

Quantifying the Risks of Stratospheric Aerosol Injection Termination Shock

Anthony Harding*

Jimmy and Rosalynn Carter School of Public Policy, Georgia Institute of Technology

September 1, 2026

Abstract

Climate-impact projections typically embed adaptation relationships estimated from historical climate variation, leaving uncertain how damages evolve when temperatures change much faster than historically observed. Abrupt termination of large-scale solar geoengineering provides an extreme case: temperatures could rebound within years to decades, pushing impact projections into rates of change with little historical analogue. Here, I develop an empirically grounded framework that uses empirically estimated adaptation to recent climate exposure to quantify the additional impacts associated with incomplete adaptation during rapid warming. Holding temperature exposure fixed while varying only the adaptation state isolates a maladaptation penalty: the excess mortality from remaining adapted to the cooler, geoengineered climate. Applied to temperature-attributable mortality in 24,378 global regions, sudden termination considerably increases impacts relative to the same warming reached gradually (10 versus 3 deaths per 100,000 per year per °C). Thus, damages depend on the pace of climate change, not only its magnitude, strengthening the case for gradual ramp-down over abrupt cessation in the context of solar geoengineering.

*tony.harding@gatech.edu

Introduction

A salient concern around solar geoengineering, particularly for global deployment, is that of abrupt and lasting suspension or termination of deployment, often referred to as *termination shock* or *termination shock risk*^{1,2}. There is evidence that solar geoengineering through stratospheric aerosol injection could moderate climate changes induced by a given concentration of greenhouse gases in the atmosphere^{3,4}. However, without dealing with the root cause of those climate changes, the atmospheric greenhouse gas (GHG) concentrations, solar geoengineering simply masks the underlying warming. The effects of solar geoengineering deployment are temporary – for example sulfate aerosols have an expected lifetime of 1-1.5 years when released in the stratosphere⁵⁻⁸. Thus, if deployment were to stop abruptly and underlying GHG concentrations had not sufficiently declined, then there would be rapid warming and temperatures would restore to levels consistent with the underlying GHG concentrations. This would all happen on the timescale of a decade or less⁹. Although the analysis below focuses on stratospheric aerosol injection, and I use “solar geoengineering” and “stratospheric aerosol injection” interchangeably from here onward unless otherwise noted, the risk of termination shock also applies to other forms of solar geoengineering, such as marine cloud brightening¹⁰, because the underlying mechanism is the same. Fig. 1 illustrates this rapid rise of global mean temperatures for the HadGEM2-ES climate model simulations following the sudden termination of stratospheric aerosol injection in 2070. Over the 10 years following termination, temperatures rise over 1°C, coming in line with the temperatures of the background RCP4.5 concentrations.

While *termination shock* is a salient concern, there is a dearth of research examining the subsequent impacts. A number of studies have examined the physical effects of sudden termination. Early climate modeling research of solar geoengineering through stratospheric aerosol injection, often proxied as solar dimming, identified the potential for rapid changes following termination. These studies find sudden termination could lead to global mean temperatures rising by as much as 2-10 times faster than in the case of no solar geoengineering^{11,12}.

This was further explored through experiments in the Geoengineering Model Intercomparison Project (GeoMIP)^{13,14}. Each of the G2, G3, and G4 experiments models the sudden termination of solar geoengineering at a future date. These experiments and the participating models have been leveraged to examine different physical climate responses and climate hazard responses to the sudden termination of solar geoengineering. Moore et al.¹⁵ examine the effect on Hurricane activity in the Atlantic using the G3 and G4 experiments. Bhowmick et al.¹⁶ examine the effect on the Indian monsoon using the G2 experiment. Other

ers have examined regional temperature and precipitation extremes over Africa and the Indonesian Maritime Continent under G4, including the post-termination period^{17,18}.

Yet, there is little work quantifying the subsequent impacts of a sudden termination of a large-scale solar geoengineering deployment. To date, there are only four papers, to the author’s knowledge, that empirically quantify the potential impacts of termination shock. Trisos et al.¹⁹ examine the potential ecological impacts of termination shock by estimating the impact on temperature and precipitation velocities. Xia et al.²⁰ examine the potential agricultural impacts of termination shock in China using the Decision Support System for Agrotechnology Transfer crop model. Zhan et al.²¹ examine the potential agricultural impacts of termination shock in China using the ORYZA version 3 crop model. Estrada et al.²² examine the potential economic impacts of abrupt warming following sudden termination of solar geoengineering by developing a damage function that mixes separable non-catastrophic and catastrophic parameters. Yet the effects of rate-of-change enter as an exogenously parameterized risk of catastrophic damages rather than being disciplined by empirical estimates of adaptation. The framework below instead bounds rate-of-change damages using econometrically estimated heterogeneity in exposure–response functions with respect to recent climate.

Here, I propose a novel approach to quantifying the impacts of termination shock from empirically based estimates of climate impacts. A key challenge in quantifying the impacts of termination shock is that most empirical estimates of climate impacts assume gradual changes in climate that are consistent with historical observations. In this way, impacts depend only on the level changes, not the rate of change. Further, minimal variability in historical rates of change makes it difficult to recover a statistically significant effect of rates of change on outcomes of interest. While this approach is sufficiently suited to evaluate long-run climate change, it is less informative for situations in which temperatures change rapidly. For termination shock, the salient concern regarding the physical climate response is not just the level changes but the rate of change. More generally, this illustrates a broader issue in climate risk assessment: damages depend not only on how much the climate changes but on how quickly it changes relative to the pace of adaptation. Termination shock represents an extreme but informative case of this broader phenomenon. The core of the idea I propose is to constrain the potential additional effects driven by the rate of climate changes above and beyond the level changes by leveraging estimated information about adaptation to recent climate exposure from climate econometric models. By demonstrating how empirically estimated adaptation can be used to constrain rate-of-change damages, this work contributes to ongoing efforts to better account for adaptation limits and

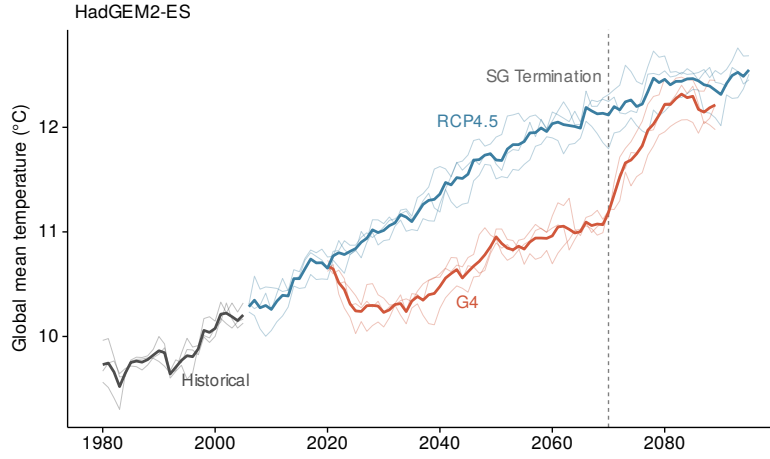


Fig. 1 | Termination Shock. Global mean surface temperatures across climate model experiments and ensemble members for the HadGEM2-ES climate model. Historical is shown in black, RCP4.5 is shown in blue, and G4 is shown in red. Darker lines indicate annual average across the three ensemble members, while lighter lines indicate individual ensemble member runs. Plots are for global mean surface temperature after downscaling and bias correction (See [Methods](#)). The termination of SG in 2070 for the G4 experiment is denoted by the vertical dashed line.

transient risks in climate impact modeling.

Model

Adaptation is a costly process that inherently unfolds over time. It depends on factors such as infrastructure development, behavior changes, economic resources, and governance capacity, all of which have inertia. When warming occurs gradually, societies may have time to develop and adjust adaptation mechanisms. When warming is abrupt, and perhaps even more so when it is unexpected, the rate of change can overwhelm physiological tolerance, disrupt ecological and social systems, and outpace adaptive responses. Infrastructure built for a cooler climate may become inadequate faster than it can be replaced; public health systems may be caught off-guard by an unanticipated surge in heat-related illness; and behavioral norms may lag behind the climatic reality.

Here, I develop an empirically grounded framework to quantify termination shock impacts as a problem of excess impacts caused by *maladaptation*—the failure or inability to adapt following a sudden change. After abrupt warming, populations are exposed to a warmer climate while remaining adapted to the cooler climate that preceded termination. I use climate-econometric estimates of adaptation to recent climate exposure to distinguish these short-run impacts from the long-run impacts that would occur after adaptation to the warmer climate, thus bounding the additional damages from the rate-of-change. Here, I use the impact sector of temperature-attributable mortality as a setting to illustrate the methodology, but the framework could be applied to other impacts.

As a motivating illustration of this approach, rather

than thinking about changes across time, let us consider differences across space. Let us compare Mumbai, India and Boston, USA. Fig. 2a plots the empirically estimated temperature-attributable mortality exposure response curves for the respective regions. One can see that Boston, which is exposed to a colder climate as illustrated by the distribution of temperatures in Fig. 2b, is adapted to a colder climate with a minimum mortality temperature—the temperature that minimizes temperature-attributable mortality rates—of just under 20°C. On the other hand, Mumbai, which is exposed to a warmer climate, has a minimum mortality temperature of around 27°C.

An intuitive, though extreme, illustration of the impacts of termination shock is to consider suddenly exposing the population of Boston to the temperatures of Mumbai versus exposing the population of Mumbai to the temperatures of Mumbai. This is shown in Fig. 2c. In orange is the distribution of temperature-attributable mortality for Mumbai exposed to Mumbai temperatures. This represents the long-run impact of warming if the population of Boston were given time to adapt to the climate as the population of Mumbai has. In this case, temperature-attributable mortality rates actually fall by 16 deaths/100,000/year relative to the temperature-attributable impacts of Boston, shown in blue. In purple is the (extreme) illustrative example of termination shock. Exposing the population of Boston to Mumbai temperatures without allowing any adaptation increases temperature-attributable mortality rates by 82 deaths/100,000/year. Comparing these two impacts illustrates how important a factor adaptation, and thus the rate-of-change in temperatures, can be. This *maladaptation* penalty, in grey, is 98 deaths per 100,000 per year. Ignoring this factor would greatly underestimate the impacts of the warming. The compar-

ison therefore illustrates the central bounding strategy of holding temperature exposure fixed while varying the adaptation state. The difference in mortality isolates the penalty associated with maladaptation. Because the Boston–Mumbai comparison also confounds differences in the regions’ incomes and population age distributions, it is intended only as a motivating illustration; I implement the same comparison formally below using common populations and climate-model experiments.

I formalize this comparison by letting $M(T^X; A^Y)$ be the impact, say on mortality rates, of temperatures under climate state X given regions are adapted to climate state Y . The difference in impacts under a climate change climate state (CC) given adaptation to that state and impacts under a solar geoengineered climate state (SG) given adaptation to that state represents the long-run impacts.

$$\Delta M^{\text{Long-run}} = M(T^{CC}; A^{CC}) - M(T^{SG}; A^{SG}) \quad (1)$$

Alternatively, if temperatures rapidly transition from those under a solar geoengineered climate state to those experienced under a climate change climate state such that adaptation cannot occur, those termination shock impacts can be represented as:

$$\Delta M^{\text{Termination Shock}} = M(T^{CC}; A^{SG}) - M(T^{SG}; A^{SG}). \quad (2)$$

Putting these together, the additional impacts of maladaptation, a plausible upper bound of the additional impacts due to the rate-of-change following sudden termination of solar geoengineering, can be represented as the difference between the short-run termination shock impacts and the long-run impacts of transitioning between climate states.

$$\Delta M^{\text{Maladaptation}} = \Delta M^{\text{Termination Shock}} - \Delta M^{\text{Long-run}}. \quad (3)$$

To implement this framework, I combine climate econometric impact functions that incorporate a climate adaptation channel with output from Earth system model experiments (See [Methods](#)). Specifically, I focus on a climate econometric model of temperature-attributable mortality estimated by Carleton et al.²³ as an illustration of the framework, though it could be applied in other impact settings.

For Earth system model experiments, I consider two different modeling settings. First, I consider time invariant climate model runs from the GFDL-FLOR model that simulate a 1990s baseline climate (CTL), an experiment with a doubling of atmospheric CO₂ concentrations (2xCO₂), and a doubling of atmospheric CO₂ concentrations offset by a globally uniform solar constant reduction of 1.7% (SG).²⁴ Being time-invariant, this model does not explicitly simulate the termination of SG and the evolution of climate changes that follow. Instead, I model termination shock as an instantaneous shift from exposure to the SG experiment to exposure to the 2xCO₂ experiment while still

being adapted to the climate of the SG experiment. While imperfect in simulating the dynamics of termination shock, the long time-invariant runs from the GFDL-FLOR model provide better statistical precision than time-varying models of termination shock.

As an alternative, I also estimate impacts under the time-varying GeoMIP G4 experiment, which does simulate the dynamics following termination shock, though at the expense of statistical precision. The GeoMIP G4 experiment simulates a background of Representative Concentration Pathway 4.5 (RCP4.5) concentrations and injection of 5 Tg SO₂ per year at the equator in the years 2020 through 2070, after which injection is suddenly stopped^{13,14}. I use two participating climate models—HadGEM2-ES²⁵ and CanESM2²⁶—and their corresponding ensemble member runs. To capture the impacts of termination shock, one could compare the decade immediately preceding termination (2060–2069) to a decade following termination (2080–2089), when temperatures have approximately returned to temperatures observed in the background no solar geoengineering scenario. The maladaptation penalty from the rate-of-change can be captured by comparing impacts under RCP4.5 and under the G4 experiment in a decade following termination (2080–2089). Throughout, I account for both econometric and climate model uncertainty through Monte Carlo simulations, sampling across econometric uncertainty and model years for GFDL-FLOR and climate model ensemble members for time-varying climate models.

Results

Global Impacts

Let us start with the global temperature-attributable impacts (Figure 3). For the time-invariant GFDL-FLOR climate model simulations, sudden exposure to 2xCO₂ temperatures of a world adapted to SG temperatures increases global temperature-attributable mortality by 10 deaths/100,000/year/1°C (90% CI: -4 to 25) under 2080 SSP3 incomes and population distribution, a plausible timeline for termination shock. Long-run impacts are considerably smaller at 3 deaths/100,000/year/1°C (90% CI: -9 to 17). Taking the difference between these, I find that the additional impacts caused by maladaptation are 6 deaths/100,000/year/1°C (90% CI: -2 to 10). Under 2015 incomes, impact levels are considerably higher, with termination shock impact of 21 deaths/100,000/year/1°C (90% CI: 2 to 43), highlighting the sensitivity of the termination shock impacts to income levels. However, the relative impact of maladaptation to long-run impacts remains consistent, 9 deaths/100,000/year/1°C (90% CI: 4 to 15) and 12 deaths/100,000/year/1°C (90% CI: -5 to 32), respectively. These results indicate that accounting for the suddenness of termination shock can as much as double temperature-attributable impacts.

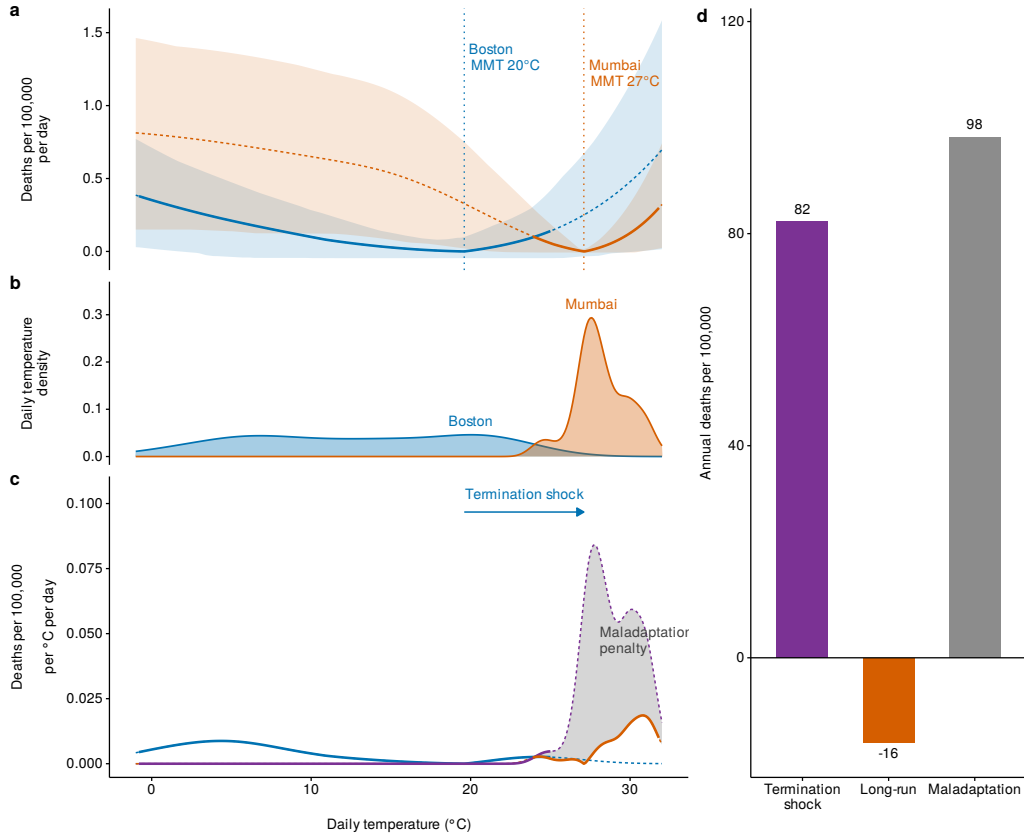


Fig. 2 | Illustrative example. Using HadGEM2-ES daily temperatures for Boston and Mumbai in 2010–2019, the figure contrasts mortality under different combinations of temperature exposure and adaptation state. **a** Population-age-weighted temperature-attributable mortality exposure-response functions, with 90% uncertainty intervals and minimum-mortality temperatures. Solid lines indicate temperatures within each city’s support and dashed lines indicate extrapolation. **b** Distributions of daily temperature for 2010–2019. **c** Distribution of temperature-attributable mortality across daily temperature distributions. **d** Decomposition of annual temperature-attributable mortality impacts. Across subpanels, Boston is shown in blue, Mumbai is shown in orange. In subpanels **c** and **d** mortality impacts of termination shock, represented by applying Mumbai temperatures to Boston’s exposure-response function, are shown in purple and increases in mortality rates due to maladaptation are shown in grey.

These impact estimates from the time-invariant GFDL-FLOR model are likely an overestimate for at least two reasons: the transition to higher 2xCO₂ temperatures from SG temperatures is assumed to be instantaneous, and the change in climate states is extreme, which, when interacted with a nonlinear impact function, can generate large impacts. The time-varying climate models relax both of these factors.

Under SSP3 income and population, I estimate the impacts of termination shock, measured as the difference in mortality rate impacts from just before termination shock 2060–2069 to 10 years after termination 2080–2089 under the G4 experiment. For HadGEM2-ES, the impact of termination shock is 11.2 deaths/100,000/year (90% CI [-7.9 to 37.6]). For CanESM2, the impact is smaller at 5.8 (90% CI [-6.2 to 21.8]). This smaller impact of termination shock is likely due to the smaller change in temperatures following termination since the deployment of solar geoengineering in CanESM2 has a smaller effect on global tem-

peratures than under HadGEM2-ES (Extended Data Fig. 2).

A decade after the termination of solar geoengineering in the G4 experiment (2080–2089), temperatures have risen sharply from pre-termination levels, approaching but still slightly below RCP4.5 temperatures in that decade. For the temperature-attributable mortality, I define impacts as relative to a counterfactual of no climate changes beyond the 2000–2009 state. I find that the impacts under the G4 experiment for the decade after termination are roughly comparable to the impacts in the RCP4.5 experiment, 9.7 deaths/100,000/year (90% CI [-20.2 to 51.7]) for HadGEM2-ES and 2.6 deaths/100,000/year (90% CI [-18.0 to 31.5]) for CanESM2. The impacts being comparable despite global temperatures still being slightly lower for the G4 experiment indicates that, while the effect of maladaptation is not as large as it was in the GFDL-FLOR estimates, they are still larger than 0.

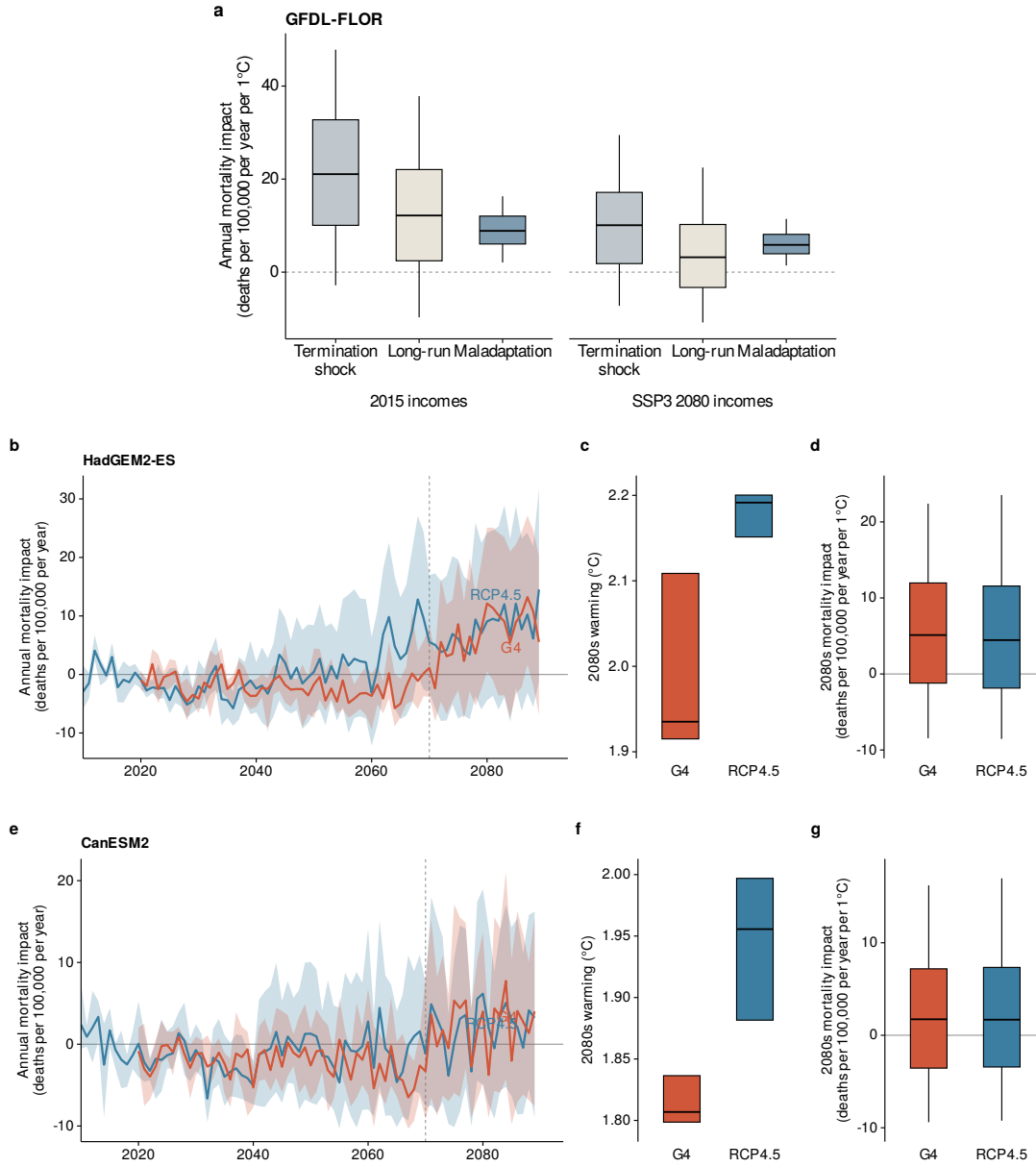


Fig. 3 | Global Temperature-Attributable Impacts. Impacts for **a** GFDL-FLOR climate model, **b-d** HadGEM2-ES climate model, and **e-g** CanESM2 climate model. **a** impacts of termination shock, long-run, and maladaptation penalty based on 2015 income levels and SSP3 income levels. For all box-and-whisker plots, the thick horizontal line represents median estimates, the box shows the interquartile range, and lines show the 90% confidence interval. **b** and **e** plot the impact of temperature changes relative to 2000-2009 under the RCP4.5 and G4 experiments for the respective climate models under SSP3 income and population scenarios. The solid lines represent median estimates, and the shaded areas represent the 90% confidence interval. The vertical grey dashed line in 2070 denotes the termination of solar geoengineering deployment in the G4 experiment. **c** and **f** illustrate the differences in average temperatures in 2080-2089 under the G4 and RCP4.5 experiments relative to the 2000-2009 benchmark. **d** and **g** illustrate the mortality rate impacts averaged 2080-2089 relative to the average global mean surface temperature change from the 2000-2009 benchmark.

Regional Impacts

Next, let us consider the regional impacts of termination shock. To decompose these regional impacts, let us return to the two regions from the illustrative example above, Boston and Mumbai. Fig. 4 plots the short-run termination shock impacts, long-run impacts, and maladaptation penalty for each of the respective regions for the GFDL-FLOR climate model experiment.

For both regions, the impact of termination shock is above the long-run impact, less negative in the case of Boston and more positive in the case of Mumbai. The difference between these impacts thus gives a positive maladaptation penalty for both regions. As with the global impacts, the level impacts, both short-run and long-run as well as the maladaptation penalty, are larger with lower 2015 income levels than under higher

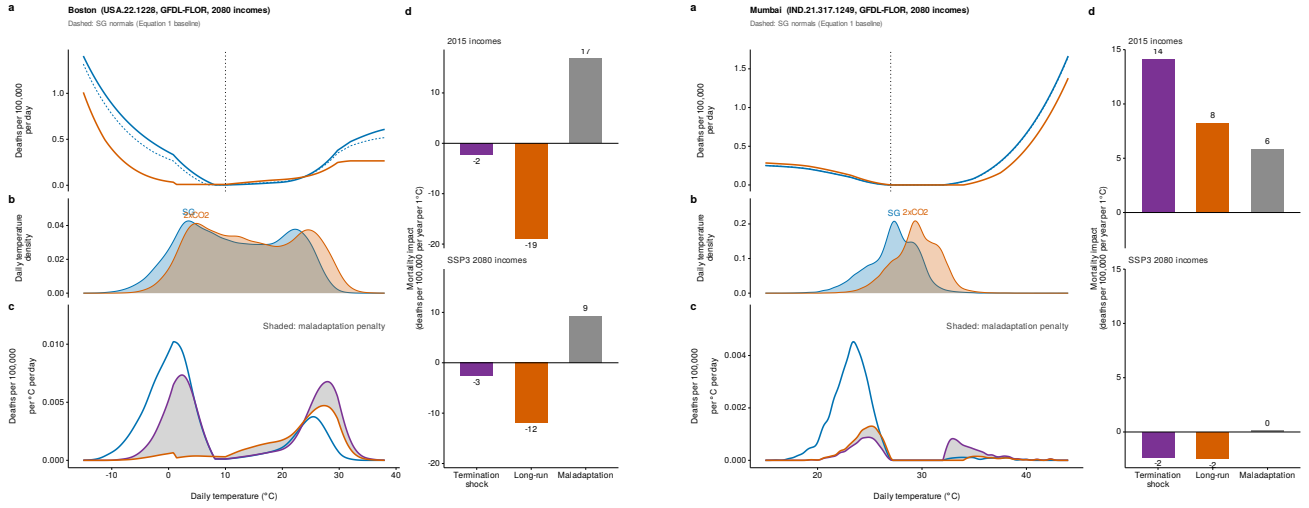


Fig. 4 | Decomposition of regional termination shock impact. Impacts based on GFDL-FOR climate model. **a** Population-age-weighted temperature-mortality response functions and minimum-mortality temperature. **b** Distributions of daily temperatures under 2xCO₂ and 2xCO₂+SG experiments. **c** Mortality impacts for Mumbai when adapted to the respective climate experiment (blue and orange) and when maladapted to the SG experiment and exposed to 2xCO₂ temperatures (purple). **d** Annual mortality impact decomposition, where termination shock equals the long-run effect plus maladaptation.

2080 income levels.

Now let us consider the impacts across all 24,378 impact regions modeled (Fig. 5). As found in Carleton et al.²³ (and Harding et al.²⁴), increases (decreases) in global mean temperature have a heterogeneous impact on temperature-attributable mortality across regions. For both the termination shock impact and the long-run impact, warming, generally, increases temperature-attributable mortality rates in hotter, poorer regions, while it can reduce temperature-attributable mortality rates in colder, richer regions. Comparing these two, the additional impacts of maladaptation under termination shock relative to the long-run lead to an increase in temperature-attributable mortality in the majority of regions (76% of the global population for median maladaptation impact and 78% for mean impact). Regions that suffer from warming suffer even more when it happens quickly, while regions that benefit from warming do not benefit as much.

These regional findings are qualitatively consistent for the time-varying experiments under the HadGEM2-ES climate model (Extended Data Figure 3) and the CanESM2 climate model (Extended Data Figure 4). Yet, additional impacts of maladaptation across regions are not as clear because termination shock and long-run impacts are not directly comparable. Global temperatures in the 2080s under G4 are still below the RCP4.5 temperatures for both climate models, which would lead to lower global impacts under G4, all else equal.

Discussion

Limitations

The framework and analysis considered in this paper are not without limitations. In Table 1, I outline a few of the key limitations and sign the expected bias when possible. I separate these into limitations of the Framework, the econometric methodology applied in Carleton et al.²³ as applied to this analysis in particular, and of the analyses conducted above.

Starting with the limitations of the framework, a key limitation is that termination is treated as exogenous and unanticipated. This is perhaps a realistic assumption in some scenarios, such as intentional destruction of deployment infrastructure, global catastrophe, or sudden and unexpected political termination¹. But, if the termination were planned and, further, gradual rather than binary, it could be expected that the estimates captured in the framework above would overstate the impacts of termination shock and maladaptation. Instead, if termination were anticipated, adaptive capacity could be invested in and positioned prior to termination, which would moderate the impacts of termination. Yet, this would come at a cost, as would any adaptation investment immediately following a sudden termination shock. The framework above does not consider the costs of any such adaptation or defensive costs, and, in this way, is likely an underestimate of the total costs of termination shock. Relatedly, I also assume that any termination is permanent. If it were instead temporary, for example lasting only a year or two before deployment resumes, impacts would likely be smaller.

Next, there are limitations of the econometrics ap-

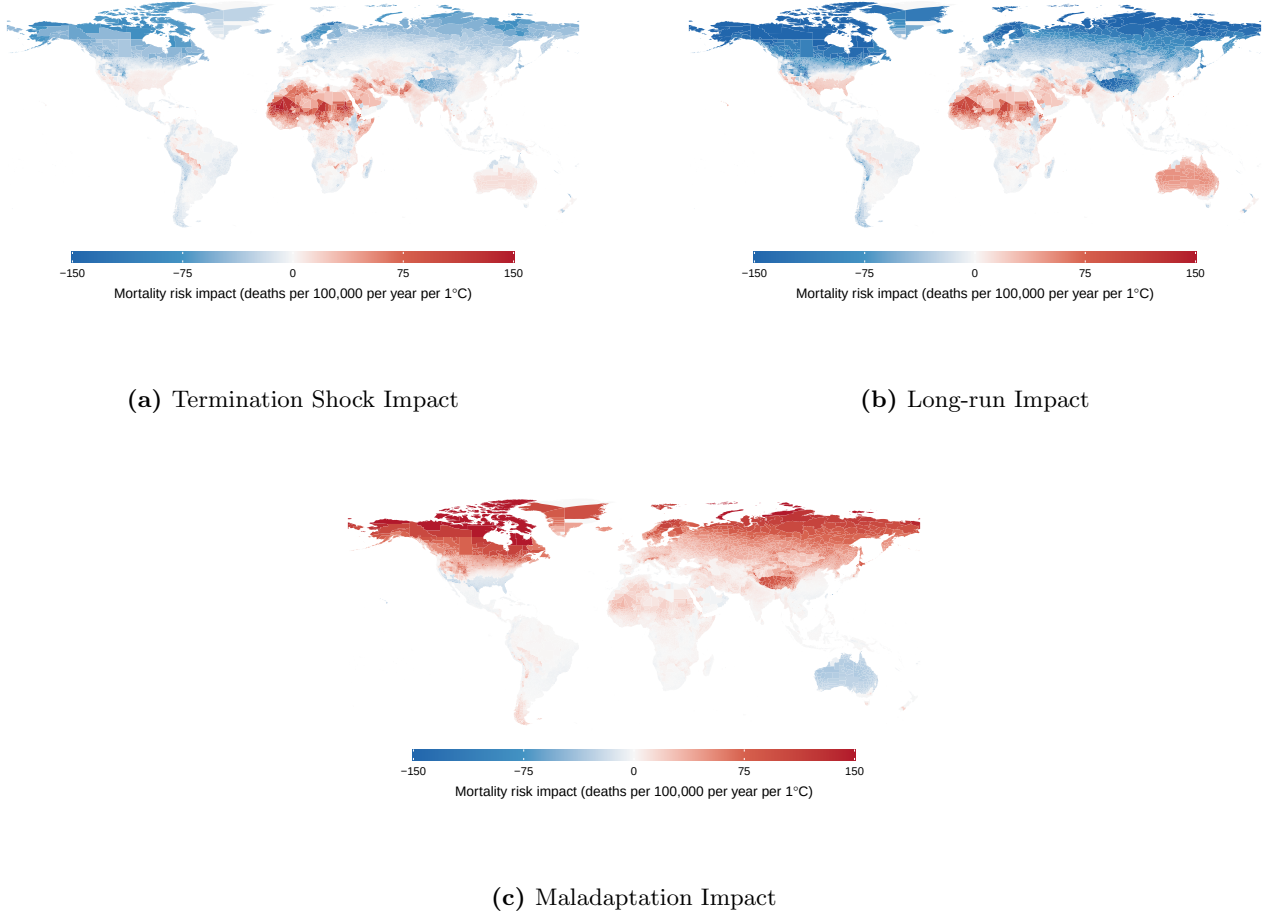


Fig. 5 | Regional Impacts - GFDL-FLOR. Region temperature-attributable impacts estimated using the GFDL-FLOR climate model. **a** impact of termination shock with instantaneous shift from SG temperatures to 2xCO₂ temperatures when adapted to SG climate. **b** impact of long-run shift from SG temperatures to 2xCO₂ when adapted to respective climate. **c** impact of maladaptation, as an upper bound on rate-of-change impacts, measured as the difference in impacts between **a** and **b**.

proach particular to its application to termination shock. Perhaps central to these limitations is the external validity of empirically estimated adaptation from historical data. Adaptation is largely identified from cross-sectional climate variation and a 30-year Bartlett kernel sets the adaptation timescale. While this assumption is grounded in the best available empirical evidence, it may not fully capture behavioral, technological, or institutional responses that could emerge under unprecedented rates of temperature change. If space-for-time overstates achievable adjustment, then I would overstate the impacts of termination shock.

Finally, limitations arise from the specific application of the framework and econometric model to the measurement of the temperature-attributable mortality impacts of termination shock under specific deployment schemes and background climates. Of course, the physical response to sudden termination will depend on the deployment scheme, particularly the level and distribution of aerosol burden prior to termination. In both sets of climate models, deployment is an

idealized hemispherically balanced deployment of solar geoengineering—uniform solar dimming in the case of GFDL-FLOR and equatorial deployment of aerosols in the case of the GeoMIP G4 experiments. Results may differ in alternative distributions of solar geoengineering deployment, particularly in the case of regional deployments, e.g. marine cloud brightening rather than stratospheric aerosol injection. The amount of solar geoengineering and the background concentrations also matter, as evidenced by the size of the termination shock impact between the GFDL-FLOR deployment where global mean temperatures are reduced by around 2.2°C and the G4 experiments where global mean temperatures are reduced by closer to 1°C.

Beyond the scenarios considered, it should be acknowledged that I do not allow for any nonlinear feedbacks or cross-sectoral feedbacks. I consider a path of income and population that is exogenous to the termination shock. Yet, a sudden termination shock would likely disrupt populations and particularly income levels which would be critical for defensive and adaptation

investments.

Our analysis focuses exclusively on temperature-attributable mortality, leveraging a well-established and globally comprehensive impact function. While mortality represents a salient and policy-relevant outcome, it is only one dimension of termination risk. Rapid warming following termination could also affect agricultural productivity, labor supply, energy demand, ecosystem stability, and conflict risk, among other outcomes. Some of these impacts may exhibit stronger rate dependence than mortality, particularly where thresholds or irreversible damages are involved. Others may be more easily buffered in the short run. These could also have feedback effects with implications for temperature-attributable mortality, for example changes in economic capacity to invest in adaptation. Our estimates should therefore not be interpreted as comprehensive measures of termination damages, but rather as illustrative of how rate-of-change effects can be empirically bounded.

Conclusions

This analysis bounds how much the impacts of abrupt solar geoengineering termination depend, not only on the magnitude of the resulting warming, but also on its pace relative to the speed of adaptation. By distinguishing impacts under a rapidly changing climate from those that would occur after populations adapt to the same warmer conditions, I estimate a maladaptation penalty associated with termination shock. For temperature-attributable mortality, accounting for these adaptation constraints can considerably increase estimated impacts relative to those implied by temperature changes alone.

This distinction has important implications for the assessment and governance of solar geoengineering. Impact estimates that focus solely on temperature levels may systematically understate the risks of abrupt termination by neglecting adaptation dynamics. This indicates that measures that reduce the rate of post-termination warming—such as gradual ramp-down strategies, safeguards against abrupt cessation, and parallel reductions in greenhouse gas emissions—could therefore reduce termination risks. More broadly, the results demonstrate the importance of incorporating adaptation dynamics and rates of climate change into climate impact assessments. Of course, any risks imposed by the potential of termination shock should be weighed against the potential benefits of deployment in a risk-risk assessment^{24,27–29}.

Methods

GFDL-FLOR.

The GFDL-FLOR model uses a high-resolution (50 km) atmosphere and land component taken from the Coupled Model, v.2.5 (CM2.5) and a lower-resolution (1°) ocean and sea ice complement taken from the Cou-

pled Model, v.2.1 (CM2.1). Full details of the GFDL FLOR model can be found in³⁰. For GFDL-FLOR, a control simulation is run for 300 years with conditions of 1990. The 2xCO₂ experiment and solar dimming experiments branch off the control simulation in year 101 and run for 200 years. In the 2xCO₂ experiment, atmospheric concentrations of CO₂ are doubled from the control simulation. In the solar dimming experiment, atmospheric concentrations of CO₂ are doubled from the control simulation and the solar constant is reduced by 1.7%. Extended Data Fig. 1 shows the global mean temperature across the climate model experiments. I use the last 100 years of each simulation for our analyses.

GeoMIP G4 Climate Models.

I consider two climate models that run the GeoMIP G4 climate model experiment¹⁴: HadGEM2-ES²⁵ and CanESM2²⁶. HadGEM2-ES uses a horizontal resolution of 1.25°×1.875° atmosphere component and a lower-resolution (1°) ocean component. CanESM2 uses a horizontal resolution of 2.8125°.

Each climate model simulates an RCP4.5 forcings experiment and a GeoMIP G4 experiment, which follows RCP4.5 forcings with 5 Tg SO₂/yr injected into the stratosphere at the equator starting in 2020 and ending in 2070. Each model simulates three ensemble members for each experiment. To calculate the Bartlett Kernel for historical temperatures and to conduct bias-corrections (described below), I also employ the historical experiments. For each climate model I project temperature-attributable mortality from 2010 through 2089, allowing for at least 20 years of simulation after the sudden termination of stratospheric aerosol injection. Extended Data Fig. 2 illustrates global mean surface temperatures for each of the climate models, experiments, and ensemble members.

Downscaling and Bias-Correction.

Before applying the climate models in projections of temperature-attributable mortality, I downscale climate model simulations to a 0.25° x 0.25° spatial resolution using bilinear interpolation and bias-correct following the ISI-MIP method³¹. For the GFDL-FLOR, the first 10 years of the control scenario is bias-corrected relative to the GMFD data³² for 1990 to 1999 since the control is set to 1990s conditions. For the time-varying climate models running the GeoMIP G4 experiment, I similarly bias-correct relative to the GMFD for 1990-1999. This downscaling and bias-correction is conducted to mitigate concerns of stationary bias³³.

Temperature-attributable Mortality Exposure Response Functions

Econometric estimates of temperature-attributable mortality risk come from Carleton et al.²³. Application of these estimates to projections of temperature-attributable mortality follows the approach outlined in their paper for the climate models and experiments described below. Here, I describe key aspects of the model estimation and projection. For a complete overview,

Table 1: Limitations and Expected Bias

	Impact Estimates	Maladaptation
Framework		
Termination is unanticipated; no pre-positioned adaptive capacity	+	+
Adaptation and defensive costs excluded	-	-
Termination is permanent	+	+
Econometrics		
Adaptation identified largely from cross-sectional climate variation	+/-	+/-
30 yr Bartlett kernel sets the adaptation timescale	+/-	+/-
External validity of historical adaptation under unprecedented rapid warming	+/-	+/-
Application		
Idealized hemispherically balanced deployment	+/-	+/-
Nonlinear dependence on the magnitude of SG deployment	+/-	+/-
Transition from SG to 2xCO ₂ is instantaneous (GFDL-FLOR)	+	+
Income and population paths exogenous to the shock	-	-
Only consider temperature-attributable mortality	+/-	+/-

see Carleton et al.²³.

Econometric estimates of temperature-attributable mortality are derived from subnational statistics on all-cause mortality, annual mean surface temperature, annual precipitation, and incomes for 40 countries covering 38% of the global population. Specifically, Carleton et al.²³ regress all-cause mortality across three age bins ($< 5, 5 - 64, 65+$) on a fourth-order polynomial of subnational daily average temperature summed annually, interacted with a Bartlett kernel of annual mean temperature with a length of 30 years and a Bartlett kernel of income with a length of 13 years as well as on a second-order polynomial of precipitation and a vector of fixed effects.

Coefficients and covariance matrix for these econometric estimates of historical temperature-attributable mortality sensitivity are used to construct exposure-response curves for the 24,378 impact regions covering the globe, each around the size of a US county, defined in²³. In constructing the exposure-response curves, I substitute temperature measures from each respective climate model and simulation and 2015 incomes. I follow the procedures outlined in section E of their Appendix to define the minimum mortality temperature and correct the exposure-response curves to changes in income and climate.

Uncertainty

I account for uncertainty both in the econometric estimates and the climate simulations using Monte Carlo simulations. To account for econometric uncertainty, I randomly sample econometric coefficient values using a multivariate normal distribution characterized by the covariance matrix between all the parameters. To account for climate uncertainty in the GFDL-FLOR model I randomly draw simulation years. To account for climate uncertainty in the GeoMIP G4 participating climate model simulations, I randomly draw across ensemble members. This process of randomly drawing a vector of coefficients and a simulation model year or

an ensemble member is repeated 1,000 times.

Temperature-attributable Mortality Impacts Estimation

Impacts are estimated by applying the empirically estimated exposure-response curve together with temperature data from the climate model simulations and SSP scenario income and population data from Carleton et al.²³.

For each climate experiment, temperature-attributable mortality impacts are calculated relative to a common reference climate. For the time-invariant GFDL-FLOR experiments, impacts are evaluated as differences between the stationary SG and 2xCO₂ climate states, so that the decomposition is not dependent on a particular calendar-year baseline. For the time-varying GeoMIP experiments, I instead use the 2000-2009 climate as the baseline and define subsequent mortality impacts as the change in temperature-attributable mortality relative to that baseline. This normalization isolates the effects of subsequent changes in temperature exposure and adaptation while providing a common benchmark across the RCP4.5 and G4 experiments.

For GFDL-FLOR, temperature exposure and adaptation state are varied independently. I first calculate mortality under the SG climate using an exposure-response function adapted to the SG climate, ($M(T^{SG}; A^{SG})$). The long-run impact of moving from the SG climate to the warmer 2xCO₂ climate is then calculated allowing the population to be adapted to the climate experienced in each state,

$$\Delta M^{\text{Long-run}} = M(T^{2xCO_2}; A^{2xCO_2}) - M(T^{SG}; A^{SG}).$$

To approximate an abrupt termination of solar geo-engineering, I instead expose a population adapted to the SG climate to temperatures from the 2xCO₂ experiment,

$$\Delta M^{\text{Termination}} = M(T^{2xCO_2}; A^{SG}) - M(T^{SG}; A^{SG}).$$

Holding the realized 2xCO₂ temperature exposure fixed, the difference between the termination and long-run impacts isolates the additional mortality associated with the population remaining adapted to the cooler SG climate. I refer to this difference as the maladaptation penalty,

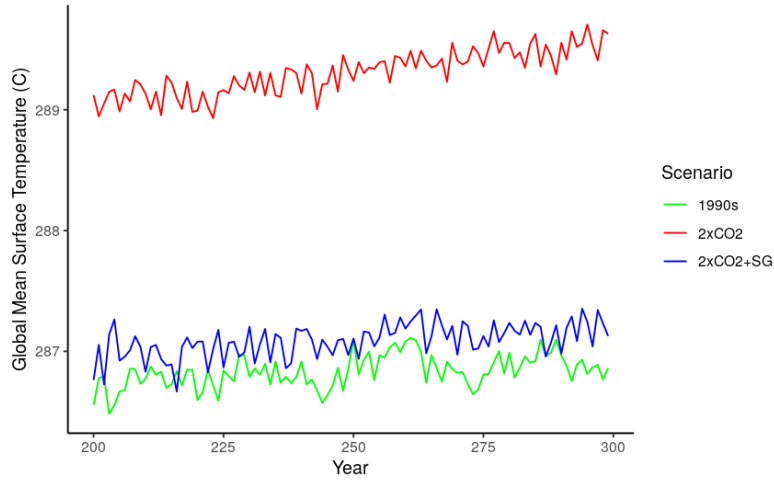
$$\Delta M^{\text{Maladaptation}} = \Delta M^{\text{Termination}} - \Delta M^{\text{Long-run}}.$$

Because the shift between the stationary SG and 2xCO₂ experiments is imposed instantaneously, this calculation represents an upper bound-style approximation to the consequences of warming that occurs faster than adaptation.

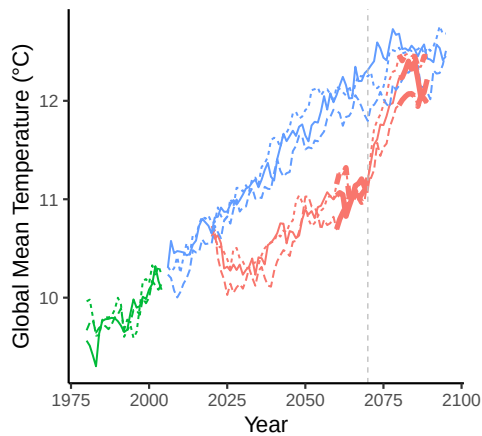
Unlike the GFDL-FLOR calculation, the adaptation state in the G4 experiment evolves during and after termination as the recent-climate history used to construct the exposure-response function incorporates progressively warmer post-termination conditions. The resulting estimate therefore captures mortality under incomplete rather than entirely absent post-termination adaptation.

$$\overline{M}_{2080-2089}^{G4} - \overline{M}_{2080-2089}^{RCP4.5}$$

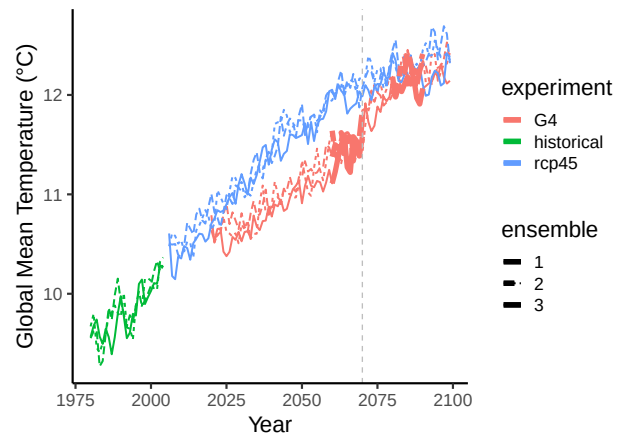
therefore provides an empirical analogue to the maladaptation comparison in the time-invariant framework. This comparison is not exact because temperatures under G4 and RCP4.5 do not coincide perfectly in the 2080s; in both HadGEM2-ES and CanESM2, G4 temperatures remain somewhat below those under RCP4.5. Accordingly, the comparison is interpreted jointly with the corresponding temperature differences rather than as a perfectly controlled decomposition.



Extended Data Fig. 1 | Global Mean Surface Temperature - GFDL FLOR. Global mean surface temperatures under CTL (green), 2xCO₂ (red), and SG (blue) experiments.

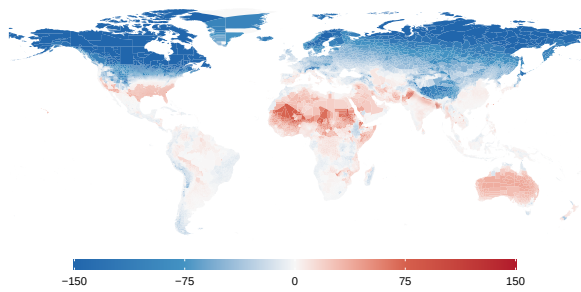


(a) HadGEM2-ES

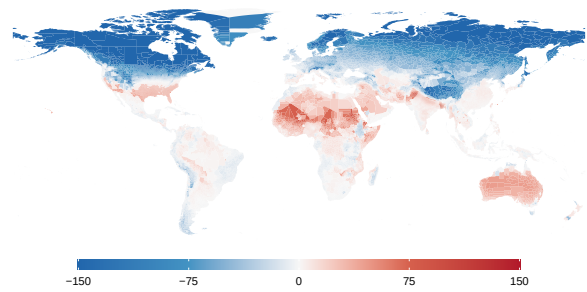


(b) CanESM2

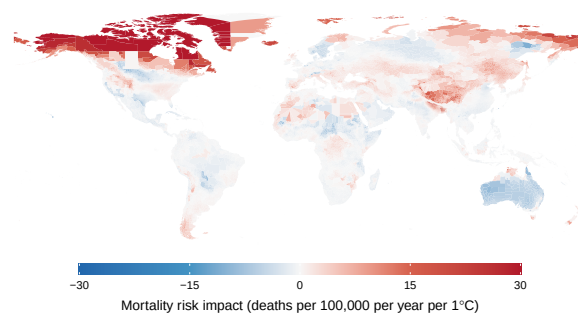
Extended Data Fig. 2 | Global Mean Surface Temperature - G4 experiment. Global mean surface temperatures for the (a) HadGEM2-ES and (b) CanESM2 climate models for the RCP4.5 (blue) and G4 (red) experiments across ensemble members. Termination of solar geoengineering occurs in 2070 (vertical dashed line). Bolded years are used in the estimation of termination shock impacts.



(a) Termination Shock Impact

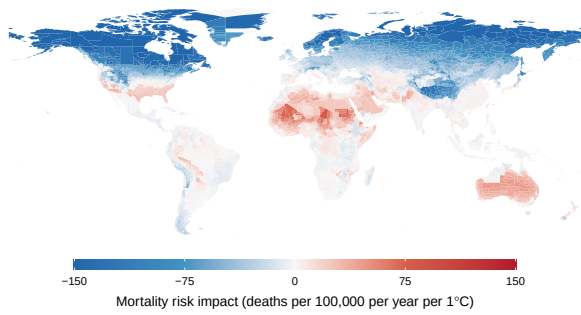


(b) Long-run Impact

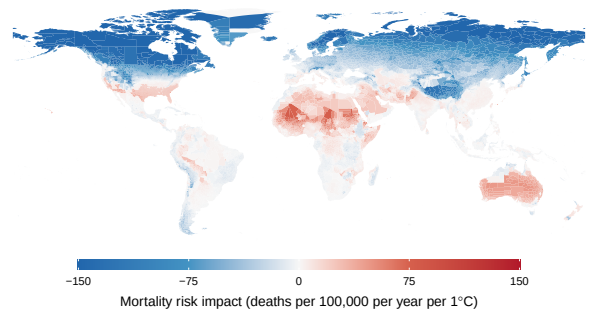


(c) Maladaptation Impact

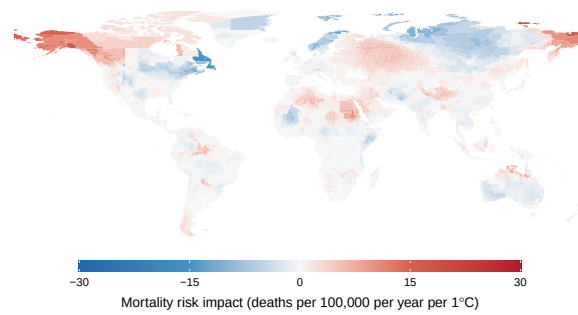
Extended Data Fig. 3 | Regional Impacts - HadGEM2-ES. Region temperature-attributable impacts estimated using the HadGEM2-ES climate model. **a** impact of termination shock as temperatures rapidly rise from 2060-2069 to 2080-2089 under the G4 experiment. **b** Impact of RCP4.5 temperatures in 2080-2089 relative to the historical counterfactual. **c** Difference in impact of G4 temperatures during 2080-2089 period relative to the counterfactual and the impact of RCP4.5 temperatures during 2080-2089 period relative to the counterfactual.



(a) Termination Shock Impact



(b) Long-run Impact



(c) Maladaptation Impact

Extended Data Fig. 4 | Regional Impacts - CanESM2. Region temperature-attributable impacts estimated using the CanESM2 climate model. **a** impact of termination shock as temperatures rapidly rise from 2060-2069 to 2080-2089 under the G4 experiment. **b** Impact of RCP4.5 temperatures in 2080-2089 relative to the historical counterfactual. **c** Difference in impact of G4 temperatures during 2080-2089 period relative to the counterfactual and the impact of RCP4.5 temperatures during 2080-2089 period relative to the counterfactual.

Data availability

Data and code used in this analysis will be made publicly available upon publication.

Acknowledgments

This research was supported in part by the Brook Byers Institute for Sustainable Systems (BBISS) at the Georgia Institute of Technology through a BBISS Faculty Fellowship. This research was supported in part through research cyberinfrastructure resources and services provided by the Partnership for an Advanced Computing Environment (PACE) at the Georgia Institute of Technology, Atlanta, Georgia, USA. RRID:SCR_027619. The author thanks participants at the Degrees Global Forum and AGU Fall Meeting 2025 for feedback.

Competing Interests

The author declares no competing interests.

References

1. Andy Parker and Peter J. Irvine. The Risk of Termination Shock From Solar Geoengineering. *Earth's Future*, 6(3):456–467, 2018. ISSN 2328-4277. doi: 10.1002/2017EF000735.
2. Luke Kemp, Chi Xu, Joanna Depledge, Kristie L. Ebi, Goodwin Gibbins, Timothy A. Kohler, Johan Rockström, Marten Scheffer, Hans Joachim Schellnhuber, Will Steffen, and Timothy M. Lenton. Climate Endgame: Exploring catastrophic climate change scenarios. *Proceedings of the National Academy of Sciences*, 119(34):e2108146119, August 2022. doi: 10.1073/pnas.2108146119.
3. Peter Irvine, Kerry Emanuel, Jie He, Larry W. Horowitz, Gabriel Vecchi, and David Keith. Halving warming with idealized solar geoengineering moderates key climate hazards. *Nature Climate Change*, 9:295–299, March 2019. ISSN 1758-6798. doi: 10.1038/s41558-019-0398-8.
4. Peter J. Irvine and David W. Keith. Halving warming with stratospheric aerosol geoengineering moderates policy-relevant climate hazards. *Environmental Research Letters*, 15(4):044011, March 2020. ISSN 1748-9326. doi: 10.1088/1748-9326/ab76de.
5. P Heckendorn, D Weisenstein, S Fueglistaler, B P Luo, E Rozanov, M Schraner, L W Thomason, and T Peter. The impact of geoengineering aerosols on stratospheric temperature and ozone. *Environmental Research Letters*, 4(4):045108, November 2009. ISSN 1748-9326. doi: 10.1088/1748-9326/4/4/045108.
6. U. Niemeier, H. Schmidt, and C. Timmreck. The dependency of geoengineered sulfate aerosol on the emission strategy. *Atmospheric Science Letters*, 12(2):189–194, 2011. ISSN 1530-261X. doi: 10.1002/asl.304.
7. J. M. English, O. B. Toon, and M. J. Mills. Microphysical simulations of sulfur burdens from stratospheric sulfur geoengineering. *Atmospheric Chemistry and Physics*, 12(10):4775–4793, May 2012. ISSN 1680-7316. doi: 10.5194/acp-12-4775-2012.
8. Daniele Visioni, Giovanni Pitari, and Valentina Aquila. Sulfate geoengineering: a review of the factors controlling the needed injection of sulfur dioxide. *Atmospheric Chemistry and Physics*, 17(6):3879–3889, March 2017. ISSN 1680-7316. doi: 10.5194/acp-17-3879-2017.
9. Andy Jones, Jim M. Haywood, Kari Alterskjær, Olivier Boucher, Jason N. S. Cole, Charles L. Curry, Peter J. Irvine, Duoying Ji, Ben Kravitz, Jón Egill Kristjánsson, John C. Moore, Ulrike Niemeier, Alan Robock, Hauke Schmidt, Balwinder Singh, Simone Tilmes, Shingo Watanabe, and Jin-Ho Yoon. 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: Atmospheres*, 118(17):9743–9752, 2013. ISSN 2169-8996. doi: 10.1002/jgrd.50762.
10. Tianle Yuan, Hua Song, Lazaros Oreopoulos, Robert Wood, Huisheng Bian, Katherine Breen, Mian Chin, Hongbin Yu, Donifan Barahona, Kerry Meyer, and Steven Platnick. Abrupt reduction in shipping emission as an inadvertent geoengineering termination shock produces substantial radiative warming. *Communications Earth & Environment*, 5(1):281, May 2024. ISSN 2662-4435. doi: 10.1038/s43247-024-01442-3.
11. H. Damon Matthews and Ken Caldeira. Transient climate-carbon simulations of planetary geoengineering. *Proceedings of the National Academy of Sciences*, 104(24):9949–9954, 2007. doi: 10.1073/pnas.0700419104.
12. Andrew Ross and H Damon Matthews. Climate engineering and the risk of rapid climate change. *Environmental Research Letters*, 4(4):045103, October 2009. ISSN 1748-9326. doi: 10.1088/1748-9326/4/4/045103.
13. Ben Kravitz, Alan Robock, Olivier Boucher, Hauke Schmidt, Karl E. Taylor, Georgiy Stenchikov, and Michael Schulz. The geoengineering model intercomparison project (GeoMIP). *Atmospheric Science Letters*, 12(2):162–167, 2011.
14. B. Kravitz, A. Robock, S. Tilmes, O. Boucher, J. M. English, P. J. Irvine, A. Jones, M. G.

- Lawrence, M. MacCracken, H. Muri, J. C. Moore, U. Niemeier, S. J. Phipps, J. Sillmann, T. Storelvmo, H. Wang, and S. Watanabe. The Geoengineering Model Intercomparison Project Phase 6 (GeoMIP6): simulation design and preliminary results. *Geoscientific Model Development*, 8(10):3379–3392, October 2015. ISSN 1991-959X. doi: 10.5194/gmd-8-3379-2015.
15. John C. Moore, Aslak Grinsted, Xiaoran Guo, Xiaoyong Yu, Svetlana Jevrejeva, Annette Rinke, Xuefeng Cui, Ben Kravitz, Andrew Lenton, Shingo Watanabe, and Duoying Ji. Atlantic hurricane surge response to geoengineering. *Proceedings of the National Academy of Sciences of the United States of America*, 112(45):13794–13799, November 2015. ISSN 0027-8424. doi: 10.1073/pnas.1510530112.
16. Mansi Bhowmick, Saroj Kanta Mishra, Ben Kravitz, Sandeep Sahany, and Popat Salunke. Response of the Indian summer monsoon to global warming, solar geoengineering and its termination. *Scientific Reports*, 11(1):9791, May 2021. ISSN 2045-2322. doi: 10.1038/s41598-021-89249-6.
17. Salomon Obahoundje, Vami Hermann N’guessan Bi, Arona Diedhiou, Ben Kravitz, and John C. Moore. Influence of stratospheric aerosol geoengineering on temperature mean and precipitation extremes indices in Africa. *International Journal of Climate Change Strategies and Management*, 14(4):399–423, 2022.
18. Heri Kuswanto, Ben Kravitz, Brina Miftahurrohman, Fatkhurokhman Fauzi, Ardhasena Sopahaluwaken, and John Moore. Impact of solar geoengineering on temperatures over the Indonesian Maritime Continent. *International Journal of Climatology*, 42(5):2795–2814, 2022. ISSN 1097-0088. doi: 10.1002/joc.7391.
19. Christopher H. Trisos, Giuseppe Amatulli, Jessica Gurevitch, Alan Robock, Lili Xia, and Brian Zambri. Potentially dangerous consequences for biodiversity of solar geoengineering implementation and termination. *Nature Ecology & Evolution*, 2(3):475–482, March 2018. ISSN 2397-334X. doi: 10.1038/s41559-017-0431-0.
20. Lili Xia, Alan Robock, Jason Cole, Charles L. Curry, Duoying Ji, Andy Jones, Ben Kravitz, John C. Moore, Helene Muri, Ulrike Niemeier, Balwinder Singh, Simone Tilmes, Shingo Watanabe, and Jin-Ho Yoon. Solar radiation management impacts on agriculture in China: A case study in the Geoengineering Model Intercomparison Project (GeoMIP). *Journal of Geophysical Research: Atmospheres*, 119(14):8695–8711, 2014. ISSN 2169-8996. doi: 10.1002/2013JD020630.
21. Pei Zhan, Wenquan Zhu, Tianyi Zhang, Xuefeng Cui, and Nan Li. Impacts of Sulfate Geoengineering on Rice Yield in China: Results From a Multimodel Ensemble. *Earth’s Future*, 7(4):395–410, 2019. ISSN 2328-4277. doi: 10.1029/2018EF001094.
22. Francisco Estrada, Bernardo A Bastien-Olvera, Oscar Calderon-Bustamante, Miguel A Altamirano, Rodrigo Muñoz-Sánchez, Juan Moreno-Cruz, and Wouter Botzen. Economic assessment of SRM under socio-political and geophysical tipping dynamics. *Environmental Research: Climate*, 5(1): 015015, January 2026. ISSN 2752-5295. doi: 10.1088/2752-5295/ae33df.
23. Tamma Carleton, Amir Jina, Michael Delgado, Michael Greenstone, Trevor Houser, Solomon Hsiang, Andrew Hultgren, Robert E Kopp, Kelly E McCusker, Ishan Nath, James Rising, Ashwin Rode, Hee Kwon Seo, Arvid Viaene, Jiacan Yuan, and Alice Tianbo Zhang. Valuing the Global Mortality Consequences of Climate Change Accounting for Adaptation Costs and Benefits*. *The Quarterly Journal of Economics*, 137(4):2037–2105, April 2022. ISSN 0033-5533. doi: 10.1093/qje/qjac020.
24. Anthony Harding, Gabriel A. Vecchi, Wenchang Yang, and David W. Keith. Impact of solar geoengineering on temperature-attributable mortality. *Proceedings of the National Academy of Sciences*, 121(52):e2401801121, December 2024. ISSN 0027-8424, 1091-6490. doi: 10.1073/pnas.2401801121.
25. W. J. Collins, N. Bellouin, M. Doutriaux-Boucher, N. Gedney, P. Halloran, T. Hinton, J. Hughes, C. D. Jones, M. Joshi, S. Liddicoat, G. Martin, F. O’Connor, J. Rae, C. Senior, S. Sith, I. Totterdell, A. Wiltshire, and S. Woodward. Development and evaluation of an Earth-System model – HadGEM2. *Geoscientific Model Development*, 4(4):1051–1075, November 2011. ISSN 1991-959X. doi: 10.5194/gmd-4-1051-2011.
26. Canadian Centre for Climate Modelling and Analysis. Climate model: second generation Canadian earth system model, October 2017. Last Modified: 2018-06-07.
27. Aaron Tang and Luke Kemp. A Fate Worse Than Warming? Stratospheric Aerosol Injection and Global Catastrophic Risk. *Frontiers in Climate*, 3, November 2021. ISSN 2624-9553. doi: 10.3389/fclim.2021.720312.
28. Tyler Felgenhauer, Govindasamy Bala, Mark E. Borsuk, Matthew Brune, Ines Camilloni, Jonathan B. Wiener, and Jianhua Xu. Solar Radiation Modification: A Risk-Risk Analysis. Technical report, Carnegie Climate Governance Initiative (C2G), New York, NY, March 2022.

29. Anthony R. Harding, Mariia Belaia, and David W. Keith. The value of information about solar geo-engineering and the two-sided cost of bias. *Climate Policy*, 23(3):355–365, June 2022. ISSN 1469-3062. doi: 10.1080/14693062.2022.2091509.
30. G. A. Vecchi, T. Delworth, R. Gudgel, S. Kapnick, A. Rosati, A. T. Wittenberg, F. Zeng, W. Anderson, V. Balaji, K. Dixon, L. Jia, H.-S. Kim, L. Krishnamurthy, R. Msadek, W. F. Stern, S. D. Underwood, G. Villarini, X. Yang, and S. Zhang. On the Seasonal Forecasting of Regional Tropical Cyclone Activity. *Journal of Climate*, 27(21):7994–8016, November 2014. ISSN 0894-8755, 1520-0442. doi: 10.1175/JCLI-D-14-00158.1.
31. S. Hempel, K. Frieler, L. Warszawski, J. Schewe, and F. Piontek. A trend-preserving bias correction – the ISI-MIP approach. *Earth System Dynamics*, 4(2):219–236, July 2013. ISSN 2190-4979. doi: 10.5194/esd-4-219-2013.
32. Justin Sheffield, Gopi Goteti, and Eric F. Wood. Development of a 50-Year High-Resolution Global Dataset of Meteorological Forcings for Land Surface Modeling. *Journal of Climate*, 19(13):3088–3111, July 2006. ISSN 0894-8755, 1520-0442. doi: 10.1175/JCLI3790.1.
33. Maximilian Auffhammer, Solomon M. Hsiang, Wolfram Schlenker, and Adam Sobel. Using Weather Data and Climate Model Output in Economic Analyses of Climate Change. *Review of Environmental Economics and Policy*, 7(2):181–198, July 2013. ISSN 1750-6816. doi: 10.1093/reep/ret016.