

# A New Path Forward for an Empirical Social Cost of Carbon

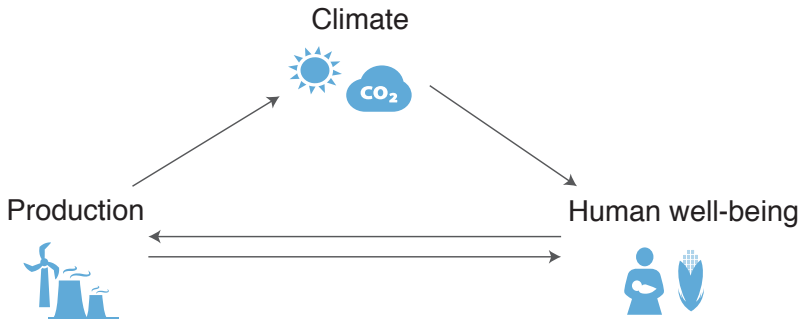
Michael Greenstone

Milton Friedman Professor of Economics, University of Chicago

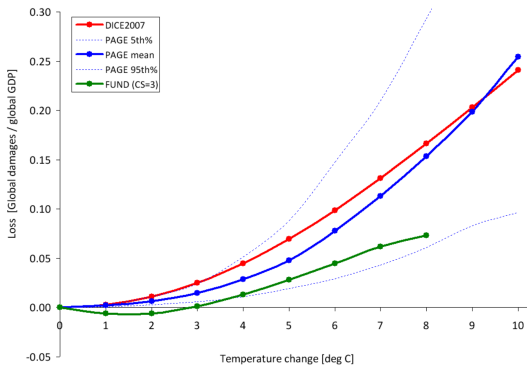
May 5<sup>th</sup>, 2016

# History

The Integrated Assessment Models (e.g. Nordhaus, 1994) provided a monumental step forward in understanding the complex relationship between CO<sub>2</sub> emissions and human well-being.



# Climate damages



Source: Interagency Working Group on Social Cost of Carbon, 2010

## Two proposed criteria for a damage function

We propose that the estimates that underlie any reliable damage function must satisfy two key criteria:

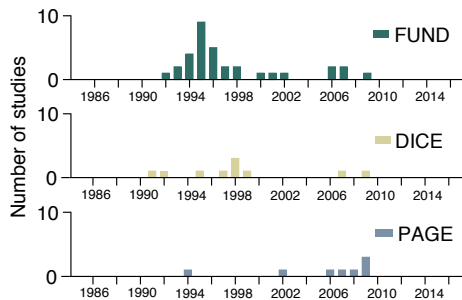
1. **Plausibly causal:** Damage functions should be derived from empirical estimates that are purged of sources of unobserved heterogeneity and are plausibly causal
2. **Reflect adaptation and its costs:** Damage functions should reflect that agents choose optimal adaptation opportunities and incur the costs of compensatory investments

## Additional criteria for developing damage functions

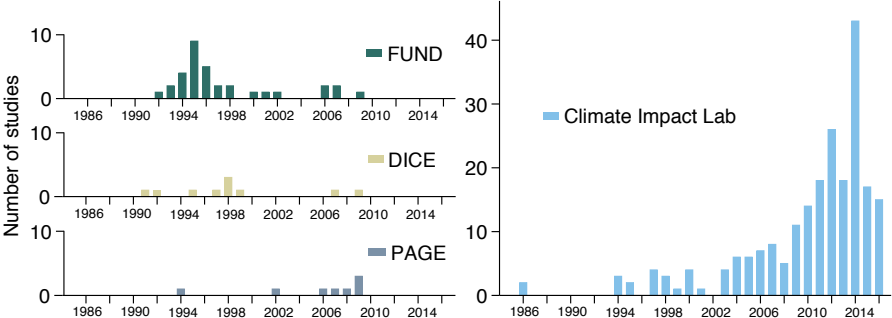
We propose the following additional criteria for judging whether a damage function is reliable:

- ▶ **Representative:** Estimate should be representative of the population that it is applied to
- ▶ **Flexible:** Allow for non-linearity using semi-parametric approaches
- ▶ **Non-market valuations:** Allow for valuations of market and non-market impacts
- ▶ **Risk and inequality:** Capture distributional effects of climate impacts
- ▶ **Updatable and transparent:** SCC estimating framework should be easily updatable to incorporate the latest research, be replicable, and transparent

# Literature



# Literature



## A brief history of damage function estimation

	<b>Research Advances</b>	Causal	Adaptation
v1.0	Functional form assumptions about the shape of GDP-temperature response function		
v2.0	Greenhouse experiments of the response of crop yields to temperature	✓	
v3.0	Cross-sectional hedonic equation (e.g., Mendelsohn, Nordhaus, & Shaw AER 1994)		✓
v4.0	Exploit inter-annual variation in weather (e.g., Deschenes & Greenstone AER 2007)	✓	
v5.0	Exploit inter-annual variation and directly model adaptation as function of observables (e.g., Auffhammer & Aroonruengsawat CEC 2012)	✓	✓



# Version 5.0 in action: Climate Impact Lab

## *Preliminary Results*



# Climate Impact Lab

M. Greenstone

T. Carleton

T. Kulczycki

I. Nath

J. Rising

T. Houser

M. Delgado

M. Landin

S. Ori

A. Rode

S. Hsiang

R. Goyal

K. Larsen

S. Phan

J. Yuan

R. Kopp

A. Jina

S. Mohan

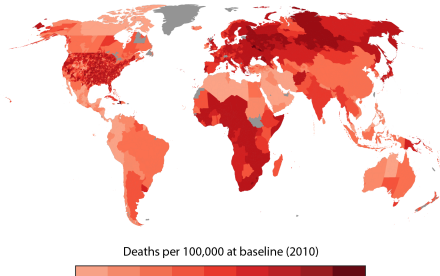
D. Rasmussen



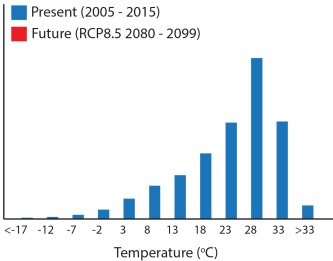
# Climate Impact Lab Cookbook

1. Develop “plausibly causal” estimates of relationship between measures of climate and human welfare in multiple sectors using continuously updating estimates
  - ▶ Reanalyze studies to ensure estimates meet research criteria
  - ▶ Conduct new analyses to achieve representative coverage
  - ▶ Incorporate results from new studies as they emerge
2. Build a model of direct responses based on historical adaptation and interpolate around the world, where no studies exist
3. Project responses into the future using high resolution climate projections
  - ▶ Develop cost estimates of compensatory investments
4. Obtain empirical damage function that accounts for multiple sources of uncertainty to **calculate an SCC that meets all criteria**

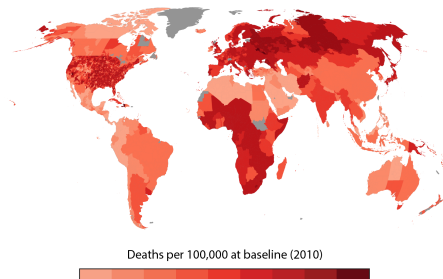
# Case study: Mortality



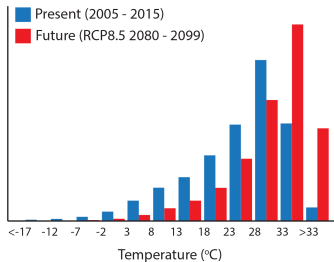
Number of days per year in temperature range



# Case study: Mortality



### Number of days per year in temperature range



# Climate Impact Lab Cookbook

1. Develop “plausibly causal” estimates of relationship between measures of climate and human welfare in multiple sectors using continuously updating estimates
  - ▶ Reanalyze studies to ensure estimates meet research criteria
  - ▶ Conduct new analyses to achieve representative coverage
  - ▶ Incorporate results from new studies as they emerge
2. Build a model of direct responses based on historical adaptation and interpolate around the world, where no studies exist
3. Project responses into the future using high resolution climate projections
  - ▶ Develop cost estimates of compensatory investments
4. Obtain empirical damage function that accounts for multiple sources of uncertainty to **calculate an SCC that meets all criteria**

# Data

## Mortality data

- ▶ Universe of mortality data from 6 countries, 46.7% of global population

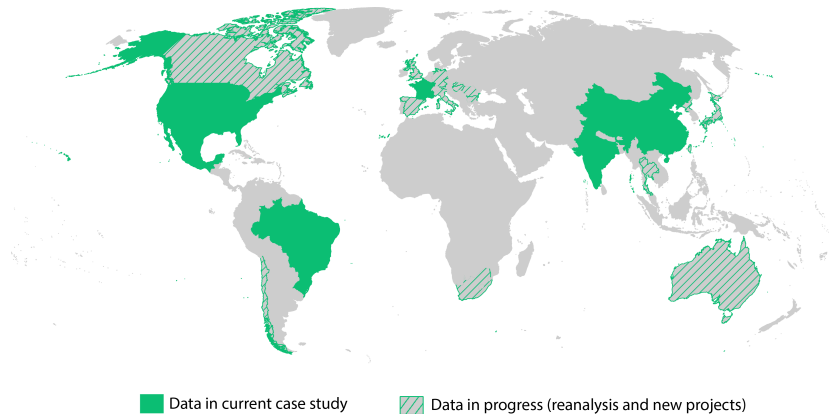
## Climate data

- ▶ Daily historical county temperature and precipitation
- ▶ High-resolution projections of ~ 20 GCMs to 2100
- ▶ RCPs 4.5, 8.5, approx. 100 datasets of daily future weather

## Covariate data for interpolation

- ▶ Income and population for 25,000 regions
- ▶ Nightlights for high resolution income

# Mortality data covers 46.7% of global population



# Estimating direct local mortality-temperature relationships

$$\underbrace{M_{it}}_{\text{mortality rate}} = \underbrace{\sum_k \beta_j^k T_{it}^k}_{\text{binned daily temp}} + g_j(\text{precip}_{it}) + \underbrace{\gamma_i + \delta_j \times t}_{\text{fixed effects \& trends}} + \varepsilon_{it}$$

## Our state-level estimation

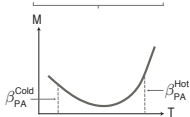
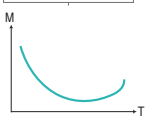
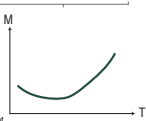
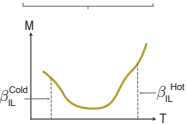
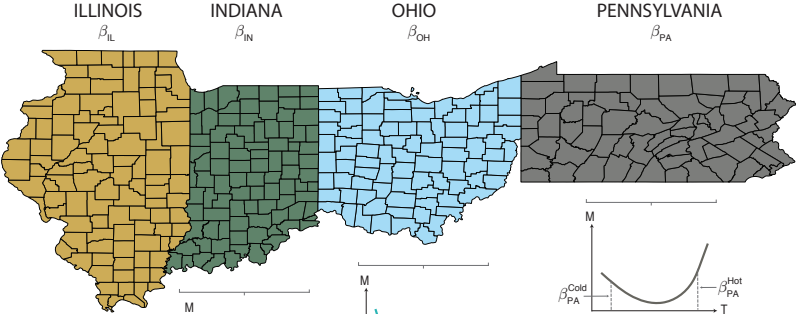
For each state  $j$  in **6 countries**, we estimate this nonparametric temperature response using annual mortality data for counties  $i$  and **daily** temperature data, **saving  $k$  temperature coefficients** for each state.

▶ [More details](#)



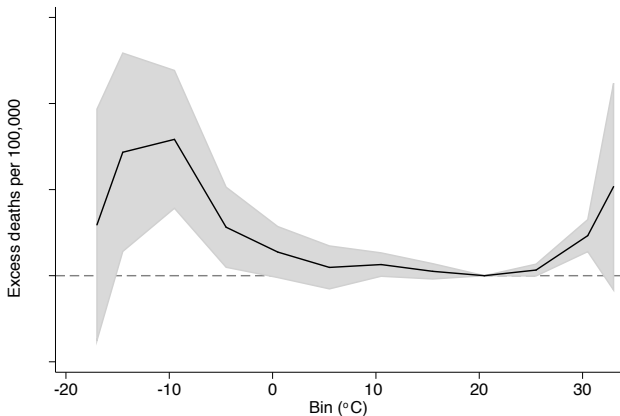
# Estimating direct local mortality-temperature relationships

$$\underbrace{M_{it}}_{\text{mortality rate}} = \underbrace{\sum_k \beta_j^k T_{it}^k}_{\text{binned daily temp}} + g_j(\text{precip}_{it}) + \underbrace{\gamma_i + \delta_j \times t}_{\text{fixed effects \& trends}} + \varepsilon_{it}$$



Note: Illustrative example only; not actual data.

# The global mortality-temperature relationship



Note: Precision weighted estimates from global regression on state level coefficients.

→ Full adaptation would imply a flat line

# Climate Impact Lab Cookbook

1. Develop “plausibly causal” estimates of relationship between measures of climate and human welfare in multiple sectors using continuously updating estimates
  - ▶ Reanalyze studies to ensure estimates meet research criteria
  - ▶ Conduct new analyses to achieve representative coverage
  - ▶ Incorporate results from new studies as they emerge
2. Build a model of direct responses based on historical adaptation and interpolate around the world, where no studies exist
3. Project responses into the future using high resolution climate projections
  - ▶ Develop cost estimates of compensatory investments
4. Obtain empirical damage function that accounts for multiple sources of uncertainty to **calculate an SCC that meets all criteria**

# Modeling adaptation

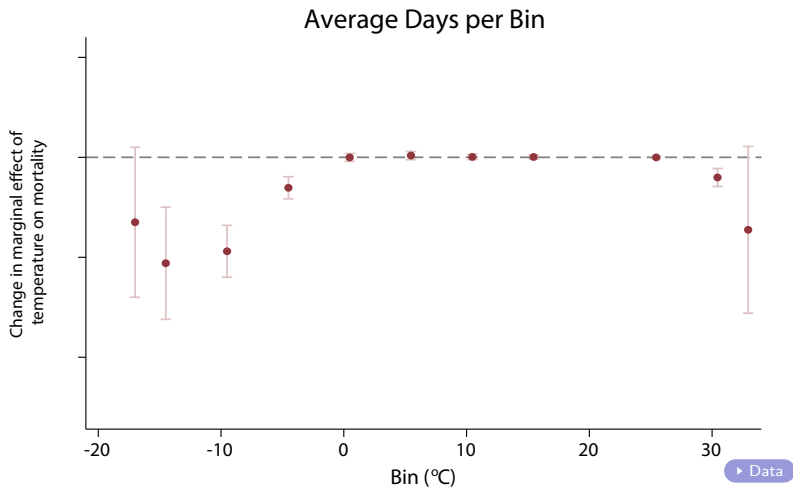
$$\hat{\beta}_j^k = \alpha^k + \underbrace{\gamma_1^k \text{Avg\_days\_bin\_}k_j}_{\text{adaptation due to CLIMATE directly}} + \underbrace{\gamma_2^k \log(\text{GDP\_pc}_j)}_{\text{adaptation due to INCOME changes}} + \underbrace{\gamma_3^k \log(\text{Pop\_density}_j)}_{\text{adaptation due to POPULATION changes}} + \varepsilon_j^k$$

## Determining adaptation response

- ▶ **Temperature:** People adapt to temperature directly, based on average exposure (e.g., Auffhammer & Aroonruengsawat, 2012)
- ▶ **Income:** Richer people are more able to make adaptive investments (e.g., Hsiang and Narita, 2012)
- ▶ **Population density:** Urban infrastructure decreases temperature sensitivity (e.g., Burgess et al., 2016)

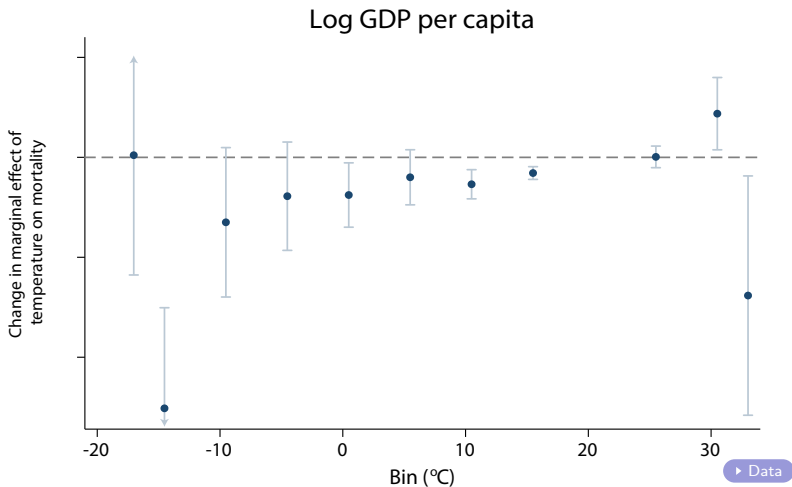
# Modeling adaptation

$$\hat{\beta}_j^k = \alpha^k + \gamma_1^k \text{Avg\_days\_bin\_}k_j + \gamma_2^k \log(\text{GDP\_pc}_j) + \gamma_3^k \log(\text{Pop\_density}_j) + \varepsilon_j^k$$



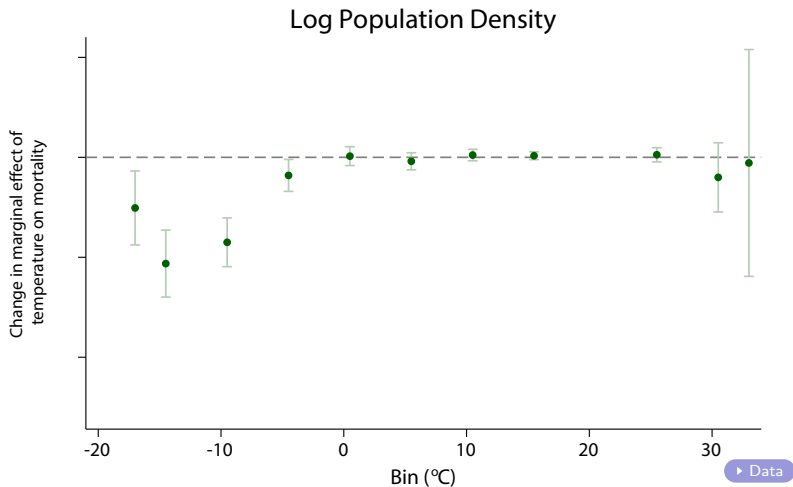
# Modeling adaptation

$$\hat{\beta}_j^k = \alpha^k + \gamma_1^k \text{Avg\_days\_bin\_}k_j + \gamma_2^k \log(\text{GDP\_pc}_j) + \gamma_3^k \log(\text{Pop\_density}_j) + \varepsilon_j^k$$



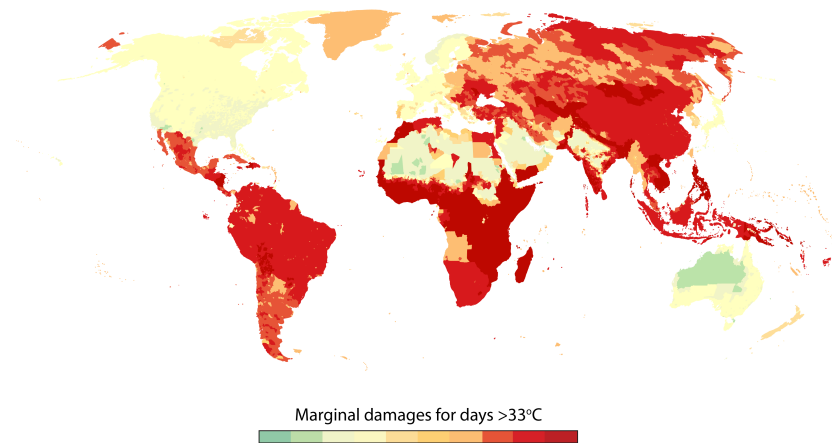
# Modeling adaptation

$$\hat{\beta}_j^k = \alpha^k + \gamma_1^k \text{Avg\_days\_bin\_}k_j + \gamma_2^k \log(\text{GDP\_pc}_j) + \gamma_3^k \log(\text{Pop\_density}_j) + \varepsilon_j^k$$



# Predicting marginal effects where no data exist

**2010**



→ Marginal effects vary with climate, income, and population density

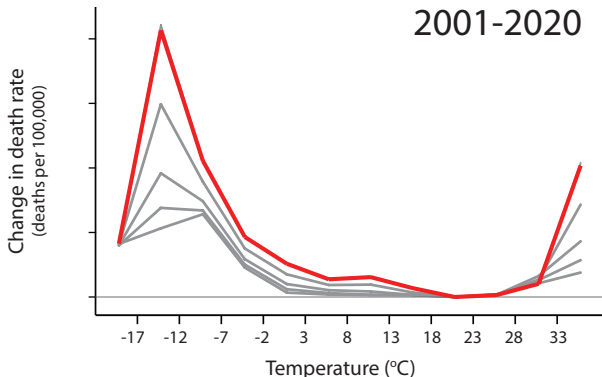


# Climate Impact Lab cookbook

1. Develop “plausibly causal” estimates of relationship between measures of climate and human welfare in multiple sectors using continuously updating estimates
  - ▶ Reanalyze studies to ensure estimates meet research criteria
  - ▶ Conduct new analyses to achieve representative coverage
  - ▶ Incorporate results from new studies as they emerge
2. Build a model of direct responses based on historical adaptation and interpolate around the world, where no studies exist
3. Project responses into the future using high resolution climate projections
  - ▶ Develop cost estimates of compensatory investments
4. Obtain empirical damage function that accounts for multiple sources of uncertainty to **calculate an SCC that meets all criteria**

# Adaptation over time

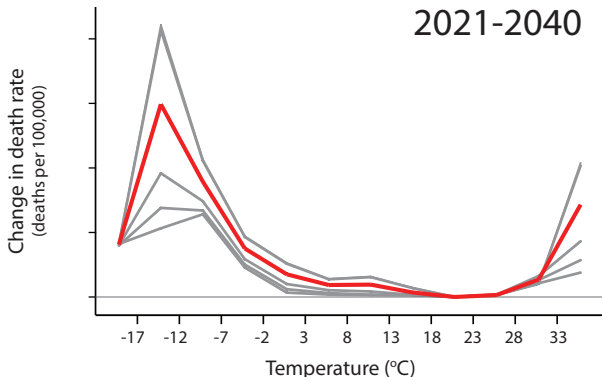
Mortality-temperature response function  
(for Firozapur, Haryana, India)



→ Marginal effects vary with climate, income, and population density

# Adaptation over time

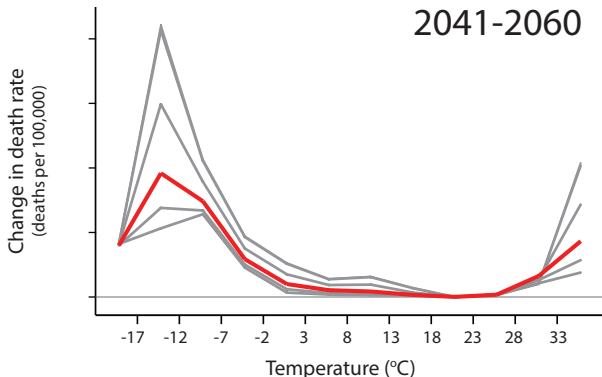
Mortality-temperature response function  
(for Firozapur, Haryana, India)



→ Marginal effects vary with climate, income, and population density

# Adaptation over time

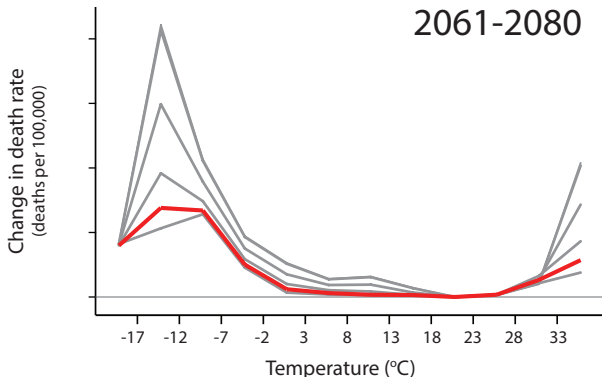
Mortality-temperature response function  
(for Firozapur, Haryana, India)



→ Marginal effects vary with climate, income, and population density

# Adaptation over time

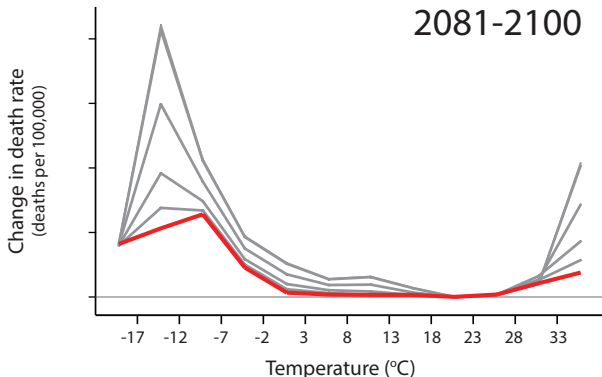
Mortality-temperature response function  
(for Firozapur, Haryana, India)



→ Marginal effects vary with climate, income, and population density

# Adaptation over time

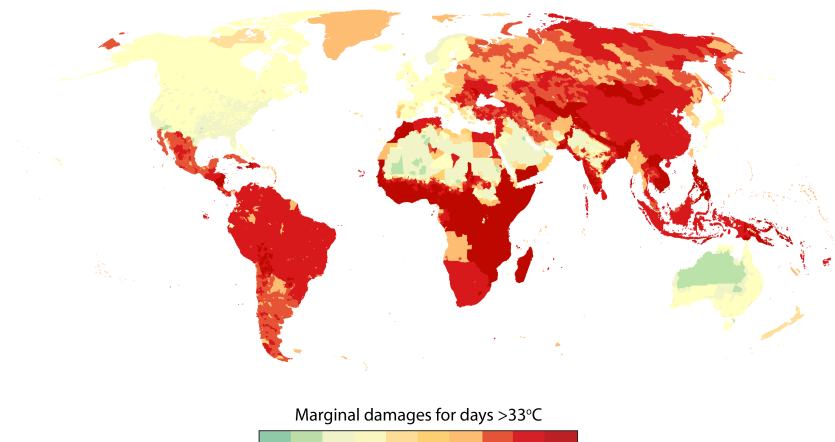
Mortality-temperature response function  
(for Firozapur, Haryana, India)



→ Marginal effects vary with climate, income, and population density

# Projecting sensitivity to temperature into the future

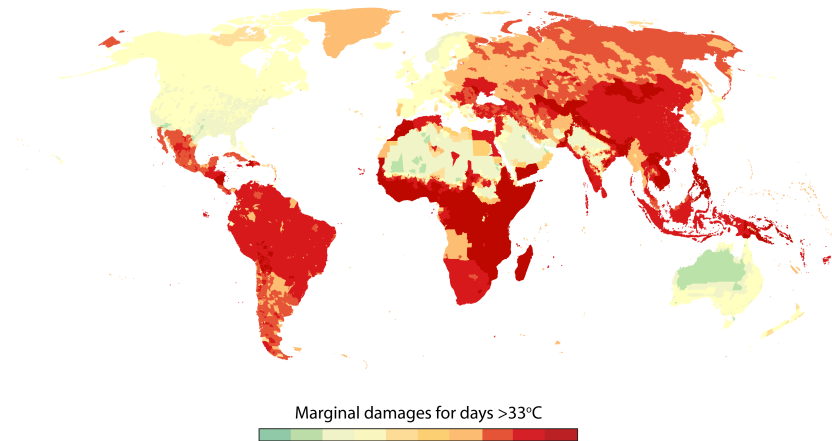
**2010**



→ Marginal effects vary with climate, income, and population density

# Projecting sensitivity to temperature into the future

**2020**

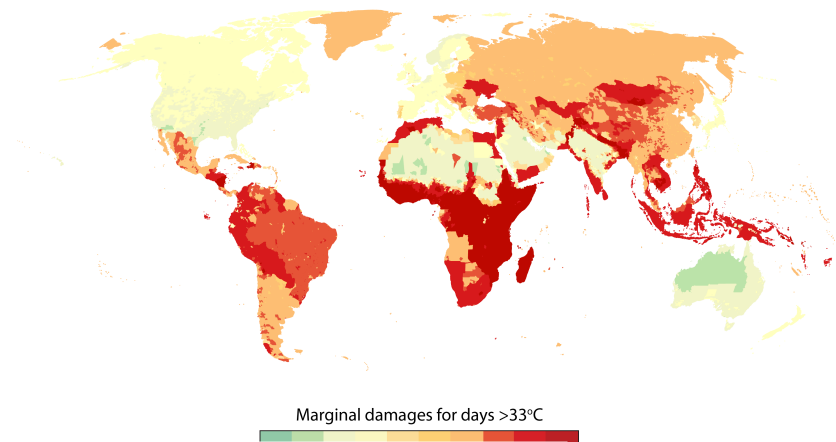


→ Marginal effects vary with climate, income, and population density



# Projecting sensitivity to temperature into the future

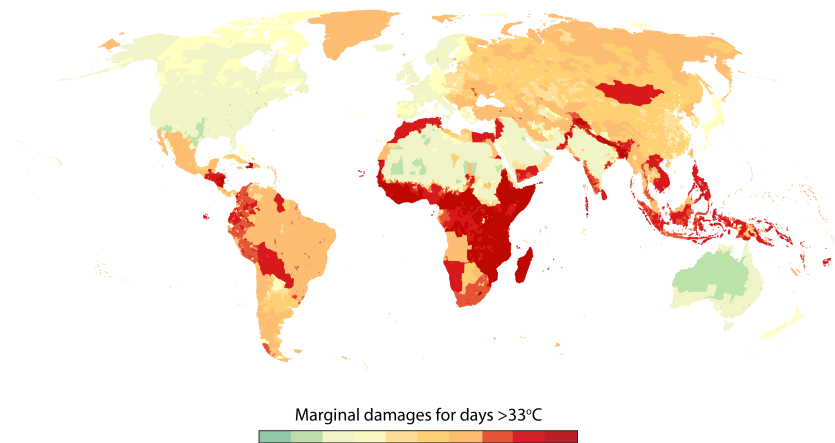
**2030**



→ Marginal effects vary with climate, income, and population density

# Projecting sensitivity to temperature into the future

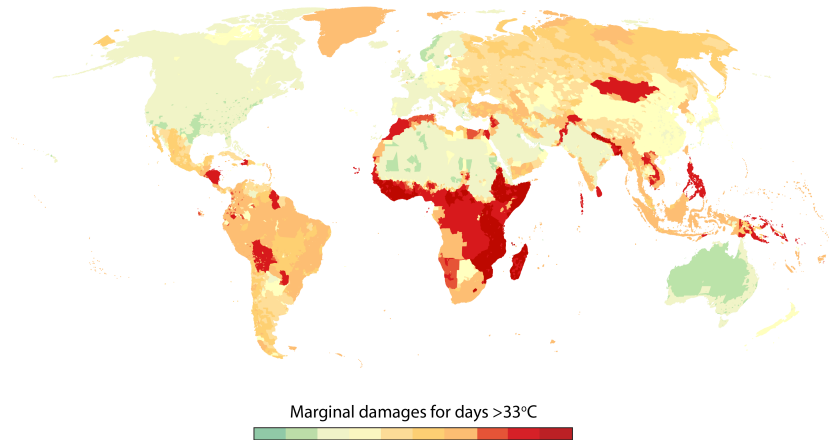
**2040**



→ Marginal effects vary with climate, income, and population density

# Projecting sensitivity to temperature into the future

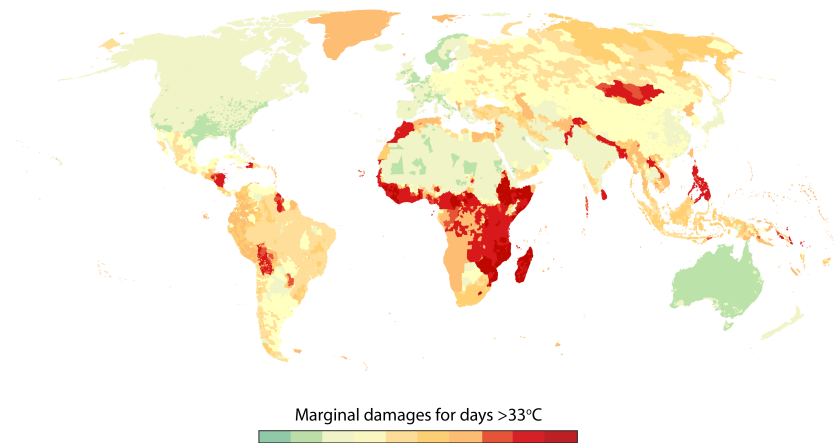
**2050**



→ Marginal effects vary with climate, income, and population density

# Projecting sensitivity to temperature into the future

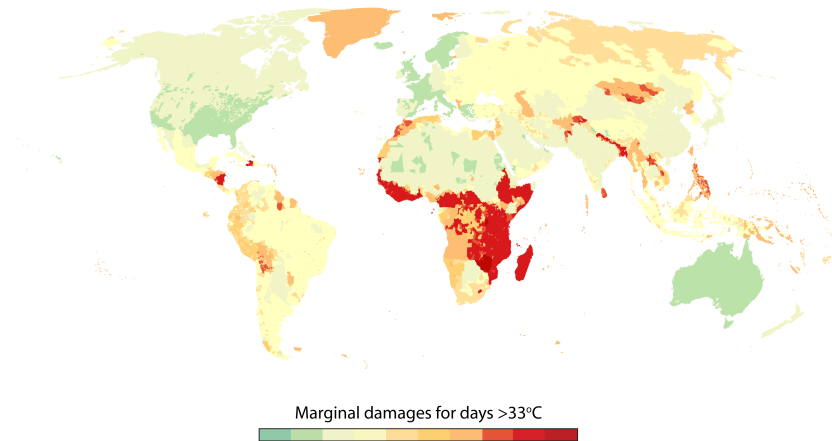
**2060**



→ Marginal effects vary with climate, income, and population density

# Projecting sensitivity to temperature into the future

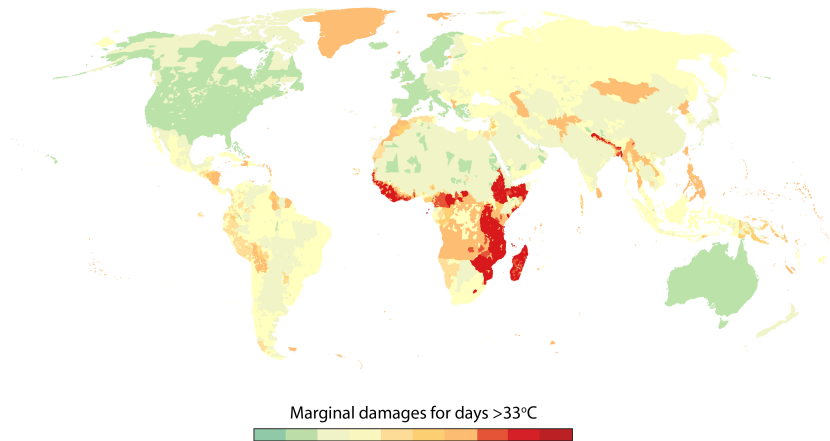
**2070**



→ Marginal effects vary with climate, income, and population density

# Projecting sensitivity to temperature into the future

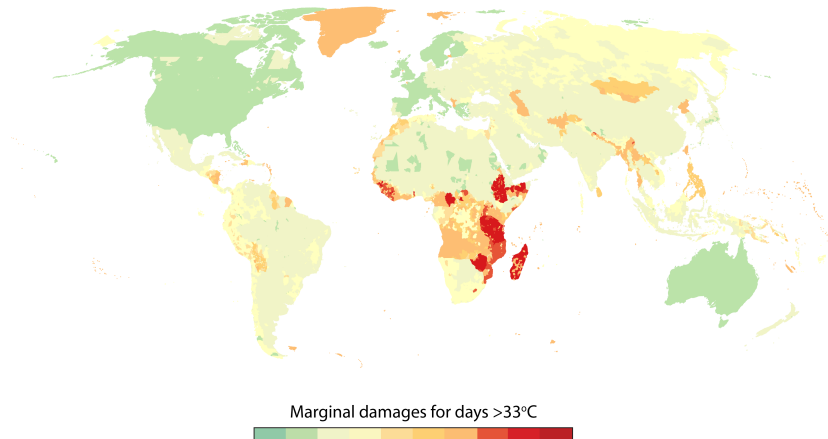
**2080**



→ Marginal effects vary with climate, income, and population density

# Projecting sensitivity to temperature into the future

**2090**



→ Marginal effects vary with climate, income, and population density

# Climate Impact Lab cookbook

1. Develop “plausibly causal” estimates of relationship between measures of climate and human welfare in multiple sectors using continuously updating estimates
  - ▶ Reanalyze studies to ensure estimates meet research criteria
  - ▶ Conduct new analyses to achieve representative coverage
  - ▶ Incorporate results from new studies as they emerge
2. Build a model of direct responses based on historical adaptation and interpolate around the world, where no studies exist
3. Project responses into the future using high resolution climate projections
  - ▶ **Develop cost estimates of compensatory investments**
4. Obtain empirical damage function that accounts for multiple sources of uncertainty to **calculate an SCC that meets all criteria**



# Calculating the “full” mortality costs of climate change

**Adaptation reduces temperature sensitivity, but it requires costly compensatory investments (e.g. air conditioning).**

## Measuring adaptation costs

**Challenge:** Reduced form results reveal how mortality-temperature relationships evolve in response to adaptation. However, they do not reveal the costs of unobserved compensatory investments

⇒ If adaptation were costless, there would be a flat relationship between mortality and temperature throughout the world

**Solution:** It is possible to bound adaptation costs in units of mortality by using a revealed preference argument

# Revealed preference approach to measuring adaptation costs

- ▶ Let  $\beta^k$  be the increase in mortality caused by a day in bin  $k$  relative to a day in a neutral bin
- ▶ Let  $T^k$  be the number of days in bin  $k$
- ▶  $C(\beta^k)$  are the compensatory investments required to realize  $\beta^k$ , the impact of temperature on mortality

## Individual's cost minimization problem (for each bin):

$$\min_{\beta^k} \beta^k T^k + C(\beta^k)$$

- ▶ Optimal  $\beta^k$  is defined by:  $T^k = -C'(\beta^k)$
- ▶  $\beta^k$  is lower when  $T^k$  is higher (costs are decreasing in  $\beta^k$ )

## Calculating the “Full” Mortality Costs [▶ back](#)

- ▶ Climate change causes  $T_0^k \rightarrow T_1^k$
- ▶ No Adaptation costs of climate change (e.g., Deschenes and Greenstone 2011):

$$\beta_0^k \times T_1^k - \beta_0^k \times T_0^k$$

- ▶ Full costs of climate change:

$$(\beta_1^k T_1^k - \beta_0^k T_0^k) + C(\beta_1^k) - C(\beta_0^k)$$

- ▶ Costs cannot be directly observed, but can be **bounded**:

Lower bound:  $C(\beta_1^k) - C(\beta_0^k) > (\beta_0^k - \beta_1^k) T_0^k$

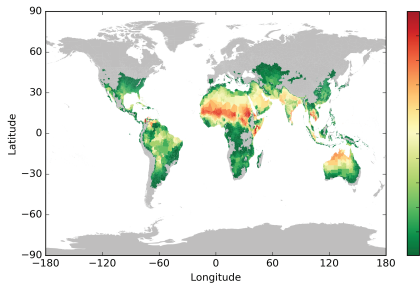
- Otherwise, Agents Would have Chosen  $\beta_1^k$  at  $T_0^k$

Upper Bound:  $C(\beta_1^k) - C(\beta_0^k) < (\beta_0^k - \beta_1^k) T_1^k$

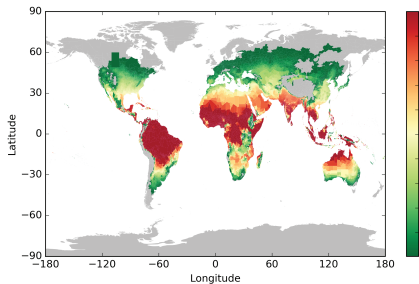
- Otherwise, Agents Would have Chosen  $\beta_0^k$  at  $T_1^k$

# Linking to climate projections

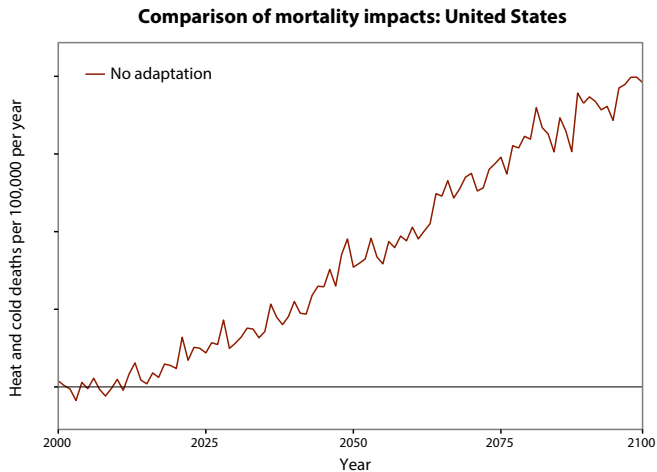
**Number of days above 28 °C in each region  
1986-2005 average**



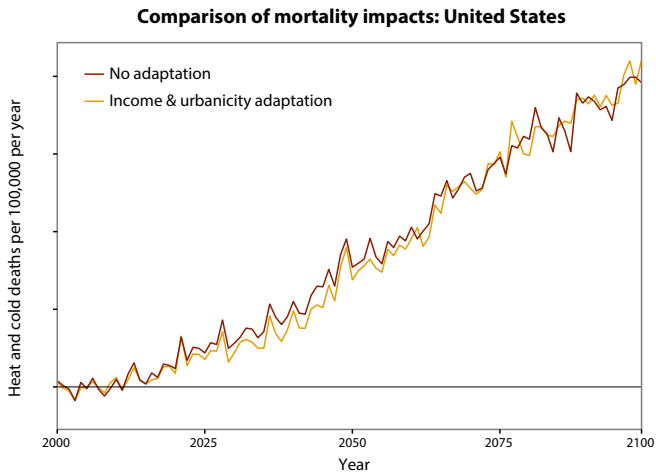
**Number of days above 28 °C in each region  
RCP8.5 2080-2099 average**



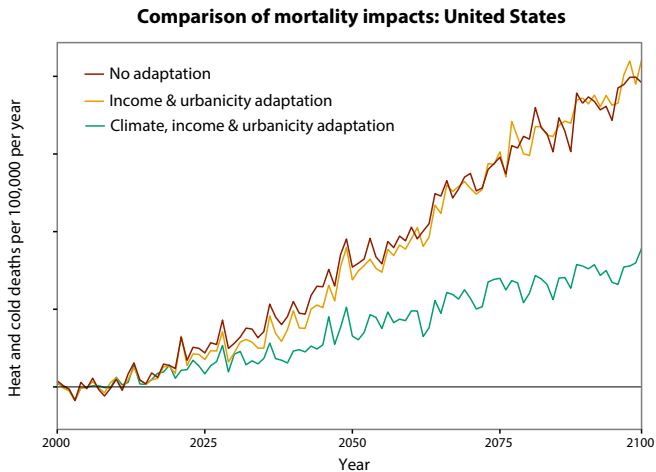
# Projected impacts for USA under RCP8.5



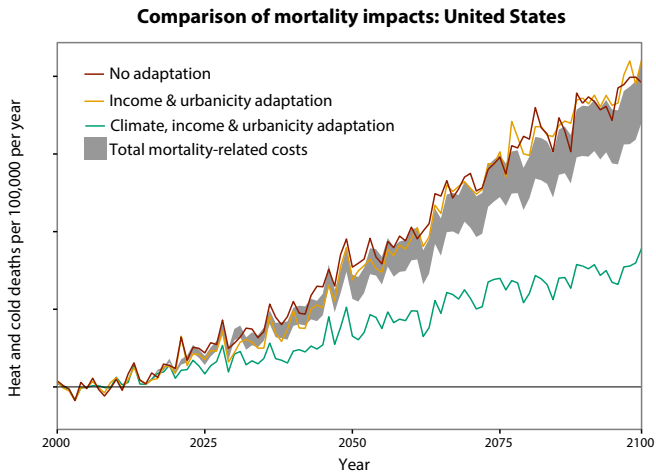
# Projected impacts for USA under RCP8.5



# Projected impacts for USA under RCP8.5



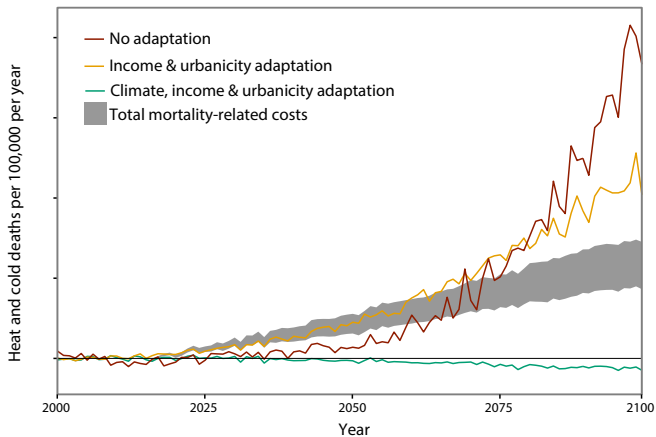
# Projected impacts for USA under RCP8.5





# Projected impacts for the globe under RCP8.5

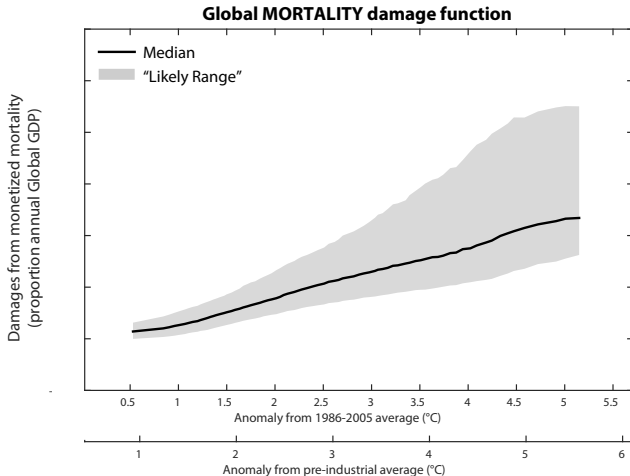
## Comparison of mortality impacts: Entire Globe



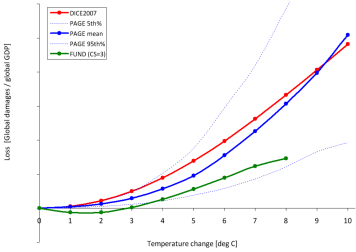
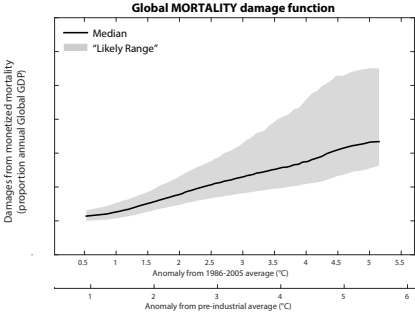
# Climate Impact Lab cookbook

1. Develop “plausibly causal” estimates of relationship between measures of climate and human welfare in multiple sectors using continuously updating estimates
  - ▶ Reanalyze studies to ensure estimates meet research criteria
  - ▶ Conduct new analyses to achieve representative coverage
  - ▶ Incorporate results from new studies as they emerge
2. Build a model of direct responses based on historical adaptation and interpolate around the world, where no studies exist
3. Project responses into the future using high resolution climate projections
  - ▶ Develop cost estimates of compensatory investments
4. Obtain empirical damage function that accounts for multiple sources of uncertainty to **calculate an SCC that meets all criteria**

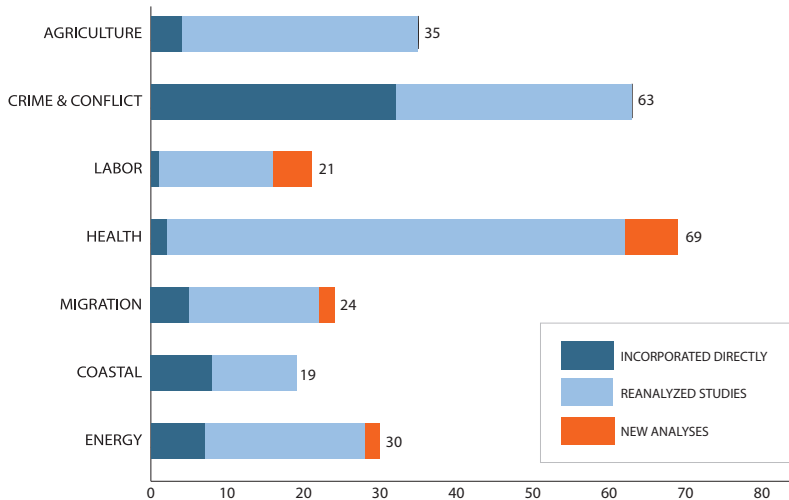
# An illustrative empirical global MORTALITY damage function



# Damage function comparison



## Apply procedure to other sectors



# Conclusion

1. We recommend that damage functions be based on **plausibly casual empirical estimates** and reflect **adaptation costs**
2. We recommend that damage functions reflect a series of other **“best practices”** for modern empirical work, including taking full advantage of an exploding empirical climate damages literature
3. Climate Impact Lab work demonstrates that such damage functions will be available soon

## Extra Slides

# State-level mortality-temp specification [▶ back](#)

$$\underbrace{M_{it}}_{\text{mortality rate}} = \underbrace{\sum_k \beta_j^k T_{it}^k}_{\text{binned daily temp}} + g_j(\text{precip}_{it}) + \underbrace{\gamma_i + \delta_j \times t}_{\text{fixed effects \& trends}} + \varepsilon_{it}$$

## Our state-level estimation

For each state  $j$  in **6 countries**, we estimate this nonparametric temperature response using annual mortality data for counties  $i$  and **daily** temperature data, **saving  $k$  temperature coefficients** for each state.

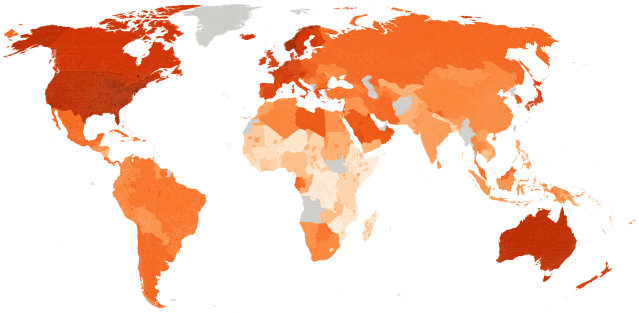
- ▶ 3 months of lags are included in the lagged monthly regressions where monthly data are available
- ▶ County fixed effects are included, as well as linear time trends
- ▶ Standard errors are heteroskedasticity robust, but not clustered, due to small numbers of clusters (counties) in many countries



# Data for interpolation: Income

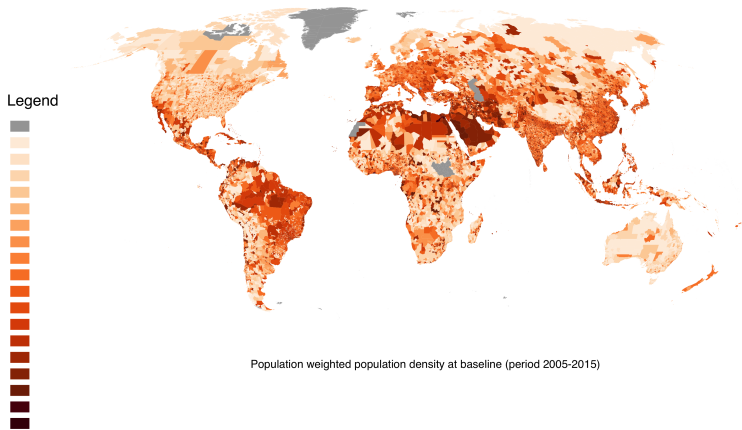
[▶ back](#)

Legend  
GDPPC



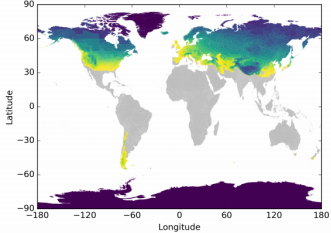
GDP per capita at baseline (period 2005-2015)

# Data for interpolation: Population Density [▶ back](#)

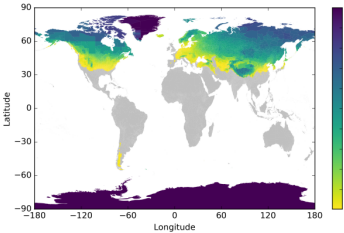


# Data for interpolation and projection: Climate ▶ back

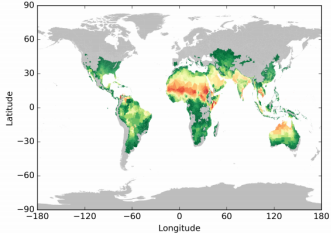
(a) # days/year Tavg below 0C in 1986-2005



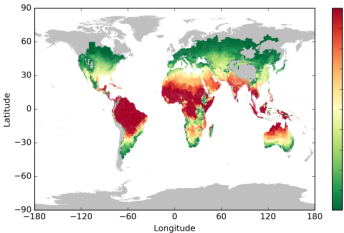
(b) # days/year Tavg below 0C in 2080-2099



(c) # days/year Tavg above 28C in 1986-2005



(d) # days/year Tavg above 28C in 2080-2099



## Measuring adaptation cost with revealed preferences [▶ back](#)

Damages today < damages after adapting + **costs of adaptation**

$$T_0 \cdot \beta(Y_0, P_0, \bar{T}_0) < T_0 \cdot \beta(Y_0, P_0, \bar{T}_1) + \mathbf{C}$$

$$T_0 \cdot [\beta(Y_0, P_0, \bar{T}_0) - \beta(Y_0, P_0, \bar{T}_1)] < \mathbf{C}$$

Damages tomorrow + **costs of adaptation** < unadapted damages tomorrow

$$T_1 \cdot \beta(Y_1, P_1, \bar{T}_1) + \mathbf{C} < T_1 \cdot \beta(Y_1, P_1, \bar{T}_0)$$

$$\mathbf{C} < T_1 \cdot [\beta(Y_1, P_1, \bar{T}_0) - \beta(Y_1, P_1, \bar{T}_1)]$$

$$\implies -T_0 \frac{\partial \beta}{\partial \bar{T}} < \mathbf{C} < -T_1 \frac{\partial \beta}{\partial \bar{T}}$$