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Potential for Perceived Failure of Stratospheric Aerosol Injection Deployment

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

[1] Department of Atmospheric Science, Colorado State University
[2] School of Global Environmental Sustainability, Colorado State University
[3] Doerr School of Sustainability, Stanford University
[4] International Programs Department, United States Naval War College

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

Email: patrick.keys@colostate.edu

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Abstract

As anthropogenic activities 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 adaptive capacity is exceeded. Thus, there is emerging interest in solar radiation modification, 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 strategy to slow, pause or reverse global warming. If SAI is ever pursued it will likely be for a specific aim, such as affording time to implement mitigation strategies, lessening extremes, or reducing the odds of reaching a biogeophysical tipping point. Using an ensemble climate model experiment that simulates the deployment of SAI in the context of an intermediate greenhouse gas trajectory, we quantify the probability that internal climate variability masks the effectiveness of SAI deployment on regional temperatures. We find that, while global temperature is stabilized, substantial land areas continue to experience warming. For example, in the SAI scenario we explore, 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 could therefore have major implications for policy decisions in the years immediately following SAI deployment.

Significance Statement

Even if aggressive mitigation policies are implemented soon, climate change impacts will worsen in the coming decades. One proposed response is stratospheric aerosol injection (SAI), which would reflect a small amount of the sun's energy back to space, thereby cooling the planet. This approach is broadly considered to be relatively inexpensive and straightforward to deploy, and global cooling could occur rapidly. However, on regional scales, internal climate variability is likely to dominate over SAI forcing. This means that in the decade after SAI is deployed, many regions of the world could locally experience even higher temperatures. Our study provides conceptual insight for the possible perception of failure of SAI, or other climate mitigation strategies.

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 (1). This global warming may exceed 1.5ºC above pre-industrial temperatures later this decade, at least for a short-period of time, and most years are likely to exceed the 1.5ºC threshold by 2040 across a range of emissions scenarios (IPCC 2021). By the middle of this century (2041-2060), warming in excess of 2.0ºC would be reached under intermediate, high and very high emission scenarios (1), and current policies have the world on track to warm by roughly 3.0ºC by the end of the century (2). Moreover, emissions scenarios that target global temperature stabilization at either 1.5 or 2.0ºC require net-zero carbon emissions trajectories, which in practice will necessitate new and enormously-scaled-up carbon dioxide removal technology (3).

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 (4). These and other climate changes are leading to a broad suite of impacts, such as migration of ecological niches (5), increases in global tree mortality (6), increases in financial losses from extremes (e.g., 7), and amplification of existing economic inequality (8) and social injustices (9). 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 (10). These so-called tipping points are highly uncertain — in terms of whether, when, and how they may occur (1). Despite this uncertainty, there is paleoclimate evidence that tipping points have been crossed in the past, and emerging evidence suggests that they could be crossed as a result of anthropogenic change (11–13).

To possibly 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 modification (SRM) — a speculative form of climate change response that has the potential to offset human-induced warming by reflecting a small amount of solar energy back to space before it enters and warms the planetary environment (14).

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 well into the future (15) or deciding when and how to ramp down SRM deployment (16–19). Second, there are important concerns related to how climate intervention may drive changes in essential Earth system processes (20, 21). 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 (22, 23). Research investigating public opinion has found considerable heterogeneity in attitudes toward either research or use of climate intervention (24).

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 (25, 26). This variability can lead to substantial short-term variation in socially-relevant climate phenomena, such as the frequency of extreme hot and cold spells (27), the severity of drought (28), the path of the midlatitude storm tracks (29), changes in regional temperature and precipitation (30), the state of Arctic sea ice (31), or the strength of tropical modes of variability such as the El Nino Southern Oscillation (32) or the Madden-Julian Oscillation (33). 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 an internally-varying climate system (34).

Stratospheric aerosol injection (SAI) is the SRM strategy of releasing particles into the stratosphere to slow, pause, or reverse global warming (35). While climate simulations provide evidence that the long-term result of SAI could lead to stabilized global temperatures (17), the impacts of SAI may be regionally heterogeneous with temperature and precipitation varying considerably (36–39). Moreover, internal climatic variability may mask the short-term perceived effectiveness of SAI. That is, it is possible that while SAI could successfully 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 (40, 41). Moreover, people who are residents of a specific location may tacitly incorporate 10-year trends in their perception of changes in climate (42). 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 (e.g., 19, 43, 44), the perception of failure carries particular risks.

If SRM is ever pursued, it will likely be for a specific social or geophysical aim (22). This may include halting an anticipated geophysical tipping point (such as accelerated Antarctic ice loss (45) permafrost melting or forest die-off), or lessening the impacts of extremes (such as deadly heat waves in large population centers (46)). 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 (47). 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 (48). 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 or Earth system models to simulate how the natural system may respond to different intervention approaches (49). Here, we leverage just one of them: the Assessing Responses and Impacts of SRM on the Earth system withStratospheric Aerosol Injection (ARISE-SAI) ensemble carried out with the Community Earth System Model, version 2 (50). ARISE-SAI simulates a plausible deployment of SAI, designed to hold global mean temperature at 1.5°C above pre-industrial conditions in the context of the SSP2-4.5 future emissions scenario (Fig. 1A) (50). Extending out to the year 2069, ARISE-SAI includes 10 ensemble members, each initiated from slightly different initial conditions to enable quantification of the irreducible uncertainty arising from internal climate variability (e.g., 51). The 1.5°C threshold is relevant for global policy discourse in part because this is a global mean temperature increase 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 (52). 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 useful testbed for probing the possibility 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., 48, 53). 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 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 trend threshold is chosen to reflect the approximate warming over the observational record (54); 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.

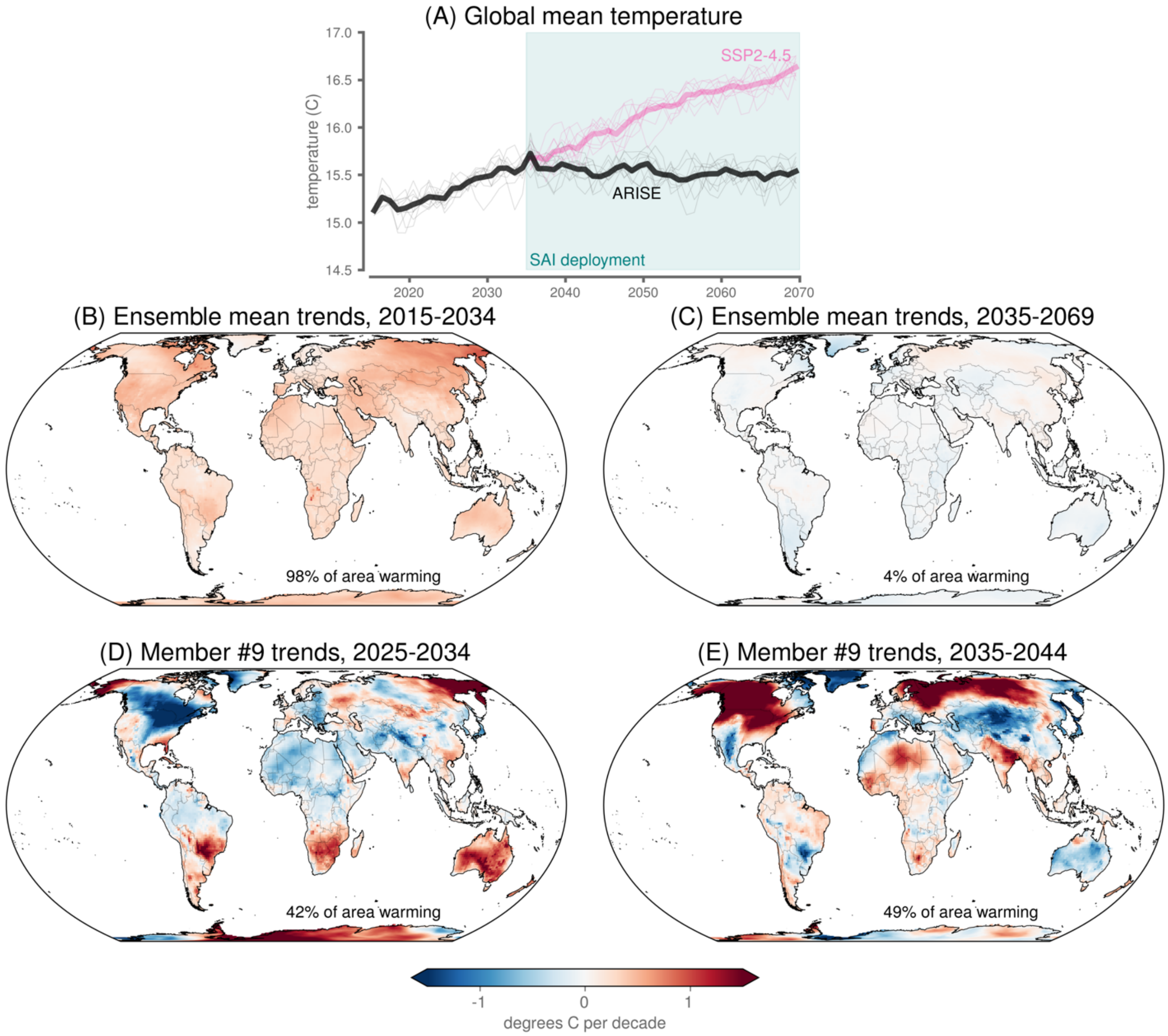

Figure 1. Surface temperature trends. (A) Global mean surface temperature. Gray lines denote individual ensemble members and the black line denotes the ensemble mean. (B,C) Ensemble-mean trends over (B) 2015-2034 under SSP2-4.5 and (C) 2035-2069 with ARISE-SAI deployment. (D,E) Trends over the (D) pre-deployment 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.

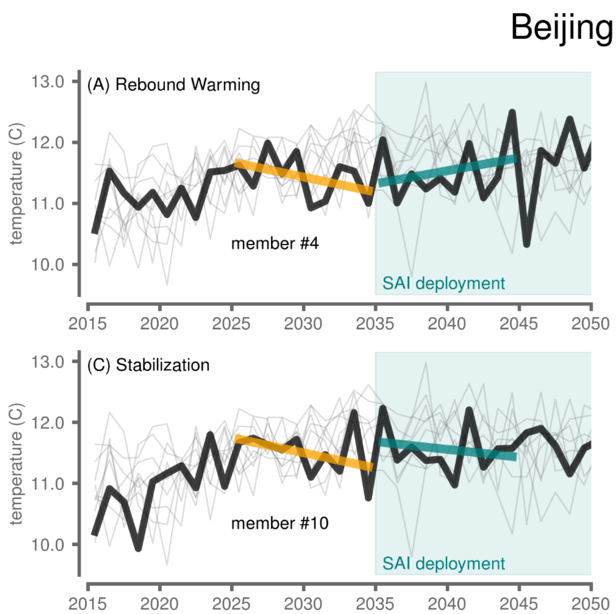

Figure 2. Pre-deployment and post-deployment surface temperature trends for Beijing, China. Each panel highlights a different ensemble member denoted in each panel by the thick black line, with the other nine members shown as thin gray lines. SAI deployment is initiated in the year 2035 (teal shading).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

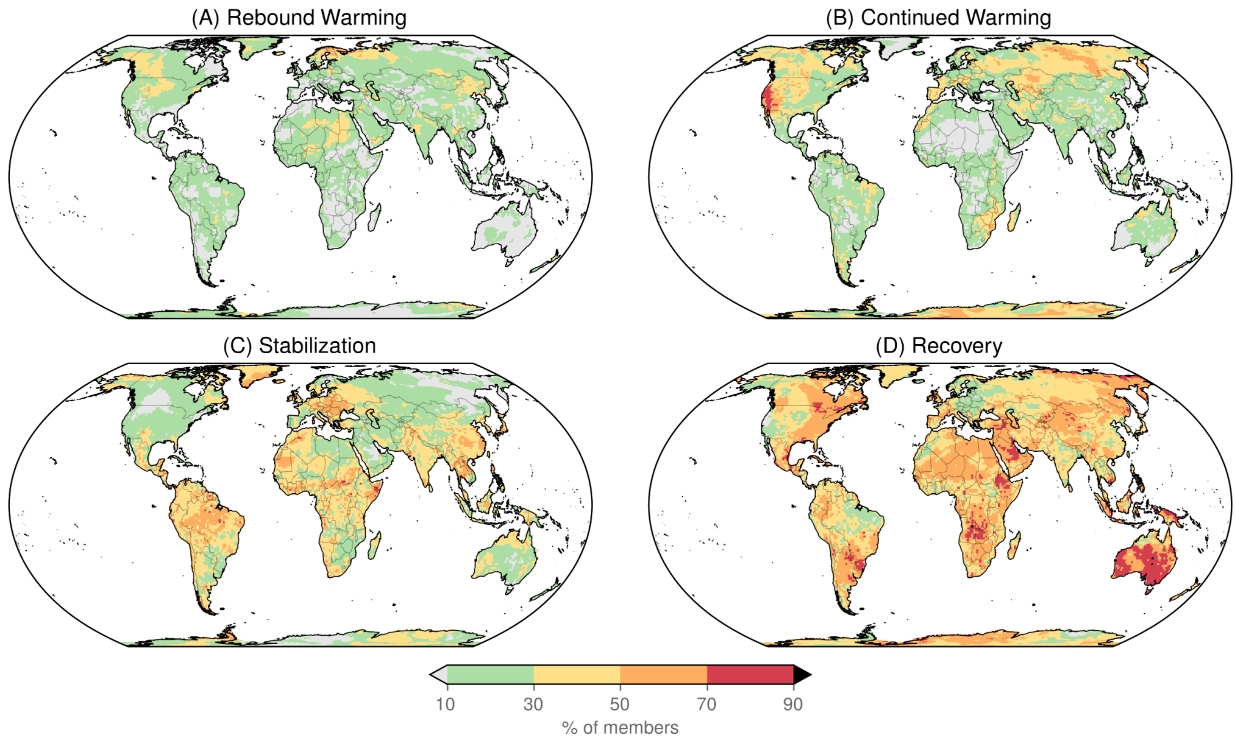

Figure 3. Archetypal regional responses to ARISE-SAI. The percent of ensemble members that exhibit specific archetypal responses over the ten years pre- and post-deployment: (A) Rebound Warming (not warming followed by warming), (B) Continued Warming (warming followed by warming), (C) Stabilization (not 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 percentages of 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 forced 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 in the ARISE-SAI experiment (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 (55) — 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 (56) – could be a key factor confounding the effects of climate intervention (Fig. S3).

We emphasize that these results are specific to the ARISE-SAI deployment, which is only one of many possible SAI deployment scenarios (e.g., 57). Regardless, they suggest that internal variability in the climate system, whether arising from random noise in the atmosphere or oceans (Deser et al. 2017) or from potentially predictable coupled ocean-atmosphere modes of variability, can effectively mask SAI deployment.

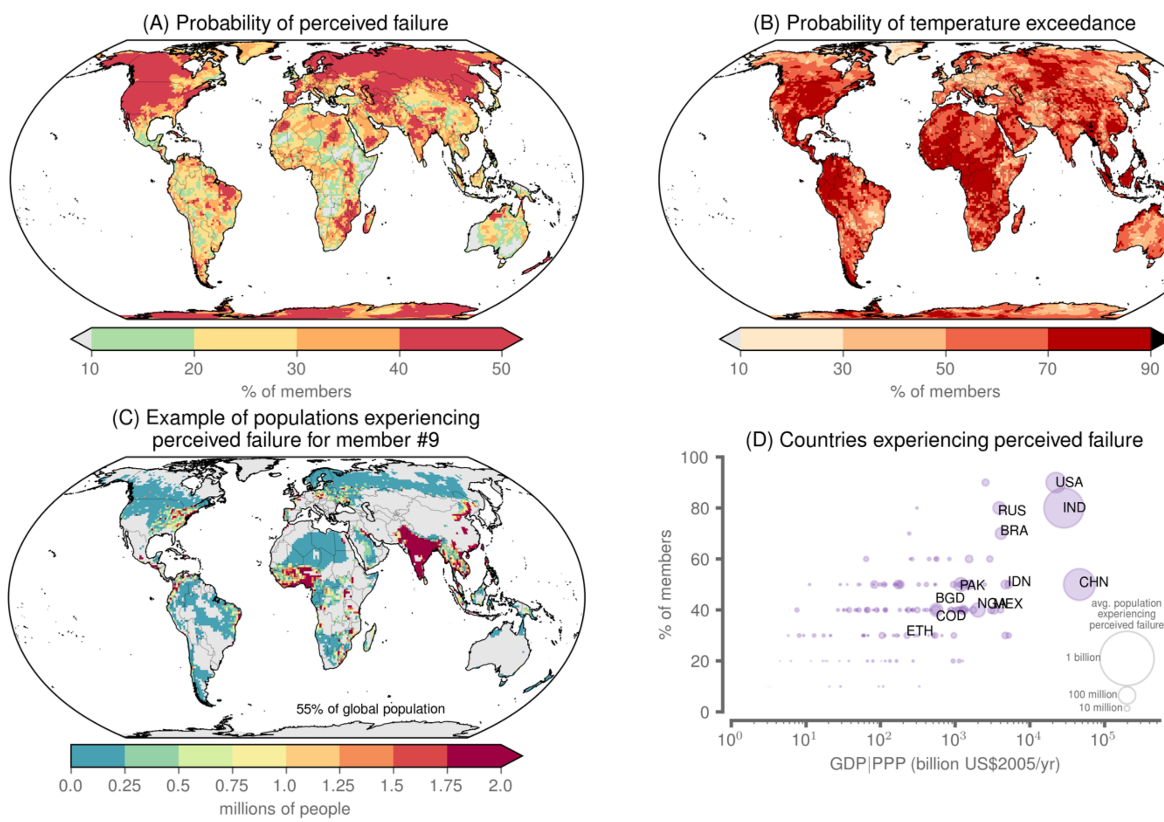

Figure 4. Perceived failure over the ten years following SAI deployment under ARISE. (A) Probability of perceived failure over the post-deployment period, where the probability is computed as the fraction of ensemble members exhibiting warming trends. (B) Probability of a location exceeding its 2015-2034 (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 (27, 58), 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). For example, for broad areas of Africa, Eurasia, North America, South America and Antarctica, at least one year in the decade after SAI deployment is hotter than the hottest year that occurred in 2015-2034. 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 (40), we next explore the populations exposed to perceived failure of SAI in the specific ARISE-SAI deployment scenario examined here. Using gridded population data projected for 2040 in SSP-2 (59, 60), 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 are exposed to the potential of perceived failure over the decade following ARISE-SAI deployment.

Perceptions of climate change-related phenomena can be related to both individual local experiences, as well as collective socio-cultural experiences (40, 61, 62). 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) (63). All of the largest economies in the world experience substantial probability of perceived failure in the post-deployment decade of ARISE-SAI (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 (64) — experience at least a 50% probability of large populations being exposed to the potential of perceived failure of SAI. These countries also cover substantial land areas, potentially increasing the odds that internal climatic variability could mask the benefits of SAI. Yet, the fact remains that the countries that are apparently most prone to high potential 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 (14, 24). However, we find that substantial areas of the world could experience warming trends and extremely hot years, even after ten years of continuous deployment in the ARISE-SAI scenario—raising the possibility that SAI may not be perceived locally as effective. Given the potential social, 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) (35, 64).

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 (65). Moreover, different types of SAI deployment scenarios could lead to different levels of masking (both more and less) of internal climate variability. However, this issue will also emerge in the midst of more general mitigation efforts (66), 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 (67). 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 (68).

To further explore the relevance of the perceived failure archetypes, we performed a similar analysis using data from the Geoengineering Large-Ensemble SAI experiment (GLENS-SAI; Tilmes et al. 2018). The results provide complementary insights into SAI deployed under a much higher emissions scenario (Representative Concentration Pathway 8.5; RCP8.5) and different stabilization targets and deployment year (deployment in the year 2020 with the main aim to keep global temperatures around 1°C above pre-industrial values). Because of this, GLENS-SAI represents a much more aggressive SAI scenario than ARISE-SAI. The GLENS-SAI results (see Supplementary Materials) again illustrate the regional significance of internal climate variability, and thus further indicate that the potential for perceived failure will exist across many different SAI deployment strategies.

Given that specific regions of the planet are predisposed to the effects of large internal climate variability, such as that produced by El Niño Southern Oscillation or the Pacific Decadal Oscillation (69), 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 (25, 26). 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 (70).

Conclusions

Our results 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 for a specific social or geophysical aim. Internal climate variability, however, may mask the short-term perceived effectiveness of that intervention, including in the targeted 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) (50). The ARISE ensemble was simulated with the Community Earth System Model, version 2 (71) using WACCM6 (Whole Atmosphere Community Climate Model Version 6, WACCM6) (72). 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) (72). Further details about the ARISE SAI configuration and aerosol injection strategy are provided in (50).

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).

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Supplementary Information for

Potential for Perceived Failure of Stratospheric Aerosol Injection Deployment

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

[1] Department of Atmospheric Science, Colorado State University
[2] School of Global Environmental Sustainability, Colorado State University
[3] Doerr School of Sustainability, Stanford University
[4] International Programs Department, United States Naval War College

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

Email: patrick.keys@colostate.edu

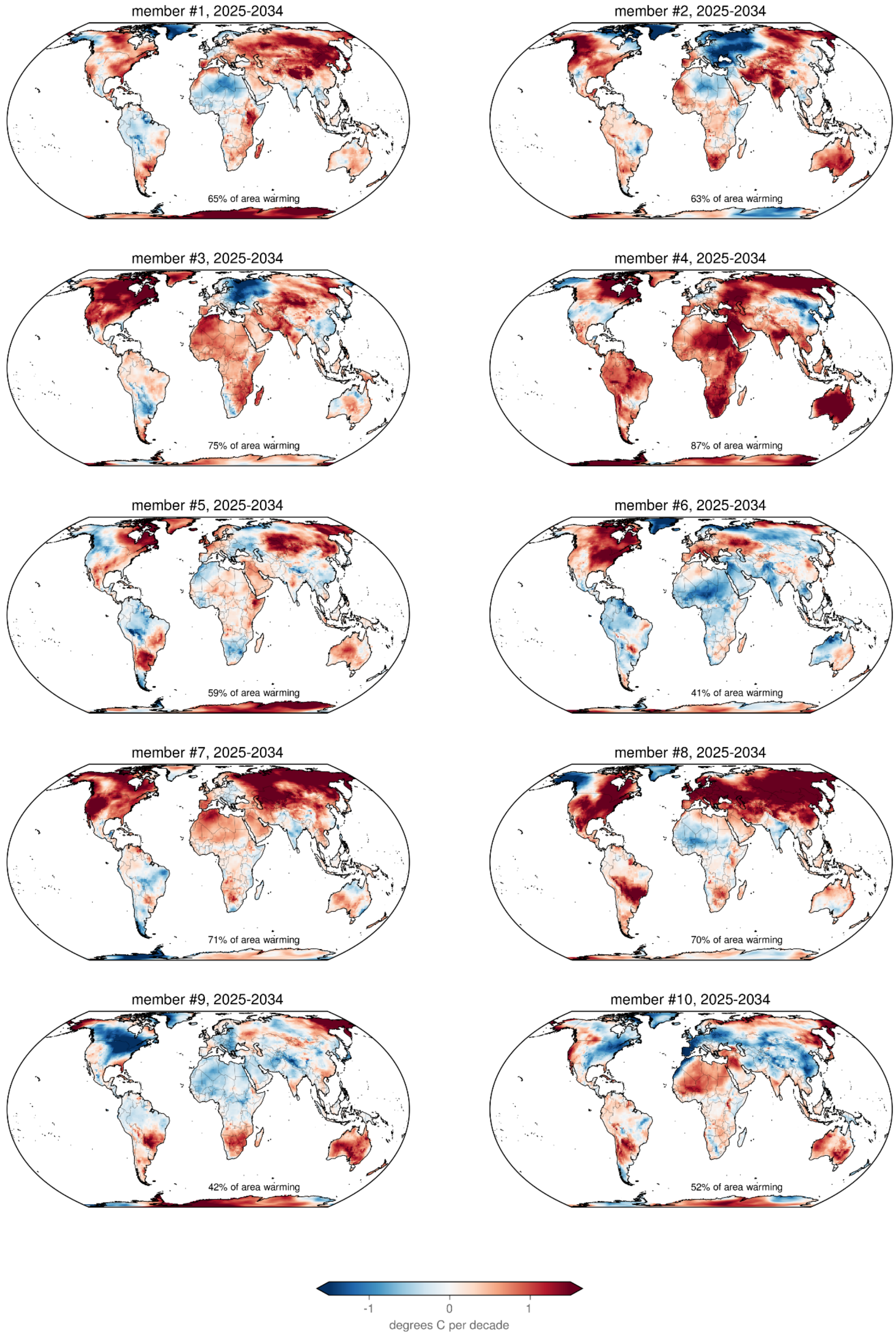

Fig. S1. As in Figure 1D but for all 10 ensemble members.

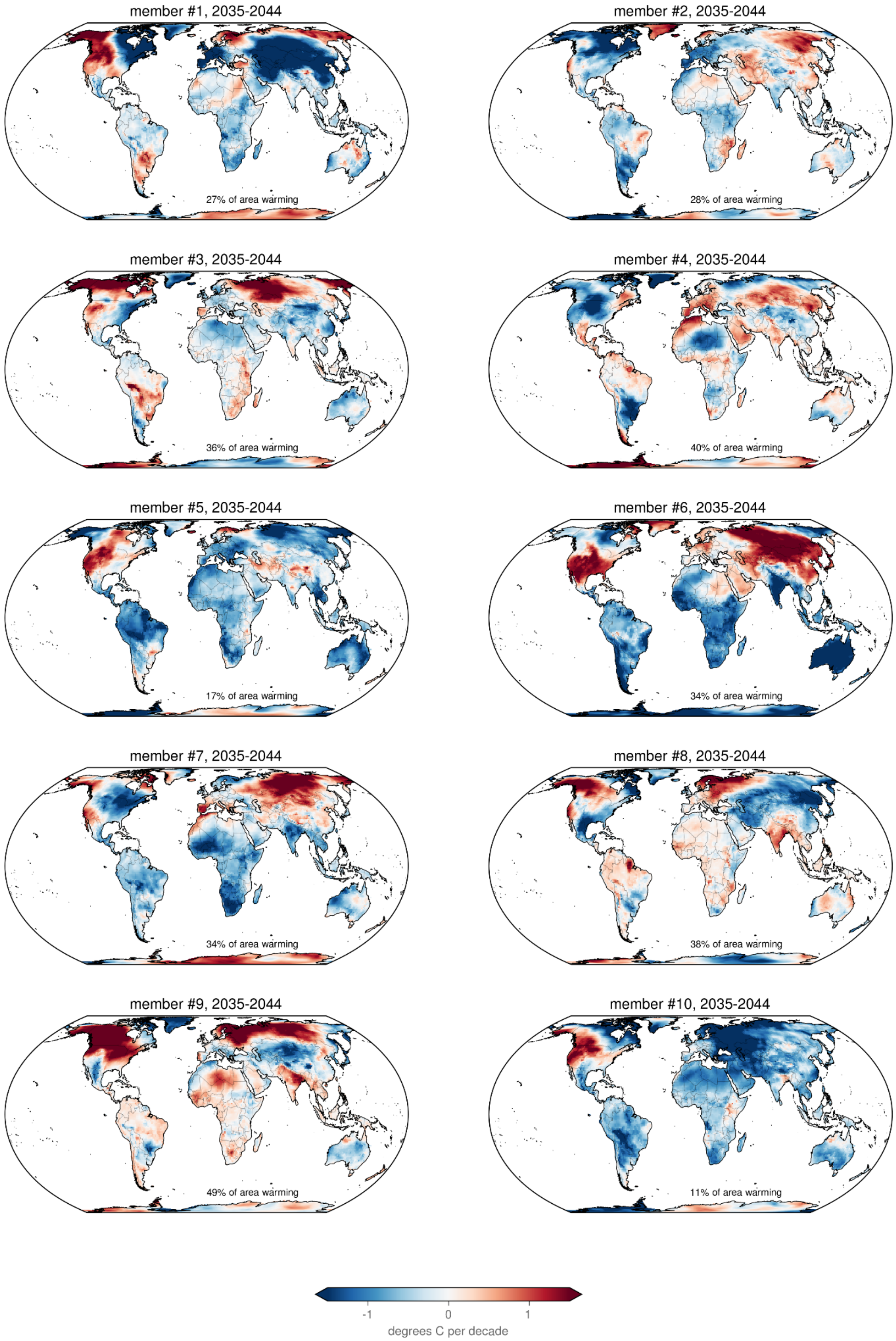

Fig. S2. As in Figure 1E but for all 10 ensemble members.

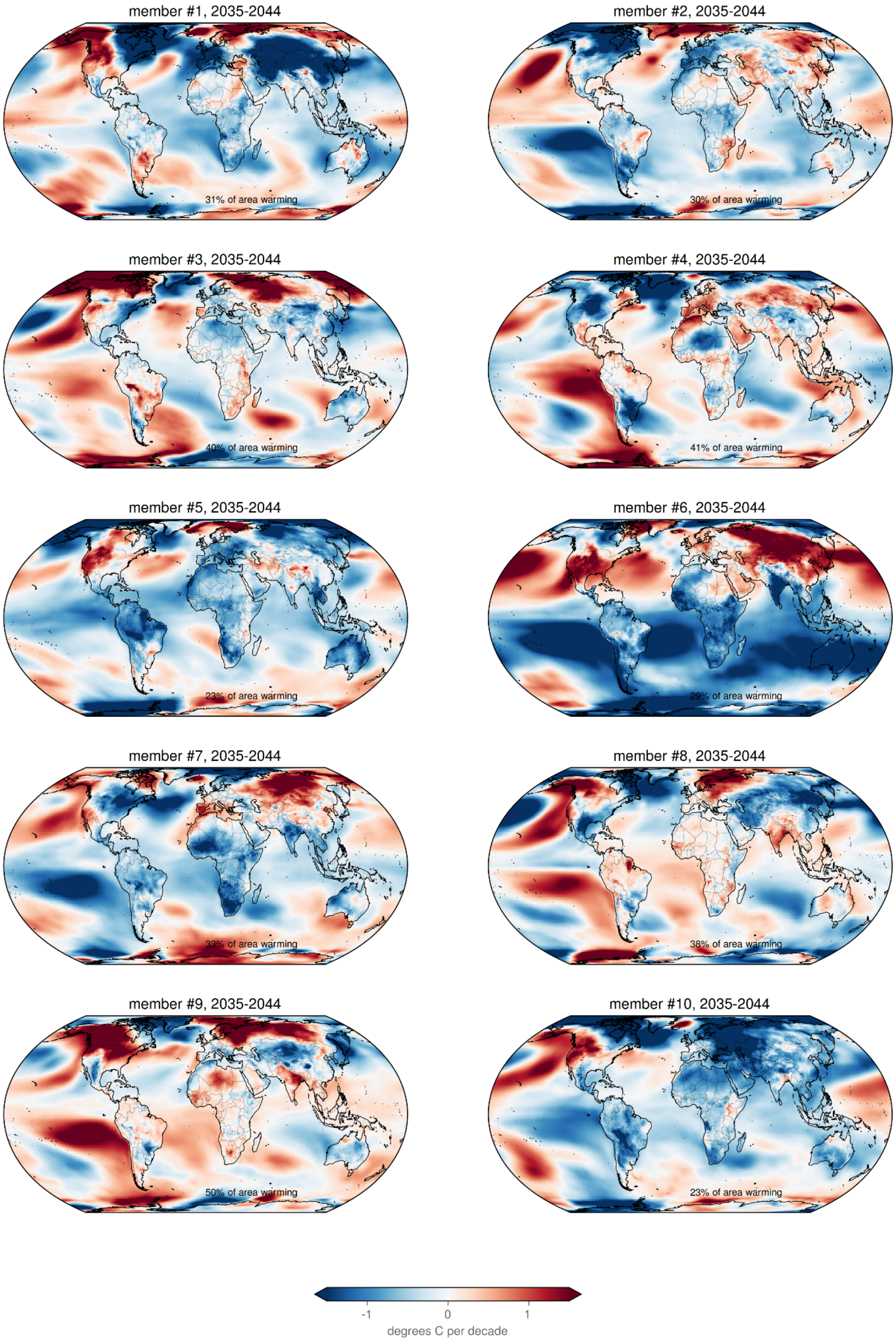

Fig. S3. As in Fig. S2 but including temperatures over the oceans.

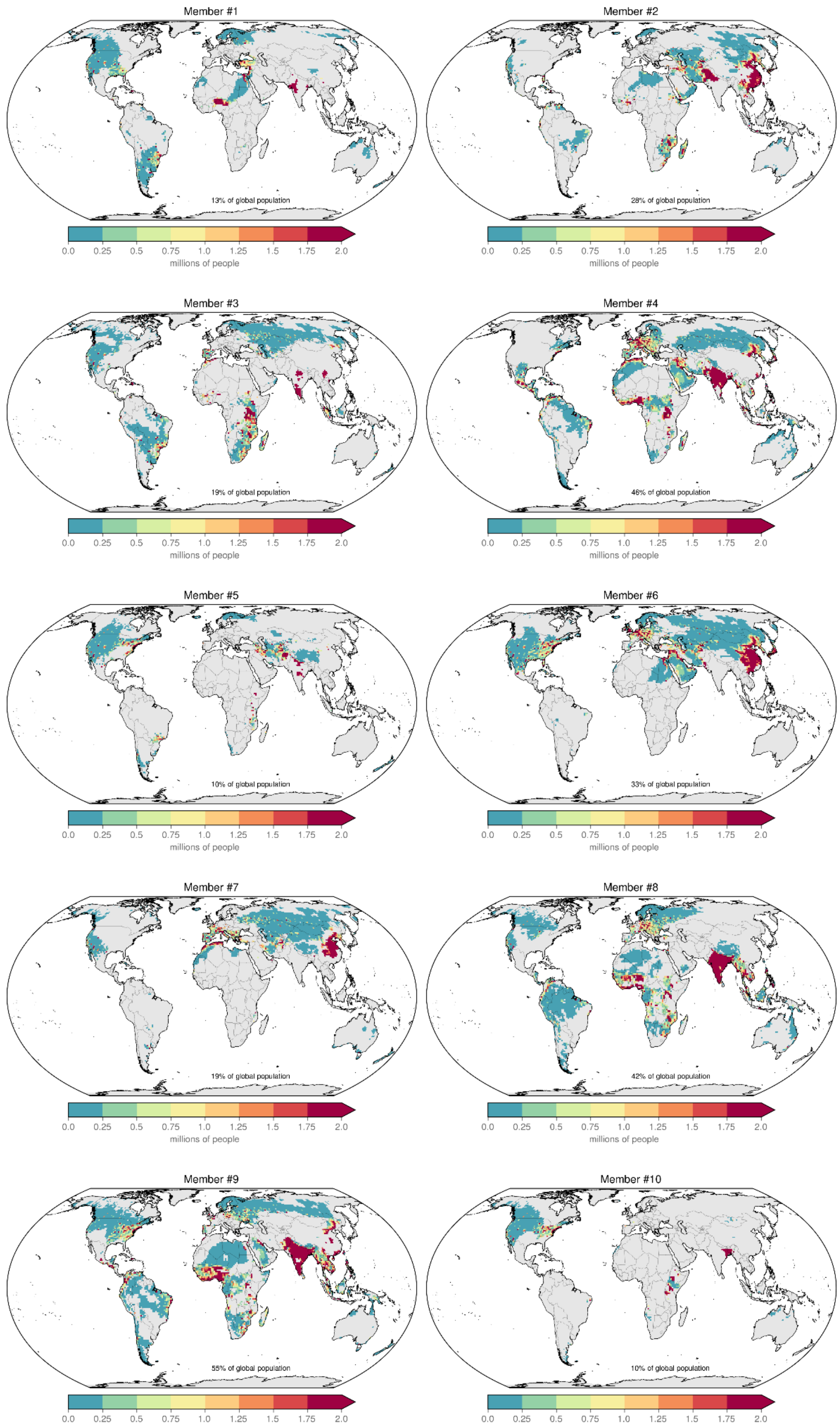

Fig. S4. As in Fig. 4A but for all 10 ensemble members.

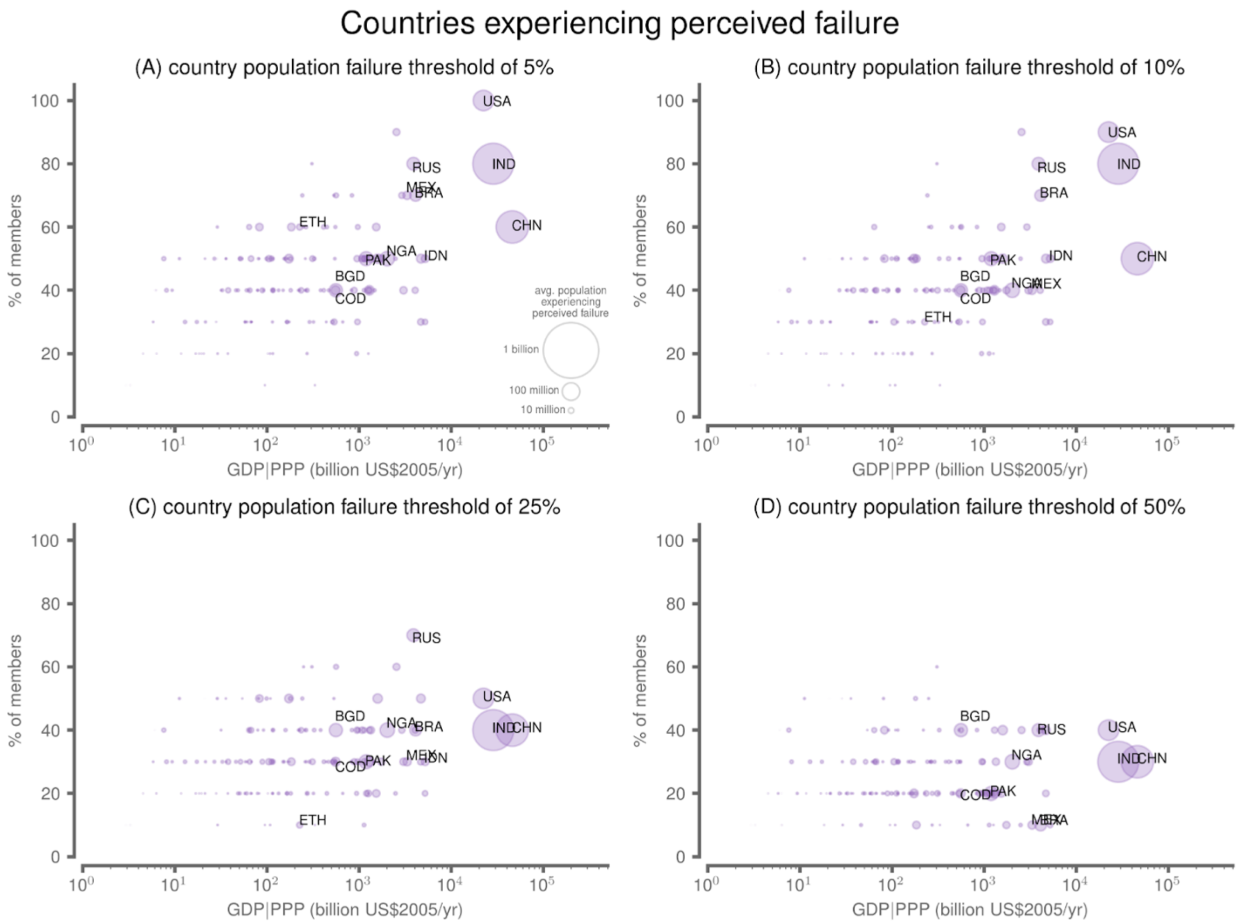

Fig. S5. As in Fig. 4B but for different population failure thresholds. The 10% threshold shown here in panel **(B)** is what is displayed in the main text.

Supplemental Methods

GLENS Data

Gridded, monthly near surface air temperature fields (variable name TREFHT) were obtained from the ensemble of simulations performed for the Stratospheric Aerosol Geoengineering Large Ensemble (GLENS-SAI) project (73). The GLENS-SAI ensemble was simulated with the Community Earth System Model, version 1, as described in (57). We average together the gridded, monthly fields to produce annual-mean fields, with each field having a grid resolution of 0.9 degrees latitude by 1.25 degrees longitude.

The GLENS-SAI data set includes two sets of simulations composed of twenty one ensemble members each. The first set follows the RCP8.5 emissions scenario while the second is identical to the first but with the inclusion of stratospheric aerosol injection (SAI) beginning in the year 2020. 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 2020. The 2020 mean conditions are calculated based on the first 13 members of the RCP8.5 scenario simulations. Further details about the GLENS-SAI configuration and aerosol injection strategy are provided in (73).

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 (2010-2019) and (2) the post-deployment decade (2020-2029). Since SAI under GLENS 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 20) that experience perceived failure at each location.

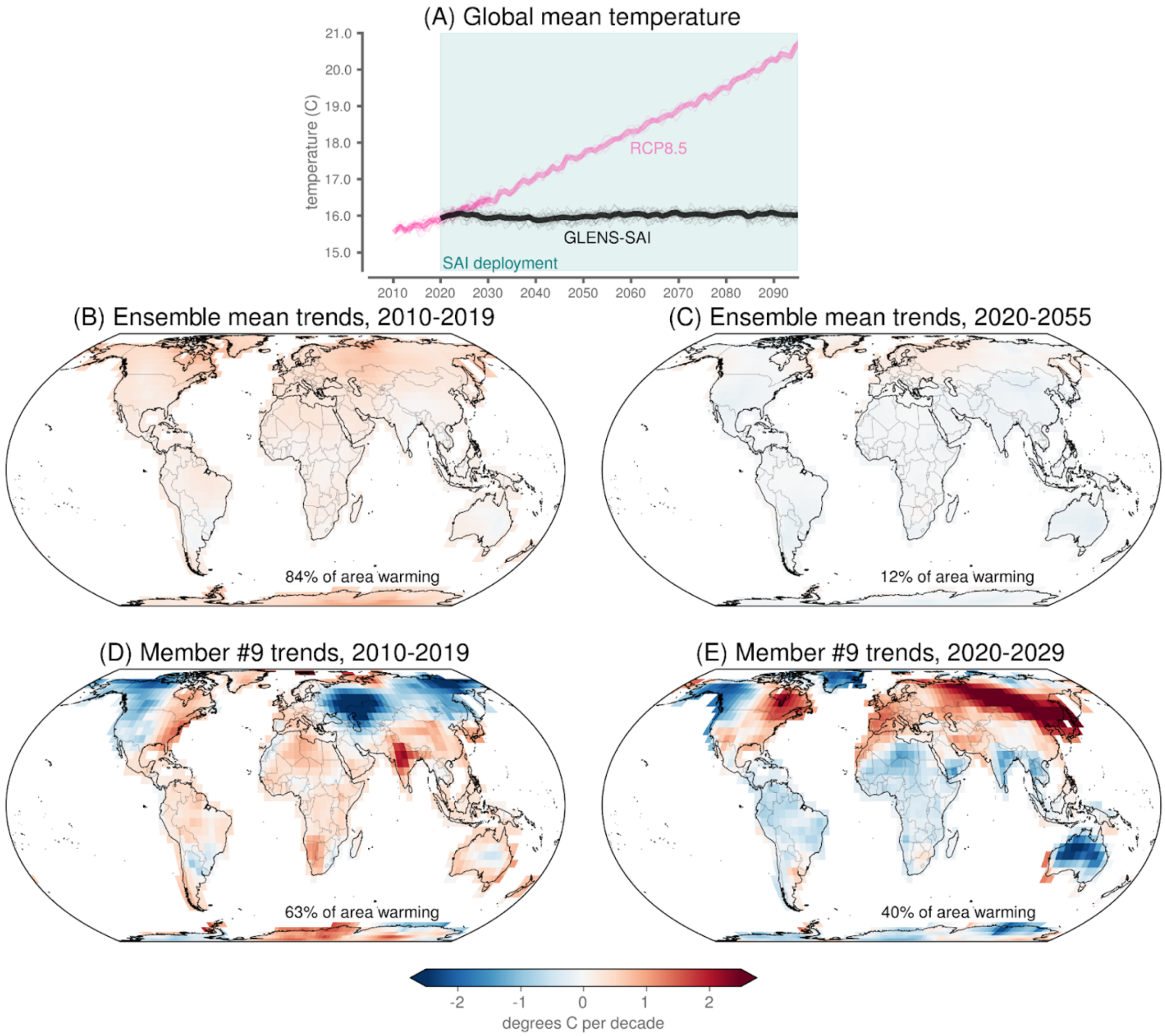

Figure S6. Surface temperature trends. (A) Global mean surface temperature. Gray lines denote individual ensemble members and the black line denotes the ensemble mean. **(B,C)** Ensemble-mean trends over **(B)** 2010-2019 under RCP8.5 and **(C)** 2020-2055 with GLENS SAI deployment. **(D,E)** Trends 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. Similar figure as in Figure 1 of the Main text.

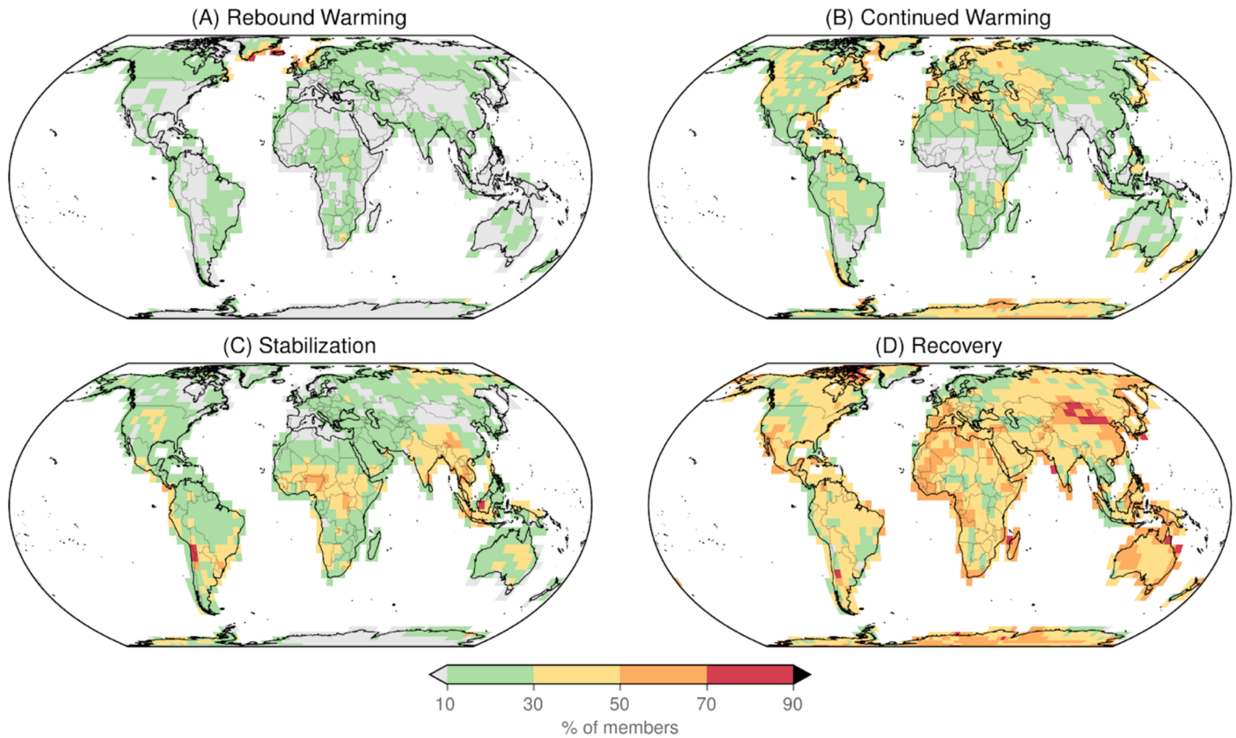

Figure S7. Archetypal regional responses to GLENS-SAI. The percent of ensemble members that exhibit specific archetypal responses over the ten years pre- and post-deployment: **(A)** Rebound Warming (not warming followed by warming), **(B)** Continued Warming (warming followed by warming), **(C)** Stabilization (not warming followed by not warming) and **(D)** Recovery (warming followed by not warming). Similar figure as in Figure 3 in the Main text.

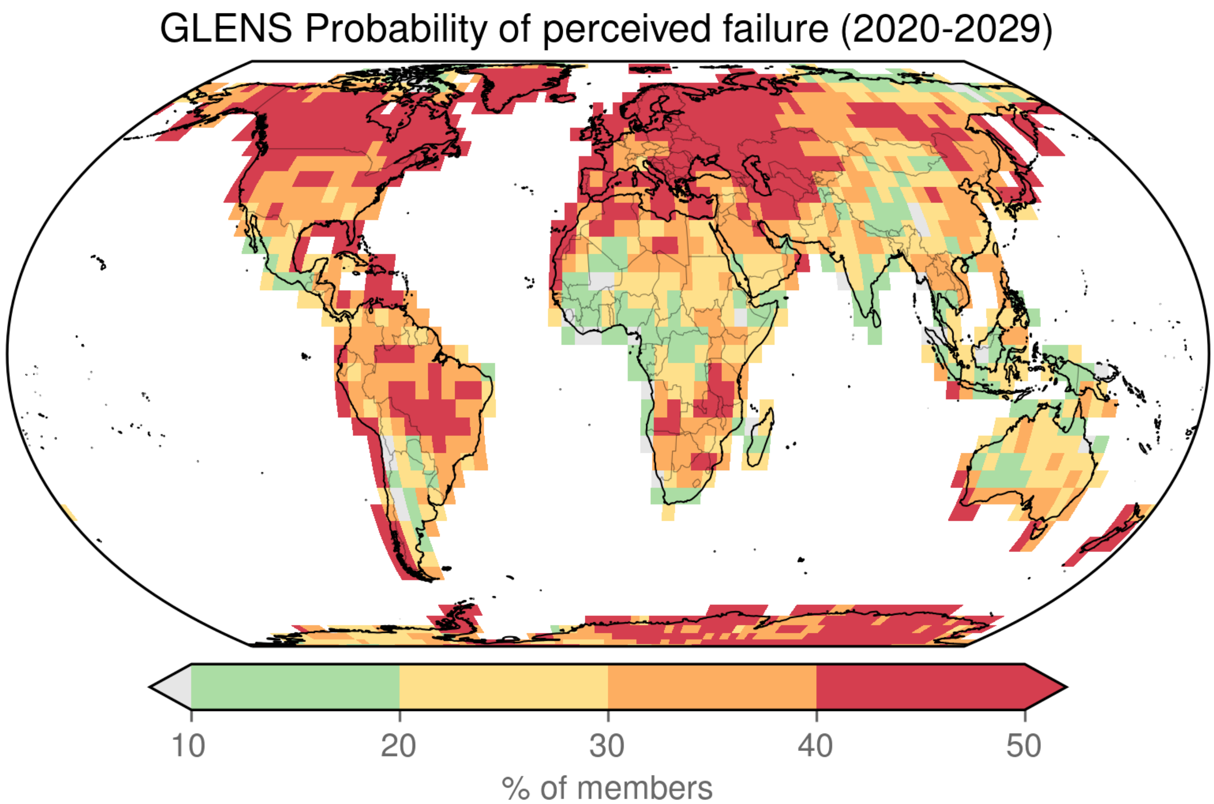

Figure S7. Probability of perceived failure under GLENS-SAI over the post-deployment period, where the probability is computed as the fraction of ensemble members exhibiting warming trends (similar to Figure 4A in the Main text).