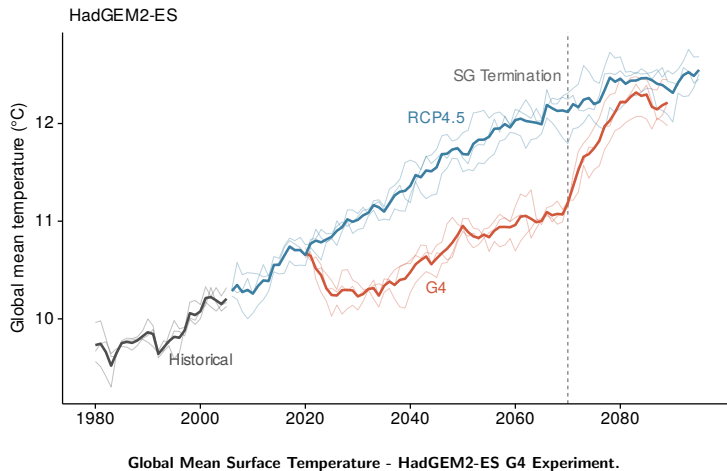


Quantifying the Risks of Stratospheric Aerosol Injection Termination Shock

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Termination Shock



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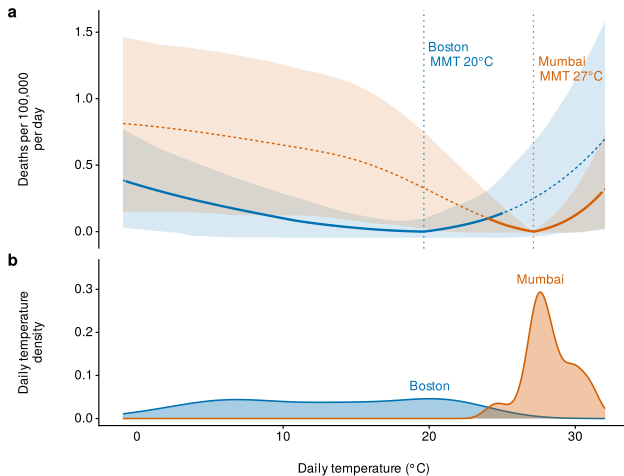
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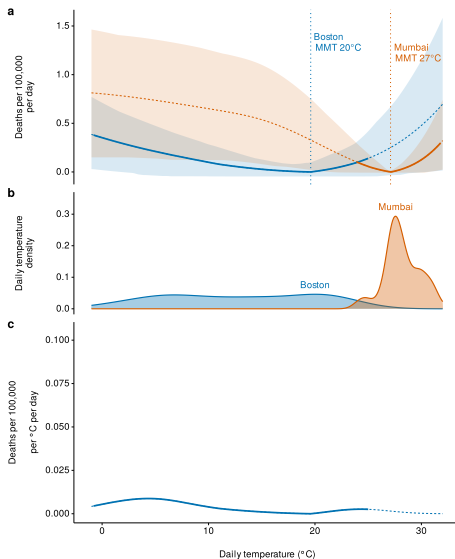
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Historically this has been hard to identify because there is little variation in rates of change.

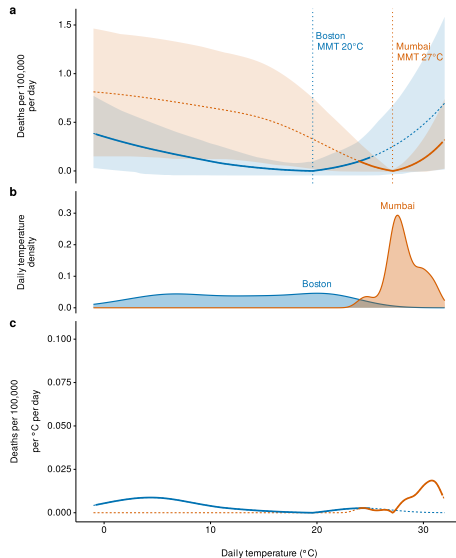
An Intuitive Illustration



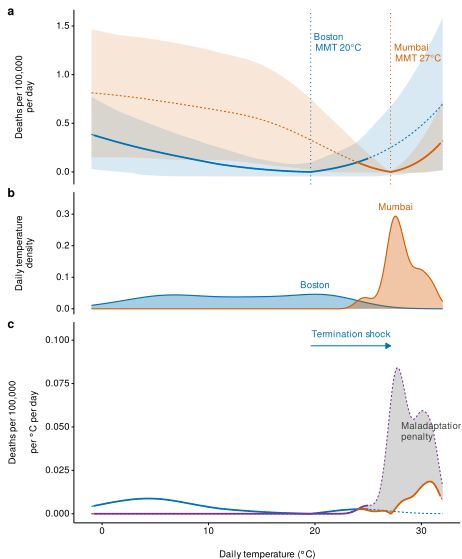
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An Intuitive Illustration



The Core Idea

Impacts depend not just on *how much* the climate changes, but on *how fast*.

Adaptation takes time.

Framework for Termination Shock

Let $M(T^X; A^Y)$ be mortality rates under temperature exposure from experiment X , given adaptation to the climate of experiment Y .

This lets us separate two things that are normally bundled together:

- 1 the temperature you experience
- 2 the climate you're adapted to

Termination Shock Impact

The impact of sudden termination is given as:

$$\Delta M^{\text{Termination Shock}} = M(T^{2\times CO_2}; A^{SG}) - M(T^{SG}; A^{SG}) \quad (1)$$

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Let the long run impacts of a change in climate be:

$$\Delta M^{\text{Long-run}} = M(T^{2\times\text{CO}_2}; A^{2\times\text{CO}_2}) - M(T^{\text{SG}}; A^{\text{SG}}) \quad (2)$$

From this, we can recover the additional component due to rate of change or *Maladaptation*:

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

Empirical Model

Carleton et al. (2022) estimate mortality sensitivity to temperature that varies with recent climate exposure:

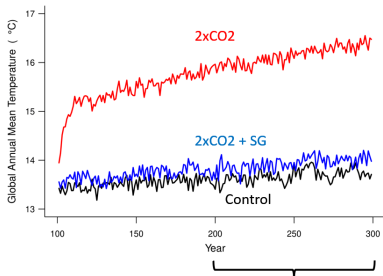
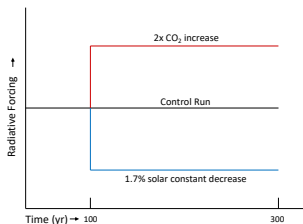
$$M_{ait} = g_a(\mathbf{T}_{it} | TMEAN_s, \log(GDPpc)_s) + q_{ac}(\mathbf{R}_{it}) + \alpha_{ai} + \delta_{act} + \epsilon_{ait}$$

- Mortality regressed on a polynomial in local temperature
- **Interacted** with a 30-year Bartlett kernel of historical temperature (and 13-year of income)
- Result: the mortality curve adjusts based on recent climate exposure and income levels
- Data:
 - Data for 40 countries covering 38% of the global population
 - Resolution of ADM-2 regions, equivalent to US county

Two Empirical Settings

- **GFDL-FLOR**: time-invariant CTL / $2\times\text{CO}_2$ / SG runs
 - Cleaner identification, but termination is simulated as an instantaneous exposure switch
- **GeoMIP G4** (HadGEM2-ES, CanESM2): time-varying RCP4.5 / G4, actual termination in 2070
 - Physically more realistic, but noisier estimates

- 0.5° resolution land and atmosphere
- 1° resolution ocean



Mortality Risk Impact (FLOR)

Global impact:

- $$\Delta M^{\text{Long-run}} = M(T^{2\times CO_2}; A^{2\times CO_2}) - M(T^{SG}; A^{SG})$$
$$= 4 \text{ deaths per } 100,000 \text{ per year per } 1^\circ\text{C}$$

Mortality Risk Impact (FLOR)

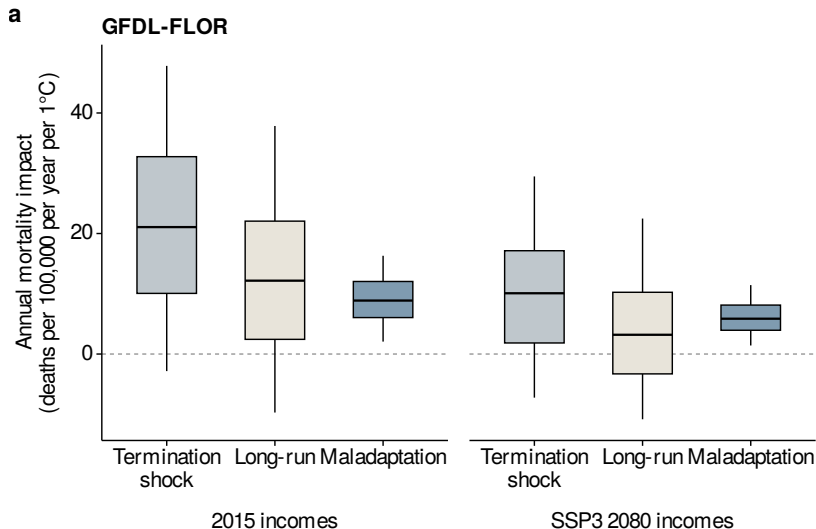
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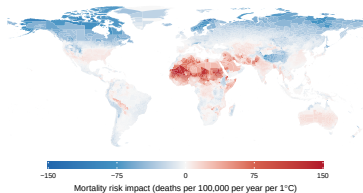
For reference:

- Global annual mortality rate: ~ 800 per 100,000 per year
- Air pollution mortality rate: ~ 100 per 100,000 per year
- COVID-19 mortality rate (2020-2021): ~ 100 per 100,000 per year

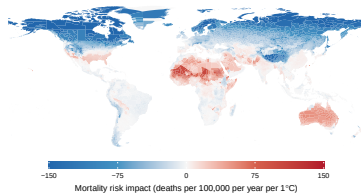
Mortality Risk Impact (FLOR)



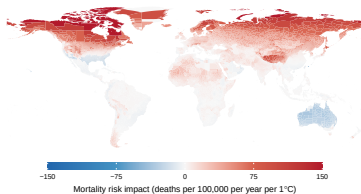
Regional Risk Impact (FLOR)



(a) Termination Shock Impact

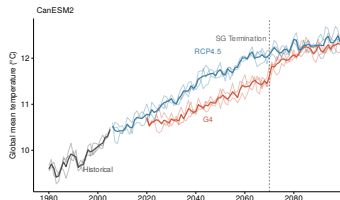
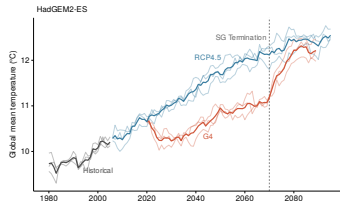
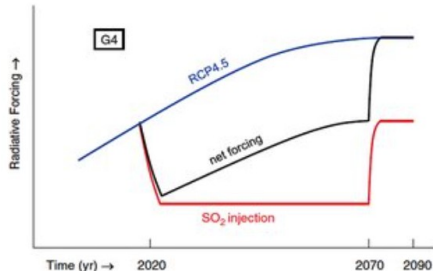


(b) Long-run Impact



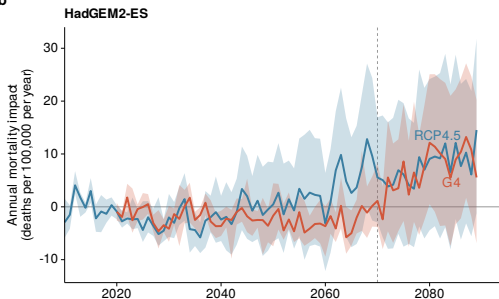
G4 Experiment

What about a more realistic modeling scenario?

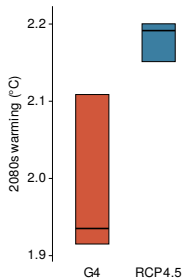


Mortality Risk Impact (HadGEM2-ES)

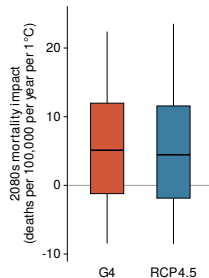
b



c

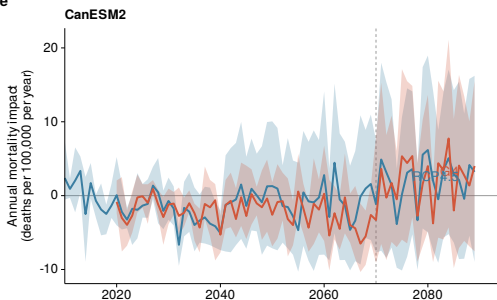


d

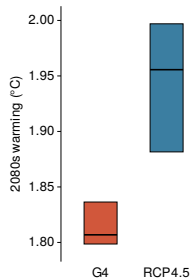


Mortality Risk Impact (CanESM2)

e



f



g

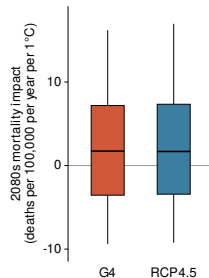


Table: Limitations and Expected Bias

	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	+/-	+/-

Findings:

- Adaptation lessens the impacts of climate changes
- Penalty from “suddenness” of termination shock and maladaptation can be large
- In our setting, it can double the impacts of rising temperatures

Appendix: Recovering the Adaptation Channel in Carleton et al. (2022)

Estimating equation (simplified):

$$y_{it} = \sum_{n=1}^3 \beta_n(\bar{T}_{i,t}, \bar{I}_{i,t}) T_{it}^n + f(P_{it}) + \alpha_i + \alpha_t + \epsilon_{it} \quad (4)$$

where the coefficients $\beta_n(\cdot)$ are themselves a function of:

- $\bar{T}_{i,t}$: a 30-year Bartlett-weighted average of local temperature
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Intuition: The mortality response to a hot day is not fixed.

- A 35°C day is unremarkable in Mumbai, but dangerous in Boston
- The β_n shift with a location's climate history

Estimating Equation

$$M_{ait} = g_a(\mathbf{T}_{it} | TMEAN_s, \log(GDPpc)_s) + q_{ac}(\mathbf{R}_{it}) + \alpha_{ai} + \delta_{act} + \epsilon_{ait}$$

where

- $a \in \{< 5, 5 - 64, > 64\}$
- i denotes second administrative level
- c denotes country
- t denotes year
- M_{ait} is mortality rate
- $g_a(\cdot)$ is sum of fourth-order polynomial of daily temperature interacted with average annual temperature and average income
- q_{ac} is sum of second-order polynomial of daily precipitation
- α_{ai} and δ_{act} are fixed effects
- ϵ_{ait} is an error term