceptions of global warming. *Social Science Quarterly*, *97*(5), 1023–1057.

Sheldon, K. S. (2019). Climate Change in the Tropics: Ecological and Evolutionary Responses at Low Latitudes. *Annual Review of Ecology, Evolution, and Systematics*. https://doi.org/10.1146/annurev-ecolsys-110218-025005

Smith, W., & Wagner, G. (2018). Stratospheric aerosol injection tactics and costs in the first 15 years of deployment. *Environmental Research Letters: ERL [Web Site]*, *13*(12), 124001.

Tjiputra, J. F., Grini, A., & Lee, H. (2016). Impact of idealized future stratospheric aerosol injection on the large-scale ocean and land carbon cycles. *Journal of Geophysical Research. Biogeosciences*, *121*(1), 2–27.

UNEP. (2021). *Emissions gap report 2021: the heat is on—a world of climate promises not yet delivered*. United Nations Environment Programme Nairobi, Kenya.

Woollings, T., Barnes, E., Hoskins, B., Kwon, Y.-O., Lee, R. W., Li, C., Madonna, E., McGraw, M., Parker, T., Rodrigues, R., Spensberger, C., & Williams, K. (2018). Daily to Decadal Modulation of Jet Variability. *Journal of Climate*, *31*(4), 1297–1314.

Xu, Y., & Ramanathan, V. (2017). *Well below 2 °C: Mitigation strategies for avoiding dangerous to catastrophic climate changes*. PNAS; National Acad Sciences. https://www.pnas.org/content/pnas/114/39/10315

Supplementary Information for

Potential for Perceived Failure of Stratospheric Aerosol Injection Deployment

Patrick W. Keys[1*], Elizabeth A. Barnes[2], Noah S. Diffenbaugh[3], James W. Hurrell[2] and Curtis M. Bell [4]

[1] School of Global Environmental Sustainability, Colorado State University
[2] Department of Atmospheric Science, Colorado State University
[3] Department of Earth System Science and Woods Institute for the Environment, Stanford University
[4] International Programs Department, United States Naval War College

***Corresponding Author:** Patrick W. Keys

Email: patrick.keys@colostate.edu

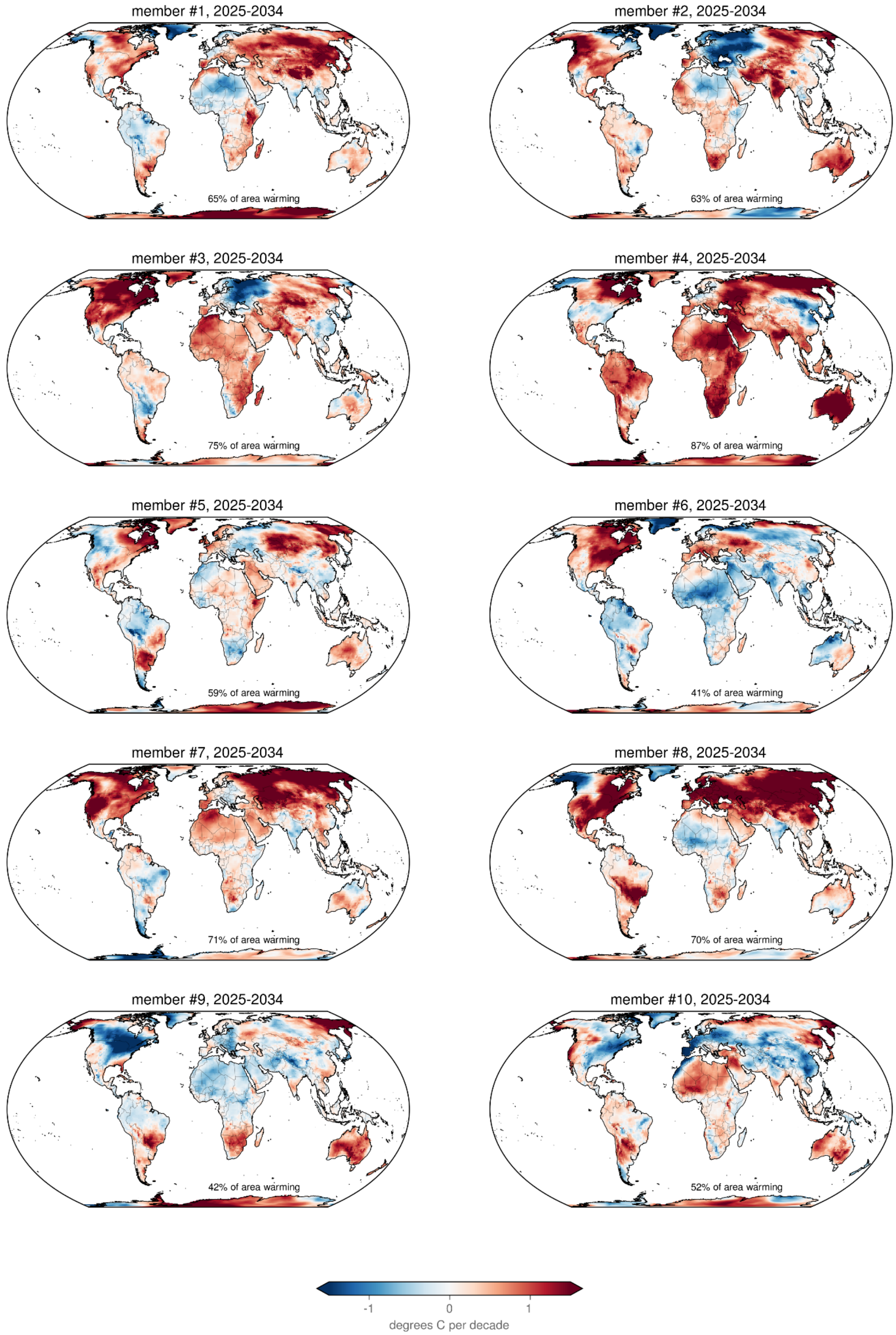

Fig. S1. As in Figure 1D but for all 10 ensemble members.

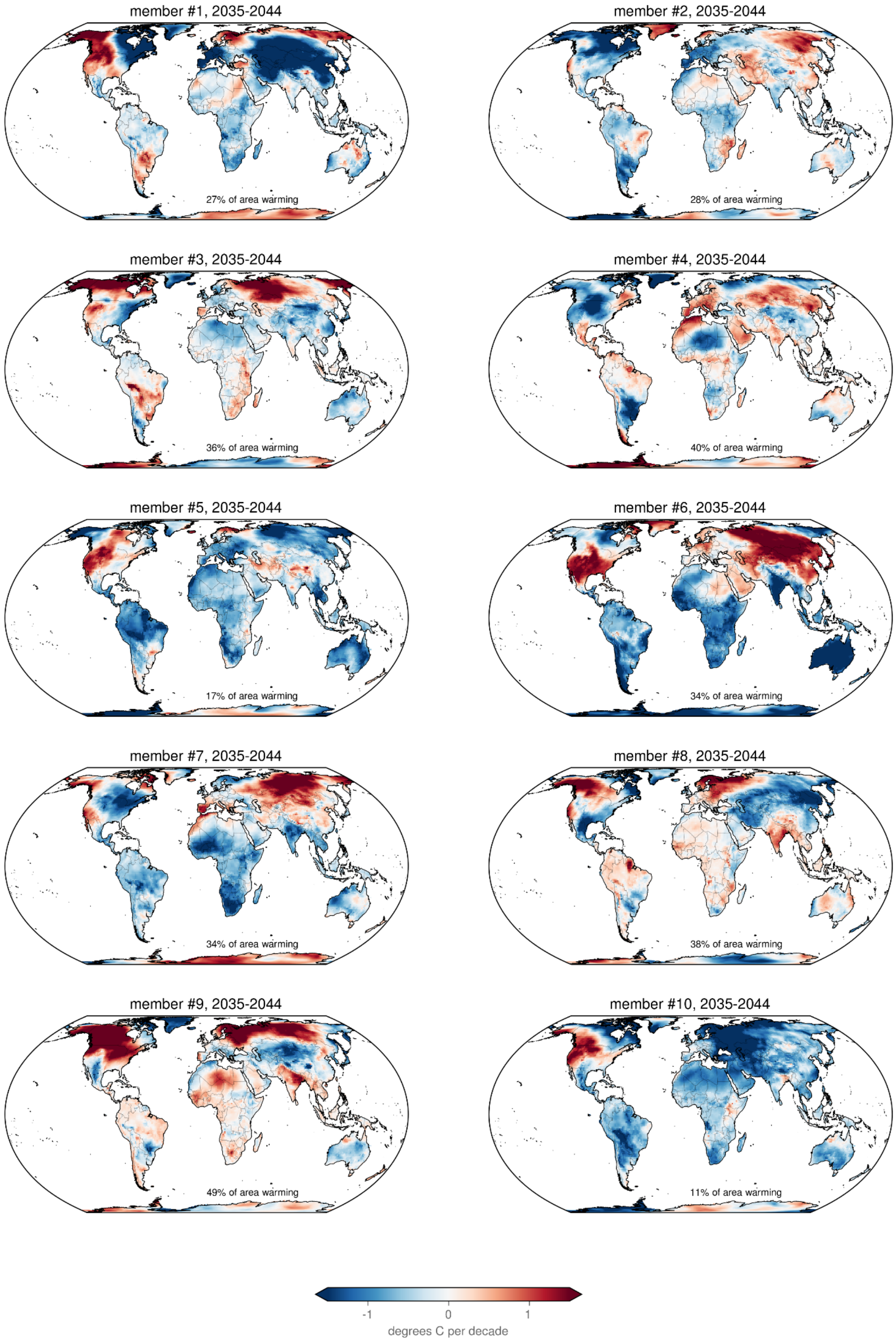

Fig. S2. As in Figure 1E but for all 10 ensemble members.

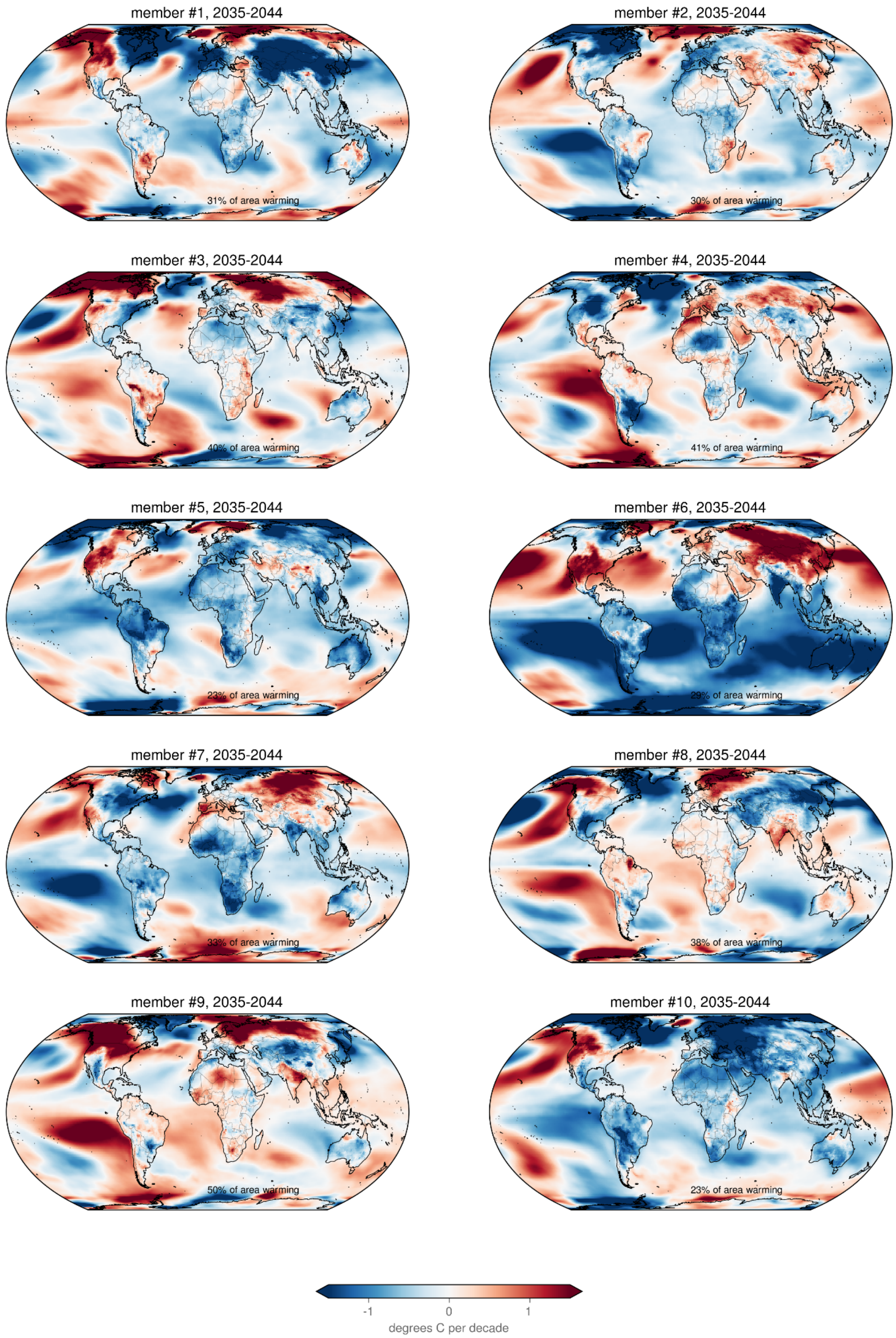

Fig. S3. As in Fig. S2 but including temperatures over the oceans.

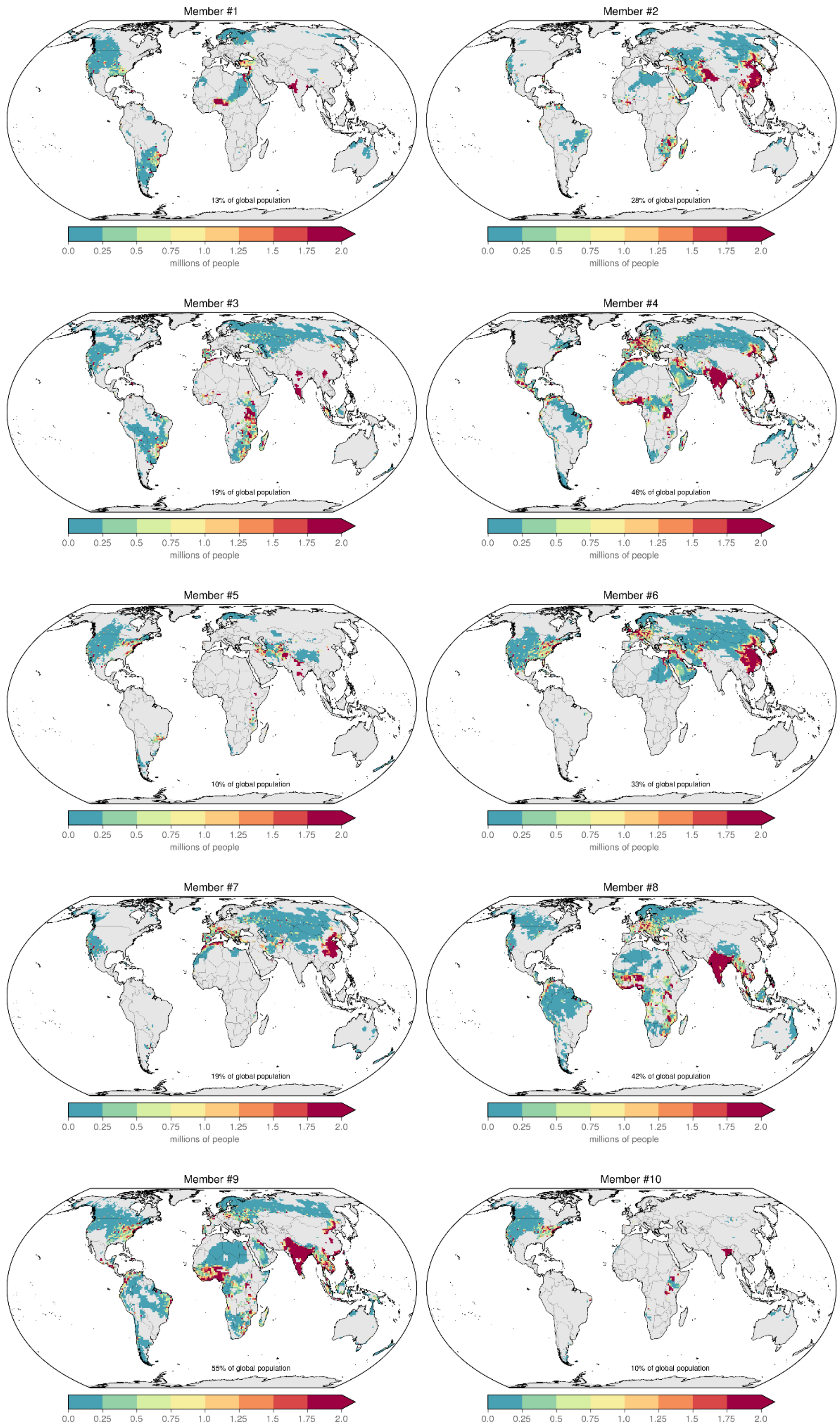

Fig. S4. As in Fig. 4A but for all 10 ensemble members.

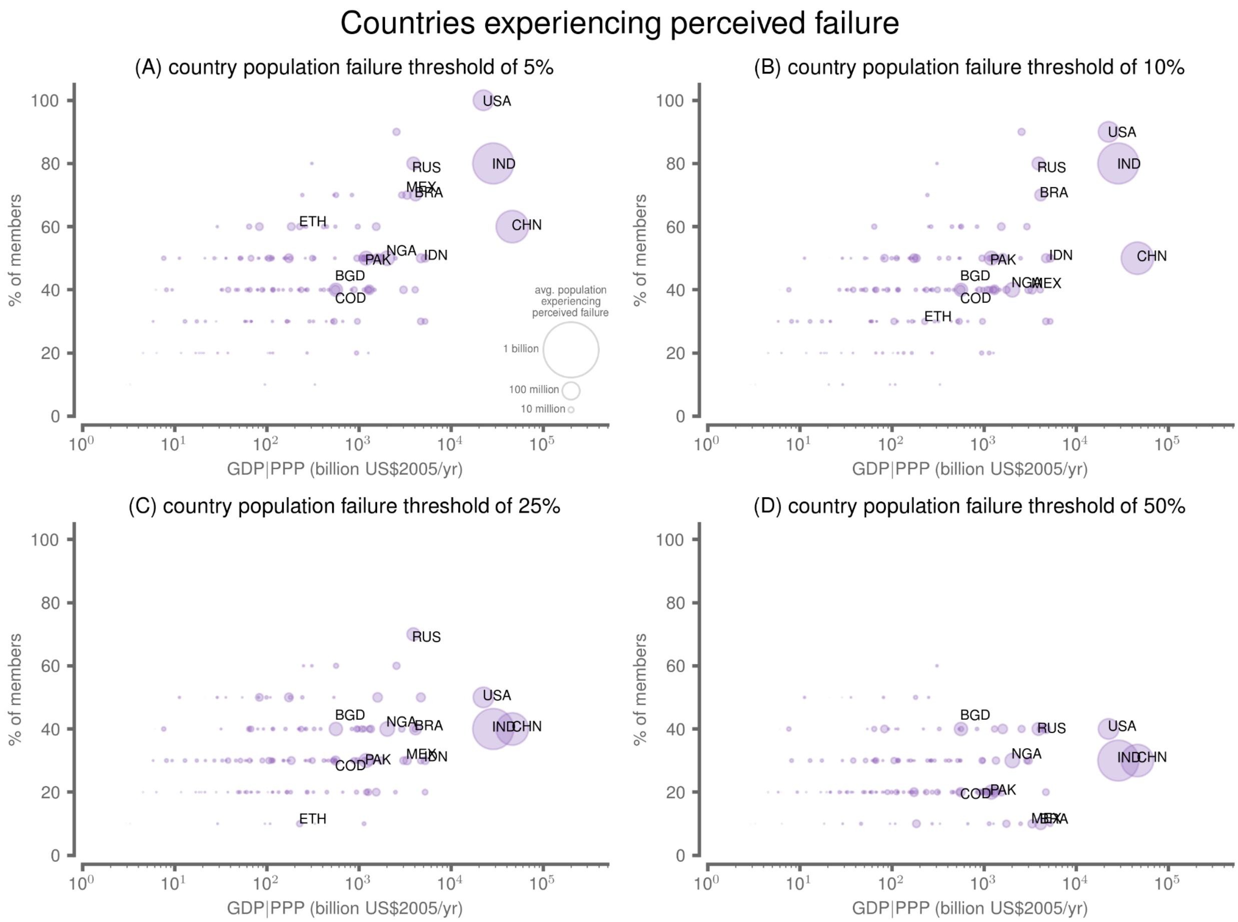

Fig. S5. As in Fig. 4B but for different population failure thresholds. The 10% threshold shown here in panel **(B)** is what is displayed in the main text.