

1. Background and Motivation

Researchers, practitioners and policymakers increasingly require multi-scale electricity consumption data to understand how climate, demographics, and urban development shape residential energy demand.

No study has applied a principled downscaling framework to residential electricity consumption across the entire United States over multiple decades

Research problem

The “Spatial disaggregation” challenge in reported electricity data

- We only observe aggregated consumption (state).
- Yet we need fine-scale estimates (county, census-tract, or even grid cell)

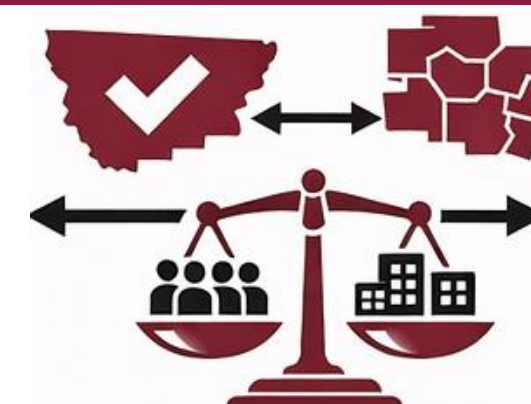
The Naïve “top-down” disaggregation

- Ecological fallacy
- Spatial and temporal dependency and heterogeneity hidden
- Misleading confidence

Objective and Theoretical aims

Develop a Bayesian latent Gaussian framework to downscale state-level residential electricity consumption to the county level—enforcing aggregate coherence using a hierarchical structure with spatio-temporal components.

Coherence



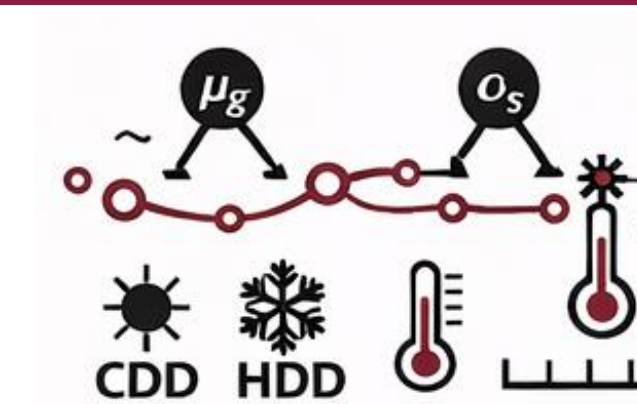
State ↔ County

Spatio-temporal smoothing



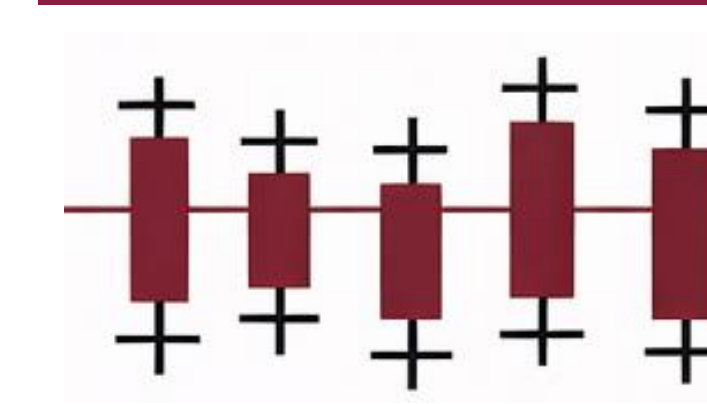
Structure random effects

Latent Gaussian regression



Climate based covariates

Outputs



Estimates-uncertainties

2. Research Objective

3. Data and Methods

Electricity usage	Population	Built land cover	Climate
Response variable	Downscaling weights	Downscaling weights	Covariates
Residential total electricity consumption (kWh)	Population counts	building type, indoor area	CDD and HDD
State-level, monthly	Annual, Gridded 1 km ²	5-yr, gridded 250 m	County-level, monthly

Bayesian latent Gaussian Hierarchical Model

Data (state-months) → Latent process (county-months) → Hyperparameter
Inference using Integrated nested Laplace approximations (INLA)

$$y_{obs} \sim \text{Gamma}(\mu, \kappa), \quad \mu = A_{obs} \exp(\eta)$$

$$\eta = X_{county} \beta + Zb$$

$$b \sim \mathcal{N}(0, Q(\theta)^{-1})$$

Where **b** collects all random effects, and **Q(θ)** is a block diagonal precision matrix parameterized by hyperparameters **θ**.

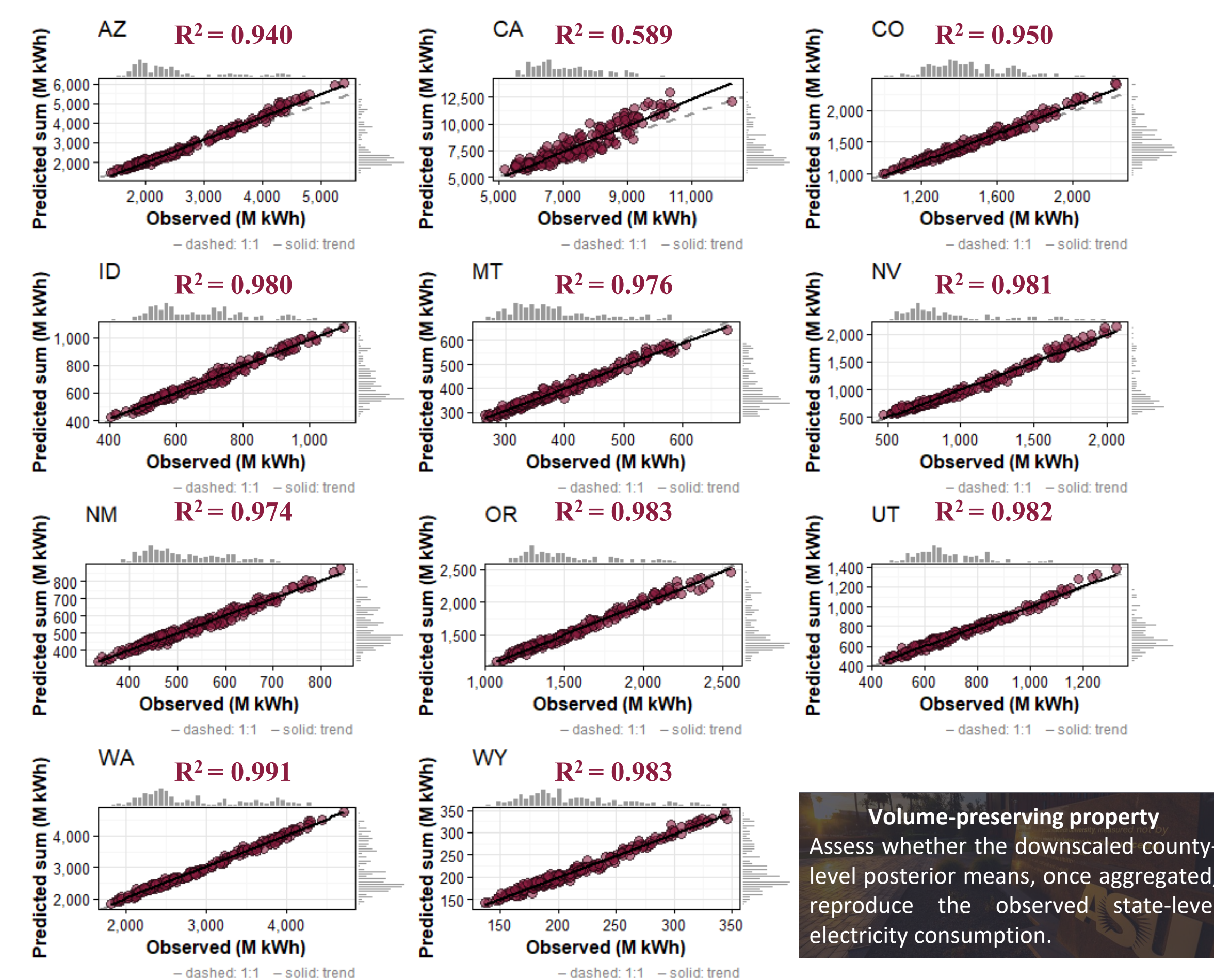
- The link between scales is captured by the projection matrix A_{obs}
- The spatial BYM ICAR component introduces local dependence
- The temporal precision matrices from the random walk RW2 enforce smoothness

5. Key Takeaway

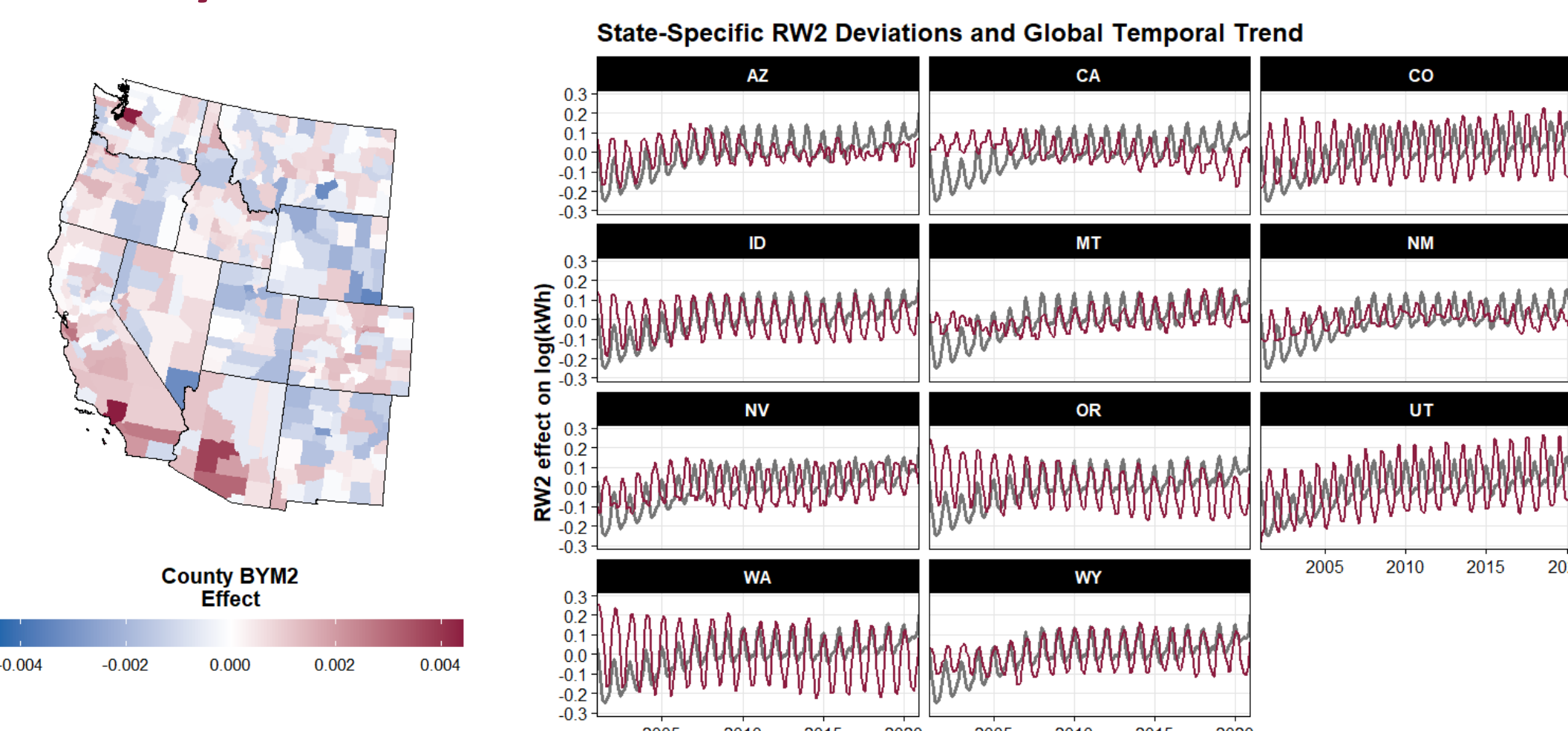
A single hierarchical latent-Gaussian model—with unstructured and structured random effects, a weighted projection matrix, and a Gamma likelihood—coherently downscales state-level electricity data to the county level, reconciling aggregates while capturing spatial and temporal dependence.

Datasets

4.1 Volume Preserving Property Validation by State

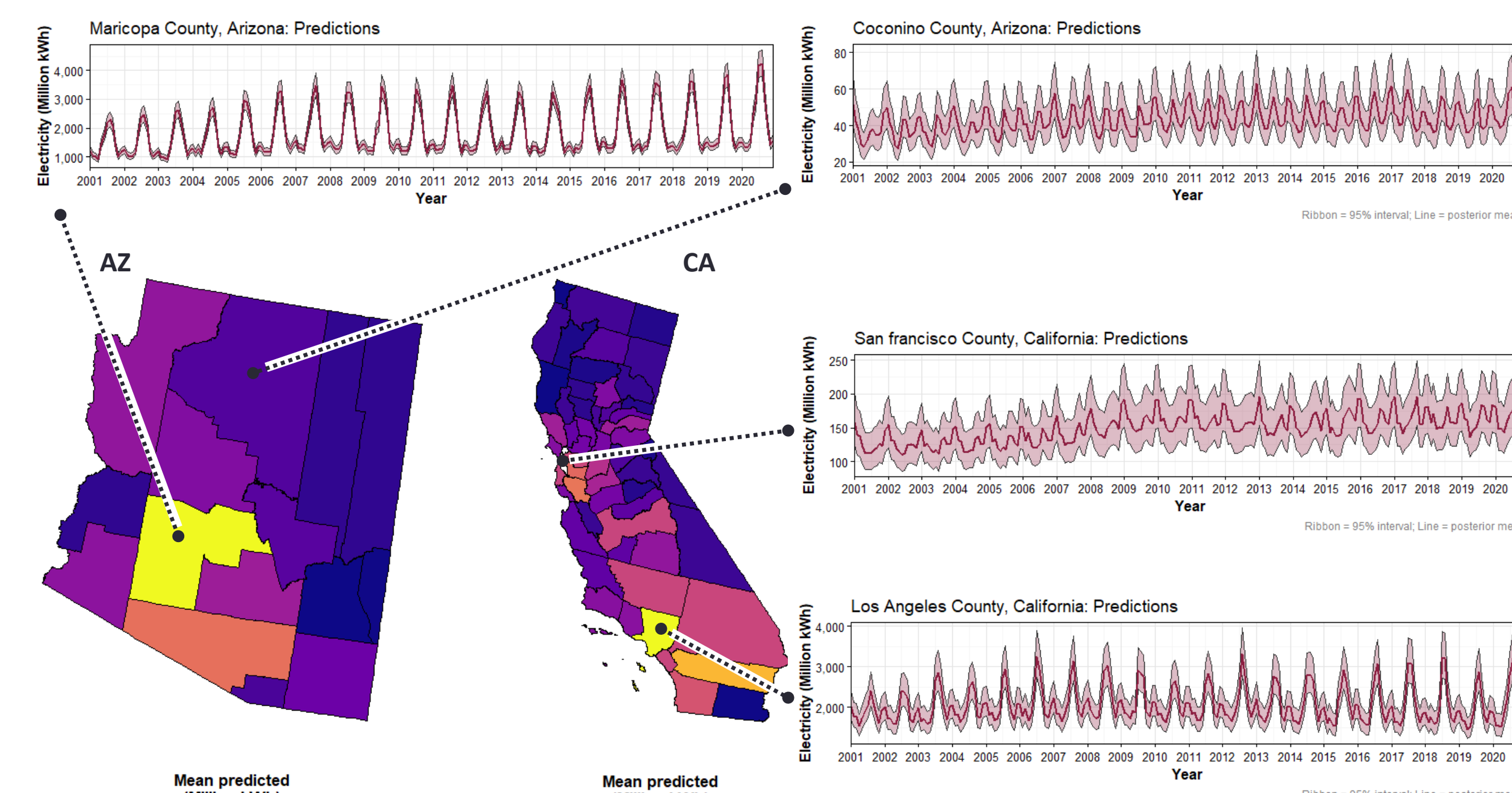


4.2 County-level BYM2 and Global vs State RW2 Random Effects



4. Results and Discussions

4.3 County Level Monthly Predictions



Average predicted residential electricity consumption over study period
County values are posterior means aggregated across time

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County values are posterior means aggregated across time

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