

30 Years of Climate Damage Estimation: What we know, how we know it and what is missing.

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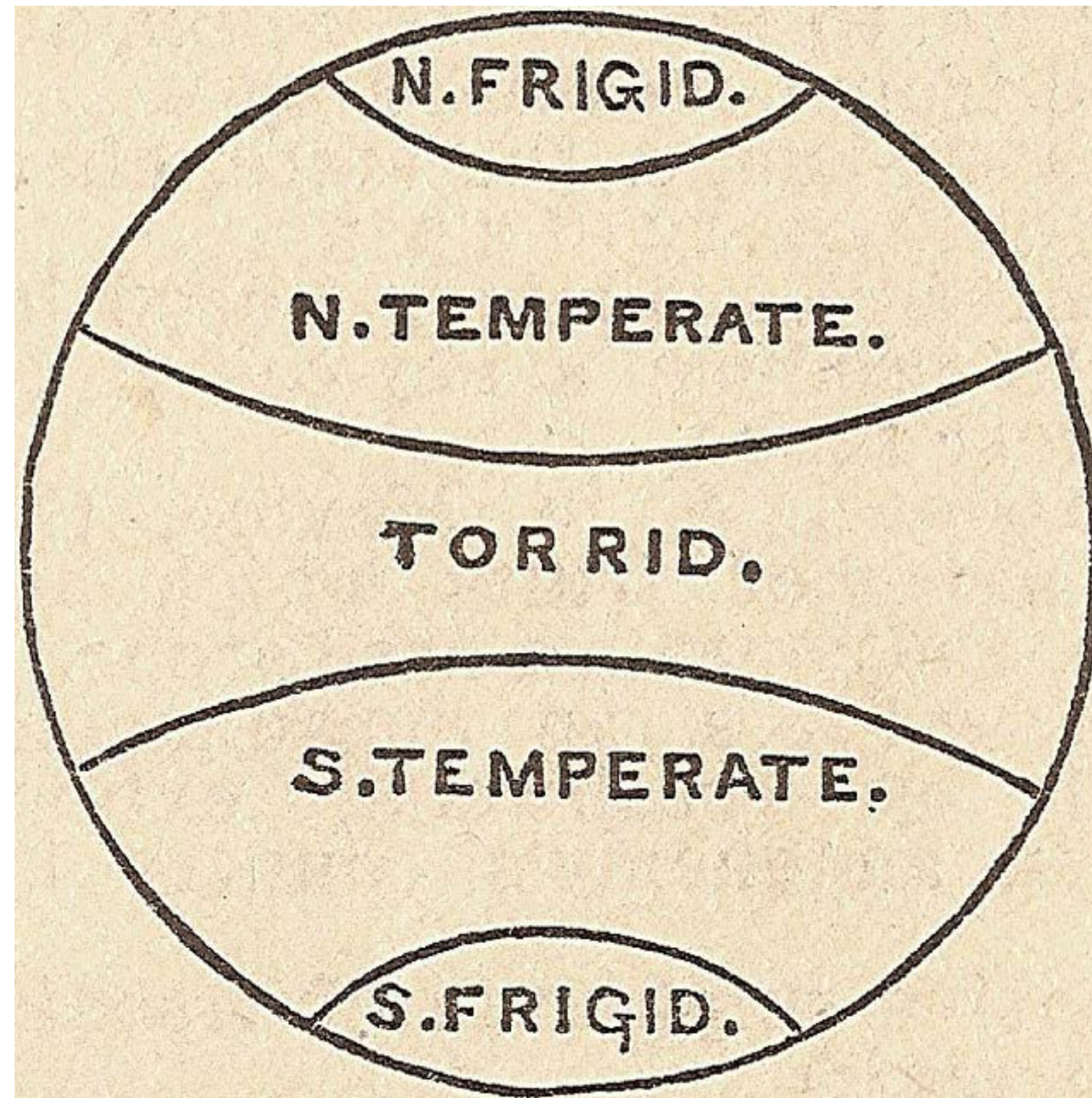
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Skodsborg - August 14, 2017



The notion of “the climate” goes back to Aristotle

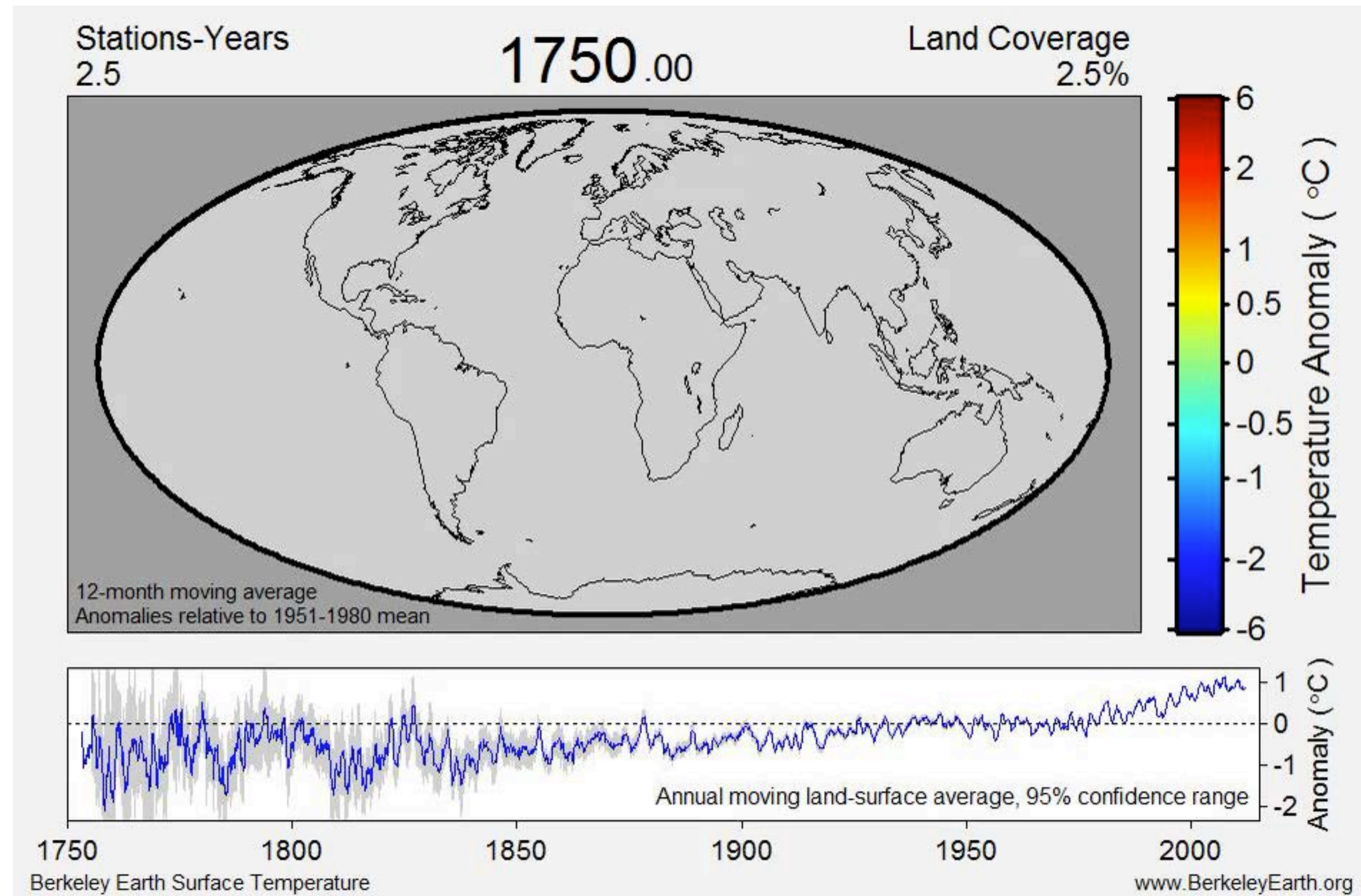


Montesquieu's cross-sectional conclusion

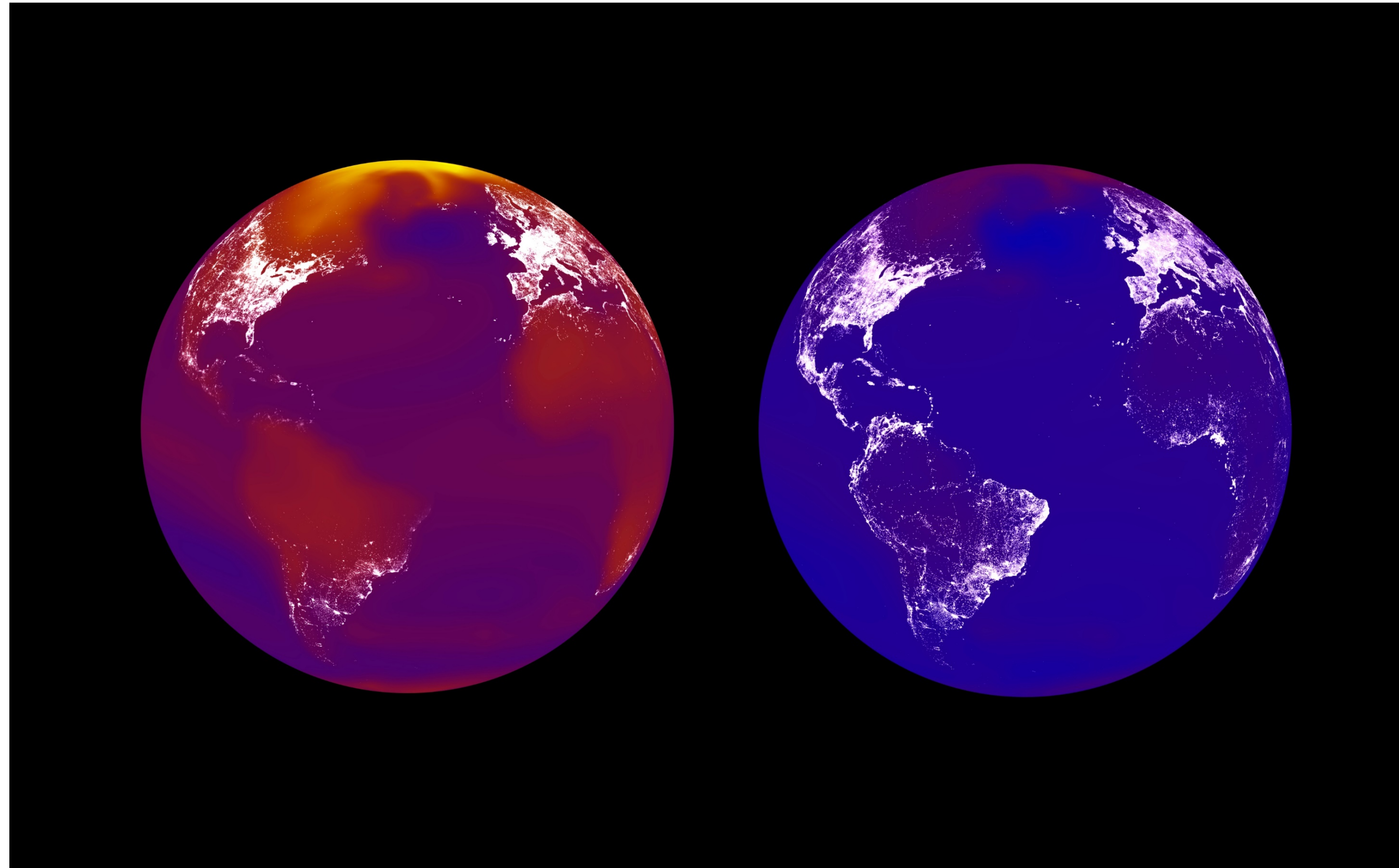
“If it be true that the temper of the mind and the passions of the heart are extremely different in different climates, the laws ought to be in relation both to the variety of those passions and to the variety of those tempers.”

Montesquieu, Of laws in relation to the nature of climate.

The climate is no longer stationary.



The historical or future counterfactual we seek



Source: Hsiang

The experiment we would like to run



This is the closest physical counterfactual we have



Source: NASA

The solution to our conundrum



Some notation to help us organize our thoughts

- ▶ The production of an output y in period t depends on weather (w) and inputs/technology/management practices
$$y_t = g(w_t, \psi)$$

- ▶ Weather in a given period is a draw from the current climate distribution:
$$w_t \sim c(w, \theta_t)$$

What does the rational agent do?

- ▶ Agent maximizes expected output by choosing *technology*, subject to their belief about the current state of the climate.

$$\psi^*(c(\theta_t)) = \max_{\psi} \int_{\underline{w}}^{\bar{w}} g(w, \psi) c(w, \hat{\theta}_t) dw$$

- ▶ Conditional on a set of climate beliefs, the restricted function describing the weather response becomes

$$y_t = g(w_t, \psi^*(c(w, \hat{\theta}_t)))$$

The short run response to climate change

If climate shifts from $c(w, \theta_0)$ to $c(w, \theta_1)$ and the agent **does not change inputs** or management practices, short run impacts are given by:

$$\Delta y_{sr} = \int_{\underline{w}}^{\bar{w}} g(w, \psi^*(c(w, \theta_1))) c(w, \theta_1) dw - \int_{\underline{w}}^{\bar{w}} g(w, \psi^*(c(w, \theta_0))) c(w, \theta_0) dw$$

The long run response to climate change

If climate shifts from $c(w, \theta_0)$ to $c(w, \theta_1)$ and the agent **does change** inputs or management practices, long run impacts are given by:

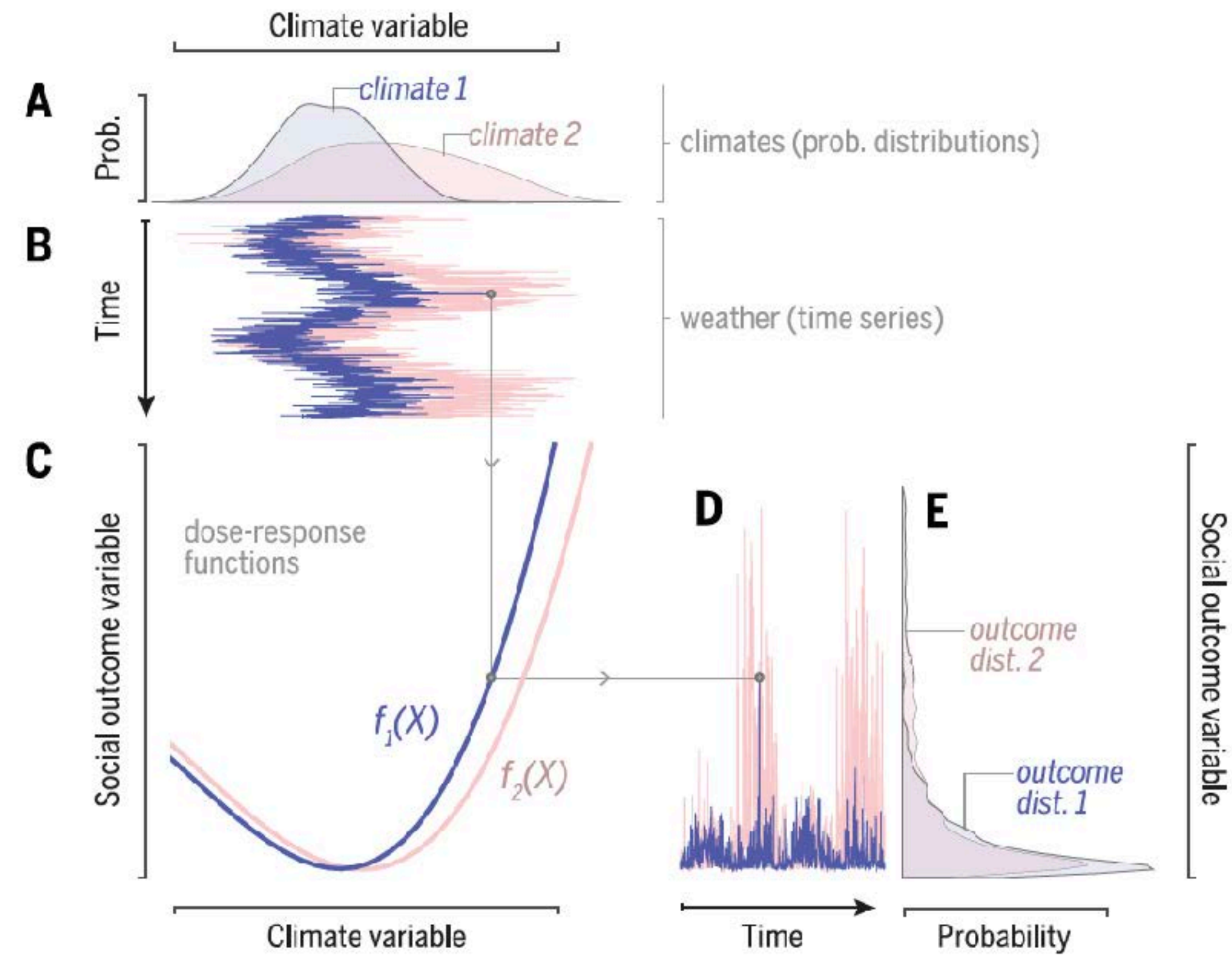
$$\Delta y_{LR} = \int_{\underline{w}}^{\bar{w}} g(w, \psi^*(c(w, \theta_1))) c(w, \theta_1) dw - \int_{\underline{w}}^{\bar{w}} g(w, \psi^*(c(w, \theta_0))) c(w, \theta_0) dw$$

The impact of adaptive response

$$\Delta y_{LR} - \Delta y_{SR} = \int_{\underline{w}}^{\bar{w}} g(w, \psi^*(c(w, \theta_1))) c(w, \theta_1) dw - \int_{\underline{w}}^{\bar{w}} g(w, \psi^*(c(w, \theta_0))) c(w, \theta_1) dw$$

- ▶ Both terms are evaluated using the changed climate
- ▶ Only the technology/management responses differ

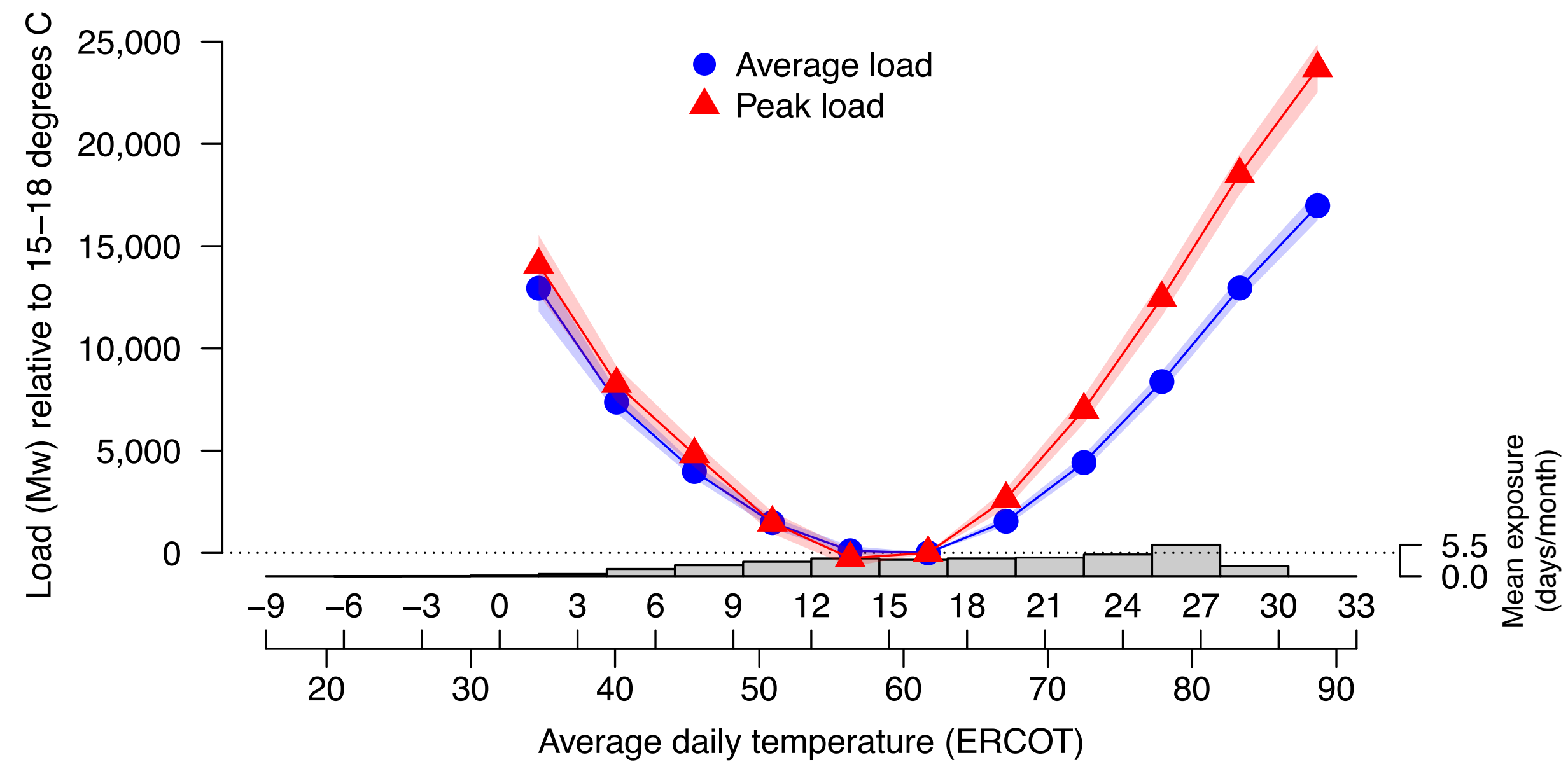
Translating weather into impacts.



Source: Carleton and Hsiang (2016)

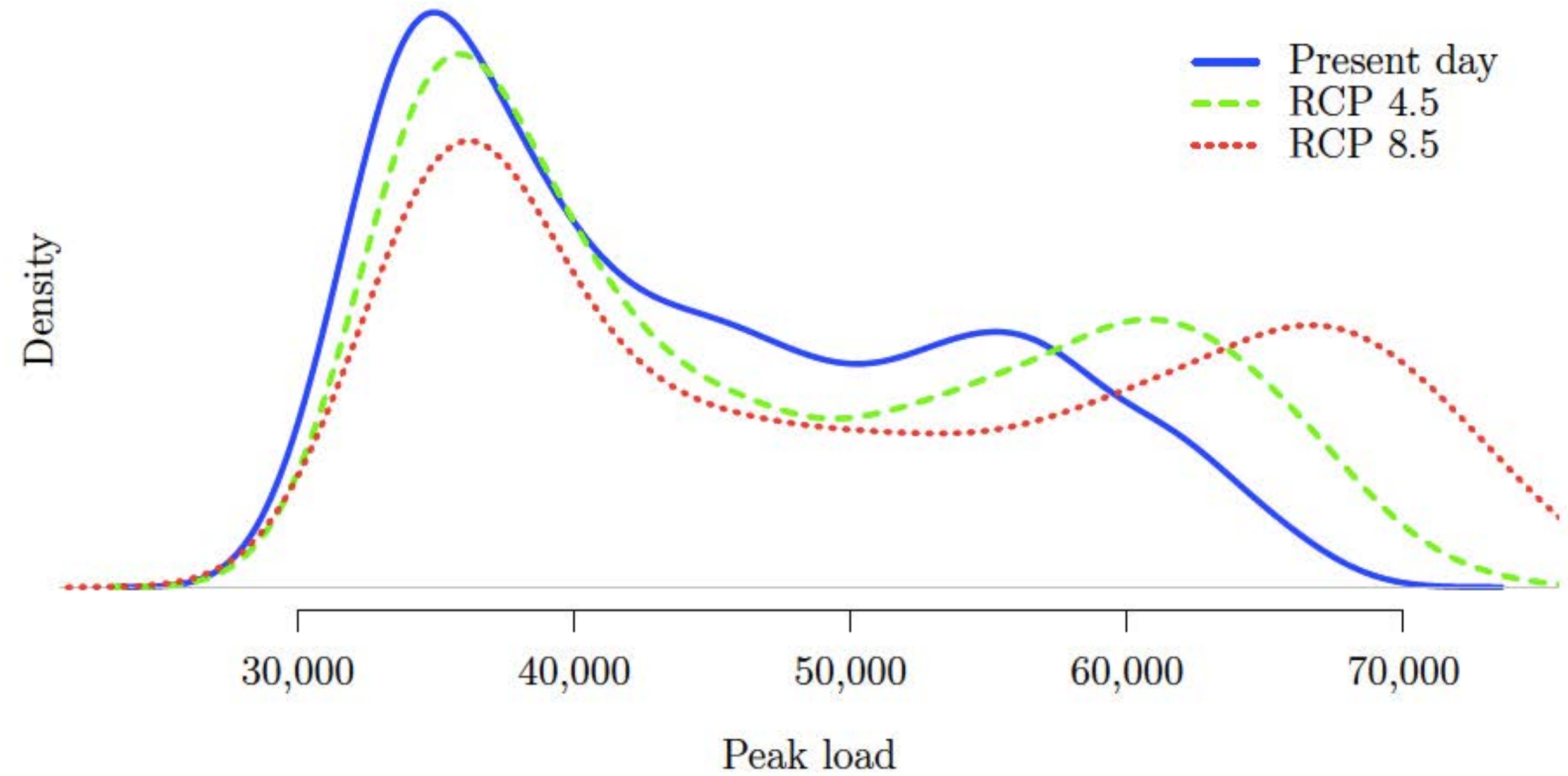
Version 1: Time Series Regressions

$$y_t = \beta \cdot f(w_t) + g(t) + \varepsilon_t$$



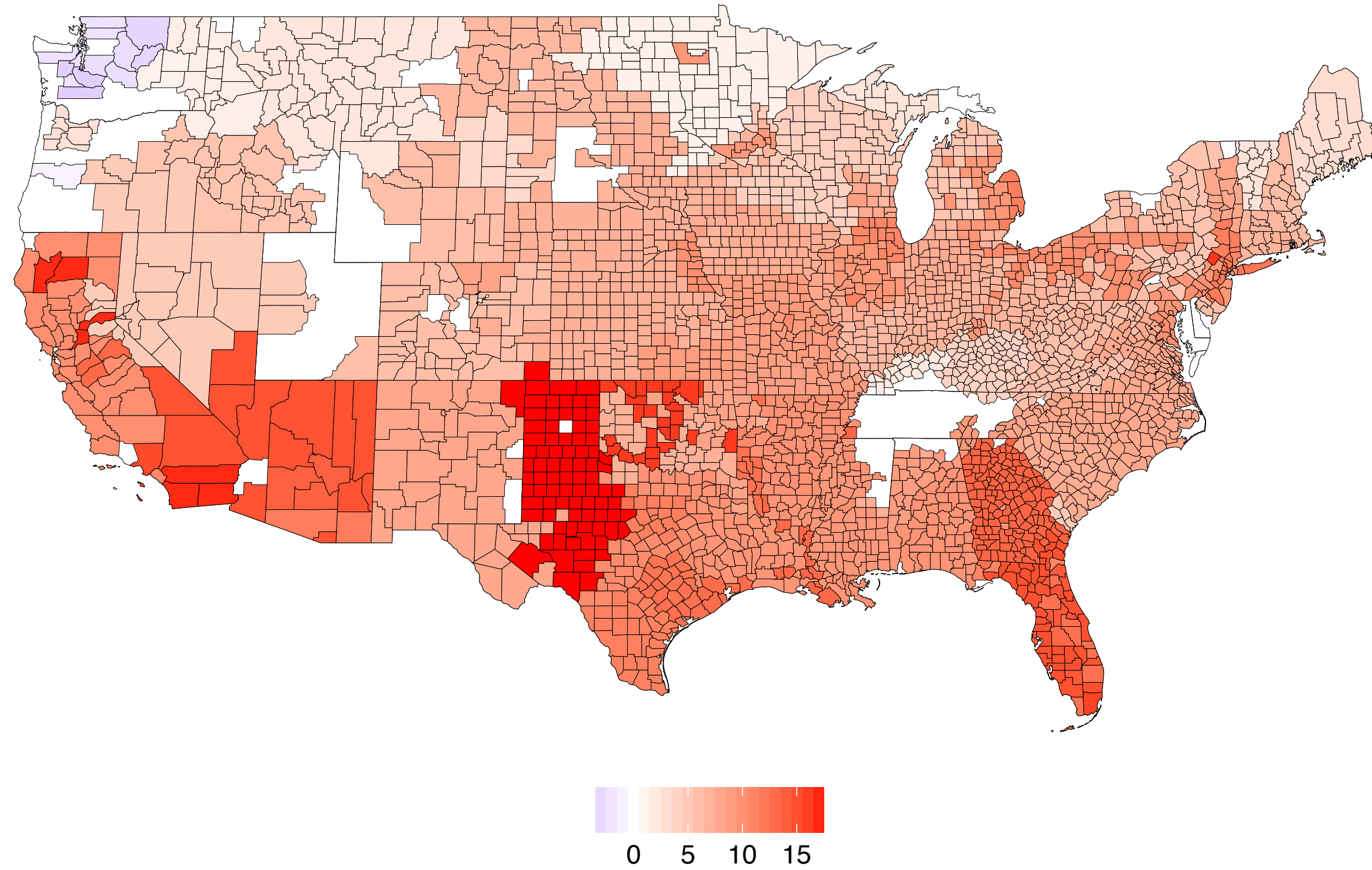
Source: Auffhammer, Baylis, Hausman (2017)

ERCOT: Distribution of peak load by end of century



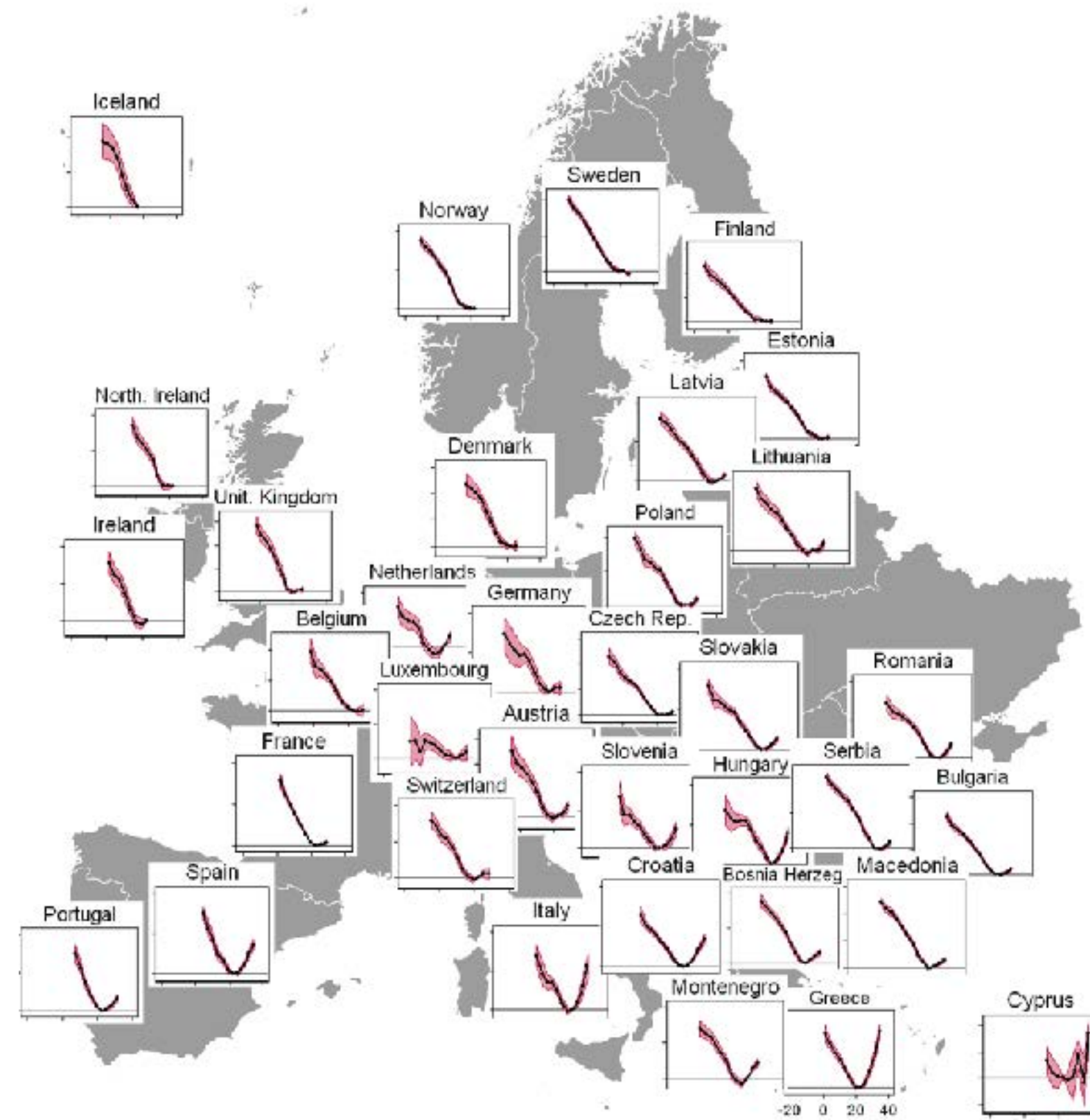
Source: Auffhammer, Baylis, Hausman (2017)

Map out impacts by Load Balancing Authority



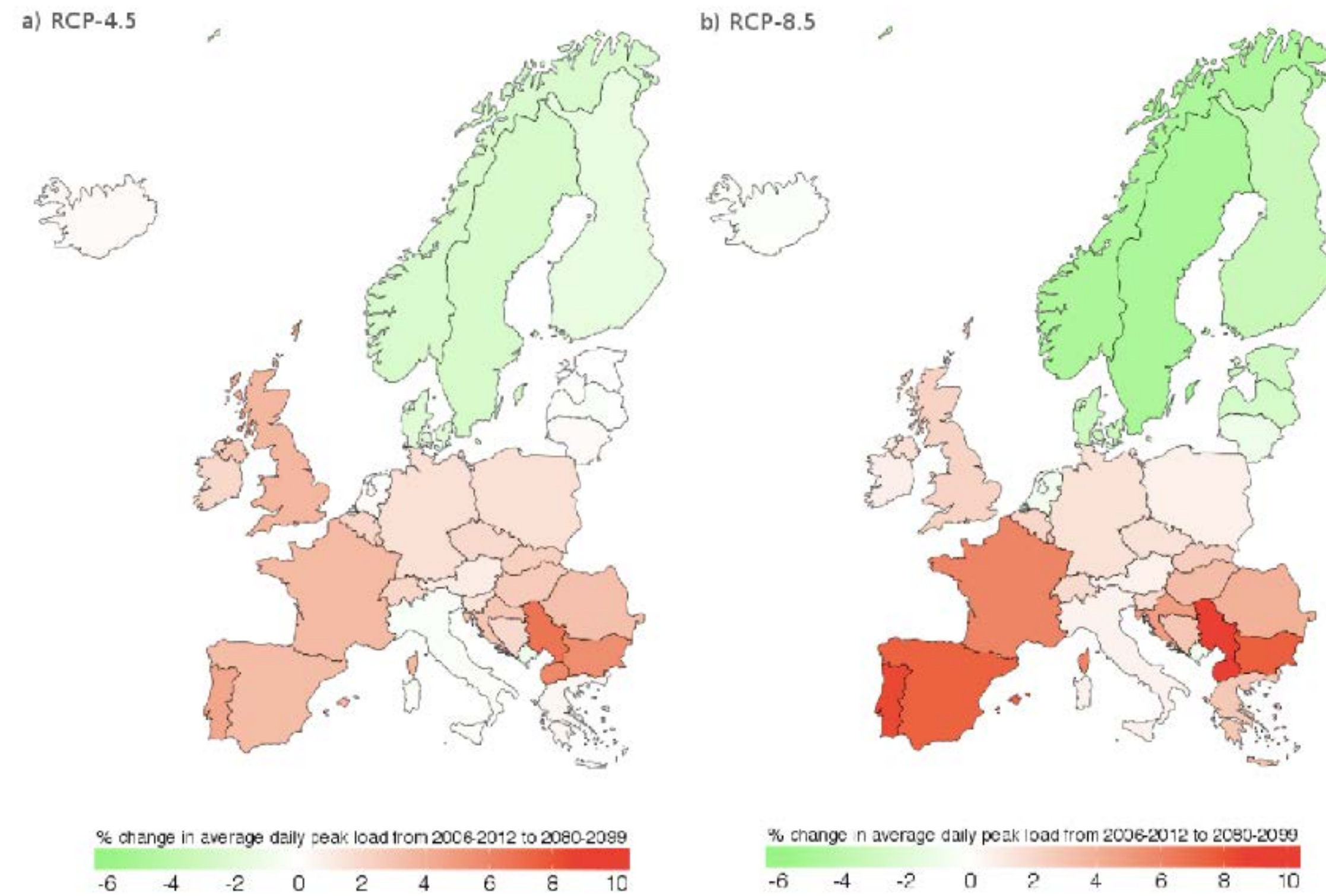
Source: Auffhammer, Baylis, Hausman (2017)

Electricity Load Response: Europe



Source: Wenz, Auffhammer, Levermann (2017)

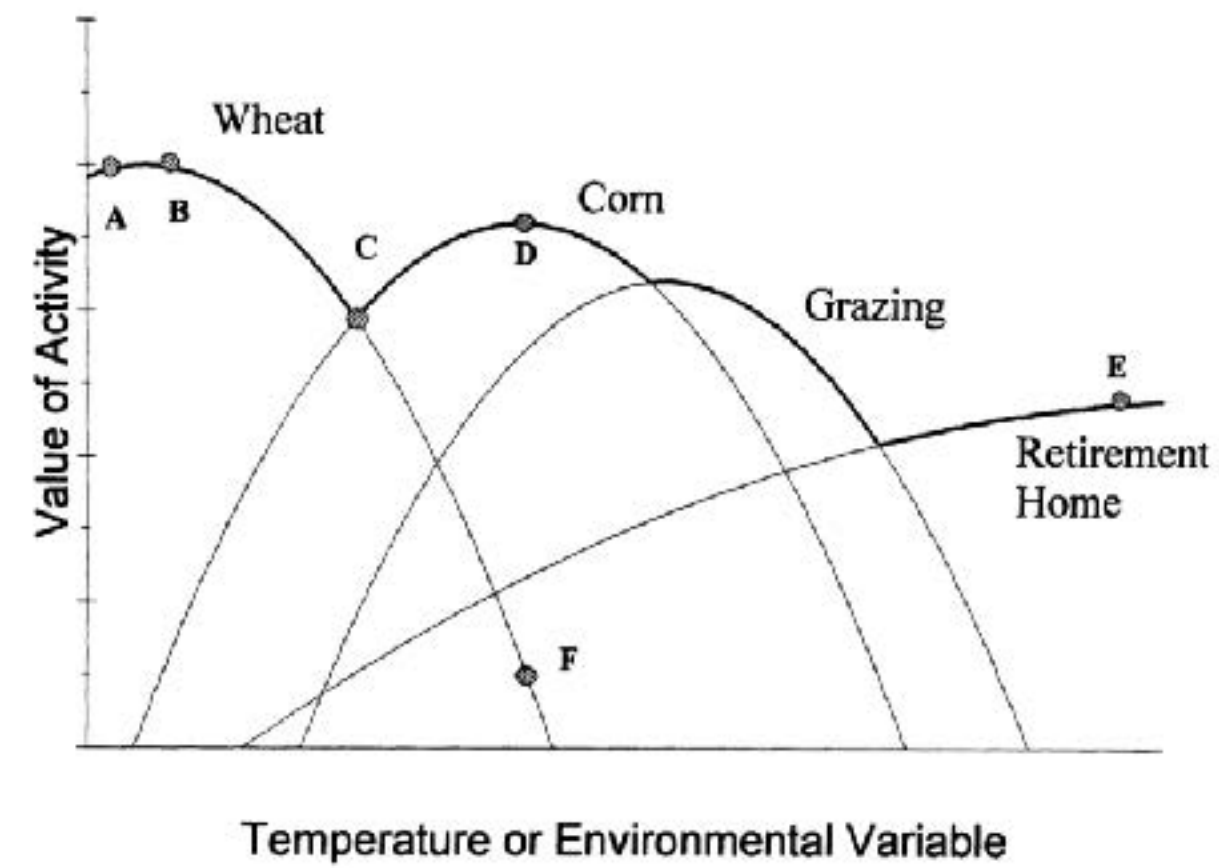
Electricity Load Impacts: Europe



Source: Wenz, Auffhammer, Levermann (2017)

Version 2: Ricardian Model (Cross Section)

$$y_i = \beta \cdot f(c_i) + \gamma \cdot x_i + \varepsilon_i$$



Mendelsohn, Nordhaus and Shaw, 1994

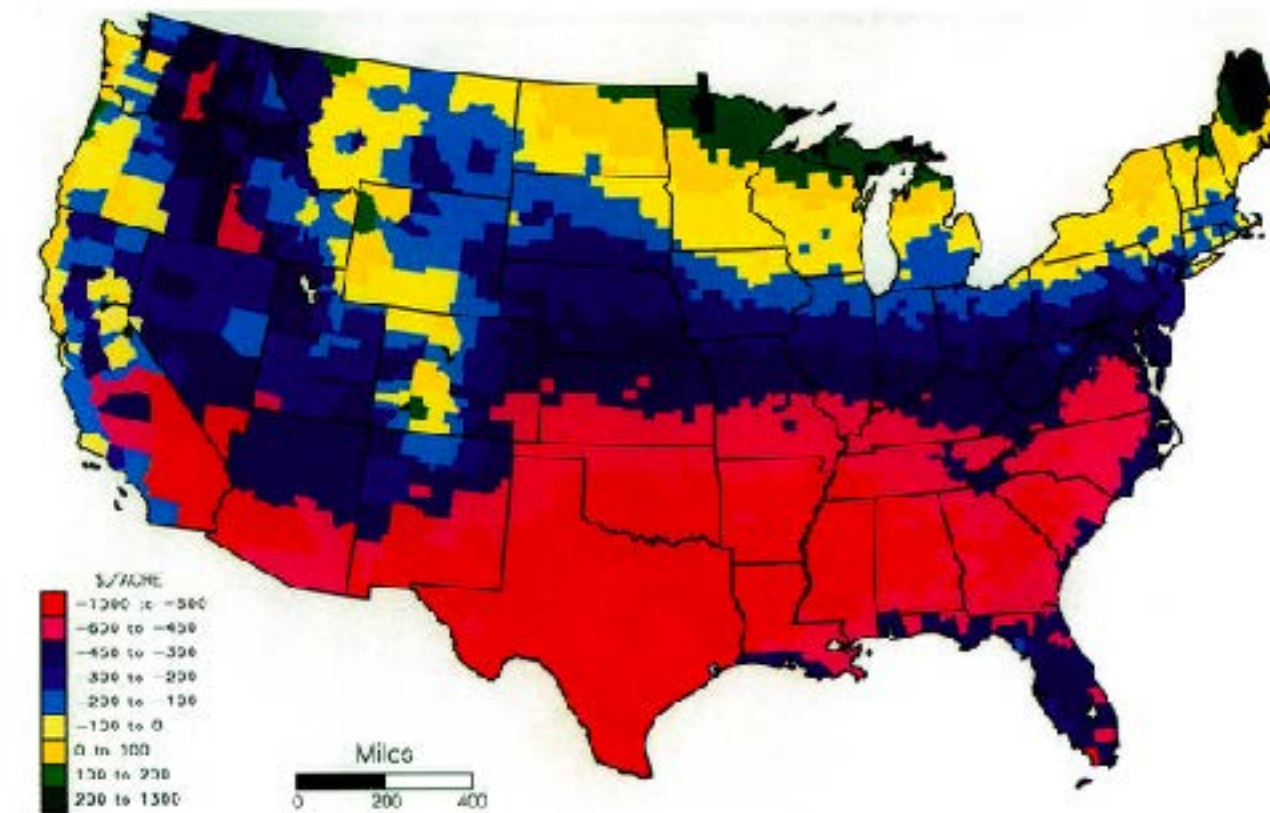
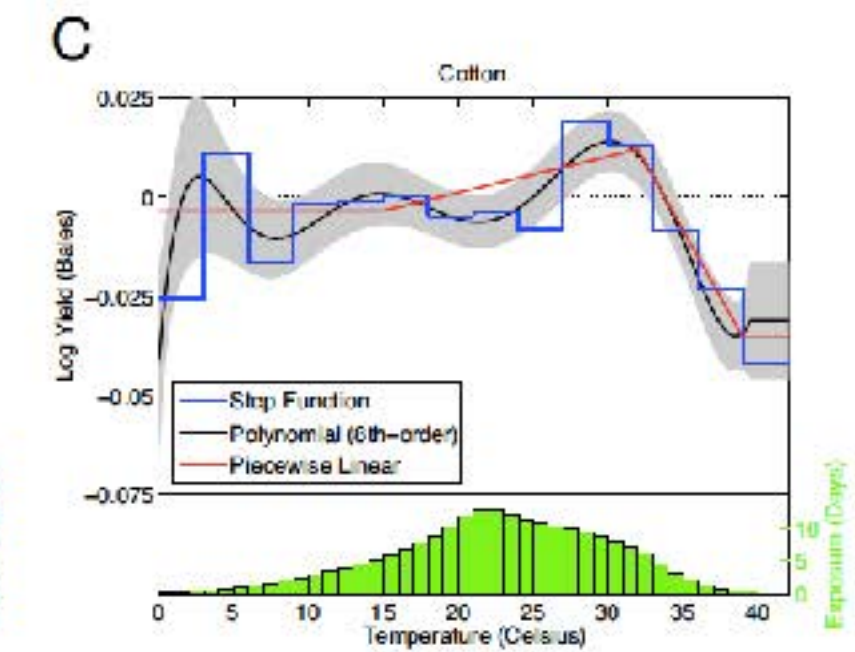
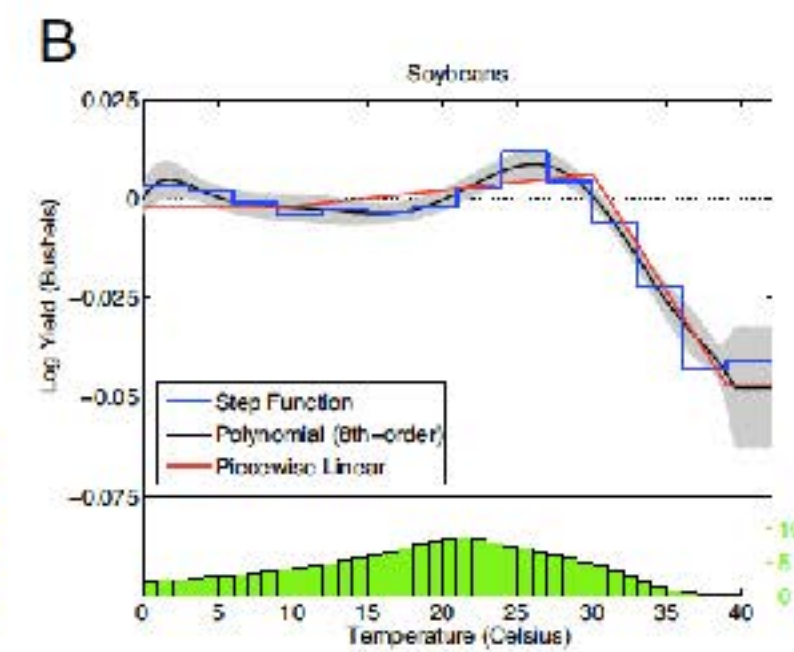
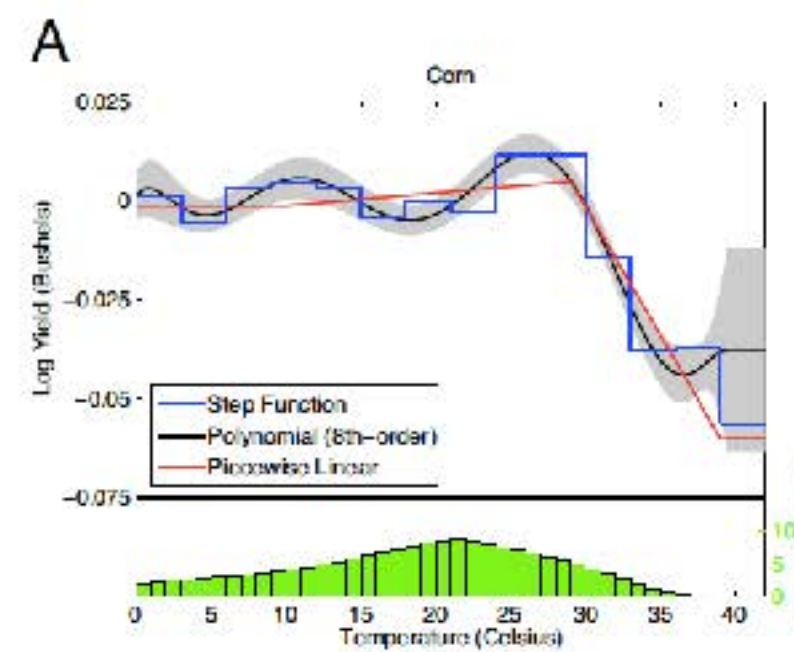
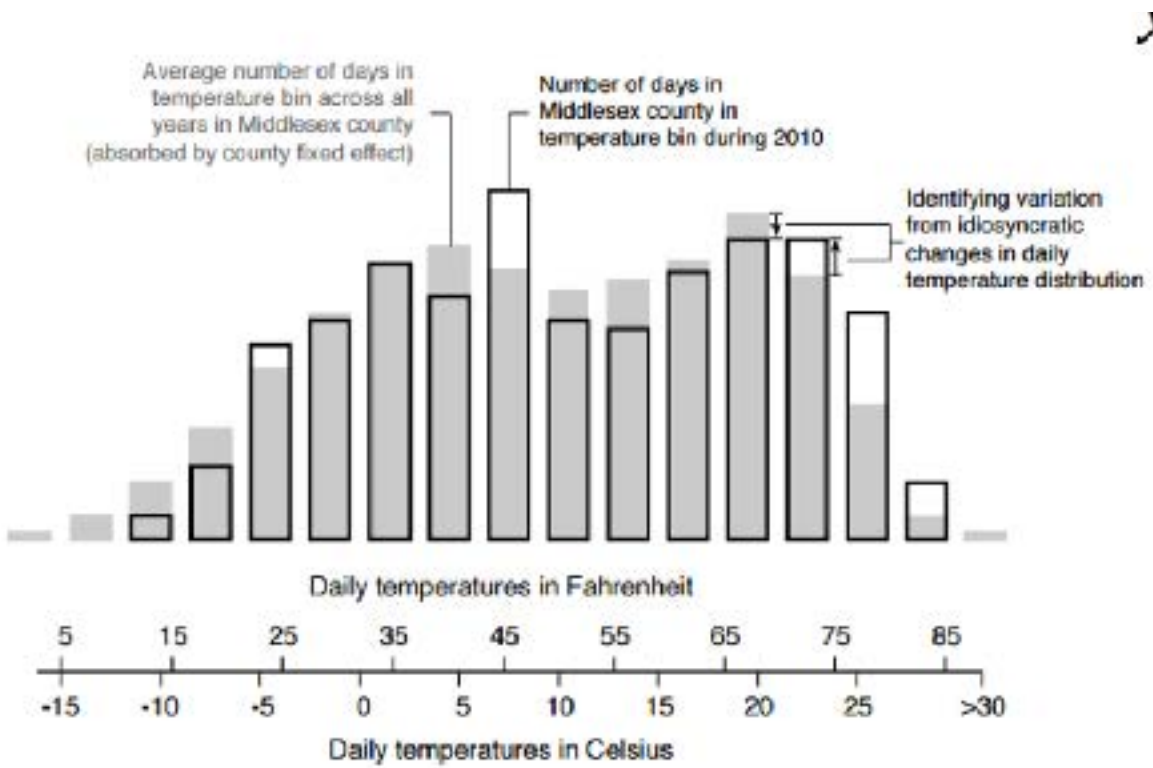
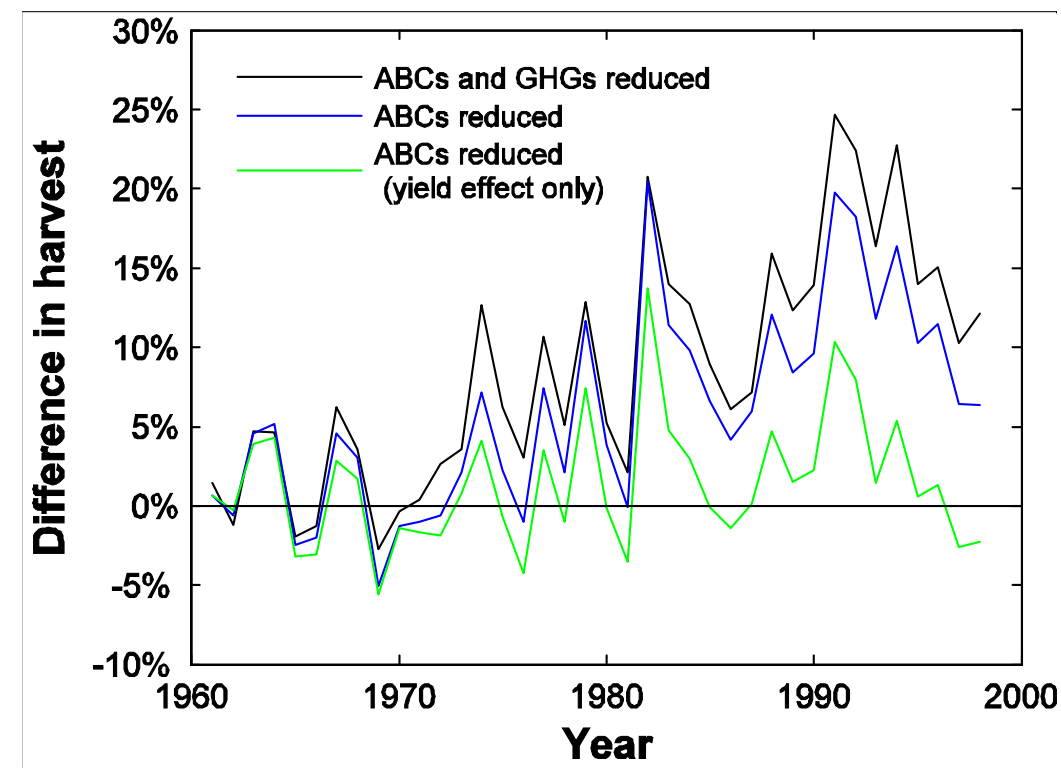


FIGURE 4. CHANGE IN FARM VALUE FROM GLOBAL WARMING: CROPLAND WEIGHTS
NOTE: The map shows the change in terms of dollars per acre for a 5°F uniform warming and an 8-percent increase in precipitation, 1992 prices.

Source: Mendelsohn, Nordhaus & Shaw (1994)

Version 3: Panel Data Weather Regressions

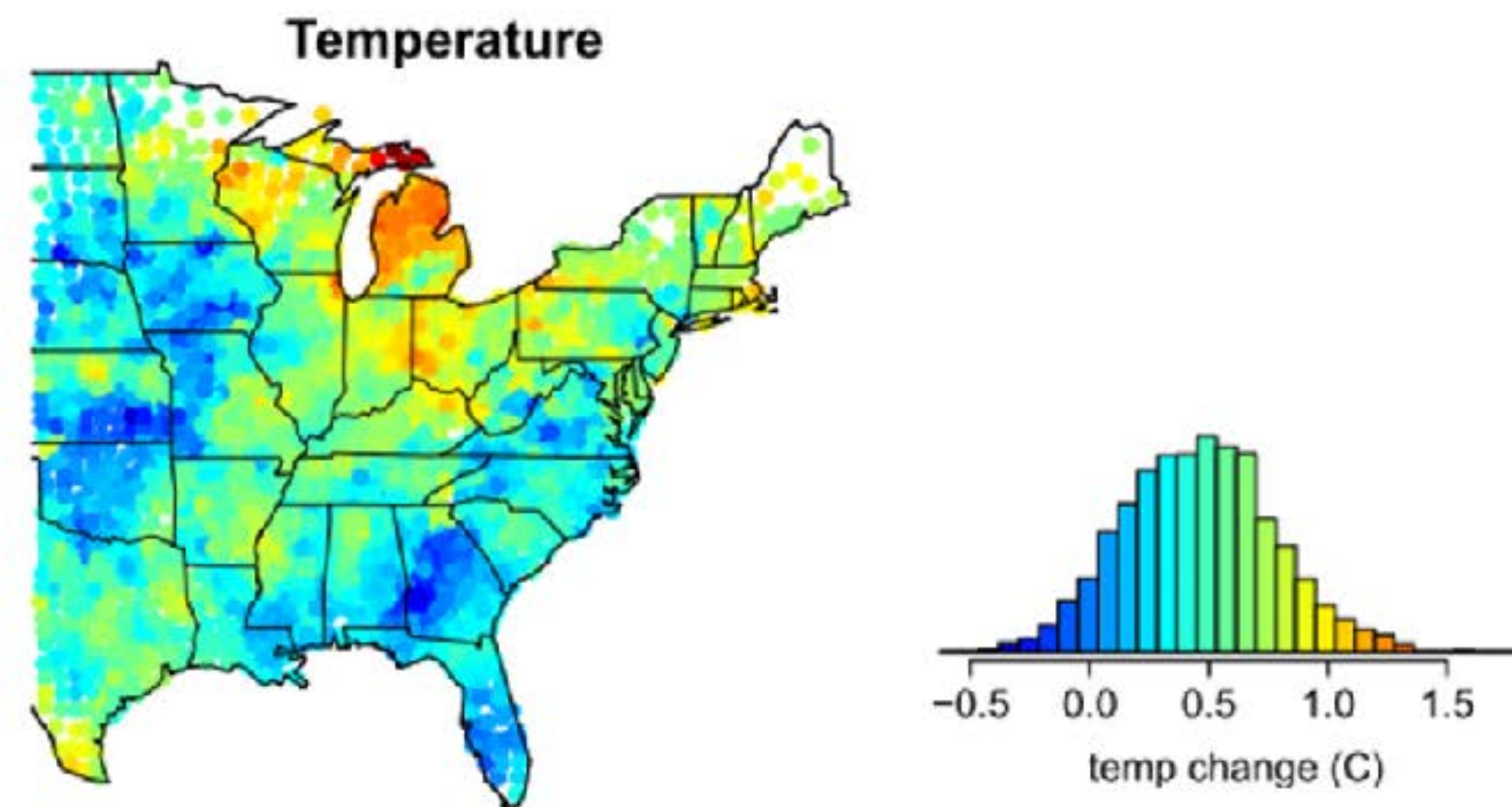
$$y_{it} = \beta \cdot f(w_{it}) + \alpha_i + \delta_t + \varepsilon_{it}$$



Sources Auffhammer, Ramanathan, Vincent (2006), Schlenker and Roberts (2009), Hsiang and Deruygina (2014)

Version 4: Long Differences

$$y_{i,t} - y_{i,(t-h)} = \beta \cdot f(w_{i,t} - w_{i,(t-h)}) + \varepsilon_i$$



Source: Burke and Emerick (2015)

Version 5: Hybrid (CARE Regressions)

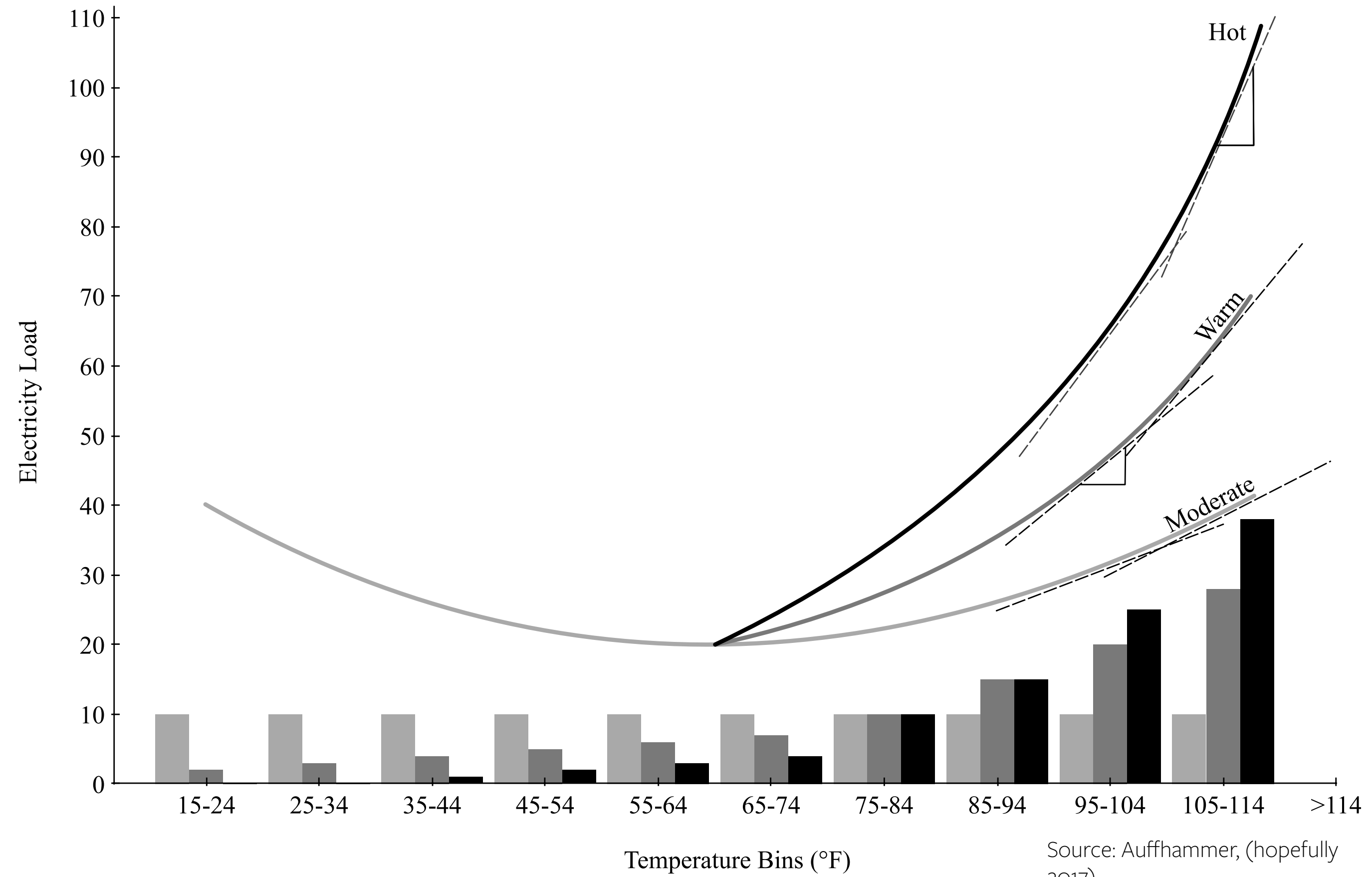
Run a regression separately for each e.g. ZIP code j using a set of households i

$$y_{it} = \sum_{p=1}^P \beta_{jp} \cdot D_{pit} + \alpha_i + \delta_t + \varepsilon_{it}$$

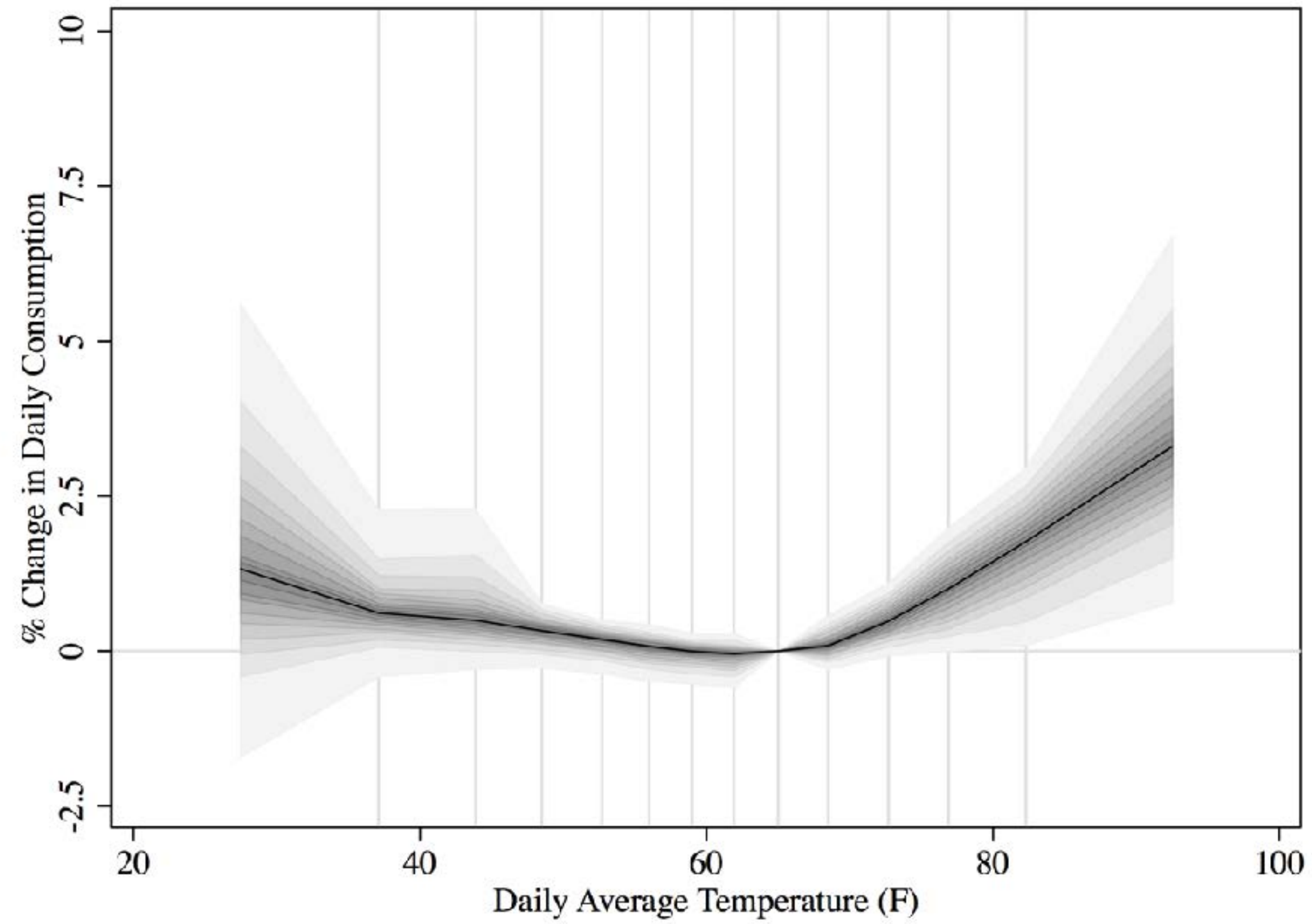
Run second cross sectional regression across all j ZIP codes.

$$\beta_{jp} = \gamma_0 + \gamma_1 \cdot C_{jp} + \gamma_3 \cdot Z_j + \eta_{jp}$$

CARE Visually: Estimate short run response

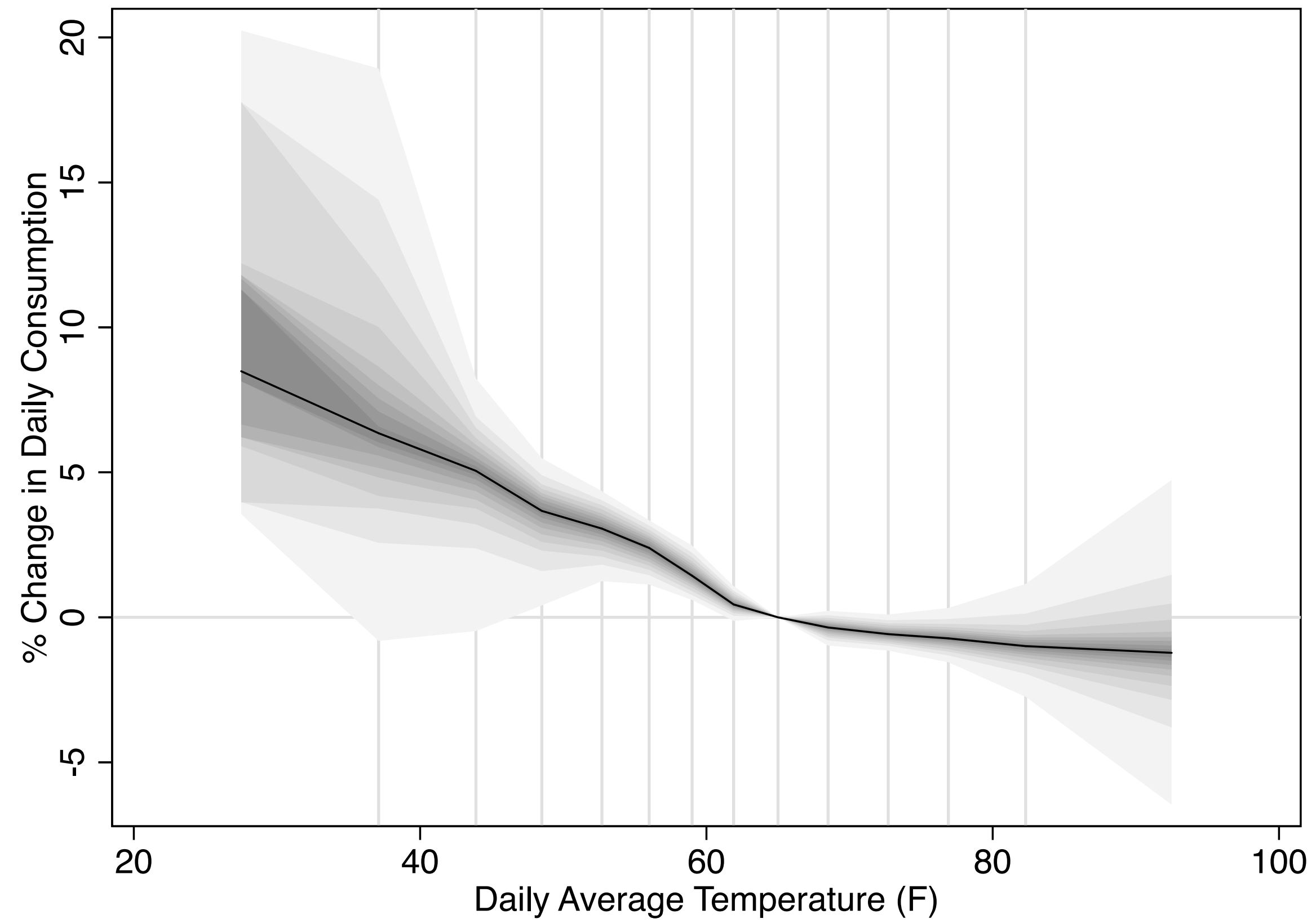


A plot of 1165 Temperature Response Functions



Source: Auffhammer, (hopefully 2017)

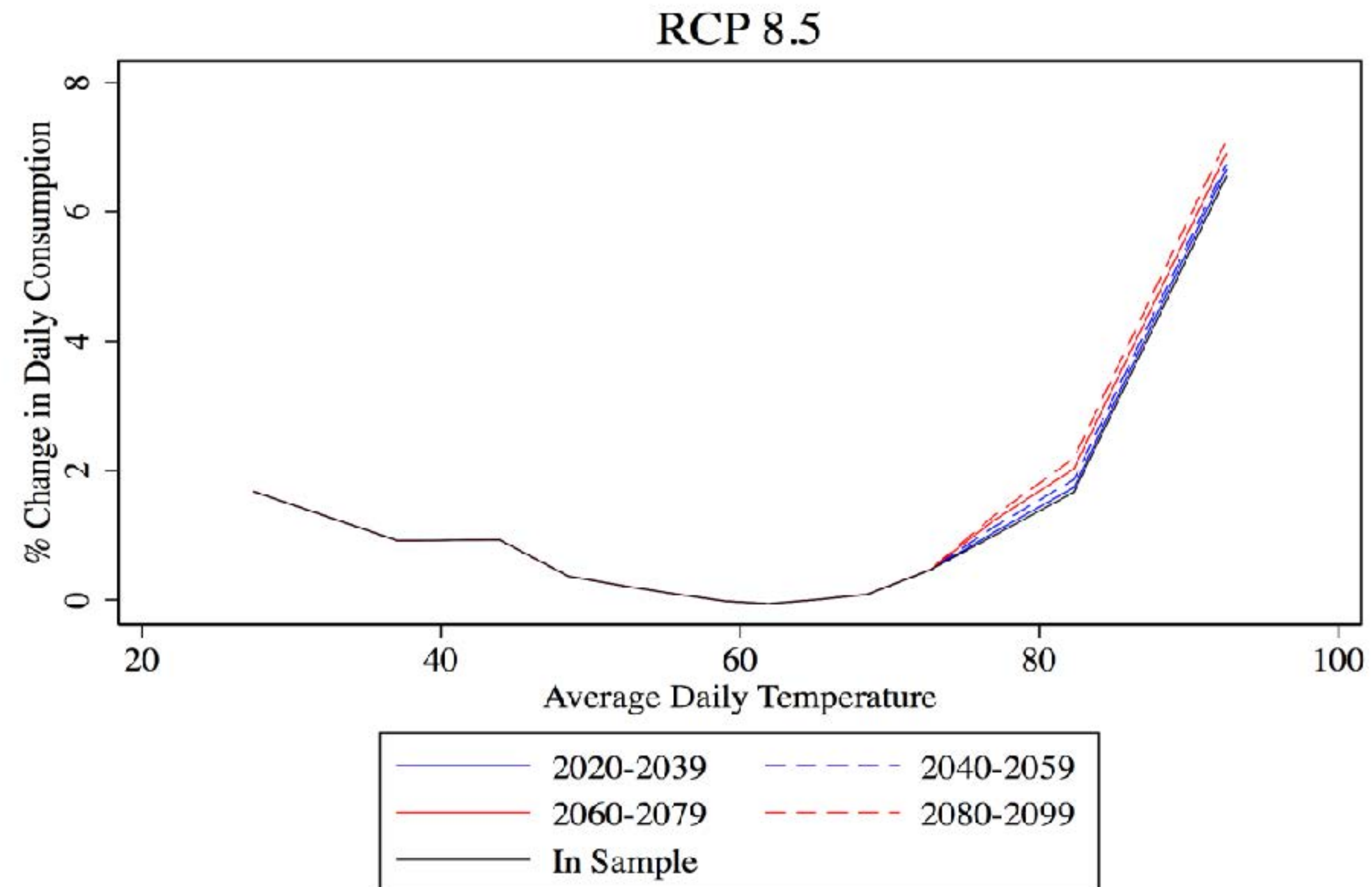
A plot of 1165 Temperature Response Functions



2017)

r, (hopefully

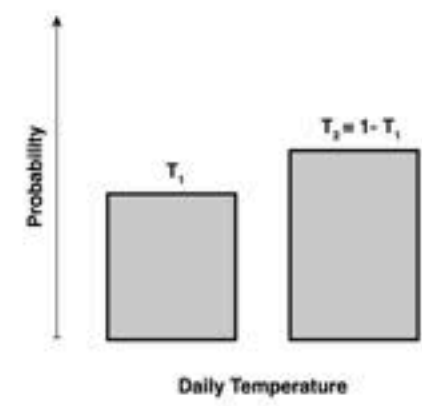
An empirically estimated “adapted” response function



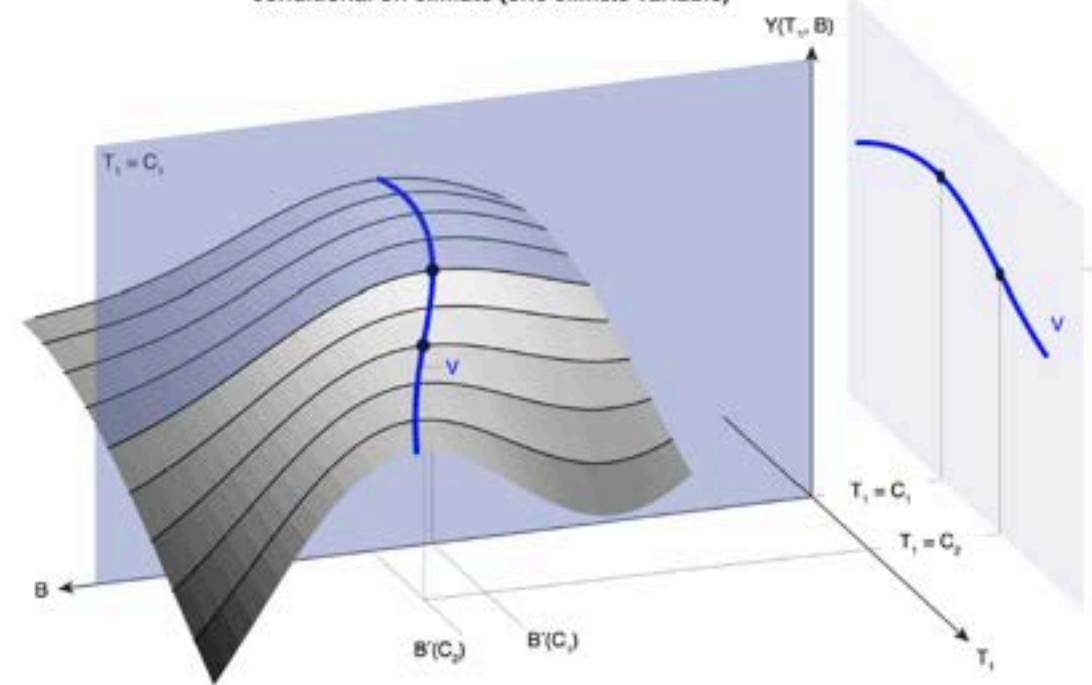
Source: Auffhammer, (hopefully 2017)

Version 6: The Envelope Theorem Revisited

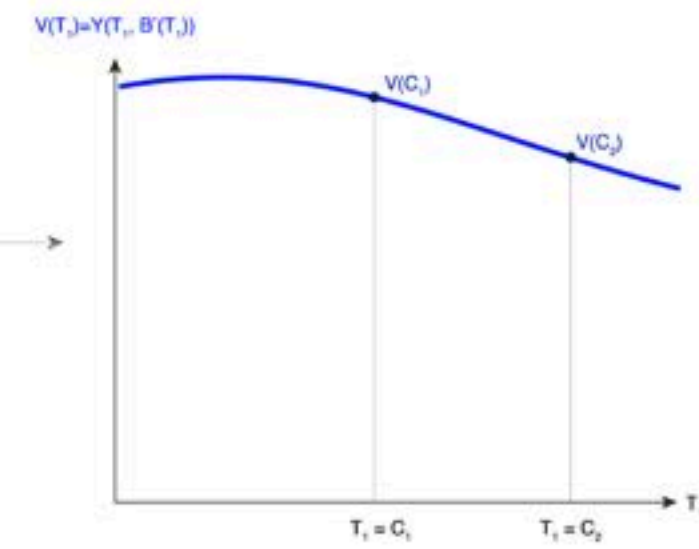
A) Climatological distribution described by one variable



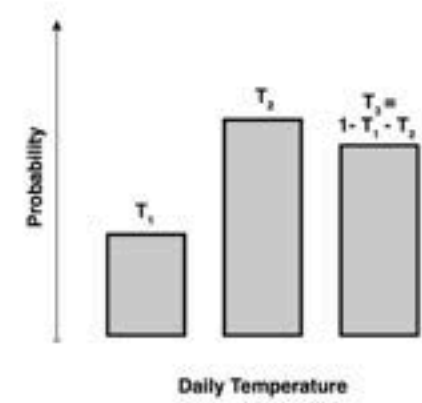
B) Income maximization via adaptation conditional on climate (one climate variable)



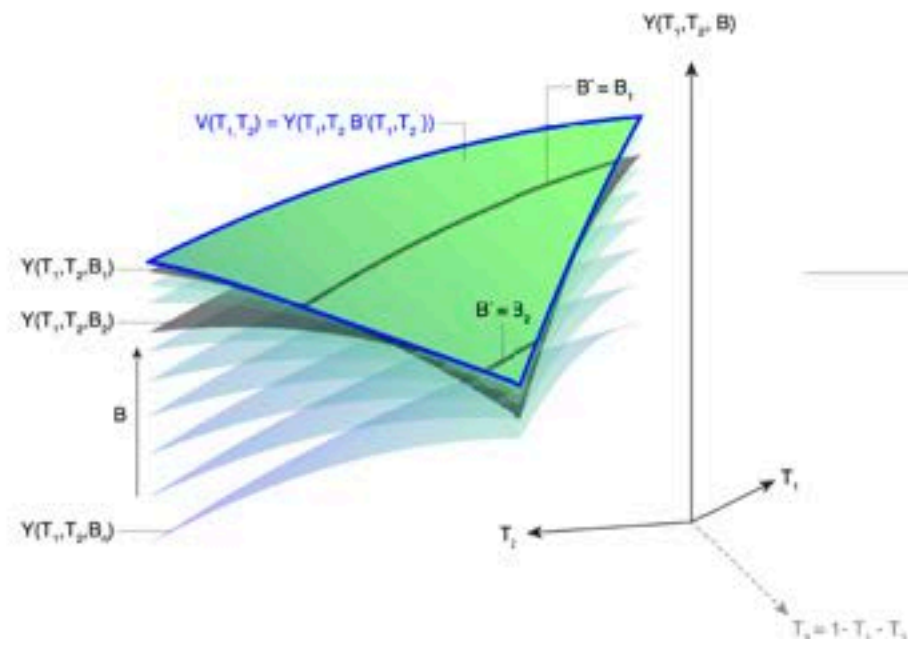
C) Climate value function (one climate variable)



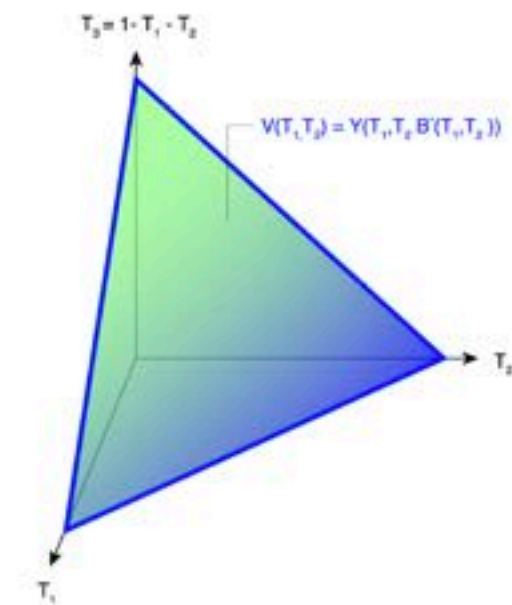
D) Climatological distribution described by two variables



E) Income maximization via adaptation conditional on climate (two climate variables)

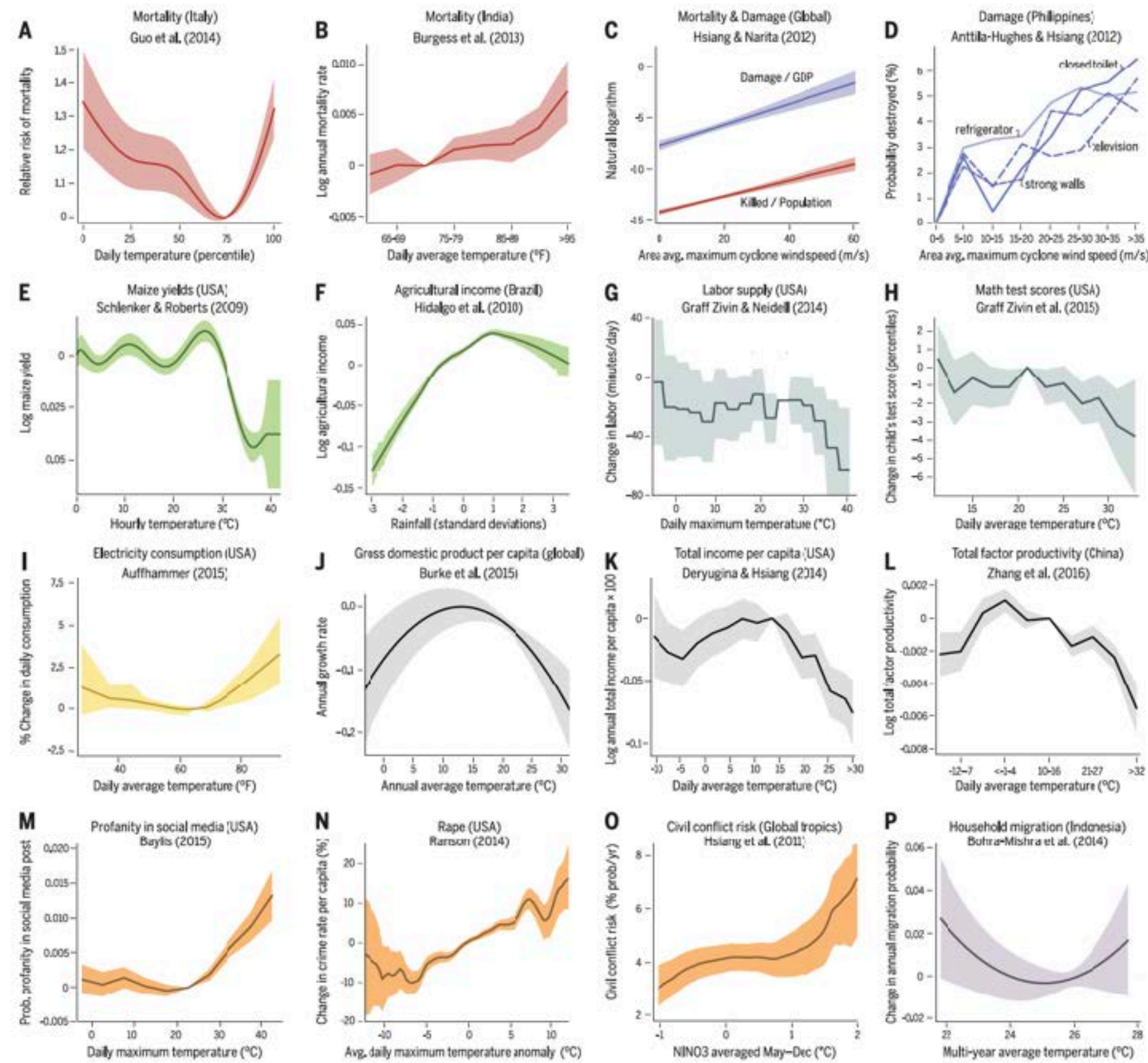


F) Climate value function (two climate variables)



Source: Deryugina and Hsiang, (2017)

Sectoral Coverage



Source: Carleton and Hsiang (2016)

Weather Impacts on the Macro Economy

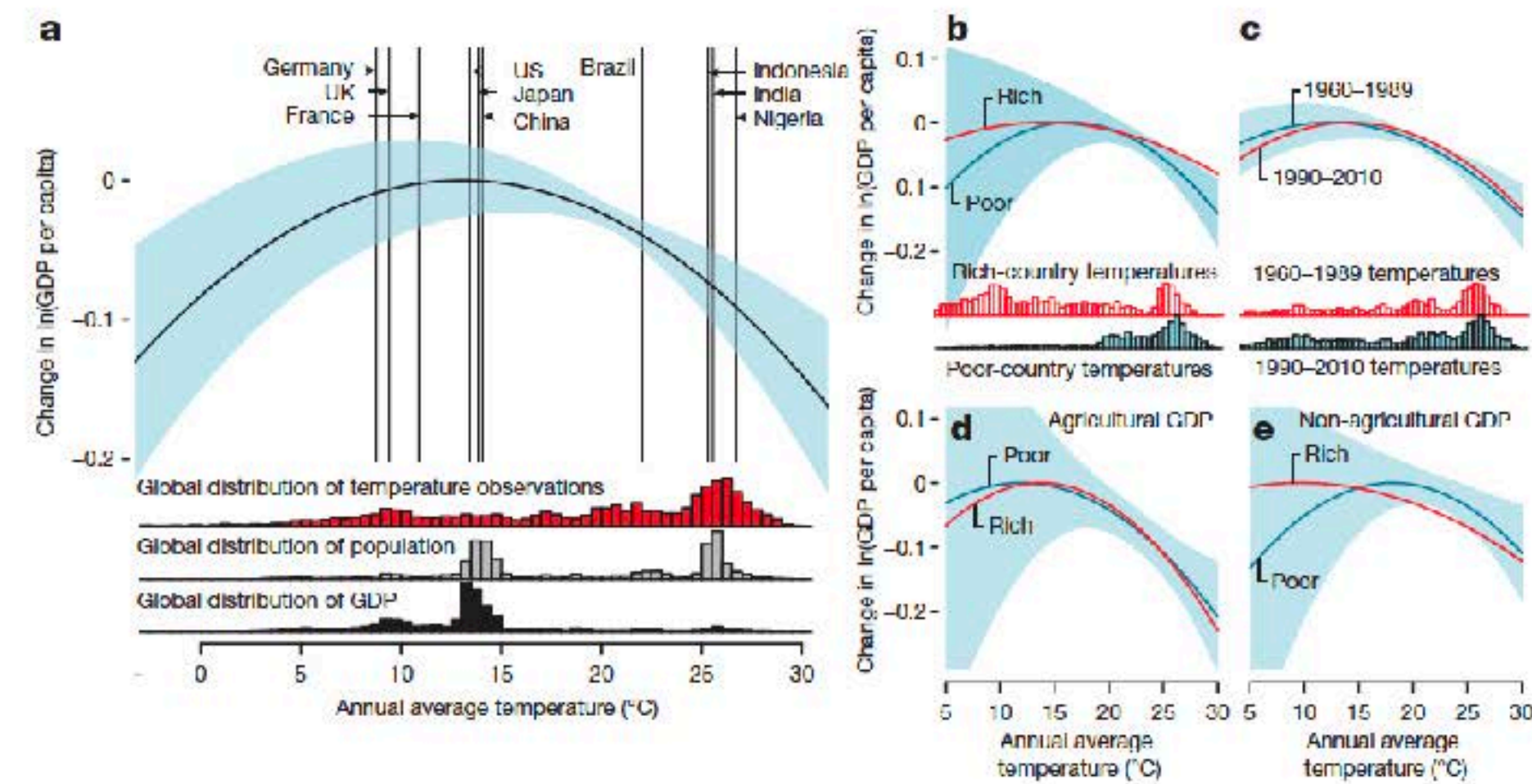
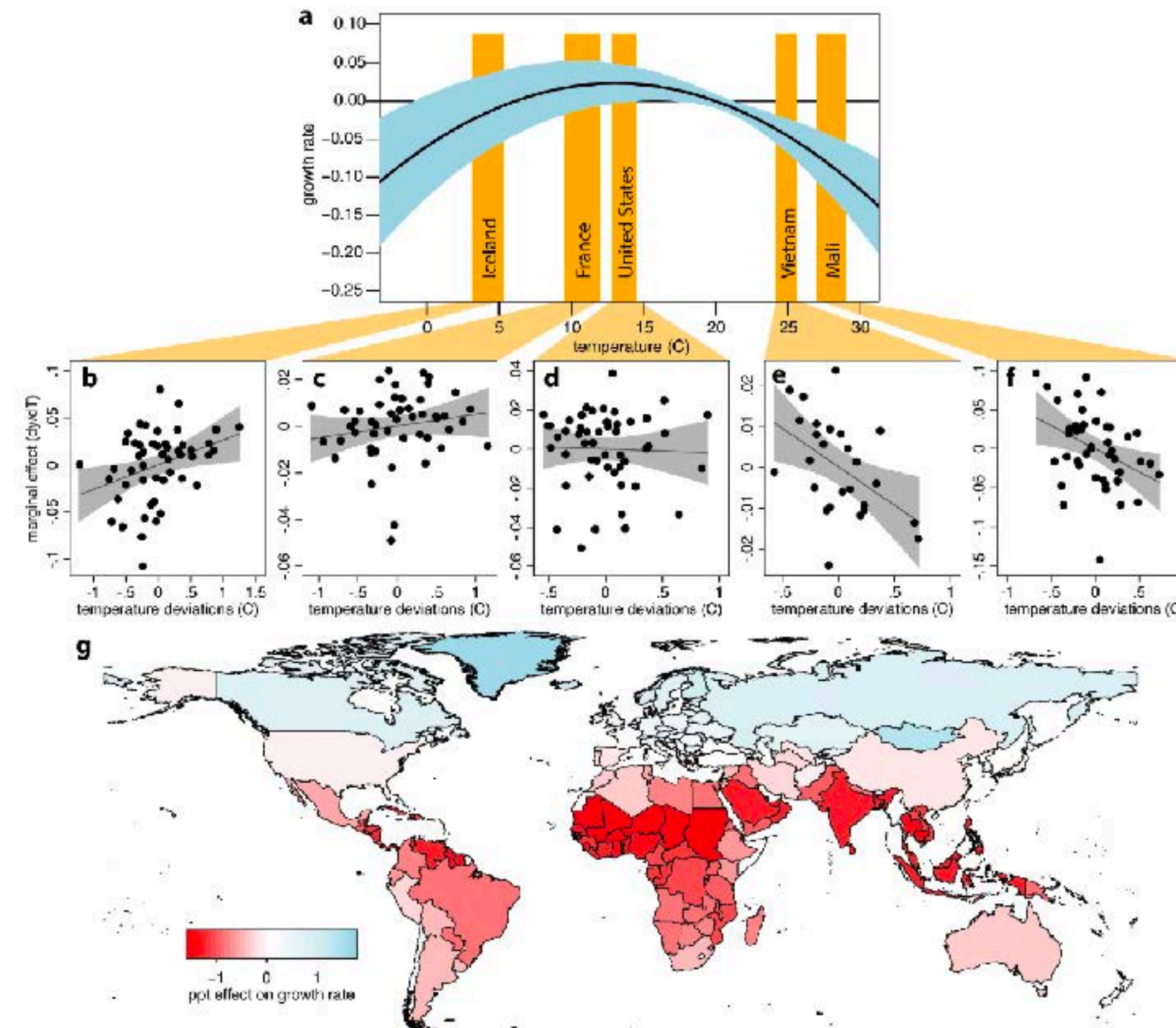


Figure 2 | Effect of annual average temperature on economic production. **a**, Global non-linear relationship between annual average temperature and change in log gross domestic product (GDP) per capita (thick black line, relative to optimum) during 1960–2010 with 90% confidence interval (blue, clustered by country, $N = 6,584$). Model includes country fixed effects, flexible trends, and precipitation controls (see Supplementary Methods). Vertical lines indicate average temperature for selected countries, although averages

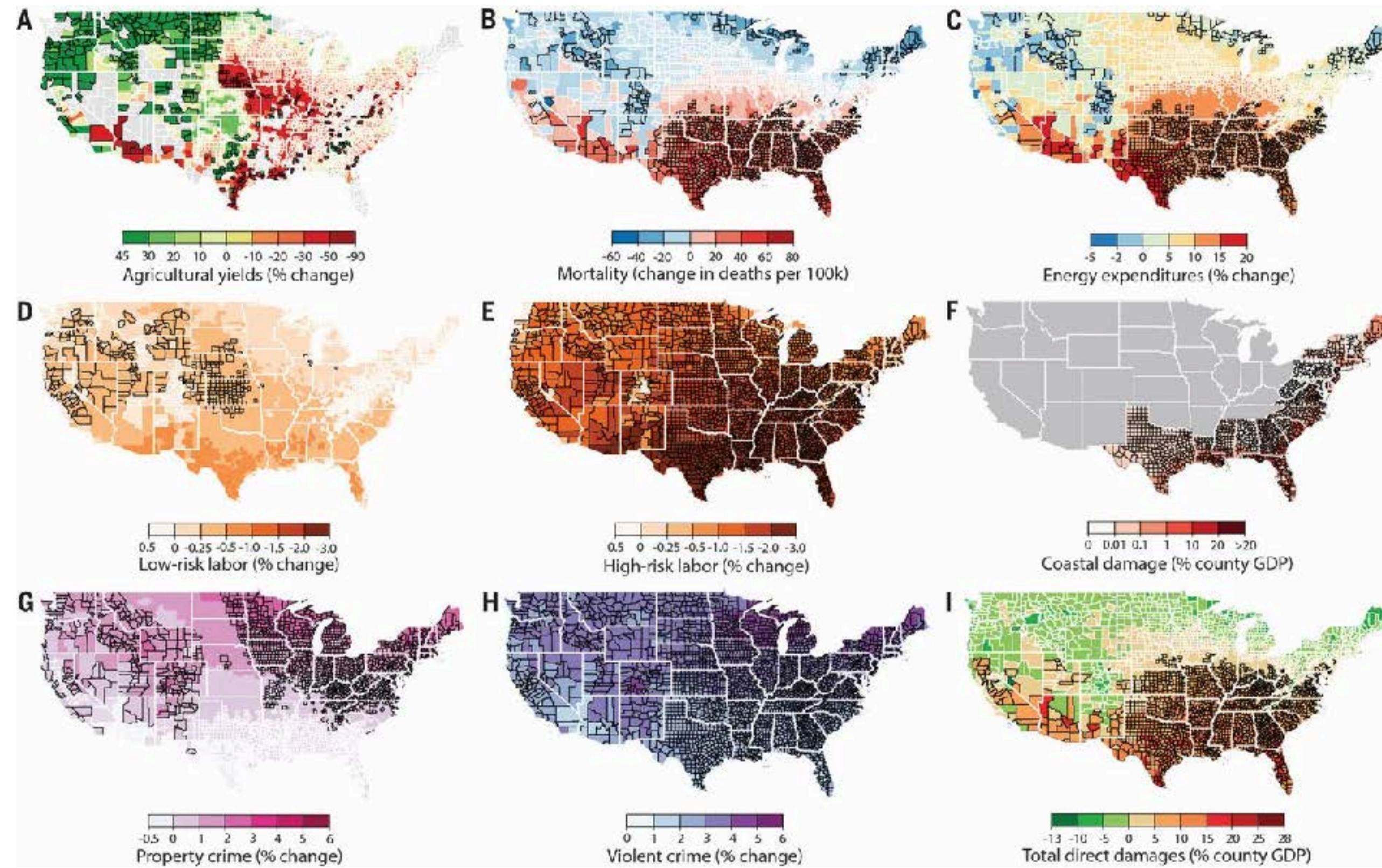
are not used in estimation. Histograms show global distribution of temperature exposure (red), population (grey), and income (black). **b**, Comparing rich (above median, red) and poor (below median, blue) countries. Blue shaded region is 90% confidence interval for poor countries. Histograms show distribution of country-year observations. **c**, Same as **b** but for early (1960–1989) and late (1990–2010) subsamples (all countries). **d**, Same as **b** but for agricultural income. **e**, Same as **b** but for non-agricultural income.

Country Level Impacts of Weather



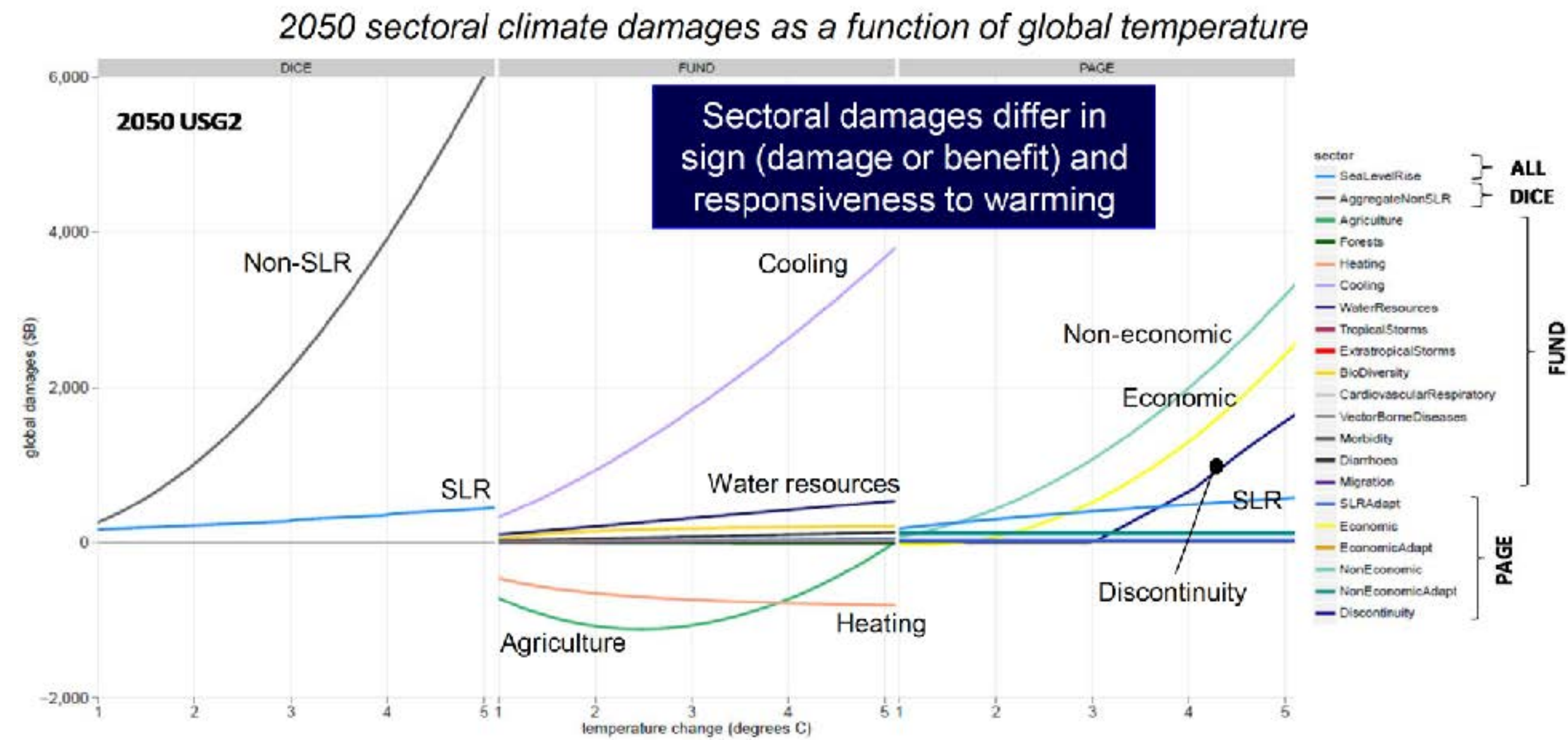
Source: Burke, Hsiang and Miguel (2016)

US Distributional Impacts of Weather



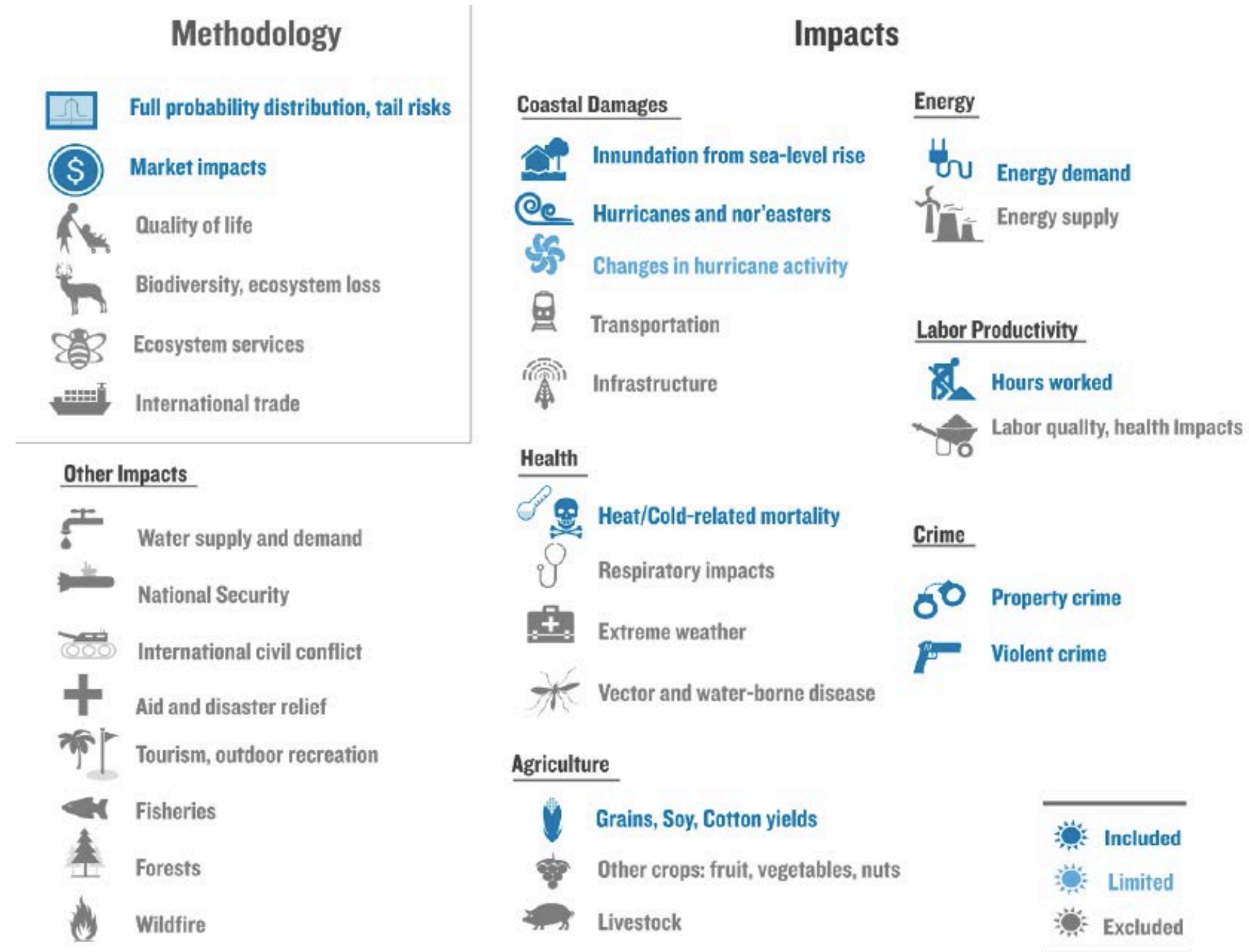
Source: Hsiang et al. (2017)

The most important number in climate change research



Source: EPRI

What are we missing?



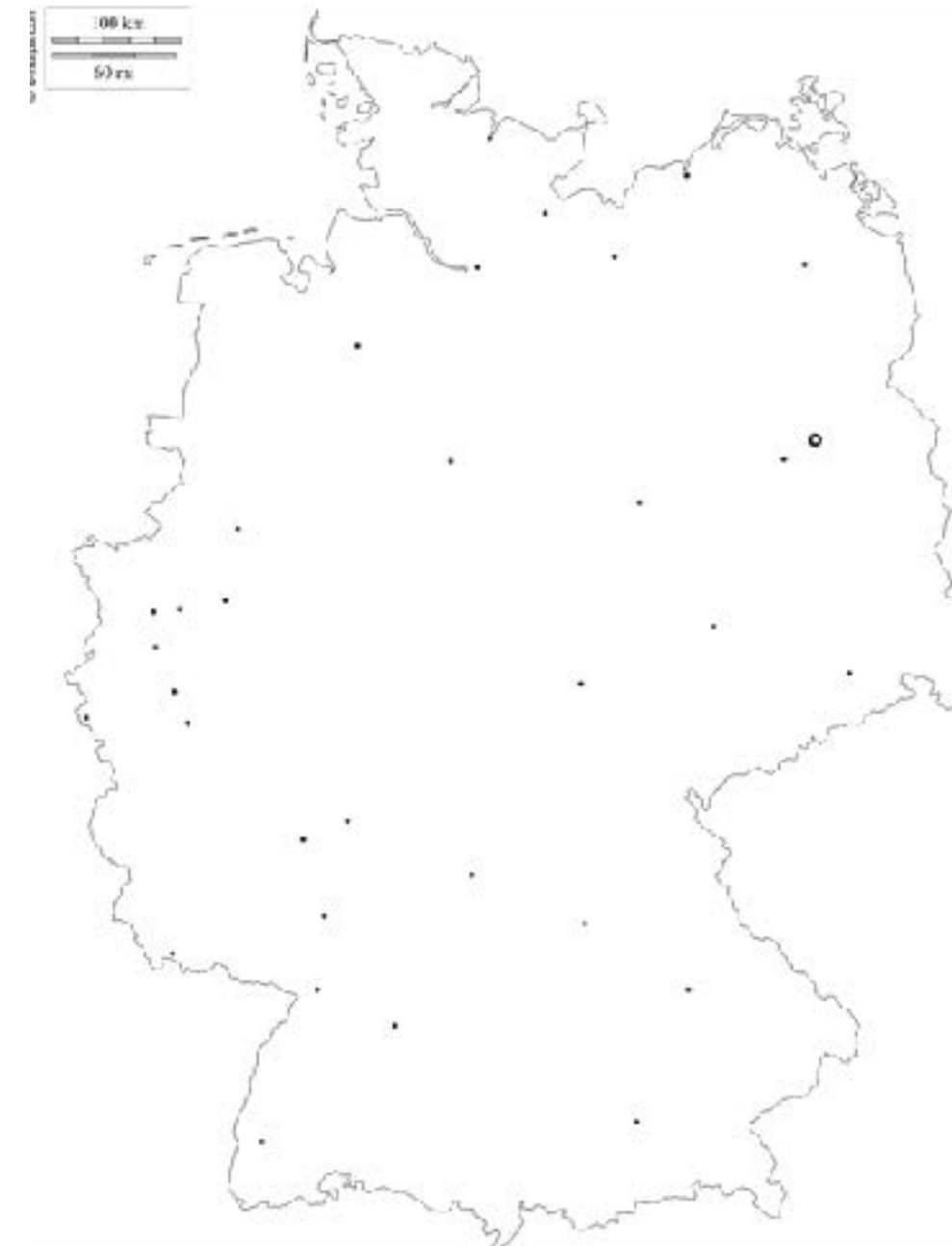
Source: American Climate Prospectus

What should we be working on?

- ▶ Extreme Events
- ▶ Migration
- ▶ Sea Level Rise Impacts
- ▶ Fisheries
- ▶ Non-Market Damages
- ▶ Labor Productivity
- ▶ Crops that Americans and Danes not staying at this hotel don't eat

Something that I am struggling with

Greece



Some final thoughts

- ▶ Incorporating adaptation may be impossible. It requires “knowing” available technological options by end of century. We don’t and these may be endogenous.
- ▶ Using your cooler neighbor as a pre-climate change counterfactual may be problematic. The sorting literature provides some insights on this.
- ▶ Expert elicitation, as Bob Pindyck is pushing for in this space, is of limited use. Experts replicate model findings.
- ▶ Building a better Social Cost of Carbon is of key importance. RFF and GCP are embarking on separate efforts.