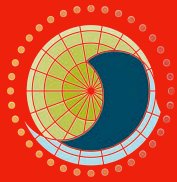


Integrating Variability Changes into Impacts Projections

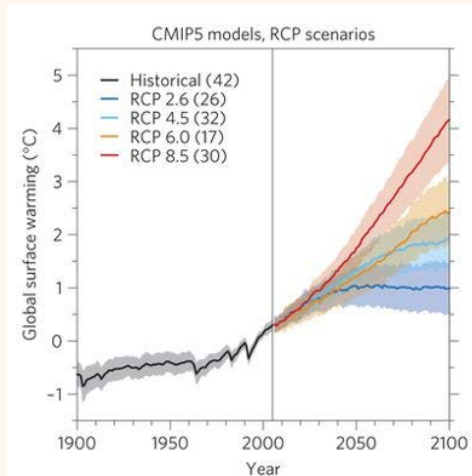
Kevin Schwarzwald
RDCEP, EPIC, University of Chicago

Based on work with Amir Jina, Matz Haugen, and Elisabeth Moyer

Where Climate Data Affects Impacts Uncertainty

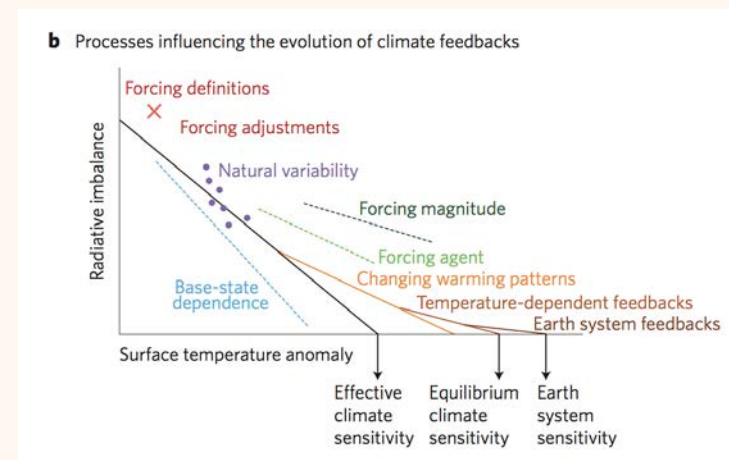


Scenario Uncertainty



(Knutti et al. 2013)

Response Uncertainty



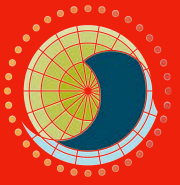
(Knutti et al. 2017)

Internal Variability

Large Ensembles,...

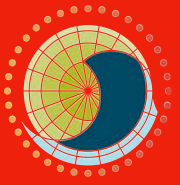
Projection Method Uncertainty

What We Mean By „Projections“



- Calculating future impacts of climate change requires an estimate of the future climate
- Climate models are biased; raw future data can't be used
- Climate projections used in impacts projections combine model output with historical weather data

What We Mean By „Projections“



Our Projection Philosophy, Commonly Used in Climate Economics

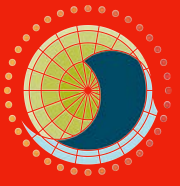
„Delta Change“:

Future climate = current observations + (future model - current model)

Assumes that the changes in the model reflect real-world changes

Can be used for any (combination of) characteristic of the climate - different variables, different moments (mean, standard deviation, skewness, different quantiles, etc.)

The Problem With Projections

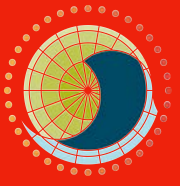


Question: How do changes in climate variability affect impacts projections?

Motivation:

Economic impacts of climate change are routinely calculated under assumptions that:

The Problem With Projections



Question: How do changes in climate variability affect impacts projections?

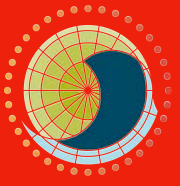
Motivation:

Economic impacts of climate change are routinely calculated under assumptions that:

1. Climate variability does not change

(i.e. Schlenker, Hanemann, and Fischer 2005; Deschênes and Greenstone 2011; Hsiang, Burke and Miguel 2013)

The Problem With Projections



Question: How do changes in climate variability affect impacts projections?

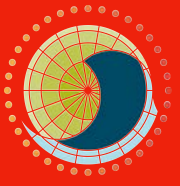
Motivation:

Economic impacts of climate change are routinely calculated under assumptions that:

1. Climate variability does not change
2. Only the seasonality of climate changes

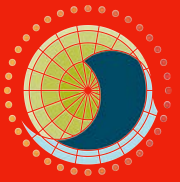
(i.e. Fischer et al. 2005; Schlenker and Roberts 2009)

The Problem With Projections



Question: How do changes in climate variability affect impacts projections?

Test: Sensitivity analysis of a well-known climate damage function to fine-scaled temperature variability changes



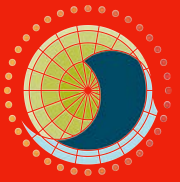
Test: Sensitivity analysis of a well-known climate damage function to fine-scaled variability changes

Damage function: temperature vs. mortality, Deschênes and Greenstone, 2011

Base, fixed variability projection: ERA-INTERIM, scaled by CESM large ensemble yearly means („fixedvar“)

Ideal projection with fine-scaled variability changes: ERA-INTERIM, scaled by CESM large ensemble quantile changes („varchange“)

Result: omitting variability changes leads to overestimating future mortality in cold regions and underestimating it in warmer inland areas.



Test: Sensitivity analysis of a well-known climate damage function to fine-scaled variability changes

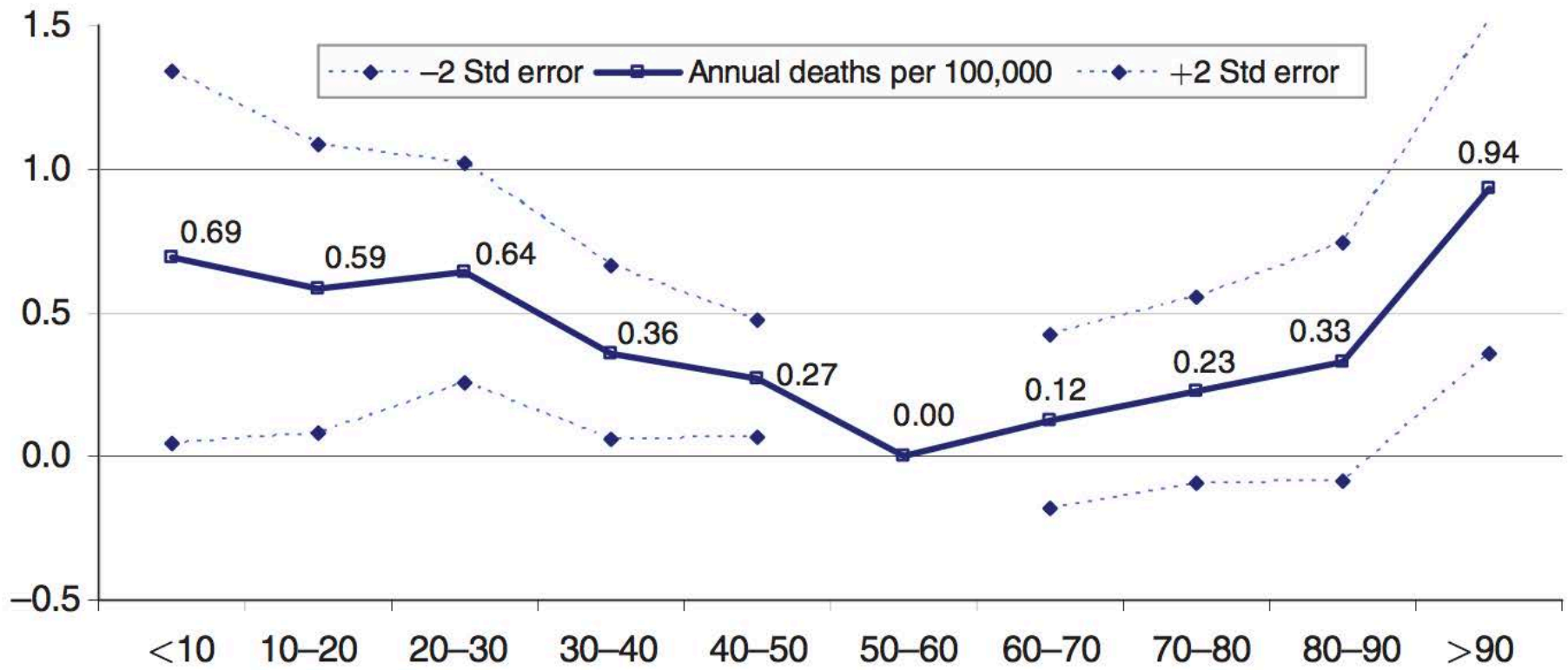
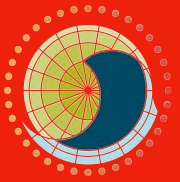
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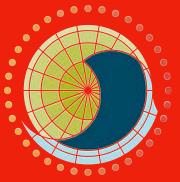
Result: omitting variability changes leads to overestimating future mortality in cold regions and underestimating it in warmer inland areas.

Damage Function



Estimated impact of a day in 9 daily mean temperature (F) bins on annual mortality rate, relative to a day in the 50°–60° F bin

(from Deschênes, Olivier, and Michael Greenstone. 2011. "Climate Change, Mortality, and Adaptation: Evidence from Annual Fluctuations in Weather in the US." *American Economic Journal: Applied Economics* 3 (4): 152–85. <https://doi.org/10.1257/app.3.4.152>.)



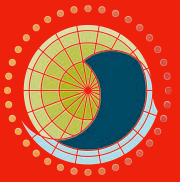
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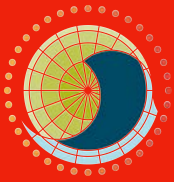
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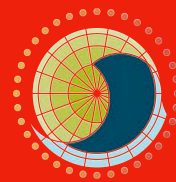
„By how much will the coldest Jan 1st / median Apr 21 / hottest Aug 15 change in the future?“

- Based on the estimation of the shape of *daily T* distributions using quantile regression; distributional changes are imposed on historical ERA-INTERIM
- Basis functions are smooth cubic splines, allowing for
 - within year variation (seasonal cycle)
 - inter-year variation (long-term trend)
 - an interaction (long-term changes in the seasonal cycle)
- As a result, each quantile for each day-of-year (i.e. the median Jan 1st) is estimated using 40 runs x 121 years (1979-2099) = 4840 points



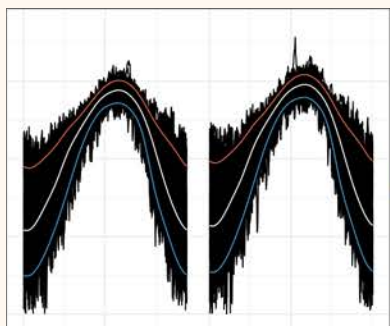
ks905383/quantproj

Variability Projection

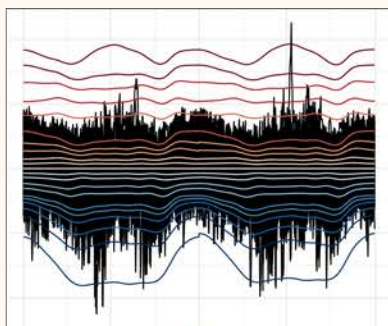


LENS, 40 runs
(projecting data)

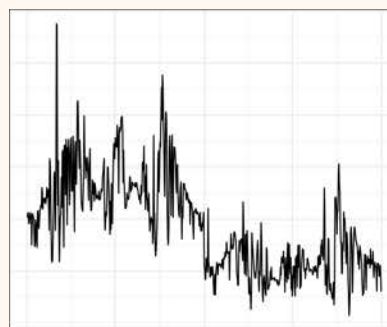
1. Normalize



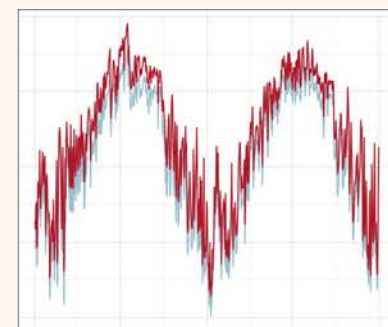
2. Estimate quantiles



3. Apply LENS change
in matched quantiles

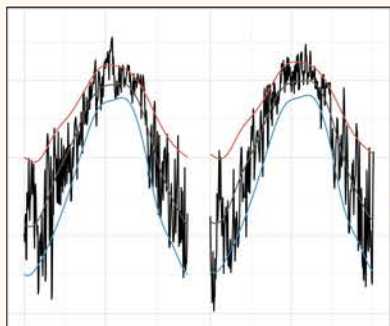


4. Un-normalize

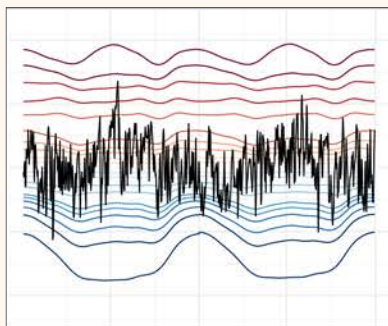


ERA-INTERIM
(reanalysis/base data)

1. Normalize

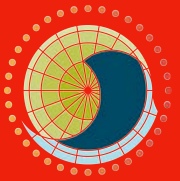


2. Match to LENS quantiles



ks905383/quantproj

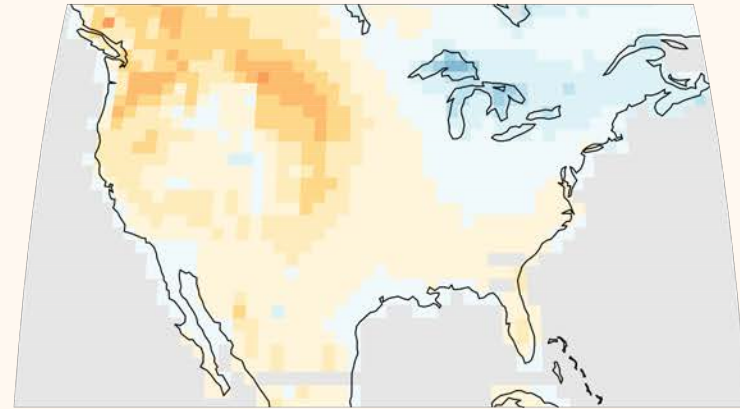
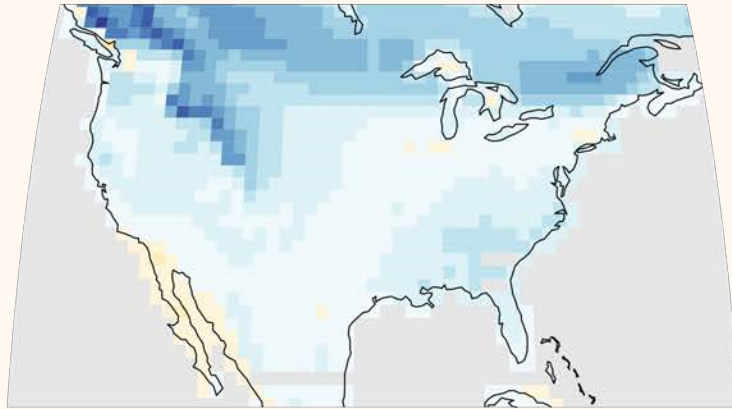
Variability Projection



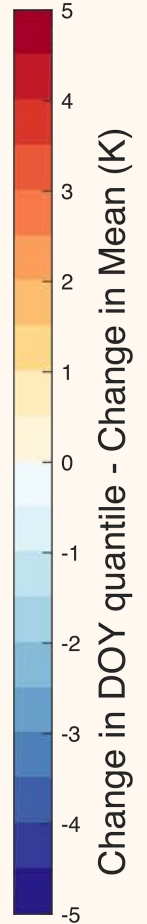
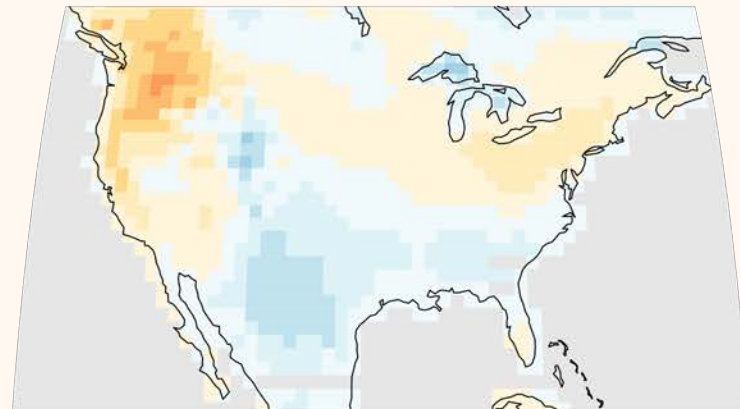
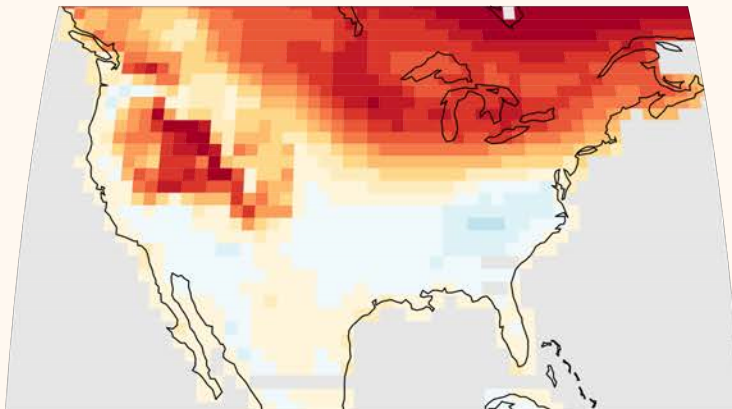
Jan 1

Jul 1

0.9 quantile
(hotter Ts)

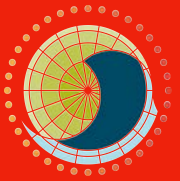


0.1 quantile
(colder Ts)

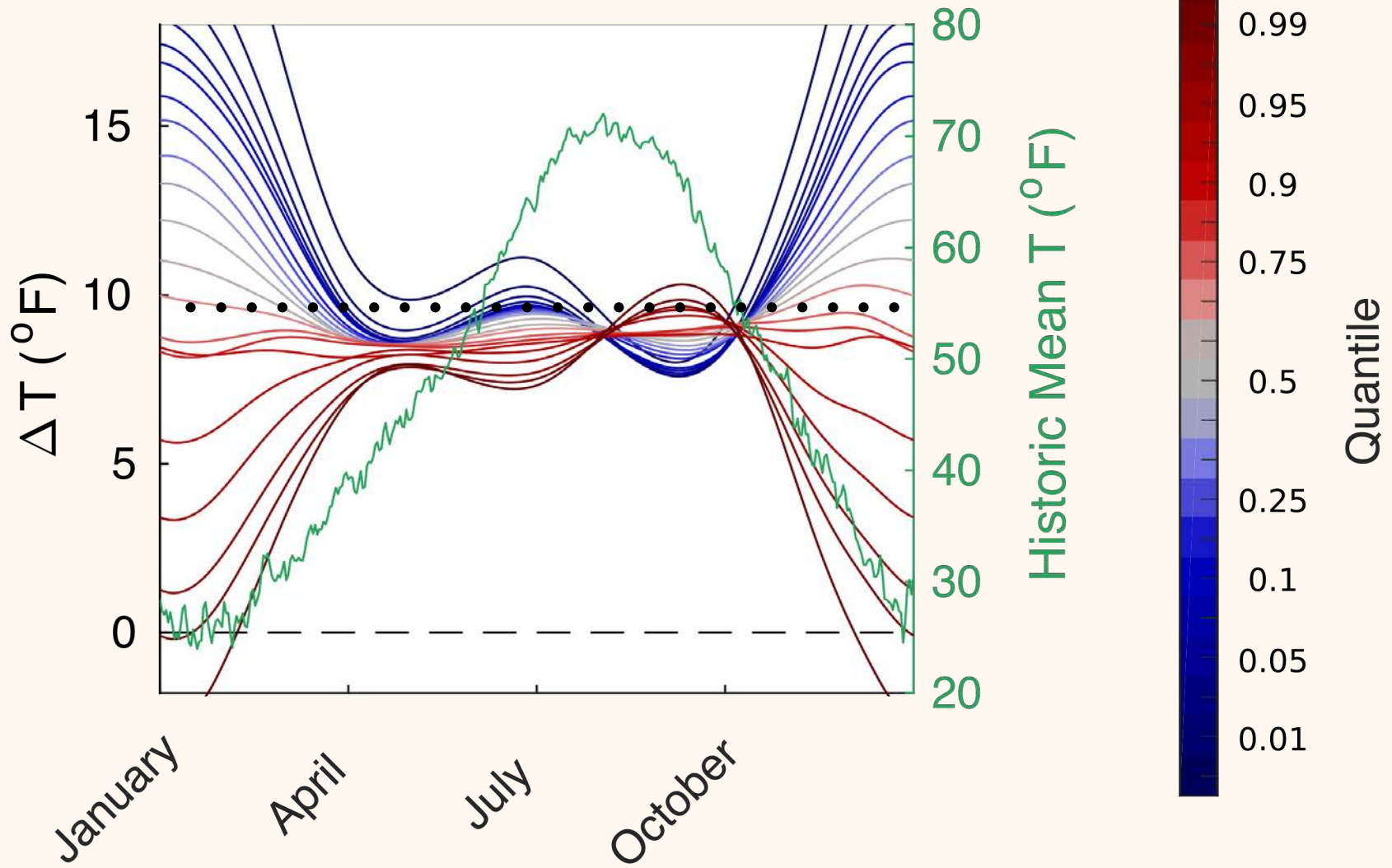


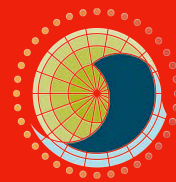
(average of [2068-2099] - average of [1979-2010] from LENS)

Variability Projection



Milwaukee County, WI





Test: Sensitivity analysis of a well-known climate damage function to fine-scaled variability changes

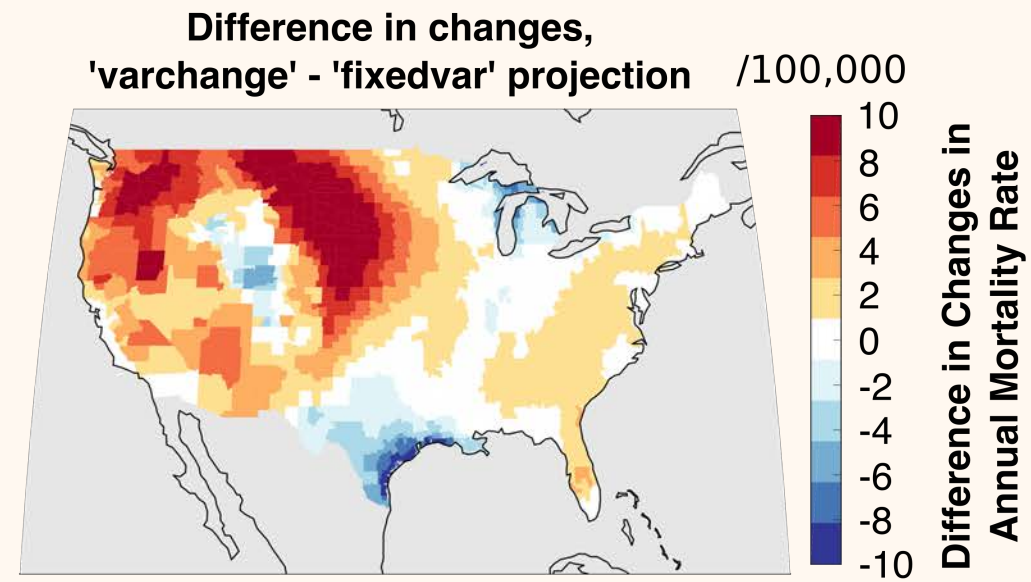
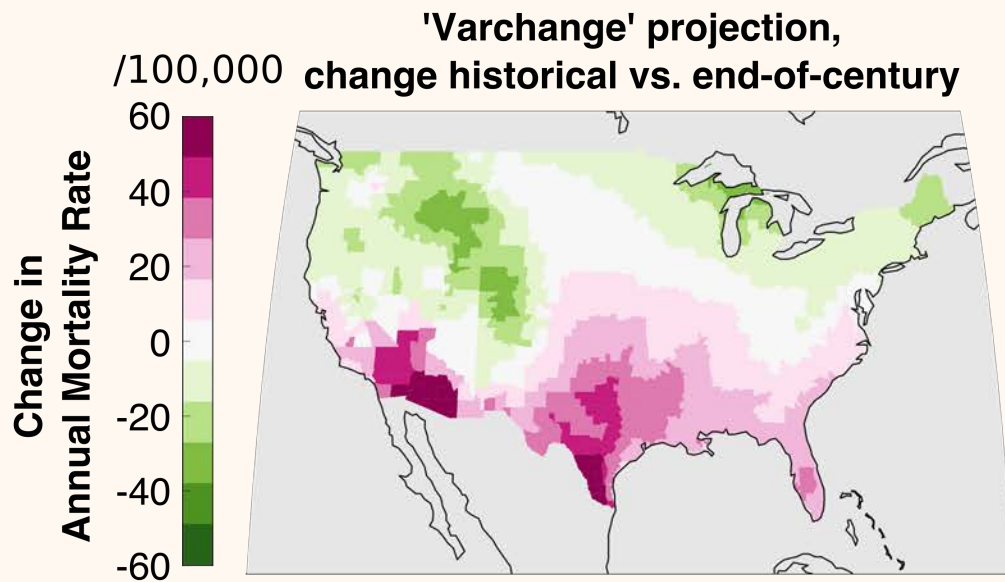
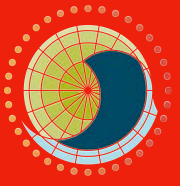
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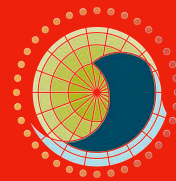
Mortality Changes Under Variability Changes



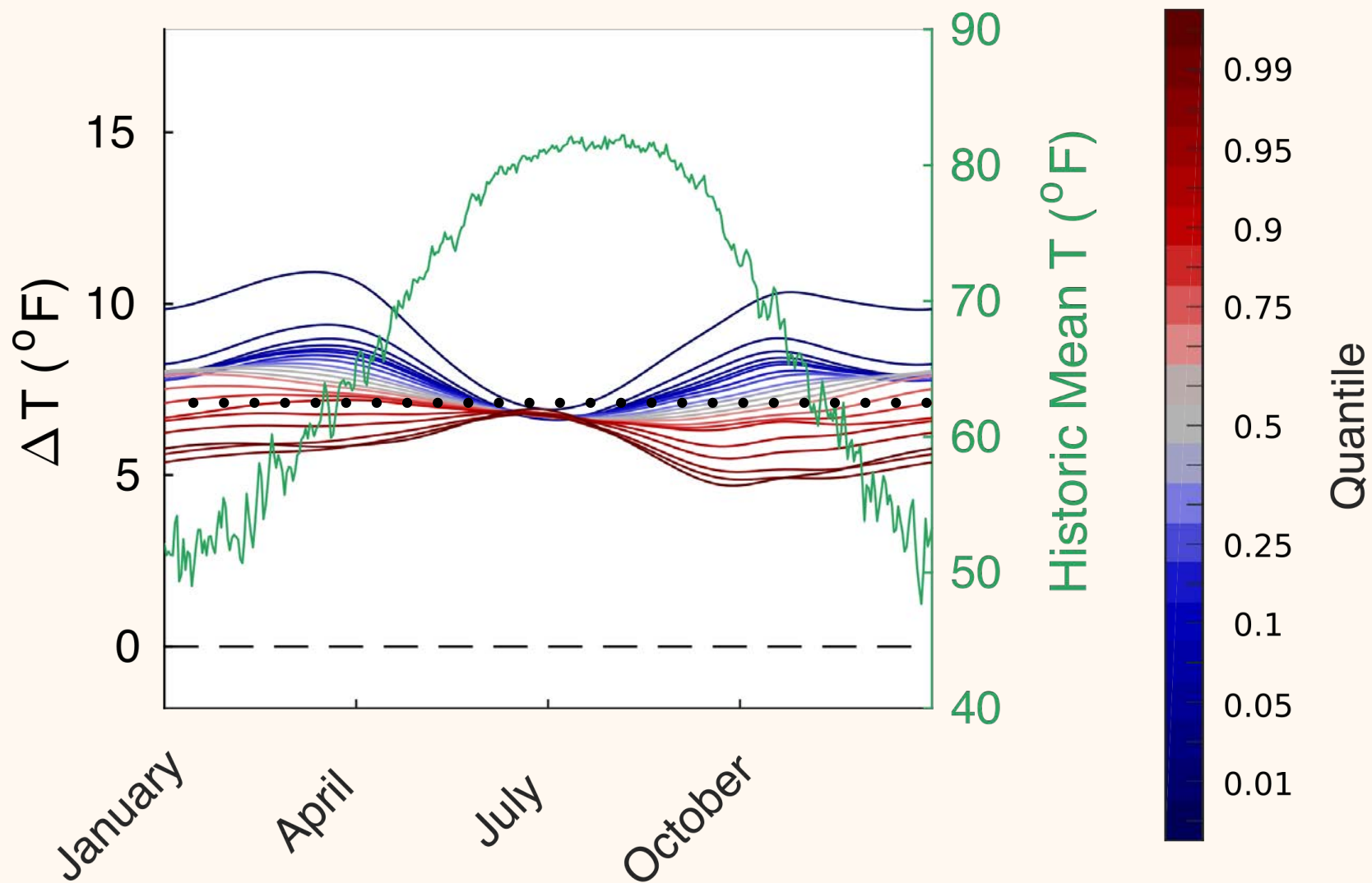
 Ignoring variability changes in projections *overestimates* future mortality

 Ignoring variability changes in projections *underestimates* future mortality

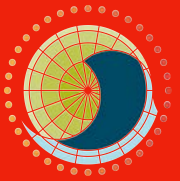
Mortality Changes Under Variability Changes



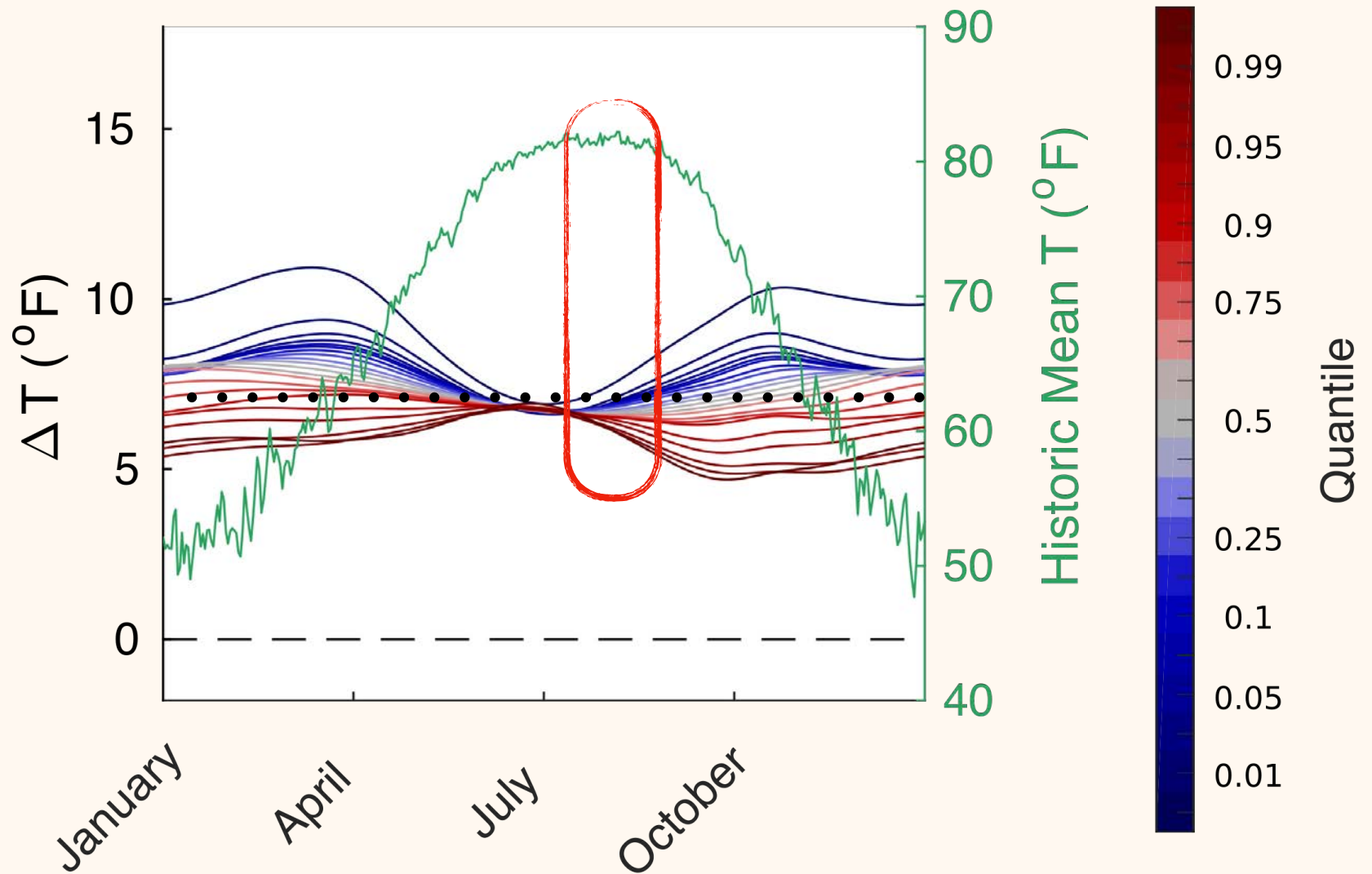
Harris County, TX (Houston)



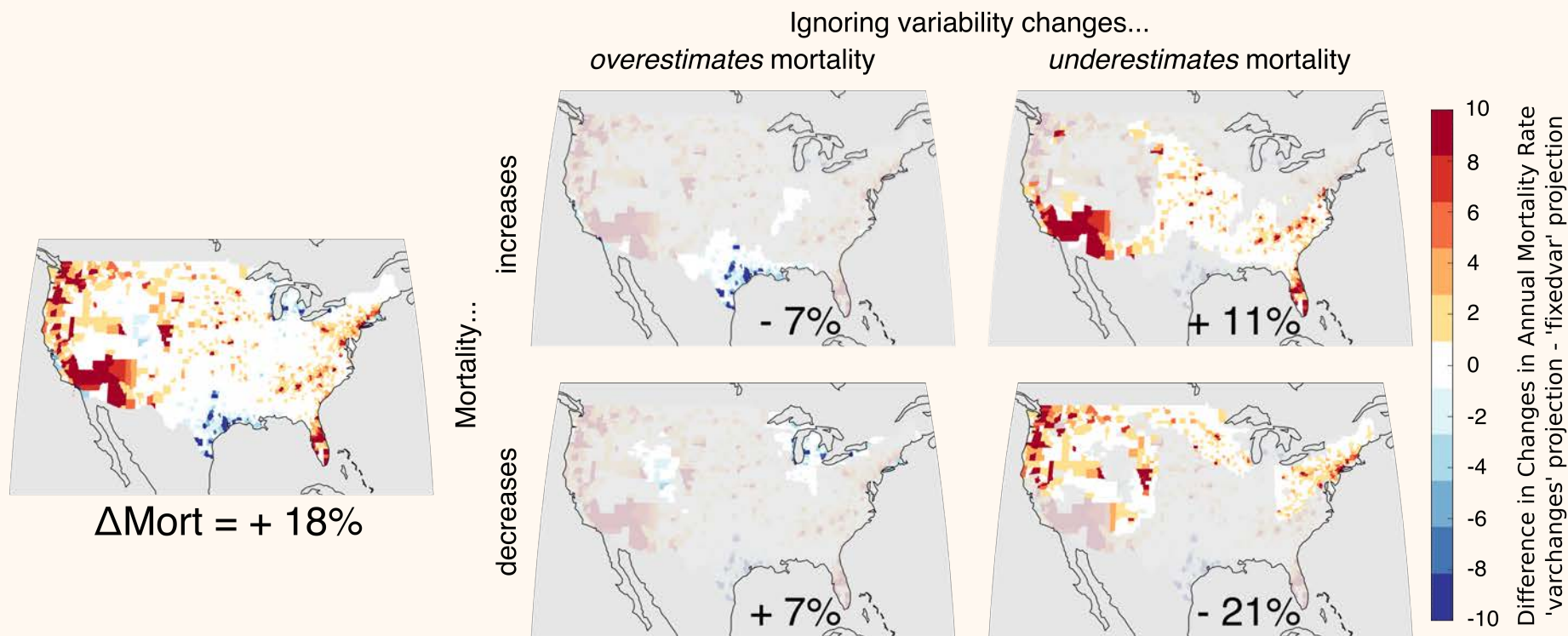
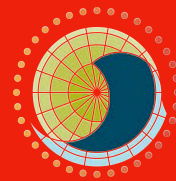
Mortality Changes Under Variability Changes



Harris County, TX (Houston)



Mortality Changes Under Variability Changes



1. Large ensembles allow us to extract more information from a given climate model, improving impacts projections
2. A better understanding of variability changes (estimated using large ensembles) suggests heat-related mortality changes from climate change in the US are underestimated