Measuring the inequities of climate change

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BREAD-IGC Virtual PhD Lecture
Inequality of Environmental Damages

Climate Impact Lab

emLab

Climate change is a **global** challenge, but its impacts are felt **locally**

Source: Associated Press

Climate change is a **global** challenge, but its impacts are felt **locally**

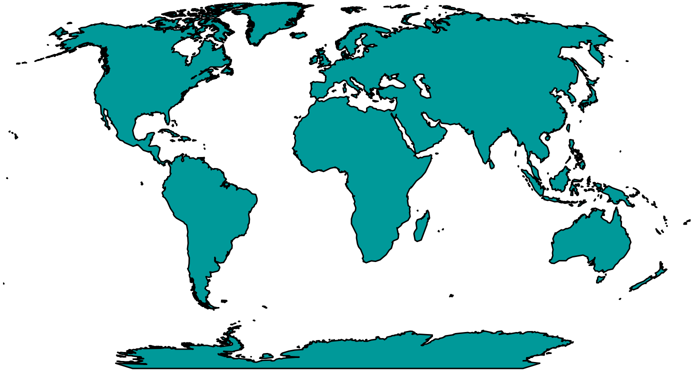

Accurate local damage estimates are critical to climate policy

- **Mitigation:** Aggregate climate damages are inaccurate if heterogeneity is ignored
- **Adaptation:** Planning for climate impacts requires accurate local projections

Early global climate damage assessments

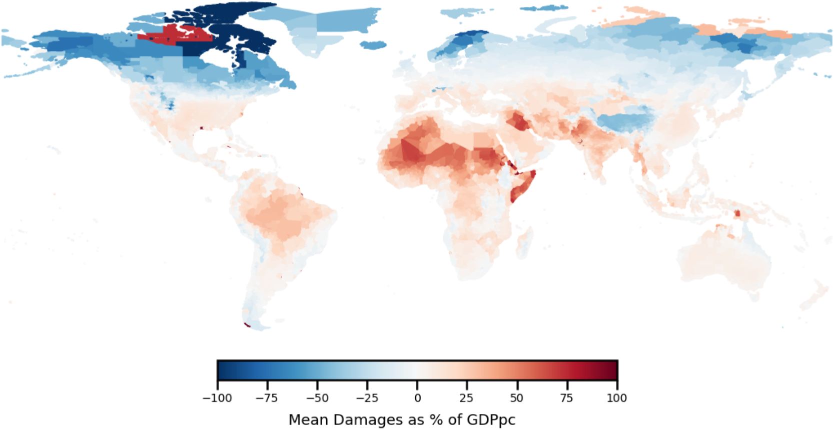
"Estimating the damages from greenhouse warming has proved to be extremely difficult. The DICE model assumes that a 3°C warming would lower world output by **1.3 percent**."

–Nordhaus (AER, 1993)



A new era for climate damage estimation

Climate Impact Lab: ∼25,000 regions capture subnational inequality of damages



A new era for climate damage estimation

Spatial equilibrium models increasingly can be resolved at high resolution and account for feedbacks and other general equilibrium effects

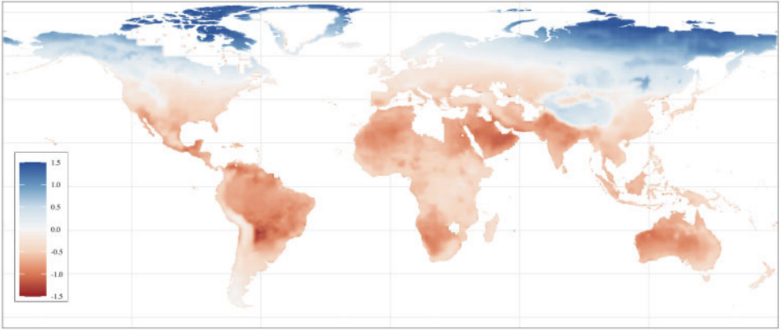
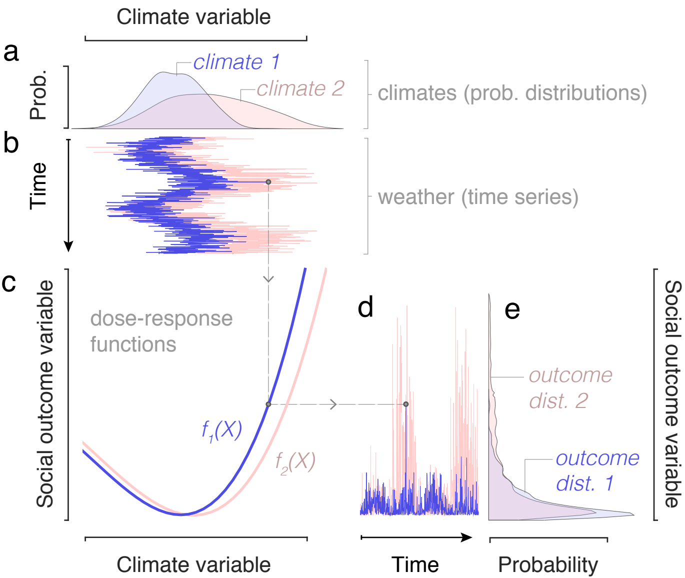


Figure 7. Effect of climate change on real output per capita in 2200
Note: The log of real output per capita under climate change minus the log of real output per capita under no climate change in period 200.

Conte, Desmet, Nagy, Rossi-Hansberg (J Econ Geo, 2021)

Using data to quantify local-level climate impacts



Carleton & Hsiang (2016)

Climate Impact Lab: interdisciplinary collaboration for local climate impacts analysis

Mortality — heat and cold deaths (Carleton et al., *2022*)

All cause mortality (<5) All cause mortality (>64) All cause mortality (5-64)

Agriculture — crop yields (Hultgren et al., *in review*)

Maize Wheat Rice

Soybean Sorghum Cassava

Energy — energy and electricity demand (Rode et al., *2021*)

Electricity consumption Other fuels consumption

Labor — labor supply & disamenity (Rode et al., *in review*)

High risk labor Low risk labor

Coastal — sea level rise and storm damages (Depsky et al., *2023*)

Sea level rise inundation SLR $\times$ tropical cyclone surge

Integration — valuing marginal damages (Nath et al., *in prep.*)

Intertemporal discounting Valuing inequality Pricing risk

Estimating data-driven local climate damages

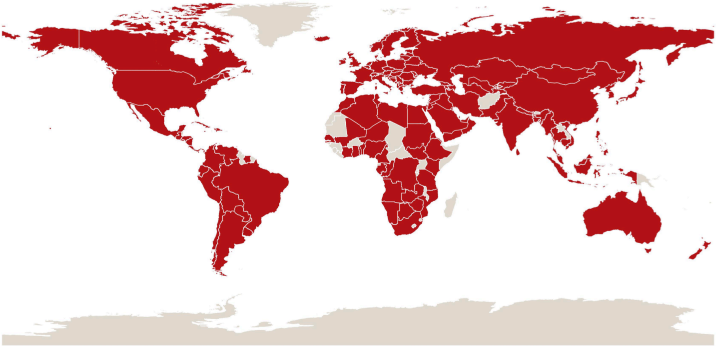
Step 1: Collect and harmonize **comprehensive data** for each sector

Step 2: Estimate **causal impact relationships**, accounting for key drivers of adaptation

Step 3: Project impacts globally today and into the **future** using high resolution climate projections

Energy (Rode et al., 2021)

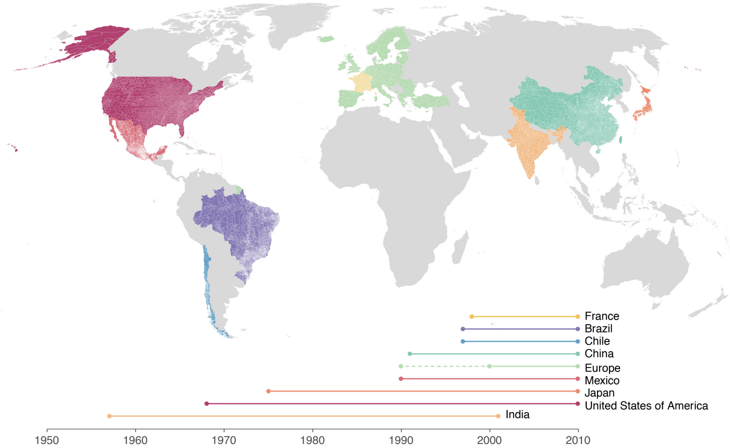
International Energy Agency (IEA) provides data from 146 Countries (1971-2012).



Annual consumption of residential, commercial, and industrial electricity and other fuels

Mortality (Carleton et al., QJE 2022)

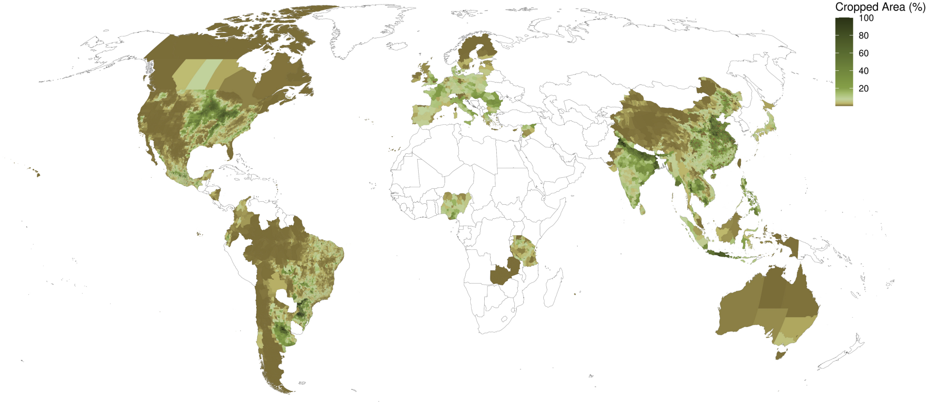
Subnational mortality records covering 55% of the global population



Age-specific annual mortality rates at ∼county level

Agriculture (Hultgren et al., in review)

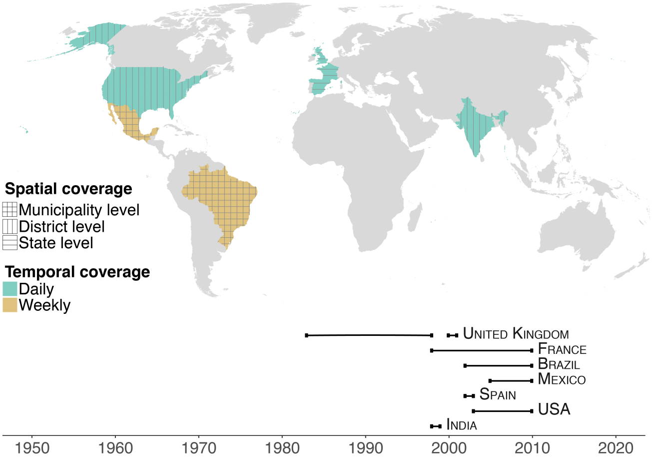
Collection of subnational crop production data covering 41,186 region × crop units



Annual yield for maize, soybean, rice, wheat, sorghum and cassava

Labor (Rode et al., in review)

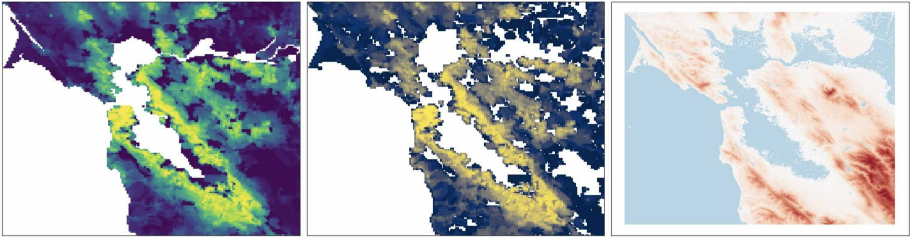
Time use and labor force surveys representing ∼30% of the global population



Minutes worked per day/week for labor force participants ages 15-65

Coastal (Depsky, et al., 2023)

Downscaled, globally-comprehensive measures of exposure and hazard



- Coastal elevation from CoastalDEM (Climate Central)
- Asset value data downscaled from national accounts by LitPop (Climada)
- Population data from Gridded Population of the World
- Extreme sea level distributions from Global Tide and Surge Reanalysis (GTSR)

High-resolution climate & covariate observations

Dataset	Variables	Resolution
Historical		
GMFD	Temp, precip	$0.25^\circ \times 0.25^\circ$
BEST	Temp	$1^\circ \times 1^\circ$
UDEL	Precip	$0.5^\circ \times 0.5^\circ$
Gennaioli et al. (2014)	GDP	ADM1
NASA DMSP-OLS	Nighttime lights	30 arcsecond
LandScan	Gridded population	30 arcsecond
FAO	Irrigated area	5 arcminute
Future		
NASA NEX-GDDP	Temp, precip	$0.25^\circ \times 0.25^\circ$
IIASA SSPs	Age-specific national populations	National
OECD Env-Growth	Age-specific national populations & GDP	National

Estimating data-driven local climate damages

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Exposure and vulnerability in climate impacts

Damages from climate come from exposure e (e.g., how many hot days) and vulnerability x (e.g., access to A/C):

$$Damage = f(e, x)$$

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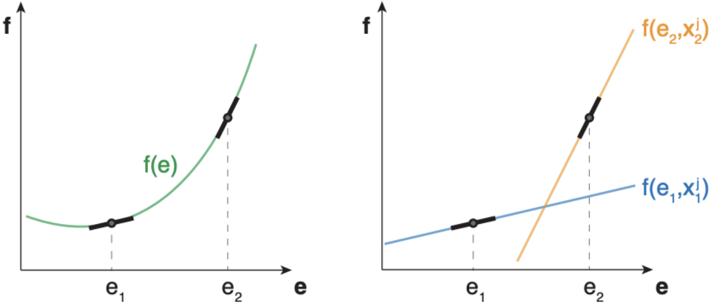
$$Damage = f(e, x)$$

Local differences in climate change impacts arise: due to differential **exposure**, **nonlinearities**, and differential **vulnerability**:



Hsiang, Oliva & Walker (2019)

Estimating an impact relationship (nonlinearity)

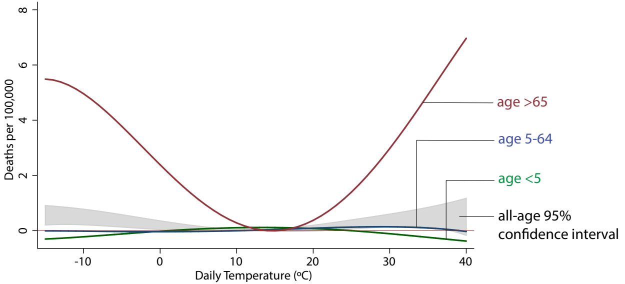
Use random variation in short-run weather to causally identify the effect of weather realizations on sector-specific outcomes.

Estimating an impact relationship (nonlinearity)

Use random variation in short-run weather to causally identify the effect of weather realizations on sector-specific outcomes.

For example:

$$Mortality\_rate_{ait} = f_a(Temp_{it}, Precip_{it}) + \underbrace{\alpha_{ai} + \delta_{act}}_{\text{nonparametric location \& time controls}} + \varepsilon_{iat}$$



Reviews of related literature: Auffhammer (*JEP*, 2018), Carleton & Hsiang (*Science*, 2016), Dell et al. (*JEL*, 2014)

Heterogeneity in response to weather (vulnerability)

Allow the shape of the function describing the impact relationship at a location be a function of conditions at that location.

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Allow the shape of the function describing the impact relationship at a location be a function of conditions at that location.

$$Outcome_{it} = \sum_p \beta^p \, Weather^p_{it} \; ... \; controls$$

$$\uparrow$$

$$\beta^p(i) = \gamma^p_0 + \gamma^p_1 \, Climate_i + \gamma^p_2 \, \log(GDPpc)_i + ...$$

Covariates determining heterogeneity depend on sector

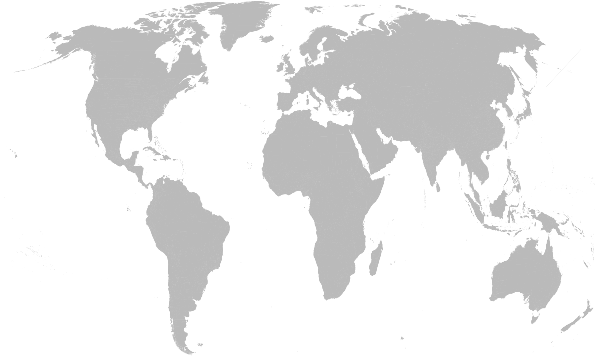
→ $Climate_i$ = long-run avg. climate (e.g. temperature, degree days, precipitation)

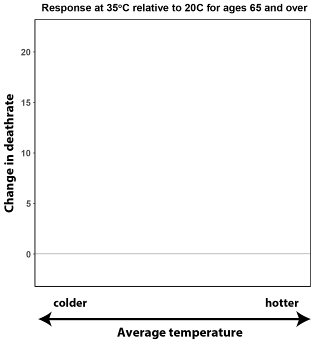
→ $\log(GDPpc)_i$ = average log income per capita

→ $area\_irrigated_i$ = share of area equipped for irrigation

Similar approaches: Auffhammer (*JEEM*, 2022); Heutel et al. (*ReStat*, 2021); Garg et al. (*WP*, 2020); Butler & Huybers (*Nat. Clim. Chg.*, 2013); Roberts & Schlenker (*PNAS*, 2009)

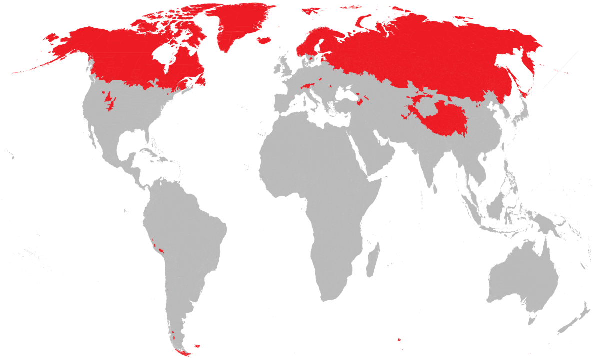
Mortality: adaptation to climate

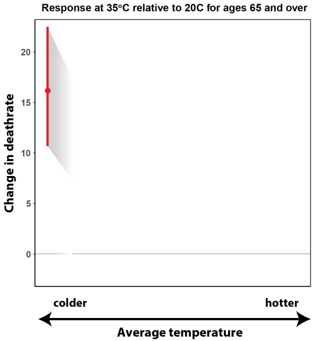




Effect day at 35°C relative to 20°C for ages 65 and over.
Coefficient calculated for deciles of *TMEAN* (red shaded area).

Mortality: adaptation to climate





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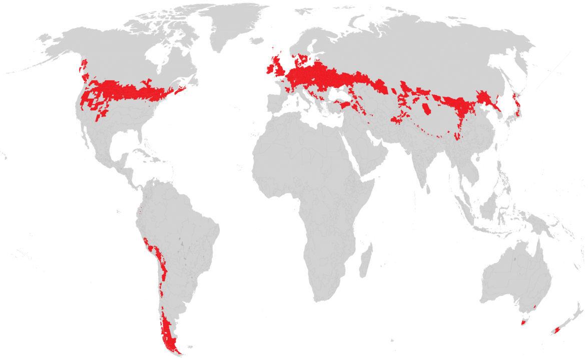

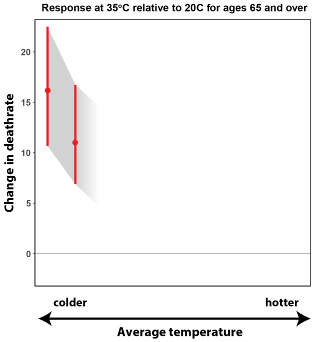

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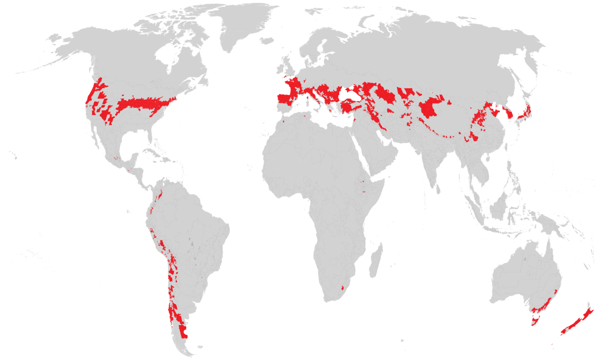

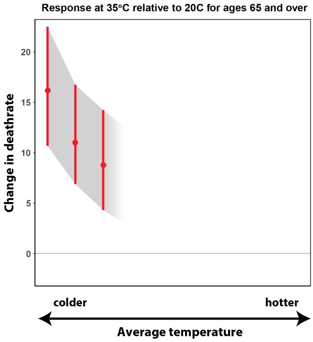

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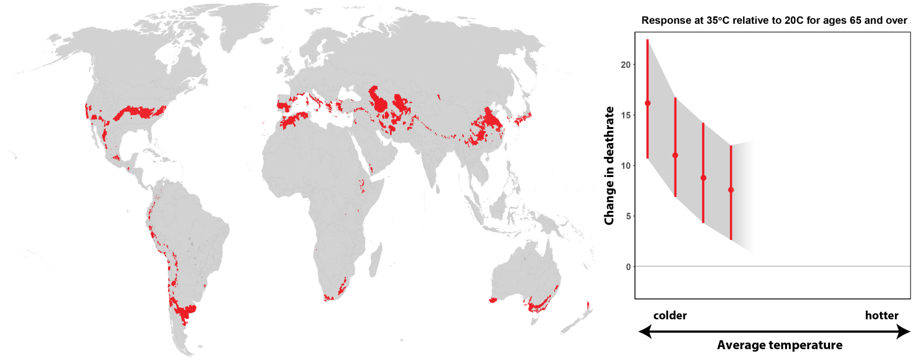

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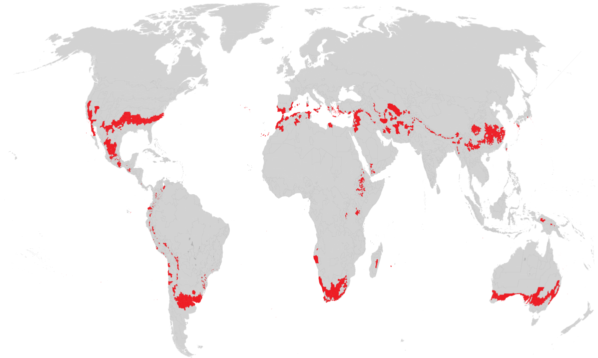

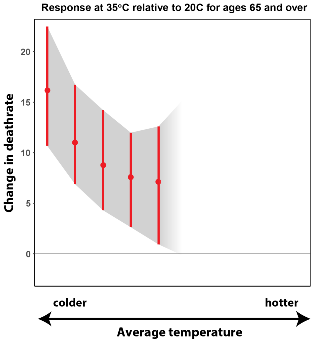

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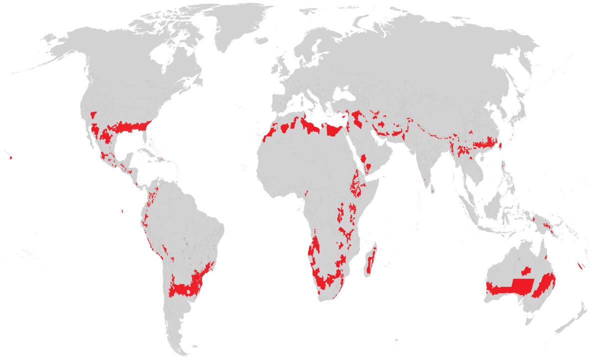

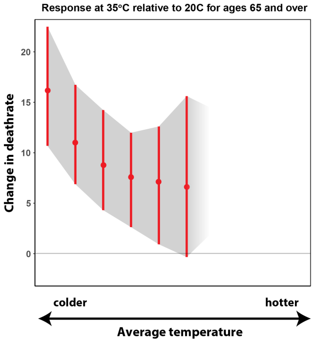

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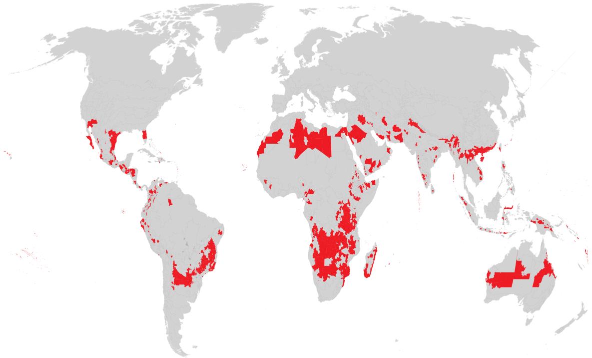

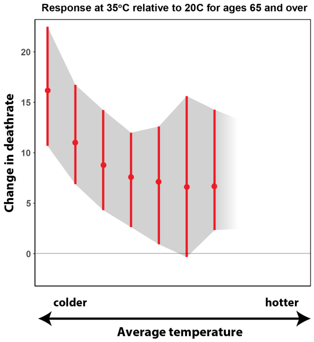

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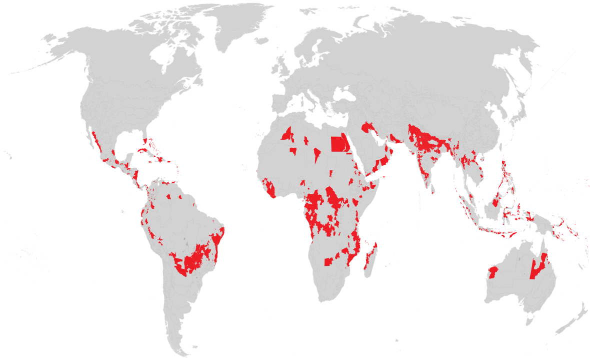

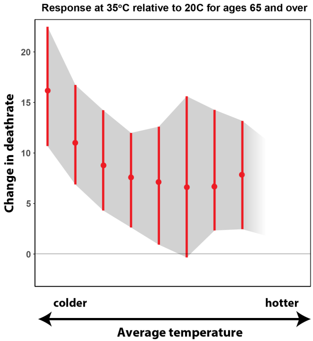

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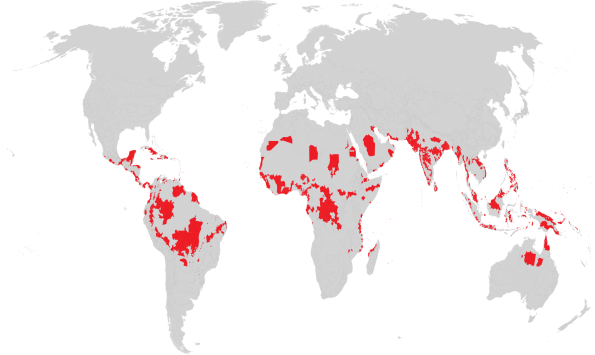

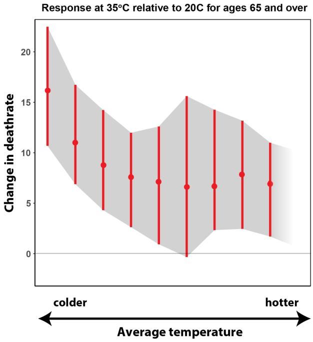

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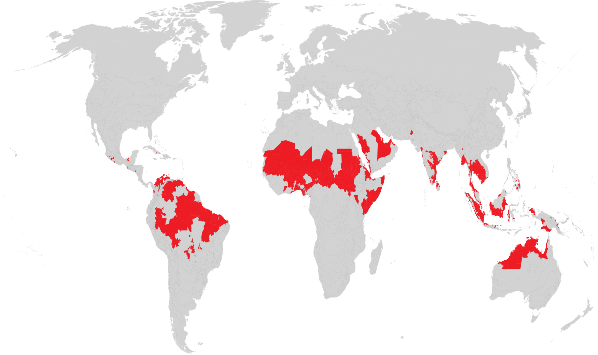

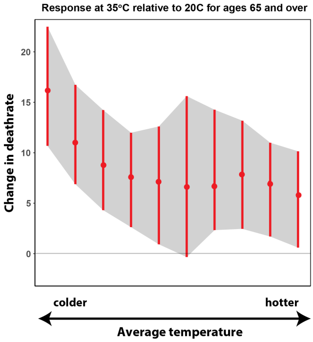

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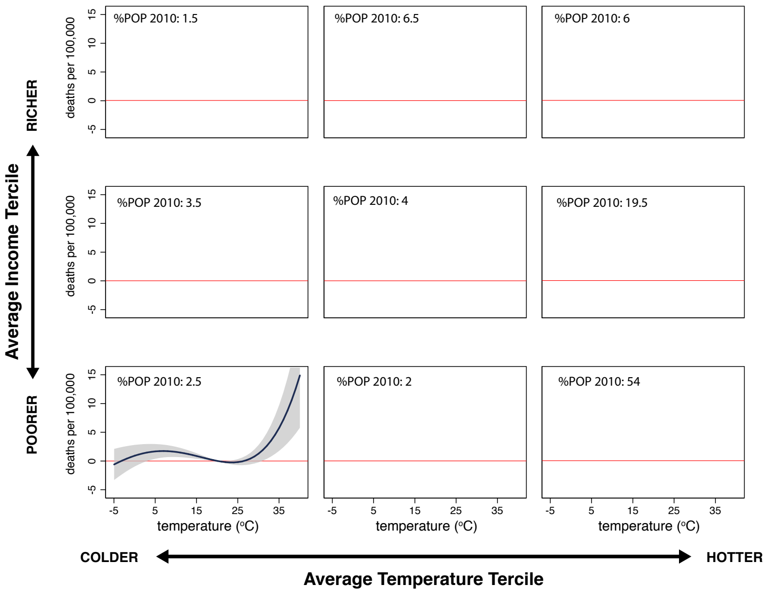
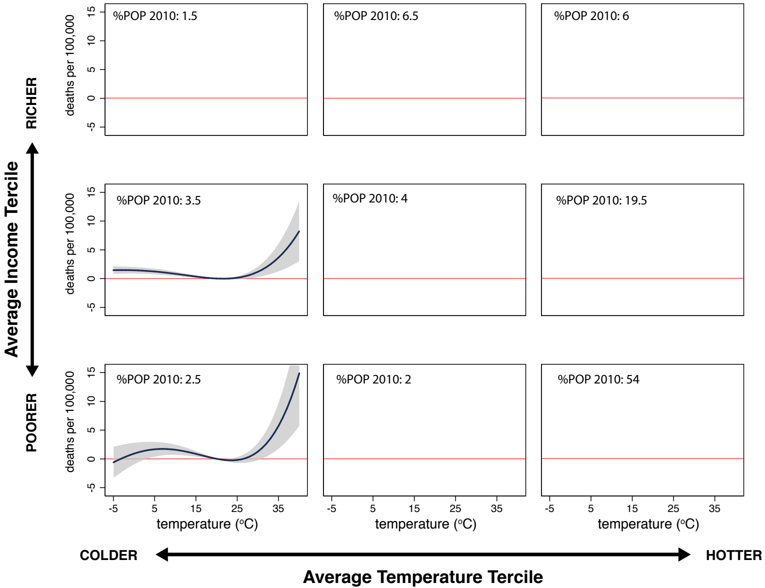
Adaptation to income × climate



Adaptation to income × climate



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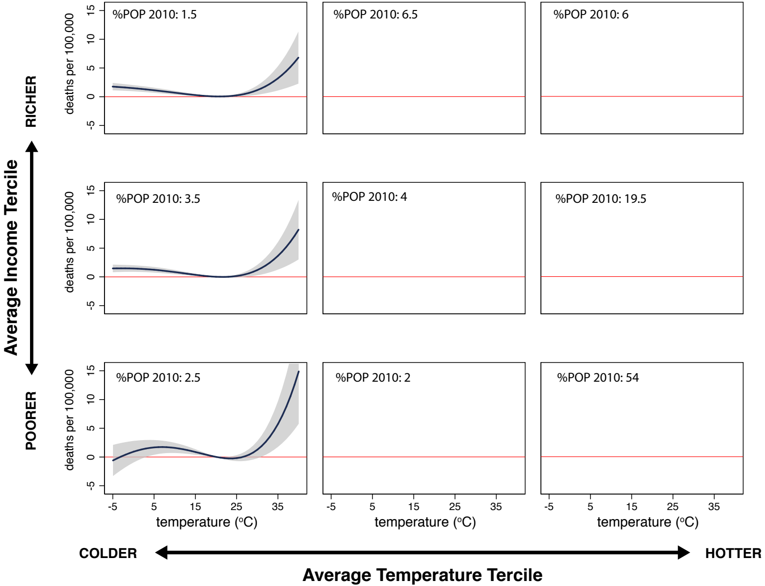

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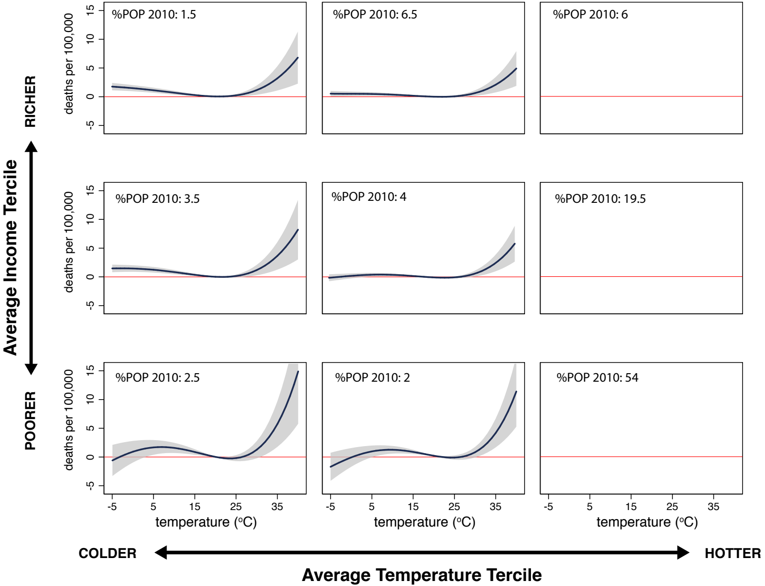

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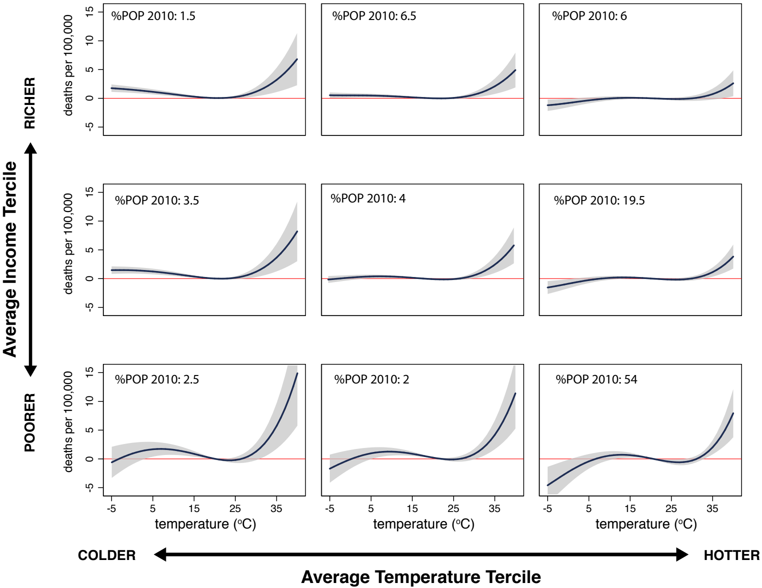

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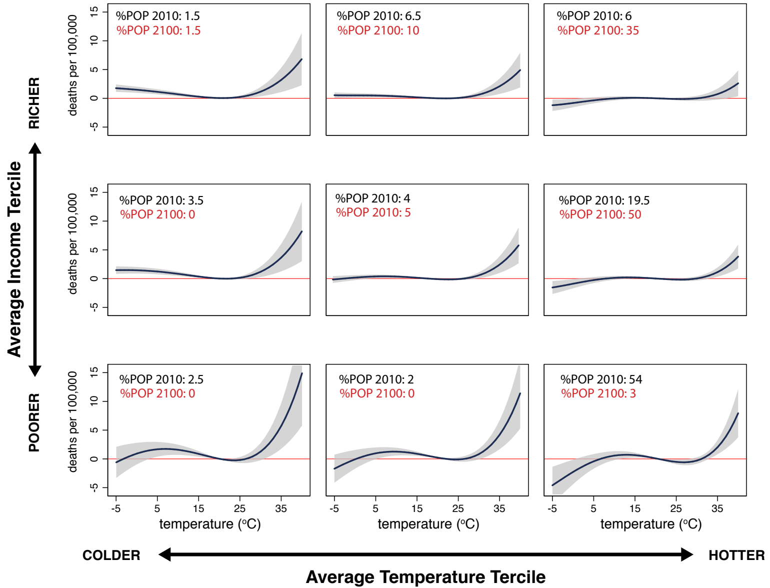
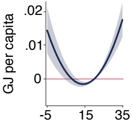


Electricity: consumption determined by income

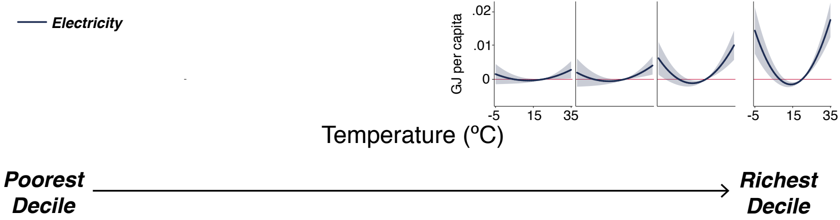
—— *Electricity*



Temperature (ºC)

Poorest Decile ⟶ ***Richest Decile***

Electricity: consumption determined by income



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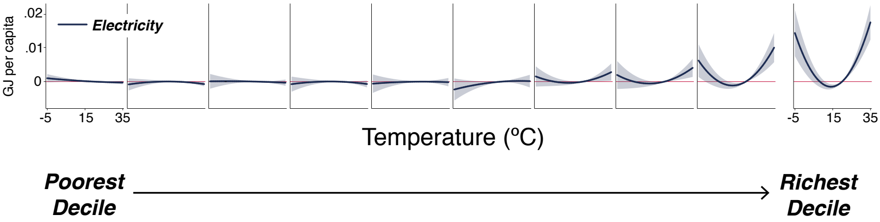

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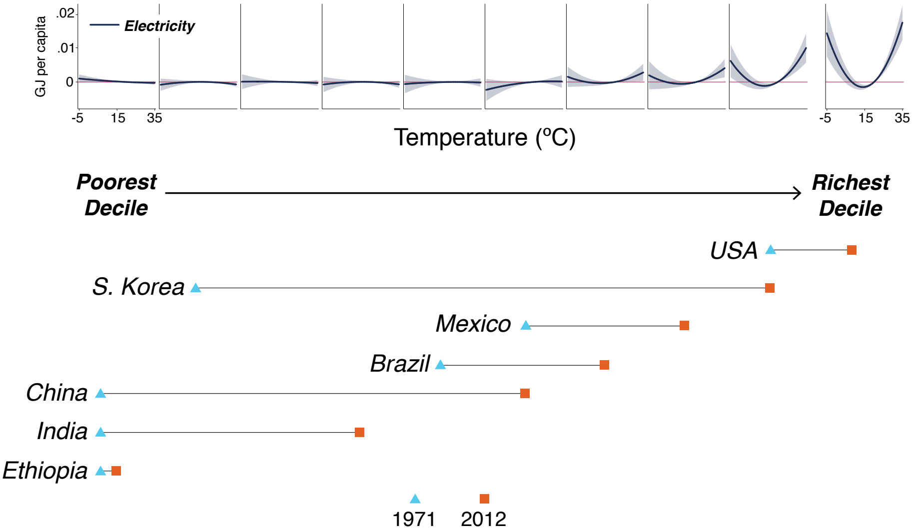

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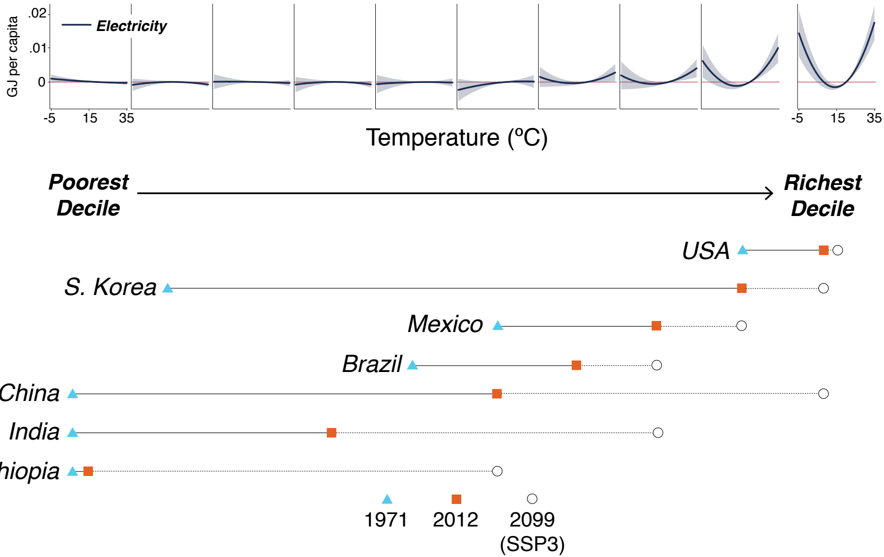
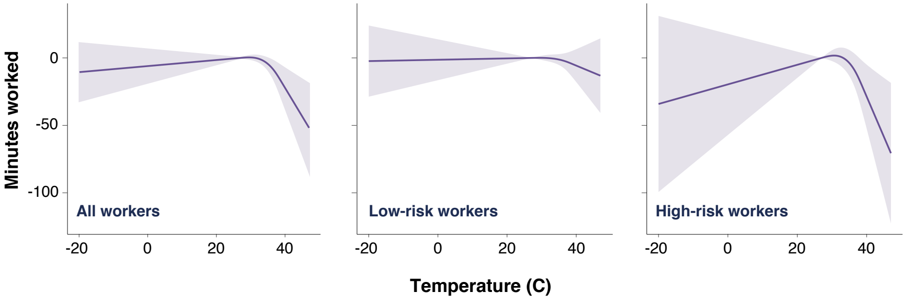


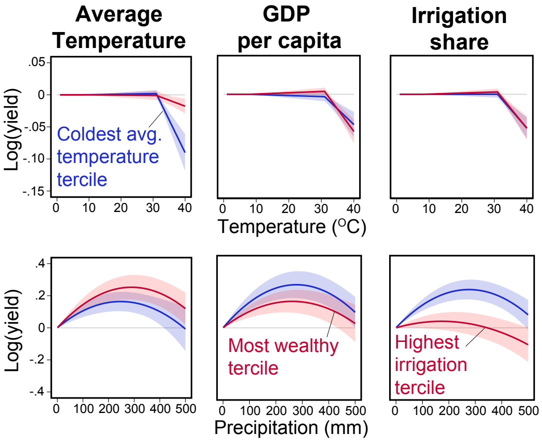
Labor: Sector of employment determines sensitivity

- **High risk workers:** Agriculture, mining, construction, manufacturing
- **Low risk workers:** All other sectors



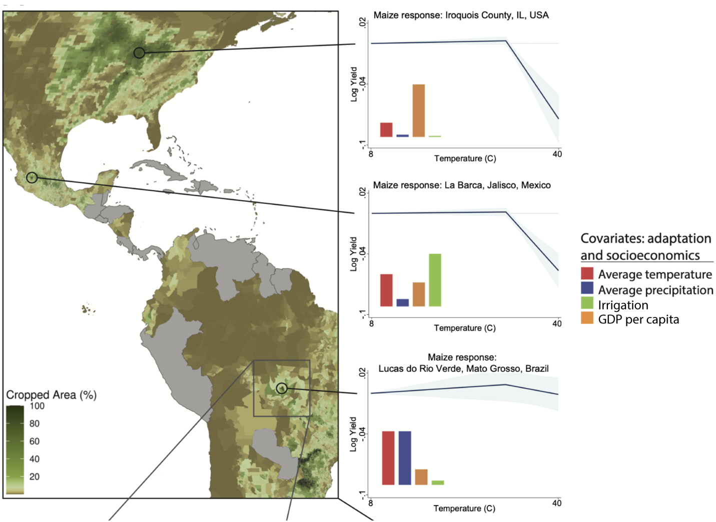
Workforce composition is empirically modeled based on income and climate

Agriculture: adaptation determined by climate, income, irrigation



Crop-specific cross-validation used to select from many functional forms and possible interactions.

Agriculture: adaptation determined by climate, income, irrigation



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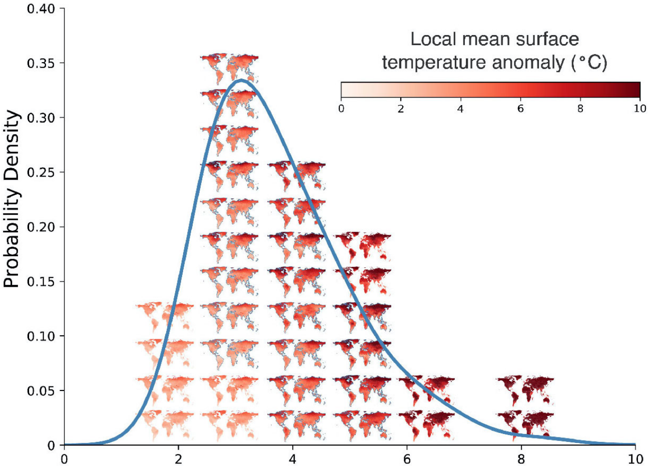
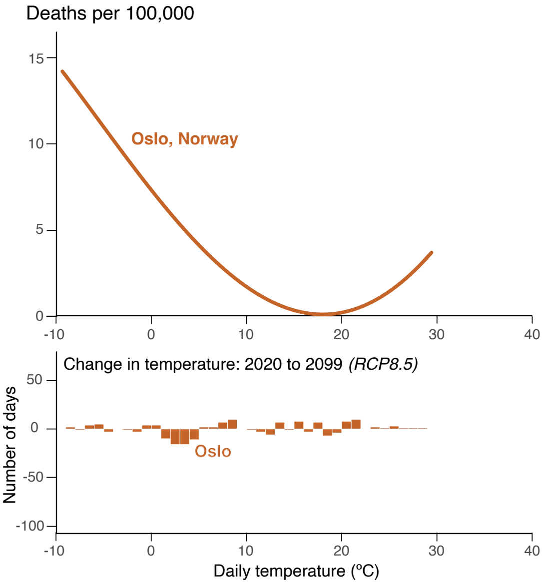
Project future climate using climate model ensemble

The probability distribution of estimated change in Global Mean Surface Temperature in 2080-2099 of the 33 models and model surrogates under RCP 8.5



Capturing differential vulnerability



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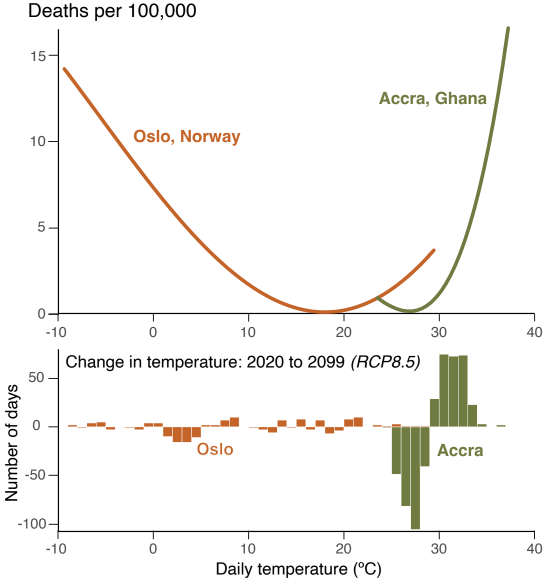

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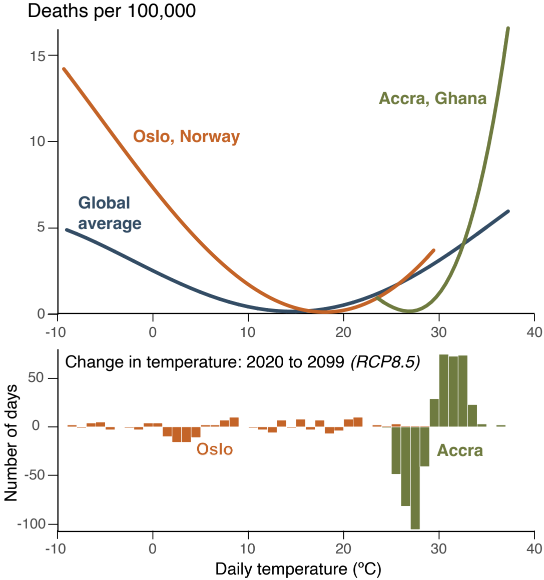
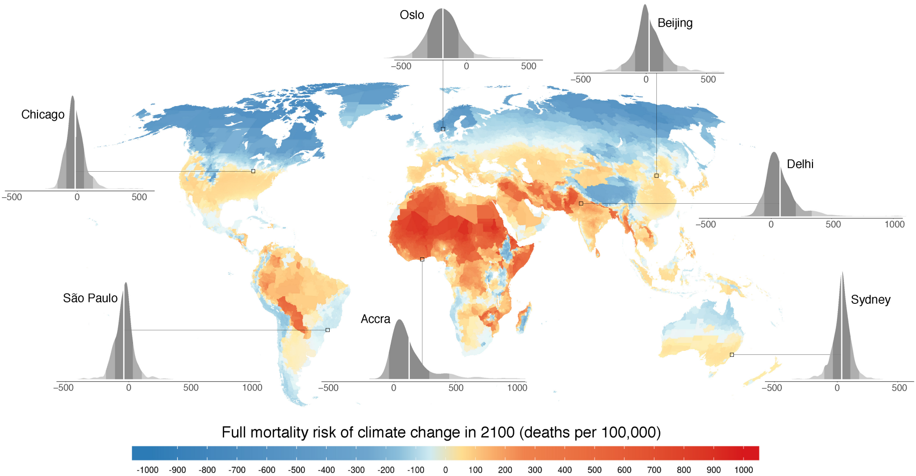


Impacts are distributed unequally across the globe

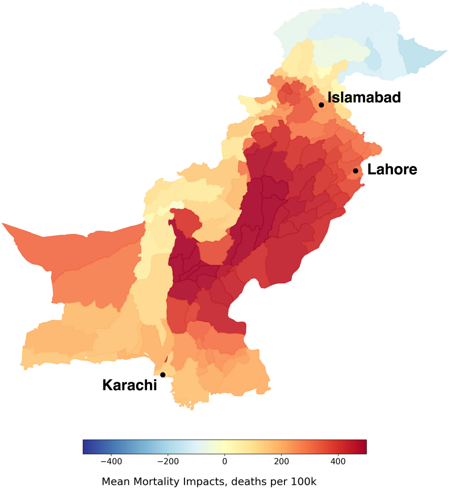


Δ Mortality + adapt. costs due to warming; 2099, high-emissions scenario

Mortality impacts are distributed unequally

Pakistan: 376 deaths/100k
Heart disease: 110 deaths/100k

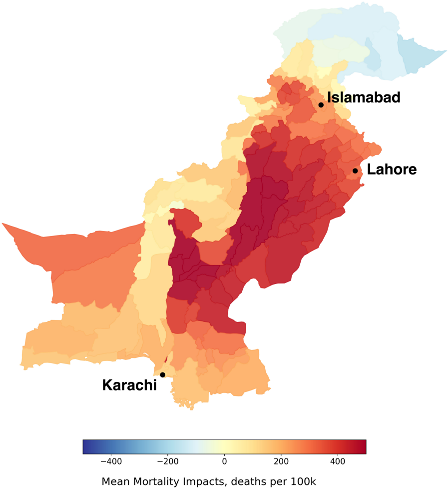
Ghana: 200 deaths/100k
Respiratory infections: 55 deaths/100k

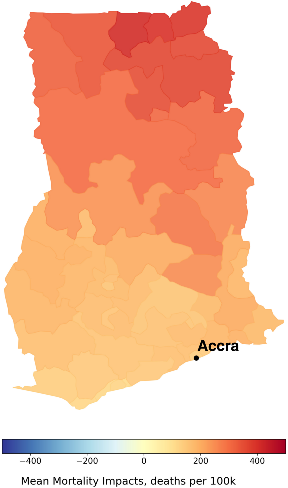


Mortality impacts are distributed unequally

Pakistan: 376 deaths/100k
Heart disease: 110 deaths/100k

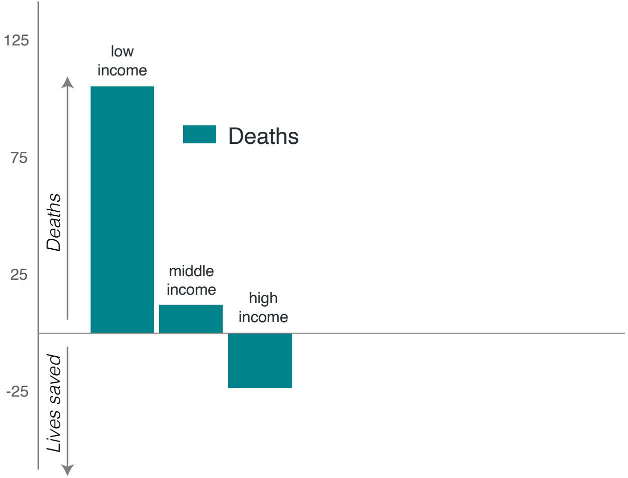
Ghana: 200 deaths/100k
Respiratory infections: 55 deaths/100k





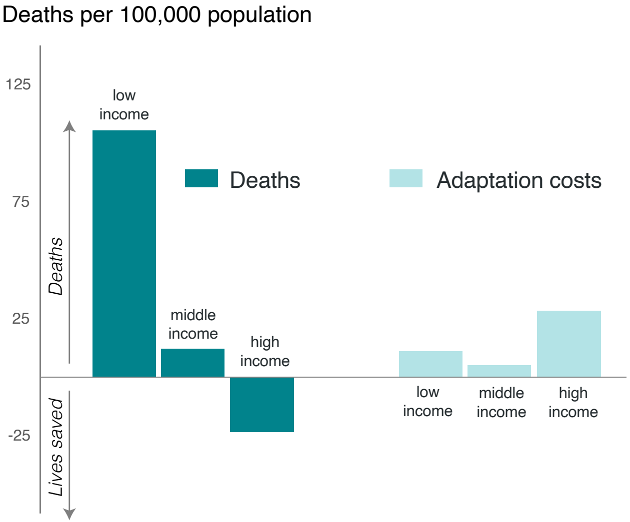
Mortality impacts are distributed unequally

Deaths per 100,000 population



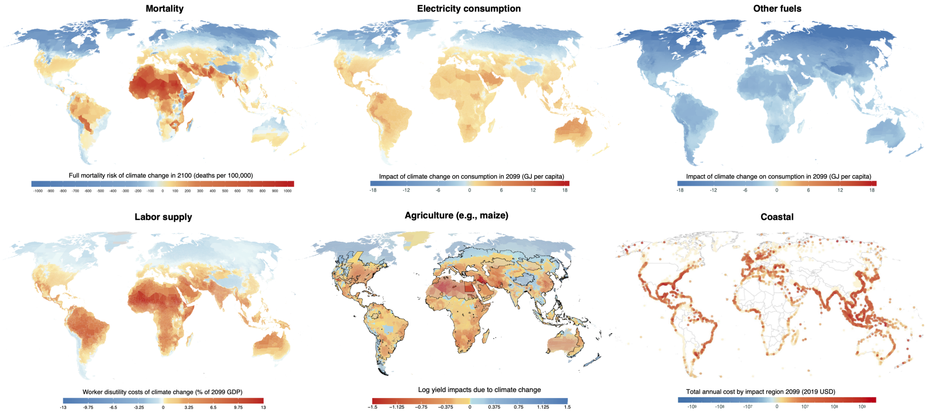
2100, RCP8.5 (high emissions), SSP3

Mortality impacts are distributed unequally



2100, RCP8.5 (high emissions), SSP3

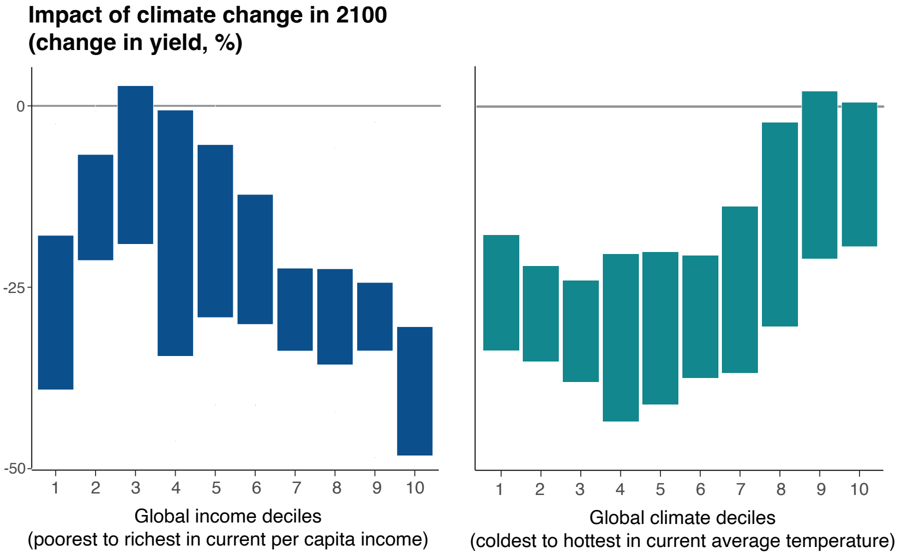
Impacts are distributed unequally across the globe



2100, RCP8.5 (high emissions), SSP3

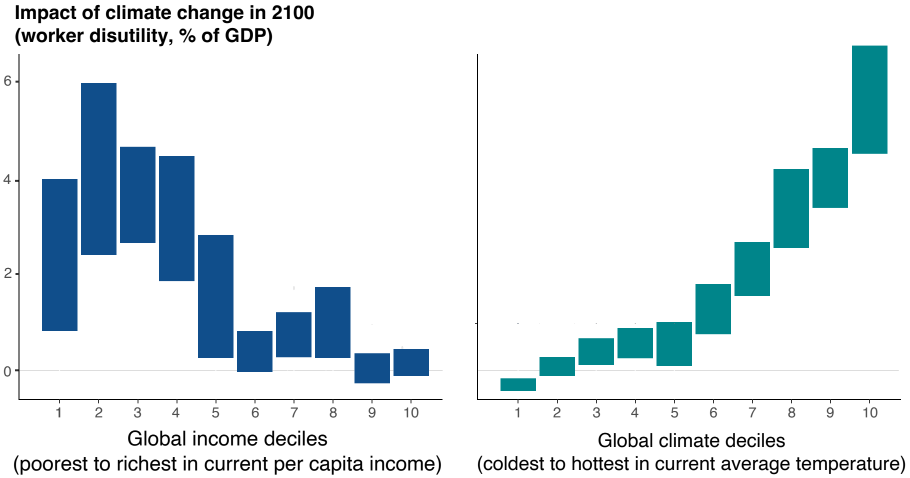
Uncertainty

Agriculture: Losses greatest in breadbaskets



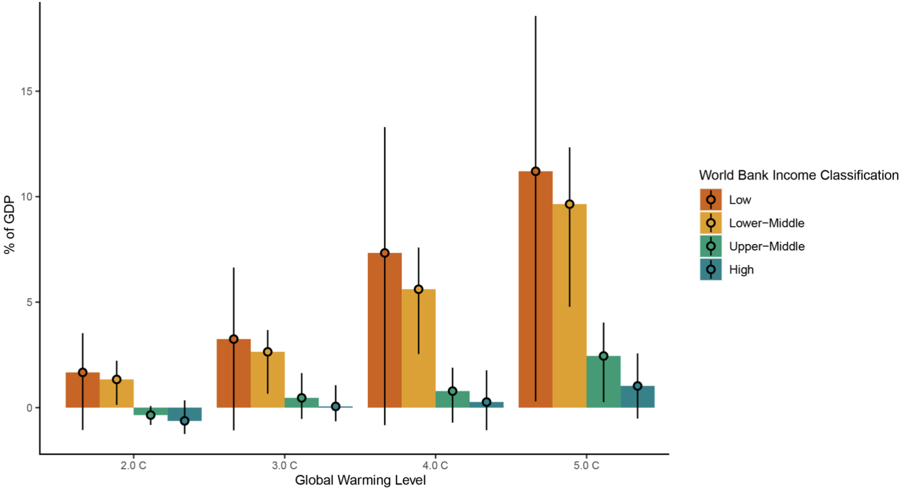
Hultgren et al. (in review)

Labor: Disutility impacts in hot & poor places



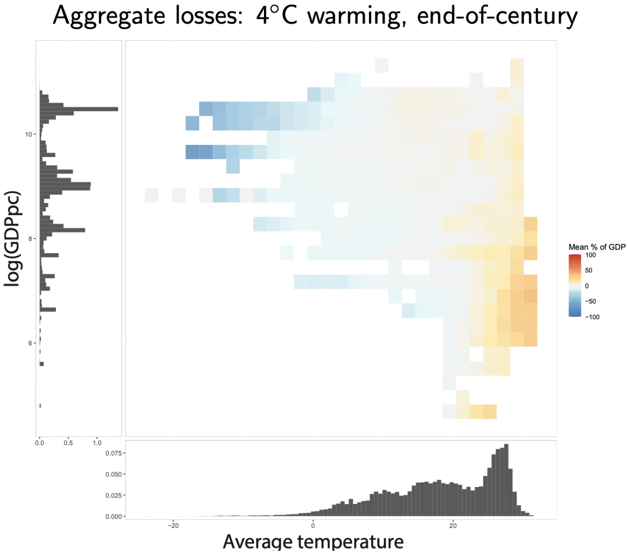
Rode et al. (in review)

Aggregate damages are borne disproportionately by today's poor...



Jina, Carleton, Hultgren, Rode et al (in prep.)

...and particularly by the poor in hot climates



Jina, Carleton, Hultgren, Rode et al. (in prep.)

Making local damage estimates relevant for climate policy

- **Mitigation:** Social cost of carbon (SCC) drives mitigation and can embed distributional consequences *(next section)*
- **Adaptation:** Local and regional planning for climate impacts can leverage local impact projections *(extra slides)*

The Social Cost of Carbon

The Social Cost of Carbon (SCC) - the monetary value of the damages imposed by the release of one additional ton of carbon-dioxide.

The SCC enables analysis of policy tradeoffs involving climate change mitigation.

The SCC in practice

Increasingly influences a wide range of government actions

SEPTEMBER 21, 2023

FACT SHEET: Biden-Harris Administration Announces New Actions to Reduce Greenhouse Gas Emissions and Combat the Climate Crisis

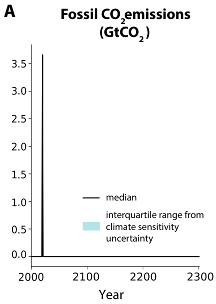
BRIEFING ROOM ▸ STATEMENTS AND RELEASES

New steps will catalyze action across the federal government to account for climate change impacts in budgeting, procurement, and other agency decisions, and save hardworking families money

US President Joe Biden addresses the 78th United Nations General Assembly at UN headquarters in New York City on September 19, 2023. Credit: Ed Junes/AFP via Getty Images

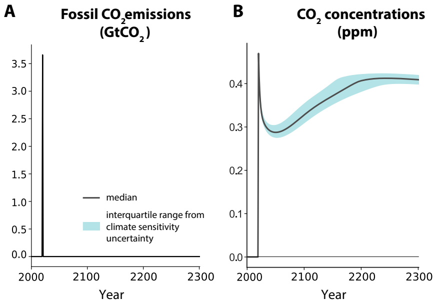
- US govt. spends $600bn/year and has vehicle fleet of 600,000
- SCC now being incorporated into: procurement, international aid, budgeting, ...

Computing the SCC



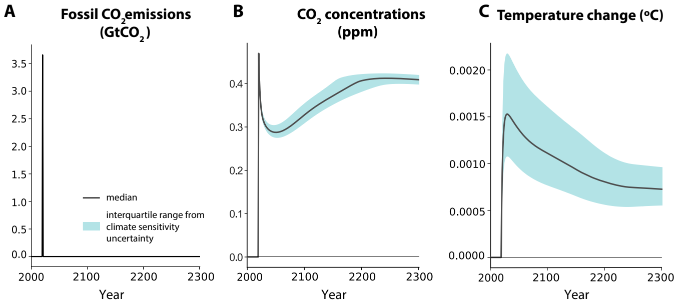
Interquartile range generated by resampling ∼100,000 climate model input parameters to capture the full range of climate sensitivity uncertainty

Computing the SCC



Interquartile range generated by resampling ∼100,000 climate model input parameters to capture the full range of climate sensitivity uncertainty

Computing the SCC



Interquartile range generated by resampling ∼100,000 climate model input parameters to capture the full range of climate sensitivity uncertainty

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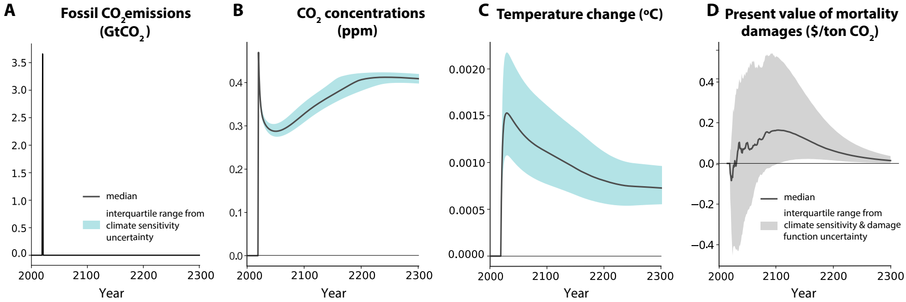
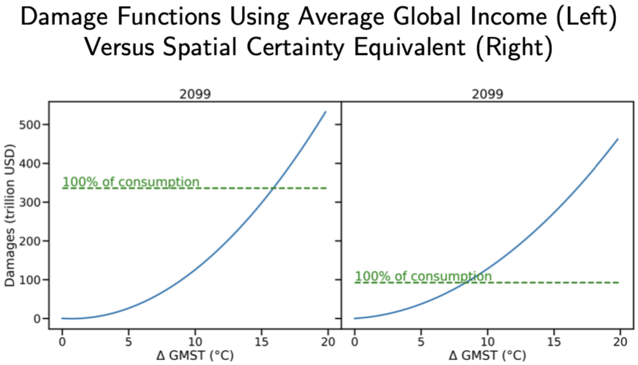


Interquartile range generated by resampling ∼100,000 climate model input parameters to capture the full range of climate sensitivity uncertainty

Accounting for inequality in the SCC calculation

Implementation: compute a **spatial certainty equivalent damage function** that places higher weight on damages accruing to poor regions, where each dollar is worth more utility (CRRA utility with $\eta = 2$)



Nath et al. (*WP, 2023*)

Accounting for inequality in the SCC calculation

Sectors: Mortality, energy, labor, agriculture, coastal

	Constant discounting: $\delta = 2\%$			Endogenous discounting
	Mean over uncertainty	**Certainty equivalent**	**Equity weighting**	**Ramsey w/ uncertainty**
RCP4.5	\$43	\$58	\$77	\$156
RCP7.0	\$71	\$116	\$112	\$941

Assumptions: $\eta = 2$ and $\rho = 0$; SSP3 (constant δ); SSPs 2-4 (endog. discounting)

→ Many alternative valuation metrics presented in Nath et al (in prep.)

→ With EPA probabilistic socioeconomic and emissions trajectories: \$190

→ Also used to compute SC-methane (\$850) and SC-nitrous oxide (\$49,000)

Accounting for inequality in the SCC calculation

nature

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Article | Published: 21 April 2021

Equity is more important for the social cost of methane than climate uncertainty

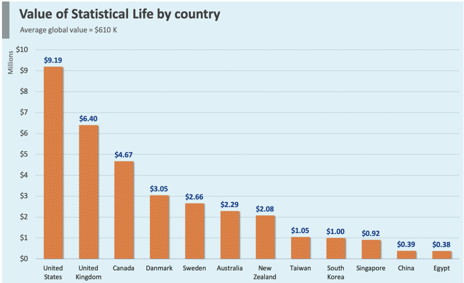
Frank C. Errickson, Klaus Keller, William D. Collins, Vivek Srikrishnan & David Anthoff

Nature **592**, 564–570 (2021) | Cite this article

Challenges in integrating local sectoral damages into aggregate damage metrics

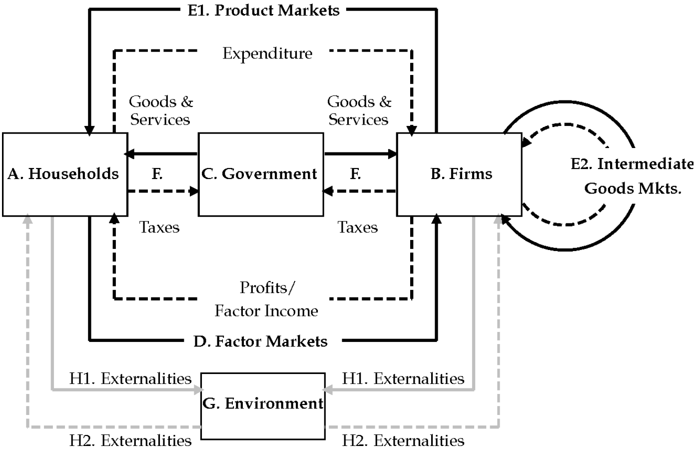
#1: Monetization Conversion from physical units ⟶ $$ can be difficult and depend critically on strong assumptions.

- **Mortality:** Whether and how to use an income elasticity of the VSL? (Carleton et al., 2022)
- **Labor:** Disutility estimates depend on a set of stylized assumptions (Rode et al., 2023)
- **Crime and conflict:** ?? **Mental health:** ??



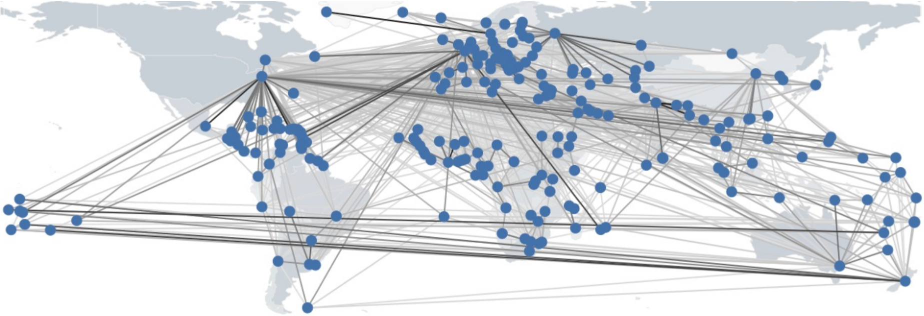
Challenges in integrating local sectoral damages into aggregate damage metrics

#2: Feedbacks Interactions and feedbacks are poorly characterized



Challenges in integrating local sectoral damages into aggregate damage metrics

#3: Migration Migration is likely first-order but a very difficult problem



- Inherently a general equilibrium problem ⟶ difficult to characterize with reduced form approaches
- Climate-driven expectation formation poorly understood

Key research gaps in climate inequality

1. Climate damage estimates that account for differential exposure and vulnerability are lacking for **key categories of impacts**
    - Specialty agricultural crops
    - Wildfire
    - Ecosystem services
    - Vector borne disease
    - ...

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   - Individual-level data could enable investigation of race, class, gender, education, access to healthcare, etc.

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   - Vector borne disease
   - ...

2. Many **dimensions of inequality** are insufficiently studied
   - Individual-level data could enable investigation of race, class, gender, education, access to healthcare, etc.

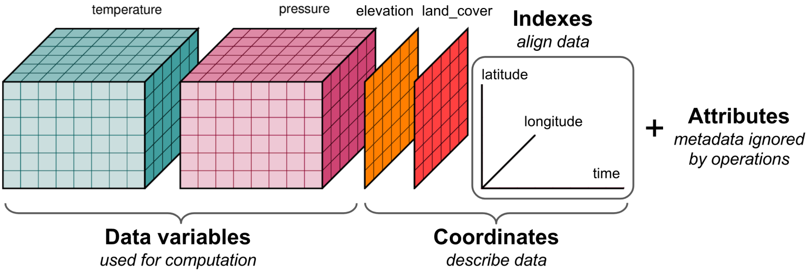
3. **Mechanisms behind adaptation** are poorly understood
   - Experimental work can help with causality and precision (e.g., Masuda et al. (2021))
   - When is adaptation optimal or suboptimal? When is adaptation intervention necessary? (e.g., Baylis & Boomhower (2022))

Tools: Using multidimensional data

Scientific and climate data is often stored as multidimensional arrays and saved in file formats like **netcdf**

- Data variables are indexed by coordinates (such as longitude, latitude, time, etc.) and can be assigned attributes containing metadata

- Packages such as **xarray** (for python) and **tidync** (for R) are useful tools for working with large datasets stored in this format



Tools: Processing climate data easily in R

https://github.com/tcarleton/stagg

stagg:: spatiotemporal aggregation of climate data in R

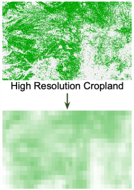
Cheat Sheet

The R Package stagg enables simple and efficient pairing of climate and economic or political data for use in nonlinear regression analyses. This is accomplished by aggregating gridded ERA5 data to the level of administrative regions in a 3 step process.

1. secondary_weights()

Resample a raster layer to a different spatial resolution

Argument	Description	Format
secondary_raster	Data on a seperate variable to weight climate data by during aggregation	Raster layer, raster brick, or raster stack
grid	Grid with the same resolution as climate data to resample the secondary raster to, defaults to the ERA5 grid	Raster layer, raster brick, or raster stack
extent	Longitude and latitude boundaries to crop the secondary raster for greater efficiency, defaults to reading in entire raster	Numeric vector of length 4, in the order c(xmin, xmax, ymin, ymax)



High Resolution Cropland

ERA5 Resolution Cropland

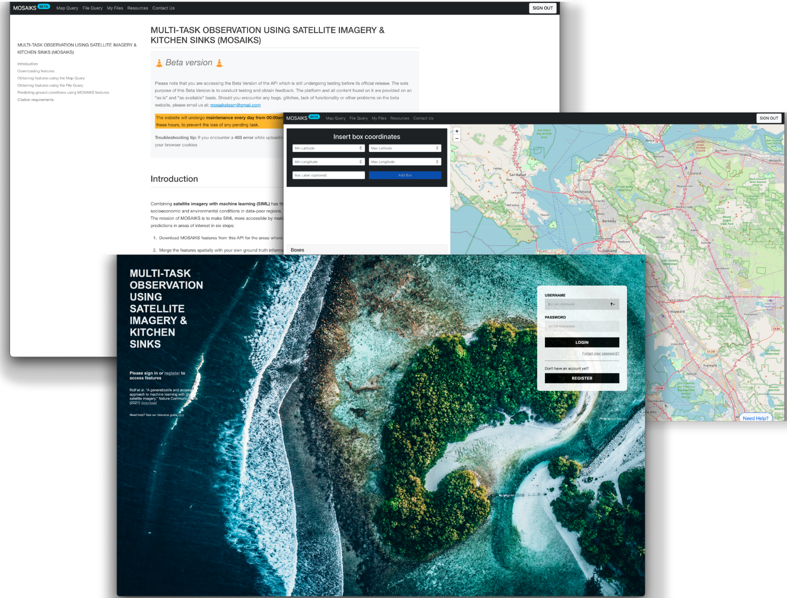
3. staggregate_*

staggregate_* is a family of functions which take mostly
difference between each is the transformation performe

Argument	Descriptio
Common to all stag	
data	Climate data to aggregate
overlay_weights	Table of area weights (and poss secondary weights) to use in ag polygon level, created using pre
daily_agg	How to convert hourly values int
time_agg	The temporal scale to aggregate to
Unique to staggregate_polynomi	
degree	The highest order to raise the da
Unique to staggregate_spline() - [Re	
knot_locs	Knot locations
Unique to staggregate_bin	
num_bins	Number of non-edge bins to dra
binwidth	Width of non-edge bins, overrid
min	Minimum value that non-edge b defaults to minimum in data pro
max	Maximum value that non-edge b defaults to maximum in data
start_on	Where to draw the left edge of a placement (start_on, center_on, be specified. If none of these ar

Collaborators: Tyler Liddell, Anna Boser, Sara Orofino, Tracey Mangin

Tools: Build your own remotely sensed measures



Tools: Build your own remotely sensed measures

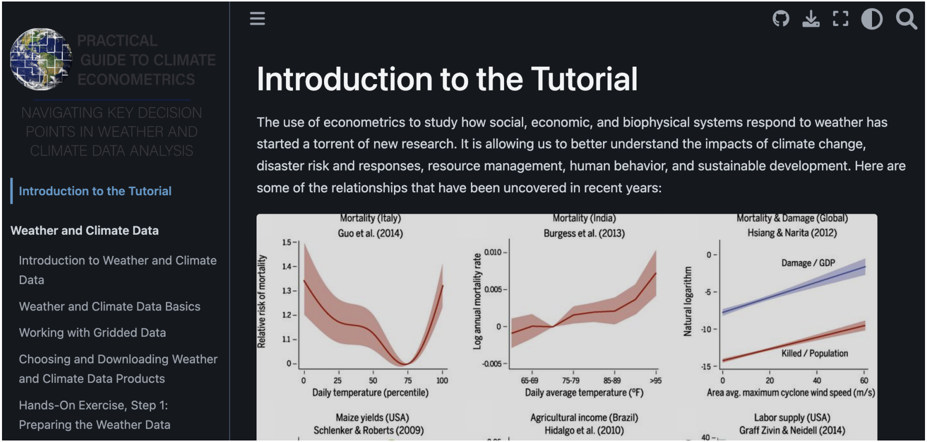
MOSAIKS = featurized daytime imagery + tutorial resources to help you do low-cost satellite imagery based machine learning on your own

- Method: Rolf et al. (2021)
- API: `https://siml.berkeley.edu/portal/index/`
- Processed data outputs: `www.mosaiks.org`
- Questions? Email us at `mosaiksteam@gmail.com`

Collaborators: Trinetta Chong, Hannah Druckenmiller, Solomon Hsiang, Eugenio Noda, Jonathan Proctor, Esther Rolf

Tools: A practical guide to climate econometrics

Interactive tutorial:
https://climateestimate.net/content/getting-started.html



Contributors: Azhar Hussain, James Rising, Kevin Schwarzwald, Ana Trisovic

Thank you!

tcarleton@ucsb.edu

EXTRA SLIDES

Local damage estimates informing adaptation policy

Policy makers are faced with the following questions when considering how to best deploy adaptation and resiliency investments:

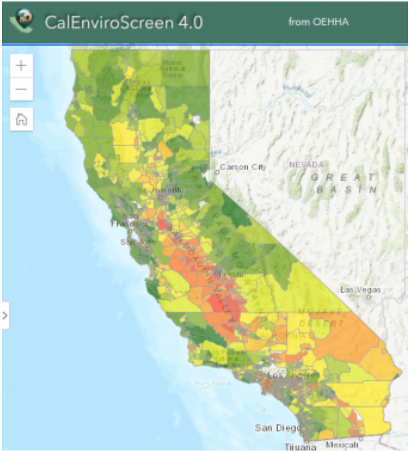
- How well prepared are today's populations for tomorrow's climate?
- Which communities will experience the greatest impacts from climate change?
- Through which channels will they be the most prevalent?

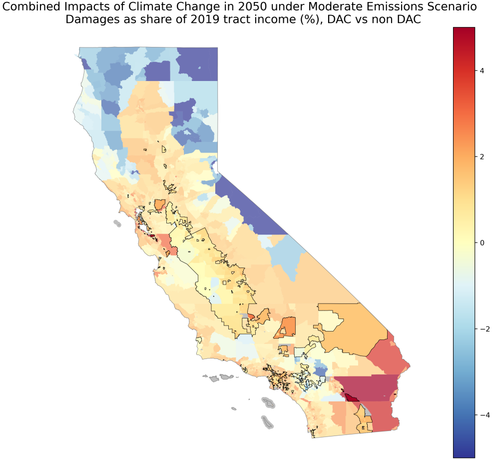
The California Climate Vulnerability Metric

- California uses CalEnviroScreen to assess community-level vulnerability to pollutant exposure and other local environmental harms
- But there is no existing quantitative framework for measuring vulnerability to climate change

As part of its 2022 Climate Change Scoping Plan, the California Air Resources Board (CARB) contracted the development of a **Climate Vulnerability Metric (CVM)** at the census tract level

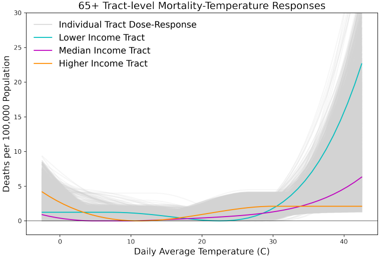
A CVM complements other environmental justice screening tools

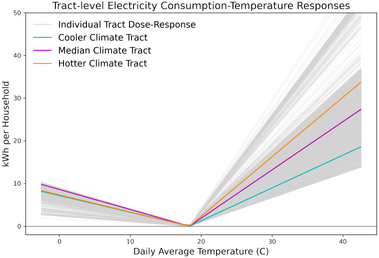




Differential vulnerability

Unique response functions are estimated for each census tract based on tract-level determinants of vulnerability (demographics, economics, climate, etc.)



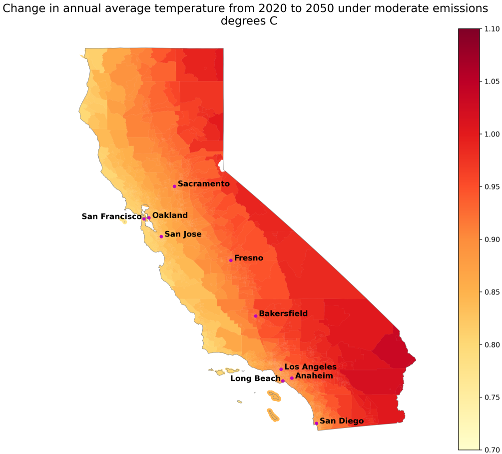


Tract-level response functions built from:

- **Mortality** Carleton et al. (2022)
- **Natural gas & electricity** Auffhammer (2022)
- **Labor supply** Rode et al. (in review)
- **Flooding** Bates et al. (2021)

Differential exposure

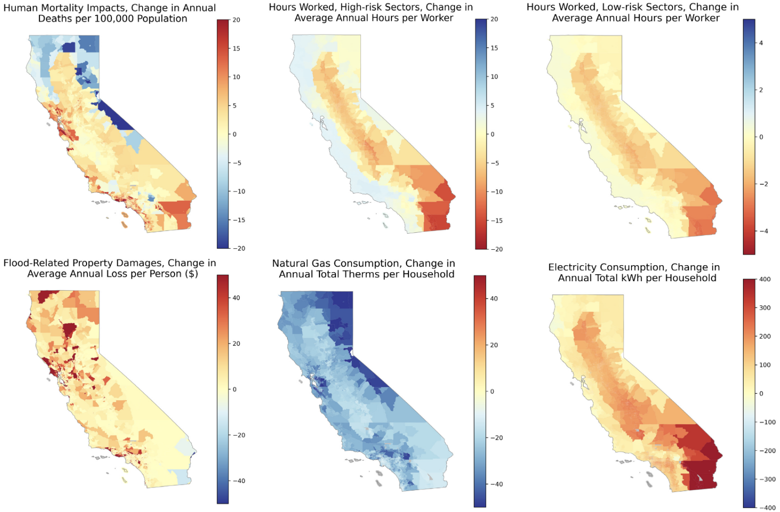
CMIP5 climate models are downscaled to the census tract level and projected to 2050 under a moderate emissions scenario (RCP 4.5)



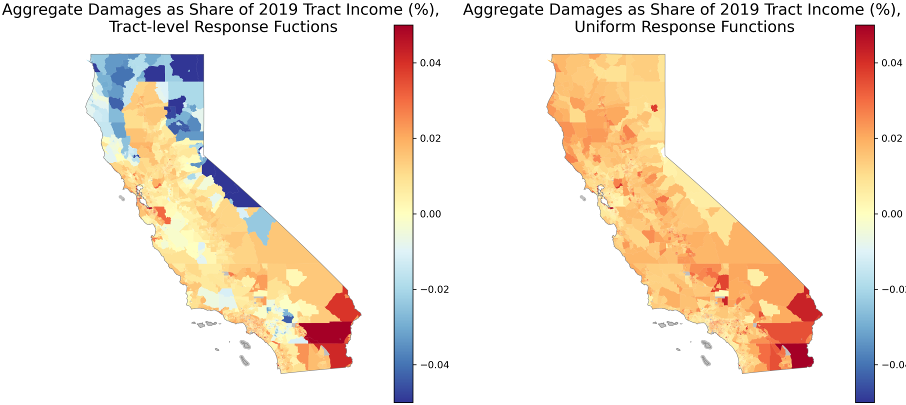
Note: Bias correction is needed when using models from studies that leverage other climate models such as PRISM

Sector-specific results

Category specific impacts of climate are estimated, then monetized using category specific valuation techniques so that they can be summed.



The importance of accounting for differential vulnerability



Left: accounting for differential vulnerability
Right: accounting only for differential exposure