Integrating Empirical Estimates with IAMs for Climate Impact Assessments: Energy Case Studies

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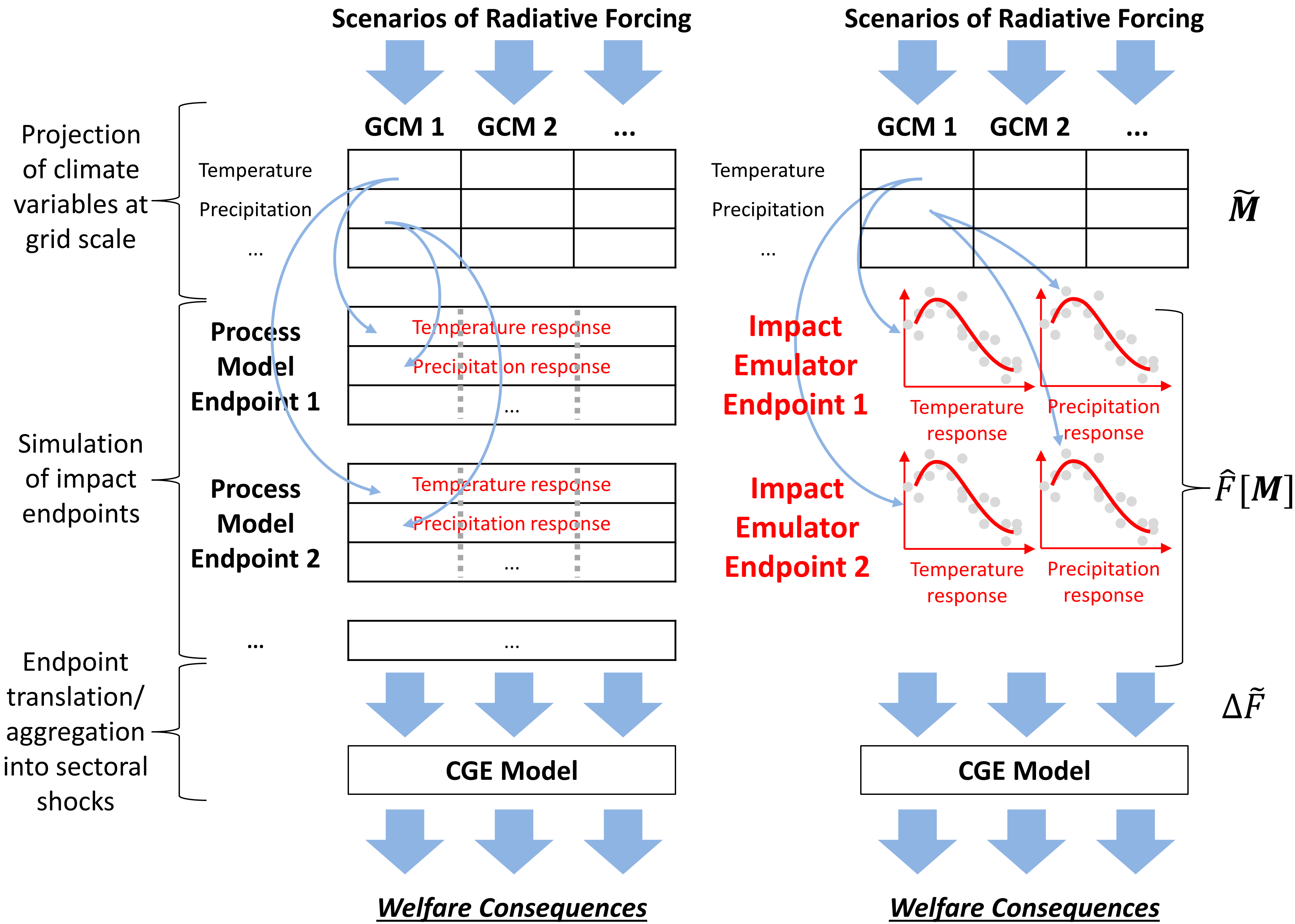
Societal Consequences of Climate Impacts: Challenges for Integrated Assessment

- The challenge
  - Shifts in meteorological variables due to climate change potentially affect a wide range of human activities
  - Effects manifest themselves through numerous biophysical “impact endpoints”, of which several can occur within a single sector of the economy
  - The processes linking meteorology to endpoints occur at a finer level of temporal, spatial and sectoral granularity than IAMs can represent
  - Process simulation of multiple impact pathways’ temporal, spatial and sectoral details is generally computationally intractable
- “Emulation”: a potential solution
  - Computationally efficient emulators of impact endpoints’ responses to changing meteorological variables
  - Reduced form response surfaces derived from statistically estimated relationships between endpoints and meteorological variables observed in the historical record
  - Response surfaces forced by GCM outputs to generate projections of “shocks” that can then be incorporated into broad sectors modeled by IAMs
  - Leverages possibilities opened up by data and econometric modeling in empirical climate economics literature
- Needed: (A) empirical analysis as if IAMs matter, (B) translational research to link estimates to IAMs across spatial and temporal scales



Scenarios of Radiative Forcing
GCM 1
GCM 2
...
Projection of climate variables at grid scale
Temperature
Precipitation
...
Simulation of impact endpoints
Process Model Endpoint 1
Temperature response
Precipitation response
...
Process Model Endpoint 2
Temperature response
Precipitation response
...
...
...
Endpoint translation/ aggregation into sectoral shocks
CGE Model
Welfare Consequences
Scenarios of Radiative Forcing
GCM 1
GCM 2
...
Temperature
Precipitation
...
$\widetilde{M}$
Impact Emulator Endpoint 1
Temperature response
Precipitation response
Impact Emulator Endpoint 2
Temperature response
Precipitation response
$\hat{F}[M]$
$\Delta\tilde{F}$
CGE Model
Welfare Consequences

Implementational Challenges

- **<u>Goal</u>**: use $\widehat{F}$ to construct "shocks" to IAMs' regions and sectors, large-scale economic consequences of which can then be assessed
- Need to address potential disconnects with IAMs along several dimensions
  - Geographic coverage
    - Many IAMs global in scope, whereas $\widehat{F}$ may be specific to a country or even sub-national region
    - How can $\widehat{F}$ estimated at one scale be validly applied at another?
  - Sectoral specificity
    - Differences across economic sectors in $\widehat{F}$ likely
  - Constructing shocks: connecting $\widehat{F}$ with future climate forcing
    - Easiest to construct shocks by forcing $\widehat{F}$ with exogenous climate info (e.g., CMIP5 GCM outputs)
    - HOWEVER, shocks and subsequent assessments "locked in" to specific GCM x warming scenario combinations
    - For IAMs that incorporate a reduced-form climate model, using $\widehat{F}$ requires translating global mean temperature change into local temperature shifts
- Controlling for past adaptation
  - IAMs (especially CGE models) tend to capture passive market responses ("Type I" adjustments, Fisher-Vanden et al, 2013)
    - To get these right $\widehat{F}$ has to be purged of the influences of past adaptation, but these are often not observed (viz $\boldsymbol{Z}$), leading to potential double-counting
  - Calculating $\widehat{F}$ gross as opposed to net of adaptation generates shocks to IAMs that are biased downward, leading to potential further biases in simulated GE effects

Empirical Estimates

Let i index observational units (countries, states, dams), t index time periods (years, months)

Of interest is the relationship (F) between the impacted endpoint ($Y_{i,t}$) and one or more meteorological variables ($\boldsymbol{M}_{i,t}$), controlling for time-invariant individual heterogeneity (μ_i), unspecified exogenous influences affecting all units (τ_t), and confounding factors ($\boldsymbol{Z}_{i,t}$):

$$Q_{i,t} = \mu_i + \tau_t + F\left[\boldsymbol{M}_{i,t}\right] + \boldsymbol{Z}_{i,t}\boldsymbol{\gamma} + \varepsilon_{i,t}$$

Endpoints (Y)	Spatial/Temporal/Sectoral Scope	Climate Predictors (M)
Demand		
I. Energy use	Global, 1970-2010 (annual), ~100 countries, 3 energy carriers [IEA]	Temperature, Humidity [GLDAS]
II. Electricity sales	USA, 1990-2013 (monthly), 48 states, 4 sectors [EIA]	Temperature, Humidity [NLDAS]
Supply		
III, IV. Hydro	Global, 1970-2010 (annual), ~80 countries [IEA]	Runoff, Temperature, SPI [GLDAS]
generation	USA, 1970-2013 (monthly), ~900 dams [EIA]	Runoff, Temperature [GLDAS]

Choices Over M: Temporal

- Studies I and II use "bins" of temperature and humidity exposure
- Dependent variable is the sum over an averaging period (year or month)
- Within each t, compute length of time at each i spent in k temperature and m humidity intervals ($DT_{i,t}^{k}$, $DH_{i,t}^{m}$)
- Use high frequency historical weather observations from reanalysis data: 3-hr GLDAS/1-hr NLDAS forcing files
- Exposures correspond to the counts of 3-hr/1-hr observations in each bin
- <u>Implications</u>:

1. Future values of covariates calculated from GCM outputs will have to be temporally averaged in the same way as above
2. Because we force $\hat{F}$ with GCM outputs ($\widetilde{\boldsymbol{M}}$), we should ensure in advance that $\widetilde{\boldsymbol{M}}$ are available on the same or similar time-step [cf Risky Business!]
   - Use 3-hr fields for current and future periods from CMIP5 archive
3. Since $\hat{F}$ is generally nonlinear, <u>do not</u> calculate $\tilde{F}^{\text{Future}} = \hat{F}\left[\widetilde{\boldsymbol{M}}^{\text{Future}}\right]$ by first temporally averaging $\widetilde{\boldsymbol{M}}^{\text{Future}}$! This washes out fine temporal scale exposure to extremes, and associated potentially large responses. Instead, calculate $\tilde{F}^{\text{Future}}$ for <u>each</u> future t, <u>then</u> average. (Thanks Erwan!)

Choices Over M: Spatial

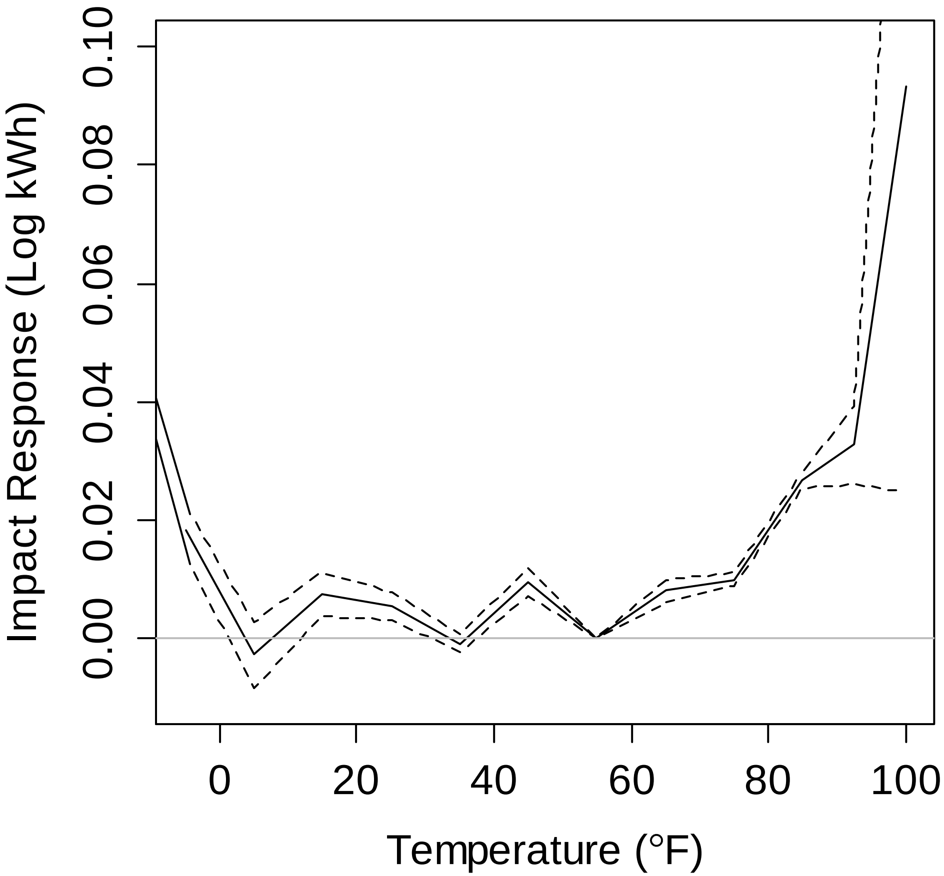
- Studies I, II and III use spatially averaged meteorological variables
- Study IV uses point estimates of temperature and runoff at a dam locations
- Dependent variable is the sum over a spatial domain (country or state)
- Within each i, compute exposure bins at scales close to climate data's native grids: 0.25° GLDAS/0.125° NLDAS
- Spatially aggregate exposure bins up to i
  - Studies I and II use gridded population
  - Study III uses geocoded locations of 37,000 dams, weighted by size of impoundment
- <u>Implications</u>:

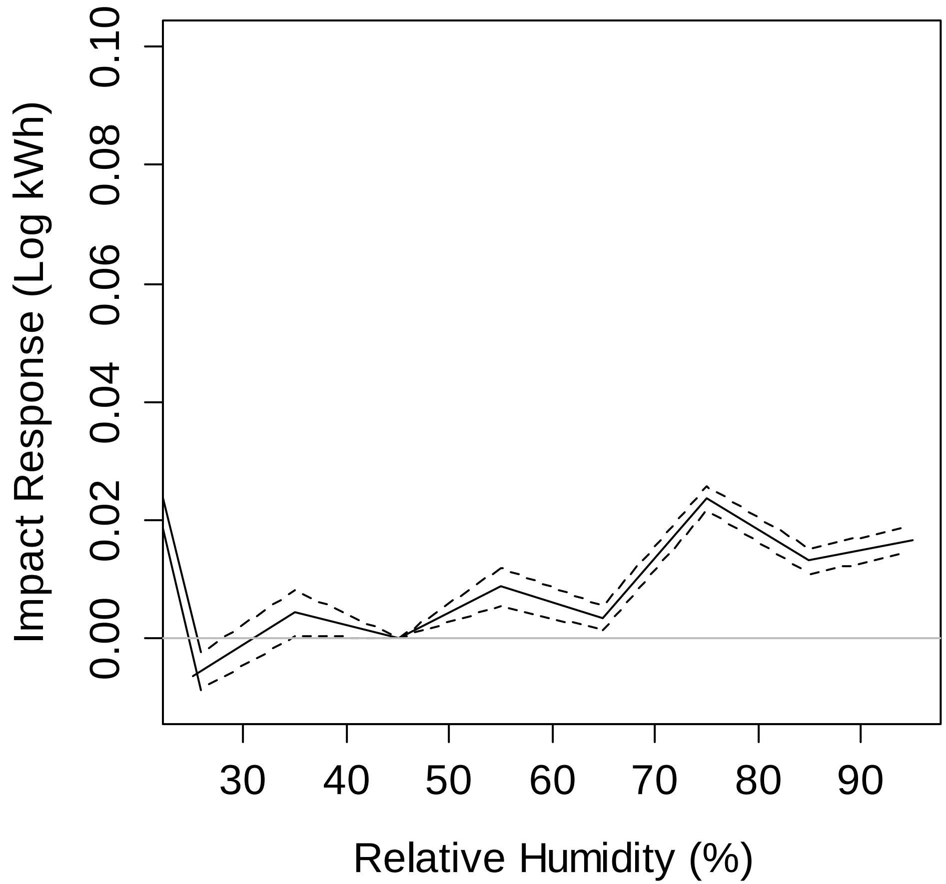
1. Open question whether future values of covariates calculated from GCM outputs have to be spatially averaged in the same way as above. Nonlinearity of estimated response suggests that we should force $\widehat{F}$ with $\widetilde{\boldsymbol{M}}$ calculated at fine spatial scales, and <u>only then</u> spatially aggregate the resulting responses. However, grid cells in GCM much coarser than those in reanalysis data, so differences may be small. (Testing = research in progress.)
2. In any case, aggregation will depend on future spatial distribution of population. We cannot foresee this, so calculate $\widetilde{F}^{\text{Future}}$ using current map as a placeholder. (SSPs to the rescue????)

A Success Story: US Electricity Demand

$$\log Q_{i,j,t} = \mu_{i,j} + \tau_{t,j} + \Sigma_k \beta_j^k DT_{i,t}^k + \Sigma_m \eta_j^m DH_{i,t}^m + \boldsymbol{Z}_{i,t}\boldsymbol{\gamma_j} + \varepsilon_{i,j,t}$$

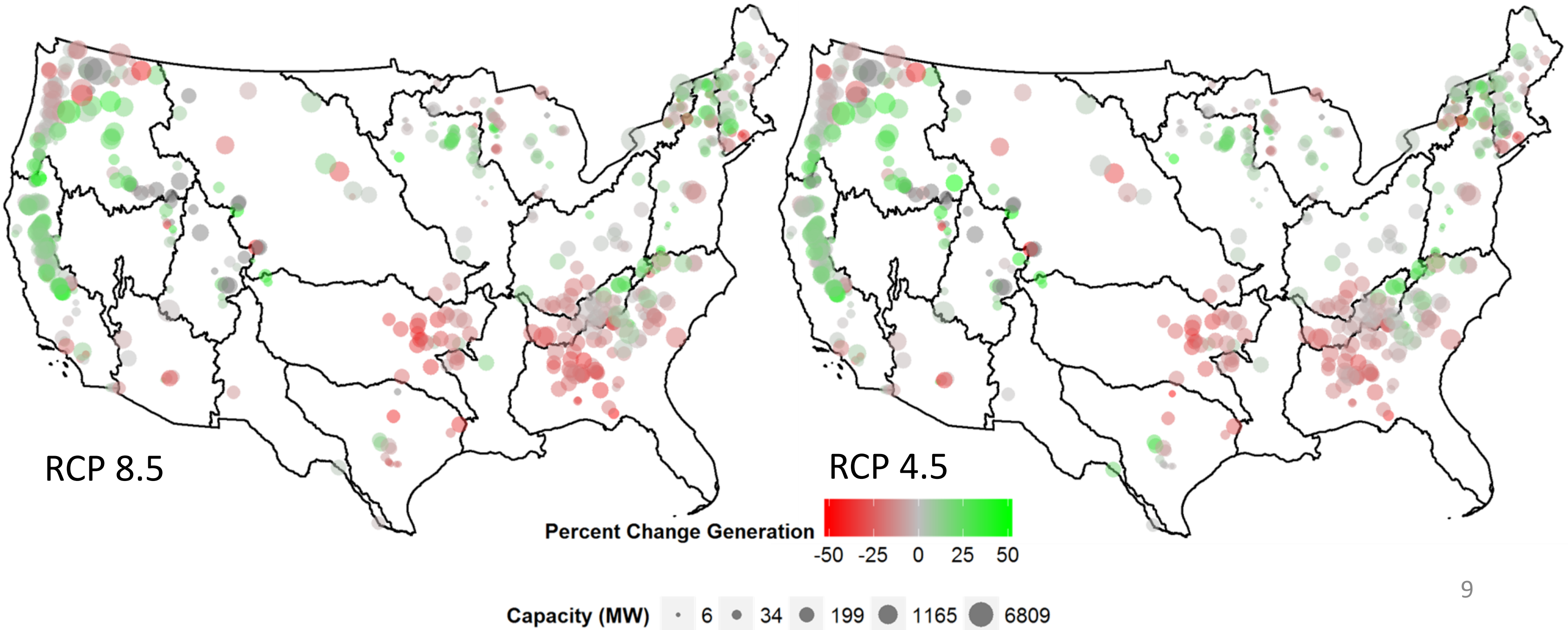
- $DT_{i,t}^k$, $DH_{i,t}^m$ calculated at county scale, aggregated to states using population weights
- Current work is using GCM data to compute $\widetilde{DT}^k$, $\widetilde{DT}^k$ at county scale, substitute into fitted regression model to obtain future county-level demands





A Failure: Climate Change Impact on Hydropower Production circa 2050

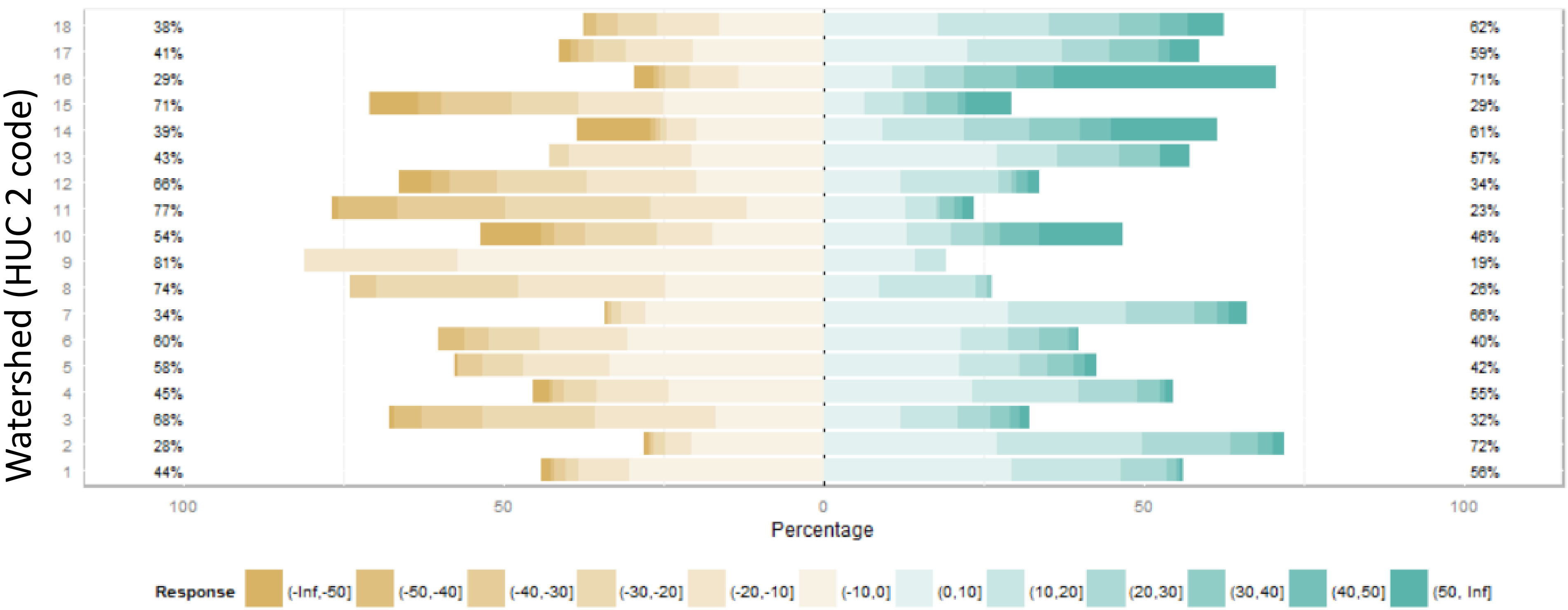
- The dependence of hydropower operating rules on meteorology is too complex to be captured by the simple piecewise-linear panel data model used in studies (I-III)
- Individual units' monthly generation time series had to be modeled using a hidden Markov model (HMM) that identifies latent states (low production/high production) and estimates Markov state transition probabilities as a function of current and cumulative runoff
- Future production has to be simulated as a Markov chain, forced by GCM data...



And on that note of failure...

- Wide variation in projections of total runoff from one GCM to another, and over space for each GCM
- Implication: within a given watershed (HUC2) large variation in effect of climate change, with as many units exhibiting increases in generation as reductions
- Net regional/national impact is small: around -2% of total hydro generation

← Fraction of units generating less　　Fraction of units generating more →



← Larger % generation decrease　　Larger % generation increase →