Probabilistic U.S. county-level climate projections: A new data set for local climate risk analysis

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Climate risk assessment requires probability distributions

The risk of an adverse event is defined by its probability times its consequence. Low probability, high consequence events are of interest to those managing financial and economic risks

The Problem:

•Quantitative assessment of future climate change risk requires probabilistic projections of physical climate variables

•Coupled Model Intercomparison Project (CMIP) climate model (GCM) ensembles are not probability distributions and GCMs may exclude extreme climate outcomes

Approach and Key Findings:

•Combine spatially detailed projections from GCMs with probabilistic projections of global mean temperature from a simple climate model

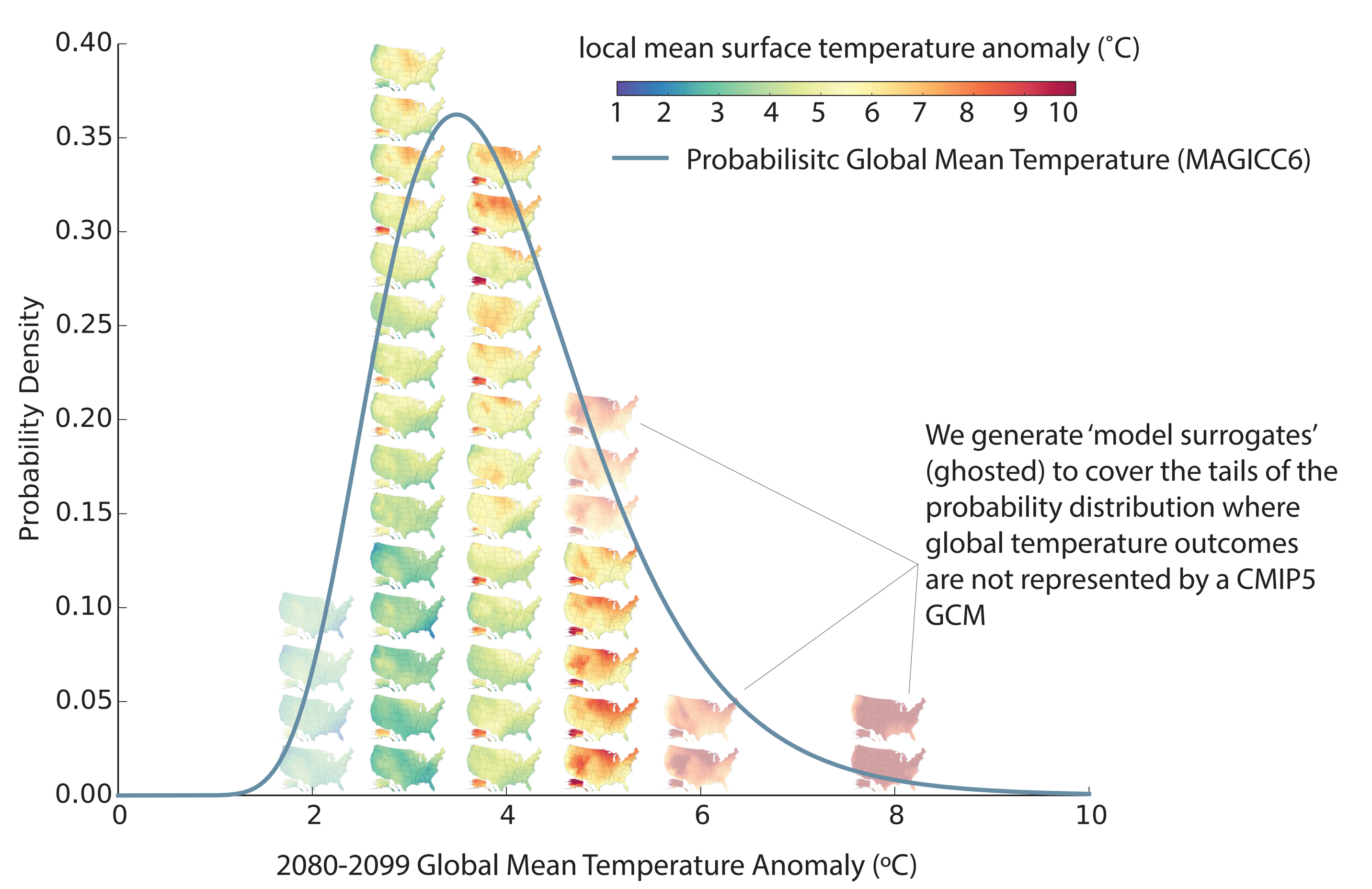
•We reproduce the *likely* (67% probability) outcome range from the CMIP5 and also provide estimates of low probability, high consequence outcomes not produced by GCMs.

"So What?":

•We have created an open-source data set of county-level probabilistic climate projections to support decision making at local scales and climate risk assessments, such as *Economic Risks of Climate Change: An American Prospectus*

GCM ensembles are not probability distributions

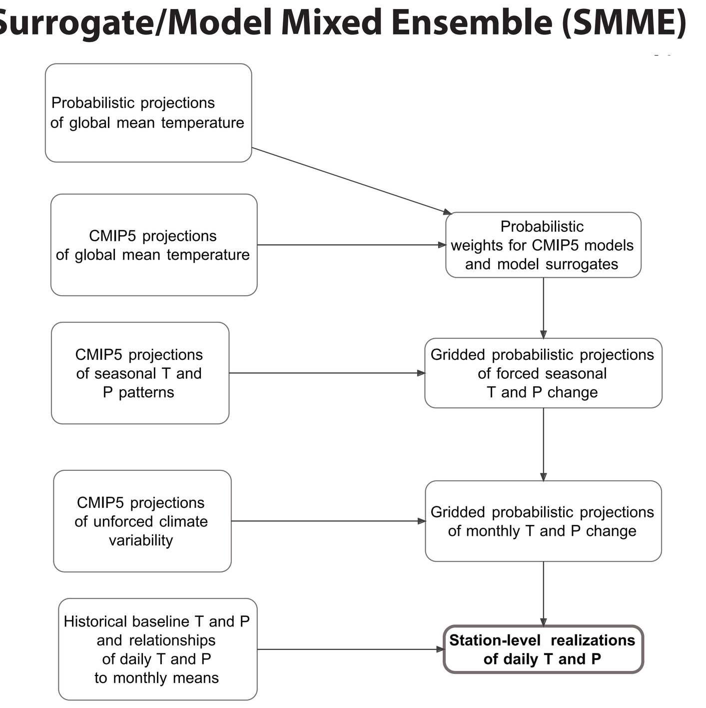
GCM model ensembles, like the CMIP5, are arbitrarily compiled on the basis of modeling center participation. Sampling from such a distribution by assigning equal probability to all models may therefore yield a biased outcome[1]



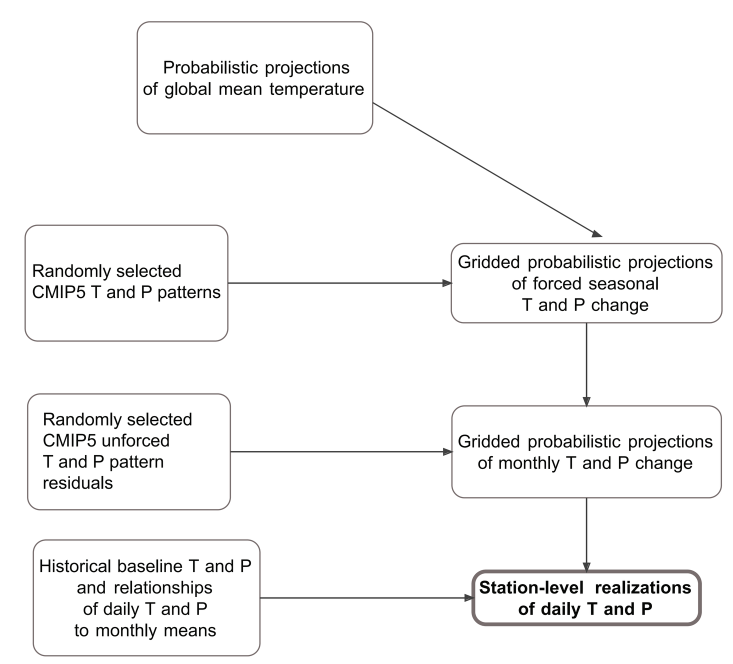
Simple Climate Models (SCMs) like MAGICC6[2,3], can produce probability distributions of global mean temperature, but lack the spatial resolution necessary for local climate risk assessment. To solve this, we combine spatially resolving GCMs with SCM projections of probabilistic global mean temperature.

Roadmaps for two methods: SMME & MCPR

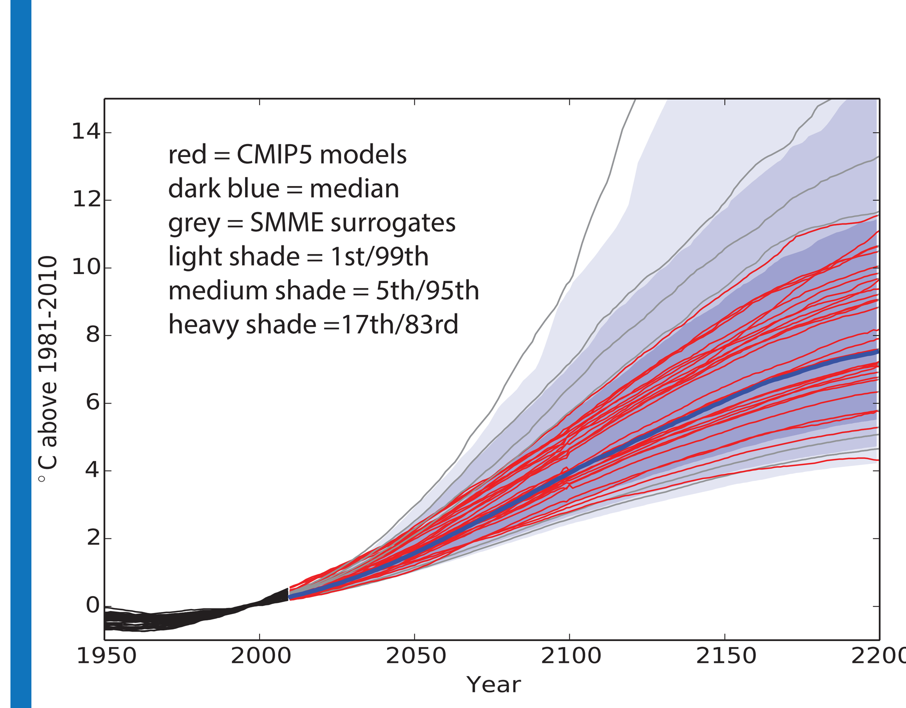
1. Surrogate/Model Mixed Ensemble (SMME)



2. Monte Carlo Pattern/ Residual (MCPR)



Probabilistic global mean temperature projections



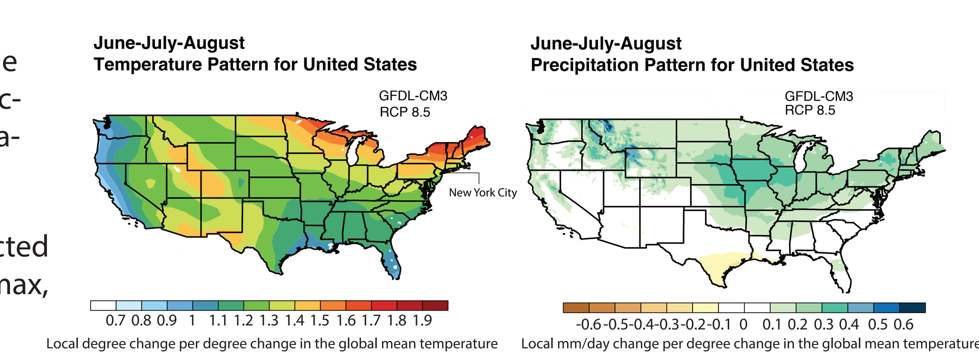
Probabilistic projections of global temperature from SCMs include temperature pathways and equilibrium climate sensitivities (ECS) that are not simulated or observed in GCMs. For instance, in the CMIP5, the ECS range is 2.1-4.7°C per CO_2 doubling[4], observations and non-GCM constraints suggest ~ 17% probability ECS could be higher than 4.5°C[5]

We generate probabilistic projections of global mean temperature using 600 runs of MAGICC6 in probabilistic mode (all four RCPs). Note that these projections are conditional on one PDF and the use of other prior PDFs may be more appripriate[6]

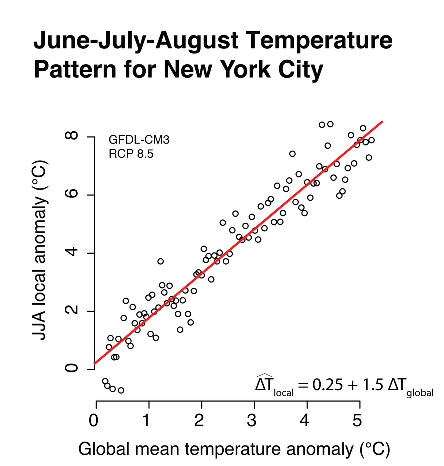
Construction of model surrogates

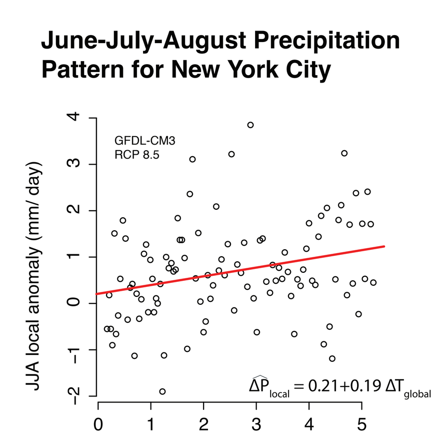
Model surrogates used to cover the tails of the distribution must spatially resolve local projections of climate change under global temperature pathways not simulated in GCMs.

We use GCM output that has been bias-corrected and spatially-disaggregated (BCSD)[7] (Tmin, Tmax, Tavg, Precipitation)



Pattern scaling[8] is used to estimate global-local climate relationships

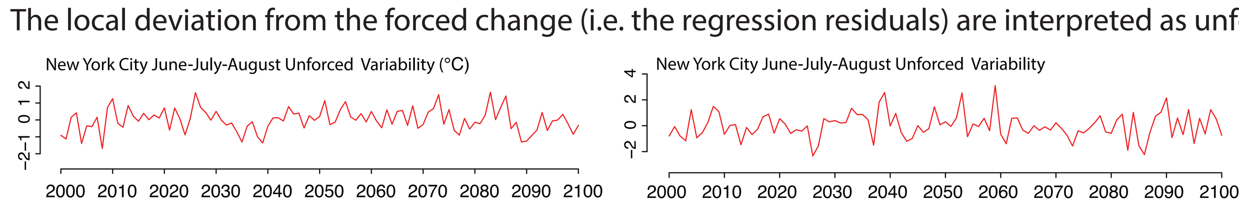


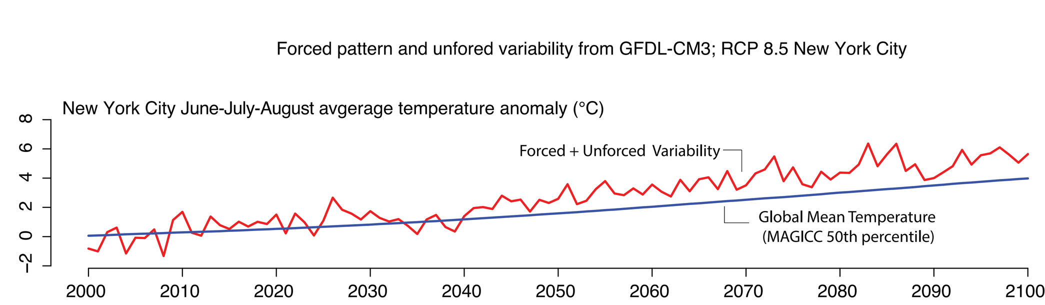


Pattern scaling uses ordinary least squares regression to construct global-local relationships. Pattern scaling assumes the average change in local temperature and precipitation is proportional to forced climate change (30-yr running average change in global mean temperature from the parent GCM, here GFDL-CM3)

Pattern scaling assumes that global-local relationships are constant with global forcing, which may or may not be true

The local deviation from the forced change (i.e. the regression residuals) are interpreted as unforced climate variability

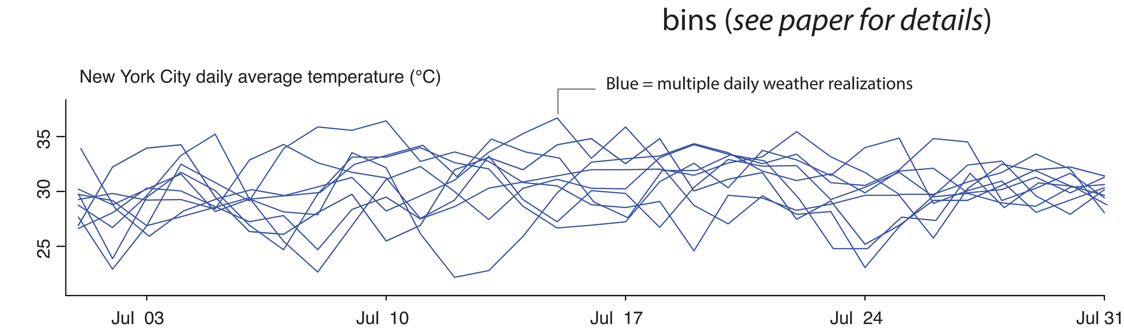




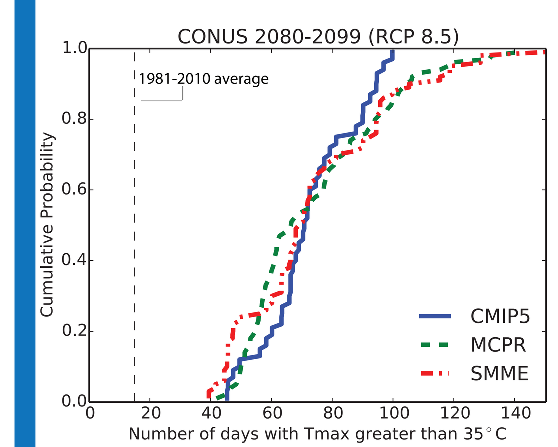
We sum unforced variability and forced temperature change (a time series of MAGICC global mean temperature scaled by the local pattern, i.e. $1.5\Delta T_{global}$ for NYC temperature, GFDL-CM3)

For MCPR, randomly assign patterns and residuals, SMME has *ad hoc* method based on GCM representation in assigned global temperature bins (*see paper for details*)

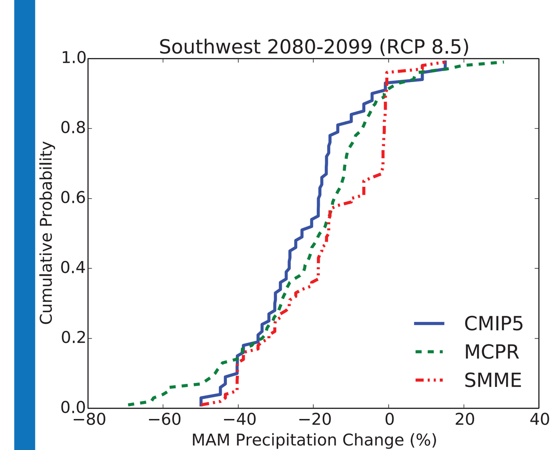
Finally, historical weather variability from gridded weather observations[9] is used to temporally downscale monthly averages to daily weather realizations



Probabilistic climate projections for the U.S.



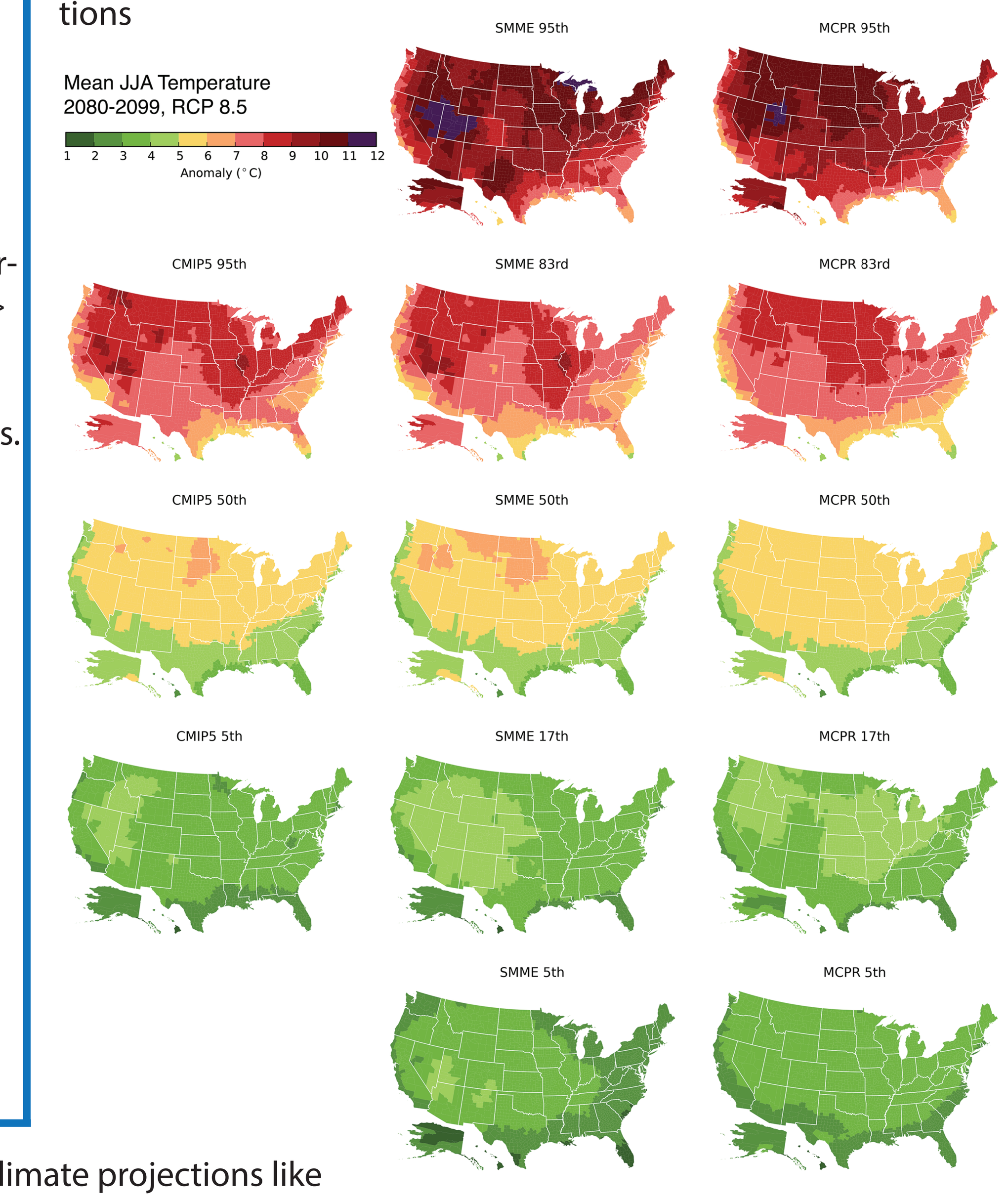
Probabilistic estimates of 95th percentile number of days with T_{max} > 35°C experienced by the average American (SMME, MCPR) exceed warmest CMIP5 model projections.



All ensembles project *likely* (67% probability) drying in the Southwest during March-April-May

The probabilistic projections reproduce *likely* (67% probability) outcomes and also project 5th/95th percentile outcomes not simulated in the CMIP5

Probabilistic estimates of 95th percentile temperature increase (SMME, MCPR) exceed warmest CMIP5 projection for many locations

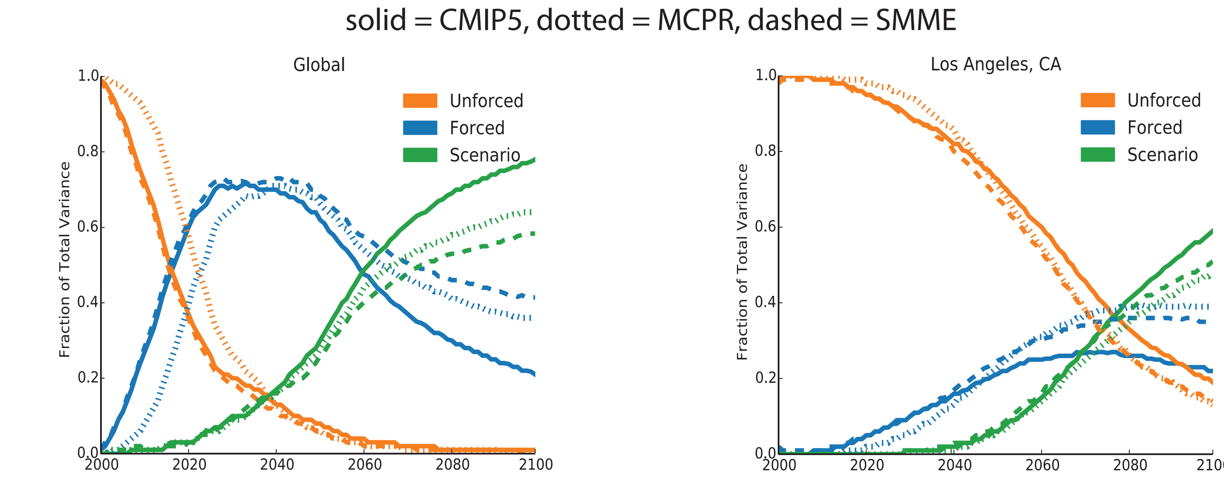


Time series of daily probabilistic climate projections like these are well suited for use with sector-specific impacts models and damage functions, including those jointly dependent on temperature and precipitation.

Quantifying local projection uncertainty

For decision making purposes, it is useful to quantify future climate change projection uncertainty. Following Hawkins and Sutton (2009), we decompose local temperature projections into 1) forced 2) unforced and 3) scenario (i.e. emissions) variability, each evolving with time. Pattern scaling regression residuals are used as estimates of unforced variability.

solid = CMIP5, dotted = MCPR, dashed = SMME



Globally, model uncertainty dominates until late century and locally, unforced variability dominates until late century.

Download the Dataset

Our dataset will be available for download through a URL given in the final paper, currently in review with *Journal of Applied Meteorology and Climatology*. Summary statistics of both probabilistic climate projections and sectoral impacts are currently available at www.climateprospectus.org. A draft of our paper is currently available on arXiv: Rasmussen D.J., M. Meinshausen, and R.E. Kopp, Probability-weighted ensembles of U.S. county-level climate projections for climate risk analysis.

References:
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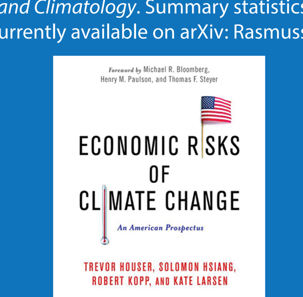

Economic Risks of Climate Change: An American Prospectus is now available through Columbia University Press and Amazon

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