Assessing Uncertainty in Regional Climate Experiments

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Supported by NSF ATM/DMS.

Goals

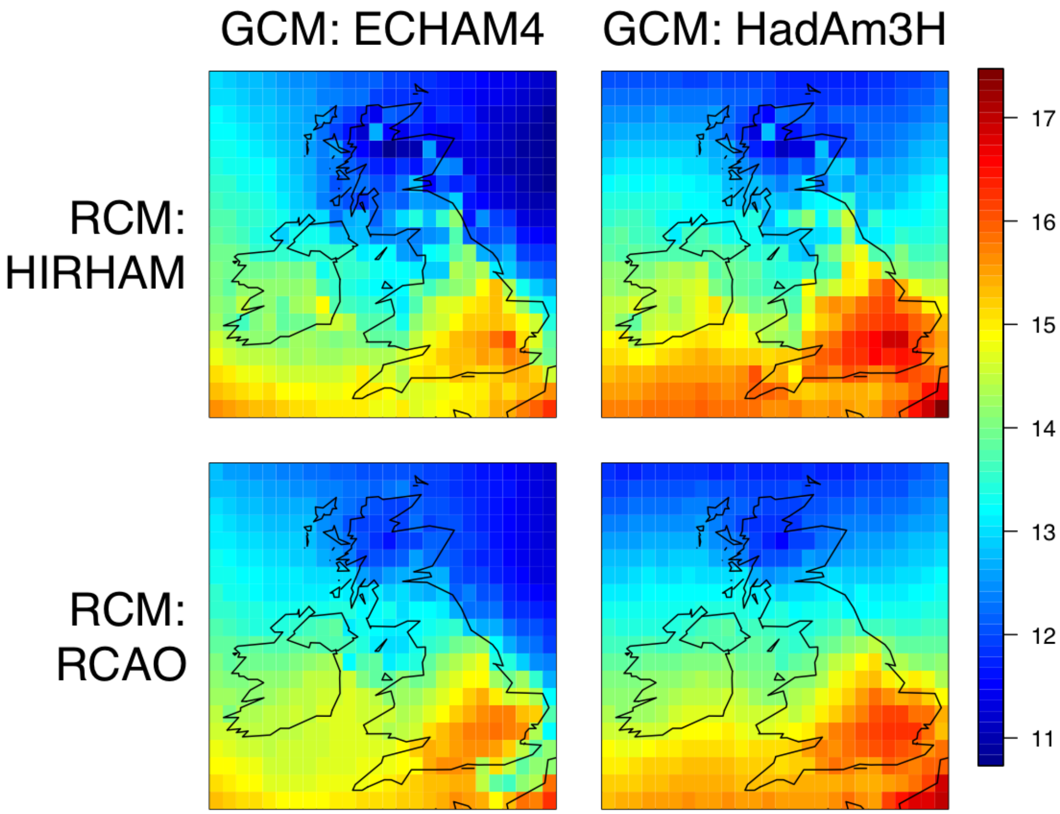
- Describe the distribution of model output.

- Understanding sources of variation.
  - GCM, RCM, GCM$\times$RCM, Time Slice, etc.

- Combining model output – moving towards a scheme for weighting models.

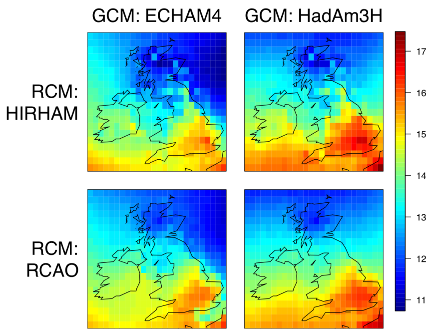
- Recognizing that the climate model output represents spatial and/or spatial-temporal fields, we are developing methodology for a type of *functional ANOVA*.
  - Gaussian process ANOVA (Kaufman and Sain, 2007).

Functional ANOVA



- 2x2 “experiment”
  - 2 GCMs, 2 RCMs
  - PRUDENCE
- 1961-1990
- JJA average temp

Functional ANOVA

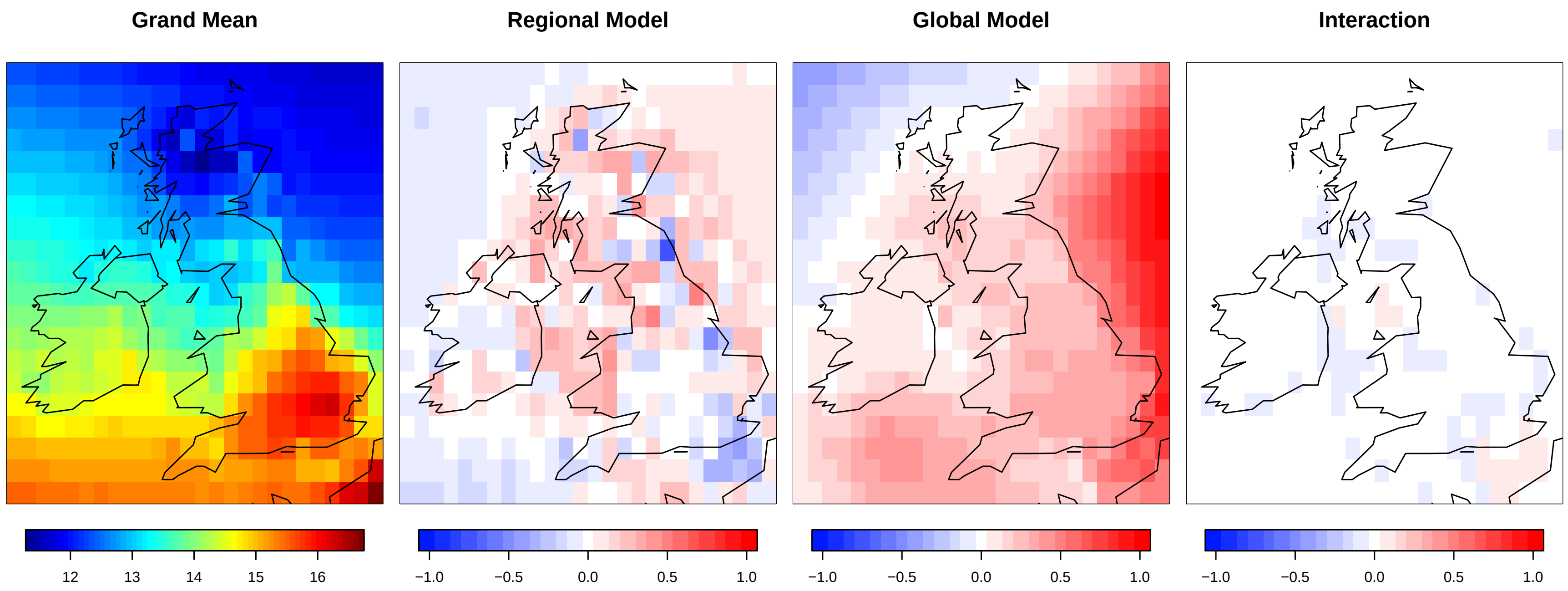


$Z_{ijt}(s)$	$=$	$\mu_{ijt}(s)$	$+$	$\epsilon_{ijt}(s)$
Output of RCM i, GCM j, at time t and location s	$=$	Expected/ "Climate" response	$+$	Spatially correlated residual/ "internal model variability"

$$\begin{array}{ccccccccccc} \mu_{ijt}(s) & = & \mu(s) & + & i\alpha(s) & + & j\beta(s) & + & ij(\alpha\beta)(s) & + & \gamma t, \\ & = & \text{Common} & + & \text{RCM} & + & \text{GCM} & + & \text{Interaction} & + & \text{Time} \end{array}$$

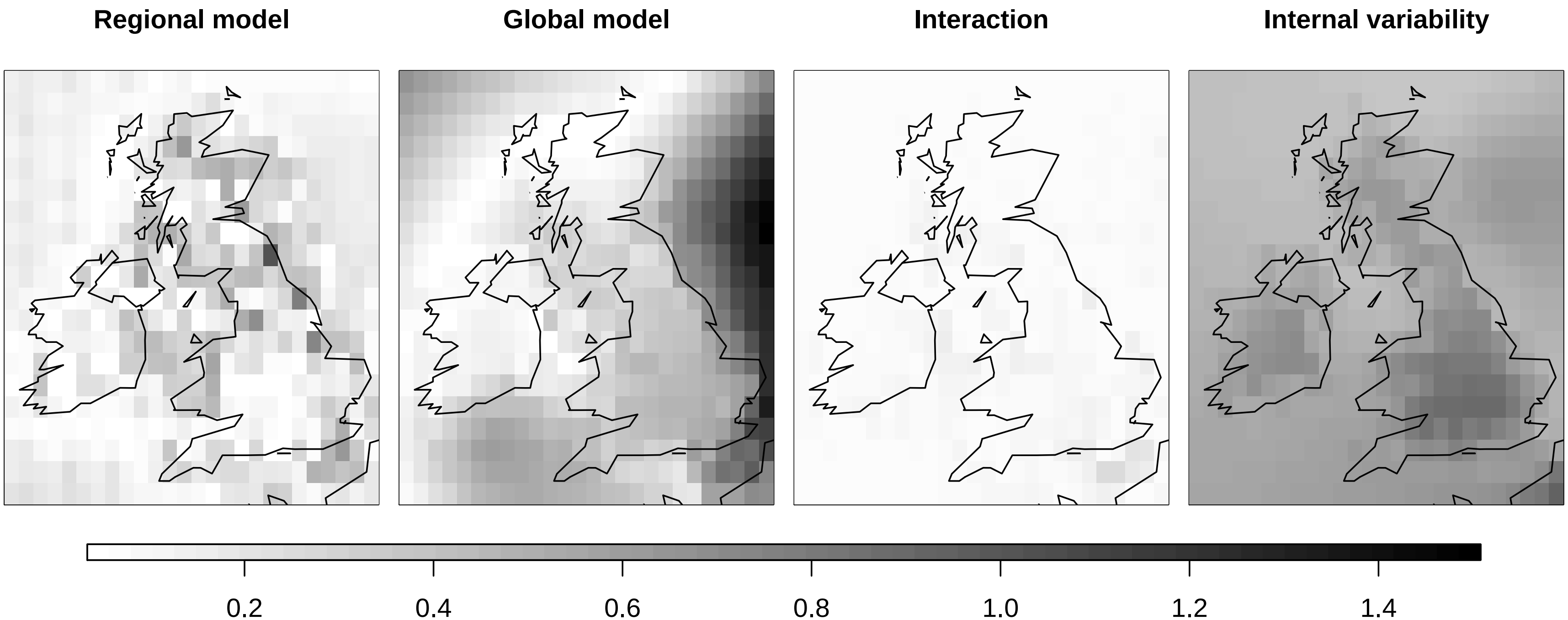
- $i, j = -1, 1$ (contrast coding)
- Hierarchical model with Gaussian process priors used for each effect.
- MCMC used to estimate parameters, posterior inference, etc.

Functional ANOVA



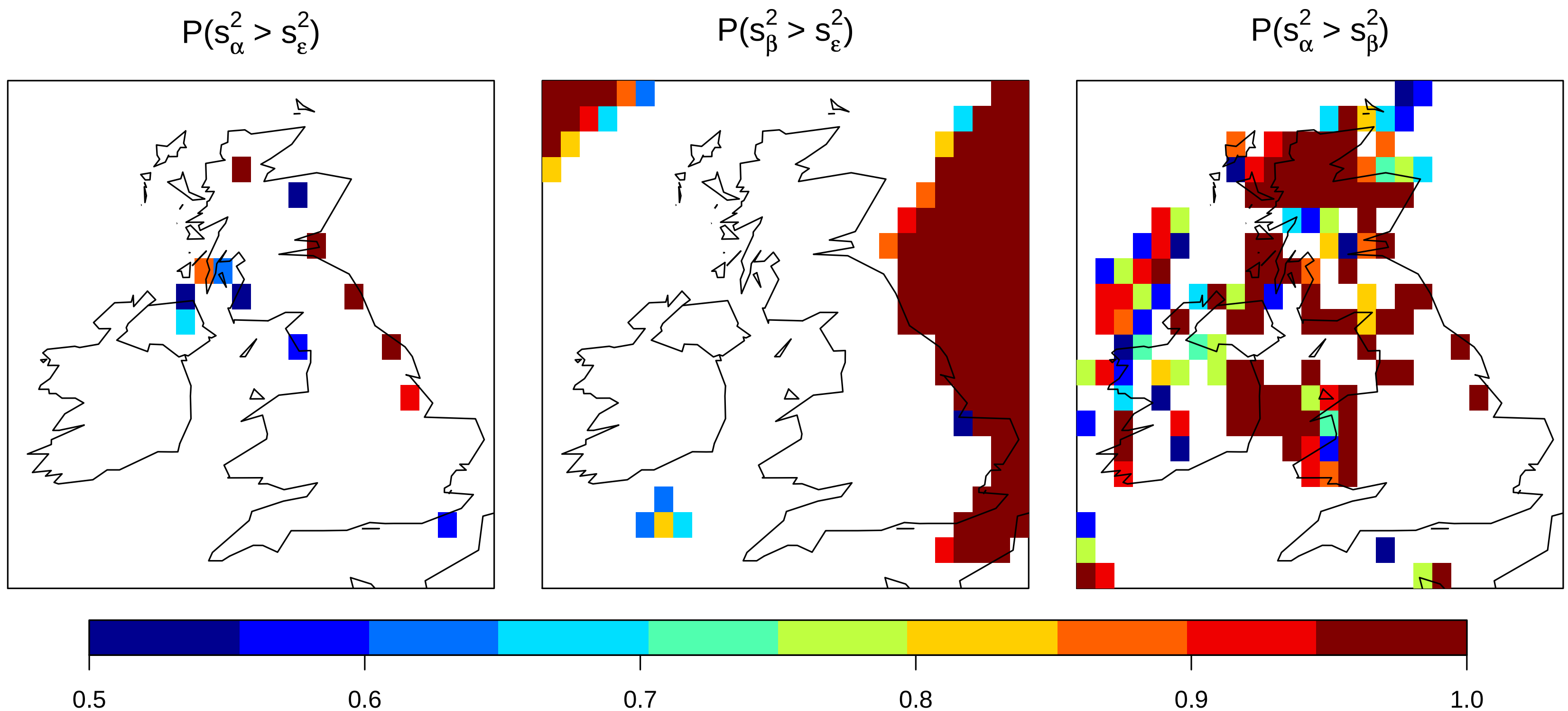
- Estimates of spatial effects.

Functional ANOVA



- Posterior mean of variance components.

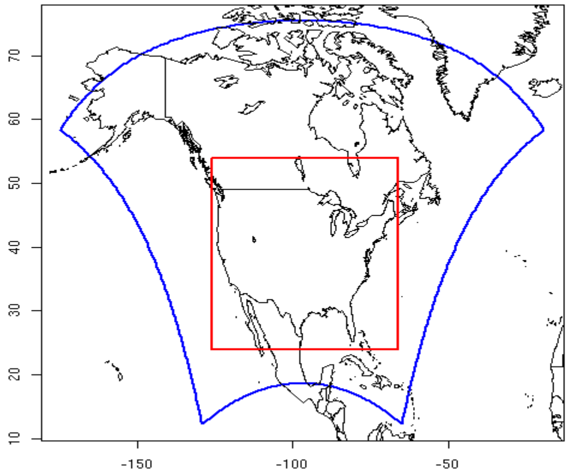
Functional ANOVA



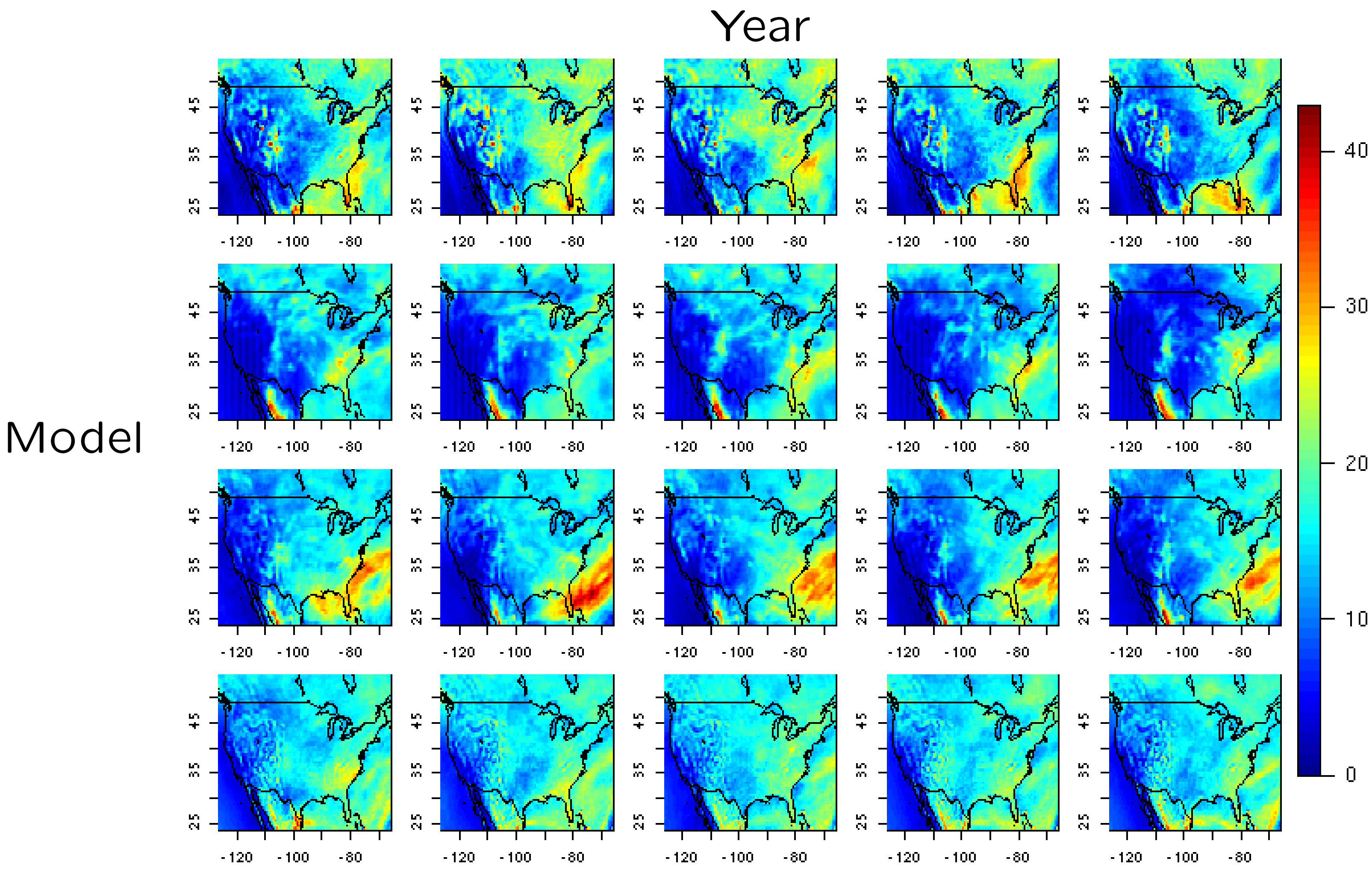
- Ratios of variances.

A Work in Progress

- 4 regional models.
- Total JJA precipitation, 1996-2000.



Model Output



A Functional ANOVA Model

- A single-factor ANOVA model:

$$\begin{aligned} Z_{it}(s) &= \mu(s) + h_i(s) + \epsilon_{it}(s) \\ &= \text{Common} + \text{RCM} + \text{Error} \end{aligned}$$

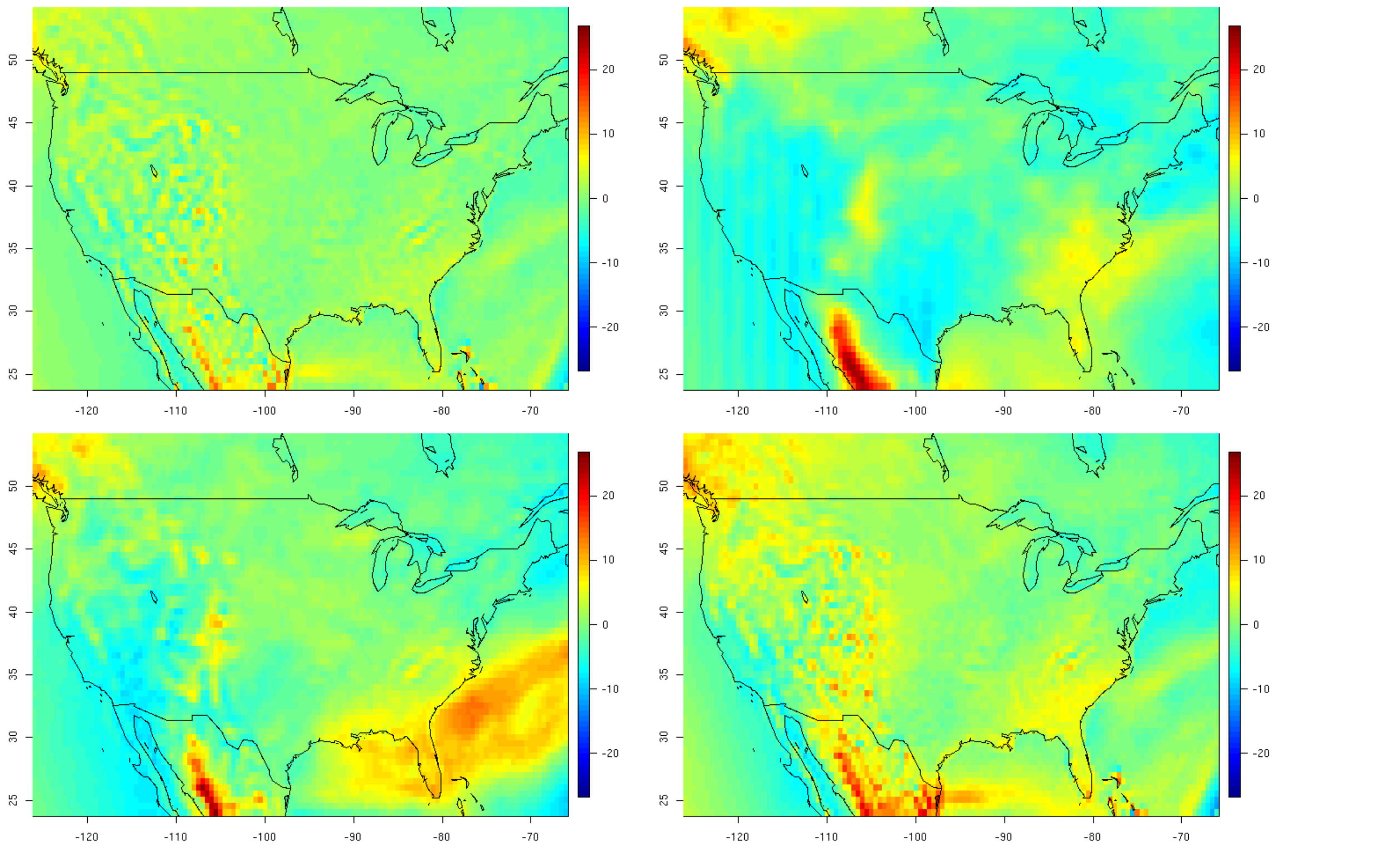
- Hierarchical model with Gaussian prior (with spatial covariance) on $h_i(s)$.

- $\mu(s) = x(s)'\beta$ (based on NCEP).

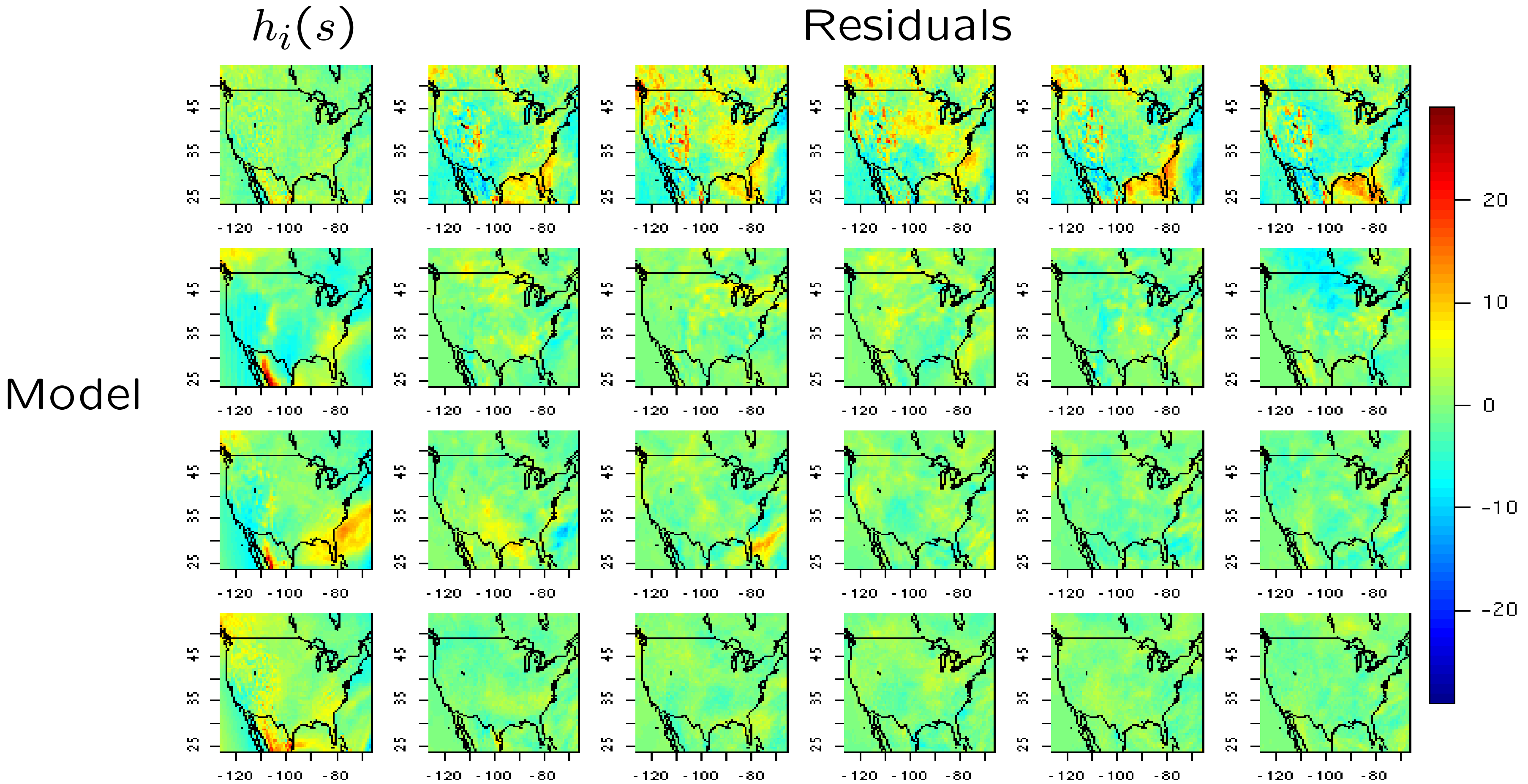
- Errors $\epsilon_{it}(s)$ are also spatially correlated Gaussian.

- MCMC to estimate parameters, posterior inference, etc.

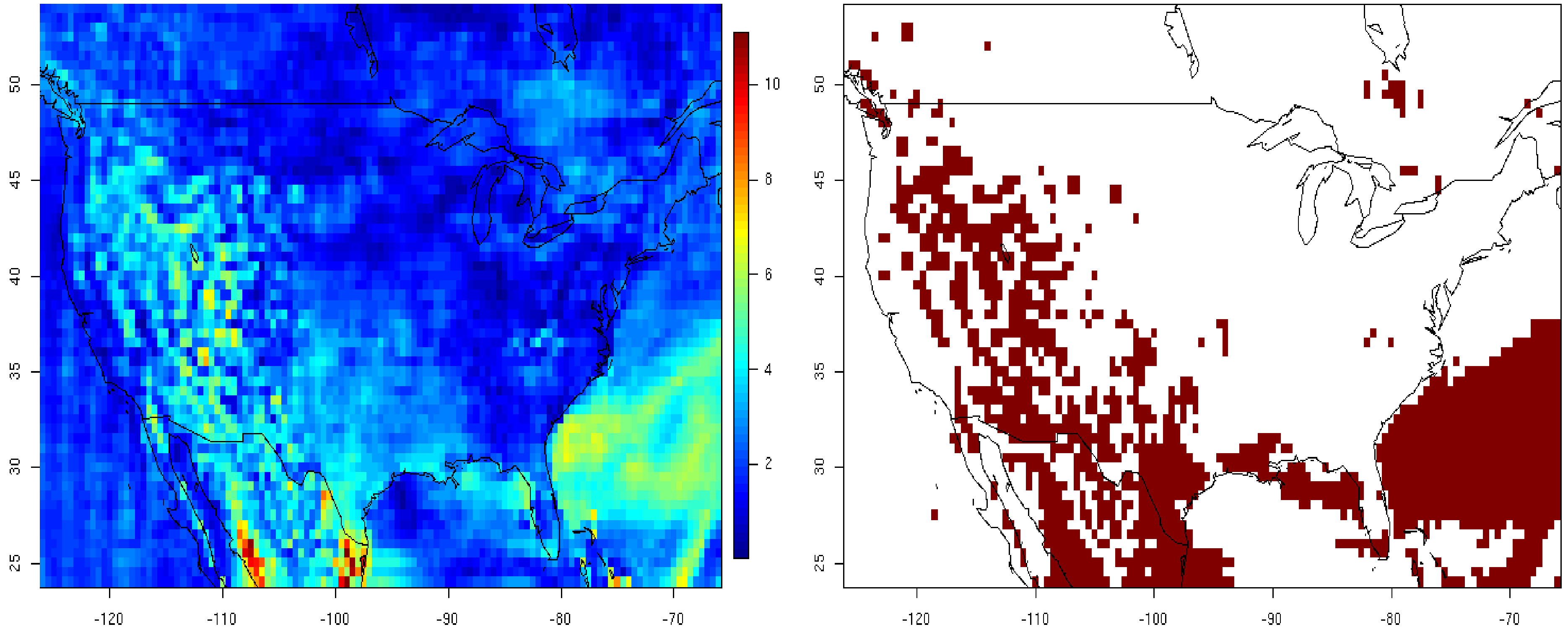
Results ($h_i(s)$, Posterior Means)



Results (A Posterior Draw)

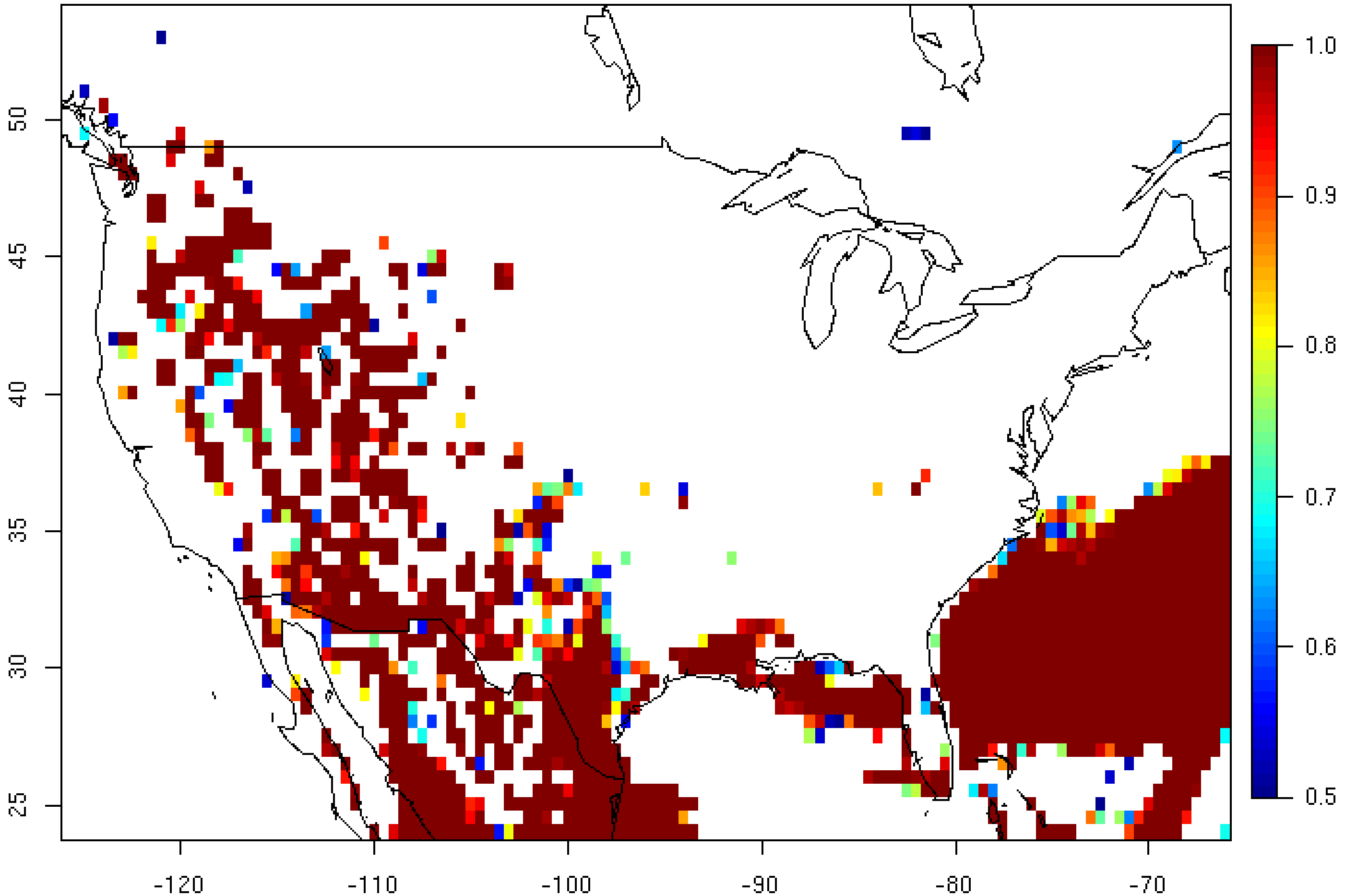


Results (A Posterior Draw)



- Compare s_h^2 to s^2; highlight where $s_h^2 > s^2$.

Results ($P[s_h^2 > s^2]$)



A Proposal for Combining Model Output

- Assumption of model output representing iid random draws may not be reasonable.

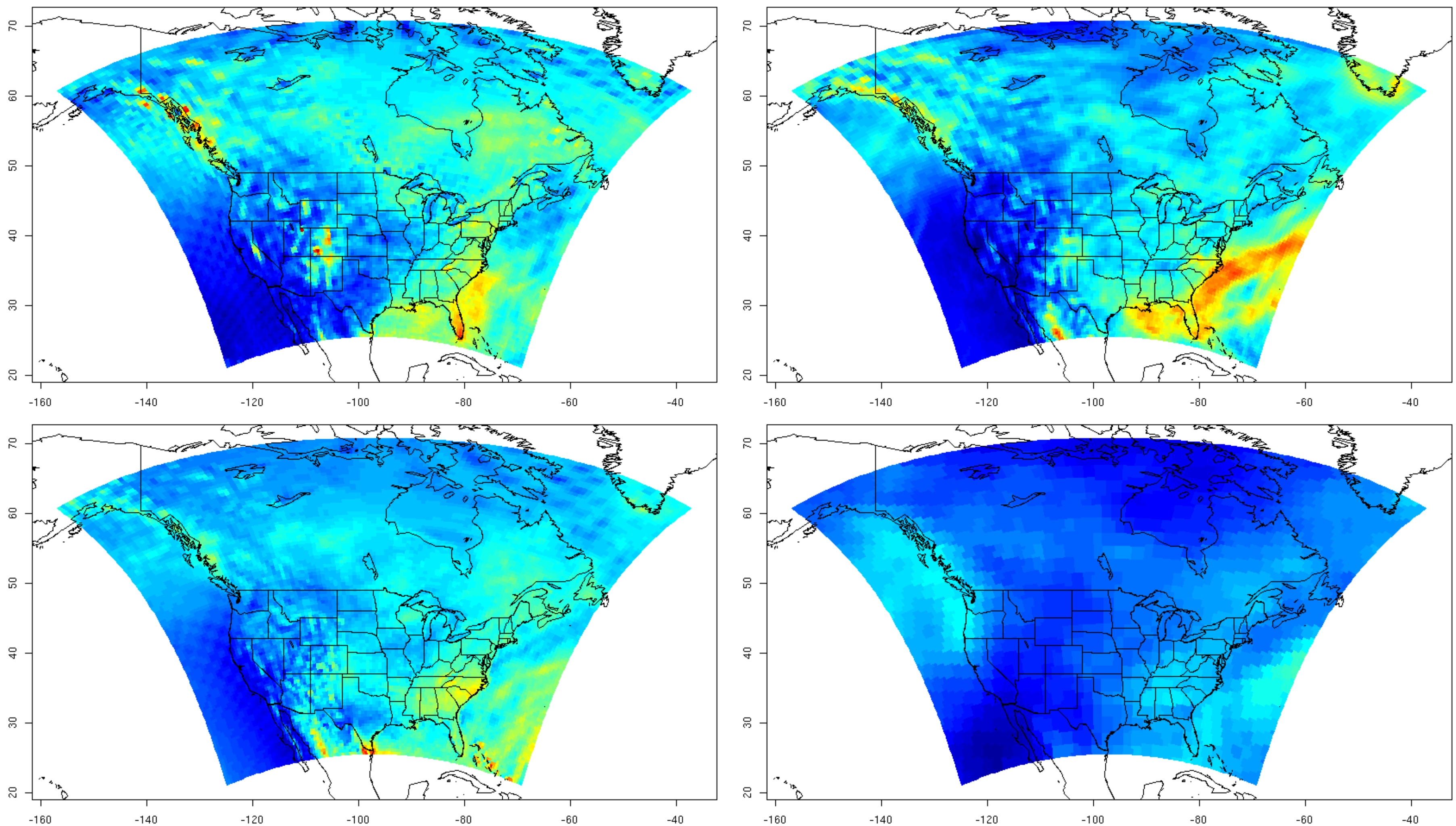
- A modified model:

$$\begin{aligned} Z_{it}(s) &= \mu(s) + h_i(s) + \epsilon_{it}(s) \\ &= \text{Common} + \text{RCM} + \text{Error} \end{aligned}$$

- The key difference is the prior on $h_1(s), h_2(s), h_3(s)$ is Gaussian with mean $\mathbf{0}$ and

$$\text{Var}\begin{pmatrix} h_1(s) \\ h_2(s) \\ h_3(s) \end{pmatrix} = \Sigma_h$$

A Proposal for Combining Model Output



A Proposal for Combining Model Output

- The model-to-model covariance, Σ_h, can be used to create a linear combination of the $h_i(s)$.

- Assuming $E[h_i(s)] = \mu(s)$, it is easy to show that the $\mathbf{w}$ that minimizes the variance of $\sum_i w_i h_i(s)$ is the solution to

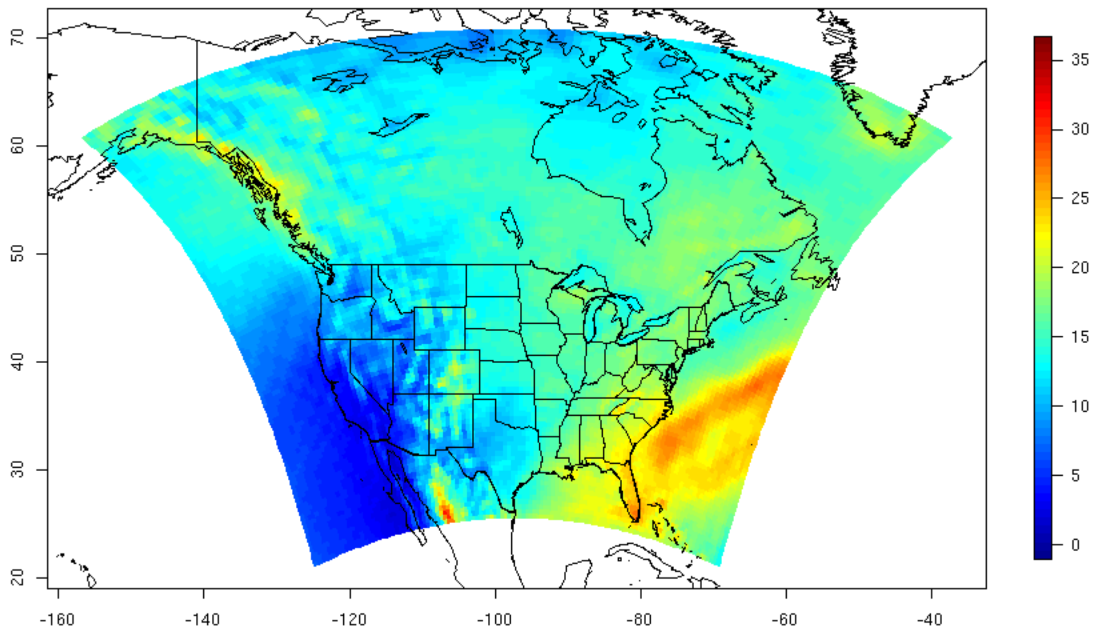
$$\begin{pmatrix} \Sigma_h & -\mathbf{1} \\ \mathbf{1} & 0 \end{pmatrix} \begin{pmatrix} \mathbf{w} \\ \lambda \end{pmatrix} = \begin{pmatrix} \mathbf{0} \\ 1 \end{pmatrix}.$$

- Other ideas: maximize variance (principal components), etc.

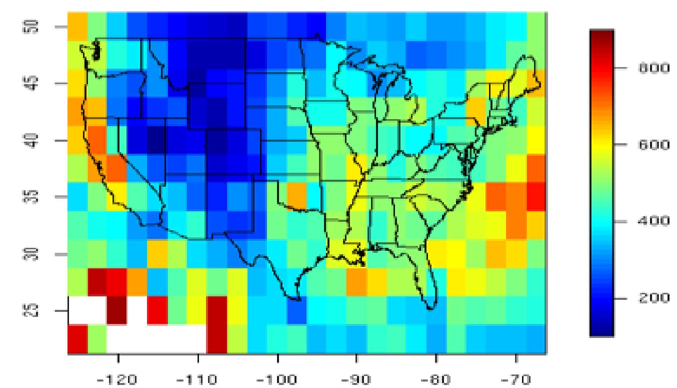
A Proposal for Combining Model Output

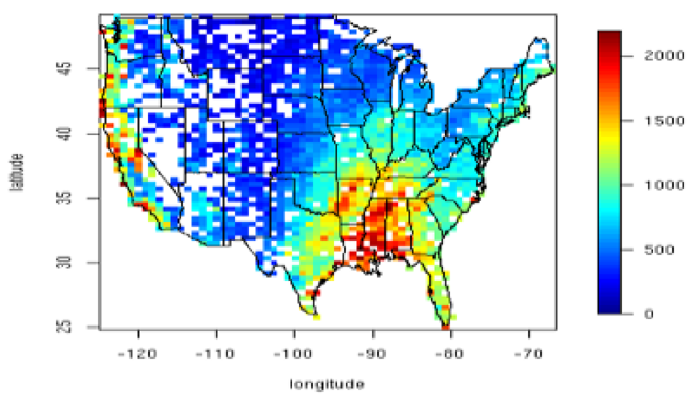
$$\widehat{\Sigma}_h = \begin{pmatrix} 2.05 & 0.66 & 0.37 \\ & 0.94 & 0.50 \\ & & 1.37 \end{pmatrix}$$

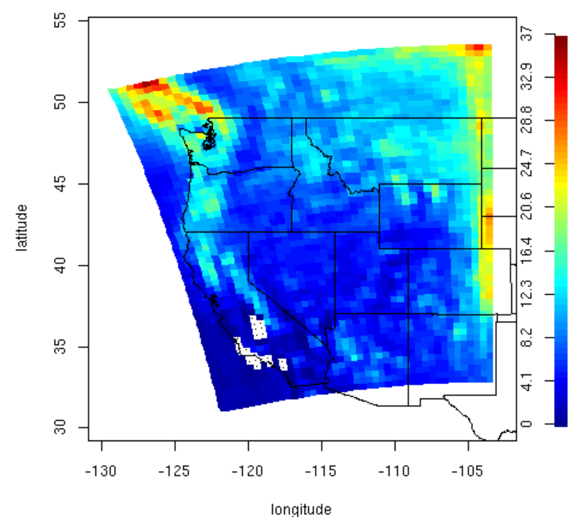
$$\widehat{\mathbf{w}} = \begin{pmatrix} 0.14 \\ 0.54 \\ 0.32 \end{pmatrix}$$

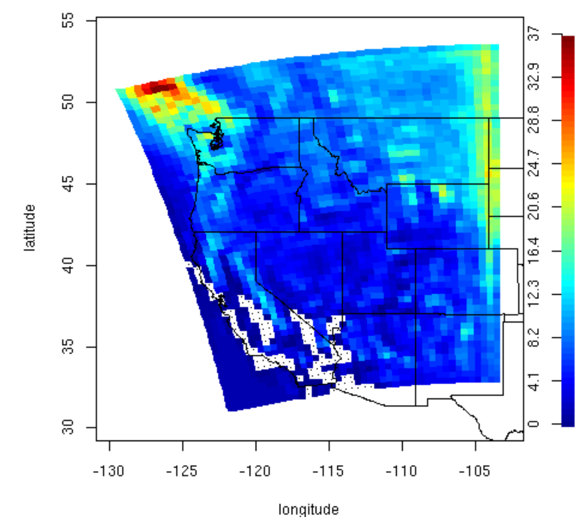


Extremes









- Spatial scaling of return levels.

- Comparing spatial distributions of extremes.

Questions?

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